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Analysing the performance of nonlisted real estate funds: a panel data analysis

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The rapid growth of nonlisted real estate funds over the last several years has contributed towards establishing this sector as a major investment vehicle for gaining exposure to commercial real estate. Academic research has not kept up with this development, however, as there are still only a few published studies on nonlisted real estate funds. This article aims to identify the factors driving the total return over a 7-year period. Influential factors tested in our analysis include the weighted underlying direct property returns in each country and sector as well as fund size, investment style gearing and the distribution yield. Furthermore, we analyse the interaction of nonlisted real estate funds with the performance of the overall economy and that of competing asset classes and find that lagged Gross Domestic Product (GDP) growth and stock market returns as well as contemporaneous government bond rates are significant and positive predictors of annual fund performance.

Keywords: nonlisted real estate funds; performance analysis; commercial real estate; panel data analysis

JEL Classification: C23; F21; G11; R33

I. Introduction

Investors and fund managers require accurate and timely information on the performance of markets and of funds under management in order to make informed investment decisions. This article seeks to extend previous research by analysing the underlying drivers of performance of total return for nonlisted real estate funds, across funds and over time simultaneously. Given the rapid growth of the nonlisted real estate sector over the last few years and its considerable size as an investment vehicle, it has remained relatively under- researched. This study employs a panel data regression framework, drawing on the proprietary European Association for Investors in Nonlisted Real Estate Vehicles (INREV) database of nonlisted funds and various complementary data sources over the period of 2001 to 2007. After this period, the data collection process, as well as key definitions were changed, thereby rendering any possible extension of this analysis into more recent years invalid.

This article is organized as follows. After a brief overview of the nonlisted real estate sector, we review existing work on investment style analysis for real estate and then describe the data characteristics and methodology used to determine the categories that are pertinent for understanding the drivers of nonlisted real estate funds. We then present the results of the empirical analysis across all nonlisted funds in the INREV universe. Finally, we discuss the implications of these findings and comment on how the undertaken work may be extended.

II. Characteristics of Nonlisted Funds

Interest in commercial real estate as a global investment asset class has grown considerably over the last 10 years, with

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investment in real estate now well established in mature markets. Commercial real estate investment vehicles, both listed and nonlisted, have emerged in the US, European and Asian markets. While it is debatable as to how large a fund needs to be before it can or should embark on direct investment in commercial real estate, it remains the case that diversified real estate portfolios are beyond the means of most investors. A common obstacle to invest directly in commercial property is the lumpy and illiquid nature of property as an asset class. For example, investing in a shopping centre or a Central Business District (CBD) office frequently entails raising large amounts of capital, which could run into several hundred million euros. Furthermore, at the portfolio level, considerable idiosyncratic risk exists for all but the largest institutional investors. However, it has been possible to gain indirect exposure to commercial property through publically traded vehicles such as listed commercial property companies (latterly Real Estate Investment Trusts or REIT). A possible drawback of these types of investment vehicles is, however, that their performance volatility is more akin to that of the equity markets than that of the underlying asset class (real estate). Furthermore, the market-quoted returns are poorly correlated with the underlying direct asset holdings over the medium term. The differential performance of the traded (stock market-listed) funds compared to their underlying property assets can be explained by a combination of factors, notably equity market sentiment, variations in fund leverage as well as valuation-based performance measurement of the underlying assets.

Before proceeding, it is important to point out that the term nonlisted real estate fund comprises of a number of different types of investment vehicles from a variety of countries with different institutional and financial structures. To give just one example, most nonlisted funds in the UK and Luxembourg have finite life, whereas the majority of funds in Germany and the Netherlands do not have a fixed termination year.

Fund valuation and volatility

The impressive returns in the commercial real estate sector in the years leading up to the Global Financial Crisis (GFC) have provided incentives to create innovative new products. For example, recent developments in real estate markets have resulted in new investment instruments such as swaps and futures contracts, which have facilitated alternative routes to direct commercial property exposure. In contrast to these investment vehicles which have come under severe criticism as one of the sources of the GFC, nonlisted real estate funds or private property vehicles were not in the focus of critics but have nonetheless been found to exhibit some quite serious shortcomings. Notwithstanding this criticism, these funds have thrived over the last decade and offer the advantages of indirectly investing in commercial property, albeit without the attendant volatility in values associated with stock market activity and sentiment. The reason for this is that the pricing of the underlying assets is based on direct professional valuations and not on market-determined trading prices. However, this characteristic of nonlisted funds can become problematic during recessions as book values and market values can diverge considerably, at least in the short run, due to a lack of transactions in the direct real estate market.

However, some of the advantages of investing in a nonlisted fund include: the facility to gain direct exposure to commercial real estate resulting from smaller capital exposure, easier implementation of investment decisions compared with investing directly in real estate, diversification benefits by way of international exposure/diversification and access to expert management (Baum, 2009).

Liquidity

One of the main impediments to achieve sufficient liquidity is the relatively thin secondary market. Typically, investors in nonlisted funds have to transfer interests as a means of selling their share. This is typically carried out by the fund manager or an intermediary in an effort to match sellers to potential buyers. Search costs and time scales can be considerable, particularly in countries with thin markets and where fund managers are not actively involved in facilitating the transfer process in the secondary market. A notable exception are Property Unit Trusts (PUTs) in the UK which exhibit higher trading volumes, but even these markets have proved to be vulnerable to liquidity shocks in times of financial crises.

Transparency

Nonlisted funds arguably lack transparency compared to listed real estate investment vehicles. The latter generally provide more information to investors and are better covered by analysts' reports and market information systems. However, a report prepared by Deloitte Touche Tohmatsu (2010) demon- strates that compliance with industry guidelines drawn by INREV and adopted by Asian Association for Investors in Nonlisted Real Estate Vehicles (ANREV), has been relatively low in previous years but has increased considerably over the last 2 years. In particular, opportunity funds which showed the lowest compliance rates in areas such as general fund information, manager's report as well as property, accounting and financial reports have adopted these reporting transpar- ency guidelines. In 2009, 77% of the surveyed opportunity funds in Asia had adopted half or more of the guidelines on financial reporting. The share in 2008 had been much lower (33%). The corresponding figures for the other two investment style groups are 94% for core funds (up from 78% in 2008) and 88% for value-added funds (up from 87% in 2008).

These figures underline a general trend towards higher transparency and adoption of industry-wide standards among nonlisted real estate funds, not least because of the initiatives of organizations such as INREV and ANREV. These organizations provide regular news flow information, surveys, in-depth fund analyses and quarterly investment performance indices. In an attempt to mitigate the liquidity problems of nonlisted funds, guidelines regarding the emergence of a secondary market are being developed by these industry associations and INREV (2008) provides an example of such guidelines.

Given the advantages of the nonlisted real estate funds outlined above, it is not surprising that they have experienced rapid growth over the last 10 years. Figure 1 shows the evolution of funds by value and by number of funds over the period 1998 to 2011. The current market value of European funds exceeds E265 billion distributed across 525 funds.

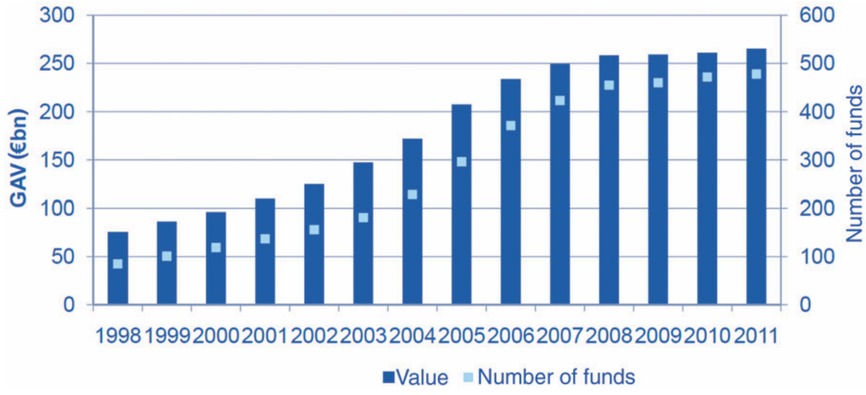

Fig. 1. Market growth of nonlisted funds
Source: INREV (2011).

Several factors have contributed to this growth, among others the fact that commercial real estate has generally become a global asset. The demand for more exposure to commercial real estate as an investment asset has been driven by international institutions and professional and retail investors. International investment through nonlisted real estate investment vehicles has allowed investors to access new and emerging markets such as Central and Eastern Europe, taking advantage of specialist expertise in these markets. Finally, nonlisted funds have allowed small investors to gain exposure to large-valued real estate assets, such as shopping centers or CBD offices, which otherwise they would not have had direct access to.

Classifying funds

The nonlisted funds are classified into one of three investment styles, namely core, value-added and opportunity funds. This classification seeks to demarcate relative risk classes and each fund is allocated to one of the three categories. Consequently, core funds are the least risky and opportunity funds the most risky. Until recently, this has been determined by a fixed set of rules, including the target rate of return a fund was aiming to achieve, being a proxy for 'risk'. These style classification rules were widely recognized as being inadequate and have recently been revised by INREV, now including additional factors such as the level of gearing and development exposure. Another distinguishing feature of a fund is its lifespan. Generally, a fund can either be an open-ended or a closed-ended fund. Open-ended funds have no set maturity date and can raise capital as and when required for investment. Closed-ended funds on the other hand have a finite life with a set of maturity dates, commonly up to 10–12 years, with one or two fund- raising periods in the interim. As of the end of 2010, the INREV database contained information on 301 open-ended funds valued at E124.3 billion and 166 closed-ended funds valued at E129.2 billion.

The distribution of funds by number and style is shown in Fig. 2. The single largest category is core funds accounting for 70% of the total by value (Gross Asset Value (GAV)), followed by value-added funds with 20% and opportunity funds with 10%.

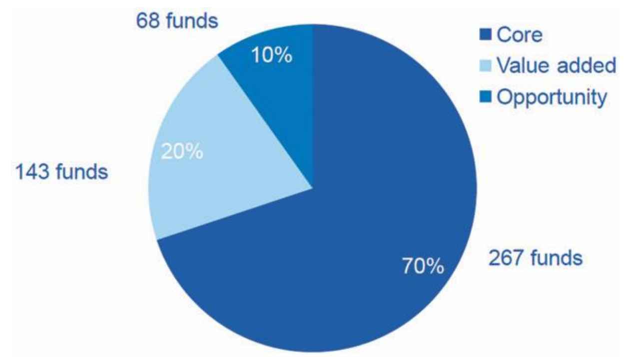

Fig. 2. Distribution of funds by investment style
Source: INREV (2011).

III. Previous Studies

Academic studies investigating nonlisted funds' investment performance are sparse. One such study was undertaken by Stevenson (2006), covering the period 2001 to 2004. However, the regression analysis results of nonlisted fund performance did not provide significant results, which the author attributed to the large number of young funds and the short history of available information at the time. Key and Lee (2008) identify enduring styles for nonlisted funds using survey techniques, but their analysis is not based on empirically observed investment performance.

In contrast to research on nonlisted funds, the drivers and overall predictability of direct commercial real estate returns have been more intensely researched and are better under- stood. 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 invest- ment. 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. Fuerst and Marcato (2009) demonstrate that the alpha performance of direct real estate investments, as estimated in a conventional Fama and French (1993) framework, is significantly reduced when additional property- specific tenant and lease risk attributes are considered. Their analysis of investment styles in the UK also underlines that multi-dimensional style analysis yields more accurate results compared to the commonly used region/sector classification and attendant analysis typically employed by real estate practitioners.

Hoesli and Lekander (2005) argue that nonlisted funds have the desirable feature of being highly correlated with the underlying real estate market. The corollary of this is that, compared to other real estate investment vehicles, nonlisted funds offer the diversification benefits of investing directly in commercial real estate. Brounen et al. (2007) also pick up on this aspect of nonlisted real estate funds, illustrating their significant growth over the last 15 years while Haran et al. (2008) explore the instrumental role of nonlisted funds in urban renewal and regeneration property. A common finding of these studies is that the considerable growth of the nonlisted sector was driven by the fact that they allow institutional investors to not only diversify their investments, but at the same time avoid some of the risks associated with direct real estate investments, particularly liquidity and management risks.

One issue that is of particular importance to managers of nonlisted real estate funds is the persistence of fund returns over time. Young and Graff (1996) demonstrate serial persis- tence for US direct real estate, particularly for the bottom and top 25% performers in the market. Using Investment Property Databank (IPD) data for their analysis, Devaney et al. (2007) demonstrate that serial persistence is prevalent in UK property returns as well. In related research, Young et al. (2007) show that real estate return distributions are nonnormal. The authors conclude that this impedes the effectiveness of strategies aimed at diversifying away nonsystematic risk. While our research does not address this issue directly, it is important to bear in mind that asymmetry and nonnormality of fund returns may limit the conclusions for active fund management drawn from this analysis.

Based on an attribution approach, Baum and Farrelly (2009) look to further attribute returns performance to alpha and beta components. The four components of their risk and return attribution framework include portfolio structure, stock selection, fund structure and timing. Implicit in their calculations is the contribution the selected property benchmark makes to performance. The authors employ a broad bench- mark, namely the IPD universe. Based on the performance record of a nonlisted value-added fund consisting of 20 quarterly observations, the authors report a significant market impact in accounting for net total returns, but observe no significant manager outperformance apart from the basic fact that higher leverage, and hence extra risk taking, is a significant attribution factor. In contrast, this article is solely concerned with the drivers of performance from broad property market factors and fund-specific features and no attempt is made to interpret the empirical results in terms of alpha and beta performance because of the methodological difficulties associated with this approach.

A more fundamental issue in investment performance research was raised by Gruber (1996) and revisited more recently by Lynch and Musto (2003) and Busse et al. (2010). If funds with better performance tend to attract a large amount of new investment while funds with bad performance simply discard their unsuccessful investment strategy, this might induce persistence among high performers, and thus, bias allocations in subsequent periods towards them. Under these conditions, past performance is not a good predictor for strategy-switching bad performers. Testing this hypothesis empirically, Lynch and Musto (2003) show that future performance of bad performers who discard their strategy is not as sensitive to past and current performance as it is for funds retaining their investment strategy. Using a sample free of survivorship bias, Busse et al. (2010) find that alpha performance and persistence of fund performance are somewhat sensitive to model choice, but the majority of the models applied (conditional and unconditional three, four and seven factor models) show little or no alpha persistence over time.

IV. Methodology and Empirical Analysis

The panel configuration of the dataset provides an ideal structure for capturing the dynamics of fund performance in relation to the overall market movements. A primary advan- tage in employing fixed effects or random effects models for panel data is the ability of these models to control for omitted variables. Generally, fixed effects regression is used when one wishes to control for omitted variables whose impact will differ between cases, for example, omitted variables having a differential impact on investment style returns. If there is reason to believe that there are omitted variables which may have the same constant impact, but vary randomly between cases, such as investment styles, a random effects model would be preferable. The Appendix outlines the fixed effects and random effects regression models applied in the present analysis.

Data characteristics

To understand the characteristics of nonlisted real estate funds investment performance, we first profile the distribution of funds in general before presenting summary statistics by style and vintage. Table 1 shows the distribution of the annual Total Rates of Return (TRR) over the period 2001 to 2007. It can be seen that the annual returns span the range from 71% to 133%, with an average of 12%, the distribution of returns being skewed towards positive returns, representing some 80% of the total number of returns. Although only some 4% of the returns (58 individual 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 panel data analysis results, excluding these outliers.

Sample selection and fund distributional characteristics

Annual total return as used in the panel regression analysis in the next section is calculated as

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

Table 1. Distribution of TRR over 2001 to 2007 (1082 observations)

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

Source: INREV and authors' calculations.

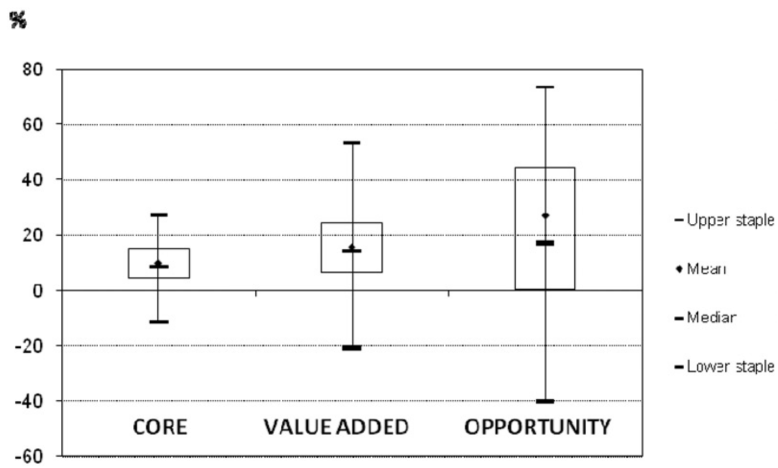

Fig. 3. Distribution of returns by style category
Source: INREV database and authors' calculations.

where NAV is net asset value, XD is distributed dividends, CI is increases in capital and RD redemptions. Having removed the extreme values outside of the range 20% and 40%, Fig. 3 shows the distribution of annual returns for the three types of fund styles, core, value-added and opportunity funds. These three investment style categories are defined by fund managers at the inception, taking into account the level of gearing and target rate of return along with other investment attributes, as outlined earlier. The boxplot shows that total returns of core funds are relatively homogeneous and clustered around the median and their Inter-Quartile Range (IQR) is relatively small. Value-added funds are somewhat more dispersed and opportunity funds show the highest IQR, with total returns in the middle 50% ranging from slightly negative to around 30%. These observations appear to be in line with the general assumption that the higher the variability in returns, the riskier the style group, with the opportunity funds displaying the highest volatility. Furthermore, within each style group, opportunity funds have the largest percentage of outliers.

Applying the adopted outlier rule (20% to 40% range), the number of cross-section time-series observations of the funds reduces to 1024, representing some 95% of the total observations. The definition of outliers has been subject to a substantive debate in the existing statistical and financial literature (e.g. Frecka and Hopwood, 1983; Charles and Darne, 2005; Schluter and Trede, 2008). Provided that extreme values are genuine observations and not data errors, they are vital for shaping the distribution of returns over time and cross-section. The reason for not including them in this analysis is that after inspecting funds with extreme values and ensuring that all observations are valid on a case-by-case basis, it appears that some unusually high or low returns were caused by nonmarket arrangements or are purely reporting errors in the database. For example, unusually high or low returns may occur when a fund undergoes major restructuring, so that these returns may be temporary accounting effects which should be excluded from an analysis of the market.

A priori, we would expect core funds to exhibit a lower, yet more stable pattern of returns than value-added funds and, particularly, opportunistic funds. Table 2 confirms that both the mean and the median total returns of core funds are considerably lower than those of value-added and

Table 2. Average annual total returns by style category

Style	Mean	Median	SD	Observations
Core	10.06	8.48	11.43	803
Value added	15.83	14.39	19.36	235
Opportunity	26.94	17.20	42.30	44
All	12.00	9.59	16.26	1082

Source: INREV and authors' calculations.

Table 3. WMR by style category

Style	Mean	Median	SD	Observations
Core	10.32	9.84	5.92	996
Value added	11.79	11.89	7.80	308
Opportunity	11.97	12.10	7.19	68
All	10.73	10.27	6.49	1372

Source: INREV and authors' calculations.

opportunistic funds. Core funds average annual returns are 10% whereas opportunity funds are 26.9%. Furthermore, for the three fund types, the SD, measured both cross-sectionally and over time is lowest for the core funds and highest for the opportunity funds. In other words, individual core fund returns are more clustered around the group average in a given year and overall, and are also less volatile over time for the period 2001 to 2007 than their value-added and opportunistic counterparts.

In commercial real estate investment, asset allocation to specific countries and property sectors is perceived to be a crucial factor for the overall performance of funds. A standard approach in capturing and analysing geographical and sectoral diversification in a regression-based model involves the use of dummy variables for each sector and country exposure. Apart from being a rather crude indicator of fund diversification, this approach ignores the distribution (weighted exposure) of individual funds across countries and sectors. To resolve this problem, we generate annual weighted return figures for each fund, based on the overall performance of property sectors in each country, weighted by the relative 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 average in that country. In a few cases only the sector exposure, but not the country, was known, so 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 gearing levels, the impact of gearing being treated as a separate regressor in the panel models.

Summarizing the performance figures, Table 2 shows the average performance by style for the whole cohort of funds over the period 2001 to 2007. As noted above, core funds exhibit lower average total returns and volatility than value- added funds and markedly lower returns and volatility than opportunity funds.

To contrast the average total returns of the funds with composite market returns, we construct returns weighted by the individual allocations known for each fund before calcu- lating summary statistics for each style category. Put differ- ently, the Weighted Market Returns (WMRs) are obtained by calculating an anticipated portfolio return for each fund individually. The WMR expresses what the anticipated port- folio return would have been, had the individual properties that the fund holds performed exactly in line with the sector and country averages. Table 3 reports the annual average weighted returns for each style group.

Although the achieved returns are higher for value-added and opportunistic funds than for core funds, the spread of returns falls to 1.65%, a much smaller range than the actual observed fund returns shown in Table 2. A possible explana- tion for the similarity of returns based on average country/ sector returns is that the higher returns for opportunistic funds are due to fund-specific rather than market characteristics, since opportunity funds generally pursue a strategy of high leverage, high exposure to development and active asset management. Thus, it seems likely that the excess returns generated by opportunity funds stem mainly from the capital structure of these funds and individual asset attributes rather than asset allocation to particular countries or sectors 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.

Next, we establish whether or not there is a systematic change in either the mean or the variance in the data. To this end, unit root tests are conducted and Table 4 shows the results obtained from running panel unit root tests for the three key variables, namely total return, gearing and WMRs. The Levin–Lin–Chu (LLC) test strongly indicates the presence of a common unit root process for the total return-dependent variable, while evidence for such a process is not found for the gearing and WMR variables. The Im–Pesaran–Shin (IPS), Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests, which assume individual unit 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 for first differences, strong evidence against a unit root was found for all variables, even for the critical common unit root in the TRR variable.

V. Panel Data Regression

We apply a fixed-effects panel regression to identify the main drivers of nonlisted fund performance. We specify a two-way error component model, testing for fund specific cross-section effects and for period effects. The panel regression we estimate in the article can be written as

$$y_{it} = \alpha + X'_{it}\beta + \mu_{it} \qquad \text{for } i = 1,\ldots\ldots,N \quad t = 1,\ldots..,T$$

The X_{it} represent the regressors driving y, the total fund returns in the analysis. The two-way error component model assumes an unobservable (cross-section) individual fund

Table 4. Panel unit root tests of the levels of total return, gearing and WMR

Method	TRR	Gearing	WMR
Null: Unit root (assumes common unit root process)			
LLC test[a]	18.2	765.5	47.8
	(1.00)	(0.00)	(0.00)
Null: Unit root (assumes individual unit root process)			
IPS W-statistic	2.6	82.7	6.0
	(0.00)	(0.00)	(0.00)
ADF – Fisher Chi-square	401.8	490.7	462.8
	(0.00)	(0.00)	(0.00)
PP – Fisher Chi-square	378.4	650.2	500.4
	(0.00)	(0.00)	(0.00)

Note: [a]Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution.

effect and an unobservable (period) time effect. The fund-invariant time effect accounts for any time-specific effect that is not included in the regression (Baltagi, 2008). For example, a yearly impact on sentiment towards commercial property impacting on all funds.

The Appendix provides an overview of model specifications and the tests that have been undertaken. In line with previous studies, we expect that the total return of a fund is mainly a function of country and sector-weighted property returns proportionate to the fund's asset allocation (WMR), the level of gearing in the previous period, the size of the fund (measured as GAV in million Euros) and the distribution yield (Yield). Table 5 shows the results of the estimation over the entire study period.

The reported redundant/fixed effects tests, together with a Lagrange Multiplier (LM) p-value5 0.0000, support the validity of panel estimation. The Hausman test rejects the random effects model in favour of the fixed effects estimation. The joint significance of the two-way fixed error component model is strongly confirmed.

The results broadly indicate that for all funds over the whole period, some 70% of the variation in total returns can be accounted for by four fundamental factors. A strong relationship is confirmed between average market returns in sectors and countries that a fund is invested in and its observed rates of return. This underlines the importance of systematic risk for direct real estate returns. Furthermore, as real estate funds are typically poorly diversified, Brown and Matysiak (2000), the impact of a fund's idiosyncratic risk adds to the overall volatility.

The level of gearing also shows the expected positive impact on a fund's return. For each additional 10% increase in gearing, total returns are on average enhanced by 0.67%. We also find a negative relationship between the size of a fund (GAV) and its returns. This appears to be in line with expectations formulated in the literature (e.g. Fama and French, 1993). If larger funds are less risky, for example because of size efficiency gains or because they are able to absorb unexpected shocks better, this should result in lower expected returns. However, more recent research suggests that there may be an endogeneity problem at play as funds that were more efficient to begin with may experience higher than average growth, which would mean that it is not actually size but unobserved factors that drive these findings (Matallın- Saez, 2011). Indeed, when we re-run the model with initial size (GAV) only, the coefficient turns insignificant. It is difficult to determine whether this confirms the endogeneity hypothesis, however, particularly as nonlisted real estate funds frequently deploy considerable amounts of capital in the first few years after they are launched so that initial GAV may not be an accurate measure of overall fund size. Thus, we use contemporaneous GAV as the size variable of choice in this specification.

Fund size

To investigate the relationship of size and fund performance further, we test an alternative model specification using fund size quartiles (small, medium small, medium large and large). By interacting the size category dummy variables with the WMR, we allow for a differential impact of size class on the relationship between market and fund return. Hence, this interaction term represents the average anticipated return by size group and reflects the responsiveness and volatility by fund size category. Table 6 shows the results of this alternative model.

From the results in Table 6, all reported statistics support the two-way fixed error component model. The results of this model specification underline the positive and significant impact of gearing and yield on fund returns. Again, all regression diagnostics support the two-way fixed effects component model. Moreover, larger funds generally exhibit higher volatility than smaller funds. The sequence of coeffi- cients for the WMR from the smallest to the largest category,
0.81, 0.94, 1.15 and 1.15 confirms that larger funds tend to amplify the anticipated market returns weighted by country and sector, whereas smaller funds tend to be less volatile than the markets they invest in.

It is important to note, however, that the 'small' category exhibits slightly larger within-group variations compared with the other three fund size groups. This means that, while 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 the range of the other three size groups. There are several possible explanations for the relationship between size and return reported above. Small funds tend to be younger funds, so that high initial transaction costs are likely to result in lower performance. To further investigate this proposition, we examine if there is such a relationship between size and age. Indeed, the mean age of
'small' funds is 2.5 years, 'medium small' is 4.8 years, medium large is 6.82 years and large funds are on average 13.19 years old. This appears to support Matallın-Saez's (2011) proposi- tion in that the higher performance of larger funds may at least partially be explained by their advanced maturity, particularly when the general performance pattern over a nonlisted fund's lifetime follows a stylized J-curve. Further research is required to capture these complex dynamics at the fund level. Since nonlisted real estate funds are still a relatively new product, it is difficult to disentangle the effects of a maturing market from maturing individual funds.

Table 5. Panel regression of total return 2001–2007

Dependent variable: total return (%)				
Variable	Coefficient	SE	t-statistic	Probability
C	1.799535	1.025951	1.754017	0.0799
WMR	1.074634	0.050719	21.18793	0.0000
Gearing (1)	0.067469	0.033246	2.029395	0.0428
GAV	0.089421	0.044842	1.994142	0.0465
Yield	0.176418	0.059271	2.976451	0.0030
R^2	0.702177	Akaike information criterion		6.857216
Adjusted R^2	0.582881	Schwarz criterion		8.264621
SE of regression	6.631904	Durbin Watson statistic		2.116748
Sum squared residual	31403.26			
Log likelihood	–3145.036			
F-statistic	5.886003			
Prob (F-statistic)	0.000000	Observations (N)		1001
Redundant fixed effects test		Statistic	d.f.	Probility
Cross-section/period F		2.561147	(282 714)	0.0000
Cross-section/period Chi-square		699.602165	282	0.0000
Hausman test		Chi-square	Chi-square d.f.	Probability
Random/fixed effects		25.147778	4	0.0000

Note: Breusch–Pagan (B–P) test LM p-value50.0000; d.f. – degrees of freedom.

Table 6. Panel regression, fund size and total return 2001–2007

Dependent variable: total return (%)				
Variable	Coefficient	SE	t-statistic	Probability
C	2.716686	0.890715	3.050006	0.0024
WMR * small	0.814539	0.091733	8.901256	0.0000
WMR * medium small	0.944920	0.070275	13.44600	0.0000
WMR * medium large	1.154949	0.063358	18.22888	0.0000
WMR * large	1.149796	0.065903	17.41652	0.0000
Gearing (1)	0.075605	0.033002	2.290886	0.0223
Yield	0.208632	0.058826	3.546568	0.0004
R^2	0.707904	Akaike information criterion		6.842323
Adjusted R^2	0.589586	Schwarz criterion		8.260664
SE of regression	6.578220	Hannan–Quinn criterion		7.381391
Sum squared residual	30767.09	Durbin–Watson statistic		2.123225
Log likelihood	3132.161			
F-statistic	5.983085			
Prob (F-statistic)	0.000000	Observations (N)		1001
Redundant fixed effects test		Statistic	d.f.	Probability
Cross-section/period F		2.492416	(282 711)	0.0000
Cross-section/period Chi-square		687.407417	282	0.0000
Hausman test		Chi-square	Chi-square d.f.	Probability
Random/fixed effects		38.774144	6	0.0000

Note: B–P test LM p-value50.0000.

Investment style

We next investigate how the self-reported investment style of a fund relates to fund performance via the WMR. Table 7 shows the response of fund returns to changes in WMRs by investment style category.

The results reported in Table 7 show that all the statistics support the two-way fixed error component model. As can be seen from Table 7, we test for the impact of investment style by interacting the continuous WMR variable with a dummy variable indicating the investment style of the fund (core, value-added or opportunity). The regression diagnostics support the two-way fixed effects component model. The estimated coefficients can be interpreted as the average relationship between the hypothetical WMR and the observed rate of return for each style category. The largest response to market movements is by opportunity funds, where a 1% increase in the market produces, on average, a 1.32% increase in fund returns. For value-added funds the corresponding figure is 1.11% and for core funds 1.04%. These results are not surprising in that the investment style of a fund represents a number of strategic factors influencing returns above and

Table 7. Two-way fixed effects panel regression of total return by style 2001–2007

Variable	Coefficient	SE	t-statistic	Probability
C	1.644681	1.034996	1.589069	0.1125
WMR * core	1.046500	0.059477	17.59513	0.0000
WMR * value added	1.108560	0.080779	13.72332	0.0000
WMR * opportunity	1.316843	0.255788	5.148188	0.0000
GAV	0.089319	0.044891	1.989697	0.0470
Yield	0.159739	0.061332	2.604515	0.0094
Gearing (1)	0.066210	0.033344	1.985677	0.0475
R^2	0.702751	Akaike information criterion		6.859281
Adjusted R^2	0.582516	Schwarz criterion		8.276494
SE of regression	6.634803	Hannan–Quinn criterion		7.397894
Sum squared residual	31342.68	Durbin-Watson statistic		2.113830
Log likelihood	3144.070			
F-statistic	5.844799			
Prob (F-statistic)	0.000000	Observations (N)		1001
Redundant fixed effects test		Statistic	d.f.	Probability
Cross-section F		2.462551	(276,712)	0.0000
Cross-section Chi-square		670.847769	276	0.0000
Hausman test		Chi-square	Chi-square d.f.	Probability
Random/fixed effects		44.935849	6	0.0000

Note: B–P test LM p-value 50.0000.

Table 8. Two-way fixed effects panel regression, asset classes, 2001–2007

Variable	Coefficient	SE	t-statistic	Probability
C	2.843375	3.421895	0.830936	0.4063
Gearing (1)	0.080477	0.041779	1.926260	0.0545
GAV	0.059357	0.055684	1.065951	0.2868
Yield	0.281470	0.073386	3.835464	0.0001
Stocks	0.056391	0.057989	0.972430	0.3312
Stocks (1)	0.148298	0.050243	2.951636	0.0033
GDP	2.065877	0.528863	3.906265	0.0001
GDP (1)	2.840756	0.567977	5.001532	0.0000
Bonds	1.600842	0.663684	2.412056	0.0161
R^2	0.553670	Akaike information criterion		7.279361
Adjusted R^2	0.370447	Schwarz criterion		8.709445
SE of regression	8.178189	Hannan–Quinn criterion		7.823051
Sum squared residual	47085.47	Durbin–Watson statistic		2.117505
Log likelihood	3327.842			
F-statistic	3.021829			
Prob (F-statistic)	0.000000	Observations (N)		994
Redundant fixed effects test		Statistic	d.f.	Probability
Cross-section F		2.745651	(281 704)	0.0000
Cross-section Chi-square		735.552744	281	0.0000
Hausman test		Chi-square	Chi-square d.f.	Probability
Random/fixed effects		25.882860	8	0.0011

Note: B–P test LM p-value 50.0000.

beyond the effects of gearing, yield and size. These include, for instance, exposure to development projects and/or properties requiring major repositioning to become profitable. Opportunity funds typically seek properties with a high potential for capital appreciation that might otherwise be considered too risky for the more income-oriented core funds.

Competing asset classes

Finally, we explore whether there is a statistical relationship between the performance of nonlisted funds and that of competing asset classes, in particular long-term bonds and stock markets. To enable a close comparison for all single and multi-country funds, we construct for each fund and year-weighted stock market and bond returns applying the same method as for the WMR variable. Thus, a fund's allocation across countries is used to calculate weighted stock market returns along with the returns on 10-year government bonds. This variable shows the returns a fund with an identical country allocation would have achieved in nonreal estate asset classes. To control for the impact of macro-economic growth on the performance of all asset classes, we also include weighted Gross Domestic Product (GDP) growth in the model. Table 8 shows the results of this model.

The regression diagnostics reported in Table 8 show that all the statistics support the two-way fixed error component model. The main finding of this model is that overall no contemporaneous relationship between stock market and nonlisted real estate fund performance is found. Interestingly, stock market performance lagged by 1 year is a significant predictor of nonlisted fund performance, hence suggesting that real estate fundamentals and the resulting nonlisted fund returns may react with a time lag to positive or negative shocks from the equity markets. This may be due to the more liquid nature of equity markets reflecting information more quickly than the valuation-based real estate markets. Previous studies (e.g. Quan and Titman, 1999; Okunev et al., 2000) provide some further empirical support for a causal relationship flowing from the stock markets to the real estate markets. Similarly, contemporaneous GDP growth appears to be neg- atively related to fund returns but exhibits the expected positive sign when lagged by 1 year. As expected, a significant positive association between contemporaneous 10-year government bond returns and nonlisted funds is also found while lagged bond rates (not included in the above model specification) did not reveal any significant relationships. As the bond rates can be viewed as a proxy for risk-free rates, it appears reasonable that the returns from riskier investments such as nonlisted real estate funds ought to be linked to these 'hurdle' rates via a number of channels such as, for example, the cost of capital.

VI. Conclusions and Further Work

In this study we have analysed a large number of nonlisted property funds over the period 2001 to 2007 using a panel data framework in order to determine the drivers of total returns across funds, sectors and countries as well as over time. The most robust results are accounted for by a weighted factor representing country and property sector direct returns, gearing and distribution yield. Furthermore, fund character- istics such as fund size, investment style, the performance of the overall economy and that of competing asset classes were found to be important factors accounting for fund performance.

One aspect that has not been explicitly explored is the contribution of 'risk' to overall performance. While gearing is an implicit measure of one aspect of risk, further work should look at more wide-ranging dimensions of real estate risk. Overall, the findings of this study raise the question: Where is value being added by nonlisted fund vehicles compared with direct real estate investment and how is this appropriately attributed? For example, it might be due to individual property selection, alpha value or market timing by selecting appropri- ate country and sector exposure. Future research on nonlisted funds should seek to measure more robustly which funds are generating out-performance and what drives out-performance relative to a benchmark. To this aim, systematic and idiosyn- cratic risk factors need to be considered more formally.

An important caveat of the findings presented is that the empirical analysis does not cover the years of the GFC while avoiding the shortcomings of the simple alpha-beta decom-position from 2008 onwards. Critics of nonlisted vehicles have argued that it was precisely this period that has revealed some fundamental shortcomings of the structure and modus ope-randi of nonlisted funds that were not visible in the pre-GFC period. The most serious criticisms among these are lack of liquidity and transparency, heavy reliance on valuations in thin markets, limited accountability and nonalignment of fund managers' incentives with investors' interests. Since many nonlisted funds seek to diversify across countries, contagion effects during times of crisis are a further concern (see, e.g. Marcal et al., 2011). To test whether these criticisms stand up to rigorous empirical analysis and whether these problems are particular to nonlisted funds, or apply more broadly to most other investment vehicles, is beyond the scope of this article. However, the authors intend to pursue these questions further in a follow-up study which is expected to elucidate the behaviour of funds and fund performance under severe financial and economic distress.

Looking ahead, two major changes for nonlisted funds that are almost certain to emerge from the global financial crises appear to be a tightening of regulations, in the case of European nonlisted funds emanating from the European Union regulatory bodies, and stricter demands by investors regarding the transparency of fund operations. Investors will also seek better control over sectors and regions they are invested in by giving more specific mandates compared to the rather laissez-faire approach of pre-crisis times. Follow-up research is also needed to investigate the consequences of these changes for nonlisted fund performance.

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Appendix 1: Fixed-effects estimation

The fixed effects model assumes 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 in the following manner:

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

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

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

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}). The structure of the fixed-effects model is thus:

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

where βx_{it} is a vector of time-varying characteristics comprising the weighted market returns, gearing levels and lagged total return with $u_{it} \sim IID(0, \sigma^2)$, i individual-level observations, and t time series observations.

Appendix 2: Random-effects estimation

The random effects model generally allows individual intercepts which are expressed as random deviations 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 estimating N parameters as in the fixed effects approach, the random-effects parameters describe 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. Our random-effects model is thus:

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

The error is defined as

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

The regression equation can then be rewritten 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 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 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:

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

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:

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

The guide for choosing a model specification is both the standard Hausman test and Hsiao and Sun's (2000) recommendation that the choice of a model be therefore theoretically and practically driven. 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 dataset used in the present analysis (Hsiao 2003). The fixed- and random effects models yielded relatively similar results regardless of the econometric differences in the estimation process as shown in the results section.

Appendix 3: Diagnostic Panel Tests

A number of specification tests were undertaken in order to support the validity of the two-way error component panel regression analysis and to distinguish between fixed effects and random effects models. Two tests for *poolability* against unobserved heterogeneity were undertaken. First, a test for the presence of fixed effects within funds (accounting for distinct and unobserved fund features such as fund management skill, including property selection). This is a standard Chow test for coefficient (intercept) stability amongst the funds. The null being tested is that all intercepts are identical, that is H_0: $\mu_1 = \mu_2 \ldots = \mu_{N-1} = 0$, where Ni is the number of intercepts, against the alternative that at least one is different. The second test is the Breusch-Pagan (B-P) test of significance for random variation (variance) in the intercept terms i.e. random effects against no effects. This is a LM test which, for a random one-way error components model under the null of no random individual effects i.e. H_0: $\sigma_\mu^2 = 0$, has an asymptotic $\chi^2_{(1)}$ distribution (Baltagi 2008). The third test is the Hausman test for correlated random effects. The random effects model assumes that the random effects are uncorrelated with the explanatory variables and, if this is not the case, it gives rise to endogeneity problems thereby rendering the estimates inconsistent. Essentially, it is a test of whether the GLS (random effects) estimator is biased and inconsistent, and if so, the fixed effects estimator is preferred as it is consistent. We report estimates of the block (all coefficients) test statistic, which is calculated as $W = (\beta_{FE} - \beta_{RE})'\psi^{-1}(\beta_{FE} - \beta_{RE})$, where β_{FE} and β_{RE} are the fixed effects and random effects estimates and $Var(\beta_{FE} - \beta_{RE}) = \psi$, with *W* being asymptotically distributed as $\chi^2_{(K)}$ and K the number of slope coefficients (Baltagi 2008).