University of Connecticut

Department of Economics Working Paper Series

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

Giorgio Canarella
California State University, Los Angeles, and University of Nevada, Las Vegas

Stephen M. Miller
University of Connecticut and University of Nevada, Las Vegas

Stephen K. Pollard
California State University, Los Angeles

Working Paper 2010-04R

February 2010, revised December 2010

341 Mansfield Road, Unit 1063
Storrs, CT 06269–1063
Phone: (860) 486–3022
Fax: (860) 486–4463
http://www.econ.uconn.edu/

Abstract

This paper addresses two issues. First, we employ unit-root tests that allow for two endogenous breaks as suggested by Lumdaine and Papell (1997) and, more recently, Lee and Strazicich (2003) to investigate the integration properties of the returns on the SP/Case-Shiller Home Price Indices. The findings of the tests that assume structural stability provide no evidence against the unit-root hypothesis in all returns series. Conversely, the Lumdaine-Papell and Lee-Strazicich tests indicate that significant structural breaks exist in the US housing market. 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. Second, we apply these tests to analyze what UK researchers call the ”ripple effect” in the British housing markets. Following Meen (1999), we 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. This provides limited evidence that some ripple effects do indeed exists in the US housing market.

Journal of Economic Literature Classification: G10, C30, C50

Keywords: House-price indexes, Time-series properties, ”Ripple” effects

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 characteristics of house price time series.

This paper employs a battery of unit-root tests to analyze two separate, but intertwined, issues of the housing markets. First, this paper considers whether the rate of capital gains on houses exhibit trend reverting or unit-root movement. Meen (1999) and Peterson *et al.* (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 *et al.* (1998), confirm the stationarity characteristic of house-price changes but find that house prices exhibit structural change. Using quarterly data from 1975 to 1996 from the 50 US States, Muñoz (2003) finds unit roots in house-price changes, using the Dickey-Fuller Generalized Least Squares (*DF-GLS*) test (Elliott, *et al.,* 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 capital gains on houses should prove $I(0)$, since the rate of capital gains 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.

Two extensions deserve consideration – nonlinear unit-root tests and linear unit-root tests with structural breaks. Conventional unit root tests, which assume structural stability and linear adjustment, can interpret departures from linearity and structural instabilities as permanent stochastic disturbances. We control for two sources of nonlinearities in the dynamics of house prices when applying unit-root tests. First, nonlinearities can exist in the form of threshold effects, whereby the price dynamics follows a nonstationary process at some threshold, but follows a stationary process outside of the threshold. Second, the series of capital gains probably suffers from structural changes. Bierens (1997) suggests modeling these changes broken time trends with nonlinear trends. Kapetanios *et al.* (2003) propose a nonlinear unit root test, which permits a stable dynamic process with an inherently nonlinear adjustment caused by market frictions and transaction costs, and show that the nonlinear test proves more powerful than the standard unit-root tests. Alternatively, Lumsdaine and Papell (1997) and Lee and Strazicich (2003) propose tests that directly incorporate structural changes. Much research argues that the presence of structural breaks distorts the results of conventional unit-root tests (Perron, 1989, 1997).

Lee *et al.* (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. Consequently, we analyze the time-series characteristics of the rate of capital gains 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 use of tests that allow for the possible presence of structural breaks, possesses at least two advantages. First, it protects against test results that, in the linear framework, are biased towards non-rejection, as suggested by Perron (1989). Second, since this procedure can, unlike the nonlinear tests, identify when structural breaks occur, it can provide valuable information about whether the break associates with a particular government policy, economic crises, war, regime shifts, or other factors.

The tests that assume structural constancy and linear adjustment serve as a comparison for the effect of adding endogenous breaks into the test procedure. Researchers have not applied linear unit-root tests with two structural breaks or nonlinear unit-root tests to US metropolitan house rate of capital gains. Compared with the Lumsdaine-Papell tests, the Lee-Strazicich unit-root tests incorporate the endogenous breaks also 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 Lagrange Multiplier (*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 house-price diffusion effect or "ripple effect" and address the issue of convergence/divergence in US metropolitan housing markets. UK housing experts identify a "ripple effect" of house prices that begins in the Southeast UK and proceeds toward the Northwest. 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 or spatial transmission of shocks in house prices.

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.[1] The ripple effect means that deviations of regional prices from the national price do not contain any long-run trend and, thus, are stationary. The ripple effect hypothesis does not

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[1] 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 predict price changes in other regions using a vector autoregressive (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.

receive too much support in the US economy, although exceptions do exist. For example, most analyses relate to a given geographic housing market, such as a metropolitan area (Tirtiroglu, 1992; 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 (2010a, 2010b) find evidence of house-price linkages between Los Angeles, Las Vegas, and Phoenix and between the eight Southern California metropolitan statistical areas (MSAs).

Several econometric approaches to examine the "ripple effect" exist in the empirical literature. A number of studies investigate the links between regional housing markets using Granger causality (Giussani and Hadjimatheou, 1991; MacDonald and Taylor, 1993; Alexander and Barrow, 1994; Berg, 2002; Peterson *et al*., 2002; Gupta and Miller, 2010a, 2010b), and the Engle-Granger two-step or Johansen cointegration procedures (MacDonald and Taylor, 1993; Alexander and Barrow, 1994; Munro and Tu, 1996; Ashworth and Parker, 1997; Luo, Liu, and Picken, 2007).[2] Other approaches include Kalman filtering (Drake, 1995), cross-correlation matrices (Peterson *et al*., 2002), and unit root methods (Meen, 1999; Cook, 2003, 2005a, 2005b). Still other methods compare the long-run equilibrium relationships between house prices and "fundamentals" (Alexander and Barrow, 1994; Malpezzi, 1999; Case and Shiller, 2003).[3] More

[2] The ripple effect, the interregional or spatial transmission of shocks in house prices, for example, may reflect the arbitrage of construction costs across differing regions. Glaeser and Gyourko (2003) examine evidence on deviations of home prices from that implied by construction costs, finding that in most regions, home prices do not differ much from construction costs. Exceptions do occur. Home prices exceed construction costs largely on the East and West coasts and fall short construction costs in the older central cities of the Northeast and Midwest.

[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 market events. Macroeconomic effects come through several channels. For example, changes in house prices affect aggregate consumption and saving (Case *et al.,* 2005; Benjamin *et al.,* 2004; Campbell and Cocco, 2007; Carroll *et al.,* 2006). Also, house-price adjustments possess implications for risk-sharing and asset pricing (Lustig and van

recently, researchers study the ripple effect using non-parametric methods (Cook and Thomas, 2003), principal component analysis (Holmes and Grimes, 2008), panel unit-root tests (Holmes, 2007), spatial versions of autoregression and Granger-causality models (Kuethe and Pede, 2009), as well as spatial and temporal diffusion models (Holly, Pesaran, and Yamagata, 2010).

Following the analysis in Meen (1999), we cast the issue as a univariate unit-root problem. That is, we consider the time-series characteristics of the ratios of the metropolitan house-price indices to the national house-price index in the US. This approach provides an advantage over the other methods in that it directly models structural breaks in the series. 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 characteristics 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 *et al.*, 1996) and the Kwaitkowski-Phillips-Schmidt-Shin (*KPSS*) stationarity test (Kwiatkowski *et al*. 1992).

The rest of the paper is structured as follows. Section 2 discusses the data and method. Section 3 reports results of linear and nonlinear unit-root tests of house rate of capital gains in 10

Nieuwerburgh, 2005; Piazzesi *et al.,* 2007) as well as distributional effects in heterogeneous-agent economies (Bajari *et al.,* 2005).

US metropolitan areas under alternative assumptions regarding linearity of the model or structural constancy in the deterministic components of the trend. We find that the integration characteristics of house rate of capital gains 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 assumptions of linearity and structural constancy significantly affect the time-series characteristics 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

This section considers the data and method of analysis. We briefly describe seven unit-root tests used in the analysis of the "ripple effect" and the dynamics of the home price indices. The first five include linear and nonlinear tests that assume structural stability in the time-series pattern of the data. The last two, instead, test the unit-root hypothesis under the assumption of two structural breaks.

2.1 Data

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* Composite10 index: Boston, Chicago, Denver, Las Vegas, Los Angeles, Miami, New York, San Diego, San Francisco, and Washington, DC. The sample period of each series equals monthly data from January 1987 through April 2009, 268 observations.

House-price indices possess well-known issues surrounding their validity or appropriateness, reflecting mainly the non-fungible nature of housing. The S&P/Case-Shiller *HPI* data possess several advantages over the Federal Housing Finance Agency (FHFA) (formerly Office of Federal Housing Enterprise Oversight) house-price indices, ordinarily used in the literature (Deng and Quigley, 2008; Himmelberg *et al.*, 2005, among others). These two indices measure house prices quite differently. For instance, the S&P/Case-Shiller house price index includes foreclosed houses, while the FHFA indices do not. Consequently, the S&P/Case-Shiller house price index shows a larger decline in national and metropolitan house prices than the FHFA indices. Both the FHFA and S&P/Case-Shiller *HPI* use the weighted repeated-sales methodology.[4] The FHFA indices, however, exhibit more limitations than the S&P/Case-Shiller indices. First, the FHFA indices (at the MSA level) appear quarterly, while the S&P/Case-Shiller indices appear monthly. Monthly data provide a better opportunity to model the house-price and the rate of capital gains on the house in a shorter time interval. Second, the S&P/Case-Shiller indices only include actual house transactions and do not include, like the FHFA indices, refinance appraisals, which produce "appraisal smoothing bias" for house rate of capital gains measurement (Geltner, 1989; Edelstein and Quan, 2006). Third, the FHFA indices only incorporate Fannie Mae and Freddie Mac conforming mortgages, which concentrate at the lower end of prices in the housing markets. Finally, the Chicago Mercantile Exchange (CME) uses the S&P/Case-Shiller indices for housing futures and options. These derivatives enable investors to take positions on the movement of the Composite10 index and any of the indices that compose it.

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[4] Case and Shiller (1989) extend this method, originally developed by Bailey, Muth, and Nourse (1963). In order to compare "apples to apples," the method only uses homes that sell at least twice. Two adjacent sales then define a linear change in the value of the home over the time period between the sales dates. While this method improves on the FHFA house price indices, it assumes that the characteristics of the property do not change between observations. Moreover, the requirement to include only repeat sales excludes much information. In a recent paper, Dorsey, Hu, Mayer, and Wang (2010) compare the repeat-sales method to a hedonic method of creating indices for San Diego and Los Angeles. The data requirements of the hedonic method currently make it impossible to apply for the metropolitan areas that we consider in this paper. They conclude "Some findings lend support to those of the S&P/Case-Shiller™ (sic) repeat sales index. … Other findings, however, indicate important differences…" (p. 92). The hedonic method possesses its own issues. Zietz, Zietz and Sirmans (2008), for example, show using quantile regression that individual home buyers place different value on some home characteristics, depending on the price of the house. Other characteristics do not exhibit differential effects.

The CME housing futures contracts trade on the CME Globex electronic trading platform, and the options on futures trade on the trading floor in an open outcry style. Although trading volumes for the CME housing futures and options remain relatively thin, the analysis of the S&P/Case-Shiller *HPI* also provides practical implications for the homebuilding industry (Jud and Winkler, 2008).[5]

Figure 1 exhibits the time-series plots of the rate of capital gains on the house indices, Δy_t, defined as follows:

$$\Delta y_t = y_t - y_{t-1}, \quad (1)$$

where y_t refers to the natural logarithm of the house-price index at time *t*. Upon visual inspection, all 11 series of rate of capital gains, including the rate of capital gains on the Composite10 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 rate of capital gains 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

[5] The value of the futures contracts are set at 250 times the level of the S&P/Case-Shiller® indices. Thus, if the level of the Composite10 index, for example, is 250, the value of the associated futures contract is $62,500 (250 x 250). At maturity, the contract's value is 250 multiplied by the average value of the index over the 3-month period ending two calendar months prior to the contract month.

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, 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. As shown in Table 2, the significant Ljung-Box (Ljung and Box, 1978) statistics for the rate of capital gains $Q(6)$ and $Q(12)$ indicate serial correlation of those rate of capital gains. Similarly, the significant Ljung-Box statistics for the squared rate of capital gains $Q^2(6)$ and $Q^2(12)$ also provides evidence of strong second-moment dependencies.

2.2 The Unit-Root Model

The long-standing debate on housing market efficiency (Case and Shiller, 1989) connects intimately to the question of unit roots in the house-price data. Assuming that y_t follows an autoregressive process with two structural breaks, we can write:

$$y_t = \alpha + \beta t + \theta DU_{1t} + \gamma DT_{1t} + \omega DU_{2t} + \psi DT_{2t} + \rho y_{t-1} + \varepsilon_t \qquad (2)$$

where the variable t is a time trend, and ε_t is an error term. DU_{1t} and DU_{2t} are indicator variables for the breaks in the intercept, occurring at times TB_1 and TB_2, respectively, while DT_{1t}

and DT_{2t} are indicator variables for the breaks in the time trend occurring at times TB_1 and TB_2, respectively. TB_1 and TB_2 denote the dates of the two structural breaks. The values of the coefficients α, β, and ρ determine the basic character of the time series.The parameter α represents "drift" (i.e., a fixed movement in each time period), while the parameter β represents the effect of a linear time trend. The most important parameter for determining the character of the series, however, is ρ. Subtracting y_{t-1} from both sides of equation (2) and rearranging the model generates the following:

$$\Delta y_t = \alpha + \beta t + \theta DU_{1t} + \gamma DT_{1t} + \omega DU_{2t} + \psi DT_{2t} + (\rho - 1) y_{t-1} + \varepsilon_t , \qquad (3)$$

where Δ is the difference operator. If $\rho < 1$, then $(\rho - 1) < 0$, and the house-price change Δy_t depends on the price at t-1. This denotes a lack of efficiency. Such a series is called mean- or trend-reverting ($\beta = 0$, or $\beta \neq 0$, 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 ε_t. Thus, researchers cannot forecast future prices from past prices and the market is (weak-form) efficient. 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 nonstationarity (if $\rho = 1$). We can test for (weak-form) market efficiency by testing for the value of ρ, that is, by testing whether the series possesses a unit root.

If the house-price time series is nonstationary, then the issue emerges as to the time-series characteristics of the rate of capital gain on owning a house. That is, Δy_t approximates the rate of capital gain, excluding the implicit consumption benefits from living in the house. If y_t is $I(1)$, then Δy_t is $I(0)$, in theory. If Δy_t is $I(1)$ or nonstationary, then y_t is $I(2)$, in theory. Researchers, therefore, need to assess the empirical reliability of the unit-root hypothesis.

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 rate of capital gains 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 (i.e, more likely rejects the unit-root hypothesis against the stationary alternative hypothesis when the alternative is true). Second, the point-optimal, unit-root test developed by Elliott *et al.* (1996) ($ERS\text{-}P_T$). Finally, Ng and Perron (2001) developed modified versions of the *PP* test ($NP\text{-}MZ_t$) and of the *ERS* point optimal test of Elliott, *et al.* (1996), ($NP\text{-}MP_T$), both of which exhibit excellent size and power characteristics.

The *DF-GLS* of Elliott *et al.* (1996) is essentially an *ADF* test, except that they transform the data via a Generalized Least Squares (*GLS*) regression prior to performing the test. They perform the test in two steps. First, they detrend (demean) the data using the *GLS* approach. Second, they use an *ADF* test to test for a unit root. For a detailed discussion of the *DF-GLS* test, see Stock and Watson (2003).

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

$$\Delta y_t^d = \alpha y_{t-1}^d + \sum_{j=1}^{p} \beta_j \Delta y_{t-j}^d + \nu_t, \qquad (4)$$

where y_t^d equals the detrended (demeaned) series and ν_t equals an error term. The *DF-GLS* statistic equals the *t*-ratio testing H_0: $\alpha = 0$ against H_1: $\alpha < 0$. In addition to the *DF-GLS* test, Elliott *et al.* (1996) compute a second unit-root test, the so-called point-optimal test. They derive the power envelope and maximize the power for a given alternative hypothesis (point optimal test) against the background that no uniformly most powerful unit-root test exists. The test statistic that consistently asymptotically satisfies this condition is:

$$P_T = \left[SSR(\overline{a}) - SSR(1)\right] / f_0, \qquad (5)$$

The point-optimal test involves the computation of the sum of squared residuals $SSR(\overline{a}) = \sum_{i=1}^{t} \hat{\eta}_t^2(\overline{a})$. The null hypothesis for the point optimal test is $\alpha = 1$ and the alternative hypothesis is $\alpha = \overline{a}$. The test statistic equals

$$P_T = \left[SSR(\overline{a}) - SSR(1)\right] / f_0, \qquad (6)$$

where f_0 estimates the residual spectrum at frequency zero. *SSR*(*a*) equals the sum of the squared residuals of a quasi-differenced OLS-regression, given the alternative hypothesis $\overline{a}$. The Akaike information criterion (*AIC*) determines the lag length in f_0.

Ng and Perron (2001) construct four test statistics that use the *GLS* detrended data y_t^d. Two of these statistics modify the Z_t statistic of Phillips and Perron (1988) and point-optimal statistics of Elliott, *et al.* (1996). Letting $\kappa = \sum_{t=2}^{T} (y_{t-1}^d)^2 / T^2$, we can write the GLS detrended modified statistics as follows:

$$NP-MZ_t = (\kappa / f_0)^{1/2}(T^{-1}(y_T^d)^2 - f_0)/2\kappa \text{, and} \tag{7}$$

$$NP-MP_T = (\bar{a}^2\kappa - \bar{a}T^{-1}(y_T^d)^2)/f_0 \qquad \text{if } x_t = \{1\} \text{ where } \bar{a} = \text{-7, or} \tag{8}$$

$$NP-MP_T = (\bar{a}^2\kappa + (1-\bar{a})T^{-1}(y_T^d)^2)/f_0 \qquad \text{if } x_t = \{1, t\} \text{ where } \bar{a} = \text{-13.5.} \tag{9}$$

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 *AIC* procedure assuming the maximum lag $k = 12$.

2.3 Nonlinear Unit-Root Tests

Linear unit-root tests assume that a symmetric adjustment process exists. A number of studies provide empirical evidence for nonlinear dynamics for unit-root testing procedures (Caner and Hansen, 2001; Shin and Lee, 2001; Kapetanios, *et al.*, 2003). Taylor (2001) indicates that the power of linear unit-root tests is poor, if the series follows a nonlinear threshold process. To accommodate the possibility of a nonlinear dynamics of house prices, we employ the nonlinear test of Kapetanios *et al*. (2003), which tests for a unit root against a nonlinear stationary process based on an exponential smooth transition autoregressive (*ESTAR*) process. The use of this test can clearly and directly advance the discussion of whether house prices follow a stable dynamic process with an inherently nonlinear adjustment caused by market frictions and transaction costs.

Kapetanios *et al.* (2003) extend the standard *ADF* test and introduce a new unit-root test to test for a linear unit root against an alternative of nonlinear stationary exponential smooth transition autoregressive process. Kapetanios *et al.* (2003) propose the following univariate STAR model:

$$\Delta y_t = \gamma y_{t-1} + \left[1 - \exp(-\theta y_{t-1}^2)\right] + \varepsilon_t, \tag{10}$$

where $\left[1-\exp(-\theta y_{t-1}^2)\right]$ is the exponential transition function and $\theta \geq 0$. The test focuses on the parameter θ, which equals zero under the null and is positive under the alternative. Since γ is not identified under the joint null hypothesis of linearity and a unit root, testing the null hypothesis of $H_0 : \theta = 0$ against the alternative hypothesis of $H_1 : \theta > 0$ is not feasible. Thus, Kapetanios *et al.* (2003) reparameterize equation (11) using a Taylor series approximation to obtain:

$$\Delta y_t^d = \delta\left(y_{t-1}^d\right)^3 + e_t \text{, or} \tag{11}$$

$$\Delta y_t^d = \delta\left(y_{t-1}^d\right)^3 + \sum_{j=1}^{p} \rho_j \Delta y_{t-j}^d + e_t \, , \tag{12}$$

where y_t^d equals the detrended (demeaned) series and p equals the maximum autoregressive lag order to eliminate serially correlated errors. Equations (11) and (12) correspond to the Dickey Fuller and the Augmented Dickey Fuller regressions, respectively, differing only in that the lagged level of y_t^d is raised to the power of 3 rather than the power of 1. In both equations (11) and (12), we test the null hypothesis of $H_0 : \delta = 0$ against the alternative of $H_0 : \delta > 0$ by using familiar t ratio obtained for δ. Since the asymptotic distribution of t is not standard normal, asymptotic critical values of the test statistic are tabulated by Kapetanios *et al.* (2003). We determine the lag length for the test regressions by the *AIC* procedure assuming the maximum lag $k = 12$.

2.4 Unit-Root Tests with Two Structural Breaks

One major drawback of linear unit-root tests exists. In all such tests, we implicitly assume that we correctly specify the deterministic trend. The nonlinear unit-root test allows for structural change in a smooth process. But, a superficial visual inspection of the house rate of capital gains series suggests the presence of potential structural breaks, which reflect shocks rather than smooth change. 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:

$$\boldsymbol{\Delta} y_t = \mu + \beta t + \theta DU_{1t} + \gamma DT_{1t} + \omega DU_{2t} + \psi DT_{2t} + \alpha y_{t-1} + \sum_{i=1}^{k} c_i \boldsymbol{\Delta} y_{t-i} + \varepsilon_t \, . \qquad (13)$$

We include the lagged terms Δy_{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.

Lumsdaine and Papell (1997) describe the estimation procedure in more detail. We reject the null hypothesis of a unit root in favor of broken trend-stationarity, if α significantly differs from zero. Since the asymptotic distribution of *t* is not standard normal, Lumsdaine and Papell (1997) provide asymptotic critical values of the test statistics. We determine the lag length for the test regressions by the *AIC* procedure, assuming the maximum lag *k* = 12.

The minimum *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. According to the minimum LM principle, a unit-root test statistic comes from the following regression:

$$\Delta y_t = \delta' \Delta Z_t + \phi y_{t-1}^d + \sum_{i=1}^{k} \gamma_i \Delta y_{t-i}^d + \mu_t \quad , \tag{14}$$

where the detrended series y_t^d is defined as follows: $y_t^d = y_t - \tilde{\psi}_x - Z_t \tilde{\delta}$, $t = 2,...,T$; $\tilde{\delta}$ equal the coefficients in the regression of Δy_t onto ΔZ_t; $\tilde{\psi}_x$ equals $y_1 - Z_1 \tilde{\delta}$, where y_1 and Z_1 correspond to the first observations of y_t and Z_t, respectively. The lagged terms $\Delta \tilde{S}_{t-i}$ are included to correct for serial correlation. Considering structural breaks in both the intercept and the slope of the trend function (model C), $\Delta Z_t = [1, t, DU_{1t}, DU_{2t}, DT_{1t}, DT_{2t}]$ where, as in Lumsdaine and Papell (1997), DU_{1t} and DU_{2t} are indicator variables for the intercept changes in the trend function occurring at times TB_1 and TB_2, respectively, and DT_{1t} and DT_{2t} are indicator variables for the slope changes in the trend function occurring at times TB_1 and TB_2, respectively. We test the null hypothesis of a unit root in equation (14) that $\phi = 0$ with a *t*-ratio. Lee and Strazicich (2003) provide the critical values, which depend on the location of the breaks.

3. Empirical Results

Table 3 reports the results of linear and nonlinear unit-root tests with a constant and trend without structural breaks. This table presents overwhelming evidence in favor of a unit root in all series for the linear tests, including the Composite10 index, as each test reaches the same conclusion regarding each time series. The nonlinear test, however, does reject the null hypothesis of a unit root at the 5-percent level for Los Angeles and San Francisco.[6] This suggests

[6] The inclusion of a trend in the unit-root test equation, when the trend is, in fact, unnecessary, reduces the power of the test. Consequently, we repeat the tests with only the constant in the specification, but the findings prove identical in every respect. Results are available from the authors.

that for Los Angeles and San Francisco, the trend-reverting characteristics of the rate of capital gains could follow a nonlinear path.[7]

Table 4 reports the empirical results of the Lumsdaine-Papell test using model *CC*, which allows for two breaks in the constant and the trend. 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 *et al.* (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 Composite10 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 Composite10 indices, the changes in the intercept and the slope of the trend function prove

[7] A referee asks whether the findings of nonstationarity only reflect important changes in market conditions following the dramatic decline in housing prices at the end of our sample. We address this question by applying the linear and nonlinear unit-root tests to a reduced sample of observations that eliminates the last 20 observations of the original sample (i.e., we eliminate the period starting in September 2007, which coincides with the beginning of the financial crisis and the economic recession). We do not find significant differences in our results. The linear tests of Elliott, Rothenberg, and Stock (1996) and Ng and Perron (2001) uniformly and consistently fail again to reject the unit-root null. The nonlinear test of Kapetanios et al. (2003), on the other hand, rejects the unit-root hypothesis for Los Angeles and San Francisco, as in the original sample. In addition, this test also rejects the unit-root hypothesis for Chicago. Thus, except for Chicago, it does not appear that the housing price collapse explains our overall results. These findings are available from the authors.

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 minimum *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).

Table 5 reports the results of the Lee-Strazicich unit-root test based on model *C*, which allows for two breaks in the constant and the trend. The findings overturn most of the previously presented results suggesting that house rate of capital gains are nonstationary and provide significant evidence in favor of segmented trend stationarity for the majority of the rate of capital gains series. We can reject the unit-root hypothesis at the 10-percent level for Boston, Denver, Los Angeles, New York, Washington DC, and the Composite10 indices; 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.[8] The Kapetanios-Shin-Snell (*KSS*) tests reported in Table 3 reject the unit-root hypothesis at the 5-percent level for Los Angeles and

[8] We repeat the tests assuming that the breaks only occur in the constant. That is, we estimate model *AA* (Lumsdaine and Papell, 1997) and model *A* (Lee and Strazicich, 2003). In both cases, however, we find significant evidence of unit root in all series. The findings are available from the authors.

San Francisco. Thus, combining the findings of the nonlinear *KSS* unit-root tests with the results of the Lee-Strazicich tests with two structural breaks leads to the rejection of the unit-root null hypothesis for every city, except Chicago, and the Composite10 index.

The two date breaks that minimize the *LM* statistics provide suggestive information. 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, which corresponds to the dramatic rise in house prices nationally.

4. The "Ripple Effect"

The "ripple effect" or interregional transmission of house-price shocks 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 (2010a, 2010b) 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.

This section concerns the time-series characteristics of the ratios of the metropolitan house-price indices to the national house-price index in the US.[9] Define the metropolitan house-price ratio d_t as follows:

$$d_t = y_t - m_t, \tag{21}$$

where m_t refers to the natural logarithm of the Composite10 index, t = 1,2,…T . Under the assumption that d_t comes from a first-order autoregressive with two structural breaks process as follows:

$$d_t = \varsigma + \xi t + \theta DU_{1t} + \gamma DT_{1t} + \omega DU_{2t} + \psi DT_{2t} + \rho d_{t-1} + \varepsilon_t. \tag{22}$$

Subtracting d_{t-1} from both sides of equation (22) and rearranging the model generates the familiar ADF regression:

$$\Delta d_t = \varsigma + \xi t + \theta DU_{1t} + \gamma DT_{1t} + \omega DU_{2t} + \psi DT_{2t} + \tau d_{t-1} + \varepsilon_t, \tag{23}$$

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

Figure 2 exhibits the time-series plots of the house-price ratios. Casual observation indicates that only limited commonality exists in the ten graphs. All ten series of house-price ratios probably are nonstationary and experience at least two structural breaks. A pattern of peaks and troughs appear in a common pattern for two groups of house price ratios. For example, the price ratios for Los Angeles, Miami, San Diego, and, to a lesser extent, Las Vegas and Washington show a peak at the time of the sub-prime financial crisis, while the price ratios for

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[9] According to Meen (1999), the ripple effect implies stationarity of a region's house-price index to the national house-price index.

Boston, Chicago, Denver and New York show a trough. The price ratios for Los Angeles and San Diego also show a peak, albeit lower, at the time of the recession of 1990-1991. Conversely, the price ratios for Boston, Chicago, Denver, and New York show a trough at the time of the recession of 1990-91. Only the price ratios for Miami and Las Vegas show opposite patterns in 1990-1991 and 2006.

Table 6 reports the results of applying the conventional linear unit-root tests as well as the nonlinear unit-root test previously used in the paper, which do not allow for structural breaks, but allow for a constant and a trend. The findings sometimes prove inconsistent. For example, the *ERS* test, as well as the two Ng-Perron tests, provide evidence of stationarity for the Chicago price ratio. The *DF-GLS* test, however, fails to reject the unit root. Conversely, the *DF-GLS* test finds stationarity for the Denver and Miami price ratios, but the remaining three linear tests do not. For all remaining price ratio series, each of the four linear test statistics consistently rejects the hypothesis of linear stationarity. The nonlinear unit-root test, however, rejects the unit-root hypothesis at the 5-percent level or better in five cases – Boston, Denver, Miami, New York, and San Diego.[10]

Table 7 reports the results of applying the Lumsdaine-Papell two-break, unit-root test for the house-price ratios based on model *CC*, which assumes a constant and a trend. The results of the Lumsdaine-Papell test consistently fail to reject the null of nonstationarity of the price ratios for all metropolitan areas. Consequently, these empirical results fail to support the ripple effect

[10] We repeat the tests with only the constant in the specification, but the findings prove identical in every respect save one. Now, the nonlinear test rejects the null for San Francisco as well. We also repeat the linear and nonlinear unit-root tests for the reduced sample that ends in August 2007. We do not find substantial differences in the results for the linear tests. We fail to reject the unit-root null in all cases except Chicago (based on the $ERS\text{-}P_T$, $NP\text{-}MZ_t$, and $NP\text{-}MP_T$ tests) and Denver (based on the *DF-GLS* test), which matches our findings for the original sample. We do find one difference, however, using the nonlinear test. As in the original sample, the test rejects the unit-root null for Boston, Denver, Miami, New York, and San Diego. In addition, using the reduced sample, the test also rejects the unit-root null for San Francisco. Results are available from the authors.

for each metropolitan area. In other words, the housing markets are segmented, and 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 based on model *C*, which assumes a constant and a trend. In contrast to the Lumsdaine-Papell tests, the Lee-Strazicich tests reject the null hypothesis of a unit root with two structural breaks at the 5-percent level for Boston, Miami, and New York. In turn, the nonlinear *KSS* tests reject the null hypothesis of a unit root for Denver, San Diego, and San Francisco (in the constant only specification), in addition to Boston , Miami, and New York. These findings reject the notion of segmentation of the US housing market and suggest that convergence and the ripple effect are not UK-specific phenomena. The findings provide new insight about the dynamics of the US housing market. The house-price shocks stemming from Boston, Denver, Miami, New York, San Diego, and San Francisco "ripple out" and significantly influence house-price changes in the US. The dynamics of the ripple effect also provides important consequences for the US economy. The findings imply a significant wealth distribution, given that housing comprises a large share of assets for many households (Alexander and Barrow, 1994; Holmes and Grimes, 2008). Furthermore, the analysis affects labor mobility as well as migration, although it is weak because most households move from one region to another not only for house-price differences but also for other factors (job opportunities, etc). Finally, the ability to predict house prices correctly in one region of the US may improve, if we consider the significant effect of other regional house prices.

5. Conclusions

This paper contributes to the literature on the long-run behavior of the house prices and the "ripple effect" in the US by addressing the issue of nonstationarity using an empirical approach not previously considered in the literature. US house prices provide an interesting demonstration of nonlinearities. We address this issue by applying Lumsdaine-Papell and Lee-Strazicich two-break unit-root tests, and the *KSS* nonlinear unit-root test. The two structural-break 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 rejects the null of a unit root only for one of the eleven series (Las Vegas). The Lee-Strazicich test finds broken-trend stationarity for three of eleven series (Las Vegas, Miami, San Diego). The *KSS* test finds nonlinear stationarity for two of the eleven series (Los Angeles and San Francisco). This contrasts with the results of the standard linear tests that reject stationarity in all eleven series.

Although the two structural-break tests provide contradictory findings, both tests indicate that structural breaks exist in the rate of capital gains to houses. No common significant structural breaks exist that characterize all rate of capital gains 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.

The tests used offer further insights about the "ripple effect." Following Meen (1999) and Cook (2003, 2005a, 2005b), we examine the ratio of the S&P/Case-Shiller 10 metropolitan price indices to a national house price index (Composite 10). The Lumsdaine-Papell test fails to reject the null of a unit root in for all ten series of price ratios. Conversely, the Lee-Strazicich test finds broken-trend stationarity for three of the ten series (Boston, Miami, and New York), while the *KSS* tests finds nonlinear stationarity for six of the ten series (Boston, Denver, Miami, New

York, San Diego, and San Francisco.) These findings provide partial evidence that rejects the notion of segmentation of the US housing market, and confirms the findings of previous research (e.g., MacDonald and Taylor, 1993), which indicate that house-price changes in the East and West Coast metropolitan areas exert a significant influence on house price changes in the rest of the US.

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Table 1: Summary Statistics

Series	*Mean*	*Max*	*Min*	*Sd*	*Sk*	*Ku*	*JB*
Boston	0.003	0.019	-0.022	0.007	-0.419	3.262	8.566
Chicago	0.003	0.024	-0.044	0.008	-2.024	11.998	1083.080
Denver	0.003	0.017	-0.02	0.005	-0.621	4.434	40.058
Las Vegas	0.002	0.053	-0.046	0.014	-0.471	7.191	205.271
Los Angeles	0.004	0.033	-0.039	0.012	-0.571	3.757	20.900
Miami	0.003	0.023	-0.043	0.012	-1.314	6.032	179.142
New York	0.003	0.018	-0.025	0.007	-0.443	3.395	10.477
San Diego	0.004	0.05	-0.037	0.012	-0.369	4.541	32.466
San Francisco	0.003	0.031	-0.048	0.013	-1.042	5.439	114.526
Washington, DC	0.004	0.026	-0.023	0.009	-0.507	3.573	15.124
Composite 10	0.003	0.018	-0.026	0.008	-0.998	4.212	60.703

Note: *Mean*, *Max*, *Min*, and *Sd* are the sample mean, maximum, minimum and standard deviation of the rate of capital gains 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 rates of capital gains series as natural logarithmic differences.

Table 2: Ljung- Box Statistics

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

Note: $Q(k)$ and $Q^2(k)$ equal Ljung-Box Q-statistics distributed asymptotically as χ^2 with k degrees of freedom, testing for rate of capital gains and squared rate of capital gains for autocorrelations up to k lags.

Table 3: Unit-Root Tests without Structural Breaks for Rate of Capital Gains on S&P/Case-Shiller *HPI*.

Series	***DF-GLS***	***ERS-P_T***	***NP-MZ_t***	***NP-MP_T***	***KSS***
Boston	-1.121	33.823	-1.337	23.572	-2.791
Chicago	-0.861	144.588	-1.747	14.612	0.686
Denver	-0.546	37.795	-1.153	33.943	-2.072
Las Vegas	-1.682	62.126	-1.137	22.079	-0.308
Los Angeles	-1.981	34.984	-1.209	26.913	-3.525*
Miami	-1.492	90.103	-0.651	45.888	-1.597
New York	-1.106	85.789	-0.456	81.262	-2.003
San Diego	-2.092	34.659	-1.231	28.207	-2.502
San Francisco	-1.847	44.349	-1.085	38.167	-3.773*
Washington, DC	-2.335	46.825	-1.166	33.241	-2.481
Composite 10	-1.334	68.348	-1.069	32.464	-2.889

Note: The test critical values with constant and trend 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, *et al.*, 1996, Table 1);
2) *ERS-P_T* Elliott-Rothenberg-Stock: 4.019 (1-percent level), 5.646 (5-percent level), and 6.870 (10-percent level) (Elliott, *et al.*, 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).
5) *KSS,* Kapetanios-Shin-Snell: -3.93 (1-percnt level); -3.40 (5-percent level); and -3.13 (10-percent level) (Kapetanios, *et al.*, 2003, Table 1).

* denotes rejection of the null hypothesis at the 5-percent significant level.

Table 4: Lumsdaine-Papell Two-Break, Unit-Root Test for Rate of Capital Gains on S&P/Case-Shiller *HPI*

Series	***TB1*** ***TB2***	y_{t-1}	DU_{1t}	DT_{1t}	DU_{2t}	DT_{2t}	***k***
Boston	Apr. 1991	-0.598	0.548	0.333	0.026	-0.019	6
	Mar. 2000	(-6.06)	(4.24)	(3.30)	(4.24)	(-5.53)	
Chicago	Mar. 1999	-0.511	0.243	0.249	-0.001	-0.039	12
	Aug. 2005	(-4.58)	(2.02)	(1.57)	(-0.58)	(-4.70)	
Denver	June 1994	-0.497	-0.450	-0.392	-0.003	-0.009	12
	May 2001	(-4.81)	(-4.14)	(-4.09)	(-1.78)	(-3.97)	
Las Vegas	Sept. 1991	-0.703*	-0.635	2.087	-0.001	-0.088	8
	Nov. 2003	(-7.14)	(-3.15)	(5.89)	(-0.29)	(-7.30)	
Los Angeles	Aug. 1993	-0.207	0.275	0.325	0.012	-0.019	2
	June 2003	(-5.34)	(2.67)	(2.67)	(4.04)	(-4.52)	
Miami	July 1996	-0.054	-0.111	0.714	0.010	-0.080	10
	Jan. 2005	(-5.83)	(-1.06)	(3.28)	(4.25)	(5.60)	
New York	Apr. 1991	-0.477	0.4157	-0.453	0.019	-0.023	7
	Dec. 2005	(-6.03)	(4.39)	(-4.79)	(3.98)	(-4.30)	
San Diego	July 1991	-0.278	-0.099	0.238	0.015	-0.025	3
	June 2003	(-4.46)	(-0.61)	(1.46)	(2.64)	(3.89)	
San Francisco	Apr. 1996	-0.209	0.395	0.417	0.001	-0.015	3
	June 2003	(-4.77)	(2.49)	(2.33)	(0.58)	(-3.01)	
Washington, DC	Apr. 1991	-0.308	0.120	0.414	0.021	-0.021	11
	July 2003	(-5.16)	(1.03)	(3.28)	(3.56)	(-4.59)	
Composite 10	Mar. 1991	-0.208	0.121	0.237	0.011	-0.014	4
	June 2003	(-5.48)	(2.01)	(3.55)	(4.14)	(-5.27)	

Notes: The numbers in parenthesis equal the *t*-statistics for the estimated coefficients. TB_1 and TB_2 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 DT_{1t} and DT_{2t} equal the breaks in the slope of the trend function. Critical values for the coefficients on the dummy variables follow the standard normal distribution. The critical values, from Ben-David, *et al.* (1997, Table 3), equal -7.19 (1-percent level), -6.75(5-percent level), and -6.48 (10-percent level).

* denotes rejection of the null hypothesis at the 5-percent significant level.

Table 5: Lee-Strazicich Minimum LM Two-Break Unit-Root Test for Rate of Capital Gains on S&P/Case-Shiller *HPI*

Series	***TB₁*** ***TB₂***	y_{t-1}^{d}	DU_{1t}	DT_{1t}	DU_{2t}	DT_{2t}	***k***
Boston	Mar. 1991	-0.521	-0.517	0.360	0.253	-0.415	11
	Oct. 2002	(-5.39)	(-1.49)	(4.41)	(0.75)	(-5.25)	
Chicago	Jan. 1994	-0.298	-1.501	0.566	0.596	-0.698	12
	Aug. 2006	(-4.26)	(-3.62)	(4.34)	(1.44)	(-5.66)	
Denver	Jan. 1991	-0.348	-0.451	0.230	1.023	-0.508	6
	Mar. 2001	(-5.60)	(-1.59)	(-3.41)	(3.44)	(-5.54)	
Las Vegas	Aug. 2003	-0.678*	-0.677	1.396	0.431	-0.830	11
	Oct. 2005	(-6.57)	(-1.11)	(5.60)	(0.74)	(-4.54)	
Los Angeles	June 1990	-0.287	-0.227	-0.315	0.274	-0.434	11
	Sept. 2005	(-5.33)	(-0.66)	(-3.12)	(0.78)	(-4.98)	
Miami	June 1992	-0.374*	-2.833	0.788	0.954	-1.304	10
	Jan. 2007	(-6.66)	(-7.08)	(6.02)	(2.38)	(-6.63)	
New York	Dec. 1990	-0.337	-1.058	0.671	0.099	-0.453	12
	Mar. 2006	(-5.53)	(-4.14)	(5.41)	(0.40)	(-5.76)	
San Diego	Mar. 1990	-0.447*	0.545	-0.808	0.576	-0.303	11
	Apr. 2004	(-5.78)	(1.07)	(-4.47)	(1.12)	(-3.64)	
San Francisco	Mar. 1995	-0.268	0.126	0.224	0.790	-0.812	11
	Feb. 2007	(-5.15)	(0.25)	(2.80)	(1.50)	(-4.47)	
Washington, DC	Dec. 1990	-0.283	-1.347	0.215	0.277	-0.624	11
	Nov. 2005	(-5.41)	(-4.29)	(3.37)	(0.84)	(-5.07)	
Composite 10	Dec. 1990	-0.271	-0.435	0.094	0.183	-0.400	10
	Nov. 2005	(-5.41)	(-0.99)	(2.72)	(0.96)	(-5.84)	

Notes: See Table 4. The coefficient on y_{t-1}^{d} tests for the unit-root. 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).

* denotes rejection of the null hypothesis at the 5-percent significant level.

Table 6: Unit-Root Tests for House-Price Ratios without Structural Breaks

Series	*DF-GLS*	*ERS-P_T*	*NP-MZ_t*	*NP-MP_T*	*KSS*
Boston	-2.381	155.422	-0.264	115.352	-4.939*
Chicago	-0.173	0.980*	-8.158*	0.702*	-1.505
Denver	-3.816*	328.374	-0.377	302.091	-4.201*
Las Vegas	-1.820	62.973	-0.213	48.792	-0.465
Los Angeles	-1.932	60.903	-0.811	60.101	-2.334
Miami	-2.976	81.878	-0.551	66.347	-3.617*
New York	-1.631	250.408	0.771	125.258	-4.487*
San Diego	-2.073	109.664	-0.007	76.051	-5.440*
San Francisco	-0.911	170.831	0.868	81.349	-2.919
Washington, DC	-1.351	27.606	-1.214	30.687	-2.105

Note: See Table 3.
* denotes rejection of the null hypothesis at the 5-percent significant level.

Table 7: Lumsdaine-Papell Two-Break, Unit-Root Test for House-Price Ratios

Series	***TB1*** / ***TB2***	d_{t-1}	DU_{1t}	DT_{1t}	DU_{2t}	DT_{2t}	***k***
Boston	Mar. 2003	-.0173	.0026	-.0043	-.0001	-.0003	7
	Feb. 2005	(-5.68)	(2.60)	(-3.06)	(4.17)	(4.77)	
Chicago	Feb. 1996	-.0357	.0007	-.0054	-.0002	-.0002	4
	Dec. 2003	(-4.38)	(0.56)	(-3.15)	(-4.43)	(4.67)	
Denver	Sep. 1998	-.0166	.0015	-.0025	-.0002	-.0002	9
	Dec 2004	(-5.55)	(1.69)	(-1.89)	(-4.96)	(-4.45)	
Las Vegas	Feb. 1994	-.0283	.0018	.0137	-.0002	-.0002	9
	Feb. 2006	(-3.96)	(0.99)	(4.81)	(-3.46)	(-3.76)	
Los Angeles	Mar. 1998	-.0124	-.0005	.0019	.0000	-.0001	4
	Oct. 2004	(-4.86)	(-0.65)	(1.95)	(2.68)	(-2.38)	
Miami	July 1992	-.0230	.0037	.0079	.0000	-.0001	7
	July 2004	(-4.96)	(3.15)	(5.01)	(0.35)	(-3.39)	
New York	Jan. 2000	-.0182	-.0007	-.0022	.0000	.0000	9
	May 2003	(-5.39)	(-0.88)	(-2.49)	(0.97)	(-0.58)	
San Diego	July 1994	-.0327	-.0042	.0036	.0000	-.0002	5
	May 2003	(-5.10)	(-2.73)	(2.35)	(1.03)	(3.83)	
San Francisco	Apr. 1999	-.0272	.0044	.0028	-.0001	-.0001	4
	Jan. 2006	(-4.71)	(3.30)	(1.64)	(-3.16)	(-2.21)	
Washington, DC	Feb. 1994	-.0489	.0010	-.0030	-.0002	.0002	7
	Jan. 1999	(-5.08)	(1.07)	(-2.61)	(-4.01)	(4.59)	

Note: See Table 4. The critical values, from Ben-David, *et al.* (1997, Table 3), equal -7.19 (1-percent level), -6.75(5-percent level), and -6.48 (10-percent level).

* denotes rejection of the null hypothesis at the 5-percent significant level.

Table 8: Lee-Strazicich Minimum LM Two-Break, Unit-Root Test for House-Price Ratios

Series	TB_1 / TB_2	d_{t-1}^{d}	DU_{1t}	DT_{1t}	DU_{2t}	DT_{2t}	*k*
Boston	Dec. 1994	-.0244*	-.0054	.0066	-.0044	-.0034	9
	Apr. 2004	(-5.81)	(-8.44)	(7.99)	(1.40)	(-3.91)	
Chicago	Jun. 1994	-.0299	.002	-.0018	.0028	-.0033	8
	May. 2003	(-3.95)	(1.67)	(1.02)	(0.67)	(-2.82)	
Denver	Feb. 1995	-.0143	.0025	.0017	-.0023	-.0018	11
	Aug. 2003	(-5.22)	(-2.04)	(1.81)	(0.72)	(-2.16)	
Las Vegas	Nov. 1991	-.0202	.0282	.0023	.0022	-.0002	9
	Dec. 2003	(-3.57)	(2.01)	(1.68)	(0.38)	(-0.15)	
Los Angeles	Feb. 1994	-.0185	-.0009	-.0037	.0024	.0001	7
	Oct. 2004	(-4.84)	(-5.33)	(-4.13)	(0.86)	(-0.21)	
Miami	Aug. 1994	-.0271	.0023	.0003	-.0007	.0038	8
	May 2004	(-5.38)	(2.97)	(0.43)	(-0.19)	(4.15)	
New York	Oct. 1992	-.0335*	-.0023	.0052	-.0018	.0004	9
	Oct. 2004	(-6.09)	(-11.7)	(9.93)	(-0.88)	(0.82)	
San Diego	Jun. 1996	-.0332	.0001	-.0048	.0006	.0013	5
	Mar. 2003	(-5.19)	(5.59)	(-4.32)	(0.14)	(1.02)	
San Francisco	Oct. 1992	-.0362	.0000	-.0044	-.0013	.0024	4
	July 1999	(-4.96)	(6.72)	(-4.79)	(-0.31)	(1.91)	
Washington, DC	Jan. 1993	-.0397	.0023	-.0031	-.0013	.0022	12
	Jul. 2000	(-3.64)	(6.25)	(-6.96)	(-0.50)	(-4.91)	

Note: See Table 4. The coefficient of d_{t-1}^{d} tests for the unit-root. 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).

* denotes rejection of the null hypothesis at the 5-percent significant level.

Figure 1: Time-Series Plots of S&P/Case-Shiller Rate of Capital Gains

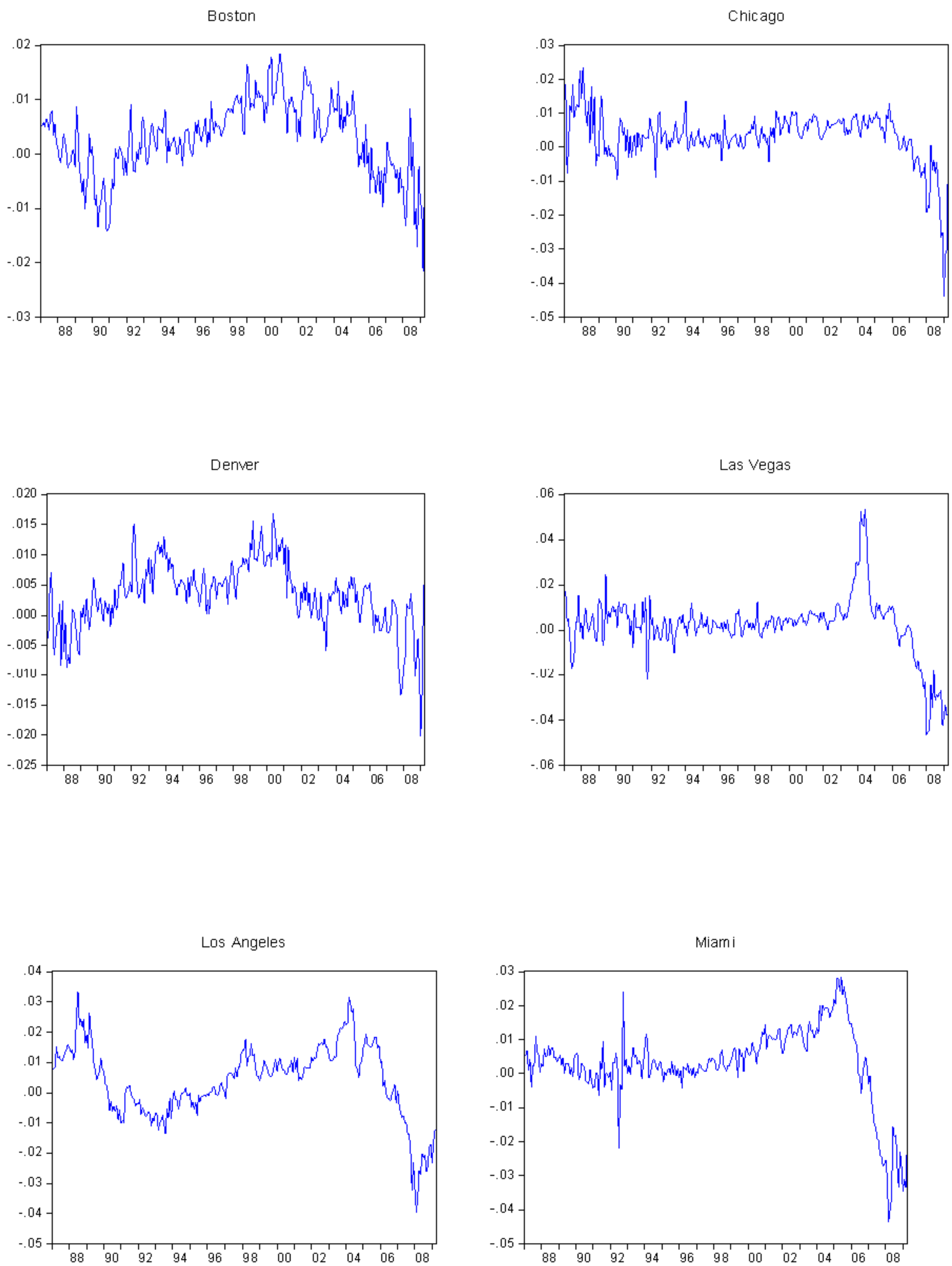

Figure 1: Time-Series Plots of S&P/Case-Shiller Rate of Capital Gains (continued)

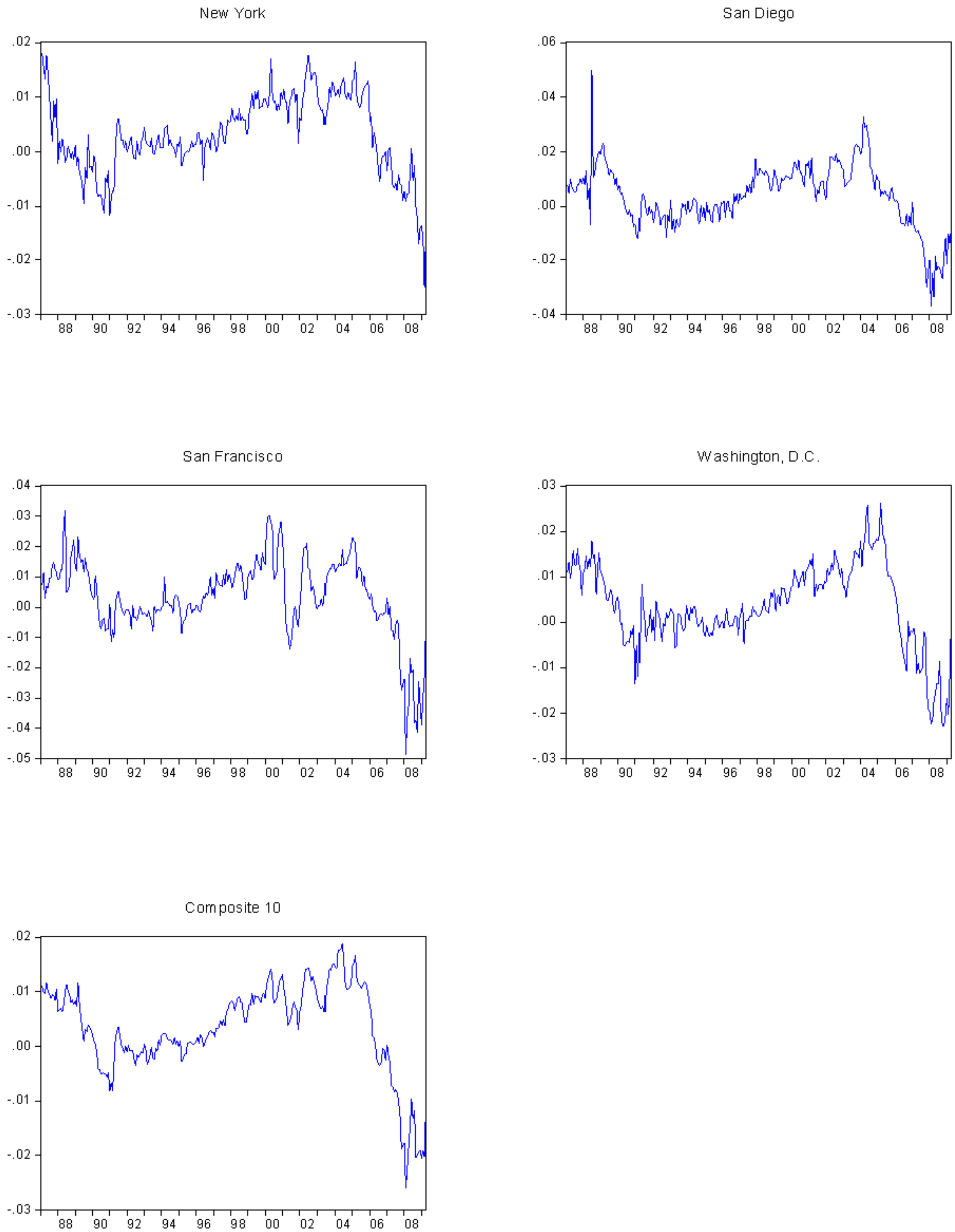

Figure 2: Time-Series Plots of S&P/Case-Shiller House-Price Ratios

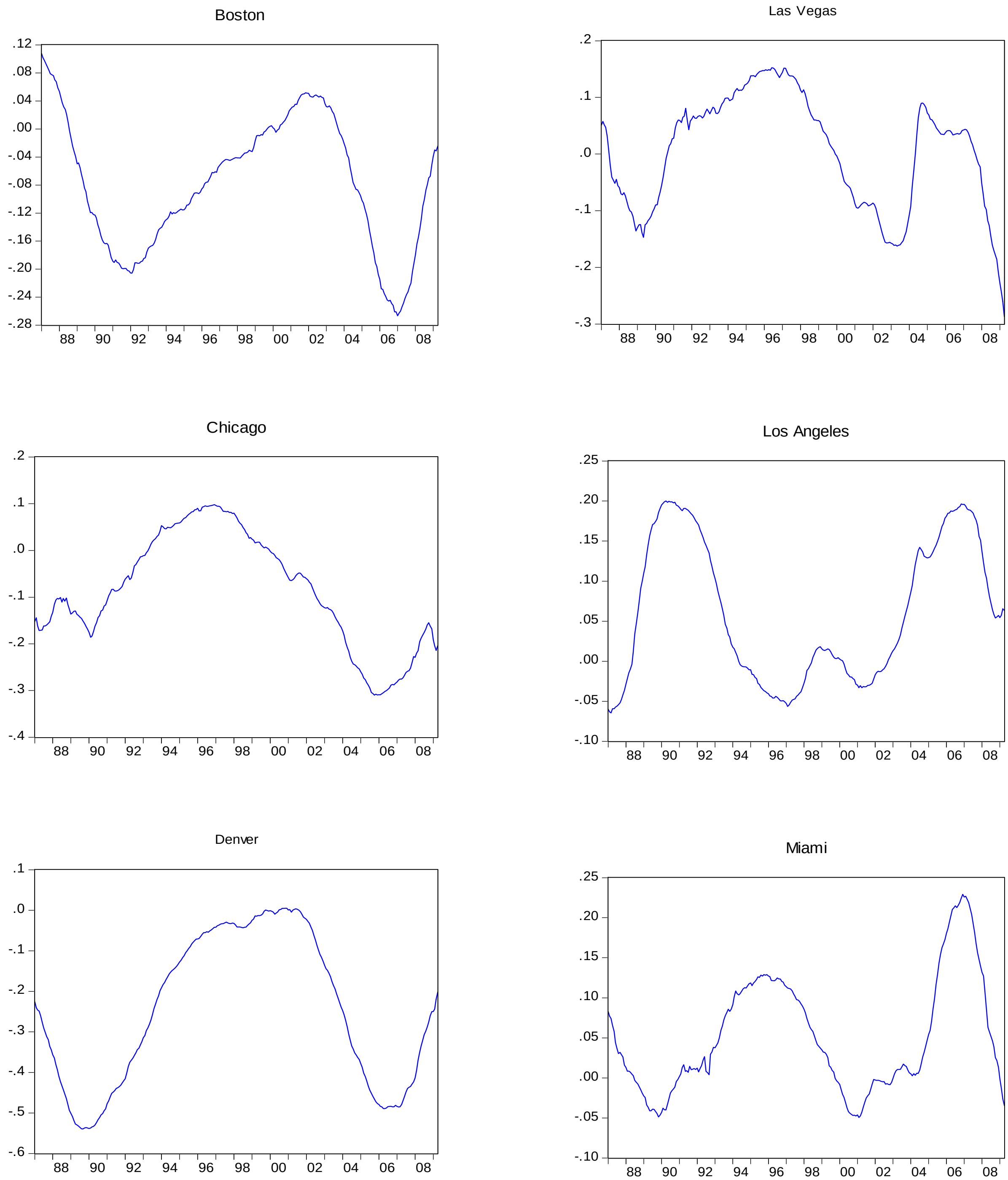

Figure 2: Time-Series Plots of S&P/Case-Shiller House-Price Ratios (continued)