Building and Monitoring an Optimal Real Estate Portfolio

A Case Study

CBRE Investors

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By Nadja Savic, Associate Director and Porntawee Nantamanasikarn, Associate

Abstract

This paper is written from a global property fund management perspective. We develop a tool for a fund manager to build, monitor, and rebalance a real estate portfolio by applying Modern Portfolio Theory and our in-house forecasts of property market performance. This tool has immediate practical use for portfolio managers as it helps identify sales candidates and potential acquisitions that enhance risk-return profile of the portfolio. The tool is intuitive and easy to implement for any fund manager to optimise a portfolio as well as to verify if a portfolio is compatible with a fund's investment objective. We use Monte Carlo Simulation to generate a distribution of forward-looking return (IRR) of an existing portfolio and its individual properties by varying rent and yield assumptions. The distribution allows us to compute expected return as well as risk of the portfolio.

Keywords: Risk Management, Monte Carlo Simulation, Modern Portfolio Theory

Introduction/Background

This paper is written from a global property fund management perspective. Our global research platform is fundamental to investment decision making throughout CBRE Investors. Most specifically, the need to anticipate and translate future market conditions into investment strategy is a critical factor in delivering out-performance whilst minimising risk. At the heart of our research lie forecasts of property market performance. Over the past decade, property has become a more mature asset class, subject to greater use of leverage and more international capital flows. In addition, looking ahead it is likely we will be operating in a volatile economic environment. Accordingly, in the future, we would expect to see shorter and higher amplitude return cycles. Therefore, there is a need for policies and mechanisms in place that will ensure that we can deliver the best return in relation to the risk undertaken.

In order to increase our competitive advantage we are implementing a more robust risk management policy, which will help us reduce unpredictable costs, make informed decisions, negotiate debt with banks and strengthen client relationships. This paper is part of a larger project to establish a more rigorous risk management practice in real estate investment *at the portfolio level*. Many investment managers diligently assess the property risk return characteristics at the time of the purchase. However, much less time is dedicated to evaluate how each property contributes to the risk of the portfolio and the management house as a whole.

This paper is a case study, where we use the existing real estate portfolios data. We outline the practical challenges of the implementation of risk management process to a real estate portfolio and propose a tool that is suitable for use in managing risk of a real estate portfolio.

Aim

Our prime aim in this paper is to develop a tool for a fund manager to build, monitor, and rebalance a real estate portfolio by applying Modern Portfolio Theory and our in-house forecasts of property market performance. This tool will help optimize the portfolio by identifying sales candidates and potential acquisitions that enhance risk-return profile of the portfolio.

We aim to build the tool that is flexible enough to be used by various investment initiatives with different investment horizons (close-ended and open-ended funds as well as segregated accounts and joint ventures). Moreover, the tool must be flexible enough to allow users to specify various inputs including leasing structures that vary across countries. This means that the tool must be applicable to any portfolio, including properties across Europe and rest of the world.

Numerous academic studies have been carried out on hypothetical real estate portfolios. Most employ mean-variance optimization approaches to determine an optimal allocation to each sector/segment, based on investors' varying return requirements and risk tolerance. Instead, we carry out our study at a property level because we want to develop a tool that has immediate practical use for fund managers. In reality and in real estate in particular, each asset is unique, with its own location, building characteristics, size, tenants, lease terms, etc. The interaction between these variables at the asset-specific level is a key determinant of risk and return.

This study was performed on an actual commercial real estate portfolio, with a total value of £57 million. The total number of properties in the portfolio, at the time of implementation was 22, comprising 90 units, all located in the UK. As of March 2010, the baseline five-year go-forward internal rates of return (IRR) of the individual properties in the portfolio range from -16.5% to 26.4% and the expected aggregate portfolio IRR is 9.5%.

Modern Portfolio Theory

Studies on how to quantify risk started in 1952, when Harry M. Markowitz associated risk with the variance in the value of the portfolio. Markowitz introduced two important concepts:

- The effect of diversification
- Risk/return trade-off on the portfolio as a whole

The theory of the effect of diversification is that, when the number of assets held in a portfolio increases, the variance of the portfolio decreases and approaches average covariance of all pairs of assets in the portfolio. If assets are all uncorrelated from each other, the portfolio variance will approach zero. Markowitz derived the first portfolio optimization method. He proposed the portfolio's mean (expected) and variance of return as criteria for portfolio selection based on investors' preference. Academia has provided the investment community with a rich set of theories following Markowitz's portfolio selection theory. Merton (2003) and Campbell and Viceira (2002) provided important extensions of the Markowitz theory in their writings:

- Investment contexts require the consideration of multiple horizons rather than a single horizon.
- Prospective future cash flows typically offer a more useful perspective for assessing the reward and risk of long-horizon investment strategies than do future wealth prospects.
- Long-horizon prospects for investment returns have time-variant, predictive components. Therefore, strategic asset allocation should always be a dynamic rather than a static process.

One of the key assumptions of Markowitz's portfolio selection theory is that asset returns are normally distributed so that mean and variance provide a complete characterization of the distribution. However, in reality most asset returns are not normally distributed. Thus the Gaussian (normal) distribution when used in a standard mean-variance optimization might understate portfolio risk due to higher moments (skewness and kurtosis).

Modern Portfolio Theory and Real Estate Investment

The mean-variance optimization theory has been widely applied in traditional asset classes of stocks and bonds. The application of the theory to real estate portfolios poses some major challenges. First, the theory's key assumptions of an efficient market and zero transaction costs are much more likely to be violated in real estate investments. Unlike stocks and bonds, buildings do not trade on public exchanges or in markets where brokers/dealers stand ready to trade on their bid/ask quotes. Real estate transactions are private, marketed through an exclusive broker, which hinders the transmission of information in the market through publicly available prices and transaction volumes. Therefore, the real time pricing information is not available for the real estate investors to arbitrage away unexploited opportunities. Real estate is also much more illiquid than stocks and bonds – due diligence is much more costly and can take months to complete.

Second, real estate is different from stocks and bonds because investors can actively manage each individual asset. As a shareholder of a stock, investors can't change the way company does business unless they are major shareholders. Fixed income investors can do nothing to affect coupon payments of a bond. But property investors can improve buildings, actively look for or work on retaining tenants, negotiate rents and incentives, etc. These actions can improve cash flows, and thus enhance value/return and mitigate risks.

Third, due to infrequent valuations, heterogeneity and low transparency of the direct property market, there is less data for the property markets available in comparison to stocks and bonds. In most of the world including much of continental Europe, the real estate data series are very short. Optimization processes built on expected time-weighted returns that rely on short-term data series are not suitable for real estate, because short time series compromise the stability of the expected returns and covariance matrices. Such issues are referred to as estimation errors. These deficiencies in the optimization methodology can provide statistically incorrect outputs.

As a result of these differences between real estate and other asset classes, investors primarily hold real estate on a long-term basis, usually five years or more, with a relatively clear exit strategy. Longer holding periods allow investors to actively manage properties to enhance value as well as avoid high transaction costs associated with frequent trading. The long, pre-specified investment horizon means that real estate investors are more concerned about the risk of not achieving target returns by the exit date (shortfall risk), rather than the risk as usually defined by monthly or annual volatility (i.e., standard deviation) of asset values before the exit date.

We deal with the challenges of applying the theory in practice. We incorporate the three extensions to Markowitz's portfolio selection theory mentioned in the previous section to our risk management tool. The tool can be applied to both long and short time investment horizons. Risk-reward assessment is made on prospective future cash flows, which are fundamental for real estate investments. This tool can be used at any time to test our portfolios as a part of a dynamic asset allocation process. Furthermore, it is forward-looking, where optimization is performed on expected cash-flows/IRRs.

Methodology

We measure the shortfall risk by varying the two key determinants of real estate investment return – rent growth and exit yield. We conduct a Monte Carlo Simulation, which is akin to a sensitivity analysis. The advantage of this approach is that it does not require an assumption that returns are normally distributed. We vary rent growth and yield assumptions to generate a distribution of returns (IRRs) across a large number of scenarios. The distribution of IRRs at both the individual property and portfolio levels allow us to compute a measure of risk, which could be a standard deviation or other measures that emphasize downside risks such as the probability of negative IRR or a VaR (Value at Risk).

This approach is practical and beneficial to a fund manager since it allows us to ask questions at the portfolio level, such as:

- Is return/risk of a specific property lower or higher than its peers in the portfolio?
- How does a specific property contribute to risk/return profile of the entire portfolio? Supposing we were to sell or buy that property, we can simulate the risk/return profile of the new portfolio. A lower return and/or higher risk of a specific property does not necessarily mean that it does not belong to the portfolio. It may be a good diversifier for the portfolio overall if it is negatively or weakly correlated with other properties.
- Should we use more or less leverage for a specific property? Again, this depends on the correlation of returns between that property and portfolio overall. If the correlation is negative or low, this would allow more leverage since it actually helps reduce volatility of the entire portfolio.

We apply the Monte Carlo simulation for portfolio optimization purposes. The Monte Carlo Algorithm works based on the Law of Large Numbers. It says that if you generate large number of samples, eventually you will get the approximate desired distribution. The simulations are performed in the statistical package Eviews.

In order to generate probability distributions of each property's IRR, first a set of 1,000 scenarios was generated of: deviation of market rent growth from baseline and deviation of yields from baseline. These input scenarios are at market level – "City Office", "West-End Office", "South East Industrial", "Rest of UK Standard Retail", etc. These scenarios are linked to an IRR model, which takes into account asset-specific features such as number of tenants, lease expiry schedule, capital expenditures, leverage level, etc. The output is a distribution of the asset's IRR based on those 1,000 scenarios.

We used a VAR (Vector Auto-regression) model to generate market forecasts. The model is built up with 3 variables at annual frequency: rental value change, yield, and inflation over the period 1980-2009. Inflation enters the model as exogenous variable and is specified as AR(1) model, which is an autoregressive process of order 1, in which the inflation rate depends on the previous year's inflation rate, as following:

$\mathrm{Dlog}(RPI_t) = \alpha + \beta * \mathrm{Dlog}(RPI_{t-1})$,

where RPI stands for the retail price index. For rents and yields, we let the model determine significant variables and lag length. The lag length is determined by the information criteria (AIC, SC, FPE, LR)[1], which give the same answer about the lag length in most cases.

[1] Akaike Information Criterion (AIC), Schwarz Criterion (SC), Final Prediction Error (FPE) criterion, and Log-Likelihood Ratio (LR) criterion.

Rental value change depends on the previous years' change in rental values, as following:

$$\mathrm{Dlog}(R_t) = \alpha + \beta * \mathrm{Dlog}(R_{t-1}) + \ldots \gamma * \mathrm{Dlog}(R_{t-n}),$$

where R denotes nominal rental value. Change in yields is determined by its own lags, the change in real rent, and the previous year's inflation rate, as shown in the following equation:

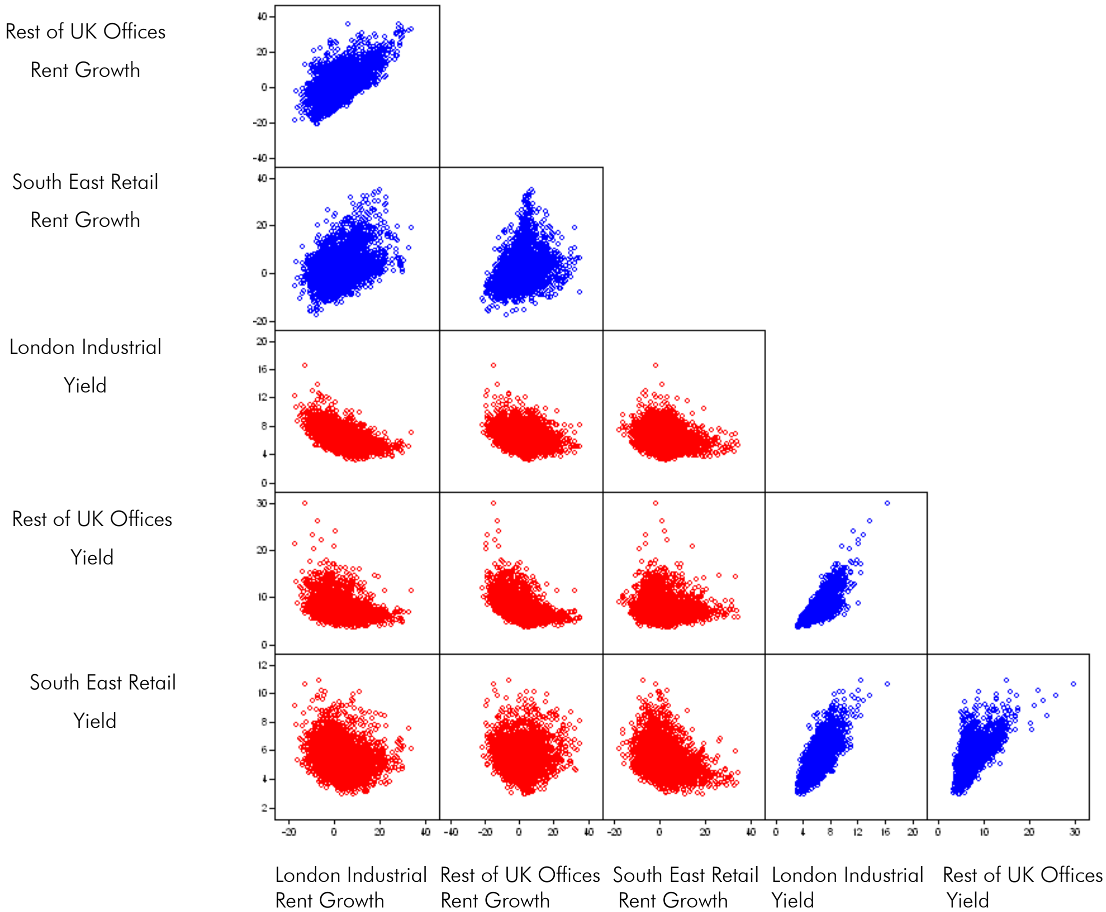
$$\mathrm{Dlog}(Y_t) = \alpha + \beta * \mathrm{Dlog}(Y_{t-1}) + \ldots \gamma * \mathrm{Dlog}(Y_{t-n}) + \delta * \mathrm{Dlog}(R_t/RPI_t) + \partial * \mathrm{Dlog}(RPI_{t-1}),$$

where Y denotes yield. The model consists of 23 stochastic equations (1 for inflation, 2 for rent and yield for each of the 11 segments). The choice to use yield and rental data is supported by the fact that the yield and rental value data is available for much longer time periods in the Continental Europe and rest of the world than total returns data. The procedure and the model are appropriate for any country-sector in the world where reliable rent and yield data are available. The regression results are shown in Appendix I.

Rent and yield scenarios are generated by solving the model forward stochastically, using a bootstrap method. This method has a number of advantages, as follows:

1. The risk and return are forward looking since the rent and yield inputs are actual forecasts.
2. IRR calculations take into account asset-specific characteristics.
3. It is important to note that these forecasts are at market levels. It is possible to adjust our baseline (mean) rent and yield forecasts to reflect asset-specific characteristics that could result in deviations from market levels. The key value added of the VAR model is the set of scenarios that provide information about how rent and yields (and thus IRR) could deviate from the baseline forecast.
4. Since the residual terms are chosen ("re-sampled" in the bootstrap) from a pool of actual historical errors, we are not making any restrictive assumption about the distribution of the error terms, such as normality. "Rare" events are as likely to happen as they actually did historically.
5. Since error terms for rent and yield for each scenario are drawn from the same set of years in the bootstrap, the (negative) correlation between rent and yield is preserved (see Exhibit 1).
6. Since error terms for each market are drawn from the same set of years in the bootstrap, the (positive) correlation of rent and yield between markets is preserved (see Exhibit 1).

Exhibit 1: Correlations of Rent Growth and Yield Scenarios



Note: This chart shows correlations for three selected IPD segments (Industrial London, Office Rest of UK, and Standard Retail South East). The three blue boxes in the upper left corner show positive correlations between rent growth across sectors. The three blue boxes in the lower right corner show positive correlations between yields across sectors. The nine red boxes show negative correlations between rent growth and yields both across (off-diagonal) and within (diagonal) sectors.

The method makes some key assumptions:

1. Since the baseline rent growth and yield forecasts for each property are adjusted from the market-level forecasts to reflect property-specific characteristics, we are assuming that the adjusted forecasts are unbiased and independent. That is, forecasts are correct on average (unbiased) and a too optimistic forecast does not tend to be followed by another too optimistic forecast (independent, errors are not serially correlated). If the adjusted baseline forecasts are biased and serially correlated, the resulting distribution of IRR will either overstate or underestimate actual risk.

2. We are only varying two key inputs that determine IRR. There are other factors that affect IRR – the lease renewal probability being among the most important. To the extent that this and other key inputs do not vary, risk is understated especially for single-tenant building. Allowing lease renewal to be random is a logical next step.

A property contributes positively to the risk-adjusted return of a portfolio if it increases the Sharpe Ratio of the portfolio. The Sharpe Ratio is a measure of excess return over a risk-free return generated per unit of risk (a ratio of the excess return for an asset to the standard deviation of that asset). A specific property is identified as a "hold" candidate if the following condition holds:

$$\left(\frac{R_i - RF}{\sigma_i}\right) \geq \left(\frac{R_p - RF}{\sigma_i}\right) corr(R_i, R_p),$$

where R_i and σ_i denote expected return and standard deviation of property *i*, respectively. R_p and σ_p denote expected return and standard deviation of the portfolio, respectively. RF is the risk-free rate. If the sign is reversed, the property is identified as a "sell" candidate. This equation compares the Sharpe Ratio of the property with that of the portfolio, adjusted for the correlation between property and portfolio's returns. The threshold Sharpe Ratio is raised if the property is highly correlated with the portfolio, while the threshold is lowered if the correlation is low.

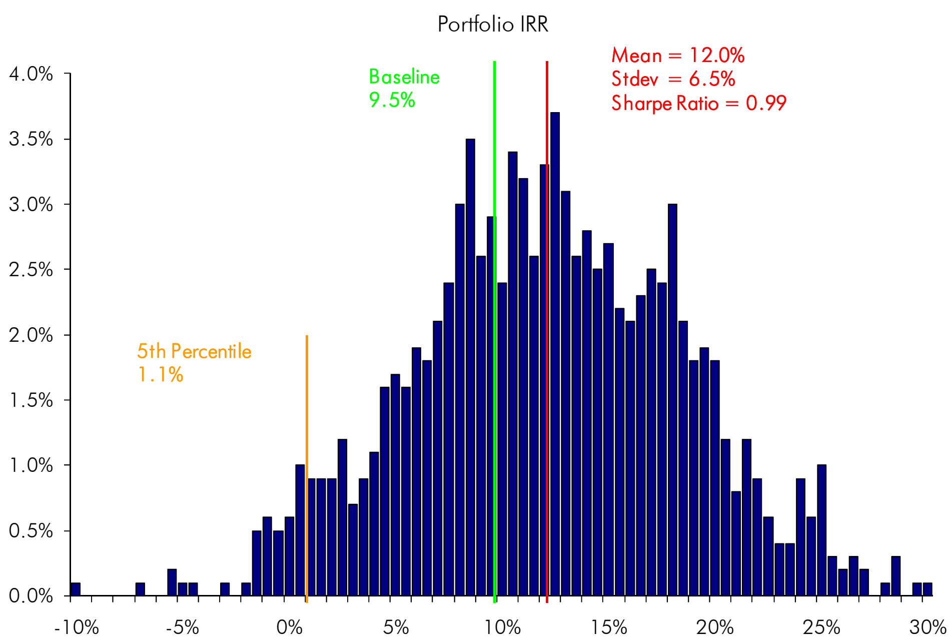
We use the Economist Intelligence Unit's average forecast over the next 5 years of the 10 year government bond rates as a proxy for the risk free rate. The Sharpe Ratio is calculated using the mean and standard deviation of the 1,000 scenario IRRs generated by Monte Carlo simulation.

Results and Applications

The resulting probability distribution of portfolio's IRR created by rent and yield scenarios for the property segments is shown in the Exhibit 2. The distribution is not normal, with kurtosis (fat tails) appearing on both sides, indicating that in the case of extreme events it is likely that the portfolio will either perform worse or better than suggested by the normal distribution. At a 95% confidence level we can say that portfolio does not generate a lower return than 1.1% and the return does not fall below 3.9% at a 90% confidence level.

The distribution is also skewed, as evidenced by the difference between the baseline IRR and mean IRR. The sensitivity of yield and rental value suggest that there is upside potential to the return from the baseline IRR. The baseline portfolio IRR was calculated to 9.5% by a valuation software whereas the mean value of the portfolio IRR, generated by the scenarios is 12.0%. The standard deviation that indicates the concentration of the IRRs around the mean value is 6.5%, meaning that around 70% of all the possible IRR outcomes are in the range from 5.5% to 18.5%. The portfolio's Sharpe Ratio is 0.99, signifying that the excess return per unit of risk is close to 1. A portfolio manager should aspire to increase this ratio as much as possible by new acquisitions and selective sales of the properties from the portfolio.

Exhibit 2: Probability Distribution of Portfolio's IRRs



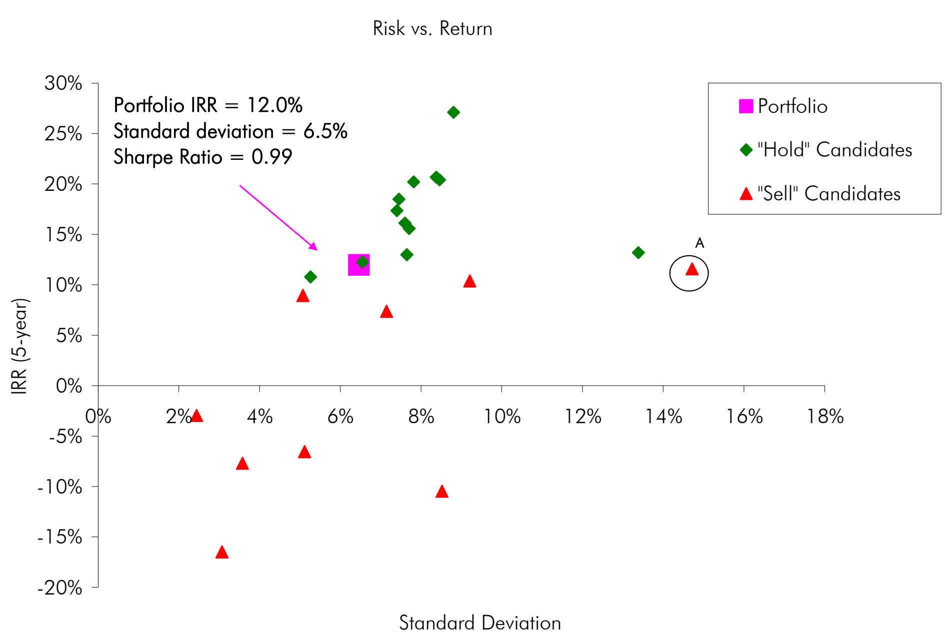
Individual properties' IRR distributions are shown in Appendix II. Several properties IRRs, in particular number 3,4,10,15,16 and 20, show signs of a fat right-tail distribution (skewness>0, excess kurtosis>0). This means that the probability or fraction of very high IRRs occurring is higher than if the distribution were normally distributed. Moreover, we identify 12 properties that have positive IRRs at a 95% confidence level and 13 properties at a 90% confidence level. There is only one property for which the entire distribution of the IRRs is always positive, even in the case of extreme adverse happenings. This is a single let industrial building located in South West England, with a very long lease (expiring in 2031). It is let well under current and forecast market rent, thus a solid uplift in rents is expected at the rent review in 2011.

Subsequently, the correlation of IRR between each individual property and the portfolio is computed. The scatter plots are shown in Appendix III. Whereas the mean correlations are all positive and range from 0.56 to 0.87, as demonstrated by the table in the Appendix IV, many of the property scenario IRRs are negative, meaning that it is possible that these move in opposite direction from the overall portfolio.

Furthermore, high dispersion in property risk return profiles is revealed, with Sharpe Ratios ranging from -7.19 (generated by a combination of the mean IRR of -16.5% and standard deviation of 3.1%) for the property no. 20 to 2.44 (mean IRR 27.10% and standard deviation of 8.81%) for the property no.15 (see table in Appendix IV for complete results).

As mentioned earlier, by maximizing the Sharpe Ratio we identify the sale and hold candidates. Exhibit 3 shows the hold-sell analysis result. If we are aiming to acquire a property the same approach can be used to identify "buy" candidates. Of the 22 properties, we identified 13 properties as "hold" candidates, shown as green diamonds, and 9 as "sell" candidates, shown as red triangles in the exhibit. An interesting case is the property labeled A in the mentioned exhibit. This property has comparable mean IRR as the portfolio (13.2% vs. 12.0%) but has a much higher standard deviation (13.4% vs. 6.5%). Yet this property is still identified as a hold candidate because it has a low correlation with the portfolio (0.56).

Exhibit 3: Risk and Return Profile



Note: "Hold" and "Sell" candidates are identified by comparing portfolio's and individual properties' Sharpe Ratios, adjusted for correlation.

Conclusions

Real estate investors are more concerned about the risk of not achieving the return by the exit date (shortfall risk) rather than the volatility of property returns. In this study, we developed a tool to measure this shortfall risk. We used Monte Carlo Simulation to vary the key determinants of real estate return: rent growth and yield. The resulting distribution of IRRs at both portfolio and individual property levels allow us to compute a measure of risk that does not depend on the assumption of returns being normal distributed.

Applying the method to an actual portfolio, we find that the IRR distributions at both property and portfolio level have characteristics of skewness and kurtosis, proving once again that the normality assumption doesn't hold, signifying that models relying on this assumption will give erroneous results.

We find out that the probability of negative IRR for the portfolio is less than 5% and that at a 90% confidence level we can say that portfolio will not generate a return lower than 3.85%. Moreover, the portfolio IRR generated considering the sensitivity of yield and rental values is higher than the IRR computed by the valuation software, suggesting that there is upside potential to the return from the baseline IRR.

Taking into account all asset-specific characteristics, this approach generated a significant number of sale candidates: 9 out of the 22 properties in the portfolio. Very interestingly, there is one property that has return comparable to the portfolio return but has a much higher risk (standard deviation). Yet this property is identified as a hold candidate because it as a low correlation with the portfolio as a whole.

The time has come to integrate the powerful insights offered by theoretical framework, numerical risk management tools and qualitative judgment into a holistic, comprehensive theory of real estate investing. This tool developed in this paper can be used as part of the new holistic risk management process.

Plans for Further Work

We only vary two key inputs that determine IRRs, although we recognize that there are other factors that affect IRRs. The lease renewal probability and tenant covenant strength are some of the most important factors to be incorporated. To the extent that these and other key inputs are not considered in our approach, risk may be understated especially for single-tenant buildings.

The portfolio on which this analysis has been performed doesn't have any gearing. However, the model should be appropriate even for a portfolio that has leverage. A natural step would be to test it on a leveraged portfolio.

Our approach ignores transaction costs such as sales commissions, management fees and stamp duties if the portfolio managers decide to sell properties *now* based on our hold/sell recommendation. Therefore it may be appropriate to hold rather than sell properties that have lower correlation-adjusted Sharpe Ratios than the portfolio average. Transaction costs could be incorporated into future models.

Rent and yield scenarios can be generated for the rest of the world where funds are invested. The same model can be extended to gauge the risk for the management house as a whole.

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Appendix I

Results of Inflation Regression

	DLOG(RPI)
DLOG(RPI(-1))	0.450
	(3.52)
C	0.019
	(3.17)
Adj. R-squared	0.297

Note: Sample period = 1980-2009, *t*-statistics in parentheses.

Results of Rent Growth Regressions

	Industrial London	Industrial Rest of UK	Industrial South East	Office London City	Office Rest of UK	Office South East	Office London West End	Retail Warehouse	Shopping Center	Standard Retail Rest of UK	Standard Retail South East
DLOG(R(-1))	1.300	1.254	1.366	1.057	1.216	1.300	1.185	0.648	1.423	1.398	1.390
	(8.72)	(7.56)	(9.66)	(5.89)	(6.67)	(8.88)	(7.50)	(3.29)	(7.45)	(6.57)	(8.62)
DLOG(R(-2))	-0.700	-0.647	-0.752	-0.539	-0.581	-0.751	-0.714	-	-0.664	-0.612	-0.689
	(-4.69)	(-3.88)	(-5.32)	(-2.99)	(-3.18)	(-5.16)	(-4.48)	-	(-3.42)	(-2.91)	(-4.30)
C	0.012	0.009	0.010	0.003	0.010	0.006	0.014	0.015	0.008	0.006	0.011
	(1.60)	(1.32)	(1.44)	(0.15)	(1.07)	(0.64)	(0.78)	(1.17)	(1.04)	(0.69)	(1.49)
Adj. R-squared	0.761	0.705	0.798	0.569	0.658	0.756	0.678	0.267	0.741	0.688	0.778

Note: Sample period = 1980-2009, *t*-statistics in parentheses.

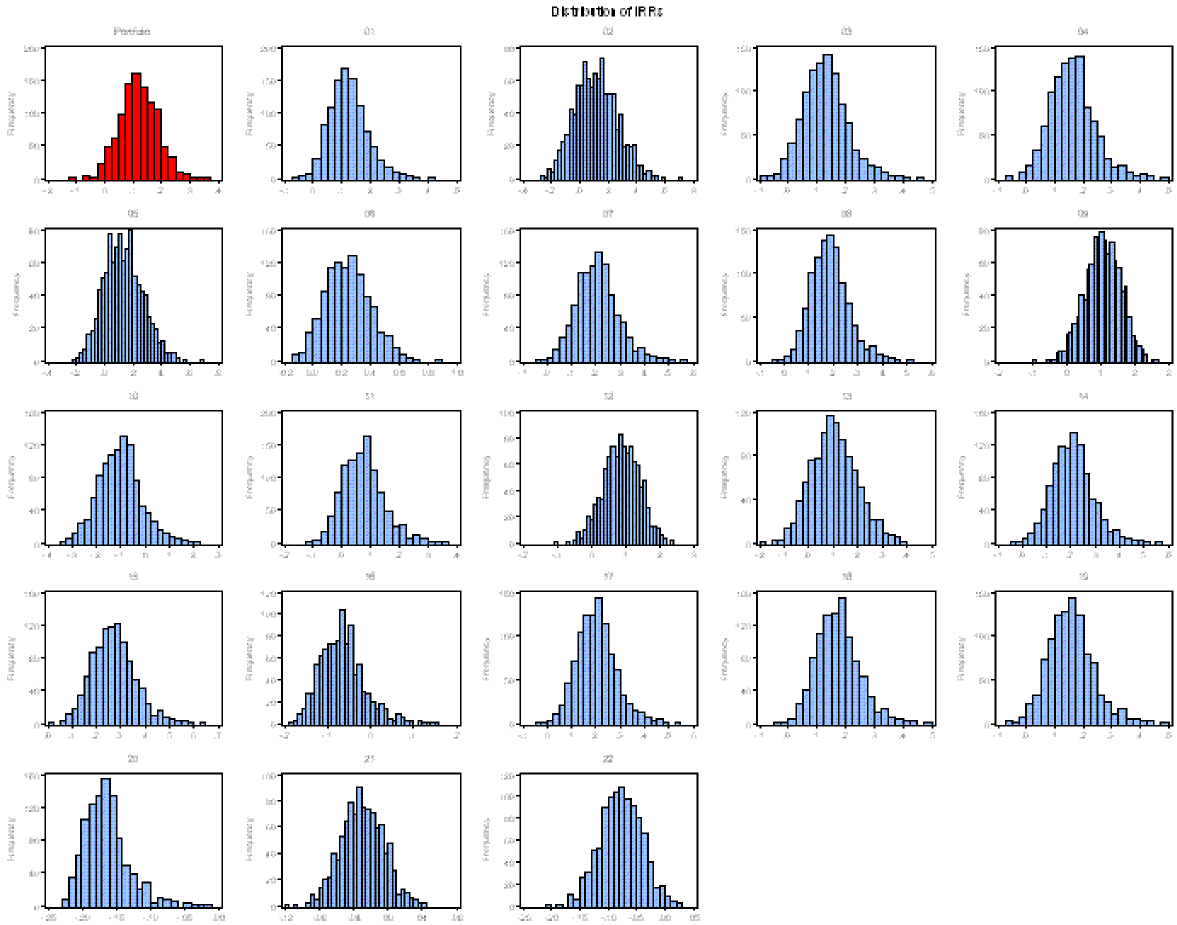
Results of Yield Change Regressions

	Industrial London	Industrial Rest of UK	Industrial South East	Office London City	Office Rest of UK	Office South East	Office London West End	Retail Warehouse	Shopping Center	Standard Retail Rest of UK	Standard Retail South East
DLOG(Y_IL(-1))	0.203	0.155	0.205	0.055	0.264	0.354	-0.199	0.060	0.326	0.411	0.360
	(1.14)	(0.70)	(1.05)	(0.27)	(1.37)	(1.78)	(-0.90)	(0.29)	(1.55)	(1.96)	(1.90)
DLOG(Y_IL(-2))	-0.479	-0.234	-0.415	-0.548	-0.399	-0.478	-0.272	-0.358	-0.433	-0.524	-0.508
	(-2.61)	(-0.95)	(-1.95)	(-3.17)	(-1.94)	(-2.21)	(-1.37)	(-1.51)	(-2.10)	(-2.56)	(-2.77)
	-	-0.301	-	-	-	-	-0.294	-0.382	-	-	-
	-	(-1.26)	-	-	-	-	(-1.67)	(-1.55)	-	-	-
C	-0.104	-0.078	-0.094	-0.159	-0.103	-0.098	-0.124	-0.083	-0.079	-0.079	-0.093
	(-3.15)	(-1.80)	(-2.37)	(-3.89)	(-2.48)	(-2.36)	(-3.35)	(-1.86)	(-2.27)	(-2.45)	(-2.95)
DLOG(R_IL/RPI,1)	-0.678	-0.688	-0.644	-0.462	-0.711	-0.342	-0.779	-1.074	-0.549	-0.373	-0.440
	(-2.55)	(-1.47)	(-2.02)	(-2.61)	(-2.03)	(-1.23)	(-3.88)	(-1.88)	(-1.41)	(-0.90)	(-1.55)
DLOG(RPI(-1),1)	2.550	1.645	2.320	4.056	2.887	2.703	3.075	2.188	2.519	2.350	2.695
	(3.14)	(1.53)	(2.37)	(4.01)	(2.74)	(2.69)	(3.29)	(2.06)	(2.78)	(2.86)	(3.42)
Adj. R-squared	0.487	0.284	0.351	0.579	0.425	0.368	0.712	0.406	0.410	0.442	0.536

Note: Sample period = 1980-2009, *t*-statistics in parentheses.

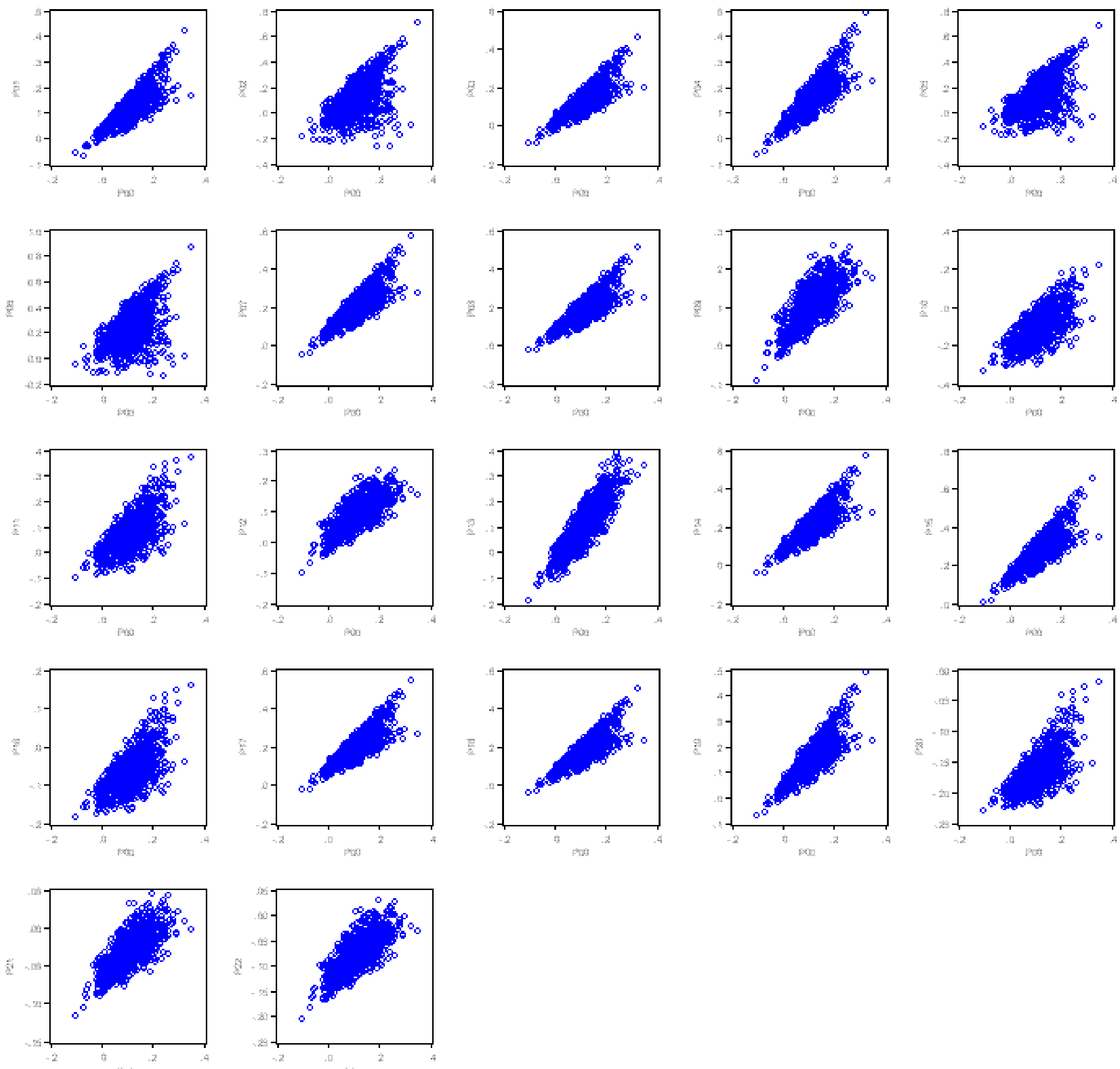
Appendix II

Probability Distribution of Portfolio's and Individual Properties' IRRs



Appendix III

Correlations between Portfolio's and Individual Properties' IRRs



Appendix IV Recommendation based on Property Sharpe Ratio

	P01	P02	P03	P04	P05	P06	P07	P08	P09	P10	P11	P12	P13	P14	P15	P16	P17	P18	P19	P20	P21	P22
(1) Property Sharpe Ratio	1.02	0.41	0.97	1.38	0.57	1.20	1.75	1.73	0.98	-1.89	0.25	0.66	0.52	1.80	2.44	-2.38	1.87	1.59	1.29	-7.19	-3.51	-3.72
(2) Property IRR Correlation with the portfolio IRR	0.84	0.57	0.85	0.85	0.56	0.56	0.85	0.85	0.74	0.66	0.66	0.74	0.87	0.85	0.85	0.66	0.85	0.85	0.85	0.65	0.72	0.73
(3) (Portfolio Sharp Ratio = 0.99) x (Correlation between Property IRR and Portfolio IRR)	0.83	0.56	0.84	0.84	0.55	0.55	0.84	0.84	0.73	0.65	0.65	0.73	0.86	0.84	0.84	0.65	0.84	0.84	0.84	0.64	0.71	0.72
Recommendation ["hold" if (1)>=(3), "sell" if (1)<3)]	hold	sell	hold	hold	hold	hold	hold	hold	hold	sell	sell	sell	sell	hold	hold	sell	hold	hold	hold	sell	sell	sell