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Seasonality in Australian Capital City House and Unit Prices

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Abstract:

In this paper we examine seasonality in house and unit (apartment) prices in the eight Australian state and territory capital cities (Adelaide, Brisbane, Canberra, Darwin, Hobart, Melbourne, Perth, and Sydney) using monthly data over the period December 1995 to July 2015. Employing a threshold autoregressive modelling approach, we determine in which months house and unit prices are, on average, more expensive or cheaper and in which capital cities seasonal price rises or falls are more significant. Our main finding is that sizable seasonal effects exist for both the very smallest (Darwin and Hobart) and very largest (Melbourne and Sydney) capital cities and that these seasonal effects are mostly predictable. We find that the relative seasonal return variations are more significant for house than unit prices. Further, the observed month-of-the-year effects have undergone significant changes in almost all capital cities for both house and unit prices since the 2008 global financial crisis (GFC). For example, before 2008 the most and least, expensive months of the year to purchase houses in Melbourne were January (+1.08%) and November (–0.74%). However, the most and least expensive months after 2008 for Melbourne were July (+3.22%) and May (–2.52%). By utilising such seasonal variations, both buyers and sellers can make informed financial decisions.

Keywords: House, apartment, price, seasonality, Australia.

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ABSTRACT

In this paper we examine seasonality in house and unit (apartment) prices in the eight Australian state and territory capital cities (Adelaide, Brisbane, Canberra, Darwin, Hobart, Melbourne, Perth, and Sydney) using monthly data over the period December 1995 to July 2015. Employing a threshold autoregressive modelling approach, we determine in which months house and unit prices are, on average, more expensive or cheaper and in which capital cities seasonal price rises or falls are more significant. Our main finding is that sizable seasonal effects exist for both the very smallest (Darwin and Hobart) and very largest (Melbourne and Sydney) capital cities and that these seasonal effects are mostly predictable. We find that the relative seasonal return variations are more significant for house than unit prices Further, the observed month-of-the-year effects have undergone significant changes in almost all capital cities for both house and unit prices since the 2008 global financial crisis (GFC). For example, before 2008 the most and least, expensive months of the year to purchase houses in Melbourne were January (+1.08%) and November (–0.74%). However, the most and least expensive months after 2008 for Melbourne were July (+3.22%) and May (–2.52%). By utilising such seasonal variations, both buyers and sellers can make informed financial decisions.

KEY WORDS: House, apartment, price, seasonality, Australia.

Introduction

Seasonality is a common characteristic of many time series in which the data experiences regular and predictable changes over some period, usually a year. Real estate agents and house buyers and sellers alike accept it as almost an article of faith that housing markets display seasonality (Carliner 2002; Kolko 2012; Croucher 2014; Morrell 2014; Miller 2015; Thistleton, 2015). Understanding seasonality in house prices is important for several reasons. First, seasonal influences affect demand and supply, and corresponding price fluctuations, over the course of the year. For example, in the northern hemisphere, spring/summer and autumn/winter housing markets in the United Kingdom (UK) and the United States (US) are argued to experience systematic above-trend increases in both prices and transactions during the second (June) and third (September) quarters (the so-called ‘hot season’) and below-trend falls during the fourth (December) and first (March) quarters (the so-called ‘cold season’), respectively.

Second, there are multiple interactions between housing markets and the rest of the economy. Housing and mortgage markets play an important role in influencing the economy's cyclical dynamics via the operation of monetary policy (Muellbauer and Murphy, 2008). Seasonal fluctuations in housing market are, therefore, important for understanding the influence of fluctuations in housing prices on a range of more general macroeconomic indicators. Third, seasonal fluctuations in housing prices have important implications for buyers and sellers in the market. Seasonality, exemplified by month-of-the-year effects, represent calendar anomalies that contradict the (weak-form) efficient market hypothesis, such that prices (and thus returns) can be predicted using historical market information. Such calendar anomalies provide opportunities for buyers or sellers to make potential abnormal gains.

A small, but influential, academic literature has emerged that tests for seasonality in housing markets, primarily in North America and/or the UK (see eg. Alexander and Barrow, 1994; Case and Shiller, 1989; Hosios and Pesando 1991; Rosenthal 2006; Kajuth and Schmidt, 2015; Ngai and Tenreyro 2014). These studies complement a closely-related literature, that seeks to test for calendar effects in real-estate-related securities, such as real estate investment trusts (REITs), (Colwell and Park, 1990; Ma and Goebel, 1991; Hui et al., 2013). Among the more recent studies testing for calendar effects in housing markets, in the UK Rosenthal (2006) used the Nationwide Building Society database of newly transacted dwellings to develop a monthly, quality-adjusted, regional house price series for the period 1991–2001, but found little evidence of either stochastic or deterministic seasonal effects. Conversely, Kajuth and Schmidt (2015) and Ngai and Tenryo (2014) identified clear and identifiable seasonal patterns in UK and US housing markets. In terms of magnitude, Ngai and Tenryo (2014) identified an annualized difference in house price growth rates between hot and cold seasons of 6.5% for the UK and 4.6% for the US, with US cities tending to display greater seasonality, with upwards of 6.7% differences in growth rates across seasons.

The purpose of this paper is to examine seasonality in house and unit (apartment) prices in the eight Australian state and territory capital cities (Adelaide, Brisbane, Canberra, Darwin, Hobart, Melbourne, Perth and Sydney) using monthly data over the period December 1995 to July 2015. Australia provides an interesting case to examine seasonality, compared with the more studied North American and UK housing markets. Australia represents one of the most consistently expensive, unaffordable and strongest growing housing markets in the world.

According to the most recent Annual International Housing Affordability Survey, housing in the five major metropolitan areas (Sydney, Melbourne, Brisbane, Adelaide and Perth) is rated as "severely unaffordable", with Sydney and Melbourne, Australia's two largest cities, considered to be the third and sixth least affordable city in the world respectively (Demographia, 2015).

Australia's population is relatively small compared to the US and UK,[1] but its landmass is similar in size to the US. As a result, Australia's population spreads across a diverse geographic area with pockets of concentration in just a few major cities—almost 70% of the population live in the five-largest capital cities—that are geographically distant from each other. Hence, compared with the housing market in the UK, one might expect that regional differences in economic conditions might be more reflective of house price movements, in particular, in the smaller, more remote, capital cities (Akimov et al., 2015). Specifically, in terms of studying seasonality in housing markets, in the Northern hemisphere, seasonal fluctuations in housing prices have been linked to different seasons of the year (Ngai & Tenreyro, 2014). Because of its sheer size, Australia has a variety of climates. For example, the southern capital cities (Sydney, Canberra, Melbourne, Hobart, Adelaide and Perth) are located in temperate zones, while Brisbane and Darwin are respectively in subtropical and tropical zones. Compared with the southern capital cities, Brisbane and Darwin have high temperatures and high humidity throughout the year, as well as distinct wet and dry seasons, which may potentially account for seasonality in house prices.

We make the following important contributions. First, we test for seasonality in house and unit (apartment) prices for a housing market that is of international interest, given the extent, and duration, of the housing boom that has persisted, largely uninterrupted, for the last two decades. To do so, we have a long time series, spanning from December 1995 to July 2015, corresponding with much of Australia's ongoing long upward trend in housing prices. In particular, the housing boom in Australia and associated concerns about affordability, have focused attention on the housing market. However, there is little research on seasonality in Australian housing markets. Apart from those studies concerning seasonality in housing construction and financing as possible underlying causes of seasonality in housing prices (see, for instance, Karamujic, 2012), there is only a single, now rather dated, study by Costello (2001). Costello (2001) confirms the

[1] In 2015, Australia's population was 23.1 million people, compared with 64.1 million in the UK and 320 million in the US.

presence of significant seasonal influences in housing prices, suggesting that the volume of transactions, and hence demand and prices, are greatest during the first quarter of the year and lowest during the last quarter. However, Costello's (2001) study has other limitations that limit the generality of his conclusions. He uses transaction data from the Western Australian Valuer General's Office, so the analysis is limited to just a single regional (state) market. In addition, Costello (2001) only employs quarterly observations and is, thus, unable to provide the more nuanced analysis possible with monthly data.

Second, we employ SIRCA's CoreLogic RP database, which constitutes a novel source of data on Australian property prices, specifically developed as a reference asset for the settlement of exchange-traded property contracts. The accuracy and robust characteristics of this database make it preferable to other series, such as those maintained by the Australian Bureau of Statistics (ABS). One of the most attractive features of the CoreLogic database is that it contains housing price data at a higher frequency (monthly) than other alternative Australian housing price series that are available from the ABS or the Real Estate Institute of Australia (REIA).

Third, more generally, we test for seasonality in house and unit prices separately. As such, this is the first study to examine seasonality in different types of housing. In addition to consumption, housing is an investment good (Piazzesi et al., 2007). For instance, the purchase and sale of investment properties is likely unaffected by the time of the year when it is easiest to move and more likely to be influenced by taxation considerations, such as the end of the financial year. Investors treat different sorts of housing differently for investment purposes. In Australia, tax concessions around negative gearing, have made it attractive for individuals to purchase, and rent out, an investment property. According to the Australian Tax Office, in 2010, 10% of Australian taxpayers were negatively geared property owners (Colebatch, 2010). Units (apartments) are also more likely to be purchased as investment properties than houses. This raises the possibility of differing month-of-the year effects across houses and units.

Empirical Methodology

If the month-of-the-year effect holds, house and unit prices will not be independent of the month observed. Following the approach adopted in Hui's et al. (2013) study, in which they test three well-known calendar effects (day of-the-week, month-of-the-year, and sell-in-May effects) in real estate security indices across 20 countries, we specify an autoregressive model augmented with 11 dummy variables to capture any fixed calendar effects:

$$\Delta Ln(P_t) = \alpha + \sum_{i=2}^{12} \beta_i M_{it} + \eta \Delta Ln(P_{t-1}) + \varepsilon_t \tag{1}$$

where P_t denotes monthly house/unit prices at time t, α is a constant, M_{it} is a dummy variable that takes the value of one in month i and zero otherwise (excluding the reference month), P_{t-1} is the one-period lagged value of monthly house/unit prices, β and η are parameters to be estimated and ε is the error term. Month-of-the-year effects (β) can undergo significant structural shifts over time. To address this problem, we propose the following model:

$$\Delta Ln(P_t) = \left[\sum_{i=1}^{12} \beta_i^j M_{it} + \eta^j \Delta Ln(P_{t-1}) \right] 1\left(T_t < T_b\right) + \left[\sum_{i=1}^{12} \beta_i^j M_{it} + \eta^j \Delta Ln(P_{t-1}) \right] 1\left(T_t \geq T_b\right) + \varepsilon_t \tag{2}$$

where β_i^j and η^j are the respective estimated coefficients for the month and lagged dependent variable before (j=1) and after (j=2) an endogenously determined break date (T_b), $1(\cdot)$ is an indicator function, which equals one if the condition in parentheses is met and zero otherwise, and all other variables are as previously defined.

We add the lagged dependent variable in equation (2) to ensure that ε_t is well behaved. To avoid the dummy variable trap, some studies (e.g. Hui et al. 2013) exclude a desired or arbitrary month as a benchmark while retaining the intercept (α). Others exclude the intercept and retain all 12 monthly dummy variables (e.g. Choudhry, 2001). We follow the latter approach. The interpretation of the coefficients is straightforward. For example, in equation (2) if house prices seasonally peak in June, then we expect the estimated coefficient for β_6 to be greater than zero and statistically significant. Equation (2) can be written in a more compact form as follows:

$$\Delta Ln(P_t) = \sum_{j=1}^{2} 1_j (T_t, T_b) \cdot \left[\sum_{i=1}^{12} \beta_i^j M_{it} + \eta^j \Delta Ln(P_{t-1}) \right] + \varepsilon_t \tag{3}$$

We correct for unknown forms of heteroskedasticity and/or autocorrelation using Newey–West estimators of the heteroskedasticity and autocorrelation consistent covariance (HAC) matrix.[2] In equations (2) and (3), T_t serves as a threshold variable. To estimate T_b (i.e. the break date), it is standard practice to conduct a grid search for all possible dates within the sample. For each possible date in the grid, we estimate equation (3) after defining the indicator function. In order to have at least 40 observations at each end of the sample period (*j* = 1,2), we set the trimming percentage at 20%. Within the specified lower and upper dates for T_t (i.e. T^l and T^u), we seek to minimise the residual sum of squares (RSS) with respect to the three sets of parameters:

$$S(\beta_i^j, \eta_j, T_b) = \sum_{t=1}^{T} \left\{ \Delta Ln(P_t) - \sum_{j=1}^{2} 1_j (T_t, T_b) \cdot \left[\sum_{i=1}^{12} \beta_i^j M_{it} + \eta^j \Delta Ln(P_{t-1}) \right] \right\}^2 \quad (4)$$

For all possible dates within the trimming region, we estimate the RSS in an iterative manner. We choose the date T_b as the threshold parameter that yields the lowest RSS. That is:

$$\hat{T}_b = \underset{\gamma \in [T^l, T^u]}{\arg\min} \ \text{RSS}(T_b) \quad (5)$$

After determining $\hat{T}_b$, we divide the whole sample into two subsamples and apply a conventional estimation method to each subsample. To justify the relevance of our proposed model, we also conduct the Bai and Perron (2003) test to compare the threshold autoregressive model (equations 1–2) with a standard non-threshold linear model. Given limited observations, we only allow for two regimes to ensure both subsamples have more than 40 observations.

Data

We obtain monthly house and unit prices from December 1995 to July 2015 for Australia's eight capital cities (Adelaide, Brisbane, Canberra, Darwin, Hobart, Melbourne, Perth, and Sydney) from SIRCA's (2015) CoreLogic RP online database. The series employ a hedonic imputation methodology, recognised as being robust at varying levels of disaggregation, across both time and space (Goh et al., 2012). In terms of comparable studies, Rosenthal (2006) also used hedonic price indexes, employing data from the Nationwide Building Society mortgage database on UK dwelling transactions. Meanwhile, Ngai and Tenryo (2014) used repeat-sales price indexes

[2] The White heteroskedasticity consistent covariance matrix is useful when the residuals are not homoscedastic, whereas the Newey–West estimators can deal with both heteroskedasticity and autocorrelation.

created using prices from the Land Registry for England and Wales in the UK and the Federal Housing Finance Agency and Standard and Poor's (S&P) Case–Shiller price series in the US.

Both types of indexes represent attempts to control for changes in housing quality, with the hedonic price index adjusting for observed housing characteristics and the repeat-sales index measuring the average price changes in repeat sales of the same properties. We believe that by considering a wide range of property attributes for a large number of dwellings, the approach underlying our chosen database reduces the bias that exists in other house price indicators for Australia, such as median or repeat-sales prices. Moreover, unlike the price indices available from the ABS or REIA, which are both only available at a quarterly frequency, our price data are monthly. This should yield a more accurate assessment of seasonality in the housing market, compared to the use of quarterly data that may lead to seasonality going undetected.

Table 1 presents a summary of descriptive statistics of the monthly price changes for the eight capital city house and unit markets. The largest mean monthly house price growth rates (log differences expressed in percentages) have occurred in Melbourne (0.721%) and Sydney (0.646%) and the smallest have been in Hobart (0.467%) and Darwin (0.529%). For units, the largest monthly mean returns have occurred in Melbourne (0.588%) and Darwin (0.562%) and the lowest in Brisbane (0.396%) and Canberra (0.446%). The standard deviations (volatilities) of price changes range from 1.019% (Adelaide) to 1.899% (Darwin) for houses and from 0.894% (Sydney) to 3.286% (Hobart) for units. On this basis, Hobart and Darwin are the most volatile markets for both houses and units, while Adelaide and Brisbane are the least price volatile house markets and Sydney and Melbourne are the least price volatile unit markets.

The distributional properties of all 16 series appear to be mostly not normal. In terms of skewness, the unit market in Adelaide and the house and unit markets in Melbourne are moderately negatively skewed (skewness between −1 and −½), indicating greater probability of large decreases in prices than rises, but the remaining markets with relatively low values of skewness (between –½ and +½) are all approximately symmetric. Nevertheless, the kurtosis, or degree of excess, in all of the markets are quite large. In the Sydney house market and the Canberra house and unit markets, the values of kurtosis are <3, thereby indicating platykurtic (short thin-tailed) distributions with relatively few extreme observations. In contrast, in all the other house and unit markets the values of kurtosis are well in excess of 3, suggesting leptokurtic (long fat-tailed) distributions, with many extreme observations. We use the calculated Jacque-Bera (JB) statistics and corresponding *p*-values in Table 1 to more formally test the null hypothesis that the distribution of monthly price growth rates are normally distributed. Other than the Adelaide and Sydney house markets and the Canberra house and unit markets, all *p*-values are smaller than .05, suggesting the rejection of the null hypothesis. Therefore, the monthly growth rates of house and unit prices generally do not follow a normal distribution.

Table 1. Descriptive statistics and unit root tests

City	Mean[(a)] (%)	Std. Dev. [(a)] (%)	Skewness	Kurtosis	JB stat.	JB *p*-value	*n*	ADF stat.	ADF *p*-value
Adelaide									
Houses	0.546	1.019	-0.21	3.56	4.81	0.09	235	-2.64	0.09
Units	0.475	1.428	-0.73	6.81	163.13	0.00	235	-2.74	0.07
Brisbane:									
Houses	0.554	1.056	0.18	4.30	17.85	0.00	235	-3.19	0.02
Units	0.396	1.232	-0.46	4.15	21.35	0.00	235	-2.77	0.06
Canberra:									
Houses	0.551	1.187	-0.14	2.83	1.06	0.59	235	-3.05	0.03
Units	0.446	1.420	-0.17	2.62	2.54	0.28	235	-2.55	0.10
Darwin:									
Houses	0.529	1.899	-0.13	4.68	23.35	0.00	195	-2.97	0.04
Units	0.562	2.285	0.00	4.31	13.98	0.00	195	-3.54	0.01
Hobart:									
Houses	0.467	1.598	-0.06	5.21	47.81	0.00	235	-1.98	0.30
Units	0.529	3.286	-0.38	5.30	52.06	0.00	214	-2.66	0.08
Melbourne:									
Houses	0.721	1.245	-0.51	4.65	36.94	0.00	235	-4.86	0.00
Units	0.588	1.137	-0.70	6.06	110.56	0.00	235	-3.22	0.02
Perth:									
Houses	0.602	1.083	0.26	4.22	17.24	0.00	235	-2.85	0.05
Units	0.526	1.323	-0.37	5.70	76.95	0.00	235	-2.35	0.16
Sydney:									
Houses	0.645	1.108	-0.11	2.69	1.39	0.50	235	-2.87	0.05
Units	0.519	0.894	0.31	5.88	84.95	0.00	235	-2.61	0.09

Notes: [(a)] Monthly percentage growth rate. ADF is the augmented Dickey-Fuller unit root test. JB is the Jacque Bera test. Akaike information criterion (AIC) is used to determine optimal lag length in ADF test.

Table 1 also provides the results of the augmented Dickey and Fuller (ADF) (1981) unit root test for each series, in which we test the null hypothesis of nonstationary against the alternative of no unit root. For 14 of the 16 markets (excluding the Perth unit market and the Hobart house market), we reject the null hypothesis at the 10% level or better, and so conclude these series are stationary or I(0). However, the Zivot and Andrews (1992) unit root test, reveals that all series are I(0) (results not shown). We may therefore safely conclude all the log differenced series are stationary, at least when one allows for the possibility of an endogenous structural break. Finally,

Figure 1 plots the monthly growth rates of house and unit prices for each capital city, from which it is obvious that the volatility of all series increase markedly from late 2007 onwards, with this conclusion rather less (more) noticeable for Canberra and Sydney (Adelaide and Melbourne). This visually supports our earlier suggestion concerning both the high levels of volatility and a possible structural break in Australian capital city house and unit markets.

Results and discussion

Table 2 presents the estimated coefficients, standard errors and *p*-values of the seasonal and other parameters outlined in our methodology. We have endogenously selected and tested separate break dates (months) for each of the 16 models and provided the estimated parameters in the period before, and after, the corresponding threshold. According to the Bai and Perron (2003) test results shown in Table 3, we reject the null hypothesis of no structural break against one structural break at the .05 level for all estimated 16 equations. The detected dates for structural breaks vary across both the capital cities and the house and unit markets, but are closely clustered, as you would expect from a single national housing market. Apart from the Brisbane and Hobart house markets, in which the break dates occurred in 2009, all the remaining break dates were observed in 2011. There is rather more variation in the break dates in the unit markets, with the break date in the Canberra unit market occurring in 2003, Adelaide in 2010, Brisbane and Perth in 2009, Hobart, Melbourne and Sydney in 2011 and Darwin in 2012.

In Table 2, for each capital city, we provide the estimated results for houses and units for the first threshold (from December 1995 to the break date) above the line and those for the second threshold (after the break date until July 2015) under the line. While all 12 seasonal dummy variables are included in each of the 16 models, we generally only display the statistically significant coefficients. The exception is that if β_i^j is statistically significant at the 5% level for a given threshold, we report the corresponding coefficient for the other threshold, irrespective of its significance. To illustrate, above the line in the first threshold, the coefficient for β_3^1 in March for Adelaide house prices when T_t < 2011M08, is 0.0139, which is statistically significant at the 5% level. Thus, while this same coefficient (i.e. β_3^2 = -0.0013) is insignificant when $T_t \geq$ 2011M08, we report the results. But, if β_3^1 was insignificant, we would not have reported β_3^2.

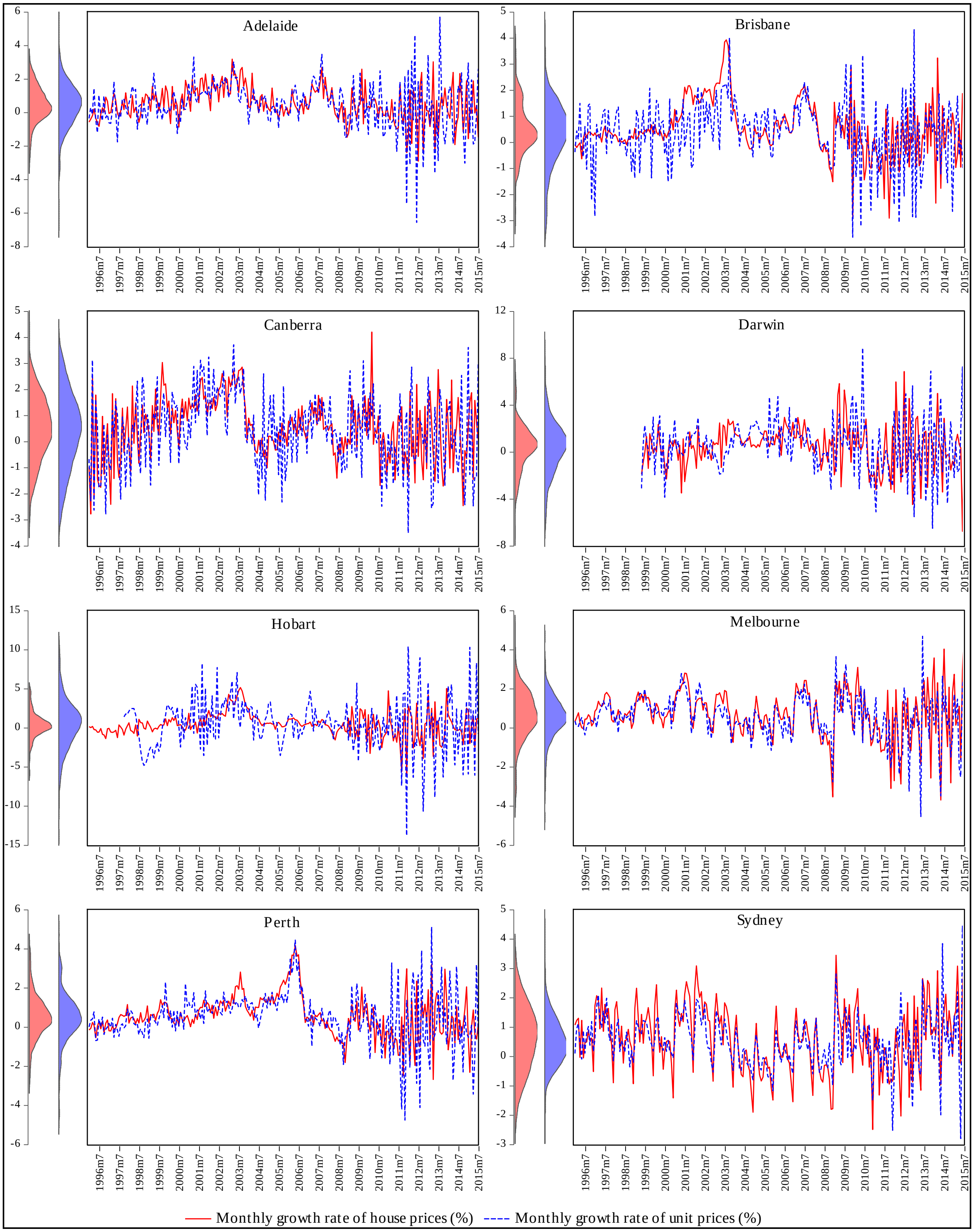

Figure 1. Monthly growth rates (log differences) of house and unit prices.

Notes: Kernel density distributions of the series are shown on the left vertical axes.

Table 2. Estimated month-of-the-year effects

$$\Delta Ln(P_t) = \sum_{j=1}^{2} 1_j(T_t, T_b)\cdot\left[\sum_{i=1}^{12}\beta_i^j M_{it} + \eta^j \Delta Ln(P_{t-1})\right] + \varepsilon_t$$

	Adelaide						Brisbane					
	Houses			Units			Houses			Units		
Description	Coeff.	*SE*	*p*-value	Coeff.	*SE*	*p*-value	Coeff.	*SE*	*p*-value	Coeff.	*SE*	*p*-value
	T_t < 2011M08 (*n*=186)			T_t < 2010M02 (*n*=168)			T_t < 2009M01 (*n*=155)			T_t < 2009M09 (*n*=163)		
January	-0.0023	0.0009	0.01	0.0009	0.0023	0.71	0.0050	0.0008	0.00			
February										0.0105	0.0013	0.00
March	0.0139	0.0017	0.00	0.0082	0.0019	0.00				0.0047	0.0019	0.01
April	-0.0027	0.0016	0.09	0.0131	0.0024	0.00						
May							0.0005	0.0008	0.54	0.0065	0.0022	0.00
June				**-0.0023**	0.0027	0.40	0.0019	0.0008	0.02	0.0077	0.0017	0.00
July	-0.0030	0.0011	0.00				0.0034	0.0006	0.00	0.0043	0.0020	0.03
August	0.0076	0.0013	0.00	0.0064	0.0027	0.02	-0.0017	0.0006	0.01			
September	0.0075	0.0017	0.00	0.0054	0.0021	0.01				0.0062	0.0024	0.01
October	**-0.0064**	0.0013	0.00	0.0052	0.0013	0.00				0.0088	0.0030	0.00
November	0.0108	0.0017	0.00	-0.0001	0.0021	0.95				**-0.0082**	0.0027	0.00
December				0.001	0.0013	0.46	**-0.0019**	0.0006	0.00	0.0016	0.0017	0.33
$\Delta Ln(P_{t-1})$	0.7067	0.0656	0.00	0.4749	0.0766	0.00	0.9475	0.0366	0.00	0.3360	0.1000	0.00
	$T_t \geq$ 2011M08 (*n*=48)			$T_t \geq$ 2010M02 (*n*=66)			$T_t \geq$ 2009M01(*n*=79)			$T_t \geq$ 2009M09 (*n*=71)		
January	-0.0073	0.0045	0.11	0.0139	0.0077	0.07	0.0078	0.003	0.01			
February										0.0003	0.0036	0.92
March	-0.0013	0.0053	0.81	0.0088	0.0042	0.04				-0.0013	0.0051	0.81
April	0.0214	0.0041	0.00	0.0012	0.0056	0.83						
May							**-0.0061**	0.0025	0.02	**-0.0119**	0.0039	0.00
June				**-0.0172**	0.0056	0.00	0.0052	0.0028	0.07	0.0035	0.0061	0.57
July	**-0.0151**	0.0049	0.00				-0.0027	0.0044	0.54	0.0001	0.0067	0.98
August	0.0117	0.0048	0.02	0.0205	0.006	0.00	0.0030	0.0041	0.46			
September	0.0132	0.0049	0.01	0.0220	0.0058	0.00				0.0024	0.0045	0.59
October	-0.0072	0.0045	0.11	-0.0096	0.0048	0.05				0.0034	0.0028	0.23
November	0.0041	0.004	0.31	-0.0163	0.0076	0.03				0.0081	0.0095	0.40
December				-0.015	0.0077	0.05	0.0026	0.0057	0.64	**-0.0119**	0.0048	0.01
$\Delta Ln(P_{t-1})$	-0.2083	0.1035	0.05	-0.4721	0.0805	0.00	-0.2006	0.1213	0.10	-0.4062	0.1048	0.00
R^2	0.638			0.468			0.617			0.335		
$\bar{R}^2$	0.609			0.421			0.594			0.276		
DW	2.31			2.09			1.86			2.17		
SIC	-6.936			-5.826			-6.898			-5.898		

Notes: The standard errors of the coefficients (and the resulting *p*-values) were computed using the Newey-West HAC (Heteroskedasticity and Autocorrelation Consistent Covariance) matrix. The maximum and minimum calendar effects are shown in shaded and bold fonts, respectively.

Table 2. Estimated month-of-the-year effects (continued)

$$\Delta Ln(P_t) = \sum_{j=1}^{2} 1_j(T_t, T_b) \cdot \left[\sum_{i=1}^{12} \beta_i^j M_{it} + \eta^j \Delta Ln(P_{t-1}) \right] + \varepsilon_t$$

	Canberra						Darwin					
	Houses			Units			Houses			Units		
Description	Coeff.	*SE*	*p*-value	Coeff.	*SE*	*p*-value	Coeff.	*SE*	*p*-value	Coeff.	*SE*	*p*-value
	$T_t <$ 2011M05 (*n*=183)			$T_t <$ 2003M12 (*n*=94)			$T_t <$ 2011M12 (*n*=150)			$T_t <$ 2012M01 (*n*=151)		
January	0.0057	0.0022	0.01				-0.0010	0.0027	0.71			
February	**-0.0023**	0.0022	0.31	-0.0088	0.0035	0.01						
March	0.0151	0.0031	0.00	0.0182	0.0028	0.00	0.0151	0.0047	0.00	0.0110	0.0044	0.01
April							0.0048	0.0051	0.35			
May	0.0091	0.0025	0.00				**-0.0144**	0.0049	0.00			
June				0.0139	0.0029	0.00	0.0093	0.0031	0.00			
July	0.0047	0.0024	0.06									
August	0.0023	0.0027	0.40	0.0025	0.0051	0.63	0.0062	0.0034	0.07	0.0065	0.0016	0.00
September	0.0118	0.0015	0.00	0.0139	0.0031	0.00	-0.0016	0.0035	0.65	**-0.0010**	0.0029	0.74
October	0.0000	0.0024	0.99	0.0113	0.0032	0.00						
November	0.0060	0.0014	0.00	**-0.0104**	0.0045	0.02						
December							0.0072	0.0030	0.02	0.0122	0.0051	0.02
$\Delta Ln(P_{t-1})$	0.4472	0.1003	0.00	0.3963	0.1319	0.00	0.4520	0.0878	0.00	0.2818	0.0800	0.00
	$T_t \geq$ 2011M05 (*n*=51)			$T_t \geq$ 2003M12 (*n*=140)			$T_t \geq$ 2011M12 (*n*=44)			$T_t \geq$ 2012M01 (*n*=43)		
January	0.0024	0.0061	0.69				-0.0232	0.0045	0.00			
February	0.0124	0.0063	0.05	0.0113	0.0029	0.00						
March	0.0156	0.0043	0.00	0.0017	0.0039	0.66	0.0406	0.0077	0.00	-0.0175	0.0062	0.01
April							0.0205	0.0051	0.00			
May	-0.0077	0.0046	0.09				-0.0116	0.0101	0.26			
June				-0.0029	0.0019	0.12	**-0.0328**	0.0102	0.00			
July	0.0131	0.0044	0.00									
August	0.0131	0.0022	0.00	0.0092	0.0023	0.00	0.0175	0.0060	0.00	0.0172	0.0230	0.46
September	0.0010	0.0046	0.83	-0.0017	0.0049	0.72	-0.0169	0.0053	0.00	-0.0274	0.0069	0.00
October	**-0.0183**	0.0038	0.00	0.0065	0.0045	0.15						
November	-0.0090	0.0055	0.10	**-0.0054**	0.0039	0.16						
December							-0.0082	0.0105	0.44	0.0108	0.0229	0.64
$\Delta Ln(P_{t-1})$	-0.4261	0.1080	0.00	-0.0864	0.0785	0.27	-0.5010	0.1153	0.00	-0.4185	0.0843	0.00
R^2	0.422			0.246			0.353			0.140		
$\bar{R}^2$	0.370			0.194			0.290			0.098		
DW	2.15			2.12			2.00			2.15		
SIC	-6.119			-5.583			-5.044			-4.613		

Notes: The standard errors of the coefficients (and the resulting *p*-values) were computed using the Newey-West HAC (Heteroskedasticity and Autocorrelation Consistent Covariance) matrix. The maximum and minimum calendar effects are shown in shaded and bold fonts, respectively.

Table 2. Estimated month-of-the-year effects (continued)

$$\Delta Ln(P_t) = \sum_{j=1}^{2} 1_j(T_t, T_b) \cdot \left[\sum_{i=1}^{12} \beta_i^j M_{it} + \eta^j \Delta Ln(P_{t-1}) \right] + \varepsilon_t$$

	Hobart						Melbourne					
	Houses			Units			Houses			Units		
Description	Coeff.	*SE*	*p*-value	Coeff.	*SE*	*p*-value	Coeff.	*SE*	*p*-value	Coeff.	*SE*	*p*-value
	$T_t <$ 2009M12 (*n*=166)			$T_t <$ 2011M12 (*n*=169)			$T_t <$ 2011M09 (*n*=187)			$T_t <$ 2011M10 (*n*=188)		
January	0.0063	0.0020	0.00				0.0108	0.0019	0.00	0.0072	0.0020	0.00
February	**-0.0045**	0.0019	0.02	0.0150	0.0048	0.00	0.0083	0.0015	0.00	0.0085	0.0025	0.00
March				0.0162	0.0068	0.02				0.0018	0.0021	0.37
April				-0.0140	0.0056	0.01				0.0037	0.0015	0.01
May				0.0099	0.0056	0.08	-0.0010	0.0015	0.52	0.0062	0.0020	0.00
June				0.0254	0.0078	0.00	-0.0011	0.0014	0.45			
July	0.0049	0.0021	0.02	**-0.0159**	0.0066	0.02	0.0078	0.0016	0.00	0.0088	0.0019	0.00
August	0.0042	0.0030	0.17							0.0029	0.0015	0.05
September	-0.0004	0.0014	0.76	0.0028	0.0102	0.79				-0.0016	0.0020	0.44
October	-0.0001	0.0015	0.97	0.0004	0.0076	0.96				0.0059	0.0011	0.00
November				0.0132	0.0057	0.02	**-0.0074**	0.0012	0.00	**-0.0049**	0.0021	0.02
December	0.0049	0.0018	0.01				-0.0036	0.0016	0.03			
$\Delta Ln(P_{t-1})$	0.8099	0.0890	0.00	0.2792	0.1809	0.12	0.8226	0.0441	0.00	0.5210	0.0959	0.00
	$T_t \geq$ 2009M12 (*n*=68)			$T_t \geq$ 2011M12 (*n*=44)			$T_t \geq$ 2011M09 (*n*=47)			$T_t \geq$ 2011M10 (*n*=47)		
January	0.0291	0.0058	0.00				0.0094	0.0126	0.46	0.0080	0.0032	0.01
February	0.0049	0.0092	0.60	0.0595	0.0171	0.00	0.0087	0.0049	0.07	0.0112	0.0030	0.00
March				0.0360	0.0133	0.01				0.0130	0.0035	0.00
April				0.0003	0.0183	0.99				-0.0093	0.0061	0.13
May				-0.0575	0.0076	0.00	**-0.0252**	0.0044	0.00	**-0.0369**	0.0054	0.00
June				-0.0041	0.0192	0.83	0.0194	0.0044	0.00			
July	0.0041	0.0031	0.19	0.0167	0.0129	0.20	0.0322	0.0073	0.00	0.0279	0.0079	0.00
August	-0.0132	0.0052	0.01							0.0195	0.0023	0.00
September	**-0.0262**	0.0094	0.01	0.0347	0.0068	0.00				0.0125	0.0027	0.00
October	-0.0248	0.0046	0.00	**-0.0675**	0.0178	0.00				-0.0070	0.0070	0.32
November				-0.0575	0.0175	0.00	-0.0240	0.0039	0.00	-0.0073	0.0064	0.26
December	0.0021	0.0134	0.87				0.0139	0.0047	0.00			
$\Delta Ln(P_{t-1})$	-0.2781	0.1046	0.01	-0.5247	0.1559	0.00	-0.0127	0.0886	0.89	-0.5031	0.1672	0.00
R^2	0.523			0.384			0.652			0.549		
$\bar{R}^2$	0.490			0.323			0.628			0.504		
DW	2.27			2.21			2.20			2.06		
SIC	-5.802			-3.974			-6.618			-6.398		

Notes: The standard errors of the coefficients (and the resulting *p*-values) were computed using the Newey-West HAC (Heteroskedasticity and Autocorrelation Consistent Covariance) matrix. The maximum and minimum calendar effects are shown in shaded and bold fonts, respectively.

Table 2. Estimated month-of-the-year effects (continued)

$$\Delta Ln(P_t) = \sum_{j=1}^{2} 1_j(T_t, T_b) \cdot \left[\sum_{i=1}^{12} \beta_i^j M_{it} + \eta^j \Delta Ln(P_{t-1}) \right] + \varepsilon_t$$

	Perth						Sydney					
	Houses			Units			Houses			Units		
Description	Coeff.	*SE*	*p*-value	Coeff.	*SE*	*p*-value	Coeff.	*SE*	*p*-value	Coeff.	*SE*	*p*-value
	T_t < 2011M09 (*n*=187)			T_t < 2011M12 (*n*=155)			T_t < 2011M09 (*n*=187)			T_t < 2011M10 (*n*=188)		
January							0.0215	0.0011	0.00	0.0072	0.0008	0.00
February	-0.0009	0.0007	0.19	0.0053	0.0016	0.00	0.0094	0.0017	0.00	0.0101	0.0013	0.00
March	0.0047	0.0010	0.00	**0.0000**	0.0020	0.98	-0.0031	0.0021	0.13	0.0032	0.0016	0.05
April	-0.0022	0.0010	0.03	0.0046	0.0019	0.02	-0.0050	0.0013	0.00			
May							0.0040	0.0017	0.02			
June	0.0030	0.0013	0.02				-0.0051	0.0010	0.00	0.0055	0.0009	0.00
July				0.0013	0.0016	0.40	0.0091	0.0013	0.00	0.0037	0.0013	0.00
August	0.0029	0.0013	0.03									
September				0.0043	0.0011	0.00				-0.0018	0.0012	0.13
October										0.0019	0.0014	0.19
November	**-0.0025**	0.0018	0.16	0.0071	0.0024	0.00	-0.0051	0.0013	0.00			
December	0.0042	0.0009	0.00				**-0.0111**	0.0013	0.00	**-0.0051**	0.0010	0.00
$\Delta Ln(P_{t-1})$	0.8706	0.0561	0.00	0.7216	0.0735	0.00	0.7725	0.0535	0.00	0.5963	0.0596	0.00
	$T_t \geq$ 2011M09 (*n*=47)			$T_t \geq$ 2009M01 (*n*=79)			$T_t \geq$ 2011M09 (*n*=47)			$T_t \geq$ 2011M10 (*n*=46)		
February	**-0.0133**	0.0044	0.00	**-0.0087**	0.0065	0.18	0.0121	0.0041	0.00	0.0041	0.0036	0.25
March	0.0104	0.0069	0.14	0.0192	0.0053	0.00	0.0025	0.0040	0.52	0.0076	0.0019	0.00
April	-0.0023	0.0062	0.71	-0.0030	0.0088	0.74	0.0162	0.0058	0.01	0.0134	0.0040	0.00
May							-0.0067	0.0029	0.02			
June	0.0104	0.0057	0.07				**-0.0121**	0.0020	0.00	0.0301	0.0090	0.00
July				0.0156	0.0046	0.00	0.0233	0.0033	0.00	0.0087	0.0064	0.18
August	-0.0028	0.0037	0.45				0.0129	0.0035	0.00			
September				0.0004	0.0109	0.97				0.0089	0.0041	0.03
October										0.0075	0.0029	0.01
November	0.0156	0.0041	0.00	-0.0063	0.0089	0.48	0.0011	0.0031	0.72			
December	0.0201	0.0057	0.00				-0.0037	0.0025	0.14	**-0.0100**	0.0059	0.09
$\Delta Ln(P_{t-1})$	-0.1971	0.0889	0.03	-0.2037	0.1106	0.07	0.4672	0.1435	0.00	0.1202	0.1496	0.42
R^2	0.651			0.350			0.712			0.5344		
$\bar{R}^2$	0.627			0.311			0.686			0.4977		
DW	2.42			2.11			2.70			2.07		
SIC	-6.896			-5.917			-6.946			-6.942		

Notes: The standard errors of the coefficients (and the resulting *p*-values) were computed using the Newey-West HAC (Heteroskedasticity and Autocorrelation Consistent Covariance) matrix. The maximum and minimum calendar effects are shown in shaded and bold fonts, respectively.

Table 3. The Bai–Perron test for zero versus one structural break

City	Scaled F stat.	5% critical value**
Adelaide		
House	164.53	24.91
Unit	237.49	26.38
Brisbane:		
House	202.80	21.33
Unit	58.91	26.38
Canberra:		
House	82.00	26.38
Unit	123.73	23.19
Darwin:		
House	119.59	24.91
Unit	98.91	17.66
Hobart:		
House	95.10	23.19
Unit	105.38	26.38
Melbourne:		
House	714.37	23.19
Unit	289.47	26.38
Perth:		
House	238.66	23.19
Unit	86.76	21.33
Sydney:		
House	242.96	26.38
Unit	57.27	24.91

** Critical values are from Bai-Perron (2003).

While simple in terms of the explanatory variables included, all models appear to perform adequately in explaining housing price growth rates in each of the eight capital cities. In terms of R^2, the Melbourne and Sydney models perform best, explaining about 65.2% and 71.2% of the variation in monthly house price changes and 54.9% and 53.4% of monthly unit price changes, respectively. The worst performing models are for Canberra and Darwin, where the respective proportion of variance explained for houses and units is only 42.2% and 24.6% for the former and 35.3% and 14.0% in the latter. The only variable included in the models, other than the seasonal effects, is the lagged price change. Prior to the specified break dates the signs on the lagged price changes are mostly positive and significant in the first threshold, with more negative and significant coefficients in the second threshold. During the period $T_t < \hat{T}_b$, the estimated autoregressive coefficients were mainly positive and well below +1, suggesting that property prices were subject to greater inertia and hence more predictable. However, in more recent times (i.e. $T_t \geq \hat{T}_b$), there has been a systematic fall in the autoregressive coefficients, making future price changes less path dependent and more difficult to predict. This finding is consistent with the increasing volatility of residential housing prices in the post-2007 era (see Figure 1).

Now consider the seasonal effects in the first period for houses, which is the period before late 2011 for all markets except Brisbane and Hobart, for which it is before 2009. The month-of-the-year effect results for houses and units across capital cities are summarized in Table 4. For Adelaide, Canberra, Darwin, and Perth, the largest positive month-of-the year effect is in March, while for Brisbane, Hobart, Melbourne and Sydney it is in January. These months broadly corresponds to the so-called ‘hot season’ in Australia, in which the largest positive price changes have been observed in the northern hemisphere. Not only do these months correspond to the second month of summer and the first month of autumn, they are also broadly aligned with the start of the new school year, the commencement of public service contracts (especially in education), and the ending of the summer holiday period. These results are also consistent with the position put forward by Matusik (2014), who maintains “[o]ften, decisions about moving are made during the Christmas break, thus listings increase soon after.”

In terms of economic magnitude across the capital cities, in the first period the positive seasonal effect (and the opportunity for largest abnormal gains/losses by sellers/buyers) for houses is most significant for Canberra in March (1.51%) and Sydney in January (2.15%). The positive calendar effects shown in Table 4 translate to significant monetary values. For example, based on median house prices in July 2015, this equates to an abnormal monthly seasonal gain (loss) for sellers (buyers) of $9,700 in Canberra and $21,600 in Sydney.

The positive seasonal effect for units in the first period was more variable than for houses. In three-quarters of the capital cities, the positive seasonal effect was still broadly concentrated at the beginning or end of the year, which corresponds to the warmer months in Australia. The exceptions are Hobart and Melbourne, in which the positive seasonal effect is clustered around the end of the financial year and beginning of the next financial year. In Australia, many units are owned as investment properties. As such, the market for units is likely to be less sensitive to the logistics of moving house in time for commencement of the new school year or a new job. Moreover, investors can minimize the amount of capital gains tax (CGT), payable on an investment property by selling it shortly before June 30. If a property sells in mid-June, for example, but the sale does not settle until July or August investors will not have to pay the CGT on the capital growth achieved on their property for 12 months or more. At the same time, investors are in a position to increase and maximize deductions on a rental property in the financial year in which it sells. As shown in Table 4, the positive seasonal effect for units in the first period is most pronounced in Canberra in March (1.82%) and June in Hobart (2.54%).

In the second period (i.e. recent years), the positive seasonal effect has become more difficult to predict. For houses, it is similar for Adelaide, Brisbane, Canberra, Darwin, or Hobart, but it has shifted for Melbourne, Perth and Sydney. For units, the positive seasonal effect has shifted between periods in most cities. For most capital cities, the positive seasonal effects in the second period continue to be in the warmer months toward the end, or beginning, of each year. Important exceptions are Melbourne and Sydney, in which the positive seasonal effect for houses and units in the second period is in June/July. This result likely reflects the fact that Melbourne and Sydney have been at the centre of the investment boom in housing and units in recent years in Australia and that the month-of-the-year effect in these cities, likely reflects listing prior to the end of the financial year. Another exception is Darwin, for which the positive seasonal effect for units in the second period is in August. While the positive seasonal effects for houses (both periods) and units (first period) occur in the Darwin wet season, which is November to April, the second period effect for units coincides with the dry season in Darwin.

The seasonal effects for both houses and units in the second period (i.e. recent years) are greater than the first period. For example, in the second period, the June effect in the Sydney unit market (3.01%) was three times greater than the February effect (1.01%) in the first period. This result, again, at least in part, likely reflects the investment boom in property in the second period, which, in the case of Melbourne and Sydney, is linked to the timing of the seasonal effect.

Table 4. Most expensive month to buy

City	Houses				Units			
	First period		Second period		First period		Second period	
	Month	% rise	Month	% rise	Month	% rise	Month	% rise
Adelaide	March	1.39	April	2.14	April	1.31	September	2.2
Brisbane	January	0.5	January	0.78	February	1.05	November	0.81
Canberra	March	**1.51**	March	1.56	March	**1.82**	February	1.13
Darwin	March	1.51	March	**4.06**	December	1.22	August	1.72
Hobart	January	0.63	January	2.91	June	**2.54**	February	**5.95**
Melbourne	January	1.08	July	**3.22**	July	0.88	July	2.79
Perth	March	0.47	December	2.01	November	0.71	March	1.92
Sydney	January	**2.15**	July	2.33	February	1.01	June	**3.01**

Note: The two largest calendar effects are shown in bold.

Table 5. Cheapest month to buy

City	Houses				Units			
	First period		Second period		First period		Second period	
	Month	% fall	Month	% fall	Month	% fall	Month	% fall
Adelaide	October	-0.64	July	-1.51	June	-0.23	June	-1.72
Brisbane	December	-0.19	May	-0.61	November	-0.82	May/Nov	-1.19
Canberra	February	-0.23	October	-1.83	November	**-1.04**	November	-0.54
Darwin	May	**-1.44**	June	**-3.28**	September	-0.10	September	-2.74
Hobart	February	-0.45	September	**-2.62**	July	**-1.59**	October	**-6.75**
Melbourne	November	-0.74	May	-2.52	November	-0.49	May	**-3.69**
Perth	November	-0.25	February	-1.33	March	0.00	February	-0.87
Sydney	December	**-1.11**	June	-1.21	December	-0.51	December	-1.00

Note: The two largest (in absolute value) calendar effects are shown in bold.

The 'cold season' (largest negative price changes), summarised in Table 5, is likewise very variable, but also tends to be mostly in the second half of the year. For houses in the first period, the largest negative price changes are in October in Adelaide, November in Perth and Melbourne and December in Brisbane and Sydney. The three cities in which the largest negative price changes occur in the first half of the year are February in Hobart and Canberra and May in Darwin. In the second period, particularly for houses, there is a greater concentration in the cooler months in the middle of the year. This result is consistent with findings from the northern hemisphere (e.g. Ngai & Tenreyo, 2014). The two largest negative monthly price changes in the second period were observed in the cooler season in Hobart (6.75% in October) and in Melbourne (3.69% in May). These two calendar effects in the last column of Table 5 translate to $19,929 (Hobart) and $18,953 (Melbourne) monetary gain (loss) for buyers (sellers).

Finally, comparing the first (lower volatility) period and the second (higher volatility) period in Table 4, there has been no change in the most expensive month to buy (most beneficial month to sell) in Brisbane, Canberra, Darwin and Hobart for houses, but the only city for which there has been no change in the most expensive month to buy for units is Melbourne. In other words, the timing of the positive seasonal effects remained more stable for houses than units.

Conclusion

This paper has examined seasonality in the form of a month-of-the-year effect in both house and unit (apartment) prices across eight Australian capital cities (Adelaide, Brisbane, Canberra, Darwin, Hobart, Melbourne, Perth and Sydney) over the period December 1995 to July 2015. We firstly found strong evidence of a structural break in seasonality broadly corresponding to the

GFC. We then identified strong monthly seasonal effects in all markets, which varied across both capital city and property type. The estimated threshold autoregressive models tended to perform better (in terms of explanatory power) for house prices than unit prices, particularly in the larger capital cities. The significance and general consistency of the monthly seasonal effects lend some support to the belief of industry practitioners and house buyers and sellers that some months represent a 'hot season', in which prices are systematically higher than what they otherwise would be, while others are suggestive of a 'cold season' with correspondingly lower prices. This presents a respective opportunity for sellers and buyers to make systematically higher abnormal gains than they would otherwise, up to 6% on a month-on-month basis. In general, we do not find clear systematic differences in seasonality in house prices between the capital cities located in the temperate climate and Brisbane and Darwin, located in sub-tropical and tropical climates.

We also found that the Australian market has experienced significant change in the 20-year sample period. In the two largest markets of Melbourne and Sydney, there is evidence that the investment boom has influenced the seasonal effect in the second period with the month-of-the-year effect coinciding with the end of the financial year. In addition, both house and unit prices were noticeably more volatile in the most recent regime. Interestingly, while volatility has been on the rise, the highest negative and positive month-of-the-year seasonal effects have also increased in magnitude. Problematically for buyers (sellers) seeking to predict the best month in which to to purchase (sell) , the best, and poorest, selling months implied by our analysis have moved around, whereas in the earlier period prior to the GFC they were much more stable. Therefore, while it may be possible to make abnormal gains with knowledge of these seasonal effects, there is no guarantee that they will not experience further change in the future. We conjecture that the presence of these seasonal effects represents a significant challenge to the notion that residential housing markets are efficient. Moreover, these seasonal effects may lie at the heart of the ongoing volatility in housing prices with short-term local market conditions and expectations primarily driving house price changes, rather than any longer-term broader fundamentals. Such an outcome would be consistent with the existence of concentrated housing markets in metropolitan areas that are geographically a long way apart from each other.

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