Information Content when Real Estate Funds Deviate from Benchmark

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Abstract

This paper analyzes the informative content when real estate (LRE) funds deviate form their benchmark at a asset-level rather than at a fund level for the case of the European market. We construct a measure that allows us to sort investment strategies based on their deviation from benchmark (DFB). Using a sample of 132 real estate funds and 1,170 real estate stocks from 2001 to 2020, we show that on the LRE European market, strategies which are the closest to the benchmark composition led to higher performance over the whole period of study. Looking at sub-periods rolling abnormal performance, the difference between strategies tend to disappear overtime. Increased liquidity and market efficiency as well as increased regulation and competition could be an explanation to this finding.

Keywords: Real estate investment funds, listed real estate, performance analysis, portfolio management, active and passive strategies.
JEL: G11, G14, G15, L85

1 Introduction

An active fund manager can attempt to outperform the fund's benchmark by taking positions that are different from the latter. Fund holdings can differ from the benchmark holdings in two general ways: either because of stock selection or factor timing (or both).The traditional characterization of fund managerial skill is thus related to market timing or stock selection abilities. In this paper, we analyze the informative content when real estate mutual funds (REMF) deviate form their benchmark at a listed real estate-level rather than at a fund level for the case of the European market.

A listed real estate company is a firm that owns or finances income-producing real estate. Such a company provides regular income streams, diversification and long-term capital appreciation to investors of all types. Listed real estate companies acquire commercial properties – such as office buildings, shopping centres and industrial buildings – and lease the space in the structures to tenants, who pay rent. After paying the expenses associated with operating their properties, the listed real estate company pays out the majority of the income they collect to their shareholders as dividends. The European listed sector has evolved considerably in recent years, with new entrant real estate companies obtaining Real Estate Investment Trust (REIT) status. REIT funds are carrying favour with professional and individual investors in the latest year. Indeed, the market is driven by a favorable financial environment: low interest rates and a still volatile equity market. It is also helped by the dynamism and innovation of professionals in the sector. According to European Public Real Estate Association (EPRA),[1] "the combination of a relatively strong, long-term performance compared to other European assets and moderate long-term correlation with financial sector stocks has meant that Listed Real Estate (LRE) will have its separate classification in the FTSE Russell's Industry Classification Benchmark (ICB) from Q1 2021"[2]. Overall, LRE companies (represented by the FTSE EPRA Nareit Developed Europe REITs Index) provide a relatively high yield, particularly in comparison to current European interest rates and bond yields. Consequently, when share markets are volatile and bond markets are nervous about an increase in interest rates, bricks and mortar investments become a safe haven for many investors. Hoesli and Oilarinen (2019)(21) investigated the correlation between direct[3] and listed RE in the UK, France, Germany, the Netherlands, the US and Australia for the period of 1998-2017 and found the return and risk characteristics to be highly correlated over the medium to long term. Besides, LRE and direct property investments have different drivers over the short and medium-term, but over the full real estate cycle, the differences disappear and returns become similar[4]. From the legal side, the European regulatory framework imposed by the Directive on Alternative Investment Fund Managers (AIFMD III) has strengthened investor confidence by improving transparency on governance and by harmonizing the presentation of financial data for these funds, which makes it possible to achieve comparisons between funds across the European Union. In addition, the Solvency II regulation, which had limited the inflow from European insurance companies, was amended on June 8, 2019 to lower the reserve requirement for listed property. The latter is expected to drive new inflows into the sector.

An extensive literature on mutual funds performance exists. Beginning with Jensen (1968) (15) who quantified the performance of mutual fund managers by linking the difference between the average excess return on their portfolio and the average excess return on the index portfolio in the CAPM[5] relationship. Over time, researchers expanded the measurement if risk to include multi-factor models (Fama and French (1993(12), 2010(13), 2015(14)), Carhart (1997)(5), Daniel et al.(1997)(10), Pastor and

[1] EPRA report, 2020, Features and trends in European listed real estate.
[2] Directive 2011/61 / EU of the European Parliament and of the Council of 8 June 2011 on investment fund managers.
[3] Physical real estate.
[4] EPRA Features and trends in European listed, November 2020.
[5] The Capital Asset Pricing Model.

Stambaugh (2003)(22)). Jensen ascertained that on average, management was not able to outperform a buy-and-hold strategy: fund managers did not add a higher return for the amount of risk taken. Jensen's study was based on annual returns with dividends reinvested at year's end. Mains (1977)(20) supported Jensen's findings that on average mutual fund managers were not able to outperform the market after transaction costs. Berk and Green(2004)(4) confirmed precedent findings showing that stock-picking talents of active mutual fund managers concerns persistent positive alphas gross of fees. However, after taking fees into consideration, the superior performance is negated.

More recently, researchers have developed various measures of active management level in mutual funds, labelled "activeness", and examined how these measures relate to fund performance. (Kacperczyk, et al. (2005)(17), Cremers and Petajisto (2009)(8), Amihud and Goyenko (2013)(1), Kacperczyk, Sialm, and Zheng (2008)(18), Lantushenko and Nelling (2017)(23). Even thought not all proposed measures are significant, some of them show the link that exists between "activeness" and performance. Jiang et al. (2014)(16) find that the consensus wisdom of active mutual fund managers, as reflected in their average over- and underweighting decisions, contains valuable information about future stock returns. Based on active U.S. equity funds between 1984 and 2008, these authors show that stocks heavily overweighted by active funds outperform their underweighted counterparts. However, this large premium dissipates as the consensus view becomes public and this contributes to increase the informativeness of stock price. Jiang et al.(2014)(16), also demonstrate that active mutual funds invest only a small portion of the fund in high alpha stocks. This finding contributes to the fact that active funds do not outperform passive one as documented in many previous study. Even thought most previous authors focus on equity mutual funds, few of them investigate real estate mutual funds (REMF), where the literature is still scarce. REMF industry has expanded as the underlying REIT industry has developed over time, especially before the subprime crisis. In an attempt to beat their benchmark, REMFs may attempt to identify undervalued firms. In addition, fund managers may focus on specific property types or geographic regions that they believe will generate abnormal performance. Researchers have shown that REITs differ from the broader equity market, and that REMFs are different from diversified equity funds. For instance, Anderson et al.(2012) (2) document that REIT returns are more volatile in response to unexpected changes in monetary policy than are general equity markets. Following the global financial crisis, the number of REMFs in the US market experienced a sharp decline as signaled by Lantushenko and Nelling (2017)(23). Much of the existing research on REMFs also focuses on performance with mixed findings. Kallberg et al.(2000)(19) find that actively managed REMFs generate higher alphas than passively managed ones. On the contrary, Chiang et al.(2008)(6) find that REMFs do not exhibit abnormal performance. Derwall et al. (2009)(11), in an attempt to complete previous studies, highlight the importance of controlling for momentum in REITs when measuring fund performance. Cici et al. (2011) (7) find that REMF managers display evidence of property selection ability and generate positive alpha. More recently, Lantushenko and Nelling (2017)(23) examine the evolution of REMF active management and its effect on fund performance. Their work suggests that the REMF industry has become less competitive after the financial crisis, and fund managers have become less active after the crisis. Besides, among four measures of activeness, only one of them show a significant link between the level of active management and fund performance, especially amoung large funds. This slight significance of activeness measures could be explained by the fact that the latter may not be indicative of REMF managerial skill since an REMF manager faces more constrained investment opportunities.

Our paper relates to the work of Cremers and Petajisto (2009), Cremers et al.(2013)(9) and Jiang et al (2014)(16) and extend their work by applying their methodolody to real estate investment funds in

Europe to highlight its specific features and evolution throught time and periods of distress. (whereas their work are related to equity mutual funds in the U.S. in a different context). We extend these previous studies by considering the impact of activeness, especially by testing the performance of overweighted and underweighted LRE that are held by REMF. To reach this aim, we construct a measure called "Deviation from benchmark" that will represent investment decisions that are close to replicating the benchmark and those we deviate from it in a way to reflect "activeness". Indeed, rather than examine the total returns to a fund's portfolio, we aggregate decisions by active mutual funds to deviate from benchmarks into a stock-level measure and then assess its information content. If active real estate mutual funds deviate from benchmarks to exploit their information advantages, this measure can aggregate various pieces of information scattered among managers and thus should possess high statistical power to detect information advantages. Moreover, in order to measure the performance of these strategies, we use several multi-factor models to control for market, size, value, momentum factors. Furthermore, we explore these investment strategies accross different market conjunctures to assess arbitrage opportunies or LRE market efficiency. Section 2 describes the database construction and the methodology used; section 3 provides the empirical investigation of the tested market and the results; section 4 concludes.

2 Data and methodology

2.1 Data

To construct our real estate fund database, we extract data from Factset and Lipper-Reuter database. From an initial number of 700 funds, we end up with 132 real estate funds after taking into consideration of class property grouping. We keep thus only funds that are classified as real estate fund. Moreover, we consider only actively managed European RE funds with available data from 2001 to 2019. We then look at fund composition by extracting listed assets that have been held at least once by these funds. We performed data processing to eliminate outliers and common issues such as survival bias. Our database includes thus living funds as well as funds that closed during the study period. we do not impose an additional filter for fund size but require that a fund has been in existence for a minimum of five years as done by McGregor (2021)(3). The initial number assets was 3328 and we end up (after data processing) with 1170 assets identified as belonging to the real estate sector and thus LRE. More precisely, our database gathers 132 real estate funds that held 1170 listed assets. For each fund, we compute the weights of each asset held with repect to the total fund size on a quarterly basis. We label this data as $w^j_{i,t}$ to indicate the weight of asset i in the funds porfolio at time t. $w^b_{i,t}$ represents the weight of asset i in the benchmark portfolio. We construct the market portfolio by considering all LRE that were held at least once by two RE funds. The market index is value-weighted and composed of 1170 LRE observed over the 2001-2019 period. We hypothesis that each manager's decision of portfolio tilting reflects the expectation of future returns to that asset conditional on the information set he or she posses (Roll 1992). Figure 1 shows the development of the listed real estate market in terms of both number of securities and market capitalization. Indeed, starting from almost 470 assets in early 2000, the number of asset experienced a significant growth and stood at a little more than 700 assets in 2020. As regards the market cap, it is multiplied by more than 5 from 2000 to 2020. We can clearly see in the graph the fall in capitalization during the subprime crisis. However, the number of exchanged assets did not experience the same effect. Figure 2 allows us to observe the evolution of the number of real estate funds in our database. The number of real estate funds increased significantly between 2000 and 2020, from almost zero to nearly 117 funds. These have also undergone changes in terms of

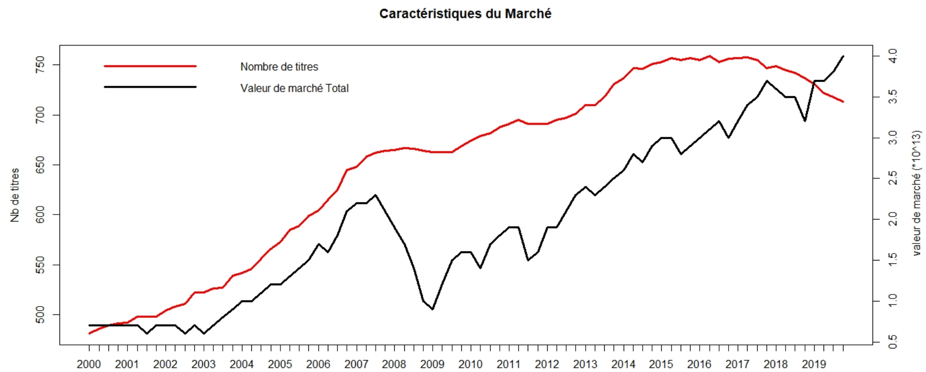

Figure 1: Evolution of the listed real estate market in number of listed securities and market capitalization from 2000 to 2020

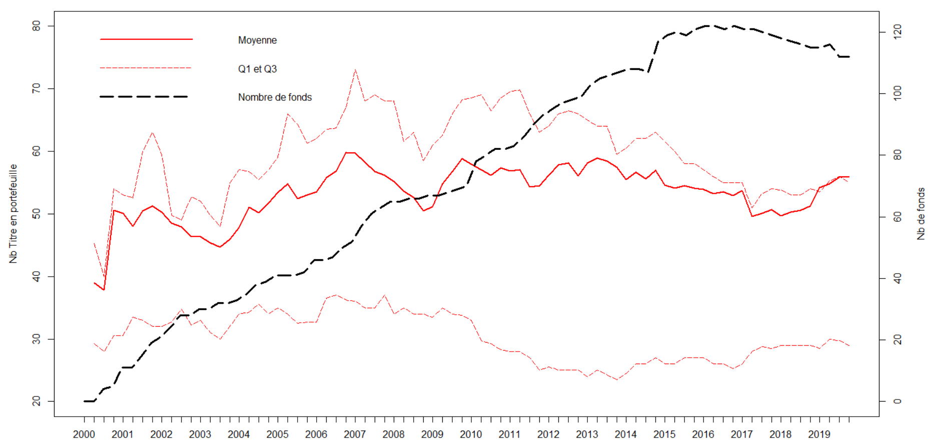

Figure 2: Evolution of the number of funds and average number of listed real estate in the database from 2000 to 2020

composition. The number of securities held on average rose from a little less than 40 securities in 2000 to nearly 75 in 2020. We also note through this graph that the average is closer to the third quartile towards the end of the study period.

2.2 Methodology

Following the paper of Jiang et al.(2014), we measure a real estate fund j's deviation from its benchmark for stock i in quarter $t$as the difference between this LRE's weight in the fund portfolio, $w^j_{i,t}$ and its weight in the market index (denoted RMKT_RE hereafter) against which the fund's performance is benchmarked, $w^b_{i,t}$. Then we create a LRE-level measure of RE funds' deviations from benchmarks, DFB[6], by averaging the difference in portfolio weights across all real estate funds whose investment universe comprises this listed real estate asset. We thus define a measure of mutual funds' deviations

[6]Jiang et al. (2014) argue, and provide evidence, that this measure is more powerful to detect active funds'information advantages than previously used proxies based on the level or breadth of active fund ownership.

from benchmarks for asset i as:

$$DFB_{i,t} = \frac{1}{N_i} \sum_{1}^{N} \left(w_{i,t}^{j} - w_{i,t}^{b} \right) \tag{1}$$

where N_i is is the number of REMF whose investment universe includes asset i at time t[7].
As previously stated, an active fund manager can attempt to outperform the fund's benchmark by taking positions that are different from the benchmark. If active mutual funds aim to outperform a passive benchmark index, they will overweight a stock, relative to the benchmark when they expect it to outperform, and underweight it otherwise. At the end of each quarter, we compute for each LRE a measure of RE funds' deviations from benchmarks, DFB, which is the simple average of the LRE's weight in a fund portfolio in excess of its weight in the fund's benchmark index, across all funds in the LRE-fund cohort. We then sort LRE into deciles in ascending order based on DFB and calculate the LRE characteristics for each decile portfolio. Based on computed DFBs, we identify 10 deciles. The later is used to create investments strategies that we classify from 1 to 10. Classification 1 represents LRE that have been the more underweighted by RE funds compared to the benchmark. On the contrary, strategy 10 is a portfolio containning LRE that have been the most overweighted by the RE funds compared to benchmark. We build 20 left-hand portfolios: 10 equally-weighted portfolios and 10 equally-weighted ones. Besides, we build our right-hand portfolios based on our database. We thus build a market portfolio that is specific to our database. The later is a value-weighted portfolio gatering all LRE in the database. We also adopt Fama and French (1993, 1998, 2015) methodology to build Small minus Big specific to our database (SMBRE) factor as well as High minus Low for the considered sample (HMLRE). Thus, to construct the SMBRE and HMLRE factors, we sort LRE into two market cap and three book-to-market (B/M) groups at the end of each June[8]. SMBRE is the equal-weight average of the returns on the three small LRE portfolios minus the average of the returns on the three big LRE portfolios and HMLRE is the equal-weight average of the returns for the two high B/M LRE portfolios minus the average of the returns for the two low B/M portfolios. In the same way, we use three different benchmark portfolios. First, we consider the standard market benchmark collected from Fama - French library as a main factor to capture market risk, the latter is referred to as RMKT. Second, we considered the constructed real estate benchmark market portfolio devoted to capture the spectic risk related to Real estate sector (RMKT_RE). More precisely, RMKT_RE is contructed from all assets present in our database, i.e. all assets that have been traded at least one time. Third, we use NAREITS Europe index which is comparable to our RMKT_RE custom made benchmark. We consider that RMKT_RE gives a more accurate information on what is the basket with which real estate fund managers deal whereas the NAREITS Index is a more synthetic information.[9]

Before carrying out our main empirical investigations, we first launched a horse race between different specifications in order to identify the one that best captures the returns variation for our 10 decile portfolios. Among various specifications, we mainly perform and compare regression results from

[7]A stock enters a mutual fund's investment universe if it (1) is held by the mutual fund or (2) is a member of the fund's benchmark index. We thus define a measure of mutual funds' deviations from benchmarks for stock i.

[8]Big LRE are those in the top 90% of June market cap, and small LRE are those in the bottom 10%. The B/M breakpoints are the 30th and 70th percentiles of B/M for the big LRE.

[9]The FTSE EPRA Nareit Developed Europe Index is a subset of the FTSE EPRA Nareit Developed Index and is designed to track the performance of listed real estate companies and REITS.

following models :

$$r_{i,t} = \alpha_i + \beta_{m,i} \times RMKT_t + \beta_{s,i} \times SMBRE_t + \beta_{h,i} \times HMLRE_t + \epsilon_{i,t} \quad (2)$$

$$r_{i,t} = \alpha_i + \beta_{mre,i} \times RMKTRE_t + \beta_{s,i} \times SMBRE_t + \beta_{h,i} \times HMLRE_t + \epsilon_{i,t} \quad (3)$$

$$r_{i,t} = \alpha_i + \beta_{m,i} \times RMKT_t + \beta_{n,i} \times NAREIT_t + \beta_{s,i} \times SMBRE_t + \beta_{h,i} \times HMLRE_t + \epsilon_{i,t} \quad (4)$$

$$r_{i,t} = \alpha_i + \beta_{m,i} \times RMKT_t + \beta_{mre,i} \times RMKTRE_t + \beta_{s,i} \times SMBRE_t + \beta_{h,i} \times HMLRE_t + \epsilon_{i,t} \quad (5)$$

It is worth to notice that $r_{i,t}$, $RMKT_t$, $RMKTRE_t$ and $NAREIT_t$ are calculated in excess of risk free (EURIBOR 1-month). More importantly to avoid the endogeneous problem between the market benchmark (RMKT) and the real estate sectorial benchmark ($RMKTRE_t$ and $NAREIT_t$) we orthogonalize them. So that $RMKTRE_t$ and $NAREIT_t$ capture only the variations that are not captured by the market. As a results the last specification (equation 5) is the more accurate with a R^2 up to 70%, that is 20% higher than the others[10].

3 Empirical investigation

In this section, we present our empirical investigation. First, we examine the performance dynamics of DFB decile portolios in order to check if there is a dominant strategy. Second, we examine the return forecasting power of DFB deciles portfolios to evaluate the investment value of activeness related to each strategy.

3.1 Performance of DFB decile portolios

We explore the absolute and relative performance of DFB decile portfolios. It is worth to notice that we present all our analysis both for equally-weigthed and value-weighted portfolios. Since equally-weighted portfolio returns may be driven by tiny stocks that are numerous in number but small in economic significance, whereas value-weighted portfolio returns may be driven by a few very large caps.

3.1.1 Absolute performance of DFB decile portfolios

Table 1 displays descriptive statistics related to the 10 strategies established from the calculated DBFs. It turns out that the strategy showing the most important arithmetic mean returns is strategy D6 for equally-weighted returns and strategy D5 for value-weighted returns. This is also verified by observing the geometric mean returns. Strategy D6 displays significant positive skewness and higher kurtosis than other strategies. This therefore indicates a longer distribution on the right and that the distribution tails are thicker. In addition, the D8, D9 and D10 strategies exhibit significant negative skewness coupled with a strong positive kurtosis. In terms of volatility, strategies D5 and D7 have the largest standard deviation for equally-weighted returns while strategies D2 and D7 have the largest standard deviation for value-weighted returns. However, extreme strategies, D1 and D10, present the lowest volatility. Strategy D6 displays the highest maximum returns. We can also observe that the strategy which consists of being long on D5 and short on D1 displays positive average value-weighted and equally weighted returns. The opposite is observable for being long on D10 and short on D5. Figure 3 and Figure 4 show the cumulative absolute returns of our 10 decile portfolios. Figure 3 draws the equally-weighted portfolios cumulative returns whereas figure 4 exhibits the value-weighted ones. The two figures permit to observe the evolution of compound returns over time. It confirms the dominance

[10] Results are not reported here given the number of tables to be included. We can send them upon request.

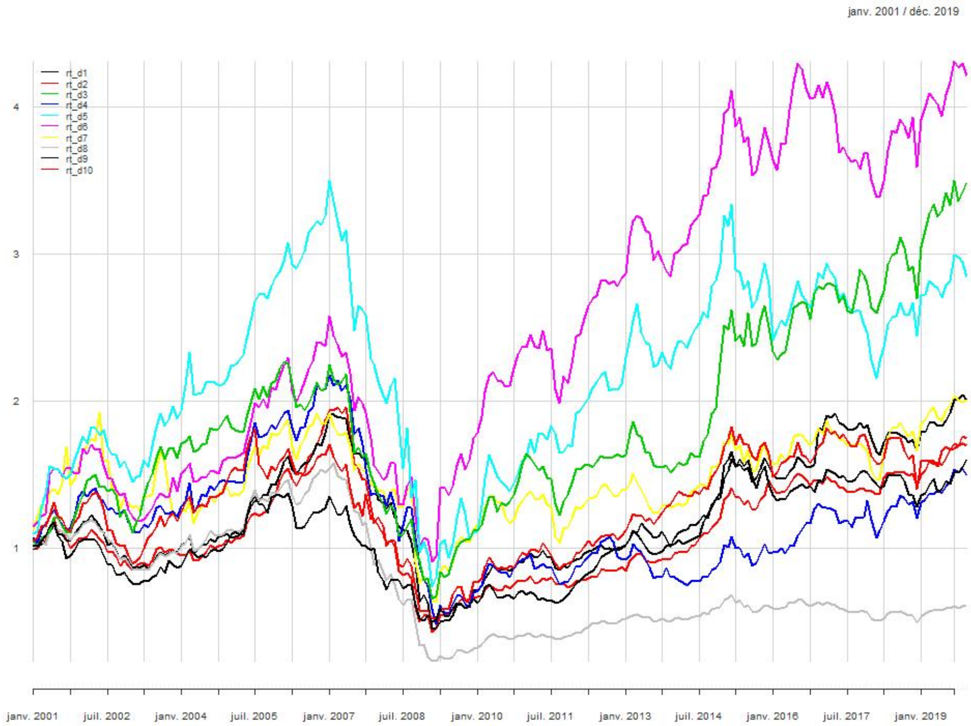

Figure 3: Equally-weighted portfolios cumulative returns

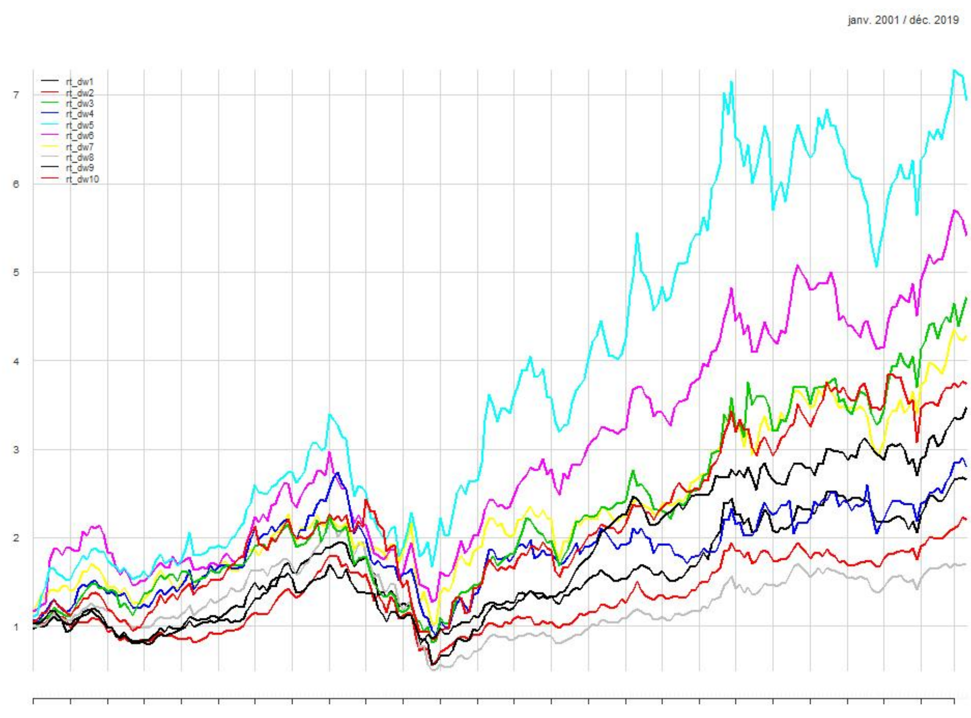

Figure 4: Value-weighted portfolios cumulative returns

Table 1: **Decile portfolios returns summary statistics**

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D10 - D1	D10 - D5	D5-D1
	Equal-weighted portfolios												
Minimum	-0.187	-0.202	-0.175	-0.213	-0.335	-0.184	-0.372	-0.313	-0.287	-0.247	-0.166	-0.339	-0.266
Quartile 1	-0.027	-0.024	-0.025	-0.033	-0.023	-0.020	-0.025	-0.022	-0.017	-0.015	-0.020	-0.024	-0.025
Median	0.008	0.008	0.010	0.005	0.011	0.007	0.007	0.008	0.007	0.006	-0.000	-0.000	0.004
Arithmetic Mean	0.003	0.004	0.007	0.004	0.007	0.008	0.005	-0.001	0.004	0.004	0.000	-0.003	0.004
Geometric Mean	0.002	0.002	0.005	0.002	0.005	0.006	0.003	-0.002	0.003	0.002	-0.000	-0.005	0.002
Quartile 3	0.034	0.035	0.039	0.039	0.042	0.035	0.039	0.029	0.032	0.032	0.025	0.020	0.031
Maximum	0.158	0.173	0.247	0.259	0.283	0.489	0.330	0.147	0.190	0.201	0.196	0.212	0.279
Stdev	0.047	0.053	0.054	0.060	0.068	0.059	0.064	0.053	0.050	0.047	0.041	0.053	0.058
Skewness	-0.544	-0.549	-0.137	-0.254	-0.698	2.015	-0.558	-1.808	-1.339	-1.246	0.278	-0.775	-0.198
Kurtosis	1.580	1.981	2.255	1.959	4.857	18.847	7.564	7.921	9.102	6.407	3.500	8.056	4.169
	Value-weighted portfolios												
Minimum	-0.143	-0.184	-0.173	-0.153	-0.155	-0.156	-0.270	-0.272	-0.288	-0.243	-0.189	-0.153	-0.107
Quartile 1	-0.019	-0.021	-0.021	-0.027	-0.023	-0.017	-0.020	-0.017	-0.018	-0.015	-0.026	-0.027	-0.024
Median	0.006	0.011	0.008	0.006	0.011	0.005	0.006	0.012	0.006	0.007	-0.001	0.000	0.000
Arithmetic Mean	0.006	0.007	0.008	0.006	0.010	0.009	0.008	0.004	0.006	0.005	-0.003	-0.005	0.003
Geometric Mean	0.005	0.006	0.007	0.004	0.008	0.007	0.006	0.002	0.004	0.004	-0.004	-0.006	0.002
Quartile 3	0.033	0.038	0.039	0.040	0.039	0.037	0.045	0.034	0.034	0.034	0.021	0.023	0.026
Maximum	0.118	0.317	0.301	0.193	0.190	0.380	0.331	0.142	0.163	0.176	0.175	0.107	0.166
Stdev	0.043	0.056	0.055	0.054	0.055	0.055	0.059	0.051	0.052	0.050	0.041	0.041	0.043
Skewness	-0.398	0.387	0.457	-0.078	0.031	1.407	-0.056	-1.622	-1.334	-1.128	-0.167	-0.459	0.317
Kurtosis	0.704	5.250	3.914	0.966	1.016	9.728	6.024	6.403	7.807	4.928	2.962	0.833	0.858
Observations	228	228	228	228	228	228	228	228	228	228	228	228	228

of D5 and D6 portfolios in terms of absolute performance. We may be tempted to interpret it as a superiority of strategies that are close to replicate the benchmark. Strategies that deviate a lot from the benchmark such as D1 and D10 are among the worst. It remains to be seen whether these results are confirmed after taking into account the risk dimension.

3.1.2 Relative performance of DFB decile portfolios

Table 2 reports the relative performance of the 10 investment strategies. The latter reports the relative performance measures; namely the Sharpe ratio[11], the tracking error[12] and the information ratio[13]. We consider two market benchmarks: NAREIT and MKTRE.

Table 2: **Relative and active performance for decile portfolios**

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D10 - D1	D10 - D5	D5-D1
Benchmark: NAREITS Europe													
	Equal-weighted portfolios												
Annualized Sharpe Ratio (Rf=1.4%)	0.066	0.075	0.283	0.034	0.178	0.308	0.103	-0.218	0.131	0.093	-0.134	-0.379	0.053
Tracking Error	0.051	0.043	0.046	0.050	0.055	0.042	0.047	0.040	0.040	0.039	0.062	0.082	0.069
Annualized Tracking Error	0.176	0.151	0.160	0.174	0.192	0.146	0.163	0.137	0.140	0.136	0.215	0.285	0.238
Information Ratio	-0.144	-0.149	0.108	-0.167	0.031	0.192	-0.081	-0.560	-0.094	-0.152	-0.260	-0.375	-0.108
	Value-weighted portfolios												
Annualized Sharpe Ratio (Rf=1.4%)	0.355	0.293	0.369	0.218	0.480	0.410	0.317	0.079	0.208	0.162	-0.408	-0.598	0.055
Tracking Error	0.052	0.050	0.048	0.051	0.047	0.047	0.037	0.039	0.039	0.039	0.055	0.068	0.059
Annualized Tracking Error	0.181	0.172	0.166	0.177	0.162	0.163	0.129	0.134	0.135	0.135	0.192	0.236	0.204
Information Ratio	0.095	0.123	0.208	0.029	0.349	0.259	0.224	-0.164	0.015	-0.060	-0.497	-0.517	-0.138
Benchmark: MKTRE													
	Equal-weighted portfolios												
Tracking Error	0.027	0.031	0.033	0.040	0.051	0.039	0.048	0.034	0.031	0.028	0.059	0.071	0.068
Annualised Tracking Error	0.095	0.107	0.113	0.140	0.178	0.135	0.165	0.116	0.109	0.098	0.205	0.246	0.237
Information Ratio	-0.336	-0.269	0.096	-0.255	-0.003	0.160	-0.119	-0.717	-0.180	-0.277	-0.304	-0.460	-0.136
	Value-weighted portfolios												
Tracking Error	0.027	0.037	0.037	0.040	0.038	0.040	0.039	0.035	0.033	0.028	0.054	0.057	0.057
Annualised Tracking Error	0.094	0.128	0.128	0.137	0.133	0.138	0.135	0.120	0.113	0.098	0.188	0.199	0.198
Information Ratio	0.115	0.115	0.219	-0.009	0.379	0.260	0.167	-0.237	-0.039	-0.147	-0.539	-0.645	-0.175

Overall, we obtain three main findings. First, whatever performance measure considered, the

[11]The Sharpe ratio devides the excess return of an investment by its risk (standard deviation).

[12]The tracking error is the divergence between the price behavior of a position or a portfolio and the price behavior of a benchmark.

[13]The information ratio measures the additional performance achieved compared to the benchmark divided by the tracking error. The higher the information ratio, the skilled the portfolio manager.

two portfolios D5 and D6 display the better performance. These results are observed for the two benchmarks and also either for equally-weighted or for value-weighted portfolios. The fact that these two portfolios had a level of risk slightly superior than the others did not ultimately have a major impact on their performance. Second, the investment strategies $D10 - D1$; $D10 - D5$ and $D5 - D1$ exhibit negative performance for all performance measures used. It seems to indicates that there are information advantages to buys stocks from middle decile portfolios and short those is extreme deciles. Third, results for value-weighted portfolios are all Superior to those for equally-weighted portfolios indicating a significant role of the size in the investment strategy.

As a consequence, cumulative returns and performance measures bring out a fairly clear hierarchy between the different decile strategies. They put forward middle decile D5 and D6. Let's recall that D5 and D6 decile portfolios are those with DFB close to 0; i.e. strategies that are close to replicating the benchmark. All in all, this confirms our main issues of information content from DFB portfolios. Managers and investors can value their investment either by adopting a strategy mimicking the market, or close to replicating it.

3.2 Forcasting power of DFB portfolios

In this part, we pursue our analysis by explore in depth or previous findings. The aim is to examine the return forcasting power of DFB portfolios. To do so, we run Fama and MacBeth (1973) cross-sectional multifactor regressions in order to estimate DFB risk-adjusted returns as well their magnitude related to standard risk factors, market ($RMKT$), real estate market ($RMKTRE$), size ($SMBRE$) and value($HMLRE$). The last two factor are proper to our listed real estate market.

3.2.1 Risk-adjusted performance of DFB portfolios

Let's recall that forecasting power is based on the fact that the risk-adjusted performance is estimated on the subsequent quarter after the constitution of all deciles portfolios, that is 1-quarter later. Table 3 presents both equally-weighted and value-weighted results from our cross-sectional regressions. First, we notice that risk factors' coefficients are highly significant and the adjusted R^2 are also high. Moreover, We observe that, except strategy $D6$ that displays a positive and significant alpha, all other alphas are negative for equally-weighted returns portfolios. Conversely, value-weighted portfolios display positive and negative alphas. Again it confirms the significant impact of size in performance dynamics. A closer look on these latter results shows that $D1$, $D2$ and $D5$ display positive risk-adjusted performance, whereas other strategies lead to null or negative performance. Overall, the best investment strategy, in terms of risk adjusted return, is strategy $D6$ when we opt for equally-weighting. Second, Table 3 shows that the beta coefficients related to market risk $RMKT$ do not give specific information. We only observe that the slopes are in a range of $[0.50; 0.84]$ indicating the features of real estate compared to stock market. The beta coefficients related to real estate sector ($RMKTRE$) is higher and closer to 1 for all our cross-sectional regressions. This is a good news insofar as it validate the fact that $RMKT\_RE$ can be a useful marker for monitoring the activeness of LRE funds. Its importance is all the greater since we have calculated them from all traded real estate stocks and not from standard indexes such as NAREITS that we also used previously. Third, the results related to SMB and HML style factors bring out information content which would undoubtedly deserve an in-depth analysis. Once again, we observe different results from equally-weighted and value-weighted portfolios. This plainly validates the idea that size matter to evaluate investment value in real estate stocks. As with our previous results, equally-weighted portfolio regressions does not allow a clear difference between deciles portfolios. They all display positive coefficients with SMB_RE and negative ones with HML_RE, respectively. On the contrary, results for value-weighted portfolios are very instructive. On the one hand, we observe all middle decile portfolios display a positive coefficient related to SMB_RE. The two extreme decile portfolios, namely $D1$ and $D10$ (as well as $D9$) display negative coefficients. This indicates that $D1$ and $D10$ are composed mainly by big real estate stocks. Conversely, middle decile portfolios seems to be invested in small or mid-size real estate stocks. This observations is consistent with the results from equally-weighted decile portfolios from which all coefficients related to SMB_RE are positive. On the other hand, coefficients related to HML_RE are all negative. This seems to indicate that the basket on which funds traded and/or are invested is composed by numerous real estate stocks with low book to market value. Nonetheless, the two extreme decile and the $D2$ portfolios are those with a HML_RE negative but very close to 0. Thus, they appear to be slightly different and seems to make some bet on high book to market value real estate stocks. All in all these results confirms that decile portfolios contain information on investment value. It is clear that these findings need to be explored in depth in future research.

Table 3: **Risk-adjusted performance for DFB portfolios**

	Equally-weighted portfolios						*Value-weighted portfolios*					
	Alpha	RMKT	RMKT_RE	SMB_RE	HML_RE	Adj R^2	Alpha	RMKT	RMKT_RE	SMB_RE	HML_RE	Adj R^2
D1	-0.284***	0.691***	0.958***	0.056***	-0.071***	0.719	0.042	0.575***	0.837***	-0.094***	-0.072***	0.655
	(0.041)	(0.013)	(0.011)	(0.021)	(0.010)		(0.039)	(0.016)	(0.015)	(0.021)	(0.012)	
D2	-0.237***	0.831***	0.940***	0.590***	-0.125***	0.797	0.117***	0.832***	0.949***	0.661***	-0.028***	0.763
	(0.028)	(0.007)	(0.011)	(0.020)	(0.006)		(0.033)	(0.009)	(0.012)	(0.035)	(0.011)	
D3	-0.104***	0.749***	1.106***	0.642***	-0.094***	0.774	-0.065	0.649***	1.073***	0.522***	-0.108***	0.677
	(0.040)	(0.014)	(0.008)	(0.021)	(0.007)		(0.040)	(0.014)	(0.010)	(0.030)	(0.015)	
D4	-0.441***	0.693***	1.185***	1.259***	-0.028***	0.738	-0.323***	0.592***	0.972***	0.853***	-0.133***	0.638
	(0.050)	(0.010)	(0.012)	(0.026)	(0.009)		(0.048)	(0.012)	(0.015)	(0.029)	(0.010)	
D5	-0.180***	0.730***	1.073***	0.256***	-0.165***	0.629	0.016	0.601***	1.132***	0.424***	-0.178***	0.721
	(0.039)	(0.014)	(0.013)	(0.070)	(0.018)		(0.035)	(0.012)	(0.010)	(0.041)	(0.014)	
D6	0.249***	0.737***	1.056***	0.513***	-0.126***	0.769	-0.042	0.613***	0.939***	0.277***	-0.242***	0.720
	(0.057)	(0.014)	(0.013)	(0.017)	(0.013)		(0.031)	(0.011)	(0.010)	(0.021)	(0.009)	
D7	-0.254***	0.768***	1.081***	0.896***	-0.070***	0.739	0.002	0.703***	1.042***	0.591***	-0.226***	0.766
	(0.055)	(0.016)	(0.012)	(0.026)	(0.010)		(0.060)	(0.017)	(0.010)	(0.027)	(0.011)	
D8	-0.717***	0.605***	1.009***	0.081*	-0.310***	0.811	-0.344***	0.577***	0.956***	0.096**	-0.316***	0.778
	(0.045)	(0.010)	(0.009)	(0.045)	(0.019)		(0.037)	(0.012)	(0.010)	(0.040)	(0.020)	
D9	-0.193***	0.634***	0.954***	0.216***	-0.151***	0.722	-0.080***	0.674***	0.945***	-0.070**	-0.199***	0.715
	(0.032)	(0.007)	(0.009)	(0.037)	(0.007)		(0.025)	(0.008)	(0.013)	(0.036)	(0.009)	
D10	-0.087**	0.526***	0.894***	0.321***	0.030***	0.696	-0.091**	0.607***	1.041***	-0.119***	-0.036***	0.752
	(0.040)	(0.014)	(0.012)	(0.018)	(0.007)		(0.040)	(0.010)	(0.013)	(0.034)	(0.007)	
D10 - D1	-1.057***	-0.120***	-0.026	0.269***	0.117***	0.212	-1.473***	0.089***	0.168***	0.076*	0.053***	0.235
	(0.105)	(0.023)	(0.020)	(0.031)	(0.014)		(0.094)	(0.024)	(0.016)	(0.041)	(0.015)	
D10 - D5	-1.160***	-0.159***	-0.141***	0.070	0.212***	0.214	-1.317***	0.063***	-0.068***	-0.440***	0.153***	0.310
	(0.136)	(0.018)	(0.022)	(0.065)	(0.023)		(0.110)	(0.015)	(0.017)	(0.030)	(0.020)	
D5 - D1	-1.150***	0.085***	0.152***	0.204***	-0.077***	0.221	-1.310***	0.059**	0.272***	0.662***	-0.036***	0.307
	(0.079)	(0.025)	(0.020)	(0.077)	(0.018)		(0.084)	(0.024)	(0.012)	(0.040)	(0.013)	
Note: (xxx) standard error												*p<0.1; **p<0.05; ***p<0.01

3.2.2 Persistence of returns forcasting power of DFB portfolios

To examine the persistence of DFB return-forecasting power, we extract all coefficients from our cross-sectional regressions. We then roll and plot them in order to identify if there are significant dominance between strategies. Here, we focus our analysis on three main portfolios to make the figures easier to read: two extreme portfolios in terms of DFB, $D1$ (under-weighting the market) and $D10$ (over-weighting the market), and a portfolio that is close to mimicking the benchmark, $D5$. Figure 5 presents the rolling alphas obtained from our cross-sectional regressions. The figure does not allow to conclude on the superiority of a strategy with respect to the others over the whole period of observation. However, strategy $D5$, which is the closest to the benchmark in terms of LRE weights, appears to be more secure. No massive losses are observed for this strategy compared to $D1$ and $D10$. Besides, we observe rather different trajectories that seem to match with the different cycles of real estate

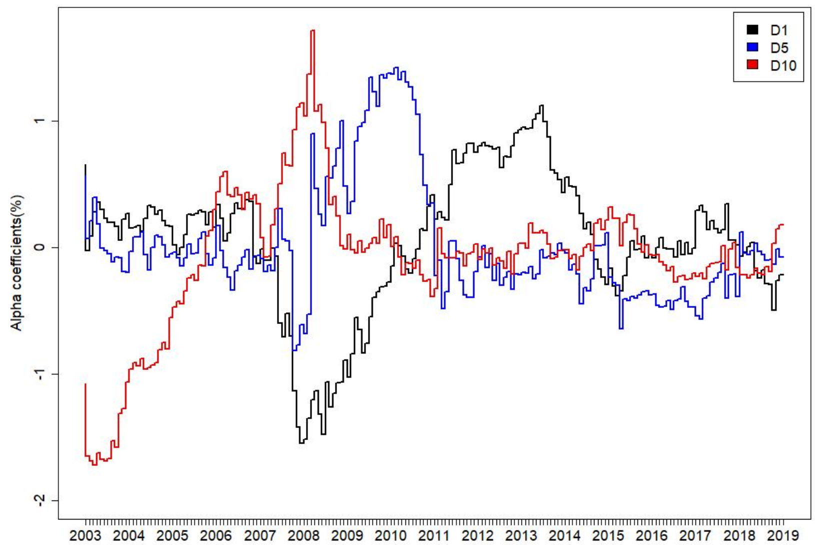

Figure 5: Value-weighted decile portfolios rolling alphas

investment over the past 20 years. Figure 5 shows that extreme strategies D1 et D10 seem to be inverse in terms of rolling alphas. Depending on the period of observation, one strategy is winner and the other loser. We can divide the period into 4 major sub-periods. The first sub-period is 2001-2007. During this period, $D1$ and $D5$ display the same magnitude. Alphas are slightly superior to 0 for $D1$ whereas they are close to 0 or slightly negative for $D5$. $D10$ portfolio displays negative alphas that seem to increase overtime. It seems to be the golden age for $D10$ until the subprime crisis appears. The second period is around subprime crisis until 2011 associated to the European debt crisis. This period is that of passive management. $D5$ dominates the two other strategies. From 2011 until the end of 2014, the third sub-period is propice to $D1$ strategy. Over the last sub-period, from 2014 to 2019, we observe a convergence of all strategies. All alphas are narrowly closed to 0 and the gap between investment strategies is reduced considerably. We can associate this sub-period to the maturity of the listed real estate market. Moreover, it corresponds to the implementation of the Alternative Investment Fund Management Directive (AIFMD) in Europe. This regulation targets, among others, real estate funds and aims to improve information disclosure and fund governance. Even though this finding indicates that the listed real estate market tend to efficiency, it implies that there is lesser information content that we can extract from DFB strategies. Furthermore, the NAREIT composition became public starting from this last sub-period which leads also to enhanced transparency. Also, the ongoing democratization of this market and the bigger competition within it could be an additional argument for the scarcer of arbitrage opportunities that finally lead to an enhanced efficiency within this market segment.

4 Conclusion

The recent development of listed real estate funds gives us the opportunity to explore the trend on which they grow toward efficiency. More specifically, we examine how and at what extent fund managers can built their strategies with regards to market information. Following Cremers and Petajisto (2009)(8) and Jiang et al. (2014)(16) methodology, we extract value of the deviation that LRE funds display from benchmark weighting to estimate their ability to trade and so their activeness. The main question that we addressed is which of the strategies is better: under-weighting, over-weighting or being close to replicating the market. The answer is quite logical : it depends on the market cycle.

Indeed, our results provide some interesting insights. We observe significant predictive power of DFB portfolio returns which means that this tool can be very useful for managers to identify and evaluate the investment value of consensus of active real estate funds. We also observe that the difference between strategies seems to disappear over time. Economically, it suggests that rapid expansion of listed real estate industry is followed directly by the disappearance of arbitrage opportunities. Hence, the puzzle related to efficiency or the debate on the superiority of active vs. passive management remain topical.

Last but not least, European cities will gradually transform into smart cities. Optimization of resources and the compliance with the evolving legislation will be prioritized with particular attention to environmental protection. Besides, a novel macroeconomic context seem to take place with increased interest rates and the comeback of inflation. This context is a strong market driver that influences the performance of listed real estate (LRE) among other assets. It impacts lease contracts, maintenance costs, development expenses and property valuations among others and this translates to impacts on the LRE market and portfolio management decisions. It could be interesting to explore how the ongoing projects, regulation and the new macroeconomic conjuncture would influence the real estate fund market and the activeness within it in future research.

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Appendix

Table 4: correlation of risk-adjusted performance of DFB portfolios

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
D1	1.00	0.14	0.09	0.18	-0.27	-0.01	-0.78	0.27	-0.06	-0.42
D2	0.14	1.00	0.36	0.53	0.34	-0.10	0.09	-0.35	0.07	-0.69
D3	0.09	0.36	1.00	0.46	0.56	0.56	0.28	-0.58	0.03	-0.33
D4	0.18	0.53	0.46	1.00	0.05	0.05	-0.14	0.05	0.13	-0.61
D5	-0.27	0.34	0.56	0.05	1.00	0.51	0.58	-0.83	0.17	-0.01
D6	-0.01	-0.10	0.56	0.05	0.51	1.00	0.19	-0.39	0.39	0.33
D7	-0.78	0.09	0.28	-0.14	0.58	0.19	1.00	-0.58	-0.10	0.22
D8	0.27	-0.35	-0.58	0.05	-0.83	-0.39	-0.58	1.00	-0.10	0.08
D9	-0.06	0.07	0.03	0.13	0.17	0.39	-0.10	-0.10	1.00	0.26
D10	-0.42	-0.69	-0.33	-0.61	-0.01	0.33	0.22	0.08	0.26	1.00