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Trends, Cycles and Convergence in U.S. Regional House Prices

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Abstract In this study we present a statistical analysis of the time series properties of the geographic regions in the OFHEO U.S. house price database. The time period for our study is first quarter 1975 through second quarter 2005. We 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. We then apply bivariate unit root tests for absolute and relative convergence of the regions and factors, allowing for the possibility of a structural break. We find the two super-regions have slightly different patterns of trends and cycles until the early to mid-1990s, when a common pattern of strong and sustained price appreciation is seen. The evidence for regional convergence is mixed, with little for the first super-regional factor and some examples of relative convergence within the second factor. Thus support for a simple error correction model for regional house prices in our study is mixed.

Keywords Convergence · Regional house prices · Structural time series models · Trends and cycles · Unobserved components

JEL Classification C32 · C33 · E32 · R11

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Introduction

The topic of U.S. house prices is one of increasing interest and scrutiny over the past several years. This is primarily due to the strong and sustained growth in house prices beginning in the early to mid-1990s. The current concern centers around the nature of the dramatic price rise, its subsequent decline, how it will ultimately impact the U.S. economy.

In this study, we present a detailed statistical analysis of the time series properties of trends, cycles and convergence of U.S. regional house prices up through the second quarter 2005, the approximate peak of the latest run-up. In particular, we examine the question of whether U.S. regional house prices are converging. This question is of interest given the literature examining growth and convergence in other U.S. demographic and macroeconomic variables. For example, some recent studies of U.S. regional per capita income find evidence of some type of convergence among most regions. Carvalho and Harvey (2005a) fit a multivariate structural time series model to eight U.S. census regions from 1950 to 2000 and find evidence that all but the two richest regions display absolute convergence of per capita income.

The data for this analysis are the regional house price indexes compiled and maintained by the U.S. Office of Federal Housing Enterprise Oversight (OFHEO). After reducing the dimensionality of the ten geographic regions to two super-regional factors via principal components factor analysis, we apply the methodology of unobserved components, structural time series modeling to explore the existence of trends and cycles in these regions and factors. Specifically we fit a classic model of the business cycle, the *smooth trend plus cycle* model, to nine OFHEO regions and 2 factors. We then examine the question of regional convergence. That is, we test to see if the regions and factors are converging to a common growth path, allowing for the possibility of a structural break.

Our study is organized as follows. The next section provides the theoretical background and literature review for our study. The "Data and Methodology" section describes our data and details the methodology of structural time series modelling of trends and cycles and unit root testing for convergence. The "Results" section presents our results. We describe the two super-regional factors and give a detailed presentation of the trends and cycles in each region and the two factors. We also present and discuss the bivariate unit root tests for convergence. The "Summary and Discussion" section summarizes and discusses our results. The "Conclusion" section concludes the study.

Theoretical Background and Literature Review

If regional per capita incomes are converging, then it is tempting to conjecture that this phenomenon may, in turn, be driving convergence in regional house prices, at least in a relative sense. In addition, other factors like labor and capital mobility (which are often cited as causes of income convergence) may also be contributing to regional house price convergence. However, there is a well-developed literature on the role of wages and house prices in allocating workers to different locations that suggests this reasoning may be overly simplistic. For example, Roback (1982) developed a model in which local amenities affect the equilibrium and introduce ambiguity into the relationship between wages and rents for a given location. In Roback's model, with all else equal, labor prefers amenities and migration of labor into more amenable locations puts upward pressure on rents in these locations. Firms for whom these amenities are unproductive (but for whom land is productive), seek to reduce costs by locating in less amenable areas. So less competition for land due to firm migration tends to offset the upward pressure on rents from labor migration, rendering ambiguous the net effect of amenities on rents. However, wages are unambiguously reduced as more workers compete for fewer jobs in amenable locations. The model predicts a similar ambiguity between wages and rents in the case of productive amenities. Although we do not attempt include a quantitative measure of local amenities in this paper, our convergence results are consistent with the predictions of the Roback (1982) model. Indeed, we find that the evidence for convergence of U.S. regional house prices is much *weaker* than the evidence in the literature on convergence of regional per capita income.

There is an established and growing literature on regional differences and convergence of key demographic and macroeconomic variables such as population and income. For a recent comprehensive summary of this literature, see Magrini (2004). Some examples of the application of structural time series and convergence models of non-U.S. housing markets include Drake (1995), Chen et al. (2004), Chen and Sing (2006) and Chien (2008).

As noted by Meen (2002), and Cameron et al. (2006), there is relatively little published research on U.S. *regional* house prices. Notable exceptions include the studies by Pollakowski and Ray (1997), and Fadiga and Wang (2009) using U.S. Census regions, and the study by Gallin (2006) which tests for cointegration of per capita income and house prices at both national and local levels. There are several studies of U.S. MA's (metropolitan areas) [see, e.g., Abraham and Hendershott (1996), Malpezzi (1999), Capozza et al. (2004), and Hwang and Quigley (2006)]. There is, however, a sizable literature on regional house prices in the U.K., an extensive review of which is provided in Meen and Andrew (1998).

A number of early studies in this literature found both serial correlation and mean reversion in house prices. This literature is summarized in Capozza et al. (1997). Specifically, as derived and discussed by Capozza et al. (1997), the interaction of the two allow the existence of convergence and cycles in regional house prices. To facilitate our discussion, we introduce the simple *error correction* model used by Capozza, Mack and Mayer:

$$\Delta P_t = \alpha \Delta P_{t-1} + \beta \left(P_{t-1} - P^*_{t-1} \right) + \gamma \Delta P^*_t, \tag{1}$$

where P_t denotes log of real housing price at time t, α denotes the degree of serial correlation, Δ is the standard forward difference operator, β denotes the degree of mean reversion, P^* denotes the fundamental value determined by economic conditions, and γ is the contemporaneous adjustment of prices to current shocks. This model is typical and broadly representative of many error correction models for house prices in this literature. As discussed by Meen (2002), models of the U.S. housing market have used both the error correction model [e.g., Abraham and

Hendershott (1996), and Malpezzi (1999)] and the standard time series regression model [e.g., DiPasquale and Wheaton (1994)] to specify the relationship between real house prices and key micro- and macroeconomic variables.

Meen (2002) notes that a basic tenet of theoretical housing economics states that any positive demand shock will lead to a temporary increase in *real* house price *levels* due to a short-run inelastic housing supply. Thus, in the short-term, real house prices may overshoot but, in the long-term, they will change in line with construction costs. If we assume that construction costs change with overall price levels in the general economy, then long-term real house price levels should be stationary (and mean reverting). That is, the observed rise in house prices is due solely to the rise in construction costs. In the face of his finding that real house prices are *nonstationary*, Meen (2002) suggests that some modification of the basic theory is required. A complete review and discussion of the factors contributing to the finding of nonstationarity of national and regional real house prices is beyond the scope of this study. However, some major candidates include the cost of land (Malpezzi, 1999), population, real interest rate, and real household income [see, e.g., Meen (1990), Meen and Andrew (1998), and Meen (2002)], any or all of which may themselves be nonstationary.

Thus it is appropriate to test whether real national and regional house prices are stationary or nonstationary. Stationarity suggests that short-term shocks to real regional house prices will error correct to bring prices back to their long-term equilibrium, implying a "short-term error correction" such as described in Eq. 1 above. It is important to make clear that this is different from long-term convergence to a new equilibrium resulting from shocks along some specific dimensions such as per capita income, education, wealth, etc. In this study, we focus on the former, not the latter.

Specifically, consistent with the model in Eq. (1), in this study we test for convergence to a stable equilibrium relationship among housing regions in a super-region, and between super-regions in the U.S. Thus we will present a test of a simple error correction model for regional house prices. As in Eq. (1), our short-term error correction model for real house prices has *changes* in real regional house prices as the LHS (dependent) variable. However, as we will explain, our error correction model tests for convergence between *pairs of regions* within a super-region defined by a principal components factor analysis. Thus, in our model of regional convergence, the LHS variable will be changes in the *difference* between pairs of regions (within the same super-region). Included in this analysis is an investigation of existence of trends and cycles in the regions and super-regions using modern structural time series models.

Data and Methodology

Data

The primary data for our study are the U.S. regional house prices compiled and maintained by the U.S. Office of Federal Housing Enterprise Oversight (OFHEO). Our primary data are quarterly index price levels, not seasonally adjusted, 1980=100, calculated using the Case–Shiller geometric-weighted repeat-sales procedure fully described in Calhoun (1996).[1] These data include nine regional indexes, plus the United States: East North Central (ENC), East South Central (ESC), Middle Atlantic (MA), Mountain (MT), New England (NE), Pacific (PAC), South Atlantic (SA), West North Central (WNC), West South Central (WSC) and United States (USA), with quarterly index price levels from 1975(Q1) through 2005(Q2) [n=122 quarters]. The geographic regions are identical to the U.S. Census regions. The states within each region are presented in the Appendix. For our statistical analysis, the quarterly regional index price levels are expressed in March 2005 dollars using the CPI *less Shelter* [i.e., the monthly Consumer Price Index (CPI), all urban consumers, U.S. city average, all items less shelter, not seasonally adjusted, 1982–84=100], and converted to natural logs.

The OFHEO index should be distinguished from the S&P/Case–Shiller/Finserve house price index that trades on the Chicago Mercantile Exchange. The OFHEO index relies on data collected by Fannie Mae and Freddie Mac, which the OFHEO regulates. Thus it excludes loans that are either too big (currently>$417,000) or too risky for Fannie Mae and Freddie Mac to guarantee. The Case–Shiller index includes these data, but is currently limited to 20 major U.S. housing markets. The OFHEO index is used by the Federal Reserve to estimate household wealth, while the Case–Shiller index is increasingly used as the basis for futures contracts on the U.S. housing market. For a more complete discussion of these indexes, see Gallin (2004), Drieman and Pennington-Cross (2004), and Wessel (2008).

Methodology

In a series of papers, Carvalho et al. 2005; Carvalho and Harvey (2005a, b) describe a two-stage procedure for investigating the convergence of macroeconomic time series. In the first stage, the stylized facts of the time series are investigated using an unobserved components, structural time series model. In the second stage, a bivariate unit root test is used to test for *absolute* versus *relative* convergence. This is the procedure we shall use here.

Trends and Cycles

As in the papers by Carvalho and Harvey cited above, we fit a smooth trend plus cycle model to the regional house prices data here. Before we discuss that model, we briefly describe the basic unobserved components, *trend plus cycle* structural time series model, which is fully developed in Harvey (1989, 2006) and summarized in Carvalho et al. 2005; Carvalho and Harvey (2005a, b,). The (univariate) trend plus cycle model for a time series variable y_t can be written as:

$$y_t = \mu_t + \psi_t + \varepsilon_t \tag{2}$$

where t=1,...n (n=the number of time periods), $\varepsilon_t \sim \mathrm{NID}\left(0, \sigma_\varepsilon^2\right)$ and μ_t , ψ_t, and ε_t are trend, cyclical and irregular unobserved components, respectively. The nature of

[1] These data are not available from OFHEO in a "seasonally adjusted" format. In fact, there is some question as to whether or not seasonal adjustment of these data is even appropriate. Our pretesting showed that adding a seasonal component to the models does not materially affect our results or conclusions.

the components depends on their disturbances, and allows the components to change over time rather than necessarily being deterministic. Furthermore, the component disturbances are independent of each other and the irregular component, ε_t .

A stochastic trend component in y_t is defined as:

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \tag{3}$$

$$\beta_t = \beta_{t-1} + \varsigma_t \tag{4}$$

where $\eta_t \sim \mathrm{NID}\left(0, \sigma_\eta^2\right)$, $\varsigma_t \sim \mathrm{NID}(0, \sigma_\varsigma^2)$, and the level and slope disturbances, η_t and ς_t, respectively, are uncorrelated. When σ_ς^2 is zero, y_t is called a *random walk plus drift*, and when σ_η^2 is also zero, we have a *deterministic linear trend.* A relatively smooth trend (similar to a cubic spline) is obtained when a zero value for σ_η^2 is combined with a positive value for σ_ς^2. This model is sometimes called an *integrated random walk.*

The cycle component is defined as:

$$\begin{bmatrix} \psi_t \\ \psi_t^* \end{bmatrix} = \rho \begin{bmatrix} \cos\lambda_c & \sin\lambda_c \\ -\sin\lambda_c & \cos\lambda_c \end{bmatrix} \begin{bmatrix} \psi_{t-1} \\ \psi_{t-1}^* \end{bmatrix} + \begin{bmatrix} \kappa_t \\ \kappa_t^* \end{bmatrix} \tag{5}$$

where λ_c is the frequency in radians in the range $0<\lambda_c<\pi$, κ_t, and κ_t^* are two uncorrelated white noise disturbances with zero means and common variance σ_ς^2, and ρ is a damping factor. The period of the cycle in this model is $2\pi/\lambda_c$. The stochastic cycle becomes a first-order autoregressive process if λ_c is 0 or π. A *similar cycle* model is one in which the damping factor ρ and the frequency λ_c are defined to be the *same* for each time series. Similar cycles means each time series has the *same* autocorrelation function and spectrum. Thus the strength of a cycle in a particular time series depends on the variance of its disturbance term. This univariate model can be directly restated as a multivariate model with the application of matrix notation.[2]

As noted by Carvalho and Harvey, in the smooth trend plus (similar) cycle model used here, the trend extracted from the integrated random walk tends to be smoother and permits a more clear separation into trend and cycle components. The advantages of this model in comparison with more traditional models of the business cycle (i.e., ARIMA and Hodrick-Prescott) are fully discussed in Harvey and Jaeger (1993). For example, Harvey and Jaeger (1993) argue that ARIMA models are not likely to be consistent with a classic "trend+cycle" (business cycle) model, especially in small samples; while the popular Hodrick–Prescott filter may create spurious cycles and distort estimates of the cyclical component.

[2] A non-linear unobserved components time series model which allows interactions between the trend-cycle component and the seasonal component was recently presented in Koopman and Lee (2008).

Estimating the Model

We estimate the multivariate trend plus cycle model using the STAMP computer software package Koopman et al. (2000), which is based on the state space format (SSF). As described in Koopman et al. (2000), once a time series model has been put into SSF, the Kalman filter is used to get estimates of the unobserved components based on current and past observations. Specifically, the individual components are estimated by signal extraction based on smoothing recursions that run backwards from the last observation. Predictions are obtained by extending the Kalman filter forward. Root mean square errors (RMSEs) are computed for all estimators and prediction or confidence intervals constructed. The unknown variance parameters are estimated by constructing a likelihood function from the one-step-ahead prediction errors produced by the Kalman filter, and maximizing it by an iterative procedure (maximum likelihood here). For a more complete explanation and discussion, see Harvey (1989, 2006).

One attractive feature of structural time series models is that, while providing useful and appropriate statistical results, they also easily allow the production of graphical results that clearly show the over time behavior of trends and cycles. In fact, a typical and very important way of evaluating and interpreting the results of structural time series models is to closely examine the graphical output. In this paper, we rely on graphs of the trends and cycles to display their behavior. With regard to statistical output of the models, the key feature of trends is the growth rate in the final state, which is the full period growth rate. We will present both the full period growth rate and relevant sub-period growth rates. With regard to cycles, perhaps the key statistic is the *periodicity*. We will present and discuss the cycle period for each region.

Principal Components

In order to reduce the dimensionality of the data and check for common factors, we first performed a principal components factor analysis, with communalities and a varimax rotation (sometimes called principal axis factor analysis). This is a standard and time-honored method of factor analysis for data reduction [see, e.g., Harman (1976)]. The use of principal components analysis on the ten regions allows us to discover the formation of smaller regional subgroups, identify their time series properties, and test for the existence of "club convergence" as it is sometimes called in the econometric literature. The results of the principal components analysis are presented in Table 1.

In Table 1 we see that the principal components analysis reduces the ten regions (including USA) to two super-regional factors. These two factors correspond to the five highest ranked regions by mean real price level in Factor 2, and the next four highest ranked in Factor 1.[3] West South Central (WSC) is not included due to its relatively small and negative factor loadings on Factors 1 and 2, respectively.

[3] We will later note that that these regional indexes are nonstationary. Therefore, strictly speaking, there is no *constant* mean value. However, it is still useful and instructive to rank the regional index means *for this specific time period*.

Table 1 Results of principal components analysis of real index-level correlations,with varimax rotation

	Factor Loadings		Real index mean[a]	Mean rank
Region	1	2		
East South Central (ESC)	0.97	0.23	220.66	7
West North Central (WNC)	0.90	0.32	213.89	9
East North Central (ENC)	0.83	0.41	228.85	6
Mountain (MT)	0.68	0.40	219.56	8
New England (NE)	0.23	0.94	341.75	1
Middle Atlantic (MA)	0.23	0.92	294.28	2
Pacific (PAC)	0.35	0.83	265.26	3
USA	0.56	0.80	241.97	4
South Atlantic (SA)	0.57	0.79	239.71	5
West South Central (WSC)	0.12	−0.28	190.89	10
Eigenvalues	7.08	1.91		
Cumulative % variance accounted for	71	90		

[a] Real index mean is the mean of the real regional index values, before converting to natural logs

Figures 1 and 2 display the graphs of the (log) real regional price levels for the two factors.

The WSC region includes the energy producing states of Oklahoma, Texas and Louisiana. In a separate analysis not presented here to save space, we investigated the possibility that this region distinguishes itself from the others due to its dependence on crude oil and natural gas prices. Specifically, we checked to see if real house prices for WSC were cointegrated with real U.S. crude oil (West Texas Intermediate) and natural gas prices (Wellhead Price) for this time period. Our analysis revealed that they are not cointegrated. A more detailed investigation of this anomaly is beyond the scope of the current analysis.

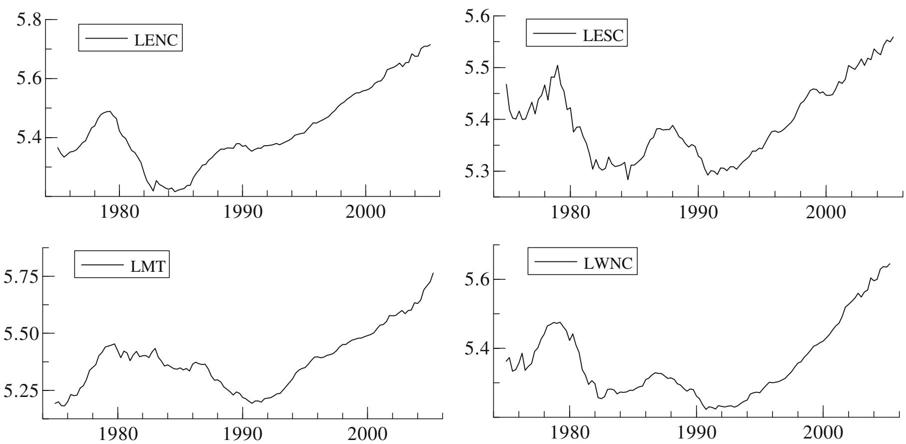

Fig. 1 Log of real regional price levels in Factor 1

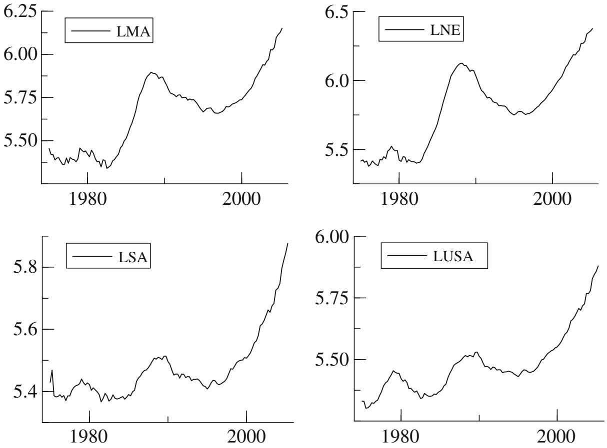

Fig. 2 Log of real regional price levels in Factor 2

We note that we estimated the principal components with and without including the USA (total) region. Except for the fact that the USA was absent from one analysis, the regional composition of the factors was unaffected. We included the USA in the analysis presented here to indicate its location in the factors.

Testing Convergence

Before we implemented our tests for convergence, we applied unit root tests to each regional index. Using the standard Dickey–Fuller unit root test [Dickey and Fuller (1979), Said and Dickey (1984)] and the test of Zivot and Andrews (1992), which allows a single structural break at an *a priori* unknown time point, we verified that each region contains a unit root. That is, our tests suggest each regional house price index is (unit root) nonstationary. These tests are omitted here to preserve space.

One methodology that can be used to test for the convergence of two time series is to test for the presence of a unit root in their time series *differences*. Harvey and Bates (2004) examined a number of unit root tests and suggested that the Dickey-Fuller ADF t-test is the most satisfactory since it is robust to initial conditions different from zero. They also found that the power of the ADF test *increases* the further the initial conditions are from equilibrium. Hence one can test for *absolute* convergence by omitting the constant term in the bivariate ADF regression, or *relative* convergence by including it. We note that, as shown in Carvalho and Harvey (2005b), tests of absolute convergence tend to have greater power.[4]

Following the procedure in Carvalho and Harvey (2005a) and *consistent with our emphasis on short-term error correction as our model*, tests of regional convergence are conducted by carried out by examining the information in an error correction

[4] As noted in Carvalho and Harvey (2005b), including a time trend in the ADF regression is inconsistent with convergence *and* virtually assures that the test will have very little power against the unit root null.

specification of bivariate (pairwise) Dickey–Fuller ADF unit root regression tests for each pair of regions of the form:

$$\Delta\left(y_{1,t} - y_{2,t}\right) = \alpha_0 + \alpha_1\left(y_{1,t-1} - y_{2,t-1}\right) + \sum \lambda_j \Delta\left(y_{1,t-j} - y_{2,t-j}\right) + \varepsilon_t \qquad (6)$$

where $y_{1,t}$ is the log of the real index value for region 1 at time t, $y_{2,t}$ is the value for region 2 at time t, j is the number of lags of y_i , and ε_t is a random error term. In this study we set max j=4. As noted above we omit the constant term for tests of absolute convergence and include it for tests of relative convergence. In this test, acceptance of the unit root null implies the *absence* of convergence.

Note that we could have specified the dependent variable in Eq. 5 as regional deviations from a weighted-average of *all* regions. However as noted in Evans and Karras (1996), Harvey and Bates (2004) and Carvalho and Harvey (2005a), such a specification implicitly assumes *a priori* that all regions are converging. To the extent that some are not, using a weighted-average of all regions complicates (and potentially invalidates) bivariate ADF tests of convergence. Hence we chose focus on individual pairwise deviations to allow a more clear and relatively uncomplicated evaluation of the details of pairwise regional convergence.

We also acknowledge that an *overall* test for convergence can be conducted by combining the information in the individual unit root tests into a multivariate test for a large panel as in Evans and Karras (1996), Levin et al. (2002), Im et al. (2003), and Harvey and Bates (2004). However as noted above, since some regions may be converging while others may not, Carvalho and Harvey (2005a) rightly suggest that individual tests are likely to be more informative. Hence that is the approach we adopt here. Finally, some have argued (e.g., Hobijn and Frances (2000) for the use of pairwise *stationarity* tests for convergence. We agree with Carvalho and Harvey that such tests are of less value than unit root tests if regions are *in the process* of converging.

Results

Smooth Trends and Cycles

Factor 1 regional trends

Figure 3 presents a graph of the smoothed trends extracted by the structural time series analysis from the regions in Factor 1. In Fig. 3 we see that each regional trend in Factor 1 exhibits price spikes in the late 1970s and the late 1980s. Each regional trend saw price troughs in the mid-1980s and early 1990s. Following the trough of the early 1990s, each index trend begins a dramatic and sustained increase.

Factor 2 regional trends

Figure 4 presents a graph of the smoothed trends for the regions in Factor 2. In Fig. 4 we see a very mild price peak towards the end of the 1970s and a more pronounced peak at the late 1980s. We also see very mild troughs at the mid-1980s and a more pronounced trough at the mid-1990s. The late 1990s begin a dramatic and sustained increase.

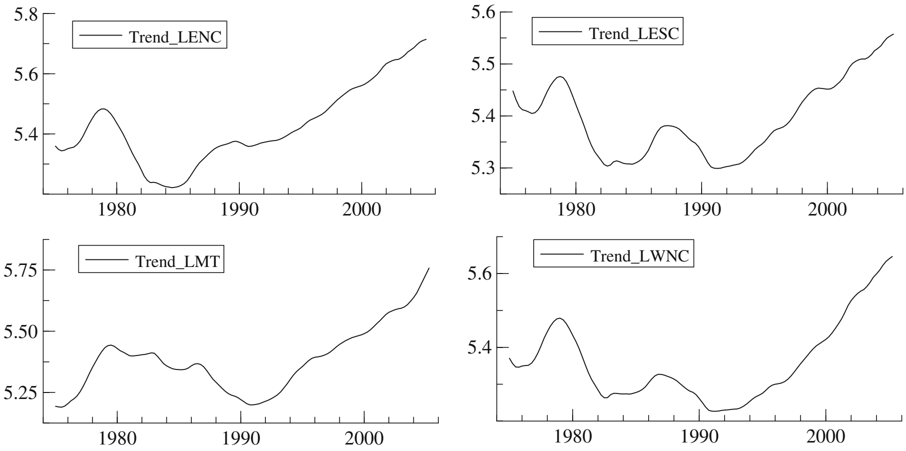

Fig. 3 Smoothed regional trends in Factor 1

Factor 1 regional cycles

Figure 5 presents a graph of the smoothed cycles extracted from the regions in Factor 1. In Fig. 4 we clearly see the cycles begin to dampen after 1980, although the damping is slightly less pronounced for the East South Central (ESC) and West North Central (WNC) regions. The estimated period of the cycles in Fig. 5 is 9.01 quarters or 2.25 years.

Factor 2 regional cycles

Figure 6 presents a graph of the smoothed cycles extracted from the regions in Factor 2. Unlike the regional cycles in Factor 1, the cycles in Factor 2 are less damped, more compressed, and appear not to be uniformly decreasing over time. The estimated period of the cycles in Fig. 5 is 5.49 quarters or 1.37 years.

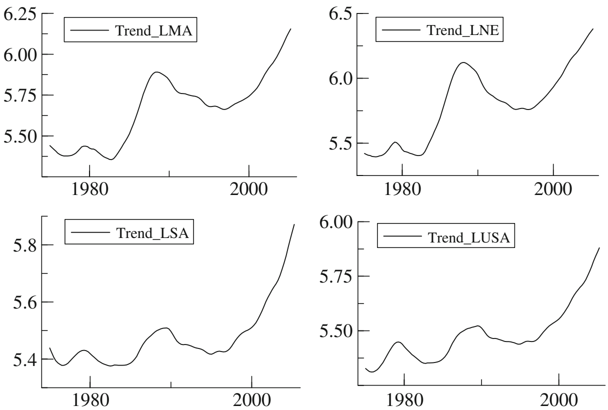

Fig. 4 Smoothed regional trends in Factor 2

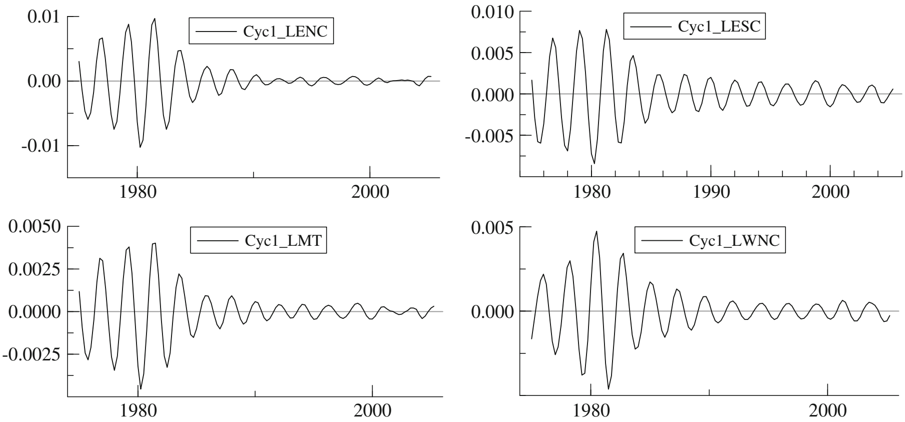

Fig. 5 Smoothed regional cycles in Factor 1

Super-regional Factors 1 and 2 Trends and Cycles

Figure 7 presents a graph of the smoothed trends and smoothed cycles in the super-regional Factors 1 and 2. Each factor is defined as a weighed average of its regional (log) price indexes, where the weights are the factor loadings presented in Table 1. In Fig. 7 we see that the smoothed trends for each factor display different time paths until the mid- to late 1990s, when both trends show dramatic and consistent growth.

The smoothed cycles for the two factors in Fig. 7 tell a different story. Despite the fact that the individual regions showed significant damping (Factor 1 regions) to slight damping (Factor 2 regions), the weighed averages for each factor show no such pattern. A key contributor to this result is the fact that the cycles within each factor to not have the same amplitudes (vertical displacement). Thus, when combined in a weighted average, damping can appear to be minimized.

The estimated regional housing cycles are 2.25 years for Factor 1 and 1.37 years for Factor 2. The average post-WWII business cycle in the U.S. is about 5.5 years.

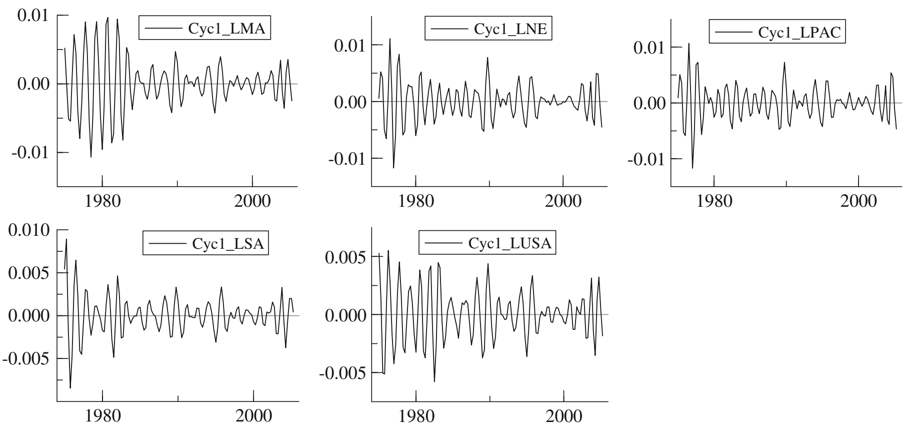

Fig. 6 Smoothed regional cycles in Factor 2

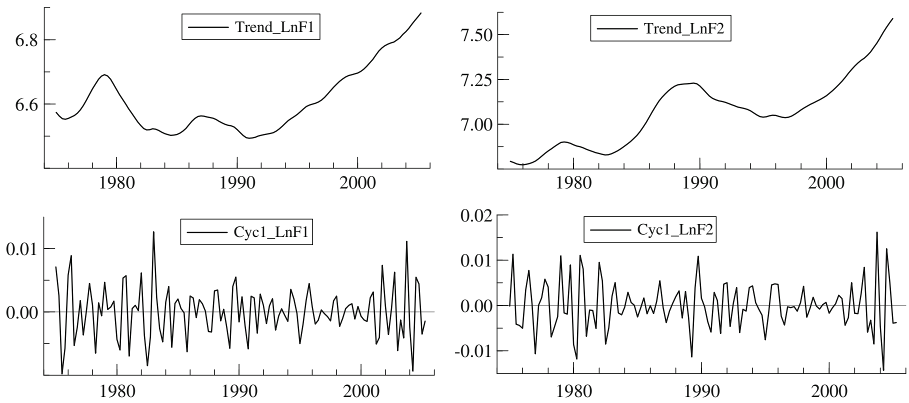

Fig. 7 Trends and cycles in super-regional Factors 1 and 2

This suggests that the U.S. housing cycle is shorter (and more volatile) than the U.S. business cycle. We will return to this finding in the "Summary and Discussion" section.

Convergence

As discussed above, our tests for regional convergence take the form of bivariate, error correction ADF unit root tests on regional differences. These bivariate tests can also be considered tests for *cointegration* between pairs of regions, where the cointegrating vector is [0, −1]. Table 2 presents the results of these tests. We note again that rejection of the unit root null hypothesis implies that a bivariate regional difference is stationary (mean reverting) and thus converging. Panel A of Table 2 for Factor 1 indicates that one pair (WNC and MT) implies relative convergence and two pairs (ENC and MT, and MT and WNC) imply absolute convergence. Panel B for Factor 2 indicates that five pairs imply relative convergence (PAC and MA/NE, SA and NE, USA and NE/SA) and two pairs imply absolute convergence (MA and PAC, and SA and USA). The two super-regional factors do not reject the unit root null for either type of convergence.

Since a visual inspection of our time series graphs suggests that a major structural break in the pattern of U.S. house prices may have occurred in the mid- to late 1990s, we also included our bivariate version of the ADF unit root test of Zivot and Andrews (1992) for their Model A. Their Model A allows a single structural break in the level (intercept) of the time series regression at an *a priori* unknown point in time and is thus a test of relative convergence. These results are presented in Table 3. Panel A of Table 3 for Factor 1 shows that the unit root null cannot be rejected for any pair of regions. Panel B for Factor 2 indicates that four pairs (MA and PAC, and NE and PAC/SA/USA) reject the unit root null, thus implying relative convergence. The two super-regional factors do not reject the unit root null.

In summary the bivariate unit root tests in Tables 2 and 3 suggest that, before and after allowing a single structural break, there is little or no evidence of any type of convergence for the regions in Factor 1, and more substantial evidence of relative convergence for the regions in Factor 2.

Table 2 Results of Dickey–Fuller ADF unit root *t*-tests for bivariate regional differences within factors (data with normal font=no constant; italicized data=with constant)

	ENC	ESC	MT	WNC	MA	NE	PAC	SA	USA	No constant	With constant
	Panel A. Factor 1				Panel B. Factor 2						
ENC		*−0.66*	*−2.53*	*−1.37*							
ESC	−0.18		*−1.20*	*−0.11*							
MT	−2.60[a]	−1.29		*−2.64*[b]							
WNC	−0.71	−0.78	−2.00[a]								
MA						*−2.05*	*−3.44*[a]	*−1.60*	*−1.78*		
NE					−0.42		*−3.32*[a]	*−2.85*[b]	*−3.02*[a]		
PAC					−2.65[a]	−1.53		*−1.86*	*−1.69*		
SA					−0.51	−1.21	−1.09		*−2.58*[b]		
USA					−0.49	−0.96	−0.93	−2.24[a]			
F1–F2										0.40	−2.23

95%/90% C.V.=−1.95/−1.61 (no constant), −2.90−2.59 (with constant) for n=100, from Fuller (1996), Table 10.A.2. ADF regressions with four lags. F1–F2=difference of logs of weighed-averages of Factors 1 and 2. Weighted-averages are calculated using regional factor loadings as weights within each factor. ADF regressions with max four lags

[a] Denotes significance at the 95% level

[b] Denotes significance at the 90% level

Another way to examine convergence is to look at the time path of the cross-sectional standard deviations of the price indexes within each regional factor. A pattern of decreasing SDs indicates within-factor convergence, while increasing SDs indicate divergence. In our case, we looked at the cross-sectional standard deviations of the weighted logs of the real price levels for the regions within each factor, where the weights are the factor loadings as discussed earlier. A graph of this relationship is

Table 3 Results of Zivot–Andrews ADF Model A unit root *t*-tests for bivariate regional differences within factors

	ENC	ESC	MT	MA	NE	PAC	SA
	Panel A. Factor 1			Panel B. Factor 2			
ENC							
ESC	−4.48						
MT	−4.07	−3.70					
WNC	−3.88	−2.60	−3.63				
MA							
NE				−3.49			
PAC				−5.58[a]	−5.37[a]		
SA				−4.54	−5.47[a]	−4.62	
USA				−4.67	−5.30[a]	−4.45	−2.84
F1–F2				−4.33			

95%/90% finite-sample C.V.= −5.21/−4.90, from Zivot and Andrews (1992), Table 9, *Model A* with constant term

[a] Denotes significant *relative* convergence at the 95% level. ADF regressions with max four lags

presented in Fig. 8. In Fig. 8 we see a pattern of convergence in within both super-regional factors until about 1983, followed by divergence (especially pronounced for Factor 2) until about 1988, followed by moderate convergence for Factor 1 through to the end of our data in mid-2005. Factor 2 shows more significant convergence from 1988 until about 1999, when a pattern of divergence emerges. The regions within Factor 2 begin to converge again at the very end. While this graph is useful, recall that the results of the unit root tests indicate that any patterns of convergence or divergence tend to be region specific.

Finally, yet another way to measure convergence is accomplished by an examination of real quarterly growth rates. While not a perfect measure, *ceteris paribus*, it is reasonable to assume that converging regional price levels will exhibit similar growth rates. Table 4 presents the real quarterly percentage growth rates for the regions and factors. In this table, we supply growth rates for the full period and for two sub-periods. The definitions of the subperiods recognize the recent dramatic growth in U.S. house prices. Panel A shows the growth rates for Factor 1, where the growth period began at about 1990/3, and Panel B shows the growth rates for Factor 2, where the growth period began at about 1996/1.

We see in Panel A for Factor 1 that, as expected, the growth rates for the period 1990/3-2005/2 are much larger than those for the beginning period. Also, the growth rates vary across regions, with MT having the largest growth rates in each period, and ESC having the smallest growth rates in each period. We see in Panel B for Factor 2 that the growth rates for the period 1996/1–2005/2 are also much larger than those for the beginning period. As with Factor 1, the growth rates vary across regions, with PAC having the highest growth rates in each period and SA having the lowest growth rates in each period (excluding USA). In terms of the weighted-average factors, Factor 2 growth rates are larger than Factor 1 in each period.

Summary and Discussion

We found that nine U.S. regional house price indexes could be grouped into two super-regional factors via principal components factor analysis. The Factor 1

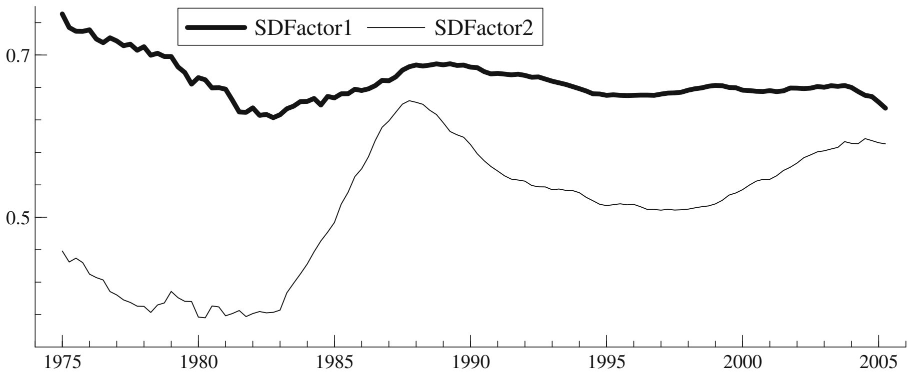

Fig. 8 Cross-sectional standard deviations for super-regional Factors 1 and 2

Table 4 Real quarterly growth rates in regions and factors (in %)

Time period	ENC	ESC	WNC	MT	MA	NE	PAC	SA	USA	Factor 1	Factor 2
	Panel A. Factor 1				Panel B. Factor 2						
1975/1–1990/2	0.012	−0.235	−0.179	0.033						−0.109	
1990/3–2005/2	0.571	0.392	0.655	0.922						0.614	
Full period	0.289	0.075	0.234	0.473						0.249	
1975/1–1995/4					0.282	0.435	0.707	0.008	0.154		0.316
1996/1–2005/2					1.226	1.594	1.762	1.166	1.116		1.406
Full period					0.577	0.797	1.036	0.370	0.455		0.657

includes the four lowest ranked regions by mean price level for the full period (1975/1–2005/2), and Factor 2 includes the five highest ranked. West South Central (WSC) was deleted due to its distinction as an outlier in the factor analysis.

Using an unobserved components, structural time series analysis of the regions and factors, we fit the smooth trend plus cycle model and found that the smoothed regional trends within each factor behaved similarly until the early to mid-1990s, when the regions within each factor exhibited strong and sustained growth until the end of the our data (2005/2). The smoothed cyclical components behaved more distinctively. The smoothed regional cycles in Factor 1 damped substantially beginning with the mid-1980s, when the regional prices within the factor began their steep rise. The smoothed cycles in Factor 2, while more compressed than those in Factor 1, generally stayed constant, except for a short period of increased volatility at the beginning of the period. This suggests that the regional house prices within Factor 2 are not only higher than those of Factor 1 but also more volatile, with the increased cyclicality of Factor 2 as a major contributor. This is confirmed by the difference in the periodicities of the cycles in Factors 1 and 2 (2.25 years vs. 1.37 years), and by the difference in the coefficients of variation of the logged (weighted-average) price levels for Factors 1 and 2 (0.0154 vs. 0.0276).

The post-WWII U.S. business cycle has an average length of about 5.5 years. This is over twice the length of the regional housing cycles we estimate here. While we do not investigate it here, this suggests the possibility that the U.S. housing cycles have a different macroeconomic specification than the business cycle. Moreover, a recent study by Owyang et al. (2009) documents the fact that there is a surprising amount of *between-region* (and *between-state*) variation in business cycles in the U.S. A further examination of this finding as it relates to regional housing cycles is an interesting and quite logical next step to follow the results presented in this study.

In order to test our version of the simple and widely used error correction model for house prices in Eq. (1), we used a bivariate, error correction specification of the Dickey–Fuller ADF unit root *t*-test to test for convergence of the regions and factors. The evidence for regional convergence is mixed. Before allowing for a structural break we found evidence of absolute convergence for regions ENC and MT, and MT and WNC; and evidence of relative convergence for WNC and MT in Factor 1. After allowing for a single structural break using a bivariate Zivot–Andrews unit root *t*-test, we found no evidence for relative convergence in Factor 1.

Before allowing for a structural break we found evidence of absolute convergence for regions MA and PAC, and SA and USA; and evidence for relative convergence for regions PAC and MA, PAC and NE, SA and NE, USA and NE, and USA and SA in Factor 2. After allowing for a structural break, we found evidence for relative convergence for regions MA and PAC, NE and PAC, NE and SA, and NE and USA in Factor 2. We found no evidence of absolute or relative convergence for the two super-regional factors, before or after allowing a structural break.

Our graph of the cross-sectional standard deviations for Factors 1 and 2 showed distinct patters of convergence and divergence, with an indication of emerging convergence at the end point of our data. An examination of the growth rates for the regions and factors confirmed that both regional factors experienced significant growth from the early to mid-1990s on, and further revealed that the growth rates for Factor 2 (and its regions) are significantly larger than those for Factor 1. This is generally consistent with the finding that the regions in Factor 2 have higher mean price levels than those in Factor 1, as shown in Table 1.

Conclusion

We have presented a detailed statistical analysis of the time series properties of the OFHEO U.S. regional house price data for the period 1975(Q1)–2005(Q2). Our study is among the first to focus on U.S. housing regions. We fit a classic smooth trend plus cycle structural time series model to nine regions and two super-regional factors. We also tested for absolute and relative convergence of the regions and factors using bivariate unit root tests. The evidence for convergence, and hence support for our simple error correction model of regional house prices, was mixed.

It has now become apparent that the ending time period of our analysis closely approximates the end of the dramatic price appreciation in U.S. house prices that began in the early to mid-1990s. Specifically, our data end with second quarter 2005, and it now appears that the dramatic rise in house prices began to lose momentum at about the third quarter 2005. Our analysis found that the evidence for regional convergence is mixed. An extension of our analysis would therefore seek to accumulate more quarters of data as time passes and ultimately test the robustness of our results to those in the post-price appreciation period. That is, it may well be the case that a subsequent analysis will find more clear-cut evidence of regional convergence, thus offering more support for the simple error correction model in the post-price appreciation period.

A further extension of our analysis would be to focus specifically on the existence of a "house price bubble" in our data. This would involve identifying and collecting additional macroeconomic data to test for a departure of the national and regional house prices from their underlying economic fundamentals. Finally, an investigation of the macroeconomic determinants of the observed difference in the length of the house price cycle for the different regions and their relationship to the overall business cycle is potentially of interest.

Appendix

Table 5 U.S. States by OFHEO region

Region	State
East South Central	Kentucky
	Tennessee
	Mississippi
	Alabama
West South Central	Oklahoma
	Texas
	Arkansas
	Louisiana
East North Central	Wisconsin
	Michigan
	Illinois
	Indiana
	Ohio
West North Central	North Dakota
	South Dakota
	Minnesota
	Nebraska
	Iowa
	Kansas
	Missouri
Mountain	Montana
	Idaho
	Wyoming
	Nevada
	Utah
	Colorado
	Arizona
	New Mexico
New England	Maine
	Vermont
	New Hampshire
	Massachusetts
	Rhode Island
	Connecticut
Middle Atlantic	New York
	New Jersey
	Pennsylvania
South Atlantic	Delaware
	Maryland

Table 5 (continued)

Region	State
	District of Columbia
	Virginia
	West Virginia
	North Carolina
	South Carolina
	Georgia
	Florida
Pacific	Alaska
	Washington
	Oregon
	California
	Hawaii

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