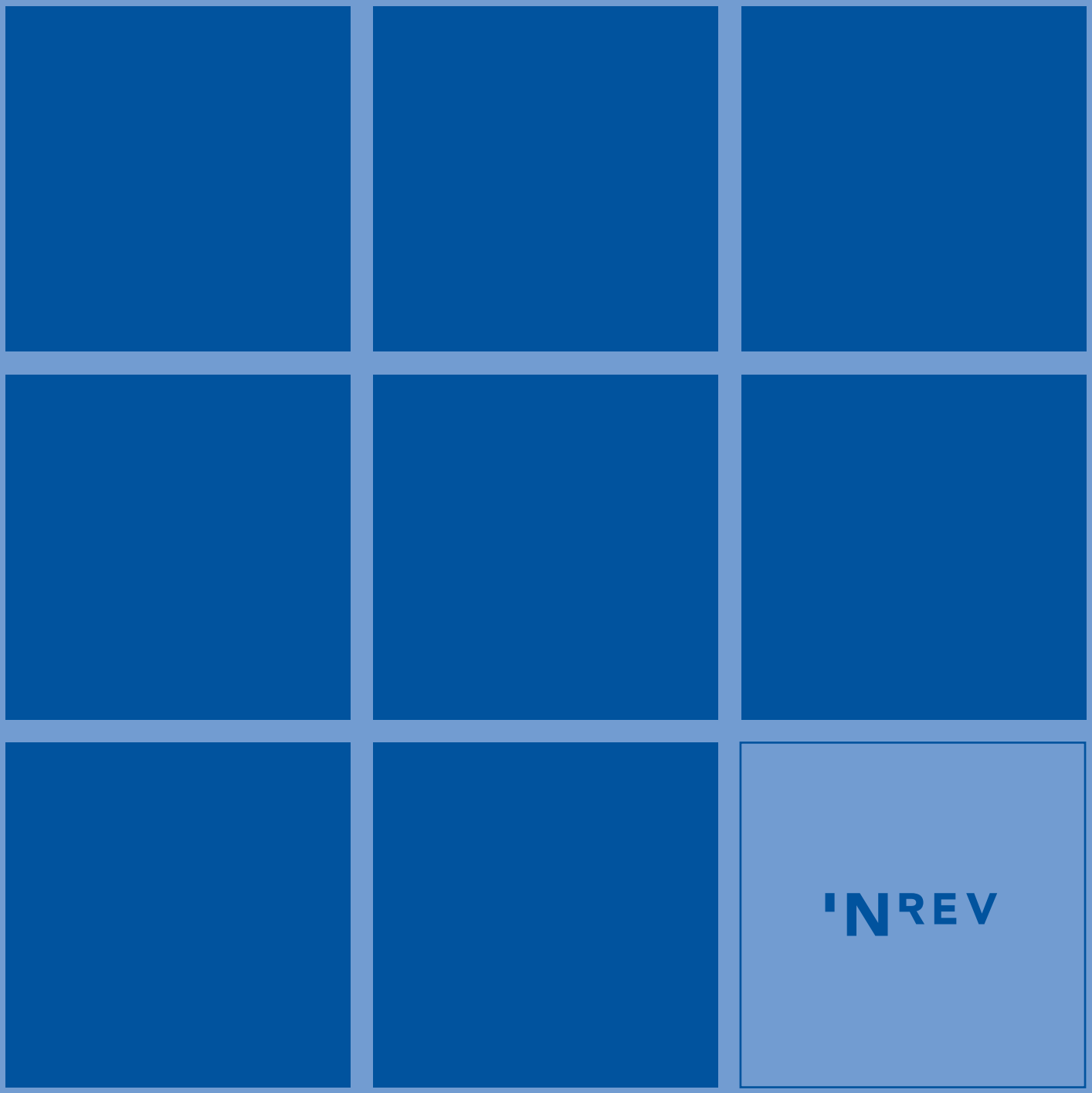
INREV RESEARCH & MARKET INFORMATION

DRIVERS OF FUND PERFORMANCE

ACADEMIC PAPER



SEPTEMBER 2013

CONTENTS

1. INTRODUCTION

With the increasing significance of non-listed real estate funds as an investment vehicle, research on the performance attributes of non-listed real estate funds is becoming increasingly important. Nevertheless, there have been few published studies on non-listed real estate funds (Fuerst & Matysiak, 2013).

This report aims to provide a better understanding of the key drivers of European non-listed real estate funds performance, which in turn will aid portfolio managers in making more informed investment decisions. It seeks to understand the extent to which stock-selection and management skills contribute to a fund's total return. The attribution of fund performance is primarily based on average return data in the markets to which the fund is exposed. Using a unique database compiled by INREV for the 2001-2012 period allows us to analyse the characteristics and performance of non-listed funds and investigate whether funds performance depends solely on leverage and market/sector exposure to deliver above-average returns. We are also able to track fund performance and its drivers through the years of rapid expansion of the sector, followed by the sharp contraction during the global financial crisis to determine whether performance drivers have a differential impact on fund performance during market upturns and downturns.

The study starts off by discussing non-listed real estate funds as an asset class in general, followed by a detailed analysis of data characteristics and a description of the methodology adopted. The study looks in detail at the drivers of fund performance, fund outperformance and risk weighted fund performance. The results of the study are presented with a critical evaluation and discussion of further research implications.

This paper has been commissioned by INREV and written by:
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2. PREVIOUS STUDIES

Real estate investments, both equity and debt, make up a substantial portion of private equity portfolios and are increasingly becoming an established alternative investment asset class. The recent explosion of growth of non-listed real estate funds over the last decade has helped establish the asset class as a major investment vehicle (Fuerst & Matysiak, 2013). The growth in non-listed real estate funds has helped facilitate growing cross-border property investments globally, and is now the preferred conduit for investors looking for real estate exposure outside their home markets (Baum & Farrelly, 2009). Brounen, Veld, & Raitio (2007) provide further evidence for the significant growth of non-listed real estate funds over the last 15 years.

For many investors, directly investing in the real estate sector may not be a viable option given investment lumpiness (large lot sizes and capital intensity), high transaction costs and asset illiquidity (it takes time to sell). Investors looking to gain exposure to underlying property assets can do so by way of 1) direct investing; 2) listed real estate securities in the form of Real Estate Investment Trusts (REITs); and 3) non-listed real estate funds .

Furthermore, illiquidity is a major concern for institutional investors. REITs offer investors a viable option to gain exposure to the underlying property assets. However, evidence points towards REITS being highly correlated with equities and may not offer sufficient portfolio diversification benefits (Georgiev, Gupta, & Kunkel, 2003). Non-listed real estate funds offer investors the same underlying exposure to property cash flows less the risk of fluctuating market trading sentiment. Current literature on private real estate funds is sparse. Hoesli and Lekander (2005) published one of the first academic studies on this topic and found that non-listed funds were highly correlated with underlying real estate markets and that non-listed funds captured the diversification benefits of direct real estate investing. Another study conducted by Stevenson (2006) on the drivers of non-listed fund performance yielded inconclusive results, mainly due to the short history of the funds' performance, 2001-2004, and the small sample size. Survey methodology (Key & Lee, 2008) was subsequently adopted to establish investment styles for private funds, but the analysis was not built on empirical investment return figures.

A more recent study by Fuerst and Matysiak (2013) using panel data for the period of 2001-2007 finds that fund characteristics, specifically, fund size, investment style, overall macroeconomic performance and performance of competing asset classes were important factors in accounting for non-listed funds' performance. However, there has hitherto been no research covering the global financial crisis – a period of high volatility which could provide valuable insights on fund performance characteristics.

Real estate funds allow individual investors to invest in the large-scale commercial real estate enterprises, such as office and residence buildings, with the usual mutual funds benefits of professional fund management and diversification. Furthermore, compared to investing directly in the property market, investors are sheltered from liquidity and management risks (Haran, McGreal, Adair, & Webb, 2008). The remarkable growth of these funds is evidently crucial in property development and urban regeneration (Brounen, Veld, & Raitio, 2007).

Private investment in real estate has undertaken evolutionary growth over the recent decade, providing investors with the benefit of indirectly investing in commercial property. Contrary to the traditional argument that non-listed funds are less transparent compared to public real estate vehicles, evidence has shown that compliance with industry guidelines in the property sector has been emerging, pointing towards a trend of higher transparency. An increasingly regulated investment environment has meant that the private real estate funds market has been thriving. Overall, research has suggested that the growth of non-listed real estate funds as a real estate investment vehicle can be partially attributable to the diversification benefits from the exposure to the underlying property assets without the illiquidity, management and idiosyncratic risks of direct property investment.

Given the thriving private equity fund sector, the need for an in-depth assessment of fund performance is apparent. Traditionally, the Capital Asset Pricing Model (CAPM) attempts to quantify the relationship between the systematic risks, namely beta, of an asset and its corresponding expected return. The model suggests that an asset is expected to earn the risk-free rate plus a risk premium reward which depends on the beta associated with the asset (Black, Jensen, & Scholes, 1972).

Apart from the associated risk of assets, other determinants of fund performance have also been widely explored. Kolouchova and Markova attempted to associate fund returns with the investment environment, including factors such as interest rates, GDP growth and geographical regions. Furthermore, the underlying stock market, a proxy for general market sentiment and a benchmark often used in assessing the abnormality of the returns, is frequently quoted as a fundamental determinant of fund performance (Gottschalg, Talmor, & Vasvari, 2010). Other drivers such as the gearing level and fund size are also cited as common factors impacting on fund performance.

3. DATA CHARACTERISTICS

The data set used in this study was provided by INREV, the European Association for Investors in Non-listed Real Estate Vehicles, and tracks fund level net performance of European non-listed real estate funds between 2001 and 2012. The data set included funds that categorised themselves as "Core" and "Value-Added" investing strategies.

The INREV database contains information on the following variables that were used in our return attribution analysis:

- Year of First Closing
- Investment Style (Core or Value-Added)
- Investment Strategy (Single or Multi Country, Single or Multi Sector)
- Fund Valuation Method (RICS or other)
- Fund Structure (Open Ended or Closed Ended)
- Gross Asset Value
- Gearing (% of GAV)
- Fund Asset Allocation (Allocation by Country & Sector)

Fund Return

As a first step in processing the available data for our study, INREV calculated Total Returns (TR) for each fund and year using the modified Dietz method. This method calculates the average invested capital for the period, as the initial net assets adjusted by weighting all external cash flows based on the amount of time they are held in the investment or fund using the actual dates of such cash flows. This method is chosen due to the fact that the majority of funds are closed-end funds and therefore time their cash flows. Exhibit 1 shows the definition of total return employed in the analysis:

Exhibit 1: Definition of total rate of return

$$TR_{(I)} = \frac{(NAV_{(t)} - NAV_{(t\text{-}1)}) + Distributions_{(t)} - Equity\ Calls_{(t)} + \text{Redemptions}}{NAV_{(t\text{-}1)} - (\sum_{1}^{N} W_1 \times Distributions) - (\sum_{1}^{N} W_1 \times \text{Redemptions}) + (\sum_{1}^{N} W_1 \times Equity\ Calls)}$$

Total return is defined here as the return investors receive, net of management fees and all other costs. During the observed period, returns range from -100% to 73.6%, with a median of 3.7% annually (Exhibit 2). The returns are negatively skewed and exhibit leptokurtosis (Exhibit 3). The fat tail is possibly due to the extreme negative fund returns recorded during the global financial crisis (GFC) in late 2007.

In order to preserve the sample size and lessen the influence of the spurious outliers, Winsorization was applied to the dataset of Fund Returns at the 1% level on both tails to replace extreme values with the closest non-extreme observation (Hastings, 1947). Winsorization keeps median values unchanged while shifting the mean closer to the median.

To better understand the characteristics of the non-listed funds in the dataset, the distributions of the various listed parameters are examined. As a preliminary step, the funds are classified by Gross Asset Value into the following categories: "Small" (<€250m), "Small Medium" (€250m<>€500m), "Medium Large" (€500m<>€1000m), and "Large" (>€1000m). Interestingly, returns increased progressively with fund size. Small funds returned 3.2% annually while large funds 5.1% (Exhibit 4). This raises the question whether better performing funds attract more capital or if larger funds actually perform better, given their ability to diversify or negotiate more favourable financing or asset purchasing terms. However, it should be borne in mind that many small funds are subjected to the so-called J-curve effect, whereby, they are still at the investment stage and costs are a dominant factor in shaping performance.

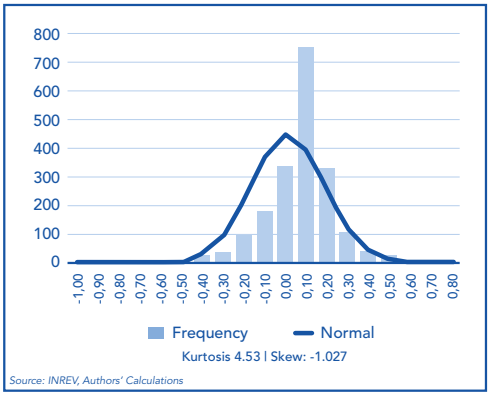
The trade-off between fund specialisation and diversification is often discussed. Here, the issue of sector and country specialisation is examined. From Exhibit 5, there seems to be little difference between the median returns of single sector and multi sector funds. However, funds with single country investments seem to enjoy a specialisation advantage, where annual median returns are 4.6% against the 2.1% for multi country funds.

Exhibit 2: Key Distribution Statistics of Fund Annual Returns, 2001-2012 (1985 observations)

Fund Return Range (%)	Median	Mean	Min	Max	Count	Percentage	Cumulative Percentile
[-100, -80)	-94.6%	-91.6%	-100.0%	-80.5%	7	0.4%	0.4%
[-80, -60)	-68.7%	-69.3%	-77.3%	-62.2%	10	0.5%	0.9%
[-60, -40)	-45.8%	-46.7%	-59.0%	-40.4%	39	2.0%	2.8%
[-40, -20)	-25.7%	-27.1%	-40.0%	-20.0%	139	7.0%	9.8%
[-20, 0)	-6.8%	-7.9%	-19.9%	0.0%	525	26.4%	36.3%
[0, 20)	6.8%	7.6%	0.0%	19.8%	1,090	54.9%	91.2%
[20, 40)	25.6%	27.0%	20.0%	40.0%	152	7.7%	98.8%
[40, 60)	44.8%	45.4%	40.3%	55.7%	17	0.9%	99.7%
[60, 80)	67.5%	67.9%	62.3%	73.6%	6	0.3%	100.0%
All	3.7%	1.3%	-100.0%	73.6%	1,985	100.0%	100.0%

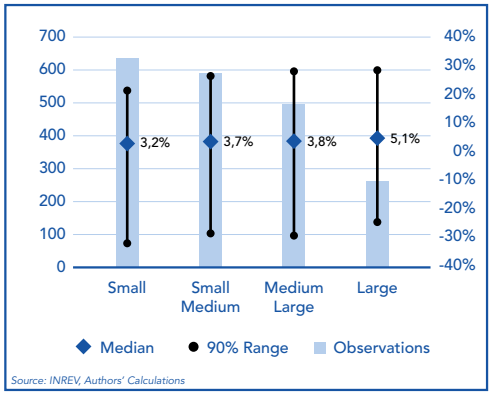
Source: INREV, Authors' Calculations

Exhibit 3: Distribution of Annual Fund Returns, 2001-2012



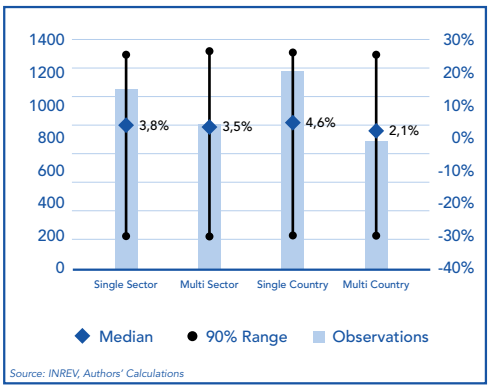
Source: INREV, Authors' Calculations

Exhibit 4: Annual Fund Returns by GAV, 2001-2012



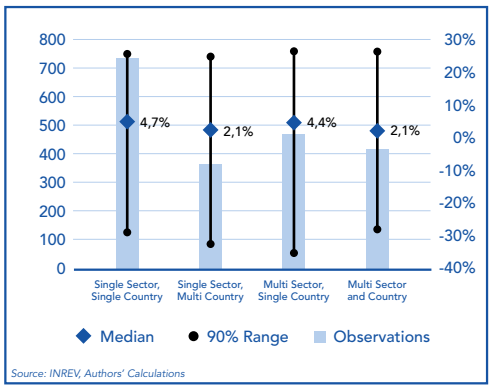
Source: INREV, Authors' Calculations

Exhibit 5: Annual Fund Returns by Strategy, 2001-2012



Source: INREV, Authors' Calculations

Exhibit 6: Annual Fund Returns by Strategy, 2001-2012



Source: INREV, Authors' Calculations

Next, the fund strategies are dissected into four mutually exclusive but collectively exhaustive categories. From Exhibit 6, the single sector-single country funds seem to have the best median annual fund return of 4.7%. Of the other three categories of multi strategy funds, the Multi Sector-Single country category was a stand out with 4.4% annual median returns. The descriptive statistics seem to suggest that country specialisation seem to offer better returns, perhaps due to the better local knowledge these fund managers may have, thereby having less diversification. Taking the three multi strategy fund categories together, in general, specialised funds seem to have provided better returns to multi-styled funds (Exhibit 7).

Compared to core funds, value-added funds take more risk and hence investors expect higher returns. However, the annual median fund return of value-added funds between 2001 and 2012 was only 0.59%, less than the median 4.29% returns core funds enjoyed (Exhibit 8). Core funds restrict their investments, largely, to prime properties and derive most of their returns from rental income, while value-added funds would also invest in higher yielding, non-prime assets and derive a large part of their income from capital appreciation (Fuerst & Marcato, 2009). The GFC resulted in the collapse of the commercial mortgage-backed securities (CMBS) market and banks were reluctant to lend. With

little financing, capital was sucked out of the capital intensive real estate market and consequently, real estate values have struggled to hold up. Conversely, with base rates at an all-time low, and coupled with the flight to safety, there was a hunger for yield and prime real estate (which core funds mostly invest in) was in demand. Hence, the lower median returns of value-added funds vis-à-vis core funds can be largely explained by a combination these macroeconomic trends and the impact of leverage.

In general, fund returns experienced increased volatility during the GFC (Exhibit 9). It must also be noted that the yearly number of observations for the period of 2001-2006, where funds enjoyed high median returns, is comparatively small, hence the high observations of negative fund returns post GFC has polarising the combined 2001-2012 median returns downwards.

Decomposing the annual fund returns by style, core funds exhibited noticeably less volatile returns than value-added funds (Exhibit 10 & Exhibit 11). Value-added funds enjoyed solid returns in the run up to the GFC. The higher risks of value-added investing proved to be evident during the GFC, where median returns were highly negative. Post GFC, value-added funds still seem to struggle to recover.

Exhibit 7: Annual Fund Returns by Strategy, 2001-2012

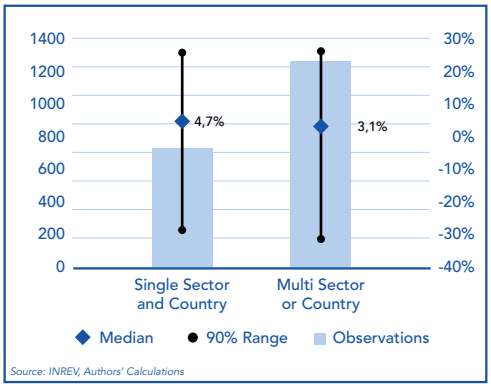


Exhibit 8: Annual Fund Returns by Style, 2001-2012

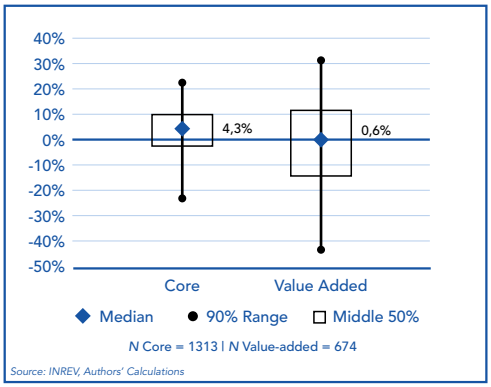


Exhibit 9: Annual Fund Returns, 2001-2012

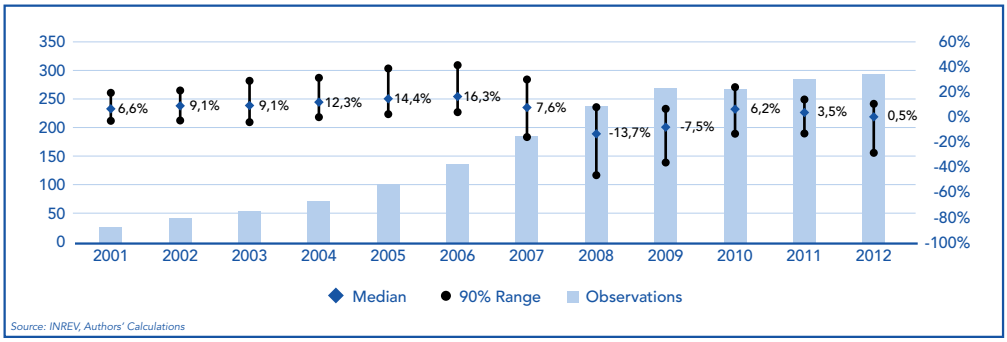
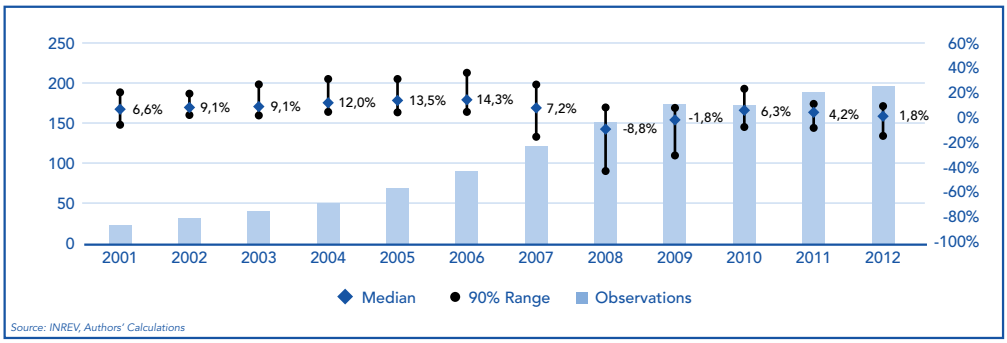
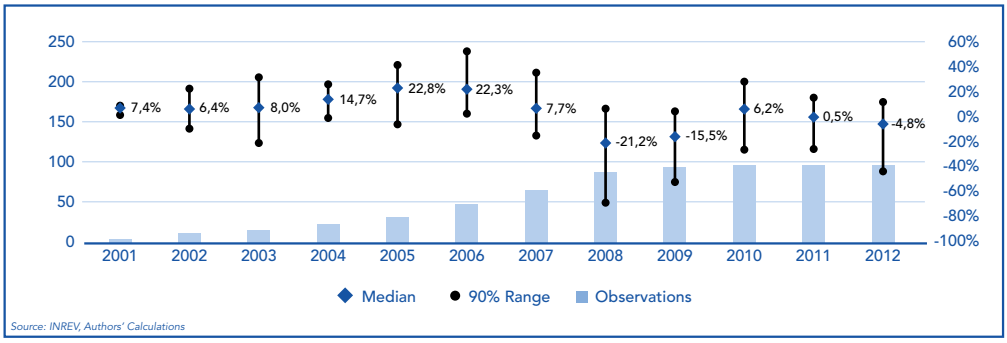


Exhibit 10: "Core" Fund Annual Returns, 2001 -2012



Source: INREV, Authors' Calculations

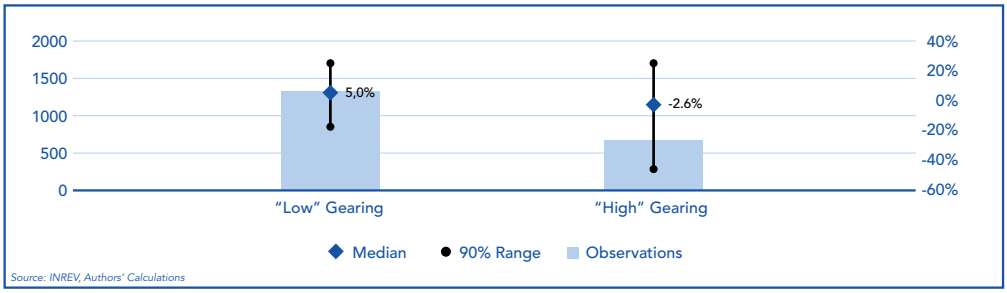
Exhibit 11: "Value-Added" Annual Fund Returns, 2001-2012



Source: INREV, Authors' Calculations

Funds with gearing of less than 50% were categorized as "Low Gearing" while funds with 50% or more leverage are categorized as "High Gearing". From Exhibit 12, high gearing funds exhibited lower median returns compared to low gearing funds. This is largely due to the increased number of observations of negative fund returns during the more recent years. On a yearly basis, highly geared funds exhibited considerable more volatility in returns, especially during the GFC (Exhibit 13 & Exhibit 14).

Exhibit 12: Annual Fund Returns by Gearing, 2001-2012



Source: INREV, Authors' Calculations

Exhibit 13: "Low" Gearing Annual Fund Returns, 2001-2012

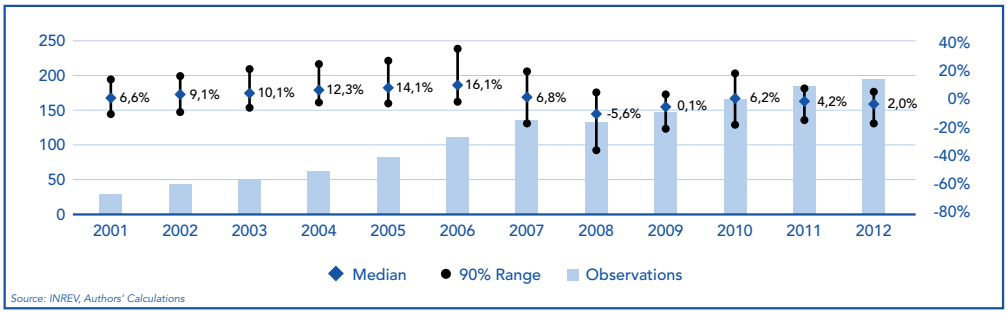
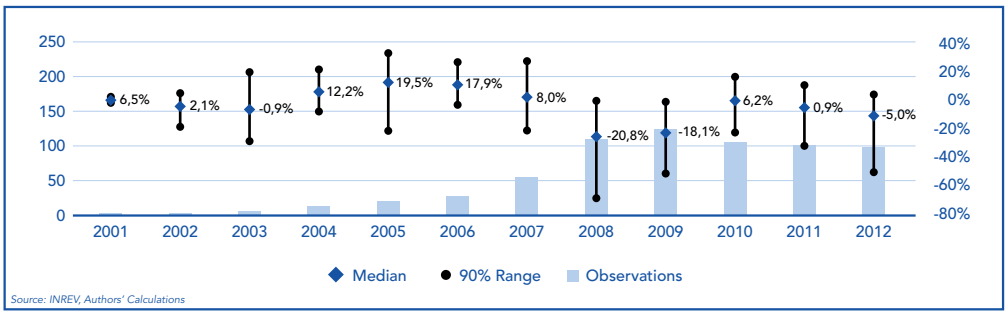


Exhibit 14: "High" Gearing Annual Fund Returns, 2001-2012



From Exhibit 15, open-ended funds had a median fund return of 4.3% as compared to closed-ended's 2.2%. Closed-ended funds also exhibited higher volatility of returns (Exhibit 16 & Exhibit 17). Most significantly during the GFC, open-ended funds returns were only slightly negative, compared to the highly negative returns of closed-ended funds. This is perhaps the result of closed-ended funds' tendency to have higher gearing.

Exhibit 15: Annual Fund Returns by Investment Structure, 2001-2012

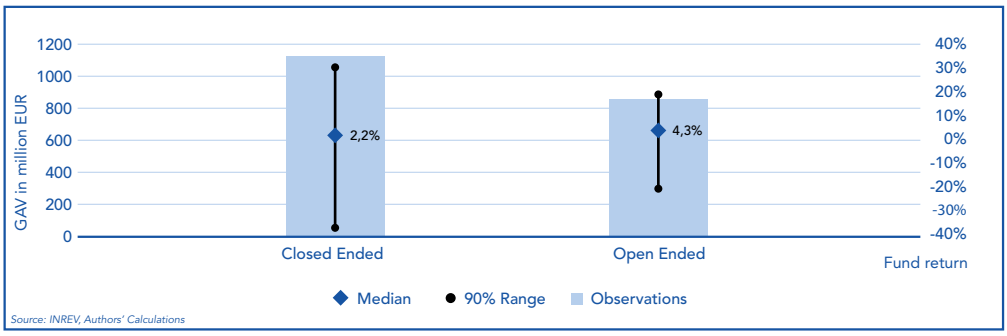
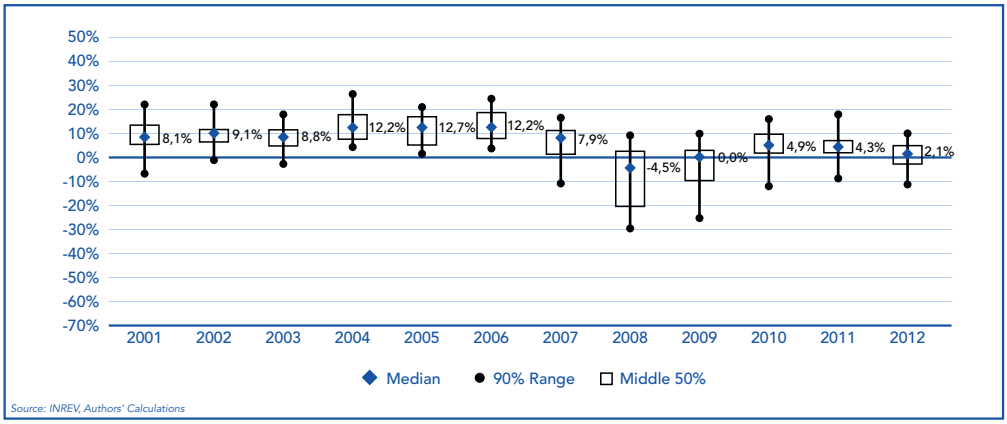
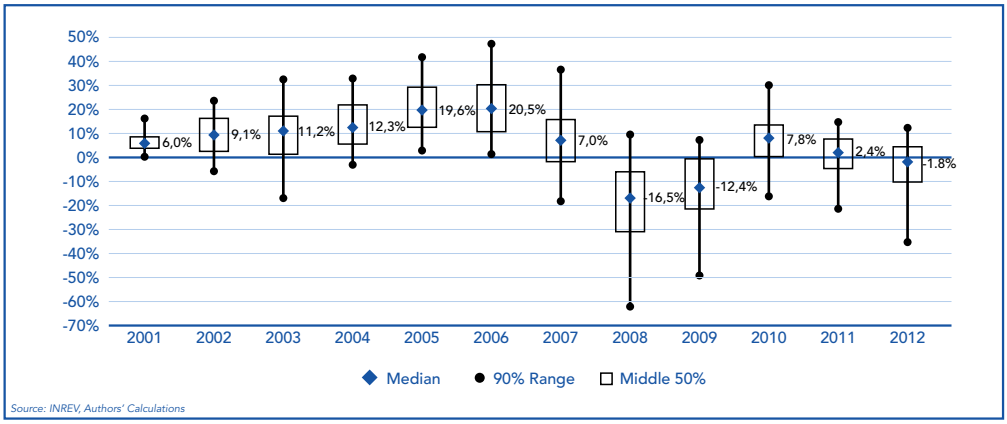


Exhibit 16: Open Ended Annual Fund Returns, 2001-2012



Source: INREV, Authors' Calculations

Exhibit 17: Closed Ended Annual Fund Returns, 2001-2012



Source: INREV, Authors' Calculations

Gross Asset Value (GAV)

As noted earlier, real estate funds have grown significantly between 2001 and 2008, both in terms of cumulative GAV and number of funds (Exhibit 18). However, since the GFC, growth has slowed. Unsurprisingly, the GFC has reduced funds' GAV as asset values plunged. The mean and median GAVs have post crisis fell to 2003 levels and have yet to recover to pre-crisis highs (Exhibit 19).

Diversified funds had a median GAV of €413m, greater than the median of €344m of specialised funds (Exhibit 20). The 90% range of diversified funds' GAV also had a higher upper limit. Given the large lot sizes and capital intensity of property investments, perhaps the benefits of diversification can only be realised with larger assets under management.

From Exhibit 21, the median fund size of core and value-added funds were not significantly different; however, there were numerous very large core funds. Likewise, median fund size of lowly and highly geared funds did not differ much. However, larger funds tend to be lowly geared (Exhibit 22). There was also no significant difference in the fund sizes of open ended and closed ended funds (Exhibit 23).

Exhibit 18: Evolution of Total GAV and Number of Funds, 2001-2012

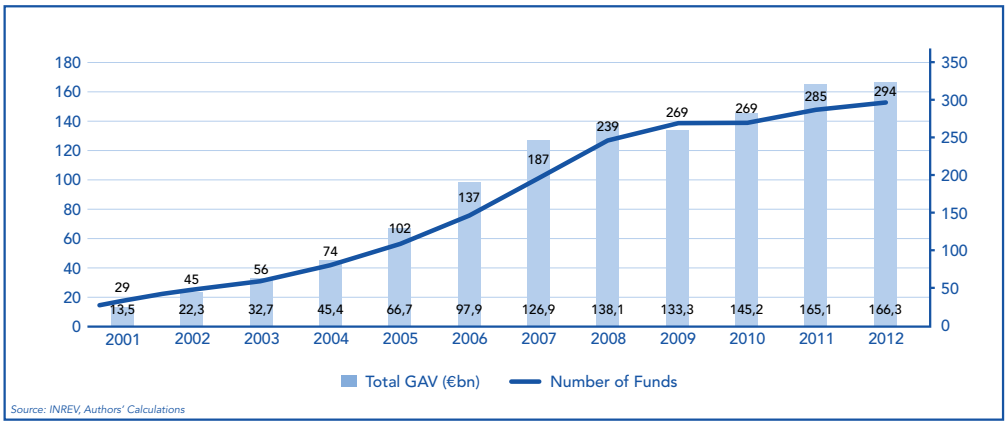


Exhibit 19: Evolution of Fund GAV, 2001-2012

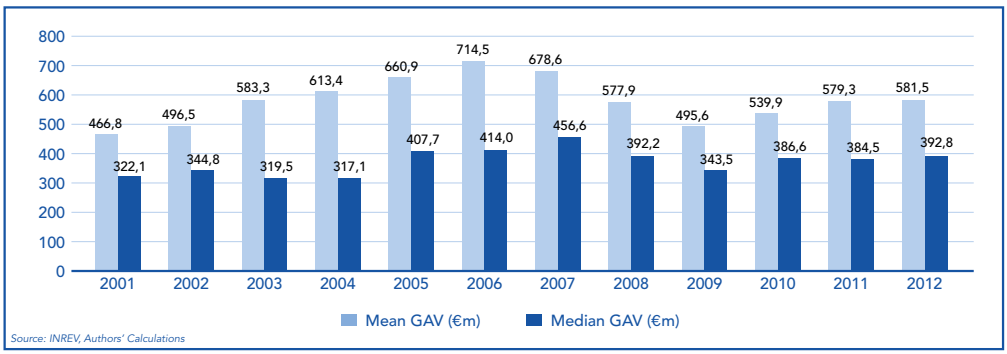
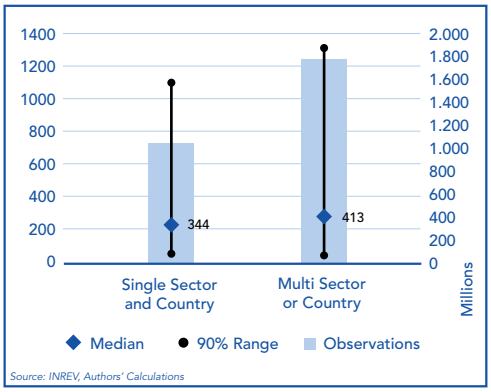
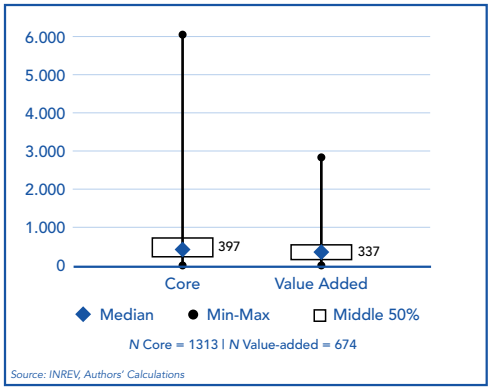


Exhibit 20: GAV by Fund Strategy, 2001-2012



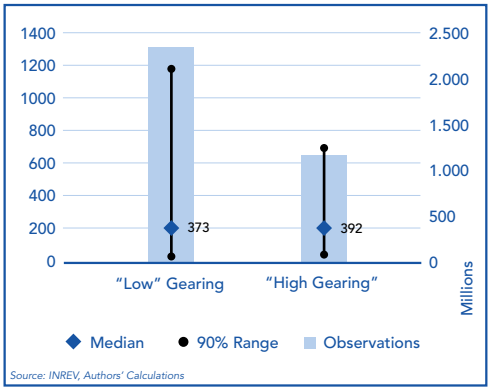
Source: INREV, Authors' Calculations

Exhibit 21: GAV by Style



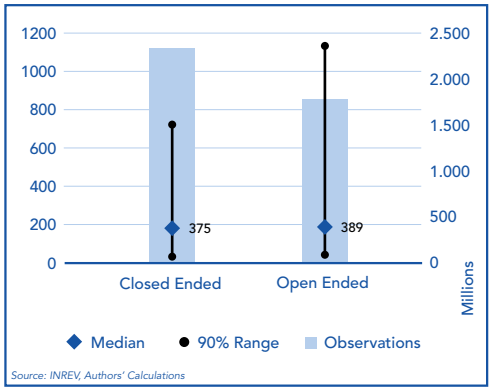
Source: INREV, Authors' Calculations

Exhibit 22: GAV by Gearing, 2001-2012



Source: INREV, Authors' Calculations

Exhibit 23: GAV by Structure, 2001-2012



Source: INREV, Authors' Calculations

Gearing

Funds are often differentiated based on their level of financial leverage. With higher leverage, funds typically take on higher risk, making the level of debt a primary attribute of performance. While leverage should, theoretically, not affect the level of risk adjusted return of funds, it is probable that funds with higher gearing may trade differently than funds using lower level of leverage, hence varying fund performance may result (Schneeweis, Martin, Kazemi, & Karavas, 2005).

The Global Financial Crisis in 2008 drew further research attention to the role of financial leverage in underperformance of funds in general. Furthermore, empirical evidence suggests that gearing increases the probability of fund failure, especially in times of financial crisis (Amoako & Samarbakhsh, 2012). At the fund level, it is important to remember that gearing, as defined by INREV, measures fund level gearing and not net asset level gearing.

Overall, specialised funds exhibit lower median gearing of 31.2% compared to a median of 45.7% for diversified strategy funds (Exhibit 24). Further decomposition reveals that single sector, multi country funds had the highest median gearing of 50.7% (Exhibit 25). Unsurprisingly, the riskier value-added funds have higher median gearing of 53% (Exhibit 26). Possibly due to their structure and style characteristics, close ended funds had median gearing of 49.6%, which is almost twice the median gearing of open ended funds.

Exhibit 24: Gearing by Strategy, 2001-2012

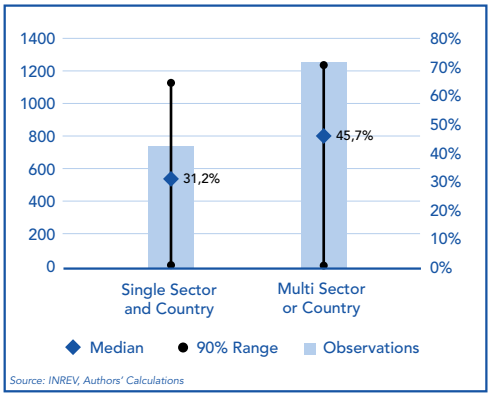


Exhibit 25: Gearing by Strategy, 2001-2012

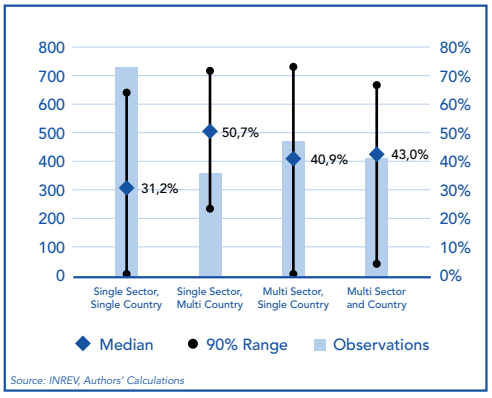


Exhibit 26: Gearing by Style, 2001-2012

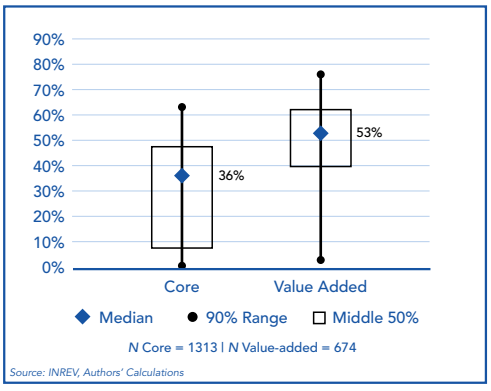
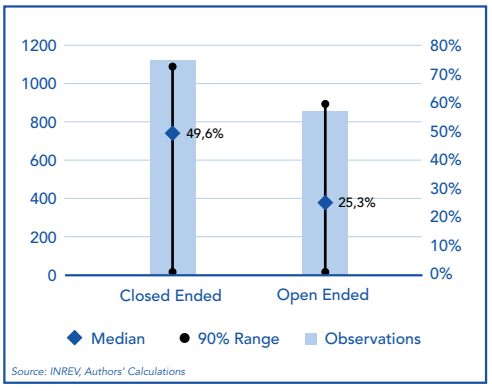


Exhibit 27: Gearing by Structure, 2001-2012



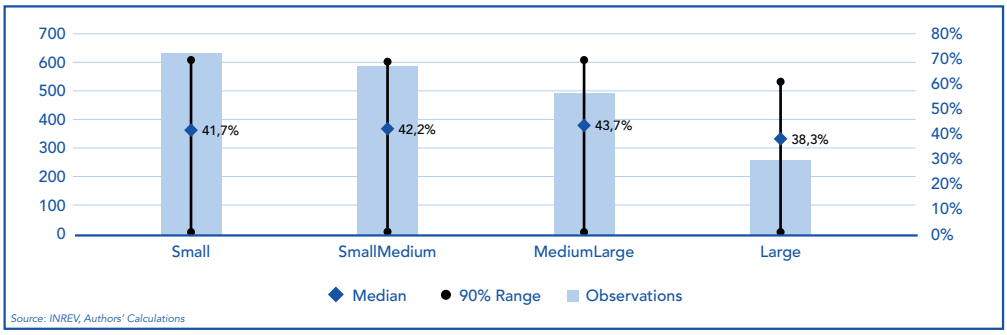
Average gearing is broadly similar across all fund sizes (see page 25 for *Fund Size* classifications), although large funds have slightly lower gearing at 38% (Exhibit 28).

INREV only record a snapshot of gearing as at year end. In theory, the net effect of gearing on fund returns for a given year is the result of the effect of monthly gearing levels (or quarterly depending on accounting frequency). Taking into account the impact of gearing of the previous period, gearing is expressed as the average gearings of two consecutive years:

For example, if the gearing for a fund is 20% in December 2006 and 40% in December 2007, the gearing effect on returns for the year of 2007 is calculated as the average between the two data points i.e. 30%.

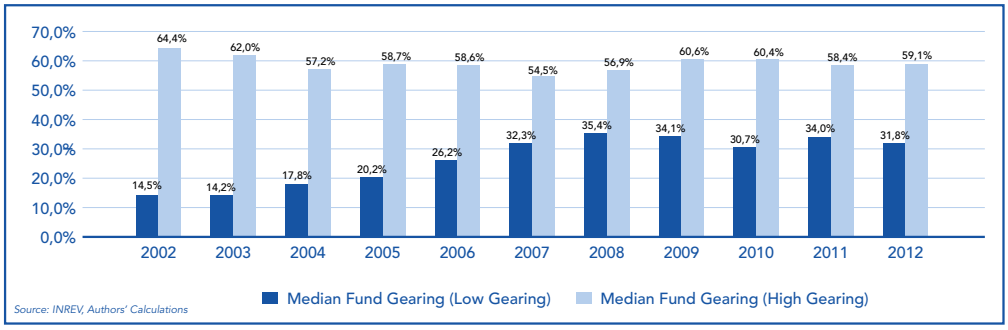
As such, in the empirical analysis that follows, the "Average Gearing" variable is used. From Exhibit 29, the median average gearing of highly geared funds remained relatively constant at around 60%. However, the average gearing of low geared funds seems to have increased until the GFC, perhaps fuelled by cheap debt. The caveat is that during periods when underlying asset values are falling, the equity value of the fund is reduced and, mathematically, gearing may seem to increase.

Exhibit 28: Gearing by Fund Size, 2001-2012



Source: INREV, Authors' Calculations

Exhibit 29: Median Average Fund Gearing 2002 – 2012



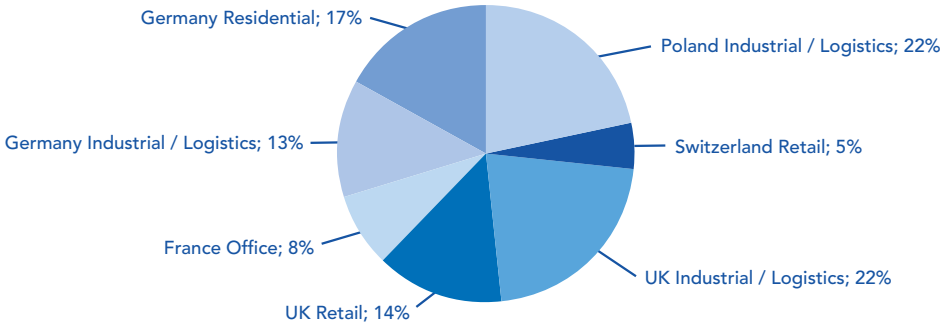
Source: INREV, Authors' Calculations

Weighted Market Return (WMR)

To compare fund returns with underlying market performance, a new variable, the Weighted Market Return (WMR) was constructed by collating the weighted returns of individual sector-geographical specific allocations of each fund for each year.

As an example of how the WMR was constructed (Exhibit 30), for a particular fund in year 2011 with capital invested in the countries and sectors as listed, using the sum-product of their allocation and IPD returns for the specific country-sector, the weighted return is the WMR.

Exhibit 30: Example of WMR construction



Year	Country	Sector	Allocation	IPD Country-Sector Index Return	Weighted Return
2011	France	Office	8.00%	7.25%	0.58%
2011	Germany	Industrial / Logistics	12.50%	6.99%	0.87%
2011	Germany	Residential	16.80%	7.84%	1.32%
2011	Poland	Industrial / Logistics	21.80%	6.36%	1.39%
2011	Switzerland	Retail	5.00%	8.50%	0.43%
2011	United Kingdom	Industrial / Logistics	21.80%	7.26%	1.58%
2011	United Kingdom	Retail	14.10%	7.10%	1.00%
	WMR		**100%**		**7.17%**

In short, the WMR for a specific fund in a specific year is the expected portfolio return for that specific fund for that year. The WMR hence serves as a benchmark that reflects primarily the skill to select countries and sectors that deliver better risk-adjusted or nominal returns than the overall property index (Baum A. , 2009). The spread between the WMR and the individual fund return can then be hypothetically attributed to the performance of the individual assets in local markets within the broad country and sector return that the WMR represents. In general, outperformance can be attributed on two levels:

- Portfolio structure - the allocation of investments to outperforming geographies and sectors
- Stock level – sourcing and managing outperforming assets

An important caveat for the comparability between WMRs and fund returns is the inclusion of management fees in the two return series. All INREV returns are reported net of fees, i.e. after all fees were deducted. By contrast, IPD return data are calculated at the individual asset level, thereby excluding the impact of fund management fees and fund costs on

portfolio returns. However, IPD returns will take into account asset-level fees such as property maintenance and improvement costs. As a result of this difference in performance measurement, the comparability between INREV returns and IPD returns is limited as the performance of the former may appear to be lower due to the deduction of fees.

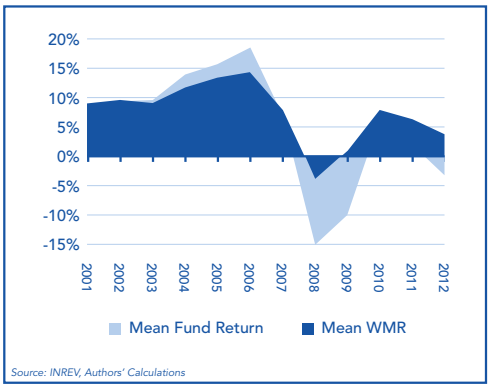
Also, the IPD indices are more like core indices as developments are not taken into account. A further aspect which needs to be taken into account is that IPD uses standing investments (i.e. properties which are reported at the beginning and end of year). This means that properties that are sold or bought during a year are not taken into account and, therefore, the impact on the 'true' IPD returns is unknown.

However, since this study is mainly concerned with the dynamics of fund returns, the IPD-based WMRs can still give some important insights regarding market dynamics and the contribution of particular countries and sectors to a fund's overall performance in a given year.

Exhibit 31 and Exhibit 32 illustrate that fund returns outperformed the underlying market from 2003-2007 before the relationship reverses in 2007/8. There are a number of possible explanations for this including differences in risk exposure, valuation smoothing, the impact of management fees together with caveats discussed in the previous two paragraphs. Exhibit 33 shows marked differences in fund performance when the indices are broken down by level of gearing. Exhibit 34 shows further that the market returns (depicted on the horizontal axis) exhibit a smaller relative variability in values than the fund returns. This is perhaps not surprising given that market returns are more aggregated than fund returns, therefore have much of the variability of the underlying assets removed. Exhibit 35 illustrates the distribution of market outperformance over the Pan-European IPD index. The variance of outperformance/underperformance increased markedly during the GFC of 2008.

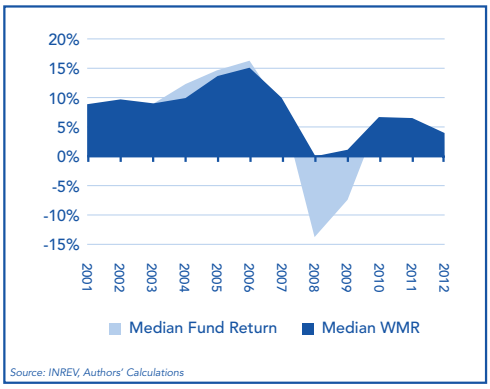
The percentage of funds outperforming the WMR and Pan-European IPD index respectively are largely similar, with more than 50% of the funds outperforming the two benchmarks during in the years prior to the financial crisis (Exhibits 36 and 37). However, since the financial crisis, funds' returns have lagged the benchmarks. In the 2001-2012 period, the average percentage of funds outperforming the WMR was 37% compared to 41% of funds outperforming the Pan-European IPD. This may suggest that managers were possibly more successful with portfolio structure than property level selection within a specific market. This is an area of interest that warrants more research.

Exhibit 31: Mean Fund Annual Returns and WMR



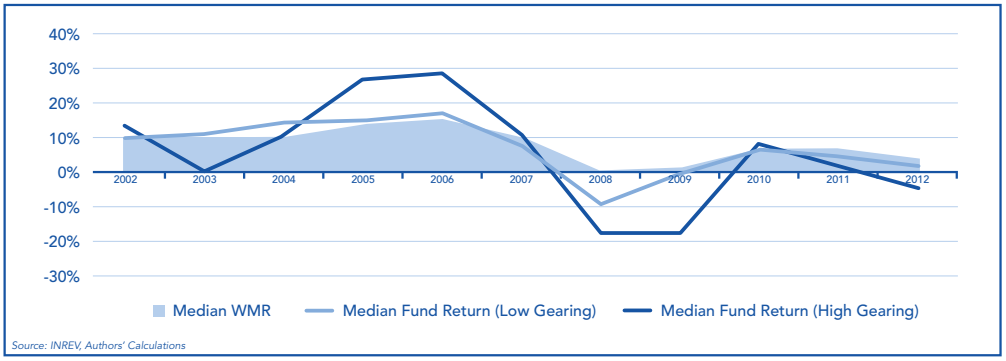
Source: INREV, Authors' Calculations

Exhibit 32: Median Fund Annual Returns and WMR



Source: INREV, Authors' Calculations

Exhibit 33: Median Fund Annual Returns and WMR



Source: INREV, Authors' Calculations

Exhibit 34: Scatter of WMR vs. Fund Returns

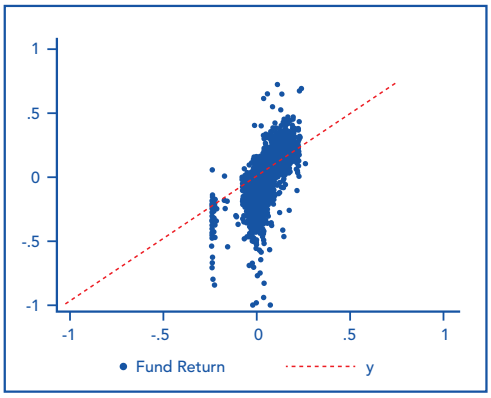


Exhibit 35: Scatter of WMR Outperformance by Year

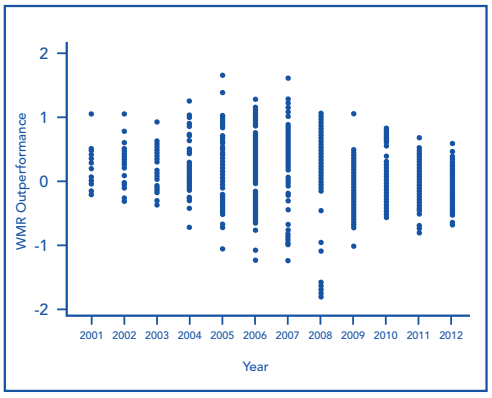


Exhibit 36: WMR Outperformance by Year

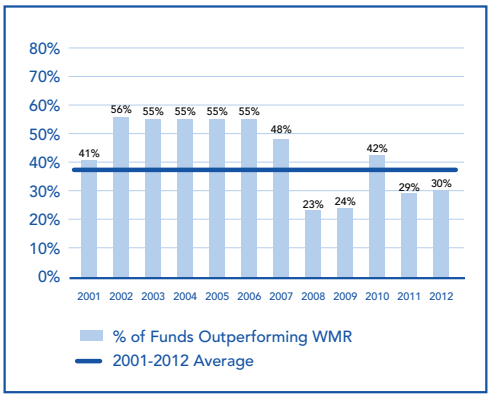
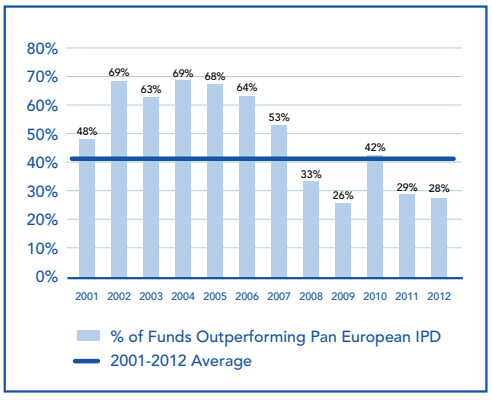


Exhibit 37: Pan-European IPD Outperformance by Year



4. MODEL SPECIFICATION: DATA CONSIDERATIONS

An important preliminary step of the analysis involves examining the distributions and other statistical characteristics of the dataset as well as aggregating continuous variables into categories where appropriate. Specifically, we categorise gearing level and fund size to work out the differential effect of low and high values for each of these two variables. We conducted robustness checks using both categorical and continuous versions of these variables and obtained consistent results as described in the following section. Our performance attribution analysis considered the following initial set of variables:

1. WMR: The percentage weighted market return measures underlying market performance, based on fund portfolio selection of geographical and sector for a specific year..
2. Gearing: The percentage average of gearing at time t and gearing at t-1.
3. Gearing Level Dummies:
    - Low Gearing Dummy: 1 if fund gearing for a specific year is less than 50%, 0 if not.
    - High Gearing Dummy: 1 if fund gearing for a specific year is greater or equal to 50%, 0 if not.
4. GAV: Fund's gross asset value in a particular year in million Euros.
5. Fund Size Dummies:
    - Small Medium Dummy: 1 if GAV is greater than or equal to €250m but less than 500m.
    - Medium Large Dummy: 1 if GAV is greater than or equal to €500m but less than 1,000m.
    - Large Dummy: 1 if GAV is greater than or equal to €1,000m.
6. Up-Fund Dummy: 1 if fund's annual performance is greater than or equal to 0% for a particular year
7. Fund Age: Fund age in discrete number of years, e.g.: 1 year old, 5 years old, etc.

To establish if there is a systematic change in the mean or variances of the data, the unit root tests were conducted for key variables, namely Fund Return, WMR, Gearing and GAV. Assuming individual unit root processes, both augmented Dickey-Fuller test and the Phillips-Perron tests strongly reject the null hypothesis that a unit root exists, hence indicating the data is stationary and do not need to be differenced (Exhibit 38).

Exhibit 38: Unit Root Tests on Key Variables

Method	Fund Return	Gearing	WMR	GAV
Fischer Chi Square (Dickey-Fuller)	1699.5594 (0.000)	1056.0093 (0.000)	3319.0327 (0.000)	1236.22 (0.000)
Fischer Chi Square (Philips-Perron)	1094.4672 (0.000)	923.7808 (0.000)	1451.387 (0.000)	2430.287 (0.000)

5. EMPIRICAL ANALYSIS: DRIVERS OF FUND RETURN

The dataset configuration makes a panel data analysis highly suitable. Furthermore, employing fixed or random effects models for panel data controls for omitted variables. In general, fixed effect models are employed to control for omitted variables between cases, such that the omitted variables account for a differential impact on investment style returns. However, if each omitted variable is estimated to have a consistent effect while randomly varying between cases, then the random effects model would be suitable. (Refer to Appendix 1 for further details.)

Weighted Market Return (WMR)

Previous studies have showed that fund returns are driven mainly by the WMR, gearing and fund size. Beginning with pooled OLS models, from Regression (1) (Exhibit 39), the Heteroskedasticity robust standard errors suggest that WMR is a significant predictor of fund returns. For every 1 percentage change in the WMR, fund returns change by 1.5%. Next, fund size, gearing and fund age were individually added to the model. Gearing, Regression (2) and GAV Regression (3) (Exhibit 39) were statistically significant. However fund age, Regression 4) (Exhibit 39), was insignificant and only turned significant when Gearing and GAV were added in Regression (5) (Exhibit 39). Part of the reason could be that Regression (4) has suffered from omitted variable bias given the correlations between Fund Age and Gearing of 0.38, and Fund Age and GAV of 0.23 (Exhibit 40). Overall, the pooled OLS offers strong support that the WMR, Gearing, Fund Size and Fund Age are significant predictors of fund performance.

Exhibit 39: Pooled OLS of WMR, Fund Size, Gearing and Fund Age on Fund Return

	(1) Fund Return		(2) Fund Return		(3) Fund Return		(4) Fund Return		(5) Fund Return	
WMR	1.504***	(0.000)	1.526***	(0.000)	1.502***	(0.000)	1.505***	(0.000)	1.519***	(0.000)
Gearing			-0.130***	(0.000)					-0.150***	(0.000)
GAV (€Bil)					0.0134***	(0.001)			0.0163***	(0.000)
Fund Age							0.000684	(0.105)	-0.00194***	(0.000)
C	-0.0718***	(0.000)	-0.0242***	(0.000)	-0.0797***	(0.000)	-0.0762***	(0.000)	-0.0129	(0.110)
Observations (*N*)	1985		1640		1977		1985		1637	
R^2	0.434		0.504		0.438		0.435		0.512	
Adjusted R^2	0.434		0.503		0.438		0.435		0.511	
Akaike Criterion	-2663.0		-2416.9		-2657.4		-2663.6		-2433.2	
Schwarz Criterion	-2651.8		-2400.7		-2640.6		-2646.8		-2406.2	
F-Statistic	1523.1		831.7		769.9		763.5		428.2	
d.f. Model	1		2		2		2		4	
d.f. Regression	1983		1637		1974		1982		1632	
Log Likelihood	1333.5		1211.5		1331.7		1334.8		1221.6	

p-values in parentheses

*** p<0.05 ** p<0.01 *** p<0.001**

Exhibit 40: Correlations between Gearing, GAV, Fund Age & WMR

	Gearing	GAV (€Bil)	Fund Age	WMR
Gearing	1.0000			
GAV	-0.0454	1.0000		
Fund Age	0.3751	0.2307	1.0000	
WMR	0.0822	0.0346	0.0196	1.0000

In order to remove the effects of time-invariant characteristics from the predictor variables, the fixed effects model, with the support of the Hausman test results, was applied. From Regression (6), the WMR is a significant predictor of fund returns – for every 1% change in the WMR, fund returns change by 1.1%. From Regression (7), gearing on average has a negative impact on fund returns. For a 10% change in gearing, fund returns falls by 1.8%. This finding contrasts with the positive impact of gearing a previous study where for a 10% increase in gearing, fund returns increase by 0.67% on average (Fuerst & Matysiak, 2013). That study, however, only used data between 2001 and 2007 and did not take into account the adversely negative impact of gearing during the GFC that started in late 2007.

In their study, Fuerst and Matysiak (2013) also showed a negative relationship between fund size and fund returns. In contrast, the analysis here shows that fund performance is positively associated with fund size. For every 1bn increase in fund size, fund returns increase by 0.04%. However, it is argued that the observation that larger funds enjoy higher returns could be the result of an endogeneity issue – that better performing funds would attract more investors which then leads to larger fund sizes. Hence it may be that other factors rather than fund size which may be responsible for the higher returns (Matallin-Saez, 2011).

Exhibit 41: Fixed Effects Models of WMR, Fund Size, Fund Age and Gearing on Fund Return

	(6) Fund Return		(7) Fund Return	
WMR	1.092***	(0.000)	1.153***	(0.000)
Gearing			-0.177*	(0.018)
GAV (€Bil)			0.0383**	(0.003)
Fund Age			-0.00848***	(0.000)
Yr_2002	0.0152	(0.256)	0	(.)
Yr_2003	0.0234	(0.165)	0.00509	(0.740)
Yr_2004	0.0382*	(0.011)	0.0161	(0.238)
Yr_2005	0.0365*	(0.028)	0.0303	(0.100)
Yr_2006	0.0568***	(0.000)	0.0467**	(0.002)
Yr_2007	0.0236	(0.118)	0.0357**	(0.003)
Yr_2008	-0.0623***	(0.000)	-0.0351**	(0.007)
Yr_2009	-0.0681***	(0.000)	-0.0396***	(0.000)
Yr_2010	0.0107	(0.453)	0.0447***	(0.000)
Yr_2011	-0.0204	(0.152)	0.0233**	(0.002)
Yr_2012	-0.0471**	(0.002)	0	(.)
C	-0.0337*	(0.017)	0.0401	(0.187)
Observations (*N*)	1985		1637	
R^2	0.524		0.575	
Adjusted R^2	0.521		0.572	
Akaike Criterion	-3516.9		-3132.3	
Schwarz Criterion	-3449.8		-3062.1	
F-Statistic	76.92		72.05	
d.f. Model	11		12	
d.f. Regression	344		314	
Log Likelihood	1770.4		1579.1	
Hausman Test	106.36		47.91	
P>Chi^2	(0.000)		(0.000)	

p-values in parentheses

*** p<0.05 ** p<0.01 *** p<0.001**

Fund Size

To further examine the interaction of fund size and fund returns, an alternative model was specified using fund size dummies. The funds have been categorized as: Small (<€250m), Small Medium (€250m<>€500m), Medium Large (€500m<>€1000m), and Large (>€1000m). From Regression 8, relative to small funds, larger funds on average performed marginally better – Small Medium (+0.05%), Medium Large (+0.09%), and Large fund (+0.08%). The findings here echo the findings in Regression 5 of positive association between fund size and fund returns. There are two potential reasons for the observation. First, bigger funds might indeed perform better for some reason such as their ability to diversify, better industry relationships, cost advantages or having the capital base to make large acquisitions (an area with fewer competitors since there are not so many large funds). Second, funds that exhibit a track record of better performance attract more capital inflows.

Although the results show that fund size has a statistically significant effect on fund performance, using this fund characteristic in the investment strategy would be quite

difficult as for many funds there is no opportunity to gain entry into a larger fund via the secondary market. Alternatively, investors would only be able to use this in their strategy if they could find a way of predicting which of the newer, smaller funds might grow large. Additional analysis should be performed to look at the target fund size and if funds that planned to be large actually performed better.

To examine the first potential explanation in greater detail, the same model was applied to close-ended funds only to minimize of the effects the second reason. This is because once a close ended fund is closed, no or limited further investment is accepted, which then leaves funds limited exposure to changes in fund size and mitigates the endogeneity problem. From Regression (9) the coefficients of the dummies increase in magnitude as compared to Regression (8). Relative to small funds, larger funds resulted in better performance – Small Medium (+0.09%), Medium Large (+0.13%), and Large fund (+0.12%). These results reinforce the observation that larger funds indeed perform better. Further research on why this may be so would certainly yield interesting results.

If the argument that better performance attracts more investments is true, this should be observed very prominently in open-ended funds. However, from Regression (10) the fund size dummies are insignificant predictor of fund performance.

Exhibit 42: Fixed Effects Models on Fund Size

	(8) Fund Return		(9) Fund Return		(10) Fund Return	
Condition			Closed Ended Funds Only		Open Ended Funds Only	
WMR	1.146***	(0.000)	1.277***	(0.000)	0.930***	(0.000)
Gearing	-0.170*	(0.017)	-0.140	(0.099)	-0.0504	(0.099)
Fund Age	-0.00862***	(0.000)	-0.00917**	(0.002)	0.00640	(0.456)
Small Medium	0.0484***	(0.000)	0.0781***	(0.000)	0.00355	(0.782)
Medium-large	0.0874***	(0.000)	0.129***	(0.000)	-0.00162	(0.909)
Large	0.0842**	(0.002)	0.120**	(0.002)	-0.000475	(0.245)
Yr_2002	0	(.)	0	(.)	0.0515**	(0.004)
Yr_2003	0.00562	(0.712)	-0.00687	(0.829)	0.0551***	(0.000)
Yr_2004	0.0142	(0.294)	0.00155	(0.939)	0.0670***	(0.000)
Yr_2005	0.0292	(0.093)	0.0569*	(0.041)	0.0347	(0.087)
Yr_2006	0.0472**	(0.001)	0.0611*	(0.011)	0.0600***	(0.000)
Yr_2007	0.0346**	(0.003)	0.0497**	(0.003)	0.0395**	(0.001)
Yr_2008	-0.0389**	(0.002)	-0.0423*	(0.023)	-0.0176	(0.279)
Yr_2009	-0.0401***	(0.000)	-0.0492**	(0.003)	-0.0193	(0.090)
Yr_2010	0.0446***	(0.000)	0.0691***	(0.000)	0.0173	(0.112)
Yr_2011	0.0235**	(0.001)	0.0209*	(0.041)	0.0265**	(0.006)
Yr_2012	0	(.)	0	(.)	0	(.)
C	0.0137	(0.645)	-0.0416	(0.319)	-0.0256*	(0.043)
Observations (*N*)	1640		927		713	
R^2	0.582		0.632			
Adjusted R^2	0.578		0.626			
Akaike Criterion	-3160.2		-1619.5		.	
Schwarz Criterion	-3079.2		-1547.1		.	
F-Statistic	65.47		64.16			
d.f. Model	14		14		16	
d.f. Regression	314		185			
Log Likelihood	1595.1		824.8		0.930***	(0.000)
Chi^2					670.9	
Hausman Test	116.29		7587.92		18.8	
P>Chi^2	(0.000)		(0.000)		(0.223)	
FE/RE	FE		FE		RE	

p-values in parentheses
*** p<0.05 ** p<0.01 *** p<0.001**

J-Curve

The much referenced J-Curve effect in private equity or private property funds is the result of their historical tendency to produce negative returns at the beginning of the investment horizon due to capital deployment (and often high capital expenditures) and immature investments, the effects of which are negated over the course of the investment period. In the event of funds being well managed, gains should eventually cover mitigate the initial losses.

Exhibit 43: Fund Age Effects

	(11) Fund Return		(12) Fund Return		(13) Fund Return	
WMR	1.159***	(0.000)	1.158***	(0.000)	1.159***	(0.000)
Gearing	-0.184*	(0.012)	-0.184*	(0.011)	-0.185*	(0.011)
GAV (€Bil)	0.0354**	(0.003)	0.0348**	(0.003)	0.0340**	(0.003)
Fund Age 2 or Less	-0.0206*	(0.048)				
Fund Age 3 or Less			-0.0211*	(0.022)		
Fund Age 1 or Less					0.0103	(0.671)
Fund Age 2					-0.0133	(0.230)
Fund Age 3					-0.0169	(0.065)
Fund Age 4					0.00169	(0.866)
Yr_2002	0.00509	(0.751)	0.00766	(0.635)	0.00812	(0.616)
Yr_2003	0	(.)	0	(.)	0	(.)
Yr_2004	0.000156	(0.990)	-0.000145	(0.991)	-0.000376	(0.976)
Yr_2005	0.00646	(0.715)	0.00468	(0.794)	0.00518	(0.781)
Yr_2006	0.0146	(0.370)	0.0122	(0.464)	0.0128	(0.449)
Yr_2007	-0.00498	(0.758)	-0.00765	(0.639)	-0.00698	(0.678)
Yr_2008	-0.0850***	(0.000)	-0.0884***	(0.000)	-0.0876***	(0.000)
Yr_2009	-0.101***	(0.000)	-0.105***	(0.000)	-0.105***	(0.000)
Yr_2010	-0.0274	(0.127)	-0.0331	(0.081)	-0.0334	(0.111)
Yr_2011	-0.0588***	(0.001)	-0.0652***	(0.000)	-0.0658**	(0.002)
Yr_2012	-0.0906***	(0.000)	-0.0992***	(0.000)	-0.0991***	(0.000)
C	0.0483	(0.108)	0.0561	(0.057)	0.0569	(0.054)
Observations (*N*)	1637		1637		1637	
R^2	0.577		0.578		0.578	
Adjusted R^2	0.573		0.574		0.574	
Akaike Criterion	-3136.2		-3138.2		-3134.3	
Schwarz Criterion	-3060.6		-3062.6		-3042.5	
F-Statistic	67.50		67.23		57.29	
d.f. Model	13		13		16	
d.f. Regression	314		314		314	
Log Likelihood	1582.1		1583.1		1584.1	
Hausman Test	51.67		47.85		42.76	
P>Chi^2	(0.000)		(0.000)		(0.000)	
Joint-F test					..	

p-values in parentheses
*** p<0.05 ** p<0.01 *** p<0.001**

The results show that funds aged 2 or less years, on average, had returned 0.02% less (Regression (11)) and similarly, funds aged 3 or less years, on average, returned 0.02% less (Regression (12)). The effects of the J curve slowly taper off as funds aged 4 or more years, on average, returned 0.002% more (Regression (13)). Overall the findings indicate the presence of the J-curve effect. A possible explanation of this limited effect of the J-curve might be that opportunity funds are not included in the sample. Especially these funds will experience a J-curve due to their high investment costs during the first years of the fund.

Exhibit 44: Distribution of Fund Age by Size Categories

	Median	Average
Small	3	4.601256
Small Medium	5	5.690355
Medium Large	5	7.512097
Large	6	9.490494

From Exhibit 44, smaller funds on average are younger. This relationship is an important finding since before, it has been established that larger funds tend to perform better. The J-curve effect may be a plausible cause for lower returns in small funds and seems to be in congruence with the finding that higher returns from larger funds could partially be accounted for by their latter stages of maturity (Matallin-Saez, 2011). However, as the models have controlled for the age and size effects with both variables included, the findings still hold.

Gearing

Regression 6 showed that gearing on average had a negative impact on fund returns. However, the average negative impact is thought to be caused by the numerous extremely high magnitude negative returns in certain funds.

An alternate model was specified to capture the asymmetric effects of gearing. The model estimated:

$$R_t = \beta_0 + \beta_1 WMR + \beta_2\, GearingAve + \beta_3 Dummy_1 GearingAve + \beta_i X + \varepsilon_t$$

The idea is to capture and test for asymmetric effects due to gearing exposure. $Dummy_1$ takes the value of 1 when some fund return condition is satisfied, in this case when fund return ≥ 0. As such, the conditions of $\beta_2 > 0$ and $\beta_3 < 0$ should be observed.

If the impact of market returns is expected to be greater in down markets (for example negative market returns) than in up markets (for example positive market returns) i.e. an asymmetric impact where the down market beta is greater than the up market beta, the magnitude of negative fund returns will be greater than the magnitude of positive fund returns. Consequently, the following conditions are expected to be satisfied:

- $\beta_2 < 0, \beta_3 > 0$
- $\beta_2 + \beta_3 > 0$
- $|(\beta 3 + \beta_5)| < |\beta_5|$ (the downside impact of leverage outweighs the upside impact)

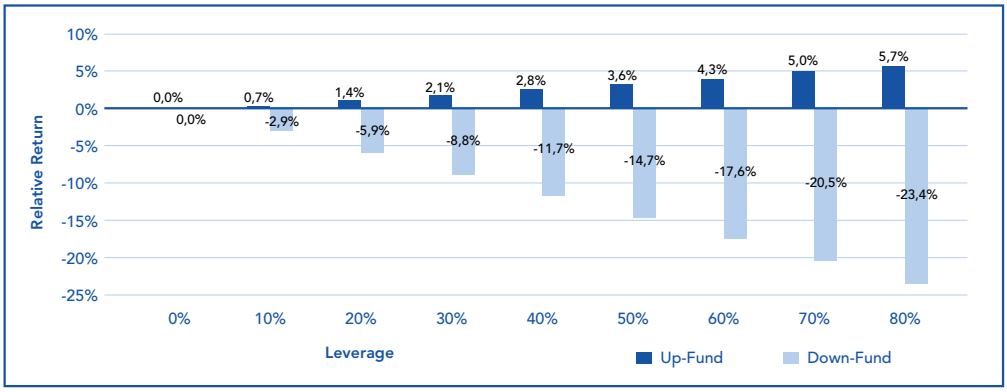
These conditions can be formally tested. From Regression (14), all three conditions are satisfied. For each additional 10% of gearing, when fund returns are greater or equal to 0%, fund returns are expected to increase by 0.7% on average. But when fund returns are less than 0% they are expected to decrease by 2.9% on average for every additional 10% of gearing. These results are graphically illustrated in the Exhibit 46.

Exhibit 45: Gearing Effects

	(14) Fund Return		(15) Fund Return	
"Up-Fund" Gearing	0.364***	(0.000)	0.313***	(0.000)
Gearing	-0.293***	(0.000)	-0.186**	(0.003)
WMR	0.956***	(0.000)	0.967***	(0.000)
GAV (€Bil)	0.0347***	(0.000)	0.0344***	(0.000)
Fund Age	-0.00433**	(0.006)	-0.00459**	(0.003)
"Up-Fund" "High" Gearing			0.0690*	(0.030)
"High" Gearing			-0.107***	(0.001)
Yr_2002	0	(.)	0	(.)
Yr_2003	0.00216	(0.876)	0.00246	(0.858)
Yr_2004	0.00327	(0.798)	0.00324	(0.799)
Yr_2005	0.00919	(0.549)	0.00886	(0.571)
Yr_2006	0.0233	(0.056)	0.0232	(0.055)
Yr_2007	0.0121	(0.233)	0.0110	(0.274)
Yr_2008	-0.00870	(0.378)	-0.0103	(0.302)
Yr_2009	-0.00870	(0.295)	-0.00792	(0.333)
Yr_2010	0.0114	(0.128)	0.0125	(0.096)
Yr_2011	0.00621	(0.349)	0.00727	(0.274)
Yr_2012	0	(.)	0	(.)
C	-0.00171	(0.946)	-0.0146	(0.558)
Observations (*N*)	1637		1637	
R^2	0.740		0.744	
Adjusted R^2	0.738		0.741	
Akaike Criterion	-3933.2		-3953.4	
Schwarz Criterion	-3857.5		-3867.0	
F-Statistic	160.9		147.1	
d.f. Model	13		15	
d.f. Regression	314		314	
Log Likelihood	1980.6		1992.7	
Hausman Test	36.91		35.86	
P>Chi^2	(0.001)		(0.003)	

p-values in parentheses
*** p<0.05 ** p<0.01 *** p<0.001**

Exhibit 46: Results of Asymmetric Gearing Effects



Next, to examine if the impact of gearing on fund performance during periods of positive and negative returns differed for highly and lowly geared funds, a new model was specified. Two new dummies, "High Gearing" (gearing >= 50%) and "Low Gearing" (gearing <50%) were added to analyse the impact of gearing on the individual fund's performance. While the underlying WMR can be positive, any individual fund may record negative returns given poor stock (individual property) selection and they will hence suffer the downside impact of gearing. To capture the fund size specific gearing effects, the following equation was estimated:

$$R_t = \beta_0 + \beta_1(WMR) + \beta_2(Gearing), \beta_3 Dummy_1 Dummy_2(Gearing) + \beta_4 Dummy_1(Gearing) + \beta_5 Dummy_2(Gearing) + \beta_i X + \varepsilon_t$$

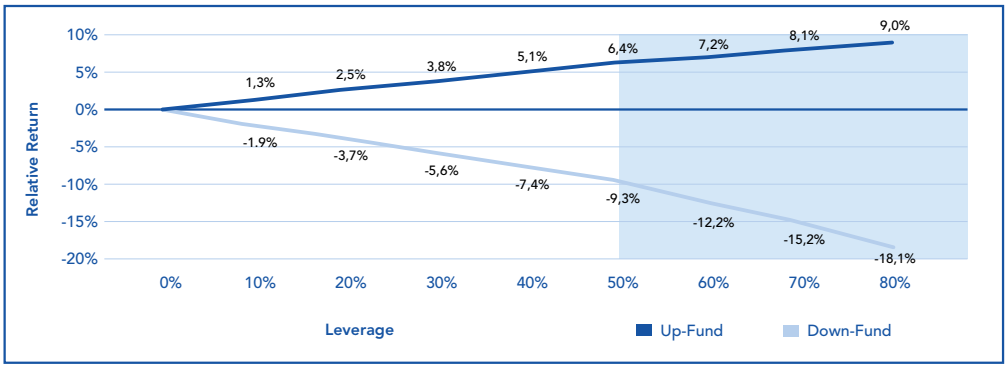
$Dummy_1$ if fund return >=0, 0 if not

$Dummy_2$ if high gearing, 0 if not

From Regression (15) and Exhibit 47, the benefits of taking more leverage incrementally tapers off. The lines in the graph show a simulation of the effects of higher gearing (horizontal axis) on returns (vertical axis). The shaded area on the right-hand side show the results for highly-geared funds. On the upside, for funds with gearing less than or equal to 50%, every additional 10% leverage results in +1.3% fund returns on average. However when gearing exceeds 50%, for every additional 10% in leverage, fund returns are only expected to increase by 0.9% on average. The increased risks associated with higher debt levels would have likely increased the costs of borrowing, which offsets a large part of the earnings enhancing capacity of leverage. On the downside, when a fund is highly geared, the marginal loss is amplified. For funds with gearing of less than or equal to 50%, every additional 10% of leverage results in an expected fund return of -1.9% on average. And for funds with gearing in excess of 50%, every additional 10% of leverage results in fund return of -2.9% on average. This is largely because, in addition to subpar asset level performance, funds will still have to service their debt and hence, contributing to further earnings erosion.

The asymmetric effects of gearing on fund returns were also analysed in the paper "Leverage: Please Use Responsibly", where authors come to the same conclusion. It was also found that using more than 40% leverage destroys value (Spek & Hoorenman, 2011).

Exhibit 47: Asymmetric Gearing Effects for High/Low Gearing Funds - Results



One caveat to mention here is that in addition to interest payments, fixed management fees and variable performance fees could have also resulted in the observed asymmetric effects. However, since management fees and performance fees are set independently from leverage, the aforementioned analysis is still largely valid.

Macroeconomic Drivers & Competing Asset Classes

Last but not least, this report directs the research focus to potential statistical relationships between fund returns of non-listed real estate funds and that of other competing asset classes including EU Bond Yields, EU Stock Returns and Listed Real Estate Vehicles (EU REITs). The foreign exchange effects on fund returns were also examined with a weighted FX variable, constructed in the same way as the WMR. The EU Gross Domestic Product growth was included in the models to serve as a control for the impacts of macro-economic growth on all asset classes.

As expected, EU GDP growth EU Bond Yields and EU stock returns were positively associated with and are significant predictors of non-listed real estate fund returns. As long-term bond yields are somewhat a proxy for risk free cost of capital, it is plausible that the higher risk investments such as non-listed real estate fund's performance displays certain correlation with interest rates through several linkages such as cost of capital.

Exhibit 48: Competing asset classes

	(16) Fund Return		(17) Fund Return		(18) Fund Return	
Gearing	-0.145***	(0.000)	-0.215*	(0.016)	-0.158	(0.068)
Fund Age	-0.00163***	(0.001)	-0.0179***	(0.000)	-0.0163***	(0.000)
GAV (€Bil)	0.0146**	(0.003)	0.0325*	(0.014)	0.0198	(0.077)
EU GDP	1.053***	(0.000)	0.528*	(0.021)	0.391	(0.121)
EU Bonds	7.055*	(0.011)				
EU Stocks	0.141*	(0.022)				
EU REITS			0.114***	(0.000)		
Weighted FX					-0.962***	(0.000)
Yr_2002	-0.0489	(0.489)	0	(.)	0	(.)
Yr_2003	-0.0491	(0.493)	0.00650	(0.717)	0.0612**	(0.002)
Yr_2004	-0.0309	(0.674)	0.0229	(0.216)	0.0483**	(0.001)
Yr_2005	0.0303	(0.624)	0.0823***	(0.000)	0.102***	(0.000)
Yr_2006	0.0231	(0.748)	0.0871***	(0.000)	0.132***	(0.000)
Yr_2007	-0.0925	(0.212)	0.0840***	(0.000)	0.0422**	(0.007)
Yr_2008	-0.168***	(0.000)	-0.0637**	(0.007)	-0.0938***	(0.000)
Yr_2009	-0.126**	(0.002)	-0.0607***	(0.000)	-0.0133	(0.507)
Yr_2010	0.00945	(0.790)	0.0826***	(0.000)	0.0691***	(0.000)
Yr_2011	0.0152	(0.428)	0.0878***	(0.000)	0.0589***	(0.000)
Yr_2012	0	(.)	0	(.)	0	(.)
C	-0.135*	(0.021)	0.151***	(0.000)	0.142***	(0.000)
Observations (*N*)	1597		1597		1595	
R^2			0.426		0.472	
Adjusted R^2			0.421		0.467	
Akaike Criterion	.		-2568.9		-2695.5	
Schwarz Criterion	.		-2493.7		-2620.2	
F-Statistic			33.59		47.55	
d.f. Model	16		13		13	
d.f. Regression			308		308	
Log Likelihood			1298.5		1361.7	
Chi2	516.9					
Hausman Test	16.07		53.78		1361.7	
P>Chi²	(0.139)		(0.000)		(0.001)	

p-values in parentheses
*** p<0.05 ** p<0.01 *** p<0.001**

As expected, EU GDP growth, EU Bond Yields, and EU stock returns were positively associated with of non-listed real estate fund returns (Regression 16). With REITS and non-listed fund returns driven largely by their underlying property assets, REITS have exhibited the expected positive and significant relationship with non-listed real estate fund returns (Regression (17). For every 1% increase in EU REIT returns, non-listed real estate funds returns increase 0.1% on average. The coefficient value makes sense since REITs are widely regarded to be strongly correlated with equities and are more volatile than non-listed real estate funds. Finally the Weighted FX was also a significant driver of fund returns, with an unfavorable impact on average (Regression 18).

It should be noted that some one-third of the funds within the total sample did not apply RICS fund valuation accounting and, consequently, concerns arise about the comparability of the data. Consequently all of the reported regression results were repeated only on those funds that used RICS valuation guidelines and the findings were broadly similar.

6. EMPIRICAL ANALYSIS: OUTPERFORMANCE

Fund managers often sell themselves as being able to outperform benchmarks. As discussed earlier in the report, managerial outperformance can be attributed to portfolio structure or stock level out performance. In this section, the analysis will focus on stock level outperformance, with the WMR being the benchmark. As such, the dependent variable, "Outperformance" is calculated as:

(Fund Return – WMR)

Exhibit 49: Outperformance Drivers – Fund Size

	(19) Outperformance		(20) Outperformance		(21) Outperformance	
Conditions / Restrictions					Closed Ended Funds Only	
Gearing	-0.228**	(0.008)	-0.219**	(0.007)	-0.209*	(0.035)
GAV (€Bil)	0.0390**	(0.004)				
Fund Age	-0.00966***	(0.000)	-0.00990***	(0.000)	-0.0110***	(0.000)
Small Medium			0.0516***	(0.000)	0.0819***	(0.000)
Medium Large			0.0985***	(0.000)	0.142***	(0.000)
Large			0.0964**	(0.001)	0.130**	(0.003)
Yr_2002 (omitted)	0	(.)	0	(.)	0	(.)
Yr_2003	0.00583	(0.707)	0.00586	(0.702)	-0.00445	(0.887)
Yr_2004	0.0229	(0.087)	0.0198	(0.138)	0.0162	(0.397)
Yr_2005	0.0414*	(0.023)	0.0386*	(0.022)	0.0792**	(0.003)
Yr_2006	0.0686***	(0.000)	0.0672***	(0.000)	0.103***	(0.000)
Yr_2007	0.0419***	(0.001)	0.0392**	(0.001)	0.0590**	(0.001)
Yr_2008	-0.0500***	(0.000)	-0.0542***	(0.000)	-0.0723***	(0.000)
Yr_2009	-0.0431***	(0.000)	-0.0435***	(0.000)	-0.0563***	(0.001)
Yr_2010	0.0568***	(0.000)	0.0562***	(0.000)	0.0900***	(0.000)
Yr_2011	0.0293***	(0.000)	0.0293***	(0.000)	0.0309**	(0.005)
Yr_2012 (omitted)	0	(.)	0	(.)	0	(.)
C	0.0711*	(0.030)	0.0394	(0.213)	0.00248	(0.957)
Observations (*N*)	1637		1640		927	
R^2	0.191		0.206		0.290	
Adjusted R^2	0.185		0.200		0.279	
Akaike Criterion	-2839.9		-2871.3		-1392.0	
Schwarz Criterion	-2775.1		-2795.6		-1324.4	
F-Statistic	12.80		11.52		12.47	
d.f. Model	11		13		13	
d.f. Regression	314		314		185	
Log Likelihood	1432.0		1449.6		710.0	
Hausman Test	28.67		54.83		30.06	
P>Chi^2	(0.004)		(0.000)		(0.008)	

p-values in parentheses
*** p<0.05 ** p<0.01 *** p<0.001**

From Regression (19), the continuous fund size variable GAV in €billion was positive and significant, suggesting that for every additional €1 billion in fund size, expected fund returns would increase by 0.04%. The alternative specification of grouped fund size dummy

variables in Regression 20 yield a similar result – relative to Small funds, Small Medium (+0.05%). Medium Large (+0.10%), and Large (+0.10%). To minimise the effect of the endogeneity problem (of better fund performance attracting more investment capital) as discussed earlier, Regression (21) looked at closed ended funds only and showed that relatively to small funds, Small Medium (+0.08%), Medium Large (+0.14%), Large (+0.13%). The results are in congruence the findings with Fund Returns as the dependent variable (Exhibit 42). Although the results show that funds' size has a statistically significant effect on fund performance, using this fund characteristics in the investment strategy would be quite difficult. To do this investors needs to find a way of predicting which of the newer, smaller funds might grow. Additional analysis should be undertaken in order to look at the target fund size and if funds that planned to be large actually performed better.

While fund age in Regression (19) was a significant predictor of fund returns, the alternative model specifications used to detect the presence of the J-curve show that fund age was (just) insignificant in predicting fund outperformance (Exhibit 50)

Exhibit 50: Fund Age's effect on Outperformance

	(22) Outperformance		(23) Outperformance	
Gearing	-0.236**	(0.006)	-0.234**	(0.005)
GAV (€Bil)	0.0361**	(0.005)	0.0362**	(0.004)
Fund Age2	-0.0202	(0.063)		
Fund Age3			-0.0166	(0.086)
Yr_2002	0.00550	(0.736)	0.00721	(0.661)
Yr_2003	0	(.)	0	(.)
Yr_2004	0.00523	(0.670)	0.00539	(0.674)
Yr_2005	0.0147	(0.418)	0.0136	(0.461)
Yr_2006	0.0326	(0.093)	0.0309	(0.117)
Yr_2007	-0.00429	(0.808)	-0.00604	(0.734)
Yr_2008	-0.107***	(0.000)	-0.109***	(0.000)
Yr_2009	-0.113***	(0.000)	-0.114***	(0.000)
Yr_2010	-0.0242	(0.202)	-0.0273	(0.172)
Yr_2011	-0.0631***	(0.001)	-0.0663***	(0.001)
Yr_2012	-0.102***	(0.000)	-0.107***	(0.000)
C	0.0791*	(0.014)	0.0827**	(0.008)
Observations (*N*)	1637		1637	
R^2	0.194		0.193	
Adjusted R^2	0.187		0.187	
Akaike Criterion	-2842.6		-2842.1	
Schwarz Criterion	-2772.4		-2771.9	
F-Statistic	12.20		12.44	
d.f. Model	12		12	
d.f. Regression	314		314	
Log Likelihood	1434.3		1434.0	
Hausman Test	74.39		74.98	
P>Chi²	(0.000)		(0.000)	

p-values in parentheses
*** p<0.05 ** p<0.01 *** p<0.001**

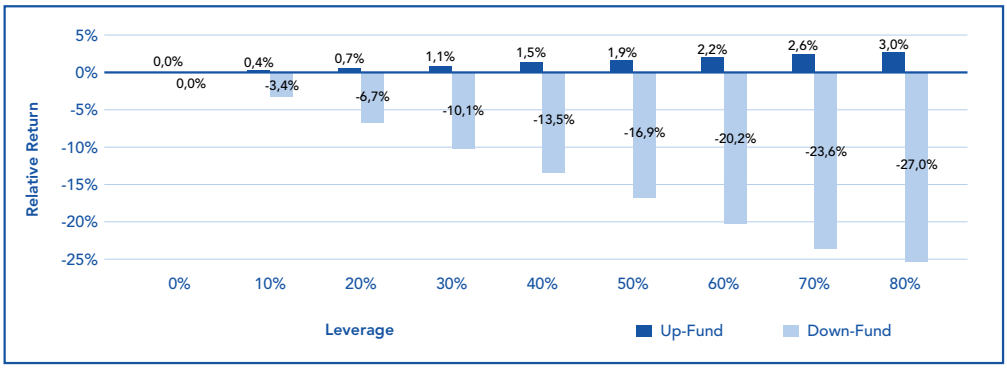
Regression (19) showed that gearing was a significant predictor of outperformance. Here, the asymmetric effects of up-fund gearing and down-fund gearing on outperformance and underperformance were evaluated in greater detail. From Regression (24), on the downside, every 10% of additional gearing resulted in -3.4% fund underperformance. On the upside, every additional 10% of gearing resulted in a 0.4% increase in fund outperformance. In short, gearing was a strong driver for underperformance but less so outperformance. The results are graphically illustrated in Exhibit 52.

Exhibit 51: Gearing's Effect on Outperformance

	(24) Outperformance 1		(25) Outperformance 2	
UF_Gearing	0.372***	(0.000)	0.309***	(0.000)
Gearing	-0.337***	(0.000)	-0.216**	(0.002)
GAV (€Bil)	0.0366***	(0.000)	0.0363***	(0.000)
Fund Age	-0.00414**	(0.008)	-0.00456**	(0.003)
UF_H_Gearing1			0.0854*	(0.018)
H_Gearing1			-0.123***	(0.001)
Yr_2002	0	(.)	0	(.)
Yr_2003	0.00161	(0.908)	0.00208	(0.880)
Yr_2004	0.00144	(0.908)	0.00197	(0.874)
Yr_2005	0.00748	(0.621)	0.00794	(0.607)
Yr_2006	0.0289*	(0.027)	0.0299*	(0.021)
Yr_2007	0.0166	(0.139)	0.0154	(0.166)
Yr_2008	-0.00220	(0.813)	-0.00547	(0.558)
Yr_2009	-0.00251	(0.775)	-0.00220	(0.797)
Yr_2010	0.0163*	(0.046)	0.0178*	(0.030)
Yr_2011	0.00779	(0.279)	0.00922	(0.201)
Yr_2012 (omitted)	0	(.)	0	(.)
C	0.00415	(0.883)	-0.00844	(0.758)
Observations (*N*)	1637		1637	
R^2	0.471		0.480	
Adjusted R^2	0.467		0.475	
Akaike Criterion	-3533.5		-3555.7	
Schwarz Criterion	-3463.3		-3474.7	
F-Statistic	41.62		38.57	
d.f. Model	12		14	
d.f. Regression	314		314	
Log Likelihood	1779.8		1792.9	
Hausman Test	32.60		41.15	
P>Chi^2	(0.002)		(0.000)	

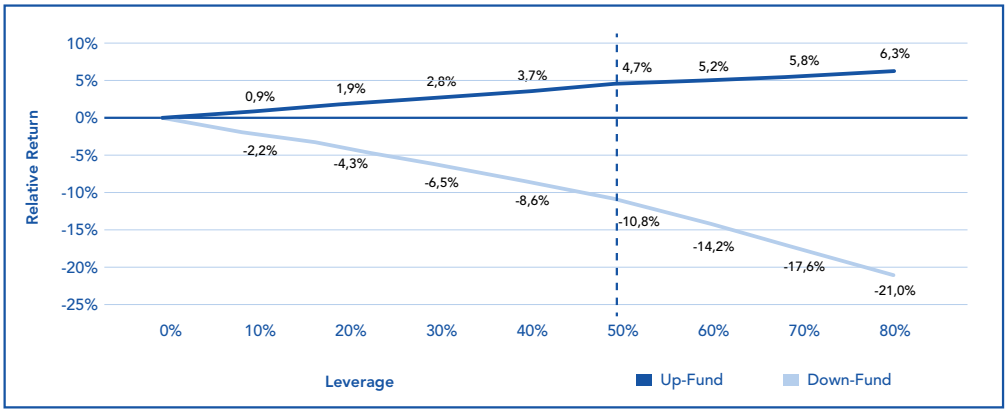
p-values in parentheses
*** p<0.05 ** p<0.01 *** p<0.001**

Exhibit 52: Gearing Effects



Next, the outperformance effects are decomposed further to funds with high and low gearing (Regression (25). On the upside, for every additional 10% of gearing, low gearing funds achieved 0.9% outperformance while highly geared funds achieved 0.6% outperformance on average. On the downside, for every additional 10% of gearing, low gearing funds had an underperformance of -2.2% while highly geared funds had an underperformance of 3.4%. In conclusion, the marginal benefits of gearing on outperformance decreases with higher gearing while in a down fund situation, underperformance is accelerated with higher gearing. The results are graphically illustrated in Exhibit 53.

Exhibit 53: Gearing Effects



7. EMPIRICAL ANALYSIS: RISK WEIGHTED PERFORMANCE

This section briefly explores the drivers of risk weighted performance in addition to divers of fund performance and outperformance. Investors have traditionally focused on returns and fund managers have been taking excessive risk to achieve high returns. Since the GFC in 2007, there has been increased scrutiny on risk taking and risk weighted performance. In this section, the oft discussed topic is the drivers of risk weighted performance will be examined with respect to non-listed real estate funds. The dependent variable, the Sharpe Ratio, was used as a measure of risk weighted performance.

The Sharpe ratio measures the excess return per unit of risk, measured by the deviation of returns of an asset or strategy (Sharpe W. ,1994). Where $r_{(t)}$ is the portfolio return at time t, $rf_{(t)}$ the risk free rate at time t and $\sigma_{(2001\text{-}2012)}$ being the portfolio standard deviation of returns for its lifespan between 2001 and 2012, the Sharpe ratio is calculated as follow:

$$S_{(t)} = \frac{r_{(t)} - rf_{(t)}}{\sigma_{(2001\text{-}2012)}}$$

Exhibit 54: Risk Weighted Performance Drivers

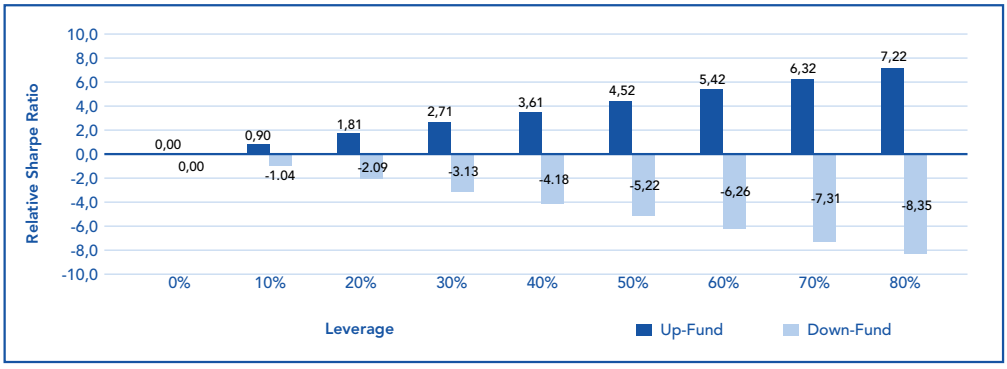
	(26) Sharpe Ratio		(27) Sharpe Ratio		(28) Sharpe Ratio	
WMR	5.713***	(0.000)	6.238***	(0.000)	5.025***	(0.000)
GAV (€Bil)			0.0380	(0.452)	0.00194	(0.972)
Fund Age			0.00687	(0.387)	-0.0196	(0.171)
Gearing			-0.579*	(0.015)	-1.044**	(0.002)
UF Gearing					1.947***	(0.000)
H Gearing						
UF H Gearing						
Yr_2002	0.0336	(0.794)	0.492**	(0.002)	0	(.)
Yr_2003	0.0782	(0.633)	0.463***	(0.000)	0.00621	(0.959)
Yr_2004	0.161	(0.329)	0.502***	(0.000)	0.0450	(0.713)
Yr_2005	0.209	(0.217)	0.587***	(0.000)	0.136	(0.250)
Yr_2006	0.338*	(0.046)	0.692***	(0.000)	0.282**	(0.007)
Yr_2007	0.0719	(0.669)	0.538***	(0.000)	0.170	(0.071)
Yr_2008	-0.604***	(0.001)	-0.155	(0.123)	-0.233*	(0.011)
Yr_2009	-0.569***	(0.001)	-0.237**	(0.002)	-0.245***	(0.000)
Yr_2010	0.0201	(0.901)	0.316***	(0.000)	0.0397	(0.528)
Yr_2011	-0.119	(0.470)	0.182**	(0.003)	0.0330	(0.525)
Yr_2012	-0.291	(0.090)	0	(.)	0	(.)
C	-0.239	(0.179)	-0.468**	(0.006)	-0.203	(0.305)
N	1861		1560		1560	
R^2					0.643	
Adjusted R^2					0.639	
Akaike Criterion	.		.		2492.8	
Schwarz Criterion	.		.		2567.7	
F-Statistic					186.8	
d.f. Model	12		14		13	
d.f. Regression					271	
Log Likelihood					-1232.4	
Hausman Test	2.69		7.08		115.61	
P>Chi^2	(0.997)		(0.898)		(0.000)	
Chi^2	1966.2		2036.3			

p-values in parentheses
* p<0.05 ** p<0.01 *** p<0.001

Funds aged 2 years or less were excluded since there were too few recorded too few observations of returns to derive a reliable Sharpe ratio.

As expected the WMR is a strongly significant driver of risk-adjusted performance as it captures the underlying market risk-reward dynamic (Regression 26). Fund age and GAV are insignificant drivers of risk-adjusted performance. This seems to follow logic that fund age and fund size is not typically associated with risk. Most noticeably, gearing was a significant driver of risk-adjusted performance. The model specificantions and interpretion is similar to that in the Gearing section results provided earlier. On average, gearing had a negative relationship with risk-adjusted performance (Regression 27). Like gearing's effects on fund returns and outperformance, the asymmetric effects of gearing on risk-adjusted performance persists. On the downside, for every 1% increase in gearing, the Sharpe ratio decreases by 1.0 unit on average (Regression 28). On the upside, for every 1% increase in gearing, the Sharpe ratio increases by 0.9 units on average. The results are graphically illustrated in Exhibit 55 and confirm the widely recognized risks gearing brings.

Exhibit 55: Asymmetric Effects of Gearing on Risk Weighted Performance



The Sharpe ratio was used as a measure of risk-adjusted performance given its relative simplicity and that its returns are not tied to any asset class. It offers an advantage over alpha and beta measures of CAPM since the CAPM is tied to specific benchmarks, such as the FTSE100. However, using the standard deviation as a proxy for risk is not satisfying, since it does not distinguish upward volatility from the more concerning downward volatility.

Further research on risk-adjusted performance using more advance risk analysis techniques and applying other risk measures such as Treynor ratio (Treynor, 1961), Bias ratio, Sortino ratio (Rom, 1993) or Jensen's Alpha (Jensen, 1968) would certainly yield other insightful results.

8. CONCLUSIONS AND FURTHER WORK

The research sought to identify the key drivers of fund performance in the non-listed real estate sector. To this aim, a large number of non-listed real estate funds were examined based on 2001-2012 INREV data. The drivers of fund performance were analysed on three levels:

- Fund returns, as measured by annual NAV based fund returns (%)
- Fund stock (property) selection outperformance, as measured by fund returns (%) less WMR (%)
- Risk-adjusted fund returns, as measured by the Sharpe ratio

This research has focused on three types of drivers of fund performance:

- The underlying market sector and country returns
- Fund characteristics like leverage, fund age, etc
- External factors like competing asset classes and macroeconomic drivers

The underlying market sector and country returns, as measured by the WMR, are found to be the strongest predictors of fund performance. This means that when selecting funds, investors need to focus on the markets funds invest into as this determines, for the most part, the performance of a fund. There is also a noticeable shift in the relationship between the WMR benchmark and average fund returns over time in that funds generally outperformed the benchmark returns consistently up to the Financial Crisis but have been underperforming since then despite improvements in performance in absolute terms.

A number of fund characteristics have also been found to be predictors of fund performance, although less than WMR. One of the key highlights was the asymmetric effects of gearing, where gearing was significant driver of fund returns, fund outperformance and risk-adjusted performance. On all three levels, the hypothesized results were observed: the magnitude of up-fund gearing effects were less than the magnitude of down-fund gearing effects. In other words, higher gearing levels increase the risks in a down-market, but do not guarantee substantially higher returns in an up-market. Although the optimal capital structure has not been dealt with in this research, investors should be aware of risks that higher gearing levels bring to the fund.

It has also been established that competing asset classes such as stocks, REITs and bonds exhibit positive and significant contemporaneous correlation with fund returns, even when controlling for macroeconomic and general business cycles. However, it will be interesting to see how alternative asset classes including hedge funds, commodity funds and corporate private equity funds compare with non-listed real estate funds.

It has to be noted that the returns of the non-listed sector were affected disproportionately by the Financial Crisis, particularly funds with above-average leverage levels. It should be noted that the period that was used to analyse the drivers of performance is rather short and it would be interesting to see if in the longer run the same conclusions would hold.

The underlying market sector and country returns together with fund characteristics and external factors, which were analysed in this research, explain more than half of the variation in performance of non-listed real estate funds. Other factors need to be identified and analysed in order to see if a better understanding of fund performance is possible. A possible extension of this study is to analyse if fund managers are able to generate alpha, despite a number of known problems in the empirical measurement process of fund outperformance. The effects of risks on fund performance can also be further explored using other measures such as the Treynor ratio, Jensen's Alpha or the Sortino Ratio, for example. Although the Sharpe ratio is a measure of risk-adjusted performance and gearing is an implicit gauge of risk, more advanced techniques that capture the time-varying nature of real estate risks could be applied in a more comprehensive study on the risk element of fund returns.

As the data on opportunistic funds were not available at the time of writing this report, the research findings do not apply to the entire non-listed real estate funds universe and are limited only to core and value-added funds. Also, with data on opportunistic funds and a bigger sample size, it may well be possible to perform a comprehensive study on the difference in fund performance drivers by investment style and investment strategy.

Acknowledgements

The authors are indebted to Casper Hesp and Vitaliy Tonenchuk of INREV for valuable comments and insights. We also wish to thank the participants of the annual INREV conference in Barcelona and of the INREV-sponsored session at the 2013 annual meeting of the European Real Estate Society in Vienna.

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Appendix 1

As indicated by the Hausman test, fixed-effects panel regression was adopted to identify the main drivers of fund performance. The fixed-effects model runs under the assumption that all α remain constant over time and λ_t coefficients stay the same across all funds. As a result, the constant term absorbs the unit effects in the model in the following manner:

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

$$E(\alpha_i \chi_{it}) = E(\lambda_t \chi_{it}) = E(\mu_{it} \chi_{it}) = 0$$

$$Var(\alpha_i) = \sigma_\alpha^2 \,;\; Var\ (\lambda_t) = \sigma_\lambda^2 \,;\; Var\ (\mu_{it}) = \sigma_\mu^2$$

A two-way error component model is constructed to investigate fund specific effects and cross section effects, both encompassed in the disturbance term. The structure of the fixed-effects model is therefore written as:

$$y_{it} = \alpha + \chi_{it}\beta + \mu_{it} \text{ for } i=1,2,3\ldots, N,\ t=1,2,3\ldots, T$$

$$where\ \mu_{it} = \lambda_t + v_{it}$$

In the regression equation, χ_{it} denotes the independent variables, namely the WMR, gearing and fund size explaining fund return, y_{it} for fund i in year t. This two-way error component model is based on the assumption that there are unobservable time and cross section effects and that these effects are correlated with the independent variables in the regression model Baltagi, 2008).

Next, we conduct a dynamic panel estimation following Arellano and Bond (1991) as a robustness check to account for potential endogeneity of the regressors in our model. This procedure incorporates lagged dependent variables as additional regressors and uses lagged values of all covariates as instruments. While dynamic panel methods are more advanced and less straightforward to implement than the standard fixed or random effects estimations, we apply a GMM dynamic panel estimation as it seems plausible that some of our independent variables, for example GAV or gearing, are not strictly exogenous and that both the dependent and the independent variables are serially correlated. The general GMM estimators are particularly designed for datasets with many observations but relatively few time periods which is the case here. The results of these estimations are reported in Appendix 2.

Appendix 2:

Arrelano-Bond dynamic panel estimation of fund return drivers.
Dependent variable: Annual fund return

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
L.FundReturnWin	0.0586***	0.0530***	0.0238***	0.0948***	0.162***	0.151***	0.00998*
	(27.90)	(14.07)	(3.83)	(18.72)	(17.98)	(20.54)	(2.01)
WeightedMarketReturn	1.418***	1.424***	1.629***	1.101***			
	(391.56)	(182.10)	(188.76)	(83.67)			
GearingAve	-0.112***	-0.149***	-0.136***	-0.0220	-0.0103	-0.0381	-0.0101
	(-9.84)	(-5.92)	(-5.84)	(-0.97)	(-0.55)	(-1.92)	(-0.58)
GAV (€ billion)	0.0402***				-0.0301***	-0.00931*	-0.00951*
	(49.48)				(-5.96)	(-2.07)	(-2.26)
FundAge	-0.00666***	-0.00662***	-0.00707***	-0.00445***	-0.00861***	-0.0145***	-0.0207***
	(-84.45)	(-28.44)	(-21.91)	(-34.17)	(-14.24)	(-42.09)	(-123.04)
SmallMedium		0.0460***	0.0781***	0.0118***			
		(13.23)	(8.81)	(3.72)			
MediumLarge		0.0847***	0.154***	0.00325			
		(22.26)	(14.71)	(0.95)			
Large		0.107***	0.177***	0.0212***			
		(15.22)	(13.66)	(3.72)			
EU_GDP					2.148***	2.078***	1.356***
					(59.66)	(57.36)	(46.36)
EU_Bonds					1.828***		
					(7.84)		
EU_Stocks					0.225***	0.125***	
					(48.45)	(39.36)	
EU_Reits						0.0712***	
						(16.73)	
WeightedFX							-1.141***
							(-43.25)
_cons	-0.00195	-0.0151	-0.0742***	0.00396	-0.0190	0.0744***	0.131***
	(-0.40)	(-1.35)	(-4.68)	(0.54)	(-1.92)	(8.16)	(17.95)
N	1322	1325	741	584	1287	1287	1285
Wald χ^2 *(prob)*	453526	1.20e+06	2.84e+07	157587	74144.50	40899.9	48716.1
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Sargan test (prob)	173.9	160.6	113.2	91.04	149.1	156.1	152.1
	(0.96)	(0.34)	(0.99)	(1.00)	(0.00)	(0.00)	(0.00)

t **statistics in parentheses**
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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