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Two Countries, Sixteen Cities, Five Thousand Kilometres: How Many Housing Markets?

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Abstract

We test whether a single housing market exists across sixteen cities covering two countries, Australia and New Zealand. Distances between these cities are vastly greater than commuting distances. We define a single housing market as one in which a single stochastic trend describes the long run path of real house prices in all cities. A strong form single housing market occurs when an innovation to the stochastic trend affects house prices across all cities multiplicatively to an equal degree. A weak form occurs when an innovation to the stochastic trend affects house prices in all cities, but not to an equal degree. We find that the sixteen housing markets are characterised by a weak form single housing market. The dynamic structure of adjustment reveals three groups of cities. House price shocks are first reflected in the price dynamics of a leading group of Australian cities (including Melbourne and Sydney), then flow to a group of follower cities comprising peripheral Australian and major New Zealand cities, and then to a group of laggard cities within New Zealand. Our theoretical model demonstrates how a weak form single housing market may arise due to differences between cities in house price responses to land prices, migration responses to house prices and/or land price responses to migration flows.

JEL codes

R21, R31

Keywords

House prices; convergence; single housing market; Australia; New Zealand

Contents

Figures

Tables

1. Introduction

We examine whether a single housing market exists across sixteen cities covering two countries, Australia and New Zealand (Australasia). Distances between almost all of these cities are vastly greater than commuting distances. For instance, Perth is over 2,000 kilometres (kms) from its nearest large city neighbour, Adelaide, and is over 5,000kms from the New Zealand cities. If there is a single housing market across these cities, then the economic forces that lead to such convergence must be other than commuting arbitrage forces that have been posited as driving convergence in densely populated countries such as the United Kingdom. Other possible convergence forces may include migration flows or similar demand and supply conditions across the two countries.

We define a single housing market as one in which a single stochastic trend determines the long run path of real house prices in all cities. Local shocks may still impact on prices in each city in the short run, but these shocks are stationary and so do not affect long run house prices of a city.[1] We adopt a strong and a weak definition of a single housing market. The strong form occurs when an innovation to the single stochastic trend affects house prices across all cities multiplicatively to an equal degree. The weak form occurs when an innovation to the single stochastic trend affects house prices in all cities, but not to an equal degree. In the strong case, ratios of real house prices between all city pairs stay the same in the long run, while in the weak case house price ratios between cities will tend to diverge even though they are affected by the same long run influences.

The issue of whether a single housing market exists across two countries is important for understanding policy impacts. If a single housing market is observed across both countries, then macroeconomic policies must either have been convergent across the two countries or they have been incapable of independently controlling real house prices despite both countries running independent monetary and fiscal policies. (Macroeconomic policies could still, however, affect the short run path of prices relative to the long run trend.) We show that if the strong form of a single market occurs, then housing and land supply and migration elasticities must have had identical long run effects over multiple regions. If the weak form of a single market occurs, then supply (including regulatory policies) or migration responses may have modified the impact of identical shocks across cities.

[1] Strictly, we examine the natural logarithm (log) of real house prices, so our analysis is in terms of the long run ratio of city real house prices. By 'real' house prices, we mean house prices relative to the aggregate price of local goods and services.

Our focus is on eight main cities in each of Australia and New Zealand. The Australian cities comprise the six state capitals (Sydney, Melbourne, Brisbane, Perth, Adelaide, Hobart), the Northern Territory capital (Darwin) and the Federal capital (Canberra). The New Zealand cities comprise the eight largest metropolitan urban areas (Auckland, Wellington, Christchurch, Hamilton, Tauranga, Dunedin, Napier-Hastings, and Palmerston North).

Our methodology extends the principal components methodology outlined in Holmes and Grimes (2008) to include dynamic factor analysis methods. This approach enables us to test whether there exists a dynamic relationship that links multiple factors underlying house price movements across cities over time, and we indeed find such a relationship. After accounting for these dynamic relationships, we establish that the sixteen cities constitute a single weak form housing market.

Section 2 of the paper outlines prior studies of Australian and New Zealand housing markets plus convergence-related studies in the US and the UK. Section 3 briefly discusses the Australian and New Zealand housing markets and describes the New Zealand and Australian data that we use. Section 4 presents our methodology and empirical results, while section 5 provides economic interpretation of our econometric results. The Appendix contains the canonical housing market model that we use to interpret our results.

2. Prior Studies

A limited number of prior studies have interpreted movements in regional house prices within each of Australia and New Zealand. Maher (1994) found spatial variability in Australian house prices both at an intra-metropolitan (suburban) scale and at an inter-metropolitan (city) scale. Using cointegration and causality testing, Smyth and Nanda (2003) find weak evidence of market segmentation in house prices in the South East and East Coast of Australia with few cointegrating relationships between capital cities. In terms of causality, their results suggest that housing prices in Melbourne and Adelaide Granger-cause housing prices in Canberra and housing prices in Perth and Sydney Granger-cause housing prices in Brisbane. In a similar vein Slade (2006) finds evidence of both linkages and segmentation. Luo et al. (2007) find evidence that is supportive of a ripple effect being present among Australian cities with Sydney and Melbourne being present in the top tiers. Liu et al. (2008) use VAR and impulse-response analysis to show that house price diffusion is such that the most important subnational markets in Australia do not point to Sydney, but rather towards Canberra and Hobart, while the Darwin market plays a role of buffer. More recently, Ma and Liu (2013) consider the importance of spatial heterogeneity and autocorrelations in house price behaviour. Using a spatio-temporal approach they argue that demographic distance, constructed by demographic structure and housing market scales, can be used to investigate the house price convergences in Australian capital cities. Their results confirm that the house price levels in Canberra, Brisbane and Perth converge to those in Sydney. Ma and Liu (2015) also develop a spatio-temporal autoregressive model based on a framework of panel regression methods. Their results confirm that house prices in Sydney approach a steady state in the long run, whereas house prices in Brisbane, Canberra, Melbourne and Perth do so with lower confidence. However, little evidence supports the existence of long-run equilibrium in the house prices of Adelaide, Darwin and Hobart.

In the case of New Zealand house prices, Grimes et al (2003) found that New Zealand house prices had increased more rapidly in higher priced (generally urban) regions than in lower priced regions since 1991. Hall et al (2006) found that while regional house price cycles have often coincided with national housing cycles, there have also been deviations in cycles across regions. Using a principal components decomposition of regional house price series, Grimes et al (2010) isolated one clear non-stationary (static) factor affecting all regions of New Zealand, with ambiguous evidence of a second factor. Each of these studies indicates the possibility of multiple housing markets within (and hence across) each country. Shi et al. (2010) conclude that in the long run, a ripple effect is most likely constrained within regions. They find little evidence to suggest that the ripple effect spreads nationally between main regional centres. The results support the theory that the ripple effect is likely to be caused by a region's internal economic factors rather than migration and spatial arbitrage.

In an alternative approach, Grimes and Hyland (2015) model New Zealand's regional housing markets based on fundamentals, using a four equation system. The equations for house prices (an inverted demand equation), housing supply, land prices and rent interact to determine the four outcomes. A modified version of this model, that has closed form solutions, is outlined in the Appendix. This model demonstrates how a shock that affects all cities identically can nevertheless produce long run house price outcomes that differ across cities, depending on the impact of land prices on house prices, the reaction of land prices to population and the reaction of population (migration) to house prices. It therefore illustrates how a weak form single housing market may eventuate even with identical shocks.

Several United Kingdom studies have analysed whether house prices are convergent across regions. A specific focus has been on whether there is a "ripple effect", in which a shock to house prices in London spreads out dynamically to other regions according to contiguity.[2] In the UK context, the principal explanation for a ripple effect is that an upward price shock in London causes commuters to purchase houses further from the city so raising prices in neighbouring locations which, in turn, spreads to house prices in their neighbouring locations, and so on. Holmes and Grimes (2008) undertake unit root testing of the first principal component of regional-national house price differentials and find that all UK regional house prices are driven by a single common stochastic trend. Using a pairwise unit root testing approach in assessing the percentage of unit root rejections among all house price differentials, Abbott and De Vita (2012) investigate the long-run convergence of district-level house prices in Greater London. No overall multidistrict long-run convergence is found. Some evidence of district-level segmentation of house prices in Greater London is found, with the sub-group of the boroughs contiguous to the 'City of London' district and the wider 'central' sub-market emerging as the clubs with the highest rate of convergence. Abbott and De Vita (2013) also find pairwise evidence against long-run house price convergence across the UK regions. In contrast to these studies, Tsai (2014) using panel-based unit root tests indicates that the relative price and volume ratios show constancy, signifying that long-run equilibrium relationships exist between the regional and national housing markets in the UK. Cook (2012) finds that β-convergence is not detected over the whole UK sample period available, but it is observed over the housing market cycle, with overwhelming evidence of convergence detected, particularly during the downturn.

Looking at studies of regional house price convergence in the US, Clark and Coggin (2009) perform an unobserved components structural time series analysis of nine regional indexes and two super-regional factors and fit a classic "smooth trend plus cycle" model. The evidence for regional convergence is mixed, with little evidence for the first super-regional factor and some examples of relative convergence within the second factor. Support for a simple error correction model for regional house prices in their study is mixed. Kim and Rous (2012) study house price convergence in panels of US states and metropolitan areas. They find little evidence of overall convergence, but strong evidence of multiple convergence clubs. Holmes et al. (2011) examine long-run house price convergence across US states using a pairwise approach. They find evidence in favour of convergence such that speed of adjustment towards long-run equilibrium is inversely related to distance. Barros et al. (2014) examine the degree of persistence in the ratio

[2] For other UK studies, see: Meen (1999), Cook and Thomas (2003), Cook (2003, 2005a, 2005b), Drake (2005), Holmes (2007). For studies of other countries, see: Gallet (2004), Gros (2007), Chien (2010), Burger and Van Rensburg (2008), Fadiga and Wang (2009).

of state house price to U.S. house price indices using fractional integration and autoregressive models. The results provide mixed evidence on the degree of convergence in housing prices across the U.S.

Many of the above studies use time series techniques based on tests of cointegration across regional house price indices to examine whether the ripple effect reflects short run adjustments or whether long run divergences remain across regions. One problem in interpreting studies using this methodology in cases where divergence is found, is that the divergence result may be the result of adopting tests that have low power to reject the null of no cointegration.[3] The factor-based tests that we use are less subject to this problem than earlier forms of cointegration tests by exploiting the panel nature of the dataset. Our methodology also enables us to examine dynamic relationships amongst variables enabling us to distinguish whether multiple factors, if they exist, are dynamically related to one another.

3. Data

We focus on eight metropolitan areas (cities) within each country: Sydney (SYD), Melbourne (MEL), Brisbane (BRI), Adelaide (ADL), Perth (PTH), Hobart (HOB), Darwin (DRW), Canberra (CNB), Auckland (AKL), Wellington (WEL), Hamilton (HAM), Tauranga (TAU), Hastings (HAS),[4] Palmerston North (PMN), Christchurch (CHC), and Dunedin (DUN). There is an equal balance of Australian and New Zealand cities in the panel to ensure that the factor analysis is not biased towards one country. For each city we deflate the house price index by a consumer price index. We refer to these as real house prices indices. Each is normalized to one at the beginning of the sample. For the Australian cities we obtain a CPI for each individual city from the Australian Bureau of Statistics (ABS). Comparable data for the New Zealand cities is lacking, and so we use the national CPI from Statistics New Zealand (SNZ).[5]

We obtain quarterly house price data for New Zealand cities from Quotable Value New Zealand (QVNZ, a state owned enterprise) and for Australian cities from the ABS. In each case, the series are quality-adjusted and are recognised as the official or principal house price series for

[3] Grimes et al (2010) provide an example of rejection of cointegration for two obviously closely related real house price series.
[4] We select Hastings for the Napier-Hastings metro area because it is slightly larger than Napier. House prices in the twin cities follow each other very closely.
[5] We make no exchange rate adjustment when comparing trans-Tasman house prices since we are examining whether the relative price of houses to other goods and services moves similarly in the long run across regions.

their respective country's cities.[6] The ABS data are available from 1986q1 onwards while QVNZ officially released data are available from 1989q4 onwards. We use data through to 2015q1, the most recent data available at date of commencement of the research. The New Zealand series have been backdated to 1986q1 using QVNZ's median house sale price series for each city over 1986q1 – 1989q4. Grimes and Young (2010) demonstrate that alternative methods of quality adjustment produce indices with very similar long run properties, with only minor short run deviations. Given that our interest is in long run outcomes, the precise method of quality adjustment used by each of ABS and QVNZ therefore makes little difference for our analysis.

Figure 1: Real House Prices, 16 Cities (1986q1 = 1.0)

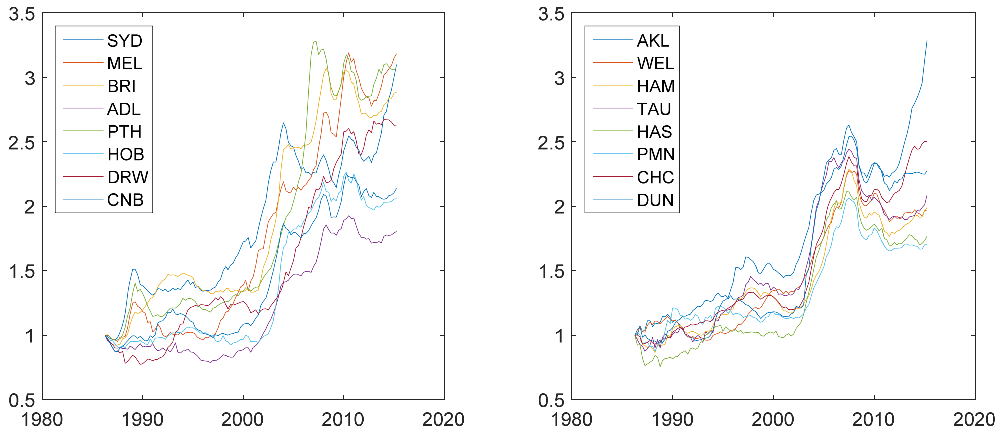


Figure 1 graphs the sixteen real house price series split between the Australian and New Zealand cities, for our sample period (1986q1 – 2015q1). The time series trend upwards over time (indicating that house prices grew at a much faster rate than the general price level over the sample period) and are clearly non-stationary, as confirmed by the Augmented Dickey-Fuller (ADF) tests presented in Table 1, in which fifteen of the sixteen cities are estimated to be integrated of order one. (For the remaining city, Auckland, we can reject stationarity if we do not include a time trend, but cannot reject stationarity about a linear trend.)

From Figure 1, we observe divergence in real house price ratios across cities within each country, while also observing broadly similar patterns across the two countries. Focusing on two major cities in each country, Figure 2 graphs real house prices for Sydney and Melbourne in Australia, and Auckland and Wellington in New Zealand. Over the first part of the sample, Wellington and Sydney prices move together; over the full sample, Auckland appears to co-move

[6] For analyses of methods to control for housing quality in house price indices see, for Australia: Abelson and Chung (2005) and Hansen (2009); and, for New Zealand: Grimes and Young (2010).

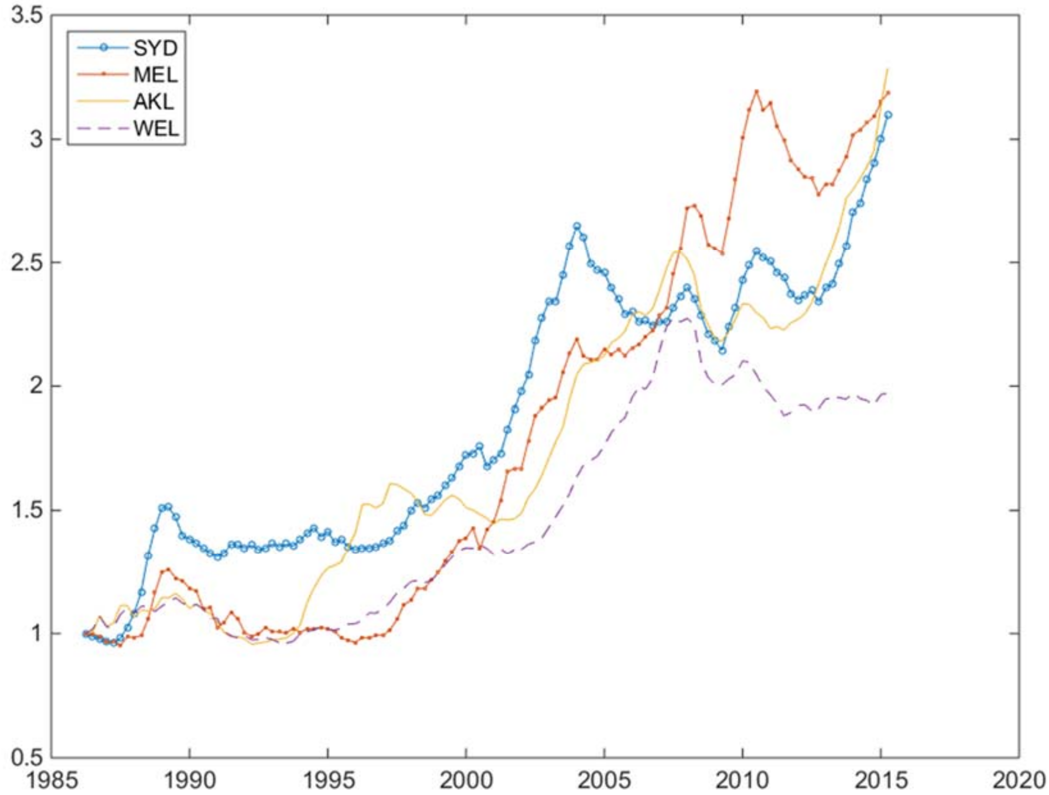
with Melbourne and Sydney. These full sample co-movements again suggest that house price trends may not be country-specific, while some intra-country divergences may be apparent.

Table 1: Estimated ADF Coefficients of (log) Real House Prices

City	levels (constant and trend)	differences (constant)
SYD	0.9417	0.5586***
MEL	0.9663	0.3580***
BRI	0.9753	0.6784***
ADL	0.9754	0.414***
PTH	0.9735	0.6856***
HOB	0.9729	0.6007***
DRW	0.9470	0.4958***
CNB	0.9703	0.5514***
AKL	0.9017***	0.6369***
WEL	0.9719	0.5184***
HAM	0.9487	0.5974***
TAU	0.9619	0.3731***
HAS	0.9686	0.4767***
PMN	0.9430	0.4752***
CHC	0.9568	0.6127***
DUN	0.9648	0.6395***

Notes: The ADF coefficients presented are the estimated coefficients on the lagged dependent variable in an ADF equation (where lags are selected by the BIC with a maximum of 8 lags); *** denotes significantly less than unity at the 1% level.

Figure 2: Real House Prices, 4 Cities (1986q1 = 1.0)



4. Methodology and Econometric Results

Let $x_{i,t}$ denote the natural logarithm of the real house price index in city *i* at time *t*. We begin with a general static approximate factor structure of the form

$$x_{i,t} = f_t'\delta_i + \mathrm{e}_{i,t} = \sum_{s=1}^{r} f_{s,t}\delta_{s,i} + \mathrm{e}_{i,t} \tag{1}$$

where f_t is an *r x 1* vector of unobserved common factors, δ_i is a vector of factor loadings and $\mathrm{e}_{i,t}$ is an idiosyncratic component that is weakly dependent in the cross sectional and time series dimensions. The static factor model nests a dynamic factor structure of the sort given in equation (2) below.

Because each time series of (log) real house prices $x_{i,t}$ is non-stationary, we follow the Bai and Ng (2004) approach for estimating the factor structure (1). This general approach permits both the common factors and the idiosyncratic components to be I(1). We first-difference each time series in the panel to ensure that it is I(0). We then estimate the factor number r using the Bai and Ng (2002) model selection criteria. Based on the first-differenced data we estimate the factor structure by principal components, and take the cumulative sum of the common factors and idiosyncratic components. We then apply unit root tests to each of the r (re-cumulated) common factors, and panel unit root tests to the (re-cumulated) idiosyncratic components, in order to determine which components of the factor structure (1) generate the observed non-stationary behavior in the cross section of time series.

4.1. Factor Number Estimation

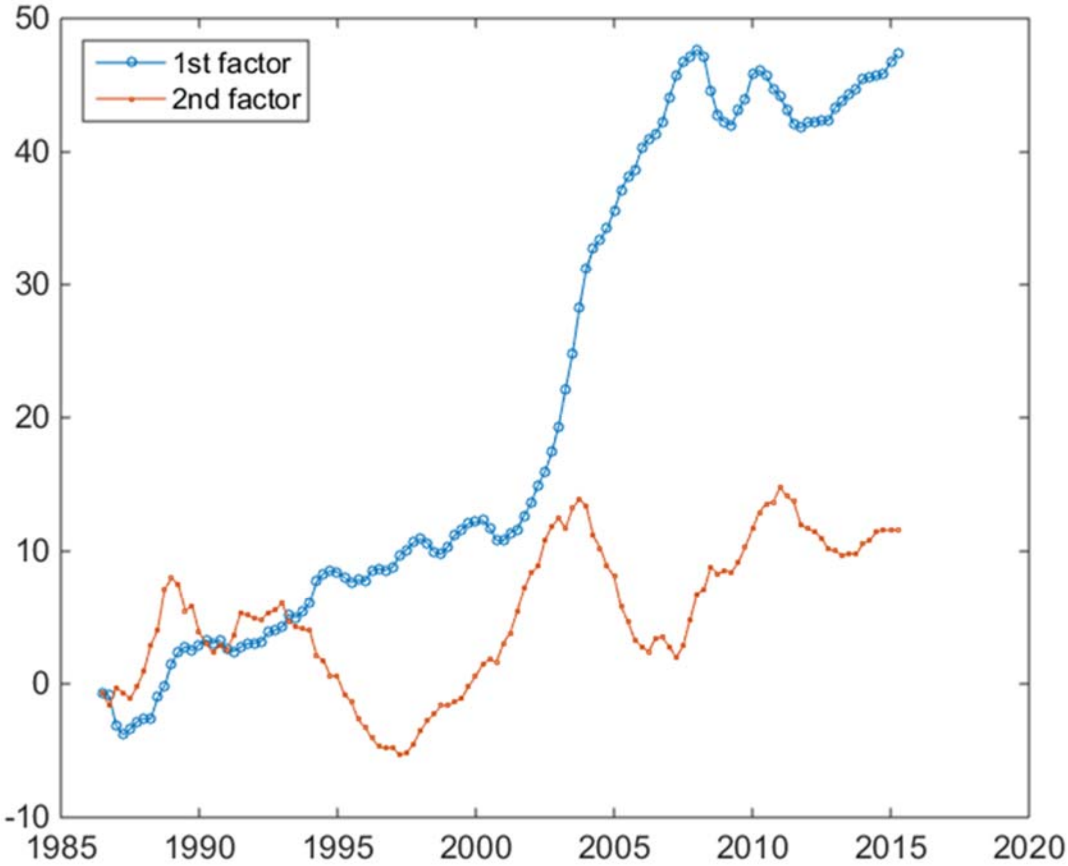
Given the relatively constrained cross-sectional dimension of the panel, we allow for a maximum of four common factors. The Bai and Ng (2002) $IC_2(k)$ criterion selects two factors, while the $IC_1(k)$ and $IC_3(k)$ criteria select the maximum number of factors . Given that the $IC_2(k)$ criterion is the most conservative, and given the limited cross sectional dimension of the panel ($n=16$), we choose to model two common factors.[7] Figure 3 exhibits the two (re-cumulated) estimated common factors.

Figure 3 demonstrates that the first common factor exhibits much more long-run variation than the second common factor. We fit the standard ADF regression to each time series, using the Schwarz criterion to select the number of lags. For the first estimated factor the t-statistic (with only a constant in the ADF regression) is -0.495, with an associated p-value of 0.887. When a trend is included in the ADF regression the t-statistic is -2.16, with an associated p-value of 0.505. Thus we accept the null of a unit root in the first estimated common factor.

The second factor exhibits much less persistence than the first. The t-statistic from the ADF regression is -1.844 (with a p-value of 0.358), indicating acceptance of the null of a unit root. However, when we augment the ADF regression with a linear trend, the t-statistic is -3.402, with an associated p-value of 0.056, which leads to a rejection of the null hypothesis of a unit root at the 10% level. In terms of subsequent modelling it is thus unclear whether we should treat the second common factor as I(1) or trend-stationary. We return to this issue below after analyzing the persistence in the idiosyncratic components.

[7] When the idiosyncratic components exhibit dependency or distributional heterogeneity, the Bai and Ng (2002) criteria often over-select the factor number in small samples (Greenaway-McGrevy, Han and Sul, 2012a; 2012b). Serial dependence in particular is likely to be a problem in our dataset.

Figure 3: Re-cumulated Common Factors



To test non-stationarity in the re-cumulated estimated idiosyncratic components we apply a Levin, Lin and Chu (2002) panel unit root test. The test imposes a common root on the different time series but permits heterogeneity in the short-run dynamics of the AR(p) processes. We apply the Schwarz criterion to each time series in order to select the lag order for the AR(p) model, and we allow for both time series and cross sectional heteroskedasticity by adopting White standard errors. The resultant t-statistic is -7.914, which is well beyond the conventional critical values of the Normal distribution, indicating a rejection of the null hypothesis. We also apply the Choi (2001) individual-based panel unit root test, again using the Schwarz criterion to select the AR(p) lag order for each time series in the panel. The test-statistic (based on the sum of the natural log of the p-values of each individual DF statistic) is 3.509, which is statistically different from zero at the 1% level. The null of a common unit root is again rejected. We therefore proceed treating the idiosyncratic components in (1) as being stationary. The stationarity of the idiosyncratic components implies that our decision to include just two common factors does not lead to the omission of any non-stationary common factor.

With stationary idiosyncratic components but at least one non-stationary common factor, the panel follows a common trend representation, with the common trends being the I(1) common factors. We can gain more precise estimates of the common factors by extracting them directly from $x_{i,t}$ (i.e., we need not first-difference the data; see Bai, 2004). Figure 4 exhibits the resulting two common factors. Evidently the first factor continues to exhibit more long run variation than the second factor.

We re-estimate ADF regressions as before in order to test for unit roots in the two estimated factors. For the first factor, the t-statistic is -0.515 with an associated p-value of 0.883 (with only a constant in the regression). For the second factor we have a t-statistic of -3.621 with a p-value of 0.007 (with only a constant in the regression), meaning a rejection of the null hypothesis of a unit root at the 5% level. This is strong evidence that the second factor extracted from the data should be treated as I(0). Our economic interpretation of this result follows in the next section.

Table 2 exhibits the estimated loadings for each city on the two estimated factors. Bold face font indicates statistical significance at the 5% level. Standard errors are calculated using a Newey-West HAC estimator (with lag truncation set to 8 quarters and an Epanechnikov weighting kernel), and treating the first factor as I(1) and the second factor as I(0). Note that all loadings on the first factor are positive and significant, ranging from 0.22 to 0.42. Only eleven of the sixteen loadings on the second factor are significant. Five of the Australian cities load positively and significantly onto the second factor, whereas six of the eight NZ cities (i.e. all cities other than Auckland and Wellington) load negatively and significantly onto the second factor. We interpret this pattern further in the final section.

Figure 4: Common Factors Derived from Levels Data

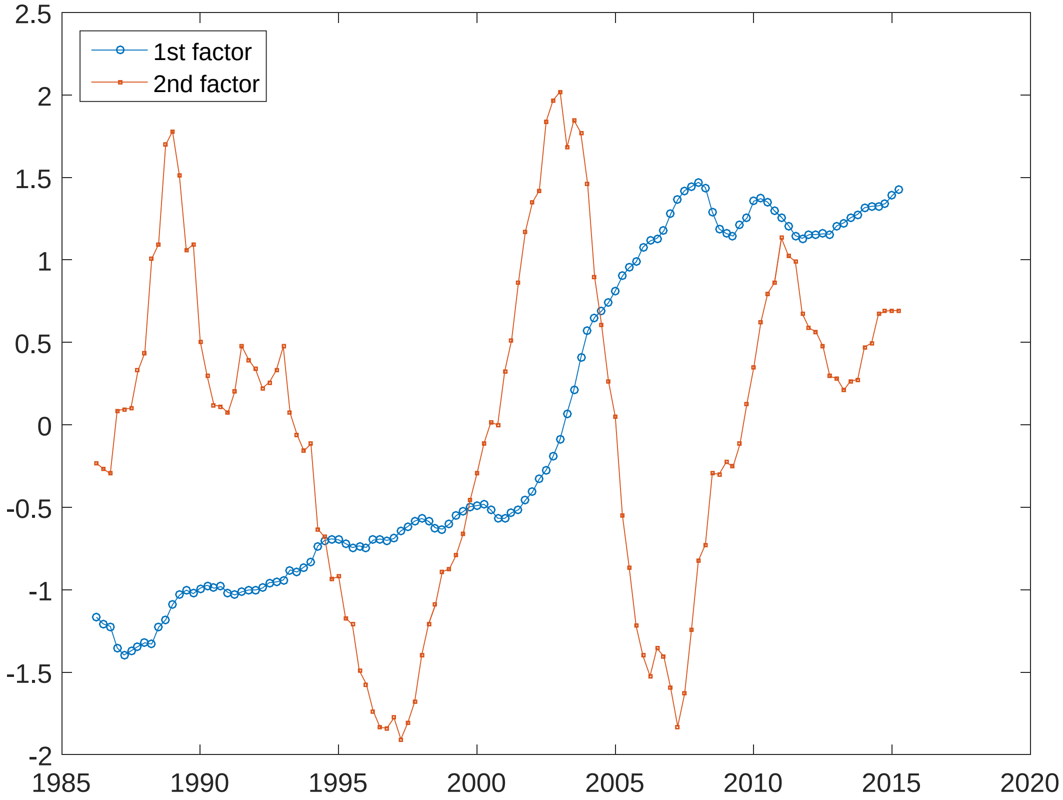


Table 2: Estimated Factor Loadings

	1st Factor	2nd Factor
Sydney	**0.28**	**0.07**
Melbourne	**0.42**	**0.11**
Brisbane	**0.37**	**0.02**
Adelaide	**0.30**	**0.06**
Perth	**0.41**	0.02
Hobart	**0.35**	0.01
Darwin	**0.39**	-0.03
Canberra	**0.32**	**0.05**
Auckland	**0.33**	-0.02
Wellington	**0.28**	0.01
Hamilton	**0.27**	**-0.06**
Tauranga	**0.31**	**-0.05**
Hastings	**0.32**	**-0.04**
Palmerston North	**0.22**	**-0.04**
Christchurch	**0.32**	**-0.04**
Dunedin	**0.33**	**-0.04**

4.2. Dynamic Factor Structure

We now consider whether the common factor structure (1) nests a dynamic factor model of the general form

$$x_{i,t} = \sum_{s=0}^{p} F_{t-s}{}'\beta_{i,s} + \mathrm{e}_{i,t} \tag{2}$$

where the $m \times 1$ vector of dynamic factors F_t is a subset of the static factors f_t, so that $m < r$. Because r is set to two in our case, we can have a single dynamic factor underlying the static factor structure.

We use the Bai (2004) IPC in order to select the number of common factors underlying the panel $x_{i,t}$. In the presence of a dynamic factor structure with I(1) common factors the IPC(k) criteria select the number of dynamic factors with probability one in large samples (see Theorem 5 of Bai, 2004). Both the IPC_1(k) and IPC_2(k) select a single common factor, suggesting a dynamic factor model.

Further analysis suggests the presence of a single, dynamic factor structure underlying the static, two factor model. Consider the following two-lag version of the dynamic factor structure.

$$x_{i,t} = F_t\beta_{i,0} + F_{t-p}\beta_{i,p} + \mathrm{e}_{i,t} \tag{3}$$

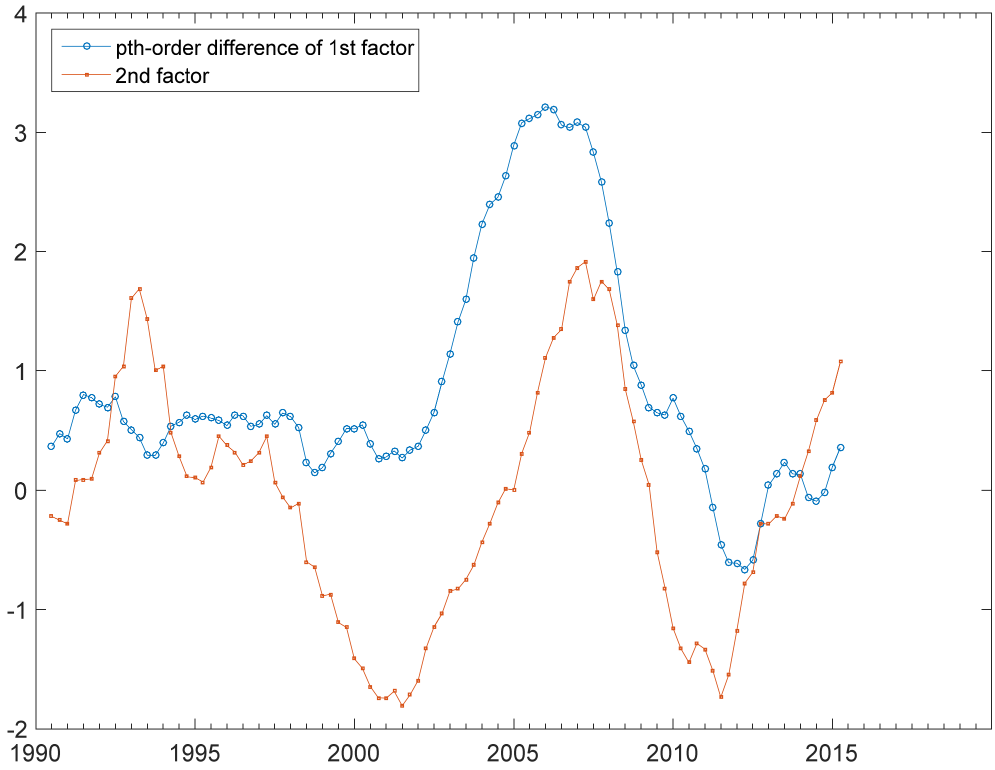
for some $p > 0$, where F_t denotes the single dynamic factor. This structure would yield a two factor static model. This model can be re-written as

$$x_{i,t} = F_t\gamma_{i,1} + \Delta_p F_t{}'\gamma_{i,p} + \mathrm{e}_{i,t} \tag{4}$$

where $\Delta_p F_t = F_t - F_{t-p}$, $\gamma_{i,1} = \beta_{i,0} + \beta_{i,p}$ and $\gamma_{i,p} = -\beta_{i,p}$. To further examine the potential of a dynamic factor representation, we compare the second common factor to the pth difference of the estimated first common factor (each extracted from $x_{i,t}$). To select p we estimate (3) for each $p=1,2,\ldots,24$, and select the lag order p by maximizing the R-squared of the regression (note that the number of regressors does not vary across the candidate models under consideration). This procedure yields a lag order of 17 quarters (or approximately 4 years).

Figure 5 exhibits $\{\Delta_p\, \hat{f}_{1,t}\}_{t=p+1}^{T}$ against the second common factor $\{\hat{f}_{2,t}\}_{t=p+1}^{T}$. Both time series have been standardized to have unit variance. Both factor estimates were extracted from the panel data in levels. The correlation between the two time series is 0.49.

Figure 5: Second Factor versus Differenced First Factor (p=17)



We run Granger causality tests based on a bivariate VAR of the two time series. The Schwarz criterion selects three lags for the VAR. We can easily reject the null that $\{\hat{f}_{2,t}\}_{t=p+1}^{T}$ does not Granger-cause $\{\Delta_p\, \hat{f}_{1,t}\}_{t=p+1}^{T}$ at conventional significance levels (the p-value of the block exogeneity restriction is 0.002), but can reject Granger-casuality in the other direction. Meanwhile the Akaike information criterion is minimized when five lags are included in the VAR. Under this model specification, we can again reject the null that $\{\hat{f}_{2,t}\}_{t=p+1}^{T}$ does not Granger-cause $\{\Delta_p\, \hat{f}_{1,t}\}_{t=p+1}^{T}$ (with a p-value of 0.0001) as well as the null that $\{\Delta_p\, \hat{f}_{1,t}\}_{t=p+1}^{T}$ does not Granger-cause $\{\hat{f}_{2,t}\}_{t=p+1}^{T}$ at the 5% significance level (the p-value of 0.048). There is therefore strong evidence to suggest the presence of a dynamic factor structure.

5. Interpretation and Conclusions

The results of section 3 demonstrate that the sixteen cities considered across Australia and New Zealand possess a single non-stationary factor that affects real house prices in all the cities. Thus there is just one aggregate source of shock that drives the non-stationary trend component of all sixteen cities across the two countries. All other idiosyncratic shocks to city prices are stationary and so their effects whither in the long run.

The dynamic structure of price adjustment, however, reveals a more differentiated pattern. Cities with negative loadings on the second factor lag behind the other cities, whereas cities with positive loadings lead the other cities.[8] Consistent with their economic pre-eminence within Australasia, Melbourne and Sydney lead the other 14 cities. On average, Australian cities (with an average second factor loading of 0.039) lead the New Zealand cities (with an average loading of -0.035). However, Auckland, Wellington, Perth, Hobart and Darwin each have second factor loadings that are not significantly different from zero. Thus there are three groups of cities in terms of price dynamics: leaders (Melbourne, Sydney, Adelaide, Canberra, Brisbane[9]); followers (Perth, Hobart, Wellington, Auckland, Darwin); and laggards (Dunedin, Christchurch, Palmerston North, Hastings, Tauranga, Hamilton).

All leader cities are within Australia and all laggards are within New Zealand, while the (mid-group) followers comprise a mix of Australian and New Zealand cities. The cities within this group are all geographically very distant and/or separated by water, from the core Australian cities of Sydney and Melbourne. Together, these results indicate that non-stationary shocks to Australasian house prices are first experienced in the major Australian cities, then flow through to the more peripheral Australian cities plus Auckland (New Zealand's largest city) and Wellington (New Zealand's capital city), and subsequently flow through to the more peripheral New Zealand cities.

There are no other common sources of non-stationary influence on city house prices, and all idiosyncratic city house price shocks are found to be stationary. However, cities have

[8] The principal components estimator consistently estimates the column space of the common factors, meaning that in general the factor loadings can only be estimated up to a linear rotation (Bai, 2003). In the general case it is therefore difficult to make statements about the sign and magnitude of the true factor loadings based on the estimated loadings. However, in this particular case we can make such statements, subject to the restriction that the estimated factors and loadings are normalized so that each time series loads positively onto the first common factor. (Note this normalization holds in our case.) Then, if the first factor is I(1), the second estimated factor must consistently estimate the second common factor up to a positive linear scaling; it cannot be a linear combination of the I(1) and I(0) factors, since in this case it would itself be I(1) in the limit. This implies that the second estimated loadings share the same sign as the true second loadings in large samples.

[9] Brisbane's second factor loading is significantly different from zero but is small in absolute value so may alternatively be grouped as a follower.

different responses to the first (non-stationary) factor implying that house price ratios diverge in response to innovations in this factor. The average first factor loading across the eight Australian cities, at 0.355, is higher than the average loading for the New Zealand cities, at 0.298. Thus a positive innovation to this factor raises real house prices in Australian cities, on average, by more than in New Zealand cities. Nevertheless, there is again not a clear country bifurcation: Sydney has lower responsiveness to this factor than do five of the New Zealand cities, while Auckland has greater responsiveness than do three of the Australian cities. The greatest city-pair differential sees Melbourne's loading on the first factor being almost twice that of Palmerston North. Thus we observe a weak form of a single housing market in which there is a single source of non-stochastic shock but the impact of the shock differs across cities. This pattern leads to divergence in long run real house prices across cities over time, despite the existence of only a single source of non-stationary shock.

What economic forces may explain the finding of a single source of non-stationary innovations to house prices across all the cities, coupled with differing long run (and dynamic) responsiveness to these innovations? Distances between the cities rule out a commuter arbitrage explanation for the observed patterns. Instead, as detailed in the Appendix, the differential long run real house price effect – in the face of an identical shock – may be due to differences in house price responses to land prices, migration responses to house prices or to land price responses to migration flows. The latter may reflect either geographical constraints (Saiz, 2010) or planning constraints (Grimes and Liang, 2009; Saks, 2008; Gyourko, Saiz and Summers, 2008; Kulish et al., 2012) each of which may affect the effective degree of land availability and hence affect the elasticity of land prices to population flows. The theoretical role of migration flows in each of these explanations accords, at least intuitively, with the nature of the dynamic responses that we estimate.

Our findings also have implications for macroeconomic policy. Given the differential effects of the non-stationary factor on house prices within each of Australia and New Zealand, and given the similarity of response between cities across the two countries, there is little evidence that the countries' independent monetary and/or other macro-economic policies have been instrumental in determining long run real house price outcomes in either country. In interpreting this finding, recall that our focus is on real house prices, a relative price variable. The implication that monetary policy has been ineffective in controlling this relative price variable is consistent with standard monetary theory, i.e. with the classical dichotomy.

A natural extension of our research is to analyse whether Australasian real house prices are hostage to international forces in a manner similar to the observed co-dependence between

New Zealand and Australian city house prices. A second extension would be to examine the economic forces that determine individual cities' differential responsiveness to the non-stationary stochastic shocks and, in particular, to examine whether differential planning regimes help explain these differentials. We leave these extensions to future work.

References

Abbott, A., & De Vita, G. (2012). Pairwise Convergence of District-Level House Prices in London. *Urban Studies*, *49*(4), 721-740.

Abbott, A., & De Vita, G. (2013). Testing for long-run convergence across regional house prices in the UK: a pairwise approach. *Applied Economics*, *45*(10), 1227-1238.

Abelson, P., & Chung, D. (2005). The Real Story of Housing Prices in Australia from 1970 to 2003. *Australian Economic Review*, *38*(3), 265-281.

Bai, J. (2003). Inferential Theory for Factor Models of Large Dimensions. *Econometrica*, *71*(1), 135-171.

Bai, J. (2004). Estimating Cross-Section Common Stochastic Trends in Nonstationary Panel Data. *Journal Of Econometrics*, *122*(1), 137-183.

Bai, J., & Ng, S. (2002). Determining the Number of Factors in Approximate Factor Models. *Econometrica*, *70*(1), 191-221.

Bai, J., & Ng, S. (2004). A Panic Attack on Unit Roots and Cointegration. *Econometrica*, *72*(4), 1127-1177.

Barros, C. P., Gil-Alana, L. A., & Payne, J. E. (2014). Tests of Convergence and Long Memory Behavior in U.S. Housing Prices by State. *Journal Of Housing Research*,*23*(1), 73-87.

Burger, P., & van Rensburg, L. J. (2008). Metropolitan House Prices in South Africa: Do They Converge?. *South African Journal Of Economics*, *76*(2), 291-297.

Chien, M. (2010). Structural Breaks and the Convergence of Regional House Prices. *Journal Of Real Estate Finance & Economics*, *40*(1), 77-88.

Choi, I. (2001). Unit Root Tests for Panel Data. *Journal Of International Money And Finance*, *20*(2), 249-272.

Clark, S. P., & Coggin, T. D. (2009). Trends, Cycles and Convergence in U.S. Regional House Prices. *Journal Of Real Estate Finance & Economics*, *39*(3), 264-283.

Cook, S. (2003). The convergence of regional house prices in the UK. *Urban Studies*, *40*(11), 2285.

Cook, S. (2005a). Regional house price behaviour in the UK: application of a joint testing procedure. *Physica A*, *345*(3/4), 611-621.

Cook, S. (2005b). Detecting Long-run Relationships in Regional House Prices in the UK. *International Review Of Applied Economics*, *19*(1), 107-118.

Cook, S. (2012). Beta-Convergence and the Cyclical Dynamics of UK Regional House Prices. *Urban Studies*, *49*(1), 203-218.

Cook, S., & Thomas, C. (2003). An alternative approach to examining the ripple effect in UK house prices. *Applied Economics Letters*, *10*(13), 849-851.

Drake, L. (1995). Testing for Convergence between UK Regional House Prices. *Regional Studies*, *29*(4), 357-366.

Fadiga, M., & Wang, Y. (2009). A multivariate unobserved component analysis of US housing market. *Journal Of Economics & Finance*, *33*(1), 13-26.

Gallet, C. A. (2004). Housing market segmentation: An application of convergence tests to Los Angeles region housing. *Annals Of Regional Science*, *38*(3), 551-561.

Greenaway-McGrevy, R., Han, C., & Sul, D. (2012a). Estimating the Number of Common Factors in Serially Dependent Approximate Factor Models. *Economics Letters*, *116*(3), 531-534.

Greenaway-McGrevy, R., Han, C., & Sul, D. (2012b). Standardization and Estimation of the Number of Factors for Panel Data. *Journal Of Economic Theory And Econometrics*,*23*(2), 79-88.

Grimes, A., & Aitken, A. (2010). Housing Supply, Land Costs and Price Adjustment. *Real Estate Economics*, *38*(2), 325-353.

Grimes, A., Holmes, M., & Tarrant, N. (2010). New Zealand Housing Markets: Just a Bit-Player in the A-League? Motu Working Paper 10-07, Wellington: Motu.

Grimes, A., & Hyland, S. (2015). Housing Markets and the Global Financial Crisis: The Complex Dynamics of a Credit Shock. *Contemporary Economic Policy*, *33*(2), 315-333.

Grimes, A., Kerr, S., & Aitken, A. (2003). House Prices and Regional Adjustment. New Zealand Geographical Society 22nd Conference Proceedings, 238-241.

Grimes, A. & Liang Y. (2009). Spatial Determinants of Land Prices: Does Auckland's Metropolitan Urban Limit Have an Effect? *Applied Spatial Analysis and Policy*, 2, 23-45.

Grimes, A., & Young, C. (2010). A Simple Repeat Sales House Price Index: Comparative Properties Under Alternative Data Generation Processes. Motu Working Paper 10-10, Wellington: Motu.

Gros, D. (2007). Bubbles in Real Estate? A Longer-Term Comparative Analysis of Housing Prices in Europe and the US, CEPS Working Document No. 276, Centre for European Policy Studies, Brussels.

Gyourko, J., Saiz, A., & Summers, A. (2008). A New Measure of the Local Regulatory Environment for Housing Markets: The Wharton Residential Land Use Regulatory Index. *Urban Studies*, *45*(3), 693-729.

Hansen, J. (2009). Australian House Prices: A Comparison of Hedonic and Repeat-Sales Measures. *Economic Record*, *85*(269), 132-145.

Holmes, M. J. (2007). How Convergent are Regional House Prices in the United Kingdom? Some New Evidence from Panel Data Unit Root Testing. *Journal Of Economic & Social Research*, *9*(1), 1-17.

Holmes, M. J., & Grimes, A. (2008). Is There Long-run Convergence among Regional House Prices in the UK?. *Urban Studies*, *45*(8), 1531-1544.

Holmes, M. J., Otero, J., & Panagiotidis, T. (2011). Investigating Regional House Price Convergence in the United States: Evidence from a Pair-Wise Approach. *Economic Modelling*, *28*(6), 2369-2376.

Kim, Y. S., & Rous, J. J. (2012). House price convergence: Evidence from US state and metropolitan area panels. *Journal Of Housing Economics*, *21*(2), 169-186.

Kulish, M., Richards, A., & Gillitzer, C. (2012). Urban Structure and Housing Prices: Some Evidence from Australian Cities. *Economic Record*, *88*(282), 303-322.

Levin, A., Lin, C., & Chu, C. J. (2002). Unit Root Tests in Panel Data: Asymptotic and Finite-Sample Properties. *Journal Of Econometrics*, *108*(1), 1-24.

Luo, Z., Liu, C., & Picken, D. (2007). Housing price diffusion pattern of Australian state capital cities, *International Journal Of Strategic Property Management*, 11(4), 227-242.

Luo, Z., Liu, C., Ma, L., & Picken, D. (2008). Identifying housing price diffusion pattern of Australian state capital cities, *International Journal Of Strategic Property Management*, 12(4), 237-250.

Ma, L. & Liu, C., (2013). Spatio-temporal analysis of house price convergence based on a demographical distance, *International Journal Of Strategic Property Management*, 17(3), 263-277.

Ma, L. & Liu, C., (2015). Is there Long-Run Equilibrium in the House Prices of Australian Capital Cities? *International Real Estate Review*, 18(4), 503-521.

Maher, C. (1994). Housing prices and geographical scale: Australian cities in the 1980s. *Urban Studies*, *31*(1), 5-27.

Meen, G. (1999). Regional House Prices and the Ripple Effect: A New Interpretation. (cover story). *Housing Studies*, *14*(6), 733-753.

Saiz, A. (2010). The Geographic Determinants of Housing Supply. *Quarterly Journal Of Economics*, *125*(3), 1253-1296.

Saks, R. E. (2008). Job Creation and Housing Construction: Constraints on Metropolitan Area Employment Growth. *Journal Of Urban Economics*, *64*(1), 178-195.

Song, S., Young, M., & Hargreaves, B. (2010). House Price-Volume Dynamics: Evidence from 12 Cities in New Zealand. *Journal Of Real Estate Research*, *32*(1), 75-99.

Slade, P. (2006). House Price Cointegration: The Gold and Sunshine Coasts and Major Cities on the Eastern Australian Seaboard. *Journal Of Economic And Social Policy*, *11*(1), 109-130.

Smyth, R., & Nandha, M. (2003). Cointegration and Causality in Australian Capital City House Prices 1986-2001. *Journal Of Economic And Social Policy*, *7*(2), 35-50.

Tsai, I. (2014). Ripple Effect in House Prices and Trading Volume in the UK Housing Market: New Viewpoint and Evidence. *Economic Modelling*, *40*68-75.

Wheaton, W. C. (1974). A Comparative Static Analysis of Urban Spatial Structure. *Journal Of Economic Theory*, *9*(2), 223-237.

Appendix: Canonical Long Run Housing Market Model

We present a simple model, that enables closed form solutions, explaining long run house price and other housing market outcomes. The approach is based on Grimes and Hyland (2015) and Grimes and Aitken (2010), which in turn reflect a range of prior housing models. We add a further relationship to these prior studies – equation (2) – specifying population as a function of house prices. The (long run) model comprises four equations as follows:

$$hp = \alpha\, pop - \alpha\, H + \varepsilon_1 \qquad (1)$$

$$pop = \beta\, hp + \varepsilon_2 \qquad (2)$$

$$hp = \gamma\, lp + \varepsilon_3 \qquad (3)$$

$$lp = \delta\, pop + \varepsilon_4 \qquad (4)$$

where *hp* is (log) house price, *pop* is (log) population, *H* is the (log) house stock, *lp* is (log) land price (per lot); ε_1, ε_2, ε_3, ε_4 are (permanent) exogenous shift variables; and α (>0), β (<0), γ (>0), δ (>0) are parameters.

Equation (1) is an inverse demand function for housing, derived explicitly from a utility maximisation approach in Grimes and Aitken, in which house prices are a function of (i) the ratio of population to the housing stock and (ii) the user cost of capital; the latter is taken here to be exogenous to the locality and included in the shift variable, ε_1.

Equation (2) reflects a spatial equilibrium approach in which population is determined by the level of house prices and by other area characteristics such as local productivity and amenities that are included in the shift variable, ε_2.

Equation (3) is a supply function for housing based on a q-theory approach (see Grimes and Aitken). The supply of houses increases (or stagnates) until such time as the market price of houses is equated to the sum of all costs of obtaining a new house. These costs include the lot price (*lp*), construction costs and all other costs (e.g. including permitting costs) included in the shift variable, ε_3.

Equation (4) is a land price equation in which the land price is an increasing function of local population. This relationship arises (as a mean price within a locality) from a standard urban economic model such as the Alonso-Muth-Mills model (e.g., see Wheaton, 1974). The shift variable, ε_4, includes the effects on land scarcity (and hence land prices) of new planning constraints and also includes shocks to speculative or investment behavior in residential land.

Closed form solutions for the four variables are as follows (where $\theta \equiv 1 - \beta\gamma\delta$):

$$H = \frac{1}{\alpha}\varepsilon_1 + \frac{\alpha-\gamma\delta}{\alpha\theta}\varepsilon_2 - \frac{1-\alpha\beta}{\alpha\theta}\varepsilon_3 - \frac{\gamma(1-\alpha\beta)}{\alpha\theta}\varepsilon_4 \quad (5)$$

$$pop = \frac{1}{\theta}\varepsilon_2 + \frac{\beta}{\theta}\varepsilon_3 + \frac{\beta\gamma}{\theta}\varepsilon_4 \quad (6)$$

$$lp = \frac{\delta}{\theta}\varepsilon_2 + \frac{\beta\delta}{\theta}\varepsilon_3 + \frac{1}{\theta}\varepsilon_4 \quad (7)$$

$$hp = \frac{\gamma\delta}{\theta}\varepsilon_2 + \frac{1}{\theta}\varepsilon_3 + \frac{\gamma}{\theta}\varepsilon_4 \quad (8)$$

Equation (8) has several implications for the long run determinants of house prices. First, a pure demand shock (ε_1), while appearing in the partial equilibrium housing demand equation, has no effect on long run house prices. This is due to the housing supply process in (3) through which new housing continues to be built until such time as house prices equal land prices and other costs. Unless these cost elements change directly in response to (or are correlated with) a demand shock then house prices must remain unchanged following a pure demand shock.[10]

Second, noting that $\theta > 0$,[11] a positive population shock (ε_2) raises house prices. The larger is $|\beta|$, the smaller is the house price response to a population shock, since population itself partially adjusts downwards following the house price response to an initial upward population shock. The larger is the elasticity of house prices to land prices (γ) and/or the elasticity of land prices to population (δ), the larger is the reaction of house prices to a population shock. This can be seen by rewriting the coefficient on ε_2 in (8) as:

$$\frac{\gamma\delta}{\theta} \equiv \frac{1}{(\gamma\delta)^{-1} - \beta}$$

Thus, as $\gamma\delta$ becomes larger, so does $\frac{\gamma\delta}{\theta}$. Together, $\gamma\delta$ represents the reaction of house prices to population through the channels of population affecting land prices and land prices affecting house prices. The former may reflect the severity of existing planning or geographical constraints that translate a population increase into land scarcity while the latter reflects the proportion of land prices in house prices (which will tend to be high in large and/or land-constrained cities relative to other cities).

[10] We note that if ε_1 were a cost of capital shock (e.g. following a central bank interest rate change), then ε_1, ε_3, and ε_4 may be correlated.

[11] This follows since $\beta<0$, $\gamma>0$ and $\delta>0$.

Third, the larger is the absolute value of β, γ and δ, the smaller is the responsiveness of house prices to a housing supply cost shock (ε_3). A high γ means that land costs form a high proportion of total housing costs so a rise in other costs has a lower proportionate effect on house prices than occurs with a lower γ. Together, the β and δ effects act through the responsiveness of population, and thence land prices, to a cost shock, inducing a partially offsetting land price movement following the rise in other construction costs.

Fourth, a positive shock to land prices (ε_4), for example through an increase in (onshore or offshore) investor demand for land, raises house prices. As in the previous case, higher values of β and δ will reduce the house price responsiveness to a given ε_4 shock through population-related effects. Noting that the coefficient on ε_4 in (8) can be rewritten as $\frac{1}{\gamma^{-1}-\beta\delta}$, we see that a higher γ leads to greater responsiveness of house prices to a land price shock. Thus cities in which land prices form a high proportion of house prices will have high house price responsiveness to a land price shock.

The closed form solution for house prices in (8) demonstrates how an identical shock – for example to investor demand for land – that affects a range of cities can induce differing responses across those cities depending on the specific parameters within their population, house price and land price relationships. Thus differing migration and supply-related elasticities across cities can result in a weak form of single housing market even where all cities face identical shocks.

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