Investigating regional house price convergence in the United States: Evidence from a pair-wise approach

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Abstract

In this paper we examine long-run house price convergence across US states using a novel econometric approach advocated by Pesaran (2007) and Pesaran et al. (2009). Our empirical modelling exercise employs a probabilistic test statistic for convergence based on the percentage of unit root rejections among all state house price differentials. Using a sieve bootstrap procedure, we construct confidence intervals and find evidence in favour of convergence. We also conclude that speed of adjustment towards long-run equilibrium is inversely related to distance.

JEL Classification: C2, C3, R1, R2, R3.

Keywords: Panel data, cross-section dependence, pair-wise approach, house prices, convergence.

1. Introduction

Housing is distinct from other assets given that it is a durable consumption good and is often the most important asset in household portfolios. Therefore house prices have a significant effect on economic activity (see, for example, Goodhart and Hofman (2007) and Paiella (2009) who provide evidence of a positive elasticity of consumption to housing wealth). While fluctuations in regional house prices have the potential to influence relative regional economic activity, there is also the potential to influence labour mobility through the affordability of housing and relocation costs. Against this background, the degree and nature of house price convergence can have implications for the necessity and form of regional adjustment policies. For a variety of reasons, there is hence considerable value in understanding how regional house prices behave in relation to each other over time.

Starting from the work of Meen (see for example, Meen (1999)), it has been argued that shocks to regional house prices “ripple out” across the economy. While the notion of such a ripple effect may rely on factors such as spatial patterns in the determinants of house prices, migration, equity transfer, and spatial arbitrage, it also requires some degree of long-run constancy, or a long-run equilibrium relationship, between regional house prices. Evidence in favour of extensive long-run equilibrium relationships across all US states is sparse. The main focus of our paper is the investigation of long-run equilibrium relationships or convergence between US state house prices. Existing studies such as Pollakowski and Ray (1997) consider whether house price relationships between contiguous states are any stronger than between non-contiguous states. This is an unresolved issue and we contribute to the debate by considering whether distance between states is a factor that helps explain the speed of adjustment towards long-run equilibrium involving bivariate house price differentials.

In our investigation of long-run convergence, we utilise a novel econometric procedure advocated by Pesaran (2007). In this approach, a probabilistic definition of convergence is proposed and forms the basis of the test. The idea behind this is that for a sample of N states, unit root tests are conducted on all $N(N-1)/2$ house price differentials. Under the null hypothesis of non-stationarity or non-convergence, one would normally expect the fraction of house price differentials for which the unit-root hypothesis is rejected to be close to the size of the underlying unit-root tests (α). However, it can be argued that the null of non-stationarity for all state pairs can be rejected if the fraction of rejections exceeds α. This test is applicable when N is large relative to T (the time dimension of the panel). Although the underlying individual unit-root tests are not cross-sectionally independent, under the null of non-convergence (or divergence) it can be shown that the fraction of the rejections converges to α, as $N, T \rightarrow \infty$.

In testing for non-stationarity, panel unit root tests such as Maddala (1999), Levin et al. (2002) and Im et al. (2003) have been employed as a means of addressing low test power attached to univariate methods. As noted by Pesaran et al. (2009), the pair-wise methodology offers three key advantages over existing panel methods. First, the joint null hypothesis of these panel unit root tests is that all the series have a unit root. This hypothesis can be rejected even if the proportion of the series for which the unit root null is rejected is small. The pair-wise approach directly addresses the question of what proportion of the house price differentials is stationary. Second, the presence of unobserved common factors complicates the application of the panel unit root tests where cross-section dependence can lead to size distortion. The so-called second generation panel unit root tests (following the terminology in Breitung and Pesaran (2008)) have attempted to allow for possible cross-section dependence through unobserved common factors, but their applications are complicated by the uncertainties surrounding the number of unobserved factors, the nature of the unit root process (whether it is common or country specific), and the fact that longer data spans are required for modelling the cross-section dependence. The pair-wise method is robust to cross-sectional dependence. Third, the use of panel unit root tests can necessitate that all series measured against a common base. In a wider sense, this is common practice in studies of regional convergence. However, the outcome of the convergence test can be sensitive to the choice of base region or state.[1] The pair-wise methodology does not involve what can be a problematic choice of a single reference state in the computation of log house price differentials.

The paper is organised as follows. Section 2 discusses the relevant background literature on house price convergence. Section 3 describes the pair-wise methodology. While this paper is primarily concerned with the degree and nature of regional convergence for the US states, we are neither concerned with identifying the determinants of house prices themselves nor with establishing whether these determinants have the long-run effects postulated in the proposition of convergence. Section 4 discusses the data employed and results. Our results are supportive of long-run regional house price convergence where distance between regions is a significant factor driving the speed of adjustment towards long equilibrium. Our results are robust to house prices that are adjusted by per capita state income. The final section offers concluding remarks.

[1] For example, the house prices of regions i and j might be found as non-stationary when measured against a third numeraire region k, but stationary when measured against one another. This would be the case when there is a highly persistent factor that is common to regions i and j, but is not shared by the region k.

2. Existing Literature

While the majority of time-series studies of housing markets are carried out on national data, Meen (1996) argues that housing markets may be better characterised as a series of interconnected sub-national markets. In this vein, examples of recent work on the US includes Hwang and Quigley (2006) who confirm the importance of changes in regional economic conditions, income, and employment on local housing markets, along with the lags in market responses to exogenous shocks and the variations arising from differences in local parameters; and Holly et al. (2010) who model the dynamic adjustment of state real house prices and identify a significant spatial effect, even after controlling for state specific real incomes, and allowing for a number of unobserved common factors.

Regional house price interactions may occur from the gradual dissemination of information across space following any shock. In an efficient market, we might expect all regions to react at the same time to a common shock. However, there are many reasons why lags may arise in the case of housing. Indeed, studies such as Tirtiroglu (1992) have contributed to the accumulating evidence of inefficiency. Given the presence of lags in house price adjustment, one might expect price relationships between contiguous areas to be stronger than between non-contiguous areas because information can be transmitted and acted upon relatively more quickly. Clapp and Tirtiroglu (1994) find a strong positive association between the change in an index of prices for constant quality housing in a given town and lagged prices in neighbouring as opposed to non-neighbouring towns. Using a study period of 1975 to 1994, Pollakowski and Ray (1997) find a relationship between spatial prices, but the relationship is no stronger between contiguous than non-contiguous regions.

More recently, Capozza et al. (2002) explore the dynamics of real house prices by estimating serial correlation and mean reversion coefficients from a panel data set of 62 metropolitan areas from 1979-1995. They find that mean reversion is greater in large metropolitan areas and faster-growing cities with lower construction costs. They also find that substantial overshooting of prices can occur in high real construction cost areas, which have high serial correlation and low mean reversion. Kuethe and Pede (2009) analyse the effects of macroeconomic shocks on house prices in the Western United States using quarterly state level data from 1988-2007. They explicitly incorporate locational spillovers through a spatial econometric adaptation of a vector autoregression. Their results suggest that the inclusion of spatial information leads to significantly lower mean square forecast errors. Gupta and Miller (2009) examine time-series relationship between house prices in Los Angeles, Las Vegas, and Phoenix. Estimating VAR models and undertaking Granger causality tests, they obtain reasonably good forecasts of turning points. Finally, Rapach and Strauss (2009) investigate differences in real housing price forecasting ability across US states during the period 1995-2006. They find important differences across states relating to differences in average housing price growth.

With regard to house price linkages in other countries, a large literature now exists supporting the notion of a causal link or ripple effect from house prices in the South East of England to other regions of the UK. However, the literature to date can only offer mixed evidence that long-run equilibrium relationships across regional house prices actually exist (see, for example, Holmes and Grimes (2008) and references therein). Other studies include Stevenson (2004) who finds evidence of ripple effects taking place in the Irish housing market based on Dublin as the epicentre; Oikarinen (2006) who finds that Finnish house price changes in a diffuse manner from the Helsinki Metropolitan Area to the regional centres, and then to the peripheral areas; Luo et al. (2007) who consider eight Australian cities and identify the existence of four levels of diffusion patterns based on Sydney, then Melbourne followed by Perth and Adelaide and then other cities; and Burger and Rensburg (2008) who examine five metropolitan areas of the South African housing market. They find that the large middle-segment house prices strongly converge in the long-run, but the evidence of convergence in medium middle-segment house prices is relatively weak. The methodologies employed by these studies draw on unit root and cointegration testing, causality testing and impulse-response analysis.

3. A pair-wise approach to testing for convergence

We employ the Pesaran (2007) pair-wise testing procedure to analyse convergence across a large number of cross section units. As argued above, this approach avoids the pitfalls associated to the utilisation of a particular cross sectional unit as a benchmark. Let y_{it} be house price data in US State i at time t, where $i=1,...,N$ and $t=1,...,T$. Pesaran's pair-wise approach is based on the examination of the time series properties of all $N(N-1)/2$ possible house price gaps (or differentials) between States i and j, denoted as $g_{ijt}=y_{it}-y_{jt}$, where $i=1,...,N-1$ and $j=i+1,...,N$. Consider next the application of the augmented Dickey and Fuller (ADF) (1979) or the Elliott, Rothenberg and Stock (ERS) (1996) test of order p to each of the possible house price gaps, and let $Z_{ij,T}$ be an indicator function equal to one if the corresponding unit-root test statistic is rejected at significance level α. More formally, in the case of the ADF test, $Z_{ij,T}=1$ if $\text{ADF}(p)<K_{T,p,\alpha}$, where $\text{ADF}(p)$ is the test statistic of order p, $K_{T,p,\alpha}$ is the critical value for the $\text{ADF}(p)$ of size α, using T observations. Similarly, when applying the ERS test, $Z_{ij,T}=1$ if

$\text{ERS}(p) < K_{T,p,\alpha}$.

Pesaran (2007) considers the fraction of the $N(N-1)/2$ gaps for which the unit-root hypothesis is rejected, which is given by:

$$\bar{Z}_{NT} = \frac{2}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} Z_{ij,T} , \tag{1}$$

and shows that under the null hypothesis of non-stationarity the expected value of $\bar{Z}_{NT}$ is:

$$\lim_{T\to\infty} E\left(\bar{Z}_{NT} \middle| H_o\right) = \alpha . \tag{2}$$

In the case of a unit-root test (such as ADF or ERS), under the null hypothesis of convergence one would expect the proportion of rejections to be high and tending towards 100% as $T \to \infty$; analogously, under the divergence alternative the proportion of rejections ought to be low and around α. Pesaran (2007) indicates that there are some difficulties involved in developing a formal procedure to test whether the proportion of rejections $\bar{Z}_{NT}$ is statistically different from α, because the derivation of the variance of $\bar{Z}_{NT}$ is complicated due to the fact that $Z_{ij,T}$ and $Z_{ik,T}$ are not independent from each other. Thus, inference on $\bar{Z}_{NT}$ can be based on the derivation of the empirical distribution of the fraction of rejections using the bootstrap methodology.

The implementation of the bootstrap is not an issue pursued by Pesaran (2007), but in a subsequent paper by Pesaran, Smith, Yamagata and Hvozdyk (PSYH) (2009) when applying the pair-wise approach to test for purchasing power parity. More specifically, the model considered by these authors consists of the following set of equations:

$$y_{it} = \boldsymbol{\alpha}_i^{'}\mathbf{d}_t + \boldsymbol{\gamma}_i^{'}\mathbf{f}_t + \varepsilon_{it} \tag{3}$$

$$\Delta\varepsilon_{it} = \eta_i + \lambda_i \varepsilon_{i,t-1} + \sum_{l=1}^{p_i} \psi_{il} \Delta\varepsilon_{i,t-l} + \upsilon_{it} \tag{4}$$

$$\Delta f_{st} = \boldsymbol{\mu}_s^{'}\mathbf{d}_t + \phi f_{s,t-1} + \sum_{l=1}^{p_s} \xi_{sl} \Delta f_{s,t-l} + e_{st} \tag{5}$$

where $s = 1, 2, ..., m$ is the number of assumed common factors, $\mathbf{d}_t = (1, t)^{'}$ is a vector of deterministic components that includes intercept, and intercept and trend, $\mathbf{f}_t$ is a $m \times 1$ vector of unobserved factors, with elements denoted f_{st} , and ε_{it} denotes the corresponding idiosyncratic elements. The factors f_{st} and/or the idiosyncratic elements ε_{it} may be $I(0)$ or $I(1)$.

Following PSYH, we use the cross-sectional average of y_{it} , denoted $\bar{y}_t = N^{-1}\sum_{i=1}^{N} y_{it}$, as an estimate of the common factor that induces cross-section dependence. To account for cross-section dependence house prices for each state are then regressed on the estimated common factor, that is:

$$y_{it} = \hat{\alpha}_i + \hat{\delta}_i t + \hat{\gamma}_i \bar{y}_t + \hat{\varepsilon}_{it}, \tag{6}$$

where the trend term is included if the corresponding estimated coefficient, $\hat{\delta}_i$, is found to be statistically significant. The tables in the Appendix summarise the results of estimating the factor equations for the two house price datasets used in the paper (details of which are provided in the next section); it should be noted that the linear trend term is included if statistically significant at the 5% level.

The next step is to examine the time series properties of the estimate of the common factor $\bar{y}_t$, which may be $I(0)$ or $I(1)$. This involves estimating the following $\text{ADF}(p)$ regression for $\bar{y}_t$:

$$\Delta\bar{y}_t = \hat{\mu} + \hat{\phi}\bar{y}_{t-1} + \sum_{l=1}^{p} \hat{b}_l \Delta\bar{y}_{t-l} + \hat{e}_t, \tag{7}$$

which may also include a trend term if it is statistically significant, and where the optimal number of lags of the dependent variable p may be determined e.g. using the Akaike information criterion. To illustrate the implementation of the bootstrap, let us assume that $\bar{y}_t$ has a unit root with no drift and no deterministic trend. Imposing a unit root on (7) and not allowing for a drift, that is setting $\hat{\phi} = 0$ and $\hat{\mu} = 0$, implies the following restricted version of (7):

$$\Delta \bar{y}_t = \sum_{l=1}^{p} \hat{c}_l \Delta \bar{y}_{t-l} + \hat{u}_t \,. \tag{8}$$

Thus, when a unit root is imposed on the factor $\bar{y}_t$, the bootstrap samples of $\bar{y}_t$, denoted $\bar{y}_t^{(b)}$, can be computed using the following mechanism:

$$\bar{y}_t^{(b)} = \bar{y}_{t-1}^{(b)} + \sum_{l=1}^{p} \hat{c}_l \Delta \bar{y}_{t-l}^{(b)} + \hat{u}_t^{(b)} \,, \tag{9}$$

where bootstrap residuals $\hat{u}_t^{(b)}$ are generated by randomly drawing with replacement from the set of estimated and centred residuals $\hat{u}_t$ in (8), and the first $(p+1)$ values of $\bar{y}_t$ are used to initialised the process $\bar{y}_t^{(b)}$.

In turn, the bootstrap samples of y_{it}, denoted $y_{it}^{(b)}$, are generated as:

$$y_{it}^{(b)} = \hat{\alpha}_i + \hat{\delta}_i t + \hat{\gamma}_i \bar{y}_{it}^{(b)} + \hat{\varepsilon}_{it}^{(b)} \,, \tag{10}$$

where $\hat{\alpha}_i$, $\hat{\delta}_i$ and $\hat{\gamma}_i$ are the OLS estimates of α_i, δ_i and γ_i in (6), respectively, and

$$\varepsilon_{it}^{(b)} = \hat{\eta}_i + \left(1 + \hat{\lambda}_i\right) \varepsilon_{i,t-1}^{(b)} + \sum_{l=1}^{p_i} \hat{\psi}_{il} \Delta \varepsilon_{i,t-1}^{(b)} + \upsilon_{it}^{(b)} \,, \tag{11}$$

where bootstrap residuals $\upsilon_{it}^{(b)}$ are generated by randomly drawing with replacement from the set of estimated residuals υ_{it} in equation (4), and the first $(p+1)$ values of $\hat{\varepsilon}_{it}$ are used to initialised the process $\varepsilon_{it}^{(b)}$. The AIC is used to select the optimal lag order p_i.

Having obtained $y_{it}^{(b)}$, it is possible to compute all possible house price gaps (or differentials) between States i and j, that is $g_{ijt}^{(b)} = y_{it}^{(b)} - y_{jt}^{(b)}$, so that one can then calculate the fraction of these price gaps for which the unit root hypothesis can be rejected the fraction either using the $\text{ADF}(p)$ or $\text{ERS}(p)$ test. The procedure already described is repeated $b = 1,...,B$ times to derive the empirical distribution of the bootstrapped fraction of rejections.

4. Data and empirical analysis

We follow Pollakowski and Ray (1997) among others and employ the Freddie Mac Conventional Mortgage Home Price Index (CMHPI) for 48 US states.[2] The quarterly house price data, expressed in natural logarithm form, covers the study period 1975Q1-2008Q4. The computation of the index is based on mortgages that were purchased or securitized by Freddie Mac or Fannie Mae since January 1975.[3] The CMHPI uses a statistical method based entirely on "repeat transactions". Any time a house's value is observed twice over time (via either a sale or an appraisal), the change in the price

[2] We exclude Alaska and Hawaii from our analysis on the grounds that these states are not geographically contiguous with any other state in the US, so some of the mechanisms that may underpin long-run constancy of house price ratios across states within the US may not operate in these cases.

[3] These mortgages are "conventional" in their financing in that they are not insured or guaranteed by any federal government agency such as the Federal Housing Administration or Veterans Administration. Although not specified in the name, the index is based on mortgages for single unit residential houses only; it does not reflect condominiums, multi-family or commercial properties. Finally, the mortgages are "conforming": at the time of purchase they met Freddie Mac or Fannie Mae underwriting standards, and they did not exceed the allowable loan limit set for the two companies.

contributes one observation of house price growth over that time period. As argued by Stevens et al. (1995), this method can produce “constant quality indices”. In this study, we also consider house price affordability across states. This is of importance insofar as affecting business and household migrations in areas, as well as rental vacancy levels, municipal tax revenues, and building industry activity (see, for example, Strassman (2000)). We therefore also examine regional convergence using house prices that are expressed in per capita state income terms. For this purpose, we adjust house prices by state income using data provided by the Bureau of Economic Analysis and interpolated state population data obtained from the US Census Bureau (where the latter variable is available only until 2007Q4). Thus, when accounting for affordability and state population the house price data are available for the period 1975Q1-2007Q4, and will be referred to as “adjusted” as opposed to “unadjusted”.

Table 1 reports the percentage of rejections of both the ADF and ERS tests. As can be seen, in all cases the percentage of rejections exceeds the size of the unit root test statistics. For example, the ADF test applied to unadjusted house prices leads to a rejection frequency of 31.83% at the 5% significance level. In the case of unadjusted house prices the corresponding rejection frequency is lower (i.e. 19.24%). These results are focused on the point estimates of the proportion of the pair-wise tests that reject the null hypothesis of no convergence. It is important to consider the precision of these estimates because the positive cross-section dependence between the test outcomes is likely to increase the uncertainty considerably. We therefore employ the factor augmented sieve bootstrap approach outlined in the previous section. In doing so, the cross-section dependence is interpreted in terms of a factor model. As explained, the parameters of an underlying factor model are estimated directly, and we subsequently use these estimates to bootstrap the pair-wise rejection rates, treating this factor model as an approximation to the true data generation process (the bootstrap results are based on 2,000 replications).

Tables 2 and 3 report the respective distributions of the bootstrapped fraction of rejections for the unadjusted and adjusted house price data. Focusing on unadjusted prices and the case where a unit root is imposed on the factor (Table 2, upper panel), the mean of the bootstrap distribution for the ADF test at 27.22% for $\alpha = 0.05$ is close to the corresponding point estimate at 31.83% reported in Table 1. When the unit root is not imposed (Table 2, lower panel), the corresponding proportion of rejections for the same unit-root test is higher at 29.38%, and the error band around this mean estimate is rather wide, largely due to the strong positive dependence that exists across the test outcomes. Nevertheless, the 95% bootstrap confidence interval, which ranges from 19.86% to 40.34%, does not cover 5% which is the value we would expect if the null of non-convergence were true everywhere. Notice also that in the case where a unit root is imposed on the factor, the confidence intervals are not symmetric about the mean; with the interval above the mean being wider than the one below the mean. It is clear that cross-section dependence introduces a large degree of uncertainty into the estimate of the proportion of rejections. Table 3 reports the distribution of the bootstrapped fraction of rejections based on adjusted prices. The results are in line with those from Table 2.

The results so far are supportive of long-run convergence between US state house prices.[4] Studies such as Clapp and Tirtiroglu (1994), Pollakowski and Ray (1997) and Meen (1999) have considered the hypothesis that house price relationships between contiguous regions might be stronger than between non-contiguous regions, but the

[4] With regard to support in the literature on income convergence, Carlino and Mills (1996) provide an example where unit root testing leads to the conclusion that per capita earnings convergence occurs across US states and regions. In this particular case, this is after allowing for a break in the data.

evidence is not conclusively in favour of this. In terms of the pair-wise methodology, evidence of an inverse relationship involving distance between any two states and the speed of adjustment towards long-run equilibrium would be consistent with support for the hypothesis. In order to address this hypothesis, we employ the Euclidian distance between the population centroids of any two states, based on the geographic coordinates obtained from the Census Bureau for the year 2000.[5] In the case of measuring the speed of adjustment, we employ an approximation of the half-life of a shock to long-run equilibrium based on the estimated autoregressive parameters obtained from the unit root tests. The estimated half-life is inversely related to the speed of adjustment.

For the 525 cases where non-stationarity is rejected using the ADF test at the 10% significance level, the approximated half-life (in quarters) and distance (in logs) are plotted in Figure 1. One can observe a clear positive relationship and therefore supportive evidence that is consistent with the hypothesis and spatial effects in regional house price convergence.[6] Indeed, a simple OLS regression provides a statistically significant estimate of the slope coefficient, equal to 2.56 with a heteroskedasticity-consistent standard error of 0.44. If we were to investigate any potential asymmetry in this relationship, the employment of quantile regression techniques (see Koenker and Bassett (1978) and Koenker and Hallock (2001)) provides a median coefficient of 2.28 accompanied by a (Huber Sandwich) standard error of 0.47. Figure 2 reveals that the slope coefficient only increases up to the 0.8 quantile. In other words, the relationship between half-life and distance is positive but not necessarily be symmetric, insofar as distance has an increasing

[5] We are most grateful to Gary Wagner who kindly provided these data, which were used in Garrett, Wagner and Wheelock (2007).

[6] Rey and Montouri (1999) represent an early example of detailed evidence of the role played by spatial effects in the context of US regional income convergence.

effect up to a point which might be regarded as a threshold effect.[7]

5. Concluding remarks

In this paper, we have presented evidence that long-run house price convergence is present across the US states. This finding has important implications for relative affordability and labour mobility as well as state-wide wealth effects. In reaching our finding, we have conducted a probabilistic test of convergence based on the unit root testing of all pair-wise house price combinations. This is an approach that provides several key advantages over existing panel unit root methods. We have also provided further insight into regional house price behaviour through the identification of a positive relationship involving distance between states and the half-life of shocks to long-run equilibrium. With regard to an unresolved issue, this finding is consistent with the view that house price relationships are likely to be stronger between contiguous than non-contiguous regions.

[7] To examine conditional symmetry we carry out the symmetric quantiles test proposed by Newey and Powell (1987). The idea of the test is the following. Let $\beta(\tau)$ and $\beta(1-\tau)$ be the values of two sets of coefficients for symmetric quantiles around the median, and let $\beta(\frac{1}{2})$ be the value of the coefficients at the median. Newey and Powell (1987) test whether the average value of $\beta(\tau)$ and $\beta(1-\tau)$ is equal to $\beta(\frac{1}{2})$, that is $\frac{1}{2}\left[\beta(\tau)+\beta(1-\tau)\right]=\beta(\frac{1}{2})$. The results are available upon request and reveal asymmetry; for instance, for $\tau=0.1$ the test yields $\chi_2^2=23.421\left[0.000\right]$.

Table 1. Proportion of price differentials for which the unit-root null hypothesis is rejected

Unit-root test	Unadjusted house prices		Adjusted house prices	
	α = 10%	α = 5%	α = 10%	α = 5%
ADF	46.54	31.83	29.43	19.24
ERS	50.53	37.50	32.54	23.32

Notes: The unit-root regressions include linear trend if it is statistically significant at the 5 per cent level, and the number of lags is selected using the Akaike information criterion. The significance level of the unit-root test statistics is α.

Table 2. Distribution of the bootstrapped fraction of rejections – Unadjusted prices

Imposing a unit root on factor

Test	α	Mean	Median	SD	2.5%	5%	10%	90%	95%	97.5%
ADF	10%	36.71	36.70	5.94	25.35	26.95	28.90	44.42	46.72	48.50
	5%	27.22	27.13	5.59	17.02	18.35	20.21	34.57	36.88	38.83
ERS	10%	36.11	35.99	5.50	25.44	27.12	29.08	43.26	45.12	46.72
	5%	26.33	26.15	5.09	16.84	18.35	20.04	32.98	34.75	36.26

Without imposing a unit root on factor

Test	α	Mean	Median	SD	2.5%	5%	10%	90%	95%	97.5%
ADF	10%	39.05	39.10	5.45	28.81	30.32	32.00	46.01	48.14	50.00
	5%	29.38	29.34	5.23	19.86	21.10	22.87	36.08	38.30	40.34
ERS	10%	37.99	38.03	5.13	27.75	29.61	31.38	44.51	46.63	48.14
	5%	27.78	27.66	4.79	18.35	19.95	21.72	33.95	35.99	37.41

Table 3. Distribution of the bootstrapped fraction of rejections – Adjusted prices

Imposing a unit root on factor

Test	α	Mean	Median	SD	2.5%	5%	10%	90%	95%	97.5%
ADF	10%	28.14	28.01	5.18	18.44	20.04	21.54	34.85	36.97	38.39
	5%	19.28	19.15	4.50	11.08	12.23	13.65	25.27	26.68	28.46
ERS	10%	30.74	30.76	4.99	21.54	22.78	24.38	37.23	39.10	40.96
	5%	21.29	21.01	4.40	13.48	14.36	15.69	27.13	28.91	30.41

Without imposing a unit root on factor

Test	α	Mean	Median	SD	2.5%	5%	10%	90%	95%	97.5%
ADF	10%	27.51	27.31	5.14	18.00	19.42	21.10	34.05	36.08	38.03
	5%	18.82	18.62	4.43	10.81	12.06	13.30	24.65	26.06	27.93
ERS	10%	30.23	30.05	4.97	20.66	22.34	23.94	36.79	38.65	40.25
	5%	20.90	20.66	4.39	13.03	14.01	15.43	26.77	28.55	30.14

Figure 1. Half-life (in quarters) against distance (in logs)

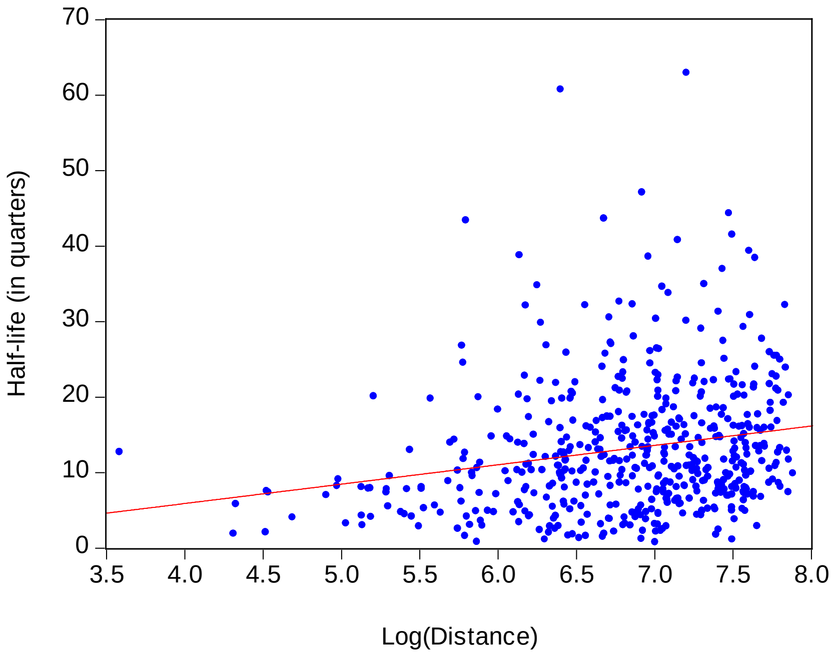
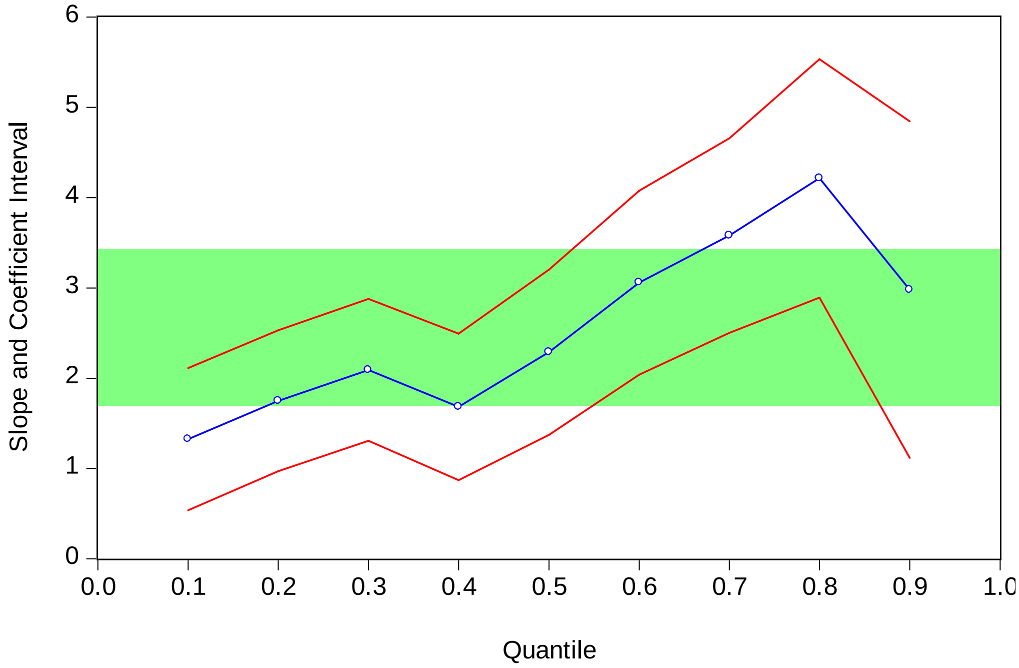


Figure 2. Slope and 95% coefficient intervals



Note: The shaded area indicates the 95% confidence interval for the OLS slope coefficient. Coefficient covariances were calculated using a Huber Sandwich method. A bootstrap selection does not provide qualitatively different results.

References

Breitung, J., Pesaran, M.H., 2008. Unit roots and cointegration in panels. In: Mátýas, L., Sevestre, P. (Eds.), The Econometrics of Panel Data, Springer-Verlag, Berlin Heidelberg, pp. 279-322.

Burger, P., Rensburg, L., 2008. Metropolitan house prices in South Africa: do they converge? South African Journal of Economics 76, 291-297.

Carlino, Gerald and Leonard Mills, 1996. Convergence and the US States: A Time-Series Analysis. Journal of Regional Science 36, 597-616.

Capozza, D.R., Hendershott, P.H., Mack, C., Mayer, C., 2002. Determinants of real house price dynamics. NBER Working Paper 9262.

Clapp, J.M., Tirtiroglu, D., 1994. Positive feedback trading and diffusion of asset price changes: Evidence from housing transactions. Journal of Economic Behavior & Organization 24, 337-355.

Dickey D.A., Fuller W.A., 1979. Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association 74, 427-431.

Elliott, G., Rothenberg, T.J., Stock, J.H., 1996. Efficient tests for an autoregressive unit root. Econometrica 64, 813-836.

Garrett, T.A., Wagner, G.A., Wheelock, D.C., 2007. Regional disparities in the spatial correlation of state income growth, 1977–2002. Annals of Regional Science 41, 601-618.

Goodhart, C., Hofmann B. (2007) House prices and the Macroeconomy, Oxford University Press, Oxford.

Gupta, R., Miller, S.M., 2009. Ripple effects and forecasting home prices in Los Angeles, Las Vegas, and Phoenix. Working Paper No. 200901, University of Pretoria, Department of Economics.

Holly, S., Pesaran, M.H., Yamagata, T., 2010. A spatio-temporal model of house prices in the US. Journal of Econometrics, forthcoming.

Holmes M.J., Grimes, A., 2008. Is there long-run convergence among regional house prices in the UK? Urban Studies 45, 1531-1544.

Hwang, M., Quigley, J.M., 2006. Economic fundamentals in local housing markets: evidence from US metropolitan regions. Journal of Regional Science 46, 425-453.

Im K., Pesaran, M.H., Shin, Y., 2003. Testing for unit roots in heterogeneous panels. Journal of Econometrics 115, 53-74.

Koenker, R., Bassett, G., 1978. Regression quantiles. Econometrica 46, 33-50.

Koenker, R., Hallock, K.F., 2001. Quantile regression. Journal of Economic Perspectives 15, 143-156.

Kuethe, T.H., Pede, V., 2009. Regional housing price cycles: A spatio-temporal analysis using US state level data. Regional Studies, forthcoming.

Levin A., Lin C-F., Chu C-S., 2002. Unit root tests in panel data: Asymptotic and finite-sample properties. Journal of Econometrics 108, 1-24.

Luo, Z., Liu, C., Picken, D., 2007. Housing price diffusion pattern of Australia’s state capital cities. International Journal of Strategic Property Management 11, 227-242.

Maddala, G.S., Wu, S., 1999. A comparative study of unit root tests with panel data and a new simple test. Oxford Bulletin of Economics and Statistics 61, 631-652.

Meen, G., 1996. Spatial aggregation, spatial dependence and predictability in the UK housing market. Housing Studies 11, 345-372.

Meen, G. 1999. Regional house prices and the ripple effect: A new interpretation. Housing Studies 14, 733-753.

Newey, W.K., Powell, J.L., 1987. Asymmetric least squares estimation. Econometrica 55, 819-847.

Oikarinen, E., 2006. The diffusion of housing price movements from centre to surrounding areas. Journal of Housing Research 15, 3-28.

Paiella, M., 2009. The stock market, housing and consumer spending: a survey of the evidence on wealth effects. Journal of Economic Surveys 23, 947-973.

Pesaran, M.H., 2007. A pair-wise approach to testing for output and growth convergence. Journal of Econometrics 138, 312-355.

Pesaran, M.H., Smith, R.P., Yamagata, T., Hvozdyk, L., 2009. Pairwise tests of purchasing power parity. Econometric Reviews 28, 495-521.

Pollakowski, H.O., Ray, T.S., 1997. Housing price diffusion patterns at different aggregation levels: An examination of housing market efficiency. Journal of Housing Research 8, 107-124.

Rapach, D.E., Strauss, J.K., 2009. Differences in housing price forecastability across US states. International Journal of Forecasting 25, 351-372.

Rey, Sergio J. and Brett Montouri, 1999. US Regional Income Convergence: A Spatial Econometric Perspective, Regional Studies 33, 143-56.

Stevens, W., Li, Y., Lekkas, V., Abraham, J., Calhoun, C., Kimner, T., 1995. Conventional mortgage home price index. Journal of Housing Research 6, 389-418.

Stevenson, S., 2004. House price diffusion and inter-regional and cross-border house price dynamics. Journal of Property Research 21, 301-320.

Strassmann, W.P., 2000. Mobility and affordability in US housing. Urban Studies 37, 113-126.

Tirtiroglu, D., 1992. Efficiency in housing markets: Temporal and spatial dimensions. Journal of Housing Economics 2, 276-292.

Appendix 1a. Factor estimate equations for unadjusted house prices

State	Intercept	(s.e.)	Trend	(s.e.)	$\bar{y}_t$	(s.e.)	$\bar{R}^2$
AL	1.914	(0.1173)	0.004	(0.0004)	0.542	(0.0298)	0.997
AR	0.194	(0.2008)	-0.003	(0.0006)	0.987	(0.0510)	0.989
AZ	-3.808	(0.3545)	-0.012	(0.0011)	1.954	(0.0900)	0.982
CA	-5.787	(0.5020)	-0.013	(0.0016)	2.416	(0.1274)	0.980
CO	-0.261	(0.0826)			1.067	(0.0172)	0.966
CT	-2.982	(0.7662)	-0.006	(0.0024)	1.658	(0.1945)	0.937
DE	-0.625	(0.0847)			1.128	(0.0176)	0.968
FL	-3.078	(0.4495)	-0.009	(0.0014)	1.776	(0.1141)	0.974
GA	1.403	(0.1923)	0.004	(0.0006)	0.643	(0.0488)	0.994
IA	3.111	(0.3483)	0.007	(0.0011)	0.275	(0.0884)	0.971
ID	0.463	(0.0651)			0.922	(0.0136)	0.972
IL	2.087	(0.2224)	0.008	(0.0007)	0.472	(0.0564)	0.994
IN	2.880	(0.2400)	0.007	(0.0008)	0.307	(0.0609)	0.988
KS	1.140	(0.0405)			0.758	(0.0084)	0.984
KY	2.266	(0.1712)	0.006	(0.0005)	0.451	(0.0435)	0.995
LA	-1.643	(0.4692)	-0.009	(0.0015)	1.465	(0.1191)	0.943
MA	-2.384	(0.1429)			1.443	(0.0298)	0.946
MD	-1.749	(0.4157)	-0.003	(0.0013)	1.423	(0.1055)	0.981
ME	-1.106	(0.0942)			1.213	(0.0196)	0.966
MI	3.512	(0.4226)	0.011	(0.0013)	0.130	(0.1073)	0.974
MN	-0.219	(0.0497)			1.059	(0.0104)	0.987
MO	0.750	(0.1614)	0.001	(0.0005)	0.821	(0.0410)	0.995
MS	1.268	(0.0365)			0.722	(0.0076)	0.985
MT	0.116	(0.0832)			1.002	(0.0173)	0.961
NC	1.630	(0.1997)	0.005	(0.0006)	0.584	(0.0507)	0.993
ND	1.409	(0.0657)			0.703	(0.0137)	0.951
NE	1.904	(0.2837)	0.004	(0.0009)	0.556	(0.0720)	0.983
NH	-3.365	(0.7092)	-0.007	(0.0022)	1.750	(0.1800)	0.945
NJ	-1.734	(0.1055)			1.329	(0.0220)	0.964
NM	-0.891	(0.3384)	-0.004	(0.0011)	1.239	(0.0859)	0.978
NV	-3.342	(0.3567)	-0.011	(0.0011)	1.863	(0.0905)	0.980
NY	-1.927	(0.1159)			1.374	(0.0242)	0.960
OH	3.504	(0.2479)	0.009	(0.0008)	0.149	(0.0629)	0.988
OK	-2.065	(0.4992)	-0.012	(0.0016)	1.587	(0.1267)	0.909
OR	1.707	(0.6381)	0.008	(0.0020)	0.590	(0.1620)	0.961
PA	1.225	(0.4051)	0.005	(0.0013)	0.675	(0.1028)	0.979
RI	-1.715	(0.1241)			1.332	(0.0259)	0.952
SC	1.387	(0.1254)	0.003	(0.0004)	0.661	(0.0318)	0.997
SD	2.616	(0.3326)	0.006	(0.0010)	0.366	(0.0844)	0.978
TN	1.646	(0.1447)	0.004	(0.0005)	0.592	(0.0367)	0.996
MN	-0.219	(0.0497)			1.059	(0.0104)	0.987
TX	-1.919	(0.3998)	-0.010	(0.0013)	1.524	(0.1015)	0.951
UT	1.772	(0.5573)	0.006	(0.0017)	0.568	(0.1415)	0.956
VA	-1.389	(0.3232)	-0.003	(0.0010)	1.338	(0.0820)	0.987
VT	-0.604	(0.0785)			1.121	(0.0164)	0.972
WA	-0.120	(0.4049)	0.004	(0.0013)	1.019	(0.1028)	0.986
WI	2.324	(0.2709)	0.007	(0.0008)	0.442	(0.0688)	0.989
WV	1.313	(0.0648)			0.735	(0.0135)	0.956
WY	-1.520	(0.7221)	-0.008	(0.0023)	1.448	(0.1833)	0.887

Appendix 1b. Factor estimate equations for adjusted house prices

State	Intercept	(s.e.)	Trend	(s.e.)	$\bar{y}_t$	(s.e.)	$\bar{R}^2$
AL	1.411	(0.3966)	-0.003	(0.0001)	0.881	(0.0457)	0.931
AR	2.373	(0.3837)	-0.003	(0.0001)	0.769	(0.0442)	0.937
AZ	-7.250	(0.5597)	0.002	(0.0001)	1.782	(0.0645)	0.854
CA	-6.074	(1.1318)	0.007	(0.0003)	1.632	(0.1305)	0.808
CO	0.984	(0.6180)	0.001	(0.0002)	0.852	(0.0712)	0.527
CT	3.692	(1.3388)	0.001	(0.0003)	0.508	(0.1543)	0.077
DE	3.972	(0.9379)	0.001	(0.0002)	0.513	(0.1081)	0.158
FL	-10.627	(0.5594)	0.003	(0.0001)	2.170	(0.0645)	0.908
GA	-1.009	(0.3511)	-0.003	(0.0001)	1.123	(0.0405)	0.948
IA	2.554	(0.6168)	-0.002	(0.0002)	0.753	(0.0711)	0.767
ID	0.900	(0.6433)	-0.001	(0.0002)	0.918	(0.0742)	0.708
IL	2.750	(0.3905)	0.001	(0.0001)	0.681	(0.0450)	0.710
IN	5.983	(0.2212)	-0.002	(0.0001)	0.340	(0.0255)	0.937
KS	-1.753	(0.4850)	-0.003	(0.0001)	1.235	(0.0559)	0.926
KY	3.864	(0.3944)	-0.001	(0.0001)	0.590	(0.0455)	0.739
LA	-1.754	(1.0359)	-0.001	(0.0003)	1.234	(0.1194)	0.571
MA	6.427	(1.3910)	0.004	(0.0004)	0.404	(0.1603)	0.469
MD	-1.219	(0.8536)	0.002	(0.0002)	1.109	(0.0984)	0.538
ME	-3.948	(0.7983)	0.002	(0.0002)	1.230	(0.0920)	0.594
MI	3.048	(0.5087)	0.001	(0.0001)	0.657	(0.0586)	0.582
MN	-4.449	(0.3301)			1.517	(0.0383)	0.923
MO	0.259	(0.2731)	-0.001	(0.0001)	0.988	(0.0315)	0.938
MS	1.011	(0.4357)	-0.004	(0.0001)	0.951	(0.0502)	0.951
MT	1.261	(0.7816)			0.889	(0.0906)	0.421
NC	1.644	(0.1707)	-0.002	(0.0000)	0.826	(0.0197)	0.982
ND	-1.124	(0.8135)	-0.003	(0.0002)	1.183	(0.0938)	0.800
NE	2.979	(0.5295)	-0.002	(0.0001)	0.690	(0.0610)	0.836
NH	-4.550	(1.0279)	0.002	(0.0003)	1.452	(0.1185)	0.565
NJ	1.256	(1.2903)	0.003	(0.0003)	0.791	(0.1487)	0.386
NM	-6.637	(0.6248)	0.002	(0.0002)	1.770	(0.0720)	0.823
NV	-3.750	(0.9555)			1.355	(0.1108)	0.531
NY	2.632	(1.2145)	0.003	(0.0003)	0.648	(0.1400)	0.428
OH	3.369	(0.3661)	-0.001	(0.0001)	0.638	(0.0422)	0.755
OK	2.167	(0.7375)	-0.003	(0.0002)	0.778	(0.0850)	0.816
OR	-3.186	(0.9057)	0.004	(0.0002)	1.361	(0.1044)	0.743
PA	3.202	(0.6715)	0.001	(0.0002)	0.639	(0.0774)	0.336
RI	-0.326	(1.3472)	0.003	(0.0003)	1.004	(0.1553)	0.438
SC	0.168	(0.3628)	-0.002	(0.0001)	1.006	(0.0418)	0.908
SD	0.855	(0.6870)	-0.003	(0.0002)	0.957	(0.0792)	0.856
TN	1.694	(0.3009)	-0.002	(0.0001)	0.827	(0.0347)	0.946
TX	0.475	(0.5252)	-0.004	(0.0001)	0.943	(0.0605)	0.923
UT	-0.414	(1.0552)	0.001	(0.0003)	1.045	(0.1216)	0.355
VA	-3.184	(0.5095)	0.001	(0.0001)	1.351	(0.0587)	0.803
VT	1.637	(0.7715)	0.001	(0.0002)	0.804	(0.0889)	0.394
WA	-1.285	(0.5221)	0.004	(0.0001)	1.120	(0.0602)	0.868
WI	0.666	(0.3271)			0.944	(0.0379)	0.825
WV	-0.018	(0.7918)	-0.002	(0.0002)	1.071	(0.0913)	0.747