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Asymmetric dynamics in REIT prices: Further evidence based on quantile regression analysis

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ABSTRACT

This study examines whether mean reversion in REIT prices presents an asymmetric behavior across various quantiles. Distinguished from previous literature that applied the traditional linear unit-root test, a state-of-the-art quantile unit-root test is employed to identify financial asset predictability in five real estate investment trust (REIT) classifications. Our empirical results reveal a distinct pattern that mean reversion is found for those relatively high REIT prices, while random walk properties only exist for those relatively low REIT prices. More specifically, the higher the price is, the faster the speed of mean reversion of REIT toward its long-run equilibrium will be.

1. Introduction

The issue of whether financial asset prices follow a random walk or revert to the long-run trend has relevant financial implications. This conflict of interest is motivated by the predictability of financial market returns and implication on investment strategies and decisions. In the case of random walk, price level adjustments are random and unpredictable. On the other hand, mean reversion demonstrates that investors are able to develop a trading strategy to profit from the predictable returns. Therefore, empirical research studies in finance have long presented a great deal of attention on the time-series properties of financial asset prices — for example, Stevenson (2002), Narayan and Smyth (2007), Goddard et al. (2008), Lee et al. (2010), Chien (2010), Lee and Chien (2011), and Chen et al. (2011), to mention a few.

Despite this extensive research, the empirical evidence on mean reversion in financial asset prices is still inconclusive. Yet another investment vehicle appears to be on the way, in the form of real estate securities. Real estate investment trusts (REITs) have played an increasingly key role in US real estate investment. REITs not only provide alternative investment channels to investors, but also enable individual investors to invest in real estate or real estate-related assets. As discussed by Payne and Zuehlke (2006), the cyclical behavior of REITs has become a critical issue as their increasing growth to be an investment vehicle for investor. Our motivations for the present study are rooted in whether REIT prices can be characterized as unit-root (random walk) or mean reverting (trend stationary) processes. If REITs are mean reverting, then a series should return to its long-run trend whose path is determined by structural fundamentals over time and it should be possible to forecast future movements in REITs based on past behavior, providing information for financial investment decisions and strategies. By contrast, if REITs are a unit-root process, then any shock to REITs is likely to be permanent. Thus, the random walk (non-stationary) properties also imply that the volatility of asset prices can grow without boundaries in the long run. These time-series properties have important implications not only for determining the effects of random shocks, but also for helping to shed light on asset pricing.

The nonlinearity of financial time series processes is becoming an increasingly important issue at both the theoretical and empirical levels. As such, we have no reason to assume that the mean reverting process is, or has to be, linear. Traditional unit-root tests are computed assuming a linear specification and suffer from low power to reject the non-stationary hypothesis if the series mean reverts in a non-linear fashion (Taylor et al., 2001). Many studies in the literature may explain such non-linear dynamics for financial variables and we summarize them as follows: transaction costs or the existence of market frictions (Chen et al., 2014; Dumas, 1992; Lee et al., 2013; Sercu et al., 1995), heterogeneity of buyers and sellers (Taylor and Allen, 1992), noisy traders causing abrupt changes (De Long et al., 1990), and heterogeneity of central banks' interventions (Dominguez, 1998). All the above articles imply that there is either a non-linear relationship between the financial

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variables and the economic fundamentals, or a non-linear adjustment effect with time-dependence properties. Consequently, the impact of a transitory shock may last for a long period of time when the nonlinearity of the series is significant.

This paper attempts to fill this vacuum. Whereas the presence of nonlinearity would put a priori constraints on examinable theories, we deem it important that researchers know whether certain REIT series contain a linear or a nonlinear structure. Our paper takes a different route. A unit-root test based on the *quantile autoregression* (QAR) approach, which is widely applied to time-series analysis including Koenker and Zhao (1996) for quantile ARCH models, Clements et al. (2008) for the conditional autoregressive VaR model, Koenker and Xiao (2006), Zietz et al. (2008), Lima et al. (2008), and Baur et al. (2012) for the QAR approach, and Koenker and Xiao (2004) and Nikolaou (2008) for unit-root QAR inference, is used to examine the stationary properties of REIT prices. In contrast to the existing financial literature on mean reversion, the REIT prices are modeled as quantile-dependent where episodes of stationarity or non-stationarity can be identified and analyzed. The QAR approach provides a way to directly examine how past information affects the conditional distribution of a time series. Our study offers novel insights on REITs' mean reverting behavior.

Specifically, it is one of the first to examine the non-linear mean reversion in five REIT classifications for the period from January 1972 to March 2010 by using the advanced QAR models. A key feature of a QAR model is the examination of data distribution rather than a single measure of a central tendency in the REIT prices' distribution. It offers a more flexible modeling by relaxing restriction on particular distribution, thereby allowing for different and possibly asymmetric adjustment speeds of mean reversion at various quantiles of distribution and providing information to detect local persistence in time series. Koenker and Xiao (2004) point out that many empirical applications, especially with respect to economics and finance, exhibit a heavy-tailed behavior, causing the conventional unit-root tests to perhaps have misleading inferences which are based on the conditional mean. This difficulty can be readily solved by the QAR method, which allows us to explore a whole range of conditional quantiles.[1]

In addition, econometric modeling and financial theories require knowledge on the unit-root properties of REIT data. For the case of rational speculative bubbles, the presence of a cointegration relationship between prices and their fundamentals is often taken as evidence in favor of the absence of bubbles. When examining for cointegration, a prerequisite is that both series contain a unit-root — that is, not rejecting the null hypothesis is a primary step toward conducting a test for a long-run relationship (Lee, 2013). If relevant econometric works lack a diagnostic analysis of the order of integration, then this could result in misleading inferences as well as the conduct of cointegration analysis being perhaps inappropriate, thereby losing the meaning of bubble detection (Lee et al., 2010; Manning, 2002). Thus, it is also crucial for bubble detection to fully understand the unit-root properties.

The present study contributes overall to the existing literature with a more comprehensive and accurate analysis. It not only extends the sample period from January 1972 to March 2010, but also broadens the scope of analysis by dividing the REITs into five REIT classifications – all, equity, mortgage, hybrid, and composite REITs – in order to investigate the presence of the mean reversion property across different REITs. Most importantly, with the quantile unit-root test, our empirical results are more capable of identifying the mean reversion properties under different quantiles. This study further posits heterogeneity in the conditional density of REIT prices, and these heterogeneous distributions can be effectively represented by the QAR models. Finally, to provide a complete analysis of short-run adjustments and the mean reversion process of REIT prices, we proceed by measuring the half-lives when stationarity is confirmed. The half-life provides a summary measure of how long it takes for REIT prices to dissipate by one-half after facing a unit of shock.

The rest of the paper is organized as follows. Section 2 provides a brief summary of the literature. Section 3 outlines the econometric methodology used in this paper. Section 4 illustrates the data and performs an empirical application using a quantile unit-root test on five REIT classifications, while Section 5 examines the robustness of the results. Section 6 presents the conclusions drawn plus a few salient policy implications as well as directions for future research based on the empirical findings from this extensive research.

2. Literature review

As is well known in asset pricing theory, the basic premise of the present value model is that financial asset prices are determined by the discounted values of expected future cash flows. However, in the case of asset prices which always deviate from fundamentals can be interpreted as rational speculative bubbles. In this regard, investors should be concerned about whether the deviations will return to its long-run equilibrium over time. This issue has been widely discussed using various financial assets in many empirical studies, such as Kleiman et al. (2002) for real estate share prices, Evans (2006) for future prices, and Lee et al. (2010) for stock prices, ever since the seminal works of Fama and French (1988), Lo and MacKinlay (1988), and Poterba and Summers (1988). If the mean reversion property holds, then asset prices should be characterized by a stationary process. This implies that random shocks have temporary effects on asset prices and future returns are predictable from historical price movements. The opposite is true when we are unable to reject the unit-root hypothesis for asset prices.

Even though there is a large body of literature that investigates the issue of mean reversion in financial markets, there is no consensus among analysts due to the inconclusive results therein. Some previous studies, for instance, support the mean reversion behavior (e.g., Chaudhuri and Wu, 2004; Lee et al., 2010), while others do not (e.g., Evans, 2006; Kleiman et al., 2002; Narayan and Smyth, 2007) or even support asymmetric mean reversion (Koutmos and Philippatos, 2007; Nam et al., 2002). Different findings on the validity of mean reversion depend on different techniques, time periods, and different financial assets.

For REITs, like any other financial assets, it may reasonably be expected that the analogous statement mentioned above applies to REIT markets. As discussed in Jirasakuldech et al. (2006) and Payne and Waters (2007), for example, a study of REIT markets presents three main reasons of interest as follows. First of all, there is a close link between REITs and the stock market from an empirical standpoint. As for the analogy to the stock market, rational speculative bubbles should be addressed in the REIT markets. Indeed, numerous empirical researchers note the existence of speculative bubbles in the housing market. Thus, REITs may be sensitive to speculative bubbles. The second reason is with regard to liquidity in REIT markets. According to the findings of Diamond and Verrecchia (1987) and Desai et al. (2002), short selling can be regarded as a signal of overvaluation in markets where prices continually rise beyond fundamental values. However, the REITs lack the capability to provide enough liquidity in support of short selling to signal overpricing or even a bubble forming in the market (Li and Yung, 2004). The third concern relates to the presence of asymmetric information, leading to the under-pricing of REITs' seasoned equity offerings such that market overvaluation is hard to detect (Ghosh et al., 2000). This study presents a detailed statistical analysis of the time-series properties to investigate the possible existence of the unit-root hypothesis in the REIT markets.

[1] For instance, Koenker and Xiao (2004) and Nikolaou (2008) respectively show asymmetries in the dynamic adjustment of interest rates and real exchange rates. In these cases, the characteristics of financial assets are described differently across the distribution of asset prices.

The number of REIT studies is still limited. Most of the earlier works which perform the linear unit-root test mainly focus on analyzing the linkage between varied REIT classifications — for example, He (1998), Payne and Mohammadi (2004), and Payne (2006), to mention a few. The results, roughly speaking, overwhelmingly suggest that the respective REITs are integrated of order one, I(1). Another strand of contemporary literature proceeds with detecting the presence of rational speculative bubbles by examining the possible existence of the unit-root hypothesis and the relationship between REIT prices and their fundamentals. Jirasakuldech et al. (2006), for instance, adopt four different bubble identification procedures – the linear unit-root test, Engle–Granger test, cointegration test, and a duration dependence test – to investigate the presence of rational speculative bubbles in REITs. From the unit-root test results, similar evidence shows that REIT prices and macroeconomic fundamentals are both I(1) series. Moreover, there exists a cointegration relationship between these two series, supporting the absence of bubbles.

It is now extensively supported that financial asset prices may exhibit non-linearity. Relying on momentum threshold autoregressive (MTAR) models, Payne and Waters (2005) address the possible asymmetries in the adjustment toward the long-run equilibrium between REIT prices and dividends. Waters and Payne (2007) extend the work of Jirasakuldech et al. (2006) to the non-linear context and discover the asymmetric dynamics of REIT prices. Furthermore, Tsai and Chiang (2013) apply the threshold error correction model to examine the asymmetric price adjustment behaviors of REIT and stock markets. This arouses our interest in understanding whether mean reversion property is affected by the price levels. This motivates us to apply the newly developed quantile unit-root test, which makes it possible that the mean reversion properties of REITs under different prices are identifiable and comparable to each other, and we propose some explanations for these inconclusive results.

3. Methodology

In this section, we briefly describe the quantile autoregression unit-root testing method proposed by Koenker and Xiao (2004), which is more powerful than the widely used augmented Dickey–Fuller (ADF) test when the shocks follow heavy-tailed processes. This procedure allows us to analyze the speed of mean reversion for a series with different shock magnitudes. More specifically, the QAR methodology is capable of revealing different mean reverting patterns by explicitly testing for a unit-root at different quantiles.

Consider the following ADF regression model:

$$y_t = \alpha_1 y_{t-1} + \sum_{j=1}^{q} \alpha_{j+1}\Delta y_{t-j} + u_t,\; t = 1, 2, \ldots, n, \tag{1}$$

where $y_t = \tilde{y}_t - \gamma_0 - \gamma_1 t$ denotes the de-trended REIT index with γ_0 and γ_1 being the parameter estimates, and u_t is random variable with zero mean and constant variance. In this setting, the AR coefficient α_1 measures the persistence of y_t. If $\alpha_1 = 1$, then y_t contains a unit-root, and if $|\alpha_1| < 1$, then y_t is mean reverting. Following the methodology suggested in Koenker and Xiao (2004), the τth conditional quantile of y_t, conditional on the $t - 1$ period information set $\Im_{t-1}$, can be expressed as a linear function of lagged values y_t as follows:

$$Q_{yt}(\tau|\Im_{t-1}) = x_t'\alpha(\tau), \tag{2}$$

where $x_t = (1, y_{t-1}, \Delta y_{t-1}, \ldots, \Delta y_{t-q})'$ and $\alpha(\tau) = (\alpha_0(\tau), \alpha_1(\tau), \ldots, \alpha_{q+1}(\tau))'$, with $\alpha_0(\tau)$ denoting the τth quantile of u_t. Note that $\alpha_1(\tau)$ measures the persistence of y_t within each quantile and is dependent on the τth quantile under investigation.

The estimation of $\alpha(\tau)$ in Eq. (2) involves solving this problem:

$$\min \sum_{t=1}^{n} \rho_\tau\left(y_t - x_t'\alpha(\tau)\right), \tag{3}$$

where $\rho_\tau(u) = u(\tau - I(u < 0))$ as given in Koenker and Bassett (1978) with I denoting an indicator function. Given the solution of Eq. (3) denoted by $\hat{\alpha}(\tau)$, Koenker and Xiao (2004) suggest testing the time-series properties of y_t within the τth quantile by using the following t ratio statistic:

$$t_n(\tau) = \frac{\hat{f}\left(F^{-1}(\tau)\right)}{\sqrt{\tau(1-\tau)}}\left(Y_{-1}' P_X Y_{-1}\right)^{1/2}\left(\hat{\alpha}_1(\tau) - 1\right), \tag{4}$$

where $\hat{f}\left(F^{-1}(\tau)\right)$ is a consistent estimator of $f(F^{-1}(\tau))$, with f and F respectively showing the density and distribution function of u_t in Eq. (1), Y_{-1} is the vector of lagged dependent variables (y_{t-1}), and P_X is the projection matrix onto the space orthogonal to $X = (1, \Delta y_{t-1}, \ldots, \Delta y_{t-q})$. Equipped with the test statistic $t_n(\tau)$, we can examine the unit-root properties of the series by looking at the behavior of each quantile. In other words, this not only enables us to take a closer look at the dynamics of the series, but also investigates possibly different mean reverting behaviors in the different quantiles. By contrast, the ADF test lacks the ability to detect such behavior.

Another approach to the analysis of the unit-root behavior based on the quantile framework involves testing the non-stationary properties over a range of quantiles, instead of only focusing on the selected quantile. For this purpose, the quantile Kolmogorov–Smirnov (KS) test is proposed by Koenker and Xiao (2004) and is given by:

$$\text{QKS} = \sup|t_n(\tau)|, \tag{5}$$

where $t_n(\tau)$ is defined in Eq. (4). In practice, we calculate $t_n(\tau)$ at $\tau \in \Gamma$, and thus the QKS test can be constructed by taking maximum over Γ.

The limiting distributions of the $t_n(\tau)$ and QKS tests are non-standard and dependent on nuisance parameters. A bootstrap procedure, suggested by Koenker and Xiao (2004), approximates their small-sample distributions as described below.

1 Fit the following q-order autoregression with Δy_t by ordinary least squares (OLS):

$$\Delta y_t = \sum_{j=1}^{q} \hat{\beta}_j \Delta y_{t-j} + \hat{u}_t, \tag{6}$$

and obtain estimates $\hat{\beta}_j$ for $j = 1, 2, \ldots, q$, as well as the residuals $\hat{u}_t$. This study chooses the lag length q by the Bayesian information criterion (BIC) with maximum lag set at 24.

2 Draw a bootstrap sample of u_t^* with replacement from the empirical distribution of the centered residuals $\tilde{u}_t = \hat{u}_t - (n-q)^{-1}\sum_{t=q+1}^{n}\hat{u}_t$.

3 Generate the bootstrap sample of Δy^*_t recursively using the fitted autoregression given by:

$$\Delta y_t^* = \sum_{j=1}^{q} \hat{\beta}_j \Delta y^*_{t-j} + u_t^*, \tag{7}$$

with $\hat{\beta}_j$ being OLS estimates in Eq. (6), and initial values $\Delta y_j^* = \Delta y_j$ for $j = 1, 2, \ldots, q$.

4 A bootstrap sample of y_t^* can be obtained based on:

$$y_t^* = y_{t-1}^* + \Delta y_t^*, \tag{8}$$

with $y_1^* = y_1$.

5 With the re-sample y_t^*, compute the bootstrap counterpart of the $t_n(\tau)$ and QKS tests, denoted by $t_n^*(\tau)$ and QKS*, respectively.

6 Repeat Steps 2 to 5 NB times, where NB is 3000 in this paper.

7 Compute the empirical distribution function of the NB values of the bootstrap $t_n(\tau)$ and QKS tests, and use this empirical distribution function as an approximation to the cumulative distribution function of the respective tests under the null.
8 Use the bootstrap *p*-value to make an inference.

4. Data and results

The data used in the paper are the natural logs of monthly prices for all, equity, mortgage, hybrid, and composite REITs, which are obtained from the National Association of Real Estate Investment Trusts (NAREITs). The sample data cover the time period from January 1972 to March 2010. Fig. 1 provides an overview of the movements of these REITs. It is obvious that the entire series exhibit similar trends, but different fluctuations. The plots also reveal some downturns including the two oil price shocks that occurred respectively in 1973–1974 and in 1979–1980, the stock market crash in the late 1980s, the Asian and Russian economic crises and the Internet bubble in the late 1990s, as well as the global financial crisis of 2008–2009.

For the purpose of comparison, the empirical work begins by considering traditional unit-root tests with a conditional mean specification for the respective REITs, as shown in Table 1. The ADF^{GLS} of Elliott et al.

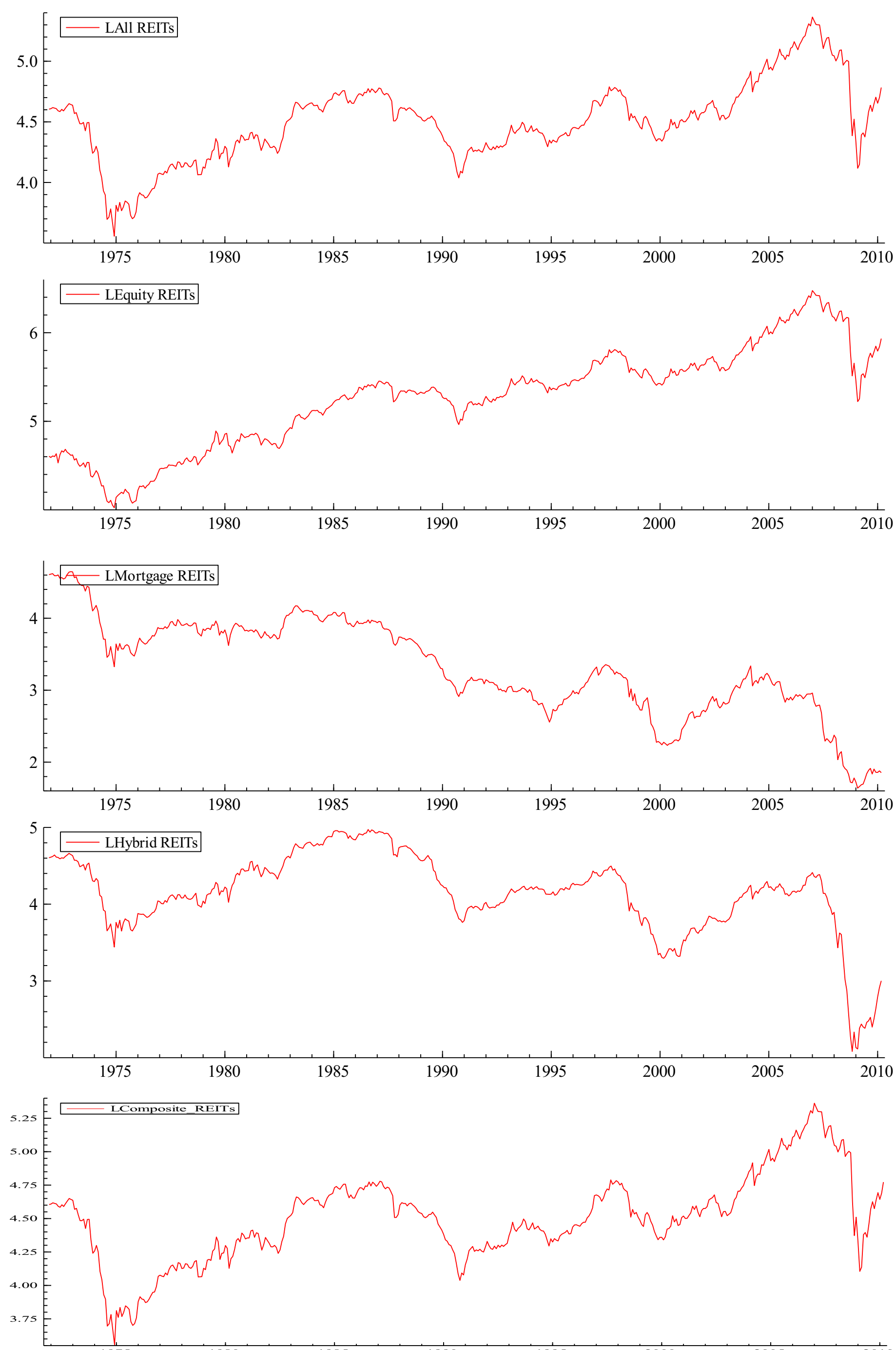

Fig. 1. Plots of REITs in log levels.

Table 1
The unit root tests for the REITs.

Classification	ADF^{GLS}	MZ_{α}^{GLS}
All REITs	−2.120 (6)	−9.811 (6)
Equity REITs	−2.618 (3)	−14.296† (3)
Mortgage REITs	−1.887 (1)	−7.378 (1)
Hybrid REITs	−2.251 (3)	−10.815 (3)
Composite REITs	−2.131 (6)	−9.905 (6)

Notes: †, * denotes significance at 10% and 5% levels, respectively. The 10%, 5% critical values are −2.620, −2.910 for ADF^{GLS}, and −14.200, −17.300 for MZ_{α}^{GLS}, respectively. Numbers in parenthesis denote the lag length chosen by the MAIC with the maximum lag set to be 24.

(1996) and MZ_{α}^{GLS} tests of Ng and Perron (2001) are employed to test the null hypothesis of a unit-root. The model is estimated with an intercept and a time trend. Moreover, since the estimation might be biased if the lag length is pre-designated without any rigorous determination, we adopt the newly developed Modified Akaike's Information Criterion (MAIC), as suggested by Ng and Perron (2001), in order to select the optimal number of lags based on the principle of parsimony. Overall, there is no evidence against the unit-root hypothesis no matter if it is all, equity, mortgage, hybrid, or composite REITs. The result is consistent with those of He (1998), Payne and Mohammadi (2004), Jirasakuldech et al. (2006), as well as Waters and Payne (2007), who utilize the traditional unit-root tests.

Instead of focusing attention on the mean of the distribution, we proceed to present the results of the quantile unit-root tests at the 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, and 0.9 probabilities over the 3000 replications of the estimated model. Moreover, we construct half-lives to investigate the persistence of deviations in REIT prices. Table 2 reports the results of QAR for a range of quantiles, including the estimated values of constant term $\alpha_0(\tau)$, autoregressive coefficient $\alpha_1(\tau)$, the QKS test, and half-lives. Note that the p-value for $\alpha_0(\tau)$ is investigating the null of zero with Student-*t* test, while the counterpart for $\alpha_1(\tau)$ is testing the unit-root null with $t_n(\tau)$ statistic. Obviously, both $\alpha_0(\tau)$ and $\alpha_1(\tau)$ have different behaviors for different quantiles. The coefficients of the intercept, which capture the magnitude of shocks, have a monotone increasing behavior. The impacts of shock are also similar across symmetric deciles — for example, the first and ninth deciles or the second and eighth deciles. This means that effects of a shock are symmetric. Negative (positive) sign of $\alpha_0(\tau)$ represents negative (positive) shock which might result from tightened (loosened) financial policy or economic recession (boom).

This QAR approach is in sharp contrast to existing studies of mean reversion and offers valuable new insights into REIT prices behavior. With respect to the autoregressive coefficients, which provide a closer look at the REIT dynamics by examining whether different quantiles exhibit the same mean reversion process, evidence shows that the behaviors of the entire REIT series are not constant. Specifically, we are able to reject the unit-root hypothesis on the middle quantiles for the all, hybrid, and composite REITs. With the other series, the equity REITs do not reject unit-root for the first two deciles, while the mortgage REITs do reject it for the last two deciles. Generally speaking, the null hypothesis of unit-root cannot be rejected for those relatively low REIT prices (low quantiles), while it can be rejected for those relatively high prices (middle and high quantiles). These results imply that the higher REIT prices are more likely to offer trading strategy for abnormal returns, while there are no abnormal returns when the prices are low.

One possible explanation for this asymmetric pattern is the lack of a complete market in REITs. In fact, as mentioned earlier, when the REIT prices continue to increase, it is difficult to perceive overvaluation because of constraints on short selling. Lack of a signal of overvaluation will likely broaden the scope of asymmetric information faced by investors, leading to noise trading and an increase in arbitrage opportunities for informed investors who capitalize on private information. In addition, the sequential information arrival models of Copeland (1976) and Jennings et al. (1981) suggest that a positive bi-directional causal relation exists between prices and trading volume. In other words, a market with relatively high REIT prices is more active than those of relatively low price levels. This active market is liquid enough to support arbitrage behavior driving prices back toward their long-run values. Furthermore, the finance literature has long recognized that trading activity is negatively related to the bid-ask spread, which presents implicit costs of transaction — for example, Demsetz (1968), Tinic (1972), and Stoll (1978), to mention a few. Thus, the higher active market also reflects the lower transaction cost, resulting in more profitable arbitrage opportunities.

Noteworthy here is that we also observe that the equity REITs reveal much more stationarity and the mortgage REITs present much less

Table 2
Empirical results of quantile estimation and unit-root tests for each quantile.

	τ	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
All	$\alpha_0(\tau)$	−0.055 (0.000)*	−0.028 (0.000)*	−0.018 (0.000)*	−0.008 (0.000)*	0.001 (0.314)	0.01 (0.000)*	0.02 (0.000)*	0.035 (0.000)*	0.052 (0.000)*
	$\alpha_1(\tau)$	0.975 (0.303)	0.977 (0.166)	0.989 (0.412)	0.984 (0.225)	0.979 (0.067)†	0.975 (0.021)*	0.976 (0.091)†	0.963 (0.015)*	0.954 (0.004)*
	Half−lives	∞	∞	∞	∞	32.659	27.377	28.533	18.384	14.719
	QKS for quantiles of 10–90%: 3.211 (0.042)*									
Equity	$\alpha_0(\tau)$	−0.051 (0.000)*	−0.027 (0.000)*	−0.016 (0.000)*	−0.007 (0.003)*	0.001 (0.353)	0.011 (0.000)*	0.02 (0.000)*	0.032 (0.000)*	0.051 (0.000)*
	$\alpha_1(\tau)$	0.995 (0.796)	0.979 (0.329)	0.972 (0.051)†	0.972 (0.035)*	0.973 (0.06)†	0.975 (0.078)†	0.967 (0.033)*	0.956 (0.010)*	0.946 (0.008)*
	Half−lives	∞	∞	24.407	24.407	25.323	27.377	20.655	15.404	12.486
	QKS for quantiles of 10–90%: 2.947 (0.100)†									
Mortgage	$\alpha_0(\tau)$	−0.067 (0.000)*	−0.035 (0.000)*	−0.02 (0.000)*	−0.01 (0.014)*	0.004 (0.132)	0.015 (0.000)*	0.026 (0.000)*	0.043 (0.000)*	0.061 (0.000)*
	$\alpha_1(\tau)$	1.022 (0.984)	1.008 (0.972)	0.997 (0.764)	1 (0.888)	0.992 (0.424)	0.985 (0.182)	0.987 (0.361)	0.98 (0.066)†	0.966 (0.013)*
	Half-lives	∞	∞	∞	∞	∞	∞	∞	34.309	20.038
	QKS for quantiles of 10–90%: 2.863 (0.120)									
Hybrid	$\alpha_0(\tau)$	−0.064 (0.000)*	−0.036 (0.000)*	−0.02 (0.000)*	−0.008 (0.001)*	0.002 (0.232)	0.013 (0.000)*	0.025 (0.000)*	0.04 (0.000)*	0.069 (0.000)*
	$\alpha_1(\tau)$	1.022 (0.99)	1.017 (1.000)	1.006 (0.983)	0.996 (0.643)	0.989 (0.092)†	0.977 (0.000)*	0.971 (0.001)*	0.96 (0.000)*	0.936 (0.000)*
	Half-lives	∞	∞	∞	∞	62.666	29.788	23.553	16.979	10.480
	QKS for quantiles of 10–90%: 5.686 (0.000)*									
Composite	$\alpha_0(\tau)$	−0.055 (0.000)*	−0.027 (0.000)*	−0.018 (0.000)*	−0.008 (0.000)*	0.001 (0.314)	0.01 (0.000)*	0.02 (0.000)*	0.036 (0.000)*	0.052 (0.000)*
	$\alpha_1(\tau)$	0.976 (0.331)	0.977 (0.168)	0.989 (0.405)	0.983 (0.194)	0.979 (0.056)†	0.976 (0.031)*	0.975 (0.097)†	0.963 (0.015)*	0.954 (0.004)*
	Half-lives	∞	∞	∞	∞	32.659	28.533	27.377	18.384	14.719
	QKS for quantiles of 10–90%: 3.178 (0.055)†									

Notes: † and * denote significance at 10% and 5% levels, respectively. Numbers in parenthesis denote bootstrap *p*-values with the bootstrap replications set to be 3000. Lag length was chosen by the BIC with the maximum lag set to be 24. For $\alpha_0(\tau)$, the null of zero is tested with the student-*t* test, while for $\alpha_1(\tau)$, the unit-root null is examined with the $t_n(\tau)$ statistic.

Table 3
Robustness analysis for different chosen levels of probabilities.

	τ	0.05	0.10	0.15	0.20	0.25	0.50	0.75	0.80	0.85	0.90	0.95
All	$\alpha_0(\tau)$	−0.081	−0.055	−0.039	−0.028	−0.022	0.001	0.027	0.035	0.042	0.051	0.065
		(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.307)	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*
	$\alpha_1(\tau)$	1.005	0.975	0.981	0.978	0.984	0.979	0.972	0.962	0.956	0.954	0.940
		(0.865)	(0.316)	(0.493)	(0.184)	(0.180)	(0.065)†	(0.039)*	(0.008)*	(0.001)*	(0.008)*	(0.058)†
	QKS for quantiles of 10–90%: 3.187 (0.044)*											
Equity	$\alpha_0(\tau)$	−0.076	−0.051	−0.038	−0.027	−0.021	0.001	0.026	0.032	0.04	0.051	0.061
		(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.401)	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*
	$\alpha_1(\tau)$	0.976	0.995	0.994	0.98	0.98	0.975	0.966	0.959	0.952	0.948	0.952
		(0.616)	(0.801)	(0.776)	(0.396)	(0.278)	(0.112)	(0.050)†	(0.016)*	(0.004)*	(0.003)*	(0.044)*
	QKS for quantiles of 10–90%: 3.106 (0.066)*											
Mortgage	$\alpha_0(\tau)$	−0.123	−0.067	−0.047	−0.035	−0.025	0.004	0.035	0.043	0.053	0.061	0.082
		(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.131)	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*
	$\alpha_1(\tau)$	1.019	1.022	1.014	1.008	0.998	0.992	0.977	0.98	0.965	0.966	0.946
		(0.941)	(0.978)	(0.988)	(0.969)	(0.841)	(0.436)	(0.038)*	(0.065)†	(0.003)*	(0.013)*	(0.011)*
	QKS for quantiles of 10–90%: 2.869 (0.134)											
Hybrid	$\alpha_0(\tau)$	−0.112	−0.064	−0.048	−0.036	−0.028	0.001	0.033	0.04	0.051	0.069	0.088
		(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.378)	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*
	$\alpha_1(\tau)$	1.07	1.023	1.022	1.017	1.012	0.993	0.967	0.96	0.951	0.935	0.925
		(1.000)	(0.991)	(0.999)	(0.999)	(0.998)	(0.341)	(0.001)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*
	QKS for quantiles of 10–90%: 5.642 (0.000)*											
Composite	$\alpha_0(\tau)$	−0.081	−0.055	−0.039	−0.028	−0.022	0.001	0.027	0.035	0.043	0.051	0.066
		(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.312)	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*
	$\alpha_1(\tau)$	1.004	0.976	0.982	0.978	0.984	0.979	0.972	0.961	0.955	0.953	0.941
		(0.858)	(0.326)	(0.514)	(0.203)	(0.187)	(0.057)†	(0.046)*	(0.006)*	(0.001)*	(0.007)*	(0.058)†
	QKS for quantiles of 10–90%: 3.183 (0.053)*											

Notes: † and * denote significance at 10% and 5% levels, respectively. Numbers in parenthesis denote bootstrap *p*-values with the bootstrap replications set to be 3000. Lag length was chosen by the BIC with the maximum lag set to be 24. For $\alpha_0(\tau)$, the null of zero is tested with the student-*t* test, while for $\alpha_1(\tau)$, the unit-root null is examined with the $t_n(\tau)$ statistic.

stationarity than otherwise. This implies that the equity REITs facilitate the presence of mean reversion. The reason for this probably is related to different types of the invested assets in real estate. More specifically, the equity REITs hold at least 75% of their assets in income generating real estate properties, whereas the mortgage REITs hold at least 75% of their assets in mortgages secured by real estate, as classified by NAREITs. Different forms of REITs may possess different behavior characteristics (He, 1998; Horng and Wei, 1999; Payne and Mohammadi, 2004). In general, equity REITs possess a stock-like behavior and mortgage REITs possess a bond-like behavior (Glascock et al., 2000), leading to different characteristics on their own price, return, risk, and liquidity. In this regard, equity REITs outperform mortgage REITs, even though the risk of equity REITs is less than that of mortgage REITs (see Chan et al., 2003, for a survey). Given that the equity REITs are more dominated by large investors along with increased market liquidity, equity REITs are liquid enough to support arbitrage behavior driving prices back toward their long-run values.

In summary, our empirical results show that the random walk properties only hold for those of low REIT prices, whereas mean reversion properties only exist in relatively high REIT prices. In contrast to the existing literature, which applies unit-root tests to detect the mean reverting tendency but does not further provide a reason of whether the mean reversion is supported or not, our study employs the advanced quantile unit-root test to carefully analyze the specification of the model and identifies REIT prices as a mixture of I(0) and I(1) processes, implying that there are different mean reverting behaviors for different REIT prices. Another noteworthy insight of the above-mentioned findings is that the results of bubble detection are able to be obtained from the analysis when the REIT prices are low. The fragility and lack of meaningful results, on the other hand, abound when the prices of REITs are high.

It is important to note that the degree of mean reversion, i.e., the speed of convergence toward the long-run equilibrium. With this in mind, the half-life is conducted to explore the persistence of deviations in REIT prices. Only stationary series are allowed to calculate half-lives. The results show that the half-life decreases as one moves from the lower quantiles to the upper quantiles. Notice that a higher speed of reversion implies a shorter half-life. Our results demonstrate that the adjustment speed of mean reversion depends on the size of the shock. The extreme quantiles (either 0.8 or 0.9 quantiles) reveal that the convergence speed is much faster when the REIT prices are high toward the long-run equilibrium, stressing the role of the price level. In general, these results not only exhibit the asymmetric dynamic adjustment patterns, but also emphasize that the speed of convergence is affected by the level of prices.

The convergence speeds of different REIT classifications at different quantiles are also comparable to each other. Except for the 0.9 quantile, the speed of equity REITs appears to be the fastest across all REIT classifications. When the 0.9 quantile is considered, however, the speed of hybrid REITs becomes the fastest. Some additional information emerges after taking the average speed of adjustment toward the equilibrium for those of the five respective REITs. The fastest average adjustment speeds are found in equity REITs (21.44 months), followed by all and composite REITs (24.33 months), mortgage REITs (27.17 months), and hybrid REITs (28.69 months). Therefore, the classification of REITs is an important factor affecting the convergence speed.

We also apply the Kolmogorov–Smirnov test (QKS) to examine the null of a constant unit-root process for a range of quantiles of 10–90%. The results show that we are able to reject the unit-root hypothesis at the 5% level for both all and hybrid REITs, at the 10% level for both equity and composite REITs, but not for mortgage REITs. Though not for all REIT classifications, we generally obtained strong evidence that REITs do not follow a constant unit-root process. Therefore, the traditional linear unit-root test (as shown in Table 1) is not suitable for detecting the unit-root properties of financial assets.

5. Robustness checks

In this section, we conduct a number of sensitivity analyses to assess the robustness of the result. First, one may suspect that REIT prices have a unit root for the lower quantiles, but not for those of upper quantiles, which may be affected by the chosen level of probabilities. In this regard, we split the two extremes (lower and upper) of the quantiles into smaller value of probabilities and repeat the quantile unit-root test utilized above for this specification. Specifically, the more the quantiles are considered, the more accurate and detailed the picture of

Table 4
Robustness analysis for individual REIT prices.

	τ	0.05	0.10	0.15	0.20	0.25	0.50	0.75	0.80	0.85	0.90	0.95
Apartments	$\alpha_0(\tau)$	−0.104	−0.071	−0.048	−0.037	−0.024	0.000	0.032	0.042	0.050	0.065	0.081
		(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.478)	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*
	$\alpha_1(\tau)$	0.930	0.971	0.922	0.937	0.946	0.955	0.949	0.929	0.924	0.942	0.942
		(0.147)	(0.592)	(0.212)	(0.279)	(0.258)	(0.064)†	(0.186)	(0.105)	(0.071)†	(0.224)	(0.069)†
	QKS for quantiles of 10–90%: 2.760 (0.155)											
Equity diversified	$\alpha_0(\tau)$	−0.107	−0.074	−0.045	−0.034	−0.022	0.005	0.030	0.040	0.050	0.058	0.080
		(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.103)	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*
	$\alpha_1(\tau)$	1.043	0.974	0.938	0.924	0.943	0.954	0.976	0.969	0.969	0.972	0.927
		(0.937)	(0.679)	(0.295)	(0.107)	(0.153)	(0.009)*	(0.323)	(0.238)	(0.373)	(0.467)	(0.056)†
	QKS for quantiles of 10–90%: 2.970 (0.075)†											
Free standing	$\alpha_0(\tau)$	−0.081	−0.062	−0.052	−0.043	−0.029	0.005	0.029	0.035	0.046	0.062	0.074
		(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.197)	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*
	$\alpha_1(\tau)$	1.012	0.954	0.930	0.925	0.942	0.958	0.964	0.956	0.910	0.877	0.829
		(0.868)	(0.343)	(0.159)	(0.166)	(0.341)	(0.310)	(0.215)	(0.176)	(0.021)*	(0.004)*	(0.006)*
	QKS for quantiles of 10–90%: 3.324 (0.040)*											
Health care	$\alpha_0(\tau)$	−0.106	−0.058	−0.047	−0.038	−0.032	0.000	0.037	0.044	0.049	0.060	0.085
		(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.485)	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*
	$\alpha_1(\tau)$	0.964	1.014	1.010	0.991	1.004	0.987	0.912	0.931	0.930	0.901	0.929
		(0.672)	(0.925)	(0.930)	(0.715)	(0.916)	(0.605)	(0.000)*	(0.000)*	(0.033)*	(0.047)*	(0.202)
	QKS for quantiles of 10–90%: 3.773 (0.009)*											
Industrial	$\alpha_0(\tau)$	−0.118	−0.062	−0.055	−0.045	−0.032	0.006	0.041	0.047	0.057	0.065	0.088
		(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.160)	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*
	$\alpha_1(\tau)$	0.988	0.964	0.968	0.973	0.965	0.976	0.978	0.977	0.966	0.969	0.976
		(0.797)	(0.219)	(0.355)	(0.339)	(0.077)†	(0.186)	(0.177)	(0.109)	(0.055)†	(0.154)	(0.194)
	QKS for quantiles of 10–90%: 1.963 (0.538)											
Industrial/office	$\alpha_0(\tau)$	−0.111	−0.054	−0.048	−0.035	−0.023	0.004	0.040	0.043	0.048	0.059	0.075
		(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.214)	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*
	$\alpha_1(\tau)$	0.999	0.933	0.928	0.945	0.944	0.968	0.951	0.945	0.939	0.950	0.954
		(0.818)	(0.132)	(0.113)	(0.060)†	(0.009)*	(0.145)	(0.013)*	(0.004)*	(0.002)*	(0.054)†	(0.144)
	QKS for quantiles of 10–90%: 3.311 (0.044)*											
Lodging/resorts	$\alpha_0(\tau)$	−0.124	−0.098	−0.066	−0.048	−0.036	0.010	0.054	0.062	0.073	0.082	0.109
		(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.077)†	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*
	$\alpha_1(\tau)$	1.058	1.024	1.005	0.991	0.989	0.960	0.932	0.930	0.935	0.936	0.918
		(0.982)	(0.969)	(0.898)	(0.743)	(0.696)	(0.096)	(0.001)*	(0.000)*	(0.004)*	(0.029)*	(0.071)†
	QKS for quantiles of 10–90%: 4.557 (0.002)*											
Manufactured homes	$\alpha_0(\tau)$	−0.096	−0.053	−0.042	−0.031	−0.019	0.004	0.030	0.035	0.045	0.055	0.066
		(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.196)	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*
	$\alpha_1(\tau)$	1.144	0.992	1.009	1.019	0.973	0.953	0.907	0.908	0.855	0.820	0.830
		(0.994)	(0.816)	(0.914)	(0.949)	(0.545)	(0.069)†	(0.000)*	(0.002)*	(0.000)*	(0.000)*	(0.008)*
	QKS for quantiles of 10–90%: 6.196 (0.000)*											
Office	$\alpha_0(\tau)$	−0.100	−0.069	−0.051	−0.039	−0.032	0.004	0.035	0.044	0.052	0.062	0.084
		(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.210)	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*
	$\alpha_1(\tau)$	0.942	0.936	0.931	0.929	0.927	0.962	0.952	0.958	0.953	0.934	0.957
		(0.503)	(0.227)	(0.104)	(0.055)†	(0.025)*	(0.129)	(0.032)*	(0.183)	(0.085)†	(0.120)	(0.255)
	QKS for quantiles of 10–90%: 2.333 (0.384)											
Regional malls	$\alpha_0(\tau)$	−0.124	−0.075	−0.050	−0.043	−0.033	0.004	0.038	0.044	0.056	0.064	0.085
		(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.220)	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*
	$\alpha_1(\tau)$	0.999	0.961	0.983	0.986	0.987	0.964	0.966	0.967	0.974	0.978	0.956
		(0.820)	(0.352)	(0.606)	(0.662)	(0.620)	(0.037)*	(0.064)†	(0.040)*	(0.195)	(0.307)	(0.238)
	QKS for quantiles of 10–90%: 2.560 (0.210)											
Residential	$\alpha_0(\tau)$	−0.102	−0.069	−0.049	−0.036	−0.024	0.000	0.032	0.041	0.050	0.064	0.080
		(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.498)	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*
	$\alpha_1(\tau)$	0.926	0.956	0.930	0.934	0.946	0.941	0.942	0.928	0.926	0.947	0.939
		(0.105)	(0.438)	(0.337)	(0.241)	(0.266)	(0.013)*	(0.123)	(0.095)†	(0.078)†	(0.252)	(0.088)†
	QKS for quantiles of 10–90%: 2.968 (0.099)†											
Retail	$\alpha_0(\tau)$	−0.097	−0.061	−0.044	−0.035	−0.023	0.002	0.031	0.043	0.050	0.058	0.075
		(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.337)	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*
	$\alpha_1(\tau)$	0.995	0.975	0.956	0.957	0.961	0.966	0.980	0.983	0.978	0.988	0.973
		(0.806)	(0.495)	(0.295)	(0.188)	(0.092)†	(0.057)†	(0.238)	(0.281)	(0.188)	(0.563)	(0.461)
	QKS for quantiles of 10–90%: 2.454 (0.275)											
Self-storage	$\alpha_0(\tau)$	−0.094	−0.061	−0.047	−0.040	−0.032	0.004	0.033	0.045	0.051	0.066	0.085
		(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.259)	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*
	$\alpha_1(\tau)$	0.901	0.956	0.950	0.945	0.958	0.972	0.990	0.974	0.956	0.928	0.932
		(0.478)	(0.396)	(0.235)	(0.111)	(0.262)	(0.515)	(0.707)	(0.507)	(0.224)	(0.069)†	(0.295)
	QKS for quantiles of 10–90%: 2.029 (0.623)											
Shopping centers	$\alpha_0(\tau)$	−0.100	−0.053	−0.042	−0.033	−0.025	0.002	0.029	0.035	0.046	0.057	0.074
		(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.340)	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*
	$\alpha_1(\tau)$	0.937	0.974	0.962	0.966	0.967	0.975	0.992	0.987	1.000	0.994	0.993
		(0.473)	(0.492)	(0.257)	(0.187)	(0.145)	(0.200)	(0.614)	(0.472)	(0.777)	(0.699)	(0.626)
	QKS for quantiles of 10–90%: 2.509 (0.234)											
Specialty	$\alpha_0(\tau)$	−0.107	−0.075	−0.061	−0.034	−0.027	0.006	0.040	0.047	0.055	0.070	0.096
		(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.012)*	(0.009)*	(0.233)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*
	$\alpha_1(\tau)$	0.941	0.975	0.996	0.981	0.985	0.990	0.971	0.976	0.985	0.996	0.984
		(0.541)	(0.598)	(0.827)	(0.656)	(0.648)	(0.692)	(0.108)	(0.155)	(0.535)	(0.705)	(0.550)
	QKS for quantiles of 10–90%: 1.560 (0.902)											

Notes: † and * denote significance at 10% and 5% levels, respectively. Numbers in parenthesis denote bootstrap p-values with the bootstrap replications set to be 3000. Lag length was chosen by the BIC with the maximum lag set to be 24. For $\alpha_0(\tau)$, the null of zero is tested with the student-t test, while for $\alpha_1(\tau)$, the unit-root null is examined with the $t_n(\tau)$ statistic.

the conditional distribution. To highlight the accurate behavior of the lower and upper quantiles, we proceeded to present the results of the quantile unit-root tests at the 0.05, 0.10, 0.15, 0.20, 0.25, 0.50, 0.75, 0.80, 0.85, 0.90 and 0.95 probabilities over the 3000 replications of the estimated model, as reported in Table 3. We also found that all REIT classifications reject the unit-root null only for those of upper quantiles, which are robustly supported by taking different chosen level of probabilities into account.

Second, it is worth asking whether the pattern is also present for more REIT sub-sectors. To this end, we redo the quantile unit-root test utilized above for individual REITs: apartments, equity diversified, free standing, health care, industrial, industrial/office, lodging/resort, manufactured homes, office, regional malls, residential, retail, self storage, shopping centers, and specialty. The test results are presented in Table 4.

Different from previous works, such as Payne and Waters (2007), which find that prices of various REIT sub-sectors including apartment, industrial, lodging, manufactured homes, office and regional malls are stationary after first-differencing, we offer novel insights on the dynamics and persistence in the REIT sub-sectors under different quantiles. It turns out that most of the individual REITs reveal similar patterns in price series, except for retail, shopping centers, and specially price series. Therefore, the robustness of the results is fully supported, and a clear conclusion as to the mean reversion properties only holds for those of relatively high REIT prices (middle and high quantiles) emerges.

6. Concluding remarks and implications

This paper is devoted to providing new insights on the dynamics and persistency in REITs and broadening our capacity to conduct rigorous empirical research. The main objective is to examine the failure of previous studies to properly characterize the time-series properties by not incorporating potentially asymmetric dynamics. Unlike traditional linear unit-root tests, the advanced quantile unit-root test seems to have more robustness and better power, particularly for the non-normality of the REITs, in detecting the presence of the unit-root hypothesis. As a result, our quantile analysis is capable of identifying the mean reversion property under different quantiles. Moreover, compared to the traditional counterparts, the quantile framework makes no assumption about the distribution of the REITs, and can accommodate its potential heavy-tailed characteristic, which leads to a significant power improvement.[2]

If the presence of nonlinearities is empirically supported, then researchers should try to incorporate them into theoretical models and empirical analyses. By inspecting the results as a whole, we find various behaviors across different quantiles, representing asymmetric dynamics in REITs. The price of REITs is a mixture of I(0) and I(1) processes, and the stationary properties only hold for those relatively high REIT prices (middle and high quantiles), supporting the notion of existing mean reversion only for high REIT prices. When the prices are relatively low (low quantiles), there is no evidence of mean reversion supporting the random walk hypothesis in the REIT market. These results indicate that there are different mean reverting behaviors for different levels of REIT prices. With respect to econometric modeling and requiring knowledge on the unit-root properties, one can obtain meaningful results of bubble detection from the analysis when the REIT prices are relatively low.

The equity REIT prices reveal that most stationary quantiles and the mortgage REITs have the most non-stationary quantiles. This result seems to reflect that the possibility of mean reversion is high in equity REITs, while it is low in mortgage REITs. Finally, for the persistence measures, the higher the price is, the faster the speed of convergence will be. For a detailed comparison, on average, the adjustment speed of equity REITs is the fastest in contrast with the other REIT classifications. For a specific quantile, the speed of hybrid REITs is the fastest in the 0.9 quantile. Overall, these results not only exhibit asymmetric dynamic adjustment, but also stress that the level of prices and the classifications of REITs stand as the key factors affecting the convergence speed. To check the robustness of these results, we also perform several investigations by using more detailed levels of probabilities in both lower and upper quantiles, and individual REITs. It turns out that we are confident the results are robust.

Our ability to identify mean reverting series with different quantiles allows us to focus on the half-lives of the mean reverting REIT prices only. Several implications can be drawn from our empirical results. First, the mean reversion series, belonging to the higher prices, suggest that shocks to the REIT prices have no long-lasting effects. Any intervention policies may not be over-implemented in the REIT market for high quantiles. The series will revert back to its trend path over time. Second, evidence in favor of a unit-root is found for lower prices, implying that REIT prices are characterized by the random walks and shocks have permanent effects. This further shows that price movements are unpredictable for the low quantile. In addition, the unit-root hypothesis supports the use of a cointegration framework for econometric modeling. Third, higher REIT prices are more likely to offer profitable trading strategy, while there are no abnormal returns when the prices are low. Finally, the administrative policy of the government for the REIT market should be concerned about the potential influence of the price levels as well as asset types.

The understanding of the asymmetric behavior of REIT prices can be improved along with many dimensions. First, one avenue of inquiry would be inclusion of covariates which leads to a more precise estimated autoregressive coefficient when testing for unit root, such as a newly developed unit-root test based on the *covariate quantile autoregression* (CQAR) approach proposed by Galvao (2009). Second, future research could further generalize to examine the cases of heterogeneous adjustment in time series models which control for lagged regressors and exogenous covariates like how the *Quantile autoregressive distributed lag* (QADL) model developed by Galvao et al. (2013) did. It is hoped that similar studies are conducted in the future.

[2] As shown by Koenker and Xiao (2004), the quantile-based tests have superior power than the conventional least squares-based unit root tests in the presence of non-Gaussian disturbances by means of the Monte Carlo simulation.

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