INTERNATIONAL REAL ESTATE REVIEW

2010 Vol. 13 No. 1: pp. 30 – 45

Can Investors Hedge Residential Price Dynamics of Australia's Capital Cities?

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The study described in this paper focuses on testing the short-run and long-run relationships between house price and consumer price indices in Australia's capital cities from 1998 to 2008. The autoregressive distributed lag model is adopted to obtain the estimates of the short-run relationships, while the error correction model is used to investigate the long-run relationships. The t-statistic is used to compute the significance of these relationships. The research results give no evidence that house price indices are correlated with consumer price indices in the short run. However, the long-run relationships between house and consumer price indices exist in most of the cities.

Keywords

House price indices; Consumer price indices; Autoregressive distributed lag model; Error correction model

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1. Introduction

Real estate is conventionally regarded as an efficient hedge against price inflation. In Australia, the increase rate in the house price index (HPI) has far outpaced the growth rate of the consumer price index (CPI), which is widely used to measure the inflation rate. For example, the annual average percentage increase of the Australian HPI from 1986 to 2006 was about 7.5%, while the annual average CPI increase was about 3.6% (ABS 2009a; ABS 2009b). Since Fama and Schwert (1977) first estimated the inflation-hedging characteristics of different assets and argued that real estate is a complete hedge against inflation, numerous studies have analysed inflation-hedging characteristics of real estate assets in different countries and concluded with various findings.

It was found that commercial property does not hedge against the inflation rate in the short run, but a positive correspondence exists between such property and inflation (Matysiak et al. 1996). In another study, Newell (1996) compares the hedging characteristics of Australian commercial properties with different types, places and market factors, which indicate that the hedging characteristics of Australian commercial properties would be different. It was concluded that commercial properties can provide a perfect hedge against actual inflation in the observed cities; namely, Adelaide, Brisbane, Canberra, Melbourne, Perth and Sydney, during 1984 to 1995. The commercial properties in Adelaide, Brisbane and Canberra can also hedge expected inflation while the other cities are not able to do so. Moreover, except for Canberra, the unexpected inflation hedging characteristics of the commercial properties are proven in the other six cities. Liu et al. (1997) studies the performance of real estate in foreign countries given security design differences, and the results show that real estate securities act as an efficient hedge in some countries, but inefficient in others. Barber et al. (1997) find that commercial properties can provide a hedge against inflation in some forms, based on an investigation of statistical similarities among UK commercial property capital and rental values, and the price levels. The relationship between the return of real estate investment trusts and inflation is deemed to be a manifestation of the effects of changes in monetary policies (Glascock et al. 2002). Kolari (2002) examines the long-run impact of inflation on homeowner equity and concludes that there is a long-run relationship between the house prices and the non-housing goods and services prices. Another research studies the relationships between Australian housing dynamics and macroeconomic factors; namely, all ordinaries index, the real household disposable income per capita, trade-weighted exchange rate, consumer price index, unemployment rate, and detached housing stock per capita (Abelson et al. 2005). The results showed that the consumer price index has a positive and significant impact on Australian housing dynamics. Newell (2007) shows that strong risk-adjusted returns are delivered by both direct industrial property and industrial list property trusts. Further research on

Australian residential property investments indicate that the main factors which drive the investments, are wealth-related factors rather than life-style factors (Brown et al. 2008).

Previous research has investigated relationships between house and consumer prices at national levels rather than regional levels, although the latter is valuable for both local government and investors. The present study estimates the short-run and long-run relationships between the HPI and CPI in Australia's capital cities. The next section will introduce the econometric theories used in the study, including the autoregressive distributed lag (ADL) model and the error correction model (ECM) for building short-run and long-run relationships between the HPI and CPI, respectively. The following section presents the collected data and a summary of preliminary test results. The empirical results section identifies the parameters that are applied to the analysis, and the short-run and long-run relationships between the HPI and CPI of Australia's capital cities. The conclusions of this study are provided in the final section.

2. Econometrical Models for Relationship Analyses Between the HPI and CPI

The methodology investigates the relationships between the HPI and CPI. Previous research shows that a linear relationship exists between the natural logarithm values of the house prices and the CPI, when the annual rent and discount rate are constant (Kolari 2002). In the research of Kolari, the relationship at period t, between house prices, HP_t, and consumer price index, CPI_t, is estimated as:

$$\ln HP_t = (\ln R - \ln r) + \beta \ln CPI_t, \tag{1}$$

where R and r, which are constants, stand for the annual rent and the discount rate respectively. In this study, the HPI and CPI are used to estimate the relationships between house and consumer prices through econometric methods. Most of the economic data is influenced by its past values, and therefore, the ADL model is introduced to estimate the regression. The ECM is also adopted to test whether long-run relationships exist between the HPI and CPI.

2.1 ADL Model and Optimal Lags

The ADL model is often introduced to estimate the regression because most time series are auto-correlated. The model is expressed as:

$$Y_t = a + b_i \sum_{i=1}^{m} Y_{t-i} + c \sum_{i=1}^{m} X_{t-i} + \varepsilon_t, \tag{2}$$

where *m* is the optimal lag, *a*, *b*, and *c* are the estimates, and ε_t is the residual term. In this study, the ADL model is estimated via the first differenced time series, thus *Eq*. (2) is rewritten as:

$$\Delta HPI_t = c + \alpha_i \sum_{i=1}^{n} \Delta HPI_{t-i} + \beta_i \sum_{1}^{n} \Delta CPI_{t-i} + \mu_t \tag{3}$$

where $\Delta \mathrm{HPI}_t$ and $\Delta \mathrm{CPI}_t$ is the differencing HPI and CPI at period *t* respectively, and *c*, α_i, β_i are estimates, while μ_t is the error term. The problem of estimating the ADL model is determining ways to choose the number of lags in the model. If there are not enough lags included, the estimates will be biased and the statistics will be unreliable. If there are too many lags included in the model, multi-collinearity may exist, which can make the t-statistic unreliable (Gujarati 2003).

The Akaike information criterion (AIC) (Akaike 1974) and Schwartz Bayesian criteria (SBC) (Schwartz 1978) are used to choose the optimal lags for the ADL model. The formulae for the AIC and SBC are:

$$AIC = (-2)\ln(ML) + 2(p/n) \tag{4}$$

$$SBC = (-2)\ln(ML) + 2\ln n(p/n) \tag{5}$$

where ML represents the maximised likelihood estimates of the model, while n is the number of observations and p is the number of estimates including the constant. In most cases, ML could be calculated as the sum of squared errors, known as the residual variation (RSS). RSS represents what the model cannot explain or how closely the model fits the data. If a model fits the data well, the values of these criteria should be small. Therefore, the judgement of whether the model is efficient is based on comparing the values of the criteria with different lengths of lag. Including an extra lag could lead to an increase in p and decrease of the RSS. If the degree of decrease in RSS is greater than the degree of increase of p, only then will the value of these criteria fall.

2.2 Error Correction Model

The long-run relationships between the HPI and CPI can be identified by computing a *t-statistic* to determine whether the lagged HPI and CPI result in significant coefficients, as shown in the following ECM:

$$\Delta HPI_t = c + \alpha_i \sum_{i=1}^{n} \Delta HPI_{t-i} + \beta_i \sum_{1}^{n} \Delta CPI_{t-i} + \delta HPI_{t-1} + \varphi CPI_{t-1} + \mu_t \tag{6}$$

If $\delta = \varphi = 0$, no long-run relationship exists between the HPI and CPI. Alternatively, if δ and φ are both significantly different from 0, the long-run relationship exists.

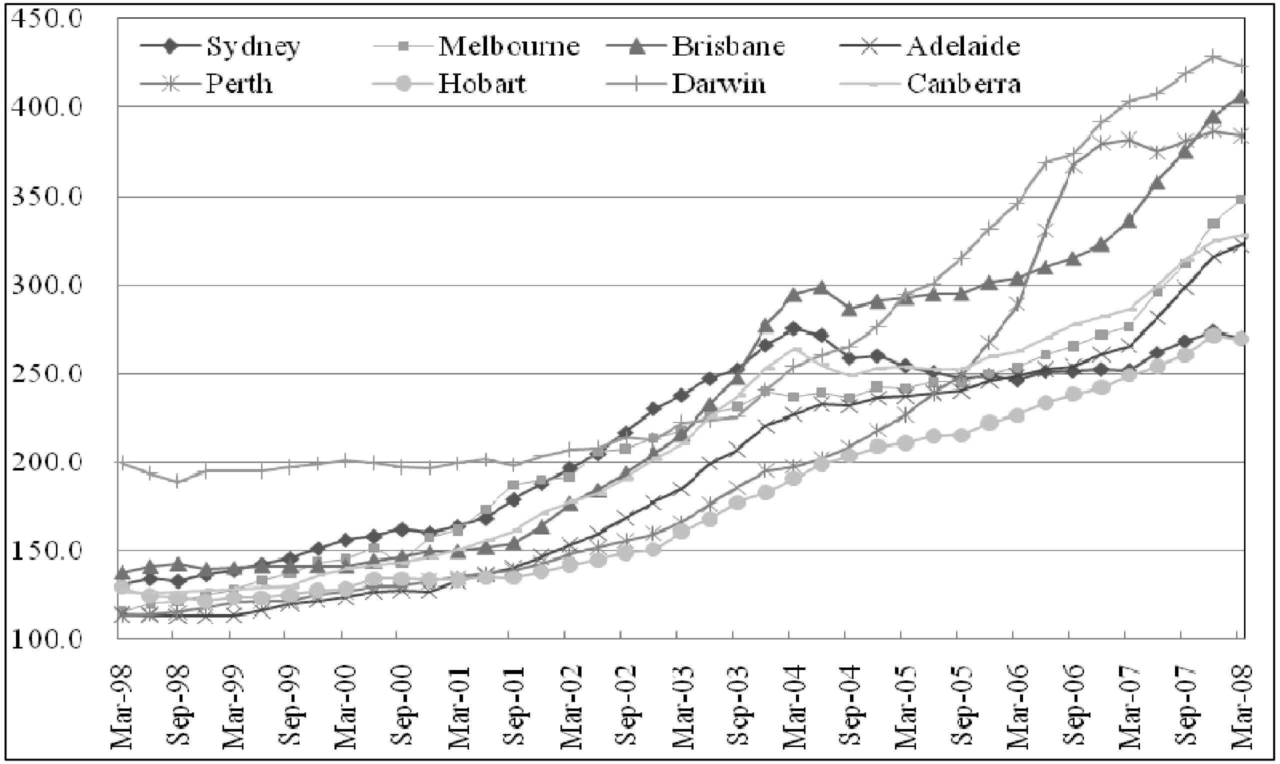
3. Historical Data of House and Consumer Price Indices in Australia

As mentioned before, this study focuses on the relationships between the HPI and CPI in the eight capital cities of Australia. The HPIs are a series of price indices that measure changes in the prices for each of the eight capital cities of Australia. Two sets of HPIs, which are indices for project houses and established houses respectively, are published by the Australian Bureau of Statistics (ABS). The index for project homes is compiled by the ABS for use in calculating the house purchase expenditure class of the CPI, while the index for established houses does not contribute to the CPI, which is the one used in this study. The HPI is constructed with reference to the current and historical market prices of the entire stock of residential dwellings (ABS 2005; ABS 2009b). The CPI measures quarterly changes in the price of goods and services which account for a high proportion of expenditures by the CPI population group (ABS 2009a). The CPI covers a wide range of goods and services, which are arranged in eleven groups: food, alcohol and tobacco, clothing and footwear, housing, household furnishings, supplies and services, health, transportation, communication, recreation, education, and miscellaneous. The housing expenditure that contributes to the CPI is made up of rents, utilities and other housing, such as house purchases, property rates, house maintenance and so on. The catalogue numbers of the two indices are 6416.0 and 6401.0 respectively. The observation period is from the March quarter of 1998 to March quarter of 2008. Both of these two indices were established quarterly and calculated on the reference base 1989-90 =100.

Figure 1 describes the movements of the HPI in the eight Australian capital cities. All HPIs have been increasing during the last decade. The HPI of Darwin has the highest rate of increase among the eight cities, while Hobart’s HPI experiences the lowest increase. The HPI began to decline in Sydney after 2004, while a huge increase came about in Perth’s HPI after 2004. The HPI of the other four cities; namely Adelaide, Brisbane, Canberra and Melbourne, grew moderately during 1998 to 2008.

Table 1 describes the population and number of dwelling units in the Australian capital cities for the latest three years. More than 60% of the Australian population live in the eight capital cities, especially in Sydney and Melbourne. From 2006 to 2008, the population increased by about 6.88%, 5.49% and 5.47% in Brisbane, Darwin and Perth respectively, while the proportions in the other five cities were less than 4%.

Figure 1 HPI of the Australian Eight Capital Cities from 1998-2008



Ma and Liu 35

The monthly average numbers of dwelling units in Adelaide and Melbourne continued to increase from 2006 to 2008, while a huge decrease is evident in Perth. Moreover, the number in Brisbane fluctuates significantly and moderate movements are observed in Canberra, Darwin, Hobart and Sydney. Surprisingly, the dwelling number of Sydney, which has the largest population, is fourth after Melbourne, Perth and Brisbane. Darwin has the lowest number during these three years.

Table 1 Population and the Monthly Average Number of Dwelling Units in Eight Capital Cities

Cities	Population			Number of dwelling units		
	2006	2007	2008	2006	2007	2008
ADE	1 146 119	1 159 131	1 172 105	442	507	520
BRI	1 820 400	1 902 235	1 945 639	857	1005	844
CAN	333 940	340 766	345 257	103	96	104
DAR	114 368	117 333	120 652	47	46	40
HOB	205 566	207 330	209 287	92	88	94
MEL	3 744 373	3 817 806	3 892 419	1615	1710	1802
PER	1 519 510	1 559 178	1 602 559	1278	1018	938
SYD	4 284 379	4 344 675	4 399 722	533	550	526

Moreover, Table 2 shows the means and standard deviations of the HPI and CPI for each capital city. Over the observation period, Darwin has the highest average HPI at 262.83, while Hobart has the lowest one, at 177.05. During 1998 to 2008, surprisingly, the house prices of residential property in Darwin have the highest increase, followed by Brisbane, Sydney and Melbourne, while the house prices in Hobart have the smallest growth. Aside from the housing assistance to Australians, such as home purchase assistance, the special housing assistance policy for the Aboriginal and Torres Strait Islander people may partly account for the huge increase of house prices in Darwin (ABS 2008). The standard deviation of HPI in Perth is the highest among the eight cities, and the lowest one is in Hobart. This indicates that the residential property market of Perth has the highest price volatility. One of the potential reasons for the high volatility in the Perth residential housing market is that its market has the highest rate of increase, which is about 10.87% yearly during the decade. Particularly during the December quarter of 2005 to December quarter of 2006, the residential house prices of Perth increase by nearly 50%. On the other hand, the house prices in cities, where standard deviations are low, move moderately. House prices in Hobart, Sydney and Melbourne are less volatile than the house prices in the other capital cities. The statistic values for the CPI vary little from city to city, compared to the results of the

HPI. The highest average CPI is in Adelaide at 142.26, and the lowest one is in Darwin at 137.23. The standard deviations for each city's CPI do not appear as different from each other as the average CPI. Adelaide has the highest standard deviation at 13.48, while Darwin has the lowest at 11.11.

Table 2 Statistics for HPI and CPI of Australia's Capital Cities

		ADE	BRI	CAN	DAR	HOB	MEL	PER	SYD
HPI	Mean	191.48	232.67	209.90	262.83	177.05	210.36	206.02	212.09
	Min	113.00	137.90	126.40	189.20	121.70	115.60	113.70	130.90
	Max	322.83	406.47	327.84	428.94	271.31	348.12	386.54	275.30
	Std. Dev.	64.86	85.56	65.21	80.63	49.55	61.70	94.46	51.20
CPI	Mean	142.26	141.04	139.70	137.23	139.57	138.88	137.74	140.47
	Min	121.70	121.90	120.60	121.50	121.50	119.60	118.00	120.70
	Max	165.50	165.60	163.00	158.50	161.30	160.60	162.50	161.70
	Std. Dev.	13.48	13.32	12.94	11.11	12.36	12.31	13.19	12.43

4. Numerical Results

4.1 Stationary Test

A time series is said to be stationary if its mean and variance are constant and the variance depends on the distance of two time periods. The stationary process plays an important role in the time series analysis. It is difficult to generalise valuable information from its behaviour because the non-stationary time series behaviour is unpredictable over time. Before estimating the model with a time series, it is important to test the stationarity of these data.

A unit root test is used to detect the variable stationarity and the order of integration. Three methods are widely used; namely, the Dicky-Fuller unit root test, the augmented Dicky-Fuller (ADF) unit root test (Dicky and Fuller 1979) and the Phillips-Perron unit root test (Phillips and Perron 1988). In this study, the ADF test is adopted to test the stationarity of the time series.

$$\Delta y_t = \delta y_{t-1} + \sum_{i=2}^{p} \beta_i \Delta y_{t-i+1} + e_t \tag{7}$$

$$\Delta y_t = \delta y_{t-1} + \sum_{i=2}^{p} \beta_i \Delta y_{t-i+1} + e_t + \beta_0 \tag{8}$$

$$\Delta y_t = \delta y_{t-1} + \sum_{i=2}^{p} \beta_i \Delta y_{t-i+1} + e_t + \beta_0 + \beta_1 t \tag{9}$$

Eq. (7) is used to test whether the time series are non-stationary, because of a simple random walk. Where δ is the estimate, $\sum_{i=2}^{p} \beta_i \Delta y_{t-i+1}$ is the lagged values of Δy_t to eliminate autocorrelation from the equation, and e_t is the error term. If δ is equal to 0, which means that the data is generated by a random walk, it is proven that the data is non-stationary, while β_0 in *Eq.* (8) represents a drift and *Eq.* (9) is used when testing for the presence of both the drift and trend, where the trend is expressed by $\beta_1 \mathrm{t}$.

Table 3 is the summary of the ADF unit root test results for HPI and CPI. According to the ADF test, none of the house price indices are stationary. However, at the first difference, most of them become integrated, except those in Brisbane and Darwin. Table 3 also shows that consumer price indices of the eight capital cities are integrated at the first difference.

4.2 Selection of Optimal Lags

Since both HPI and CPI are stationary at the first difference, the ADL model can be estimated with those differenced variables. Several lags are introduced into the model, in order to find the optimal lag. In this study, lags 1, 2, 3, and 4 are involved. The lag, with which the model has the smallest value of the AIC and SBC, is determined to be the optimal lag.

Table 4 shows the AIC and SBC values with different lags for the eight cities. According to the values of the AIC, the ADL models for Brisbane and Canberra are efficient with lag 1, while the data of Adelaide, Perth and Sydney fit the model well when lag 2 is also included. Moreover, more lags (lag 3) are needed for Darwin, Melbourne and Hobart. On the other hand, the SBC values for Adelaide, Brisbane and Canberra point to lag 1 while the values for Hobart, Melbourne, Perth and Sydney point to lag 2. It is also indicated that lag 3 is needed for the model of Darwin. Since a large number of lags will lead to loss of freedom of the regression, the models for each of the eight capital cities are estimated under the SBC criterion.

Table 3 Augmented Dicky-Fuller Test for HPI and CPI of Australia's Capital Cities

		ADE	BRI	CAN	DAR	HOB	MEL	PER	SYD
HPI	***t*-test for level**	0.2224	-0.0477	-0.6193	-2.8957	0.4913	-1.6159	3.4766	-1.9786
	***p*-value**	0.9978	0.9948	0.9746	0.1706	0.9991	0.7768	1.0000	0.6023
	***t*-test for first difference**	-5.2589	-2.5477	-4.3765	-2.2600	-3.4381	-7.3534	-3.9334	-4.1162
	***p*-value**	0.0003	0.3051	0.0044	0.4493	0.0548	0.0000	0.0158	0.0095
CPI	***t*-test for level**	0.6654	-0.4977	-0.6743	-0.4519	-0.7729	-0.8789	0.0946	-1.0938
	***p*-value**	0.9906	0.9815	0.9708	0.9836	0.4423	0.9522	0.9967	0.9225
	***t*-test for first difference**	-7.5857	-7.7110	-7.1026	-6.7283	-7.7478	-7.7107	-7.3539	-6.5926
	***p*-value**	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Notes: test critical values: 1% level -4.0966, 5% level -3.4762, 10% level -3.1656

Table 4 Values of AIC and SBC of ADL Models for Australia's Capital Cities

	AIC				SBC			
	Lag 1	**Lag 2**	**Lag 3**	**Lag 4**	**Lag 1**	**Lag 2**	**Lag 3**	**Lag 4**
ADE	5.4506	5.3851*	5.4209	5.4648	5.5477*	5.5483	5.6513	5.7634
BRI	5.9137*	5.9699	5.9579	5.9559	6.0108*	6.1331	6.1883	6.2546
CAN	5.5689*	5.6398	5.6019	5.6431	5.6661*	5.8030	5.8322	5.9417
DAR	6.0869	6.0169	5.9155*	5.9406	6.1841	6.1801	6.1459*	6.2392
HOB	4.9316	4.7014	4.7520	4.6993*	5.0287	4.8646*	4.9824	4.9980
MEL	5.9671	5.8344	5.8226	5.7943*	6.0642	5.9976*	6.0530	6.0930
PER	5.9242	5.8543*	5.9033	5.9634	6.0213	6.0175*	6.1337	6.2620
SYD	5.9218	5.8417*	5.8840	5.9458	6.0189	6.0049*	6.1143	6.2444

Note: * indicates the smallest values of AIC and SBC

4.3 Identification of Relationships between the HPI and CPI of Australia's Capital Cities

The results show several characteristics of the relationships between the HPI and CPI. The estimations and *p*-values of the *t*-statistic of the estimators are shown in Table 5. The ADL models for Adelaide, Brisbane and Canberra are estimated with one lag, while two lags are introduced in the models for Hobart, Melbourne, Perth, and Sydney. The model for Darwin is estimated with three lags. In the first row of the table, c denotes the constant, while α_i and β_i $(i = 1, 2, \text{ and } 3)$ stand for the correlation coefficients of the lagged movements of the HPI and CPI respectively. The p-values of α_i suggest that the movements of the HPI are influenced by themselves significantly, in the short run. The cities of Adelaide, Brisbane, Canberra and Sydney have positive relationships with the dynamics of HPI in the previous quarter. Not only do the changes of the HPI in Perth have a positive relationship with its value for the previous quarter, but it also has a negative relationship with the one quarter before the previous quarter. Hobart and Melbourne are influenced by the HPI dynamics at lag 2, while the HPI dynamics at lag 3 have a positive significant influence in Darwin. According to the p-values of the β_i, none of the correlation coefficients of the HPI and CPI are significantly different from 0 at the 5% critical level, although the coefficients in the models for Hobart and Melbourne are significant at the 10% critical level. This implies that short-run relationships between the HPI and CPI do not exist in most of Australia's capital cities.

Table 5 The Estimates and the *P*-Values of the ADL Models for Australia's Capital Cities

		c	α_1	β_1	α_2	β_2	α_3	β_3
ADE	**Estimates**	1.9443	0.6504	-0.0456	n/a	n/a	n/a	n/a
	***p*-value**	0.0643	0.0000**	0.9422	n/a	n/a	n/a	n/a
BRI	**estimates**	2.0067	0.6783	0.2559	n/a	n/a	n/a	n/a
	***p*-value**	0.1968	0.0000**	0.8133	n/a	n/a	n/a	n/a
CAN	**estimates**	1.7035	0.5783	0.4011	n/a	n/a	n/a	n/a
	***p*-value**	0.1546	0.0001**	0.6190	n/a	n/a	n/a	n/a
DAR	**estimates**	1.2530	0.1260	-0.5397	0.1808	0.1509	0.4905	0.3894
	***p*-value**	0.4593	0.4622	0.6489	0.2740	0.8906	0.0095**	0.7235
HOB	**estimates**	2.3326	0.1421	-1.0429	0.5517	-0.1605	n/a	n/a
	***p*-value**	0.0177	0.3763	0.0638*	0.0027**	0.7616	n/a	n/a
MEL	**estimates**	0.0082	0.1919	2.1095	0.4746	0.2651	n/a	n/a
	***p*-value**	0.9964	0.2213	0.0508*	0.0089**	0.8072	n/a	n/a
PER	**estimates**	1.0235	0.9568	1.6069	-0.3112	-0.4301	n/a	n/a
	***p*-value**	0.5853	0.0000**	0.1823	0.0541*	0.7163	n/a	n/a
SYD	**estimates**	3.4477	0.4531	-1.2796	0.1369	-0.8985	n/a	n/a
	***p*-value**	0.0310	0.0123**	0.1936	0.4294	0.3496	n/a	n/a

Notes: c denotes the estimated constant in the regressions, α_i and β_i denote the correlation coefficients of the lagged movements of HPI and CPI. "**" and "*" denotes that the coefficients are significantly different from 0 at the 5% and 10% critical levels respectively.

Table 6 shows the correlation coefficients of the lagged HPI and CPI *Eq.* (6) for each of the eight capital cities. The p-values of these coefficients can also be found in Table 6. The t statistical test indicates that the coefficients of the lagged HPI and CPI are significantly different from 0 in the models for Adelaide, Brisbane, Canberra and Hobart at the 5% critical level. In the models for Melbourne and Sydney, these relationships only appear to be significant at the 10% critical level. Moreover, the coefficient of the CPI in the model for Darwin and the coefficient of the HPI in the model for Perth are not significantly different from 0 even at the 10% critical level. This suggests that long-run relationships between the HPI and CPI exist in the cities of Adelaide, Brisbane, Canberra and Hobart. Weaker long-run relationships are found in Melbourne and Sydney. The existence of long-run relationships between the HPI and CPI cannot be proven in Darwin and Perth.

Table 6 Identification of Long- run Relationships of the HPI and CPI of Australia's Capital Cities

	δ	***p-value***	φ	***p-value***
ADE	*-0.0946*	*0.0403***	0.5062	0.0193**
BRI	-0.1014	0.0177**	0.7387	0.0078**
CAN	-0.1415	0.0082**	0.7457	0.0062**
DAR	-0.0602	0.0681*	0.3697	0.1492
HOB	-0.0902	0.0229**	0.4409	0.0080**
MEL	-0.1770	0.0997*	0.9307	0.0724*
PER	-0.0542	0.1024	0.4338	0.0650*
SYD	-0.0975	0.0296**	0.3581	0.0604*

Notes: δ and φ denote the correlation coefficients of the lagged HPI and CPI respectively. "**" and "*" denotes that the coefficients are significantly different from 0 at 5% and 10% critical levels respectively.

The statistical results indicate that from the March quarter of 1998 to March quarter of 2008, the HPI does not correlate with the CPI in most Australian capital cities, in the short run. Weak short-run relationships can be found in Hobart and Melbourne. Long-run relationships between HPI and CPI are proven to exist in Adelaide, Brisbane, Canberra, Hobart, Melbourne and Sydney. This suggests that the movement of consumer prices is not an important factor in the dynamics of house prices in the short run. In the long run, however, house prices in most of Australia's capital cities are correlated with consumer prices.

5. Conclusion

This paper has examined the short-run and long-run relationships between the HPI and CPI in Australia's capital cities. The ADL model and ECM are adopted to estimate the regressions, and the t-statistic test is used to investigate the significance of the short-run and long-run relationships. The empirical results and findings are discussed.

In summary, the dynamics of the HPI strongly depend on their past values in the short run. However, the lengths of lags are different in cities. The movements of the HPI in Adelaide, Brisbane, Canberra and Sydney are significantly impacted by the values in the previous quarter, while the HPI movements in Hobart and Melbourne are impacted by the changes in the one quarter before the previous quarter. The movements of the HPI in Perth are influenced not only by the values at lag 1, but also by the values at lag 3. Darwin is the least sensitive to the self-impact of the HPI, which is influenced by the HPI movements of two quarters before the previous quarter.

The results of this study also indicate that the relationships between the HPI and CPI are not statistically significant in most of Australia's capital cities in the short run. This implies that the inflation risk may not be effectively hedged by short-term investment in Australian residential real estate markets. Moreover, the results suggest that inflation hedging characteristics of Australian residential properties vary across cities in the long run. Investors, therefore, may have to adopt different strategies in different markets. Since there is no evidence to support the existence of long-run relationships between the HPI and CPI in the cities of Darwin and Perth, the long-term investments in these two residential markets may not be a good choice for hedging the inflation risk. As the relationships are found to be significant in Adelaide, Brisbane, Canberra and Hobart, long term investors may select the properties in these markets as the inflation hedges for investments. The weak long-run relationships in Sydney and Melbourne reflect the uncertainty of inflation hedges in these two largest residential property markets in Australia and they are just regarded as a diversified long-term investment opportunity.

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