Journal of
Risk and Financial Management

MDPI

Article

Overreaction in the REITs Market: New Evidence from Quantile Autoregression Approach

Geoffrey M. Ngene [1,*], Catherine Anitha Manohar [2] and Ivan F. Julio [3]

1 Stetson-Hatcher School of Business, Mercer University, 1501 Mercer University Drive, Macon, GA 32107, USA
2 Ageno School of Business, Golden Gate University, 536 Mission St. San Francisco, CA 94105, USA; cmanohar@ggu.edu
3 Metropolitan College, Boston University, 1010 Commonwealth Avenue, RM 428, Boston, MA 02215, USA; julio@bu.edu
* Correspondence: ngene_gm@mercer.edu; Tel.: +1-478-301-2719

Received: 9 October 2020; Accepted: 10 November 2020; Published: 15 November 2020

check for updates

Abstract: Real estate investment trusts (REITs) provide portfolio diversification and tax benefits, a stable stream of income, and inflation hedging to investors. This study employs a quantile autoregression model to investigate the dependence structures of REITs' returns across quantiles and return frequencies. This approach permits investigation of the marginal and aggregate effects of the sign and size of returns, business cycles, volatility, and REIT eras on the dependence structure of daily, weekly, and monthly REIT returns. The study documents asymmetric and misaligned dependence patterns. A bad market state is characterized by either positive or weakly negative dependence, while a good market state is generally marked by negative dependence on past returns. The results are consistent with under-reaction to good news in a bad state and overreaction to bad news in a good state. Past negative returns increase and decrease the predictability of REIT returns at lower and upper quantiles, respectively. Extreme positive returns in the lower (upper) quantiles dampen (amplify) autocorrelation of daily, weekly, and monthly REIT returns. The previous day's REIT returns dampen autoregression more during recession periods than during non-recession periods. The marginal impact of the high volatility of daily returns supports a positive feedback trading strategy. The marginal impact of the Vintage REIT era on monthly return autocorrelation is higher than the New REIT era, suggesting that increased participation of retail and institutional investors improves market efficiency by reducing REITs' returns predictability. Overall, the evidence supports the time-varying efficiency of the REITs markets and adaptive market hypothesis. The predictability of REIT returns is driven by the state of the market, sign, size, volatility, and frequency of returns. The results have implications for trading strategies, policies for the real estate securitization process, and investment decisions.

Keywords: EREIT; MREIT; quantile; dependence; overreaction; autoregression

1. Introduction

Real estate investment trusts (REITs) are broadly categorized into equity REITs (EREITs) and mortgage REITs (MREITs). EREITs typically own and operate income-producing physical real estate. The total returns of EREITs consist of rental income paid by the tenants and changes in the value of properties they own. The MREITs invest in mortgage-backed securities (MBS) and engage in the provision of mortgages by real estate debt owners. The total returns of MREITs consist of interest income and changes in the present value of MBS. EREITs and MREITs significantly differ in their funding profile, business model, and asset base. These differences underlie their classifications where

EREITs (MREITs) are classified under the Real Estate (Financial) sector, according to the Global Industry Classification Standard (GICS).

The singular features that define the REIT market have evolved primarily due to structural and regulatory reforms (Shen et al. 2020). For example, the seminal studies of Peterson and Hsieh (1997) and Karolyi and Sanders (1998) show that the 90% distribution requirement on REITs ensures a steady and predictable income stream to REIT investors, making REITs bond-like financial assets. Indeed, REIT returns and bond returns were strongly positively correlated, particularly before the 1990s. Following a series of regulatory and structural reforms in the REIT market in the early 1990s, REIT returns started to mirror non-REIT stock returns (Glascock et al. 2000; Clayton and MacKinnon 2003, among others), vastly co-moving with the small-cap stock returns. These features make the REIT market an exciting area of research. Unlike non-REIT stocks, REITs offer portfolio diversification and tax benefits, inflation hedging, and a stable income stream.[1]

Feng et al. (2011) note that since its inception in 1960, the REIT market has experienced several regulatory and structural changes, triggering dramatic changes in its size, nature, and structure. The reforms in the 1990s caused a remarkable growth in the REIT market.

The market capitalization (MC) of EREIT (MREIT) soared from \$26B (\$3.4B) in 1993 to \$400B (\$29B) in 2006 before dipping to \$289B (\$19B) in 2007 due to the GFC. The MC recovered \$1.25T and \$83B in 2019 for the EREIT and MREIT, respectively. Figure 1a graphically illustrates the growth of MC of EREIT and MREIT since 1972. The 1994–2020 period defines the New REIT Era. The 1982–1993 period defined the Vintage REIT Era when the REITs were merely passive income-generating, long-term, real estate assets without the flexibility to operate as growth-oriented property trading mutual funds. (See Shen et al. 2020 and Feng et al. 2011).

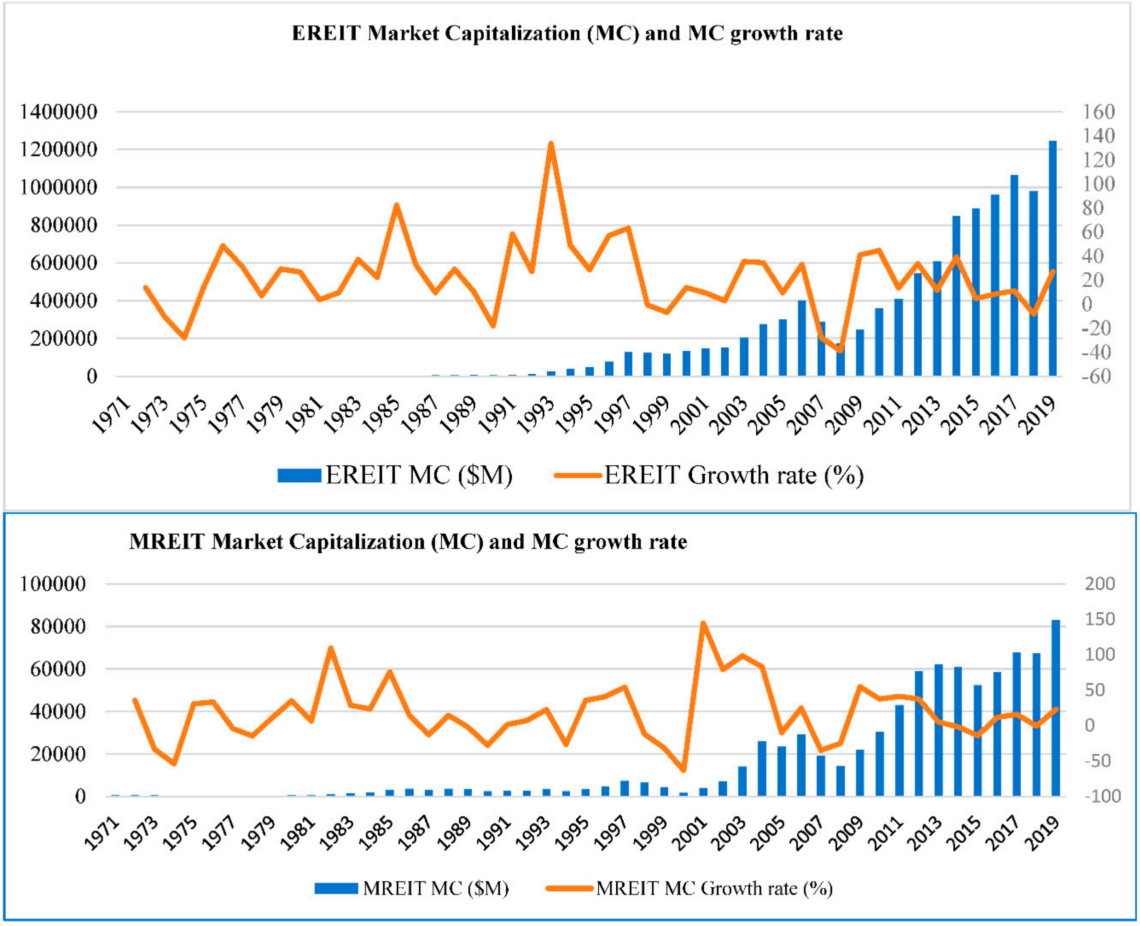
Autocorrelation is one of the most extensively studied features of financial asset returns. The presence of autocorrelation in returns implies the predictability of asset returns and contradicts the efficient market hypothesis (EMH). Past studies on the efficiency of the REITs markets have provided mixed evidence. On the one hand, Ho and Tay (2016); Aguilar et al. (2018); Hui et al. (2014); Zhou and Lee (2013); Schindler (2011); Jirasakuldech and Knight (2005); Lee and Chiang (2004) and Kleiman et al. (2002), among others, have offered evidence in support of random walk and efficiency of the REITs markets. Conversely, other studies have documented evidence of inefficiency or predictability in the REITs markets. Quintessentially, market inefficiency is inferred from evidence of (i) mean reversion of REITs returns and the failure of REITs prices to follow a random walk process (Mei and Gao 1995; Kuhle and Alvayay 2000; Simon 2002; Schindler et al. 2010), (ii) pricing anomalies in the REITs markets (Hui and Yam 2014; Lee et al. 2014), (iii) long memory in REITs returns and volatility (Assaf 2015; Cotter and Stevenson 2008 and Liow 2009) and (iv) short-term continuation of previous price movements or momentum (Chui et al. 2003; Hung and Glascock 2008; Goebel et al. 2013; Feng et al. 2014 and Hao et al. 2016).

These studies employ conditional mean of the return distribution to examine the influence of a lagged REITs' return on the current REIT return.

In contrast, the present study attempts to offer a detailed description of the full return distribution conditional on a lagged return. To this end, we use the quantile autoregression (QAR) framework of Koenker and Xiao (2006), a variant of the quantile regression developed by Koenker and Bassett (1978). In the present study, the QAR model is used to study the impact of lagged REIT returns

1 Chandrashekaran (1999) shows that REITs offer portfolio diversification benefits in a dynamic asset allocation setting. REITs' diversification benefit is increasing in holding period (Stephen and Simon 2005). Regarding inflation hedge, Mull and Soenen (1997) find that EREITs fare well during periods of rising prices. For example, US EREITs with underlying commercial holdings commonly have agreements allowing them to increase rents in response to a rise in inflation. REITs' investors sidestep double taxation on corporate income and personal income (dividends) since REITs earnings are untaxed at the corporate level. REITs offer a stable income stream, especially to retirement savers and retirees, since REITs are legally mandated to distribute at least 90% of their taxable earnings. Furthermore, tenants' contractual rent (or interest income in the case of MREITs) on real estate properties ensures a stable income stream.

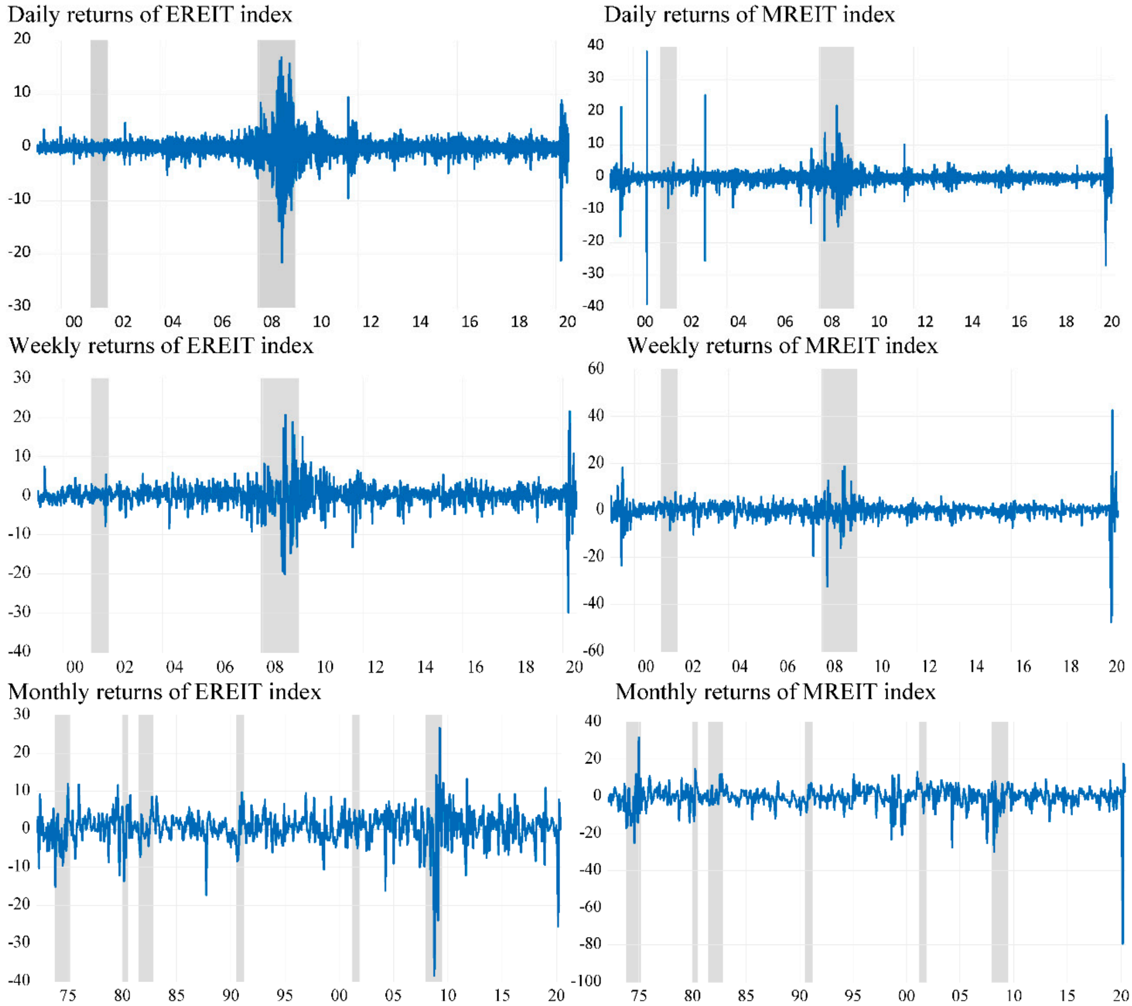
on all quantiles of REIT returns. The model has been applied by Baur et al. (2012); Baur (2013); and Li et al. (2016), inter alia, to investigate asymmetric autocorrelation in stock market returns. Chevapatrakul and Mascia (2019) also employ the QAR model to investigate investors' overreaction in the cryptocurrency market. We utilize the QAR model to analyze REITs' return dynamic dependence patterns on past returns, the impact of extreme past positive and negative returns, and business cycles' influence on REITs' returns autocorrelation. The study adds a new dimension to the emerging literature in REITs research by investigating the potential presence of investors' overreaction and under-reaction to macroeconomic news across different return distributions and return frequencies. Existing studies have not addressed the autocorrelation structure of daily, weekly, and monthly REIT returns.



Note: The market capitalization data is from National Association of Real Estate Investment Trusts (NAREIT). The authors computed the growth rate.

(**a**)

Figure 1. *Cont.*



(**b**)

Figure 1. (**a**) Market capitalization (MC) of equity real estate investment trusts (EREITs) and mortgage real estate investment trusts (MREITs) since 1972. (**b**) Time series of EREIT and MREIT returns at daily, weekly and monthly frequencies.

What causes return autocorrelation? Finance literature provides the theoretical foundation of stock returns autocorrelation.[2] Among the most prominent causes of the autocorrelation of returns is delayed price adjustment, which causes a partial price adjustment effect (PPA). There are three major perspectives on the PPA effects. First, according to Copeland (1976) and Jennings et al. (1981), sequential arrival of information in the market, followed by the sequential acquisition of information by investors (Holden and Subrahmanyam 2002), creates trends in stock price movement, thereby, generating positive autocorrelation of returns. Second, even in the presence of instantaneous arrival of information, there is a delay by the agents in processing the information and acting on it due to transaction costs and limited mental capabilities (Mech 1993). The slow price adjustments would create a trend in price formation behavior, resulting in positive autocorrelation of returns. Lastly,

[2] A natural question is whether REITs are similar to non-REIT stocks. There are unique requirements which differentiate REITs from non-REIT stocks and bonds. Specifically, at least 75 % of a REIT's assets must be invested in real estate. REITs must also redistribute at least 90% of their taxable income as dividends to shareholders. These idiosyncratic and restrictive requirements ensure that the performance of REITs and the underlying assets are closely linked. Past studies have found that REITs are more similar to non-REIT equities (stocks) than bonds. Therefore, models and theories associated with non-REIT stocks can be applied to REITs.

investors generally make systematic errors in interpretation of information leading to overreaction, overshooting of the asset price, and subsequent price reversals to the fundamental value, thereby generating a negative autocorrelation of returns. Overreactions to information may be initiated by the interplay of the conservatism and representativeness (Barberis et al. 1998) or overconfidence and self-attribution bias of irrational investors (Daniel et al. 1998). The existence of positive (negative) feedback trading may reinforce (dampen) price overreactions.[3] Using an intertemporal, rational expectations equilibrium model of asset pricing, Veronesi (1999) finds that investors' reaction to macro news is state-dependent. Specifically, investors tend to overreact to bad news during market booms (good state or upper quantiles) and under-react to good news during market depressions (bad state or lower quantiles). Therefore, the impact of lagged returns or degree of return persistence differs across quantiles of conditional distribution on current returns, thereby engendering inconsistent predictability of REIT returns.

The behavioral finance empirical models of Barberis et al. (1998) and Lewellen (2002) can empirically explain the price "momentum" and "reversal" phenomena, which are, respectively, attributed to under-reaction and overreaction to macro news.[4] Investors' under-reaction and overreaction occur at different market states. Therefore, different return dependence patterns are likely to emerge across conditional distributions of current returns associated with each quantile.

This study hypothesizes that investors in EREIT and MREIT markets may not act in an entirely rational way in bad and good (extreme) market states when returns are very low or very high, respectively. The presence of significant positive or negative autocorrelation (serial dependence)[5] of REIT returns at any quantile, either due to under-reaction or overreaction of the investors, coupled with an intermittent absence of autocorrelation, supports the time-varying (adaptive) market hypothesis (AMH) postulated by Lo (2004, 2017) and Brennan and Lo (2011). The autoregression pattern will vary with the frequency of returns due to time aggregation, information, and the motives of the investors.

The study briefly documents asymmetric and misaligned dependence patterns where lower quantiles or bad market states are characterized by either positive or weakly negative dependence, while upper quantiles or good market states are generally marked by negative dependence on past returns. The results are consistent with under-reaction to good news in a bad state and overreaction to bad news in a good state. Lagged negative returns increase the predictability of REIT returns at lower quantiles (bad state) and decrease predictability in the upper quantile (good state), which is chiefly consistent with the overreaction hypothesis. Extreme positive returns in the lower (upper) quantiles dampen (amplify) autocorrelation of daily, weekly, and monthly REIT returns. The effects of the recession on the autocorrelation of returns are frequency specific. Recession induces increased autoregression for weekly returns, mainly in the lower and central quantiles but does not affect autoregression of monthly returns. For daily returns, the previous day's returns reduce autoregression more during recession periods compared to non-recession periods. Overall, the dependence structure is a function of the state of the market, sign, size, volatility and time aggregation (frequency) of returns, and the class (EREIT and MREIT) of REITs. The episodic predictability and non-predictability of REITs returns at different quantiles, and return frequencies support the REITs' markets time-varying efficiency and adaptive market hypothesis.

The study's remaining parts are organized as follows: Section 2 details data sources and its characterization. Section 3 explains the econometric methodology. Section 4 offers empirical results, while Section 5 summarizes the results and concludes.

3 See the studies by Sentana and Wadhwani (1992); Sias and Starks (1997); or Nofsinger and Sias (1999).

4 Investors' overreaction, according to Daniel et al. (1998), is a psychological phenomenon arising from individuals' tendency to allocate excessive weight to the most recent information. Specifically, when investors acquire new information, their initial reaction is too strong, causing rapid price increase and positive return autocorrelation. However, as investors receive new information, overreaction is corrected in subsequent periods, originating price and return reversal (negative autocorrelation). Return reversals are essentially "corrections" of past mistakes.

5 The terms dependence, autocorrelation and serial correlation are used fairly interchangeably in this study.

2. Data Sources and Data Characterization

We cull the data from daily, weekly and monthly data from Bloomberg. The daily and weekly data are available from 01/04/1999. The monthly data are available from February 1972. The sample period for all three frequencies ends on 07/14/2020. The corresponding number of observations is N = 5617 for daily data, N = 1124 for weekly data, and N = 581 for monthly data. The use of daily, weekly, and monthly frequency data is motivated by the findings of Campbell et al. (1997) and Lo and MacKinlay (1990). Using the US stock indices returns, the authors document higher daily return autocorrelations than weekly and monthly autocorrelations. They attribute the higher daily return autocorrelations to the potential presence of either non-trading or non-synchronous trading.

The percent return, R_t, of EREIT (MREIT) index at period t, is computed as the natural log difference of the closing index value at t and $t-1$; that is, $R_t = ln(Index_t/Index_{t-1}) * 100$. The daily close to close index is used to derive the daily returns. Weekly returns are computed from Friday close to Friday close the following week. In case there was no trading due to market closure, we utilize the last obtainable closing index value to calculate the weekly return. Monthly returns are equal to the natural log difference between the closing price indices in two successive months. The summary descriptive statistics of the three data frequencies are presented in Table 1.

Table 1. Descriptive statistics at different return frequencies.

	EREITs			**MREITs**		
	Daily	**Weekly**	**Monthly**	**Daily**	**Weekly**	**Monthly**
Mean	0.014	0.070	0.303	−0.031	−0.153	−0.601
Maximum	16.876	21.602	26.623	38.590	42.574	31.631
Minimum	−21.532	−29.862	−38.434	−38.693	−47.464	−79.44
Std. Dev.	1.765	3.450	5.062	2.016	4.135	6.6634
Skewness	−0.547 ***	−0.744 ***	−1.462 ***	−0.415 ***	−2.214 ***	−3.339 ***
Kurtosis	26.917 ***	16.408 ***	13.267 ***	83.591 ***	46.939 ***	38.367 ***
Jarque−Bera	134,137 ***	8515 ***	2754 ***	1,519,959 ***	91,257 ***	31,306 ***
N	5616	1123	580	5616	1123	580

Notes: EREITs (MREITs) is the equity (mortgage) Real Estate Investment Trusts. ***, ** and * are significance level at 1%, 5% and 10% level.

Results in Table 1 reveal that at every frequency, EREIT has higher average returns but a lower range of returns, volatility (standard deviation) of returns, negative asymmetric distribution (as measured by skewness except for daily frequency), leptokurtic (as measured by kurtosis) and non-normal distribution of returns (as measured by the Jarque-Bera statistic) than the MREIT returns. The average, maximum, and minimum returns and the volatility and asymmetry of returns distribution increase as the frequency decreases (time-aggregation increases). It is also apparent that the leptokurtic (non-normal) distribution of returns is decreasing in frequency. This is due to the smoothing associated with the time-aggregation of returns. While the results in Table 1 are point estimates, they suggest that EREIT and MREIT returns have different autoregressive patterns. Figure 1b illustrates the time-series of EREIT and MREIT returns at daily, weekly and monthly frequencies. We have also included recession periods (gray bars) as defined by the National Bureau of Economic Research (NBER).

Since the sample period ends in mid-July, it is also interesting to observe the impact of the COVID-19 pandemic on the performance of REITs. The sharp decline in returns occurred in 2020M03. Both categories of REITs respond differently to recession shocks. For example, the daily returns of EREIT (MREIT) troughed at 21% (27%) in 2020M03. The weekly returns of EREIT (MREIT) troughed at 30% (47%) in 2020M03, while the monthly returns troughed at 38% (79%) during the same month. Generally, returns seem more volatile during periods of economic or financial turmoil. Unsurprisingly, the minimum returns are, in absolute terms, higher than the maximum returns, especially for monthly data, which cover additional recessionary and crisis periods compared to daily and weekly data.

For example, the sharp decline in EREIT returns in October 1987 coincided with the Black Monday panic sell-off.

3. Econometric Model

Given a stationary return series, R_t, a first-order autoregressive process, AR (1), based on the ordinary least squares (OLS) would be modeled as follows:

$$R_t = \alpha_0 + \beta_1 R_{t-1} + z_t \tag{1}$$

where α_0 is a constant, β_1 is the slope which measures the mean or average persistence of returns and z_t is white noise disturbances. The equivalent first-order conditional quantile autoregression-QAR (1) model is expressed as follows:

$$Q_\tau(R_t|\pi_{t-1}) = \alpha_\tau + \beta_\tau R_{t-1} \tag{2}$$

In Equation (2), Q_τ (•) designates the conditional quantile function at the τth quantile where $\tau \in (0,\ 1)$; π_{t-1} is the publicly available set to the market participants up to and including period $t-1$. According to Nikolaou (2008), $\alpha_z(\tau) = \alpha_\tau$ is the error term, z_t, of the τ^{th} quantile and includes the impact of unexpected shocks of different sizes and signs in period $t-1$ that initiate variations in REIT returns in period t. Negative and positive shocks are associated with negative and positive market sentiments, respectively. β_τ, which is the primary focus of the present study, is the coefficient estimate of the quantile-specific autoregressive parameter. The estimates of α_τ and β_τ in Equation (2) are derived by resolving the following minimization problem:

$$\min_{\alpha_\tau,\ \beta_\tau} \sum_{t=1}^{T} \rho_\tau(R_t - \alpha_\tau - \beta_\tau R_{t-1}) \tag{3}$$

In Equation (3), T is the total number of return observations, $\rho_\tau(z) = z\left(\tau - I_{[z\le 0]}\right)$ and $I_{[z\le 0]} = 1$ if $z \le 0$ and 0 otherwise. Relative to the first-order conditional mean model, AR (1), the QAR (1)[6] model presented in Equation (2) offers the advantages of investigating the return dependence patterns across the entire return distributional features. Therefore, we can gain vibrant and dynamic insights into the predictability of returns during different market states and sentiments. For example, extremely low (high) or negative (or positive) returns are generally indicative of negative (positive) market sentiments. The quantile regression is robust in the presence of outliers in the data. The median, which acts as the location parameter, is more efficient than the mean in the presence of heavy-tailed return distributions. Indeed, Baur et al. (2012) argue that each quantile can be interpreted as a state or a regime of asset return. The lower (upper) quantiles are consistent with a current bad (good) market state or regime.

Equation (1) is considered as the base QAR model. We extend and augment the model to account for the impact of the sign and size of the lagged REIT returns on dependence patterns. The model that accounts for the sign effects ("Sign Model"), in line with the Glosten et al. (1993) Generalized Autoregressive Conditional Heteroskedasticity (GJR-GARCH) model, is specified as:

$$Q_\tau(R_t|\pi_{t-1}) = \alpha_\tau + \beta_\tau R_{t-1} + \gamma_\tau R_{t-1} I_{NEG}(R_{t-1} < 0) \tag{4}$$

where the indicator variable, $I_{NEG}(R_{t-1} < 0)$ is equal to one if the REIT return in period $t-1$ is negative and zero otherwise. In Equation (4), β_τ measures the dependence in $\tau - th$ quantile when returns are positive while $\beta_\tau + \gamma_\tau$, measures the dependence in the $\tau - th$ when REITs returns are negative. According to Basu (1997), asymmetric dependence occurs whenever γ_τ is statistically different from zero.

[6] A lag order of one was selected using the Swartz Bayesian information criterion (BIC).

Likewise, the following "Size Model" can help in assessing the impact of extreme positive previous month returns (measured by coefficient estimate θ_τ) on the current period's REIT return.

$$Q_\tau(R_t|\pi_{t-1}) = \alpha_\tau + \beta_\tau R_{t-1} + \theta_\tau R_{t-1} I_{SIZE}(|R_{t-1}| > R^q) \quad (5)$$

In Equation (5), $I_{SIZE}(|R_{t-1}| > R^q$, is an indicator variable equal to one when the past period's REIT return exceeds a pre-specified threshold and zero otherwise. We then select R^q at the 90th and 95th quantiles of the unconditional distribution of absolute returns of EREIT and MREIT. The coefficient estimate θ_τ is used to evaluate the impact of the previous period's extreme positive or upper tail REIT returns on current REIT returns.

Lastly, the degree of dependence of REIT returns may be an artifact of business cycles as defined by crisis versus non-crisis periods. Figure 1a,b show that REIT returns may differ across business cycles (recession versus non-recession periods) in the US. Therefore, it is plausible to test the marginal effects of economic recessions on REITs' returns dependence patterns. We use the following model to assess that possibility.

$$Q_\tau(R_t|\pi_{t-1}) = \alpha_\tau + \beta_\tau R_{t-1} + \varphi_\tau(R_{t-1} * DUM) \quad (6)$$

where DUM is a dummy variable equal to one if the period (day, week, or month) falls within a recession period (as defined by NBER) and zero otherwise. The expression, $\varphi_\tau(R_{t-1} * DUM)$, captures the marginal effects or differences in the degree of return dependence between recession and non-recession periods. Specifically, φ_τ measures the marginal effects during the crisis period while $\varphi_\tau + \beta_\tau$ measures the aggregate effect on dependence for a specific quantile during the crisis period. If φ_τ is not constant across all quantiles; then, the recession is likely to change the dependence structure. Following Baur (2013), we test the following two hypotheses:

(1) $H_0 : \overline{\varphi} = 0$ (there is no recession-specific change in the average degree of dependence.) Rejecting the null hypothesis implies that the degree of return dependency, on average, changes during the crisis period.
(2) $H_0 : \varphi_\tau \neq \varphi_{\tau^*}\ \forall\ \tau \textit{ and } \tau^* \textit{with } \tau \neq \tau^*$ (there is no recession-specific change in the structure of dependency or φ_τ is not constant across all quantiles). Rejection of the null means that dependence structure changes during recession periods relative to non-recession periods.

There is a need to generate asymptotic standard errors in estimating coefficients in Equation (2) through Equation (6). To this end, we use the pair bootstrapping procedure proposed by Buchinsky (1995) to mitigate the adverse effects of potential misspecifications of the QAR model and heteroskedasticity.

4. Empirical Results

The results for the AR (1) and QAR (1) models are gathered in Table 2a,b for EREIT and MREIT, respectively. Consistent with the autocorrelation test based on the data-driven Portmanteau tests[7], all the AR (1) coefficients, except for the daily returns of EREIT, are insignificant at daily, weekly, and monthly frequency, implying that the behavior of EREIT and MREIT returns at the means is characterized by a white noise process or unpredictability. This evidence partly supports the findings of Jirasakuldech and Knight (2005), who confirm the weak-form efficiency of EREIT but some predictability of MREIT returns. However, the results contradict the conclusions of Nelling and Gyourko (1998). The authors find that while the EREIT returns are predictable based on past performance, the exploitable arbitrage profits are eroded by transaction costs. Our evidence partially supports or contradicts past

[7] Escanciano and Lobato (2009) developed a Portmanteau test which, unlike the Ljung and Box (1978) test, permits the data to automatically select the lag length. The test is also robust to conditional heteroskedasticity.

studies due to the more extended sample periods, econometric modeling, and different frequencies covered by the present study.

Table 2. (**a**) Time aggregation and autoregression of EREIT returns. (**b**) Time aggregation and autoregression of MREIT returns. (**c**) Slope equality test results.

a

Q	Daily		Weekly		Monthly	
τ	α_τ	β_τ	α_τ	β_τ	α_τ	β_τ
AR(1)	0.016	−0.169 ***	0.076	−0.086	0.281	0.078
0.05	−2.141 ***	−0.074 *	−4.792 ***	0.003	−7.792 ***	0.356 ***
0.10	−1.391 ***	−0.062 **	−3.099 ***	−0.036	−5.376 ***	0.265 ***
0.15	−0.950 ***	−0.032 **	−2.261 ***	−0.039	−3.510 ***	0.128 **
0.20	−0.723 ***	−0.032 **	−1.665 ***	−0.059	−2.641 ***	0.090 *
0.25	−0.537 ***	−0.034 ***	−1.183 ***	−0.074 **	−1.965 ***	0.104 **
0.30	−0.367 ***	−0.048 ***	−0.796 ***	−0.078 ***	−1.230 ***	0.108 ***
0.35	−0.242 ***	−0.051 ***	−0.518 ***	−0.076 ***	−0.863 ***	0.096 ***
0.40	−0.125 ***	−0.060 ***	−0.234 ***	−0.080 ***	−0.407 ***	0.079 **
0.45	−0.032 ***	−0.061 ***	−0.015	−0.070 ***	0.028 ***	0.068 *
0.50	0.044 ***	−0.069 ***	0.283 ***	−0.093 ***	0.624 ***	0.040 ***
0.55	0.139 ***	−0.095 ***	0.534 ***	−0.106 ***	1.161 ***	0.020
0.60	0.250 ***	−0.117 ***	0.757 ***	−0.115 ***	1.523 ***	−0.015
0.65	0.379 ***	−0.107 ***	1.023 ***	−0.150 ***	2.018 ***	−0.041
0.70	0.500 ***	−0.118 ***	1.324 ***	−0.131 ***	2.591 ***	−0.034
0.75	0.650 ***	−0.118 ***	1.597 ***	−0.129 ***	3.093 ***	−0.019
0.80	0.813 ***	−0.123 ***	1.931 ***	−0.127 ***	3.726 ***	−0.076 *
0.85	1.009 ***	−0.137 ***	2.442 ***	−0.170 ***	4.484 ***	−0.105 **
0.90	1.360 ***	−0.189 ***	3.114 ***	−0.239 ***	5.266 ***	−0.099 *
0.95	2.030 ***	−0.237 ***	4.267 ***	−0.267 ***	7.620	−0.223 ***

b

	Daily		Weekly		Monthly	
τ	α_τ	β_τ	α_τ	β_τ	α_τ	β_τ
AR(1)	−0.035	−0.113	−0.173	−0.093	−0.589 **	0.013
0.050	−2.375 ***	0.013	−5.000 ***	0.030	−7.792 ***	0.356 ***
0.100	−1.472 ***	0.034	−3.667 ***	0.055	−5.376 ***	0.265 ***
0.150	−1.075 ***	0.008	−2.664 ***	0.017	−3.510 ***	0.128 **
0.200	−0.773 ***	0.007	−1.985 ***	0.036	−2.641 ***	0.090 *
0.250	−0.571 ***	−0.002	−1.532 ***	0.042	−1.965 ***	0.104 **
0.300	−0.392 ***	−0.005	−1.091 ***	0.036	−1.230 ***	0.108 ***
0.350	−0.269 ***	−0.015	−0.703 ***	0.007	−0.863 **	0.096 ***
0.400	−0.158 ***	−0.017 **	−0.425 ***	0.025	−0.407	0.079 **
0.450	0.000	0.001 ***	−0.098	−0.006	0.028 ***	0.068 ***
0.500	0.069 ***	−0.029 ***	0.187 ***	−0.018	0.624 ***	0.040
0.550	0.174 ***	−0.025 ***	0.384 **	−0.038 **	1.161 ***	0.020
0.600	0.270 ***	−0.040 ***	0.648 **	−0.043 **	1.523 ***	−0.015
0.650	0.380 ***	−0.047 ***	0.910 **	−0.050 **	2.018 ***	−0.041
0.700	0.486 ***	−0.044 ***	1.249 ***	−0.079 ***	2.591 ***	−0.034
0.750	0.585 ***	−0.055 ***	1.494 ***	−0.086 ***	3.093 ***	−0.019
0.800	0.757 ***	−0.084 ***	1.829 ***	−0.107 ***	3.726 ***	−0.076 *
0.850	0.947 ***	−0.097 ***	2.237 ***	−0.149 ***	4.484 ***	−0.105 **
0.900	1.277 ***	−0.125 ***	2.968 ***	−0.166 ***	5.266 ***	−0.099 *
0.950	1.974 ***	−0.167 ***	4.107 ***	−0.221 ***	7.620 ***	−0.223

c

	EREIT			MREIT		
	Daily	Weekly	Monthly	Daily	Weekly	Monthly
Null hypothesis	Chi-Sq.	Chi-Sq.	Chi-Sq.	Chi-Sq.	Chi-Sq.	Chi-Sq.
$\beta_{0.05} = \beta_{0.95}$	22.180 ***	7.427 **	19.105 ***	27.035 ***	15.984 ***	15.189 ***
$\beta_{0.05} = \beta_{0.50}$	0.015	1.007	7.835 ***	1.618	0.615	2.365
$\beta_{0.50} = \beta_{0.95}$	22.175 ***	6.411 **	10.194 ***	25.461 ***	15.361 ***	12.493 ***
$\beta_{0.05} = \beta_{0.25} = \beta_{0.50} = \beta_{0.75} = \beta_{0.95}$	64.465 ***	8.721 *	20.085 ***	48.096 ***	33.114 ***	29.486 ***
All quantiles	175.328 ***	42.834 ***	45.027 ***	136.004 ***	68.729 ***	58.657 ***

Note: The results in this table are based on the model shown in Equation (2). We set $\tau = 0.05, 0.10, 0.15, \ldots, 0.95$. The estimates of the ordinary least squares (OLS) model are based on Equation (1). The rest of the coefficient estimates are based on Equation (2). ***, **, and * indicates the statistical significance at 1%, 5%, and 10% level, respectively; The slope equality test was developed by Koenker and Bassett (1982). ***, **, and * indicates the statistical significance at 1%, 5%, and 10% levels, respectively.

In the QAR(1) model, the autoregressive parameter (β_τ) estimate is the focus of our attention. Results in Table 2a reveal that daily EREIT returns have significant and monotonically increasing negative dependence (downward sloping) patterns at all quantiles. The weekly returns have significant and rising negative autoregression from 25th quantile and above, suggesting white noise or weak-form efficiency in the majority of lower quantiles (5th to 20th quantiles). Although the monthly returns exhibit decreasing (increasing) positive (negative) autoregression at lower (upper) quantiles, the dependence pattern vastly contrasts that of the weekly returns. Specifically, while the monthly returns exhibit positively significant autoregression in the lower and middle (5th to 50th) quantiles, insignificant (weak-form efficiency) dependence at some middle quantiles, the parameter estimates for the upper (85th to 95th) quantiles show negative return dependence.

Table 2a discloses an interesting dependence structure across different frequencies. The daily (weekly) MREIT returns exhibit independence in the lower quantiles since β_τ is insignificant at 5th to 35th (50th) quantiles and negative autoregression in the middle and upper quantiles. However, the monthly returns exhibit almost an inverse dependence pattern where positive return dependence is in the lower and middle (10th to 45th) quantiles and return unpredictability (independence), or weak negative dependence is evident in the middle and upper quantiles.

Graphically, Figure 2a,b display return dependence patterns. The middle "line and symbol" represent quantile coefficient estimates. The estimates, α_τ, measures the intercept (magnitude or the average daily, weekly, and monthly return per quantile) while β_τ is the slope coefficients in the QAR(1) model where τ ranges between 0.05 and 0.95. The two outer lines define 95% confidence bands for all quantile estimates.

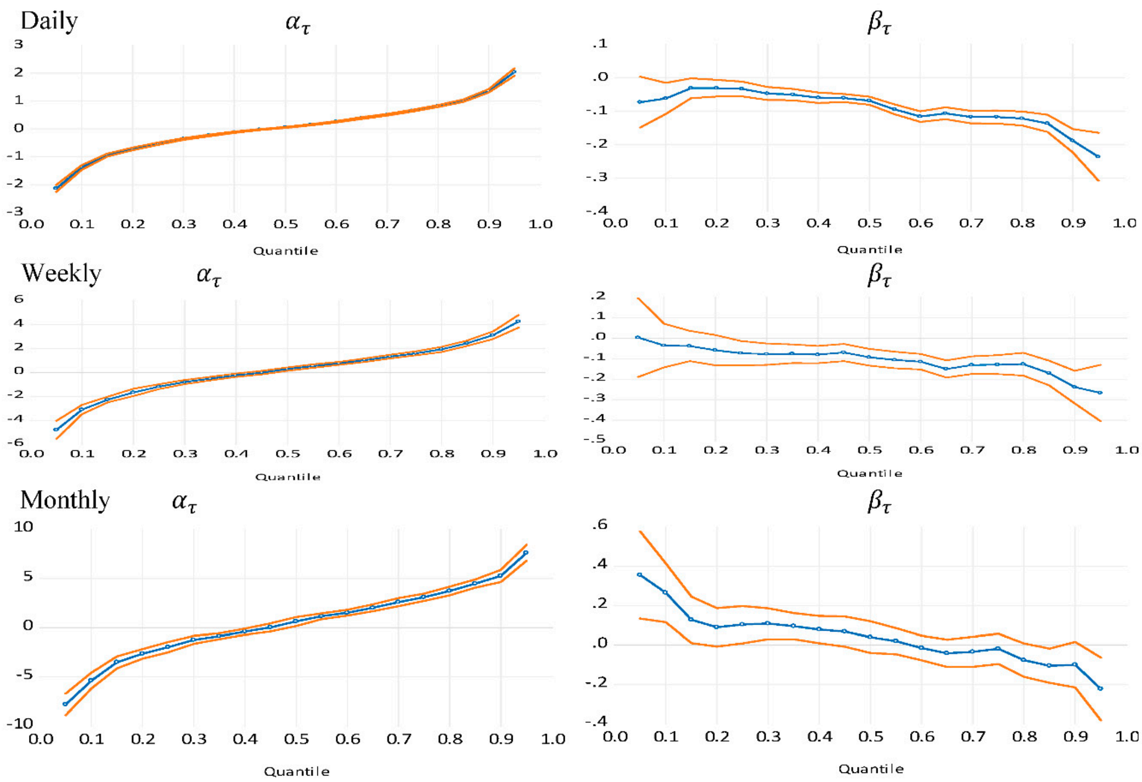
It should be noted that unlike the results in Table 2a,b, Figure 2a,b cannot disclose the statistical significance of either the magnitude and the autoregression coefficient as measured by α_τ and β_τ estimates, respectively, across frequencies or time aggregations.

For the daily and weekly (monthly) returns, the lower quantiles are marked by insignificantly (significantly positive) autocorrelations or slope coefficients while the middle and upper tail slope coefficients exhibit significantly negative return dependency. In contrast, the middle quantiles autoregressive coefficient estimates of monthly returns are mostly statistically immaterial and economically small. Figure 2a,b graphically confirm the downward-sloping autoregressive pattern of EREIT and MREIT daily, weekly, and monthly return frequencies. Several inferences can be made from the base results gathered in Table 2a,b and Figure 2a,b.

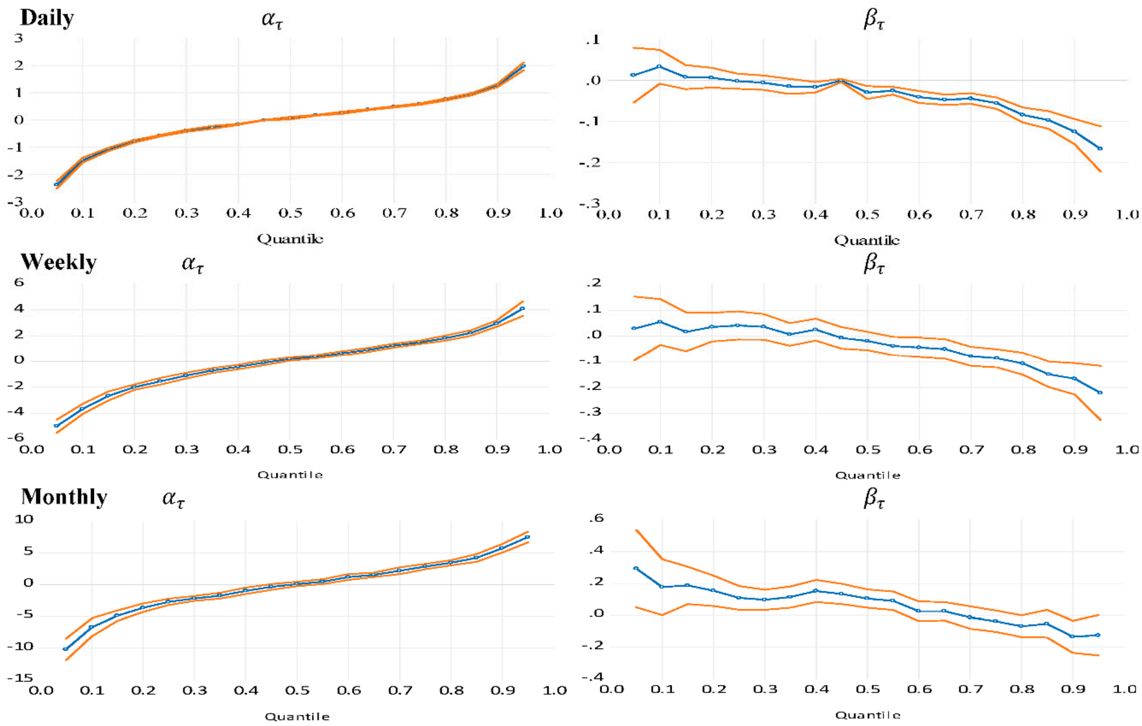
First, according to Figure 2a,b, EREIT and MREIT returns have a similar dependence structure across different returns frequencies. However, Table 2a,b reveal that the statistical significance, sign, and size of autoregression vastly differ across return frequencies and the three states comprising the bad state (lower quantiles), normal state (central quantiles), and good state (upper quantiles)[8]. We attribute these differences to non-trading and non-synchronous trading for the daily prices, short-term arbitrage opportunities, and differing investment horizons of the investors such as day traders versus swing traders.

Second, the evidence of statistically negative and positive autoregressive and statistically insignificant coefficient estimates for EREIT and MREIT index returns supports the REITs market's adaptive market hypothesis where predictability of REITs returns is quantile- or state-dependent. Indeed, the decreasing autoregressive parameter pattern as we move from lower to upper quantiles signifies a higher degree of negative autocorrelation or predictability. The evidence suggests that the response of the current period's return on its most recent return is dependent on the state or the side of the EREIT and MREIT return distribution.

[8] For ease of interpretation of results, define 5th to 35th quantiles as lower quantiles, 40th to 70th quantiles as central or middle quantiles, and 75th to 95th quantiles as upper quantiles.



(**a**)



(**b**)

Figure 2. (**a**) Autoregression or dependence patterns of EREITs. (**b**) Autoregression or dependence patterns of MREITs.

Third, the overall evidence in Figure 2a,b implies that the previous period's positive return mostly reduces the current period's positive returns, thereby exacerbating the bad state. This is consistent with overreaction to bad news at period $t-1$, which either further reduces future positive returns or magnifies future negative returns. Declining positive (increasing negative) autocorrelation in the lower quantiles (bad state) is consistent with a negative momentum (price continuation)[9] or price reversals. The statistically significant negative serial correlation in the upper quantiles (good state) also evinces price reversals. It is mainly consistent with a market where positive returns are more likely to be followed by negative returns and vice versa. Another way to explain overreaction based on the negative dependence or predictability patterns of EREIT and MREIT is postulated by Baur et al. (2012) and Lehmann (1990). For example, the estimates of α_τ (intercept) and β_τ (slope) at the 10th quantile in Table 2a (EREIT) is −1.391 and −0.062, respectively. Both estimates are statistically material. The intercept's negative value reflects both the magnitude of the daily return at roughly 1.4% and negative market sentiments. The negative market sentiment is characterized by falling EREIT prices, causing the investors to overreact, followed by a hasty exit from the market, thereby causing further price declines and negative autoregression. This interpretation can be extended to the daily and weekly MREIT returns. At monthly frequency, EREIT and MREIT return in Table 2a,b follow a white noise process at the upper quantiles, suggesting that any mispricing during the month is arbitraged away in a good state, resulting in a weak negative autoregression or serial independence of returns.[10] In terms of investment strategy, a negative serial correlation in the good state would suggest that investors can buy EREIT and MREIT after periods with negative returns and sell after periods with positive returns. However, this is only possible if negative autocorrelations are high enough to absorb transaction costs. Positive-feedback investors (trend followers) make investment decisions by extrapolating historical price patterns and return sequences. The investors perceive price variations to have inertia. A trend strategy investor will take a positive (long) position if prices have recently exhibited momentum or positive autocorrelation and a negative or short position if REIT prices have lately declined (negative autocorrelation or return reversals).

Fourth, the autoregressive coefficient estimates increase as time aggregations increases (return frequency decreases). Specifically, the autoregressive estimates for monthly (weekly) returns are higher than those of weekly (daily) returns. This evidence is consistent with the findings of Campbell et al. (1997) and Lo and MacKinlay (1990).

The results described so far indicate a downward sloping pattern of the autoregressive coefficient estimates for EREIT and MREIT indices. We find varying statistical significance and magnitude of autoregressive parameter estimates across different quantiles of the conditional EREIT and MREIT return distributions across different return frequencies. Specifically, lower quantiles exhibit either a positive or low negative dependence on past returns than upper quantiles, which are characterized by negative dependence patterns. The results for the upper quantiles (good state) are mainly consistent with the findings of Baur et al. (2012) and Lewellen (2002), who find negative stock index return autocorrelation, especially for monthly returns. The authors attribute the negative serial correlation to investors' overreaction to macroeconomic news in a good state.[11] In line with Baur et al. (2012) and Veronesi (1999), the positive or low negative autoregression patterns in lower quantiles (bad state) point to investors' under-reaction to macroeconomic news. The rationale for under-reaction phenomena

[9] As Lewellen (2002) notes, momentum is not synonymous with positive autocorrelation. While momentum is a cross-sectional result where winning stocks beat losing stocks, autocorrelation is a time-series phenomenon where a stock's or an index's past and future returns are correlated. However, Lo and MacKinlay (1990) show that indeed, momentum may be caused by serial correlation of returns, lead-lag relations among stocks (cross-serial correlation), or cross-sectional dispersion in unconditional means. Lewellen (2002), for example, shows that negative autocorrelations tend to reduce momentum profits.

[10] Anderson et al. (2013) intimate that daily return autocorrelation is attributable to market microstructure biases such as nonsynchronous trading effect and bid-ask bounce, partial price adjustment (PPA), and time-varying risk premia. However, Mech (1993) argues that weekly and monthly return autocorrelations are generally caused by changing investment opportunities, which are naturally low-frequency events. The strong daily return autocorrelation is also consistent with profit taking by technical analysts and day traders.

[11] Since EREIT and MREIT are well diversified portfolios, their returns and dependence patterns reflect systematic risks caused by macroeconomic factors, as opposed to individual firm-specific or idiosyncratic risk.

is associated with partial price adjustment effect (PPA) either due to "conservative" response of the investors to news, sequential arrival of information in the market, followed by the gradual acquisition of the information by investors (either due to delay in acquisition of information or limited mental ability to process the information or market frictions such as transaction costs), resulting in trend formation, positive serial correlation, and momentum in returns.[12]

The evidence so far supports the narrative that a single autoregressive coefficient estimate based on the expected EREIT and MREIT returns, will often obfuscate the state- and return frequency-dependent nature of the autoregressive processes in terms of the sign, economic and statistical significance. The lagged REIT returns have a material influence on current returns across different quantiles and frequencies. Our results support evidence by Clayton and MacKinnon (2003) and Zhou and Lee (2013), who find that REIT return behavior and predictability are time-varying. Zhou and Lee (2013) further show that market conditions indeed influence return predictability.

We further investigate whether autocorrelation is asymmetric using a variation of the Wald test proposed by Koenker and Bassett (1982). The test is employed to assess the hypotheses that the slope coefficients, β_τ, are identical at different quantiles. Specifically, we test the following null hypotheses: (i) $\beta_{0.05} = \beta_{0.95}$; (ii) $\beta_{0.05} = \beta_{0.50}$; (iii) $\beta_{0.50} = \beta_{0.95}$ and (iv) $\beta_{0.05} = \beta_{0.25} = \beta_{0.50} = \beta_{0.75} = \beta_{0.95}$.

Table 2c gathers the F-statistics for each of the two REITs indices at different return frequencies. The results suggest that apart from the statistically insignificant difference between β_τ estimated at the 5th against the 50th quantiles of daily and weekly returns for the EREIT and MREIT index, the rest of the test statistics reject each null hypothesis of equality of slopes between or among different quantiles.

Collectively, the slope equality test results provide compelling evidence that autocorrelations of REITs return vary across quantiles of the conditional return distributions of different return frequencies. This supports the evidence from Table 2a,b, where autocorrelations tend to be positive or low negative (negative) for REITs returns in the respective low (high) conditional quantiles. Therefore, the response of a representative (median) return to the previous month's return certainly differs from that observed for two successive observations from the (upper or lower) tail of return distribution.

The 'Sign Model' described in Equation (4) is used to assess the likelihood that daily, weekly, and monthly lagged positive and negative returns differentially influence the conditional return distribution of REITs.

The coefficient estimates of lagged positive and negative returns, β_τ *and* γ_τ, respectively, are gathered in Table 3a,b and graphically illustrated using Figure 3a,b. We make the following observations and inferences. First, dependence patterns seem to be state-dependent since the parameter estimates, β_τ, markedly vary in magnitude, sign, and statistical significance across quantiles and frequencies. From Table 3a,b, the daily and weekly returns exhibit negative (positive) dependence patterns in the lower (upper) quantiles or bad (good) state. For the monthly returns, the past and current EREIT and MREIT returns are largely independent, except at the 80th to 95th (80th and 85th) quantiles in Table 3a,b, which show positive autoregression and partly support the findings of Lo and MacKinlay (1990) and Campbell et al. (1997).

---

[12] See the studies by Holden and Subrahmanyam (2002); Mech (1993); Jennings et al. (1981) and Copeland (1976).

Table 3. (**a**) Marginal impact of the sign of EREIT returns on autoregression (sign model). (**b**) MREIT: marginal impact of size and sign of MREIT returns on autoregression.

a

	Daily			Weekly			Monthly		
τ	α_τ	β_τ	γ_τ	α_τ	β_τ	γ_τ	α_τ	β_τ	γ_τ
0.05	−1.216 ***	−0.990 ***	1.989 ***	−2.783 ***	−0.618 ***	1.953 ***	−5.768 ***	−0.037	0.688 *
0.10	−0.799 ***	−0.740 ***	1.363 ***	−1.963 ***	−0.495 ***	1.417 ***	−3.548 ***	−0.144	0.752 ***
0.15	−0.598 ***	−0.521 ***	0.963 ***	−1.374 ***	−0.473 ***	1.089 ***	−2.634 ***	−0.116	0.692 ***
0.20	−0.428 ***	−0.396 ***	0.771 ***	−0.886 ***	−0.417 ***	0.953 ***	−1.943 ***	−0.112	0.504 ***
0.25	−0.316 ***	−0.334 ***	0.636 ***	−0.647 ***	−0.308 ***	0.613 ***	−1.249 ***	−0.142	0.527 ***
0.30	−0.224 ***	−0.237 ***	0.428 ***	−0.446 ***	−0.293 ***	0.496 ***	−0.819 ***	−0.031	0.280 **
0.35	−0.130 ***	−0.198 ***	0.336 ***	−0.238 **	−0.227 ***	0.347 ***	−0.802 ***	0.094	0.018
0.40	−0.047 ***	−0.164 ***	0.230 ***	−0.027	−0.218 ***	0.267 ***	−0.418 *	0.079	−0.012
0.45	0.009	−0.119 ***	0.121 ***	0.199 **	−0.201 ***	0.220 ***	0.073	0.061	0.028
0.50	0.041 ***	−0.064 ***	−0.007	0.311 ***	−0.118 ***	0.036	0.496 ***	0.069	−0.136
0.55	0.094 ***	−0.031 ***	−0.132 ***	0.499 ***	−0.080 **	−0.045	1.027 ***	0.048	−0.131
0.60	0.181 ***	−0.008	−0.205 ***	0.621 ***	0.008	−0.188 ***	1.346 ***	0.034	−0.176 *
0.65	0.263 ***	0.066 ***	−0.309 ***	0.787 ***	0.040	−0.297 ***	1.692 ***	0.048	−0.173 *
0.70	0.353 ***	0.119 ***	−0.443 ***	0.961 ***	0.091 **	−0.411 ***	2.029 ***	0.124	−0.250 **
0.75	0.444 ***	0.166 ***	−0.592 ***	1.181 ***	0.114 **	−0.570 ***	2.650 ***	0.092	−0.293 **
0.80	0.531 ***	0.247 ***	−0.806 ***	1.486 ***	0.169 ***	−0.675 ***	3.107 ***	0.142 *	−0.366 ***
0.85	0.668 ***	0.336 ***	−1.001 ***	1.766 ***	0.194 ***	−0.742 ***	3.395 ***	0.192 **	−0.564 ***
0.90	0.881 ***	0.407 ***	−1.213 ***	2.027 ***	0.292 ***	−1.075 ***	4.368 ***	0.113 ***	−0.481 ***
0.95	1.218 ***	0.670 ***	−1.751 ***	3.047 ***	0.363 ***	−1.387 ***	6.346 ***	0.012 ***	−0.472 **

b

	Daily			Weekly			Monthly		
τ	α_τ	β_τ	γ_τ	α_τ	β_τ	γ_τ	α_τ	β_τ	γ_τ
0.05	−1.574 ***	−0.619 ***	1.525 ***	−3.384 ***	−0.639 ***	1.933 ***	−5.768 ***	−0.037	0.688 *
0.10	−1.045 ***	−0.388 ***	0.989 ***	−2.820 ***	−0.268 ***	0.813 ***	−3.548 ***	−0.144	0.752 ***
0.15	−0.732 ***	−0.275 ***	0.747 ***	−1.900 ***	−0.240 ***	0.619 ***	−2.634 ***	−0.116	0.692 ***
0.20	−0.539 ***	−0.252 ***	0.633 ***	−1.506 ***	−0.196 ***	0.477 ***	−1.943 ***	−0.112	0.504 ***
0.25	−0.381 ***	−0.209 ***	0.488 ***	−1.094 ***	−0.183 ***	0.417 ***	−1.249 ***	−0.142	0.527 ***
0.30	−0.281 ***	−0.152 ***	0.342 ***	−0.784 ***	−0.152 ***	0.311 ***	−0.819 ***	−0.031	0.280 **
0.35	−0.164 ***	−0.133 ***	0.252 ***	−0.499 ***	−0.109 ***	0.237 ***	−0.802 ***	0.094	0.018
0.40	−0.117 ***	−0.075 ***	0.126 ***	−0.258 **	−0.090 **	0.179 ***	−0.418 *	0.079	−0.012
0.45	0.000	−0.028 ***	0.028 **	0.081	−0.098 ***	0.197 ***	0.073 ***	0.061	0.028
0.50	0.058 **	−0.020 *	−0.022	0.275 ***	−0.078 **	0.110 **	0.496 ***	0.069	−0.136
0.55	0.156 ***	0.006	−0.063 ***	0.371 ***	−0.029	−0.024	1.027 ***	0.048	−0.131
0.60	0.189 ***	0.051 ***	−0.195 ***	0.574 ***	−0.002	−0.063	1.346 ***	0.034	−0.176 ***
0.65	0.290 ***	0.085 ***	−0.271 ***	0.845 ***	−0.012	−0.093 *	1.692 ***	0.048	−0.173 *
0.70	0.347 ***	0.134 ***	−0.403 ***	1.016 ***	0.039	−0.224 ***	2.029 ***	0.124	−0.250 **
0.75	0.404 ***	0.200 ***	−0.594 ***	1.268 ***	0.038	−0.319 ***	2.650 ***	0.092	−0.293 **
0.80	0.478 ***	0.323 ***	−0.829 ***	1.497 ***	0.107 ***	−0.383 ***	3.107 ***	0.142 *	−0.366 ***
0.85	0.556 ***	0.473 ***	−1.148 ***	1.686 ***	0.158 ***	−0.594 ***	3.395 ***	0.192 **	−0.564 ***
0.90	0.722 ***	0.591 ***	−1.475 ***	1.834 ***	0.372 ***	−1.282 ***	4.368 ***	0.113	−0.481 ***
0.95	1.092 ***	0.810 ***	−1.779 ***	2.633 ***	0.571 ***	−1.464 ***	6.346 ***	0.012	−0.472 **

Notes: The results in this table are based on the model shown in Equation (4). We set $\tau = 0.05,\ 0.10,\ 0.15, \ldots, 0.95$. ***, ** and * indicates the statistical significance at 1%, 5%, and 10% level, respectively.

Second, the γ_τ coefficient estimates vary in sign, statistical and economic significance. Specifically, the estimates are significantly positive, insignificant, and significantly negative at the bad, normal, and good state, respectively, across all frequencies. Therefore, the previous period's negative and positive REIT returns have a state- or quantile-specific predictive power on future returns. The statistical significance of γ_τ also implies that positive and negative lagged EREIT and MREIT returns asymmetrically induce changes in current returns at daily, weekly and monthly frequencies. In cases when γ_τ is insignificant, for example, $\gamma_{0.50}$ for daily returns, $\gamma_{0.50}$ and $\gamma_{0.55}$, for weekly returns and $\gamma_{0.35}$ and $\gamma_{0.55}$ for monthly returns in Table 3a, past positive and negative returns symmetrically impact the current returns, while negative returns have insignificant effects on current returns. Third, for both EREIT and MREIT, evidence that $\beta_\tau + \gamma_\tau > \beta_\tau$ ($\beta_\tau + \gamma_\tau < \beta_\tau$) suggests that current REIT returns are more sensitive to past negative (positive) returns than positive (negative) returns. Take the case of daily returns in Table 3a where $\beta_{0.05}$ $(-0.990) + \gamma_{0.05}(1.989) = 0.999$. This is greater than $\beta_{0.05} = -0.990$. Furthermore, take the case of weekly returns in Table 3b where $\beta_{0.85}$ $(0.158) + \gamma_{0.85}(-0.584) = -0.436$. This is less than $\beta_{0.85} = 0.158$. The overall evidence from Table 3a,b is that in the bad (good) state (lower (upper) quantiles), past period's negative (positive) returns provide more predictive power on current EREIT and MREIT returns than vice versa.[13] This evidence is pervasive across all return frequencies.

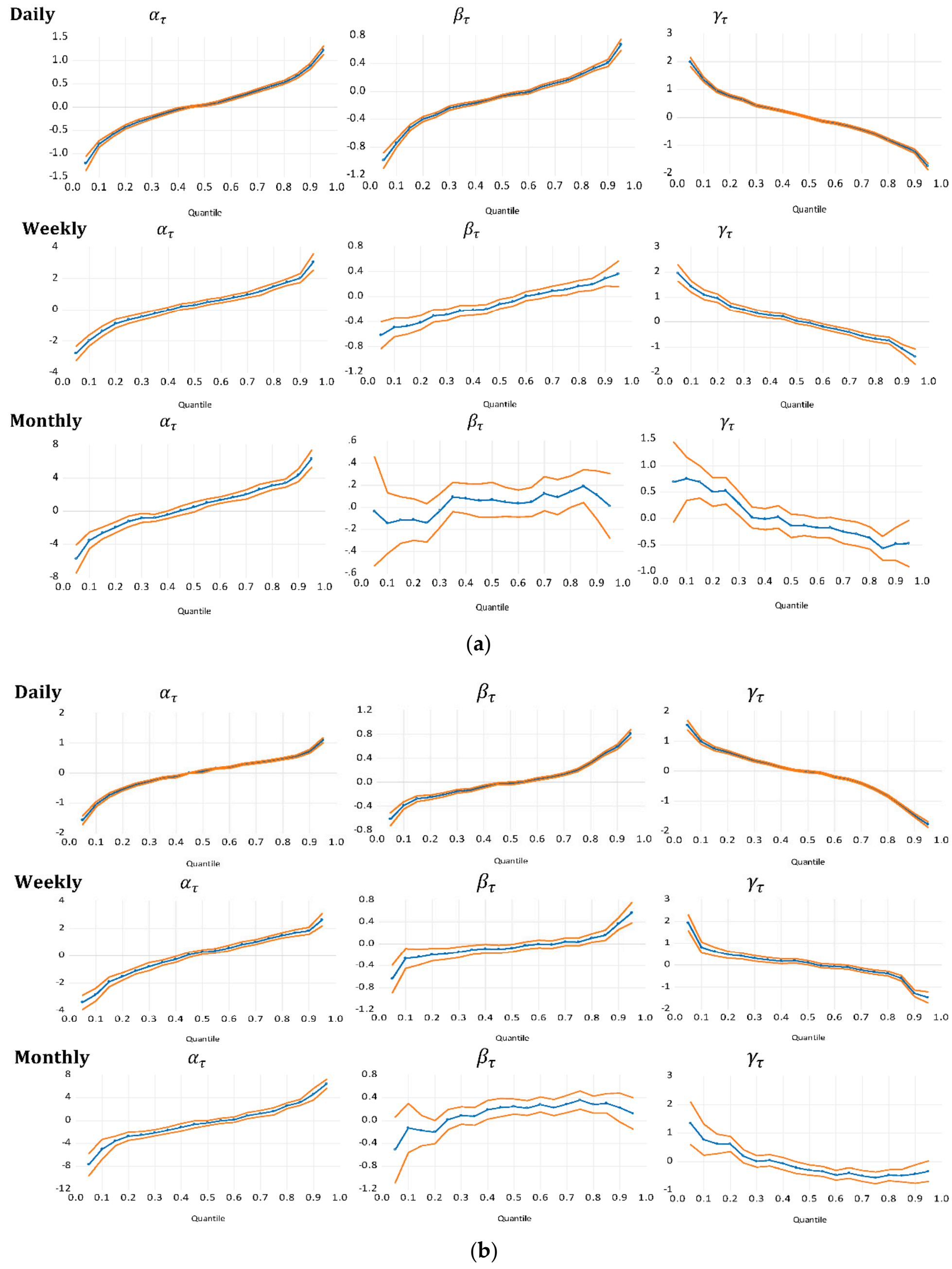


Figure 3. (**a**) Sign model: impact of negative returns on dependence pattern of EREIT returns. (**b**) Sign model: Impact of negative returns on dependence pattern of MREIT returns.

[13] It should be noted that the primary source of income for MREITs is interest from the debt capital MREITs provide. While increase in interest rate (tightening monetary policy) may be indicative of healthy economic growth and inflation activity, which is good for MREITs, higher interest rates tend to decrease the value of mortgage-backed securities (MBS) and increase short-term borrowing costs for MREITs. Additionally, higher interest rates make the comparatively high MREITs' dividend yields less appealing to income-seeking investors who may find the lower-risk, fixed income securities more attractive, thereby causing a decline in MREIT return autocorrelations. Therefore, positive market sentiments may result in declining MREIT returns.

The rationale for this evidence is that in the bad (good) state, price changes are driven by negative (positive) sentiment, albeit asymmetrically, as indicated by the upward sloping intercept, which is negative in the lower quantiles and positive in the upper quantiles. Indeed, the composite effect of negative returns on the autocorrelation of returns, as measured by $\beta_\tau + \gamma_\tau$, supports this view. Since γ_τ is positive (negative) in the lower (upper) quantiles, then the aggregate effect of negative returns at the lower (upper) quantiles is to amplify (dampen) autocorrelation of REIT returns. For example, at the 5th, 10th, and 15th quantiles of Table 3a,b, negative weekly returns increase autocorrelation or predictability of EREIT (MREIT) returns by 1.335, 0.922, and 0.616 (1.294, 0.546, and 0.380), respectively.

Conversely, in the upper quantiles such as the 85th and 90th quantiles, weekly negative returns will reduce autocorrelation of EREIT (MREIT) conditional returns by −0.548 and −0.783 (−0.436, −0.911), respectively. In summary, negative returns increase (decrease) predictability of REIT returns at lower quantiles or bad state (upper quantile or good state). The evidence of positive (negative) autocorrelation of negative returns in the lower (upper) is consistent with overreaction to macro news.

As Figure 3a,b demonstrate, the addition of lagged negative returns as an explanatory variable reverses the autoregressive pattern of the slope estimates, β_τ[14] from downward sloping (as portrayed by Figure 2a,b) to upward sloping. Interestingly, the lagged negative returns now take the downward-sloping dependence pattern. Therefore, the autoregression pattern seems to be an artifact of past negative returns.

The results in Table 2a,b and Figure 3a,b suggest that investors react differently to positive and negative lagged returns and that their reaction is mostly state- or quantile-dependent. As Baur et al. (2012) note, the presence of lagged positive (negative) returns in a current good (bad) state, means that the lagged returns and current states are aligned, resulting in positive autocorrelation. This is closely associated with investors' under-reaction in the preceding period. Contrastingly, misalignment of lagged returns and current states causes negative autocorrelation, which is in line with the notion of investors' overreaction in period $t-1$. Investors' overreaction to macro news causes overshooting of asset price and the subsequent price reversals to the fundamental value, producing negative autocorrelation patterns. Evidence from Figure 3a,b points to investors' under-reaction to positive news (upward sloping β_τ estimates of positive returns) in the good state and overreaction to negative news (downward sloping γ_τ estimates of negative returns) in a bad state, which is consistent with the findings of Barberis et al. (1998); Veronesi (1999); Lewellen (2002); and Chevapatrakul and Mascia (2019).

The 'Size Model' described in Equation (5) explicitly considers the impact of the size of a previous period's return on the daily, weekly, and monthly return distribution of EREITs and MREITs.

The estimated coefficients of lagged returns (β_τ) and of the 95th percentile[15] of extreme positive returns (θ_τ), which account for the impact of lagged extreme positive returns, are summarized in Table 4a,b and graphically illustrated using Figure 4a,b. We make the following substantive observations from Table 4a,b. First, θ_τ is negative (positive) in the lower (upper) quantiles.[16] Therefore, large positive lagged returns negatively (positively) and asymmetrically impact the conditional EREIT and MREIT returns at the lower (upper) quantiles.

---

[14] In addition to testing the impact of lagged negative returns on dependence patterns, we tested the impact of extreme negative returns using 10th, 5th and 2.5th quantiles as thresholds. The results, which are available on request, mirror those presented in Table 3a,b and Figure 3a,b.

[15] We also tested the effects on 90th and 97.5th percentiles of return on predictability of the conditional returns of EREITs and MREITs at different frequencies. The evidence remains qualitatively the same as shown in Table 4a,b. Results are available on request.

[16] That is, 5th to 45th quantiles for the daily EREIT returns, 5th to 50th quantiles for the EREIT weekly returns and 5th to 25th quantiles for the monthly EREIT returns. The upper quantiles refer to 50th, 55th and 70th quantile and above for daily, weekly and monthly EREIT returns. Similar interpretations can be made from Table 4b.

Table 4. (**a**) Impact of the size of EREIT returns on autoregression pattern. (**b**) Impact of the size of MREIT returns on autoregression pattern.

a

	Daily			Weekly			Monthly		
τ	α_τ	β_τ	θ_τ	α_τ	β_τ	θ_τ	α_τ	β_τ	θ_τ
0.05	−1.945 ***	−0.013	−0.908 ***	−4.176 ***	0.147 *	−1.131 ***	−7.086 ***	0.165	−0.710 ***
0.10	−1.253 ***	−0.009	−0.692 ***	−2.912 ***	0.142 ***	−0.732 ***	−4.665 ***	0.140 *	−0.439 ***
0.15	−0.897 ***	−0.018	−0.449 ***	−2.243 ***	0.076 **	−0.628 ***	−3.259 ***	0.076	−0.539 ***
0.20	−0.677 ***	−0.009	−0.370 ***	−1.585 ***	0.027	−0.501 ***	−2.551 ***	0.110 **	−0.453 ***
0.25	−0.507 ***	−0.012	−0.294 ***	−1.128 ***	−0.044	−0.350 ***	−1.918 ***	0.112 **	−0.282 ***
0.30	−0.352 ***	−0.023 **	−0.209 ***	−0.746 ***	−0.034	−0.268 ***	−1.227 ***	0.103 **	0.007
0.35	−0.231 ***	−0.034 ***	−0.158 ***	−0.475 ***	−0.073 ***	−0.203 ***	−0.885 ***	0.075 **	0.022
0.40	−0.123 ***	−0.048 ***	−0.108 ***	−0.219 ***	−0.074 ***	−0.135 ***	−0.412 **	0.071 *	0.010
0.45	−0.029 ***	−0.058 ***	−0.053 ***	0.028	−0.099 ***	−0.099 ***	0.015	0.074 *	−0.011
0.50	0.042 ***	−0.069 ***	0.058 ***	0.286 ***	−0.109 ***	−0.101 ***	0.701 ***	0.007	0.063
0.55	0.132 ***	−0.091 ***	0.081 ***	0.530 ***	−0.095 ***	0.091 ***	1.119 ***	−0.010	0.069
0.60	0.234 ***	−0.097 ***	0.137 ***	0.756 ***	−0.078 ***	0.168 ***	1.512 ***	−0.023	0.039
0.65	0.359 ***	−0.096 ***	0.170 ***	0.968 ***	−0.086 ***	0.178 ***	1.931 ***	−0.036	0.064
0.70	0.477 ***	−0.109 ***	0.252 ***	1.268 ***	−0.128 ***	0.326 ***	2.496 ***	−0.016	0.192 ***
0.75	0.622 ***	−0.116 ***	0.376 ***	1.544 ***	−0.147 ***	0.356 ***	3.036 ***	−0.005	0.182 ***
0.80	0.786 ***	−0.116 ***	0.456 ***	1.888 ***	−0.135 ***	0.357 ***	3.615 ***	−0.026	0.150 **
0.85	0.951 ***	−0.105 ***	0.579 ***	2.357 ***	−0.167 ***	0.412 ***	4.344 ***	−0.082 *	0.196 ***
0.90	1.260 ***	−0.142 ***	0.653 ***	2.837 ***	−0.203 ***	0.591 ***	5.171 ***	−0.082	0.256 ***
0.95	1.762 ***	−0.163 ***	0.942 ***	3.811 ***	−0.301 ***	0.897 ***	6.768 ***	−0.059	0.479 ***

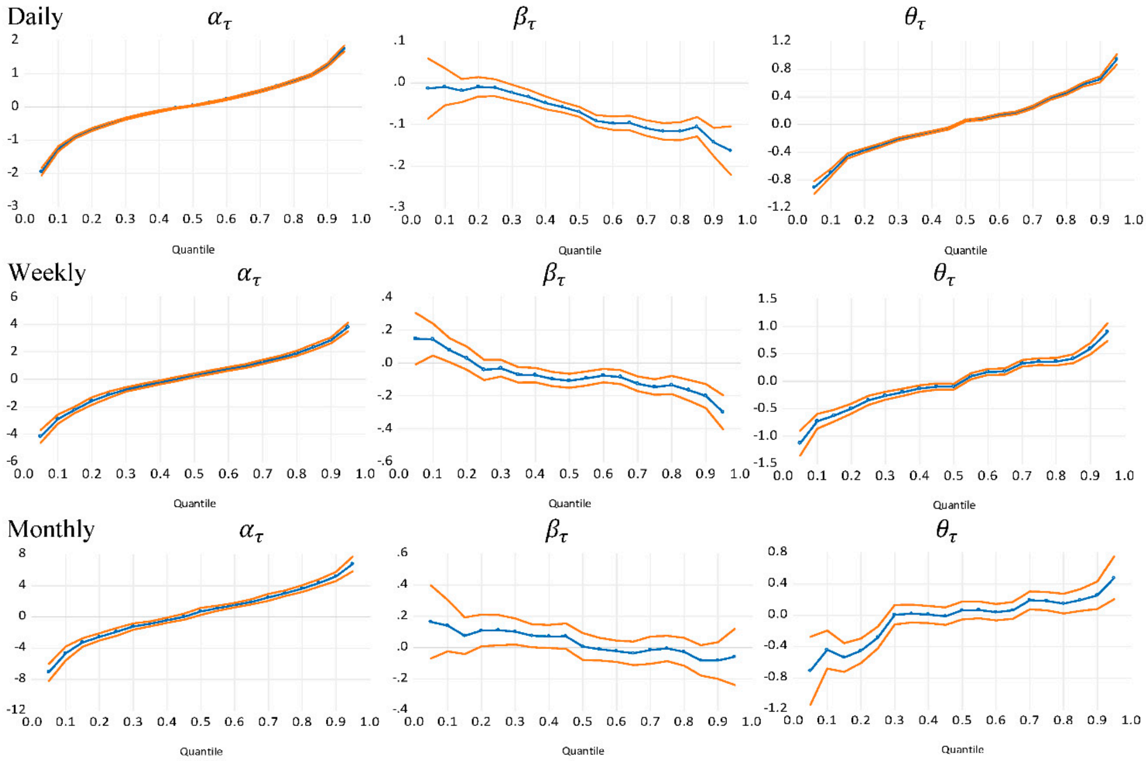
b

	Daily			Weekly			Monthly		
τ	α_τ	β_τ	θ_τ	α_τ	β_τ	θ_τ	α_τ	β_τ	θ_τ
0.05	−2.144 ***	0.178 ***	−0.564 ***	−4.715 ***	0.179 ***	−1.314 ***	−9.885 ***	0.263	−0.238 ***
0.10	−1.384 ***	0.107 ***	−0.452 ***	−3.479 ***	0.123 **	−0.621 ***	−6.516 ***	0.159	−0.241 ***
0.15	−1.017 ***	0.070 ***	−0.304 ***	−2.456 ***	0.016	−0.332 ***	−4.812 ***	0.116	−0.252 **
0.20	−0.743 ***	0.058 ***	−0.280 ***	−1.896 ***	0.014	−0.228 ***	−3.530 ***	0.095	−0.271 ***
0.25	−0.546 ***	0.035 ***	−0.223 ***	−1.435 ***	0.006	−0.178 ***	−2.732 ***	0.109 **	−0.154 **
0.30	−0.384 ***	0.024 ***	−0.150 ***	−1.051 ***	0.000	−0.105 ***	−2.174 ***	0.117 ***	0.022
0.35	−0.242 ***	−0.010	−0.107 ***	−0.680 ***	−0.004	−0.123 ***	−1.701 ***	0.127 ***	0.080
0.40	−0.156 ***	−0.010	−0.050 ***	−0.417 ***	0.009	−0.095 ***	−1.068 ***	0.141 ***	0.088
0.45	0.000	0.000	−0.028 ***	−0.057	0.000	−0.095 ***	−0.436 *	0.152 ***	0.175 ***
0.50	0.065 ***	−0.035 ***	0.025 ***	0.187 ***	−0.007	−0.093 ***	0.069	0.108 ***	0.222 ***
0.55	0.172 ***	−0.021 ***	0.043 ***	0.383 ***	−0.038 **	0.008	0.404 **	0.100 ***	0.277 ***
0.60	0.260 ***	−0.057 ***	0.122 ***	0.626 ***	−0.036 *	0.021	0.873 ***	0.115 ***	0.276 ***
0.65	0.369 ***	−0.055 ***	0.170 ***	0.901 ***	−0.054 ***	0.033	1.459 ***	0.074 *	0.276 ***
0.70	0.471 ***	−0.062 ***	0.319 ***	1.243 ***	−0.074 ***	0.032	1.795 ***	0.085 **	0.283 ***
0.75	0.565 ***	−0.052 ***	0.433 ***	1.487 ***	−0.104 ***	0.171 ***	2.753 ***	0.055 ***	0.240 ***
0.80	0.716 ***	−0.075 ***	0.539 ***	1.772 ***	−0.089 ***	0.181 ***	3.355 ***	0.057 ***	0.235 ***
0.85	0.884 ***	−0.085 ***	0.690 ***	2.200 ***	−0.141 ***	0.735 ***	4.010 ***	0.063 ***	0.233 ***
0.90	1.169 ***	−0.101 ***	0.844 ***	2.858 ***	−0.145 ***	0.743 ***	5.288 ***	0.070 ***	0.324 ***
0.95	1.711 ***	−0.099 ***	1.042 ***	3.643 ***	−0.209 ***	0.789 ***	6.982 ***	0.026 ***	0.206 *

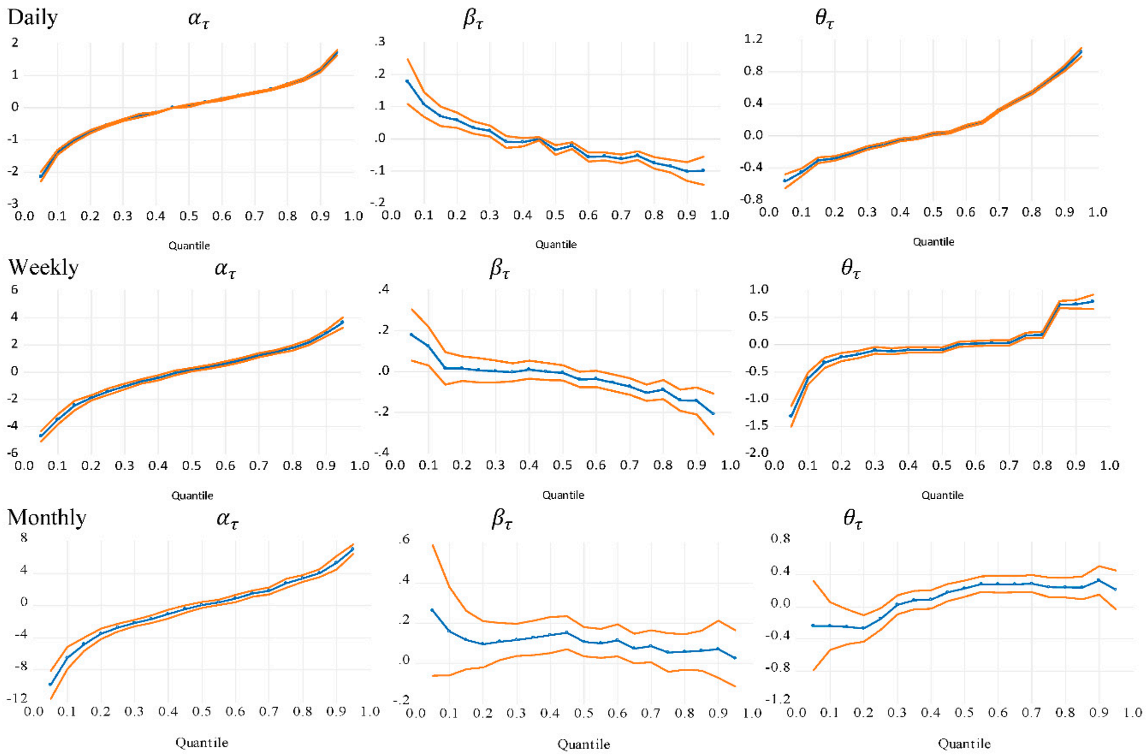
Notes: The results in this table are based on the model shown in Equation (5). We set $\tau = 0.05,\ 0.10,\ 0.15, \ldots, 0.95$. ***, ** and * indicates the statistical significance at 1%, 5%, and 10% level, respectively.

Second, the inclusion of large lagged positive returns subsumes the predictive power of the lagged returns. Still, this effect depends mainly on the quantile, the frequency of returns, and the category of REITs. For example, relative to the results in Table 2a, results in Table 4a,b show that β_τ is insignificant or unpredictable at 5th to 25th (35th to 45th) quantiles for daily returns, 20th to 30th (15th to 50th) quantiles for weekly returns, and 50th to 95th (5th to 20th) quantiles for monthly returns once large lagged positive returns are included in Equation (5).

Third, Table 4a,b demonstrate that the past extreme positive returns align with the current state since negative (positive) autoregressive coefficient estimates in the lower (upper) quantile or current bad (good) state. This indicates positive autocorrelation as supported by the upward sloping estimates of, θ_τ, in Figure 4a,b. The positive dependence pattern aligns with investors' under-reaction to positive news associated with extreme positive returns and sequential arrival of information, and partial price adjustment. The positive serial correlation arises since the previous period's negative returns result in lower negative returns in the current period, thereby alleviating its bad state.



(**a**)



(**b**)

Figure 4. (**a**) Impact of size of returns on dependence pattern of EREIT returns. (**b**) Size model: impact of size of returns on dependence pattern of MREIT returns.

Lastly, the aggregate effect of substantial positive returns on autoregression patterns at each quantile is assessed using $\beta_\tau + \theta_\tau$. For example, at $\beta_{0.10}$ and $\theta_{0.10}$ in Table 4a, extreme positive returns diminish autoregression by 0.590 (0.142–0.732) and 0.299 (0.140–0.439) for the weekly and monthly returns. At $\beta_{0.90}$ and $\theta_{0.90}$, past extreme positive returns upsurge autoregression of weekly and monthly EREIT returns by 0.388 (−0.203 + 0.591) and 0.174 (−0.082 + 0.256), respectively. Similarly, at $\beta_{0.10}$ and $\theta_{0.10}$ in Table 4b, extreme positive returns diminish autoregression by 0.345 (0.107–0.452), 0.498 (0.123–0.621) and 0.082(0.159–0.241) for the daily, weekly and monthly returns, respectively. At $\beta_{0.90}$ and $\theta_{0.90}$, past extreme positive returns improve autoregression of daily, weekly, and monthly MREIT returns by 0.743 (−0.101 + 0.844), 0.598 (−0.145 + 0.743), and 0.254 (0.070 + 0.324), respectively. Overall, extreme positive returns in the lower (upper) quantiles dampen (amplify) autocorrelation of EREIT and MREIT returns. The downward sloping dependence patterns documented in Figure 4a,b essentially mirrors those shown in Figure 2a,b based on the QAR (1) model. Therefore, we conclude that the shape of dependence across quantiles using the QAR (1) is not an artifact of the previous period extreme positive returns. The increase in confidence intervals at the lower and upper tails is attributable to increased dispersion of returns in bad and good states, respectively, and increased risk premium.

Table 5a,b gather the results assessing the marginal and aggregate impact of business cycles (recession and non-recession periods) on conditional returns and dependence patterns of REIT returns. The average recession quantile coefficient estimate, $\overline{\varphi_\tau}$ for EREIT (MREIT) is −0.215 (−0.161), 0.092 (0.123) and 0.199 (0.077) for daily, weekly and monthly frequency, respectively. Each average is significantly different from zero. Since the average quantile estimate for daily (weekly and monthly) is negative (positive), there is a negative (positive) recession-induced change in the average degree of dependence relative to the average degree of dependence, $\overline{\beta_\tau}$, associated with daily (weekly and monthly) REIT returns. Furthermore, we test the hypothesis that $H_0 : \varphi_\tau \neq \varphi_{\tau^*}\ \forall\ \tau\ and\ \tau^* with\ \tau \neq \tau^*$ (there is no recession-specific change in the structure of dependence. The chi-square statistic for this null for EREIT (MREIT) was statistically significant (insignificant) at every conventional level with an F-statistic of 37.021 (24.302), 140.110 (23.200), and 41.115 (17.632) for daily, weekly, and monthly frequency, respectively. The rejection of (failure to reject) the null confirms the presence (absence) of a recession-specific change in the structure of dependence of conditional returns of EREIT (MREIT) across the return frequencies.

According to the results in Table 5a, the recession coefficient estimate, φ_τ, for weekly and monthly frequency is significantly positive in the lower and central quantiles of EREIT returns but largely insignificant for the upper quantiles. This implies that lagged weekly and monthly EREIT returns cause a higher degree of dependence in the lower tail and central quantiles during recession periods (recession-induced autoregression) than non-recession periods.

However, lagged returns have an insignificant effect on the predictability of weekly and monthly returns during the recession, particularly in the upper quantiles. Results in Table 5b reveal that recession induces increased autoregression of weekly returns, mainly in the lower and central quantiles, but has no effect on autoregression patterns using monthly returns. In both Table 5a,b, the recession coefficient estimate, φ_τ, is significantly negative across all quantiles based on the daily frequency of returns. This suggests that previous day returns reduce autoregression more during recession periods compared to non-recession periods. To assess the aggregate quantile-specific effect of the recession on dependence pattern, we use the sum of the coefficient estimates, $\beta_\tau + \varphi_\tau$. Anecdotally, $\beta_{0.05} + \varphi_{0.05}$ for the daily returns in Table 5a,b is −0.217 (−0.095). Therefore, the daily autoregression coefficient estimates declined from 0.057 (0.079) to −0.217 (−0.095) for the daily returns of EREIT (MREIT) at the extreme lower tail. Likewise, $\beta_{0.95} + \varphi_{0.95}$ in Table 5a,b is −0.392 (−0.337), suggesting that at the extreme upper tails, the autoregression coefficient estimates declined from −0.165 (0.081) to −0.392 (−0.337) for the daily[17] EREIT (MREIT) returns.

[17] Similar interpretations can be extended to the other quantiles. However, it should be noted the dummy estimates in Table 5a are mainly insignificant from the 40th and 65th quantiles and above for weekly and monthly returns. Similarly, the dummy coefficient estimates in Table 5b are insignificant across all quantiles for monthly returns.

Table 5. (**a**) Impact of recession on autoregression of EREIT returns. (**b**) Marginal impact of the recession on autoregression of MREIT returns.

a

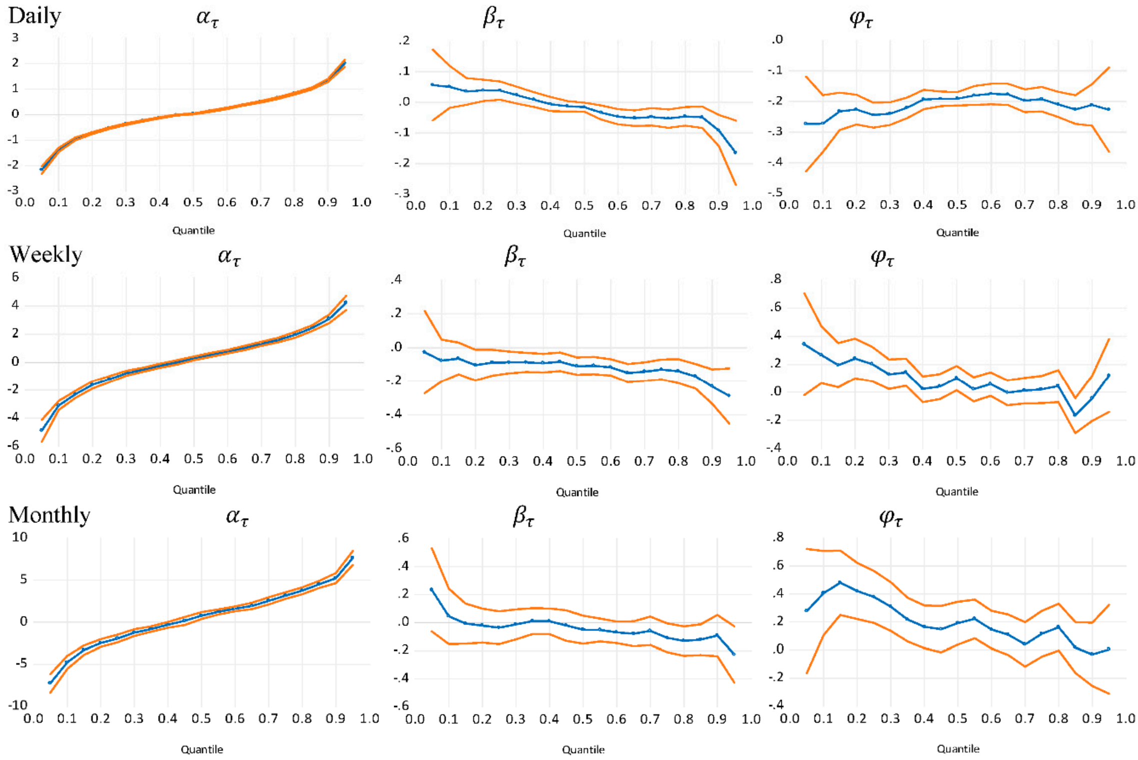
	Daily			Weekly			Monthly		
τ	α_τ	β_τ	φ_τ	α_τ	β_τ	φ_τ	α_τ	β_τ	φ_τ
0.05	−2.176 ***	0.057	−0.274 ***	−4.888 ***	−0.027	0.342 *	−7.275 ***	0.234	0.277
0.10	−1.386 ***	0.050	−0.273 ***	−3.088 ***	−0.076	0.267 ***	−4.763 ***	0.044	0.406 ***
0.15	−0.957 ***	0.036	−0.232 ***	−2.289 ***	−0.064	0.194 **	−3.332 ***	−0.007	0.480 ***
0.20	−0.732 ***	0.039 **	−0.227 ***	−1.620 ***	−0.103 **	0.241 ***	−2.495 ***	−0.022	0.421 ***
0.25	−0.532 ***	0.038 **	−0.245 ***	−1.204 ***	−0.089 **	0.202 ***	−1.936 ***	−0.037	0.378 ***
0.30	−0.377 ***	0.023 ***	−0.240 ***	−0.779 ***	−0.087 ***	0.129 **	−1.246 ***	−0.013	0.310 ***
0.35	−0.253 ***	0.009	−0.221 ***	−0.523 ***	−0.087 ***	0.144 ***	−0.819 ***	0.010	0.217 ***
0.40	−0.132 ***	−0.006 ***	−0.194 ***	−0.239 ***	−0.091 ***	0.022	−0.317 *	0.009	0.165 **
0.45	−0.018	−0.013	−0.192 ***	−0.003	−0.083 ***	0.040	0.136	−0.020	0.148 ***
0.50	0.026 ***	−0.016 **	−0.191 ***	0.286 ***	−0.109 ***	0.101 **	0.776 ***	−0.051	0.191 **
0.55	0.131 ***	−0.033 ***	−0.181 ***	0.538 ***	−0.107 ***	0.021	1.213 ***	−0.053	0.221 ***
0.60	0.246 ***	−0.047 ***	−0.176 ***	0.759 ***	−0.117 ***	0.058	1.587 ***	−0.070 ***	0.146 **
0.65	0.376 ***	−0.052 ***	−0.177 ***	1.023 ***	−0.150 ***	−0.004	1.922 ***	−0.080 ***	0.108
0.70	0.503 ***	−0.047 ***	−0.198 ***	1.325 ***	−0.142 ***	0.011	2.540 ***	−0.059	0.039
0.75	0.646 ***	−0.053 ***	−0.193 ***	1.597 ***	−0.129 ***	0.020	3.169 ***	−0.108 **	0.115
0.80	0.819 ***	−0.046 ***	−0.210 ***	1.966 ***	−0.140 ***	0.044	3.748 ***	−0.131 **	0.163 *
0.85	1.013 ***	−0.049 ***	−0.227 ***	2.442 ***	−0.170 ***	−0.167 ***	4.492 ***	−0.122 **	0.017
0.90	1.338 ***	−0.092 ***	−0.212 ***	3.090 ***	−0.232 ***	−0.044	5.233 ***	−0.093	−0.031
0.95	2.016 ***	−0.165 ***	−0.227 ***	4.223 ***	−0.287 ***	0.119	7.643 ***	−0.228 **	0.004

b

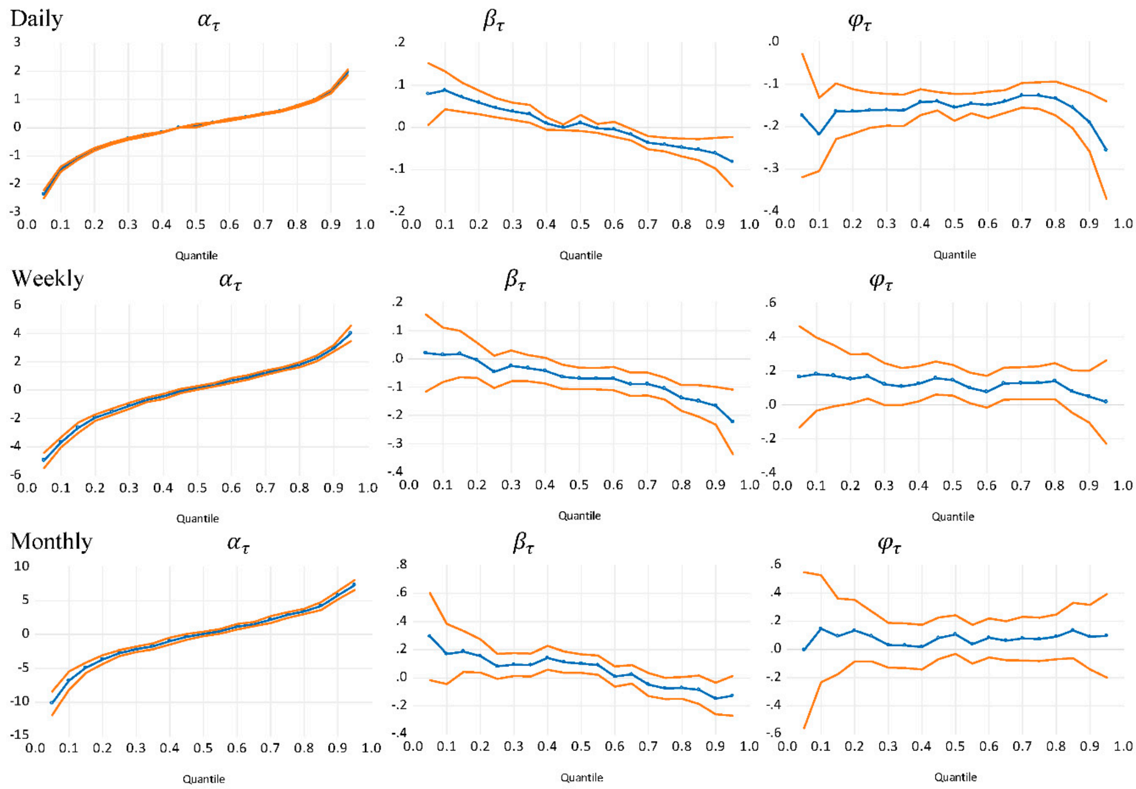
	Daily			Weekly			Monthly		
τ	α_τ	β_τ	φ_τ	α_τ	β_τ	φ_τ	α_τ	β_τ	φ_τ
0.05	−2.362 ***	0.079 ***	−0.174 **	−4.984 ***	0.021	0.165	−10.177 ***	0.293 *	−0.004
0.10	−1.476 ***	0.088 ***	−0.218 ***	−3.686 ***	0.014	0.181 *	−6.806 ***	0.169	0.146
0.15	−1.088 ***	0.072 ***	−0.164 ***	−2.664 ***	0.017	0.172 *	−4.898 ***	0.187 **	0.093
0.20	−0.774 ***	0.059 ***	−0.164 ***	−1.955 ***	−0.005	0.153 ***	−3.679 ***	0.155 ***	0.133
0.25	−0.561 ***	0.046 ***	−0.161 ***	−1.536 ***	−0.046	0.169 ***	−2.723 ***	0.082 *	0.093
0.30	−0.398 ***	0.038 ***	−0.160 ***	−1.117 ***	−0.025	0.122 *	−2.178 ***	0.095 **	0.030
0.35	−0.272 ***	0.032 ***	−0.162 ***	−0.698 ***	−0.033	0.108 *	−1.763 ***	0.091 **	0.027
0.40	−0.164 ***	0.009	−0.142 ***	−0.451 ***	−0.042 *	0.125 ***	−0.989 ***	0.142 ***	0.016
0.45	0.000	0.000	−0.140 ***	−0.071	−0.064 ***	0.158 ***	−0.343	0.111 ***	0.080
0.50	0.074 *	0.011	−0.154 ***	0.160 **	−0.069 ***	0.145 ***	0.083	0.102 ***	0.107
0.55	0.173 ***	−0.003	−0.146 ***	0.380 ***	−0.070 ***	0.101 ***	0.463 **	0.091 **	0.037
0.60	0.285 ***	−0.005	−0.149 ***	0.668 ***	−0.070 ***	0.077	1.151 ***	0.010	0.083
0.65	0.377 ***	−0.017 **	−0.141 ***	0.911 ***	−0.090 ***	0.126 ***	1.525 ***	0.025	0.062
0.70	0.488 ***	−0.036 ***	−0.126 ***	1.226 ***	−0.089 ***	0.128 ***	2.192 ***	−0.047	0.077
0.75	0.588 ***	−0.041 ***	−0.126 ***	1.490 ***	−0.105 ***	0.130 ***	2.872 ***	−0.075 *	0.072
0.80	0.758 ***	−0.047 ***	−0.134 ***	1.796 ***	−0.138 ***	0.140 **	3.411 ***	−0.071 *	0.090
0.85	0.959 ***	−0.053 ***	−0.155 ***	2.237 ***	−0.149 ***	0.079	4.218 ***	−0.084	0.135
0.90	1.287 ***	−0.061 ***	−0.190 ***	2.959 ***	−0.166 ***	0.049	5.792 ***	−0.147	0.088
0.95	1.961 ***	−0.081 ***	−0.255 ***	4.007 ***	−0.223 ***	0.017	7.334 ***	−0.128 *	0.096

Notes: The results in this Table are based on the model shown in Equation (6). We set $\tau = 0.05,\ 0.10,\ 0.15, \ldots, 0.95$. ***, ** and * indicates the statistical significance at 1%, 5%, and 10% level, respectively.

In Figure 5a,b, the general downward-sloping pattern of dependence coefficient estimate, β_τ confirms investors' overreaction to the news. However, the recession coefficient estimate, φ_τ is mainly flat for the daily returns in Figure 5a and daily, weekly, and monthly MREIT returns in Figure 5b. Furthermore, the daily and weekly returns exhibit a downward sloping pattern at the extreme upper tails coupled with an increase in the confidence interval of φ_τ. This illustrates an increase in dispersion of returns triggered by higher risk-premium at the tails of the negative return distributions compared to the intermediate quantiles. The nearly flat, negative autoregressive structure of daily returns in Figure 5a,b suggests daily prices generally decline due to negative sentiment associated with recession. Indeed, the intercept is upward sloping in Figure 5a,b, but even when it is positive (positive sentiment), daily negative autocorrelation persists, suggesting that past negative investor sentiments dominate current positive sentiments in trading decisions.



(**a**)



(**b**)

Figure 5. (**a**) Impact of economic recessions (business cycles) on the dependence of EREIT returns. (**b**) Impact of economic recessions (business cycles) on the dependence of MREIT returns.

Additional Analysis

We conduct further analysis and investigate two main issues: (i) What is the marginal effect of the low and high volatility of REIT returns on autocorrelation? (ii) Does the return autocorrelation pattern differ between the REIT eras? (Vintage REIT Era and the New REIT Era).

According to Black (1989), feedback traders base their trading decisions on the previous period's price movements. Their trading activity is driven by returns volatility. Positive feedback (trend following) arises whenever increased volatility engenders further demand for portfolio insurance-type trading activity such as stop-loss orders. The rising demand will intensify positive feedback trading, resulting in negative or lower positive return autocorrelation when a market correction occurs. Conversely, a negative feedback trading activity will increase the return autocorrelation. Overall, an increase in volatility reduces return autocorrelation (Faff and McKenzie 2007). Campbell et al. (1993) offer a parallel view. Specifically, during periods of higher than average volatility, return autocorrelation should be relatively lower since investors know, with high precision, the aggregate level of risk aversion. In light of this evidence, we implement the following model to test the marginal impact of low and high volatility on return autocorrelation at different market states or quantiles.

$$Q_\tau(R_t|\pi_{t-1}) = \alpha_\tau + \left(\beta_\tau^L D_L + \beta_\tau^H D_H\right) R_{t-1} \tag{7}$$

In Equation (7)[18], D_L (D_H) is equal to unity if conditional volatility is low (high) and zero otherwise. Low (high) is the conditional volatility (measured using the threshold GARCH model to account for the asymmetric response of volatility to positive and negative shocks) when the volatility is below (above) the average volatility. Table 6a,b summarizes the coefficient estimates β_τ^L and β_τ^H.

Table 6a,b reveal that the positive and negative feedback trading story is driven by the market state and return frequency. For example, for EREITs and MREITs, high volatility of daily returns negatively and incrementally impacts return autocorrelation in all quantiles (bad state or low quantile, central quantiles, and good state or high quantiles), and is consistent with the positive feedback trading. However, the positive marginal impact of low volatility of MREIT returns at daily and monthly frequency supports the negative feedback trading thesis in the bad state. The MREITs coefficient estimate, β_τ^L, for the monthly return frequency is higher than β_τ^L of the daily frequency at every quantile (market state) due to aggregation of information over a longer period.

As Feng et al. (2011) note, the REITs' regulatory framework has undergone several changes since the market was initiated in 1960, triggering dramatic changes in the industry's size, nature, and structure. However, the watershed point was in 1993, when the government enacted the Revenue Reconciliation Act (RRA). The RRA was stipulated in part XIII of the Omnibus Budget and Reconciliation Act (OBRA) of 1993[19]. The law eliminated the REITs ownership rule of five-or-fewer people, triggering an influx of institutional investors (such as pension funds), the rapid expansion of REITs property types, and massive capital inflow in the REIT market. Shen et al. (2020) note that the evolutionary and structural changes in the REIT market created two distinct REIT eras, namely the Vintage or old REIT Era (1982–1993) and the New REIT Era (1994–2020). We interact each REIT's era dummy variable with

---

18 The equation can be augmented with R_{t-1} but the marginal impact of low and high volatility remain qualitatively the same with and without the lagged returns.

19 Other notable regulatory reforms were the formation of open-ended, REITs-devoted, mutual funds in 1985; the Tax Reform Act (TRA) of 1986, which abolished the favorable tax treatment of real estate limited partnerships, permitted internal advisement and management, and established vertical integration in the REITs industry; The inception of REITs' initial public offering (IPO) in 1991; the IRS private letter ruling which paved the path for the creation of the umbrella partnership REITs (UPREIT) structure and the first UPREIT IPO in 1992; and the REIT Modernization Act (RMA) of 1999, which reduced required percentage of taxable income distributed to investors from 95% to 90% and permitted REITs to form wholly-owned, taxable REIT subsidiaries through which REITs could offer supplementary services to their tenants.

lagged monthly returns to assess each era's marginal impact on REITs' return autocorrelation using the following model:

$$Q_\tau(R_t|\pi_{t-1}) = \alpha_\tau + \left(\beta_\tau^{OLD} D_{OLD} + \beta_\tau^{NEW} D_{NEW}\right) R_{t-1} \quad (8)$$

Table 6. (**a**) The impact of low and high volatility on the autocorrelation of EREIT returns. (**b**) Impact of low and high volatility on the autocorrelation of MREIT returns.

a

	Daily		Weekly		Monthly	
τ	β_τ^L	β_τ^H	β_τ^L	β_τ^H	β_τ^L	β_τ^H
0.05	0.052	−0.205 ***	0.228	−0.042	0.381 **	0.355 **
0.10	0.039	−0.260 ***	0.107	−0.086	0.238 *	0.266 ***
0.15	0.033	−0.231 ***	0.045	−0.112 **	0.091	0.196 ***
0.20	0.032 *	−0.227 ***	0.050	−0.142 ***	0.025	0.165 ***
0.25	0.033 **	−0.234 ***	−0.017	−0.163 ***	0.018	0.139 **
0.30	0.024 *	−0.232 ***	−0.008	−0.158 ***	0.102	0.110 **
0.35	0.005	−0.244 ***	−0.037	−0.158 ***	0.103 *	0.095 **
0.40	−0.008 *	−0.251 ***	−0.028	−0.205 ***	0.095 *	0.068
0.45	−0.015	−0.245 ***	−0.044	−0.219 ***	0.100	0.040
0.50	−0.017 **	−0.243 ***	−0.058	−0.214 ***	0.119 *	0.022
0.55	−0.036 ***	−0.239 ***	−0.081 **	−0.244 ***	0.022	0.019
0.60	−0.056 ***	−0.233 ***	−0.078 **	−0.256 ***	−0.012	−0.015
0.65	−0.055 ***	−0.229 ***	−0.086 **	−0.265 ***	0.018	−0.042
0.70	−0.054 ***	−0.237 ***	−0.106 ***	−0.280 ***	−0.006	−0.038
0.75	−0.064 ***	−0.246 ***	−0.113 ***	−0.293 ***	0.015	−0.079
0.80	−0.063 ***	−0.257 ***	−0.102 *	−0.310 ***	0.043	−0.134
0.85	−0.057 ***	−0.276 ***	−0.116 **	−0.334 ***	−0.039	−0.130 **
0.90	−0.102 ***	−0.290 ***	−0.148 **	−0.328 ***	−0.067	−0.122 *
0.95	−0.193 ***	−0.334 ***	−0.185	−0.296 ***	−0.268 **	−0.219 **

b

	Daily		Weekly		Monthly	
τ	β_τ^L	β_τ^H	β_τ^L	β_τ^H	β_τ^L	β_τ^H
0.05	0.208 ***	−0.033	0.342 **	0.030	0.675 ***	0.060
0.10	0.158 ***	−0.050 *	0.145	0.014	0.509 ***	−0.010
0.15	0.120 ***	−0.034 *	0.094	0.014	0.324 ***	−0.018
0.20	0.100 ***	−0.041 ***	0.012	0.036	0.327 ***	0.024
0.25	0.073 ***	−0.043 ***	−0.042	0.050	0.300 ***	0.030
0.30	0.065 ***	−0.071 ***	−0.036	0.062 *	0.308 ***	−0.007
0.35	0.073 ***	−0.072 ***	−0.025	0.060 *	0.298 ***	−0.032
0.40	0.041 ***	−0.069 ***	−0.002	0.029	0.275 ***	−0.056
0.45	0.000	−0.076 ***	−0.073	0.015	0.243 ***	−0.035
0.50	0.037 ***	−0.071 ***	−0.057	0.000	0.194 ***	−0.006
0.55	0.010	−0.074 ***	−0.050	−0.032	0.140 *	−0.072 *
0.60	0.027	−0.089 ***	−0.029	−0.044 *	0.131 *	−0.077 *
0.65	0.005	−0.099 ***	−0.011	−0.093 ***	0.084	−0.055
0.70	−0.016	−0.111 ***	−0.031	−0.100 ***	0.119 *	−0.072 *
0.75	−0.020 *	−0.115 ***	−0.017	−0.132 ***	0.069	−0.152 ***
0.80	−0.046 ***	−0.112 ***	0.008	−0.158 ***	0.067	−0.161 ***
0.85	−0.075 ***	−0.132 ***	0.013	−0.217 ***	0.037	−0.167 ***
0.90	−0.121 ***	−0.126 ***	−0.002	−0.248 ***	0.012	−0.149 *
0.95	−0.248 ***	−0.098 ***	−0.047	−0.222 ***	0.026	−0.132 *

Notes: The results in this Table are based on the model shown in Equation (7). We set $\tau = 0.05,\ 0.10,\ 0.15, \ldots, 0.95$. ***, ** and * indicates the statistical significance at 1%, 5%, and 10% level, respectively.

In Equation (8), D_{OLD} (D_{NEW}) is a binary variable equal to one for the OLD or vintage (NEW) REIT Era else zero. β_τ^{OLD} (β_τ^{NEW}) measures the marginal impact of the passive (integrated) REIT market period on return autocorrelation. We expected that the reform during the New REIT Era made the REIT market more integrated with the other financial markets and increased investor participation, thereby improving market efficiency. Table 7 presents results based on monthly REIT's returns.

Table 7. Marginal impact Vintage REIT Era and New REIT Era on the autocorrelation of monthly returns.

		EREITs		MREITs		
τ	α_τ	β_τ^{OLD}	β_τ^{NEW}	α_τ	β_τ^{OLD}	β_τ^{NEW}
0.05	−7.810 ***	0.354	0.357 ***	−10.276 ***	0.276	0.152
0.10	−4.711 ***	0.409 *	0.147	−6.840 ***	0.606 **	0.195 *
0.15	−3.499 ***	0.430 **	0.048	−4.897 ***	0.212	0.244 ***
0.20	−2.586 ***	0.313 **	0.011	−3.606 ***	0.165	0.210 ***
0.25	−2.041 ***	0.295 **	−0.005	−2.713 ***	0.212 *	0.111 **
0.30	−1.323 ***	0.278 **	0.001	−2.155 ***	0.233 *	0.113 ***
0.35	−0.823 ***	0.227 **	0.022	−1.660 ***	0.295 **	0.120 ***
0.40	−0.338 *	0.258 **	0.037	−1.080 ***	0.273 **	0.147 ***
0.45	0.002	0.245 **	0.014	−0.369 *	0.247 **	0.105 ***
0.50	0.692 ***	0.217 *	−0.037	0.008	0.239 **	0.085 **
0.55	1.146 ***	0.263 **	−0.067	0.477	0.265 **	0.089 **
0.60	1.598 ***	0.131	−0.103 ***	1.173 ***	0.324 ***	−0.001
0.65	1.939 ***	0.175	−0.092 **	1.535 ***	0.308 ***	−0.055
0.70	2.549 ***	0.103	−0.095 **	2.205 ***	0.279 **	−0.068
0.75	3.119 ***	0.085	−0.152 ***	2.799 ***	0.319 ***	−0.075 *
0.80	3.759 ***	0.122	−0.150 ***	3.302 ***	0.293 **	−0.088 *
0.85	4.412 ***	0.068	−0.127 **	4.423 ***	0.442 **	−0.130 **
0.90	5.104 ***	0.014	−0.128 *	5.759 ***	0.380 **	−0.148 **
0.95	7.451 ***	0.058	−0.216 **	7.107 ***	0.248	−0.131 *

Notes: The results in this Table are based on the model shown in Equation (7). We set $\tau = 0.05,\ 0.10,\ 0.15, \ldots, 0.95$. ***, ** and * indicates the statistical significance at 1%, 5%, and 10% level, respectively.

The results in Table 7 offer interesting evidence. For either EREITs or MREITs, $\beta_\tau^{OLD} > \beta_\tau^{NEW}$ suggesting that the New REIT Era reduced autocorrelation of REIT returns. This is logical since retail and institutional investors' increased participation improved the REITs' market liquidity and efficiency, thereby decreasing predictability. Alternatively, the Vintage Era was characterized by passive and infrequently traded (illiquid) REIT assets. It is challenging to determine and observe the economic price of an illiquid asset. This results in smoothing of asset returns and understating return volatility, thereby generating increased return autocorrelation relative to a more liquid asset. It is also apparent from Table 7 that when returns are high in a good market state, and many investors are making profits, return autocorrelation decreases, and market efficiency is attained.

5. Summary and Conclusions

This study contributes to the burgeoning literature on autocorrelation or predictability of REIT returns. It is the first study to provide supporting evidence of investors' overreaction to REITs price movements at different quantiles of the return distribution across different return frequencies and different REIT categories. We employ a quantile autoregression model to investigate the quantile-specific predictability of daily, weekly, and monthly EREIT and MREIT returns. Different quantiles may have varying return distributions. We find that the autoregression based on the QAR model generally follows a declining pattern over the conditional return distribution quantiles. Specifically, lower quantiles, which represent a bad market state with negative returns, are characterized by either positive or weakly negative dependence.

In contrast, upper quantiles, considered a good market state with positive returns, are generally marked by negative dependence on past returns. This evidence is consistent with overreaction in the REITs markets. However, the structure of return dependency in the REITs market seems to be a function of the state of the market, frequency of returns, size, and the sign of returns, and the category of REITs (EREIT or MREIT).

Additional analysis that considers the marginal and aggregate effects of lagged negative returns demonstrates that positive and negative returns asymmetrically predict future returns. Current returns are more sensitive to the previous period's negative returns than lagged positive returns in the bad state or lower quantiles. Contrastingly, current returns are more sensitive to the past period's positive returns than negative returns in the upper quantiles or good state, although this pattern varies with the frequency of returns. The autoregressive coefficient estimates of lagged negative returns exhibit a downward sloping dependence pattern and obliterated the statistical significance of the autoregression coefficient estimates of positive returns. Therefore, the overreaction evidenced using the base model seems to be an artifact of lagged negative returns. In the presence of large positive lagged returns, the downward sloping autoregressive pattern is mostly maintained for EREIT, and MREIT returns across daily, weekly and monthly frequencies. The finding of a positive (negative) autocorrelation in the lower (upper) quantiles is consistent with investors' overreaction to macroeconomic news. However, extreme positive lagged returns exhibit positive autocorrelation of returns, supporting an under-reaction phenomena and partial price adjustment mechanism. High volatility reduces serial dependence, consistent with a positive feedback story. The reduced serial dependence at nearly all quantiles during the New REIT Era supports the view that increased integration of the REIT market with other markets as well as increased participation by retail and institutional investors improves market efficiency.

The evidence of a quantile-specific dependency structure supports the adaptive market hypothesis as suggested by Clayton and MacKinnon (2003); Zhou and Lee (2013); and Liu et al. (2019) while partly contradicting past evidence of the efficiency of the REITs markets. The results of the study should be valuable to market participants in the REITs markets, whose successful investment decisions depend on their ability to model and forecast REITs price movements. Although REITs occupy a smaller space relative to stocks and bonds, policymakers should strengthen the regulatory and trading framework of REITs to better protect investors from aggressive price surges, which could engender risk spillover to other financial assets. The evidence from this study can inspire additional studies on the predictability of REIT returns in other developed and emerging markets.

Author Contributions: C.A.M. did the introduction and the literature review. I.F.J. gathered the data, cleaned it and performed the preliminary analysis. G.M.N. (Jeff) did the econometric modeling, interpretation and discussion of the results, drew the conclusion and edited the manuscript. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

References

Aguilar, Mike, Walter I. Boudry, and Robert A. Connolly. 2018. The dynamics of REIT pricing efficiency. *Real Estate Economics* 46: 251–83. [CrossRef]

Anderson, Robert M., Kyong Shik Eom, Sang Buhm Hahn, and Jong-Ho Park. 2013. Autocorrelation and partial price adjustment. *Journal of Empirical Finance* 24: 78–93. [CrossRef]

Assaf, Ata. 2015. Long memory and level shifts in REITs return and volatility. *International Review of Financial Analysis* 42: 172–82. [CrossRef]

Barberis, Nicholas, Andrei Shleifer, and Robert Vishny. 1998. A model of investor sentiment. *Journal of Financial Economics* 49: 307–43. [CrossRef]

Basu, Sudipta. 1997. The conservatism principle and the asymmetric timeliness of earnings. *Journal of Accounting and Economics* 24: 3–37. [CrossRef]

Baur, Dirk G. 2013. The structure and degree of dependence: A quantile regression approach. *Journal of Banking & Finance* 37: 786–98.

Baur, Dirk G., Thomas Dimpfl, and Robert C. Jung. 2012. Stock return autocorrelations revisited: A quantile regression approach. *Journal of Empirical Finance* 19: 254–65. [CrossRef]

Black, Fischer. 1989. *Mean Reversion and Consumption Smoothing*. Working Paper 2946. Cambridge, UK: NBER.

Brennan, Thomas J., and Andrew W. Lo. 2011. The Origin of Behavior. *Quarterly Journal of Finance* 1: 55–108. [CrossRef]

Buchinsky, Moshe. 1995. Estimating the asymptotic covariance matrix for quantile regression models: A Monte Carlo study. *Journal of Econometrics* 68: 303–38. [CrossRef]

Campbell, John Y., Sanford J. Grossman, and Jiang Wang. 1993. Trading Volume and Serial Correlation in Stock Returns. *Quarterly Journal of Economics* 108: 905–39. [CrossRef]

Campbell, John Y., John J. Champbell, John W. Campbell, Andrew W. Lo, Andrew W. Lo, and A. Craig MacKinlay. 1997. *The Econometrics of Financial Markets*. Princeton: Princeton University Press.

Chandrashekaran, Vinod. 1999. Time-Series Properties and Diversification Benefits of REIT Returns. *The Journal of Real Estate Research* 17: 91–112.

Chevapatrakul, Thanaset, and Danilo V. Mascia. 2019. Detecting overreaction in the Bitcoin market: A quantile autoregression approach. *Finance Research Letters* 30: 371–77. [CrossRef]

Chui, Andy C. W., Sheridan Titman, and KC John Wei. 2003. Intra-industry momentum: The case of REITs. *Journal of Financial Markets* 6: 363–87. [CrossRef]

Clayton, Jim, and Greg MacKinnon. 2003. The relative importance of stock, bond, and real estate factors in explaining REIT returns. *The Journal of Real Estate Finance and Economics* 27: 39–60. [CrossRef]

Copeland, Thomas E. 1976. A model of assets trading under the assumption of sequential information arrival. *Journal of Finance* 31: 1149–68. [CrossRef]

Cotter, John, and Simon Stevenson. 2008. Modeling long memory in REITs. *Real Estate Economics* 36: 533–54. [CrossRef]

Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam. 1998. Investor psychology and security market under- and over-reactions. *Journal of Finance* 53: 1839–86. [CrossRef]

Escanciano, J. Carlos, and Ignacio N. Lobato. 2009. An automatic Portmanteau test for serial correlation. *Journal of Econometrics* 151: 140–49. [CrossRef]

Faff, Robert W., and Michael D. McKenzie. 2007. The relationship between implied volatility and autocorrelation. *International Journal of Managerial Finance* 3: 191–96. [CrossRef]

Feng, Zhilan, S. McKay Price, and C. Sirmans. 2011. An overview of equity real estate investment trusts (REITs): 1993–2009. *Journal of Real Estate Literature* 19: 307–43.

Feng, Zhilan, S. McKay Price, and C. F. Sirmans. 2014. The relation between momentum and drift: Industry-level evidence from equity Real Estate Investment Trusts (REITs). *Journal of Real Estate Research* 36: 383–407. [CrossRef]

Glascock, John L., Chiuling Lu, and Raymond W. So. 2000. Further evidence on the integration of REIT, bond, and stock returns. *The Journal of Real Estate Finance and Economics* 20: 177–94. [CrossRef]

Glosten, Lawrence R., Ravi Jagannathan, and David E. Runkle. 1993. On the relation between the expected value and the volatility of the nominal excess return on stocks. *Journal of Finance* 48: 1779–1801. [CrossRef]

Goebel, Paul R., David M. Harrison, Jeffrey M. Mercer, and Ryan J. Whitby. 2013. REIT momentum and characteristic-related REIT returns. *Journal of Real Estate Finance and Economics* 47: 564–81. [CrossRef]

Hao, Ying, Hsiang-Hui Chu, Kuan-Cheng Ko, and Lin Lin. 2016. Momentum strategies and investor sentiment in the REIT market. *International Review of Finance* 16: 41–71. [CrossRef]

Ho, Kim Hin David, and Shea Jean Tay. 2016. REIT market efficiency through a binomial option pricing tree approach. *Journal of Property Investment & Finance* 34: 496–520.

Holden, Craig W., and Avanidhar Subrahmanyam. 2002. News events, information acquisition, and serial correlation. *Journal of Business* 1: 1–32. [CrossRef]

Hui, Eddie C. M., and Sheung-Chi Phillip Yam. 2014. Can we beat the "buy-and-hold" strategy? Analysis on European and American securitized real estate indices. *International Journal of Strategic Property Management* 18: 28–37. [CrossRef]

Hui, E. C. M., J. A. Wright, and S. C. P. Yam. 2014. Calendar effects and real estate securities. *Journal of Real Estate Finance and Economics* 49: 91–115. [CrossRef]

Hung, Szu-Yin Kathy, and John L. Glascock. 2008. Momentum profitability and market trend: Evidence from REITs. *Journal of Real Estate Finance and Economics* 37: 51–69. [CrossRef]

Jennings, Robert H., Laura T. Starks, and John C. Fellingham. 1981. An equilibrium model of asset trading with sequential information arrival. *Journal of Finance* 36: 143–61. [CrossRef]

Jirasakuldech, Benjamas, and John Knight. 2005. Efficiency in the market for REITs: Further evidence. *Journal of Real Estate Portfolio Management* 11: 123–32. [CrossRef]

Karolyi, G. Andrew, and Anthony B. Sanders. 1998. The variation of economic risk premiums in real estate returns. *The Journal of Real Estate Finance and Economics* 17: 245–62. [CrossRef]

Kleiman, Robert, James Payne, and Anandi Sahu. 2002. Random walks and market efficiency: Evidence from international real estate markets. *Journal of Real Estate Research* 24: 279–97.

Koenker, Roger, and Gilbert Bassett Jr. 1978. Regression quantiles. *Econometrica* 1: 33–50. [CrossRef]

Koenker, Roger, and Gilbert Bassett Jr. 1982. Robust tests for heteroscedasticity based on regression quantiles. *Econometrica* 50: 43–62. [CrossRef]

Koenker, Roger, and Zhijie Xiao. 2006. Quantile autoregression. *Journal of the American Statistical Association* 101: 980–90. [CrossRef]

Kuhle, James, and Jaime Alvayay. 2000. The efficiency of equity REIT prices. *Journal of Real Estate Portfolio Management* 6: 349–54.

Lee, Ming-Long, and Kevin Chiang. 2004. Substitutability between equity REITs and mortgage REITs. *Journal of Real Estate Research* 26: 95–113.

Lee, Ming-Te, M. L. Lee, Bang-Han Chiu, and Chyi Lin Lee. 2014. Do lunar phases affect US REIT returns? *Investment Analysts Journal* 43: 67–78. [CrossRef]

Lehmann, Bruce N. 1990. Fads, Martingales, and Market Efficiency. *The Quarterly Journal of Economics* 105: 1–28. [CrossRef]

Lewellen, Jonathan. 2002. Momentum and autocorrelation in stock returns. *Review of Financial Studies* 15: 533–64. [CrossRef]

Li, Lili, Shan Leng, Jun Yang, and Mei Yu. 2016. Stock Market Autoregressive Dynamics: A Multinational Comparative Study with Quantile Regression. *Mathematical Problems in Engineering* 2016: 1285768. [CrossRef]

Liow, Kim Hiang. 2009. Long-term memory in volatility: Some evidence from international securitized real estate markets. *Journal of Real Estate Finance and Economics* 39: 415–38. [CrossRef]

Liu, Jian, Cheng Cheng, Xianglin Yang, Lizhao Yan, and Yongzeng Lai. 2019. Analysis of the efficiency of Hong Kong REITs market based on Hurst exponent. *Physica A: Statistical Mechanics and Its Applications* 534: 122035. [CrossRef]

Ljung, Greta M., and George E. P. Box. 1978. On a measure of lack of fit in time series models. *Biometrika* 65: 297–303. [CrossRef]

Lo, Andrew W. 2004. The adaptive markets hypothesis. *Journal of Portfolio Management* 30: 15–29. [CrossRef]

Lo, Andrew W. 2017. *Adaptive Markets: Financial Evolution at the Speed of Thought*. Princeton: Princeton University Press.

Lo, Andrew W., and A. Craig MacKinlay. 1990. When Are Contrarian Profits Due to Stock Market Overreaction? *Review of Financial Studies* 3: 175–205. [CrossRef]

Mech, Timothy S. 1993. Portfolio return autocorrelation. *Journal of Financial Economics* 34: 307–44. [CrossRef]

Mei, Jianping, and Bin Gao. 1995. Price reversal, transaction costs, and arbitrage profits in the real estate securities market. *Journal of Real Estate Finance and Economics* 11: 153–65. [CrossRef]

Mull, Stephen R., and Luc A. Soenen. 1997. US REITs as an asset class in international investment portfolios. *Financial Analysts Journal* 53: 55–61. [CrossRef]

Nelling, Edward, and Joseph Gyourko. 1998. The Predictability of Equity REIT Returns. *Journal of Real Estate Research* 16: 251–68.

Nikolaou, Kleopatra. 2008. The behaviour of the real exchange rate: Evidence from regression quantiles. *Journal of Banking & Finance* 32: 664–79.

Nofsinger, John R., and Richard W. Sias. 1999. Herding and feedback trading by institutional and individual investors. *Journal of Finance* 54: 2263–95. [CrossRef]

Peterson, James D., and Cheng-Ho Hsieh. 1997. Do common risk factors in the returns on stocks and bonds explain returns on REITs? *Real Estate Economics* 25: 321–45. [CrossRef]

Schindler, Felix. 2011. Market efficiency and return predictability in the emerging securitized real estate markets. *Journal of Real Estate Literature* 19: 111–50.

Schindler, Felix, Nico Rottke, and Roland Füss. 2010. Testing the predictability and efficiency of securitized real estate markets. *Journal of Real Estate Portfolio Management* 16: 171–91. [CrossRef]

Sentana, Enrique, and Sushil Wadhwani. 1992. Feedback traders and stock return autocorrelation: Evidence from a century of daily data. *The Economic Journal* 102: 415–25. [CrossRef]

Shen, Jianfu, Eddie C. M. Hui, and Kwokyuen Fan. 2020. The Beta Anomaly in the REIT Market. *Journal of Real Estate Finance and Economics*, 1–23, in press. [CrossRef]

Sias, Richard W., and Laura T. Starks. 1997. Return autocorrelation and institutional investors. *Journal of Financial Economics* 46: 103–31. [CrossRef]

Simon, Stevenson. 2002. Momentum effects and mean reversion in real estate securities. *Journal of Real Estate Research* 23: 47–64.

Stephen, Lee, and Stevenson Simon. 2005. The case for REITs in the mixed-asset portfolio in the short and long run. *Journal of Real Estate Portfolio Management* 11: 55–80. [CrossRef]

Veronesi, Pietro. 1999. Stock market overreaction to bad news in good times: A rational expectations equilibrium model. *Review of Financial Studies* 12: 975–1007. [CrossRef]

Zhou, Jian, and Jin Man Lee. 2013. Adaptive market hypothesis: Evidence from the REIT market. *Applied Financial Economics* 23: 1649–62. [CrossRef]