Volatilities and Momentum Returns in Real Estate Investment Trusts

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Volatilities and Momentum Returns in Real Estate Investment Trusts

by

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Abstract

This research studies momentum returns in REITs by investigating the cross-sectional relationship between different types of volatilities and asset returns of REITs. We examine asymmetric risk effect in momentum returns with a GARCH-in-mean model. We also study the effects of idiosyncratic volatility and aggregate market volatility on asset returns. We have four main findings. First, momentum returns display asymmetric volatility. Momentum returns in REITs are higher when volatility is higher. Second, REITs with lowest past returns (losers) have higher idiosyncratic risks than those with highest past returns (winners). The difference in losers' and winners' idiosyncratic risks is significant, and can partially explain momentum returns. Third, we find investors require a lower risk premium for holding losers' idiosyncratic risks, but require a higher risk premium for holding winner's idiosyncratic risks. Four, we find a positive relation between asset returns and aggregate market volatility, and the magnitude of the relation is larger for losers than for winners.

Keywords: asymmetric volatility, idiosyncratic volatility, aggregate market volatility, REITs, momentum trading strategy, GARCH-in-mean model

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I. Introduction

Momentum trading strategy buys stocks with the highest past returns (winners), sells stocks with the lowest past returns (losers), and holds the portfolio for six to twelve months. Jegadeesh and Titman (1993) document that the U.S. stock market yields twelve percent annual return over the past thirty years using momentum trading strategy. Additionally, the authors suggest that these momentum returns are not a result of systematic risk of the securities. Chui, Titman and Wei (2003) also find significant momentum returns in Real Estate Investment Trusts (REITs) from 1982 to 2000. However, there is no conclusive explanation for momentum returns. As existing asset-pricing models cannot explain momentum returns, such returns are 'abnormal' in the sense that investors can make profits without any net investment. Abnormal returns generated from momentum trading strategies provide strong evidence against the efficient market hypothesis. Some researchers attribute momentum to investors' overreaction or underreaction to firm-specific news,[1] while others use rational risk-return theories to interpret momentum. Some recent studies on risk-based explanations on momentum returns include Lee and Swaminathan (2000), Connolly and Stivers (2003), Grundy and Martin (2001), Chordia and Shivakumar (2002), Johnson (2002), Ahn, Conrad, and

[1] Jegadeesh and Titman (2001) suggest that momentum returns cannot be explained by cross-sectional dispersion in returns. Behavioral explanations on momentum returns include investors' underreaction to firm-specific news (Barberis, Shleifer, and Vishny 1998 and Grinblatt and Han 2005) or overreaction to firm-specific news (Daniel, Hirshleifer, and Subrahmanyam 1998, 2001, Hong and Stein 1999, and Barberis and Shleifer 2003).

Dittmar (2003), and Moskowitz (2003).[2] Nevertheless, these studies do not reach a conclusive explanation. The momentum phenomenon leads to one interesting question: what risk measures can be used to explain and predict momentum returns?

This research intends to explain momentum by looking into asymmetric risk factors, idiosyncratic risk, and aggregate market risk associated with momentum returns in Real Estate Investment Trusts (REITs). Asymmetric risk is a phenomenon which stock returns and their volatilities are negatively related. In other words, negative returns increase volatility and positive returns decrease volatility [see Engle and Ng (1993), Bekaert and Wu (2000), Wu and Xiao (2002)]. Two popular theories about asymmetric volatility are leverage effects and volatility feedback effects. The leverage effect theory suggests that negative returns on stocks increase financial leverage, which increases their volatilities [see Black (1976) and Christie (1982)]. The authors argue that a fall in stock price causes an increase in debt-equity ratio (financial leverage) of the firm, and the volatility associated with the firm increases subsequently.[3] The volatility feedback hypothesis suggests that good news such as positive stock returns decreases volatility and bad news such as negative stock returns increases volatility [see Bekaert and Wu (2000), Wu (2001), and Dennis, Mayhew, and Stivers (2006)]. An anticipated volatility increase

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[2] Lee and Swaminathan (2000) and Connolly and Stivers (2003) suggest that industry past volume predicts future returns. Grundy and Martin (2001) and Jagadeesh and Titman (2001) find that cross-sectional differences in expected returns is not the dominant cause of momentum. Chordia and Shivakumar (2002) show that most momentum can be explained by lagged treasury-bill yield, market dividend yield, term spread, and default spread. Johnson (2002) suggests that a cross-sectional dividend growth rate should be responsible for momentum. Ahn, Conrad, and Dittmar (2003), Moskowitz (2003) provide a stochastic discount factor to measure risk premium in momentum, and report that when correct risk factor is used, momentum disappears.

[3] A rise in stock price due to positive past returns (winners) will decrease leverage of firms, and thus decrease volatility. On the other hand, a drop in stock price due to negative past returns (losers) will increase leverage of firms, and therefore increase volatility. As a result, the negative relation between volatilities and returns can be explained by leverages of firms.

(decrease) raises (decreases) the required return on equity for losers (winners), which leads to an immediate decrease (increase) of current stock price.[4]

The first goal of this research is to explain momentum returns with volatility feedback theory. Our logic is as follows. We consider good past returns (winners) as good news. According to the volatility feedback theory, the news will decrease future volatilities of winners, and therefore decrease their required rate of returns, causing an increase in immediate stock prices. On the other hand, if we believe poor past returns (losers) as bad news, such news will increase future volatility of losers, and therefore increase required rate of return, causing a decrease in current stock price. As a result, trends on stock prices are magnified by volatilities. Accordingly, stocks with good (bad) past performance will continue to perform well (poorly), causing the momentum effect.

The second goal of this research is to investigate whether idiosyncratic risk and aggregate market risk can explain momentum returns. We are interested in: (1) whether winners and losers have different magnitudes of idiosyncratic risks, and (2) whether winners and losers exhibit different sensitivities to market volatility or idiosyncratic volatility. Ang et. al. (2006) study aggregate volatility risk and idiosyncratic volatility in the cross-section of stock returns. The authors report that stocks with higher sensitivities to aggregate market volatility have lower expected returns. They also find that stocks with higher idiosyncratic risks provide lower returns.[5] We follow Ang et. al. (2006) and

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[4] Bekaert and Wu (2000) examine the leverage effect and time-varying risk premium and suggest that asymmetric volatility is caused by the variance dynamics at the firm level, not by changes in leverage, and thus volatility feedback effect is the dominant cause. Wu (2001) examines both the leverage effect and volatility feedback effect and finds that the volatility feedback is significant both statistically and economically. Dennis, Mayhew, and Stivers (2006) find that market-level systematic volatility is the major factor that causes asymmetric volatility in individual stock returns, and thus support the volatility feedback hypothesis.

[5] Ang et. al. (2006) find that stocks with high idiosyncratic volatility have low average returns. These low average returns to stocks with high idiosyncratic volatility cannot be explained by exposures to size, book-

examine the impact of market aggregate volatility and idiosyncratic volatility to returns of winners and losers, after controlling for other market factors.

Several asymmetric risk models have been studied to explain stock returns. Asymmetric risk models allow conditional variance to be time-variant and are able to better estimate asset returns. For example, Nelson (1991), Glosten, Jagannathan, and Runkle (1993), Laux and Ng (1993) develop asymmetric ARCH models to examine asset returns. Campbell and Hentschel (1992) present a quadratic GARCH (QGARCH) model to study volatility process of stock dividends. The model is able to explain the negative skewness and excess kurtosis of the data. Bekaert and Wu (2000) use a conditional CAPM model with a GARCH-in-mean parameterization to study asymmetric volatility in Japanese stock market, and show that volatility feedback hypothesis better explains asymmetric risk effect than leverage hypothesis does. Black and McMillan (2006) apply a GARCH-in-mean model and show that value stocks have higher asymmetric risk than growth stocks, therefore explaining the value premium (value stocks with high book-to-market ratio have higher returns than growth stocks with low book-to-market ratio). Guirguis, Giannikios, and Anderson (2005) apply a GARCH model and the Kalman Filter with Autoregressive Presentation (KAR) to explain the U.S. housing market with time-varying coefficients. Crawford and Fratantoni (2003) use ARIMA, GARCH, and regime switching univariate time series models to estimate the housing price growth rates in the U.S.

REITs provide a good opportunity to study the asymmetric risk effect in momentum returns for the following reasons. First, REITs can be viewed as one

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to-market, leverage, liquidity, volume, turnover, bid-ask spreads, coskewness, and dispersion in analysts' forecasts characteristics. The effect also persists in bull and bear markets.

homogeneous industry, with underlying assets easy to observe. Second, REITs show cyclical volatility in the past due to economic fluctuations and major structural changes. Therefore, the effect of cyclical volatility in momentum returns may be more significant in REITs. Third, REITs are not included in some previous studies in asymmetric risks.

Our findings are as follows. First, using a GARCH-in-mean model, we discover that momentum returns display asymmetric volatility. Momentum returns in REITs are higher when volatility is higher. Second, losers have higher idiosyncratic risks than winners. The difference in losers' and winners' idiosyncratic risks is significant, and has a positive relation with momentum returns, after controlling for other market risks. Third, we find losers' returns are negatively related to their idiosyncratic risks, whereas winners' returns are positively related to their idiosyncratic risks. This means for losers, higher idiosyncratic volatility is penalized with a lower required rate of return. It also implies that although losers have higher idiosyncratic risks, investors do not require a higher risk premium for holding higher idiosyncratic risks. Four, we find a positive relation between asset returns and aggregate market volatility, and the magnitude of such relation is larger for losers than for winners. It suggests that investors require higher returns for all assets when the overall market is more volatile. However, investors require a higher risk premium for losers than for winners when aggregate market volatility is high.

The rest of the paper is organized as follows. Section II presents our hypotheses and methodologies. Section III describes our data and momentum trading strategy. Results are presented and discussed in Section IV. Finally, Section V presents our conclusion.

II. Hypotheses and Methodologies

2.1 Time-series analysis

The capital asset pricing model (CAPM) and the Fama-French three factor model[6] provide two theoretical foundations for a trade-off relationship between risk and excess return. In theory, risk is to be measured by the conditional covariance of returns with the market. However, in practice, risks vary over time. Prior research has found that asset returns exhibit negative skewness and excess kurtosis. Thus, application of the GARCH-in-mean (GARCH-M) model to traditional asset pricing models improves model performance by permitting risk to be time-variant. More specifically, negative shocks typically increase volatility greater than positive shocks of equal magnitude. In other words, negative returns cause an upward revision of the conditional volatility, whereas positive returns cause a smaller upward or even a downward revision of the conditional volatility. [7] In this research, we extend the capital-asset-pricing model and Fama-French three factor model by Fama and French (1993) with a GARCH(1,1)-in-mean model to study asymmetric volatility in REITs' momentum returns. The model used for estimating Capital-Asset-Pricing Model with a GARCH-M model is as follows:

$$R_t = \beta_0 + \beta_1 R_{m,t} + \gamma\sqrt{h_t} + \varepsilon_t \tag{1}$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} \tag{2}$$

$$\varepsilon_t \,|\Omega_{t-1} \sim N(0, h_t) \tag{3}$$

Where R_t is the excess returns of winner portfolio, loser portfolio, or momentum

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[6] See Fama and French (1993)
[7] See Bollerslev, Chou and Kroner (1992) for a review of ARCH modeling

portfolio, $R_{m,t}$, the market excess return, is the monthly value-weighted return on all NYSE, AMEX, and NASDAQ stocks minus the one-month Treasury bill rate.[8] Volatility of portfolio returns is measured by conditional variance h_t, which is defined as a function of squared values of the past residuals, presenting the ARCH factor, and an auto regressive term (h_{t-1}) presenting the GARCH factor. The parameters $\beta_0, \beta_1, \gamma, \alpha_0, \alpha_1, \alpha_2$ are estimated.

Next, we apply GARCH(1,1)-M model to Fama-French three factor model. The model is as follows.

$$R_t = \beta_0 + \beta_1 R_{m,t} + \beta_2 SMB + \beta_3 HML + \gamma\sqrt{h_t} + \varepsilon_t \tag{4}$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} \tag{5}$$

$$\varepsilon_t \ \left|\Omega_{t-1} \sim N(0, h_t)\right. \tag{6}$$

Where R_t is the excess returns of winner portfolio, loser portfolio, or momentum portfolio, and $R_{m,t}$ is the market excess return. SMB is the small-minus-big size factor, and HML is the high-minus-low book-to-market ratio factor. Volatility of portfolio returns is measured by conditional variance h_t, which is defined as a function of squared values of the past residuals, presenting the ARCH factor, and an auto regressive term (h_{t-1}) presenting the GARCH factor. The parameters $\beta_0, \beta_1, \beta_2, \beta_3, \gamma, \alpha_0, \alpha_1, \alpha_2$ are estimated.

The models described above are to test whether γ equals to zero. If γ equals to

[8] Data is obtained from Kenneth R. French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

zero, there is no relationship between volatility and return. γ is interpreted as the coefficient of relative risk aversion of investors by Merton (1980), Engle, Lilien, and Robins (1987), Campbell and Hentschel (1992), and Champbell (1996). These authors point out that γ is a time-varying risk premium and the sign and magnitude of γ depend on utility functions of investors. As a result, γ can be positive, negative or zero. A positive γ indicates a higher risk premium required by investors when volatility is high. On the other hand, a negative γ means a lower risk premium required by investors when volatility is high. There are no conclusions about the signs of γ. For example, Campbell and Hentschel (1992) find the relation between volatility and expected return to be positive, while Nelson (1991), Glosten, Jagannathan, and Runkle (1993) find the relation to be negative.

We apply these two GARCH-in-mean models to three time-series of returns: returns of winner portfolio, returns of loser portfolio, and returns of momentum portfolio. We have two hypotheses. First, momentum returns display asymmetric volatility, e.g., momentum returns are higher when the volatility is higher (γ coefficient is positive). Second, winners and losers exhibit different magnitudes of risk premia (measured by the γ coefficient) corresponding to volatility (measured by h_t). If rational risk-return theory is correct, we should find γ positive for both winners and losers, and winners should have a higher γ than losers. On the other hand, if γ is negative, it contradicts risk-return trade-off theory.

Next, we study the relationship between asset returns and market volatility by using implied aggregate market volatility in options studies. Many option studies have found a negative price of risk for market volatility.[9] Following Ang et. al. (2006), we examine the relationship of market volatility and portfolio returns, using the changes in Chicago Board Options Exchange Volatility Index (VIX index) to proxy for market volatility. [10]

$$R_t = \beta_0 + \beta_1 R_{m,t} + \beta_2 SMB + \beta_3 HML + \beta_4 \Delta VIX + \varepsilon_t \qquad (7)$$

Where R_t is the monthly excess returns of winner or loser portfolio from 1983 to 2000, and $R_{m,t}$ is the market excess return. SMB is the small-minus-big factor in the Fama-French three factor model, and HML is the high-minus-low book/market ratio factor. Volatility of aggregate market return is measured by the change of the VIX index from the Chicago Board Options Exchange (CBOE). A positive β_4 would justify a rational risk-return trade-off hypothesis. Moreover, winners are expected to have higher sensitivity to market volatility than losers under the rational hypothesis. In contrast, a negative relation between aggregate market risk and asset return would support the risk aversion hypothesis by Merton (1973) and Campbell (1996). These authors suggest that during times of high volatility, risk-averse investors would hedge against changes in aggregate volatility, and therefore reduce required rate of returns.

2.2 Cross-sectional analysis

In this section, we are interested in whether winner and loser stocks have different levels of idiosyncratic risk and display different sensitivities to idiosyncratic risk and market risk. In other words, we study both the *levels* and *sensitivities* to idiosyncratic

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[9] See Bakshi, Cao and Chen (2000), Burashi and Jackworth (2001), and Eraker, Johannes and Polson (2003).

[10] The CBOE Volatility Index® (VIX®) is a key measure of market expectations of near-term volatility conveyed by S&P 500 stock index option prices. It is used widely in options studies to proxy for aggregate market volatility.

risk and market risk cross-sectionally to see if they explain asset returns after other systematic factors are controlled for.

First, we run a simple regression to test the relation between idiosyncratic risk and stock return. In equation (8) below, monthly momentum return is the dependent variable, and the difference in winners' and losers' idiosyncratic risks $DIF_{m,t}$ is one of the independent variables. $R_{m,t}$ is the market return. SMB is the small-minus-big size factor, and HML is the high-minus-low book-to-market ratio factor. If β_{DIF} coefficient is positive, it suggests that idiosyncratic risk can partially explain momentum.

$$R_t = \beta_0 + \beta_{Mkt} R_{m,t} + \beta_{SMB} SMB + \beta_{HML} HML + \beta_{DIF} DIF + \varepsilon_t \qquad (8)$$

Second, we study the sensitivities of stock returns to idiosyncratic risk and market risk, after other market factors are controlled for. Every month *t*, we run a time-series regression in equation (9) for each REITs using observations from month *t-12* to month *t+24* to obtain each stock's risk sensitivities to factors below. [11]

$$R_t = \beta_0 + \beta_{Mkt} R_{m,t} + \beta_{SMB} SMB + \beta_{HML} HML + \beta_{VIX} \Delta VIX + \varepsilon_t \qquad (9)$$

Where R_t is the individual stock excess returns, and $R_{m,t}$ is the market excess return. SMB is the small-minus-big size factor, and HML is the high-minus-low book-to-market ratio factor. Aggregate market volatility is measured as the change in Chicago Board Options Exchange Volatility Index (VIX index). Idiosyncratic volatility is measured as the mean

[11] Momentum strategy is a short-term trading strategy which relies on past returns to predict future returns. The calibration period usually ranges from past 6 to 12 months, whereas the holding period usually ranges from 6 months to 24 months. Numerous studies have shown that momentum returns become insignificant if the momentum portfolio is held longer than 24 months. As a result, we choose month t-12 to month t+24 as our testing period in our cross-sectional analysis. In other words, if a stock is identified as a winner (loser) on month t, it should yield higher (lower) returns from month t-12 to month t+24.

of square errors (MSE) in equation (9). Next, we employ series of cross-sectional regressions to two groups, winners and losers, respectively.

$$R_i = \gamma_0 + \gamma_{MSE} MSE_i + \gamma_M \beta_{iMkt} + \gamma_{SMB} \beta_{iSMB} + \gamma_{HML} \beta_{iHML} + \gamma_{VIX} \beta_{VIX} + \eta_t \qquad (10)$$

Where R_i is the monthly mean returns of a winner or a loser REIT identified on month *t* over the period *t-12 to t+24*. MSE is the mean square errors of residuals from the factor model in equation (9). β_M measures systematic risk to the market. β_{SMB} measures sensitivity to small-minus-big size factor, and β_{HML} measures sensitivity to high-minus-low book-to-market factor. β_{VIX} measures sensitivity to aggregate market risk. A statistically significant γ_{MSE} coefficient is evidence that idiosyncratic risk is priced in stock returns, whereas a statistically significant γ_{VIX} is evidence that aggregate market volatility is priced in stock returns. Furthermore, a positive γ_{MSE} or γ_{VIX} implies that risk is compensated, whereas a negative coefficient implies that risk is penalized. We run multiple regressions using one or more risk factors in equation (10) as explanatory variables. According to risk-return trade-off hypothesis, risks should be compensated for with returns. That is, coefficient γ_{MSE} in equation (10) is expected to be positive. Moreover, winners should have a higher γ_{MSE} coefficient than losers, given the fact that winners exhibit higher returns than losers. In contrast, if coefficient γ is negative, it contradicts the rational risk-return theory, but is consistent with previous findings by other researchers.[12]

[12] Ang et. al. (2006) find that firms with high idiosyncratic volatility have lower expected return.

III. Data and Momentum Trading Strategy:

REITs are first identified by the data on National Association of Real Estate Investment Trusts (NAREIT) for the years 1983 to 2000.[13] We select the REITs that have return data available in the Center for Research in Security Prices (CRSP) over the sample period. Monthly stock returns for REITs and market index returns over the sample period are obtained from the CRSP. The REIT sample includes all the REITs (including equity, mortgage, and hybrid) listed on the NYSE, AMEX, and NASDAQ. For market index return, we use value-weighted market index from the CRSP.

This study follows the procedure of forming momentum portfolios of Jegadeesh and Titiman (1993). The winner (the top 30 percent) and loser (the bottom 30 percent) are formed monthly based on six-month lagged returns and held for six months. Winner and loser portfolios are value-weighted monthly, and their respective returns are measured one-month after the portfolio formation (a 6-month/1-month/6-month strategy). [14] Monthly compound returns are defined as $\left(\prod_{i=0}^{5}(1+r_{t-i})\right)^{1/6}-1$, where r is the monthly return of REITs. The securities in the bottom 30 percent in the ranking are assigned to a loser portfolio, while those in the top 30 percent are assigned to a winner portfolio. Next, we form monthly zero-cost momentum portfolios by entering a long position in winner portfolios and a short position in loser portfolios, and hold the momentum portfolios for six months. Momentum portfolios are zero-cost because a momentum trading strategy uses the profits of short-selling losers to purchase winners.

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[13] We select this sample period because before 1983 there are only a few number of REITs.

[14] The convention of momentum studies is to use a 10 percent breakpoint. However, due to the smaller size of the REIT sample, this study chooses 30 percent as breakpoint for winners and losers. We adopt a 6/1/6 strategy by following the convention in momentum studies.

These momentum portfolios are overlapping. For example, the momentum return on December 2000 is the average monthly momentum returns of six momentum portfolios formed on July, August, September, October, November, and December 2000.

Exhibit 1 shows statistics of returns of the winner, loser, and momentum portfolios formed on July 1983 to June 2000. Panel A reports statistics over the entire sample period. It suggests that the winner portfolio has a monthly average return of 0.81% (t-value = 6.60), whereas the loser portfolio has a monthly average return of -0.22% (t-value = -1.32). The average monthly momentum return from 1983 to 2000 is 1.03% (t-value = 7.46). Our result suggests that momentum returns are generated mostly from a long position in winner portfolio. We further group REITs to two sub-periods: 1982 to 1992, and 1993 to 2000. We choose year 1993 as a breakup point because of the following reasons. First, a tax reform in 1992 caused a structural change in REITs. Second, number of initial public offerings in REITs increased dramatically since 1993. Panel B shows that from 1983 to 1992, the average monthly momentum return is 1.15%, statistically significant at one percent level. The winner portfolio has a monthly average return of 0.72% (t-value = 3.98), whereas the loser portfolio has a monthly return of negative 0.43% (t-value = -1.65). In Panel C, the average momentum return in the post-1993 period is 0.87% (t-value = 7.57), slightly lower than the return generated in the pre-1993 period. Overall, Exhibit 1 suggests that REITs create an average monthly momentum return of 1.03% over the 1983 to 2000 period, and momentum returns in REITs are more significant in the pre-1993 period.

[INSERT EXHIBIT 1 ABOUT HERE]

IV. Results and Discussion

4.1 Time-series analysis

Empirical results based on the CAPM and GARCH (1,1)-in-mean model in equation (1) to (3) are reported in Exhibit 2. For the momentum portfolio, γ is 0.3096, significantly positive at one percent level, which suggests that momentum returns are higher when volatility is higher, and supports a rational risk-return theory. Next, we estimate the γ coefficient for the winner and loser portfolios, respectively. We find γ has a negative sign in both portfolios, but insignificant for the winner portfolio. γ of the loser portfolio is -1.1263, significant at one percent level. A negative γ of losers suggests that higher conditional volatility reduces return risk premium required by investors. Glosten et. al. (1993) provide two explenations why the relation between volatility and expected return is negative. First, time periods which are relatively more risky could coincide with time periods when investors are better able to bear particular types of risk. Second, a larger risk premium may not be required because investors may want to save relatively more during periods when the future is more risky.

In the winner and momentum portfolios, α_1, coefficient of ARCH factor, is significantly positive at one percent level, but α_2, coefficient of GARCH factor, is not statistically significant. In the momentum portfolio, α_1 is 0.8891 (t-value = 6.59) and α_2 is 0.0753 (t-value = 1.68). Note that the magnitude of α_1, which shows the effect of last period's shock, is greater than that of α_2, the effect of previous shocks. The result implies that investors are more sensitive to new surprises (short-term) than to lagged shocks (long-term). Our finding is consistent with a momentum trading strategy, which uses short-term past returns (past six to twelve monthly returns) rather than long-term past returns to predict future returns. As for the loser portfolio, α_1 is 0.6589, and α_2 is 0.3315, both statistically significant at one percent level.

[INSERT EXHIBIT 2 ABOUT HERE]

Exhibit 3 reports results using the Fama-French three factor asset pricing model extended with a GARCH(1,1)-in-mean model in equation (4) to (6). It shows similar results as the CAPM model. γ has the same sign as reported by the CAPM model in Exhibit 2. For the momentum portfolio, γ is 0.2699, significant at five percent level, suggesting that increased volatility is compensated for by a higher average return. In contrast, the loser portfolio has a γ of -1.1207, significantly negative at one percent level. γ is not significant for the winner portfolio.

We examine the relation between momentum return and aggregate market volatility with equation (7), and present our results in exhibit 4. We find that the sensitivity of losers' returns to aggregate market volatility, β_4, is 0.0012 (t-value = 2.18), meaning that investors require a positive risk premium for losers when the market is more volatile. By contrast, the coefficient of winners' returns to market volatility is not significant.

[INSERT EXHIBIT 3 ABOUT HERE]

[INSERT EXHIBIT 4 ABOUT HERE]

Overall, our time-series analysis suggests that momentum returns are higher when volatility is higher, consistent with a rational risk-return trade-off theory. Moreover, returns of a loser portfolio are negatively related to its idiosyncratic risk, where idiosyncratic risk is measured as the conditional volatility in a GARCH-in-mean model. Our findings indicate that for a loser portfolio, higher idiosyncratic volatility is penalized with a lower required rate of return.   Lastly, returns of a loser portfolio are positively related with aggregate market risk, where aggregate market risk is measured as the change in Chicago Board Options Exchange Volatility Index (VIX index). It implies that investors require a higher risk premium for holding losers when market volatility is high.

4.2 Cross-sectional analysis

In this section, we are interested in whether winners and losers have different magnitudes of idiosyncratic risks and different sensitivities to market volatility and idiosyncratic volatility. We first analyze the level of idiosyncratic risks of winners and losers. Idiosyncratic risks are measured as variance of residuals h_t in equation (4). Exhibit 5 shows that losers have higher idiosyncratic risks than winners. Panel A shows that in the entire sample period, winners' average monthly idiosyncratic risk is 0.81%, while losers' average monthly idiosyncratic risk is 1.09%, both statistically significant. An equality test further confirms that the difference in winners' and losers' idiosyncratic risks is significant. This finding is consistent with Ang et. al. (2006), who report a idiosyncratic volatility puzzle that firms with high idiosyncratic volatility have lower expected returns. Panel B reports idiosyncratic risks of winners and losers in the pre-1993 period, and suggests that losers again have higher idiosyncratic risks. Panel C, however, shows that the difference in losers' and winners' idiosyncratic risks is insignificant over the post-1993 period. We plot the innovations of monthly idiosyncratic risks in winners and losers across time in exhibit 6. It again suggests that the difference in losers' and winners' idiosyncratic risks is larger in the pre-1993 period.

[INSERT EXHIBIT 5 ABOUT HERE]

[INSERT EXHIBIT 6 ABOUT HERE]

We then compare momentum returns with the difference in losers' and winners' idiosyncratic risks. As shown in exhibit 7, we find that there seems to be some correlations between momentum returns and the difference in losers' and winners' idiosyncratic risks. As a result, we run equation (8) to study the relation between idiosyncratic risks and momentum returns, and present our findings in Exhibit 8. Model 1 in exhibit 8 shows that β_{DIF} is 0.87 (t-value = 4.53). Model 2 controls for other market factors and shows a similar result. β_{DIF} in model 2 is 0.75 (t-value = 3.90). Our findings suggest that the difference in losers' and winners' idiosyncratic risks can partially explain momentum returns.

[INSERT EXHIBIT 7 ABOUT HERE]

[INSERT EXHIBIT 8 ABOUT HERE]

Our next goal is to study whether winners and losers display different sensitivities to different types of risks. Every month *t*, we run a time-series regression in equation (9) for each REIT using observations from month *t-12* to month *t+24* to obtain each stock's risk sensitivities to risk factors in the Fama-French three-factor model. We then run a cross-sectional regression in equation (10) to winners and losers respectively, using the beta coefficients and MSEs estimated from equation (9). Exhibit 9 presents our results. Model 1 and 2 study sensitivities of asset returns to idiosyncratic risks. We find that winners have a positive coefficient (γ_{MSE} = 0.1815) to their idiosyncratic risks, whereas losers have a negative coefficient (γ_{MSE} = -0.1751), both significant at one percent level. A positive (negative) coefficient implies that investors require a higher (lower) risk premium for bearing higher idiosyncratic risk. Our results suggest that winners' idiosyncratic risks are compensated with higher returns, but losers' idiosyncratic risks are penalized with lower returns. This finding is consistent with our results in a GARCH-in-mean model, where losers have a negative relation between volatility and expected return. It also implies that although losers have a higher level of idiosyncratic risk as shown in Exhibit 5, investors do not require a higher risk premium for holding losers' idiosyncratic risk. Model 3 and 4 study the relation of stock returns and sensitivities to aggregate market volatility, after controlling for market return. Losers' γ_{VIX} coefficient is 0.0005, significantly positive at one percent, but winners' γ_{VIX} is insignificant. It implies that when market is more volatile, investors require a higher risk premium for losers, but not for winners. Model 5 and 6 examine the relation between idiosyncratic risk and asset return, after controlling for market return. Results are similar to what we find in Model 1 and 2. Winners have a positive γ_{MSE} coefficient 0.1809, whereas losers have a negative γ_{MSE} coefficient -0.1713, both significant at one percent level. Model 7 and 8 include other market factors such as size and book-to-market ratio in regressions, and have similar results as previous models. Signs of γ_{MSE} for winners and losers are the same as reported in model 5 and 6. Finally, Model 9 and 10 examine the impact of both idiosyncratic risk and market aggregate risk on asset returns, after other market factors in the Fama-French three factor model are controlled for. We show that that winners' idiosyncratic risks are compensated for with higher returns (γ_{MSE} = 0.1581), whereas losers' idiosyncratic risks are penalized with lower returns (γ_{MSE} = -0.1575). With regards to aggregate market volatility, winners and losers have positive γ_{VIX} coefficients, meaning that aggregate market volatility is compensated with return across all stocks. Moreover, losers have a higher sensitivity to market aggregate volatility than winners.

The γ_{VIX} coefficient of losers is 0.0005, where as the γ_{VIX} coefficient of winners is 0.0002, both statistically significant. It suggests that when the market is in turmoil, investors require a higher risk premium for holding losers than for holding winners. Finally, note that in all our models, losers' γ_M, sensitivity to market beta, is higher than that of winners'. It is consistent with previous findings in momentum literature that higher returns offered by winners cannot be justified with a higher market beta of winners.

[INSERT EXHIBIT 9 ABOUT HERE]

Overall, our cross-sectional results are summarized as follows. First, losers have higher idiosyncratic risks than winners. The difference in losers' and winners' idiosyncratic risks is significantly positive and can partially explain momentum returns. Second, we find the losers' returns are negatively related to their idiosyncratic risks, whereas winners' returns are positively related to their idiosyncratic risks. It implies that although losers have higher idiosyncratic risk, investors do not require a higher risk premium for holding losers' idiosyncratic risks. Third, we find a positive relation between asset returns and aggregate market volatility, and the magnitude of such relation is larger for losers than for winners. It means that when market is more volatile, investors require a higher risk premium for losers than for winners.

V. Conclusion

This research investigates whether asymmetric volatility, idiosyncratic volatility, or market aggregate volatility can explain momentum returns in REITs. We apply a GARCH-in-mean model to capital-asset-pricing model and Fama-French three factor model to test asymmetric volatility effect in momentum returns in REITs. Further, we study whether cross-sectional idiosyncratic volatility and market aggregate volatility explain momentum returns. Put differently, we study whether winners and losers have different magnitudes of idiosyncratic risks and different sensitivities to market volatility and idiosyncratic volatility. We have four main findings. First, using a GARCH-in-mean model, we discover that momentum returns display asymmetric volatility. Momentum returns in REITs are higher when volatility is higher. Second, losers have a higher level of idiosyncratic risk than winners. The difference in losers' and winners' idiosyncratic risks is significantly positive and can partially explain momentum returns. Third, we find that losers' returns are negatively related to their idiosyncratic risks, whereas winners' returns are positively related to their idiosyncratic risks. The result means that for losers, higher idiosyncratic risk volatility is penalized with lower required rate of return. It also implies that although losers have higher idiosyncratic risk, investors do not require a higher risk premium for holding losers' idiosyncratic risks. Four, we find a positive relation between asset returns and aggregate market volatility, and the magnitude of the relation is larger for losers than for winners. It implies that when market is more volatile, investors require a higher risk premium for losers than for winners.

We can further investigate sources of idiosyncratic risk in future research. According to the leverage effect theory by Christie (1982), a drop in stock price increases the leverage of firms, causing a higher volatility. As a result, higher idiosyncratic risks might be caused by higher leverages.

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Exhibit 1:

Statistics of returns of winner, loser, and momentum portfolio from July 1983 to June 2000

Momentum portfolios are formed using techniques of Jegadeesh and Titiman (1993). The winner (the top 30 percent) and loser (the bottom 30 percent) portfolios are formed monthly based on six-month lagged geometric returns and held for six months. Winner and loser portfolios are value-weighted monthly, and their respective geometric returns are measured one-month after the portfolio formation (a 6-month/1-month/6-month strategy). These momentum portfolios are overlapping. For example, the momentum return on December 2000 is the average monthly momentum returns of six momentum portfolios formed on July, August, September, October, November, and December 2000.

Panel A: 1983-2000	Winner	Loser	Momentum
No. of observations	204	204	204
Mean	0.81%**	-0.22%	1.03%**
t value of mean return	6.60	-1.32	7.46
S.D.	1.75%	2.39%	1.96%
Skewness	-0.085	-1.457	1.315
Kurtosis	0.002	3.614	3.511
Maximum	5.39%	5.74%	9.16%
Minimum	-3.80%	-9.97%	-2.51%
Panel B: 1983-1992			
No. of observations	114	114	114
Mean	0.72%*	-0.43%	1.15%**
t value of mean return	3.98	-1.65	5.04
S.D.	1.94%	2.77%	2.43%
Skewness	-0.01	-1.41	1.09
Kurtosis	0.44	2.91	1.67
Maximum	5.39%	5.74%	9.16%
Minimum	-3.80%	-9.97%	-2.51%
Panel C: 1993-2000			
o. of observations	90	90	90
Mean	0.91%**	0.04%	0.87%**
t value of mean return	5.88	0.21	7.57
S.D.	1.48%	2.73%	1.09%
Skewness	-0.15	-0.75	0.48
Kurtosis	-0.93	-0.38	-0.35
Maximum	3.71%	2.36%	3.91%
Minimum	-2.05%	-4.36%	-1.08%

* Significant at 5 percent
** Significant at 1 percent

Exhibit 2

Test asymmetric volatility in momentum returns with the Capital Asset Pricing Model and GARCH(1,1)-M model.

$$R_t = \beta_0 + \beta_1 R_{m,t} + \gamma\sqrt{h_t} + \varepsilon_t \quad (1)$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} \quad (2)$$

$$\varepsilon_t \ \left| \Omega_{t-1} \right. \sim N(0, h_t) \quad (3)$$

Where R_t is the excess return of a winner portfolio, loser portfolio, or momentum portfolio, and $R_{m,t}$ is the market excess return. Volatility of portfolio returns is measured by conditional variance h_t, which is defined as a function of squared values of the past residuals, presenting the ARCH factor, and an auto regressive term (h_{t-1}) presenting the GARCH factor. The parameters $\beta_0, \beta_1, \gamma, \alpha_0, \alpha_1, \alpha_2$ are estimated. t-values are reported in parentheses.

	Winner portfolio	Loser portfolio	Momentum portfolio
β0	0.0069** (6.76)	0.0175** (51.18)	-0.0077 (-0.66)
β1	0.0005 (0.04)	0.0036 (0.87)	-0.0012 (-0.10)
α0	0.00002** (2.94)	0.0000 (1.33)	0.00002** (2.46)
α1	0.9286** (4.73)	0.6589** (14.80)	0.8891** (6.59)
α2	0.0019 (0.04)	0.3315** (7.48)	0.0753 (1.68)
γ	-0.1723 (-1.50)	-1.1263** (-23.33)	0.3096** (2.60)
$\bar{R}^2$	0.01	0.59	0.12

* Significant at 5 percent

** Significant at 1 percent

Exhibit 3:

Test asymmetric volatility in momentum returns with the Fama-French Three Factor Model and GARCH-M model.

$$R_t = \beta_0 + \beta_1 R_{m,t} + \beta_2 SMB + \beta_3 HML + \gamma\sqrt{h_t} + \varepsilon_t \tag{4}$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} \tag{5}$$

$$\varepsilon_t \; |\Omega_{t-1} \sim N(0, h_t) \tag{6}$$

Where R_t is the excess return of a winner portfolio, loser portfolio, or momentum portfolio, and $R_{m,t}$ is the market excess return. SMB is the small-minus-big factor in the Fama-French three factor model, and HML is the high-minus-low book/market ratio factor. Volatility of portfolio returns is measured by conditional variance h_t, which is defined as a function of squared values of the past residuals, presenting the ARCH factor, and an auto regressive term (h_{t-1}) presenting the GARCH factor. t-values are reported in parentheses.

	Winner portfolio	Loser portfolio	Momentum portfolio
β_0	0.0051** (4.74)	0.0172** (63.66)	0.0004 (0.31)
β_1	0.0165 (1.08)	0.0086* (2.03)	-0.0125 (-0.77)
β_2	0.0078 (0.53)	0.0029 (0.48)	-0.0101 (-0.49)
β_3	0.0383 (1.88)	0.0224* (2.45)	-0.0344 (-1.10)
α_0	0.00002** (3.16)	0.0000 (1.06)	0.00002* (2.52)
α_1	0.9186** (4.64)	0.7057** (13.37)	0.9008** (5.53)
α_2	0.0000 (-0.00)	0.2894** (5.54)	0.0637 (1.72)
γ	-0.0965 (-0.84)	-1.1207** (-26.83)	0.2699** (2.24)
$\overline{R}^2$	0.03	0.61	0.11

* Significant at 5 percent

** Significant at 1 percent

Exhibit 4

Test relation between market aggregate volatility and portfolio return

$$R_t = \beta_0 + \beta_1 R_{m,t} + \beta_2 SMB + \beta_3 HML + \beta_4 \Delta VIX + \varepsilon_t \qquad (7)$$

Where R_t is the monthly excess return of a winner or loser portfolio, and $R_{m,t}$ is the market excess return. SMB is the small-minus-big factor in the Fama-French three factor model, and HML is the high-minus-low book/market ratio factor. Volatility of aggregate market return is measured as the change in Chicago Board Options Exchange Volatility Index (VIX index). t-values are reported in parentheses.

	Intercept	Market	SMB	HML	ΔVIX	$\overline{R}^2$
Winner	0.0017 (1.31)	0.1628** (4.18)	0.1328** (3.10)	0.2281** (4.04	0.0005 (1.14)	0.20
Loser	-0.0108** (-5.87)	0.2716** (4.98)	0.2744** (4.57)	0.4277** (5.41)	0.0012* (2.18)	0.20

* Significant at 5 percent
** Significant at 1 percent

Exhibit 5

Summary statistics of idiosyncratic risks of winners and losers

Idiosyncratic risk is defined as the mean square errors of residuals from the Fama-French three-factor model and a GARCH-in-mean model in equation (4) to (6).

$$R_t = \beta_0 + \beta_1 R_{m,t} + \beta_2 SMB + \beta_3 HML + \gamma\sqrt{h_t} + \varepsilon_t \tag{4}$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} \tag{5}$$

$$\varepsilon_t \,\big|\Omega_{t-1} \sim N(0, h_t) \tag{6}$$

Where R_i is the monthly mean returns of a winner or a loser REIT identified on month *t* over the period *t-12 to t+24*. $R_{m,t}$ is the market excess return. SMB is the small-minus-big factor in the Fama-French three factor model, and HML is the high-minus-low book/market ratio factor. t-values are reported in parentheses.

Panel A:1983-2000	Average idiosyncratic risk	S.D. of idiosyncratic risk	P-value
Winners	0.81%**	1.57%	0.0001
Losers	1.09%**	1.97%	0.0001
Difference (winners-losers)	0.28%**	1.78%	0.0001
Panel B:1983-1992			
Winners	0.79%**	2.15%	0.0001
Losers	1.75%**	1.31%	0.0001
Difference (winners-losers)	0.66%**	1.78%	0.0001
Panel C:1993-2000			
Winners	0.82%**	1.75%	0.0001
Losers	0.81%**	1.76%	0.0001
Difference (winners-losers)	0.00%	1.75%	0.7293

* Significant at 5 percent
** Significant at 1 percent

Exhibit 6

Time-series plot of winners' and losers' idiosyncratic risks from 1983 to 2000

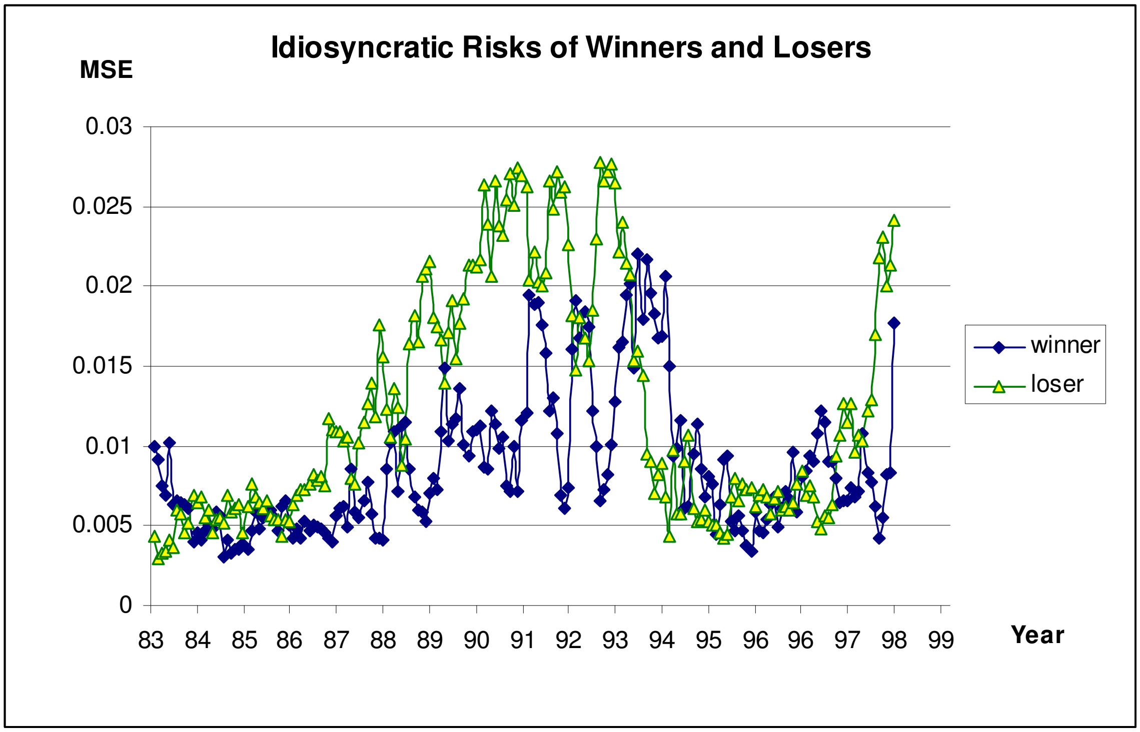

Exhibit 7

Time-series plot of momentum returns and the difference in losers' and winners' idiosyncratic risks from 1983 to 2000

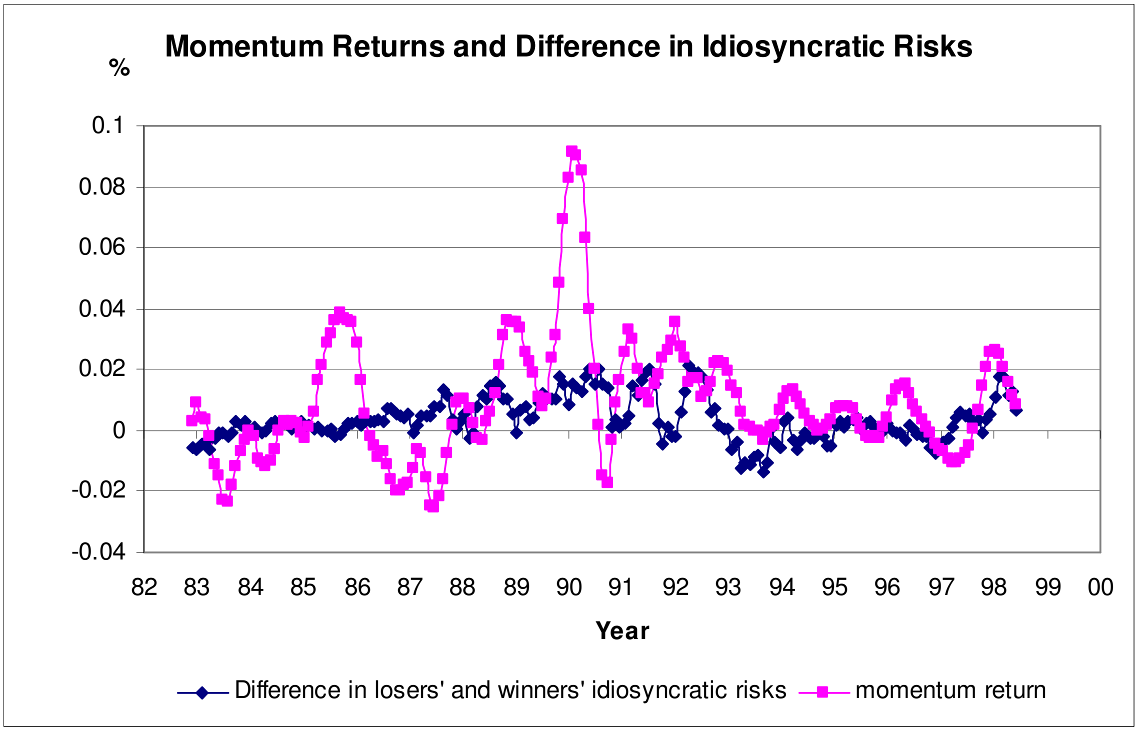

Exhibit 8

Test relation between momentum return and the difference in losers' and winners' idiosyncratic risks

$$R_t = \beta_0 + \beta_{Mkt} R_{m,t} + \beta_{SMB} SMB + \beta_{HML} HML + \beta_{DIF} DIF + \varepsilon_t \qquad (8)$$

Where momentum return is the dependent variable. $R_{m,t}$ is the market return. SMB is the small-minus-big size factor, and HML is the high-minus-low book-to-market ratio factor. The difference in losers' and winners' idiosyncratic risks, $DIF_{m,t}$, is the last independent variable. t-values are reported in parentheses.

Model	Intercept	$R_{m,t}$	SMB	HML	DIF	$\overline{R}^2$
1	0.0061** (4.02)				0.8665** (4.53)	0.09
2	0.0022 (1.39)	-0.04397 (-1.19)	-0.09158 (-1.60)	-0.14047* (-2.19)	0.7544** (3.90)	0.10

Exhibit 9

Test Volatility in Cross-Sectional Stock Returns from 1983 to 2000

$$R_t = \beta_0 + \beta_{Mkt} R_{m,t} + \beta_{SMB} SMB + \beta_{HML} HML + \beta_{VIX} \Delta VIX + \varepsilon_t \qquad (9)$$

Every month *t*, we run a time-series regression in equation (9) for each REIT using observations from month *t-12* to month *t+24* to obtain each stock's risk sensitivities to risk factors. R_t is individual stock excess return, and $R_{m,t}$ is the market excess return. SMB is the small-minus-big size factor, and the HML is high-minus-low book-to-market ratio factor from the Fama-French three factor model. Aggregate market volatility ΔVIX is measured as the change in Chicago Board Options Exchange Volatility Index (VIX index).

Next, we run a cross-sectional regression in equation (10) to winners and losers, respectively.

$$R_i = \gamma_0 + \gamma_{MSE} MSE_i + \gamma_M \beta_{iMkt} + \gamma_{SMB} \beta_{iSMB} + \gamma_{HML} \beta_{iHML} + \gamma_{VIX} \beta_{VIX} + \eta_t \qquad (10)$$

Where R_i is the monthly average return of a winner or a loser REIT identified on month *t* over the period *t-12 to t+24*. MSE is the mean square errors of residuals from the factor model in equation (9). β_{Mkt} measures an asset return's systematic risk with the market. β_{SMB} measures return sensitivity to the small-minus-big size factor, and β_{HML} measures return sensitivity to the high-minus-low book-to-market factor. β_{VIX} measures return sensitivity to changes in VIX index. t-values are reported in parentheses.

	Model	Intercept	MSE	β_{Mkt}	β_{SMB}	β_{HML}	β_{VIX}	$\overline{R}^2$
Winners	1	0.0138** (56.63)	0.1815** (13.15)					0.03
Losers	2	0.0041** (12.33)	-0.1751** (-11.75)					0.02
Winners	3	0.0149** (61.60)		0.0297** (4.70)			0.0001 (1.84)	0.01
Losers	4	0.0012** (3.84)		0.0545** (6.47)			0.0005** (3.79)	0.01
Winners	5	0.0136** (55.14)	0.1809** (13.13)	0.0017** (5.5)				0.03
Losers	6	0.0038** (11.17)	-0.1713** (-11.16)	0.0375** (5.55)				0.03
Winners	7	0.0137** (54.05)	0.1805** (13.01)	0.0231** (3.85)	0.0089 (1.36)	0.0018 (0.31)		0.03
Losers	8	0.0040** (11.42)	-0.1719** (-11.57)	0.0279** (3.44)	-0.0015 (-0.16)	-0.0235* (-2.05)		0.03
Winners	9	0.0134** (50.57)	0.1581** (11.97)	0.0309** (4.15)	0.0120 (1.71)	0.0053* (0.58)	0.0002* (2.19)	0.04
Losers	10	0.0032** (8.62)	-0.1575** (-10.14)	0.0418** (4.19)	0.0035 (0.37)	-0.0206 (-1.68)	0.0005** (3.62)	0.03

* Significant at 5 percent

** Significant at 1 percent