

DO SPATIAL EFFECTS DRIVE HOUSE PRICES AWAY FROM THE LONG-RUN EQUILIBRIUM?

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ABSTRACT

Long-run equilibrium of house prices has been investigated by researchers in multiple countries. The identification of this equilibrium not only provides references against contemporary house price levels, but also contributes to creation of stable-development policies and healthy investment strategies. However, there is little research investigating the factors that drive house prices away from the long-run equilibrium.

Based on a framework of the conventional stationarity test process, this research develops a panel regression model and a spatial regression model to investigate the roles of spatial heterogeneity and correlations on house prices preceding the long-run equilibrium, respectively. Housing data generated from the capital cities in Australia are used to illustrate the models. Spatial effects can have a strong influence in the long-run performance of house prices, while the short-run performance of house prices is not influenced by the spatial effects.

Keywords: long-run equilibrium, panel dynamic regression, spatial panel regression, house price indices.

INTRODUCTION

Immobility of houses makes location one of the most important determinants of house prices. Houses with different locations can be sold at different prices, even if they are the same in other characteristics such as structure, size, building materials and so forth. Prices of houses within a nearby location may appear similar, although they are different in their own characteristics. The locational distinctions and clusters of house prices are referred to as spatial heterogeneity and spatial dependence which, in this research, are regarded as spatial effects. Conventional house price modelling approaches, such as hedonic modelling and repeat sales modelling, account for the spatial effects on house prices by implementing corresponding indicators into the regression models. However, additional indicators may not reflect the appropriate spatial condition of houses and may make the regression more complicated.

The advantages of employing spatial statistics into real estate studies were highlighted and implemented to predict house prices by filtering the spatial and temporal dependence with weight matrices based on repeat sales models (Pace et al 1998a; Pace et al 1998b). In order to simulate temporal and spatial effects on house price evaluations, the spatial and temporal lags were substituted from both the dependent and explanatory variables. The improved spatio-temporal model provides better price predictions of individual houses at certain time points.

The advantages of spatial econometric analysis were argued by Anselin and Lozano-Gracia (2008), suggesting that 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.

It may be argued that panel data sets are advanced compared to purely cross-sectional or time-series data (Hsiao 2007). Due to the large number of data points supplied by panel data, this regression method will increase the degrees of freedom and reduce the collinearity among explanatory

variables. The advantage of the panel data regression technique is that it enables the study of temporal and spatial effects on the observable variables.

The spatial effects on house prices do not only attract attention from regional housing studies, but also are highlighted in interregional housing studies. Three issues surrounding house prices across regions or countries were the focus of many previous studies, including long-run equilibrium of house prices, segmentation of house prices and ripple effects of house prices (Drake 1995; MacDonald and Taylor 1993b; Tu 2000).

The notion of house price long-run equilibrium assumes that house prices should converge to long-run steady states across the regions. However, spatial heterogeneity drives regional house prices away from the steady states. Spatial dependence, on the other hand, makes the house price in one region correlate with the house price in another region nearby. Therefore, Meen (1999) states that the housing market should be recognised as a series of interconnected sub-markets. A house price shock in one region may spread out to the house price in other regions with temporal lags associated with their spatial characteristics. This house-price-shock spreading process is known as a ripple effect.

Early research investigating house price long-run equilibrium was mainly conducted through time-series methods, especially unit root test models. However, these methods ignore the heterogeneity and spatial effects of houses. This research, therefore, develops a spatial panel regression model, which is able to capture the effects of heterogeneity, spatial and temporal information to analyse house price long-run equilibrium.

The paper is organised as follows: the next section introduces the background of spatial regression methods; the subsequent section illustrates the methodologies of spatial regression and theoretical models for investigating long-run equilibrium of house prices; the following section then presents the characteristics of housing in Australian capital cities, followed by the testing results; and the final section draws conclusions.

LITERATURE REVIEW

Instead of accessing house prices at an aggregate level or individual regional level, research in the early 1990s began to investigate regional house prices across the UK from an interregional perspective. MacDonald and Taylor (1993a) argued that segmentations, long-run equilibrium relationships and ripple down effects were three core issues in assessing interregional house prices across the UK. Their research provided evidence to show the segmentation of regional house prices, as well as the presence of ripple effects. However, their research failed to disclose the long-run equilibrium relationships between regional house prices. Unit root tests in panel regression models are therefore developed to account for the effects of heterogeneity (Im et al 2003; Levin et al 2002). Due to the advantages of using panel unit root tests, compared to time-series tests, panel regression methods are increasingly utilised to assess long-run equilibrium issues in house prices.

Holmes (2007) proposed an innovative approach to investigation of the long-run equilibrium of price ratio, employing the unit root tests within a Seemingly Unrelated Regression (SUR) framework. In further research, Homes and Grimes (2008) employed first principal components into regional-national house price differentials of the United Kingdom. The results suggested that constancy long-run equilibrium did exist among all regions of the UK. The panel regression methods on house price long-run equilibrium have proven more reliable than the univariate and panel data unit root tests, since they consider heterogeneity of the regional speeds in proceeding to steady states. However, panel regression methods still cannot address the effects generated from spatial or regional information on house prices.

Tu (2000) carried out unit root and co-integration tests to investigate the segmentation of regional housing markets across Australia. The findings showed that the long run and short run house price economic determinants were different at the national level. The housing markets of Australia were highly segmented across cities and short run causal relationships between the house prices in Sydney, Melbourne and Brisbane were found. The issue of segmentation of housing markets was also confirmed by comparing a set of submarkets in Auckland (Bourassa et al 2003). The authors divided the Auckland housing market into several submarkets based on geographic areas. By comparing the predictions of house prices generated from different models, the model using housing market segmentation showed stronger forecasting power. Meen (1996) investigated the nature of temporal interconnections of UK regional house prices, with results showing that UK regional housing markets were heterogeneous and temporally dependent on each other.

Instead of using econometric models, Cook and Thomas (2003) applied a non-parameter method to examine ripple effects in UK regional house prices. Strong evidence in favour of ripple effects was found by their research. Not only were ripple effects of house prices discovered in the UK, but they were also found in the Irish housing markets (Stevenson 2004). Based on the results generated from a unit root test and vector error correction model, Stevenson highlighted the existence of house price diffusion patterns. Liu et al (2009) conducted a variance decomposition based on a structure VAR model to investigate the ripple effects of Australian regional house prices. Their research found significant evidence to support the interdependences of house prices across Australian capital cities.

Although interregional house prices in various countries have been explored in previous research, little literature was identified to present systematic explanations about the involved issues. Meen (1999) interpreted the ripple down behaviours among regional house prices through four potential factors including migration, equity transfer, spatial arbitrage and spatial patterns in the determinants of house prices. Meen (1999) argued that regional house price movements in the UK should be decomposed into three components: movements common to all regions; regional fundamentals; and the structures of regional housing markets.

Ma and Liu (2010) proposed a three-dimensional decomposition of house prices under a panel regression framework. They demonstrated that a regional house price change should be influenced by regional specific factors, home-market factors and neighbourhood-market factors. They applied this panel dynamic model to the Australian capital city housing markets, finding that spatial heterogeneity existed across the Australian regional housing markets.

Since spatial effects on house prices have been increasingly mentioned by previous literature on house prices, panel regression and spatial econometric techniques may be 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.

The predictive power of spatial correlation modelling in house prices was also demonstrated in previous literature, with Zhu et al 2011 proposing an approach to modelling anisotropic autocorrelation in house prices. By comparing the predictive accuracies generated from three different methods, the authors suggested that taking account for spatial autocorrelation should reduce forecast errors.

Another study established a spatial and temporal vector error correction model to investigate 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 construct spatial weights. The spatial characteristics of a city or region were assumed temporally invariable by previous studies. Ma and Liu (2013) compared spatial effects caused by geographic and demographic characteristics on house prices in Australian capital cities. Their results confirm that house price ripple effects are more dependent on spatial effects based on geographic characteristics rather than demographic characteristics.

METHODOLOGIES

General Descriptions of Spatial and Regression Models

Based on the framework of the spatial panel regression model, the notion of spatial models may be raised to deal with economic activities (Beenstock and Felsenstein 2007; Fingleton 2008). This novel model, containing both the spatial and temporal lags, allows for the disturbances of the model to be correlated with each other spatially and temporally.

This section presents the spatial models and regression techniques. The spatial model is built on the framework of the panel VAR and spatial panel regression models. In order to control the effects generated from both the temporal and spatial information, temporal and spatial lags are implemented in the panel data model. The equation of the variable y_{it} for a region i at time t is expressed as follows:

$$y_{it} = \alpha_i + \beta_i y_{it-1} + \gamma_i \sum_{j=1}^N w_{ij,t-1} y_{j,t-1} + \varepsilon_{it}, \quad (i = 1, 2, \dots, N; t = 1, 2, \dots, T)$$

Equation 1

where:

- α_i = the regional specific effect
- β_i = the elasticity of the temporal lag of the variable
- γ_i = the elasticity of the spatial lags of the variable
- ε_{it} = the error term standing for the unobserved factors

It can be seen that if $\gamma_i = 0$, Equation 1 will convert to the panel regression model. The vector expression of Equation 1 may be described as follows:

$$Y = A + BLY + \Gamma WY + E$$

Equation 2

where:

- L and W = the temporal lag operator and spatial weight matrices respectively
- Y = an $NT \times 1$ vector of the observing variables of the N regions over the time periods of T
- $A = (\alpha_1, \alpha_2, \dots, \alpha_N)' \otimes e_T$, denoting the regional specific effects
- E = a $NT \times 1$ vector indicating the error terms of the model
- B and Γ = the $NT \times NT$ block diagonal matrices, inducing the coefficients of the temporal and spatial lags respectively

They may be expressed as follows:

$$B = \begin{bmatrix} \beta_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \beta_N \end{bmatrix} \otimes I_T \text{ and } \Gamma = \begin{bmatrix} \gamma_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \gamma_N \end{bmatrix}.$$

The variance-covariance of the error terms is denoted by V , being expressed as follows:

$$V = E(\varepsilon\varepsilon') = \begin{bmatrix} \varepsilon_1\varepsilon_1' & \varepsilon_1\varepsilon_2' & \cdots & \varepsilon_1\varepsilon_N' \\ \varepsilon_2\varepsilon_1' & \varepsilon_2\varepsilon_2' & \cdots & \varepsilon_2\varepsilon_N' \\ \cdots & \cdots & \ddots & \cdots \\ \varepsilon_N\varepsilon_1' & \varepsilon_N\varepsilon_2' & \cdots & \varepsilon_N\varepsilon_N' \end{bmatrix}_{NT \times NT}.$$

The OLS estimators are constant and unbiased only if the variance-covariance of the error terms are finite and constant across the sections, denoted by:

$$E(\varepsilon_{it}\varepsilon_{js}) = \begin{cases} \sigma^2, & i = j, t = s \\ 0, & \text{otherwise} \end{cases}.$$

$V = E(\varepsilon\varepsilon') = \sigma^2 I_N \otimes I_T$, where I_N and I_T is the $N \times N$ and $T \times T$ identical matrices, respectively, with \otimes denoting the Kronecker product.

However, in the spatial model, the dependent variable of any region i , y_{it} , is correlated with its own lagged value ($y_{i,t-1}$) and the spatial lags ($y_{i,t-1}^w$). As a consequence, the dependent variable will correlate with the error terms of the equation for the local and neighbouring regions. This will lead to a situation where the error terms tend to be correlated with each other across regions. The variance-covariance may be expressed as follows:

$$V = \begin{bmatrix} \sigma_{11}^2 I_T & \sigma_{12}^2 I_T & \cdots & \sigma_{1N}^2 I_T \\ \sigma_{21}^2 I_T & \sigma_{22}^2 I_T & \cdots & \sigma_{2N}^2 I_T \\ \cdots & \cdots & \ddots & \cdots \\ \sigma_{N1}^2 I_T & \sigma_{N2}^2 I_T & \cdots & \sigma_{NN}^2 I_T \end{bmatrix} = \Sigma \otimes I_T$$

where $\Sigma = E(\varepsilon_i\varepsilon_j')$ is the $N \times N$ matrix. The role of transformations and the estimators in random effect panel data models were clarified in a dissertation that developed a framework for efficient instrumental variable (IV) estimators (Arellano and Bover 1995). Judson and Owen (1999) also argued the bias of least squares dummy variable estimators for panel data models through a Monte Carlo approach. In this research, the SUR estimation technique (Zellner 1962), which allows for a limited degree of simultaneity between error terms across regions, is used to propose the spatial model. Considering that the elements of Σ are not known directly, the error terms need to be estimated together before estimating the model.

Hence, three stage least square (3SLS) estimators based on the IV techniques were implemented to compute the model. The principle of 3SLS procedures starts by generating the regression model separately for every region by introducing IV, which is correlated from the explanatory variables but independent of the error terms. The estimated variance-covariance is then obtained based on the estimated error terms from the separate models. Finally, the coefficients of the spatial model are estimated, using the estimated variance-covariance.

Theoretical Models for House Price Long-Run Equilibrium

An augmented Dicky-Fuller (ADF) unit root test (Dickey and Fuller 1979) has been widely adopted by previous studies into house price long-run equilibriums. A conventional model of the ADF unit root test may be expressed as follows:

$$\Delta p_{it} = \alpha_i + \beta_i p_{i,t-1} + \rho_i \Delta p_{i,t-1} + u_{it} \quad \text{Equation 3}$$

where:

- p_{it} = the logarithm of house prices in a region i at a time point t
- Δp_{it} and $\Delta p_{i,t-1}$ = the movement of house prices at time points t and $t-1$ respectively
- Estimate α_i = is the average house price in a region i , indicating the long-run equilibrium
- Estimate β_i = suggests the speed at which house price will approach the long-run equilibrium
- Estimate ρ_i = is a temporal coefficient, suggesting how house price in a region i are influenced by its previous movements
- Estimate u_{it} = the residual

Since the ADF unit root model is estimated individually for house prices in each region, it assumes that house prices should be isolated from one region to another. Therefore, $Cov(u_{it}, u_{jt}) = 0$, for $i \neq j$. Under this assumption, if $\beta_i < 0$, p_{it} is stationary, it indicates house prices in a region i will reach the long-run equilibrium.

The ADF unit root test is conducted under the assumption of strong restrictions, which require house prices to be isolated from one region to another. Holmes (2007) improved the ADF unit root test model by employing a panel regression approach to investigate the long-run equilibrium. The panel unit root test model is expressed as follows:

$$\Delta P_t = A + BP_{t-1} + \Gamma \Delta P_{t-1} + U_t \quad \text{Equation 4}$$

where:

$$P_t = (p_{1t}, p_{2t}, \dots, p_{Nt})', A = (\alpha_1, \alpha_2, \dots, \alpha_N)', U_t = (u_{1t}, u_{2t}, \dots, u_{Nt})'$$

$$B = \begin{bmatrix} \beta_1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \beta_N \end{bmatrix}, \Gamma = \begin{bmatrix} \rho_1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \rho_N \end{bmatrix}$$

The SUR estimating method is applied for the calculation of Equation 4, which allows for contemporary correlations in the residuals. This panel unit root test model assumes that house price in a region i is influenced by house price in a region j at the same time point. If there is $\lambda < 0$, satisfying $|B - \lambda I| = 0$, the house prices are indicated to move towards long-run equilibrium.

The panel unit root model can be further improved by implementing spatial-temporal lags, which can capture spatial effects on house prices of previous periods. This spatial unit model is expressed

as:

$$\Delta p_{it} = \alpha_i + \beta_i p_{i,t-1} + \rho_i \Delta p_{i,t-1} + \gamma_i \Delta p_{i,t-1}^w + u_{it} \quad \text{Equation 5}$$

The model assumes that house price in a region i is not only influenced by house prices in the neighbourhood regions at the same time, but is also influenced by the previous movements of house prices in the surrounding regions. It means that the house price differentials are influenced by both the temporal lags, $\Delta p_{i,t-1}$, and the spatial-temporal lags, $\Delta p_{i,t-1}^w$.

According to the regional characteristics, steady states for the house prices of cities may be reached through specific paths that depend on initial conditions. The proceeding speeds, denoted by β_i , indicate how fast individual regional housing markets will move towards the steady state. House prices will reach the steady state $f(\alpha_i, \beta_i)$ over the whole observed period if a region where the initial price level separates further from the steady state may have the relatively higher house price growth.

Equation 5 may also be recognised as a system of equations that needs to be solved simultaneously, expressed as follows:

$$\Delta P_t = A + BP_{t-1} + \Gamma \Delta P_{t-1} + W \Delta P_{t-1}^w + U_t \quad \text{Equation 6}$$

where:

$$P_t = (p_{1t}, p_{2t}, \dots, p_{Nt})', A = (\alpha_1, \alpha_2, \dots, \alpha_N)', U_t = (u_{1t}, u_{2t}, \dots, u_{Nt})',$$

$$B = \begin{bmatrix} \beta_1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \beta_N \end{bmatrix}, \Gamma = \begin{bmatrix} \rho_1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \rho_N \end{bmatrix} + \begin{bmatrix} \gamma_1 W_1' \\ \vdots \\ \gamma_N W_N' \end{bmatrix}, \text{ and } W_i = (w_{i1,t}, w_{i2,t}, \dots, w_{iN,t})'.$$

Equation 6 presents a system of unit root test model with temporal and temporal-spatial lags. The contemporary spatial dependence and heterogeneity is captured by the covariance of the error term U_t , $Cov(u_{it}, u_{jt})$ with $i \neq j$. Those spatial dependences are constrained by the non-zero values of w_{ij} . The coefficients of the temporal lags and the temporal-spatial lags explain the magnitude of the regional house price growth influenced by the temporal and spatial effects. House prices will move to a stable equilibrium which is derived from the negative eigenvalues of the estimated matrix B. This means that whether there is a $\lambda < 0$, satisfying $|B - \lambda I| = 0$, will indicate the long-run equilibrium of house prices over continuous time.

As discussed above, each unit root test model is estimated against different assumptions regarding spatial effects on house prices respectively. This research investigates the process of house prices moving to long-run equilibrium using the ADF unit test model, panel unit test model and spatial unit test model, respectively. By comparing the estimated results, spatial effects on the proceeding house price moving to long-run equilibrium may be disclosed. The assumption made for the corresponding unit root test model is stated as follows:

- ADF unit root test: house prices are not influenced by spatial factors;
 Panel unit root test: house prices are influenced by contemporary spatial factors; and
 Spatial unit root test: house prices are influenced by contemporary and previous spatial factors.

DESCRIPTIONS OF AUSTRALIAN HOUSING

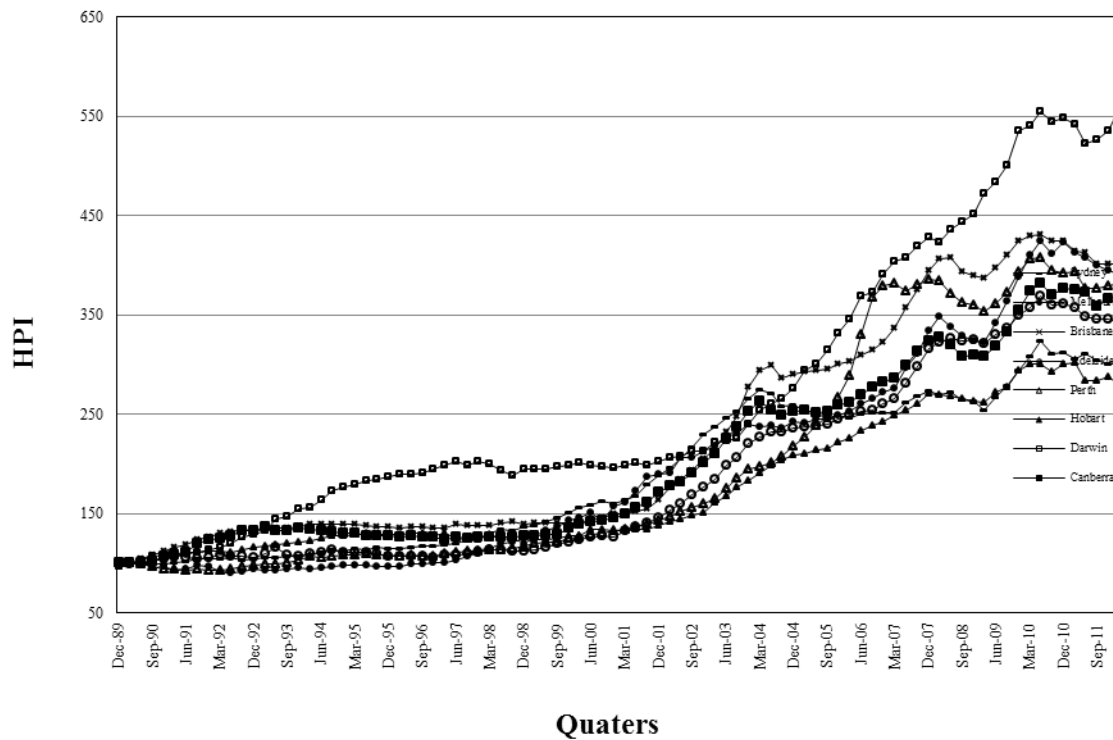
House Price Index

This research uses the House Price Indices (HPI) to represent the house price levels in Australian capital cities. The HPI of the eight capital cities of Australia were collected from the publications of the Australian Bureau of Statistics (ABS 2013). The period chosen was from the December quarter, 1989 to the March quarter, 2012. The indices are constructed by using a stratification approach. The objective of this approach is to minimise the physical heterogeneity of dwellings within each stratum. In each period the median price movement is calculated for each stratum and used to construct a stratum level price index (ABS 2005). The aggregate index is calculated by weighting together the individual stratum indices, where the weights represent the relative significance of the stock of dwellings in each stratum.

The indices were initially based on the quarterly house prices for established and newly erected dwellings with each capital city's house price indices for 1989-90 = 100. However, the reference base of the published HPI changed for the 2003-04 financial year after the September quarter, 2005 (ABS 2005). In order to maintain consistency, the old reference base (1989-90) has been used in this research. The method used to convert the re-referenced data to the previous base is described as $HPI_{89-90} = r \times HPI_{03-04}$, where HPI_{89-90} denotes the house price index on the base 1989-90 = 100, HPI_{03-04} denotes the house price index on the base 2003-04 = 100 and r is the converting factor, which is the index number for year 2003-04 on the base 1989-90 divided by 100. Figure 1 shows the house prices in the eight capital cities.

The biggest change in house prices during the investigated period was in Darwin (350.3%), the city with the smallest population of the eight. The Darwin housing market displayed a very different behaviour to the other seven markets. Darwin started its increase from the very beginning of the observation period up until the December quarter, 2008. It had an average change rate of 3.62% per quarter followed by a steady increase until the September quarter, 2000. The latest sharp increase in Darwin started in the December quarter, 2001.

The other seven cities showed a similar propensity during this period. They all have slow increase trends at first and move up dramatically after 1996. The house market boom in Melbourne, Adelaide, Perth and Sydney occurred earlier than in the other markets. Instead of being led by the biggest Australian city, Sydney, the house market boom originated in Melbourne, the second biggest city of Australia, in the December quarter of 1996. The booms in Sydney, Adelaide and Perth started in the March quarter, 1997, followed by Brisbane (June quarter, 2002), Canberra (June quarter, 2000) and Hobart (June quarter, 2000).



House Price Indices in Eight Australian Capital Cities

Source: Authors

Figure 1

Spatial Dependence of House Prices

Although spatial analysis may perform better than pure temporal and spatial analysis, one controversial issue raised in this area concerns how to measure the potential interaction between two spatial units. As discussed before, many ways of constructing the spatial weight matrices have been described. The original suggestion was to use a combination of distance measures and the relative length of the common border between two spatial units, known as the spatial weights respectively in this research. The spatial weight is expressed as $w_{ij,t} = d_{ij}^{-1}$, where d_{ij} denotes the distance between city i and city j .

City	Adelaide	Brisbane	Canberra	Darwin	Hobart	Melbourne	Perth	Sydney
Adelaide	-	-	-	-	-	-	-	-
Brisbane	1600	-	-	-	-	-	-	-
Canberra	957	946	-	-	-	-	-	-
Darwin	2615	2846	3133	-	-	-	-	-
Hobart	1161	1788	856	3734	-	-	-	-
Melbourne	653	1374	464	3146	597	-	-	-
Perth	2130	3604	3085	2651	3008	2719	-	-
Sydney	1161	732	248	3146	1057	713	3288	-

Distances Between Australian Capital Cities (Km)

Source: Authors

Table 1

Australia has six states and two territories - Brisbane, Canberra, Melbourne and Sydney are located in the east of Australia; Adelaide, Darwin and Perth are located in the middle and west. Hobart is located on a southeast island. Table 1 describes the straight-line distances between the Australian capital cities.

Sydney and Canberra are only 248 kilometres apart. The city furthest from Sydney is Perth, at 3288 kilometres. Darwin is located at the northernmost point of Australia, over 2600 kilometres from the other cities. Perth, the further west, is 2130 kilometres away from its nearest neighbour, Adelaide. Melbourne has the shortest average distance, followed by Canberra, Adelaide and Sydney. In a geographic context Melbourne can be recognised as the centre of Australian capital cities. The impact of one regional housing market on another may be distributed along the distance between them, known as spatial heterogeneity. In order to capture the spatial heterogeneity and the spatial information, a spatial weight matrix is involved in the model.

The spatial effects from one housing market on another could be negatively correlated with the distance between them. Products of house prices and inverses of the distances construct the spatial effects between house prices. Denoting d_{ij} as the logarithm of the distance between city i and city j , the spatial weight for these two cities is defined as the reverse values of the distance denoted by $w_{ij} = \frac{1}{d_{ij}}$. Accordingly, the weight matrix can be represented as:

$$W = \begin{pmatrix} 0 & w_{12} & \cdots & w_{1N} \\ w_{21} & 0 & \cdots & w_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ w_{N1} & w_{N2} & \cdots & 0 \end{pmatrix}.$$

It can be seen that the geographic weight matrix is symmetric. This indicates that there is no direction for weights between two cities. In other words, the spatial weight from city i to city j is the same as that from city j to city i . Moreover, the spatial matrix is time invariable, indicating that spatial weights will not change over time. The house price dependence, $P^s = WP$ represents a new

variable equivalent to the mean of house prices from all neighbouring markets, $p_i^s = \sum_{j \neq i}^N w_{ij} p_j$.

LONG-RUN EQUILIBRIUM TESTS

ADF Unit Root Test

This research uses ADF model, Equation 3, to identify the stationarity of the house prices while assuming that the house prices in Australia are not affected by spatial factors and isolated across the cities.

Table 2 shows the unit root test results of eight capital cities, using the ADF unit root test. Although negative estimates of the long-run equilibrium coefficients are observed in Brisbane, Canberra, Darwin, Hobart, Perth and Sydney, they performed insignificantly at a 5% confidence level. This indicates that eight capital cities' house price index data series are not stationary at the 5% significance level or that the house prices do not have long-run equilibrium. The estimated coefficients of the temporal lags, ρ_i , are positive for all the capital cities. With the exception of Melbourne and Darwin, the estimated coefficients of the temporal lags are significantly different from 0, seen from the p -values of the corresponding t -statistics. This indicates that house prices in

Adelaide, Brisbane, Canberra, Hobart, Perth and Sydney are influenced by the previous housing movements.

	A	β	ρ
Adelaide	0.0013 (0.9628)	0.0016 (0.7768)	0.3384 (0.0015)**
Brisbane	0.0186 (0.9628)	-0.0026 (0.5402)	0.6867 (0.0000)**
Canberra	0.0156 (0.5931)	-0.0016 (0.7737)	0.5137 (0.0000)**
Darwin	0.0101 (0.6984)	-0.0005 (0.9141)	0.1623 (0.1404)
Hobart	0.0155 (0.6380)	-0.0013 (0.8389)	0.2347 (0.0329)**
Melbourne	0.0070 (0.8183)	0.0002 (0.9682)	0.1693 (0.1137)
Perth	0.0082 (0.6823)	-0.0008 (0.8458)	0.7227 (0.0000)**
Sydney	0.0260 (0.3718)	-0.0040 (0.4765)	0.2703 (0.0112)**

Note: the numbers in the brackets are the p-values of the t-statistics with the null hypothesis where the coefficient is equal 0.

** and * denote the t-statistics are significant at the 5% and 10% critical levels respectively.

ADF Unit Root Test

Source: Authors

Table 2

Panel Unit Root Test

The panel unit root model, Equation 4, tests the long-run equilibrium while considering the contemporary correlations across the cities. The spatial heterogeneity pertaining to the house prices in Australian capital cities is taken into account. The estimates of the panel unit root model are reported in Table 3.

It is shown that the estimates of α_i are different across the Australian capital cities. This suggests that the house prices in the Australian capital cities should have distinct steady levels, if the long-run equilibrium exists. The estimates of α_i range from the lowest at 0.01 in Melbourne to the highest at 0.057 in Sydney. This implies that house price levels in Sydney are supposed to reach higher points than the other cities, if the house price system in Australia can reach its equilibrium. On the other hand house price levels in Melbourne should be the lowest.

Similar to the results of the ADF model, negative but insignificant estimates of the long-run equilibrium coefficients, β_i , are observed in Brisbane, Canberra, Darwin, Hobart, Perth and Sydney. This indicates the spatial heterogeneity and contemporary spatial correlations of house prices do not affect the proceeding long-run equilibrium. Once again, positive estimates of the temporal lags are observed for all the capital cities.

	α	β	ρ
Adelaide	0.0103 (0.1198)	0.0003 (0.9545)	0.1762 (0.0371)**
Brisbane	0.0300 (0.1198)	-0.0042 (0.3141)	0.5136 (0.0000)**
Canberra	0.0313 (0.1198)	-0.0041 (0.4554)	0.3157 (0.0000)**
Darwin	0.0230 (0.1198)	-0.0016 (0.7366)	0.2556 (0.0058)**
Hobart	0.0189 (0.1198)	-0.0016 (0.7957)	0.1225 (0.1751)
Melbourne	0.0100 (0.1198)	0.0009 (0.8850)	0.0884 (0.3523)
Perth	0.0165 (0.1198)	-0.0021 (0.5869)	0.6347 (0.0000)**
Sydney	0.0571 (0.1198)	-0.0092 (0.1002)	0.2220 (0.0063)**

Note: the numbers in the brackets are the p-values of the t-statistics with the null hypothesis where the coefficient is equal 0.

** and * denote the t-statistics are significant at the 5% and 10% critical levels respectively.

Panel Unit Root Test

Source: Authors

Table 3

Spatial Unit Root Test

This research utilised the information described above to estimate the spatial model for the long-run equilibrium of house prices in Australia. Table 4 presents the estimated coefficients of the long-run equilibrium model.

The estimates of α_i range from the lowest at 0.0064 in Adelaide to the highest at 0.0654 in Sydney. The estimate of β_i , is significant and negative for Sydney, which suggests that the house price level in Sydney can reach the steady state. The estimates for the remaining cities are negative but insignificant. This implies house price levels in the above cities will move to their own equilibriums potentially but not certainly. The half-lives calculated according to the estimates of β_i show that around 13 years are needed for Sydney to increase at half its current growth speed. Meanwhile, it takes nearly 26 years for Brisbane and Canberra.

The temporal coefficients are positive and significant for Brisbane, Canberra, Darwin and Perth. This suggests that house price growth is strongly influenced by previous movements. The estimates of the temporal lags for Adelaide, Hobart and Melbourne are not significant, even at the 10% critical level. This suggests that the movements of the house price levels in these cities are unlikely to be influenced by their previous behaviours. A negative and insignificant estimate of the temporal lag is reported in Hobart, suggesting a former increase in house price level would slow down the future growth in Hobart.

	α	B	ρ	ν
Adelaide	0.0064 (0.0586)*	-0.0016 (0.7296)	0.0189 (0.8389)	0.8038 (0.0000)**
Brisbane	0.0321 (0.0586)*	-0.0065 (0.1150)	0.4752 (0.0000)	0.4419 (0.0022)**
Canberra	0.0342 (0.0586)*	-0.0066 (0.2131)	0.2783 (0.0023)**	0.4409 (0.0055)**
Darwin	0.0112 (0.0586)*	-0.0003 (0.9457)	0.2770 (0.0041)**	0.0561 (0.7037)
Hobart	0.0210 (0.0586)*	-0.0043 (0.4641)	-0.0811 (0.4186)	0.6303 (0.0000)**
Melbourne	0.0129 (0.0586)*	-0.0018 (0.7606)	0.0743 (0.4634)	0.4350 (0.0213)**
Perth	0.0137 (0.0586)*	-0.0025 (0.5072)	0.7095 (0.0000)**	-0.0136 (0.9272)
Sydney	0.0654 (0.0586)*	-0.0130 (0.0167)**	0.1510 (0.0980)*	0.5531 (0.0002)**

Note: the numbers in the brackets are the p-values of the t-statistics with the null hypothesis where the coefficient is equal 0.
 ** and * denote the t-statistics are significant at the 5% and 10% critical levels respectively.

Spatial Unit Root Test
Source: Authors
Table 4

The coefficients of the spatial lags show the relationships between the house price movements and the previous behaviours of the neighbouring house price levels. Positive estimates are reported in all the cities. This suggests that a house price growth in each of the eight cities should have a positive correlation with the house price movements in neighbouring cities, except in Perth. The estimates of the spatial lags are insignificant in Darwin and Perth. This shows that the movements of house price levels in these two cities tend to be isolated from neighbouring cities, because their geographic locations are far away from the others. Strong and significant spatial coefficients are found in Adelaide, Brisbane, Canberra, Hobart, Melbourne and Sydney. Adelaide has the largest coefficient, mainly due to its central geographic location.

Spatial Effects on the Long-Run Equilibrium of House Prices

According to the estimates generated from the three models, the R-square for ADF, panel and spatial unit root test models are 0.2375, 0.2295 and 0.2742, respectively. This indicates that the spatial test model better fits the data. In order to present an insight into how spatial factors contribute in the proceeding long-run equilibrium, this research compares the confidence levels of the t-statistics of the estimates, which are presented in Figure 2. Obvious changes are observed in confidence levels of the long-run coefficients (α and β), while the changes in the confidence levels of the short-run coefficients (ρ) are not clear. A long-run equilibrium is observed in the house price in Sydney when both contemporary and previous spatial effects are taken into account by the spatial test model.

The confidence levels of the t-statistics against the estimates, α , β and ρ of the three test models are

reported in Parts 1, 2 and 3 respectively of Figure 2. Seen from Part 1, the confidence levels of α increase, either contemporary or previous spatial effects on house prices being considered, indicating that the steady states of house prices are influenced by the spatial effects, especially the spatial heterogeneity of each city. The eight capital cities provide obvious distinctions from their geography to population to economic structures. Those distinctions among the city-own characteristics lead to the different steady states of house prices in the cities. This means that the house price in the Australian capital cities would never approach a same price level, even if the information of the housing market was efficient. The spatial heterogeneity of the cities determines the inequality of the urban house price levels.

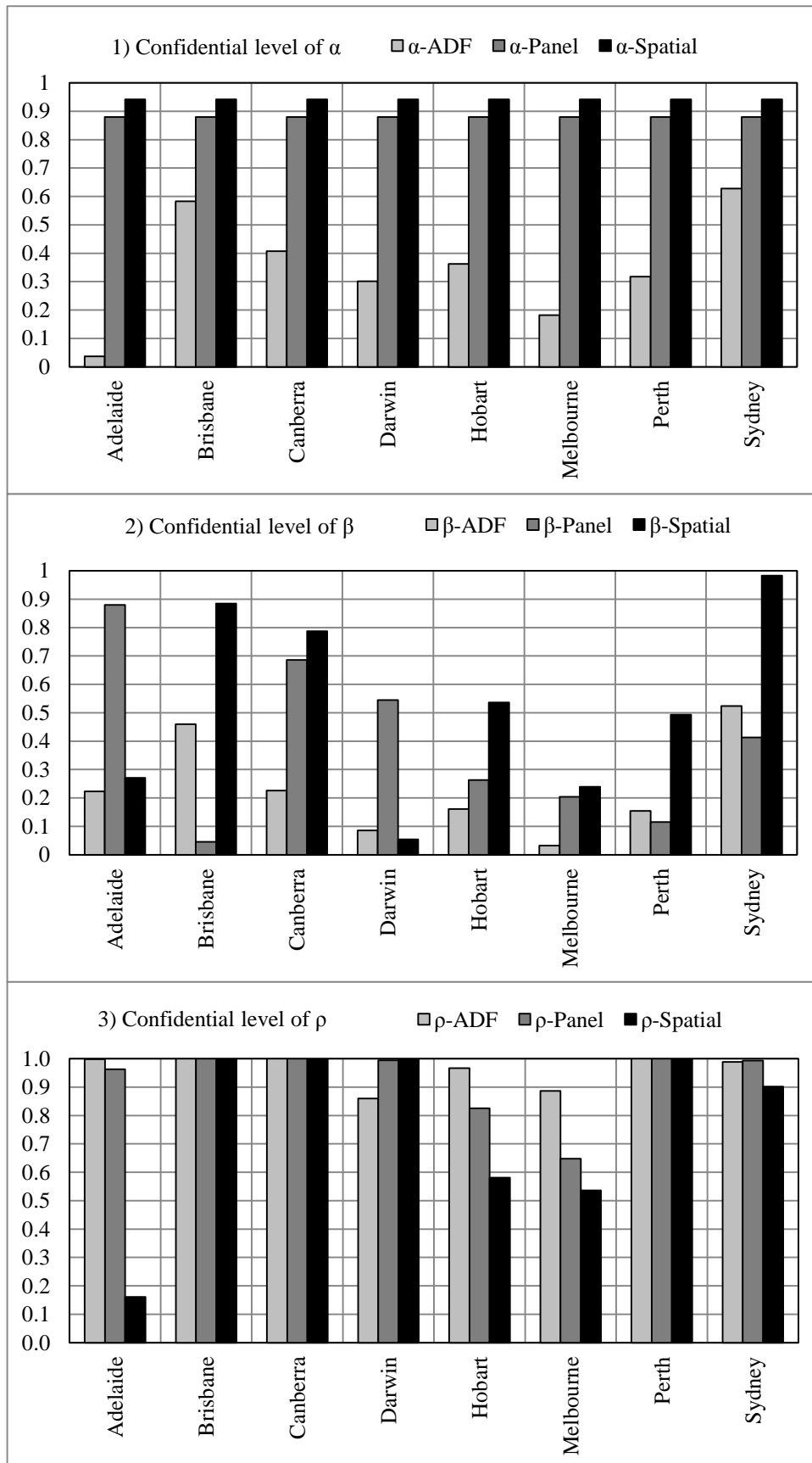
According to Part 2, the confidence levels of β increase in Adelaide, Canberra, Darwin, Hobart and Melbourne when contemporary spatial effects on house prices are included. The levels of β increase in Brisbane, Canberra, Hobart, Melbourne, Perth and Sydney, if previous spatial effects on house prices are taken into account. As discussed above in Part 1, the Australian capital cities are unlikely to have the same steady house price level due to spatial heterogeneity. However, some of the cities may have their own long-run equilibriums. The long-run equilibriums cannot be identified by either the unit root model or the panel unit root model, but the equilibriums were identified when the spatial dependence of house prices was taken into account by using the spatial unit root model. This indicates that spatial effects, especially the spatial dependence, drive house prices away from their own long-run equilibriums.

Long-run equilibrium processes in Adelaide and Darwin are more sensitive to the contemporary house prices in the neighbourhood cities, while the process in Brisbane, Perth and Sydney is more sensitive to the previous neighbourhood movements. The long-run equilibrium process in Canberra, Hobart and Melbourne is influenced by both the contemporary and previous housing behaviours in the neighbourhood cities.

Part 3 reports the confidence levels of ρ , which indicates how the temporal effects would be influenced by spatial effects on house prices. In other words, a movement of house price in a city may not influence the contemporary house prices in its neighbourhood cities, but it may affect the neighbourhood cities' house price with certain temporal lags which is one quarter in this research. It shows that there is a slight increase in the confidence of temporal lags in Darwin, which indicates that the temporal effects on its house prices are mainly caused by the previous movements of its own market.

One the other hand, the confidence levels decrease in Adelaide, Hobart, Melbourne and Sydney after the spatial effects are taken into account. This suggests that the house price movements are certainly dependent on previous house price movement in the neighbourhood cities. It is shown that the confidence levels of the temporal lags in Adelaide, Melbourne and Hobart dropped down to less than 60%, indicating the house price movements in the three cities are mainly caused by the previous movements in the neighbourhood cities.

The confidence level in Sydney decreased to about 90%, suggesting that the house price movements in Sydney may depend on the previous movements of both internal and neighbourhood markets. The confidence levels in Brisbane, Canberra and Perth are remaining high, which indicates that the movements of house prices in the cities are influenced significantly by the previous price movements in their own markets. The significant estimates of the spatial lags in Brisbane and Canberra, shown in Table 4, suggest that the house price movements in Brisbane and Canberra are caused by both internal and neighbourhood markets. On the other hand, insignificant estimates in Perth indicate that the house price movement is mainly dependent on its own market performance.



Comparison of the Confidence Levels

Source: Authors

Figure 2

In the long-run perspective, the Australian housing market cannot fulfil an equal and steady target due to the spatial heterogeneity. If spatial dependence between regional house prices can be taken into account properly, housing policy at a national level can contribute to building stable urban housing markets. In the short-run perspective, regional housing policies should be made according to the dependencies of neighbourhood markets to efficiently adjust the house price movement.

CONCLUSIONS

This research develops a series of unit root test models to investigate spatial effects on the process of house price long-run equilibrium. Based on the framework of the ADF unit root test model, a panel and a spatial unit root model are developed to capture the contemporary and previous spatial effects on house prices. House price index and straight line distances of Australian capital cities are used to interpret the models.

Insignificant processes of long-run equilibriums are investigated regardless of whether spatial effects are taken into account by the testing models. A significant process of long-run equilibrium is observed in Sydney when both contemporary and previous spatial effects on house prices are considered. By comparing the confidence levels of the estimates of the models, it is suggested that spatial effects can strongly influence the long-run performance of house prices. However, the short-run performance of house prices is not influenced by spatial effects.

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