Volatility Persistence in Equity REIT Market

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Abstract

Extreme shocks if occur will have significant and permanent impact on the risk premiums of the stock markets. Modeling these events in a conditional variance framework assuming that the stock market will mean-revert in a short time could produce spurious results. Using the Markov-switching autoregressive conditional heteroskedasticity (MS-GARCH) model to filter out the high volatility states from the low and medium volatility states, we found that the volatility persistence ("*large news*") increases the returns of the equity real estate investment trust (EREIT). However, when the volatility persistence is interacted with negative shocks, it cause the EREIT returns to decline. The negative volatility persistence effects fit the story of inter-temporal asset substitution, which explain why risk-averse REIT investors substitute risky REIT assets by risk-less assets in periods of prolong negative shocks.

Keywords: *Regime switching, volatility feedback, volatility asymmetry, volatility persistence, Markov-switching GARCH, EREIT beta*

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1. Introduction

Extreme events have repeatedly crashed the world stock markets once in every 10 years in the past three decades. The extreme shocks include the "*Black Monday*" in 1987, the Asian Financial crisis in 1997 and the most recent US Subprime crisis in 2007. Why did the major crashes repeat time after time in the history? The behavioral literature blames investors' sentiment and irrational expectation for driving excessive price movements in the markets (Shleifer and Summer, 1990; DeLong, Shleifer, Summers and Waldmann, 1990). Other financial economists (Malkiel, 1979; Merton, 1980; Pindyck, 1984), however, explain that the extreme swings in the stock prices are caused by changing risk premiums over time. A high risk premium in periods of high volatility causes sharp declines in stock prices. The leverage hypothesis also predicts the same positive stock volatility and risk premium relationship, but the direction of causality is reversed of that predicted by the time-varying risk premium hypothesis. Black (1976) and Christie (1982) argue that declines in stock prices increase leverage of firms, which in turn increases high volatility.

The generalized autoregressive conditional heteroscedastic (GARCH) model and its family of variants have been used by the past studies to test the time-varying risk premium hypothesis. The GARCH framework has also been extended by researchers to empirically test for the effects of asymmetric conditional variance (Breen, Glosten and Jagannathan, 1989; Glosten, Jaganathan and Runkle, GJR, 1993), and volatility feedback (squared variance effects) (Campbell and Hentschel, CH, 1992) in the stock markets. The test on the persistence of the volatility feedback by using the Markov-switching GARCH (MS-GARCH) model (Kim, Morley and Nelson, 2004; and Bae, Kim and Nelson, 2007) is one of the latest extensions in the GARCH family. By modeling the volatility feedback effects (CH, 1992) in the MS-GARCH model, this paper makes an attempt to empirically separate the effects of asymmetric shocks from the persistent shocks in extreme events that shock the stock markets. Unlike the earlier studies using stock market returns, we use the equity real estate investment trust (EREIT) returns in our empirical tests for two reasons. First, the low beta (defensive) EREIT stocks are less influenced by the sentiment effects of the "trend-chasers". Second, the "*defensiveness*" of EREITs could be tested to see if they offer effective hedges against the extreme shocks to the stock markets.

We test the effects of the asymmetric shocks ("bad news") and the volatility persistence ("large news") on the EREIT excess returns. Our results show that EREIT beta increases in the declining market, which are consistent with the asymmetric beta hypothesis. We also find that the asymmetric beta effects ("bad news") are stronger in the sub-period 1992M11-2009M6 relative to the earlier sub-period 1972M1-1992M10. We use the smoothed probability estimated in the MS-GARCH model to filter out high volatility regimes, and test the beta characteristics in the high persistent volatility regimes. Our results show a positive and significant volatility persistence effects on the EREIT beta especially for the post-1993 periods. Interestingly, we also observe that the bad news effects have negative impact on the EREIT returns, if the shocks were persistent, and not transitory. The volatility persistence results fit the story of inter-temporal asset substitution by GJR (1993). The results imply that if the negative shocks were persistent and pro-longed, risk-averse REIT investors substitute risky REIT assets by risk-less assets. The volatility persistence supports the story of asset substitution (Abel, 1998; Barsky, 1989; GJR, 1993).

The remainder of the paper is organized as follows: Section 2 reviews the relevant literature on time-varying risk premiums and asymmetric betas in EREITs. Section 3 discusses the empirical methodology, which includes model specification, data analysis and unit roots tests on data. Section 4 analyzes the empirical results of the MS-GARCH model and also the tests of asymmetric beta and volatility feedback effects in the EREIT markets. Section 5 concludes the study.

2. Literature Review

2.1. Time-varying Risk Premiums

The empirical studies using the GARCH models and its variants support the volatility feedback hypothesis that predicts a positive relationship between conditional volatility and returns in the stock markets (Farench, Schwert and Stambauch, 1987; CH, 1992). The empirical results offer relatively weak evidence on the leverage hypothesis (Bekaert and Wu, 2000; Wu, 2001; Black and McMillan, 2006; and Bae, Kim and Nelson, 2007). In contrary to the volatility feedback hypothesis, Breen, Glosten and Jagannathan (1989) and GJR (1993) found a negative correlation between market return and conditional variance. They argue that the result is consistent with the inter-temporal asset substitution story (Abel, 1988; Barsky, 1989), where risk-averse investors reduce their risk premiums by substituting risky assets for and riskless assets in the periods of high volatility.

Poterba and Summers (1986) are the first to question the weak persistence of return volatility in 1960s and 1980s. They found that the shocks on risk premiums decayed quickly over a half-life of less than 6 months. Affirming the result, CH (1992) showed that the half-life of high conditional volatilities persisted only between 12 and 18 months. Despite the weak persistence in the shocks, CH (1992) found that the volatility feedback effects (extreme shocks) constitute significant volatility discounts that caused large price declines in the early 1930s and the October 1987. The volatility feedback effect is enhanced when the asymmetric covariance between the market-level and the firm-level volatilities is considered (Bekaert and Wu, 2000; Wu, 2001), because large stock price declines induced by shocks to dividend variance are more likely to occur when the stock market crashes.

Kim, Morley and Nelson (2004) and Bae, Kim and Nelson (2007) tested the volatility persistence in changing volatility regimes using a Markov-Switching GARCH framework. They found that conditional variances are neither persistent nor correlated with the returns when regime switching is included in the GARCH model. Changes in the volatility regime are reflected in the stock return, not in the conditional variance.

2.2. Asymmetric Equity REIT betas

EREITs are low beta stocks (Ghosh, Miles, and Sirmans, 1996; Chan, Hendershott and Sanders, 1990; others). EREITs distribute at least 90% of their earnings back to investors as dividends. The steady streams of dividend payouts in both good and bad times "*defend*" investors against major shocks. The high payouts also imply that the future growth of EREITs is closely driven by the accessibility to new capital in the stock and bond markets. High liquidity premiums during volatile markets could significantly hamper the growth of EREITs.

The time-varying characteristic of EREIT beta was observed by Ghosh, Miles, and Sirmans (1996), who showed that the correlation coefficient of monthly return between the National Association of REIT (NAREIT) index and the stock market index dropped from 0.77 in 1985-1987 to 0.401 in 1994-1996. Clayton and Mackinnon (2003) attribute the time-varying EREIT volatility to the changing correlations of EREIT returns with different common risk factors in the stock market and the real estate market. These volatility drivers include the large-cap stock factor in 1970s, the small-cap stock factor in the late 1980s, and the real estate factor in the post-1993 periods. Glascock, Lu, and So (2000) also found that EREITs behaved more like small capitalization stocks after 1992. The changing REIT volatility reflects the maturation and increased sophistication of investor base in the EREIT markets (Clayton and MacKinnon, 2003).

There is also mixed evidence on the asymmetry of EREIT betas. Goldstein and Nelling (1999) and Sagalyn (1990) showed that equity REIT betas were higher in declining markets than in advancing markets.[1] Glascock (1991) showed that REIT beta was pro-cyclical that increased in the up-markets.[2] Chatrath, Liang and McIntosh (2000) failed to find empirical evidence to explain the asymmetric behavior of REIT betas.[3] The asymmetric beta hypothesis was rejected by Chiang, Lee and Wisen (2004), who found that REIT betas were symmetrical in rising and declining markets, after controlling for the three Fama-French (1993) factors.

3. Empirical Methodology and Data Analysis

3.1. Model Specifications

Following CH's (1992) framework, we develop a model to explain the volatility feedback effects on the stock price changes for EREITs. We first define the excess return of EREIT stock *i* as in Merton's (1986) model:

$$E(r_{i,t}) - E(r_{f,t}) = \beta E(r_{m,t}) \tag{1}$$

where $r_{f,t}$ is the risk-free rate of return, r_{mt} is the stock market return, and β is an unconditional beta measuring systematic risks. E(.) is the expectation operator.

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1 Goldstein and Neiling 1999) defines the declining market using a dummy variables that has a value of 1, if the excess market return is negative, zero otherwise. Gloscock's (1991), however, uses the non-recessionary periods classified by the National Bureau of Economic Research to represent down-market betas.

2 Glascock's (1991) samples of real estate firms include a mixed sample of builders, contractors, developers and REITs.

3 Their results rejected the hypotheses that the asymmetric REIT betas are caused by the non-stationary properties in REIT beta and the time-varying dividend yield spreads of REIT. The variance effects that drive the asymmetry in small capitalization stock beta were not found in their results.

Based on the volatility feedback model of CH (1992) (see Appendix I for details), which defines the return function as:

$$r_{m,t+1} = \mu + \varphi\sigma_t^2 + \kappa\eta_{d,t+1} - \lambda\eta_{d,t+1}^2 \tag{2}$$

we define the excess return function with three exogenous and independent variance terms as:

$$r_{m,t+1} - r_{f,t+1} = (\gamma + \lambda)\sigma_t^2 + \kappa\eta_{d,t+1} - \lambda\eta_{d,t+1}^2 \tag{3}$$

where the right-hand side of the equation is represented by three different variance sources that include conditional variance, σ_t, innovation to dividend news, $\eta_{d,t+1}$, and shocks to (squared) dividend variance, $\eta^2_{d,t+1}$. φ, κ and λ are regression coefficients, where [$\varphi = \gamma + \lambda$].

By substituting Equation (3) into the excess return for EREIT stock (Equation (1)) and also scaling the high volatility-regime using the Hamilton and Susmel's (1994) Markov Switching model (See Appendix 2 for details), we obtain:

$$E(r_{i,t}) - E(r_{f,t}) = \beta E\left[\mu + (\gamma + \lambda)\sigma_t^2 + \kappa\eta_{d,t+1} - P\{s_{t+1} = j \mid \Phi\}\psi\left(\lambda, \alpha, g_{s,t+1}\right)u_{d,t+1}^2\right] \tag{4}$$

where $P\{ s_t = j \mid \Phi \}$ is the "smoothed probability" measuring the probability of EREIT being in a particular volatility state [s_t = j] at time t , and $\sqrt{g_{s_t}}$ is the squared-root scale factor, where the value of g_{s_t} measures the volatility effects in a regime, s_t, at time t.

To implement the empirical tests for the regime-switching volatility feedback model as in Equation (4), we use two market indicators to proxy the regime-dependent asymmetric variance and volatility feedback, which are the second and the third terms in Equation (3). The "*bad news*" indicator, I_A, is used to test the asymmetric effects, where ($I_A = 1$) denotes a declining market, if ($r_{m,t} < r_{f,t}$); and $I_A = 0$ denotes an up-market, otherwise. The "*large news*" indicator, I_V, has a value of 1, if the smoothed probability for a high volatility state, (s_t = 3), is 0.5 or more, that is [P(s_t= 3|Φ) ≥ 0.5]; and otherwise, the value is zero to indicate "*no large news*" effects, that is [[*1* – P(s_t= 3|Φ)] ≥ 0.5]. The empirical specification for the excess REIT return model can be written as follows:

$$\left(r_{i,t} - r_{f,t}\right) = \tilde{\mu} + \beta_1\left(r_{m,t} - r_{f,t}\right) + \beta_2 I_A\left(r_{m,t} - r_{f,t}\right) - \beta_3 I_V\left(r_{m,t} - r_{f,t}\right) + \varepsilon_t \tag{5}$$

where ε_t denotes the residual errors. The extended version of the regime-dependent volatility feedback model that includes the three Fama-French factors can be written as:

$$\left(r_{i,t} - r_{f,t}\right) = \tilde{\mu} + \left[\beta_1 + \beta_2 I_A - \beta_3 I_V\right]\left(r_{m,t} - r_{f,t}\right) + \delta_1\ SMB + \delta_2\ HML + \varepsilon_t \tag{6}$$

where "SMB" denotes the small market capitalization risk; and "HML" denotes high book-to-market values risks. If the asymmetric beta effects, [$\beta_2 \neq 0$], is not rejected, it implies that the REIT stock returns are more correlated with the negative (bad) news than the positive news. It the "large news" coefficient is significant, [$\beta_3 \neq 0$], the volatility feedback hypothesis is not rejected, which indicates that shocks to dividend innovations, both positive and/or negative, that increase volatility persistence (high volatility regimes) could have negative impact on REIT stock returns, as indicated by the negative signs of β_3.

3.2. Descriptive Statistics

We compute the monthly returns of EREITs using the National Association of Real Estate Investment Trusts (NAREIT) Index data for the sample periods from February 1972 to June 2009. The stock market returns and the risk-free returns are represented by the New York Stock Exchange price index and the monthly Treasury bill rate respectively over the same sample period. The historical time series of the three variables that are REIT return, the stock market return and the risk free return are plotted in Figure 1. Except for the periods in the post-2007 crisis, the EREIT returns fluctuate within a tighter range relative to the NYSE returns.

[Insert Figure 1]

We also compute the descriptive statistics of the return variables and the results are summarized in Table 1. EREIT has a mean return of 0.44%, which is lower than the mean return of 0.64% for the NYSE stock market and the mean risk-free rate of return of 0.50%. The standard deviation of the risk-free return is the smallest at 0.25%. The standard deviations of the EREIT return and the market returns are 3.94% and 4.13% respectively. By the range measure, the spread of 29.07% for the EREIT returns show that EREIT returns fluctuate within a smaller range relative to the spread of 40.31% for the NYSE market returns.

[Insert Table 1]

3.3. Unit Roots Tests

As a prerequisite for the time-series analysis, we conduct unit roots tests for the excess returns for the EREIT and the NYSE stock market index using the Augmented Dicky-Fuller and the Phillips-Perron tests. The unit root tests results confirm that the two excess return series are I(0) stationary.

3.4. Ramsey Regression Equation Specification Error Test (RESET)

We conduct a Ramsey RESET test on the standard CAPM model with a constant beta by first regressing excess return of EREIT on excess NYSE market return. The estimated beta coefficient is highly significant at less than 1% level. The Ramsey RESET test on the base CAPM model rejects the hypothesis that there are no specification errors for the beta estimate. The result implies that the CAPM model is mis-specified, and the static (symmetric) beta fails to reflect the systematic risks in the

EREIT market.

4. Empirical Results

In our tests for the regime-dependent volatility feedback model, we first estimate the volatility persistence, which is the proxy for the "large news" effect, using the MS-GARCH model. After estimating the high volatility states of the market as indicated by the smoothed probability in the MS-GARCH model, we test the "large news" indicator and together with the asymmetric indicator in the unconditional CAPM models in the stage-two.

4.1. Regime Switching in NYSE Stock Returns

Based on the Akaike Information Criterion (AIC) statistics, we select the first-order autoregressive, AR(1), to generate the NYSE market return process. The Lagrange Multiplier (LM) result rejects the null hypothesis of no ARCH effects. We correct the auto-correlated error terms in the AR(1) stock market returns process by using a three-states, K=3, regime-switching volatility model, MS-GARCH (3,0,1). We also add the market volume variable to control for the liquidity risks in the stock returns. The results of the MS-GARCH (3, 0, 1) model are summarized in Table 2. The constant terms a_0 in the return process, and ω_0 in the conditional variance process are significant and positive at 5% level. The insignificance of α_1 that measure the persistence of the conditional variance, suggests that there is no heteroscedastic residual error (ARCH effects) in the process.

The two normalized scale factors, g_2 and g_3, are significant. The variances in the medium-volatility ($s_t = 2$) and the igh-volatility ($s_t = 3$) states are 1.82 times and 9.19 times higher than the variance in the low-volatility state ($s_t = 1$). The transition probability matrix, **P**, shows that the low-volatility and the medium-volatility are stable and persistent with high probabilities that the volatility will stay within the same regimes, (p_{11} = 0.8957 and p_{22} = 0.8536). The probability of intra-regime shifts is small in the stock markets, which implies strong persistence in the volatility in the stock market.

[Insert Table 2]

Using the smoothed probabilities for being in a high volatility regime and setting the cut-off probability at 0.5 or more, we filter out the high volatility-persistent states using an indicator, I_2, that has a value of 1, if $[P(s_t = 3 \mid \Phi) \geq 0.5]$; and otherwise, zero for the low-volatility states. There were 106 high-volatility states which are represented by the light vertical lines in Figure 2. By dividing the sample periods at the mid-point of October 1992 (1992M10), 56 and 50 high volatility states are determined based on the smoothed probability in the pre-1992M10 (17 states) and the post-1992M11 (16 states) periods respectively. By splitting the excess stock market returns along the horizontal axis (zero return line) in Figure 2, we define the "bad news" indicator, I_1, which has a value of 1 if the excess return is negative. The negative excess return regimes account for about 40.0% of the full sample periods.

[Insert Figure 2]

4.2. *Tests of Regime-Dependent Volatility Feedback Effects*

Based on the "bad news" and "large news" indicators derived in the previous section, we estimate the unrestricted CAPM models in equations (4) and (5) for the full sample periods, as well as for the two sub-periods divided at the mid-point of 1992M10. We first test the asymmetric beta hypothesis independently by imposing the restriction, [$\beta_3 = 0$], in the models. We then allow free estimation of β_3 in the second model, so that the volatility persistence ("*large news*") effects can be tested jointly with the "*bad news*" effects.

4.2.1. *Tests of Asymmetric Beta*

In the asymmetric CAPM model (Equation 4), without controlling for volatility persistence that is [$\beta_3 = 0$], the results in Table 3 show that the unconditional beta, β_1, and the declining market beta, β_2, are positive and highly significant in both the full sample and also the two sub-sample periods. In the full sample periods (Model 1), the coefficients β_1 and β_2 are estimated at 0.3705 and 0.4827 respectively. The systematic risk in the down market periods add up to 0.8532, which implies that the "bad news" effects cause incremental shocks to EREIT returns in the bear markets. EREIT investors are not spared of the bad news shocks. The results support the asymmetric EREIT beta hypothesis, but they show no evidence for the pro-cyclical characteristic as predicted by Glascock (1991).

[Insert Table 3]

In the sub-period results, the unconditional beta, β_1, changes from 0.4084 to 0.2982; whereas the asymmetric beta, β_2, increases from 0.3623 to 0.6601 respectively when comparing the two sub-periods between 1972M1-1992M10 (Model 5) and 1992M11-2009M6 (Model 9). The results are consistent with Glascock, Lu and So's (2000) prediction that REITs in the rapid expansion phase in the 1990s behave more like stock and less like real estate. The so-called "modern" REITs in the post-1993 periods are also more responsive to the "*bad news*" shocks relative to the earlier batch REITs in the pre-1990s periods. When we extend the asymmetric beta model to include the three Fama-French factors (Equation 5) (Models 2, 6 and 10), the results remain robust and consistent with the earlier predictions. The results disagree with the earlier findings by Chiang, Lee and Wisen (2004), which argue that the asymmetric beta effects were caused by omitted variables and can be explained by the small capitalization (SMB) and the book-to-market value (HML) factors.

4.2.2. *Tests of Volatility Persistence*

We add the "*large news*" indicator as a proxy for the volatility persistence effects in the model to empirically test for the investors' risk-aversion towards shocks that have longer-period and persistent impact in the markets. The results in show that the "*large news*" coefficients, β_3, of 0.3526 and 0.7961 are significant for the full sample period (Model 3) and the second sub-sample period 1992M11-2009M6 (Model 11) respectively. After controlling for the SMB and HML risk factors in the models, the β_3 coefficients remain significant, though the values decrease to 0.1613 and 0.4343 for the full sample periods (Model 4) and the sub-periods (1992M11-2009M6) (Model 12) respectively. The "*large news*" effects do not diminish the effects of the unconditional beta, β_1, and the "bad news" beta, β_2, in the models. The results are, however, not significant for the early sub-periods 1972M1-1992M10 (Model 7 and 8). The results show that EREIT investors are risk-averse, and they expect higher risk premiums in response to more persistent market shocks. The volatility persistence ("large news") effects are more pertinent on the EREIT returns in the recent periods after 1993.

We further test the joint effects of the "*large news*" and the "*bad news*" shocks by adding an interactive variable, $[I_{A,t}*I_{V,t}*(r_{m,t}-r_{f,t})]$, for the sub-period 1992M11-2009M6 (Models 13 and 14). The coefficient on the interactive variable is significant, but has a negative sign. The result implies that the volatility persistence ("large news") has positive effects on EREIT returns in a stable market, but the effects reverse if interacted with the bad news effects. The negative correlations with the stock market are consistent with GJR's (1993) story of the inter-temporal switching of risky REIT asset for riskless asset, if investors face prolonged negative shocks in the markets.

5. Conclusion

Extending on the literature on the asymmetric beta and the volatility feedback of CH (1992), we test the effects of the asymmetric shocks ("bad news") and the volatility persistence ("large news") on the EREIT excess returns. Our results, which show that EREIT beta increases in the declining market, are consistent with the asymmetric beta hypothesis. We also find that the asymmetric beta effects ("bad news") are stronger in the sub-period 1992M11-2009M6 relative to the earlier sub-period 1972M1-1992M10. We use the smoothed probability estimated in the MS-GARCH model to filter out high volatility regimes, and test the beta characteristics in the high persistent volatility regimes. Our results show a positive and significant volatility persistence effects on the EREIT beta especially for the post-1993 periods. However, the volatility persistence is interacted with bad news effects will have negative impact on the EREIT returns. The negative volatility persistence results fit the story of inter-temporal asset substitution by GJR (1993).

The above findings have two implications for researchers in the topics of asymmetry volatility and volatility feedback. First, it is not just "*bad news*" shocks that drive up the risk premiums of RETI stocks, investors are also concerned about the persistence of the volatility shocks. Second, if the negative shocks were persistent and pro-longed, REIT investors may exit the market by substituting the risky REIT assets with risk-less assets. The inter-temporal asset substitution story (Abel, 1998; Barsky, 1989; GJR, 1993) is more reinforced by the volatility persistence.

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Appendix I: Volatility Feedback

The volatility feedback model of CH (1992) provides a theoretical framework to test the time-varying relationship between stock return and conditional variance. We first define the log market return, r_m, in the present value model as a function of log-price, p_t, and log-dividend, d_t, (lower cases represent variables in logarithm term) as:

$$r_{m,t+1} = k + \rho\ p_{t+1} + (1-\rho)\, d_{t+1} - p_t \tag{I1}$$

where k is a constant term, ρ is the average ratio of stock price to the sum of stock price and dividend, and the subscript t indicates the time. By substituting the price terms and rearranging the equation, the unexpected return is derived as:

$$r_{m,t+1} - E_t r_{m,t+1} = (E_{t+1} - E_t)\sum_{j=0}^{\infty}\rho^j d_{t+1+j} - (E_{t+1} - E_t)\sum_{j=1}^{\infty}\rho^j r_{m,t+1+j} \tag{I2}$$

The unexpected log-return equation is written in a more compact form as follows:

$$\upsilon_{r,t+1} = \eta_{d,t+1} - \eta_{r,t+1} \tag{I3}$$

where $\eta_{d,t+1}$ and $\eta_{r,t+1}$ denote news about dividends and future stock return at time $t+1$ respectively. Following Merton (1980), the expected return is defined as a function of the conditional variance as:

$$E_t r_{m,t+1} = \mu + \gamma E_t \eta^2_{d,t+1} = \mu + \gamma\sigma_t^2 \tag{I4}$$

where μ is expected (mean) return, and γ is coefficient of relative risk aversion. By combining equations (3) and (4), the stock market return is given as:

$$r_{m,t+1} = \mu + \gamma\sigma_t^2 + \eta_{d,t+1} - \eta_{r,t+1} \tag{I5}$$

Following CH (1992), the time-varying dividend news is an exogenous shock modeled in a Quadratic GARCH (QGARCH) (1,1) process:

$$\begin{aligned} &\eta_{d,t+1} \sim N(0,\sigma_t^2) \\ &\sigma_t^2 = \omega + \alpha(\eta_{d,t} - b)^2 + \beta_2\sigma_{t-1}^2 \end{aligned} \tag{I6}$$

where ω,α and β are positive parameters for the conditional variance process, σ^2_t; and b is an asymmetric parameter that magnifies volatility effects of negative news on stock returns.

The conditional variance process for the future returns with a QGARCH dividend shocks is written as:

$$\eta_{r,t+1} = \left(E_{t+1} - E_t\right)\left[\sum_{j=1}^{\infty}\rho^j r_{m,t+1+j}\right] = \lambda\left(\eta^2_{d,t+1} - \sigma_t^2 - 2b\eta_{d,t+1}\right) \tag{I7}$$

Putting Equations (4) and (7) into Equation (5), the stock market return is driven by innovations to dividend news, dividend variance and conditional variance as:

$$r_{m,t+1} = \mu + \gamma\sigma_t^2 + [\kappa\eta_{d,t+1} - \lambda(\eta_{d,t+1}^2 - \sigma_t^2)] \quad \text{(I8)}$$

where κ = 1 + 2λb captures the predictive asymmetric effects of dividend news; the term in the squared brackets represents the volatility feedback shocks, and λ measures the strength of the shocks. We reorganize the return function of equation (8) as follows:

$$r_{m,t+1} = \mu + \varphi\sigma_t^2 + \kappa\eta_{d,t+1} - \lambda\eta_{d,t+1}^2 \quad \text{(I9)}$$

where [φ = γ + λ]. Equation (9) independently relates the stock return to three different sources of variance, which include conditional variance, innovation to dividend news, and shocks to (squared) dividend variance. The coefficient κ represents the asymmetric innovations in dividend news, $\eta_{d,t+1}$. The volatility feedback is not rejected, [λ≠0], the squared variance term cause negative impact on the stock returns. This is the "no news is good news" effect.

Appendix II: Regime-Switching Conditional Variance Model

We model the error process of the stock market return using Hamilton and Susmel's (1994) generalized Markov Switching GARCH, MS-GARCH (θ, p, q) process as follows:

$$\varepsilon_t = \sqrt{g_{s,t}} \times u_t \quad \text{(II1)}$$

$$u_{t+1} = \sqrt{h_t} \times v_t; \quad v_t \sim N(0,1) \quad \text{(II2)}$$

$$h_t = \omega + \sum_{i=0}^{q} \alpha_i u_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-i} \quad \text{(II3)}$$

where ω is a constant term, u^2_{t-j} is a q-order ARCH terms, h_{t-j} is a p-order conditional error term, and v_t is an uncorrelated innovation that follows a Gaussian distribution.

The switching across regimes is represented by a first order Markov chain process, which has the transition probability matrix:

$$\mathscr{P} = \begin{bmatrix} p_{11} & p_{21} & \cdots & p_{\theta 1} \\ p_{12} & p_{22} & \cdots & p_{\theta 2} \\ \vdots & \vdots & \cdots & \vdots \\ p_{1\theta} & p_{2\theta} & \cdots & p_{3\theta} \end{bmatrix} \quad \text{(II4)}$$

where p_{ij} indicates a transition probability of switching from state i to state j; and the probability of s_t can be determined only through the most recent value s_{t-1}:

$$p_{ij} = \mathrm{P}\{s_t = j \mid s_{t-1} = i, s_{t-2} = k, \ldots, \Phi\} = \mathrm{P}\{s_t = j \mid s_{t-1} = i\} \qquad \text{(II5)}$$

where Φ contains a vector of observed information on stock returns.

The probability density function of $r_{m,t}$ conditional on random state, s_t, and historical information Φ is given as the sum of the joint probability function of $r_{m,t}$ and s_t:

$$f(r_{m,t} \mid s_t, s_{t-1}, \ldots, s_{t-\theta}, \Phi) = \sum_{j=1}^{\theta} \mathrm{P}(r_{m,t}, s_t = j \mid \Phi) \qquad \text{(II6)}$$

The log likelihood function is defined as $L(\Phi) = \sum_{t=1}^{T} \log f(r_{m,t} \mid \Phi)$. Based on the density function and joint probability function, we forecast the "smoothed probability", $P\{ s_t = j \mid \Phi \}$,that measure the likelihood of the stock market being in a particular volatility state [s_t = j] at time t given the full sample of observations:

$$\mathrm{P}\{s_t = j \mid \Phi\} = \frac{f(r_{m,t} | s_t = j, \Phi)}{\mathrm{P}(r_{m,t}, s_t = j \mid \Phi)}, \qquad \text{(II7)}$$

Based on the transition probability matrix and historical information, we could forecast η^2_t at the period t as follows:

$$E[\varepsilon_t^2 \mid s_t, s_{t-1}, \ldots s_{t-q}; \Phi] = (g' \mathscr{P} e_i) \,.\, E[\varepsilon_t^2 \mid \Phi] \qquad \text{(II8)}$$

where g' = [g_1 g_2 … g_θ] is a (1 x θ) vector of scale factor, and e_i is the i-th column of (θ x θ) identity matrix.

We divide the volatility states of the NYSE stock market returns into three regimes, [θ =3]. [$s_t = 1$] denotes a low volatility state, and the ARCH process in this regime is scaled by $\sqrt{g_1}$, such that [$u_t = \varepsilon_t / \sqrt{g_1}$]. The ARCH processes for the medium volatility [s_t =2] and high volatility [s_t=3] regimes are scaled by $\sqrt{g_2}$ and $\sqrt{g_3}$ respectively. By normalizing the scale parameter for the low volatility state to unity, [$g_1 = 1$], the scale variable for the other two regimes is represented by [$g_k \geq 1$; and $g_2 < g_3$; where k = [2, 3]].

We replace the squared variance term in the stock return equation by the following term:

$$I_v = E\left(\varepsilon_t^2 \mid s_{t-1}, u_{t-1}^2\right) = g_{s,t} \times P\{s_t = j \mid \Phi\} \left\{ \omega + \alpha_1 \left(\frac{\varepsilon_{t-1}^2}{g_{s,t-1}} \right) \right\} \qquad \text{(II9)}$$

the regime-dependent stock return function is then rewritten as:

$$r_{m,t+1} = \mu + (\gamma + \lambda)\sigma_t^2 + \kappa\eta_{d,t+1} - P\{s_{t+1} = j \mid \Phi\} \psi(\lambda, \alpha, g_{s,t+1}) u_{d,t+1}^2 \qquad \text{(II10)}$$

where $\psi(\lambda, \alpha, g_{s,t+1})$ is the coefficient for the high volatility state in our tests.

Table 1: Descriptive Statistics

Variable	EREIT return	NYSE stock market return	Riskless rate of interest
Symbol	R_i	R_m	R_f
Mean	0.973	0.863	0.470
Median	1.240	1.250	0.440
Maximum	31.020	16.560	1.350
Minimum	-31.670	-22.540	0.000
Standard Deviation	4.925	4.648	0.248
Skewness	-0.832	-0.586	0.783
Kurtosis	12.290	5.273	4.096

This table reports the descriptive statistics of the value-weighted NYSE stock market returns, the equity REIT return, $R_{i,t}$, and the risk-free interest rate, $R_{f,t}$.

Table 2: Regime-Switching GARCH model

Variable	Coefficient		Standard Error
Mean equation:			
a_0	1.014	***	-0.247
a_1	0.020		-0.048
a_2	-0.001		-0.001
Variance equation:			
ω_0	8.057	**	-3.985
α_1	0.037		-0.082
Transition probability:			
P_{11}	0.896	***	-0.152
p_{21}	0.174		-0.679
p_{12}	0.032		-0.094
p_{22}	0.854	***	-0.155
p_{31}	0.000	***	0.000
p_{32}	0.436		-0.282
State variable:			
g_2	1.823	***	-0.691
g_3	9.192	*	-4.790

The table summarized the estimates for the regime-switching model for NYSE stock market returns. We model the NYSE stock market return series, y_t, as a first-order autoregressive process with its lagged term, y_{t-1},and a stock market trading volume term, Vol_t. The regression error, ε_t, is assumed to follow the MS-GARCH (K, p, q) or the Hamilton and Susmel's Switching-Regime ARCH, SWARCH (K, p), where K indicates the number of volatility states, and q denotes the number of lagged autoregressive term, and p denotes the lagged conditional variance term, such that if p=0, the process is reduced to the ARCH (q) process. The return model with the MS-GARCH(3, 0, 1) error process is specified below:

$$y_t = a_0 + a_1 y_{t-1} + a_2 Vol_t + \varepsilon_t$$
$$\varepsilon_t = \sqrt{g_{s,t}}\, u_t$$
$$u_t = \sqrt{h_t}\, v_t \ , \qquad v_t|\Omega_{t-1} \sim N(0, h)$$
$$h_t = \omega_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2$$

*Note: "***" denotes significance at 1% level, "**" denotes significance at 5% level, and "*" denotes significance at 10% level.*

Table 3: Regression Results for Asymmetric Response Models

a) Full Sample Period: 1972M1-2009M6

	Model 1		Model 2		Model 3		Model 4	
Intercept	1.116	***	0.339		0.989	***	0.306	
	(3.908)		(1.369)		(3.504)		(1.238)	
R_{mt}-R_{ft}	0.371	***	0.569	***	0.305	***	0.531	***
	(4.871)		(8.557)		(3.992)		(7.764)	
IA(* R_{mt}-R_{ft}*)*	0.483	***	0.272	***	0.316	***	0.202	*
	(3.956)		(2.610)		(2.505)		(1.861)	
Iv(* R_{mt}-R_{ft}*)*					0.353	***	0.161	**
					(4.166)		(2.181)	
SMB			0.413	***			0.404	***
			(8.019)				(7.849)	
HML			0.678	***			0.653	***
			(12.242)				(11.594)	
Adjusted R^2	0.369		0.551		0.392		0.555	

b) Sub-sample period: 1972M1-1992M10

	Model 5		Model 6		Model 7		Model 8	
Intercept	0.901	***	0.373		0.877	***	0.372	
	(3.205)		(1.450)		(3.127)		(1.446)	
R_{mt}-R_{ft}	0.408	***	0.483	***	0.370	***	0.471	***
	(5.796)		(7.402)		(4.976)		(6.702)	
IA(* R_{mt}-R_{ft}*)*	0.362	***	0.182	*	0.325	***	0.173	
	(3.083)		(1.712)		(2.718)		(1.597)	
Iv(* R_{mt}-R_{ft}*)*					0.130		0.037	
					(1.600)		(0.502)	
SMB			0.440	***			0.438	***
			(6.970)				(6.916)	
HML			0.283	***			0.277	***
			(4.201)				(4.030)	
Adjusted R^2	0.480		0.594		0.483		0.592	

c) Sub-sample period: 1992M11-2009M6

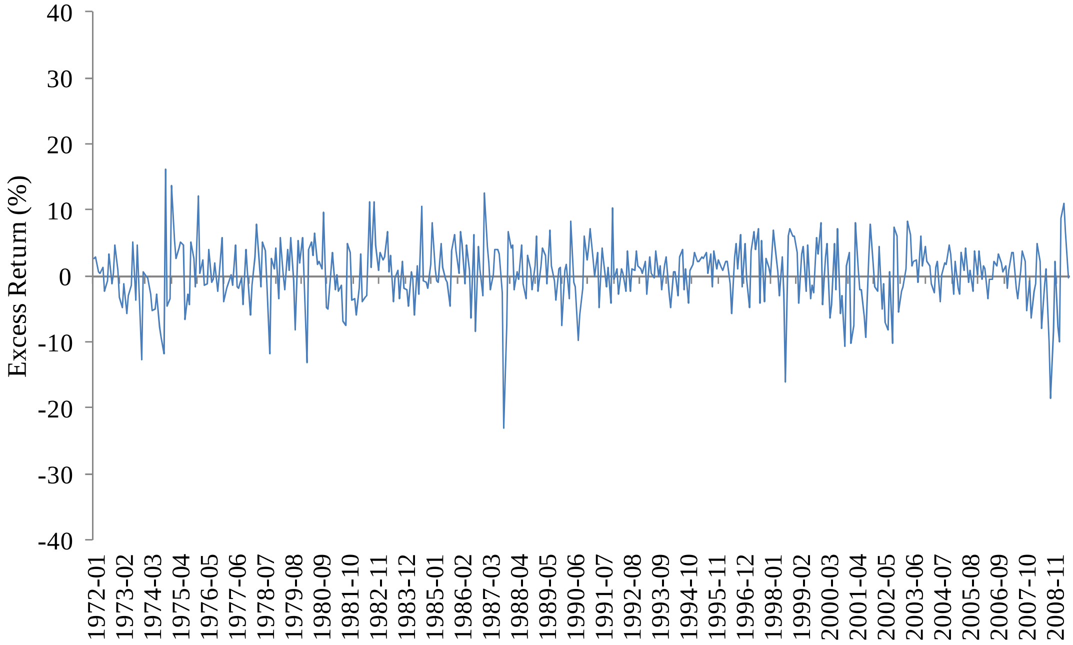
	Model 9		Model 10		Model 11		Model 12		Model 13		Model 14	
Intercept	1.436	***	0.353		0.809		0.072		0.610	*	-0.037	
	(2.533)		(0.797)		(1.444)		(0.163)		(1.747)		-(0.130)	
R_{mt}-R_{ft}	0.298	*	0.629	***	0.328	**	0.626	***	0.348	***	0.632	***
	(1.814)		(4.850)		(2.085)		(4.922)		(3.559)		(7.621)	
$IA*(R_{mt}-R_{ft})$	0.660	***	0.340	*	0.015		0.006					
	(2.631)		(1.753)		(0.052)		(0.027)					
$Iv*(R_{mt}-R_{ft})$					0.796	***	0.434	***	1.439	***	0.845	***
					(4.405)		(2.984)		(4.616)		(3.353)	
$IA*I_V*(R_{mt}-R_{ft})$									-0.768	**	-0.484	*
									-(2.345)		-(1.864)	
SMB			0.535	***			0.508	***			0.500	***
			(6.679)				(6.433)				(6.383)	
HML			1.004	***			0.946	***			0.931	***
			(11.606)				(10.880)				(10.741)	
Adjusted R^2	0.299		0.589		0.358		0.605		0.376		0.612	

The tables summarize the results of the regime-dependent volatility persistence models, where the specification in a generic form can be represented as follows:

$$\left(r_{i,t}-r_{f,t}\right)=\tilde{\mu}+\left[\beta_1+\beta_2 I_A-\beta_3 I_V+\beta_4\left(I_A * I_v\right)\right]\left(r_{m,t}-r_{f,t}\right)+\delta_1 SMB+\delta_2 HML+\varepsilon_t$$

*where ε_t denotes the residual errors; "SMB" denotes the small market capitalization risk; and "HML" denotes high book-to-market values risks. Two indicator variables are included to test the asymmetric effects ("small news"), I_A, and the volatility persistence effects ("large news"), I_V. The models are estimated for the full sample periods 1972M1-2009M6 (in Table 3a), and two sample periods 1972M1-1992M10 (Table 3b) and 1992M11-2009M6 (Table 3c). For the second sub-sample period 1992M11-2009M6, an interactive variable, I_A*I_V, is also included Models 13 and 14. In the table, the numbers in first row of each variable is the regression coefficients; and the numbers in the parentheses are the t-statistics. "***" denotes significance at 1% level, "**" denotes significance at 5% level, and "*" denotes significance at 10% level.*

Figure 1 Time Series of the Data

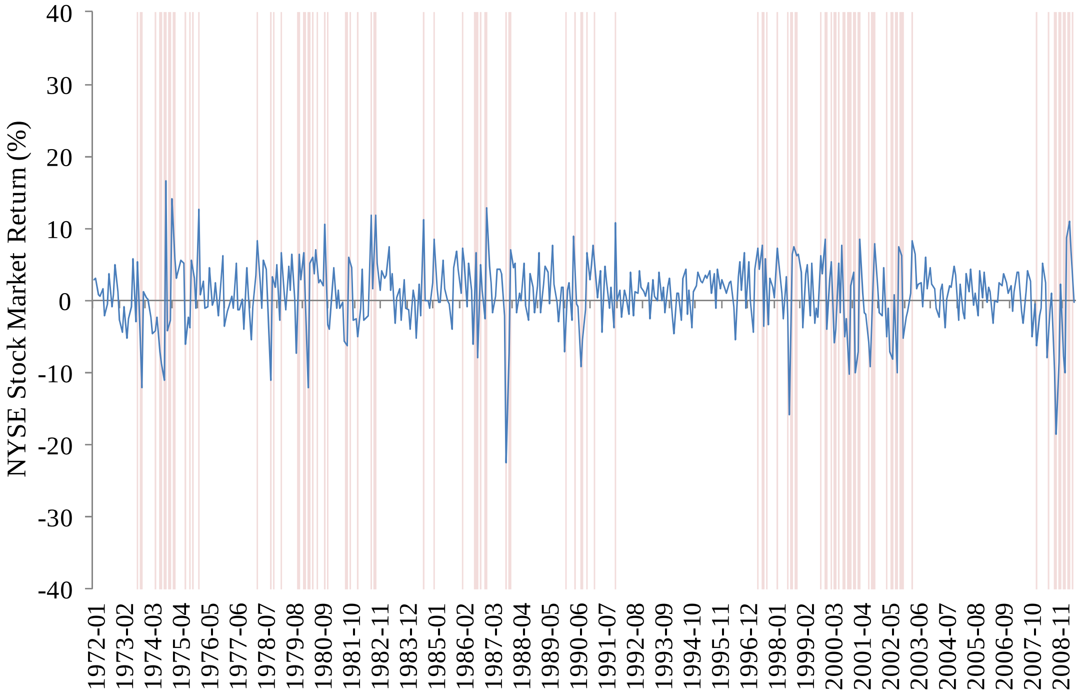


Excess NYSE Stock Market Return

Excess EREIT Return

The figures plot the time-series of excess returns of NYSE stock market index (top) and the NAREIT Equity REIT Index (bottom). The sample periods cover 1972M1-2009M6. For the excess NYSE market stock return, the negative return regime as indicated by returns below the zero return line (horizontal axis) is used to define the asymmetric indicator, I_A.

Figure 2: Market States (Declining or Advancing) in High Volatility Regimes



Notes: The darken solid line represents the monthly market return represented by the NYSE stock index, and the vertical (light) lines indicate the regimes of high volatility persistence as identified by the SWARCH (3,1) models.