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Style Analysis in Real Estate Markets:
Beyond the Sectors and Regions Dichotomy

Franz Fuerst* and Gianluca Marcato†

School of Real Estate & Planning
Henley Business School
University of Reading
Reading
RG6 6AW
United Kingdom

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* Email: f.fuerst@henley.reading.ac.uk, Tel: +44 (0)118 378 6035, Fax: +44 (0)118 378 8172.

† [Corresponding author] Email: g.marcato@henley.reading.ac.uk, Tel: +44 (0)118 378 8178, Fax: +44 (0)118 378 8172.

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Abstract

While style analysis has been studied extensively in equity markets, applications of this valuable tool for measuring and benchmarking performance and risk in a real estate context are still relatively new. Previous studies in the real estate market have identified three investment categories (rather than styles): sectors, administrative regions and economic regions. However, the low explanatory power reveals the need to extend this analysis to other investment styles. In fact real estate investors set their strategies considering factors that may differ from those found relevant for other asset classes.

Following our analysis of obstacles to transferring equity style analysis to real estate, we identify four main real estate investment styles and apply a multivariate model to randomly generated portfolios to test the significance of each style in explaining portfolio returns. Results show that significant alpha performance is significantly reduced when we account for the new investment styles, with small vs. big properties being the dominant one. Secondly, we find that the probability of obtaining alpha performance is dependent upon the actual exposure of funds to style factors. Finally we obtain that both alpha and systematic risk levels are linked to the actual characteristics of portfolios. Our overall results suggest that it would be beneficial for fund managers to use these (and possibly other) style factors to set benchmarks and to analyze portfolio returns.

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Introduction

Investors and fund managers require information on investment styles to construct a portfolio that fits defined objectives and to track the performance of benchmark portfolios in the same style category. This paper seeks to extend the application of returns-based style analysis in a real estate context. While style analysis has been studied extensively in equity markets, applications of this valuable tool for measuring and benchmarking performance and risk in a real estate context are still relatively new. Previous studies in the property market have identified three investment styles or categories: property types (i.e. sectors such as offices, retail and industrial), administrative regions (i.e. local authorities as defined by the Office for National Statistics, ONS) and economic regions (i.e. areas with similar economic and financial structure). Notwithstanding the importance of these categories, their explanatory power in predicting returns is relatively low (i.e. around 30% of the overall variability), revealing a need to extend this analysis to other investment styles. In fact, real estate investors set their strategies considering a number of additional factors that are not captured by the sector-region dichotomy. To integrate these factors into formal style analysis, we investigate the scope for a multi-dimensional approach to style analysis drawing on the IPD database, containing information about more than 12,234 UK properties with a capital value of more than US$ 300 billion). We find that all four identified risk factors are to some extent important in explaining portfolio returns. Particularly, property size is by far the dominant style, followed by value and growth (i.e. property yield) and tenant characteristics. All these factors should be considered for benchmarking purposes because the ability of generating a consistent extra performance and its level is dependent upon portfolio exposure to these factors.

The evolution of real estate style analysis

Style analysis is broadly defined as the measurement and classification of a fund's performance based on its returns. As such, its primary objective is not to show the existing asset class holdings of a fund, or to compare existing and effective asset mixes, but rather to construct a generic style benchmark that is useful in the process of portfolio performance measurement. Sharpe (1992) introduced style analysis using an asset class factor model that determines the return attributable to *style* and a residual component representing the return due to *selection*. He defines style analysis as *"the use of quadratic programming for the purpose of determining a fund's exposures to changes in the returns of major asset classes"*.

Sharpe's concept was also adopted by Kemp, Richardson and Wilson (2000) albeit with a broader definition. This type of style analysis has become a valuable tool in equity asset and portfolio management, particularly when a fund manager is seeking to mimic a portfolio of mutual funds with 'strong-form' constraints of non-negative portfolio weights and a total sum of weights equal to 1 (thus excluding lending and borrowing from the analysis). DeRoon, Nijman and TerHorst (2004) eliminate these two constraints and review several possible uses of style analysis (see also Lucas and Riepe, 1996): to evaluate mutual fund performances as a term of comparison, i.e. benchmark; to determine whether the mimicking portfolio is obtainable at a lower cost than the observed one (see also Keim and Madhavan, 1997); to identify and construct efficient portfolios of mutual funds and/or to estimate portfolio holdings (see also Brown and Goetzmann, 1997). In a similar vein, Amenc et al. (2002) note that the strong-form style analysis does not allow for abnormal return measurement. They address this issue by developing an integrated analytical framework for assessing the risk-adjusted performance using an index multi-factor model consistent with modern portfolio theory. A further recent development of style analysis was proposed by Kuenzi and Shi (2007) who extended the existing equity style analysis framework to include crucial risk and volatility factors.

To date, relatively few studies have attempted to apply style analysis in a real estate context. The existing studies can be grouped as follows: general studies on *portfolio diversification* (by sector, region, function, etc.) and its explanatory power in describing the variability of returns – Lee and Devaney (2007), Byrne and Lee (2003); Cannon et al (2006), Lee (1998); applications of *cluster analysis* combined with other techniques such as bootstrapping and tests for regression parameter stability – Shnare and Struyk (1976), Dunse et al (2000) Myer et al (1999), Lee (1999); *conceptual studies* suggesting possible designs for style analysis based on surveys and professional expertise – Kaiser (2005), NCREIF (2003); and *statistical ratio tests* as applied by Marcato (2004) that determine the best criterion to split samples to create style indices in the real estate market, and particularly growth and value properties by using their equivalent yield.

A common methodological problem found in multi-factorial models of investment style is omitted variable bias. In a real estate context, this is exacerbated by the heterogeneous nature of the asset which makes controlling for the diverse range of value drivers rather difficult. The lack of appropriate property style indices has hitherto limited style analysis to two basic options. One is to adopt and replicate techniques from equity market analysis using the value/growth or small/large cap equity indices (Liang and McIntosh, 1998, Liang and Whitaker, 2000) despite the limits to property applications mentioned above. The other approach tends to apply factors derived from real estate market analysis (i.e. mainly sectors and regions) that lack explanatory power regarding the financial aspects of investments.

An important step towards commonly accepted style box definitions utilizable in the real estate industry was taken by the NCREIF Styles Committee (2003). The White Paper summarizes several years of debate among expert professionals on the topic and specifies style boxes based on the categories (a) core, (b) value-added and (c) opportunistic. Exhibit 1 details return objectives, property types, leverage and other investment characteristics of these three categories that are widely used in equity analysis.

[INSERT EXHIBIT 1 HERE]

Although these definitions are useful in that they identify possible styles in the real estate context, they fail to address some key real estate specific issues. Thus, Kaiser (2005) contends that the consensus definitions put forward by NCREIF are vague and not portfolio-based. He suggests a composite score of up to ten factors that would then lead to the style box assignment.

The main criticism of models derived from equity analysis is however, that they are not applicable to real estate because of the vastly different way portfolio managers operate in real estate markets. Real estate is notorious for its information asymmetries. As a consequence of this, investors can use insider knowledge to generate abnormal profits. Moreover, acquiring and disposing of properties requires extensive knowledge regarding a variety of factors including (sub)market analysis, financial engineering, appraisal, as well as environmental and legal due diligence. Previous studies by Akerlof (1970) and Rock (1986) indicate that information inefficiencies in markets lead to discounts to asset value and potentially to underpricing. While not a unique feature of real estate markets, the opportunity for arbitrage due to mispricing and information asymmetry appears to be particularly large in the investment process outlined above.

Furthermore, the original concept of style analysis as developed in the equity market implies that investment decision making is a rational top-down process whereby investors define a particular investment style *a priori* and construct and re-balance a portfolio accordingly. There is ample evidence, however, that this approach does not fit the real estate decision-making process in practice. Among the more recent studies on this topic, Neo et al (2008) point to several factors intervening with strictly rational decision-making such as information asymmetry and the use of various decision-making heuristics (e.g. anchoring, representativeness, experience/search attributes). In a similar vein, Roberts and Henneberry (2007) find confirmation of cognitive shortcuts and biases in their empirical analysis of office investment decisions in various countries.

The issue is further compounded by the fact that real estate portfolio managers have more ownership control over the assets under management than their counterparts in the equity markets. They have a variety of management options at their disposal to add value and increase rental income and/or returns. These include lease management, physical alterations to the property, pro-active maintenance and facility management as well as selectivity of tenant quality and mix. In contrast, an equity portfolio manager has very little, if any, control over their assets and is thus forced to take a more passive approach to managing the assets.

The downside of this feature for style analysis is, however, that the approach derived from equity analysis does not take into account these "active management" factors. In other words, it is not possible to distinguish the impact a skillful manager may have on the total return as opposed to the property market factors listed above such as location and property sector. Conner and Liang (2003) therefore identify the categories (i) operational value-added, (ii) physical value-added and (iii) financial value-added. Kaiser (2005) estimates that such value-added activities can surpass the effect of successful asset selection by more than 1000 basis points. The presence of these real estate-specific micro-level activities poses a formidable obstacle to applying style analysis in a real estate context. Any analytical framework that does not seek to capture these specific factors is likely to miss an essential part of what drives real estate returns. Therefore, our approach incorporates into the frequently used style analysis model a number of additional investment and property-level attributes laid out in the following sections.

Data and Style Factors

A successful implementation of style analysis in a real estate context ultimately depends on a comprehensive and reliable dataset of either actual portfolio returns and characteristics, or individual property returns and property characteristics. Since confidentiality rules in the real estate benchmarking industry do not allow us to work on time series of actual portfolio returns, we have decided to solve this problem by creating randomly generated portfolios from a dataset of 557 properties which show at least 24 return figures in our 26 sample period ranging from 1981 to 2007. Thus, we create portfolios composed of 50 properties (which is an average number of properties held by UK big institutional portfolios in the IPD Index) and showing a time series with 26 annual observations. Our selection of the analysis period was guided by the availability of a reasonably large number of properties in the dataset from 1981 onwards. Regarding data frequency, annual data is used because quarterly and monthly return data are highly autocorrelated. The dataset was provided by IPD, a worldwide provider of real estate indices and benchmarking services, covering a total amount of more than 50,000 individual properties with a capital value greater than 1.2 trillion US dollars.

All 557 UK properties available for our research are *standing investment* properties according to the definition adopted by the real estate market in Great Britain. This means that at least two routine valuations are carried out annually on these properties and that any effects of buying, selling and development are not reflected in the sample. Also excluded are properties with changes in value that may have been brought about by non-market factors such as unusual terms of ownership or major capital expenditure in a given year. These rules are designed to make the sample a measure of the return to be expected from held investments without active management, and thus a fair basis for comparison across asset classes and markets. The main characteristics of our sample in terms of geographical and sectorial distribution are reported in Exhibit 2. We notice a slightly higher exposure to retail and slightly smaller exposure to offices and industrial than in the overall IPD index, and no significant differences in the composition by region. Overall, the index estimated with our sample is sufficiently similar to the All Property IPD index to draw inferences from our findings.

[INSERT EXHIBIT 2 HERE]

For each property, wecollected the following information:

- Capital Value (CV_t), representing the market value of the building at time t. This variable is used to define small and big styles.
- Total return, reflecting both the capital gain (CV_t – CV_{t-1}) and the net income achieved by the investor in percentage of the capital invested (CV_{t-1} plus capital expenditures): $TR = \frac{CV_t - CV_t - Capex_t + NetIncome_t}{CV_{t-1} + Capex_t}$
- Equivalent Yield (EY_t), representing a cap rate considering both the current rent paid by the tenant and the market rent that will be paid at the following rent review. Specifically, IPD computes this metric by equating the capital value as provided by the independent valuer and the future cash flow of the property, assuming that the current market rent is the new rent the tenant will start to pay at the next rent review (i.e. zero rental growth is assumed). This variable will be used to define growth and value styles.
- Number of tenants for each building. This variable is used to define concentrated (small number of tenants) and diversified styles (large number of tenants).
- Unexpired lease term, defined as the average number of years to lease expiry. This variable is used to classify properties with short vs. long lease terms.

In order to identify our sample, we also analyzed main descriptive statistics and distributions of total returns and other individual variables, and we applied the following rules to the dataset to eliminate outliers: firstly all observations with an equivalent yield below 2% and above 30% were excluded; secondly observations with annual total returns below -50% and above 50% were also excluded; finally no problems were found with capital values, number of tenants and unexpired lease term figures. Despite the fact that extreme values may be in line with a normal distribution of returns, they were eliminated from the dataset on the grounds that these returns were likely to be caused either by non-market forces or were simply data errors. Finally, only office, retail and industrial properties were considered in our analysis because other property types (i.e. residential, leisure and healthcare) are only marginally represented in the IPD database.

IPD also computed style indices using a capital-weighted measure to match the same methodology adopted to construct the All Property Index (i.e. index measuring the performance of the overall market) they release to the market at the end of each year. The two samples for each style factor (e.g. value and growth) have been created using the median as a criterion. We have also run indices using top and bottom quartile but differences with median as criterion are not statistically significant.

For equity markets, the obvious two style factors extensively used in the finance literature are 'value' and 'size'. We believe that these factors can be directly transferred to the real estate market with the following definitions:

- Value and growth properties are respectively showing a high and low equivalent yield – also refer to Marcato, 2005 (*HML*). This measure can be compared with value and growth stocks, where you have respectively low and high P/E ratios. The interpretation of real estate value and growth styles is however inverse because high yield properties will be classified as value and low yield properties as growth.
- Small and big properties are identified on the basis of their capital value (*SMB*), as market capitalization is used for the equity market.

Furthermore if we also consider other predominant factors concerning fund managers, we may identify other two additional styles for real estate portfolios:

- Concentrated and diversified properties depending upon the spread of tenant risk (*CMD*). In general, if the number of tenants is higher, the investment is considered less risky because the rental cash flow is spread across several tenants. However, the quality of the tenants may also be important, but IPD could not provide us quality information about the tenant for confidentiality reasons, so we only refer to the concentration effect numerically.
- Short and long average lease expiry respectively shows an expected higher and lower risk (*SML*). Instead of using the actual average lease length, however, we measure typical lease length prevalent in a given property. Apart from the desirable effect of averaging out the impact of impending break clauses and lease expirations, this choice is due to the fact that the tenancy data is only available for the second part of our sample (1998-2007) which requires a classification of properties to either short or long lease expiry for the whole period. We consequently obtain two categories of properties that are consistent over time. The composition of these two categories is not reflecting any bias to any other factor, including sectors and regions (i.e. there is not a predominant group of properties belonging to another specific style).

Descriptive statistics of indices

Main descriptive statistics are reported in Exhibit 3, showing an average performance of 10.76% and a volatility of 8.81% for the UK real estate market between 1981 and 2007. As reported in previous studies of the commercial real estate market, we also find a downward bias in the risk estimation due to the use of valuations rather than prices in the construction of real estate indices. Since all indices used in our study are subject to this valuation bias, we assume that the systematic error does not in principle invalidate comparisons of the volatility of indices.

The analysis of these real estate style indices reveals risk-reward relationships that differ remarkably from those of equity markets. Firstly, small properties tend to yield similar (or a slightly higher) returns even if they are less volatile than big properties. This may be due to a greater difficulty in selling big properties in falling markets and also due to the behavior of appraisers who tend to adjust values only if the change is bigger than an 'artificial threshold' which is normally fixed in nominal rather than percentage values. For example if appraisers are restrained to change values unless the difference is at least equal to US$ 10,000, this threshold represents 1% for a property worth US$ 1 million and only 0.01% for a property worth US$ 100 million. Secondly, despite exhibiting lower volatility, high-yield properties (i.e. value index) outperform low yield properties. A possible explanation for this is the income strength of high yield properties that may function as a cushion in a falling market (as found in previous studies for both property and other asset classes). Furthermore, the concentration variable does not seem to show differences in mean returns and volatility (i.e. slightly higher return and volatility for concentrated properties than for diversified ones), but it exhibits a different cyclical behavior as we will show below. Finally, long leases seem to perform much better than short leases, bearing a slightly smaller risk. Although some of these results may seem puzzling in that they are in contradiction to commonly accepted notions of risk-reward relationships, these findings are corroborated by similar studies of the UK commercial real estate market.

[INSERT EXHIBIT 3 HERE]

We also report the cyclical behavior of the style factors, which are computed as a difference in performance between small and big (i.e. SMB), high and low yield (i.e. HML), concentrated and diversified (i.e. CMD) and short and long leases (i.e. SML). Exhibit 4 represents the four style factors over the two main real estate cycles since 1980s. During boom periods (recessions) small properties perform better (worse) than big properties as a result of higher movement in values in percentage terms in rising markets and liquidity issues for big properties in periods of recession. Value buildings achieve higher (lower) than average returns relative to growth properties during booms (recessions) because cap rates can move further out (in) if they are not already implying price pressure. Furthermore, tenancy risk also reveals to be significant as properties with high concentration of tenants (three or less) tend to benefit in uprising markets and to suffer in falling cycles (i.e. diversification pays in recession). Finally, the performance of properties with short leases relative to buildings with long leases improves during expansion and tends to worsen during a contraction phase.

[INSERT EXHIBIT 4 HERE]

Empirical Model

As a general concept, we normally associate higher returns with higher risks. However, real estate investors have debated extensively their ability to generate alpha performance (i.e. return above the benchmark/market). Arguably, if markets were efficient, we should not expect a fund manager to be able to create an extra-return consistently over time.
As stated above, we test the ability of fund managers to generate alphas controlling for important style and risk characteristics. Rather than focusing on typical real estate investment categories (i.e. sectors and economic/administrative regions), we model four different factors, building on the finance literature and real estate-specific characteristics.
A recent study (Callender et al., 2007) showed that the measure of total risk is reduced when diversification increases and efficient market (i.e. enough big property portfolios) should price non-diversifiable (i.e. systematic) risk only. The well known Capital Asset Pricing Model defines the measure of this risk as:

$$\beta = \frac{cov(r_A, r_M)}{\sigma_M^2}$$

where $cov(r_A, r_M)$ and σ_M^2 represents respectively the covariance between our asset and the market return and the variance of market returns. The CAPM quantifies the relationship between the beta of an asset (either single asset or portfolio) and its corresponding expected return, and it thus assumes the relevance of a single common risk factor:

$$E(r_A) = r_f + \beta_A * [E(r_M) - r_f]$$

where r_f is the risk free rate and $[E(r_M) - r_f]$ the market risk premium (price of risk).
Since the CAPM predicts the expected return of an asset or portfolio in relation to its risk and the market return, this model can also be used to assess the extra performance generated by active fund managers. The CAPM gives an estimate of the return assuming that market risk is 'rewarded'. Consequently, if realized returns are greater than predicted returns, the extra-performance is normally referred to as alpha and it represents the value added by fund managers.

The alpha performance may simply be attached to the exposure to other risk factors which are not included in the systematic risk. In a Fama and French type of model, the two extra factors (i.e. SMB and HML) are computed by taking the difference between the performance of a small vs. big property index and a growth vs. value index. The SMB factor shows the additional return investors have historically received by investing in small properties (i.e. size premium) and the HML factor shows the additional return provided to investors for investing in properties with a high equivalent yield. A positive number in a given period indicates an over-performance of respectively small and high-yield properties for the two style factors. On the other hand a negative number in a given period indicates an over-performance of big and low-yield properties.

As stated and justified above, we follow the same methodology to create two extra risk factors specific to the real estate market. The CMD factor represents the difference in performance between concentrated vs. diversified properties (with a maximum of 3 tenants for a property to be defined concentrated), while the SML factor reports the difference between the return of properties with a relatively short average unexpired lease term (i.e. up to 9 years) and properties with a long lease (i.e. 10 years and above).

Using a database of 557 properties, we then randomly generate 1,000 portfolios composed by 50 properties each and we run a series of regressions to estimate the significance of different risk factors either individually or in combination with others.

Particularly we run several models starting with a market-only model and incorporating an additional risk factor with each step. Model 1 represents the classical single index model, while models 2 to 5 represent multi-factor models with different risk combinations. The full model (Model 5) includes all risk factors and will be used as a term of reference in our discussion of the main results. All other models will only be used to either make distinctions or reinforce our findings.

$$Model\ 1:\ \ r_p = \alpha + \beta\, r_{mkt,t} + \varepsilon_t$$
$$Model\ 2:\ \ r_p = \alpha + \beta\, r_{mkt,t} + \delta_1 SMB_t / \delta_1 HML_t / \delta_1 CMD_t / \delta_1 SML_t + \varepsilon_t$$
$$Model\ 3a:\ \ r_p = \alpha + \beta\, r_{mkt,t} + \delta_1 SMB_t + \delta_2 HML_t + \varepsilon_t$$
$$Model\ 3b:\ \ r_p = \alpha + \beta\, r_{mkt,t} + \delta_1 CMD_t + \delta_2 SML_t + \varepsilon_t$$
$$Model\ 4a:\ \ r_p = \alpha + \beta\, r_{mkt,t} + \delta_1 SMB_t + \delta_2 HML_t + \delta_3 CMD_t + \varepsilon_t$$
$$Model\ 4b:\ \ r_p = \alpha + \beta\, r_{mkt,t} + \delta_1 SMB_t + \delta_2 HML_t + \delta_3 SML_t + \varepsilon_t$$
$$Model\ 5:\ \ r_p = \alpha + \beta\, r_{mkt,t} + \delta_1 SMB_t + \delta_2 HML_t + \delta_3 CMD_t + \delta_4 SML_t + \varepsilon_t$$

After obtaining both alpha and beta estimates, we proceed to modeling of these estimates using the actual characteristics of the randomly created portfolios as independent variables in a multifactor model as follows:

$$Model\ 6:\ \ \alpha_i = \gamma_0 + \sum_{j=1}^{n} \gamma_j\, Char_j + \varepsilon_i$$
$$Model\ 7:\ \ \beta_i = \gamma_0 + \sum_{j=1}^{n} \gamma_j\, Char_j + \varepsilon_i$$

where the n actual portfolio characteristics are:

- Average total return (i.e. TRave);
- Beta (i.e. β) and alpha (i.e. α) coefficient respectively for the first and second equation;
- Average and standard deviation of the style classification (i.e. SMBave, SMBsd, HMLave, HMLsd, CMDave, CMDsd, SMLave and SMLsd), with numbers around 0.5 which is the value at which there is no predominance of either one or the other style;
- Sector dummy variables (i.e. SECoff and SECind), using retail as the base case estimation;
- Regional diversification, expressed as maximum number of properties in one single region (i.e. REGmaxno), maximum number of regions in which the fund is invested (i.e. REGinvest) and the percentage of properties held in a single region (REGse)

Finally a linear probability model is applied to estimate the probability of achieving alpha performance. Our dependent variable is a Bernoulli probability distribution that takes two values, the value 1 (for portfolios with significant alpha performance) has a probability p and the value 0 (for portfolios with no significant alpha performance) has a probability (1-p). The expected value of a random variable following a Bernoulli distribution is the probability the variable equals 1, i.e. the probability of achieving an alpha performance significantly different from zero. The model follows the following specification:

$$Model\ 8{:}\quad \alpha Dummy_i = \gamma_0 + \sum_{j=1}^{n} \gamma_j\, Char_j + \varepsilon_i$$

where the n actual portfolio characteristics are the same used in the previous two estimations (i.e. for alpha performances and systematic risk) and:

$$\alpha Dummy_i = \begin{cases} 1 & if\ Portfolio\ Alpha\ is\ significant \\ 0 & otherwise \end{cases}$$

Empirical Results

Exhibit 5 shows that the likelihood of fund managers to create a consistently significant alpha performance is reduced from almost 98% (when only the market risk factor is considered) to 34% (when all five factors are included). This reveals that 54% of our randomly generated portfolios (i.e. the difference between the two explained variance proportions) generated alpha performances only because they were exposed to risk factors that should hypothetically be (and actually turned out to be) rewarded in the market. Using market risk and all 4 styles (Model 5), the average beta factor is found to be equal to 0.99. As expected, it is very similar to 1.00 because the market index refers to the overall real estate market and the average extra-return is just above 2% per annum as compared to 6% found in equity markets using the two Fama and French risk factors. Thus, our model appear to capture most of the variability in portfolio returns as it ranges between 91% and 95%.

[INSERT EXHIBIT 5 HERE]

Secondly, all randomly generated funds are exposed to market risk and a high percentage is exposed to the property size factor (i.e. between 65% and 74% of our portfolios depending upon the model). Inspection of the time series reveals that the impact of property size on returns varies with the position in the market cycle, possibly because of varying availability of the substantial capital required to purchase large properties. In falling markets banks normally have less money available because they find it difficult to raise money in the capital markets. However, the average significant coefficient is equal to 0.58, showing that for every percentage point of difference between the performance of small and big properties, there is an increase in the expected portfolio return of 0.58%. Furthermore, the positive sign of this coefficient suggests that small properties are considered riskier than big properties and portfolios exposed to this style should be priced consistently.

There are a number of reasons why small properties should be considered riskier. Firstly, large assets tend to have a greater number of tenants so that default risk etc. is spread out over more tenants. Secondly, large (typically exchange-traded) companies normally tend to prefer large properties that offer large floorplates and a custom-tailored space fittings within the same building and the risk (quality) associated with the tenant is smaller (higher) for big companies than for small ones. Moreover, for some types of properties such as shopping centers, larger properties tend to be more attractive for high-quality tenants (i.e. brand shops). Being located in a well-known shopping center (which is normally associated with larger size) may be appealing because of a higher number of consumers accessing the premises and consequently higher likelihood of generating revenues.

Furthermore, larger properties tend to have a higher "iconic" premium because they are easily identified by clients and the market in general and are preferred by better quality tenants which are attracted by the opportunity to locate in such premises which in turn results in a willingness to pay higher rents.

Apart from these dominant style factors, we find a range of smaller factors that are relevant for some funds, but they seem to be a relatively small percentage of all random portfolios and do not exceed 21.2% such as the HML factor in the two-factor model. However, if we only study the characteristics of portfolios generating a significant alpha performance we also see that the likelihood of having a fund exposed to the SML risk factor is around 18.5%.

The HML and CMD risk factors suggest that for each percentage point of difference in performance between either value and growth properties or buildings with high and low tenant concentration, the expected portfolio returns decreases by a small percentage (-0.15% and -0.10% respectively). However, the average figure for all 1,000 portfolios hides the actual spread of these coefficients, which reach a value of up to 0.51 and 0.82 from a minimum of respectively -0.57 and -0.99 (i.e. around 1% increase in expected portfolio return for a 1% difference between styles). Since the coefficient is not always positive (even though it is for the HML factor of the majority of our randomly generated portfolios), we find mixed evidence of the riskiness of high vs. low yield properties and tenants concentrated vs. diversified buildings.

For HML, one may argue that low yield properties signal higher future growth potential compared to high-yield properties. Whether this growth potential will indeed materialize is uncertain, however, which translates into higher current risk and a positive HML coefficient. However, when the market records a shift in cap rates, there is more room for price movements for properties with high yields. For example in rising markets buildings with low yields may find it difficult to realize a substantial outward movement of cap rates, whilst properties with high yields may see larger adjustments under those market conditions. In fact in rising markets we tend to see further reduction of the yield spread between buildings . The HML risk factor along with systematic risk (i.e. model 2) is significant for more than 20% of our portfolios and represents the second most important style after property size. This style also reduces the likelihood of achieving alpha performance by 31.6% alone (i.e. from 97.8% for a model with systematic risk only to 69.2% for a two factor model).

At the same time, a positive CMD may reveal the riskiness of buildings with high concentration of tenants as opposed to properties with a diversified tenant mix. However the coexistence of negative and positive coefficients may hint at the fact that a large reliable corporate tenant is still considered less risky than a number of small tenants. Ultimately, this confounding factor could be isolated by using tenant credit ratings in the model which were not available to us. When considered alone, this style is significant for more than 10% of our portfolios, but it does not determine a significant decrease in alpha performance.

Finally the SML factor shows the price effect of shorter lease contract risk. In fact we find a positive coefficient of 0.31 which suggest an increase in expected portfolio returns of 0.31% for each percentage point of difference in performance between properties with short and long leases. This is in line with economic theory which would suggest the perception of higher risk for shorter contracts. Investors may in fact face difficulties in renegotiating the contract or in finding a new tenant with consequences on vacancy rates, cash flow timing and then cash flow certainty. Along with systematic risk in a two factor model, this style is significant for only 8.8% of our portfolios and it only marginally reduces their alpha performance.

[INSERT EXHIBIT 6 HERE]

Furthermore, Exhibit 6 reports the actual characteristics of randomly generated portfolios showing the percentage of funds exposed to the different risk factors among consistent alpha portfolios. If we take Model 5 as an example, we find that 39.5% of the alpha portfolios are specialized in properties with either short or long leases. This result, along with 37.5% of alpha portfolios exposed to tenant risk concentration/diversification, shows that other risk factors related to the tenancy characteristics should be explored which may lead to a further reduction in achievable significant alpha performances. Finally 30.7% and 24.5% of alpha portfolios show an exposure to respectively high vs. low yield properties and big vs. small buildings. Given these characteristics, it is interesting to understand what determines the likelihood of achieving alpha and its extent, as well as the level of systematic risk in property portfolios. In Exhibit 7, we present the results of this analysis by estimating Models 6, 7 and 8 and using the alpha and beta estimations from Model 5 only.

[INSERT EXHIBIT 7 HERE]

With respect to alpha performance, we find that the higher the average total return achieved by the portfolio over time (1981-2007), the higher are both the likelihood and the level of alpha performance. This is in line with expectations as higher returns should reflect a greater ability to generate extra performance. Secondly, alpha seems to be inversely related to the systematic risk of the portfolio because a higher linkage between market and portfolio returns will determine a smaller likelihood of achieving a performance different from the market and this extra return will also tend to be smaller. Furthermore, the higher the exposure to high yield properties, the smaller is the alpha performance and the likelihood of obtaining it. This result sheds light upon the issue we raised earlier regarding the performance of high- and low-yield properties. In fact, we found mixed findings for the HML factor in models 1-5 (i.e. big range of coefficients, which were both positive and negative). In this case the HML factor seems to suggest that greater exposure to high yield properties will generate smaller alpha performance even after this factor is priced in the original model as the alpha performance we determined in Model 5 is already net of the HML style. The variability of this exposure (i.e. standard deviation of the HML factor) is also important for explaining the alpha a fund can achieve: the higher is the variability, the smaller is the extra-performance. Moreover, tenant risk is significant and the higher are the concentration of tenants and the exposure to short term leases, the smaller are both alpha and the probability of achieving it. Again , this result suggests the need to consider other risk factors linked to tenants which may be relevant in shaping this relationship. Finally, if we consider the predominant real estate style characteristics of property sector and region, we find that office portfolios tend to achieve a higher alpha (of around 2%), while industrial portfolios tend to show a smaller than average alpha (of more than 1%). Regional exposure also increases both level and likelihood of alpha and can be predictive of the ability to generate extra performance consistently over time.

The adjusted R-square of our model is 0.34. Although the model explains a satisfactory portion of the variability of the alpha probability, there may be additional style factors investors consider in setting their investment strategies and in benchmarking their portfolio returns. Morevoer, we find that the level of alpha is better explained by our risk factors, with an overall goodness of fit equal to 63%, revealing that other styles may improve this explanatory power, but only by an extra 37% (as opposed to an extra 66% in the case of the alpha likelihood).

Analyzing the systematic risk of our randomly generated portfolios shows that higher average total returns generate higher linkage between the portfolio and the market. This result is in line with our predictions as we expect to have higher return to compensate for higher risk portfolios. Secondly, we reinforce the previous result of an inverse relationship between systematic risk and alpha performance finding a negative coefficient for alpha which indicates that a higher extra performance will probably be associated to a lower degree of linkage between portfolio and market returns. Furthermore, if there is greater exposure to any of the styles, we also expect the systematic risk to be reduced because exposure to risk factors should lead to deviation from market performance. We find that exposure to high yield properties and buildings with high tenant mix concentration determine a smaller non-specific risk than low yield properties and buildings with a diversified tenant mix. However, exposure to short leases tends to increase the linkage with the market which is in line with our expectations since rents are updated more frequently to reflect current market conditions when average lease length is short. As for alpha performance, exposure to the office sector and to specific regions (in our randomly generated portfolios this is normally represented by the London area) translates into higher systematic risk because these areas are known to drive the returns of the overall market. Finally, the new styles identified by our model may be useful for benchmarking real estate returns in practice since they explain 56% of the variability of the systematic risk.

In summary, these results are encouraging as they appear to confirm that a multi-dimensional style analysis yields superior results compared to the commonly used two-factor version and these styles are able to explain both alpha performance (and the likelihood of achieving it) and systematic risk of real estate portfolios. The analysis confirms that property size, yield, tenant diversification and lease term structure are important to distinguish between investment styles and to explain risk factors which can be used for benchmarking purposes. Fund managers and property investors may find it useful to work with the radar diagram classification of portfolios and assets reflecting the factors that we identified as essential investment style dimensions in our analysis. Finally, far from having achieved a definite investment style classification for real estate markets, we have revealed that other factors may be important in explaining property returns and envisage further work with particular focus on additional tenant characteristics.

Conclusions and further work

In this study, we use a sample of 557 properties and randomly generated portfolios measuring their exposure to investment styles. We apply a step-by-step procedure to consider a 5 factor model, starting from the single index model only considering market risk. Based on previous findings of the relevant literature, we assume that equity investment styles are not directly transferable to real estate portfolio management. The four risk factors we identify are found to be useful to explain real estate portfolio returns, with property size being by large the dominant style. Property cap rates are also found to be important and, along with concentration of tenant mix and lease length, we envisage that additional risk factors linked to the tenancy agreement may be relevant to explain property performance.

There has been extensive discussion about the ability of fund managers to achieve extra performance. In our models we have seen that the inclusion of these factors significantly reduced the ability of achieving extra-performance by fund managers. This result suggests that the ability of generating alpha should be assessed after accounting for these risk factors because a single index model (normally used in real estate markets) yields excessive alpha performance, which reflects other types of risks fund managers are indirectly taking on. Our findings also suggest that the standard used in the market for benchmarking portfolio returns is inadequate and can be improved by adding more emphasis on the risk profile of these portfolios. At the moment total returns remain the principal measure to assess fund manager performance and this may lead fund managers to increase their risk in order to achieve higher returns without being penalized in the benchmarking activity.

Finally, we note that style analysis has not received much attention in the academic real estate literature despite its obvious practical implications. Applying rigorous methods to identify appropriate styles would make real estate investments more comparable to other asset classes. This would also be beneficial for investors considering real estate investments in their multi-asset portfolios. As a new tool of investment available to institutional investors, real estate funds are a viable solution which may find transparency being beneficial for attracting more investors. There are a number of options to adopt our findings for day-to-day real estate fund management. We suggest a radar-diagram format which integrates all style dimensions to show the exposure of the fund to specific risk factors. This tool adds value and functionality to the task of analyzing and monitoring investments and allows institutional investors to choose funds, not only on the basis of past achieved returns, but also exposure to risk factors above and beyond the traditional sector-region dichotomy.

References

Akerlof, G. A. (1970): The Market for 'Lemons': Qualitative Uncertainty and the Market Mechanism, *Quarterly Journal of Economics*, 84/3,488-500.

Amenc, N., Sfeir, D. and Martellini, L. (2002): An integrated framework for style analysis and performance measurement, *Journal of Performance Measurement*. 7/4, 35-41.

Brown S., Goetzmann W. (1997): Mutual Fund Style Analysis, *The Journal of Financial Economics,* 43, 373-399.

Byrne, P. & Lee, S. (2003): An Exploration of the Relationship Between Size, Diversification and Risk in UK Real Estate Portfolios: 1989-1999, *Journal of Property Research,* 20:2, 191-206.

Cannon, S., N. G. Miller, and G. S. Pandher (2006): Risk and return in the US housing market: A cross-sectional asset-pricing approach, *Real Estate Economics* 34(4): 519-552.

Conner, P. and Y. Liang (2003): Institutional Real Estate Investment: Evolution and Innovation, *Real Estate Finance,* 20(3), 2–10.

DeRoon F. A., T. E. Nijman and J. R. TerHorst (2004): Evaluating Style Analysis, *Journal of Empirical Finance*, 11:1, 29–53.

Dunse, N., Leishman, C. and Watkins, C. (2000): Classifying Office Submarkets, *Journal of Property Investment & Finance*, 19(3), 236-250.

Fama, E. F. and MacBeth, J. (1973): Risk, return and equilibrium: Empirical tests, *Journal of Political Economy*, 81, 607-636.

Kaiser, R. W. (2005): Investment styles and style boxes in equity real estate: can the emerging model succeed in classifying real estate alternatives? *Journal of Real Estate Portfolio Management* 11 (1): 5-18.

Keim, D.B., Madhavan, A., 1997: Transaction costs and investment style: an inter-exchange analysis of institutional equity trades, *Journal of Financial Economics*, 3, 265-292.

Kemp M., M. Richardson and C. Wilson (2000): Investment Manager Style Analysis, *Faculty and Institute of Actuaries, Investment Conference*.

Kuenzi, D.E.; Shi, X. (2007): Asset Based Style Analysis for Equity Strategies: The Role of the Volatility Factor, *The Journal of Alternative Investments*, Summer 2007, 10-23.

Lee, S. (1998): The Relative Importance of Sectors vs. Regions in Determining Property Returns, *PRRES Conference*, January 1998.

Lee, S. (1999): Style Analysis and Property Fund Performance*, Journal of Property Investment and Finance*, 17:2, 145–59.

Lee, S. & Devaney, S. (2007): The Changing Importance of Sector and Regional Factors in Real Estate Returns: 1987-2002, *Journal of Property Research,* 24(1), 55-69.

Liang and McIntosh (1998): REIT Style and Performance, *Journal of Real Estate Portfolio Management*, 4:1, 69–78.

Liang, Y. and W. Whitaker (2000): Style Attributes of Equity REITs, *Journal of Real Estate Finance*, 17:2, 31–6.

Lucas, L. and M. W. Riepe (1996): The Role of Returns-Based Style Analysis: Understanding, Implementing and Interpreting the Technique, *Ibbotson Associates*.

Marcato, G. (2004): Style Analysis in Real Estate Markets and the Construction of Value and Growth Indices, *Journal of Real Estate Portfolio Management*, 10 (3), 203-215.

Myer, F. C. N., M. Young and J. R.Webb (1999): Equity REIT Clusters, *Working paper at Cleveland State University*, April 1999.

NCREIF (2003): Real Estate Investment Styles: Trends from the Catwalk, *NCREIF Styles White Paper, Chicago*, November 2003.

Neo, P.H., S.E. Ong, Y. Tu (2008): Buyer Exuberance and Price Premium, *Urban Studies*, 45(2), 331-345.

Roberts, C., J. Henneberry (2007): Exploring office investment decision-making in different European contexts, *Journal of Property Investment & Finance*, 25(3), 289-305.

Rock, K. (1986): Why new issues are underpriced, *Journal of Financial Economics,* 15(1-2), 187-212.

Schnare, A. and Struyk, R. (1976): Segmentation in urban housing markets, *Journal of Urban Economics*, 3, 146–66.

Sharpe, W. F. (1992): Asset Allocation: Management Style and Performance Measurement”, *Journal of Portfolio Management*, 18 (2), 7-19.

Exhibits

Exhibit 1: Style Box Definitions

	Core	Value-added	Growth
Return objectives	- Market level returns - Stable rental income - Low/moderate risk - Return mainly from rental income	- Expected moderate outperformance of market - Return mainly from appreciation	- Expected to significantly outperform the market - Limited rental income - Return largely dependent on future appreciation
Property types	Office, retail, industrial and apartment properties	May include other property types (hotel, storage etc.)	May include niche opportunities (NPLs, mezzanine debt), distressed and international properties and land.
Leverage	Upper limit of 50% LTV	Upper limit of 70% LTV	>70% LTV
Other investment characteristics	Institutional-grade properties, prime locations, high-quality design and tenants	May involve efforts to increase value by refurbishment and/or repositioning	Properties with high-risk and/or niche attributes.

Source: adapted from NCREIF (2003)

Exhibit 2: Sample Composition by Sector and Region and Comparison with IPD All Property Index.

Sample Composition

Sectors		Regions	
Retail	58.5%	Central London	20.2%
Office	23.3%	Other London	14.5%
Industrial	17.2%	South East	17.6%
Other	0.9%	South West	11.7%
		Midlands and Eastern	19.2%
		North of England	13.1%
No. of Properties	557	Scotland and Wales	3.6%

Total Return: IPD Index vs. Sample

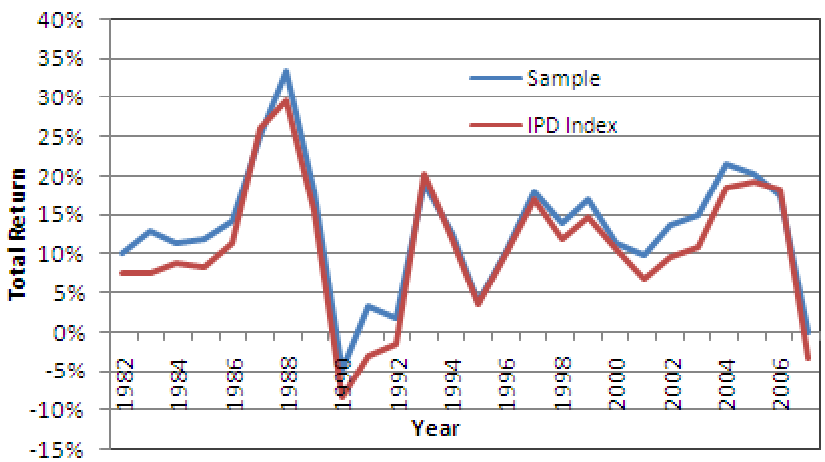

Exhibit 3: Descriptive Statistics of the Style Factors in Real Estate Markets.

	Average	**Median**	**St.Dev.**	**Kurtosis**	**Skewness**
All Property	10.76%	10.65%	8.81%	0.29	-0.14
Small	10.27%	11.03%	6.40%	0.53	-0.60
Big	9.57%	9.84%	7.67%	0.13	-0.56
Value	11.10%	10.59%	7.13%	0.03	-0.22
Growth	8.73%	9.25%	8.17%	0.37	-0.72
Concentrated	11.40%	11.27%	6.96%	0.14	-0.38
Diversified	10.44%	10.80%	6.48%	0.71	-0.68
Short lease	9.25%	9.70%	7.37%	0.28	0.05
Long lease	11.54%	12.14%	6.84%	0.80	-0.65

Exhibit 4: Cyclical Behavior of Style Factors in Real Estate Markets.

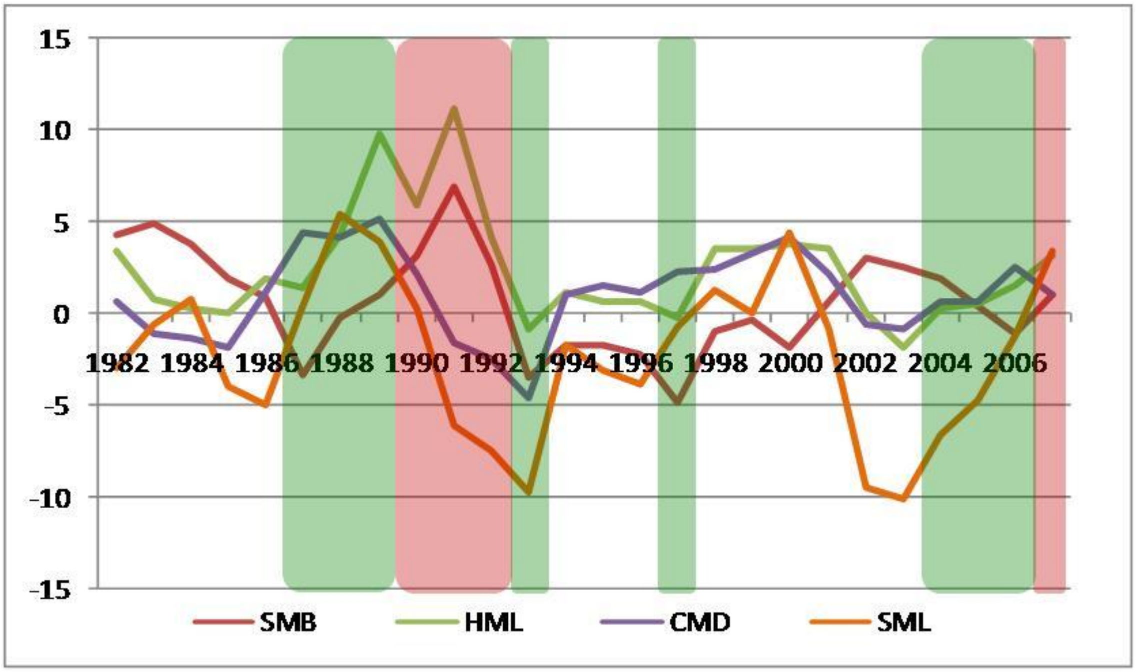

Exhibit 5: Percentage of Significant Coefficients for Style Factors.

	Significant Coefficients						R-squared
	Market	**SMB**	**HML**	**CMD**	**SML**	**Alpha**	
Model 1	100.0%					97.8%	0.91
Model 2	100.0%	74.0%				59.3%	0.94
	100.0%		21.2%			69.2%	0.92
	100.0%			11.2%		97.8%	0.92
	100.0%				8.8%	96.2%	0.92
Model 3	100.0%	66.5%	16.0%			38.7%	0.94
	100.0%			4.0%	2.0%	94.0%	0.92
Model 4	100.0%	65.7%	9.1%	12.0%		39.5%	0.95
	100.0%	66.9%	11.6%		11.6%	36.2%	0.95
Model 5	100.0%	65.1%	9.2%	4.9%	5.2%	33.9%	0.95

Exhibit 6: Actual Characteristics of Alpha Portfolios.

	Significant Coefficients					
	No Style	**SMB**	**HML**	**CMD**	**SML**	**Alpha**
Model 1	100.0%					100.0%
Model 2	22.1%	25.3%				100.0%
	23.6%		36.7%			100.0%
	21.1%			39.4%		100.0%
	20.7%				44.4%	100.0%
Model 3	26.9%	23.8%	33.1%			100.0%
	21.3%			39.4%	43.8%	100.0%
Model 4	25.1%	24.6%	35.2%	36.5%		100.0%
	25.7%	24.3%	32.9%		41.7%	100.0%
Model 5	27.4%	24.5%	30.7%	37.5%	39.5%	100.0%

Exhibit 7: Predictability of Alphas and Determinants of Alphas and Systematic Risk.

	Alpha Probability		Alpha Return	
	Coefficient	**T-stat**	**Coefficient**	**T-stat**
Intercept	-0.878	-1.632	**-2.752**	**-2.941**
TRave	**0.439**	**11.981**	**1.340**	**21.033**
BETA	**-3.534**	**-18.041**	**-11.336**	**-33.269**
SMBave	-0.076	-0.316	0.101	0.240
SMBsd	0.255	0.431	1.539	1.497
HMLave	**-2.228**	**-6.640**	**-5.332**	**-9.135**
HMLsd	-1.230	-1.427	***-2.923***	***-1.949***
CMDave	***-0.433***	***-1.647***	**-0.862**	**-1.886**
CMDsd	*-0.258*	*-0.561*	-0.659	-0.826
SMLave	***-0.190***	***-1.695***	**-0.580**	**-2.975**
SMLsd	0.760	0.727	**3.665**	**2.017**
SECoff	**0.965**	**3.672**	**2.041**	**4.465**
SECind	0.009	0.031	**-1.326**	**-2.547**
REGmaxno	***-0.014***	***-1.791***	-0.019	-1.394
REGinvest	0.008	0.791	**0.043**	**2.315**
REGse	**0.632**	**2.845**	**1.974**	**5.113**
Adjusted R^2	0.34		0.63	
F-statistics	35.34		116.85	
No Observations	1000		1000	

	Systematic Risk (Beta)	
	Coefficient	**T-stat**
Intercept	0.291	4.876
TRave	**0.073**	**16.891**
ALPHA	**-0.047**	**-33.269**
SMBave	0.032	1.179
SMBsd	-0.015	-0.223
HMLave	**-0.397**	**-10.763**
HMLsd	-0.394	-4.125
CMDave	***-0.034***	***-1.145***
CMDsd	*-0.092*	*-1.789*
SMLave	***0.007***	***0.544***
SMLsd	0.043	0.365
SECoff	**0.138**	**4.716**
SECind	0.014	0.427
REGmaxno	***0.000***	***-0.537***
REGinvest	0.001	1.054
REGse	**0.076**	**3.033**
Adjusted R^2	0.56	
F-statistics	87.30	
No Observations	1000	