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# Low Volatility Investing in U.S. Equity REITs

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We examine the market for U.S. equity real estate investment trusts (REITs) for evidence of the volatility effect, in which low volatility stocks tend to outperform high volatility ones, as has been found in the general equity market by prior research. While there is some evidence of a volatility effect in the first ten years of the sample, this disappears in a more recent time period. Furthermore, we test the efficacy of low risk portfolio construction techniques and find that none perform any better than a market cap weighted portfolio – although they are also no worse – over any of the time periods examined. Thus, there is no evidence that using a risk-based portfolio design that emphasizes low volatility would improve portfolio performance for a REIT allocation.

**Keywords**
REITs, low volatility anomaly, portfolio construction

# 1. Introduction

Do higher risk assets yield higher returns on average? While the risk-return relationship is a cornerstone of asset pricing theory, in recent years, two complementary threads of research have developed based on seeming violations of it. The first stream of research investigates the relationship between risk (generally measured by volatility or beta) and return. For instance, Blitz and van Vliet (2007), Blitz, Pang, and van Vliet (2013), as well as Ang et al. (2006, 2009) all find that lower risk stocks tend to outperform higher risk stocks. Frazzini and Pedersen (2014), by using beta as their measure of risk, find similar results across a number of different financial markets. The second stream investigates risk-based portfolio construction techniques designed to exploit this “volatility effect" or “low volatility anomaly" in realistic ways for institutional investors. For example, Clarke, de Silva, and Thorley (2006) find that a minimum variance portfolio of U.S. common stocks not only has volatility that is approximately 25% lower than the market capitalization weighted portfolio, but also a return that is 0.9% higher per year; lower risk portfolios outperform on both an absolute and risk-adjusted basis.

In this paper, we study the market for U.S. equity real estate investment trusts (REITs) to determine if the volatility effect exists within that sector and also to compare the efficacy of various low-risk portfolio construction methods to take advantage of the effect. Our results show that, over the period 1994 to 2013, the lowest volatility REITs outperform higher volatility REITs on a risk-adjusted basis. However, this difference is entirely driven by the first ten years of the sample, and there is no evidence of a volatility effect in the most recent ten year period. Furthermore, none of the low risk portfolio construction techniques tested materially outperform a market cap weighted portfolio over any of the time periods tested. Thus, there is no evidence that using a risk-based portfolio design that emphasizes low volatility for a REIT allocation would provide any benefit to investors. However, while low volatility portfolios perform no better than market capitalization weighted portfolios, they also perform no worse. A REIT portfolio manager constrained to being 100% invested in the sector (i.e. no margin and no cash holdings) might choose to utilize a low volatility strategy depending on his/her risk aversion.

Research that demonstrates that lower risk stocks tend to outperform higher risk stocks (or at least outperform expectations within a linear pricing model) can be traced to the work of Black, Jensen and Scholes (1972) and Fama and MacBeth (1973). Haugen and Baker (1991) find that minimum variance portfolios outperform market capitalization weighted portfolios, and conclude that capitalization weighted benchmarks are not mean-variance efficient, while Black (1993) finds that low beta stocks continued to produce higher than expected returns in a one-factor model through 1991.

While earlier research focused on the efficiency of benchmark portfolios or the ability of a linear factor model to price risk, more recent research has concentrated on portfolio construction techniques that attempt to take advantage of the volatility effect and improve on market capitalization weighted portfolios. Lee (2011) provides a review of the literature and an overview of the various portfolio construction approaches used, as well as critiques of the methods. Irrespective of the continued debate about low volatility portfolio strategies in the research literature, they have begun to have a significant influence on portfolio construction in practice. One variant, equal risk contribution (often referred to as risk parity) has generated significant interest amongst institutional investors; see, for example, Levell (2010) and Croce and Partridge (2013). Furthermore, both MSCI and S&P have introduced low volatility indices for benchmarking and passive investing. The suite of indices of MSCI is based on minimum variance portfolios, whereas the S & P 500 Low Volatility Index simply takes the 100 stocks with the lowest volatility from the S&P 500 and inversely weights them to their standard deviation.[1]

Despite increased investor interest in low volatility portfolios, the idea of lower risk assets consistently outperforming higher risk assets contradicts the predictions of asset pricing theory, and requires an explanation. Black (1993) attributes the flatter than expected relationship between risk and return to leverage restrictions, which reduce investor demand for low risk (and presumably low expected return) assets. Frazzini and Pederson (2014) provide a formal model in which leverage constraints result in low (high) beta stocks that have expected returns higher (lower) than predicted by the capital asset pricing model (CAPM). Baker, Bradley, and Wurgler (2011) suggest two factors which together may explain the empirical findings. The first is a behavioral explanation in which the preferences of investors for lottery-like payoffs serve to increase demand for higher volatility assets and thereby reduce their return. The second factor is that, in the presence of delegated portfolio management, investment managers are discouraged from arbitraging away the volatility effect if they are benchmarked against the market portfolio and penalized for tracking error (e.g. if they are evaluated based on their information ratio). Specifically, taking advantage of the volatility effect necessarily involves moving away from the market portfolio and increasing tracking error; this increases the return hurdle that such a strategy must meet in order to be judged worthwhile by the manager, and therefore limits the ability of managers to arbitrage the volatility effect.

In this paper, we consider the low volatility effect specifically in the context of REITS. Given the literature on their efficacy and the growing popularity of low volatility strategies, which can be considered as a part of the broader classification of "smart beta" portfolio management strategies, throughout the capital markets, it is natural for REIT portfolio managers to wonder if similar benefits might accrue to them. By restricting ourselves to the REIT sector,

[1] See MSCI (2012) and Chan and Lazzara (2013)

therefore, our results are of particular interest to REIT portfolio managers as well as other real estate investors. Furthermore, REITs may behave differently than equities in general. Asness, Frazzini, and Pedersen (2014) examine low risk investing strategies across and within industries; they show that, across 70 global industries, REITs are one of only a few sectors (see Figure 4) in which their betting-against-beta strategy does not generate value. Asness, Frazzini and Pedersen (2014), however, look at only one approach to low volatility investing, do not examine REITs in detail, and report results for REITs specifically only in passing. DeLisle, Price, and Sirmans (2013), noting that prior research on REIT volatility is "mixed", examine the pricing of volatility in REITs and find no volatility effect for systematic volatility, in contrast to non-REITs. However, they do report that idiosyncratic volatility is negatively priced in REITs. While related to our work here, DeLisle, Price, and Sirmans (2013) do not examine the efficacy of different portfolio construction methods for taking advantage of the volatility effect in REITS, as we do.

There are further reasons to believe that the role of volatility in a REIT-only portfolio may be different than that typically found in the general research on the volatility effect. By restricting our analysis to only REIT securities, we may miss some of the potential gains of the risk-based strategies. Leclerc et al. (2013) find that an industry based strategy is able to perform very well versus the market cap weighted index, which indicates that at least some of the gains of risk-based investing come from industry selection and not just from security selection within industries (although Asness, Frazzini, and Pedersen (2014) report gains both across and within (almost all) industries). Furthermore, Baker, Bradley, and Taliaferro (2014) decompose the volatility anomaly into micro (security selection) and macro (country/industry selection), and find that the micro effect primarily contributes to the anomaly via risk reduction, while the macro effect contributes via return enhancement. This has important implications for our study, in that REIT-specific investors have limited scope for industry selection, perhaps indicating that low volatility REIT portfolios may not exhibit the enhanced return often found in other studies of the volatility anomaly.

Given the prior research, an important question is whether risk-based investing has the potential to result in more efficient portfolios in the more restrictive REIT universe, or if the lack of macro effects and the restrictive nature of the investable universe (or, perhaps, simply the nature of REITs) provide too significant a constraint to overcome. As well, it is important to understand which of the typical risk-based portfolio approaches is most efficacious in taking advantage of a volatility effect in REITs, if one is present. Both of these questions are of interest to real estate investors as well as researchers, and we address both below.

The remainder of this paper proceeds as follows: the next section outlines our sample and the portfolio construction approaches that we test. The third section presents the results, and the final section concludes.

# 2. Data and Methodology

## 2.1 Sample

Our sample is based on the constituent members of the FTSE NAREIT All REITs Index over the period of December 1993 to December 2013. To minimize survivorship bias, we obtain the constituent list for the index for each month over that period, thus basing the sample of each month on REITs in existence at that time. We eliminate mortgage and hybrid REITs from the sample. To avoid our results being influenced by micro-cap stocks that would not be of interest to institutional investors due to their size and lack of liquidity, we eliminate from the sample any equity REITs with a capitalization of less than $250 million in December 2013 terms, with the cutoff indexed to inflation going back over the remainder of the sample period. Total returns and market capitalizations are obtained from FactSet. In cases where only a partial month is available for a REIT due to a corporate event, such as a merger or de-listing, we assume that merger or acquisition proceeds are held in cash until month end when the portfolio is rebalanced.

Volatilities and covariance matrices are estimated by using 60 months of trailing returns when available. We require at least 36 months of returns for estimation; otherwise, the REIT is not included in the sample for that month. Figure 1 shows the total sample size with and without the trading history restriction.

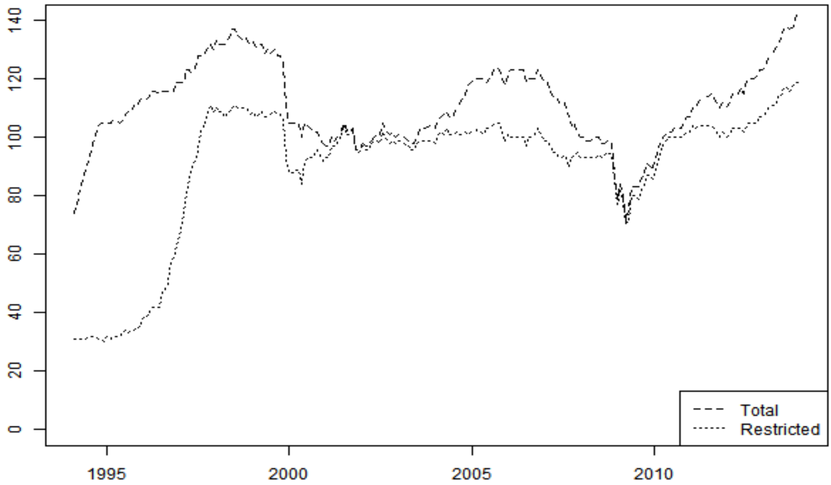
Finally, we obtain data on the Fama-French factors (plus a momentum factor) and the risk free rate from the website of Prof. Kenneth French.[2]

## 2.2 Portfolio Construction

We consider the performance and characteristics of four portfolio construction methodologies for REITs: equal weighted (EW), minimum variance (MV), maximum diversification (MD) and equal risk contribution (ERC). As discussed in Jurczenko, Michel, and Teiletche (2013), each of these portfolio construction methodologies can be viewed as specific cases of the general class of risk-based portfolio construction and, with the exception of EW, each will tend to result in a portfolio that is lower risk than the market cap weighted portfolio, despite the different methods of construction and different resulting properties.

[2] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

**Figure 1 Sample Size through Time**




In general, the four strategies can be thought of as an attempt to optimally condition on differing levels of information. For example, the EW strategy implies that the analyst has no information about the expected return, volatility, or correlation, while the MV strategy will be optimal when expected returns are equal and the analyst has perfect foresight on the variance-covariance matrix of asset returns. The MD and ERC approaches can be thought of as solutions that attempt to compromise in some way between the relatively extreme assumptions of both the EW and MV techniques.

For comparison purposes, we also examine the returns to a market cap weighted portfolio, in which each month, the sample REITs are held in proportion to their equity market capitalizations. This serves as a type of benchmark for our results for the risk-based portfolios as the market cap portfolio is optimal under the traditional portfolio theory, and can easily be obtained passively by investors. Of the other portfolio methodologies that we examine, the most straightforward is, of course, the EW portfolio in which all securities in the sample are held in equal proportion at the beginning of each month.

MV portfolios are found by minimizing the portfolio variance $w^T \Sigma w$ where $w$ is a vector of portfolio weights and $\Sigma$ is the variance-covariance matrix, which is estimated by using the shrinkage methodology of Ledoit and Wolf (2004). The MV portfolios are constrained to have no short positions, and hold no more than 10% in any one asset to preclude the extreme concentration that is sometimes observed with MV type strategies.

We use the concept of the Most Diversified Portfolio from Choueifaty and Coignard (2008) to construct our MD portfolios. The MD portfolios are defined as the portfolio allocation that maximizes the ratio of the weighted average volatility of the portfolio constituents to the volatility of the portfolio:

$$MD = \frac{w^T V}{\sqrt{w^T \Sigma w}} \tag{1}$$

where V is a vector of individual asset volatilities. As in the case of the MV portfolios, we again use the shrinkage approach to estimate the covariance matrix, and additionally constrain the MD portfolios to have no short positions.

Finally, we construct the ERC portfolios so as to equalize the total weighted contribution to portfolio risk from each asset, where the total contribution to risk for an asset is defined as in Maillard, Roncalli, and Teiletche (2010) to be:

$$TRC_i = w_i \frac{\partial \sigma_p}{\partial w_i} \tag{2}$$

where $w_i$ is the weight of asset i in the portfolio and $\sigma_p$ is the portfolio standard deviation. We solve this problem via the Newton approach of Chaves et al. (2012) – their "Algorithm 1". By construction, ERC portfolios take positions in all candidate assets, and are therefore naturally less subject to concentration risk than other risk-based portfolio construction methods, such as variance minimization, and so constraints on portfolio allocations are not required to achieve a highly diversified portfolio of REITs.

For each of the portfolio construction methodologies, the required inputs are re-estimated and the portfolios rebalanced monthly.

## 3. Results

In this section, we present our main findings. We begin by looking for evidence of the volatility effect within the REIT sector by examining portfolios formed by sorting REITs into volatility quartiles. We then compare the performance of the risk-based portfolio construction techniques described above to determine the most effective way for portfolio managers to take advantage of any volatility effect present. In both cases, we consider the robustness of the effects by splitting the sample period into two 10 year sub-periods to determine if the effects have changed over time, as well as to ensure that the results are not affected by the rapid increase in sample size during the early years of the sample (see Figure 1).

### 3.1 Quartile Portfolios Sorted on Volatility

At the end of each month, we construct four equally weighted quartile portfolios by ranking REITs on their trailing standard deviation of monthly returns. Quartile 1 contains the lowest volatility REITs while Quartile 4 contains the highest volatility REITs. Only REITs with a return history of at least 36 months for volatility estimation are included, with up to 60 months used for estimation when available.[3] Table 1 presents the results.

**Table 1 Summary Statistics (Monthly) for Portfolios Sorted on Trailing Volatility**

| | Quartile 1 (lowest volatility) | Quartile 2 | Quartile 3 | Quartile 4 (highest volatility) |
|---|---|---|---|---|
| **Average Return** | 0.0107 | 0.0101 | 0.0105 | 0.0124 |
| | | [0.14] | [0.05] | [-0.26] |
| **Std. Dev.** | 0.0407 | 0.0495 | 0.0607 | 0.0901 |
| **Ave. Comp. Return** | 0.0098 | 0.0088 | 0.0085 | 0.0082 |
| | | [0.24] | [0.27] | [0.25] |
| **Beta** | 0.48 | 0.59 | 0.75 | 1.13 |
| **Sharpe Ratio** | 0.20 | 0.16 | 0.13 | 0.11 |
| | | [-2.28]** | [-2.70]*** | [-2.21]*** |
| **1-Factor Alpha** | 0.0054 | 0.0041 | 0.0035 | 0.0030 |
| | (2.39)** | (1.19) | (1.05) | (0.62) |
| **3-Factor Alpha** | 0.0029 | 0.0009 | -0.0004 | -0.0026 |
| | (1.56) | (0.40) | (-0.17) | (-0.67) |
| **4-Factor Alpha** | 0.0032 | 0.0015 | 0.0007 | 0.0003 |
| | (1.67)* | (0.70) | (0.25) | (0.08) |

***Note:*** Numbers in parentheses are t-statistics for significance of coefficients. Square brackets contain test statistics that test the difference from Quartile 1; average returns use t-tests that assume unequal variances, Sharpe ratios use the z-statistics of Jobson and Korkie (1981). * indicates significance at a 10% level, ** indicates significance at 5%, and *** at 1%.

As would be expected, volatility, and beta, monotonically increases across the quartiles. Both volatility and beta in the highest volatility quartile are more than twice the level in the lowest volatility quartile. Of greater interest is the average return across the quartiles; Table 1 shows the average monthly return to the highest volatility REITs to be somewhat higher than the other quartiles, although the difference between the highest and lowest is insignificant.[4]

[3] As always, any requirement for a history of data does introduce potential for survivorship bias, but in our case, we believe this to be de minimus. Our minimum time frame for returns of 36 months is relatively short. Also, because we update our index constituent list each month, even if a REIT does not meet the 36 month minimum for a particular month, as long as it had 36 months of trailing data at some point over our full time period, that REIT will be included in the sample at that time.

[4] As the four quartile portfolios are constructed so as to have different volatilities, our-t-tests for differences in mean returns assume unequal variances.

Given that the quartiles are constructed to have different volatilities, an important issue, especially for long term investors, in comparing returns is the well-known fact that volatility erodes compound returns over time (see, e.g., Booth and Fama (1992)). To account for this, we also calculate the compound return each month as ln(1 + return). The average compound return will reflect the negative effect of volatility on longer run returns. The table shows that average compound returns monotonically decrease as volatility rises; however, the differences are still statistically insignificant.

The combining of differences in volatility across quartiles with average returns that are approximately the same results in differences in risk-adjusted performance. The Sharpe ratio decreases as one moves from lower to higher volatility quartiles. The use of the Jobson and Korkie (1981) test for differences in the Sharpe ratios shows that the Sharpe of the lowest volatility REIT quartile is significantly higher than that of the other three quartiles.

Finally, we compare the performance of the volatility quartiles by examining their alphas from a standard 1-factor model (where the factor is the excess return to the market), the Fama-French 3-factor model, and a 4-factor model by using the Fama-French factors plus a momentum factor. All data for the factors are obtained from the website of Kenneth French. Quartile 1, made up of the lowest volatility REITs, has positive alphas which are both statistically and economically significant in the 1-factor and 4-factor models (0.54% and 0.32% per month, respectively). The alphas for all of the other quartile portfolios are insignificantly different from zero.

Overall, although the effect is perhaps slightly less pronounced than that for the overall universe of equities, the evidence thus far suggests that investors in U.S. equity REITs were not well compensated for taking on additional return volatility over the full sample period 1994-2013, and low volatility REITs outperformed higher volatility REITs on a risk-adjusted basis. To test whether this has varied over time, we have split the sample period into two 10 year sub-periods, 1994-2003 and 2004-2013, and the quartile comparisons are repeated. Tables 2 and 3 present the results.

While the choice of equal, 10 year sub-periods is admittedly somewhat arbitrary, these sub-periods clearly represent different market conditions for REITs. Volatilities and betas are much lower in the earlier sub-period than in the latter. In fact, the volatility and beta of the highest volatility quartile from 1994-2003 are lower than those of the lowest volatility quartile from 2004-2013. It is therefore of interest to see if the results are similar across these much different regimes; it is apparent from the tables that they are not.

As with the full sample, in both sub-periods, the average returns and average compound returns across quartiles are insignificantly different from one another. In the earlier sub-period, the comparison of risk adjusted performance

**Table 2 Summary Statistics (Monthly) for Portfolios Sorted on Trailing Volatility, 1994-2003**

| | Quartile 1 (lowest volatility) | Quartile 2 | Quartile 3 | Quartile 4 (highest volatility) |
|---|---|---|---|---|
| **Average Return** | 0.0121 | 0.0106 | 0.0114 | 0.0126 |
| | | [0.41] | [0.18] | [-0.011] |
| **Std. Dev.** | 0.0268 | 0.0322 | 0.0333 | 0.0445 |
| **Ave. Comp. Return** | 0.0117 | 0.0100 | 0.0108 | 0.0116 |
| | | [0.046] | [0.23] | [0.03] |
| **Beta** | 0.13 | 0.17 | 0.20 | 0.36 |
| **Sharpe Ratio** | 0.32 | 0.22 | 0.24 | 0.21 |
| | | [-2.17]** | [-1.77]* | [-1.78]* |
| **1-Factor Alpha** | 0.0080 | 0.0061 | 0.0068 | 0.0070 |
| | (3.28)*** | (2.11)** | (2.28)** | (1.84)* |
| **3-Factor Alpha** | 0.0047 | 0.0020 | 0.0025 | 0.0015 |
| | (2.23)** | (0.80) | (0.99) | (0.46) |
| **4-Factor Alpha** | 0.0051 | 0.0026 | 0.0034 | 0.0035 |
| | (2.35)** | (1.03) | (1.34) | (1.11) |

***Note:*** Numbers in parentheses are t-statistics for significance of coefficients. Square brackets contain test statistics that test the difference from Quartile 1; average returns use t-tests that assume unequal variances, Sharpe ratios use the z-statistics of Jobson and Korkie (1981). * indicates significance at a 10% level, ** indicates significance at 5%, and *** at 1%.

is also similar to the full sample period. During 1994-2003, the lowest volatility quartile portfolio exhibits a significantly higher Sharpe ratio than the other quartiles, and alphas from all three factor models are significantly positive for the low volatility quartile. However, in the 2004-2013 period, the comparison of risk-adjusted performance shows no difference in the Sharpe ratios across the quartiles, and none of the alphas are significantly different from zero. It is apparent that the results for the full 20 year period are primarily driven by results in the first 10 years. There is little evidence of a volatility effect within the REIT sector over the most recent ten year period, at least when considering the naïve implementation of equally weighted portfolios sorted on volatility. In the next section, we explore whether more complicated risk-based portfolio construction methods, in a realistic and investable framework, would have allowed investors to capture any volatility effect in U.S. equity REITs.

### 3.2 Risk-Based Portfolios

We implement the four risk-based portfolio construction techniques, in addition to the market capitalization weighted portfolio, with monthly rebalancing; our main results are presented in Table 4. Looking first at the alphas generated, of the fifteen different alphas tested (5 portfolios that use three different factor models), only one (the MV portfolio in a 1-factor model)

**Table 3 Summary Statistics (Monthly) for Portfolios Sorted on Trailing Volatility, 2004-2013**

| | Quartile 1 (lowest volatility) | Quartile 2 | Quartile 3 | Quartile 4 (highest volatility) |
|---|---|---|---|---|
| **Average Return** | 0.0092 | 0.0096 | 0.0095 | 0.0121 |
| | | [-0.05] | [-0.03] | [-0.23] |
| **Std. Dev.** | 0.0511 | 0.0624 | 0.0793 | 0.1197 |
| **Ave. Comp. Return** | 0.0079 | 0.0076 | 0.0061 | 0.0047 |
| | | [0.04] | [0.19] | [0.25] |
| **Beta** | 0.89 | 1.09 | 1.39 | 2.04 |
| **Sharpe Ratio** | 0.16 | 0.13 | 0.10 | 0.09 |
| | | [-0.95] | [-1.56] | [-1.13] |
| **1-Factor Alpha** | 0.0025 | 0.0016 | -0.0004 | -0.0019 |
| | (0.79) | (0.42) | (-0.09) | (-0.25) |
| **3-Factor Alpha** | 0.0022 | 0.0011 | -0.0011 | -0.0031 |
| | (0.73) | (0.33) | (-0.26) | (-0.46) |
| **4-Factor Alpha** | 0.0023 | 0.0016 | -0.0004 | -0.0010 |
| | (0.78) | (0.46) | (-0.09) | (-0.17) |

***Note:*** Numbers in parentheses are t-statistics for significance of coefficients. Square brackets contain test statistics that test the difference from Quartile 1; average returns use t-tests that assume unequal variances, Sharpe ratios use the z-statistics of Jobson and Korkie (1981). * indicates significance at a 10% level, ** indicates significance at 5%, and *** at 1%.

is statistically significant, and that at only a 10% level. There is no indication that any of these approaches are able to generate excess returns on a risk-adjusted basis over the twenty years examined. In comparing the portfolio approaches, there appears to be little difference amongst them in terms of results. While the MV portfolio has a somewhat lower volatility than the other portfolios, the average returns and Sharpe ratios are very similar across the portfolios and none of the differences are significant. Based on this, there would seem to be no advantage in moving from a market cap weighted portfolio to one of the risk-based portfolios for REITs –although Table 4 shows no disadvantage either.

However, Table 4 may overstate the returns to risk-based portfolios, as it does not include the transaction costs involved in rebalancing the portfolio. Given that rebalancing costs are likely to be the lowest in a market weighted portfolio, the inclusion of trading costs may tip the balance in favor of market cap weighting.

**Table 4 Risk Based Portfolio Performance (Monthly, 1994-2013)**

| | Market Cap Weighted | Equal Weighted | Minimum Variance | Maximum Diversification | Equal Risk Contribution |
|---|---|---|---|---|---|
| **Average Return** | 0.0108 | 0.0109 | 0.0102 | 0.0099 | 0.0104 |
| | | [-0.01] | [0.13] | [0.18] | [0.08] |
| **Std. Dev.** | 0.0567 | 0.0578 | 0.0437 | 0.0564 | 0.0541 |
| **Ave. Comp. Return** | 0.0091 | 0.0091 | 0.0092 | 0.0082 | 0.0088 |
| | | [-0.00] | [-0.01] | [0.17] | [0.05] |
| **Beta** | 0.70 | 0.74 | 0.49 | 0.72 | 0.69 |
| **Sharpe Ratio** | 0.15 | 0.15 | 0.18 | 0.13 | 0.15 |
| | | [-0.13] | [1.02] | [-0.67] | [-0.03] |
| **1-Factor Alpha** | 0.0041 | 0.0040 | 0.0048 | 0.0031 | 0.0038 |
| | (1.34) | (1.29) | (1.96)* | (1.02) | (1.31) |
| **3-Factor Alpha** | 0.0005 | 0.0002 | 0.0022 | -0.0007 | 0.0003 |
| | (0.21) | (0.07) | (1.05) | (-0.32) | (0.12) |
| **4-Factor Alpha** | 0.0015 | 0.0014 | 0.0025 | 0.0006 | 0.0013 |
| | (0.61) | (0.59) | (1.19) | (0.28) | (0.60) |

***Note:*** Numbers in parentheses are t-statistics for significance of coefficients. Square brackets contain test statistics that test the difference from Quartile 1; average returns use t-tests that assume unequal variances, Sharpe ratios use the z-statistics of Jobson and Korkie (1981). * indicates significance at a 10% level, ** indicates significance at 5%, and *** at 1%.

Including the effect of trading costs is difficult in that an appropriate measure should incorporate commissions and spreads as well as the price impacts of trading. However, commissions will vary by investor, and liquidity will vary by stock as well as over time. Furthermore, price impacts will vary by size of trade (and therefore, the size of the investor), which makes it impossible to exactly quantify trading costs for representative strategies such as these. We therefore follow LeClerc et al. (2013) in applying the estimates from French (2008) of trading costs for institutional investors. However, we depart from LeClerc et al. (2013) in that we only apply the most recent estimate from French (2008). The most recent trading cost figure is the one most relevant to investors who are trying to determine if any of the portfolio approaches have an advantage on a going-forward basis. Trading costs are therefore set at 11 basis points (bps) for a one-way transaction and the results repeated with this cost applied to all required trading for each strategy each month. As many REITs, especially in the earlier years of the sample, would be classified as small cap stocks which tend to be less liquid than average, this could underestimate the true transaction costs for our low volatility REIT strategies. If so, our results would be based towards finding a benefit to low volatility investing; however, as shown below, we find no such benefit despite any potential bias.

Table 5 shows, as expected, that the market cap weighted portfolio has the lowest trading costs, at 0.7 bps per month on average. The highest average trading costs (because they involve the most monthly rebalancing) are for the MD and MV portfolios, at 2.8 and 2.5 bps per month respectively. While trading costs are higher for these risk-based approaches, the differences are not enough to create substantially different overall results for the portfolios. The net of the cost results of Table 5 are qualitatively identical to the gross of the cost results in Table 4. Despite the small differences, in the interest of realism, all further results are reported net of the trading costs.

In case volatility is not the relevant measure of risk, or does not fully encapsulate risk, and is overlooking some benefits of the risk-based portfolios, Table 6 presents some alternative risk measures across the portfolios. The MV portfolio had the lowest standard deviation and Table 6 shows that it also has the lowest semi-standard deviation (i.e. the square root of semi-variance). As well, it suffers the lowest maximum drawdown (i.e. where maximum drawdown is the largest peak-to-trough loss over the period) from amongst the portfolios. Conversely, MV shows the highest tracking error (calculated relative to the market cap weighted portfolio), a measure of importance to many investors benchmarked against a market weighted index. The ERC portfolio shows the lowest tracking error (although only slightly lower than the EW portfolio). It is also rarely the lowest returning portfolio amongst those examined, and rarely the highest returning; the ERC seems to have produced consistently middle-of-the-road results relative to the other portfolios, something perhaps of interest to investors concerned about tail risk on a month-to-month basis. However, the ERC has a maximum drawdown higher than that of the MV, and approximately equal to the other portfolios – over longer time periods, the ERC does not seem to reduce potential loss. Overall, while there are some differences across the portfolios in Table 6 that might make one approach more or less appealing to a specific investor, there does not appear to be anything that would systematically attract investors in general to a risk-based approach over the market cap weighted approach. Overall, the results indicate that despite our earlier finding that REITs in the lowest volatility quartile outperform higher volatility REITs on a risk-adjusted basis over the 20 year period, none of the standard approaches to building a diversified low volatility portfolio are able to significantly outperform a simple market capitalization approach.

Finally, as is done for the volatility quartiles, we have split the sample period into two 10 year periods to see if the results change over time. Tables 7 and 8 show again, based on the volatilities and betas observed for the portfolios, that REIT market characteristics in general are much different in the two time periods. In the earlier time period, 1994-2003, all five portfolios show significantly positive alphas in the 1-factor model, although only the MV alphas are also positive in the 3- and 4-factor models. In the latter, 2004-2013 period, all of the alphas are very small and insignificant. In both the early and latter periods, the results in comparing the portfolios are the same as for the overall sample period: there are no significant differences between the performance of risk-based portfolios and the market cap weighted portfolio.

## 4. Conclusions

An increasing amount of research documents that portfolios constructed to emphasize low volatility stocks tend to outperform market capitalization weighted benchmarks, and this has led to increasing interest in low volatility strategies amongst institutional investors. It is therefore natural that managers of REIT portfolios (and other real estate investors) wonder whether their performance can benefit by taking advantage of this low volatility effect.

While there is some evidence, based on sorting REITs into volatility quartiles, that low volatility REITs perform better than higher risk REITs on a risk-adjusted basis during the first 10 years of the modern REIT era, this effect largely disappears in the more recent time period. Furthermore, there is no evidence that any of the typical risk-based portfolio construction techniques tested perform significantly better than a market cap portfolio. This holds whether examining the full 20 year sample period or the either of the 10 year sub-samples. Given that an investor can easily implement a market cap portfolio, passively and at low cost, our results reveal no compelling reason to depart from that strategy in favor of risk-based investing within the universe of US equity REITs. A market cap weighted portfolio of REITs could be combined with long or short positions in a risk-free asset to obtain the desired risk exposure of the investor while producing similar returns to the risk-based strategies.
However, while our results show low volatility REIT portfolios to be no better than a market cap weighted portfolio, they are also no worse. A REIT portfolio

manager who is constrained to being 100% invested in that sector (i.e. no margin or cash holdings allowed), and therefore cannot adjust his/her risk exposure by using the risk-free asset, might be attracted to a low volatility REIT portfolio depending on his/her risk aversion. Of course, given the evidence presented here, investors who ultimately hire such a REIT manager, presumably at higher fees relative to a passive market cap portfolio, should carefully consider whether this provides any advantage to them on an after-fees basis.

In considering our results in the context of the prior low volatility literature, it is clear that low volatility investing is less attractive for REIT portfolios than it is for broader equity portfolios. It may be that the volatility effect is based at least partly on macro effects (weighting to low volatility industries rather than specific equities), and limiting to only REITs therefore loses a valuable industry effect. It is also possible that REITs are simply different in some way from typical equities, perhaps attracting a segmented investor clientele due to their reputation as an income producing sector as opposed to a speculative vehicle for higher risk gambles, thus indicating a behavioral contribution to the results. Despite strong prior evidence that low volatility investing outperforms in the equity market in general, and the increasing popularity amongst investors of low volatility strategies, our results indicate that the same benefits simply do not exist within the REIT sector. REITs do behave differently than the broader market equities; a definitive answer as to why this is so, we leave to future research.

**Table 5 Risk Based Portfolio Performance – Net of Transaction Costs (Monthly, 1994-2013)**

| | Market Cap Weighted | Equal Weighted | Minimum Variance | Maximum Diversification | Equal Risk Contribution |
|---|---|---|---|---|---|
| **Average Return** | 0.0107 | 0.0108 | 0.0100 | 0.0096 | 0.0103 |
| | | [-0.01] | [0.17] | [0.22] | [0.09] |
| **Std. Dev.** | 0.0567 | 0.0578 | 0.0437 | 0.0565 | 0.0541 |
| **Ave. Comp. Return** | 0.0090 | 0.0090 | 0.0089 | 0.0079 | 0.0087 |
| | | [0.00] | [0.03] | [0.21] | [0.06] |
| **Beta** | 0.70 | 0.74 | 0.50 | 0.72 | 0.69 |
| **Sharpe Ratio** | 0.148 | 0.146 | 0.174 | 0.129 | 0.147 |
| | | [-0.29] | [0.82] | [-0.87] | [-0.21] |
| **1-Factor Alpha** | 0.0041 | 0.0039 | 0.0045 | 0.0028 | 0.0037 |
| | (1.32) | (1.25) | (1.85)* | (0.93) | (1.28) |
| **3-Factor Alpha** | 0.0004 | 0.0001 | 0.0019 | -0.0010 | 0.0002 |
| | (0.18) | (0.03) | (0.93) | (-0.44) | (0.07) |
| **4-Factor Alpha** | 0.0014 | 0.0013 | 0.0022 | 0.0004 | 0.0012 |
| | (0.58) | (0.55) | (1.07) | (0.16) | (0.55) |
| **Ave. Transaction costs/month (as % of value, in bps)** | 0.7 | 1.0 | 2.5 | 2.7 | 1.0 |

***Note:*** Numbers in parentheses are t-statistics for significance of coefficients. Square brackets contain test statistics that test the difference from Quartile 1; average returns use t-tests that assume unequal variances, Sharpe ratios use the z-statistics of Jobson and Korkie (1981). * indicates significance at a 10% level, ** indicates significance at 5%, and *** at 1%.

**Table 6 Other Risk Measures (Net of Transaction Costs)**

| | Market Cap Weighted | Equal Weighted | Minimum Variance | Maximum Diversification | Equal Risk Contribution |
|---|---|---|---|---|---|
| **Tracking Error (vs Mkt Cap Weighted)** | | 1.0% | 2.7% | 2.0% | 0.9% |
| **Maximum drawdown** | -66.6% | -66.7% | -56.0% | -69.0% | -65.3% |
| **Semi-std. dev.** | 4.3% | 4.4% | 3.6% | 4.4% | 4.2% |
| **Percent of months with highest return amongst strategies** | 28.8% | 10.4% | 32.9% | 25.0% | 2.9% |
| **Percent of months with lowest return amongst strategies** | 26.7% | 13.3% | 27.1% | 30.0% | 2.9% |
| **Percent of months that strategy beat mkt cap weighting** | | 50.8% | 50.0% | 50.8% | 50.0% |

**Table 7 Risk Based Portfolio Performance – Net of Transaction Costs (monthly, 1994-2003)**

| | Market Cap Weighted | Equal Weighted | Minimum Variance | Maximum Diversification | Equal Risk Contribution |
|---|---|---|---|---|---|
| **Average Return** | 0.0116 | 0.0116 | 0.0121 | 0.0111 | 0.0115 |
| | | [-0.00] | [-0.14] | [0.11] | [0.02] |
| **Std. Dev.** | 0.0342 | 0.03189 | 0.0276 | 0.0313 | 0.0305 |
| **Ave. Comp. Return** | 0.0109 | 0.0110 | 0.0117 | 0.0106 | 0.0110 |
| | | [-0.02] | [-0.19] | [0.09] | [-0.01] |
| **Beta** | 0.21 | 0.21 | 0.12 | 0.23 | 0.20 |
| **Sharpe Ratio** | 0.15 | 0.15 | 0.17 | 0.13 | 0.15 |
| | | [0.68] | [1.50] | [0.11] | [1.02] |
| **1-Factor Alpha** | 0.0069 | 0.0069 | 0.0080 | 0.0063 | 0.0069 |
| | (2.27)** | (2.44)** | (3.19)*** | (2.29)** | (2.55)** |
| **3-Factor Alpha** | 0.0025 | 0.0026 | 0.0046 | 0.0020 | 0.0027 |
| | (0.96) | (1.12) | (2.1)** | (0.92) | (1.24) |
| **4-Factor Alpha** | 0.0032 | 0.0035 | 0.0052 | 0.0033 | 0.0036 |
| | (1.24) | (1.54) | (2.32)** | (1.51) | (1.64) |

***Note:*** Numbers in parentheses are t-statistics for significance of coefficients. Square brackets contain test statistics that test the difference from Quartile 1; average returns use t-tests that assume unequal variances, Sharpe ratios use the z-statistics of Jobson and Korkie (1981). * indicates significance at a 10% level, ** indicates significance at 5%, and *** at 1%.

**Table 8 Risk Based Portfolio Performance – Net of Transaction Costs (monthly, 2004-2013)**

| | Market Cap Weighted | Equal Weighted | Minimum Variance | Maximum Diversification | Equal Risk Contribution |
|---|---|---|---|---|---|
| **Average Return** | 0.0099 | 0.0100 | 0.0778 | 0.0081 | 0.0091 |
| | | [-0.01] | [0.25] | [0.19] | [0.09] |
| **Std. Dev.** | 0.0727 | 0.0754 | 0.0554 | 0.0736 | 0.0704 |
| **Ave. Comp. Return** | 0.0071 | 0.0070 | 0.0061 | 0.00528 | 0.0065 |
| | | [0.014] | [0.12] | [0.19] | [0.07] |
| **Beta** | 1.28 | 1.35 | 0.94 | 1.30 | 1.26 |
| **Sharpe Ratio** | 0.12 | 0.12 | 0.12 | 0.09 | 0.11 |
| | | [-0.28] | [-0.03] | [-0.92] | [-0.62] |
| **1-Factor Alpha** | 0.0007 | 0.0003 | 0.0007 | -0.0012 | 0.0000 |
| | (0.15) | (0.07) | (0.20) | (-0.28) | (0.00) |
| **3-Factor Alpha** | 0.0002 | -0.0003 | 0.0004 | -0.0019 | -0.0006 |
| | (0.04) | (-0.09) | (0.11) | (-0.51) | (-0.15) |
| **4-Factor Alpha** | 0.0008 | 0.0005 | 0.0005 | -0.0011 | 0.0002 |
| | (0.22) | (0.13) | (0.16) | (-0.30) | (0.05) |

***Note:*** Numbers in parentheses are t-statistics for significance of coefficients. Square brackets contain test statistics that test the difference from Quartile 1; average returns use t-tests that assume unequal variances, Sharpe ratios use the z-statistics of Jobson and Korkie (1981). * indicates significance at a 10% level, ** indicates significance at 5%, and *** at 1%.

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