How Smart is the Real Estate Smart Beta?

Evidence from Optimal Style Factor Strategies for REITs

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Abstract

This paper has a twofold objective. First, we contribute to the stream of literature that investigates whether traditional asset pricing factors show any predictive power for the cross-section of Real Estate Investment Trust (REIT) returns. In particular, we investigate the existence of a premium associated to the Value, Size, Momentum, Investment, and Profitability factors over the period 1993-2018. We find support for all the pricing factors but for the Profitability one. Second, we investigate whether a set of smart beta strategies, based on the combination of the identified factors, may outperform similar allocation techniques that do not exploit factors. We find that all the proposed factor-based strategies display a higher risk-adjusted out-of-sample performance than a simple buy-and-hold investment in the real estate market (proxied by the FTSE NAREIT All REITs Index). In addition, we find that when factor-based strategies are implemented, REIT-only portfolios display risk-adjusted performances comparable to those of diversified portfolios that include equity, bond, and commodities.

Key words: REITs, real estate factors, factor investing, smart beta strategies

JEL Codes: G11, G12, R30

1. Introduction

Traditional asset allocation frameworks usually involve deciding the weights to be assigned to different asset classes (such as equities, bonds, commodities, and real estate) and to different sectors within each asset class. However, in recent years a new factor-based approach, which moves the asset allocation decision from the asset space to a smaller, factor-based space, has become popular both among practitioners and in the academic literature. In fact, the literature has suggested that a strategy based on identifying systematic and uncorrelated risk factors that yield a premium and build portfolios that are able to harvest those premiums may outperform traditional asset allocations especially because they provide a much better diversification (see, e.g., Clarke, de Silva, and Murdock, 2005; Bender, Briand, Nielsen, and Stefek, 2010; Page and Taborsky, 2011; Kremer, Talmaciu, and Paterlini, 2018). These strategies, which rely on the combination of factor mimicking portfolios, have become known as factor investing, style investing or smart beta strategies (expressions that we shall use as synonyms in the rest of this paper).

In spite of the existence of a growing literature that investigates whether these strategies are able to outperform more traditional asset allocation frameworks in the equity, fixed income or commodity spaces (see, e.g., Correia, Richardson, and Tuna, 2012; Jostova, Nikolova, Philipov, and Stahel, 2013; Frazzini and Pedersen, 2014; Houweling and Zundert, 2017), to the best of our knowledge, no paper has yet tried to assess the performance of factor-based strategies when applied to real estate investments. In particular, a natural choice is to investigate the performance of smart beta strategies in Real Estate Investment Trusts (REITs), which represent the real estate counterparts of stocks. Indeed, REITs overcome a number of challenges of investing in the real estate that would otherwise prevent the implementation of factor-based strategies, such as high transaction costs, high lot size, low liquidity and short-selling constraints.[1]

[1] Because our analysis entails the construction of long-short factor portfolios, we need short sale transactions on REITs to be possible. We deem this assumption to be realistic as a few papers have documented the presence of short-selling activity in the REIT market. For instance, Blau, Hill, and Wang (2011) have reported that approximately 21% of the trading volume of REITs in 2005 and 2006 came from short sale transactions.

Our paper pursues a twofold objective. Because the implementation of style investing strategies relies on the identification of robust factors that yield persistent premiums, we review the out-of-sample (henceforth, OOS) performance of a set of long-short factor mimicking portfolios extracted from the cross-section of US REIT returns. According to Harvey, Liu, and Zhu (2016), at least 316 different factors have been identified in the literature (usually as a reaction to some emerging asset pricing anomaly, i.e., a pattern in returns that cannot be otherwise explained by established factors), most of which are unlikely to deliver robust, out-of-sample)OOS) performances. Therefore, we focus our analysis on five well-known factors: Size and Value (first identified by Fama and French, 1993), Momentum (proposed by Jegadeesh and Titman, 1993 and Carhart, 1997), and Investment and Profitability (Fama and French, 2015). In this respect, our paper contributes to the literature that has investigated which traditional asset pricing factors (if any) are able to explain the cross-section of REIT returns (see, e.g., Chui, Titman and Wei, 2003a and 2003b; Bond and Xue, 2017). We investigate a sample going from January 1993 to July 2018 thus extending the results obtained in the few existing studies that have focused on factor modelling of real estate returns. Similar to previous literature, we find support for the Size, Value and Momentum factors (and, to a lower extent, for the Investment factor). However, differently from Bond and Xue (2017) we are not able to find a statistically significant premium associated with the Profitability factor in our sample period; indeed, it seems that the premium associated to this factor is highly time-varying, a novel finding that is investigated in Section 4.2.

Second, to the best of our knowledge, ours is the first paper that applies factor-based portfolio strategies to real estate. In order to combine factor mimicking portfolios in an optimal way, we examine a wide range of different allocation schemes. First, we construct a simple equally weighted portfolio similar to DeMiguel, Garlappi, and Uppal (2009). Second, we implement two strategies that are based on the mean-variance framework of Markowitz (1952): more specifically, we invest in the tangency portfolio and, alternatively, in the minimum variance portfolio (see, e.g., Kempf and Memmel, 2006). Finally, we propose two risk-based strategies: the risk parity approach, popularized by the famous hedge fund Bridgewater in the 1990s and formalized by Qian (2006) and the maximum diversification portfolio introduced by Choueifaty and Coignard (2008). We apply these allocation strategies both to the real estate factor mimicking portfolios and to an alternative asset menu that consists of the FTSE NAREIT All REITs (the REIT index calculated by the National Association of Real Estate Investment Trusts, in short NAREIT), a stock market index built as the value-weighted return on all NYSE, AMEX, and NASDAQ stocks, the Bloomberg Barclays US Aggregate Bond Index, and the Goldman Sachs Commodity Index.

This way, we are able to perform comparisons in at least three dimensions. First, we test whether smart beta strategies applied to real estate factors are able to outperform a simple buy and hold portfolio that passively replicates the FTSE NAREIT All REITs Index. We find that, despite none of our factor-based strategies outperforms the index in terms of mean return, all of them considerably beat the benchmark when the risk-adjusted measures are considered. This is probably due to the stronger diversification opportunities that are offered by the factor investing strategies: indeed, with exceptions of Size and Value, the factors typically display low or negative correlations among each other. Second, we assess whether factor-based REITs-only portfolios are able to outperform more diversified multi-asset allocations built using the four indices discussed above. Although this clearly represents a difficult benchmark to beat, we find that the factor-based REITs-only allocations deliver higher mean returns than the benchmark strategies that involve diversification among the asset classes without entailing too much additional risk. For example, a simple, equal weighting scheme applied to factors would have produced a monthly mean excess return of 0.78% with a volatility equal to 2.6%, which entails a risk adjusted performance of 0.22 (on monthly basis). Over the same period, an equally weighted portfolio of the indices discussed above has a much lower Sharpe of 0.15 (on monthly basis). Interestingly, a passive strategy on the real estate index outperforms both the factor-based and the multi-asset equally weighted portfolios in terms of mean excess returns, but at the cost of taking on much more risk: indeed, its Sharpe ratio is equal to 0.14 only. This confirms our intuition that factor investing enormously reduces the amount of risk that is taken on when investing directly in an asset class. Despite the results are less strikingly in favour of factor-based portfolios when we investigate more complex asset allocation strategies, it remains notable that an investor who diversifies across asset classes must construct complex strategies in order to perform better than the risk-adjusted performance of a REITs-only portfolio that is built by using factor allocation.

Finally, although this does not represent the main goal of the paper, our exercises also allow us to compare the OOS performance of different portfolio construction techniques. One particular interesting result is that, while for asset-based allocations the use of risk-based optimization techniques enhances risk-adjusted performances, when smart beta allocations are assessed, the technique that it is used to combine the factors does not seem to be really important. This implies that very rudimental portfolio rules, such as equal weighting, may prove as reliable and profitable as more complicated ones, and especially the mean-variance tangency portfolio. For instance, a risk-parity optimization scheme, when applied to combine the REIT factors, delivers a monthly Sharpe ratio of 0.22, which is slightly lower than the Sharpe ratio of a simple equally weighted factor portfolio (0.224 on monthly basis). This supports the idea that simple factor-based strategies surrogates more complex portfolio construction techniques that may be very sensitive to estimation errors in the forecasts of the variance and, especially, the mean (see, e.g., the discussion in DeMiguel et al., 2009).

The rest of this paper is organized as follows. The next section shortly reviews the literature that has explored the presence of systematic factors to explain real estate returns. Section 3 presents the data and explains the methodology that we have used to build the factors and to combine them into portfolios. Section 4 discusses the main empirical results that concern both the presence of a premium associated to the factors under analysis and the OOS performance of factor-based allocation techniques. Section 5 concludes.

2. Related literature

Factor investing relies on the identification of priced risk factors to which one can get exposure through the construction and combination of factor mimic portfolios. As a consequence, this paper builds on and contributes to the literature that has investigated whether traditional and specific pricing factors are able to explain REIT returns. The first attempts to understand the nature of real estate returns have examined their link to macroeconomic variables, such as production, inflation and the term structure of the interest rates. Chan, Hendershott, and Sanders (1990) found that in a multi-factor model that includes changes in the term structure of interest rates and growth of industrial production, changes in unexpected inflation have a negative impact on real estate returns. McCue and Kling (1994) and Naranjo and Ling (1997) documented that the growth rate in the real per capita consumption, the real short-term interest rate, the term structure of interest rates, and unexpected inflation systematically affect real estate returns. More recently, Allen, Madura and Springer (2000) showed that REIT returns are sensible to changes in both short- and long-term interest rates. However, while these studies are crucial to understanding the drivers of this peculiar asset class, they are less useful for the purposes of an investor who wants to build a factor investing strategy, because it is difficult to find a tradable proxy for macroeconomic variables.

Another stream of research has instead investigated the pricing performance of traditional factors that have significant explanatory power for equity returns. In this respect, the evidence presented in the literature is quite mixed. For instance, Chen, Hsieh, Vines, and Chiou (1998) have found that a standard Fama and French (1993) three factor model outperforms a pricing model based on macroeconomic variables similar to Chen, Roll, and Ross (1986) in explaining the cross-section of REIT returns. Peterson and Hsieh (1998) have proposed a factor model that combines Fama and French (1993) factors with two additional ones derived from the fixed income literature, which represent a proxy for unexpected changes in interest rates and shifts in the probability of default. Their study shows that Size and Value factors have a significant explanatory power for the cross-section of REIT returns. In addition, the two fixed income factors contribute to explaining mortgage REIT returns. Similar results concerning the Size factor are reported by McIntosh, Liang, and Tompkins (1991), who have found a clear evidence of small firm effect in the sample period 1974-1988.

A few studies have showed that the explanatory power of traditional factors for the cross section of REIT returns is time-varying. For instance, considering a sample of equity, mortgage and hybrid REITs over two different periods, pre- and post-1990, Chui, Titman and Wei (2003b) have tested the explanatory power of four different factors: Momentum, Size, Value, and Turnover. They found that before 1990 there is evidence of a Momentum, Size, and Value effect, and also the turnover is negatively correlated with returns; on the contrary, in the post-1990 period, only the Momentum factor appears to show explanatory power for the cross-section of REIT returns (there is also some limited evidence of turnover effect). Later studies such as Hung and Glascock (2008, 2010), Derwall, Huij, Brounen, and Marquering (2009), and Goebel, Harrison, Mercer, and Whitby (2013) have confirmed the importance of Momentum factor in explaining the cross-section of REIT returns and showed that in the real estate market the momentum effect is more pervasive than in the equity market.

More recent research, such as Bond and Xue (2017), employed investment-based asset pricing models and showed that Investment and Profitability factors (similar to those in Fama and French, 2015) display substantial predictive power for REIT returns that cannot be subsumed by conventional models such as those based on Market, Size, Value, and Momentum. The Profitably factor in the REIT industry had also been extensively investigated in a previous work of Glascock and Andrews (2014), where the authors analyze different measures for profitability and their ability to explain REIT returns. In particular, they compared the predictive ability of gross profit, Funds from Operations (FFO), Net Operating Income (NOI), Earnings Before Interest and Taxes (EBIT), and Earnings Before Interest, Taxes, Depreciation, and Amortization (EBITDA) and showed that in a multi-factor regression gross profit remains positively related to REIT returns. Moreover, other factors, such as FFO, EBIT, and EBITDA, lose their predictive power on REIT returns when gross profit is included in the regression analysis. In our analysis we decided to construct portfolios that mimic the traditional factors (Size, Value, and Momentum) and the Profitability and Investment factors suggested by Bond and Xue (2017).[2]

[2] Other factors that have been investigated in the literature in addition to these five include liquidity (see, for instance, Cannon and Cole, 2011), analyst coverage (see, for instance, Chui, Titman and Wei, 2003a), earnings announcement drift (see, Price, Gatzlaff, and Sirmans, 2012; Feng, Price and Sirmans, 2014), idiosyncratic volatility (see, Hung and Glascock, 2010; DeLisle, Price, and Sirmans, 2013), and quality (see, e.g., Anzinger, Ghosh, and Petrova, 2017).

3. Data and methodology

3.1 Data description

For the purpose of our analysis, we collect the REITs of all types that appeared in the CRSP dataset in a period spanning from January 1972 to July 2018 and that have at least two years of data in the COMPUSTAT database (similar to Chui et al., 2003b).[3] Over the entire sample we have been able to identify 612 unique REITs for a total of 92,287 monthly observations. We do not remove defaulted REITs from the sample in order to mitigate the survivorship bias. For the purpose of our analysis we decide to compute total returns: in fact, because REITs must distribute at least 90% of its annual taxable income in the form of dividends to the shareholders, not considering this component would underestimate the total performance of the investment. Therefore, the monthly return R_t is defined as:

$$R_t = \frac{P_t - P_{t-1} + D_t}{P_{t-1}} \tag{1}$$

where the dividend component D_t is assumed to be reinvested in the same security at the end of the month. For each of the REITs that are included in our sample we retrieve annual and quarterly accounting data from the COMPUSTAT database. These data are used to build the sorting metrics on which we rely to construct factor mimicking portfolios.

Notably, despite we collected data for the period January 1972 – July 2018, in our core analysis we focus our attention on a shorter period, from January 1993 – July 2018. The reason of this choice depends on the fact that during the 1990s the REITs industry has undergone major changes in management style, ownership structure, and regulatory framework (see, e.g., Ling and Ryngaert, 1997; Clayton and MacKinnon, 2003; Case, Yang, and Yildirim, 2012). In particular, the evolution of the Umbrella Partnership (UPREIT) structure, that allows the transfer of ownership without triggering a taxable sale was completed in 1993. Similar choices concerning the sample period are common in the literature (see, for

[3] In order to classify a company as a REIT, we rely on CRSP internal classification, but also perform double checks using Global Industry Classification Standard (GICS) codes. In addition, we identify companies that changed their REIT status during their lives and make sure to include them in the sample only when they were registered as REITs for tax purposes.

instance, Bond and Xue, 2017). However, we also present robustness checks using the entire sample.

In order to have a benchmark to which we can compare the performance of our factor-based portfolios, we collect the returns of the FTSE NAREIT All REITs Index, which is a market capitalization-weighted index that includes all tax-qualified REITs that are listed on the New York Stock Exchange, the American Stock Exchange or the NASDAQ, for the period spanning from January 1972 to July 2018. The monthly returns of this index are available on the NAREIT website. Summary statistics for the returns (together with the mean excess return) of the index are reported in Table 1. In addition to the full sample, we report the statics for three sub-samples: the "vintage era" (January 1972 – July 2018) that precedes the introduction of new regulations and new management styles in the REITs industry; the pre-crisis period (January 1993 – September 2008) before the outbreak of the Great Financial Crisis; the crisis and post-crisis period (October 2008 – July 2018). It is easy to see that the pre-crisis period can be considered as a "golden era" for the real estate with high mean excess returns (0.66% per month, which compounds to an annualized 7.92% excess return) and modest volatility (0.04 per annum, which yields an annualized volatility of less than 14%) leading to an annualized Sharpe ratio of 0.57. The crisis and post crisis period, despite being characterized by a higher mean excess return, displays much more volatility (in the area of 23% per annum) and thus lower risk-adjusted performances.

Finally, as we also compare factor-based strategies to traditional, multi-asset allocations, we collect equity, fixed-income and commodity indices over the period January 1993 – July 2018. In particular, in order to obtain a proxy of the equity market portfolio, we retrieve the monthly returns of the Stock Market Index from the Wharton Research Data Service (WRDS); the time series of the one-month Treasury Bill rate, which we use to proxy the risk-free interest rate, comes from the Federal Reserve Economic Data (FRED) maintained by the Federal Reserve Bank of Saint Louis. Finally, as we want to include in our asset allocation exercise also two other asset classes, namely, fixed income and commodities, we collect monthly returns of the Bloomberg Barclays US Aggregate Bond Index and of Goldman Sachs Commodity Index. The Bloomberg Barclays US Aggregate Bond Index is a market capitalization-weighted index which includes US investment grade corporate bonds, treasury securities, government agency bonds, mortgage-backed bonds and a small number of foreign bonds traded in the US. The Goldman Sachs Commodity Index, available on S&P Dow Jones Indices website, includes 24 commodities from all commodity sectors (energy, industrial and precious metal, agriculture, and livestock). Each commodity is weighted by its world production and adjusted for the trading volumes of the futures.

3.2 Construction of factor mimicking portfolios

We construct portfolios that mimic five factors that have found support in the previous literature, namely Value, Size, Profitability, Investment, and Momentum. To this purpose, we follow the standard methodology introduced by Fama and French (1993). First, we rank the REITs in our sample based on each of the sorting metrics that will be presented in what follows and we divide them in five quintiles (from Q1 to Q5, where Q1 includes the companies with the highest value of the sorting metric and Q5 those with the lowest value). Then, we create a long-short portfolio based on the top (Q1) and the bottom (Q5) quintiles; in particular, because the very idea of factor investing relies on harvesting positive premia, we take a long position in Q1 and a short position in Q5 any time that the REITs in Q1 have higher returns than the REITs in Q5 and vice-versa.

The sorting is performed at quarterly frequency. This choice is due to the fact that accounting measures on which the sorts are based are not updated frequently (they are published at quarterly frequency at best). The sole exception concerns the Momentum factor mimicking portfolio, which is rebalanced monthly (similar to Chiu et al., 2003a). All the sorting variables are winsorized at 0.25th and 99.75th percentiles. The Value factor mimicking portfolio is constructed by sorting the REITs according to the book-to-market ratio (henceforth, BM), where the book value is computed as stockholders' book equity, plus balance sheet deferred taxes, and investment tax credit (if available), minus the book value of preferred stock (as in Bond and Xue, 2017). Similar to Fama and French (2015) and Chui et al. (2003b), we exclude from our analysis the REITs with negative BM. The Size factor mimicking portfolio is built by sorting the REITs according to their market value, computed as the number of common shares multiplied by their price. As far as the Profitability factor is concerned, following Bond and Xue (2017), we sort the REITs according to the return on equity (henceforth, ROE) defined as income before extraordinary items divided by the one-quarter-lagged book value of equity (computed as described in the case of the BM ratio). However, since in their comparative study of the predictive power of different profitability measures, Glascock and Andrews (2014) have found that the gross profit, measured as total revenue net of total expenses divided by total assets, actually display a better predictive ability for REIT returns compared to other metrics, being less subject to manipulations, we also check the robustness of our results by using this alternative sorting variable.

To construct the Investment factor mimicking portfolio, we follow again Bond and Xue (2017) and we sort the REITs according to the growth rate in total non-cash assets (similar to what has been proposed by Fama and French, 2015); however, differently from Bond and Xue (2017), we refer to the quarterly growth rate instead of the annual one, to be consistent with our sorting frequency. Finally, we measure Momentum by computing the cumulative total return of each REIT in the previous six months and sorting according to this metric. As discussed above, in contrast with the other portfolios which are rebalanced every quarter, the Momentum factor mimicking portfolio is adjusted every month, to be consistent with previous literature (see, e.g., Chui et al., 2003a).

3.3 Asset allocation strategies

The ultimate goal of our paper is to assess whether asset allocation strategies based on the combination of the factor mimicking portfolios are able to beat benchmark allocations in terms of OOS performance. In particular, we aim at comparing the performance of a set of well-known asset allocation strategies when applied directly to value-weighted indices and when instead applied to the factor portfolios discussed in the previous Section (smart beta investment strategies). The asset allocation exercise is conducted in a recursive fashion and we compute the expected excess returns and the covariance matrix using a twelve-month rolling window. Clearly, this entails that the allocation exercise starts at the beginning of January 1994. In addition, all the allocation strategies entertained in this paper do not entail leverage and do not allow short selling (i.e., all the weights must be positive). This last constraint appears reasonable especially in the context of mean-variance asset allocations (see e.g., Jagannathan and Ma, 2003; DeMiguel et al., 2009). In particular Jagannathan and Ma (2003) showed that this constraint has a shrinkage-like effect on the sample variance-covariance matrix, which in turn mitigate the effects of the estimation errors on the weights thus reducing their instability and generating a better OOS performance of the mean-variance portfolios.

Specifically, we propose five alternative asset allocation strategies. The first one is a naïve Equally Weighted (EW) portfolio similar to DeMiguel et al. (2009), where each factor mimicking portfolio (or index, in the case of the benchmark allocations) receives a weight equal to 1/N, and N is the total number of portfolios (indices) in the asset menu. The second and the third allocation strategies are based on the Markovitz's mean-variance framework. In particular, tangency allocation (TA) requires the investment in the tangency portfolio with a weight that is found by solving

$$\begin{cases} \boldsymbol{w_{TA}} = \arg max_w \dfrac{(\boldsymbol{w}'\boldsymbol{\mu_t} - r_{f,t})}{\sqrt{(\boldsymbol{w}'\boldsymbol{\Sigma_t}\boldsymbol{w})}} \\ s.t. \quad \boldsymbol{w}'\boldsymbol{\iota} = 1 \\ s.t. \quad \boldsymbol{w}' \geq \boldsymbol{0} \end{cases} \tag{2}$$

where $\boldsymbol{w_{TA}}$ is a Nx1 column vector containing the allocation weights, $\boldsymbol{\mu_t}$ is a Nx1 vector collecting the expected returns of the investable assets, $\boldsymbol{\Sigma_t}$ is their NxN variance-covariance matrix and $r_{f,t}$ is the risk-free rate proxied by the one-month Treasury Bill rate. Because of the presence of the positivity constraint on the weights the problem has to be solved numerically. The other strategy entails the investment in the minimum-variance portfolio (MVP) and requires solving:

$$\begin{cases} \boldsymbol{w_{MVP}} = \arg min_w \boldsymbol{w}'\boldsymbol{\Sigma_t}\boldsymbol{w} \\ \\ s.t. \quad \boldsymbol{w}'\boldsymbol{\iota} = 1 \\ s.t. \quad \boldsymbol{w}' \geq \boldsymbol{0} \end{cases} \tag{3}$$

Again, this is done numerically due to the presence of the positivity constraint on the weights. Finally, we propose two risk-based strategies. The first one is based on the risk parity (RP) approach, popularized by the famous hedge fund Bridgewater. In order to implement it, we follow the methodology proposed by Qian (2006), which is based on imposing the following condition:

$$\frac{1}{N} = \frac{w_i \sum_{j=1}^{N} w_j \Sigma_{i,j}}{\sigma_p^2} \tag{4}$$

where σ_p^2 is the total variance of the portfolio. Equation (4) essentially means that every component brings the same contribution to the overall risk (measured as total variance) of the portfolio. In order to be consistent with the other allocation strategies that we proposed, also in this case we constrain the weights to be positive; as a consequence, the problem becomes as in Maillard, Roncalli, and Teiletche (2008):

$$\begin{cases} \boldsymbol{w_{RP}} = \arg min_w \displaystyle\sum_{i=1}^{N} \left(\frac{w_i (\Sigma_t w_t)_i}{\sigma_{p,t}} - \frac{\sigma_{p,t}}{N} \right)^2 \\ s.t. \quad \boldsymbol{w}' \boldsymbol{\iota} = 1 \\ s.t. \quad \boldsymbol{w}' \geq \boldsymbol{0} \end{cases} \tag{5}$$

which is solved numerically. By solving (5), we minimize the overall sum of squared variations of each actual risk contribution from the desired risk contribution, which is $\frac{\sigma_{p,t}}{N}$.

The last strategy, proposed by Choueifaty and Coignard (2008), requires the investment in a maximum diversification portfolio (MD), defined as the one that maximizes the ratio:

$$D = \frac{\boldsymbol{w}' \boldsymbol{\sigma_t}}{\sqrt{\boldsymbol{w}' \boldsymbol{\Sigma_t} \boldsymbol{w}}} \tag{6}$$

where $\boldsymbol{w}$ is a vector Nx1 that collects the weights of the components of the portfolio; $\boldsymbol{\sigma_t}$ is a vector Nx1 collecting the volatilities of the N securities of the portfolio and $\boldsymbol{\Sigma_t}$ is the NxN variance-covariance matrix. This ratio, which can be thought of as the portfolio diversification ratio, represents the weighted average of the volatilities divided by the total volatility of the portfolio. In a portfolio with $N \geq 1$ the diversification ratio must be strictly higher than 1. Maximizing the diversification ratio means that we require each component to equally contribute to the volatility of the portfolio. It is interesting to note that when the expected returns of the portfolio's components are proportional to their volatilities ($\boldsymbol{\mu_t} = k\boldsymbol{\sigma_t}$) maximizing the diversification ratio is mathematically equivalent to maximize the Sharpe ratio of the portfolio. The maximization is carried out numerically because of the presence of the non-negativity constraint on the weights and can be written as:

$$\begin{cases} \boldsymbol{w_{MD}} = \arg max_w \dfrac{\boldsymbol{w}'\boldsymbol{\sigma_t}}{\sqrt{\boldsymbol{w}'\boldsymbol{\Sigma_t}\boldsymbol{w}}} \\ s.t. \ \ \boldsymbol{w}'\boldsymbol{\iota} = 1 \\ s.t. \ \ \boldsymbol{w}' \geq \boldsymbol{0} \end{cases} \tag{7}$$

In order to compare each strategy with its benchmark we propose two measures: the Information ratio (IR) and the Omega ratio. The IR is defined as the expected excess return of the factor allocation over the benchmark strategy, divided by the tracking error volatility, i.e., the volatility of the time series obtained as the difference among the factor allocation and the benchmark allocation:

$$IR = \frac{E(R_m) - E(R_b)}{\sigma(R_m - R_b)} \tag{8}$$

where $E(R_m)$ is the expected return on the factor allocation and $E(R_b)$ the excess return on the benchmark allocation. The omega ratio is a more sophisticated measure introduced by Keating and Shadwick (2002). According to the authors, the first two moments of a distribution are not sufficient to describe it and metrics based only on mean and variance can lead to inaccuracies in performance measurement. The omega ratio is based on splitting the returns into losses and gains relative to a certain return threshold that represents a minimum acceptable return (MAR) for an investor, and then considering the probability weighted ratio of returns above and below the threshold. The omega measure is defined as a function of the MAR threshold in the following way:

$$\Omega(MAR) = \frac{\int_{MAR}^{b} \big(1 - F(x)\big) dx}{\int_{a}^{MAR} F(x) dx} \tag{9}$$

where (a, b) is the interval of possible returns and F is the cumulative distribution function for the returns. The above formula can be restated as:

$$\Omega(MAR) = \frac{E[\max(R_t - MAR, 0)]}{E[\max(MAR - R_t, 0)]} \tag{10}$$

which is equivalent to say that the omega ratio is the ratio between the expected return in excess of the MAR and the expected return below the MAR. For our purposes, we set the MAR equal to the mean return of the benchmark allocation.

4. Results

4.1 The performance of factor mimicking portfolios

In this section, we discuss the results that concern the robustness of the five factors that we have decided to consider, namely Size, Value, Momentum, Investment and Profitability. As discussed above, we limit our analysis to the sample January 1993 – July 2018, to account for the fact that the REIT industry has changed dramatically during the 1990s. However, as we will discuss in Section 4.2, we also carry out some robustness checks on the sample 1972 – 2018. In Table 2, we report the main statistics for the five factor mimicking portfolios. As discussed in Section 3, we always report positive premia, which is the result of the methodology that we have used in order to construct the long-short factor mimicking portfolios. Indeed, because factor investing commands positive premiums, we take a long position in the top quintile and a short position in a bottom quintile when on average the REITs in Q1 outperform those in Q5, and vice-versa. In particular, the Value, Profitability and Momentum factor mimicking portfolios have been constructed by taking a long position in Q1 and a short position in Q5. Indeed, REITs with a high BM are found to outperform those with a low BM by 1.30% per month on average. REITs with high past returns outperform those with low past returns by 0.80% per month. These results are statistically significant at any conventional confidence level and comparable to those reported in earlier studies, which have found support for these two factors (see, e.g., Chui et al., 2003b; Hung and Glascock, 2008, 2010; Goebel et al. 2013). However, differently from Bond and Xue (2017), we do not find support for the Profitability factor. Indeed, the average return of a long-short portfolio that invest in REITs with a high ROE and sell those with a low ROE is 0.04% per month implying a negative excess return of approximately -0.16% per month. However, this return is not statistically significant (the p-value is equal to 0.89). In order to be sure that this result is not driven by our choice of the sorting metrics, in Section 4.2 we follow Glascock and Andrews (2014) and we conduct a robustness check that employs the gross profit as sorting variable.

The Size and the Investment factor are constructed by taking a long position on the REITs in the bottom quintile and a short position on those in the top quintile. This is coherent with both the equity and the real estate literature, which have found evidence of a small firm effect (see, e.g., McIntosh et al., 1991; Fama and French, 1993) and has documented the presence of a premium associated to firms with low level of investment (see, e.g., Fama and French, 2015). The latter effect derives from the fact that firms invest more when profitability is high, and the discount rate (that is, the expected return) is low: therefore, a low level of investment is associated with high returns. In line with previous studies, we document that small REITs outperform large ones by 1.60% per month. In addition, we find that also the Investment factor has a positive (albeit smaller compared to Size, Value, and Momentum) return equal to 0.40% on monthly basis, which compounds to an annualized return of 4.80%. However, this is only significant at a 10% confidence level. This latter result is comparable to the findings by Bond and Xue (2017), who report that the REITs with the highest 20% investment rates underperform those with the lowest 20% investment rates by 0.36% per month, over the sample 1994-2013.

From a risk-adjusted perspective, the Size factor is the one with the highest Sharpe ratio (0.23), followed by Value (0.15) and Momentum (0.13). As the excess mean return associated to the Profitability factor is negative, the Sharpe ratio associated to this factor is negative and equal to -0.03 on monthly basis. Finally, the Investment factor has a rather modest monthly Sharpe ratio of 0.05. The mean returns associated to the factors are all highly non normal; in particular, both Value and Size display large kurtosis, well in excess of 3 (25.5 and 15.3, respectively) and are positively skewed. The Profitability factor is the only one to display negatively skewed returns while the returns associated to the Momentum factor have a kurtosis lower than 3.

In Table 2 (Panel B), we report the sample correlations between the returns of the five factor mimicking portfolios, while in Panel C we show the correlations between factor returns and the FTSE NAREIT All REITs Index. We note two interesting facts. First, most of the factors show very low or even negative pair-wise correlations with few exceptions (such as Value and Size, which have a correlation equal to 0.4, and Value and Investment, which display a correlation equal to 0.38). In particular, the Profitability factor is almost orthogonal to the rest of the factors, with the exception of Value, with which it has a negative correlation of -0.22. The Momentum factor shows pair-wise negative correlations with the rest of the factors (apart from the Profitability factor with which it is close to zero), but these are generally low (-0.12 with Size, - 0.28 with Value, and -0.19 with Investment). Second, most of the factors (with exception of Value) have a low or even negative correlation with the FTSE NAREIT Index. In particular, the correlation is equal to -0.12 in the case of Size, -0.11 in the case of Profitability and -0.06 in the case of Momentum. These results reinforce our belief that factor investing may offer benefits in terms of portfolio diversification.

4.2 Robustness checks

In order to check the robustness of our results, we implement different methodologies for the construction of the factor mimicking portfolios. In particular, we focus our attention on the Profitability factor, to understand whether our failure to find a statistically significant mean return associated to this factor depends on the methodology that we employ to build it. We also extend our sample to the period January 1972 – July 2018 to assess whether the Profitability factor is time varying. Finally, we also report the statistics for alternative factor mimicking portfolios constructed by taking long-short positions in the top and the bottom deciles (D1 and D10). We report the summary statistics of the returns of these alternative factor mimicking portfolios in Table 3. In particular, on the left-side of the table (Panels A, C, E, and G), we report the results concerning the period January 1972 – July 2018, while on the right-side (Panels B, D, F, and H), we show the statistics for the period January 1993 – July 2018. For both the samples we perform a battery of robustness checks. First, we change the methodology for the computation of the returns from value-weighted to equally weighted (similar to Chan, Karceski, and Lakonishok, 1998); second, following Bond and Xue (2017), we change our rebalancing frequency from quarterly to monthly; finally, following Novy-Marx (2013) and Glascock and Andrews (2014), we employ gross profit as a sorting metrics. Indeed, in their work, they argue that even if FFO and net income are more common indicators of performance (at least in the REITs space), they can also be subject to opportunistic manipulation by the management, even if FFO is a non-GAAP measure (see, e.g. Zhu, Ong, and Yeo, 2010). For these reasons, they propose gross profit, as measured by total revenue net of total expenses scaled by total assets, to be the best predictive factor for REIT cross-sectional returns.[4]

[4] Originally Glascock and Andrews used SNL Financial database to build the indicator (Total Revenues less Total Expenses). The best proxy that we have identified in Compustat is Total Revenues less Operating Expenses, Depreciation and Amortization, SGA Expenses, and Financial Expenses.

An analysis of Table 3 shows that the returns associated to the Profitability factors are highly time-varying. Indeed, when we extend the sample to cover the entire period January 1972 – July 2018 using the same methodology that we employed to derive the results presented in Section 4.1, we obtain an average per month return of 0.50%. However, this return appears highly volatile (monthly volatility is approximately 7.50% which yields an annualized figure of 26%) and the associated p-value is 11%. In addition, using the gross profit as a sorting metric weakens the evidence in favor of the existence of a Profitability factor. In fact, in both Panel G (that report results for the entire sample) and Panel F (that contains statistics for the sample January 1993 – July 2018), we report mean returns that are close to zero and never statistically significant. In general, our robustness checks show mild evidence in support of a profitability factor: at best it is highly time varying. In particular, we believe that the poor performance of the Profitability factor can be explained by several negative data especially during the Great Financial Crisis (Profitability and Momentum are the two factors with the worst performance in 2008-2009). However, we decide not to exclude the Profitability factor from our factor investing exercise: indeed, being negatively with most of the other factors, it can still provide good diversification opportunities.

We also conduct robustness checks for the rest of the factors extending the analysis to the entire sample period (January 1972 – July 2018). The results of these robustness checks are reported in Appendix A.1. For the sake of readability, all the results presented in this table have been obtained by taking a long position in the top quantile (or decile) and a short position in the bottom one. For this reason, the mean returns associated to the Size and the Investment factors are negative. Table A.1 shows a number of interesting features of the factors under analysis. First, the mean return of the Size and Value factors over the entire sample are rather close to those computed over the restricted sample. Therefore, it seems that these factors are robust and not highly time varying. On the contrary, when the entire sample is taken into consideration, the Investment factor fails to display a statistically significant mean return. Finally, the returns associated to the Momentum factor are much higher when the entire sample is considered (1.30% on monthly basis). This is unsurprising: in fact, the Momentum factor has suffered massively during (and after) the financial crisis.

4.3 The performance of factor-based strategies

In this section, we review the performances of a set of multi-factor allocation strategies that combine factor-mimicking portfolios for Size, Value, Investment, Profitability, and Momentum over a sample going from January 1994 to July 2018 (we use data from January to December 1993 in order to estimate the expected return and the covariance matrix to be used as inputs in the optimization process). We build five different strategies, namely the EW, TA, MPV, MD, and RP portfolios, according to the definitions provided in Section 3.3. In Table 4, we report the main statistics for the returns of the alternative strategies (and in particular, the mean, the volatility, and the Sharpe ratio). For the sake of comparison, we also show the returns of a buy-and-hold strategy in the FTSE NAREIT All REITs Index. Our results indicate that, despite a buy-and-hold strategy in the FTSE NAREIT All REITs Index outperforms all the factor-based strategies in term of mean returns (0.94% per month versus 0.93% of the tangency portfolio, which displays the highest return among the factor combination strategies) this is not the case when we look at the risk-adjusted performance. In fact, all the factor-based strategies, even a naïve, equally weighted one, which is not based on the solution of an optimization problem, considerably outperforms the benchmark in terms of Sharpe ratio. In particular, the equally weighted, factor-based portfolio outperforms all the others in terms of risk-adjusted performances. This is less surprising than it may seem, and it is a well-known (see, for instance, DeMiguel, et al., 2009) consequence of the fact that the inputs of the optimization problem (namely, the covariance matrix, and, especially, the expected returns) are imprecisely estimated. Therefore, even small changes in expected returns can strongly affect portfolio composition. As a result, despite being the one with the lowest mean return after the MV portfolio (0.79% and 0.74%, respectively), the factor-based, EW portfolio displays a very low volatility (less than 3% per month, while the FTSE NAREIT Index has a monthly volatility in excess of 5%), thus achieving a Sharpe ratio slightly in excess of 0.22. In contrast, a buy-and-hold strategy on the FTSE NAREIT All REITs Index has a much lower Sharpe ratio of 0.14. Also the other factor-based strategies outperform the buy-and-hold benchmark in risk-adjusted terms, with Sharpe ratios that range from 0.22 for the RP strategy to 0.20 for the MVP and MD portfolios. Interestingly, from Panel B, which reports the correlation between the returns of each of the alternative strategies (including the buy-and-hold one), we notice that the factor-based strategies show a very low correlations with a direct investment in the index. For instance, the factor-based, RP portfolio, which is the most correlated with the index, has a correlation with FTSE NAREIT equal to 0.10. On the contrary, factor-based strategies tend to display high correlations (ranging from 0.52 to 0.92) among each other. Overall, it seems that while factor-investing delivers better risk-adjusted performances than a direct investment in the FTSE NAREIT Index, the exact allocation rule that is used to assign weights to the factors is much less important.

Figure 1 plots the recursive, optimal weights associated to each factor in each of the factor-based strategies over the sample period January 1994 – July 2018. Obviously, we do not plot the equal weights, as they are constant and equal to 0.20% for the entire period. At least three observations are of order. First, all the weights are highly time varying, but this is particularly visible in the case of the TA portfolio. This is not unexpected as the literature has often emphasized that MV weights are highly unstable (see, e.g., DeMiguel, et al., 2009). Second, the tangency portfolio seems to be dominated by the Momentum factor (the most noticeable exception concerns the period that follows the financial crisis). In contrast, the RP and the MD portfolios show much more balanced weights (as the creation of these portfolios do not rely on the estimation of the means, which are notoriously more difficult to estimate than the covariance matrix). Third, all factor-based strategies command a non-zero investment in the Profitability factor, with average weights that range from 13% (in the case of the TA portfolio) to 31% (in the case of MVP and RP portfolios). Therefore, the Profitability portfolio earns a low and unstable premium, the inclusion of this factor seems to be optimal under all the allocation rules, probably due to its hedging properties.

Figure 2 plots the performance of the different strategies and of the benchmark, buy-and-hold investment in the FTSE NAREIT All REITs Index over time. It is interesting to compare the performance of the index and of the factor-based strategies before, during and after the Great Financial Crisis of 2007-2008. While factor strategies would have produced much more moderate returns than the index during the real estate boom of 2000-2006, they would have been less affected by the burst of the bubble in 2007. Finally, after the financial crisis of 2007-2008, most of the factor-based strategies would have outperformed the index also in terms of returns.

4.4 Factor-based versus multi-asset strategies

The last goal of our analysis is to compare the performance of factor-based real estate strategies with more traditional, multi-asset ones. For this reason, we apply the same allocation techniques that we used to build smart beta real estate portfolios to an alternative asset menu that consists of the FTSE NAREIT All REITs, the market portfolio from CRSP, the Bloomberg Barclays US Aggregate Bond Index, and the Goldman Sachs Commodity Index. Table 5, which is specular to Table 4, reports the main statistics of the returns obtained for the set of different multi-asset allocation strategies. Interestingly, the results show that most of our factor-based strategies outperform the corresponding multi-asset strategies both in terms of mean returns and risk-adjusted performances. For instance, a simple, factor-based EW strategy (which has a Sharpe ratio of 0.224) outperforms four out of five of the multi-asset strategies in risk-adjusted terms (namely, the EW, the TA, the RP, and the MD strategies). The MVP is the only one among the multi-asset strategies that outperforms all the factor-based portfolio in terms of Sharpe ratio (indeed, this strategy displays a Sharpe ratio equal to 0.36). Needless to say, these results are quite impressive: in fact, multi-asset strategies represent a very though benchmark, as they entail diversification across different asset classes. Similarly to Table 4, in Panel B of Table 5 we report the pairwise correlations between the returns obtained from the different allocation rules. Also in this case, correlations are positive and relatively high, ranging from 0.45 to 0.87.

In order to understand whether this extra-performance is economically significant, we use two metrics that are popular in the asset management industry, namely the IR and the Omega ratio, described in Section 3.3. In this context, we consider the traditional multi-asset strategy as a benchmark. In Table 6, we report the results of this comparison in a matrix format. For example, the number reported in the first row of the second column represents the comparison between a TA factor portfolio and an EW multi-asset allocation. In the main diagonal, we report the comparison of each multi-asset allocation rule with its factor-based counterparts. Panel A contains the results concerning the IR metric, while Panel B for the Omega ratio. These further comparisons largely confirm our previous results: indeed, the metrics are always positive (which means that factor-based strategies beat their benchmarks) with only two exceptions: the tangency, multi-asset portfolio outperforms the factor-based MVP and MD portfolios in terms of IR.

Finally, Figure 3 plots the performance of each of the factor-based strategies against the multi-asset portfolio that is built using the same asset allocation scheme. Interestingly, we notice that while the returns of the two strategies appear similar until the outburst of the financial crisis, they start to diverge considerably from 2009. Indeed, all the factor-based strategies strongly outperform their multi-asset counterparts over the last decade.

5. Conclusions

In this paper we have investigated the ability of strategies that invest in REIT-based factors to outperform different benchmarks, namely, a buy and hold, passive allocation in the FTSE NAREIT All REIT Index and a set of multi-asset traditional allocation techniques. As the construction of smart beta investment strategies relies on the ability to identify a set of systematic factors that earn long-term risk premiums, we have started our analysis by building long-short portfolios that mimic the Size, Value, Momentum, Profitability, and Investment factors. Consistently with previous literature, we have found support in public real estate data for Size and Value (see, e.g., see McIntosh et al., 1991; Mueller et al., 1998), Momentum (see, e.g., Hung and Glascock, 2010; Derwall, et al., 2009; Goebel et al., 2013), and Investment (see, Bond and Xue, 2017). However, in contrast to Bond and Xue, 2017 (but on a longer sample period), we have not found that the Profitability factor earns a statistically significant premium. This remains true even when we adopt different sorting metrics, in line with Glascock and Andrews (2014). Second, using a number of different portfolio construction techniques, from simple equally weighting schemes to more complex risk-parity optimal allocations, we have constructed factor-based and multi-asset portfolios. We have found that all the factor-based portfolios yield a higher risk-adjusted performance than a simple buy and hold strategy on the REIT market index, irrespective of the technique that is used to (optimally) combine the factors. In line with the flourishing literature that investigate the success of smart beta strategies in the equity space (see, for instance, Clarke, de Silva, and Murdock, 2005; Bender et al., 2010; Page and Taborsky, 2011; Kremer et al., 2018), we conjecture and obtain partial evidence that this is due to the diversification benefit that is achieved through these strategies. In addition, we have also found that REIT-only, factor-based portfolios also deliver higher risk-adjusted performance than comparable multi-asset strategies, especially when simple weighting schemes are applied. This seems to suggest that the use of factor-based portfolio construction techniques may actually reduce the need to implement complex optimization methodologies.

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Table 1

Summary Statistics for the FTSE NAREIT All REITs Index

This table shows the summary statistics for the monthly returns of the FTSE NAREIT All REITs Index (including mean excess return over the one-month Treasury Bill rate) over the full sample (January 1972 – July 2018) and over three different subsamples: the "vintage era" (January 1972 – December 1992), the pre-crisis period (January 1993 – September 2008) and the crisis and post-crisis period (October 2008 – July 2018).

	Full Sample	**"Vintage" Era**	**Pre Crisis**	**Crisis and Post Crisis**
	Jan 1972 - Jul 2018	**Jan 1972 - Dec 1992**	**Jan 1993 - Sep 2008**	**Oct 2008 - Jul 2018**
Mean	0.0090	0.0082	0.0100	0.0089
Mean Excess Return	0.0052	0.0022	0.0066	0.0087
Median	0.0109	0.0074	0.0146	0.0112
Volatility	0.0502	0.0480	0.0400	0.0670
Skewness	-0.3916	0.3414	-0.6815	-0.8082
Kurtosis	10.4673	10.0668	4.2406	9.2295
Sharpe ratio	0.1027	0.0452	0.1653	0.1303
Jarque-Bera	1313***	529***	26***	203***

Table 2

Summary Statistics for Factor-Mimicking Portfolios

Panel A shows the summary statistics for the out-of-sample returns of Size, Value, Investment, Profitability and Momentum factor mimicking portfolios (over the sample period January 1993 – July 2018). The Size and the Investment factors are constructed by buying the REITs in the bottom quintile (Q5) and selling the REITs in the top quintile (Q1). The Value, Profitability and Momentum factors are constructed by buying the REITs in the top quintile (Q1) and selling the REITs in the bottom quintile (Q5). The p-value of a t-stat for the statistical significance of the mean is reported in parenthesis. We also report the Jarque-Bera test for normality. A rejection of the null hypothesis at a 10% level of significance is marked by *, at a 5% level of significance by **, and at a 1% by ***. Panel B shows sample correlations among the returns of factor mimicking portfolios while Panel C shows sample correlations between the returns of each of the factor mimicking portfolios and the FTSE NAREIT All REITs index.

Panel A

	Size	**Value**	**Investment**	**Profitability**	**Momentum**
Mean	0.0163	0.0128	0.0040	0.0004	0.0083
(p-value)	(0.000)	(0.002)	(0.071)	(0.882)	(0.004)
Median	0.0085	0.0031	0.0030	0.0028	0.0059
Volatility	0.0608	0.0733	0.0386	0.0511	0.0502
Skewness	2.4911	3.6994	0.4578	-0.9524	0.1492
Kurtosis	15.3988	25.4592	3.4268	6.7459	2.6507
Sharpe ratio	0.2350	0.1476	0.0515	-0.0308	0.1248
Jarque-Bera	3243***	8706***	154***	606***	87***

Panel B

	Size	**Value**	**Investment**	**Profitability**	**Momentum**
Size	1.0000				
Value	0.4052	1.0000			
Investment	0.1651	0.3822	1.0000		
Profitability	-0.0393	-0.2002	0.0567	1.0000	
Momentum	-0.1293	-0.2821	-0.1916	0.0088	1.0000

Panel C

	Size	**Value**	**Investment**	**Profitability**	**Momentum**
NAREIT All REITs	-0.1241	0.3188	0.0459	-0.1047	-0.0527

Table 3

Robustness Checks Applied to the Profitability Factor

This table shows several robustness checks concerning the Profitability Factor. In particular, the panels on the left side of the table (i.e., A, C, E, and G) report the summary statistics of the out-of-sample returns of a factor mimicking portfolio over a full sample January 1972 – July 2018, while the panels on the right side of the table (i.e., B, D, F, and H) concerns the restricted sample January 1993 – July 2018. We alternatively change a number of assumptions concerning the construction of the factor. In panels A and B REITs enter the portfolio with weights that are proportional to their market capitalization, while in panels C and D they are equally weighted. In panels E and F, we maintain the value-weighting scheme, but we rebalance the portfolio with monthly (instead of quarterly) frequency. Finally, in panels G and H we sort the REITs according to a different metric, namely the Gross Margin. In addition, for each different set of assumptions we also report the statistics of a factor mimicking portfolio that is constructed by using deciles instead of quintiles.

Panel A, ROE 1972-2018, value weighted

Profitability	**D10**	**D1**	**D1-D10**	**Q5**	**Q1**	**Q1-Q5**
Mean	0.0115	0.0193	0.0078	0.0124	0.0174	0.0050
(p-value)	(0.006)	(0.000)	(0.044)	(0.000)	(0.000)	(0.114)
Median	0.0075	0.0194	0.0077	0.0120	0.0190	0.0054
Volatility	0.0987	0.0553	0.0914	0.0875	0.0550	0.0749
Sharpe	0.0774	0.2795	0.0438	0.0977	0.2466	0.0161

Panel B, ROE 1993-2018, value weighted

Profitability	**D10**	**D1**	**D1-D10**	**Q5**	**Q1**	**Q1-Q5**
Mean	0.0216	0.0168	-0.0047	0.0158	0.0162	0.0004
(p-value)	(0.000)	(0.000)	(0.301)	(0.000)	(0.000)	(0.882)
Median	0.0151	0.0197	0.0024	0.0157	0.0194	0.0030
Volatility	0.0891	0.0482	0.0807	0.0678	0.0451	0.0511
Sharpe	0.2199	0.3077	-0.0833	0.2030	0.3150	-0.0305

Panel C, ROE 1972-2018, equally weighted

Profitability	**D10**	**D1**	**D1-D10**	**Q5**	**Q1**	**Q1-Q5**
Mean	-0.0030	0.0191	0.0221	0.0038	0.0173	0.0136
(p-value)	(0.408)	(0.000)	(0.000)	(0.280)	(0.000)	(0.000)
Median	-0.0023	0.0197	0.0194	0.0076	0.0187	0.0131
Volatility	0.0873	0.0600	0.0752	0.0820	0.0535	0.0607
Sharpe	-0.0782	0.2554	0.2436	-0.0008	0.2527	0.1606

Panel D, ROE 1993-2018, equally weighted

Profitability	**D10**	**D1**	**D1-D10**	**Q5**	**Q1**	**Q1-Q5**
Mean	0.0029	0.0210	0.0182	0.0077	0.0175	0.0098
(p-value)	(0.466)	(0.000)	(0.000)	(0.016)	(0.000)	(0.000)
Median	0.0038	0.0204	0.0182	0.0123	0.0204	0.0100
Volatility	0.0691	0.0517	0.0581	0.0566	0.0452	0.0385
Sharpe	0.0128	0.3687	0.2784	0.1015	0.3440	0.2028

Table 3 (continued)

Panel E, ROE 1972-2018, monthly rebalance

Profitability	D10	D1	D1-D10	Q5	Q1	Q1-Q5
Mean	0.0175	0.0176	0.0000	0.0179	0.0150	-0.0028
(p-value)	(0.000)	(0.000)	(0.010)	(0.000)	(0.000)	(0.204)
Median	0.0145	0.0182	0.0019	0.0138	0.0185	0.0021
Volatility	0.1045	0.0566	0.0955	0.0924	0.0542	0.0805
Sharpe	0.1313	0.2426	-0.0398	0.1520	0.2070	-0.0826

Panel F, ROE 1993-2018, monthly rebalance

Profitability	D10	D1	D1-D10	Q5	Q1	Q1-Q5
Mean	0.0211	0.0160	-0.0051	0.0195	0.0146	-0.0049
(p-value)	(0.000)	(0.000)	(0.224)	(0.000)	(0.000)	(0.108)
Median	0.0177	0.0201	-0.0014	0.0177	0.0201	0.0010
Volatility	0.0823	0.0494	0.0737	0.0682	0.0465	0.0534
Sharpe	0.2325	0.2840	-0.0965	0.2566	0.2706	-0.1290

Panel G, Gross Margin 1972-2018

Profitability	D10	D1	D1-D10	Q5	Q1	Q1-Q5
Mean	0.0139	0.0171	0.0032	0.0158	0.0165	0.0006
(p-value)	(0.000)	(0.000)	(0.332)	(0.000)	(0.000)	(0.812)
Median	0.0121	0.0183	0.0034	0.0111	0.0171	0.0011
Volatility	0.0811	0.0614	0.0751	0.0748	0.0580	0.0616
Sharpe	0.1246	0.2161	-0.0087	0.1606	0.2179	-0.0519

Panel H, Gross Margin 1993-2018

Profitability	D10	D1	D1-D10	Q5	Q1	Q1-Q5
Mean	0.0157	0.0136	-0.0021	0.0146	0.0143	-0.0002
(p-value)	(0.000)	(0.000)	(0.280)	(0.000)	(0.000)	(0.906)
Median	0.0153	0.0182	-0.0020	0.0149	0.0184	-0.0019
Volatility	0.0716	0.0487	0.0625	0.0621	0.0493	0.0468
Sharpe	0.1912	0.2387	-0.0651	0.2023	0.2501	-0.0476

Table 4

Summary Statistics for Multi-Factor Portfolios

Panel A shows the summary statistics for the out-of-sample returns of the multi-factor allocation strategies constructed including all the five factor mimicking portfolios under analysis. The returns concern the period January 1994 – July 2018, because factor returns over 1993 have been used to obtain initial estimates of expected excess return and covariance matrix. We also report the Jarque-Bera test for normality. A rejection of the null hypothesis at a 10% level of significance is marked by *, at a 5% level of significance by **, and at a 1% by ***. Panel B shows sample correlations between the returns of each pair of factor-based strategies and between the returns of each of the factor-based strategies and that of the FTSE NAREIT All REITs Index.

Panel A

	Nareit All REITs	**EW**	**TA**	**MVP**	**MD**	**RP**
Mean	0.0094	0.0078	0.0093	0.0074	0.0075	0.0079
Median	0.0119	0.0058	0.0085	0.0046	0.0054	0.0050
Volatility	0.0525	0.0261	0.0353	0.0278	0.0280	0.0268
Skewness	-0.8728	1.0865	0.4270	1.4237	0.9539	1.0417
Kurtosis	7.7962	7.3664	5.1478	9.4619	10.2245	7.0974
Sharpe ratio	0.1405	0.2231	0.2064	0.1960	0.1982	0.2193
Jarque-Bera	755***	699***	321***	1158***	1281***	648***

Panel B

	Nareit All REITs	**EW**	**TA**	**MVP**	**MD**	**RP**
Nareit All REITs	1.0000					
EW	0.0741	1.0000				
TA	0.0533	0.4484	1.0000			
MVP	-0.0009	0.7358	0.5709	1.0000		
MD	0.0767	0.7485	0.6049	0.9174	1.0000	
RP	0.1014	0.9199	0.5225	0.8103	0.7870	1.0000

Table 5

Summary Statistics for Multi-Asset Portfolios

In this table we report the summary statistics for the returns of multi-asset strategies. They are obtained combining equity (proxied by the Stock Market Index), fixed-income (represented by Bloomberg Barclays US Aggregate Bond Index), real estate (proxied by FTSE NAREIT All REITs Index) and commodities (represented by the Goldman Sachs Commodity Index). The different allocation strategies that are implemented are: Equally Weighted (EW), Tangency Allocation (TA), Minimum Variance (MV), Maximum Diversification (MD) and Risk Parity (RP). We also report the Jarque-Bera test for normality. A rejection of the null hypothesis at a 10% level of significance is marked by *, at a 5% level of significance by **, and at a 1% by ***. The returns concern the period January 1994– July 2018.

Panel A

	EW	**TA**	**MVP**	**MD**	**RP**
Mean	0.0063	0.0077	0.0053	0.0054	0.0054
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Median	0.0097	0.0085	0.0056	0.0062	0.0060
Volatility	0.0292	0.0296	0.0091	0.0206	0.0169
Skewness	-1.4847	-3.2565	-0.1909	-2.4853	-3.1305
Kurtosis	8.2726	38.3420	1.0464	23.1904	25.2806
Sharpe ratio	0.1474	0.1929	0.3617	0.1668	0.2015

Panel B

	EW	**TA**	**MVP**	**MD**	**RP**
EW	1.0000				
TA	0.7789	1.0000			
MVP	0.4517	0.4416	1.0000		
MD	0.8646	0.7914	0.5735	1.0000	
RP	0.8707	0.8030	0.7018	0.8752	1.0000

Table 6

Comparison between the Multi-Factor and the Multi-Asset Portfolios

This table reports a systematic comparison of the performance of each of the factor-based strategies (in columns) against each of the benchmark, multi-asset strategies (in rows). The comparison is based on two metrics: the information ratio and the omega ratio. The boldfaced statistics in the main diagonal concerns the comparison of a factor-based and a multi-asset strategy that have been constructed using the same asset allocation technique.

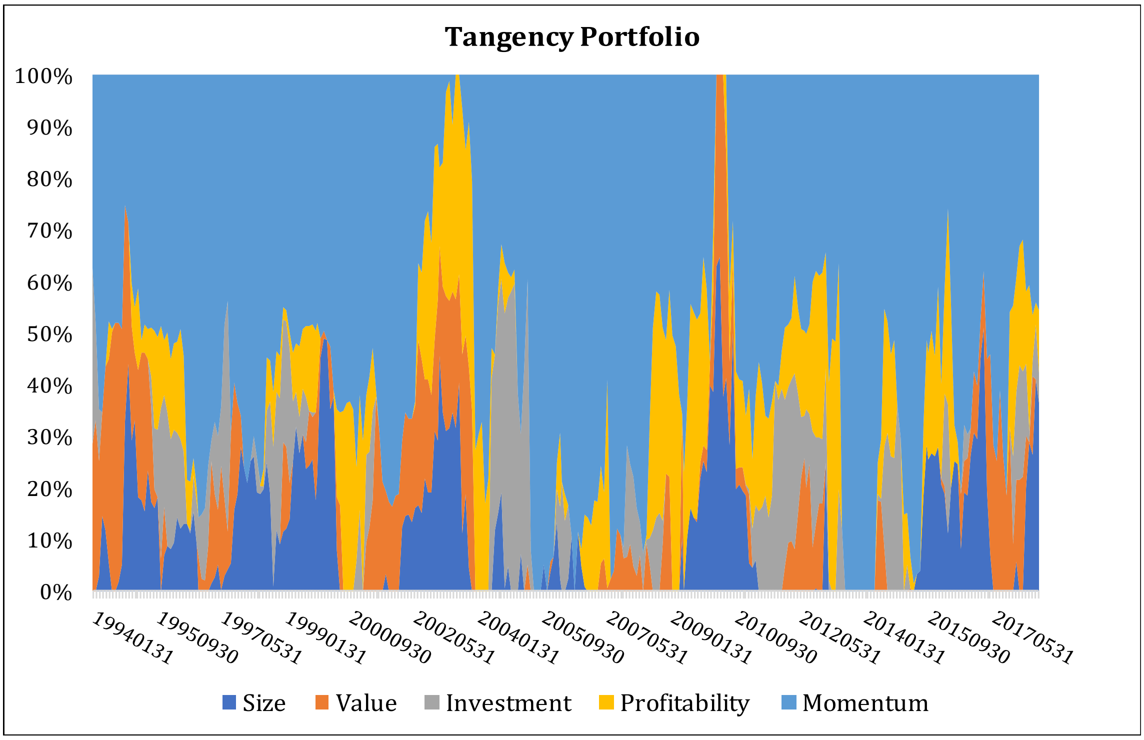
	Information Ratio	**Factor-Based Portfolios**				
		EW	**TA**	**MVP**	**MD**	**RP**
Benchmark	EW	**0.0558**	0.0927	0.0407	0.0440	0.0566
	TA	0.0052	**0.0493**	-0.0084	-0.0049	0.0066
	MVP	0.1314	0.1561	**0.1059**	0.1099	0.1307
	MD	0.1032	0.1343	0.0836	**0.0872**	0.1034
	RP	0.1113	0.1411	0.0899	0.0937	**0.1113**

	Omega Ratio	**Factor-Based Portfolios**				
		EW	**TA**	**MVP**	**MD**	**RP**
Benchmark	EW	**1.2029**	1.2875	1.1402	1.1541	1.1986
	TA	1.0173	**1.1442**	0.9734	0.9841	1.0212
	MVP	1.3625	1.4047	**1.2825**	1.2990	1.3508
	MD	1.3385	1.3874	1.2612	**1.2773**	1.3280
	RP	1.3424	1.3902	1.2646	1.2808	**1.3317**

Figure 1

Recursive Optimal Weights in the Factor-Based Portfolios

The plots below show the recursive optimal weights assigned to the factor mimicking portfolios under each alternative allocation method over the sample period January 1994-July 2018.



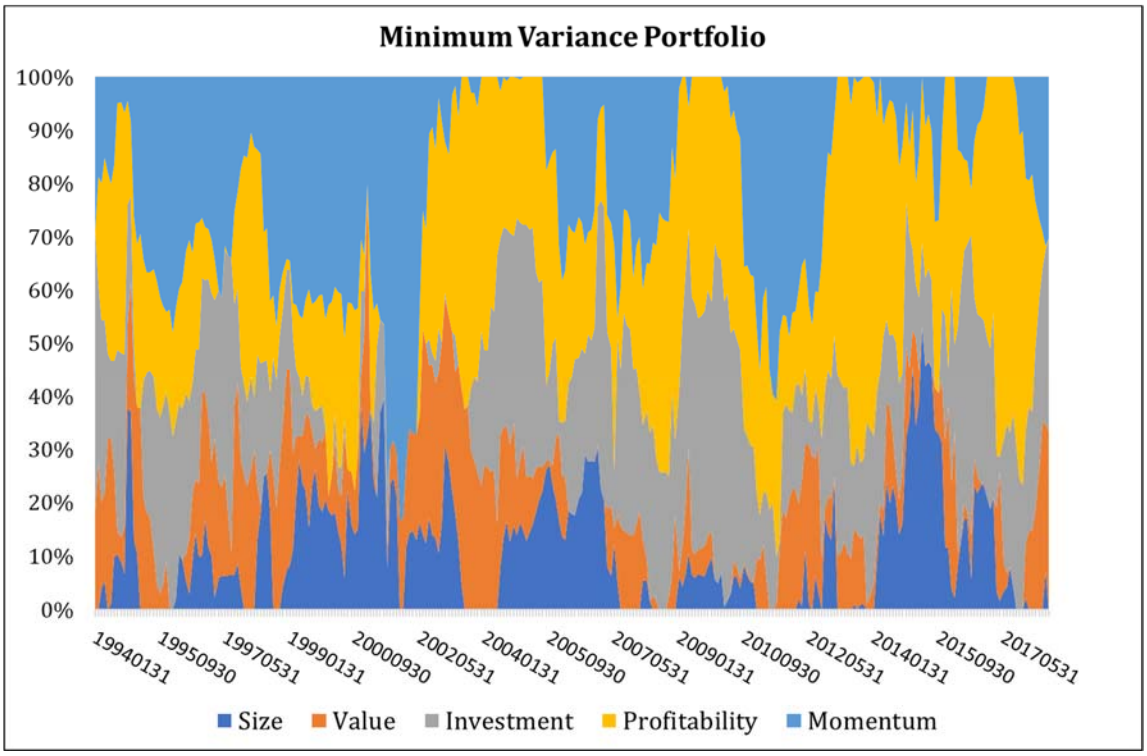
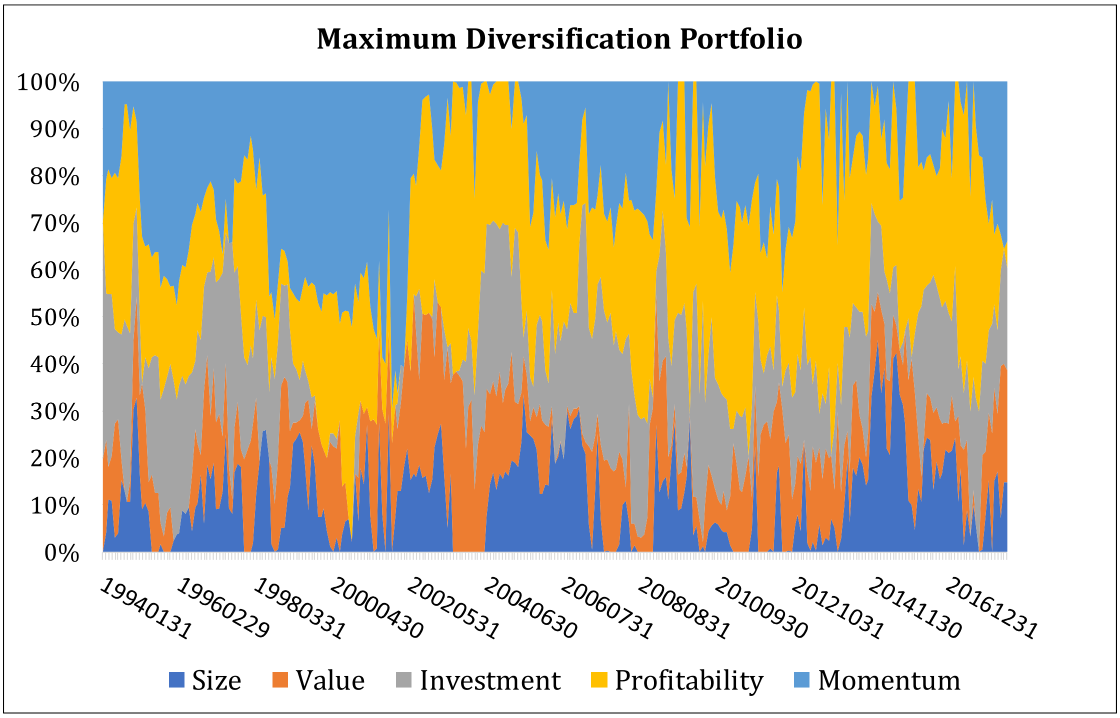


Figure 1 (continued)



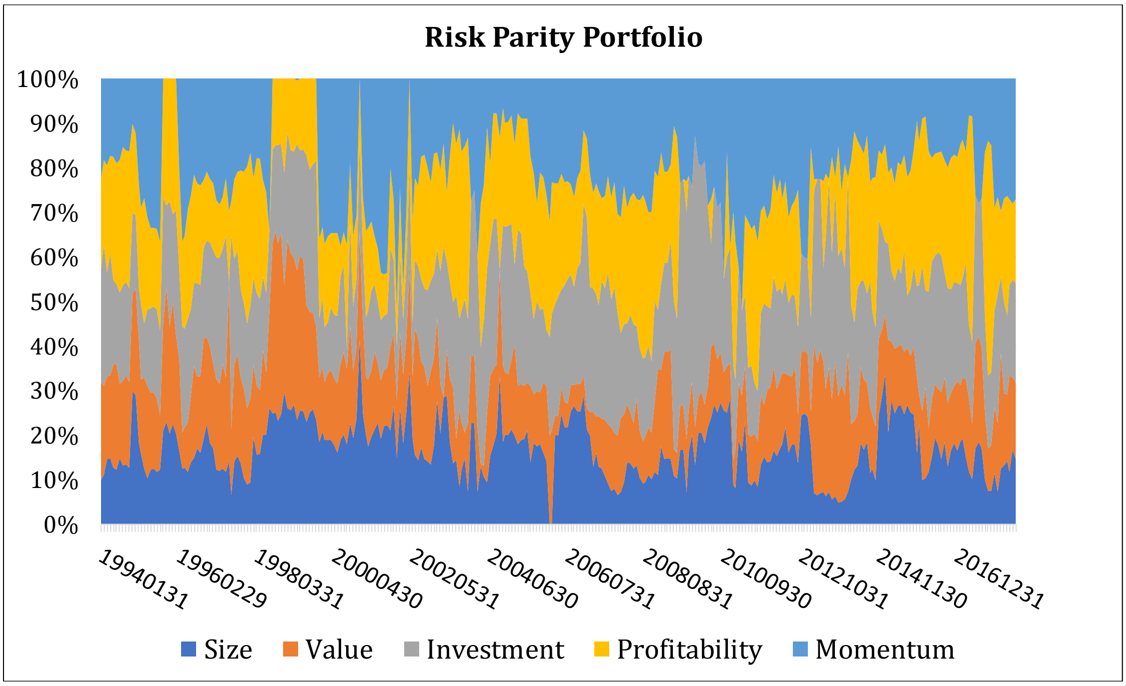


Figure 2

Cumulative Performance of the Factor-based Optimal Portfolios

The figure shows the cumulative performance, computed as the value of an index that starts at 100 in December 1993, of the five allocation methods (EW, TA, MVP, MD, RP) and compares them with the FTSE NAREIT All REITs benchmark. To allow comparison, also the FTSE NAREIR All REITs index has been rescaled to start at 100 in December 1993.

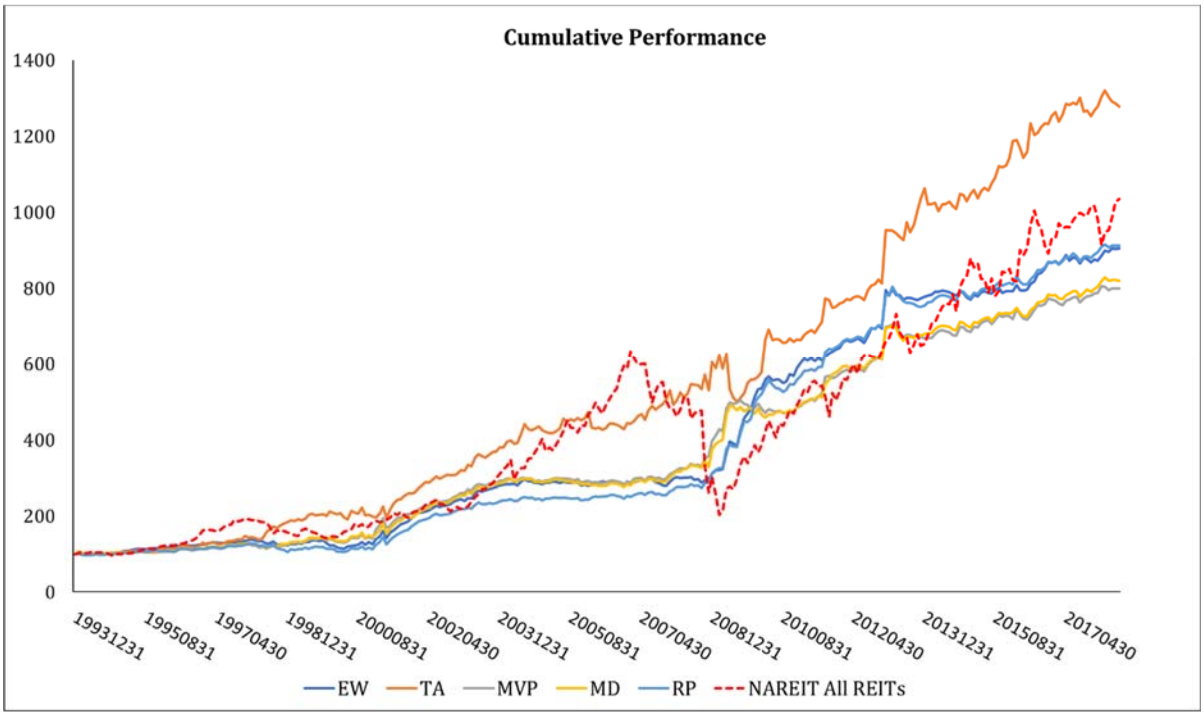


Figure 3

Performance of Factor-Based vs. Multi-Asset Allocations

The plots show the cumulative performance, computed as the value of an index that starts at 100 in December 1993, of the factor-based allocations (solid line) vs. the corresponding benchmark, multi-asset strategies (dotted line).

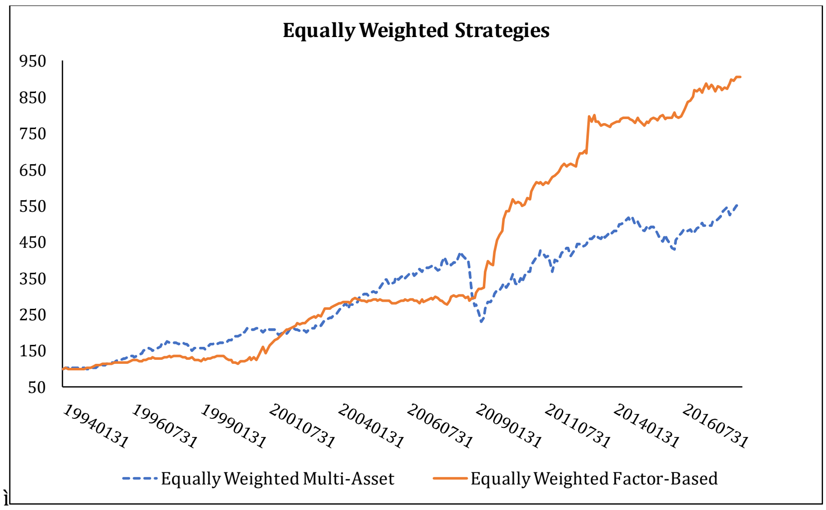
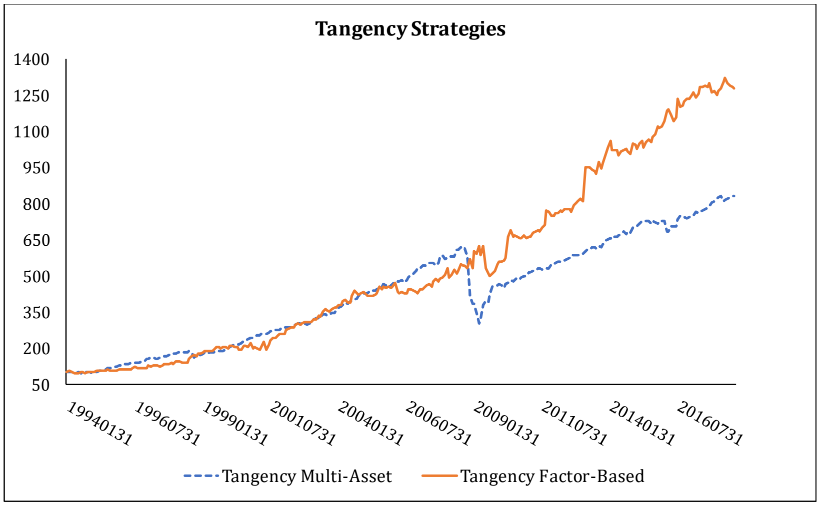
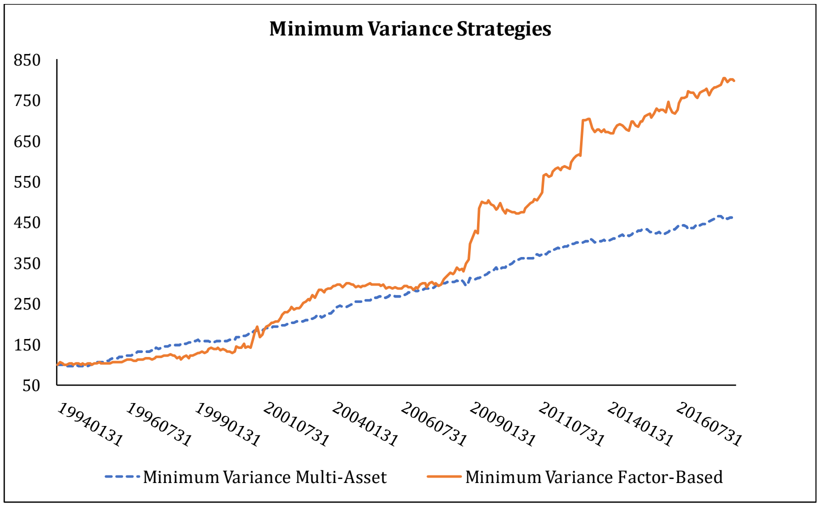


Figure 3 (continued)





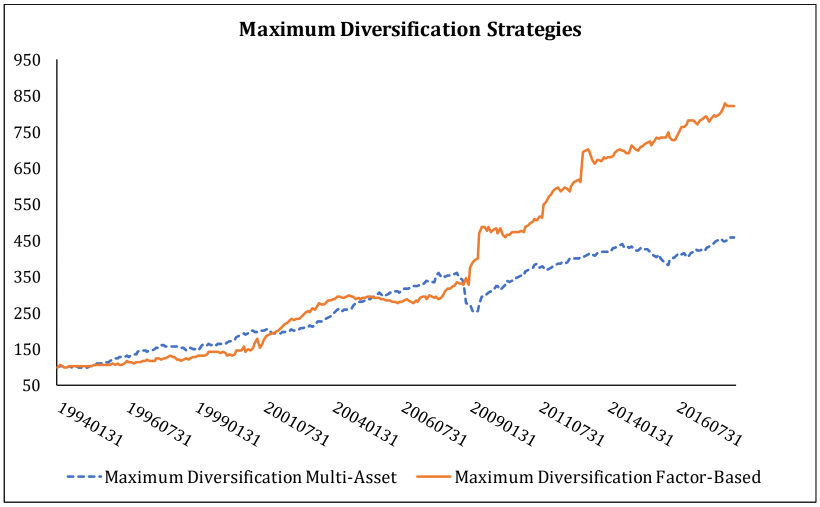


Figure 3 (continued)

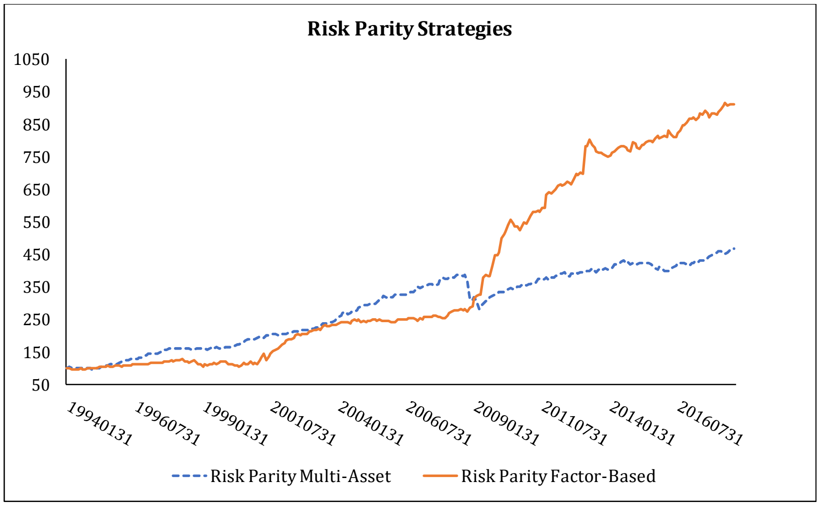


Table A.1

Robustness Checks for the Factor-Mimicking Portfolios

In this table we show different results obtained for Value, Size, Momentum, and Investment factor-mimicking portfolios for a sample period 1972-2018. We also report the results obtained using the first (D1) and the last (D10) deciles instead of quintiles to build the long-short factor-mimicking portfolios.

Size	**D10**	**D1**	**D1-D10**	**Q5**	**Q1**	**Q1-Q5**
Mean	0.0332	0.0124	-0.0208	0.0258	0.0128	-0.0130
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Median	0.0212	0.0120	-0.0123	0.0181	0.0118	-0.0064
Volatility	0.1024	0.0571	0.1048	0.0908	0.0550	0.0845
Sharpe	0.2867	0.1503	-0.2346	0.2417	0.1631	-0.1990

Value	**D10**	**D1**	**D1-D10**	**Q5**	**Q1**	**Q1-Q5**
Mean	0.0149	0.0266	0.0117	0.0131	0.0224	0.0093
(p-value)	(0.000)	(0.000)	(0.008)	(0.000)	(0.000)	(0.010)
Median	0.0155	0.0175	0.0011	0.0139	0.0144	0.0018
Volatility	0.0593	0.1102	0.1048	0.0565	0.0996	0.0847
Sharpe	0.1869	0.2068	0.0752	0.1639	0.1864	0.0647

Investment	**D10**	**D1**	**D1-D10**	**Q5**	**Q1**	**Q1-Q5**
Mean	0.0182	0.0143	-0.0039	0.0177	0.0149	-0.0028
(p-value)	(0.000)	(0.000)	(0.119)	(0.000)	(0.000)	(0.256)
Median	0.0144	0.0152	0.0018	0.0171	0.0169	-0.0027
Volatility	0.0845	0.0586	0.0751	0.0623	0.0568	0.0561
Sharpe	0.1697	0.1785	-0.1026	0.2224	0.1949	-0.1180

Momentum	**D10**	**D1**	**D1-D10**	**Q5**	**Q1**	**Q1-Q5**
Mean	0.0118	0.0261	0.0144	0.0088	0.0215	0.0128
(p-value)	(0.008)	(0.000)	(0.002)	(0.011)	(0.000)	(0.000)
Median	0.0061	0.0206	0.0134	0.0060	0.0190	0.0106
Volatility	0.1143	0.0872	0.1189	0.0905	0.0681	0.0827
Sharpe	0.0695	0.2557	0.0886	0.0544	0.2597	0.1079