Can sector specific REIT strategies outperform a diversified benchmark?

1. Introduction

There have been a lot of attempts by both practitioners and academics to develop a repeatable and consistent investment strategy that can outperform a relevant benchmark in absolute terms, whilst minimising the associated risk measures, be it volatility or maximum drawdown (the peak to trough percentage) , to deliver superior risk-adjusted returns. Our interest in this topic focusses specifically on the listed real estate (REIT) sector, which is one of 11 separate equity sectors accounting for around 3.5% of the global equity market. The generally accepted benchmark for REIT performance is the FTSE/EPRA/NAREIT Index which comprises the largest REITs, weighted according to their free float market capitalisation (i.e. investible size). Its composition is therefore agnostic to the type of asset (retail, office, industrial etc.) owned by the REITs.The asset composition of the companies in the index is extremely important to fund managers who specialise in the real estate sector, so it is important to isolate the impact on performance of selecting companies by asset type not size (as measured by free float market capitalisation). Companies who have a dominant asset type in their portfolio are designated Specialist (as opposed to Diversified) REITs. In the benchmark the changes to weightings are determined by the change in the free float market capitalisation. A key element of the paper is determining whether an automated trading strategy can be developed to change the portfolio weightings, to improve performance, independent of changes in market capitalisation. .

In this paper two specific elements have been examined relating to the performance of portfolios of specialist REITs compared to that of a diversified benchmark:

Firstly, whether automated portfolio weightings of sector specific REITs can be created that can outperform a diversified free-float market capitalisation based FTSE/EPRA/NAREIT EPRA benchmark. In contrast to the free-float market capitalisation weighting of the benchmark index, four alternative portfolio weighting strategies are considered, namely; Equal Weight, Minimum Variance, Maximum Sharpe and Risk Parity. These result in very different portfolio weightings to the index. The size of the US REIT market allows a high degree of specialisation amongst the individual companies, which enables investors to assemble portfolios with weightings based on individual property types rather than merely market capitalisation

Secondly, given that Maximum Drawdown for single sectors (be it asset specific such as Offices, or indeed equity specific such as REITs) is a major concern for practitioners we investigate whether the application of automated Trend Following strategies as an overlay to the initial portfolios can improve risk-adjusted results. The data used for this study is from NAREIT the US for the period 1995-2015 and from EPRA for the extended dataset which includes Europe and Asia for the period 2007-2015.

The paper is structured as follows:

The next section of the paper (Section 2) deals with the prior literature, as it relates to the relative performance of REITs that specialise in one sector (such as offices) compared to those which hold a portfolio diversified across sectors, and with regard to the automated trading strategies (such as Momentum and Trend Following) which could be deployed. In this section we also provide the behavioural finance rationale for the success of these strategies.

Section 3 outlines the US REIT sector data used and our methodology. The first stage of the analysis is to compute the base level returns and chosen risk characteristics for each of the sectors. The second stage is to calculate the correlations between the sectors so that we can calculate the benefits of combining the different sectors in a portfolio, The third stage constructs portfolios using 4 different weightings, to show how the results differ from a free-float market capitalisation weighting of the benchmark index, and finally the fourth stage is to apply an automated trading strategy to the portfolios, in this case a Trend Following Strategy This methodology is first employed on the US data for the full period 1995-2015, and then on a global sample (Global, European, UK Asia and US) over the shorter time period available 2007-2015.

Section 4 details the results of our study, and Section 5 provides the conclusions we draw from the results.

2. Literature Review

Although specialisation is welcomed by investors as it provides a greater level of choice, it is not clear, that specialisation per se leads to enhanced performance. Ro and Ziobrowski (2011) amongst others found no evidence of superior performance by REITs specialising in a single property type compared to REITs holding a diversified portfolio. Indeed they also found that specialised REITs carried a higher level of volatility (risk). However, by focussing purely on the underlying property type these results may be masking other factors which have been shown to contribute to performance such as size, leverage, and management. In addition, by taking specialised REITs as a whole this may ignore the fact that certain sectors (for example Industrial) do outperform diversified REITs over most periods of a cycle, after adjusting for these other factors. In order to isolate the pure impact of specialisation for this study we have put together portfolios of specialised REITs using non free-float market capitalisation weightings, to ensure that pure size (as measured by free-float market capitalisation) is not the primary driver of performance. We then overlay an automated trading strategy, incorporating trend following to the portfolios to determine whether this dynamic approach can outperform the static strategy. . There are several reasons why we use these specific automated trading strategies, which have proved resilient in other markets. The classic equity strategy highlighted by Jegadeesh and Titman (1993) involves buying the 'winners' over the past 6-12 months and selling the 'losers' over the same period. This is frequently referred to as cross-sectional momentum or relative momentum by Antonacci (2012). Studies by Erb and Harvey (2006) and Miffre and Rallis (2007) demonstrate the effectiveness of this approach within commodity markets.

An alternative type of momentum investing is where one is interested only in the direction of prices or returns rather than how they fare against their peer group. This type of activity is known as trend following (other names include time series momentum and absolute momentum) and is frequently used by Commodity Trading Advisors (CTAs) (see Szakmary et al, 2010). As examples, trend following rules may use the current price relative to a moving average (Faber, 2007), or the length of time that excess returns have been positive over a range of timeframes (Hurst et al, 2012). Indeed, Hurst et al (2012, p.2) make the following distinction:

"The most basic trend-following strategy is time series momentum – going long markets with recent positive returns and shorting those with recent negative returns. The aim is always to trade in the direction of the prevailing price, i.e. when prices are rising long positions are taken and when prices are falling then cash or short positions are taken."

Evidence for the effectiveness of trend following strategies has been presented by Faber (2007), ap Gwilym et al (2010) and Moskowitz et al (2012), amongst others. Clare et al (2016) demonstrate that when relative momentum is compared to trend following it is the latter that provides by far the more impressive investment performance enhancement for a variety of asset classes. Moskowitz et al (2012) find significant ''time series momentum'' in equity index, currency, commodity and bond futures for each of the 58 liquid instruments considered. They find persistence in returns for one to 12 months that partially reverses over longer horizons, consistent with sentiment theories of initial under-reaction and delayed over-reaction.

We believe that there are a number of factors which can explain the outperformance of the trend-following strategies, which is consistent with previous evidence, namely;

a) Continuation, reversals and behavioural finance

Trend-following, often known as time series momentum, though they are not necessarily synonymous as we point out in the introduction, is closely related to the predictions of some behavioural and rational asset pricing theories such as Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998) and Hong and Stein (1999). The empirical findings by Moskowitz et al (2012) and others that for a wide range of asset classes there is positive time series momentum that partially reverses over the long-term may well be consistent with initial under-reaction and delayed over-reaction; indeed theories of sentiment can produce these return patterns (Baker and Wurgler, 2006, 2007).

Trend following strategies work if price trends continue more often than not (e.g. see Hurst et al., 2012), but why should these trends continue? Much of our understanding of this is based on the work of Tversky and Kahneman (1979) and, in this context is typically related to the behavioural biases involved in under reaction of market prices to new information. If prices initially underreact to either good or bad news, trends tend to continue as prices slowly move to fully reflect changes in fundamental value. These trends may continue further to the extent that investors chase the trend via herding behaviour, which can lead to an overreaction in prices beyond fundamental value. Naturally all trends will eventually come to an end as deviations from fair value cannot continue indefinitely. This is the domain of Managed Futures' investing, and has been applied with some success across many asset classes (e.g. Hurst et al., 2012) and indeed with particular success during extreme up and down markets.

Moskowitz et al (2012) find that the dominant force to both time-series and relative momentum strategies is significant positive auto-covariance between a security's excess return next month and it's 1-year lagged return. This evidence is consistent with both initial under-reaction and delayed over-reaction theories of sentiment as the time series momentum effect partially reverses after one year. They also investigate the link between time series momentum returns and the positions of speculators and hedgers, finding that speculators profit from time series momentum at the expense of hedgers which is consistent with speculators earning a premium via time series momentum for providing liquidity to hedgers.

So we believe that the *raison d'etre* for the existence of trends lies firmly in the area of behavioural finance. A major shift in some fundamental variable driving an asset price is adopted into the market slowly revealing an initial under reaction to the new information, possibly due to the slow diffusion of news (Hong and Stein, 1999); the trend in price then overextends due to herding effects and finally results in a reversal. Research has linked the initial under-reaction to behavioural features and frictions that slow down the price discovery process, these include:

(i) Anchoring

Barberis, Shleifer, and Vishny (1998), Edwards (1968) and Tversky and Kahneman (1974) find that historical data provide a natural anchor for people and their views adjust slowly to new information: anchoring leads to under-reaction to news.

(ii) The disposition effect

Shefrin and Statman (1985) and Frazzini (2006) note that people tend to sell winners too early as they like to realize gains, thus slowing down the rise in price, and they hold losers too long as they wish to avoid realizing losses, hence slowing any downward move in prices. Barberis (2013) points out that this argument follows directly from prospect theory. Holding losers demonstrates risk-seeking behaviour by investors when they make losses. This is developed further by Barberis and Xiong (2012).

Of course, once a trend has become established there are a number of features which can extend the trend:

(iii) Herding

Bikhchandani, Hirshleifer, and Welch, (1992), De Long et al. (1990), Hong and Stein (1999), and others argue that when prices start moving up or down for a while then some traders will naturally join the bandwagon and the herding effect will feed on itself; this has been observed with equity analysts' forecasts and mutual fund investors.

(iv) Confirmation bias/representativeness

Tversky and Kahneman (1974) show that people tend to look for information which they already believe and take recent price changes as representative of the future. Over-confidence and self-attribution confirmation biases are present (Daniel, Hirshleifer, and Subrahmanyam, 1998) as is the representativeness heuristic (Barberis, Shleifer, and Vishny, 1998), hence more investors join the trend: it becomes self-reinforcing. Of course eventually prices extend far beyond underlying fundamental value and the trend evaporates: prices may move sideways for a period until new information moves prices once more.

b) Rules-based investing strategies and behavioural finance

A key feature of both time-series and cross-section momentum is that they are '*rules-based'*. Ever since Michaud (1989) questioned the efficacy of combining asserts in Mean Variance Efficient portfolios, there has been interest in simple alternative approaches which do not involve generating expected returns, variances and covariances: simple rules may include equal dollar weights or, indeed, equal risk weights, so-called 'risk parity'. The latter has been especially popular of late, probably because of the low interest rate environment. Some researchers have compared such simple rules with more conventional rules due to Markowitz, both with and without perfect foresight, and find that the former are superior in terms of Sharpe and other performance metrics (see, for example, Chaves et al., 2011).

Why should such simple rules perform so well? We believe that the discipline of rules-based construction has clear advantages over attempting to forecast returns in a noisy world which also incorporates substantial behavioural biases: over-reliance on recent information is but one simple example of biases which could adversely affect such forecasts. Simple rules avoid behavioural biases in portfolio formation.

3. Data & Methodology

The main dataset is for 10 NAREIT US REIT sector and subsector indices for the period 1994-2015, namely Office, Industrial, Shopping Centres, Regional Malls, Free Standing Retail, Residential, Diversified, Lodging/Resorts, Self-Storage and Healthcare. The first year of data is frequently required for calculations so results are reported from 1995-2015. All observations are monthly and in US dollars with total returns used unless otherwise stated. Where cash is referred to, we use three-month US Treasury Bills.

For a shorter period of international data EPRA indices are used for the period 2006-2015. The five regions/countries are Global, UK, US, Eurozone and Asia and each has the following five sectors: Diversified, Industrial, Office, Residential and Retail. Once again, all observations are monthly in US dollars and the first year of data is used in calculations.

The first stage of the analysis provides us with an indication of how each individual sector has performed. We compute the base level returns and chosen risk characteristics (in this case volatility, Sharpe Ratio, and Maximum Drawdown) for each of the 10 US sectors over the full period, 1995-2015. The results are shown in Table 1.

The second stage provides us with an indication as to whether there will be risk reduction benefit from diversification, or whether all the sectors move in a similar manner. We calculate the correlations between the sectors so that we can calculate the benefits of combining the different sectors in a portfolio, which we show by way of a mean-variance efficient frontier (Table 2 and Figure 1). This

The third stage attempts to reduce the size bias which is present in free float market capitalisation indices, and isolate the specific sector impact. To achieve this, we construct portfolios using 4 different weightings, to show how the results differ from a free-float market capitalisation weighting of the benchmark index. They are Miinimum Variance (MV), Maximum Sharpe (MS), Equal Weight (EW) and Risk Parity (RP). Specifically, at the beginning of each annual period we calculate the portfolio weights based on the four strategies described earlier using only information that was known at that point. The portfolios are then held for twelve months before recalculation takes place, including the returns data that has become available during that time, and new weights are assigned. .

The fourth stage is to see whether a dynamic portfolio, which uses an automated trading strategy, can generate risk-adjusted outperformance. We have chosen to apply a Trend Following Strategy to the portfolios. . Our trend following methodology simply compares, at the end of each month, a total return index for a given sector with the average of the previous 10-months' values; if it lies above the average then we put that proportion of the portfolio into that risky asset; if it lies below we shift that part into cash or similar 'risk-free'.

We have compared this rule with a myriad other rules found in the literature in an earlier paper (Clare et al (2012) and found it robust across assets and time-periods. The results are then compared with that of the benchmark index to see if there is an improvement in risk-adjusted returns.

This methodology is first employed on the US data for the full period 1995-2015, and then on a global sample (Global, European, UK Asia and US) over the shorter time period available 2007-2015.

4. Results

To establish the base level of sector returns, and differences in risk characteristics (specifically volatility and maximum drawdown) we calculated the key metrics for each sector. Table 1 reports these summary statistics for the ten sectors (all in USD). .

Table 1

Summary Statistics for REIT Sector: 1995-2015

	Office	Industrial	Shopping Centres	Regional Malls	Free Standing	Residential	Diversified	Lodging/ Resorts	SelfStorage	Healthcare
Annualized Return (%)	11.57	8.38	10.66	13.49	13.99	12.85	9.43	5.33	18.03	12.74
Annualized Volatility (%)	21.76	30.90	22.21	26.38	17.77	19.51	21.28	31.04	19.91	20.99
Sharpe Ratio	0.42	0.19	0.37	0.42	0.65	0.53	0.33	0.09	0.78	0.49
Maximum Drawdown (%)	70.90	85.37	72.91	82.02	37.93	67.01	68.85	83.89	51.63	48.07
Jarque-Bera test	390.5	5493.3	1313.3	3194.5	29.9	212.6	1023.6	1854.8	54.5	127.3

The last line in Table 1 presents the familiar Jarque-Bera test statistic for normality for each of the series. The test statistic measures the difference of the skewness and kurtosis of the series with those from the normal distribution, and is distributed as χ^2 with 2 degrees of freedom, under the null hypothesis of normality. These Jarque-Bera tests show that all of these series are non-normal. This non-normality is due, at least in part, to the drawdowns experienced in these instruments; and it is this issue that our investment strategy addresses.

We observe considerable variation in the performance of the sectors with Self Storage having the highest return over the period at 18.0% and Lodging/Resorts the lowest at 5.3%. These also have the highest and lowest Sharpe ratios at 0.78 and 0.09 respectively. Industrial and Lodging/Resorts are the most volatile sectors with both scoring over 30% on an annualised basis, whilst Free Standing and Residential are the lowest at under 20%. During the GFC The financial crisis many sectors suffered drawdowns of in excess of 50%.

The fact that there is considerable variation in performance between sectors offers encouragement that through combinations of sectors we may be able to find improved risk/reward trade-off.

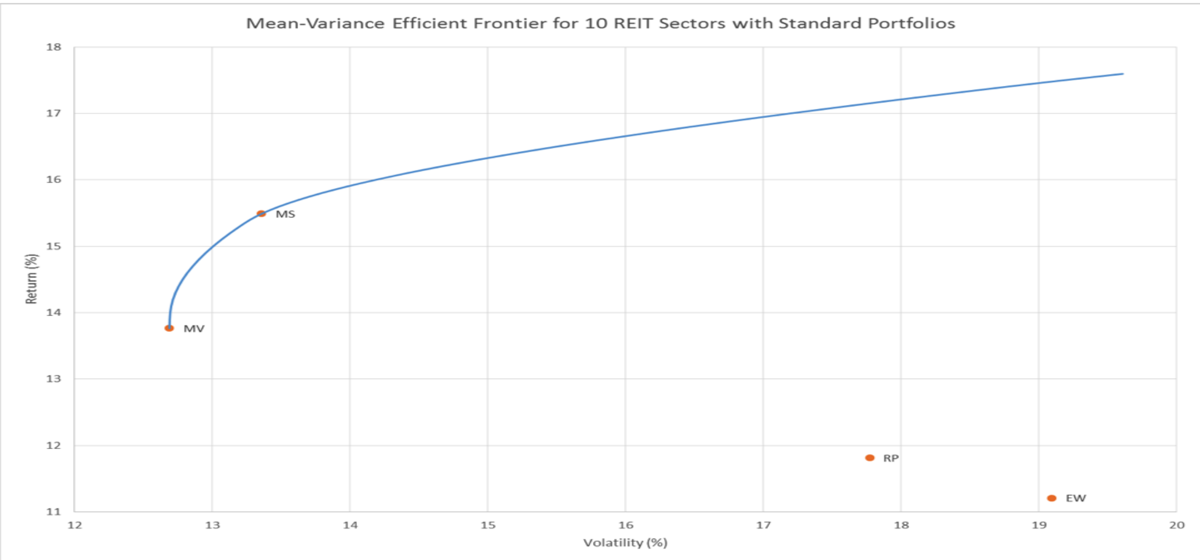
Having seen the level of absolute risk and return the next stage is to examine the correlations between sectors, as shown in Table 2.

Table 2

Correlations Between REIT Sectors

	Office	Industrial	Shopping Centres	Regional Malls	Free Standing	Residential	Diversified	Lodging/Resorts	Self Storage	Healthcare
Office	1.00									
Industrial	0.82	1.00								
Shopping Centres	0.89	0.86	1.00							
Regional Malls	0.86	0.80	0.91	1.00						
Free Standing	0.76	0.71	0.78	0.71	1.00					
Residential	0.85	0.70	0.82	0.78	0.67	1.00				
Diversified	0.90	0.78	0.88	0.86	0.73	0.84	1.00			
Lodging/Resorts	0.77	0.69	0.76	0.80	0.57	0.71	0.82	1.00		
Self Storage	0.77	0.69	0.81	0.75	0.73	0.75	0.76	0.63	1.00	
Healthcare	0.76	0.74	0.81	0.74	0.78	0.71	0.74	0.60	0.77	1.00

As might be expected when comparing different sectors of the same asset class (REITs), all of the correlations are positive, I.e. they move in the same direction, with an average value of +0.77 and a range of +0.57 to +0.91. Lodging/Resorts had the lowest average correlation with the other sectors and Shopping Centres had the highest. We then put the various risk/reward trade-offs into the form of a mean-variance efficient frontier (figure 1). This will help us show how the expected return is maximised for a given level of risk.



This is constructed with the benefit of hindsight over the whole data period.

In addition, we have indicated four standard portfolios on the chart in Figure 1 which have different weights to a standard free-float market capitalisation weighted index. They have each been chosen for a specific purpose as follows:

Minimum Variance: This methodology seeks to produce a portfolio with the lowest level of risk for the expected return

Maximum Sharpe: This methodology produces the optimal combination of risk and return, i.e. at the intersection of the tangency line and Efficient Frontier (see Figure 1)

Equal weight: This methodology eliminates the impact of size by treating each constituent similarly.

Risk Parity: This methodology seeks to allocate weights such that each constituent has a similar level of risk, so portfolio weights are proportional to the inverse of observed volatility.

. The first two, Minimum Variance (MV) and Maximum Sharpe (MS), are efficient portfolios that lie on the frontier. Our remaining portfolios are Equal Weight (EW) and Risk Parity (RP), i.e. each asset contributes the same amount of risk to the total, which are not efficient and lie away from the frontier. In this case, both EW and RP are found in the bottom right-hand corner of the chart. They each display returns that are considerably less than the Minimum Variance portfolio and volatilities some 5-6% greater. The initial impression is thus that these popular strategies have performed exceedingly poorly but we caution this analysis was done with perfect hindsight.

We next consider how the strategies perform when they are constructed based on data *available at the time* (i.e. a rolling time-period) and used to make portfolio allocations for the following year. Specifically, at the beginning of each annual period we calculate the portfolio weights based on the four strategies described earlier using only information that was known at that point. The portfolios are then held for twelve months before recalculation takes place, including the returns data that has become available during that time, and new weights are assigned.

Table 3 reports the performance of the four strategies based on data available at the time plus the NAREIT Equity REIT index as a benchmark.

Table 3

Performance of Standard Portfolios Based on Information Available at Time

	Equity REIT Index	Equal Weight	Minimum Variance	Maximum Sharpe	Risk Parity
Annualized Return (%)	11.10	12.52	12.79	11.67	12.77
Annualized Volatility (%)	19.93	20.09	18.21	22.13	19.73
Sharpe Ratio	0.43	0.50	0.56	0.41	0.52
Maximum Drawdown (%)	68.30	66.82	61.08	73.81	65.77

The results are very different to the observations made from the efficient frontier. Firstly, the Maximum Sharpe portfolio now has the lowest return of any strategy. In addition, it has clearly the highest volatility and has a Sharpe ratio that is below that of the benchmark. The Minimum Variance portfolio and Risk Parity portfolios now have almost exactly the same return at around 12.8% although the former does have a slightly lower volatility at 18.2% versus 19.7%. The gap between the two is nothing like it was, though, in the efficient frontier. This is also true of the Equal Weight portfolio which returned 12.5% with a volatility of 20.1%. *From the standpoint of combining sectors, the fact that three of the four strategies outperformed the benchmark both on a risk-adjusted and unadjusted basis is encouraging.* The excess returns displayed by the Minimum Variance portfolio is very much consistent with the evidence presented by Falkenstein (2012) across a wide range of asset classes.

Figures 2, 3 and 4 (in the Appendix) show the asset allocation of the Minimum Variance, Maximum Sharpe and Risk Parity strategies at the beginning of each annual period respectively. Looking firstly at Figure 2, it can be seen that the Minimum Variance portfolio has typically been dominated by two or three sectors with occasional small allocations to one or two more sectors. As more data became available, the portfolio converged towards a dominant weighting in Free Standing with smaller allocations to Residential and Self-Storage. In the last six years of the study (2009-15) the weights showed very little variation.

Figure 3 shows the asset allocation of the Maximum Sharpe portfolio. This is typically dominated by one or two sectors with the asset allocation having converged to a large position in Self Storage and a smaller position in Free Standing. The portfolio weights appear more volatile in this portfolio compared to the Minimum Variance although both tend to be heavily concentrated in just a handful of sectors.

The final portfolio is Risk Parity and this is shown in Figure 4. We note this has much greater diversity compared to the previous two strategies with all ten sectors having a portfolio weight in every annual period. The weights remain fairly constant over time and the composition of this portfolio is similar to an equal weight portfolio with some small tactical adjustments. This is borne out by the results we observed earlier in Table 3 where there was little difference between the Risk Parity and Equal Weight strategies.

Despite the benefits of combining REIT sectors relative to the benchmark, (annualized returns are higher as shown in Table3) we note that the maximum drawdown of the portfolios (>60% as per Table 3) remained high. We define maximum drawdown as the percentage change in the portfolios from peak to trough over the period. Even the low volatility Minimum Variance portfolio suffered a maximum drawdown in excess of 60%. The fundamental reasons for this high figure are: 1) We are dealing with a single asset class where the sectors tend to move in a similar direction, so mitigating diversification benefits are low. 2) The leverage of the REITs exacerbates value declines in their underlying assets 3) REIT valuation shifts can be dramatic (e.g. from a 25% premium to NAV to a 35% discount to NAV) which enhances the decline at certain stages of the cycle.

Therefore, we are keen to see if we can minimise this particular risk metric by employing an automated trading strategy. One strategy that has proved effective across a wide variety of asset classes for reducing volatility and drawdown, whilst still preserving much of the return, is trend following. An extensive literature is available that describes simple mechanical rules that can be used as an overlay on existing portfolios. For examples, see Faber (2007) and Clare et al (2016) for multi-asset, Szacmary et al (2010) for commodities and Moss et al (2015) for real estate whilst Hurst et al (2012) report for over 200 years of data using futures markets.

In this paper we are going to use the simple rule proposed by Faber (2009) whereby if the sector index is trading above its 10-month moving average we take a long position and otherwise we invest the allocation within the portfolio to Treasury Bills. This calculation is repeated on a monthly basis. We retain the four portfolios described earlier for asset allocation purposes and, by way of interest, also apply trend following to the benchmark index.

Table 4 reports the results of the addition of the trend following strategy.

Table 4

Performance of Standard Portfolios Based on Information Available at Time with Trend Following

	Equity REIT Index	Equal Weight	Minimum Variance	Maximum Sharpe	Risk Parity
Annualized Return (%)	10.84	12.70	12.70	14.01	12.80
Annualized Volatility (%)	14.49	12.38	13.10	13.52	12.36
Sharpe Ratio	0.58	0.82	0.78	0.85	0.83
Maximum Drawdown (%)	45.18	27.90	35.21	23.31	28.46

Looking firstly at the benchmark we note a small decline in return of around 30 basis points annually but volatility is now less than three-quarters of its previous level giving a Sharpe ratio of 0.58 versus 0.43 without trend following. The maximum drawdown has also been reduced to 45% from 68%. Moving next to the four sector combination strategies, we observe little change in return as a result of trend following with the exception of the Maximum Sharpe portfolio which has improved from 11.7% to 14.0%. The big difference comes in the volatility and drawdowns where the former is now, on average, less than two-thirds of the level prior to the implementation of the trend following filter. Average Sharpe ratios are now 0.82 compared to 0.50. The maximum drawdowns have declined substantially through the application of trend following. All of the strategies previously had values in excess of 60% whereas now three of the four are under 30% with only Minimum Variance above at 35%. All of the four strategies are now a substantial improvement on the benchmark, particularly when the index is considered without trend following.

W*e next consider the evidence using the international dataset.* Table 5 shows summary statistics for the five regions/countries over the shorter time period.

Table 5

Summary Statistics of International Sectors 2007-15

	Diversified	Industrial	Office	Residential	Retail
Global					
Annualized Return (%)	-0.90	-6.19	2.29	6.50	2.76
Annualized Volatility (%)	23.50	35.05	20.65	22.19	22.81
Sharpe Ratio	-0.07	-0.20	0.07	0.26	0.09
Maximum Drawdown (%)	68.76	86.25	63.98	62.58	68.92
UK					
Annualized Return (%)	-4.58	-11.05	2.40	-6.11	-7.41
Annualized Volatility (%)	25.21	40.98	27.45	52.46	27.75
Sharpe Ratio	-0.21	-0.29	0.06	-0.13	-0.29
Maximum Drawdown (%)	80.73	91.62	83.17	91.06	82.84
US					
Annualized Return (%)	1.14	-3.51	1.52	8.17	3.91
Annualized Volatility (%)	29.99	44.66	28.28	25.27	30.91
Sharpe Ratio	0.01	-0.10	0.03	0.29	0.10
Maximum Drawdown (%)	72.61	85.46	72.13	66.49	75.30
Eurozone					
Annualized Return (%)	-1.52	3.76	-2.44	-3.76	1.96
Annualized Volatility (%)	26.24	32.40	24.32	36.08	26.20
Sharpe Ratio	-0.09	0.09	-0.13	-0.12	0.05
Maximum Drawdown (%)	68.86	75.82	53.19	88.21	55.33
Asia					
Annualized Return (%)	-3.39	-6.73	2.88	4.91	2.78
Annualized Volatility (%)	26.37	32.77	20.82	37.36	19.51
Sharpe Ratio	-0.16	-0.23	0.10	0.11	0.10
Maximum Drawdown (%)	70.93	88.81	58.54	68.06	63.30

Average returns were highest in the US and lowest in the UK, with the UK also displaying very high volatility and large drawdowns. By sector, residential had the highest risk-adjusted returns and industrial the lowest.

Following the same pattern as Table 3, we form standard portfolios within each region using the five available sectors. The results are displayed in Table 6.

Table 6

Performance of Standard International Portfolios 2007-15

	Benchmark	Equal Weight	Minimum Variance	Maximum Sharpe	Risk Parity
Global					
Annualized Return (%)	1.93	1.39	1.42	3.79	1.53
Annualized Volatility (%)	22.07	22.96	21.62	22.64	22.63
Sharpe Ratio	0.05	0.03	0.03	0.13	0.03
Maximum Drawdown (%)	67.20	69.99	69.67	70.28	69.50
UK					
Annualized Return (%)	-5.04	-4.56	-4.53	-1.38	-4.37
Annualized Volatility (%)	26.24	30.68	26.07	43.12	29.46
Sharpe Ratio	-0.22	-0.17	-0.20	-0.05	-0.17
Maximum Drawdown (%)	82.38	85.61	82.32	87.21	85.00
US					
Annualized Return (%)	4.27	2.83	2.87	-2.53	2.94
Annualized Volatility (%)	26.89	28.67	30.55	43.19	28.46
Sharpe Ratio	0.13	0.07	0.07	-0.08	0.08
Maximum Drawdown (%)	69.88	73.48	78.46	88.22	73.54
Eurozone					
Annualized Return (%)	-0.02	0.53	-3.07	0.57	0.15
Annualized Volatility (%)	25.43	25.61	25.44	26.16	25.51
Sharpe Ratio	-0.03	-0.01	-0.15	-0.01	-0.02
Maximum Drawdown (%)	64.40	66.96	57.74	60.12	66.04
Asia					
Annualized Return (%)	0.44	1.16	3.73	1.36	1.07
Annualized Volatility (%)	23.26	23.35	19.50	30.11	22.23
Sharpe Ratio	-0.01	0.02	0.15	0.02	0.01
Maximum Drawdown (%)	67.60	69.66	59.77	61.07	68.16

In the left-hand column we report the (free-float market capitalisation weighted) benchmark index for each of the five regions as a comparison against the alternative weighting methods. There is little evidence found here to suggest that one portfolio is clearly better than any of the others. For example, the Maximum Sharpe method performs very well in the Global space but very poorly in the US. Similar variation is evident with the Minimum Variance method in Asia and the Eurozone. The Equal Weight and Risk Parity portfolios behave fairly similarly throughout, this is consistent with the earlier evidence presented in Figure 4.

Finally, in Table 7 we present the results of the same portfolio formations as Table 6 but this time with the inclusion of the trend following filter.

Table 7					
Performance of Standard International Portfolios with Trend Following 2007-15					
	Benchmark	Equal Weight	Minimum Variance	Maximum Sharpe	Risk Parity
Global					
Annualized Return (%)	6.64	5.63	6.61	6.76	5.70
Annualized Volatility (%)	11.47	10.69	10.70	12.70	10.56
Sharpe Ratio	0.51	0.46	0.55	0.47	0.47
Maximum Drawdown (%)	13.61	13.73	12.92	24.57	13.53
UK					
Annualized Return (%)	6.13	8.91	8.46	12.90	8.79
Annualized Volatility (%)	14.30	15.46	13.91	23.96	14.86
Sharpe Ratio	0.38	0.53	0.55	0.51	0.54
Maximum Drawdown (%)	17.70	18.85	15.69	27.41	18.24
US					
Annualized Return (%)	8.55	5.17	7.98	9.94	5.56
Annualized Volatility (%)	14.14	15.05	16.74	16.79	15.04
Sharpe Ratio	0.55	0.29	0.43	0.55	0.32
Maximum Drawdown (%)	20.39	31.93	33.40	24.10	31.85
Eurozone					
Annualized Return (%)	2.50	4.18	-1.14	1.79	3.71
Annualized Volatility (%)	15.16	13.55	13.92	15.70	13.53
Sharpe Ratio	0.12	0.25	-0.14	0.07	0.22
Maximum Drawdown (%)	22.27	19.80	29.77	25.13	19.84
Asia					
Annualized Return (%)	3.32	3.96	6.14	-3.38	3.97
Annualized Volatility (%)	12.33	11.96	12.12	20.00	11.43
Sharpe Ratio	0.21	0.27	0.44	-0.21	0.28
Maximum Drawdown (%)	23.07	19.28	19.13	56.32	19.11

Although the dataset for the international indices is shorter in length, it still encompasses the 2007-09 period where the listed real estate sector in general suffered very large drawdowns. The trend following filter ensured that a large part of the GFC period was spent in Treasury Bills and the results reflect the benefit of this allocation. Average returns are over 5% per annum higher compared to Table 6 and volatility is over a third lower. Sharpe ratios average 0.34 with trend following as opposed to zero without. The average maximum drawdown falls to 23% compared to over 70% previously.

5. Conclusions

In this paper we have investigated whether combinations of REIT sectors can be created that can outperform the benchmark. We have considered four strategies of Equal Weight, Minimum Variance, Maximum Sharpe and Risk Parity. With the benefit of perfect hindsight the efficient portfolios completely dominated their inefficient counterparts but when these were calculated based on only information available at the time and used to make portfolio allocations for the future the results were very different. The Minimum Variance portfolio continued to show some outperformance compared to the Equal Weight and Risk Parity portfolios but this was much diminished, whilst the Maximum Sharpe portfolio was the clear laggard. Both of the efficient portfolios tended to have large weightings to relatively few sectors, particularly the Maximum Sharpe portfolio, compared to the other strategies. Three of the four strategies were shown to outperform the benchmark index on a risk-adjusted basis.

One observation from the results was that the maximum drawdowns of the strategies tended to be rather high, indeed as was the benchmark. We therefore investigated whether the application of a trend following filter could be used to improve portfolio performance. It was observed that generally there was little change in the portfolio returns but volatility typically fell by over a third from its previous level and maximum drawdowns were, on average, less than half of the previous values. The risk-adjusted performance improved dramatically as a result.

We believe that the two step process of forming combinations of REIT sectors with the subsequent addition of a trend following overlay is beneficial relative to a passive benchmark investment. This has clear implications for practitioners, who can use this methodology to create portfolios which satisfy the criteria of improving risk-adjusted returns, with weightings directly related to the specific characteristics of REITs, i.e. the underlying asset type. In addition the use of proven automated trading strategies of trend following and momentum allow an element of performance enhancing active management without the additional cost of active management fees or the uncertainty of the discretionary element on performance.

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Appendix

Figure 2.

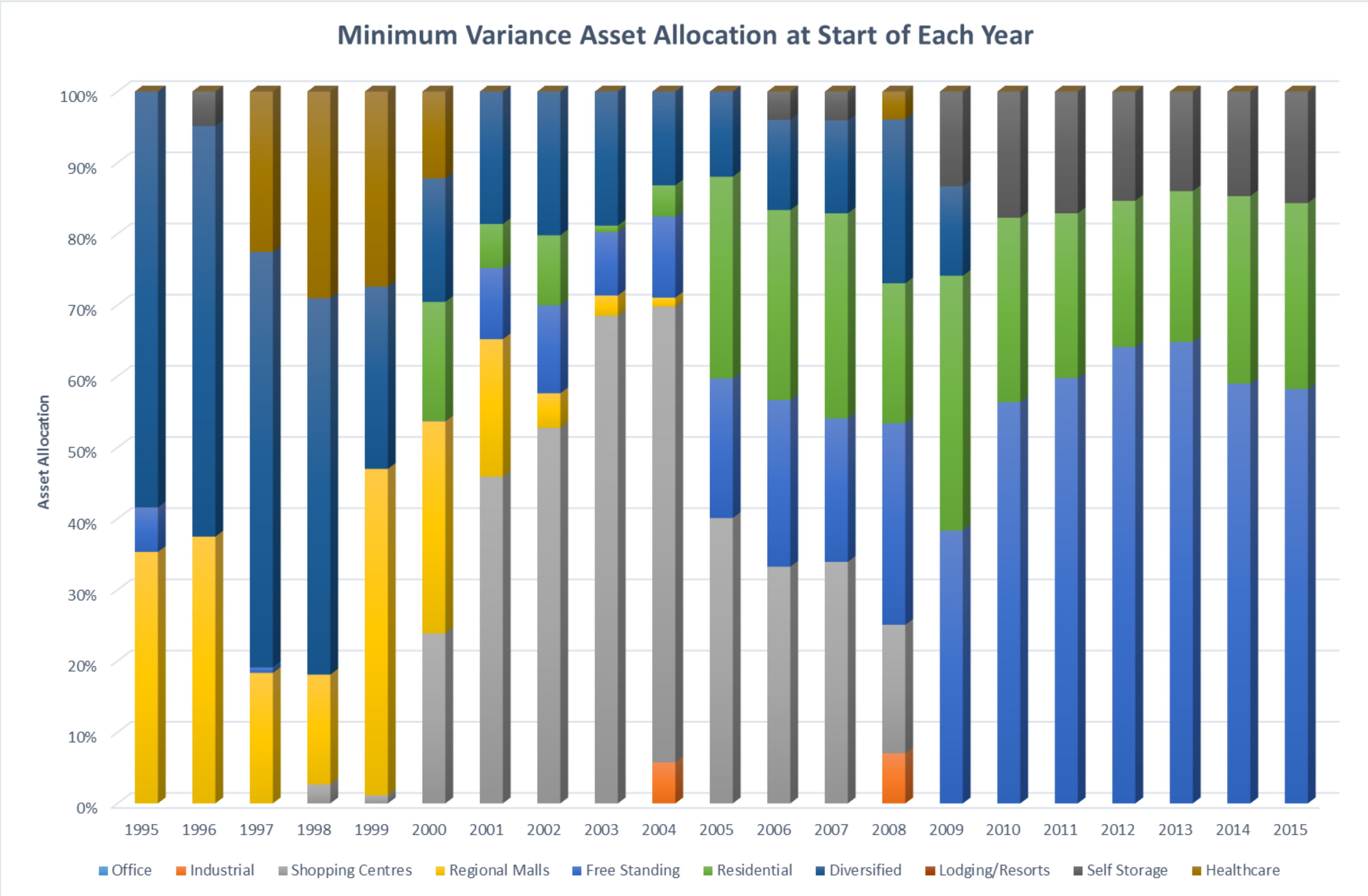

Minimum Variance Asset Allocation at Start of Each Year
Asset Allocation
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
Office
Industrial
Shopping Centres
Regional Malls
Free Standing
Residential
Diversified
Lodging/Resorts
Self Storage
Healthcare

Figure 3.

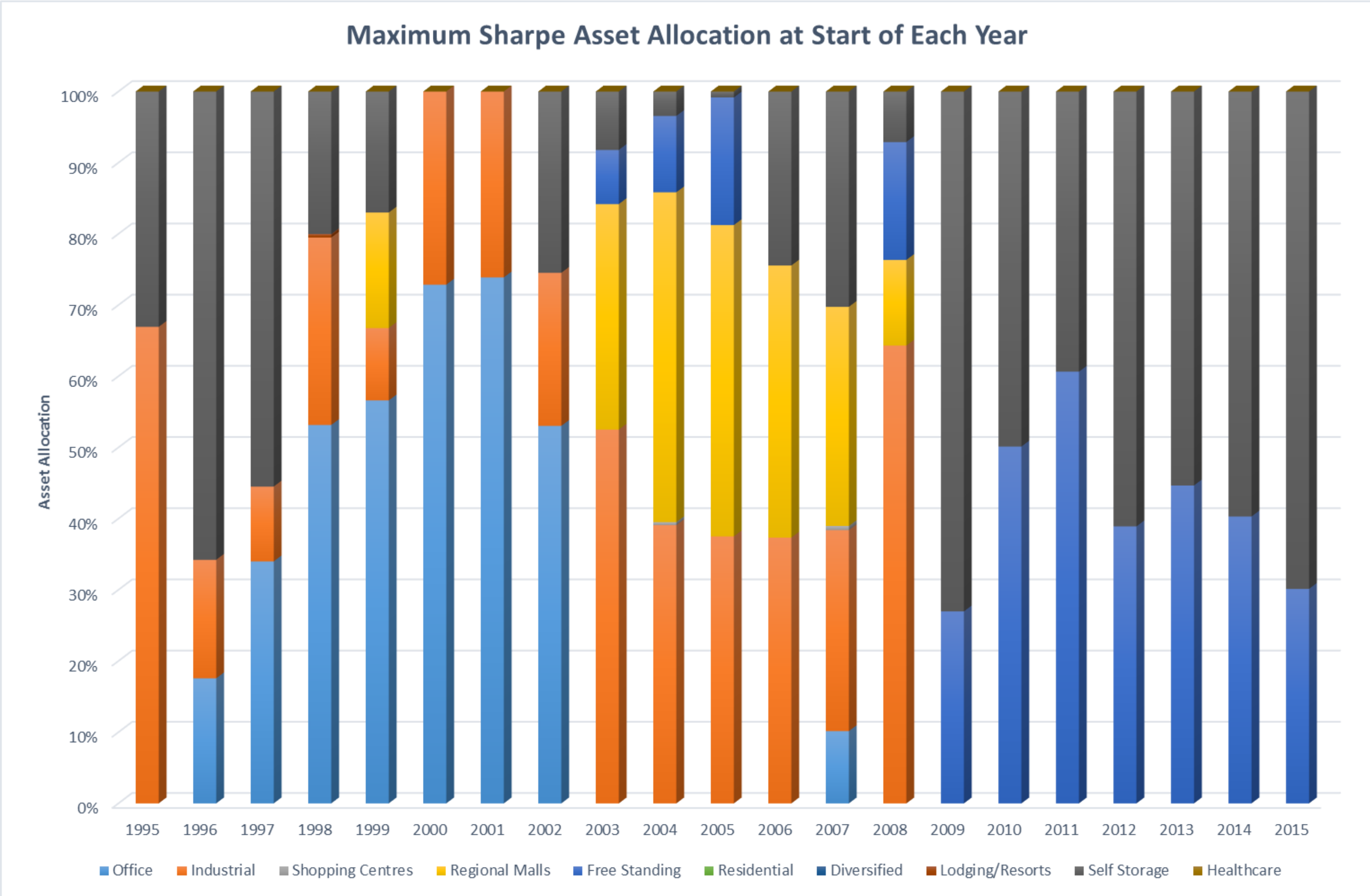
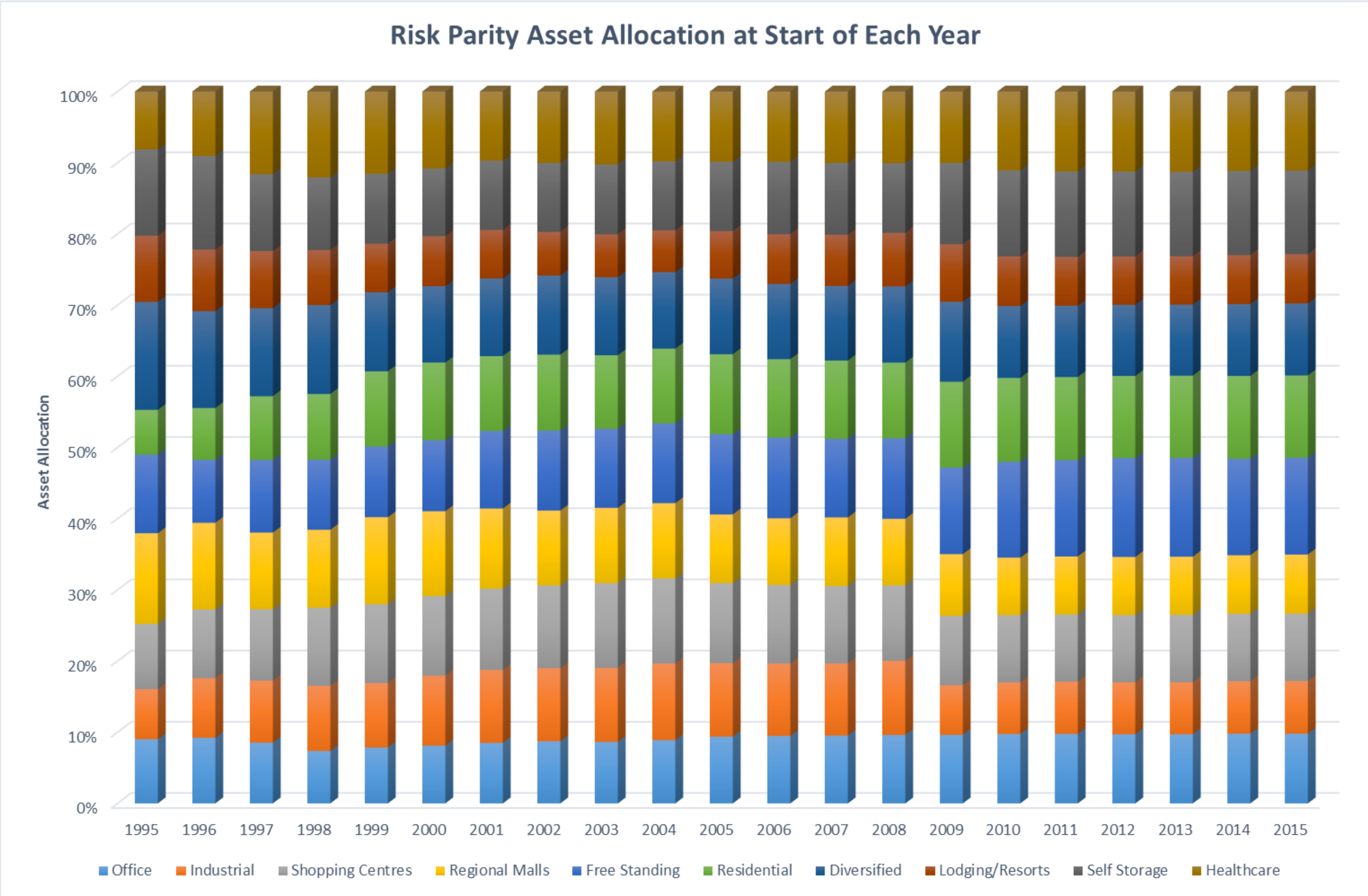

Maximum Sharpe Asset Allocation at Start of Each Year
Asset Allocation
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
Office
Industrial
Shopping Centres
Regional Malls
Free Standing
Residential
Diversified
Lodging/Resorts
Self Storage
Healthcare

Figure 4.


Risk Parity Asset Allocation at Start of Each Year
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
Asset Allocation
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
Office
Industrial
Shopping Centres
Regional Malls
Free Standing
Residential
Diversified
Lodging/Resorts
Self Storage
Healthcare