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Drivers of Fund Performance: A Panel Data Analysis

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Executive Summary

The principle aim of this research is to elucidate the factors driving the total rate of return of non-listed funds using a panel data analytical framework.

In line with previous results, we find that core funds exhibit lower yet more stable returns than value-added and, in particular, opportunistic funds, both cross-sectionally and over time. In other words, we find that for individual core funds 1) returns are more clustered around the group average in a given year and 2) returns are overall less volatile over time in the analyzed period 2001-2007.

After taking into account overall market exposure, as measured by *weighted market returns*, (derived from weighted IPD country and sector returns), the excess returns of value-added and opportunity funds are likely to stem from: high leverage, high exposure to development, active asset management and investment in specialized property sectors.

The style groups exhibit differences in performance in variation *within* these groups. A preliminary analysis of the distribution of total returns for each style group shows that the total returns of core funds are strongly clustered around the mean and median, whereas value-added funds are somewhat more disperse. Opportunity funds show the highest variability in returns and consequently the highest percentage of *outliers*.

First stage regression results are encouraging in that employing a small number of variables accounts for a statistically significant proportion of annual fund returns. The country and sector property effect comes through strongly. Detecting direct macro-economic influences on total returns turns out to be rather elusive as economic factors are more likely to be reflected indirectly through the property market channel.

Gearing has an influence on total returns. For all funds over the whole period, 2001-2007, 40% to 55% of total returns can be accounted for by exposure to the underlying property market(s), the degree of gearing and fund performance in the previous year. However, the extent of the explanatory power of these factors varies across individual years; on a year-to-year basis the explanatory power varies, being lowest in the early years.

A random effects estimation of the panel data model largely confirms the findings obtained from the fixed effects model reported above. Again, the country and sector property effect shows the strongest significance in explaining total returns. Gearing levels are also positive and significant, which is in line with previous observations. The stock market variable is negative which hints at switching effects between competing asset classes.

According as to which particular investment style a fund adopts, gearing has a differential impact. For opportunity funds, on average, the returns attributable to gearing are three times higher than those for value added funds and over five times higher than for core funds.

Overall, there is relatively strong evidence indicating that country and sector allocation, style, gearing and fund size combinations impact on annual performance.

Introduction

In this report we provide the findings based on an analysis of non-listed real estate funds in the period of 2000-2007.

Prior to undertaking the panel data analysis a series of preliminary steps were necessary to structure the data. First, all of the data has had to be transferred into a suitable format for panel data analysis within an econometric software package. Secondly, for each fund each year, the exposure of the investments to the underlying country economic and property market was calculated. This involved the construction of a series of aggregate indicators measuring the exposure of each fund to overall economic and property market exposure. The indicators, in combination with the fund specific characteristics, were then used as input variables in our panel data regression model. Our underlying approach is to reason that fund performance reflects exposure to economic/financial environments, exposure to property market conditions and, finally, exposure to fund specific features. In the process, analysis of the entire INREV universe as well as sub-samples of the data was undertaken. Details can be found in the *sample selection* section of the report.

The main variable we are seeking to explain is annual total return. This is calculated for each fund each year according to the standard INREV formula.[3]

Research objective

Investors and fund managers require information on the performance of funds and its underlying drivers for a variety of reasons. This research seeks to extend previous research commissioned by INREV in that it analyzes the drivers across funds and over

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[3] Total return is calculated as $TR_{it} = \frac{(NAV_{it} + XD_{it} - CI_{it} + RD_{it}) - NAV_{it-1}}{NAV_{it-1}}$ where NAV is net asset value, XD is distributed dividends, CI increases in capital and RD redemptions.

time simultaneously. To this aim, we investigate the scope for a panel data approach drawing on the INREV database and a variety of complementary data sources.

This report is organized as follows. Following a brief review of existing work on investment style analysis for real estate, we describe the datasets and the model used to determine the categories that are important in understanding the drivers of unlisted real estate funds. We then present the results of the empirical analysis that has been have undertaken. Finally, we discuss the implications of these findings and comment on how the work undertaken may be extended.

Previous work

There is little published work on unlisted funds attribution performance, being largely confined to two reports commissioned by INREV, namely, Stevenson (2006) and Key & Lee (2008). Stevenson's analysis covered the period 2001-2004 and his regression analysis did not provide significant results regarding the drivers of unlisted funds' performance. He attributes this to the large number of young funds and the short history of available information at the time (4 years). Whilst Key & Lee (2008) seek to identify enduring styles for non-listed funds, in the main, their analysis is not empirically motivated in seeking to identify the ex-post drivers of performance. Overall, there is little robust empirical evidence on which the current study can draw on.

In an early study of the predictability of real estate returns, Mei and Liu (1994) find that excess returns on real estate are easier to forecast relative to other asset classes. The authors conclude that the enhanced predictability leads to marginally better market timing ability for real estate. Similarly, Ling (2005) finds that expert consensus opinions on investment conditions (gathered from institutional owners and managers) are useful for forecasting subsequent real estate returns.

Hoesli and Lekander (2005) argue that non-listed funds have the desirable feature of being highly correlated with the underlying real estate market. The corollary of this is that, compared to other investment vehicles, non-listed funds offer the diversification benefits of direct real estate. The panel modeling results detailed in the present report provide further empirical support for this argument. Brounen et. al (2007) also pick up on this aspect of non-listed real estate funds, illustrating their significant growth over the last 15 years.

One issue that is of particular relevance to managers of non-listed real estate funds is the persistence of fund returns over time. Young and Graff (1996) demonstrate serial persistence for US direct real estate, particularly for the bottom and top 25% performers in the market. Using IPD data for their analysis, Devaney et al (2006) demonstrate that serial persistence is prevalent in UK property returns as well. Our research indirectly confirms these findings in that total returns lagged by one year exhibit high significance levels in our panel data model. In related research, Young et al (2007), show that real estate return distributions are also non-normal. The authors conclude that this impedes the effectiveness of strategies aimed at diversifying away non-systematic risk. While our research did not address this issue directly, it is important to bear in mind that asymmetry and non-normality of fund returns may limit the conclusions for active fund management drawn from this analysis.

Based on a standard attribution approach, Farrelly and Baum (2008) look to further attribute returns performance to Alpha and Beta. Implicit in their calculations is the contribution the property benchmark makes to performance. The authors employ a broad benchmark, being the IPD Universe. Based on the performance record of an unlisted value added fund consisting of 20 (quarterly) observations, they report a significant market (Beta) impact in accounting for net total returns. They attribute the level of Beta reported (1.73) largely to the level of fund gearing, together with a contribution from the fund's risk structure. In our analysis we are solely concerned with a broad benchmark, being the market factor alongside fund-specific factors, and do not seek to isolate components of performance within the type of attribution framework Farrelly and Baum work with[4].

[4] We would comment, however, that issues of definition surround any attribution within the type of framework adopted by Farrelly and Baum.

Empirical analysis

Before presenting the results of the panel data analysis, we examine the main characteristics of the funds by style and vintage in the dataset.

Table 1 shows in more detail the distribution of the annual total rates of return (TRR) over the period 2001-2007. It is seen that the annual returns span the range -71% to 133%, with an average of 12%, with the distribution of returns being skewed towards positive returns, representing some 80% of the total. Although only some 4% of the returns (58 yearly returns) are either less than -20% or greater than 40%, the inclusion of these returns is likely to have a significant impact on the results. Consequently, we report results including and excluding these observations.

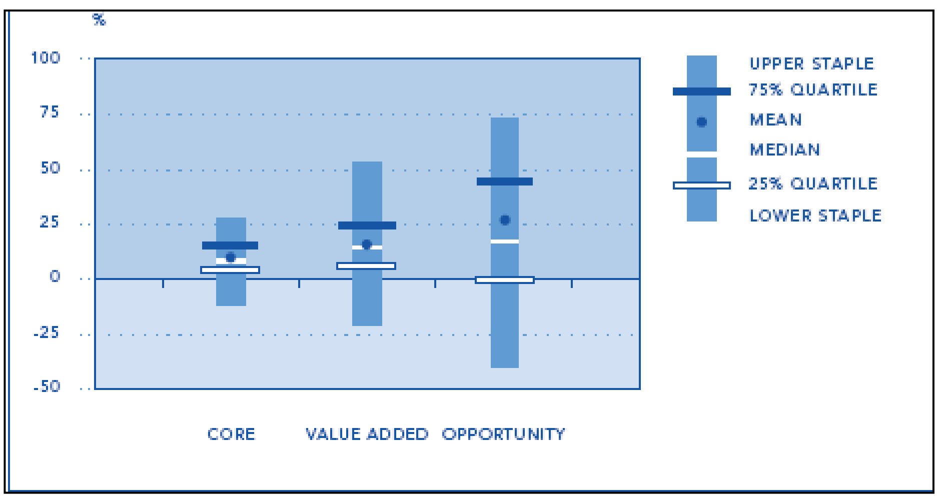
Table 1: Distribution of Total Rates of Return - 1082 observations over 2001-2007

TRR RANGES	MEAN	MAX.	MIN.	COUNT	PERCENT	CUMULATIVE COUNT	CUMULATIVE PERCENT
[-80, -60)	-70.99	-70.99	-70.99	1	0.09	1	0.09
[-60, -40)	-44.73	-40.30	-47.22	3	0.28	4	0.37
[-40, -20)	-27.54	-20.91	-39.14	12	1.11	16	1.48
[-20, 0)	-6.18	-0.01	-19.70	107	9.89	123	11.37
[0, 20)	9.15	19.96	0.00	742	68.58	865	79.94
[20, 40)	26.97	39.62	20.03	175	16.17	1040	96.12
[40, 60)	47.54	58.22	40.19	27	2.5	1067	98.61
[60, 80)	70.14	74.34	64.15	7	0.65	1074	99.26
[80, 100)	90.10	96.60	83.61	2	0.18	1076	99.45
[100, 120)	109.19	113.97	104.93	3	0.28	1079	99.72
[120, 140)	131.15	133.36	127.44	3	0.28	1082	100
ALL	12.00	133.36	-70.99	1082	100	1082	100

Sample selection and fund distributional characteristics

As indicated above, on inspecting the descriptive statistics and the distributions of individual variables, we have defined cut-off points for data inclusion in the analysis as annual total returns within the range -20% and 40%. Figure 1 shows the distribution of annual returns for three fund styles, as defined by INREV, namely core, value added and opportunity funds; the outliers are located outside the range indicated by the horizontal lines within each box. As a percentage of observations *within each style*, the boxplot of total return distributions illustrates the differences in the range of values for each group. The box portion of the boxplot represents the first and third quartiles (the middle 50 percent of the data). These two quartiles represent the inter-quartile range (IQR). The median is depicted by a line through the center of the box, while the mean is represented by a black dot. Overall, the boxplot shows that the total returns of core funds are strongly clustered around the mean and median and the IQR is relatively small. Value-added funds are somewhat more disperse and opportunity funds show the highest IQR, with total returns in the middle 50 percent ranging from slightly negative to around 30 percent. These observations are in line with the general assumption of higher variability and volatility of opportunity funds. Within each style group, opportunity funds have the largest percentage of outliers.

Figure 1: Distribution of returns by style category



Applying this rule reduces the number of cross-section time-series observations of the funds to 1,024. Table 2 gives a summary of the number and percentages of outliers. The definition of outliers has been subject to a substantive debate in the statistical and financial literature. Despite the fact that extreme values may be in line with a normal distribution of returns, they were eliminated from the dataset based on the assumption that these returns may have been largely caused by non-market forces, are largely atypical or purely errors in the database. In cases where the exclusion of outliers makes a critical difference, we report results including and excluding the outliers.

Table 2: Outlier numbers and percentages by style category

	TRR<-20			TRR>40		
STYLE	COUNT	% OF STYLE	% OF ALL	COUNT	% OF STYLE	% OF ALL
CORE	7	0.87	0.65	13	1.62	1.20
VALUE ADDED	5	2.14	0.46	17	7.26	1.57
OPPORTUNITY	4	9.09	0.37	12	27.27	1.11
TOTAL	16	1.48	1.48	42	3.89	3.89

In line with INREV definitions of this three category classification, we would expect core funds to exhibit a lower, yet more stable pattern of returns, than value-added funds and, particularly, opportunistic funds. Table 3 confirms this, in that over the period 2001-2007 both the mean and the median total returns of core funds are considerably lower than those of value-added and opportunistic funds. Core funds average annual returns are 10% whereas opportunity funds average 26.9%. Interestingly, for the three fund types, the standard deviation, measured both cross-sectionally and over time. In other words, we find that for individual core funds 1) returns are more clustered around the group average in a given year and 2) overall, returns are less volatile over time in the analyzed period 2001-2007. This conforms with the expectation of higher volatility for higher rates of return. A similar pattern emerges from the analysis of yields by style category (**Error! Reference source not found.**) with core funds showing an average yield of 3.8% and opportunity funds reaching 14.2%.

Asset allocation to specific countries and sectors is a crucial factor in the overall performance of funds. A standard approach to capturing geographical and sectoral diversification in a regression model involves the use of dummy variables for each sector and country. Apart from being a rather crude measure of fund diversification, this approach also ignores the distribution (weight) of individual funds in each country and sector. The approach undertaken in this research was to that generate annual return figures for each fund based on the overall performance of a particular property sector in each country weighted by the exposure of the fund in the respective country and sector. Property sectors for which country-specific returns were not available (hotels, leisure, health care, residential etc.) were assumed to perform in line with the overall real estate market in that country. In a few minor cases only the sector, but not the country, was known and it was assumed that the achieved return in these cases would be similar to the average European performance of the particular sector in question. The return figures do not take into account any possible effects of smoothing and gearing. Information on gearing levels is, however, included as a separate regressor in the panel models.

Table 5 shows that, although the achieved returns are higher for value-added and opportunistic funds than for core funds, the fund categories differ by only 1.6%, a much smaller range than the actually observed fund returns discussed above. One possible explanation for the similarities of returns based on average country/sector returns is that opportunistic funds generally pursue a strategy of high leverage, high exposure to development and active asset management. We do not attempt to account for these factors in the weighted market returns measure. Thus, it seems probable that the excess returns of opportunity funds stem mainly from a combination of these factors, rather than asset allocation to particular countries[5]. Furthermore, since specialized real estate sectors, such as hotel and student housing are not taken into account in our calculation of returns, these may provide an additional source of excess returns for opportunistic funds.

Similar weighted indices were created for important economic variables such as GDP growth, stock market indices and long-term bonds.

Table 3: Average Annual total return by style category

STYLE	MEAN	MEDIAN	STD. DEV.	OBSERVATIONS
CORE	10.06	8.48	11.43	803
VALUE ADDED	15.83	14.39	19.37	235
OPPORTUNITY	26.94	17.20	42.31	44
ALL	12.00	9.59	16.26	1082

[5] These 'excess' returns may well capture so-called Alpha returns, which we do not consider in this report.

Table 4: Average yield by style category

STYLE	MEAN	MEDIAN	STD. DEV.	OBSERVATIONS
CORE	3.82	3.66	5.46	1029
VALUE ADDED	6.00	3.18	24.83	317
OPPORTUNITY	14.24	0.37	52.72	72
ALL	**4.84**	**3.59**	**17.43**	**1418**

Table 5: Weighted market return by style category

STYLE	MEAN	MEDIAN	STD. DEV.	OBSERVATIONS
CORE	10.33	9.84	5.93	996
VALUE ADDED	11.79	11.89	7.80	308
OPPORTUNITY	11.97	12.10	7.19	68
ALL	**10.74**	**10.27**	**6.49**	**1372**

Table 6: Allocation-weighted GDP growth by style category

STYLE	MEAN	MEDIAN	STD. DEV.	OBSERVATIONS
CORE	2.61	2.73	1.18	996
VALUE ADDED	3.08	2.92	1.64	309
OPPORTUNITY	3.28	2.92	1.52	72
ALL	**2.75**	**2.78**	**1.33**	**1377**

Table 7: Allocation-weighted stock market indices by style

STYLE	MEAN	MEDIAN	STD. DEV.	OBSERVATIONS
CORE	8.55	13.17	16.43	996
VALUE ADDED	10.18	13.15	15.75	309
OPPORTUNITY	16.30	18.59	11.50	72
ALL	**9.32**	**13.28**	**16.14**	**1377**

Table 8: Average gearing by style category

STYLE	MEAN	MEDIAN	STD. DEV.	OBSERVATIONS
CORE	18.89	11.87	20.30	1029
VALUE ADDED	34.32	41.13	21.92	317
OPPORTUNITY	44.43	49.35	28.23	72
ALL	**23.64**	**17.48**	**22.58**	**1418**

Table 9: Average number of sectors/countries per fund

STYLE	MEAN	MEDIAN	STD. DEV.	OBSERVATIONS
CORE	4.36	3.00	4.79	994
VALUE ADDED	4.14	3.00	3.14	308
OPPORTUNITY	4.31	3.50	3.32	68
ALL	**4.31**	**3.00**	**4.41**	**1370**

The next step in the analysis involved performing unit root tests[6]. These are formal tests undertaken prior to estimating the regression equations in order that the regression results are meaningful. The tests seek to establish whether or not there is systematic change in either the mean or the variance in the time series. Formally, if the null hypothesis of a unit root with drift process is accepted, the dataset will need to be transformed (e.g. differenced) in order to avoid spurious regression results[7]. We account for this by including both the index return (level) and the annual rates of return (first differences) in the panel data model. The rejection of the unit root null hypothesis is interpreted as evidence that the NAV time-series fluctuates around zero and is therefore trend-stationary. Table **10** gives an overview of the results obtained from running a number of panel unit root tests for the three key variables total return, gearing and weighted market returns. The LLC test strongly indicates the presence of a common unit root process for the total return dependent variable while such a process is not found for the gearing and weighted market return variables. The IPS, ADF and PP tests which all assume individual root processes reject the null hypothesis of a unit root consistently and strongly, thereby indicating that the series are trend stationary. When tested for unit roots of first differences, strong evidence against a unit root was found for all variables even for the critical common unit root in the TRR variable.

Table 10: Panel unit root tests of the levels of total return, gearing and weighted market return

METHOD	TRR	GEARING	WEIGHTED MARKET TRR
NULL: UNIT ROOT (ASSUMES COMMON UNIT ROOT PROCESS)			
LEVIN, LIN & CHU T*	18.26 (1.00)	-765.53 (0.00)	-47.83 (0.00)
NULL: UNIT ROOT (ASSUMES INDIVIDUAL UNIT ROOT PROCESS)			
IM, PESARAN AND SHIN W-STAT	-2.68 (0.00)	-82.78 (0.00)	-6.02 (0.00)
ADF – FISHER CHI-SQUARE	401.81 (0.00)	490.70 (0.00)	462.83 (0.00)
PP – FISHER CHI-SQUARE	378.41 (0.00)	650.19 (0.00)	500.43 (0.00)

* PROBABILITIES FOR FISHER TESTS ARE COMPUTED USING AN ASYMPTOTIC CHI-SQUARE DISTRIBUTION. ALL OTHER TESTS ASSUME ASYMPTOTIC NORMALITY.

[6] Intuitively, these are tests determining the 'stationarity' of a series, that is, whether the series trends or not.

[7] As noted by Engle and Granger (1987), however, important information regarding equilibrium relationships (here, price levels as measured by NAVs) is lost in the differencing step.

Model

Panel data analysis allows for simultaneous regression analysis of both time-series and cross-sectional research questions. This will enable us to identify and track the drivers of individual fund performance over time. More specifically, panel analysis can be used to capture the dynamics of fund performance in relation to the overall market. There are various types and functional forms of panel data models, including *fixed effects* and *random effects*. A primary advantage in employing fixed effects or random effects models for panel data is the ability of these models to control for omitted variables. Given the more than likely presence/impact of omitted variables this is a major advantage of such models. Fixed effects regression is the model to use when one wants to control for omitted variables whose impact will *differ between cases*, for example, omitted variables having a different impact on investment style returns. If we have reason to believe that some omitted variables *may have the same constant* impact but vary randomly between cases, such as investment styles, we would then model random effects. A detailed description of these models is provided in Appendix 2.

Panel regression results

We have classified the funds based on various criteria such as size and style and have estimated regression equations based on these classifications. As noted above, the analysis was also undertaken on a sub-set of the data that excluded outlying observations. We report results based on using the whole sample of data together with the exclusion of the 4% of outliers described above.

We have undertaken analyses for a variety of specifications incorporating economic/financial variables, property market returns and fund specific variables. Appendix 1 provides details of the estimated relationships over the whole period 2000-2007 and for individual years. As a first pass analysis, we have grouped all of the funds together and have used the following variables in accounting for fund total returns:

- country weighted property sector returns in which the fund invests,
- fund total returns achieved in the previous year and

- percentage level of gearing.

The first regression result reported in Appendix 1, Table A1, is based on the whole sample of total returns data over the period 2001-2007. Total rates of return, TRR, were regressed on fund returns in the previous period, on country property market total returns and on the level of gearing in the previous years. Overall, we find that a combination of country property market returns combined with fund specific gearing provide a robust combination of factors in accounting for fund returns.

The results broadly indicate that for all funds over the whole period, some 40 per cent of total returns can be accounted for by these three factors. When the outlying observations are excluding this figure rises to 53 per cent. On a year-to-year basis, this level of explanatory power varies. When the outlier observations are excluded, in all years except 2003 and 2007 the all variables used in the analysis are significant[8]. The lowest level of explanatory power occurs in the early years, were there were relatively few funds and data points.

Based on the results over the period 2001-2007, Table A1 in the Appendix 1, on average 20 per cent of the returns achieved in the previous year are reflected in the current year's returns. The overall property market impact, the variable WMR (weighted market return), is that a 1 per cent increase in market returns leads, on average, to a 1.2 per cent increase in fund returns. The impact of lagged level of gearing, the previous year's gearing, is that, on average, for each additional 10 per cent increase in gearing returns are enhanced by 1.4%.

Given that property market exposure is an important factor in helping to account for total rates of return, we next looked at how different 'style' funds respond to property market changes. Table A15 in Appendix 1 shows the response of different style funds to market

[8] We would comment that based on adjustments to the outlier rule we have specified, for example imposing a specification that total rates of return less than -5% in 2007 would excluded, the results for 2007 would be such that the gearing variable would significant. Essentially, the reported results are highly dependent on the outlier rule adopted and further analysis is required in this regard.

changes. The largest response to market movements is by opportunity funds, where a 1 per cent increase in the market results, on average, with a 1.76 per cent increase in fund returns. For value added funds the corresponding figure is 1.36 per cent and for core funds 1.09 per cent. These results are not surprising in that the higher levels of gearing by opportunity funds will magnify the underlying market performance and core funds, other things equal, will, on average, reflect underlying market performance. However, the level of gearing is but one factor contributing to performance, enhancing management skill and property selection.

The model was next estimated using cross-sectional random effects instead of fixed effects. The random effects model allows individual intercepts instead of group intercepts. These individual intercepts are expressed as a random deviation from a mean intercept[9].

The random-effects specification over all periods included the following variables to explain total returns (see Table A17):

- total returns lagged by one year
- weighted market total return
- level of gearing
- weighted average stock market return (negative)
- yield

These results are relatively robust and confirm the findings obtained from the fixed effects model reported above. This model explains 47 per cent of the variations in returns across funds and over time. Again, the weighted market return variable shows the strongest significance in explaining total returns. Gearing levels are also positive and significant which is in line with previous observations. The stock market variable is

[9] Since the error terms of our model may be correlated we estimate robust values of standard errors and covariance, specifically, Seemingly Unrelated Regression (SUR) estimates. It has been argued in the econometric literature that for panel data with a large number of cross-sectional units and a small number of time periods random effects will be more efficient than fixed effects. Appendix 2 contains a more detailed discussion of the differences.

negative which possibly hints at switching effects between competing asset classes. A number of previous studies have also found a negative relationship between stock returns and real estate returns. The yield variable in our model is problematic, however, in that it does not exhibit the expected inverse relationship with total returns. Our *a priori* assumption was that the relationship would be inverse as capital appreciation would lead to higher total returns but lower yields. We find that contemporaneous income yields contribute positively to total return - lower income yield makes a lower contribution to total return and vice versa - therefore yield is positively correlated with returns. However, as for a *long-term* predictive positive relationship between total returns and yields, there is mixed evidence from the equities markets. Going forward, *changes* in yield are expected to be negatively related with total returns: increased yields imply falling capital values and therefore falling total returns and vice versa for falling yields. As with all ratio measures, there are several constellations that can cause a shift. The complex interaction between yields and total returns requires further in-depth analysis that is beyond the scope of this report.

We next looked at the impact of gearing by style of fund. The question being addressed was: are there differences in performance based on style and the level of gearing? By definition, style groups have different gearing levels so the finding of differences in gearing is not in itself meaningful (see INREV "Core Definitions", p.12). This does not, however, imply that returns will automatically reflect gearing. While there is bound to be some overlap between the gearing and style variables, we included the style variable because it potentially captures unobserved factors such as active property management, ability to pick undervalued properties etc. To this aim, we investigate whether higher gearing levels are indeed associated with higher returns. The question being addressed is "*Do* style returns reflect gearing?" or more precisely "Are returns consistent with expectations derived from the *a priori* style classification? [10]

Equation A18 in Appendix 1 reports the findings based on all observations, as the opportunity funds have the highest percentage of outliers, possibly reflecting the gearing

[10] A related question of interest, not pursued, is "Can the existing style classification system be improved to better account for achieved returns?"

impact. The results show that for opportunity funds gearing has the greatest impact, whereby for every 10 per cent increase in gearing annual returns, on average, increase by 3.9 per cent; for value added funds by 1.4 per cent and 0.7 per cent for core funds. In other words, the impact of gearing is three times greater for opportunity funds compared with value added funds and over five times greater compared with core funds.

Finally, a further group test that was undertaken within the framework of our panel analysis was the effect of fund size, as defined by the NAV of a fund. In other words: does the difference in achieved returns, based on average market returns, vary across fund size groups? To address this, the observations were divided into quartiles (i.e. four groups each of which represented 25% of the observations in ascending order by NAV). In combination with the previous year's total return and gearing, the effect of the four fund size group variables can be assessed. The results (Table A19) suggest that "medium-large" funds (i.e. the 50%-75% quartile) had performed best in terms of size. For every 1% increase in market return, the observed total return increased by 1.34 per cent. Conversely, small funds and medium-small, on average, performed worse, the response to market movements being 1.0 per cent and 0.85 per cent respectively. These results should by interpreted with caution, however, since inspection of the descriptive statistics shows that the "small" category exhibits slightly larger *within-group* variations compared with the other three fund size groups. This means that, whilst smaller funds on average appear to have underperformed the market in the study period, the range of achieved total returns of individual funds is larger than is in the case for the other three size groups.

There are several possible explanations for the relationship between size and return reported above. Small funds may tend to be younger funds so that high initial transaction costs may cause lower performance. To further investigate this proposition, we examine if there is such a relationship between size and age. Table 11 shows a clear positive relationship between size and age of a fund (with a correlation coefficient of 49%). While this confirms our initial proposition, we would need data on transaction costs to demonstrate positively that this is the reason why smaller (and younger) funds on average perform worse than larger and older funds. In any case, the issue of the impact of size and age merits further investigation.

Table 11: Fund age in years by size category (quartiles)

SIZE	MEAN	MEDIAN	STD. DEV.	OBSERVATIONS
SMALL	2.51	1.00	4.06	354
MEDIUM SMALL	4.77	3.00	5.94	355
MEDIUM LARGE	6.82	4.00	8.70	354
LARGE	13.19	7.00	12.43	355
ALL	6.83	3.00	9.29	1418

Conclusions and further work

In this study, we have analyzed a large number of funds over the eight year period 2000-2007, using a panel data framework to determine the drivers of total returns across funds, sectors and countries as well as over time. The most robust results we have obtained, across the whole period of data and for individual years, are accounted for by a property market factor and the level of gearing. Furthermore, fund characteristics such as style and size were found to be important factors contributing to overall performance. Essentially, there is evidence to suggest that style, gearing and fund size combinations impact on annual performance. We have reported results including and excluding outliers. To a large degree, any criterion employed in determining what constitutes an 'outlier' is judgemental. We would recommend that more analysis should be undertaken in assessing the robustness of the results to outliers.

One aspect that has not been explicitly explored is the impact of risk on overall performance. In theory, risk and return are related. The factors that have been considered in looking to account for total returns are likely to capture the broad aspects of the contribution of *systematic risk*, however, we have not looked at this in any detail. The measure of risk that will be of relevance in the present context is fund risk as captured by the extent of the fund's diversification. The degree of diversification is likely to be a contributing factor to overall performance. This also raises the question of if, and where, value is being added and how to appropriately attribute the performance. Ultimately, future research on non-listed funds would need to address which funds are generating the so-called alpha and what drives out-performance relative to a benchmark. To this aim, risk aspects need to be given closer consideration in assessing the performance of funds.

References

Brounen, D., Veld, H. O. and Raitio, V. (2007) Transparency in the European Non-Listed Real Estate Funds Market. *Journal of Real Estate Portfolio Management* 13/2, 107-118.

Devaney, S., Lee, S. and Young, M. (2007) Serial persistence in individual real estate returns in the UK. *Journal of Property Investment and Finance*, 25/3, 241-273.

Engle R. F. and Granger, C. W. J. (1987) Co-integration and error correction representation, estimation, and testing. *Econometrica*, 55, 251-276.

Farrelly, K. and Baum, A. (2008) Sources of Alpha and Beta in Property Funds, paper presented at the *ERES conference*, Krakow, 2008.

Hoesli, M. and Lekander, J . (2005) Suggested versus actual institutional allocations to real estate in Europe: a matter of size? *Journal of Alternative Investments* 8/2, 62-70.

Hsiao, C. (2003) *Analysis of Panel Data*, 2nd edition, New York: Cambridge University Press.

Hsiao, C. and Sun, B.H. (2000) To Pool or Not to Pool Panel Data. *Panel Data Econometrics: Future Directions*, J. Krishnakumar and E. Ronchetti (eds.) Amsterdam: North Holland, 181-198.

Key, T. and Lee, S. (2008) Real Estate Fund Styles, Report for INREV.

Ling, D. C. (2005) A Random Walk Down Main Street: Can Experts Predict Returns on Commercial Real Estate? *Journal of Real Estate Research*, 27/2, 137-154.

Mei, J. and Liu, C.H. (1994) The predictability of real estate returns and market timing. *The Journal of Real Estate Finance and Economics*, 8/2. 115-135.

Stevenson, S. (2006) Driving Forces in the Performance Attributes of Real Estate Funds, INREV Conference, Rome.

Young, M.S. and Graff, R.A. (1996) Systematic behavior in real estate investment risk: performance persistence in NCREIF returns. *Journal of Real Estate Research*, 12/3, 369-381.

Young, M.S., Lee, S. and Devaney, S. (2006) Non-normal real estate return distributions by property type in the UK. *Journal of Property Research*, 23/2,109-133.

Appendix 1

Panel regression results

1) Employing three variables

Table A1: Period 2001-2007

Dependent Variable: TRR
Method: Panel Least Squares
Sample (adjusted): 2002 2007
Periods included: 6
Cross-sections included: 230
Total panel (unbalanced) observations: 768

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-5.981940	0.906414	-6.599565	0.0000
TRR(-1)	0.202664	0.031397	6.454817	0.0000
WMR	1.203848	0.066976	17.97420	0.0000
GEARING(-1)	0.135479	0.021205	6.389008	0.0000

R-squared	0.405412	Mean dependent var	12.13668
Adjusted R-squared	0.403077	S.D. dependent var	15.54108
S.E. of regression	12.00716	Akaike info criterion	7.814078
Sum squared resid	110147.3	Schwarz criterion	7.838264
Log likelihood	-2996.606	Hannan-Quinn criter.	7.823387
F-statistic	173.6411	Durbin-Watson stat	1.461073
Prob(F-statistic)	0.000000		

Table A2: Period 2001-2007 excluding outliers

Dependent Variable: TRR
Method: Panel Least Squares
Sample: 2000 2007 IF TRR>-20 AND TRR<40
Periods included: 6
Cross-sections included: 223
Total panel (unbalanced) observations: 735

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-3.134461	0.548887	-5.710577	0.0000
TRR(-1)	0.129539	0.020309	6.378344	0.0000
WMR	1.043951	0.040909	25.51861	0.0000
GEARING(-1)	0.067025	0.012850	5.215935	0.0000

R-squared	0.532967	Mean dependent var	10.47660
Adjusted R-squared	0.531050	S.D. dependent var	10.13294
S.E. of regression	6.939027	Akaike info criterion	6.717627
Sum squared resid	35197.72	Schwarz criterion	6.742661
Log likelihood	-2464.728	Hannan-Quinn criter.	6.727282
F-statistic	278.0667	Durbin-Watson stat	1.303582
Prob(F-statistic)	0.000000		

Table A3: Period 2002-2002

Dependent Variable: TRR
Method: Panel Least Squares
Sample: 2002 2002
Periods included: 1
Cross-sections included: 67
Total panel (balanced) observations: 67

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.766350	3.529216	-0.500493	0.6185
TRR(-1)	0.320490	0.151072	2.121431	0.0378
WMR	1.115600	0.351796	3.171154	0.0023
GEARING(-1)	0.054000	0.059192	0.912292	0.3651

R-squared	0.194115	Mean dependent var	11.16104
Adjusted R-squared	0.155739	S.D. dependent var	8.731265
S.E. of regression	8.022606	Akaike info criterion	7.060249
Sum squared resid	4054.819	Schwarz criterion	7.191872
Log likelihood	-232.5183	Hannan-Quinn criter.	7.112332
F-statistic	5.058304	Durbin-Watson stat	0.000000
Prob(F-statistic)	0.003341		

Table A4: Period 2002-2002 excluding outliers

Dependent Variable: TRR
Method: Panel Least Squares
Sample: 2002 2002 IF TRR>-20 AND TRR<40
Periods included: 1
Cross-sections included: 66
Total panel (balanced) observations: 66

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.937797	2.395889	-0.808801	0.4217
TRR(-1)	0.285183	0.102637	2.778564	0.0072
WMR	1.039160	0.238980	4.348309	0.0001
GEARING(-1)	0.086718	0.040360	2.148599	0.0356

R-squared	0.339376	Mean dependent var	10.44806
Adjusted R-squared	0.307411	S.D. dependent var	6.544118
S.E. of regression	5.446142	Akaike info criterion	6.286384
Sum squared resid	1838.949	Schwarz criterion	6.419090
Log likelihood	-203.4507	Hannan-Quinn criter.	6.338823
F-statistic	10.61691	Durbin-Watson stat	0.000000
Prob(F-statistic)	0.000010		

Table A5: Period 2003-2003

Dependent Variable: TRR
Method: Panel Least Squares
Sample: 2003 2003
Periods included: 1
Cross-sections included: 83
Total panel (balanced) observations: 83

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.784865	2.391945	-0.746198	0.4578
TRR(-1)	0.132321	0.089813	1.473288	0.1446
WMR	1.019003	0.259581	3.925569	0.0002
GEARING(-1)	0.076267	0.040988	1.860685	0.0665

R-squared	0.231451	Mean dependent var	9.174584
Adjusted R-squared	0.202266	S.D. dependent var	7.884834
S.E. of regression	7.042414	Akaike info criterion	6.788772
Sum squared resid	3918.052	Schwarz criterion	6.905343
Log likelihood	-277.7340	Hannan-Quinn criter.	6.835603
F-statistic	7.930387	Durbin-Watson stat	0.000000
Prob(F-statistic)	0.000109		

Table A6: Period 2003-2003 excluding outliers

Dependent Variable: TRR
Method: Panel Least Squares
Sample: 2003 2003 IF TRR>-20 AND TRR<40
Periods included: 1
Cross-sections included: 83
Total panel (balanced) observations: 83

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.784865	2.391945	-0.746198	0.4578
TRR(-1)	0.132321	0.089813	1.473288	0.1446
WMR	1.019003	0.259581	3.925569	0.0002
GEARING(-1)	0.076267	0.040988	1.860685	0.0665

R-squared	0.231451	Mean dependent var	9.174584
Adjusted R-squared	0.202266	S.D. dependent var	7.884834
S.E. of regression	7.042414	Akaike info criterion	6.788772
Sum squared resid	3918.052	Schwarz criterion	6.905343
Log likelihood	-277.7340	Hannan-Quinn criter.	6.835603
F-statistic	7.930387	Durbin-Watson stat	0.000000
Prob(F-statistic)	0.000109		

Table A7: Period 2004-2004

Dependent Variable: TRR
Method: Panel Least Squares
Sample: 2004 2004
Periods included: 1
Cross-sections included: 111
Total panel (balanced) observations: 111

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-6.565905	3.672854	-1.787685	0.0767
TRR(-1)	-0.341302	0.165410	-2.063368	0.0415
WMR	1.706319	0.282819	6.033255	0.0000
GEARING(-1)	0.145779	0.067665	2.154421	0.0335

R-squared	0.272992	Mean dependent var	12.60735
Adjusted R-squared	0.252609	S.D. dependent var	17.50951
S.E. of regression	15.13728	Akaike info criterion	8.307570
Sum squared resid	24517.70	Schwarz criterion	8.405210
Log likelihood	-457.0701	Hannan-Quinn criter.	8.347180
F-statistic	13.39287	Durbin-Watson stat	0.000000
Prob(F-statistic)	0.000000		

Table A8: Period 2004-2004 excluding outliers

Dependent Variable: TRR
Method: Panel Least Squares
Sample: 2004 2004 IF TRR>-20 AND TRR<40
Periods included: 1
Cross-sections included: 108
Total panel (balanced) observations: 108

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-5.835126	1.399848	-4.168399	0.0001
TRR(-1)	0.313636	0.074437	4.213455	0.0001
WMR	1.156026	0.110079	10.50183	0.0000
GEARING(-1)	0.088268	0.026742	3.300689	0.0013

R-squared	0.656604	Mean dependent var	11.76942
Adjusted R-squared	0.646698	S.D. dependent var	9.648906
S.E. of regression	5.735234	Akaike info criterion	6.367468
Sum squared resid	3420.862	Schwarz criterion	6.466806
Log likelihood	-339.8433	Hannan-Quinn criter.	6.407746
F-statistic	66.28568	Durbin-Watson stat	0.000000
Prob(F-statistic)	0.000000		

Table A9: Period 2005-2005

Dependent Variable: TRR
Method: Panel Least Squares
Sample: 2005 2005
Periods included: 1
Cross-sections included: 136
Total panel (balanced) observations: 136

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-6.780315	1.684725	-4.024583	0.0001
TRR(-1)	0.058664	0.042132	1.392372	0.1662
WMR	1.263175	0.129746	9.735735	0.0000
GEARING(-1)	0.185933	0.029143	6.380087	0.0000

R-squared	0.612108	Mean dependent var	14.31633
Adjusted R-squared	0.603292	S.D. dependent var	11.55036
S.E. of regression	7.274966	Akaike info criterion	6.835726
Sum squared resid	6986.116	Schwarz criterion	6.921392
Log likelihood	-460.8294	Hannan-Quinn criter.	6.870538
F-statistic	69.43362	Durbin-Watson stat	0.000000
Prob(F-statistic)	0.000000		

Table A10: Period 2005-2005 excluding outliers

Dependent Variable: TRR
Method: Panel Least Squares
Sample: 2005 2005 IF TRR>-20 AND TRR<40
Periods included: 1
Cross-sections included: 131
Total panel (balanced) observations: 131

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-5.614157	1.524231	-3.683273	0.0003
TRR(-1)	0.079163	0.038474	2.057582	0.0417
WMR	1.187893	0.118194	10.05038	0.0000
GEARING(-1)	0.130571	0.027576	4.735044	0.0000

R-squared	0.617781	Mean dependent var	13.24430
Adjusted R-squared	0.608752	S.D. dependent var	10.34399
S.E. of regression	6.470142	Akaike info criterion	6.602332
Sum squared resid	5316.568	Schwarz criterion	6.690124
Log likelihood	-428.4527	Hannan-Quinn criter.	6.638006
F-statistic	68.42346	Durbin-Watson stat	0.000000
Prob(F-statistic)	0.000000		

Table A11: Period 2006-2006

Dependent Variable: TRR
Method: Panel Least Squares
Sample: 2006 2006
Periods included: 1
Cross-sections included: 165
Total panel (balanced) observations: 165

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-9.312007	2.375554	-3.919930	0.0001
TRR(-1)	0.407873	0.083308	4.895945	0.0000
WMR	1.114870	0.177035	6.297450	0.0000
GEARING(-1)	0.215019	0.040726	5.279688	0.0000

R-squared	0.565085	Mean dependent var	18.22877
Adjusted R-squared	0.556981	S.D. dependent var	16.31186
S.E. of regression	10.85712	Akaike info criterion	7.631463
Sum squared resid	18978.20	Schwarz criterion	7.706758
Log likelihood	-625.5957	Hannan-Quinn criter.	7.662028
F-statistic	69.72921	Durbin-Watson stat	0.000000
Prob(F-statistic)	0.000000		

Table A12: Period 2006-2006 excluding outliers

Dependent Variable: TRR
Method: Panel Least Squares
Sample: 2006 2006 IF TRR>-20 AND TRR<40
Periods included: 1
Cross-sections included: 151
Total panel (balanced) observations: 151

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-4.126627	1.552992	-2.657210	0.0088
TRR(-1)	0.346579	0.050381	6.879110	0.0000
WMR	0.804117	0.113891	7.060422	0.0000
GEARING(-1)	0.132682	0.024876	5.333830	0.0000

R-squared	0.607413	Mean dependent var	14.53494
Adjusted R-squared	0.599401	S.D. dependent var	9.954241
S.E. of regression	6.300327	Akaike info criterion	6.545213
Sum squared resid	5835.035	Schwarz criterion	6.625141
Log likelihood	-490.1636	Hannan-Quinn criter.	6.577684
F-statistic	75.81311	Durbin-Watson stat	0.000000
Prob(F-statistic)	0.000000		

Table A13: Sample 2007-2007

Dependent Variable: TRR
Method: Panel Least Squares
Sample: 2007 2007
Periods included: 1
Cross-sections included: 206
Total panel (balanced) observations: 206

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-7.327742	1.836767	-3.989479	0.0001
TRR(-1)	0.332255	0.060863	5.459033	0.0000
WMR	1.139726	0.144660	7.878628	0.0000
GEARING(-1)	0.049245	0.055685	0.884339	0.3776

R-squared	0.351895	Mean dependent var	7.075277
Adjusted R-squared	0.342270	S.D. dependent var	18.06294
S.E. of regression	14.64915	Akaike info criterion	8.225868
Sum squared resid	43348.71	Schwarz criterion	8.290487
Log likelihood	-843.2644	Hannan-Quinn criter.	8.252002
F-statistic	36.55931	Durbin-Watson stat	0.000000
Prob(F-statistic)	0.000000		

Table A14: Sample 2007-2007 excluding outliers

Dependent Variable: TRR
Method: Panel Least Squares
Sample: 2007 2007 IF TRR>-20 AND TRR<40
Periods included: 1
Cross-sections included: 196
Total panel (balanced) observations: 196

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.890734	0.990595	-1.908685	0.0578
TRR(-1)	0.089637	0.037963	2.361158	0.0192
WMR	0.916599	0.077048	11.89646	0.0000
GEARING(-1)	-0.003760	0.029922	-0.125669	0.9001

R-squared	0.459942	Mean dependent var	5.348772
Adjusted R-squared	0.451503	S.D. dependent var	10.07225
S.E. of regression	7.459562	Akaike info criterion	6.877068
Sum squared resid	10683.85	Schwarz criterion	6.943968
Log likelihood	-669.9526	Hannan-Quinn criter.	6.904152
F-statistic	54.50573	Durbin-Watson stat	0.000000
Prob(F-statistic)	0.000000		

2) Employing five variables: Style response to market movements

Table A15: Sample 2001-2007

Dependent Variable: TRR
Method: Panel Least Squares
Sample (adjusted): 2002 2007
Periods included: 6
Cross-sections included: 230
Total panel (unbalanced) observations: 768

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-4.828255	0.934106	-5.168851	0.0000
TRR(-1)	0.184744	0.031346	5.893778	0.0000
WMRDUMCORE	1.090881	0.071956	15.16031	0.0000
WMRDUMOPP	1.756275	0.180541	9.727863	0.0000
WMRDUMVA	1.360756	0.087441	15.56196	0.0000
GEARING(-1)	0.105991	0.021958	4.827080	0.0000

R-squared	0.420826	Mean dependent var	12.13668
Adjusted R-squared	0.417026	S.D. dependent var	15.54108
S.E. of regression	11.86604	Akaike info criterion	7.793020
Sum squared resid	107291.9	Schwarz criterion	7.829300
Log likelihood	-2986.520	Hannan-Quinn criter.	7.806984
F-statistic	110.7333	Durbin-Watson stat	1.472369
Prob(F-statistic)	0.000000		

Table A16: Sample 2001-2007 excluding outliers

Dependent Variable: TRR
Method: Panel Least Squares
Sample: 2000 2007 IF TRR>-20 AND TRR<40
Periods included: 6
Cross-sections included: 223
Total panel (unbalanced) observations: 735

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-3.055652	0.564159	-5.416299	0.0000
TRR(-1)	0.127556	0.020373	6.260981	0.0000
WMRDUMCORE	1.025768	0.043506	23.57779	0.0000
WMRDUMOPP	0.701177	0.134011	5.232242	0.0000
WMRDUMVA	1.125881	0.055363	20.33649	0.0000
GEARING(-1)	0.066845	0.013310	5.022167	0.0000

R-squared	0.540093	Mean dependent var	10.47660
Adjusted R-squared	0.536938	S.D. dependent var	10.13294
S.E. of regression	6.895328	Akaike info criterion	6.707695
Sum squared resid	34660.70	Schwarz criterion	6.745245
Log likelihood	-2459.078	Hannan-Quinn criter.	6.722177
F-statistic	171.2204	Durbin-Watson stat	1.320049
Prob(F-statistic)	0.000000		

Table A17: Random-effects model

Dependent Variable: TRR
Method: Panel EGLS (Cross-section random effects)
Sample: 2000 2007 IF YIELD>0 AND YIELD<40
Cross-sections included: 199
Total panel (unbalanced) observations: 659
Swamy and Arora estimator of component variances
Cross-section SUR (PCSE) standard errors & covariance (d.f. corrected)

	Coefficient	Std. Error	t-Statistic	Prob.
C	-5.958312	1.303716	-4.570253	0.0000
TRR(-1)	0.131472	0.111937	1.174524	0.2406
WMR	1.265970	0.075901	16.67922	0.0000
GEARING(-1)	0.099616	0.049553	2.010293	0.0448
EC_STOCK	-0.065166	0.026578	-2.451886	0.0145
YIELD	0.248867	0.131438	1.893428	0.0587

	Effects Specification			
			S.D.	Rho
Cross-section random			2.447633	0.0681
Idiosyncratic random			9.051424	0.9319

	Weighted Statistics		
R-squared	0.470365	Mean dependent var	10.15707
Adjusted R-squared	0.466310	S.D. dependent var	12.84159
S.E. of regression	9.381308	Sum squared resid	57469.83
F-statistic	115.9851	Durbin-Watson stat	1.391472
Prob(F-statistic)	0.000000		

	Unweighted Statistics		
R-squared	0.480172	Mean dependent var	11.64435
Sum squared resid	60672.22	Durbin-Watson stat	1.318540

A18: Impact of gearing by style

Method: Panel Least Squares
Sample (adjusted): 2002 2007
Periods included: 6
Cross-sections included: 230
Total panel (unbalanced) observations: 768

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-5.132524	0.895467	-5.731671	0.0000
TRR(-1)	0.188977	0.031015	6.092982	0.0000
WMR	1.185489	0.065370	18.13492	0.0000
GEAR_CORE(-1)	0.069832	0.025108	2.781278	0.0055
GEAR_VA(-1)	0.137436	0.028242	4.866386	0.0000
GEAR_OPP(-1)	0.387065	0.046209	8.376453	0.0000

R-squared	0.436298	Mean dependent var	12.13668
Adjusted R-squared	0.432599	S.D. dependent var	15.54108
S.E. of regression	11.70647	Akaike info criterion	7.765943
Sum squared resid	104425.6	Schwarz criterion	7.802222
Log likelihood	-2976.122	Hannan-Quinn criter.	7.779907
F-statistic	117.9557	Durbin-Watson stat	1.516876
Prob(F-statistic)	0.000000		

A19: Fund size and total return

Dependent Variable: TRR
Method: Panel Least Squares
Sample: 2000 2007 IF TRR>-20 AND TRR<40
Cross-sections included: 223
Total panel (unbalanced) observations: 735

	Coefficient	Std. Error	t-Statistic	Prob.
C	-3.155478	0.570809	-5.528077	0.0000
TRR(-1)	0.153410	0.020497	7.484603	0.0000
WMR*SMALL	0.847891	0.075907	11.17008	0.0000
WMR*MEDSMALL	0.956743	0.059817	15.99456	0.0000
WMR*MEDLARGE	1.033521	0.054405	18.99670	0.0000
WMR*LARGE	1.015462	0.055262	18.37528	0.0000
GEARING(-1)	0.081101	0.012873	6.299950	0.0000

Effects Specification

Period fixed (dummy variables)

R-squared	0.557857	Mean dependent var	10.47660
Adjusted R-squared	0.551130	S.D. dependent var	10.13294
S.E. of regression	6.788841	Akaike info criterion	6.684629
Sum squared resid	33321.89	Schwarz criterion	6.759729
Log likelihood	-2444.601	Hannan-Quinn criter.	6.713594
F-statistic	82.92894	Durbin-Watson stat	1.359574
Prob(F-statistic)	0.000000		

Appendix 2

Fixed and random effects approaches

The analysis presented in this report is based on a panel data regression approach. Prior to the advent of panel data techniques, the method of choice to capture both cross-sectional and time-series characteristics of a data series was a repeated-measurement ordinary least squares (OLS) procedure. This method is generally considered less efficient than a panel data model, however. One possibility to analyze data that have both a cross-sectional and a time series dimension is pooled OLS.

The pooled OLS model generally takes the following form:

$$y_{it} = \alpha + \beta x_{it} + u_{it}$$

with $i=1,......,N;\ t=1,....T.$

In this model, the observations of each fund over time would simply be stacked on top of one another. This standard pooled model is rather austere because intercepts and slope coefficients are forced to be homogeneous across all *n* cross-sections (funds) and through all *t* time periods. The application of standard OLS to this model ignores the temporal and space dimension of the data and hence discards useful information. The general assumption of consistent and unbiased estimators requires, however, that the independent variables are uncorrelated with any cross-section specific effects (e.g. fund effects). Here, each observation is given equal weight. Due to the obvious limitations of OLS in this research setting, more advanced procedures such as the Generalized Least Squares (GLS) approach are superior to the standard approach. Following the specification of Hsiao (2003), the GLS estimator is defined by:

$$\beta = (X'\Phi^{-1}X)^{-1}X'\Phi^{-1}y$$

The coefficient of interest is Φ^{-1}. We pre-multiply the vectors $y_i=(y_{i1}, y_{i2}, y_{i3}\ldots\ldots,y_{iT})'$, $x_i=(x_{i1}, x_{i2}, x_{i3}\ldots\ldots,x_{iT})'$ by:

$$\Phi^{-1} = \frac{1}{\sigma_u^2}\left(I_T - \frac{\sigma_\alpha^2}{\sigma_u^2 + T\sigma_\alpha^2}ee'\right)$$

where I_T is the identity matrix of dimensions $T \times T$ and e is a $T \times 1$ vector of 1's. T is the number of time period units.

Moreover, the variance of the GLS estimator is:

$$Var(\beta) = \sigma_u^2 (X'\Phi^{-1}X)^{-1}$$

In practice, the variance components σ_α^2 and σ_u^2 are unknown and have to be estimated. The GLS estimator is a weighted average of a 'within-group' and a 'between-group' estimator. The variance of the 'within estimator' is σ_u^2 whereas the variance of the between estimator is denoted σ_B^2. Finally, the variance of α is defined as:

$$\sigma^2_\alpha = \sigma^2_B - \frac{\sigma^2_u}{T}$$

Thus, the Φ matrix is constructed by:

$$\beta_{RE} = (X'\Phi^{-1}X)^{-1}X'\Phi^{-1}y$$

The fixed-effects approach

The basic assumption of the fixed effects model is that all α_i are constant across time and that the λ_t coefficients are constant across units (in our case: funds). Thus, unit effects are absorbed within the constant term:

$$E(\alpha_i) = E(\lambda_t) = E(u_{it}) = 0;$$

$$E(\alpha_i X_{it}) = E(\lambda_t X_{it}) = E(u_{it}X_{it}) = 0;$$

$$\mathrm{Var}(\alpha_i) = \sigma^2_\alpha; \ \mathrm{Var}(\lambda_t) = \sigma^2_\lambda; \ \sigma 2\lambda; \ \mathrm{Var}(u_{it}) = \sigma^2_u.$$

This type of model is typically referred to as a two-way error components model. Here, the disturbance term consists of a cross-sectional component (α_i) and a combined time series and cross-sectional component (u_{it}). Time series data are pooled with cross-sectional data. The general structure of such a model is as follows:

$y_{it} = \alpha + \beta x_{it} + u_{it}$ where $u_{it} \sim IID(0, \sigma^2)$ and $i = 1,2,......., N$ individual-level observations, and $t = 1,2,.......,T$ time series observations.

The 'between' estimator

The previous section introduced what has become known in the literature as the 'within' estimator. This is so called because it only uses the temporal or 'within' variation of the data to construct the relevant $\hat{\beta}$ estimator. It is also possible to introduce a 'between' estimator that exploits only the variation across (or between) groups. This is implemented by taking average values for each of the separate groups over the specified time period. Thus, we have:

$$\bar{y}_i = \frac{1}{T}\sum_{t=1}^{T} y_{it} \quad \text{and} \quad \bar{x}_i = \frac{1}{T}\sum_{t=1}^{T} x_{it}$$

The following regression is then performed using the group means:

$$\bar{y}_i = \mu + \bar{x}_i \beta_{Between} + u_B$$

where u_B is the error term and N would be the number of observations used in the analysis. The estimator is constructed as:

$$\hat{\beta}_{Between} = \left[\sum_{i=1}^{N} (\bar{x}_i - \bar{x})(\bar{x}_i - \bar{x})\right]^{-1} \left[\sum_{i=1}^{N} (\bar{x}_i - \bar{x})(\bar{y}_i - \bar{y})\right]$$

In this case the estimator $\hat{\beta}_{\text{Between}}$ represents the between estimator and explains the extent to which $\bar{y}_i$ is different from $\bar{y}$ (the overall mean). It exploits the variation between or across groups and this is why it is called a between estimator. The number of observations used in estimation is N – the number of groups in the panel. The 'between' estimator ignores any information within the individual group.

The random effects approach

In the random effects model, individual intercepts are allowed. These individual intercepts are expressed as a random deviation from a mean intercept. The intercept is drawn from a distribution for each unit, and is independent of the error for a particular observation. Instead of attempting to estimate N parameters as in the fixed effects approach, we estimate parameters describing the distribution from which each unit's intercept is drawn. For panel data with a large N random effects will generally be more efficient than fixed effects. It has N more degrees of freedom, and uses information from the 'between' estimator. The random-effects model can be written as follows:

$$y_{it} = \mu + \beta x_{it} + (\alpha_i - \mu) + \varepsilon_{it}$$

The error is defined as

$$u_{it} = (\alpha_i - \mu) + \varepsilon_{it}$$

We can then rewrite the equation as

$$y_{it} = \mu + \beta x_{it} + u_{it}$$

The random-effects approach takes into account both the 'between' and the 'within' dimensions of the data but, in contrast to the initially described pooled OLS, it does so efficiently by applying a GLS estimator which can be determined as a weighted average of the 'between' and 'within' estimators. The individual weight depends on the relative variances of the two estimators. The estimation of a random-effects model requires implementing a Generalized Least Squares (GLS) procedure. For an efficient estimation, we may therefore proceed as follows:

$$\theta = 1 - \frac{\sigma_\varepsilon}{\sigma_1}$$

with $\sigma_1^2 = T\sigma_\alpha^2 + \sigma_\varepsilon^2$

Within differences are calculated by:

$$y_{it}^* = y_{it} - \theta \bar{y}_{i.}, \quad x_{it}^* = x_{it} - \theta \bar{x}_{i.}$$

This can be estimated by simple OLS regression in the following manner:

$$y_{it}^* = \mu^* + \beta x_{it}^* + u_{it}^*$$

with $\mu^* = (1-\theta)\mu$

A Random Effects estimate of β is then obtained by:

$$\hat{\beta}_{re} = \frac{\sum\sum(x_{it}^* - \bar{x}_{i.}^*)(y_{it}^* - \bar{y}_{i.}^*)}{\sum\sum(x_{it}^* - \bar{x}_{i.}^*)^2}$$

Model selection: Random effects versus fixed effects

Since fixed and random-effects approaches frequently yield quite different results, the question of which approach to select is of obvious importance in empirical research. Ultimately, despite the availability of tests (particularly the Hausman test) there is no absolutely reliable statistical method to guide or determine model selection. Hsiao and Sun (2000) recommend that the choice of a model be therefore theoretically and practically driven. At the core of the selection problem is the question whether the intercepts α_i and slopes β_i are treated as fixed or random.

An important consideration is that the estimation of the fixed effects model consumes degrees of freedom. This becomes particularly problematic when the *N* of a dataset is large and the *T* is small as is the case for the data used in the present analysis. The random effects approach treats the random effects as independent of the independent variables. The main strengths of the Fixed Effects approach are the simplicity of the estimation process and the fact that independence of the fixed effects from the independent variables is not required. On the other hand, a large part of the variation in the data is lost in the process of estimating N separate intercepts. Therefore, the estimated coefficients of the independent variables in the fixed-effects regression model may be biased. For the purpose of this report, both fixed and random effects models were tested and the results are reported in the main section of the test. In terms of the economic and financial interpretation, the fixed- and random effects models generated quite similar results in this research project.