Unit Roots and Structural Change: An Application to US House-Price Indices

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Abstract: This paper employs unit-root tests that allow for two endogenous breaks as suggested by Lumsdaine and Papell (1997) and Lee and Strazicich (2003) to investigate the returns on the S&P/Case-Shiller Home Price Indices. The tests that assume structural stability provide no evidence against the unit-root hypothesis in all returns series. Conversely, the Lumsdaine-Papell and Lee-Strazicich tests indicate that significant structural breaks exist. Only the Lee-Strazicich test, however, which incorporates structural changes under the null hypothesis, finds that the returns to houses exhibit trend stationarity with structural breaks, in most cases, rather than a random walk. Following Meen (1999), we also investigate the stationarity of the metropolitan house-price ratios. The findings of the Lumsdaine-Papell test provide no evidence against the unit-root hypothesis in all house-price ratio series. Conversely, the Lee-Strazicich test finds broken-trend stationarity of the metropolitan house-price ratios for Boston, Miami, and New York.

Key Words: House-price indexes, Time-series properties, “Ripple” effects.
JEL Code: G10, C30, C50

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1. Introduction

The behavior of regional house prices constitutes an important area of research, which emerged in recent years, in part, because of the boom and bust cycles undergone by many local housing markets. Most analysts attribute the collapse of house prices in recent years as triggering the financial crisis that led to the significant recession in the US (and world) economy. The analysis of the run-up and collapse of house prices in the last decade requires a careful investigation of the properties of house price time series.

This paper employs unit-root tests with and without structural breaks to analyze two separate, but intertwined, issues of the housing markets. First, we examine the time-series properties of house returns in 10 US metropolitan markets and in the aggregate market. Metropolitan house-price models possess many advantages over national house-price models. Local data vary idiosyncratically, suggesting that aggregation of data to the national level will lose this information.\(^1\)

A debate exists on whether the run-up and decline in house prices in recent years represent a bubble and its collapse.\(^2\) Shiller (2007) argues that US house prices reflect psychological factors or a social epidemic based on behavioral economic analysis. Earlier, Case and Shiller (2003) conclude that house-price increases generally reflect fundamental factors, except for possible psychological factors for East and West coast prices. McCarthy and Peach

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\(^1\) Further, intuition suggests that job commuting in the metropolitan area can link house prices, which may not occur across metropolitan areas. Gupta and Miller (2009a, 2009b) argue that the purchasing power parity (PPP) concept may apply to inter-metropolitan area house prices. That is, although the housing market fails to include one important characteristics for the operation of PPP -- lack of transportability of houses between markets, since houses cannot flow between markets, the migration of buyers between metropolitan areas can link the housing markets. Second, home builders can also move their operations between metropolitan areas in response to differential returns on home-building activity.

\(^2\) Stiglitz (1990) defines a bubble as follows. A high price exists because buyers anticipate that future prices will rise to even higher levels, not based on movements in fundamental factors.
(2004) and Himmelberg, Mayer, and Sinai (2005) find that fundamental factors can explain recent house-price increases in the US. The existence of a bubble and its collapse in recent house-price movements, however, proves irrelevant for our paper, since we focus on examining the time-series properties of the house-price index and the rate of return on housing wealth.

UK housing experts identify a “ripple effect” of house prices that begins in the Southeast UK and proceeds toward the Northwest. Meen (1999) describes four different theories that may explain the ripple effect – migration, equity conversion, spatial arbitrage, and exogenous shocks with different timing of spatial effects. The ripple effect hypothesis does not yet receive much support in the US economy. For example, most analysis relates to a given geographic housing market, such as a metropolitan area (Tirtiroglu 1992; and Clapp and Tirtiroglu 1994). More recent evidence across census regions also exists, which may reflect the fourth of Meen’s explanations (Pollakowski and Ray, 1997; Meen 2002). Finally, Gupta and Miller (2009a, 2009b) find evidence of house-price linkages between Los Angeles, Las Vegas, and Phoenix and between the eight Southern California metropolitan statistical areas (MSAs).

This empirical literature on linkages between house prices across space frequently begins by investigating the Granger-causal links between regional housing markets (Giussani and Hadjimatheou 1991, MacDonald and Taylor 1993, Alexander and Barrow 1994, Berg 2002, Gupta and Miller 2009a, 2009b). Other methods compare the long-run equilibrium relationships between house prices and “fundamentals” (Alexander and Barrow 1994, Malpezzi, 1999; Case and Shiller, 2003) and between regional house prices and national prices (Meen 1999, Cook, 2003, 2005a, 2005b).³

³ Adjustments in housing markets traditionally play a critical role in macroeconomic adjustments and the business cycle. The recent financial crisis provides a most striking example of the macroeconomic implications from housing
The time-series properties of house returns, measured by the logarithmic difference in house prices, play an important role in these studies. In sum, do house returns follow a stationary process or do they contain a unit root? The answer to this question provides far reaching implications.

First, this paper considers whether the returns on houses exhibit trend reverting or unit-root movement. Some research does address this question (e.g., Muñoz 2003, and Meen 2002). Using quarterly data from 1975 to 1996 from the 50 US States, Muñoz (2003) finds unit roots in house-price changes, using the $DF-GLS$ test (Elliott, Rothenberg, and Stock 1996). Meen (2002) compares the time-series behavior of house prices in the US and UK. Using quarterly data from 1976 to 1999 for the US and from 1969 to 1999 for the UK, Meen (2002) conducts both Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit-root tests on the level of house prices and finds that in both countries house prices follow a difference stationary process. That is, house prices are $I(1)$. By implication, the rate of return on houses should prove $I(0)$, since the rate of return approximately equals the logarithmic difference in the house price between months.

Given the recent boom and bust of the housing markets in the US, compelling reasons exist to investigate further the behavior of house prices in the US. Much research argues that the presence of structural breaks distorts the results of conventional unit-root tests (Perron, 1989, 1997). Certainly, such shifts did occur in US housing markets. Federal Reserve Board data, for market events. Macroeconomic effects come through several channels. For example, changes in house prices affect aggregate consumption and saving (Case, Quigley, and Shiller 2005, Benjamin, Chinloy, and Jud 2004, Campbell and Cocco 2007, Carroll, Otsuka, and Slacalek 2006). Also, house-price adjustments possess implications for risk-sharing and asset pricing (Lustig and van Nieuwerburgh, 2005, Piazzesi, Schneider, and Tuzel, 2007) as well as distributional effects in heterogeneous-agent economies (Bajari, Benkard, and Krainer, 2005).
example, indicate that the household sector held more than $21 trillion of real estate, most of it residential, at the end of 2005. By the end of 2008, that figure declined to about $18 trillion.4

Lee, List, and Stazicich (2006) find that accurate forecasting and empirical verification of theories can depend critically on understanding the appropriate nature of structural change in time-series data. The literature on unit-root tests and structural breaks largely considers macroeconomic time series, following the seminal paper of Nelson and Plosser (1982), and does not pay much attention to the stochastic properties of microeconomic time-series data. This issue, however, proves as relevant in the analysis of microeconomic time series as it is for macroeconomic time series. Consequently, we analyze the time-series properties of the rate of return on houses, checking for unit roots both with and without structural breaks. When considering structural breaks, we implement the two endogenous-structural-break models developed by Lumsdaine and Papell (1997) and Lee and Strazicich (2003).

The tests that assume structural constancy serve as a comparison for the effect of adding endogenous breaks into the test procedure. Researchers have not applied the unit-root tests with two structural breaks to US metropolitan house returns. Compared with the Lumsdaine-Papell tests, the Lee-Strazicich unit-root tests incorporate the endogenous breaks in the null. That is, the endogenous two-break unit-root test of Lumsdaine and Papell (1997) assumes no structural breaks under the null. As Lee and Strazicich (2003) emphasize, rejection of the null does not necessarily imply rejection of a unit-root per se, but may imply rejection of a unit root without break. Similarly, the alternative does not necessarily imply trend-stationarity with breaks, but may indicate a unit-root with breaks. Lee and Strazicich (2003) propose an endogenous two-

break minimum LM unit-root test that allows for breaks under both the null and alternative hypotheses. As a result, rejection of the null unambiguously implies broken-trend stationarity.

The key to understanding the issues relates to the critical values that the research must generate through Monte Carlo simulations. The larger the breaks in the trend, the further the critical values computed under no and trend breaks diverge from each other (Lee and Strazicich 2003, p. 1082). In other words, to unambiguously determine if the time series in question achieves broken-trend stationarity, researchers must include the breaks in the trend in the null hypothesis.

Second, we consider the “ripple effect.” Following the analysis in Meen (1999), we cast the issue as a unit-root problem. That is, we consider the time-series properties of the ratios of the metropolitan house-price indices to the national house-price index in the US. Meen (1999) emphasizes that the diffusion of changes in house prices implies a long-run constancy in the ratio of regional house prices to the national house price. Alternatively, the ratio of regional house prices to the national house price exhibit stationarity under the ripple effect hypothesis, reverting to an underlying trend value. This represents an additional reason why researchers need to understand the nature of the shocks to the housing market. If the ripple effect exists, then a given price shock in a metropolitan area may produce permanent or transitory implications for house prices in other metropolitan areas, depending on the unit-root properties of the data. Meen (1999), using the ADF unit-root test, fails to find significant evidence of stationarity in the house-price ratios for the UK. Conversely, Cook (2003) detects overwhelming convergence in a number of regions in the UK, using an asymmetric unit-root test. Cook (2005b) detects stationarity by jointly applying the $DF-GLS$ test (Elliott, Rothenberg, and Stock, 1996) and the KPSS stationarity test (Kwiatkowski et al., 1992).
The rest of the paper is structured as follows. Section 2 discusses the data. Section 3 reports results of the unit-root tests of house returns in 10 US metropolitan areas under alternative assumptions regarding structural constancy in the deterministic components of the trend. We find that the integration properties of house returns differ markedly across alternative assumptions. Section 4 reports the empirical results of the analysis of the “ripple effect” in the US. We show that the assumption of structural constancy significantly affects the time-series properties of the ratios of the metropolitan house-price indices to the national house-price index in the US. Section 5 concludes.

2. Data and Method

We extract the data utilized in this paper from the S&P/Case-Shiller Home Price Indices ($HPI$) database and include seasonally adjusted monthly house-price indices for the metropolitan statistical areas (MSAs) measured by the S&P/Case-Shiller $HPI$ Composite-10 (CSXR) : Boston (BOXR), Chicago (CHXR), Denver (DNXR), Las Vegas (LVXR), Los Angeles (LXXR), Miami (MIXR), New York (NYXR), San Diego (SDXR), San Francisco (SFXR), and Washington (WDXR). The sample period of each series equals monthly data from January 1987 through April 2009, for a total of 268 observations.

While the Case-Shiller $HPI$ data exhibit some limitations, they possess several advantages over the Office of Federal Housing Enterprise Oversight (OFHEO) house-price indices, ordinarily used in the literature (Deng and Quigley, 2008; Himmelberg, Mayer, and Sinai, 2005, among others). Both the OFHEO and Case-Shiller $HPI$ use the weighted repeated-sales methodology. The OFHEO indices, however, exhibit more limitations than the Case-Shiller indices. First, the OFHEO indices (at the MSA level) appear quarterly, while the Case-Shiller indices appear monthly. Monthly data provide a better opportunity to model the house-price and
the rate of return on the house in a shorter time interval. Second, the Case-Shiller indices only include actual house transactions and do not include, like the OFHEO indices, refinance appraisals, which produce “appraisal smoothing bias” for house return measurement (Geltner, 1989; Edelstein and Quan, 2006). Third, the OFHEO indices only incorporate Fannie Mae and Freddie Mac conforming mortgages, which concentrate at the lower end of prices in the housing markets. Finally, the CME and OTC markets currently use the Case-Shiller indices for derivative trading. Thus, the analysis of the Case-Shiller HPI also provides practical implications for the exploding house-price index derivative market (Fei, 2009).

A house is an asset. Like any tradable asset in an efficient market, arbitrage should eliminate any discrepancies between house prices within the housing market (Case and Shiller, 1989). The key issue involves the definition of the geographic scope of the housing market. The ripple effect documented in the UK links house prices across the country. As noted above, less evidence exists for house-price arbitrage across geographic housing markets in the US.

Modeling time-series properties, we can capture a house-price (or house-price index) series $HPI_t$ as follows:

$$\ln HPI_t = \alpha + \beta t + \rho \ln HPI_{t-1} + \epsilon_t$$

where $\ln HPI_t$ is the natural logarithm of house-price index at time $t$, the variable $t$ is a time trend, and $\epsilon_t$ is an error term. The values of the coefficients $\alpha$, $\beta$, and $\rho$ determine the basic character of the time series. The parameter $\alpha$ represents “drift” (i.e., a fixed movement in each time period), while the parameter $\beta$ represents the effect of a linear time trend. The most important parameter for determining the character of the series, however, is $\rho$. To see this, rearrange the model in terms of changes rather than levels as follows:
\[ \Delta \ln HPI_t = \alpha + \beta t + (\rho - 1) \ln HPI_{t-1} + \epsilon_t, \]  

where \( \Delta \) is the difference operator. If \( \rho < 1 \) then \( (\rho - 1) < 0 \) and the house-price change \( \Delta \ln HPI \), depends on the price at \( t-1 \). This denotes a lack of efficiency. Such a series is called mean- or trend-reverting \( (\beta = 0, \text{ or } \beta \neq 0, \text{ respectively}) \) and enables the researcher to forecast future prices from past prices. Any house-price shock that pushes the price away from its trend will eventually dissipate. By contrast, if \( \rho = 1 \) then \( (\rho - 1) = 0 \), a price change in any period simply consists of the drift and trend component (if any) plus a random change \( \epsilon_t \). Thus, researchers cannot forecast future prices from past prices and the market is inefficient. Such a series is termed a random walk (with trend and/or drift). Any shocks will permanently affect the price and no mean- or trend-reversion tendency exists. The time series described above may exhibit either stationarity (if \( \rho < 1 \)) or non-stationarity (if \( \rho = 1 \)). We can test for (weak-form) market efficiency by testing for the value of \( \rho \), that is, by testing whether the series possesses a unit root.

Diba and Grossman (1988) discuss the link between rational bubbles and the non-stationarity properties of a time series. Although Evans (1991) questions their approach, showing that simple unit-root tests may not detect periodically collapsing bubbles, we can obviously argue that since rational bubbles describe a divergent path, evidence that house-price changes exhibit stationarity excludes the possibility of rational bubbles.

An important question remains. That is, how do house prices respond to exogenous shocks? The effect of shocks on the behavior of a time series depends on the data generation
process. If house-price changes revert to the mean or trend, then exogenous shocks are largely transitory and, consequently house-price forecasts over the long run do not merit revision.\(^5\)

Trend reversion in the house price also proves consistent with long-run competitive market adjustments. A positive demand shock will lead to a temporary increase in house prices, because of the short-run inelastic supply. In the long run after accounting for inflation, however, the house price should return to its trend or, in the language of time-series econometrics, the house price exhibits stationarity (Meen, 2002). A non-stationary time series does not return to a long-run trend. Thus, any assessment of equilibrium conditions and housing market dynamics must start with the recognition that the underlying time-series properties of the house price and its changes (Clayton 1997).

A large literature exists on examining the stochastic properties of national house prices in the UK. Meen (1999), Peterson, Holly, and Gaudoin (2002), using standard unit-root tests, find that the UK national house-price series follows a unit-root process. More recently, however, Cook and Vougas (2009) show that the use of a more sophisticated testing methodology can reverse findings derived using the conventional unit-root approach. Cook and Vougas (2009), using the smooth transition momentum-threshold autoregressive (ST-MTAR) test of Leybourne, Newbold, and Vougas (1998), confirm the stationarity property of house-price changes but find that house prices exhibit structural change.

\(^5\) Further, the macroeconomic implications of changes in house prices and housing wealth, especially with respect to aggregate consumption, depend largely on whether those changes are permanent or transitory. A permanent change in house prices will alter permanent income and, thus, affect consumption, which will occur for a non-stationary house price. On the other hand, stationarity in the house-price means that changes in house prices, which are transitory, will leave permanent income unaffected. Further, the macroeconomic implications of changes in house prices and housing wealth, especially with respect to aggregate consumption, depend largely on whether those changes are permanent or transitory. A permanent change in house prices will alter permanent income and, thus, affect consumption, which will occur for a non-stationary house price. On the other hand, stationarity in the house-price means that changes in house prices, which are transitory, will leave permanent income unaffected.
If the house-price time series is non-stationary, then the issue emerges as to the time-series properties of the financial rate of return on owning a house. That is, $\Delta \ln HPI_t$ approximates the financial rate of return on owning a house, excluding the implicit consumption benefits from living in the house. If $HPI_t$ is $I(1)$, then $\Delta \ln HPI_t$ is $I(0)$, in theory. If $\Delta \ln HPI_t$ is $I(1)$ or non-stationary, then $HPI_t$ is $I(2)$, in theory. Researchers, therefore, need to assess the empirical reliability of the unit-root hypothesis.

Figure 1 exhibits the time-series plots of the returns on the house indices. As noted above, for each MSA, we define the returns on the house index $\Delta \ln HPI_t$ as follows:

$$\Delta \ln HPI_t = \ln HPI_t - \ln HPI_{t-1}$$

where $HPI_t$ denotes the house-price index. Upon visual inspection, all 10 series of returns, including the returns on the Composite-10 index, appear to experience at least two structural breaks. The recession of 1990-1991 appears to date the first break in most series. This break is likely to prove more idiosyncratic in nature, reflecting locally differential effects of the recessionary environment. This break appears most pronounced in California (Los Angeles, San Diego, and San Francisco) as well as New York, Boston, and Washington. The second break appears to occur after the period 2004-2006, which coincides with the so-called house-price bubble and the peak of subprime lending. This most evident break appears in all series, seeming to reflect a common national shock.

Table 1 presents the summary statistics of the returns on the S&P/Case-Shiller $HPI$ for the 10 metropolitan regions. Washington DC, San Diego, and Los Angeles provide the highest average house-price changes of 0.4 percent per month, with Las Vegas providing the lowest house-price changes of 0.2 percent per month. The largest (i.e., maximum) value is 5.3 percent.
per month, corresponding to Las Vegas in June 2006. The smallest (i.e., minimum) value is -4.8 percent per month, corresponding to San Francisco in February 2008. In terms of volatility, Las Vegas records the highest with a standard deviation of 1.4 percent per month, followed by San Francisco with a standard deviation of 1.3 percent per month. Denver, Boston, and New York, on the other hand, emerge as least volatile markets, implying that volatility clustering effects prove less significant in these markets. Viewing volatility as a measure of riskiness, then Las Vegas and San Francisco exhibit the highest risk in the 10 metropolitan area housing markets.

All series exhibit significant negative skewness and leptokurtosis. The Jarque-Bera test (Jarque and Bera, 1987) confirms the non-normality of the distributions. Rejection of normality partially reflects the intertemporal dependencies in the moments of the series. The significant Ljung-Box (Ljung and Box, 1978) statistics for the returns $Q(6)$ and $Q(12)$ indicate serial correlation of those returns. Similarly, the significant Ljung-Box statistics for the squared returns $Q^2(6)$ and $Q^2(12)$ also provides evidence of strong second-moment dependencies.

3. **Empirical Results**

This section considers the various unit-root tests both with and without structural breaks in the time-series patterns. We also include and exclude the structural breaks in the alternative hypothesis within the null hypothesis.

3.1 **Unit-Root Tests without Structural Breaks**

Conventional unit-root tests such as the ADF and PP tests lose power dramatically against stationary alternatives with a low-order, moving-average (MA) process: a characterization that fits well to all the returns on S&P/Case-Shiller *HPI*. We use four more efficient procedures to test the null hypothesis that each series contain a unit root. First, the generalized least squares (GLS) version of the Dickey-Fuller (DF) test due to Elliott, Rothenberg and Stock (1996) (**DF-**)
GLS) exhibits superior power to the ADF test. Second, the point-optimal, unit-root test developed by Elliott, Rothenberg, and Stock (1996) (ERS). Finally, Ng and Perron (2001) developed modified versions of the PP test (NP-MZ) and of the ERS point optimal test of Elliott, Rothenberg, and Stock (1996), (NP-MPT), both of which exhibit excellent size and power properties.

Elliott, Rothenberg, and Stock (1996) modify the ADF tests for two cases – one with a constant and the other with a constant and a trend and develop a unit-root test based on a quasi-difference of the series. First, the quasi-difference of \( y_t \) depends on the value of \( a \) representing the specific point against which the null hypothesis is tested: 

\[
d(y_t | a) = y_t , \text{ if } t = 1 \quad \text{and} \quad d(y_t | a) = y_t - ay_t , \text{ if } t > 1.
\]

Second, we regress the quasi-differenced data \( d(y_t | a) \) on quasi-differenced \( d(x_t | a) \) as follows:

\[
d(y_t | a) = d(x_t | a)'\delta(a) + \eta_t , \tag{4}
\]

where \( x_t \) contains a constant (i.e., \( x_t = \{1\} \)) or a constant and a trend (i.e., \( x_t = \{1,t\} \)). Let \( \hat{\delta}(a) \) equal the OLS estimate of \( \delta(a) \). For \( a \), Elliott, Rothenberg, and Stock (1996) recommend using \( a = \alpha = 1 - 7 / T \), if \( x_t = \{1\} \), and \( a = \alpha = 1 - 13.5 / T \), if \( x_t = \{1,t\} \). We define the GLS detrended data \( y^d_t \) as follows:

\[
y^d_t = y_t - x_t'\hat{\delta}(\alpha).
\]

The DF-GLS test that allows for a linear time trend relies on the following regression:

\[
\Delta y^d_t = \alpha_0 y^{d}_{t-1} + \sum_{j=1}^{p} \beta_j \Delta y^d_{t-j} + \nu_t , \tag{5}
\]
where \( \nu_t \) equals an error term. The \( DF-GLS \) statistic equals the \( t \)-ratio testing \( \text{H}_0: \alpha = 0 \) against \( \text{H}_1: \alpha < 0 \).

In addition to the \( DF-GLS \) test, Elliott, Rothenberg, and Stock (1996) compute a second unit-root test, the so-called point-optimal test, using the residuals from the estimation of equation (4):

\[
\hat{\eta}_t(\bar{\alpha}) = d(y_t, \bar{\alpha}) - d(x_t, \bar{\alpha}) \hat{\delta}(\bar{\alpha}).
\]  

(6)

The point-optimal test involves the computation of the sum of squared residuals

\[
SSR(\bar{\alpha}) = \sum_{t=1}^{T} \hat{\eta}_t^2(\bar{\alpha}).
\]

The null hypothesis for the point optimal test is \( \alpha = 1 \) and the alternative hypothesis is \( \alpha = \bar{\alpha} \). The test statistic equals

\[
P_T = \left[ SSR(\bar{\alpha}) - SSR(1) \right] / f_0,
\]  

(7)

where \( f_0 \) estimates the residual spectrum at frequency zero.

Ng and Perron (2001) construct four test statistics that use the GLS detrended data \( y_t^d \). Two of these statistics modify the PP \( Z_t \) and point-optimal statistics of Elliott, Rosenberg and Stock (1996). Letting \( \kappa = \sum_{t=2}^{T} (y_{t-1}^d)^2 / T^2 \), we can write the GLS detrended modified statistics as follows:

\[
NP - MZ_t = (\kappa / f_0)^{1/2} \left( T^{-1} (y_T^d)^2 - f_0 \right) / 2\kappa, \text{ and}
\]  

(8)

\[
NP - MP_T = (\bar{\alpha}^2 \kappa - \bar{\alpha} T^{-1} (y_T^d)^2) / f_0 \quad \text{if } x_t = \{1\} \text{ where } \bar{\alpha} = -7, \text{ or}
\]  

(9)

\[
NP - MP_T = (\bar{\alpha}^2 \kappa + (1-\bar{\alpha}) T^{-1} (y_T^d)^2) / f_0 \quad \text{if } x_t = \{1,t\} \text{ where } \bar{\alpha} = -13.5. \quad \text{(10)}
\]

For each test, we include a constant and a time trend and estimate the residual spectrum at frequency zero using the GLS-detrended autoregressive spectral density estimator. We
determine the lag length for the test regressions by the Akaike information criterion (AIC) procedure assuming the maximum lag \( k = 12 \).

Table 3 reports the results of unit-root tests without structural breaks. This table presents overwhelming evidence in favor of a unit root in all series, including the Composite-10 Index, as all four tests reach the same conclusion regarding each time series.

3.2 Unit-Root Tests with Two Structural Breaks

One major drawback of unit-root tests exists. In all such tests, we implicitly assume that we correctly specify the deterministic trend. Even a superficial visual inspection of the house returns series suggests the presence of potential structural breaks. Following the seminal work of Perron (1989), we recognize that the presence of structural change can substantially reduce the power of unit-root tests. Zivot and Andrews (1992) propose a unit-root test that allows for an endogenous structural break. More recently, Lumsdaine and Papell (1997) propose a sequential ADF-type unit-root test that allows for two shifts in the deterministic trend at two distinct unknown dates. For significant breaks, the test proves more powerful than unit-root tests allowing for only one structural break. The Lumsdaine and Papell (1997) modified version of the ADF test extends the Zivot and Andrews (1992) test as follows:

\[
\Delta y_t = \mu + \beta t + \theta DU_{1t} + \gamma DT_{1t} + \omega DU_{2t} + \psi DT_{2t} + \alpha y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-i} + \epsilon_t
\]  

(11)

where the break dummy variables equal the following values: \( DU_{1t} = 1 \), if \( t > TB1 \), and zero otherwise; \( DU_{2t} = 1 \), if \( t > TB2 \), and zero otherwise; \( DT_{1t} = t - TB1 \), if \( t > TB1 \), and zero otherwise; and \( DT_{2t} = t - TB2 \), if \( t > TB2 \), and zero otherwise. TB1 and TB2 denote the dates of the two structural breaks. We include the lagged terms \( \Delta y_{t-i} \) to correct for serial correlation. Lumsdaine and Papell (1997) call this model CC in analogy to model C of Zivot and Andrews.
(1992), since it allows breaks both in the intercept and the slope of the trend function. $DU_1$, and $DU_2$, capture structural changes in the intercept at time $TB_1$ and $TB_2$, respectively, while $DT_1$, and $DT_2$, capture shifts in the slope of the trend function at time $TB_1$ and $TB_2$, respectively. The procedure involves the estimation of equation (11) by OLS for all values of $k$ and all possible pairs of break dates ($TB_1$ and $TB_2$) where $T$ is the number of observations after adjusting for first differencing and lag length $k$. We rule out the possibility of two consecutive break dates. This involves the case where a positive (negative) shock immediately follows a negative (positive) shock. This case represents one, not two, structural breaks. The selected combination of break points minimizes the value of the $t$-ratio $T_\alpha$ for testing $\alpha = 0$, (i.e., we minimize the possibility of accepting the null hypothesis of unit root). This statistic examines the stationarity of the series. More specifically, we reject (accept) the unit root when the $t$-ratio $T_\alpha$ is more (less) negative than the appropriate critical value. We determine the lag length for the test regressions by the AIC procedure, assuming the maximum lag $k = 12$. (Given a sample size of 268 observation and a maximum lag $k = 12$, the test requires approximately 240,000 regressions.)

Table 4 reports the empirical results of the Lumsdaine-Papell test. Overall, by allowing for two breaks, we cannot reject the unit-root hypothesis in favor of the (broken) trend-stationary alternative for 10 of the 11 series. We can reject the null only for the metropolitan area of Las Vegas. This implies that shocks in housing markets other than Las Vegas are permanent in nature and not trend-reverting. Overall, these findings, while illustrating the importance of allowing for breaks in the slope and the intercept of the trend function, do not produce results too dissimilar from the tests that assume structural constancy. Ben-David, Lumsdaine, and Papell (1997) point
out that allowing for additional breaks does not necessarily produce more rejections of the unit-root hypothesis, because the critical value increases in absolute value when we include more breaks. The results in Table 4, however, indicate that allowing breaks in both the intercept and the slope of the trend function proves important. The break dates themselves are of interest. We determine the significance of the breaks using the conventional $t$-statistic. For over half of the series, including the Composite-10 index, the first break occurs in 1991, and the second in 2003. For San Diego, however, the first break is not significant. For Boston, Los Angeles, New York, and the Composite-10 index, the changes in the intercept and the slope of the trend function prove significant in both breaks. For the remaining series, only either the intercept or the slope of the trend function tests significant.

As noted above, a potential problem of the Lumsdaine-Papell unit-root test exists because typically the derivation of the critical values assumes no breaks under the null hypothesis. This assumption may lead to conclude incorrectly that rejection of the null is evidence of trend stationarity, when, in fact, the series is difference-stationary with breaks (Lee and Strazicich 2001, 2003). To avoid this potential problem, Lee and Strazicich (2003) propose a LM unit-root test that allows for two endogenously determined breaks in the level and trend.

The minimum LM unit-root test of Lee and Strazicich (2003) incorporates structural breaks under the null hypothesis, and rejection of the minimum LM test null hypothesis provides genuine evidence of stationarity. In addition, the results of Lee and Strazicich (2003) show that the minimum LM test possesses greater power than the test of Lumsdaine and Papell (1997).

The LM unit-root test proposed by Lee and Strazicich (2003) allows for breaks under both the null and the alternative hypotheses in a consistent manner. The test employs a data generating process (DGP) as follows:
\[ y_t = \delta' Z_t + e_t, \quad e_t = \beta e_{t-1} + \varepsilon_t, \]  
\[ \varepsilon_t \sim iid \ N(0, \sigma^2). \]  
where \( Z_t \) is a vector of exogenous variables and \( \varepsilon_t \sim iid \ \mathcal{N}(0, \sigma^2) \). We consider two structural breaks as follows. Model AA allows two changes in levels so that \( Z_t = [1, t, D_{1t}, D_{2t}]' \), where \( D_{jt} \) is a dummy variable equal to 1 if \( t \geq T_{Bj} + 1, j = 1,2; \) and 0 otherwise and \( T_{Bj} \) represents the date of the break. Model CC allows two changes in both levels and trend, so that \( Z_t = [1, t, D_{1t}, D_{2t}, DT_{1t}, DT_{2t}]' \), where \( DT_{jt} = t - T_{Bj} \) for \( t \geq T_{Bj} + 1, j = 1, 2, \) and 0 otherwise. As Lee and Strazicich (2003) point out, the DGP includes breaks under the null (\( \beta = 1 \)) and the alternative (\( \beta < 1 \)). The null and alternative hypotheses in Model AA equal the following:

\[ H_0 : y_t = \mu_0 + d_1 B_{1t} + d_2 B_{2t} + y_{t-1} + v_{1t}, \quad \text{and} \]

\[ H_1 : y_t = \mu_t + \gamma t + d_1 B_{1t} + d_2 B_{2t} + (1 - \alpha) y_{t-1} + v_{2t}, \]  
where \( v_{1t} \) and \( v_{2t} \) equal stationary error terms, with \( B_{jt} = 1 \) for \( t = T_{Bj} + 1, \) and 0 otherwise \( j = 1, 2. \) Similarly, the null and alternative hypotheses in Model CC equal the following:

\[ H_0 : y_t = \mu_0 + d_1 B_{1t} + d_2 B_{2t} + d_3 DT_{1t} + d_4 DT_{2t} + y_{t-1} + v_{1t}, \quad \text{and} \]

\[ H_1 : y_t = \mu_t + \gamma t + d_1 B_{1t} + d_2 B_{2t} + d_3 DT_{1t} + d_4 DT_{2t} + (1 - \alpha) y_{t-1} + v_{2t}. \]  

We generate the LM unit-root test statistic from the following regression:

\[ \Delta y_t = \delta' \Delta Z_t + \phi \bar{S}_{t-1} + \sum_{i=1}^{k} \gamma_i \Delta \bar{S}_{t-i} + \mu_t, \]  

where the detrended series \( \bar{S}_t \) is defined as follows: \( \bar{S}_t = y_t - \bar{\psi}_x - Z_t \bar{\delta}, \quad t = 2, \ldots, T; \) \( \bar{\delta} \) equal the coefficients in the regression of \( \Delta y_t \) onto \( \Delta Z_t; \) \( \bar{\psi}_x \) equals \( y_1 - Z_1 \bar{\delta}, \) where \( y_1 \) and \( Z_1 \) correspond to the first observations of \( y_t \) and \( Z_t, \) respectively. We include the lagged terms
\[ \Delta S_{t-i} \] to correct for serial correlation. The LM test statistic equals the \( t \)-ratio \( \hat{\tau} \) testing the unit-root null hypothesis \( \phi = 0 \) [i.e., \( \hat{\tau}(\lambda) = \phi / \text{s.e.}(\phi) \)]. To determine the relative location of the two structural breaks endogenously (i.e., \( \lambda_1 = TB_1/T, \lambda_2 = TB_2/T \)), the minimum LM test uses a grid search \( LM = \inf_{\lambda} \hat{\tau}(\lambda) \) over the trimming region \((0.10T, 0.90T)\), where \( T \) equals the number of observations. The critical values, tabulated in Lee and Strazicich (2003, Table 2), depend upon the location of the breaks. For \( \lambda_1 = 0.2 \) and \( \lambda_2 = 0.8 \), the critical values equal, respectively, -6.32 (1-percent level), -5.71 (5-percent level), and -5.33 (10-percent level).

Table 5 reports the results of the Lee-Strazicich unit-root test. The findings in Table 5 overturn most of the previously presented results suggesting that house returns are non-stationary and provide significant evidence in favor of segmented trend stationarity for the majority of the return series. We can reject the unit-root hypothesis at the 10-percent level for Boston, Denver, Los Angeles, New York, Washington DC, and the Composite-10 index; at the 5-percent level for San Diego, and at the 1-percent level for Las Vegas and Miami. For Chicago and San Francisco, however, we cannot reject the unit-root hypothesis.

The two date breaks that minimize the LM statistics prove meaningful. As in the Lumsdaine-Papell test, the significance of the breaks is determined using a conventional \( t \)-statistic. No a priori reason exists to expect the break dates estimated by the Lee-Strazicich and Lumsdaine-Papell procedures to coincide. These break dates, however, generally fall close to each other. The recession of the early 1990s roughly coincides with the first break in both the Lumsdaine-Papell and Lee-Strazicich procedures for most series. The only exception, Las Vegas, does not exhibit a break in the 1990s under the Lee-Strazicich procedure. The second break, instead, is clustered in the first half of the current decade for all series. For the first of the two break points, significant
breaks in the slope of the trend function ($DT_i$) occur, where the break implies a more positive growth rate in house price index, except in Denver, Los Angeles and San Diego where the trend growth rate falls. In addition, for the first break point, the intercept ($B_i$) falls significantly in Chicago, Miami, New York, and Washington DC. In sum, the first break point illustrates differences between East and West coast cities, suggesting idiosyncratic effects.

The second break, instead, occurs in the 2001 to 2006 period, which coincides, as noted above, with the low interest rates environment of the Fed and the peak activity of subprime lending. We conjecture that this most evident break probably reflects common national internal shocks to the housing market. The findings in Table 5 for the second of the two break points suggest that significant breaks in the slope of the trend ($DT_2$) occur in all cases, while significant breaks in the intercept ($B_2$) only occur for Denver and Miami. In each case, a negative change in the slope of the trend function occurs, as expected from recent developments of the housing market. Miami exhibits the highest (in absolute value) coefficient, followed by Las Vegas and San Francisco. The second break point finds more consistent effects across all metropolitan areas, suggesting some national causal factors.

4. The “Ripple Effect”

Economic theory and intuition suggest that different regional house prices should not move together. House prices depend mostly on local housing market supply and demand factors, which can differ substantially between regions due to differences in regional economic and demographic environments. Yet, a variety of empirical studies present extensive evidence on the so-called “ripple effect”, the interregional transmission of shocks in house prices. If the “ripple effect” exists, then the ability to predict correctly house prices in one region may improve when the significant effects of house prices in other regions are taken into account. The “ripple effect”
emerged in studies of the UK housing markets (Meen 1999; Cook 2003, 2005a, 2005b; and Holmes and Grimes 2008). In recent papers on predictability of US house prices, Gupta and Miller (2009a, 2009b) present evidence of regional “ripple effect” (i.e., forecasting house prices in one metropolitan area improve by including house prices in nearby metropolitan areas) for Los Angeles, Las Vegas, and Phoenix as well as the eight Southern California MSAs.

Although empirical studies observe the “ripple effect,” some difficulty exists with theoretical justifications. There are, however, plausible channels through which such a ripple effect could operate. Meen (1999) suggests that ripple effects could reflect four factors: (i) external migration to the region, (ii) equity transfer between regions, (iii) spatial arbitrage, and (iv) spatial patterns in the determinants of house prices. See also Gupta and Miller (2009a, 2009b).6

This section concerns the time-series properties of the ratios of the metropolitan house-price indices to the national house-price index in the US. Define the metropolitan house-price ratio $d_t$ as follows:

---

6 Migration could cause house-price ripples, if households relocate in response to changes in the spatial distribution in house prices. House prices need not equalize among regions because long lasting differences exist in regional or metropolitan area fixed endowments (e.g., climate) or scale economies (Haurin 1980). An exogenous shock to a region, however, may disrupt local house-price levels, causing migration (Haurin and Haurin 1988). Migration spreads the effect of the shock throughout a region or country, causing a spatial ripple of house-price change. Changes in house prices change homeowners’ equity (Stein, 1995). An increase in equity relaxes down payment constraints, permitting additional mobility. In contrast, falling nominal house prices reduce equity and constrain mobility. The spatial diffusion of house prices proves a manifestation of arbitrage mitigated by search costs or by the diffusion of news throughout a region. Pollakowski and Ray (1997) test whether house-price changes in one region (or PMSA) predict price changes in other regions (or PMSAs) using a VAR model. Their work builds on Tirtiroglu (1992) and Clapp and Tirtiroglu (1994), who find that excess returns to houses in a submarket diffuses to other submarkets of the same MSA. Pollakowski and Ray (1997) find statistically significant cross-price effects at the regional level, but no sensible economic pattern to their results exists. This purely spatial approach implicitly argues that the transmission mechanism flows across space, not across economically similar housing submarkets. Finally, Meen assumes that all regions react to shocks with different speeds. House prices change first in the fastest reacting region, followed by price changes in slower reacting areas. Thus, price ripples occur, although no transmission mechanism exists. Meen (1999) develops an econometric test of this hypothesis using UK regional data. He finds evidence supporting the claim different response rates. In the long run, house prices tend to return to the same pre shock relative values.
\[ d_t = y_t - m_t, \]  

where \( y_t \) refers to the natural logarithm of the metropolitan house-price index and \( m_t \) refers to the natural logarithm of the Composite-10 house-price index, \( t = 1,2,\ldots,T \). Under the assumption that \( d_t \) comes from a first-order autoregressive process as follows:

\[ d_t = \xi + \rho d_{t-1} + \varepsilon_t, \]  

acceptance of the null hypothesis (\( H_0: \rho = 1 \)) means that \( d_t \) is a non-stationary series, whereas rejection of the null means that \( d_t \) is stationary (i.e., a ripple effect exists in the sense of Meen 1999).

Table 6 reports the results of applying the conventional unit-root tests previously used in the paper, which do not allow for structural breaks: the DF-GLS unit-root test of Elliott, Rothenberg, and Stock (1996), the ERS point-optimal, unit-root test of Elliott, Rothenberg, and Stock (1996), the Ng-Perron (2001) modified version of the Phillips and Perron test (NP-MZ_t) and the Ng and Perron (2001) modified version of the point-optimal test of Elliott, Rothenberg, and Stock, (NP-MP_t). All four tests provide consistent evidence of stationarity for the Chicago price ratio. The tests present mixed evidence for Denver and Miami price ratios. The DF-GLS tests favor stationarity of the price ratios, but the remaining three tests do not. For all remaining price ratio series, each of the four test statistics consistently rejects the hypothesis of stationarity.

Table 7 reports the results of applying the Lumsdaine-Papell two-break, unit-root test for the house-price ratios. The results of the Lumsdaine-Papell test accept the null of non-stationarity of the price ratios for all metropolitan areas. Consequently, these empirical results fail to support the ripple effect for each metropolitan area. In other words, shocks to the house prices of each city do not “ripple out” across the nation.
Table 8 reports the results of applying the Lee-Strazicich two-break, unit-root test for the house-price ratios. In contrast to the Lumsdaine-Papell tests, the Lee-Strazicich tests reject the null hypothesis of a unit root with two structural breaks for Boston, Miami, and New York. These findings support the notion of a weak segmentation of the US housing market: only the house-price shocks stemming from Boston, Miami, and New York “ripple out” to have the same effect on all regional house prices.

5. Conclusions

This paper contributes to the literature on the long-run behavior of the house prices by applying Lumsdaine-Papell and Lee-Strazicich unit-root tests, which take into account the existence of structural breaks. The two tests are dissimilar. Lumsdaine and Papell (1997) take into account the existence of segmented trend stationarity under the alternative hypothesis, while Lee and Strazicich (2003) include the segmented trend hypothesis under the null as well the alternative hypothesis. The Lumsdaine-Papell test fails to reject the null of a unit root for 10 of the 11 return series. This implies that house prices are $I(2)$. Conversely, the Lee-Strazicich test indicates that returns to houses, in most cases, follows a stationary process about a segmented trend. This implies that house prices are $I(1)$.

Although these two types of tests provide contradictory findings, both tests indicate that structural breaks exist in the returns to houses. No common significant structural breaks exist that characterize all return series, but the estimated breaks roughly cluster around two periods: the recession of the early 1990s and the first half of the current decade, which experiences low interest rate policies of the FED, the housing bubble, and significant subprime lending activity.

These tests are also used to obtain further insights about the “ripple effect”. Following Meen (1999) and Cook (2003, 2005a, 2005b), we examine the ratio of the Case-Shiller 10
metropolitan price indexes to a national house price index (Composite-10). The Lumsdaine-Papell two-break, unit-root test accepts the null of non-stationarity of the price ratios for all metropolitan areas. Conversely, the Lee-Strazicich two-break, unit-root test rejects the null hypothesis of a unit root with two structural breaks for Boston, Miami, and New York. These findings support the notion of a weak segmentation (MacDonald and Taylor, 1993) of the US housing market, whereby house price changes in East coast cities spread to other metropolitan areas.

References:


Table 1: Summary Statistics

<table>
<thead>
<tr>
<th>Series</th>
<th>Mean</th>
<th>Max</th>
<th>Min</th>
<th>Sd</th>
<th>Sk</th>
<th>Ku</th>
<th>JB</th>
</tr>
</thead>
<tbody>
<tr>
<td>Boston</td>
<td>0.003</td>
<td>0.019</td>
<td>-0.022</td>
<td>0.007</td>
<td>-0.419</td>
<td>3.262</td>
<td>8.566</td>
</tr>
<tr>
<td>Chicago</td>
<td>0.003</td>
<td>0.024</td>
<td>-0.044</td>
<td>0.008</td>
<td>-2.024</td>
<td>11.998</td>
<td>1,083.080</td>
</tr>
<tr>
<td>Denver</td>
<td>0.003</td>
<td>0.017</td>
<td>-0.02</td>
<td>0.005</td>
<td>-0.621</td>
<td>4.434</td>
<td>40.058</td>
</tr>
<tr>
<td>Las Vegas</td>
<td>0.002</td>
<td>0.053</td>
<td>-0.046</td>
<td>0.014</td>
<td>-0.471</td>
<td>7.191</td>
<td>205.271</td>
</tr>
<tr>
<td>Los Angeles</td>
<td>0.004</td>
<td>0.033</td>
<td>-0.039</td>
<td>0.012</td>
<td>-0.571</td>
<td>3.757</td>
<td>20.900</td>
</tr>
<tr>
<td>Miami</td>
<td>0.003</td>
<td>0.023</td>
<td>-0.043</td>
<td>0.012</td>
<td>-1.314</td>
<td>6.032</td>
<td>179.142</td>
</tr>
<tr>
<td>New York</td>
<td>0.003</td>
<td>0.018</td>
<td>-0.025</td>
<td>0.007</td>
<td>-0.443</td>
<td>3.395</td>
<td>10.477</td>
</tr>
<tr>
<td>San Diego</td>
<td>0.004</td>
<td>0.05</td>
<td>-0.037</td>
<td>0.012</td>
<td>-0.369</td>
<td>4.541</td>
<td>32.466</td>
</tr>
<tr>
<td>San Francisco</td>
<td>0.003</td>
<td>0.031</td>
<td>-0.048</td>
<td>0.013</td>
<td>-1.042</td>
<td>5.439</td>
<td>114.526</td>
</tr>
<tr>
<td>Washington, DC</td>
<td>0.004</td>
<td>0.026</td>
<td>-0.023</td>
<td>0.009</td>
<td>-0.507</td>
<td>3.573</td>
<td>15.124</td>
</tr>
<tr>
<td>Composite-10</td>
<td>0.003</td>
<td>0.018</td>
<td>-0.026</td>
<td>0.008</td>
<td>-0.998</td>
<td>4.212</td>
<td>60.703</td>
</tr>
</tbody>
</table>

Note: Mean, Max, Min, and Sd are the sample mean, maximum, minimum and standard deviation of the return series. JB is the Jarque-Bera (1987) test for non-normality based on the skewness (Sk) and kurtosis (Ku) of the distribution. For a normal distribution, the test statistic follows an asymptotic chi-squared with 2 degrees of freedom. We express all return series as natural logarithmic differences.

Table 2: Ljung-Box Statistics

<table>
<thead>
<tr>
<th>Series</th>
<th>Q(6)</th>
<th>Q(12)</th>
<th>Q^2(6)</th>
<th>Q^2(12)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Boston</td>
<td>767.16</td>
<td>1328.8</td>
<td>269.81</td>
<td>370.8</td>
</tr>
<tr>
<td>Chicago</td>
<td>468.25</td>
<td>652.75</td>
<td>219.36</td>
<td>243.65</td>
</tr>
<tr>
<td>Denver</td>
<td>624.51</td>
<td>1052.3</td>
<td>291.77</td>
<td>411.99</td>
</tr>
<tr>
<td>Las Vegas</td>
<td>825.79</td>
<td>1209.6</td>
<td>582.08</td>
<td>659.2</td>
</tr>
<tr>
<td>Los Angeles</td>
<td>1215.1</td>
<td>1932.9</td>
<td>629.76</td>
<td>735.28</td>
</tr>
<tr>
<td>Miami</td>
<td>1080.9</td>
<td>1758</td>
<td>725.91</td>
<td>1056.9</td>
</tr>
<tr>
<td>New York</td>
<td>939.13</td>
<td>1472.6</td>
<td>415.5</td>
<td>502.15</td>
</tr>
<tr>
<td>San Diego</td>
<td>1068.9</td>
<td>1691</td>
<td>301.13</td>
<td>353.82</td>
</tr>
<tr>
<td>San Francisco</td>
<td>920.37</td>
<td>1307.6</td>
<td>452.49</td>
<td>604.32</td>
</tr>
<tr>
<td>Washington, DC</td>
<td>1114.2</td>
<td>1839.1</td>
<td>685.33</td>
<td>1060.5</td>
</tr>
<tr>
<td>Composite-10</td>
<td>1211.5</td>
<td>1966.6</td>
<td>728.1</td>
<td>1040.1</td>
</tr>
</tbody>
</table>

Note: Q(k) and Q^2(k) equal Ljung-Box Q-statistics distributed asymptotically as \( \chi^2 \) with \( k \) degrees of freedom, testing for returns and squared returns for autocorrelations up to \( k \) lags.
Table 3: Unit-Root Tests without Structural Breaks for Returns on S&P Case-Shiller HPI.

<table>
<thead>
<tr>
<th>Series</th>
<th>DF-GLS</th>
<th>ERS-PT</th>
<th>NP MZ_t</th>
<th>NP MP_t</th>
</tr>
</thead>
<tbody>
<tr>
<td>Boston</td>
<td>-1.121</td>
<td>33.823</td>
<td>-1.337</td>
<td>23.572</td>
</tr>
<tr>
<td>Chicago</td>
<td>-0.861</td>
<td>144.588</td>
<td>-1.747</td>
<td>14.612</td>
</tr>
<tr>
<td>Denver</td>
<td>-0.546</td>
<td>37.795</td>
<td>-1.153</td>
<td>33.943</td>
</tr>
<tr>
<td>Las Vegas</td>
<td>-1.682</td>
<td>62.126</td>
<td>-1.137</td>
<td>22.079</td>
</tr>
<tr>
<td>Los Angeles</td>
<td>-1.981</td>
<td>34.984</td>
<td>-1.209</td>
<td>26.913</td>
</tr>
<tr>
<td>Miami</td>
<td>-1.492</td>
<td>90.103</td>
<td>-0.651</td>
<td>45.888</td>
</tr>
<tr>
<td>New York</td>
<td>-1.106</td>
<td>85.789</td>
<td>0.618</td>
<td>30.255</td>
</tr>
<tr>
<td>San Diego</td>
<td>-2.092</td>
<td>34.659</td>
<td>-1.231</td>
<td>28.207</td>
</tr>
<tr>
<td>San Francisco</td>
<td>-1.847</td>
<td>44.349</td>
<td>-1.085</td>
<td>38.167</td>
</tr>
<tr>
<td>Washington, DC</td>
<td>-2.335</td>
<td>46.825</td>
<td>-1.166</td>
<td>33.241</td>
</tr>
<tr>
<td>Composite-10</td>
<td>-1.334</td>
<td>68.348</td>
<td>-1.069</td>
<td>32.464</td>
</tr>
</tbody>
</table>

Note:  The test critical values equal the following:
1) DF-GLS Elliott-Rothenberg-Stock: -3.465 (1-percent level), -2.919 (5-percent level), and -2.612 (10-percent level) (Elliott, Rothenberg and Stock, 1996, Table 1);
2) ERS-PT Elliott-Rothenberg-Stock: 4.019 (1-percent level), 5.646 (5-percent level), and 6.870 (10-percent level) (Elliott, Rothenberg and Stock, 1996, Table 1);
3) NP-MZ_t Ng-Perron: -3.420 (1-percent level), -2.910 (5-percent level), and -2.620 (10-percent level) (Ng and Perron, 2001, Table 1); and
4) NP-MP_t Ng-Perron MP_t: 4.030 (1-percent level), 5.480 (5-percent level), and 6.670 (10-percent level) (Ng and Perron, 2001, Table 1).
Table 4: Lumsdaine-Papell Two-Break, Unit-Root Test for Returns on S&P Case-Shiller HPI

<table>
<thead>
<tr>
<th>Series</th>
<th>TB1</th>
<th>TB2</th>
<th>(yt-1)</th>
<th>DU1t</th>
<th>DT1t</th>
<th>DU2t</th>
<th>DT2t</th>
<th>k</th>
</tr>
</thead>
<tbody>
<tr>
<td>Boston</td>
<td>Apr. 1991</td>
<td>-0.598</td>
<td>0.548</td>
<td>0.333</td>
<td>0.026</td>
<td>0.019</td>
<td>6</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Mar. 2000</td>
<td>(-6.06)</td>
<td>(4.24)</td>
<td>(3.30)</td>
<td>(4.24)</td>
<td>(-5.53)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chicago</td>
<td>Mar. 1999</td>
<td>-0.511</td>
<td>0.243</td>
<td>0.249</td>
<td>0.001</td>
<td>0.039</td>
<td>12</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Aug. 2005</td>
<td>(-4.58)</td>
<td>(2.02)</td>
<td>(1.57)</td>
<td>(-0.58)</td>
<td>(-4.70)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Denver</td>
<td>June 1994</td>
<td>-0.497</td>
<td>-0.450</td>
<td>-0.392</td>
<td>-0.003</td>
<td>0.009</td>
<td>12</td>
<td></td>
</tr>
<tr>
<td></td>
<td>May 2001</td>
<td>(-4.81)</td>
<td>(-4.14)</td>
<td>(-4.09)</td>
<td>(-1.78)</td>
<td>(-3.97)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Las Vegas</td>
<td>Sept. 1991</td>
<td>-0.703</td>
<td>-0.635</td>
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<td>-0.001</td>
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Notes: The numbers in parenthesis equal the \(t\)-statistics for the estimated coefficients. \(TB1\) and \(TB2\) equal the break dates, \(k\) equals the lag length, the coefficient of \(yt-1\) tests for the unit-root, \(DU1\) and \(DU2\) equal the breaks in the intercept of the trend function, and \(DT1\) and \(DT2\) equal the breaks in the slope of the trend function. The critical values, from Ben-David, Lumsdaine and Papell (1997, Table 3), equal -7.19 (1-percent level), -6.75(5-percent level), and -6.48 (10-percent level).
### Table 5: Lee-Strazicich Minimum LM Two-Break Unit-Root Test for Returns on S&P Case-Shiller HPI

<table>
<thead>
<tr>
<th>Series</th>
<th>( TB_1 )</th>
<th>( S_{t-1} )</th>
<th>( B_{1t} )</th>
<th>( DT_{1t} )</th>
<th>( B_{2t} )</th>
<th>( DT_{2t} )</th>
<th>( k )</th>
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<td>(0.75)</td>
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<tr>
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<td>0.274</td>
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<td>(-3.12)</td>
<td>(0.78)</td>
<td>(-4.98)</td>
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<td>(1.12)</td>
<td>(-3.64)</td>
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<td>(3.37)</td>
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<tr>
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<td>(2.72)</td>
<td>(0.96)</td>
<td>(-5.84)</td>
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</tbody>
</table>

Notes: The numbers in parenthesis are the \( t \)-statistics for the estimated coefficients. \( TB_1 \) and \( TB_2 \) equal the break dates, \( k \) is the lag length, the coefficient on \( S_{t-1} \) tests for the unit-root, \( B_{1t} \) and \( B_{2t} \) equal the breaks in the intercept and \( DT_{1t} \) and \( DT_{2t} \) equal the breaks of the slope. Critical values for the coefficients on the dummy variables follow the standard normal distribution. The critical values for the unit-root test, tabulated in Lee and Strazicich (2003, Table 2), depend upon the location of the breaks. For \( \lambda_1 = 0.2 \) and \( \lambda_2 = 0.8 \), the critical values equal, respectively, -6.32 (1-percent level), -5.71 (5-percent level), and -5.33 (10-percent level).
<table>
<thead>
<tr>
<th>Series</th>
<th>DF-GLS</th>
<th>ERS-PT</th>
<th>NP MZ&lt;sub&gt;t&lt;/sub&gt;</th>
<th>NP MP&lt;sub&gt;T&lt;/sub&gt;</th>
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Note: The test critical values are:
1) \textit{DF-GLS} Elliott-Rothenberg-Stock: -3.465 (1-percent level), -2.919 (5-percent level), and -2.612 (10-percent level) (Elliott, Rothenberg and Stock, 1996, Table 1);
2) \textit{ERS-PT} Elliott-Rothenberg-Stock: 4.019 (1-percent level), 5.646 (5-percent level), and 6.870 (10-percent level) (Elliott, Rothenberg and Stock, 1996, Table 1);
3) \textit{NP-MZ}, Ng-Perron: -3.420 (1-percent level), -2.910 (5-percent level), and -2.620 (10-percent level) (Ng and Perron, 2001, Table 1);
4) \textit{NP-MP}<sub>T</sub>, Ng-Perron: 4.030 (1-percent level), 5.480 (5-percent level), and 6.670 (10-percent level) (Ng and Perron, 2001, Table 1).
Table 7: Lumsdaine-Papell Two-Break, Unit-Root Test for House-Price Ratios

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<th>$d_{t-1}$</th>
<th>$DU_{1t}$</th>
<th>$DT_{1t}$</th>
<th>$DU_{2t}$</th>
<th>$DT_{2t}$</th>
<th>$k$</th>
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<td>.0054</td>
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<td>.0001</td>
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</table>

Note: The numbers in parenthesis equal the t-statistics for the estimated coefficients. $TB1$ and $TB2$ equal the break dates, $k$ equals the lag length, the coefficient of $y_{t-1}$ tests for the unit-root, $DU1$ and $DU2$ equal the breaks in the intercept of the trend function, and $DT1$ and $DT2$ equal the breaks in the slope of the trend function. The critical values, from Ben-David, Lumsdaine and Papell (1997, Table 3), equal -7.19 (1-percent level), -6.75(5-percent level), and -6.48 (10-percent level).
Table 8: Lee-Strazicich Minimum LM Two-Break, Unit-Root Test for House-Price Ratios

<table>
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<th>Series</th>
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<th>B_{t1}</th>
<th>D_{t1}</th>
<th>B_{t2}</th>
<th>D_{t2}</th>
<th>k</th>
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Note: The numbers in parenthesis are the $t$-statistics for the estimated coefficients. TB1 and TB2 equal the break dates, $k$ is the lag length, the coefficient of $S_{t-1}$ tests for the unit-root, $B_{t1}$ and $B_{t2}$ equal the breaks in the intercept and $D_{t1}$ and $D_{t2}$ equal the breaks of the slope. Critical values for the coefficients on the dummy variables follow the standard normal distribution. The critical values for the unit-root test, tabulated in Lee and Strazicich (2003, Table 2), depend upon the location of the breaks. For $\lambda_1 = 0.2$ and $\lambda_2 = 0.8$, the critical values equal, respectively, -6.32 (1-percent level), -5.71 (5-percent level), and -5.33 (10-percent level).
Figure 1: Time-Series Plots of S&P Case-Shiller Returns

Boston

Chicago

Denver

Las Vegas

New York

San Diego
Figure 1: Time-Series Plots of S&P Case-Shiller Returns (continued)
Figure 2: Time-Series Plots of S&P Case-Shiller House-Price Differentials
Figure 2: Time-Series Plots of S&P Case-Shiller House-Price Differentials (continued)