# Analyses for the Effects of Investor Sentiment on the Price Adjustment Behaviors for REIT and Stock Markets

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# Analyses for the Effects of Investor Sentiment on the Price Adjustment Behaviors for Stock Market and REIT Market

Abstract

This study examines the effects of investor sentiment on the price adjustment behaviors for real estate investment trust (REIT) and the stock prices by applying the threshold error correction (EC) model. We defined the regimes and estimated the endogenously threshold level by the five investor sentiment proxies: the VIX index, the VXO index, the put/call ratio, and two search volume indexes provided by Google Trends. The empirical results reveal that there are asymmetric effects of investor sentiment on the price adjustment behaviors for both the REIT and stock returns. The coefficients of price adjustment are significantly negative values under most regimes constructed by the different investor sentiment proxies. Moreover, the adjustment degree in upper regime is greater than that in lower regime. Thus, if market participants are strongly bearish or their attention level was high (i.e., in the upper regime), they will quickly adjust their portfolios in response to an economic shock. For all regimes, the efficiency of the price adjustment behavior is greater in the REIT market than in the stock market. The results also reveal the significant lead-lag relationships between the REIT and stock markets under the most regimes.

Keywords: Threshold Error Correction Model, Cointegration, REITs, Asymmetric, Price Adjustments.

## 1. Introduction

A real estate investment trust (REIT) is a famous and useful investment tool that enables investment in real estate – without the investor pays a lots of money to actually buy the real estate. Accordingly, REITs have been getting more and more attention from investors looking for earnings through investment in real estate. The data show that global REIT markets have continued to expand. In 2019, they surpassed a total market capitalization of approximately US$1.7 trillion.[1] The number of countries offering REITs as an investment vehicle was 37 in 2019, almost double what it was in 2009.[2] Currently, the largest REIT markets in the world are in the United States. The number of publicly traded REITs in the U.S. grew from 34 in 1971 to 226 in 2018.[3] The market capitalization of REITs in the U.S. grew from 0.9 billion U.S. dollars in 1975 to 1.05 trillion U.S. dollars in 2018.[4] In consideration of this strong growth in the REIT markets, the main purpose of the present study was to investigate REIT markets with the aim of helping REIT market participants make optimal investment decisions.

Several researchers have compared the functioning of REITs with that of bonds, stocks and real estate in traditional REIT studies. Clayton and Mackinnon (2003) show that small-cap REITs are more like real estate than large-cap REITs. Glascock, Lu and So (2000) show that after the early 1990s REITs became more like stocks and less like bonds. Several findings in the literature suggest that REITs behave like small-capitalization stocks (Chan, Hendershott and Sanders, 1990; Han and Liang,

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[1] Please refer to https://en.savills.com.tw/research_articles/166995/181076-0.
[2] Please refer to https://www.ey.com/Publication/vwLUAssets/ey-global-reit-markets/$FILE/ey-global-reit-markets.pdf.
[3] Please refer to https://www.reit.com/data-research/reit-market-data/us-reit-industry-equity-market-cap.
[4] Please refer to https://www.statista.com/statistics/916665/market-cap-reits-usa/.

1995; Peterson and Hsieh, 1997). Results from Yung and Nafar (2017) support the assertion that REITs behave similarly to common stocks. Most of these studies show that changes in REIT prices are closely related to changes in stock prices (Liu, Hartzell, Greig and Grissom, 1990; Li and Wang, 1995; Ling and Naranjo, 1999; Fei, Ding and Deng, 2010; Liow and Yang, 2005; Tsai and Chiang, 2013). In addition, a number of studies have demonstrated a significant long-term equilibrium between REIT and stock indexes (Glascock et al., 2000; Tsai, Chiang and Lin, 2010; Tsai and Chiang; 2013). Liow and Yang (2005) demonstrated a cointegration relationship between REIT and stock indexes, accompanied by a significant adjustment speed, in Hong Kong and Singapore. Fei et al. (2010) report a strong correlation between U.S. REIT returns and stock market returns from 1987-2008. The above empirical evidence supports the reasonable inference that there should be a long-term equilibrium between the REIT and stock indexes.

Moreover, a number of researchers have found that stock prices, REIT prices and housing prices are characterized by nonlinearities and uncovered their asymmetric dynamics (Sarantis, 2001; Waters and Payne, 2007; Sei-Wan and Bhattacharya, 2009; Lee, Lee and Lee, 2014). Tsai and Chiang (2013) used the threshold error correction model (hereafter the threshold EC model) to estimate the asymmetric adjustment speed between the REITs and stock indexes. They found that the threshold EC model supports more reasonable explanations for the market mechanisms than the traditional error correction model (hereafter the traditional EC model). Enders and Siklos (2001) argued that if one ignores the asymmetric and threshold effects, it may result a misspecification error in the model. Accordingly, in this study we used the threshold EC model to investigate the nonlinear properties of the price adjustment behaviors in the REIT and stock markets when there is short-term disequilibrium between these two markets.

From the perspective of behavioral finance, asset pricing is affected not only by economic fundamentals but also by investor sentiment in the market. The trading patterns of investors indicate that bullish investors, who have positive market expectations, push security prices, whereas bearish investors pressure security prices. Fama (1965) explains that irrational traders constantly misprice assets and arbitrageurs who trade against them push prices toward their fundamental values, thus reducing the impact of investor sentiment on security prices. These observations explain why it is necessary to consider the effects of investor sentiment in developing models for the analyses in financial markets.

Recently, more and more researchers have studied how the prices of financial securities are influenced by investor sentiment. Several studies have found that sentiment-driven price risks, also called "noise trader risks," cause significant asset price anomalies in closed-end fund markets (De Long, Shleifer, Smmers and Waldmann, 1990; Lee, Shleiferand and Thaler, 1991; Gemmill and Thomas, 2002). Moreover, many empirical studies show that investor sentiment significantly impacts stock returns (Neal and Wheatly, 1998; Barkham and Ward, 1999; Lee, Jiang and Indro, 2002; Brown and Cliff, 2004, 2005; Baker and Wurgler, 2006, 2007).

Researchers in the REIT field have also found evidence that investor sentiment has a significant impact on REIT returns (Chan et al., 1990; Lin, Rahman and Yung, 2009; Huerta, Jackson and Ngo, 2015; Huerta, Egly and Escobari, 2016). Several studies (Neal and Wheatley, 1998; Lee, et al., 2002, Baker and Wurgler, 2007; Lin et al., 2009) show that when a proxy for investor sentiment depicts optimism (pessimism) in financial markets, REIT returns are higher (lower) (Neal and Wheatley, 1998; Lee et al., 2002; Baker and Wurgler, 2007; Lin et al., 2009). Huerta-Sanchez and Escobari (2018) shows an asymmetric impact of bearish and bullish institutional investor sentiment on returns in the REIT industry.

However, until now there has been no universal or valid way to measure investor sentiment, although researchers have developed and employed a variety of sentiment proxies. Investor/market sentiment indicators such as the VIX index, the VXO index (i.e., the old VIX index) and the put-call ratio (PCR) have been used by both academics and practitioners studying market behavior (Traub, Ferreira, Mcardle and Antognelli, 2000; Whaley, 2000; Dennis and Mayhew, 2002; Giot, 2002; Brown and Cliff, 2004; Connolly, Stivers and Sun, 2007; Hao, 2017). The VIX and VXO indexes are regarded as investor fear gauges and used to measure investor expectations of market volatility. The PCR, calculated by dividing the trading volume for put options by the trading volume for call options, is also usually used to gauge market sentiment. Sentiment is deemed excessively bearish when the PCR is trading at relatively high levels and excessively bullish when it is traded at relatively low levels.

Recently, data from internet search volumes have been used as an alternative source for measures of investor sentiment or investor attention. The online search volume (OSV) provided by Google Trends has been identified as a rich source of information about what people think and what they want. A number of studies show that OSV are positively related to trading activity, stock liquidity and volatility (Preis, Reith and Stanley, 2010; Bank, Larch and Peter, 2011; Vlastakis and Markellos, 2012; Dimpfl and Jank, 2016). Rochdi and Dietzel (2015) found a significant relationship between OSV and the performance of the U.S. REIT market. Jandl and Fuerst (2016) and Yung and Nafar (2017) found that investor sentiment, measured by OSV data from Google Trends, has a significant effect on REIT returns.

Although prior researchers have attempted to investigate the influence of investor sentiment on stock market and REIT market prices, they haven’t investigated whether the price adjustment behaviors in these two markets alters by investor sentiment. The purpose of this study was to fill this gap. We studied the price adjustment behaviors of REIT and stock markets under different degrees of investor sentiment when the REIT and stock markets deviates from their long-term equilibrium level.

The evidence provided by the studies described above reveals that the VIX index, the VXO index and the PCR series have been widely used by academicians and practitioners as measures of investor sentiment. In addition, the OSV variables are also suitable as investor sentiment indicators when analyzing activities in financial markets. Accordingly, we adopted them as the investor sentiment indicators in our analyses.

We used the threshold EC model, similar to the threshold EC model advocated by Hansen and Seo (2002), to investigate the asymmetric adjustment behaviors on REIT and stock markets under different market circumstances (hereafter defined as regimes). However, our model differs from the traditional threshold EC model which uses the degree of disequilibrium (i.e., the error correction terms) between two markets to define the regimes and to estimate the unknown threshold level of the error correction terms for distinguishing the regimes. In our threshold EC model, we used the preferred measures of investor sentiment to define the regimes and endogenously estimated unknown threshold level of investor sentiment.

We used the S&P 500 index and the REIT index, namely Dow Jones Equity All REIT, as sources for our empirical data. Our empirical results reveal that there is long-term equilibrium between the REIT and stock markets, and there is also asymmetric price adjustment behavior in both markets when the short-term market disequilibrium occurs. Moreover, if market participants are strongly bearish (i.e., in the upper regime), they will quickly adjust their portfolios in response to an economic shock. Our most empirical results reveal two-way causality between the REIT and stock markets under the both regimes of bearish and bullish sentiments.

The paper is organized as follows. In Section 2, we introduce five proxies for investor sentiment: the VIX index, the VXO index, the PCR series, and two OSV indexes provided by Google Trends. The empirical methods we used, namely the cointegration test, the traditional EC model and our threshold EC model, are described in Section 3. In Section 4, we present the data and the empirical results from the models. The final section consists of concluding remarks about our research.

## 2. Some Measures of Investor Sentiment

Investor sentiment refers to the general opinion and attitude of investors towards a particular security or financial market. Han (2007) defines investor sentiment as the aggregate error in investors' beliefs. Baker and Wurgler (2007) define sentiment as an investor's expectation of the price movement in a market that cannot be justified by market fundamentals. As measures of investor sentiment in this study, we used the VIX index, the VXO index, the PCR series and two OSV indexes provided by Google Trends as quantitative proxies for investor sentiment. We describe them in the following subsections.

### 2.1 VIX index

The Chicago Board Options Exchange (CBOE) Volatility Index (ticker symbol VIX) is a popular measure of investor sentiment. It is based on the real-time prices of options on the S&P 500 Index and is designed to reflect investors' consensus expectation of future (30-day) stock market volatility: the greater the VIX, the higher the volatility due to sentiment and uncertainty. Investors, research analysts and portfolio managers look to VIX values as a way to measure market risk and fear before they make investment decisions. Previous researchers have used VIX values as a way to measure investor sentiment when analyzing the price behavior of stock and option markets (Connolly et al., 2007; Hao, 2017; Dennis and Mayhew, 2002). Olsen (1998) notes that the volatility index has been viewed as a "sentiment indicator" in the recent behavioral finance literature and can be regarded as a market indicator of rises and falls in the underlying index. Baker and Wurgler (2007) also treated option-implied volatility as a sentiment measure in investigating the effects of investor sentiment. In this study, we used $VIX_t$ to denote the value in the CBOE Volatility Index at time $t$.

**2.2 VXO index**

The original VIX formula was based on prices of the S&P 100 (OEX) Index options. The CBOE renamed the old VIX as the VXO, and it continues to provide quotes of this index. The CBOE S&P 100 Volatility Index (VXO) is similar to the VIX, but the benchmark index from which it derives its values is the narrower S&P 100 Index (OEX). The VXO index is regarded as an investor fear gauge, since it is based on real-time option prices and thus reflects investors' consensus expectation of future stock market volatility. In addition, it is important to emphasize that as a proxy of investor sentiment, the VXO is forward-looking and measures the volatility that investors expect to see (Whaley, 2000). While the VXO is used to measure investor's fear, it also reflects the uncertainty about the future real economy, and thus it is also widely used to measure uncertainty in stock markets (Ang, Hodrick, Xing and Zhan, 2006; Connolly, Stivers and Sun, 2005; Hilal, Poon and Tawn, 2011; Li, 2012; Vahamaa and Aijo, 2011). The VXO indexes have frequently been used as investor sentiment indicators in previous studies (Traub et. al., 2000; Whaley, 2000, Giot, 2002, 2003). In this study, we denoted the value in the CBOE OEX Implied Volatility index at time $t$ as $VXO_t$.

**2.3 Put/call ratio (PCR)**

The PCR is an indicator that shows the trading volume for put options relative to the trading volume for call options. Buyers of put options bet that stock prices will drop and may be considered pessimists. Buyers of call options bet that stock prices will increase and may be considered optimists. Using trading volume as the basis of measurement, the PCR therefore reflects the ratio of pessimists. The put/call ratio is above 1 when put volume exceeds call volume and below 1 when call volume exceeds put volume. Accordingly, this indicator is used to gauge market sentiment. If the PCR is greater than 1, the pessimists outweigh the optimists. If the PCR is less than one, the optimists outweigh the pessimists. Thus, a low level of PCR is associated with a lower demand for puts, which reflects a more bullish sentiment. By contrast, a higher level of PCR reflects a more bearish sentiment. In traditional studies, the put/call ratio has been another popular indicator of investor sentiment. As the PCR rises, the market is likely to drop. In our analyses the value of the PCR, obtained from the CBOE, at time $t$ is denoted as $PCR_t$.

**2.4 The online search volume (OSV) indexes from Google Trends**

Due to the increasing use of computers and the dominant role of online search engines, OSV has the potential to reveal more personal information than other data sources. Among all the various search engines, Google had a worldwide market share close to 92% in 2019.[5] Google's search engine is the most popular and highly utilized information-supplying platform in the world (Kim, Lučivjanská, Molnár and Villa, 2019). Because Google is the leading search engine, the OSV reported by Google Trends is optimally representative of the internet search behavior of the world population. The platform of Google's search engine provides "non-real time data," that is, historical data from 2004 up to 36 hours prior to the search. Google Trends is the real-time daily index of the volume of queries that users enter in the Google

[5] Please refer to https://gs.statcounter.com/search-engine-market-share.

search engine. It allows users to obtain the volume of queries for a specific phrase, such as "stock price." Specifically, it reports the search frequency for a given term in a form of OSV index. Within each sample period, the OSV values for a search term are normalized to range from 0 to 100, such that a value of 100 means that the highest frequency of search term (Choi and Varian, 2012). For further details on how the query index is defined, please see the Google Trends website.[6]

Wu and Brynjolfsson (2009) argue that Google's OSVs can be used to predict future economic indicators. Rochdi and Dietzel (2015) found that real-estate related terms are more suitable than rather general, finance-related terms for predicting U.S. REIT market movements. They show that constructing OSV indexes by respectively using the search terms "property + properties" and "real estate company + real estate companies" in the "real estate" search categories uncover the best predictors of the U.S. REIT market. In the present study we followed this precedent to construct our two OSV indexes, which we denote as $GI1_t$ and $GI2_t$ at time $t$. Within the "real estate" categories, we constructed $GI1_t$ by using the search term "property + properties" and $GI2_t$ by using the search term "real estate company + real estate companies". We obtained the daily data for these two OSV indexes from the Google Trends website.

## 3. Methodology

In this section we describe the models we used for analyses involving the REIT price, the stock price and investor sentiment. Subsections 3.1 and 3.2 respectively describe use of the cointegration model and the traditional EC model to investigate the long-term relationship between the REIT and stock prices and their respective adjustment behavior. The threshold EC model is described in Subsection 3.3.

[6] The website of Google Trends is http://www.google.com/insights/search/#.

### 3.1 Cointegration model

We used the cointegration test and threshold EC model to analyze the long-term relationship between the REIT and stock log-prices and their price adjustment behavior, respectively. Because Balke and Fomby (1997) show that the cointegration test supported by Engle and Granger (1987) has better statistical power than that supported by Johansen (1988) in the threshold EC model, we used this test to examine the long-term relationship between the REIT and stock markets.

In traditional studies, the long-term relationship between the stock and REIT prices is usually studied by a linear form. Thus, the cointegration for stock and REIT prices is usually expressed as follows (Tsai and Chiang, 2013):

$$S_t = a_0 + a_1 R_t, \tag{1}$$

where $S_t$ is the price of stock at time $t$; $R_t$ is the price of REIT at time $t$; $a_0$ and $a_1$ are the coefficients.

In this study, we want to exam the non-linear relationship between the stock and REIT prices. Thus, the function is expressed in the following:

$$S_t = e^{a_0} R_t^{a_1}. \tag{2}$$

Accordingly, the cointegration test is expressed as follows:

$$\varsigma_t = \ln S_t - \beta' \Psi_t, \tag{3}$$

where $\varsigma_t$ is the error correction term at time $t$; $\beta$ is the cointegrated vector (i.e., $\beta = [a_0, \quad a_1]'$) and $\Psi_t = [1, \quad \ln R_t]'$. The unit root test was used to examine whether the error correction term process is a stationary process (i.e., $I(0)$). If $\varsigma_t$ is a stationary process, there is a long-term relationship between $\ln S_t$ and $\ln R_t$.

**3.2 The traditional EC model**

If there is a long-term relationship between the REIT and stocks markets, the traditional EC model can be used to find the market mechanism when there is disequilibrium between these two markets. Tsai and Chiang (2013) have used the traditional EC model to analyze the adjustment behavior for the prices of stock and REIT. Our model differs from the Tsai and Chiang (2013) model is that we use the stock and REIT log-prices to analyze the adjustment behavior. Accordingly, we can analyze the price adjustment behaviors for the stock and REITs from the return's viewpoint since the difference of asset log-price can be used to calculate the asset return. We describe the traditional EC model as follows:

$$\Xi_t = A'\Theta_{t-1}(\beta) + u_t, \tag{4}$$

where $\Xi_t = [\Delta \ln S_t, \quad \Delta \ln R_t]'$, $\Theta_{t-1} = [1, \quad \varsigma_{t-1}, \quad \Xi_{t-1}, \quad \cdots \quad \Xi_{t-p}]$, $p$ is a lag number, $u_t$ represents the residual terms, and $A$ represents the parameter matrix with a rank of (2$p$+2)×2. In the traditional EC model, the coefficient of $\varsigma_{t-1}$ represents the adjustment speed of the market to an economic shock.

**3.3 Our Threshold EC model**

If the REIT and stock markets embody structural change and asymmetric adjustment behavior, the adjustment mechanism may be different after an unknown change point (i.e., threshold level) of investor sentiment that is difficult to know beforehand. The threshold EC model introduced by Hansen and Seo (2002) allows us to endogenously estimate the unknown threshold level of investor sentiment. This model can also uncover potential nonlinearities and asymmetries in the adjustment of individual REIT and stock prices.

Tsai and Chiang (2013) have also used the threshold EC model supported by Hansen and Seo (2002) to examine the adjustment behavior of REIT and stock markets and the lead-lag relationship between them. Our model differs from the Tsai and Chiang (2013) model. In the latter, the threshold effects are driven by the difference in the degree of market disequilibrium (the error correction term in the model) between the REIT and stock markets. In our model, we intend to study whether the adjustment behavior will be different under different investor sentiment. Thus, we used investor sentiment indicators to define the unknown threshold level. Our threshold EC model is described as follows:

$$\Xi_t = B_1'\Theta_{t-1}I_{\kappa\le\kappa^*} + B_2'\Theta_{t-1}(1-I_{\kappa\le\kappa^*}) + \xi_t, \tag{5}$$

where $B_1$ and $B_2$ are the coefficients of the model under the two regimes, distinguished by the investor sentiment; each of $B_1$ and $B_2$ is a matrix with a rank of (2*p*+2)×2; $\kappa$ represents a series of investor sentiment; $\kappa^*$ is the unknown threshold level of investor sentiment; $\xi_t$ is the residual terms; and $I_\Omega$ is the indicator function: $I_\Omega$ = 1 if the state is $\Omega$ and $I_\Omega$ = 0 otherwise, with $\Omega = \{\kappa \le \kappa^*\}$.

We used the maximum likelihood function to estimate the unknown threshold level of investor sentiment and the coefficients $B_1$ and $B_2$. If $B_1$ differs significantly from $B_2$, the threshold effect holds. The adjustment mechanisms governing the REIT and stock markets are different when the investor sentiment value exceeds the threshold level. The null hypothesis is described as follows:

$H_0: B_1 = B_2$.

The Lagrange multiplier, denoted as $LM$, was used to test the null hypothesis $H_0$. The statistic $SupLM$, the supremum Lagrange Multiplier for estimators, is used to examine the threshold effect on the threshold EC model. The methods for estimating the values of $\kappa^*$, $B_1$, $B_2$, $LM$ and $SupLM$ are shown in the Appendix.

## 4. Empirical Analyses

There are six subsections in this section. Subsection 4.1 describes the data. Subsection 4.2 describes the cointegration test. Subsection 4.3 presents the estimates from the traditional EC model. The test of the threshold effect is described in Subsection 4.4. Finally, Subsection 4.5 presents the estimates from the threshold EC model.

### 4.1 Data description

We used daily data for the REIT indexes, stock indexes and the five proxies of investor sentiment, mentioned in Section 2, to perform the analyses. The sample period, from May. 20, 2010 to Oct. 04, 2019, yielded 2361 observations for each variable. The S&P 500 index, obtained from the data bank of TEJ[7], was used to represent the stock index. Generally, there are two main types of REITs that investors can buy: equity REITs and mortgage REITs. Both may be listed on the major stock exchanges, but they can also be traded privately. Of the two, equity REITs are accounting for roughly 90% of the REIT market. Thus, we use equity REITs as our sample. The REIT data used in this study are obtained from the Dow Jones Equity REIT Index, which is designed to measure all publicly traded REITs in the Dow Jones

[7] TEJ (Taiwan Economic Journal Co. Ltd) is a company which supports financial data in Taiwan.

U.S. stock universe. The data from the Dow Jones Equity All REIT index were obtained from the website of investing company.[8]

We adopted five proxies of investor sentiment. They are taken from the three market-based data sources (i.e., the $VIX_t$ index, the $VXO_t$ index and the $PCR_t$) and the two OSV indexes from Google Trends (i.e., $GI1_t$ and $GI2_t$). The data from market-based data sources were obtained from the CBOE website.[9] The daily values for $GI1_t$ and $GI2_t$ were obtained from the Google Trends website.[10] Google Trends reports daily data only for roughly 38 weeks at a time. To avoid the influences of extreme values of OSV, we use the moving average value with the 5-days window (i.e., from current to previous 4-days) to calculate the daily series of $GI1_t$ and $GI2_t$. The preliminary statistics reported for these variables in Table 1 are the mean, standard deviation, skewness, kurtosis and sample size.

[Insert Table 1 here]

### 4.2 Cointegration test for the log-stock and log-REIT indexes

To examine cointegration effects on the stock and REIT markets, we first performed a unit roots test. We used the augmented Dickey-Fuller (ADF) test to examine the unit roots (Fuller, 1976; Dickey and Fuller, 1981). The results shown in Table 2 reveal that the original REIT and stock log-prices were not stationary. However, after one difference, the null hypotheses for the unit root was rejected at the 1% confidence level. Thus, the results show that the log-prices of REIT and stock have unit roots after one difference.

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[8] The website is: https://www.investing.com/.
[9] The website is: https://www.cboe.com/.
[10] The website is: https://trends.google.com/. We firstly obtained the daily values of Google Trends in each month and then used the monthly values of Google Trends as the weights to adjust them.

[Insert Table 2 here]

We employed the Engle-Granger cointegration test to determine whether there were any long-term relationships between the REIT and stock markets. The cointegration can be achieved if $\varsigma_t$ in equation (3) represents a stationary process. Table 3 shows that the estimated coefficients of the error correction term $\varsigma_t$ in the ADF test (i.e., $b_1$) are significant at the 1% confidence level. Thus, the REIT log-price was cointegrated with the stock log-price, from which we conclude that there was non-linear long-term equilibrium between the REIT and stocks markets.

[Insert Table 3 here]

The value of the cointegrated coefficient is 1.5478, significant at the 1% confidence level, from which we conclude that the significant relationship between the REIT and stock markets is positive. These findings may be useful for investors seeking arbitrage opportunities in these two markets. For example, our results show that if the REIT log-price goes up by 1%, the stock log-price can be anticipated to increase by 1.5478%. If this does not occur, there is an arbitrage opportunity to engage in the REIT and stock markets.

**4.3 Estimates from the traditional error correction model**

The foregoing results reveal that there was a long-term relationship between the REIT and stock markets. Next, we analyze the price adjustment behavior of these two indexes using the traditional EC model. For simplify, we let the lag number to be one in the traditional EC model and our threshold EC model. The estimates from the traditional EC model are reported in Table 4, where it is shown that the estimated coefficient is -0.0038 for the stock market and -0.0083 for REIT market. The former is significant at the 10% confidence level and the latter is significant at the 1%

confidence level. Once the stock (REIT) log-index deviates from long-term equilibrium at 1%, its return decreases at an approximate speed of 0.0038% (0.0083%). We recommend that investors sell (buy) when the stock log-price and REIT log-price are below (above) equilibrium.

[Insert Table 4 here]

Table 4 also shows the lead-lag relationships between stock return ($\Delta \ln S_t$) and REIT return ($\Delta \ln R_t$). The estimated coefficient for $\Delta \ln R_{t-1}$ on $\Delta \ln S_t$ was -0.0168, and the estimated coefficient for the effect of $\Delta \ln S_{t-1}$ on $\Delta \ln R_t$ was -0.0581. However, both of them were not significant. We conclude there are no lead-lag relationships between stock return and REIT return in traditional EC model.

**4.4 Test of the threshold effect**

In this subsection, we report our analyses to determine whether there was a threshold effect in the adjustment behavior of the stock and REIT markets, using the threshold value estimated by the proxies of investor sentiment ($VIX_t$, $VXO_t$, $PCR_t$, $GI1_t$ and $GI2_t$). The results of the threshold tests for each proxy are presented in Table 5, where we find that the $SupLM$ values are 52.9557, 39.7235, 42.1913, 19.3357 and 34.9050 for $VIX_t$, $VXO_t$, $PCR_t$, $GI1_t$ and $GI2_t$ respectively. The $SupLM$ values for $VIX_t$, $VXO_t$, $PCR_t$ and $GI2_t$ but not $GI1_t$, exceed the critical values at the 1% confidence level. Thus, we infer that once a market shock destroys the long-term relationship between REIT and stock markets, the price adjustment behaviors of the two markets should have significantly asymmetric effects under the different degree of investor's sentiment when using $VIX_t$, $VXO_t$, $PCR_t$ and $GI2_t$ as the proxy of investor sentiment. We thus use these four proxies of investor sentiments in the analyses for threshold EC model.

[Insert Table 5 here]

For our model, we define the "lower regime" as cases where investor sentiments are below the estimated threshold level (i.e., $\kappa \le \kappa^*$); and the "upper regime" as cases where investor sentiment are above the estimated threshold level (i.e., $\kappa > \kappa^*$). In the lower (upper) regime, the market participants were bullish (bearish) or their attention level was low (high). Moreover, we defined the common economic situation as the regime with the larger sample size. As shown in Table 5, the endogenously estimated threshold levels were 21.4300, 20.2636, 1.2700 and 15.1168 for $VIX_t$, $VXO_t$, $PCR_t$ and $GI2_t$ respectively. The sample sizes for the pessimist regimes were 2005, 1924, 1722 and 1666 for $VIX_t$, $VXO_t$, $PCR_t$ and $GI2_t$ respectively. The corresponding percentages of the total sample are 85%, 81%, 73% and 71%. Because these percentages are all > 50%, we chose the lower regime as the common economic situation for the subsequent analyses.

**4.5 Estimates from the threshold error correction model**

The threshold EC model is used to analyze how the market mechanisms changed, and whether the lead-lag relationship was different, under the two investor sentiment regimes. Table 6 reports the estimates from the threshold EC model using each of four proxies of investor sentiment ($VIX_t$, $VXO_t$, $PCR_t$ and $GI2_t$) as the threshold variable.

[Insert Table 6 here]

With the threshold EC model, the estimated adjustment speeds for the stock and REIT indexes were negative and significant at the 1% level for both the lower and upper investor sentiment regimes, except for the stock market under the upper regime when using $PCR_t$ as investor sentiment proxy. For example, when we adopted $VIX_t$ as the investor sentiment proxy, the adjustment speeds are respectively -0.0031 and -0.0042 for stock market and REITs market in the lower regime. It means that once the stock index and REIT index deviate from their long-term equilibrium, both the stock index and REIT index will go down in the next period. Accordingly, investors should be a seller in the stock and REIT markets for earning profits under the market imbalance situations when adopted $VIX_t$, $VXO_t$ and $GI2_t$ as the proxies of investor sentiment. However, when using $PCR_t$ as investor sentiment proxy, the estimated adjustment speeds of $\Delta \ln S_t$ was positive and significant at the 1% level in the upper regime. In such case, the investors can be a buyer for getting profits in the upper regime of stock market if they use $PCR_t$ as investor sentiment proxy.

As shown in Table 6, the estimated price adjustment speed was greater in the REIT market than in the stock market no matter which investor sentiment proxy was chosen, meaning that adjustment efficiency was better in the REIT market. In addition, the magnitudes of the adjustment speeds are all greater under the upper regime than under the lower regime no matter which investor sentiment proxy was chosen. For example, using $VIX_t$ as the proxy of investor sentiment, the absolute values of estimated adjustment speeds in the stock market were 0.0031 and 0.0132 for the lower regime and upper regime respectively. Likewise, in the REIT market, the absolute values of estimated adjustment speeds were 0.0042 and 0.0429 for the lower regime and upper regime respectively. Thus, the adjustment speed was much faster in the upper regime. Thus, a bearish investor sentiment or a higher degree of investor sentiment causes the price adjustment behavior to be more efficient in both markets. We infer that investor's portfolios were quickly adjusted in response to the economic shocks when they were bearish or their attention level was high.

Regarding the analyses of the lead-lag relationships, the results from the traditional EC model (see, Table 4) show no lead-lag relationships between stock return and REIT return. However, the estimates from our threshold EC model (see, Table 6) revealed that there are two-way causalities for stock and REIT returns under the most regimes, except for under the lower regimes when using $VIX_t$ and $VXO_t$ as investor sentiment proxies as well as the upper regime when using $GI2_t$ as investor sentiment proxy. This implies that the previous information about the stock returns was useful for predicting the REIT returns in the most regimes, and vice versa.

However, the effects of previous return information in the two markets were different under the two regimes. For stock market, under the upper regime, the estimated coefficient of $\Delta \ln R_{t-1}$ on $\Delta \ln S_t$ was negative and significant at the 1% confidence level no matter which investor sentiment proxy was chosen. For example, when using $VIX_t$ as the proxy of investor sentiment, the estimated coefficient of $\Delta \ln R_{t-1}$ on $\Delta \ln S_t$ was -0.0259. This means that the lagged REIT returns negatively influenced the current stock returns under the upper regime. In the lower regime, the lead-lag relationships were different. The estimated coefficient of $\Delta \ln R_{t-1}$ on $\Delta \ln S_t$ was positive and significant at the 1% confidence level when using $PCR_t$ and $GI2_t$ as the proxies of investor sentiment. For example, when using $GI2_t$ as the proxy of investor sentiment, the estimated coefficient of $\Delta \ln R_{t-1}$ on $\Delta \ln S_t$ was 0.0313. This means that the lagged REIT returns positively influenced the current stock returns under the lower regimes.

As for REIT market, under the lower regime, the estimated coefficient of $\Delta \ln S_{t-1}$ on $\Delta \ln R_t$ was negative and significant at the 1% confidence level no matter which investor sentiment proxy was chosen. For example, when using $VIX_t$ as the proxy of investor sentiment, the estimated coefficient of $\Delta \ln S_{t-1}$ on $\Delta \ln R_t$ was -0.0548. This means that the lagged stock returns negatively influenced the current REIT returns. However, the lead-lag relationships were different under the upper regime. In this regime, the estimated coefficient of $\Delta \ln S_{t-1}$ on $\Delta \ln R_t$ was positive and significant at the 1% confidence level when using $VIX_t$ and $VXO_t$ as the proxies of investor sentiment. This means that the lagged stock returns positively influenced the current REIT returns under the upper regime of most proxies of investor sentiment. When we used $PCR_t$ as the proxy of investor sentiment, this estimated coefficient was negative and significant at 1% confidence level. Thus, the inference is opposite when using $PCR_t$ as the proxy of investor sentiment

Because more of the parameter estimates from our threshold EC model were significant than those from the traditional EC model, we conclude that our model provides a more accurate explanation of the relationship between the REIT and stock markets. In addition, most of the adjustment behavior of the REIT and stock markets and their lead-lag relationships were significant for the both two investor sentiment regimes. We thus conclude that the results from our threshold EC model are more useful in providing suggestions for investors about adjusting their portfolios than the estimates from the traditional EC model.

**5. Conclusions**

It is important for investors who want to choose trading strategies for the stock market and the REIT market pay attention to investigate the mechanisms of these two markets. A number of empirical studies show that investor sentiment influences the prices of stocks and REITs. These results led us to use the threshold EC model to analyze whether the price adjusted behavior of REIT and stock markets is asymmetric under different kinds of investor sentiment. The VIX index, the VXO index, the PCR and two OSV indexes provided by Google Trends were used as proxies of investor sentiment. Our empirical results can be summarized as follows:

1. The threshold effects held when adopting $VIX_t$, $VXO_t$, $PCR_t$ and $GI2_t$ as the proxies of market sentiment, but not $GI1_t$. Thus, the price adjustment behaviors of the stock market and REIT market have significantly asymmetric effects under the different levels of investor sentiment when these two markets were in disequilibrium. Moreover, the lower regime of investor's sentiment is the common economic situation.

2. In our threshold EC model, the adjustment speeds were all negative and significant at the 1% confidence level under both regimes, except for the upper regime when using $PCR_t$ as the investor sentiment proxy. Thus, investors can undertake the optimal investment strategies based on these empirical results. Under a market disequilibrium situation, investors could get a profit to be a seller in both stock and REIT markets when adopting $VIX_t$, $VXO_t$ and $GI2_t$ as the proxies of investor

sentiment. However, when the investor sentiment was defined by $PCR_t$, the investors could obtain a profit to act a buyer in the upper regime of stock market.

3. The adjustment speeds were faster in the REIT market than in the stock market regardless of which sentiment regimes. Thus, adjustment efficiency was better in the REIT market than in the stock market under disequilibrium situations.

4. The adjustment processes with the upper regime were faster than with the lower regime. Therefore, the market participants quickly adjusted their portfolios in response to the economic shocks when they were bearish or their attention level was high in both markets.

5. All regimes have causality relationships between stock return and REIT return. For most regimes, there are two-way causalities between two markets. Only under the three regimes: the lower regimes defined by $VIX_t$ and $VXO_t$ as well as the upper regime defined by $GI2_t$, there are one-way causalities. This implies that information about previous stock returns can be used to predict REIT returns, and vice versa.

6. The causality effects in the two markets were different under the two regimes. The lagged REIT returns negatively (positively) influenced the stock returns under the upper (lower) regimes. On contrast, the lagged stock returns negatively (positively) influenced the REIT returns under the lower (upper) regimes.

In summary, our results imply that the price adjustment behaviors, the lead-lag relationships and the mutual influence effects in these two markets indeed alter under the different degree of investor sentiment. Compared with the results from the traditional EC model, the results from the threshold EC model provide a more valid explanation of the relationship between the REIT and stock markets. Our results and analyses should enable the provision to investors of more useful information and a better understanding of the long-term equilibrium between the REIT and stock indexes, their asymmetric adjustment behavior, and their lead-lag relationships under different kinds and strengths of investor sentiment or investor’s attention level when market imbalance occurs. These results should help investors adopt optimal investment strategies and asset portfolio allocations under the different regimes of investor sentiment when there is an imbalance in the REIT and stock markets.

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## Appendix

In this appendix we show the method for examining the threshold effect and estimating the threshold level. The method is similar to the threshold model in Hansen and Seo (2002) and Tsai and Chiang (2013).

In Equation (5), if $B_1$ differs significantly from $B_2$, the threshold effect holds. The adjustment mechanisms governing the REIT and stock indexes are different when our investor sentiment measure exceeds some threshold level. We use the maximum likelihood function to estimate this threshold level of investor sentiment. In accordance with Hansen and Seo (2002), we defined $\Sigma$ as a variance-covariance matrix for Equation (5). We have: $\Sigma = E[\xi_t \xi_t']$, where $E[\cdot]$ is the expected operator. Assuming $\xi_t$ follows a Gaussian distribution, the log-likelihood function for sample size *n* is:

$$L_n(B_1, B_2, \kappa^*, \Sigma) = -\frac{n}{2}\log|\Sigma| - \frac{1}{2}\sum_{t=1}^{n}\xi_t'\Sigma^{-1}\xi_t .$$

We use the distribution of investor sentiment to estimate possible threshold values $\kappa^*$. The lower limit, $\kappa_L$, is the value of $\kappa$ at the 15% quantile of the distribution; the upper limit, $\kappa_U$, is the value of $\kappa$ at the 85% quantile. To estimate the optimal threshold, we divide the range between $\kappa_L$ and $\kappa_U$ into 100 units. The grid search method is used to obtain the optimal threshold, $\hat{\kappa}^*$, based on the maximum value of the log-likelihood function. On the optimal threshold $\hat{\kappa}^*$ we can also obtain the estimated coefficients $\hat{B}_1$ and $\hat{B}_2$.

One can use the Lagrange multiplier, denoted as $LM$, to test the null hypothesis $H_0$. The value of $LM$ can be calculated from the following function:

$$LM = \mathrm{vec}(\hat{B}_1 - \hat{B}_2)'(\hat{V}_1 + \hat{V}_2)^{-1}\mathrm{vec}(\hat{B}_1 - \hat{B}_2),$$

where $\mathrm{vec}(\cdot)$ is an operator of the stacked vector, and $\hat{V}_1$ and $\hat{V}_2$ represent the estimated variance-covariance matrices of $\mathrm{vec}(\hat{B}_1)$ and $\mathrm{vec}(\hat{B}_2)$ respectively.

If $\kappa$ is known, the traditional rules for using the $LM$ test are viable. However, as we previously mentioned, $\kappa$ is unknown. Therefore, there might be a nuisance problem (also called the Davies Problem) with the test (see Davies, 1987; Hansen and Seo, 2002). Thus, the statistic $SupLM$ is used to examine the threshold effect (see Davies, 1987). $SupLM$ is defined as follows:

$$SupLM = \sup_{\kappa_L \le \kappa \le \kappa_U} LM(\kappa).$$

The fixed regressor bootstrap method was used to obtain the critical values of $SupLM$ (Hansen and Seo, 2002; Tsai and Chiang, 2013). We randomly sampled $\xi_t$ 2000 times and obtained the optimal $SupLM$ value each time. Using the 1% significance level, the left critical value is the 0.5% quantile of the optimal $SupLM$ distribution and the right critical value is the 99.5% quantile. Using the 5% significance level, the quantiles are 2.5% and 97.5%.

**Table 1: Summary statistics for all variables**

| | $S$ | $R$ | $VIX$ | $VXO$ | $PCR$ | $GI1$ | $GI2$ |
|---|---|---|---|---|---|---|---|
| Mean | 1966.837 | 302.481 | 16.781 | 16.242 | 1.135 | 43.687 | 13.208 |
| Std | 556.587 | 52.046 | 5.646 | 5.945 | 0.259 | 8.715 | 3.739 |
| Max | 3025.860 | 411.470 | 48.000 | 50.130 | 2.310 | 63.784 | 28.880 |
| Median | 1994.290 | 312.220 | 15.360 | 14.910 | 1.110 | 46.020 | 13.104 |
| Min | 1022.580 | 180.120 | 9.140 | 6.320 | 0.350 | 19.412 | 4.914 |
| Skewness | 0.146 | -0.273 | 1.791 | 1.600 | 0.512 | -0.613 | 0.403 |
| Kurtosis | 1.889 | 2.100 | 7.085 | 6.470 | 3.610 | 2.510 | 3.193 |
| Sample Number | 2361 | 2361 | 2361 | 2361 | 2361 | 2361 | 2361 |

Note: This table shows the mean, standard deviation (Std), maximum value (Max), median, minimum value (Min), skewness and kurtosis for each variable in the study. $S$ is the S&P 500 stock index; $R$ is the REIT index (Dow Jones Equity All REIT); $VIX$ is the CBOE Volatility Index; $VXO$ is the CBOE OEX Implied Volatility; $PCR$ is the put/call ratio, defined as the put volume of the CBOE index option divided by the call volume of the CBOE index option. $GI1$ and $GI2$ are the two OSV (online search volume) indexes used in this study. We obtained the daily $GI1$ and $GI2$ values from the website Google Trends. For the "real estate" categories, $GI1$ values were identified by using the search term "property + properties" in Google Trends, and the $GI2$ values were identified by using the search term: "real estate company + real estate companies." The sample period, from May. 20, 2010 to Oct. 04, 2019, yielded 2361 observations for each variable.

**Table 2: The results of the unit-root test**

| Variables | Original series | First difference |
|---|---|---|
| $\ln S_t$ | 1.9531 | -49.8687*** |
| $\ln R_t$ | 1.2013 | -50.0727*** |

Note: This table shows the results of the Augmented Dickey-Fuller test (Dickey and Fuller, 1981) for the series at original and first difference levels. $\ln(S_t)$ is the stock log-prices and $\ln(R_t)$ is the REIT log-prices. *** denotes significance at the 1% level.

**Table 3: Results of the Engle-Granger cointegration test**

| Parameter | Estimated Value |
|---|---|
| $a_0$ | -1.2746*** |
| | (-21.5230) |
| $a_1$ | 1.5478*** |
| | (148.9562) |
| $b_1$ | -0.0091*** |
| | (-3.3201) |
| F-value | 22187.9579 |
| AIC | -0.0091 |

Note: This table shows the results of the Engle-Granger cointegration test, used to examine the long-term relationship between the stock log-prices and the REIT log-prices. In the regression, $a_0$ is the constant coefficient, $a_1$ is the cointegrated coefficient and $b_1$ is the estimated coefficient for the error term in the ADF test. The t-values are in parentheses. *** denotes significance at the 1% level.

**Table 4: Estimated results from the traditional EC models**

| | $\Delta \ln S_t$ | $\Delta \ln R_t$ |
|---|---|---|
| c | 0.0004** | 0.0004 |
| | (2.3127) | (1.5494) |
| $\varsigma_{t-1}$ | -0.0038* | -0.0083*** |
| | (-1.8272) | (-3.3508) |
| $\Delta \ln S_{t-1}$ | -0.0317 | -0.0581 |
| | (-1.0608) | (-1.6433) |
| $\Delta \ln R_{t-1}$ | -0.0168 | -0.0343 |
| | (-0.6695) | (-1.1529) |
| $R^2$ | | 0.0087 |

Note: $\varsigma_{t-1}$ is the error term obtained from the cointegration regression; $\Delta \ln S_t$ is the stock index return at time $t$; $\Delta \ln R_t$ is the REIT index return at time $t$. The t-values are in parentheses. *** denotes significance at the 1% level, ** at the 5% level and * at the 10% level.

**Table 5: Results of the threshold test and estimated threshold values**

| | **Value of** *SupLM* | **5% critical value** | **1% critical value** | **Optimal threshold value ($\kappa^*$)** | **Sample number** | |
|---|---|---|---|---|---|---|
| | | | | | **Lower Regime** | **Upper Regime** |
| $VIX_t$ | 52.9557*** | 28.4337 | 31.7860 | 21.4300 | 2005 | 356 |
| | | | | | (85%) | (15%) |
| $VXO_t$ | 39.7235*** | 27.6313 | 30.6877 | 20.2636 | 1924 | 437 |
| | | | | | (81%) | (19%) |
| $PCR_t$ | 42.1913*** | 28.5092 | 32.8581 | 1.2700 | 1722 | 639 |
| | | | | | (73%) | (27%) |
| $GI1_t$ | 19.3357 | 28.1208 | 31.5513 | 42.9619 | 876 | 1485 |
| | | | | | (37%) | (63%) |
| $GI2_t$ | 34.9050*** | 28.0271 | 32.0706 | 15.1168 | 1666 | 695 |
| | | | | | (71%) | (29%) |

Note: The critical value of *SupLM* was obtained by the bootstrapping method. $\kappa^*$ is the optimal threshold value of a market sentiment proxy. The lower (upper) regime is the regime below (above) the estimated threshold value. For other definitions, see Tables 1 and 4. In the rows for sample number, the percentage of the sample in each regime is in parentheses. *** denotes significance at the 1% level

**Table 6: Estimated results from the threshold EC model using the different investor sentiments proxies**

| Threshold Variable | $\Delta \ln S_t$ | $\Delta \ln R_t$ | $\Delta \ln S_t$ | $\Delta \ln R_t$ |
|---|---|---|---|---|
| $VIX_t$ | **Lower Regime (** $VIX_{t-1} \le \kappa^*$ **)** | | **Upper Regime (** $VIX_{t-1} > \kappa^*$ **)** | |
| c | 0.0007*** | 0.0008*** | 0.0028*** | 0.0063*** |
| | (6292.1356) | (5512.0958) | (2385.3139) | (3917.3555) |
| $\varsigma_{t-1}$ | -0.0031*** | -0.0042*** | -0.0132*** | -0.0429*** |
| | (-631.3218) | (-620.5688) | (-291.8420) | (-687.0063) |
| $\Delta \ln S_{t-1}$ | -0.0010 | -0.0548*** | -0.0607*** | 0.0128*** |
| | (-0.7689) | (-30.4964) | (-18.1381) | (2.7642) |
| $\Delta \ln R_{t-1}$ | -0.0005 | 0.0378*** | -0.0259*** | -0.1634*** |
| | (-0.4950) | (29.7244) | (-11.1462) | (-50.8714) |
| $R^2$ | | | | 0.0192 |
| $VXO_t$ | **Lower Regime (** $VXO_{t-1} \le \kappa^*$ **)** | | **Upper Regime (** $VXO_{t-1} > \kappa^*$ **)** | |
| c | -0.0002*** | -0.0005*** | 0.0002*** | -0.0017*** |
| | (-1836.9876) | (-2910.8949) | (484.6784) | (-2792.9032) |
| $\varsigma_{t-1}$ | -0.0035*** | -0.0055*** | -0.0131*** | -0.0325*** |
| | (-678.7959) | (-755.9393) | (-385.9505) | (-690.7234) |
| $\Delta \ln S_{t-1}$ | -0.0067*** | -0.0658*** | -0.0192*** | 0.0531*** |
| | (-4.5000) | (-31.7776) | (-7.5092) | (14.9166) |
| $\Delta \ln R_{t-1}$ | 0.0003 | 0.0402*** | -0.0478*** | -0.1739*** |
| | (0.2919) | (29.5631) | (-25.2539) | (-66.1668) |
| $R^2$ | | | | 0.0187 |

Note: The lower (upper) regime is the regime below (above) the threshold value $\kappa^*$. Other definitions can be found in Tables 4 and 5.

**Table 6: Estimated results from the Threshold EC models using the different investor sentiments proxies (continue)**

| Threshold Variable | $\Delta \ln S_t$ | $\Delta \ln R_t$ | $\Delta \ln S_t$ | $\Delta \ln R_t$ |
|---|---|---|---|---|
| $PCR_t$ | **Lower Regime (** $PCR_{t-1} \le \kappa^*$ **)** | | **Upper Regime (** $PCR_{t-1} > \kappa^*$ **)** | |
| c | -0.0006*** | -0.0012*** | 0.0012*** | 0.0009*** |
| | (-4067.5719) | (-6510.2911) | (3490.9258) | (1740.5670) |
| $\varsigma_{t-1}$ | -0.0055*** | -0.0098*** | 0.0003*** | -0.0037*** |
| | (-922.7863) | (-1197.1491) | (20.6174) | (-161.8321) |
| $\Delta \ln S_{t-1}$ | 0.0060*** | -0.0376*** | -0.0634*** | -0.0308*** |
| | (4.4277) | (-19.9896) | (-23.2729) | (-8.1404) |
| $\Delta \ln R_{t-1}$ | 0.0025*** | 0.0523*** | -0.0418*** | -0.1624*** |
| | (2.4965) | (37.2167) | (-23.6039) | (-65.9666) |
| $R^2$ | | | | 0.0213 |
| $GI2_t$ | **Lower Regime (** $GI2_{t-1} \le \kappa^*$ **)** | | **Upper Regime (** $GI2_{t-1} > \kappa^*$ **)** | |
| c | 0.0001*** | -0.0003*** | -0.0003*** | -0.0017*** |
| | (506.3657) | (-1796.2817) | (-756.5132) | (-3183.2709) |
| $\varsigma_{t-1}$ | -0.0042*** | -0.0047*** | -0.0036*** | -0.0191*** |
| | (-713.1130) | (-563.5385) | (-213.0342) | (-817.1886) |
| $\Delta \ln S_{t-1}$ | -0.0328*** | -0.0655*** | -0.0166*** | 0.0059 |
| | (-23.8906) | (-34.1892) | (-6.3228) | (1.6169) |
| $\Delta \ln R_{t-1}$ | 0.0313*** | 0.0462*** | -0.0730*** | -0.1541*** |
| | (30.1126) | (31.8707) | (-42.1484) | (-63.9019) |
| $R^2$ | | | | 0.0155 |

Note: The lower (upper) regime is the regime below (above) the threshold value $\kappa^*$. Other definitions can be found in Tables 4 and 5.