Style Analysis in Real Estate Markets: *Beyond the Sector and Region Dichotomy*

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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 article seeks to extend the application of returns-based style analysis in a real estate context. Although 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 real estate market studies have identified three investment styles or categories: property type (sectors such as office, retail, and industrial), administrative region (e.g., local authorities as defined by the U.K. Office for National Statistics) and economic region (based on similarity of regional industrial composition). Notwithstanding the importance of these categories, their explanatory power in predicting returns is relatively low at around 30% of overall variability; the achievable alpha performance is still significant, 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 a more formal style analysis, we investigated the scope of a multidimensional approach to style analysis drawing on the IPD database, which contains information about more than 12,000 U.K. properties with a capital value of more than U.S.$300 billion. We found that all four identified risk factors are to some extent important in explaining portfolio returns. Property size, in particular, is by far the dominant style, followed by value and growth (i.e., the cap rate), and tenant characteristics. All these factors should be considered for benchmarking purposes because the ability to generate 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 to a residual component representing the return due to selection, and defined style analysis as "the use of quadratic programming for the purpose of determining a fund's exposure 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 (i.e., no short-selling opportunity) and a total sum of weights equal to 100%, which thus excludes lending and borrowing from the analysis. De Roon, Nijman, and ter Horst [2004] eliminated these two constraints and reviewed several possible uses of style analysis for three main purposes (see also Lucas and Riepe [1996]): 1) to evaluate mutual fund performances as a benchmark; 2) to determine whether the mimicking portfolio is obtainable at a lower cost than the observed portfolio (see also Keim and Madhavan [1997]); and 3) 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, Sfeir, and Martellini [2002] noted that the strong-form style analysis does not allow for abnormal return measurement. They addressed this issue by developing an integrated analytical framework for assessing risk-adjusted performance using an index multifactor 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: 1) general studies on portfolio diversification by sector, region, function, and so forth, and its explanatory power in describing the variability of returns (Lee and Devaney [2007], Byrne and Lee [2003], Cannon, Miller, and Pandher [2006], and Lee [1998]); 2) applications of cluster analysis combined with other techniques, such as bootstrapping and tests for regression parameter stability (Shnare and Struyk [1976], Dunse, Leishman, and Watkins [2000], Myer, Young, and Webb [1999], and Lee (1999]); 3) conceptual studies suggesting possible designs for style analysis based on surveys and professional expertise (Kaiser [2005] and NCREIF [2003]); and 4) statistical ratio tests as applied by Marcato [2004] that determine the best criterion to split samples in order to create style indices in real estate markets, in particular, for growth and value properties using their equivalent yield.

A common methodological problem found in multifactorial models of investment style is the omission of factors that are relevant but not included in the analysis. 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-cap and large-cap equity indices (Liang and McIntosh [1998] and Liang and Whitaker [2000]), despite the limits to property applications previously mentioned.

The other approach tends to apply factors derived from real estate market analysis, mainly sectors and regions, even though they lack explanatory power. In a recent article, Fuerst and Marcato [2009] showed that even moving from original administrative regions to regional clusters does not yield enough explanatory power when compared with clusters identified using other property characteristics alongside regional location and property type. They used both clustering and neural network approaches to study individual property returns and found that adding other real estate characteristics, such as yield, size, tenant concentration, and lease length, significantly improves predictive power.

An important step toward commonly accepted style-box definitions usable in the real estate industry was taken by the NCREIF Styles Committee. An NCREIF [2003] white paper summarized several years of debate among expert professionals on the topic and specified style boxes based on the categories of core, value-added, and opportunistic. Exhibit 1 details return objectives, property types, leverage, and other investment characteristics of these three categories that are widely used in equity analysis.

Although these definitions are useful in that they identify possible styles in real estate investment, they fail to address some key real estate specific issues. Thus, Kaiser [2005] contended that the consensus definitions put forward by NCREIF are vague and not portfolio based. He suggested a composite score of up to 10 factors that would then lead to the style-box assignment.

The main criticism of models derived from equity analysis is that they are not directly applicable to real estate because of the vastly different ways portfolio managers operate in the market. Real estate is notorious for its information asymmetries. As a consequence, investors can use insider knowledge to generate abnormal profits. Moreover, acquiring and disposing of properties requires extensive knowledge of a variety of factors including market and submarket analysis, financial engineering, appraisal, and

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].

environmental and legal due diligence. Previous studies by Akerlof [1970] and Rock [1986] indicated that information inefficiencies in markets lead to discounts in asset value and, potentially, to underpricing. Although 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 just outlined.

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 then construct and rebalance a portfolio accordingly. Ample evidence exists, however, that this approach does not fit the real estate decision-making process in practice. Among the more recent studies on this topic, Neo, Ong, and Tu [2008] pointed to several factors intervening with strictly rational decision making, such as information asymmetry and the use of various decision-making heuristics, such as anchoring, representativeness, and experience/search attributes. In a similar vein, Roberts and Henneberry [2007] found 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, proactive maintenance and facility management, and selectivity of tenant quality and mix. In contrast, an equity portfolio manager has very little, if any, control over assets under management and is thus forced to take a more passive approach to managing them. The downside of this feature of style analysis, however, is 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, such as location and real estate sector. Conner and Liang [2003] identified the categories of operational value-added, physical value-added, and financial value-added. Kaiser [2005] estimated that such value-added activities can surpass the effect of successful asset selection by more than 1,000 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 decided to solve this problem by creating randomly generated portfolios from a dataset of 557 properties that show at least 24 return figures in our 26 sample periods ranging from 1981 to 2007. Thus, we created portfolios composed of 50 properties, which is an average number of properties held by big U.K. 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 forward. Annual data were 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 U.S.$1.2 trillion.

All 557 U.K. properties available for our research are *standing investment* properties according to the definition adopted by IPD. 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 nonmarket factors, such as unusual terms of ownership or major capital expenditures 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 distributions are reported in Exhibit 2. We notice a slightly higher exposure to retail and slightly smaller exposure to office and industrial than in the overall IPD market 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.

For each property, we collected 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 as a percentage of the capital invested (CV_{t-1} plus capital expenditures):

$$TR = \frac{CV_t - CV_t - \text{Capex}_t + \text{Net Income}_t}{CV_{t-1} + \text{Capex}_t}$$

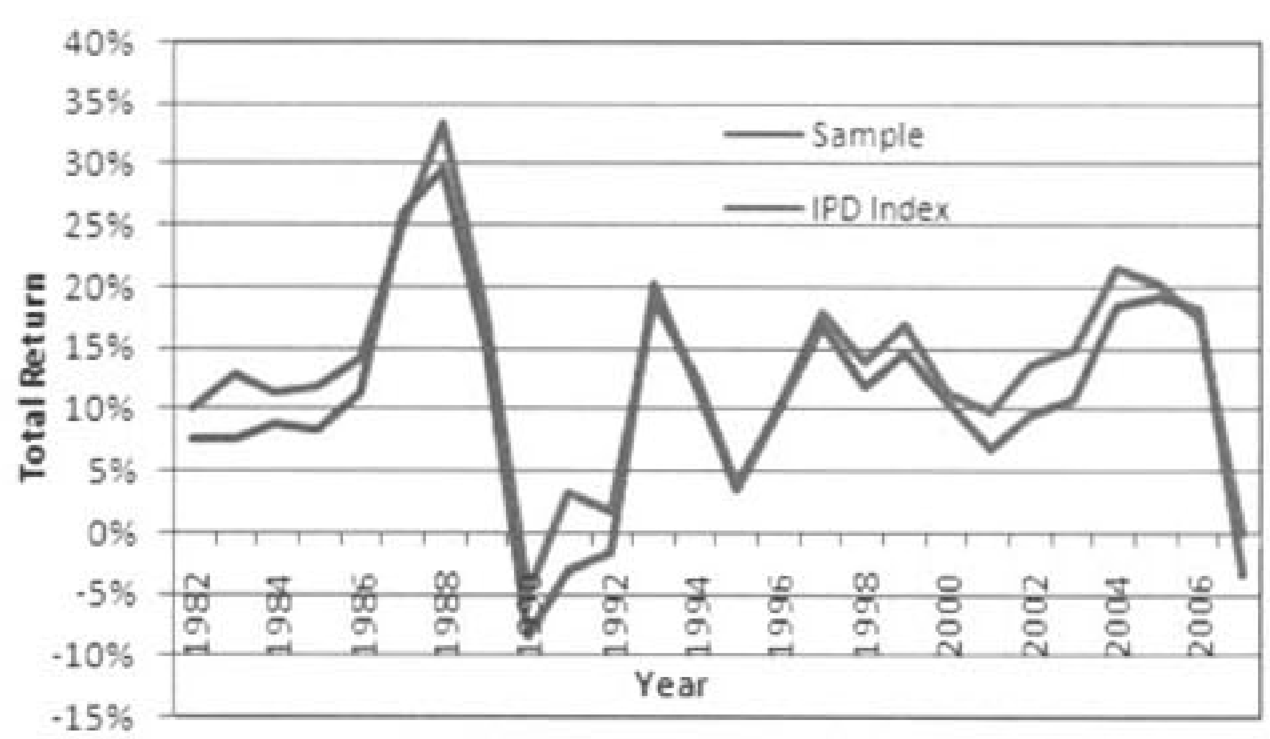
- Equivalent Yield, EY_t, representing a cap rate that considers both the current rent paid by the tenant and the market rent that will be paid at the following rent review. Specifically, IPD computes this metric by equating the capital value as provided by the independent value and the future cash flow of the property, assuming that the current market rent is the new

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



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 in 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 versus 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. First, all observations with an equivalent yield below 2% and above 30% were excluded. Second, observations with annual total returns below –50% and above 50% were excluded. 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 nonmarket forces or were simply data errors. Finally, only office, retail, and industrial properties were considered in our analysis because other property types—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, which measures the performance of the overall market. The two samples for each style factor (e.g., value and growth) were created using the median as a criterion. We also ran indices using the top and bottom quartiles, but differences with the "median" criterion were not statistically significant.

For equity markets, the two style factors that are 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 (*HML*). These property types have a high- and low-cap rate, respectively (see Marcato [2004]). This measure can be compared to a similar measure for value and growth stocks, such as high and low dividend yields, respectively, or low and high price-to-earnings ratios, respectively. The interpretation of real estate value and growth styles is then similar to the one used in the stock market, because properties with a low yield are deemed to provide future growth and properties with a high yield are classified as value because they provide higher immediate income.
- Small and big properties (*SMB*). These property types are identified on the basis of their capital value, just as market capitalization is used in the equity market. In real estate markets, this measure may be considered to show a mixed effect between size and real estate sector (i.e., office, retail, and industrial). In fact, we may find that the split between small and big properties leads to a natural split between property types where some sectors are more represented in either one or the other index. The weights of each sector in our small and big properties indices do not support this belief, however, so we can then argue that the capital value style does not reflect differences in property types.

Furthermore, considering other predominant factors that concern fund managers, we can identify two additional styles of real estate portfolios:

- Concentrated and diversified properties (*CMD*). These property types are classified based on the spread of tenant risk. In general, if the number of tenants is higher, the investment is considered less risky, because the rental cash flow is spread across more tenants. The quality of tenants, based on industry, rating, and so forth, may also be important proxies for risk, but IPD cannot provide quality information about tenants for confidentiality reasons. Consequently, we can only refer numerically to the concentration effect. We also tested the concentration factor using the percentage of the overall rent of a building paid by each tenant. But because most properties with more than three tenants tend to receive more than 60% of the overall building rent from the three largest tenants and the rental value split does not provide a more insightful set of results in our estimation than the number-of-tenants criterion, we decided to use the number of tenants as a proxy for tenancy risk (i.e., diversification).
- Short and long average lease expiry (*SML*). These categories show expected higher and lower risk, respectively. Instead of using the actual average lease length, however, we measured typical lease length prevalent in a given property type. Apart from the desirable effect of averaging out the impact of impending break clauses and lease expirations, this factor was chosen because the tenancy data were only

available for the second part of our sample period, 1998–2007, thus requiring the classification of properties to either a short or long lease expiry for the entire sample period. As a consequence, we obtained two categories of properties that are consistent over time. The composition of these two categories does not reflect any bias to any other factor, including sectors and regions; in other words, no predominant group of properties belongs to another specific style.

DESCRIPTIVE STATISTICS OF INDICES

Main descriptive statistics are reported in Exhibit 3. The average performance and volatility of the U.K. real estate market between 1981 and 2007 was 10.76% and 8.81%, respectively. As reported in previous studies, we also found a downward bias in the risk estimation due to the use of valuations rather than prices in the construction of real estate indices. Because 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. First, small properties tend to yield similar (or 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 to the behavior of appraisers who tend to adjust values only if the change in value is bigger than an artificial threshold that is normally fixed in nominal rather than percentage terms. For example, if appraisers are restrained from changing values unless the difference is at least equal to U.S.$10,000, the threshold represents 1% for a property worth U.S.$1 million and only 0.01% for a property worth U.S.$100 million. Second, despite exhibiting less risk, high-yield properties (i.e., value index) outperform low-yield properties. A possible explanation for this result 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 return and volatility (i.e., slightly higher return and risk for concentrated properties than for diversified ones), but it exhibits a different cyclical behavior, as we will show. Finally, long leases seem to perform much better than short leases, bearing slightly less risk. Although some of these results may seem puzzling in that they contradict commonly accepted notions of risk–reward relationships, these findings are corroborated by similar studies of the U.K. commercial real estate market.

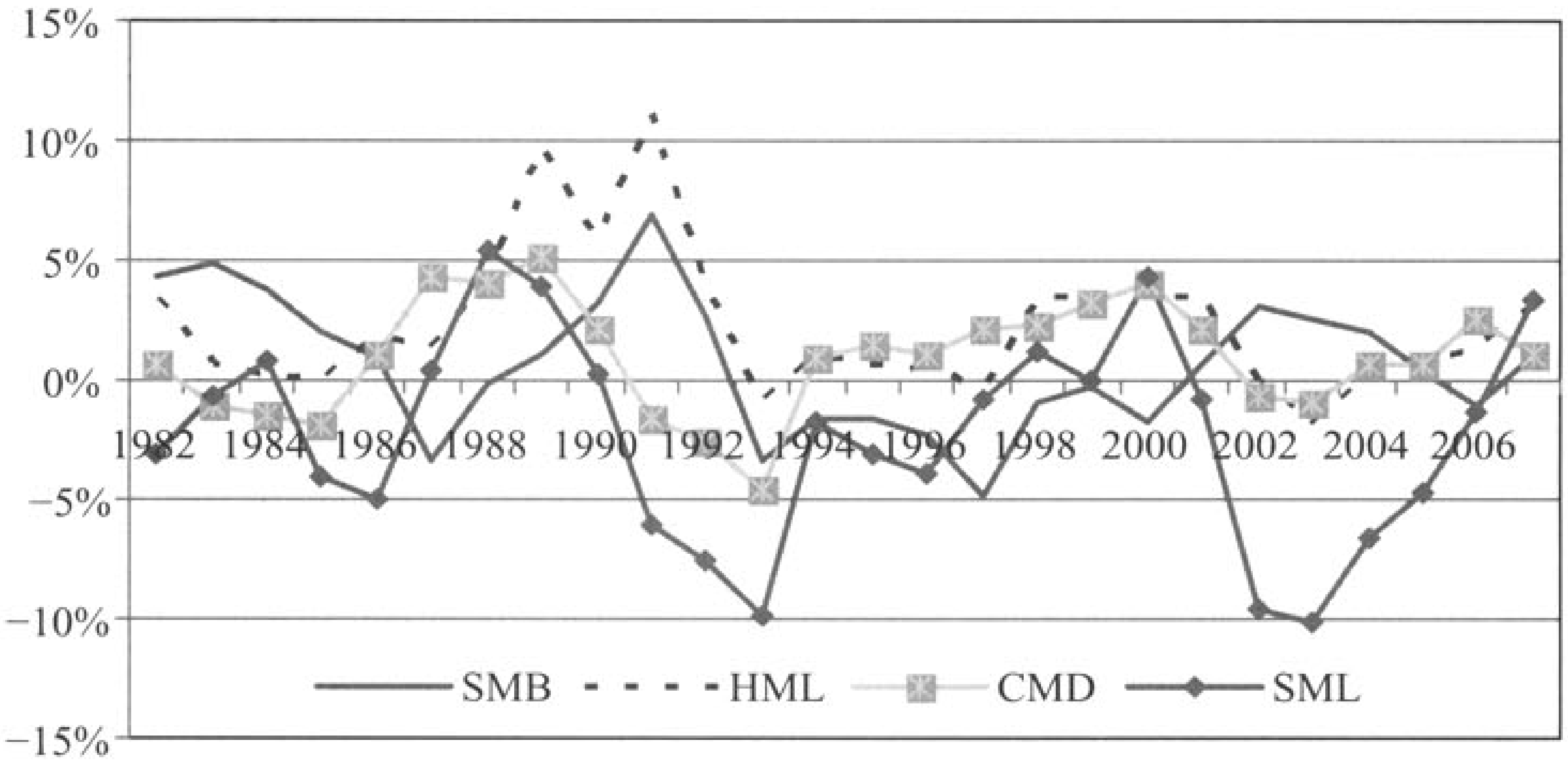
We also report the cyclical behavior of the style factors, which are computed as a difference in performance between small and big properties (*SMB*), high- and low-yield properties (*HML*), concentrated and diversified properties (*CMD*), and short and long lease properties (*SML*). Exhibit 4 represents the four style factors over the two main real estate cycles since the 1980s. Large properties tend to outperform small properties during boom periods and tend to underperform during market downturns. This pattern may be caused by large properties being less liquid than smaller properties because transactions are more complex and the vendor's search process generally takes longer. Consequently, larger properties are at a disadvantage particularly during a downturn when being able to react quickly to changes in market conditions is of particular importance. Contrary to prior expectations, value buildings tend to generally outperform growth properties in the 25-year sample period. However we see a more pronounced overperformance during the last boom–bust cycle of the late 1980s and early 1990s. This may suggest that income-driven buildings perform better in highly volatile markets. And this result is also confirmed with an upward trajectory of the SMB factor during the more recent period. Furthermore, tenancy risk also seems to be significant as properties with a high concentration of tenants (three or less) tend to benefit in rising markets and to suffer in falling markets; in other words, diversification pays during a recession. Finally, the performance of properties with short leases relative to buildings with long

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



leases improves during expansions and tends to worsen during contractions.

EMPIRICAL MODEL

Generally, higher returns are associated with higher risks. Real estate investors have debated extensively, however, their ability to generate alpha performance, a return above the benchmark or market. If markets were efficient, fund managers should not be able to consistently generate an extra return over time.

As stated earlier, we tested the ability of fund managers to generate alphas, controlling for important style and risk characteristics. Rather than focusing on typical real estate investment categories, such as sectors and economic or administrative regions, we modeled four different factors, building on the finance literature and real estate–specific characteristics.

A recent study by Callender et al. [2007] showed that the measure of total risk is reduced when diversification increases and that an efficient market (i.e., enough big property portfolios) should price nondiversifiable (i.e., systematic) risk only. The capital asset pricing model (CAPM) defines the measure of this risk as

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

where $\mathrm{cov}(r_A, r_M)$ and σ_M^2 represent the covariance between our asset and the market return and the variance of market returns, respectively. The CAPM quantifies the relationship between the beta of an asset (either a single asset or a portfolio) and its corresponding expected return and, 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 $[E(r_M) - r_f]$ is the market risk premium, or price of risk.

Because the CAPM predicts the expected return of an asset or a portfolio in relation to its systematic risk and the market return, the 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 that are not included in the systematic risk. In a Fama-French–type model, the two extra factors (*SMB* and *HML*) are computed by taking the difference in performance between a small-property and big-property index and between a growth and value index, respectively. 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 overperformance of small properties and high-yield properties for the two style factors, *SMB* and *HML*, respectively. A negative number in a given period, however, indicates an overperformance of big properties and low-yield properties.

As previously stated and justified, we followed 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 and diversified properties where a concentrated property is defined as having a maximum of three tenants, and the *SML* factor reports the difference between the return of properties with an a short unexpired lease term (9 years or less) and properties with a long lease term (10 years or more).

Using a database of 557 properties, we then randomly generated 1,000 portfolios composed of 50 properties each and ran a series of regressions to estimate the significance of different risk factors, individually or in combination with others. Results using either 40 or 60 properties in each portfolio provided similar results, so we are presenting the estimation results using 50 properties in each portfolio.

We ran several models starting with a market-only model and incorporating an additional risk factor with each step. Model 1 represents the classic single-index model, while Models 2 to 5 represent multifactor models with different risk combinations. The full model (Model 5) includes all risk factors and is used as a term of reference in our discussion of the main results. All other models are only used to either make distinctions or reinforce our findings. The models are as follows:

$$\text{Model 1}: r_p = \alpha + \beta r_{mkt,t} + \varepsilon_t$$

$$\text{Model 2}: r_p = \alpha + \beta r_{mkt,t} + \delta_1 \frac{SMB_t}{\frac{HML_t}{\delta_1 \frac{\delta_1 CMD_t}{\delta_1 SML_t}}} + \varepsilon_t$$

$$\text{Model 3a}: r_p = \alpha + \beta r_{mkt,t} + \delta_1 SMB_t + \delta_2 HML_t + \varepsilon_t$$

$$\text{Model 3b}: r_p = \alpha + \beta r_{mkt,t} + \delta_1 CMD_t + \delta_2 SML_t + \varepsilon_t$$

$$\begin{aligned}\text{Model 4a}: r_p &= \alpha + \beta r_{mkt,t} + \delta_1 SMB_t + \delta_2 HML_t \\ &+ \delta_3 CMD_t + \varepsilon_t\end{aligned}$$

$$\begin{aligned}\text{Model 4b}: r_p &= \alpha + \beta r_{mkt,t} + \delta_1 SMB_t + \delta_2 HML_t \\ &+ \delta_3 SML_t + \varepsilon_t\end{aligned}$$

$$\begin{aligned}\text{Model 5}: r_p &= \alpha + \beta r_{mkt,t} + \delta_1 SMB_t + \delta_2 HML_t \\ &+ \delta_3 CMD_t + \delta_4 SML_t + \varepsilon_t\end{aligned}$$

After obtaining alpha and beta estimates, we modeled these estimates using the actual characteristics of the randomly created portfolios as independent variables in a multifactor model,

$$\text{Model 6}: \alpha_i = \gamma_0 + \sum_{j=1}^{n} \gamma_j \text{Char}_j + \varepsilon_i$$

$$\text{Model 7}: \beta_i = \gamma_0 + \sum_{j=1}^{n} \gamma_j \text{Char}_j + \varepsilon_i$$

where the n actual portfolio characteristics are

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

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

$$\text{Model 8}: \alpha\text{Dummy}_i = \gamma_0 + \sum_{j=1}^{n} \gamma_j \text{Char}_j + \varepsilon_i$$

where the n actual portfolio characteristics are the same ones used in the previous two estimations—for alpha performance and systematic risk—and

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

EMPIRICAL RESULTS

Exhibit 5 shows that the likelihood of fund managers to consistently generate 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 finding reveals that 54% of our randomly generated portfolios (i.e., the difference between the two explained variance proportions) generated alpha performance 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 four styles (Model 5), the systematic risk, or average beta factor, was 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 year as compared to 6% per year found in equity markets using the two Fama–French risk factors. Thus, our model appears to capture most of the variability in portfolio returns because it ranges between 91% and 95%. Moreover, the alpha performance is reduced by half when all four risk factors are included. Thus, we are confident that the four identified styles are important in explaining portfolio returns and the ability of fund managers to over- or underperform the market.

All randomly generated funds were exposed to market risk and a high percentage were exposed to the property-size factor (i.e., between 65% and 74% of our portfolios, depending on the model). The time series revealed that the impact of property size on returns varies with the position in the market cycle, possibly because of the varying availability of the substantial capital required to purchase large properties. In falling markets, banks normally have less money available because it is difficult to raise money in the capital markets. The average significant coefficient is equal to 0.58, however, which shows 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 the coefficient suggests that small properties are considered riskier than big properties, and that portfolios exposed to this style should be priced consistently.

A number of reasons justify why small properties should be considered riskier than big properties. First, large assets tend to have a greater number of tenants so that default risk is spread across more tenants. Second, large companies (typically exchange-traded) tend to prefer large properties that offer large floor plates and custom-tailored space fittings within the same building, and the risk (quality) associated with a big company is lower (higher) than for a small company. Moreover, for some types of properties, such as shopping centers, larger properties tend to be more attractive to high-quality tenants, such as brand-name 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, a 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. They are also preferred by better-quality tenants who are attracted by the opportunity to locate in such premises and, in turn, results in a willingness to pay higher rents.

EXHIBIT 5

Percentage of Significant Coefficients for Style Factors

	Significant Coefficients						
	Market	**SMB**	**HML**	**CMD**	**SML**	**Alpha**	**R-squared**
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

If we move away from the dominant style factor small-minus-big, we also find a number of smaller factors that a relevant for some funds. Particularly, these styles seem to be significant only for a relatively small percentage of all random portfolios, never exceeding 21.2% (as in the case of the value/growth factor in Model 2). Moreover, if we only study the characteristics of portfolios generating significant alpha performance, we see that the likelihood of having a fund exposed to the lease-length risk factor is also relevant in almost 20% of randomly generated portfolios.

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 decrease 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 reaches a value of up to 0.51 and 0.82 from a minimum of –0.57 and –0.99, respectively (i.e., an approximate 1% increase in expected portfolio return for a 1% difference between styles). Because the coefficient is not always positive (even though it is for the *HML* factor of the majority of our randomly generated portfolios), we found mixed evidence of the riskiness of high- versus low-yield properties and tenant-concentrated versus tenant-diversified buildings.

One may argue that low-yield properties signal higher future growth potential compared to high-yield properties. Whether this growth potential would indeed materialize is uncertain, and this uncertainty translates into a higher current risk and a positive *HML* coefficient. But 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 have difficulty realizing a substantial outward movement of cap rates, while properties with high yields may experience larger adjustments under the same market conditions. In fact, we tend to see a further reduction of the yield spread between buildings in rising markets. The *HML* risk factor combined 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 alone also reduces the likelihood of achieving alpha performance by 31.6%, that is, a drop from 97.8% for a model with only systematic risk to 69.2% for the two-factor model.

At the same time, a positive *CMD* factor may reveal the riskiness of buildings with a high concentration of tenants compared 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 more significant number of smaller tenants. Ultimately, this confounding factor could be isolated by using tenant credit ratings in the model, which unfortunately 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.

The *SML* factor shows the price effect of shorter-lease contract risk. In fact, we found a positive coefficient of 0.31, which suggests 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 suggests the perception of higher risk for shorter contracts. Investors may, in fact, face difficulties in renegotiating the contract or in finding a new tenant, which would have consequences on vacancy rates, cash-flow timing, and cash-flow certainty. Combined with systematic risk in a two-factor model, this style is significant for only 8.8% of our portfolios and only marginally reduces their alpha performance.

Exhibit 6 reports the actual characteristics of randomly generated portfolios and shows the percentage of funds exposed to the different risk factors among consistent alpha portfolios. Using 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 tenancy characteristics should be explored and could lead to a further reduction in achievable significant alpha performance. Finally, 30.7% and 24.5% of portfolios that were able to consistently outperform the market showed an exposure to yield and size factors, respectively. Given these characteristics, we have gained a better understanding of what determines the likelihood of achieving alpha, its extent, and the level of systematic risk in property portfolios. Exhibit 7 presents the results of our analysis by estimating Models 6, 7, and 8, using the alpha and beta estimations from Model 5 only.

With respect to alpha performance, we found that the higher the average total return achieved by the portfolio over time, in this case the period 1981–2007, the

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	

higher were both the likelihood and level of alpha performance. This is consistent with expectations because higher returns should reflect a greater ability to generate extra performance. Second, alpha seems to be inversely related to the portfolio's systematic risk because a higher linkage between market and portfolio returns implies less likelihood of achieving performance different from the market; this extra return also tends 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 results for the *HML* factor in Models 1 to 5; that is, we found a wide range of coefficients, 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, because the alpha performance determined in Model 5 was net of the value-versus-growth style. The variability of this exposure, or the standard deviation of the *HML* factor, is also important in explaining the alpha a fund can achieve—the higher the variability, the smaller the extra performance. Moreover, tenant risk is significant and the higher the concentration of tenants and the exposure to short term leases, the smaller both alpha and the probability of achieving it will be. 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 (roughly 2%) and industrial portfolios tend to produce a smaller-than-average alpha (of more than 1%). Regional exposure also increases both the level and likelihood of alpha and can be predictive of the ability to generate extra performance consistently over time.

The adjusted R-squared of our model is 0.34. Although the model explains a satisfactory portion of the variability of the alpha probability, investors may want to consider additional style factors when setting their investment strategies and benchmarking their portfolio returns. Moreover, 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 a higher linkage between the portfolio and the market. This result is consistent with our expectations of higher returns to compensate for higher-risk portfolios. Second, the previous result of an inverse relationship between systematic risk and alpha performance is reinforced by a negative coefficient for alpha that indicates higher extra performance is probably associated with a lower degree of linkage between portfolio and market returns. Furthermore, a greater exposure to any of the styles would also suggest that systematic risk will be reduced because an exposure to risk factors should lead to a deviation from market performance.

An exposure to high-yield properties and to buildings with high tenant concentration decreases the nonspecific risk of a portfolio, and an exposure to low-yield properties and to buildings with a diversified tenant mix increases the nonspecific risk of a portfolio. However, an exposure to short leases tends to increase the systematic risk of a portfolio, because when the average lease length is short rents are updated more frequently to reflect current market conditions. As previously found for the determinants of alpha performance, an exposure to the office sector and to specific regions—in our randomly generated portfolios, the region was typically the London area—translates into a higher systematic risk, because these exposures 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 because they explain 56% of the variability of the systematic risk.

In summary, our results are encouraging as they appear to confirm that a multi-dimensional style analysis yields superior results compared to the commonly used two-factor analysis, and that the additional 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 in distinguishing among investment styles and in explaining risk factors that can be used for benchmarking purposes. Fund managers and property investors may find it useful to work with a radar diagram classification of portfolios and assets that reflects the factors we identified as the essential investment style dimensions in our analysis. Far from having achieved a definite investment style classification for real estate markets, our analysis has revealed that other factors may be important in explaining property returns; thus, we envisage further work with a particular focus on additional tenant characteristics.

CONCLUSIONS AND FURTHER WORK

The sample used in our study consists of 557 properties and randomly generated portfolios measured for their exposure to investment styles. We applied a step-by-step procedure to consider a five-factor model, beginning with a single-index model that only considered market risk. Based on previous findings in the relevant literature, we assumed that equity investment styles are not directly transferable to real estate portfolio management. The four risk factors we identified were found to be useful in explaining real estate portfolio returns, with property size being, by far, the dominant style. Property cap rates were also found to be important. We envisage that additional risk factors linked to the tenancy agreement may be relevant in explaining property performance, along with the factors of the concentration of tenant mix and lease length.

Extensive discussion has been had about the ability of fund managers to achieve extra performance. In our models we have observed that the inclusion of these factors significantly reduces the ability of fund managers achieving extra performance. This result suggests that the ability to generate alpha should be assessed after accounting for these risk factors, because a single-index model as is 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 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.

ENDNOTE

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REFERENCES

Akerlof, G.A. "The Market for 'Lemons': Qualitative Uncertainty and the Market Mechanism." *Quarterly Journal of Economics*, Vol. 84, No. 3 (1970), pp. 488–500.

Amenc, N., D. Sfeir, and L. Martellini. "An Integrated Framework for Style Analysis and Performance Measurement." *Journal of Performance Measurement*, Vol. 7, No. 4 (2002), pp. 35–41.

Brown, S., and W. Goetzmann. "Mutual Fund Style Analysis." *Journal of Financial Economics*, 43 (1997), pp. 373–399.

Byrne, P., and S. Lee. "An Exploration of the Relationship between Size, Diversification, and Risk in U.K. Real Estate Portfolios: 1989–1999." *Journal of Property Research*, Vol. 20, No. 2 (2003), pp. 191–206.

Callender, M., S. Devaney, A. Sheahan, and T. Key. "Risk Reduction and Diversification in U.K. Commercial Property Portfolios." *Journal of Property Research*, Vol. 24, No. 4 (2007), pp. 355-375.

Cannon, S., N.G. Miller, and G.S. Pandher. "Risk and Return in the U.S. Housing Market: A Cross-Sectional Asset-Pricing Approach." *Real Estate Economics*, Vol. 34, No. 4 (2006), pp. 519–552.

Conner, P., and Y. Liang. "Institutional Real Estate Investment: Evolution and Innovation." *Real Estate Finance*, Vol. 20, No. 3 (2003), pp. 2–10.

De Roon, F.A., T.E. Nijman, and J.R. ter Horst. "Evaluating Style Analysis." *Journal of Empirical Finance*, Vol. 11, No. 1 (2004), pp. 29–53.

Dunse, N., C. Leishman, and C. Watkins. "Classifying Office Submarkets." *Journal of Property Investment and Finance*, Vol. 19, No. 3 (2000), pp. 236–250.

Fama, E.F., and J. MacBeth. "Risk, Return, and Equilibrium: Empirical Tests." *Journal of Political Economy*, 81 (1973), pp. 607–636.

Fuerst, F., and G. Marcato. "Testing and Improving Commercial Real Estate Market Segmentations with Cluster Analysis and Neural Network Techniques." Working Paper, School of Real Estate and Planning Working Paper Series, Henley Business School, University of Reading, 2009.

Kaiser, R.W. "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*, Vol. 11, No. 1 (2005), pp. 5–18.

Keim, D.B., and A. Madhavan. "Transaction Costs and Investment Style: An Inter-Exchange Analysis of Institutional Equity Trades." *Journal of Financial Economics*, 3 (1997), pp. 265–292.

Kemp, M., M. Richardson, and C. Wilson. "Investment Manager Style Analysis." Faculty and Institute of Actuaries Investment Conference, 2000.

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

Lee, S. "The Relative Importance of Sectors vs. Regions in Determining Property Returns." PRRES Conference, January 1998.

——. "Style Analysis and Property Fund Performance." *Journal of Property Investment and Finance*, Vol. 17, No. 2 (1999), pp. 145–59.

Lee, S., and S. Devaney. "The Changing Importance of Sector and Regional Factors in Real Estate Returns: 1987–2002." *Journal of Property Research*, Vol. 24, No. 1 (2007), pp. 55–69.

Liang, Y., and W. McIntosh. "REIT Style and Performance." *Journal of Real Estate Portfolio Management*, Vol. 4, No. 1 (1998), pp. 69–78.

Liang, Y., and W. Whitaker. "Style Attributes of Equity REITs." *Journal of Real Estate Finance*, Vol. 17, No. 2 (2000), pp. 31–36.

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

Marcato, G. "Style Analysis in Real Estate Markets and the Construction of Value and Growth Indices." *Journal of Real Estate Portfolio Management*, Vol. 10, No. 3 (2004), pp. 203–215.

Myer, F.C.N., M. Young, and J.R. Webb. "Equity REIT Clusters." Working Paper, Cleveland State University, April 1999.

NCREIF. "Real Estate Investment Styles: Trends from the Catwalk." NCREIF Styles White Paper, November 2003.

Neo, P.H., S.E. Ong, and Y. Tu. "Buyer Exuberance and Price Premium." *Urban Studies*, Vol. 45, No. 2 (2008), pp. 331–345.

Roberts, C., and J. Henneberry. "Exploring Office Investment Decision Making in Different European Contexts." *Journal of Property Investment and Finance*, Vol. 25, No. 3 (2007), pp. 289–305.

Rock, K. "Why New Issues Are Underpriced." *Journal of Financial Economics*, Vol. 15, No. 1/2 (1986), pp. 187–212.

Schnare, A., and R. Struyk. "Segmentation in Urban Housing Markets." *Journal of Urban Economics*, 3 (1976), pp. 146–166.

Sharpe, W.F. "Asset Allocation: Management Style and Performance Measurement." *Journal of Portfolio Management*, Vol. 18, No. 2 (1992), pp. 7–19.