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Performance drivers of UK unlisted property funds

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Abstract

An unlisted property fund is a private investment vehicle which aims to provide direct property total returns and may also employ financial leverage which will accentuate performance. They have become a far more prevalent institutional property investment conduit since the early 2000's. Investors have been primarily attracted to them due to the ease of executing a property exposure, both domestically and internationally, and for their diversification benefits given the capital intensive nature of constructing a well diversified commercial property investment portfolio. However, despite their greater prominence there has been little academic research conducted on the performance and risks of unlisted property fund investments. This can be attributed to a paucity of available data and limited time series where it exists. In this study we have made use of a unique dataset of institutional UK unlisted non-listed property funds over the period 2003Q4 to 2011Q4, using a panel modelling framework in order to determine the key factors which impact on fund performance. The sample provided a rich set of unlisted property fund factors including market exposures, direct property characteristics and the level of financial leverage employed. The findings from the panel regression analysis show that a small number of variables are able to account for the performance of unlisted property funds. These variables should be considered by investors when assessing the risk and return of these vehicles. The impact of financial leverage upon the performance of these vehicles through the recent global financial crisis and subsequent UK commercial property market downturn was also studied. The findings indicate a significant asymmetric effect of employing debt finance within unlisted property funds.

I. Introduction

Commercial property as an asset class has seen strong, and growing, investor interest over the last twenty years. This is due to investors being attracted to both the diversification benefits which commercial property is thought to bring to multi-asset portfolios and to the relatively high income return. However, commercial property assets are heterogeneous, and, a typical barrier to direct investment for investors is property's relatively illiquid and 'lumpy' nature. As a consequence, constructing holdings of well diversified direct property portfolios is much more difficult than that for more traditional asset classes, such as equities and bonds, and requires significant amounts of capital.

By way of example, Callender et al (2007) found that large commercial property portfolios were required to track the market. Indeed, to reduce tracking error to 2% they found that some 60 assets were required, which would cost in the region of £800 million. If a 1% tracking error was required then a portfolio in excess of 250 assets was needed at a cost of over £3 billion. Baum (2007) shows that these results can vary by property market segment and reports that retail warehouses and Central London office sectors in the UK require the largest capital outlays. The outlay required to construct these portfolios would be in the region of £1 billion and £1.2 billion respectively, resulting in a tracking error of 2% for these segments. The significant tracking errors can largely be accounted for by the fact that many commercial property portfolios are poorly diversified and carry substantial levels of unsystematic risk, Brown and Matysiak (2000).

Clearly this level of investment is only available to the largest institutional investors. To facilitate investor access to sufficiently diversified property portfolios there are a number of indirect property investment conduits. Examples of these include unlisted property funds, listed property securities (REITs) and debt instruments such as commercial mortgage backed securities (CMBS). Hoesli and Lekander (2005), for example, argue that non-listed funds have the desirable feature of being highly correlated with the underlying property market, thereby providing a means to gain exposure to the direct property market. The corollary of this is that, compared to other property investment vehicles, unlisted property funds potentially offer the diversification benefits of investing directly in commercial property, unlike the other property investment vehicles.

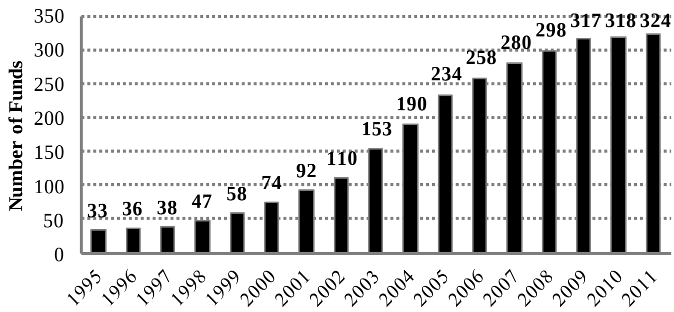
II. Unlisted Property Funds

The Association of Real Estate Funds (AREF) defines unlisted property funds as follows:

"A property fund is a collective investment scheme with a portfolio comprising mainly of direct property but may also include other property related interests. Property funds take a number of different legal structures depending on their domicile and target customer."

An unlisted property fund is a private investment vehicle which aims to provide direct property total returns, and may also employ financial leverage in order to accentuate the underlying performance. Within the fund structure, investors pool capital so as to create a larger supply of capital than could be achieved individually. This enables access to a wider selection, and exposure, to potential property investments than would otherwise have been possible. Furthermore, because of the scale effect this can result in more diversified portfolios than individual funds would be able to achieve. The scope of this study is to investigate the UK institutional unlisted fund universe, which has seen strong domestic and foreign investor interest due to its transparency and accessibility. Indeed, the UK unlisted property fund universe has seen substantial growth over the past decade as Figure 1 shows:

Figure 1: Estimated size of UK unlisted property funds universe



Source: Property Funds Research

Unlisted property funds exist in a variety of formats. Funds which have a well diversified market exposure across both property type and geography are known as balanced funds and those which are more focussed are known as specialist funds. These can vary by risk profile and the industry has adopted the core, value-added and opportunity fund style classifications to help investors assess their characteristics. Core funds generally entail the lowest risk and opportunity funds the most risk. The factors used to determine style include the level of financial leverage and the nature of property investment activity being undertaken, such as development activity, which entails higher risk.

For funds launched prior to 2011 INREV, a membership body for unlisted property funds in Europe, provided classification criteria for the three styles. For example funds would be classified as core if they targeted a return of up to 11.5% per annum, provided stable income returns and had a maximum permitted loan-to-value ratio of 60%. Opportunity funds would a total return objective in excess of 18.5% which would be driven primarily by capital growth, and have a maximum permitted loan-to-value ratio in excess of 70%. INREV (2012) recently reviewed these criteria and for funds launched after 2011introduced the following classification rules:

Table 1: INREV fund classification criteria

	Core ≤ 40% LTV	Core ≥ 40% LTV	Value Added	Opportunity
Total % of non-income producing investments	≤ 15%		> 15% - ≤ 40%	> 40%
Total % of (re)development exposure	≤ 5%		> 5% - ≤ 25%	> 25%
% of total return derived from income	≥ 60%			
Maximum LTV	≤ 40%	Core > 40%	> 40% - ≤ 60%	> 60%

Source: INREV (2012)

Another distinguishing feature of a fund is its lifespan, with funds being either an open-ended or closed-ended fund. Open-ended funds are perpetual vehicles and can raise capital as and when investor demand dictates. Units in open ended funds are issued and cancelled in response to investor demand, and importantly investors have the right, subject to predetermined redemption procedures, to redeem their holding. In order to protect the interests of ongoing investors, redemptions requiring the sale of properties in adverse market conditions may be subject to deferral. As such, this liquidity activity may have an impact upon the performance delivered by open-ended property funds. In contrast closed-ended funds are created with a fixed number of units /shares and have a finite life with a set maturity date, commonly from six to seven years and up to twelve years.

The purpose of this study is to identify which direct property portfolio and unlisted fund 'structure' characteristics best explain the performance of unlisted property funds. To do this we make use of a unique dataset covering a large sample of the UK unlisted property fund universe. This dataset has significant depth in terms of the direct property characteristics as well as performance and financial structure. A panel framework is employed which makes best use of the available data and enables us to perform empirical analysis over both cross-sections and time.

The rest of the paper is organised as follows. First, we review the literature relating to both the risk and return drivers of direct and unlisted property fund performance. We next describe the panel dataset and undertake panel unit root testing prior to performing the econometric analysis. This is then followed by an overview of the panel regression methodology and a discussion of the main results. Finally, we make concluding observations and suggestions for further research.

III. Previous Studies

Concepts

The original finance theory used to explain the returns on securities and/or portfolios is rooted in the classical Capital Asset Pricing Model (CAPM) devised by Sharpe (1964) and Linter (1965). The early empirical counterpart that has been widely employed is the single index/market model. This specifies that the excess return of an investment above an appropriate risk free return can be attributed to its sensitivity to a relevant market or benchmark return. This was then extended to multifactor models, which can be regarded as an empirical counterpart of the arbitrage pricing theory first put forward by Ross (1976). A variety of explanatory factors could be employed in multifactor models such as market related factors, macroeconomic, fundamental, technical and statistical. The widespread use of multifactor models for assessing the risks and returns on common stocks and equity portfolios started with the seminal work of Fama and French (1992, 1993), which introduced fundamental factors into multifactor models in finance.

Property Market Applications

Baum and Farrelly (2009) outline a framework which indentifies three key sources of risk and return in unlisted property funds, namely market, stock and financial structure. Market risk emanates from the market segments to which the portfolio is exposed. Stock risk refers to property specific risk and reflects the characteristics of individual properties owned within each market. These include: building quality, development activity, vacancy, lease length and type/credit quality of tenants. Financial structure risk reflects the risks within the fund structure itself. The amount of leverage employed is viewed as a key factor given it incremental risk (see for example Gordon and Tse (2003) and DeFrancesco (2007)) and another potential factor is liquidity if the fund has an open-ended structure.

Studies which have applied arbitrage pricing theory based approaches to direct property performance include Ling and Naranjo (1997) who assess the determinants of private property market returns. Macroeconomic variables that were significant included real per capita consumption, real government bond yields, the term structure and unexpected inflation. Liow (2004) assesses the time varying impact of macroeconomic variables, such as industrial output and unexpected inflation, upon Singaporean prices. Liow finds that the volatilities of the macroeconomic factors are significant predictors for the expected risk premia. De Wit and van Dijk (2003) investigate the impact of a number of market variables upon global direct office property performance and find GDP growth, unemployment rate changes, inflation and market vacancy rates have the most significant impact. Tomperi (2009) shows that vintage year i.e. fund launch year, was a significant determinant of unlisted property fund performance, highlighting the impact of market conditions upon fund performance.

Turning to property specific factors, Ziering and McIntosh (1999) investigate the relationship between property size and performance. Their results show that the largest size category of property, whilst providing investors with the highest average return, also exhibits the highest level of volatility. The study also showed that there is a significant difference in risk-adjusted returns between property asset size categories.

Blundell et al (2005) were the first to holistically identify the sources of risk and return in commercial property portfolios in their cross-sectional study of UK institutional property funds. The authors distinguished between factors which are relevant at the stock level (fundamental factors) and those which only impact at the overall portfolio risk level. This work was updated by Blundell et al (2011) and finds a number of factors which had a significant impact upon portfolio performance and risk (measured by dispersion from market returns). These included measures such as average asset size, property type and geographic exposure and average lease length. Cyclical factors included development, tenant credit strength and the portfolio vacancy rate.

Pai and Geltner (2007) used US property level data to create property specific factors, analogous to the classic Fama and French (1993) factors. Property specific factors included; size which was the return differential between large and small property assets; the performance differential between Tier I and Tier III located assets; income which was estimated using the return differential between relatively low and high yielding assets. Both the size and location factors were significant, although the coefficient signs were not consistent with a-priori expectations. Fuerst and Marcato (2009) conduct a similar analysis for the UK. They construct two additional property specific factors: the return differential between assets with short and long lease lengths and concentrated and diversified properties, defined by the number of tenants. The authors find that all factors were able to explain property portfolio returns. Size was found to be the dominant factor, followed by income.

Direct property investment returns themselves differ significantly from those of other asset classes due to the fact that they rely upon valuations, rather than transactions prices, to measure performance on a periodic basis. Owing to this, property values are said to be ‘smoothed’ i.e. there is the presence of significant serial correlation in the returns. This causes the reported return dispersion to be dampened and thus understate the true underlying volatility in property returns. This is an issue comprehensively studied in the property investment literature (for example Geltner et al (2003)). Thus, the presence of serial correlation needs to be considered when estimating risk and employing (multi)factor models. De Wit and van Dijk (2003) found lagged returns to be significant in their study of global office market total returns.

A small number of studies have assessed the impact of financial leverage upon property investment performance. De Franceso (2007) explored the relationship between financial leverage and risk, and, found that leverage did not improve risk adjusted returns. The analysis also incorporated the relationships between property returns and interest rates, and this was found to have a significant impact on the additional risk arising from leverage. Simulation based studies by Gordon and Tse (2003) and Hoorenman and van der Spek (2011) show that when financial leverage increases, downside risk measures such as value-at-risk, increase disproportionately. Blundell et al (2011) showed in their empirical analysis of private UK property portfolios that leverage amplified the falls in commercial property values seen during 2007 and 2008. They also concluded that funds employing financial leverage ratios beyond 40% saw their risk soar, which is consistent with the findings of Gordon and Tse (2003) and Hoorenman and van der Spek (2011). Blundell et al (2011) conclude that leverage significantly alters the returns delivered and 'masks' the impact of other fundamental factors.

Two studies investigate the relationship between unlisted property fund liquidity and the performance of open-end property funds. Lee (2000) examines UK unlisted property fund data and found that by using Granger causality tests, that there was no causal relationship between funds flows and returns. In their study of UK pooled property funds, Marcato and Tira (2010) employ a panel-VAR approach to deal with the likely simultaneity between liquidity and performance. Fund performance was shown to have performance persistence, which influenced by the level of financial leverage. Both GDP and the impact of stock market performance were also found to have strongly significant relationship. The authors found evidence of liquidity influenced fund performance when the absolute flow of money was used as a measure.

The most closely related study to the present study is the Fuerst and Matysiak (2013) panel study of European unlisted property funds. The authors found that lagged performance was an important factor. In addition, direct market exposure total returns, the level of financial leverage and distribution yield were all statistically significant drivers of performance. Fund characteristics such as fund size, investment style and macroeconomic variables were also important. In the Blundell et al (2011) sub-sample study of UK unlisted property funds, the level of financial leverage employed was found to be significant in amplifying risk. Interestingly it was also shown to mask the impact certain direct property return factors. Both of these studies emphasise the need to evaluate the combined direct property and fund structure characteristics of unlisted property funds, which is the objective of this study.

IV. The Dataset

This study makes use of the Investment Property Databank (IPD) UK Funds Vision dataset, as well as additional data provided by CBRE Global Multi Manager. The dataset covers a large sample of the UK institutional unlisted property funds universe. It includes funds which follow a diversified strategy i.e. seek to provide a broad market exposure and invest across all property types and geography, and specialist funds which focus on a particular market segment. The holdings also vary in terms of their fund structure in that a number of funds have an open-ended structure and as such have a perpetual life, and other funds are closed-ended and as such have fixed lives.

The dataset is unique in that there is a depth of information on both the fund structure, such as the level of financial leverage employed, as well as the characteristics of the underlying direct property portfolio including market exposures and property asset characteristics such as income yields and void rates. Following an assessment of the dataset we have chosen to only analyse the variables for which there was a sufficiently large number of observations. The description of the variables used is shown in Table 2.

Fund performance has been expressed in absolute terms, and is calculated by IPD using the following formula:

$$TR_{it} = \frac{(NAV_{it} + XD_{it} - CI_{it} + RD_{it}) - NAV_{it-1}}{NAV_{it-1}} \tag{1}$$

Where NAV is net asset value, XD is distributed dividends, CI are capital contributions and RD are fund redemptions. It should also be noted that as private investments, fund total returns are estimated by the independent valuations received by the funds on an interim basis (typically monthly or quarterly). These total returns are net of all management fees and fund administration costs.

A central tenet of financial theory and, indeed, a practical expectation, is that a positive relationship exists between ‘risk’ and return. Thus we expect funds with inherently higher risk characteristics, ceteris paribus, to deliver higher returns. The expected relationship between the available variables being analyzed and fund performance is shown in the final column of Table 2. A-priori variables pertaining to higher direct asset specific risk such as the vacancy rate and tenant concentration should be positively related to risk and return. The impact of the initial yield variables is uncertain. Arguably lower yielding assets could be viewed as being riskier as they may reflect growth assets or, conversely, a lower yield may reflect a lower risk premium which is being attached to the assets. The risk arising from the use of financial leverage is expected to lead to higher fund returns over the long-term and we expect funds to perform positively with the markets to which they have exposure.

Table 2: Variable descriptions

Variable	Variable Description	Expected Relationship with Fund Returns
Quarterly Fund Total Return (%)	Quarterly fund total return	
Market Exposure Total Return (%)	IPD quarterly market total returns weighted by fund's market exposure based on IPD PAS* market segmentation	Positive
Market Exposure Concentration	IPD PAS* market segmentation exposure Herfindahl Index	Positive
Net Initial Yield (%)	Passing rent net of ground rent, as a percentage of the gross capital value	Uncertain
Net Initial Yield Less Time Period Average (%)	Fund net initial yield less periodic market average initial yield	Uncertain
Number of Property Assets	Number of property assets with the fund's property portfolio	Negative
Gross Asset Value (GAV) of Property Assets	Current market valuation of property assets	Negative
Reversionary Potential	Ratio of hypothetical rent payable if the entire portfolio were fully leased at market rent levels	Positive
Reversionary Potential of Passing Rent	Ratio of hypothetical rent payable if portfolio's current passing rent reverted to market rent levels	Positive
Standing Asset Void Rate (% Market Rental Value)	% of portfolio rental value which is vacant	Positive
Total Void Rate (% Market Rental Value)	% of portfolio rental value either vacant or currently in development	Positive
% Leases With Term Greater Than 10 Years	% passing rent from leases with remaining lease term of 10 years or more	Negative
% Leases With Term Less Than 5 Years	% passing rent from leases with remaining lease term of less than 5 years	Positive
% Income from Top 10 Tenants	% passing rent paid by largest 10 tenants	Positive
Debt as a % Property Assets (Loan To Value Ratio)	Total borrowings as a % of property GAV	Positive
Debt Less Cash as a % Property Assets (Net Loan To Value)	Total net borrowings (i.e. total borrowings less cash holdings) as a % of property GAV	Positive

*See Appendix 1

The IPD Property Fund Vision data is provided on a quarterly basis and runs from the fourth quarter of 2004 to the present. This study makes use of data up to the fourth quarter of 2011. This dataset has been extended back to the fourth quarter of 2003 using data provided by CBRE Global Multi Manager. IPD collect the data on individual funds through a standardised questionnaire which is completed by the respective fund manager. IPD have collated these from December 2004 but the CBRE Global Multi Manager Team holds a number of these completed questionnaires from the fourth quarter of 2003 which have not been collated by IPD. Thus we have been able to use these to extend the sample time series provided by IPD.

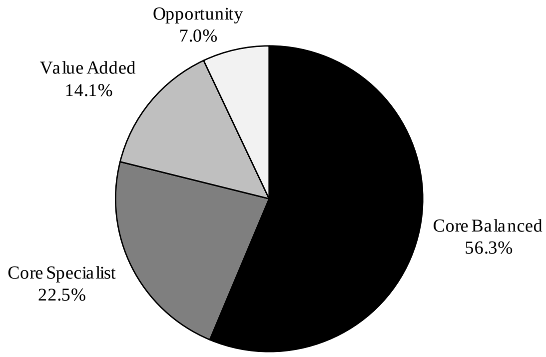
The final dataset is an unbalanced panel with quarterly frequency between the fourth quarter of 2003 and the fourth quarter of 2011. The number of cross-sections available at the start is 32 individual funds and there is a maximum of 75 individual funds in any given time period. A large proportion of the sample are open-ended funds and would be considered as having a low risk profile i.e. having well diversified portfolios comprised of income producing assets with limited risk property activity such as development, and relatively low levels of financial leverage. There is also a mix of balanced and sector specialist property funds. To illustrate the profile of the sample dataset, we have classified the funds in the fourth quarter of 2011 using the INREV style classification criteria and identify core, balanced and specialist funds. This is shown below in Figure 2. All funds in the dataset were launched prior to 2011 and thus the classification shown in Table 1 does not apply.

We have omitted fund cross-sections for which there was less than one year of available data. In addition a number of the property portfolio characteristics variables data points are missing.

The distribution of the Gross Asset Value of funds by 'style', as at the end of 2011, is summarised in Figure 2.

Figure 2: Distribution of fund values by style classification

(end 2011)

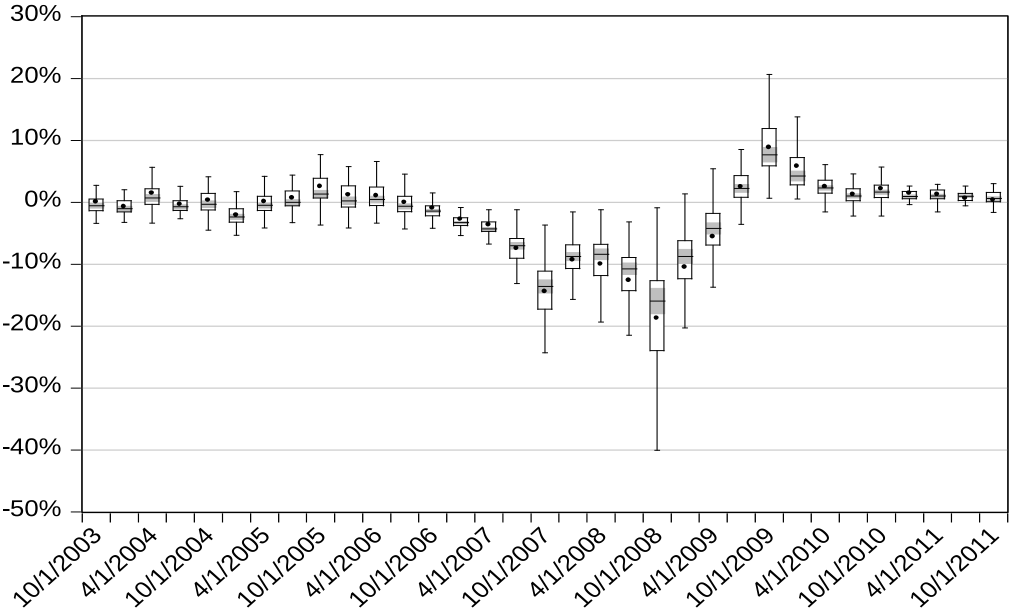


Source: Authors' calculations

It is seen that over 40 per cent of the funds are represented by the riskier categories, Core Specialist, Value Added and Opportunity funds.

There are 2,146 quarterly total return observations available, though given the absence of direct property portfolio data for some quarters, this falls to 1,600-1,700 available observations for panel regression analysis. The sample covers the period of the global financial crisis which was a period of unparalleled market volatility across all asset classes. UK commercial property values were significantly impacted over this period and the performance of leveraged property funds was particularly pronounced. This can be seen in the box plot in Figure 3 which shows the sample return distribution in each quarterly time period and clearly shows the more pronounced range in delivered fund returns during the period of the crisis.

Figure 3: Box plot of funds total quarterly returns 2003-2011



Source: Authors' calculations, CBRE Global Multi Manager, IPD

This panel dataset provides an ideal structure for exploring the drivers of property fund performance. By widening the available data we can capture heteroscedasticity both across time and individual cross-sections, and in doing so capture greater variability of the data. This greater variability in data helps mitigates multicollinearity, which as Baltagi (2001) notes, often plagues time series analysis. With less collinearity and additional degrees of freedom, panel regression analysis can produce more reliable parameter estimates than those produced by time series analysis. This is particularly pertinent for this study, where there is limited property fund performance time series data available, making any time series based analysis inefficient. Panel regression analysis also allows us to control for the impact of two potentially omitted variable biases. The first arising from unobserved individual time constant cross-section effects and the second from an unobserved time trend component in the dependent variable, which impacts all individual cross-sections.

In Table 3 we have provided descriptive statistics on the variables used in the regression analysis, as well as the number of available observations. On closer inspection of the fund total returns, we noted that there were significant outliers in the data. These outliers may arise for numerous reasons, such as when a fund undergoes major restructuring, temporary accounting and/or unusual valuation effects which should be excluded from an analysis of the wider market. To remove the impact of outliers we opted to reduce the sample size by 1% by excluding 0.5% from the lower and upper tails of the returns distribution. The result of this adjustment is shown in Table 3 and it can be seen that both the mean and median are left largely unchanged with a much lower range and standard deviation. The much higher kurtosis of the unadjusted sample data also illustrates the fact that the sample variance was being significantly impacted by the extreme outliers.

Table 3: Dataset variables summary statistics

Variable	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
Quarterly Fund Total Return (%)	0.80%	2.31%	184.00%	-85.94%	9.72%	2.77	83.12
Quarterly Fund Total Return (%) - Reduced Sample	0.79%	2.31%	24.24%	-38.78%	7.10%	-1.51	7.65
Market Exposure Total Return (%)	-1.23%	-2.52%	15.64%	-14.84%	4.85%	-1.03	4.16
Market Concentration	38.96%	16.91%	100.00%	1.48%	38.21%	0.65	1.75
Net Initial Yield (%)	5.88%	5.82%	13.78%	1.58%	1.25%	0.27	3.78
Net Initial Yield Less Time Period Average (%)	0.03%	0.06%	7.27%	-3.87%	0.92%	-0.27	5.94
Number of Property Assets	48.78	34.00	397.00	1.00	56.20	3.29	17.05
Gross Asset Value	624.92	448.51	3,446.35	1.20	602.58	1.86	6.84
Reversionary Potential	0.87	0.88	1.31	0.34	0.10	-1.23	6.91
Reversionary Potential of Passing Rent	0.93	0.94	1.27	0.46	0.06	-2.01	11.52
Total Void Rate (% Market Rental Value)	8.30%	6.79%	100.00%	0.00%	7.95%	4.46	41.80
% Leases With Term Greater Than 10 Years	37.12%	34.30%	100.00%	-9.10%	22.17%	0.73	3.41
% Leases With Term Less Than 5 Years	35.23%	33.24%	100.00%	0.00%	22.52%	0.56	3.16
% Income from Top 10 Tenants	39.16%	36.80%	100.00%	8.80%	17.44%	0.82	3.60
Loan To Value Ratio	19.48%	7.40%	100.00%	0.00%	23.74%	1.00	2.80
Net Loan To Value Ratio	12.70%	4.15%	97.89%	-200.83%	27.75%	0.22	4.23

V. Panel Unit Root Testing

Before moving onto performing panel regression analysis we conduct panel unit root testing to establish whether or not the variables in the dataset are stationary. Panel unit root tests are joint tests of stationarity across cross-sections and are viewed as being more powerful than unit root tests based upon individual time series. As the panel dataset used in this study is unbalanced, only tests which account for this dataset characteristic could be used. We have employed the Fisher-type tests as proposed by Maddala and Wu (1999) and Choi (2001), and the Pesaran (2003) [1] test which accounts for the potential presence of cross section dependence.

The Fisher-type tests are based upon a combination of the unit root tests for each individual cross-section. A unit root test is performed on each panel series separately and the test statistics (p-values) are combined to obtain an overall test of whether the panel series contains a unit root. The results shown in Table 4 for the Fisher-type tests are the three of the test statistics proposed by Choi (2001). The three methods differ in whether they use the inverse Chi-Sq distribution, inverse normal or inverse logit transformation of p-values. A limitation of these tests is that they are constructed under the assumption that the individual cross-sections are independently distributed, which is not always the case. To overcome this

[1] All panel unit root testing and regression analysis has been conducted in Stata 12.Pescadf command in STATA

potential issue we have employed the test proposed by Pesaran (2003). This can be viewed as being similar to the Im, Pesaran and Shin (2003) test, as it is based on the mean of individual Dickey-Fuller test statistics of each cross section. To eliminate the cross section dependence, the standard Dickey-Fuller regressions are augmented with the cross section averages of lagged levels and first-differences of the individual series.

Table 4:Panel unit root tests results

Variable	Fisher-Type Panel Unit Root Tests			Pesaran Panel Unit Root Test
	Inverse Chi-Sq	Inverse normal	Inverse Logit	
Quarterly Fund Total Return (%)	281.82	-6.44	-6.01	-14.42
	0.00	0.00	0.00	0.00
Market Exposure Total Return (%)	291.24	-6.91	-6.75	-6.55
	0.00	0.00	0.00	0.00
Market Concentration	367.93	-4.97	-7.77	-0.73
	0.00	0.00	0.00	0.23
Net Initial Yield (%)	144.28	-0.55	-0.24	-1.16
	0.62	0.29	0.41	0.12
Net Initial Yield Less Time Period Average (%)	600.92	-10.76	-16.31	-9.54
	0.00	0.00	0.00	0.00
Number of Property Assets	121.41	2.46	2.74	6.63
	0.98	0.99	1.00	1.00
Gross Asset Value	135.88	0.67	0.71	6.39
	0.90	0.75	0.76	1.00
Reversionary Potential	203.46	-1.35	-1.87	-2.18
	0.00	0.09	0.03	0.02
Reversionary Potential of Passing Rent	532.81	-9.78	-14.44	-6.74
	0.00	0.00	0.00	0.00
Total Void Rate (% Market Rental Value)	265.61	-4.62	-5.06	-2.09
	0.00	0.00	0.00	0.02
% Leases With Term Greater Than 10 Years	334.91	-4.45	-7.01	-0.71
	0.00	0.00	0.00	0.24
% Leases With Term Less Than 5 Years	164.58	0.56	0.83	3.13
	0.27	0.71	0.80	0.99
% Income from Top 10 Tenants	242.89	-1.81	-2.73	-0.73
	0.00	0.04	0.00	0.23
Loan To Value Ratio	286.70	-4.38	-6.19	4.81
	0.000	0.000	0.000	1.000
Net Loan To Value Ratio	304.58	-6.30	-6.57	-2.59
	0.000	0.000	0.000	0.01

Table 4 shows of the results obtained from running all four panel unit root tests on the variables. Most tests point to the variables under consideration as being variance stationary. Exceptions were for the portfolio size and number of assets variables, which were found to be integrated of order one, as was the net initial yield. The relative initial yield variable was found to be stationary and this can be considered as reflecting fund style and is analogous to the 'value/growth' style labels attached to listed equity managers. For a measure of fund financial leverage we decided to use the net leverage measure in the panel regression analysis for two reasons. Firstly we believe that it provides a more complete measure of financial leverage in funds as it includes cash held on the balance sheet and secondly the Pesaran (2003) test suggested that the gross leverage ratio was non-stationary. The tests also provided strong evidence that the percentage of leases with remaining terms of less than five years was integrated of order one and as result we adopted the ten year lease term measure instead.

VI. Panel Modelling Methodology

In undertaking panel regression analysis one could employ pooled ordinary least squares, fixed effects or random effects regressions. Fixed effects regressions are used when one wishes to control for omitted variables whose impact will differ between cross-sections. If one believed that there are omitted variables which may have the same constant impact, but vary randomly between cross section observations, such as investment styles, a random effects model would be preferable. To test which model best suited the panel dataset under consideration in this study the Hausman test was employed.

Following testing using the Hausman test which assesses the validity of either employing fixed or random effects models, we were guided to the fixed effects regression model. This is consistent with the results of Fuerst and Matysiak (2013) who also apply fixed effects regressions in their study of European unlisted property funds following the same test procedure. The results of these tests are shown in Tables 5 and 6. This was an attractive result and reflects the heterogeneity of the funds in the sample well.

When compared to the pooled OLS estimator the fixed effects specification accounts for the unobserved individual time constant effects by using a within transformation. The inclusion of time dummy variables removes the common trend component from the regression errors. Incorporating both of these effects results in what is known as the two way error component model which is specified as follows:

$$Y_{it} = \alpha + X_{i,t}\beta + \gamma_i + \delta_t + \varepsilon_{it} \tag{2}$$

Where X_{it} is a vector of strictly exogenous explanatory variables, γ_i is an unobservable individual cross section effect, δ_t is an unobservable time effect, and ε_{it} is an unobserved white-noise disturbance term. This is the specification of the regression employed in this study.

As noted earlier, it has been shown in the literature that property total returns exhibit serial correlation owing to the inherent smoothing in valuation based performance. As a consequence we expect past performance to have explanatory power and thus needs to be included in the regression analysis. This is achieved by employing a dynamic regression specification:

$$Y_{it} = \alpha + \pi Y_{it-j} + \beta X_{i,t} + \gamma_i + \delta_t + \varepsilon_{it} \tag{3}$$

Due to the inclusion of a lagged dependent variable in this specification the strict exogeneity assumption of the regressors is violated. The strict exogenieity assumption of the fixed effects estimator is as follows:

$$E(\varepsilon_{it} \,|X_{i,t}\,,\gamma_i) = 0 \qquad (4)$$

This will be violated by the inclusion of a lagged dependent variable as both the explanatory and lagged dependent variables will be correlated with future unobserved disturbances. Nickell (1981) was the first to estimate the size of thus bias for fixed effects models. When the number of time periods is large the dynamic panel bias has been shown to become insignificant (Judson and Owen (1999)). As a result, the number of available time periods (32) in this panel dataset may mitigate this issue, although we have chosen to use an estimator which ensures that any bias arising is addressed. A number of econometric estimators including bias-corrected fixed effects, Instrumental Variable (IV) and Generalized Methods of Moments (GMM) estimators are available to do this. Of these the Arrellano and Bond (1991) first difference GMM and the Blundell and Bond (1998) system GMM estimators are the most widely used.

However, as Roodman (2006) notes, these estimators are intended for panels characterized by a large number of cross-sections and with a relatively short time series. Whilst it is somewhat open to interpretation as to what dataset in fact reflects this position, we do not believe that GMM estimators are suitable for our dataset. The GMM estimators also generate moment conditions prolifically, with the instrument count quadratic in the number of time periods. This can make coefficient estimates invalid and severely weaken the power of instrument exogeneity tests (e.g. the Sargan test). This was indeed found to be the case with the dataset used in this study. As a result we employ the bias corrected fixed effects formulated by Bruno (2005). This is an extension to the bias corrected least squares dummy variable estimator derived by Kiviet (1995), which has the necessary characteristic for this study of being able to handle unbalanced panels. Bruno (2005) shows that this estimator outperforms the other more widely used IV and GMM estimators.

If θ represents the vector of fixed effects coefficient estimates, then the bias corrected coefficients would be estimated using the following:

$$\theta_{bc} = \theta_{fe} - \; bias \qquad (5)$$

Where, the estimates for the bias approximation are deducted from the original fixed effect coefficient estimates. In particular, the bias approximation is a function of the unbiased coefficients $\theta_{unb,init}$ and their variance $\sigma^2_{\theta_{unb,init}}$ i.e.:

$$bias = f\left(\theta_{unb,init}, \sigma^2_{\theta_{unb,init}}\right) \qquad (6)$$

The subscript 'init' represents the method selected to initialize the bias correction. We make use of a routine[2] which implements this model and estimates a bootstrap covariance matrix for the corrected estimator. The method chosen to initialize the bias correction in this paper is the Anderson and Hsiao (1981) instrumental variable estimator. Whilst a number of other estimators are available to do this such as the Arrellano and Bond (1991) and Blundell and Bond (1998), Bruno (2005) shows that differences in the initial estimators only have a marginal impact upon the coefficient estimates from the biased corrected fixed effects regressions. This was found to be the case in other regression iterations which we undertook.

[2] Xtlsdvc command in STATA

VII. Panel Regression Results

The objective of the panel regression analysis is to identify the factors which determine UK property fund performance on a quarterly basis. This includes a lagged dependent variable, the market exposure return over the period, direct property portfolio characteristics and the level of financial leverage employed, which impact fund returns over the quarter. We found that more dynamic lag structures had little impact upon regression explanatory power and had limited statistical significance.

The results of the panel regression analysis are shown in Table 5. All fixed effects regressions are estimated using an estimator of the covariance matrix that is robust to cross-sectional heteroskedasticity. In addition all of the regressions reported in Table 5 include quarterly time period effects, although these are not displayed for space reasons.

The results from the Hausman tests and F-tests for the significance of the time period dummy variables support the validity of panel estimation and the joint significance of the two-way fixed error component model is also strongly confirmed. As Bruno (2005) notes, a method for identifying whether bias has arisen in the fixed effects estimates due to the inclusion of a lagged dependent variable, is that the coefficient estimate from the bias corrected estimator lies between that of the pooled ordinary least squares and fixed effects regressions. We can see from above that this is not the case for the two bias corrected fixed effects regressions, thus supporting our initial view that fixed effects bias was unlikely to be an issue given the relatively large number of available time periods in the dataset. The coefficients from the fixed effects and biased corrected fixed effects regressions are largely the same.

The results show that for all funds over the whole period, some 80% of the variation in total returns can be attributed to a relatively small number of factors. A strong positive one-to-one relationship is shown between fund performance and the average market segment returns to which a fund is exposed to. This underlines the importance of market risk on the performance of unlisted property funds. We also find that a fund's lagged performance is a strong explanatory variable, which was an expected result given the serial correlation or 'smoothing' that is known to characterize commercial property returns.

The level of net gearing also shows the expected positive long-term impact on a fund's return and that it is a statistically significant explanatory variable in the fixed effects regressions. For each additional 10 per cent increase in net financial leverage, quarterly total returns are on average enhanced by 0.2%, or approximately 0.8% on an annual basis. This is consistent with the results found by Fuerst and Matysiak (2013) who found in their study of European funds, which typically employ higher levels of financial leverage than the UK funds in this study, that for every additional 10% of financial leverage employed, returns would be expected to increase by some 0.7% annually.

All of the direct property factors detailed in Tables 2 and 3 were incorporated into the regression analysis. The most significant of these are shown in the results, with the lag of both the total void rate and relative initial yield variables having the most statistical significance. The coefficients on the void rate has the corrected expected positive coefficient sign meaning that ceteris paribus, for every 10% of additional portfolio void investors should expect to earn an additional 0.4% quarterly total return. The relative initial yield variable was found to be positively related to returns. This is likely to reflect a higher risk premium which is being attached to higher yielding direct property portfolios which could be due to a number of factors related to asset quality such as location and tenant income security.

Table 5: Panel regression results based on funds' quarterly total returns

Standard errors in parentheses. ** indicates significance at the 5% probability level, *indicates significance at the 10% probability level.

	Pooled OLS	Fixed Effects	Bias Corrected Fixed Effects	Pooled OLS	Fixed Effects	Bias Corrected Fixed Effects
Lag Total Return	0.391**	0.356**	0.396**	0.376**	0.336**	0.378**
	(0.023)	(0.042)	(0.027)	(0.024)	(0.046)	(0.028)
Market Exposure Excess Total Return	0.984**	0.968**	0.925**	1.033**	1.021**	0.980**
	(0.109)	(0.229)	(0.161)	(0.104)	(0.215)	(0.132)
Lag Net Loan to Value Ratio	-0.023**	0.024**	0.022	-0.015**	0.020*	0.019
	(0.004)	(0.011)	(0.014)	(0.003)	(0.011)	(0.013)
Lag Excess Initial Yield	0.222*	0.857**	0.795**	0.080	0.768**	0.699**
	(0.115)	(0.289)	(0.295)	(0.091)	(0.281)	(0.245)
Lag Total Void (% ERV)	0.008	0.043**	0.043*	-0.001	0.040**	0.040**
	(0.013)	(0.022)	(0.022)	(0.012)	(0.015)	(0.020)
Lag Top Ten Tenant Exposure (% Rent)	-0.002	0.043*	0.042**			
	(0.006)	(0.022)	(0.021)			
Lag Passing Rental Reversion	-0.020	-0.015	-0.014			
	(0.015)	(0.021)	(0.024)			
Lag % Lease Lengths > Ten Years	-0.002	-0.018	-0.017			
	(0.005)	(0.011)	(0.014)			
Lag Property Segment Concentration	0.008**	-0.025	-0.026			
	(0.003)	(0.022)	(0.031)			
R Squared Within		0.796			0.786	
R Squared Between		0.399			0.636	
R Squared Overall	0.795	0.745		0.785	0.760	
Regression SE	0.033			0.034		
% Variance Due to Fixed Effects		0.408			0.319	
F-Statistic	154.01	148.17		169.25	120.35	
Prob F-Statistic	0.000	0.000		0.000	0.000	
Hausman Test		213.64			190.42	
Prob Chi-Sq		0.000			0.000	
Redundant Period Effects F-Statistic		5.480			5.670	
Prob F-Statistic		0.000			0.000	
No Cross Sections	70	70	70	75	75	75
No Observations	1630	1630	1630	1704	1704	1704

We have uncovered a relatively small number of factors which determine the returns of unlisted property funds namely lagged performance, market exposure, leverage and two factors which reflect the underlying direct property characteristics. As noted above, over half the sample of funds considered in this study can be regarded as having a largely low risk profile and follow, what is known in the industry, as a core style. As a result, there may be other factors which are more dominant for funds in higher risk-return vehicles. However, Fuerst and Matysiak (2013) also found that significant explanatory power (some 70%) of performance resulted from market exposure, leverage and two factors which reflect the underlying direct property characteristics. Hence, the empirical evidence suggests that only a relatively small number of return drivers need to be considered when evaluating the risk-return characteristics of unlisted property funds.

VIII. Upside and Downside Leverage Effects Regression Results

It is well known in the literature that property total returns exhibit non-normality (e.g. Devaney et al (2006)), and in particular historical performance has been shown to be negatively skewed. The impact of financial leverage upon direct property performance remains relatively unknown, although the studies by Gordon and Tse (2003) and Hoorenman and van der Spek (2011) show that the increasing use of financial leverage disproportionately increases downside risk measures. This points to the negative skew in commercial property returns being exacerbated by the use of gearing.

In this study we empirically investigate the downside impacts of financial leverage upon fund performance by using dummy variables which isolate positive and negative UK commercial property market conditions. The IPD All Property Quarterly Total Return Index was used as the reference performance market measure. A market dummy variable took a value of one between 2007 Q3 and 2009 Q2 when total market returns were negative. As noted earlier, the time period of the sample used in this study was a period of significant market volatility as a result of the global financial crisis.

The results of the panel regression analysis are shown in Table 6. Both fixed effects regressions are estimated using an estimator of the covariance matrix that is robust to cross-sectional heteroskedasticity. In addition we have shown the results including and excluding quarterly time period effects. We have reduced the number of explanatory regressors to the most statistically significant.

Table 6: Panel regression results: the impacts of financial leverage on unlisted property fund performance in positive and negative market conditions

Standard errors in parentheses. ** indicates significance at the 5% probability level, *indicates significance at the 10% probability level.

	Pooled OLS	Fixed Effects	Bias Corrected Fixed Effects	Pooled OLS	Fixed Effects	Bias Corrected Fixed Effects
Lag Total Return	0.216** (0.022)	0.168** (0.043)	0.205** (0.026)	0.107** (0.015)	0.090** (0.033)	0.107** (0.019)
Market Exposure Total Return	1.300** (0.095)	1.278** (0.183)	1.242** (0.113)	1.037** (0.021)	1.049** (0.040)	1.035** (0.025)
Lag Excess Initial Yield	0.090 (0.080)	0.501** (0.217)	0.439** (0.212)	0.047 (0.082)	0.446** (0.214)	0.415* (0.218)
Lag Net Loan to Value Ratio x Negative Market Dummy	-0.109** (0.006)	-0.104** (0.017)	-0.102** (0.014)	-0.110** (0.006)	-0.098** (0.016)	-0.095** (0.013)
Lag Net Loan to Value Ratio x Positive Market Dummy	0.022** (0.004)	0.028** (0.012)	0.027** (0.013)	0.020** (0.004)	0.030** (0.012)	0.031** (0.012)
Period Effects Included?	Yes	Yes	Yes	No	No	No
R Squared Within		0.822			0.807	
R Squared Between		0.882			0.864	
R Squared Total	0.819	0.818		0.808	0.803	
Regression SE	0.031			0.032		
% Variance Due to Fixed Effects		0.171			0.184	
F-Statistic	217.37	236.61		1442.43	377.21	
Prob F-Statistic	0.000	0.000		0.000	0.000	
Hausman Test		164.53			379.63	
Prob Chi-Sq		0.000			0.000	
Redundant Period Effects F-Statistic		4.06				
Prob F-Statistic		0.00				
No Cross Sections	75	75	75	75	75	75
No Observations	1724	1724	1724	1724	1724	1724

The regression results show that there were potential fixed effects bias arising in these regression specifications, particularly when period effects were included in the regression. In these instances the market impact coefficients rose materially, although the coefficients are not statistically different to one. However, this was the rationale for including the results without the period effects as we suspected that these period effects were to a certain extent, being captured by the positive/negative market indicator dummy variables. The coefficients on both the lagged dependent and relative initial yield variables were also lower than their panel regression estimates shown in Table 5.

The results show the asymmetric impacts of financial leverage upon unlisted property fund performance. In positive market conditions an additional 10% of financial leverage has produced a 0.25% increase in quarterly fund total returns. However, this relationships changes dramatically when market returns are negative with an additional 10% of financial leverage leading to an approximate 0.9% decrease in quarterly fund returns in negative market conditions. Thus leverage has a significant (greater than three times) impact upon performance in negative market conditions versus its longer term effect. This result is consistent with the findings from leveraged property investment studies which show the downside impacts of leverage outweighing the upside. This has significant implications for investors considering the risk-return trade-offs of leveraged property investments.

VIV. Conclusions and Further Work

In this study we have made use of a unique dataset of UK unlisted property funds over the period 2003 Q4 to 2011 Q4, using a panel modelling framework in order to determine the key factors which impact on fund performance. Unlisted property funds are a relatively new institutional investment conduit, meaning that there is limited time series data available. The panel approach employed in this paper makes best use of the available observations across both time and cross section observations. We have been able to test a rich set of fund factors including market exposures, direct property characteristics and the level of financial leverage employed. Thus, the key sources of risk and return in property funds in property funds outlined by Baum and Farrelly (2009) namely market, stock and financial structure, have all been explicitly accounted for in this analysis.

The most significant variables found through panel regression analysis were lagged performance, market exposure returns, for which there was a one-to-one relationship, the level of financial leverage (as measured by net debt relative to property value) and several direct property factors. Of the fund direct property portfolio characteristics tested for, the void rate, relative initial yield and tenant concentration were found to be the most statistically significant. Thus, the panel analysis has demonstrated that a relatively small number of variables (five) explain a large proportion of the performance of unlisted property funds. These should be considered by investors when assessing the risk and return of unlisted property funds.

The sample used in this study covered a period of unparalleled market volatility. Financial leverage and institutional property investment became more prevalent and this study highlighted the impact of leverage upon the returns delivered. This was achieved by isolating the impact of financial leverage in positive and negative market conditions during the sample period using an indicator dummy variable. This uncovered a significant asymmetric impact, with the downside effect being over three times greater than the upside effect. To our knowledge this has been the first study to empirically examine the effect of financial leverage upon private fund performance in a range of market conditions. The results have clear implications for investors in private property fund vehicles which employ gearing and how they should assess the attendant risks.

Future research should look at the quantification and assessment of risk associated with investing in unlisted property fund vehicles. In particular, the impact of financial leverage upon the risk of unlisted funds remains under researched. In particular, consideration of appropriate risk measures which better consider the downside risk impacts of employing financial leverage in property investment. Another strand of future work should also consider the asset allocation implications of investing in these vehicles to fulfil both domestic and international property allocations. Much of the asset allocation implications in considering direct property investment are focussed on direct market return indices, but there are clearly both direct property factors and financial leverage which impact on performance characteristics when implementing property allocations using unlisted funds. Extending this analysis to cover global markets would also be a natural extension. Given the increased prominence of unlisted property funds and leveraged property investment, further work is required to better understand the relevant risk and returns drivers, particularly given the recent market cycle.

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Appendix 1

Investment Property Databank Performance Analysis Service (IPD PAS) Market Segmentation:

- Shops – London and South East England
- Shops – Rest UK
- Shopping Centres
- Retail Warehouses
- City of London Offices
- West End of London Offices
- Rest of South East England Offices
- Rest of UK Offices
- Industrial Property – London and South East England
- Industrial Property – Rest UK
- Other Property Types (e.g. Hotels and Student Accommodation)