Nonlinear Short-Run Adjustments in US All REITs Market Returns

Chien-Chung Nieh*
Department and Graduate Institute of Banking and Finance
Tamkang University, Tamsui, Taipei, Taiwan

Jia-Yu Chen
Department and Graduate Institute of Banking and Finance
Tamkang University, Tamsui, Taipei, Taiwan

I-Chan Chiang
Department and Graduate Institute of Banking and Finance
Tamkang University, Tamsui, Taipei, Taiwan

ABSTRACT

This paper proposes a nolinear error-correction model based upon logistic smooth transition regression methodology. The model is specified such that the short-run adjustment toward long-run equilibrium is nonlinear and that the error correction is a smooth function of long-run deviation. We use the specified model to investigate whether rational bubbles exist in US All REITs market over the 1972:01 to 2005:09 periods provide empirical support in favor noise trader models where arbitrageurs are reluctant to immediately engage in trade when stock returns deviate substantially from their fundamental value.

Keywords: REITS, Stock Market Returns, Logistic Smooth Transition Error-Correction Model, Arbitrageurs

*Corresponding author: Professor and Chairman, Department and Graduate Institute of Banking and Finance, Tamkang University, Tamsui, Taiwan, ROC. Tel: 886-2-26215656 ext.2591. Fax: 886-2-26214755. Email: niehcc@mail.tku.edu.tw

Ⅰ. Introduction

Over the past several decades, studies have been devoted to investigate the relationship between the stock prices and dividends from both theoretical and empirical point of view (see, for example, Campbell and Shiller, 1987; Caporale and Gil-Alana, 2004; Han, 1996; McMillan, 2004; Taylor and Peel, 1998). From theoretical point of view, stock price valuation model assume that stock prices depend upon the present value of discounted future dividends, where the discount rate is equivalent to the required rate of return. This means that stock returns can be predicated by the dividend yield and implied that dividend yield are cointegrated with stock price. However, this relationship could not be expected to hold exactly and deviations may arise due to time-varying required rate of return, speculative bubbles and fads, and omission of other relevant variables such as retained earnings. A class of speculative bubbles known as rational bubbles, do not violate the rational expectations hypothesis and are consistent with the efficient markets hypothesis. Investors realize the overvaluation that is compensated with excess positive returns for the risk of speculative bubbles. Such rational bubbles are due self-fulfilling expectations that can break the connection between prices and dividends over the short term.

Recently studies have been devoted to investigate the possibility of bubbles in REITs market. Jirasakuldech et al (2005) test for the presence of rational bubbles in the equity REIT market over the period 1973:01 to 2003:12 along with the sub-periods 1973:01 to 1991:10 and 1991:11 to 2003:12 with the results indicating the absence of rational bubbles. They use unit root test and cointegration methodologies to prove no evidence of rational speculative bubbles in Equity REIT industry. However, Evans(1991) indicates that unit roots test and cointegration methodology are in fact unable to detect explosive bubbles in asset price.

Payne and Waters (2005) use other methodologies, which the momentum threshold autoregressive (MTAR) model and the residuals-augmented Dickey-Fuller(RADF) test, to examine whether exist periodically collapsing bubbles in the equity REITs market. The MTAR model did not indicate the presence of periodically collapsing bubbles, but RADF test leaved the possibility of periodically collapsing bubbles.

Motivated by the above consideration, in this study we examine the issue of rational bubbles in the US All REITs market, using Johansen maximum likelihood cointegration tests and comparing the estimation performance of a linear error-correction model and a nonlinear error-correction model.

The major contribution of this research is to compare the performance of the linear error-correction models with that of the nonlinear error-correction models, including a logistic smooth transition error-correction (LSTEC) model, for U.S. All REITs market over the period of 1972:01 to 2005:09. The LSTEC model is capable of capturing the market dynamics that differentiate between small and large deviations from long-run equilibrium, and more importantly it also allows for a gradual transition between regimes, which is consistent with the "stylized facts" of a slow mean reversion in asset returns (see, Campbell et al., 1997; McMillan, 2004).

The study is organized as follows. Section Ⅱ describes the data used in this study. Section Ⅲ presents the methodologies used in this paper and the empirical results. Section Ⅳ concludes our paper.

Ⅱ. DATA

The Real Estate Investment Trusts (REITs) become an important real estate investment tool in financial market. For example, the total capitalization of the National Association of Real Estate Investment Trusts(NAREIT) All REITs index is $308 billion, which includes all 193 publicly traded All REITs on 2004 have large than the total capitalization of $0.89 billion of 46 publicly traded All REITs in1975. This means that All REITs can be the rapid growth and become the popular tool.

All REITs are classified in the following categories: (1)Equity REITs own and operate income-producing real estate. (2)Mortgage REITs lend money directly to real estate owners and their operators, or indirectly through acquisition of loans or mortgage-backed securities. (3)Hybrid REITs are companies that both own properties and make loans to owners and operators.

We use monthly data on the prices index and dividends for All REITs were obtained from the National Association of Real Estate Investment Trusts (NAREIT) for the period 1972:01 to 2005:09. The variables of log dividends and log stock prices do not follow the normal distribution and are time serially correlated. The descriptive statistics of the sample data are summarized in Table 1.

Ⅲ. RESEARCH METHODOLOGY AND EMPIRICAL RESULTS

A. The present-value model

Within the standard present-value model relates the price of a stock to its expected future cash flows, its dividends, discount to present using a constant or time-varying discount rate. We obtain an equation relating the current stock price to the next period's expected stock price and dividend:

$$P_t = E_t\left[\frac{P_{t+1}+D_{t+1}}{1+r}\right] \qquad , \ \textit{where r is discount rate} \tag{1}$$

Here, the discount rate is assumed to be constant. This expectation difference equation can be repeatedly substituting out future prices as:

$$P_t = E_t\left[\sum_{i=1}^{K}\left(\frac{1}{1+r}\right)^i D_{t+i}\right] + E_t\left[\left(\frac{1}{1+r}\right)^K P_{t+K}\right] \tag{2}$$

Any solution can be written in the form

$$P_t = P_{Dt} + B_t \tag{3}$$

Where

$$B_t = E_t\left[\frac{B_{t+1}}{1+r}\right], \quad P_{Dt} = E_t\left[\sum_{i=1}^{K}\left(\frac{1}{1+r}\right)^i D_{t+i}\right]$$

For future convenience we write this expected present value and bubbles. The term, P_{Dt}, is sometimes called fundamental value. The bubbles, B_t, may depend either on D_t or on wholly extraneous variables. Such asset price and rational bubbles may be represented in short term as follows.

$$dP_t = \alpha_0 + \alpha_1 B_{t-1} + (\theta_0 + \theta_1 B_{t-1}) * (1 + \mathrm{e}^{-\gamma(B_{t-1}-\tau)})^{-1} + \varepsilon_t \tag{4}$$

The parameters in the above equation satisfy $\gamma, \tau > 0$. the stochastic process ε_t is iid and has conditional expectation $E_t\varepsilon_{t+1} = 1$, which ensures that a bubble will not switch sign. Specifically, the model investigates nonlinearities in rational bubbles adjustment toward its fundamental value.

B. Unit Root Tests.

A significant consensus has been emerging in the recent research, i.e. the financial time series data may exhibit nonlinearities; thus the conventional tests for stationarity such as the Augmented Dickey-Fuller (ADF) unit root tests may not be able to detect the mean-reverting tendency of financial time series variables. Should this indeed be the case, it would be necessary to perform the stationary tests in a nonlinear framework. Therefore, we adopt the nonlinear stationary test advanced by Kapetanios et al. (2003) (henceforth, the KSS test) in our study.

Central to the KSS test is the goal to detect the presence of non-stationarity against a nonlinear but globally stationary exponential smooth transition autoregressive (ESTAR) process. The model is expressed as follows.

$$\Delta Y_t = \gamma Y_{t-1}\{1-\exp(-\theta Y_{t-1}^2)\} + \nu_t, \tag{1}$$

where Y_t is the time series data studied, ν_t is an independently identically distributed error term with a zero mean and constant variance, and $\theta \geq 0$ is the transition parameter of the ESTAR model and governs the speed of transition. Under the null hypothesis, Y_t follows a linear unit root process, but under the alternative hypothesis, Y_t follows a nonlinear stationary ESTAR process. One shortcoming in this framework is that the parameter γ is not identified under the null hypothesis. Thus, Kapetanios et al. (2003) used a first-order Taylor series approximation for $\{1-\exp(-\theta Y_{t-1}^2)\}$ under the null hypothesis of $\theta = 0$ and then approximated equation (1) by using the following auxiliary regression:

$$\Delta Y_t = \xi + \delta Y_{t-1}^3 + \sum_{i=1}^{k} b_i \Delta Y_{t-i} + \nu_t, \quad t = 1, 2, \ldots, T \tag{2}$$

Under this framework, the null hypothesis and the alternative hypothesis are expressed as $\delta = 0$ (non-stationarity) against $\delta < 0$ (nonlinear ESTAR stationarity). Table 2 presents the KSS nonlinear stationarity test results. These results indicate that both stock prices and dividends are integrated of order one.

For the sake of comparison, we also incorporate the Augmented Dickey-Fuller (ADF) tests, the Phillips and Perron (1988, PP) tests, and the Kwiatkowski et al. (1992, KPSS) tests into our study and the results are shown in Tables 3A and 3B. The results imply that the U.S. All REITs market of prices and dividends are both nonstationary in levels but become stationary in the first differences, further signifying that stock prices and dividends are integrated of order one, I(1). On the basis of these results, we proceed to test whether these two variables are cointegrated by using **Johansen Multivariate Maximun Likelihood Cointegration Test.**

C. Cointegration:

Johansen Multivariate Maximun Likelihood Cointegration Test:

We applied the more powerful Johansen Multivariate Maximun Likelihood cointegration test to investigate the long-run relationship between stock prices and dividends.

The test hypothesis is formulated as the restriction for the reduced rank of Π:

$H_0(r)$: $\Pi = \alpha\beta'$ for the reduced form error correction model (ECM):

$$\Delta X_t = \Gamma_1 \Delta X_{t-1} + ... + \Gamma_{k-1}\Delta X_{t-(k-1)} + \Pi X_{t-1} + \Psi D_t + \in_t$$ (where ε_t is white noise)

where α and β are both p×r matrices, and represent the speed of the adjustment parameter and cointegrating vector, respectively.

The likelihood ratio test statistic for the hypothesis that there are at most r cointegrating vector (i.e. H(r): rank(Π) < r) is:

$$-2\ln Q\left(H(r)/H(p)\right) = -T\sum_{i=r+1}^{p}\ln\left(1-\hat{\lambda}_i\right)$$

This elaborate work has been developed from Johansen (1988) to Johansen (1994).[1] There are total five Johansen VAR models with ECM, which are

[1] Johansen (1992, 1994) developed a testing procedure based on the ideas developed

summarized as following forms:[2]

$H_0(r): \Delta X_t = \Gamma_1 \Delta X_{t-1} + ... + \Gamma_{k-1} \Delta X_{t-(k-1)} + \alpha\beta' X_{t-1} + \Psi D_t + \in_t$
(1988) (3)

$H_1^*(r): \Delta X_t = \Gamma_1 \Delta X_{t-1} + ... + \Gamma_{k-1} \Delta X_{t-(k-1)} + \alpha(\beta', \beta_0)(X'_{t-1}, 1)' + \Psi D_t + \in_t$
(1990) (4)

$H_1(r): \Delta X_t = \Gamma_1 \Delta X_{t-1} + ... + \Gamma_{k-1} \Delta X_{t-(k-1)} + \alpha\beta' X_{t-1} + \mu_0 + \Psi D_t + \in_t$
(1990) (5)

$H_2^*(r): \Delta X_t = \Gamma_1 \Delta X_{t-1} + ... + \Gamma_{k-1} \Delta X_{t-(k-1)} + \alpha(\beta', \beta_1)(X'_{t-1}, t)' + \mu_0 + \Psi D_t + \in_t$
(1994) (6)

$H_2(r): \Delta X_t = \Gamma_1 \Delta X_{t-1} + ... + \Gamma_{k-1} \Delta X_{t-(k-1)} + \alpha\beta' X_{t-1} + \mu_0 + \mu_1 t + \Psi D_t + \in_t$
(1994) (7)

To analyze the deterministic term, Johansen decomposed the parameters μ_0 and μ_1 in the directions of α and $\alpha_\perp$ as $\mu_i = \alpha\beta_i + \alpha_\perp\gamma_i$, thus we have $\beta_i = (\alpha'\alpha)^{-1}\alpha'\mu_i$ and $\gamma_i = (\alpha_\perp'\alpha_\perp)^{-1}\alpha_\perp'\mu_i$. The nested sub-models of the general model of null hypothesis $\Pi = \alpha\beta'$ are, therefore, defined as:

$H_0(r)$: $Y = 0$
$H_1^*(r)$: $Y = \alpha\beta_0$
$H_1(r)$: $Y = \alpha\beta_0 + \alpha_\perp\gamma_0$
$H_2^*(r)$: $Y = \alpha\beta_0 + \alpha_\perp\gamma_0 + \alpha\beta_1 t$
$H_2(r)$: $Y = \alpha\beta_0 + \alpha_\perp\gamma_0 + (\alpha\beta_1 + \alpha_\perp\gamma_1)t$

Johansen (1994) emphasized the role of the deterministic term, $Y = \mu_0 + \mu_1 t$, which includes constant and linear terms in the Gaussian VAR. Applying the idea of Johansen (1992), the decision procedure among the hypotheses H(r) and $H^*(r)$ for five different models is presented in the following order:

$H_0(0) \to H_1^*(0) \to H_1(0) \to H_2^*(0) \to H_2(0) \to H_0(1) \to H_1^*(1) \to H_1(1) \to H_2^*(1) \to H_2(1)$

$\to ... \to ... \to H_0(p\text{-}1) \to H_1^*(p\text{-}1) \to H_1(p\text{-}1) \to H_2^*(p\text{-}1) \to H_2(p\text{-}1)$

Table 4 represents the empirical findings from the Johansen methodology for the long-run relationship with the consideration of no trend between stock prices and dividends for U.S. ALL REITs market .

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by Pantula (1989) to determine the number of cointegrating rank in the presence of linear trend [Johansen (1992)] and quadratic trend [Johansen (1994)].

[2] The equations (4) and (5) are indeed from Johansen and Juselius (1990).

<Insert Table 4 about here>

Table 4 presents the results imply that there is a long-run cointegration equilibrium relationship between stock prices and dividends indicates a sign of the absence of rational bubbles in the U.S. All REITs market during the period of 1972:01 to 2005:09..

D. Nonlinear Tests and Estimations from the Logistic Smooth Transition Error-Correction Model

Stock valuation models customarily assume that log stock returns are determined by a linear relationship between the cointegrated log dividends and log stock prices and that any deviations from this fundamental equilibrium are most likely short-lived. After identifying a long-run equilibrium relationship between stock prices and dividends, we are now able to describe the stock returns using an error-correction model stated below.

$$\mathrm{r}_t = \alpha_0 + \alpha_1 z_{t-1} + \sum_{i=1}^{k} \alpha_{i+1} r_{t-i} + \varepsilon_t \tag{8}$$

where r_t stands for stock returns; $z_{t-1} = (p_{t-1} - \theta_0 - \theta_1 d_{t-1})$ represents the error-correction term; α_1 measures the speed of adjustment to equilibrium; p_t and d_t respectively represent log stock prices and log dividends, respectively. The optimal lag length k in $\sum_{i=1}^{k} \alpha_{i+1} r_{t-i}$ is chosen to ensure there are no serial correlations in the residuals (ε_t).

To fully capture the different dynamics of both small and large deviations from long-run equilibrium, we apply the smooth transition error-correction (STEC) model which allows for different types of return behavior in different regimes. Thus, we rewrite equation (8) as follows.

$$\mathrm{r}_t = (\alpha_0 + \alpha_1 z_{t-1} + \sum_{i=1}^{k} \alpha_{i+1} r_{t-i}) + (\beta_0 + \beta_1 z_{t-1} + \sum_{i=1}^{k} \beta_{i+1} r_{t-i}) F(z_{t-d} : \gamma, \tau) + \varepsilon_t \tag{9}$$

The STEC model is theoretically more appealing than the threshold model in that the latter imposes an abrupt switch in the parameter values, and it would be the observed outcome only when all traders act simultaneously. In other words, for a market with numerous traders behaving heterogeneously in time, the STEC model is considerably more appropriate. The STEC model is governed by the continuous transition function $F(z_{t-d}:\gamma,\tau)$, where z_{t-d} is the transition variable; d is the optimal lag length for the transition variable z_{t-d}; γ is the smoothness parameter measuring how fast the transition is from one regime (small deviations) to the other (large deviations), and τ is the threshold parameter determining where the transition occurs.

As in Teräsvirta (1994), we consider two alternative specifications for the transition function in equation (9):

$$F(z_{t-d}:\gamma,\tau)=\{1+\exp[-\gamma(z_{t-d}-\tau)/\sigma^2_{z_{t-d}}]\}^{-1},\ \ \gamma>0 \tag{10}$$

$$F(z_{t-d}:\gamma,\tau)=1-\exp[-\gamma(z_{t-d}-\tau)^2/\sigma_{z_{t-d}}],\ \ \gamma>0 \tag{11}$$

Equation (9) with the transition function (10) is called the logistic STEC (LSTEC) model, where $F(z_{t-d}:\gamma,\tau)=0\sim1$ as $z_{t-d}=-\infty\sim+\infty$. The LSTEC model specifies different dynamics for the two different return regimes with a smooth transition between them. This specification allows the parameters of α's and β's of the STEC model in equation (9) to change with the different values of the transition variable z_{t-d}. If $\gamma\to0$, the model is reduced to a linear error-correction (EC) model. If $\gamma\to+\infty$, then $F(z_{t-d}:\gamma,\tau)=1$ for $z_{t-d}>\tau$, and $F(z_{t-d}:\gamma,\tau)=0$ for $z_{t-d}\le\tau$, and accordingly the STEC model becomes a two-regime threshold model. The LSTEC model can, therefore, be viewed as a error-correction threshold (ECT) model with one threshold value τ to distinguish between two regimes including the small and large deviations from the equilibrium.

Since $F(z_{t-d}:\gamma,\tau)$ is not symmetric about τ, the LSTEC model is capable of generating the asymmetric short-run dynamics in two forms. The short-run dynamics will take on the form, $\mathrm{r}_t = (\alpha_0 + \alpha_1 z_{t-1} + \sum_{i=1}^{k} \alpha_{i+1} r_{t-i}) + (\beta_0 + \beta_1 z_{t-1} + \sum_{i=1}^{k} \beta_{i+1} r_{t-i}) + \varepsilon_t$ during a period of expansion with $z_{t-d} > \tau$. However, the dynamics will switch into $\mathrm{r}_t = (\alpha_0 + \alpha_1 z_{t-1} + \sum_{i=1}^{k} \alpha_{i+1} r_{t-i}) + \varepsilon_t$ during a period of recession with $z_{t-d} \le \tau$. The transition from one state to the other is smooth and takes on the form of $\mathrm{r}_t = (\alpha_0 + \alpha_1 z_{t-1} + \sum_{i=1}^{k} \alpha_{i+1} r_{t-i}) + (\beta_0 + \beta_1 z_{t-1} + \sum_{i=1}^{k} \beta_{i+1} r_{t-i}) F(z_{t-d}:\gamma,\tau) + \varepsilon_t$.

Equation (9) with the transition function (11) is called the exponential STEC (ESTEC) model. The ESTEC model assumes that there are similar dynamics in the extreme regimes but different dynamics in the transition period since $F(z_{t-d}:\gamma,\tau) = 1$ as $|z_{t-d}| = +\infty$. The ESTEC model allows the parameters to change symmetrically about τ with the transition variable z_{t-d}. In the extreme case, when $\gamma \to 0$, the model is reduced to a linear error-correction model with $\mathrm{r}_t = (\alpha_0 + \alpha_1 z_{t-1} + \sum_{i=1}^{k} \alpha_{i+1} r_{t-i}) + \varepsilon_t$. When $\gamma \to +\infty$, the model switches to the other regime with $\mathrm{r}_t = (\alpha_0 + \alpha_1 z_{t-1} + \sum_{i=1}^{k} \alpha_{i+1} r_{t-i}) + (\beta_0 + \beta_1 z_{t-1} + \sum_{i=1}^{k} \beta_{i+1} r_{t-i}) + \varepsilon_t$. Since $F(z_{t-d}:\gamma,\tau)$ is symmetric about τ, the ESTEC model gives similar short-run dynamics between the periods of expansion and recession. This model implies that there is a symmetric transition from one state to the other. The ESTEC model may be viewed as a generalization of the error-correction threshold (ECT) model with two threshold values to distinguish among three regimes including one within the equilibrium and two outside the equilibrium.

In the light of our pursuit to estimate the parameters of γ, τ and d, it is essential here to test the linearity with $F(z_{t-d}:\gamma,\tau) = 0$ in equation (9) for various values of d before estimating the nonlinear STEC model. The null hypothesis of linearity $H_0 : \gamma = 0$ is tested against the alternative hypothesis of nonlinearity $H_1 : \gamma > 0$. Since the nonlinear STEC model can only be identified under the alternative hypothesis, it would render the application of the conventional Lagrange multiplier (LM) test of linearity invalid. Faced with this problem, we turn to Luukkonen et al. (1988) who suggested that the transition function $F(z_{t-d} : \gamma, \tau)$ be replaced with its third-order Taylor approximation about $\gamma = 0$. Thus, the STEC model in equation (9) can be reformed as follows.

$$r_t = \pi_0 + \pi_1 ' W_t + \kappa_1 ' W_t (z_{t-d}) + \kappa_2 ' W_t (z_{t-d})^2 + \kappa_3 ' W_t (z_{t-d})^3 + \eta_t \tag{12}$$

where $W_t = (z_{t-1}, r_{t-1}, r_{t-2}, r_{t-3} ..., r_{t-k})$ in our case. If it is assumed that the delay parameter d is known, then the linearity test is equivalent to the test of the hypothesis

$$H_0 : \kappa_1 ' = \kappa_2 ' = \kappa_3 ' = 0 \tag{13}$$

An auxiliary regression can be defined as:

$$\varepsilon_t = \pi_0 + \pi_1 ' W_t + \kappa_1 ' W_t (z_{t-d}) + \kappa_2 ' W_t (z_{t-d})^2 + \kappa_3 ' W_t (z_{t-d})^3 + v_t \tag{14}$$

where ε_t is the residual obtained from equation (8) under the null hypothesis of linearity. Thus, the LM test of linearity against the nonlinear STEC model can then be performed by computing the following statistic

$$LM = \frac{(SSR_0 - SSR_1)/(3(k+1))}{SSR_1 /(T - 4(k+1) - 1)} \tag{15}$$

where SSR_0 is the sum of the squared residuals ε_t, while SSR_1 is the sum of the squared residuals v_t obtained from equation (14). The statistic has an asymmetric F-distribution with 3(k+1) and T-4(k+1)-1 degrees of freedom under the null hypothesis of linearity. One possible way to identify the appropriate model between LSTEC and ESTEC models is through a sequence of tests on equation (14).

Thus, we consider a sequence of the null hypotheses as follows.

$$\begin{aligned} &H_{03}: \kappa_3' = 0 \\ &H_{02}: \kappa_2' = 0 | \kappa_3' = 0 \\ &H_{01}: \kappa_1' = 0 | \kappa_2' = \kappa_3' = 0 \end{aligned} \quad (16)$$

We would select the LSTEC model provided that H_{03} is rejected. If H_{03} is not rejected but H_{02} is rejected, we would adopt the ESTEC model. If both H_{03} and H_{02} are not rejected but H_{01} is rejected, we would select the LSTEC model (see Teräsvirta (1994)).

Table 5 shows the results of the LM test of linearity against the nonlinear STEC model, and we find strong evidence of nonlinearity in the stock returns. In order to specify d, we estimate equation (14) across a range of values for d $(1 \le d \le 10)$, where the nonlinearity test statistic with the minimum p value determines the optimal value for d (d=7) in the subsequent estimation of equation (9). The results in Table 6 show that H_{03} is rejected for d=9. Thus, it indicates that the LSTEC model would be the more appropriate model.

Finally, we attempt to make a comparison between the linear EC model and the nonlinear LSTEC model, including the parameter estimates, model specification tests, and residual tests for both models. Not surprisingly, the results in Table 7 consistently suggest that the LSTEC model is superior to the linear alternative based on all the different criteria used. More specifically, the LSTEC model has a relatively higher adjusted R^2, lower residual variance as well as lower AIC and SBC values, while showing no evidence of the ARCH effects. Moreover, the variance ratio also shows a reduction of 8% in the residual variance of the nonlinear LSTEC model, when compared with that of the linear model.

When examining the parameter estimates of the nonlinear LSTEC model, we found that although the estimated value of γ (=312.6036) is large, it is not statistically significantly different from zero. However, Teräsvirta (1994) asserted that this should not be interpreted as evidence of weak nonlinearity. Besides, Sarantis (1999) further demonstrated the difficulty of estimating γ, while Sarno (2000) argued that the statistical significance of γ is, in essence, simply not a question because the linearity has already been rejected in the earlier tests. To estimate γ more accurately, many observations in the immediate neighborhood of τ 's are typically required. Nevertheless, it may not be appropriate since we would probably end up with a higher standard error for the γ estimates from the fitted model. The large estimated value of γ found in our study implies a fast transition (a sharp switch) from one regime to the other. The following logistic transition function is further estimated and illustrated in Figure 1.

$$F(z_{t-5} : \gamma, \tau) = \{1 + \exp[-312.6036(z_{t-5} - 0.3340)/0.2734]\}^{-1}.$$

Figure 1 shows that the transition from the lower regime (smaller deviations) to the upper regime (larger deviations) is almost instantaneous at the threshold values of $z_{t-5} = 0.0$ and 0.34. The short-run dynamics of the stock returns reach the lower regime as $(z_{t-5} - \tau) \to -\infty$ and $F(z_{t-5} : \gamma, \tau) \to 0$, whereas returns reach the upper regime as $(z_{t-5} - \tau) \to \infty$ and $F(z_{t-5} : \gamma, \tau) \to 1$. Not to be ignored, the stock return dynamics are asymmetric, with the not significantly positive coefficient (0.0817) of the error-correction term z_{t-1} included in the upper regime. It suggests that there is no sign of a mean reversion to equilibrium in the lower regime but a quick mean reversion to equilibrium in the upper regime. These results indicate that the dynamics governing the small deviations from the long-run equilibrium differ from those governing the large deviations. Theoretical models of studying the interaction between arbitrageurs and noise traders have suggested that small and large deviations may exhibit different return dynamics given that arbitrageurs must always be aware of the potential for noise traders to drive returns further away from equilibrium. Needless to say, our results confirm the results of the noise trader models, and therefore, acknowledge the potentially harmful behavior of such noise traders. Let's come straight to the point. Large deviations are characterized by a quick mean reversion because arbitrageurs have more confidence in being able to move the market in the appropriate direction and their risk exposure to the adverse price movements is lower. However, small deviations are characterized by persistence and slow reversion since arbitrageurs are reluctant to immediately act upon the mispricings due to the fact that they are now exposed to greater price risks and adverse market movements. .

Ⅳ. CONCLUSIONS

In this study, using Johansen maximum likelihood cointegration tests, we demonstrate that no rational bubbles existed in the U.S All REITs market throughout the period of 1972:01 to 2005:09. Our application of a logistic smooth transition error-correction (LSTEC) model, designed to detect the nonlinear short-run adjustments to the long-run equilibrium, provides substantive empirical evidence in favor of noise trader models where arbitrageurs are reluctant to instantaneously engage in trading when stock returns deviate insufficiently from their fundamental value.

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Table 1 Descriptive Statistics of Sample Data

	Log Dividends	Log Stock Prices
Mean	2.123380	4.439603
Median	2.135349	4.472396
Maximum	2.954910	5.100119
Minimum	1.561885	3.556550
Std. Dev.	0.218685	0.273433
Skewness	0.293379	-0.558116
Kurtosis	4.332006	3.364292
Jarque-Bera	35.75008	23.26528
	(0.000000)***	(0.000009)***
Ljung-Box Q(4)	26.381***	3.4414
Ljung-Box Q(8)	36.132***	8.3180
Ljung-Box $Q^2(4)$	17.169**	30.420***
Ljung-Box $Q^2(8)$	26.145***	86.180***

Notes: 1. Numbers in parentheses indicate the p-value for the Jarque-Bera normality test statistics.
2. *** denotes significance at the 1% level.

Table 2 The Nonlinear KSS Unit Root Tests

KSS	Log Stock Prices		Log Dividends	
	Level	1st diff	Level	1st diff
t statistics of $\hat{\delta}$	-0.0000009	-0.001255	-0.000215	-0.000705

Notes: 1. Critical values for the t statistics of $\hat{\delta}$ are tabulated in Kapetanios et al. (2003).
2. Critical values for 10%, 5% and 1% are -1.92, -2.22 and -2.82, respectively.
3. Numbers in parentheses indicate the lag length (k) of the following testing model.

$$\Delta Y_t = \xi + \delta Y_{t-1}^3 + \sum_{i=1}^{k} b_i \Delta Y_{t-i} + v_t, \quad t = 1, 2, \ldots, T$$

Table 3A The Conventional Unit Root Tests for Log Stock Prices

Log Stock	ADF		PP		KPSS	
Prices	level	1st difference	Level	1st difference	level	1st diff
Intercept	-0.9234(0)	-18.692***(0)	-1.3014(8)	-18.859***(8)	0.8771***(16)	0.1944(8)
Trend	-2.1253(0)	-18.7725***(0)	-2.4114(8)	-18.8724***(8)	0.1187***(16)	0.0811(8)

Note : *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 3B The Conventional Unit Root Tests for Log Dividends

Log Stock	ADF		PP		KPSS	
Prices	level	1st difference	Level	1st difference	level	1st diff
Intercept	-2.0355(0)	-16.747***(1)	-2.1739(10)	-19.725***(9)	1.1775***(16)	0.1602(9)
Trend	-3.6137**(4)	-16.844***(1)	-3.6552**(10)	-19.784***(9)	0.1667***(15)	0.0362(9)

Note : *,**and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 4.Johansen Cointegration test

	Model 1 $H_0(R)$		Model 2 $H_1^*(R)$		Model 3 $H_1(R)$		Model 4 $H_2^*(R)$		Model 5 $H_2(R)$	
Rank	Max-Eigen Statistic	Critical value	Max-Eigen Statistic	Critical value	Max-Eigen Statistic	Critical value	Max-Eigen Statistic	Critical value	Max-Eigen Statistic	Critical value
R≦0	20.54	11.22	26.98	15.89	26.86	14.26	43.07	19.38	43.02	17.14
R≦1	**0.1274**	**4.129**	4.969	9.164	4.840	3.841	9.846	12.51	7.799	3.841
SBC	1		1		1		1		1	

Table 5 LM Test of Linearity Against the Nonlinear STEC Model

D	1	2	3	4	5	6	7	8	9	10
LM	1.1978	0.5923	2.3401	3.3042	1.0357	1.1353	3.3413	0.7886	2.8849	0.4619
P-value	0.3064	0.7364	0.0311	0.0034	0.4014	0.3409	0.0031	0.5792	0.0092	0.8364

Note: The LM statistics are computed to test the $H_0:\kappa_1' = \kappa_2' = \kappa_3' = 0$ in the equation of $r_t = \pi_0 + \pi_1' W_t + \kappa_1' W_t(z_{t-d}) + \kappa_2' W_t(z_{t-d})^2 + \kappa_3' W_t(z_{t-d})^3 + \eta_t$,

$$LM = \frac{(SSR_0 - SSR_1)/(3(k+1))}{SSR_1/(T-4(k+1)-1)}$$

where SSR_0 is the sum of the squared residuals ε_t in $r_t = \alpha_0 + \alpha_1 z_{t-1} + \sum_{i=1}^{k} \alpha_{i+1} r_{t-i} + \varepsilon_t$, and SSR_1 is the sum of the squared residuals v_t in $\varepsilon_t = \pi_0 + \pi_1' W_t + \kappa_1' W_t(z_{t-d}) + \kappa_2' W_t(z_{t-d})^2 + \kappa_3' W_t(z_{t-d})^3 + v_t$.

Table 6 Model Specification for the LSTEC Versus the ESTEC Models

D	F Statistics for testing H_{03}	p-value	F Statistics for testing H_{02}	p-value	F Statistics for testing H_{01}	p-value
1	1.636744	0.195930	0.179140	0.836057	1.778663	0.170200
2	0.217474	0.804645	0.243483	0.784010	1.327472	0.266318
3	1.875782	0.154604	3.484669	0.031610	1.617101	0.199778
4	4.268768	0.014655	4.324153	0.013879	1.207292	0.300104
5	0.352488	0.703160	0.282646	0.753940	2.490183	0.084195
6	0.223857	0.799532	1.240958	0.290240	1.951423	0.143443
7	4.237659	0.015114	4.281408	0.014477	1.387600	0.250894
8	0.562723	0.570120	0.554346	0.574900	1.255765	0.286001
9	5.955234	0.002836	1.440112	0.238161	1.189783	0.305386
10	0.206683	0.813367	0.388899	0.678067	0.797457	0.451206

Note: The F statistics are computed to test a sequence of the null hypotheses: H_{03}, H_{02}, and H_{01} for the equation of $\varepsilon_t = \pi_0 + \pi_1' W_t + \kappa_1' W_t (z_{t-d}) + \kappa_2' W_t (z_{t-d})^2 + \kappa_3' W_t (z_{t-d})^3 + v_t$.

$H_{03} : \kappa_3' = 0$

$H_{02} : \kappa_2' = 0 | \kappa_3' = 0$

$H_{01} : \kappa_1' = 0 | \kappa_2' = \kappa_3' = 0$

Table 7 Comparison Between the Linear EC and the Nonlinear LSTEC Models

Variables	Coefficients	Linear EC Model	Nonlinear LSTEC Model
Constant	α_0	-0.0125(0.0135)	-0.0242 (0.0138)*
z_{t-1}	α_1	-0.0312(0.0115)***	-0.0362 (0.0126)***
r_{t-1}	α_2	1.0035(0.0022)***	1.0052 (0.0022)***
Constant	β_0	-	0.7930 (0.4140)*
z_{t-1}	β_1	-	0.0817 (0.2955)
r_{t-1}	β_2	-	-0.1313 (0.0830)
Transition Speed	γ	-	312.6036 (2191.726)
Threshold Parameter	τ		0.3340 (0.0339)***
Model R^2	Centered R^2	0.9983	0.9984
	Adjusted R^2	0.9983	0.9984
AIC		-3.4040	-3.4600
SBC		-3.3743	-3.3796
LM Test for ARCH Effects		4.6774	1.5637
(TR^2)		[0.0306]	[0.2111]
Ljung-Box Q(4)		1.9229	4.7459
Ljung-Box Q(8)		6.1770	16.155
SSR		0.774657	0.699830
Variance Ratio		0.92	

Note: 1. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

2. SSR stands for the sum of the squared residuals for each model.

3. Variance Ratio is the ratio of the variance of the nonlinear model relative to the variance of the linear model.

4. The models were estimated based on the following equation, with $F(z_{t-d}:\gamma,\tau)=0$ for the linear model.

$$r_t = (\alpha_0 + \alpha_1 z_{t-1} + \sum_{i=1}^{k} \alpha_{i+1} r_{t-i}) + (\beta_0 + \beta_1 z_{t-1} + \sum_{i=1}^{k} \beta_{i+1} r_{t-i}) F(z_{t-d}:\gamma,\tau) + \varepsilon_t$$

5. The numbers in parentheses are the standard errors of the estimates.

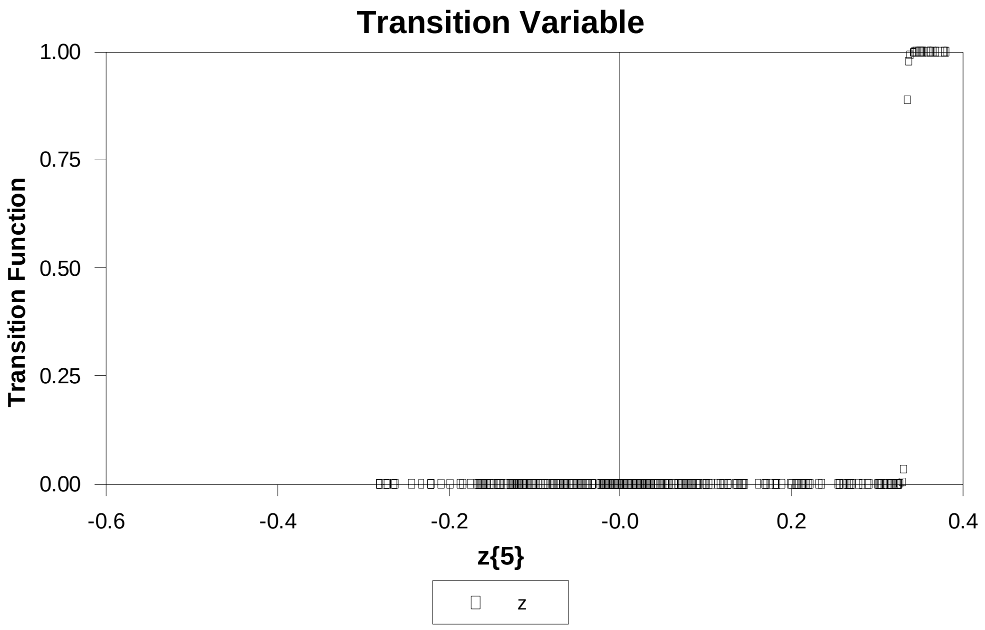

Figure 1 Relationship Between the Logistic Transition Function and the Transition Variable

$$F(z_{t-5} : \gamma, \tau) = \{1 + \exp[-312.6036(z_{t-5} - 0.3340)/0.2167]\}^{-1}$$