The Alpha and Beta of Equity Hedge UCITS Funds - Implications for momentum investing☆

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ABSTRACT

Equity hedge UCITS funds pursue hedge fund-like active management strategies subject to high liquidity and transparency constraints, ensured by regulatory oversight. Understanding the performance of these alternative UCITS funds is of utmost importance in fund selection and optimizing the portfolio allocation. When the fund-of-fund allocation is momentum-based, we show that there is economic value in using factor models to disentangle the fund-specific residual performance (alpha) from the return component that can be explained by the fund's exposure to common style and asset-based factors (beta). We obtain this result through a detailed analysis of the equity hedge UCITS funds' net returns using both the peer return style factor and asset-based risk factor models over the period 2010-2016. We find that the performance of a systematic monthly rebalanced momentum-based fund-of-fund allocation is improved when ranking funds using the residual performance after correcting for false discoveries, as compared to the traditional use of rolling averages of past returns.

KEYWORDS: Alternative UCITS, Equity Hedge, Factor model, False discoveries, Fund selection, Momentum, Peer Performance, Residual returns

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1 Introduction

Alternative UCITS is a pan-European regulatory framework that allows investment vehicles to be managed and sold throughout Europe. The unified fund structure provides retail investors access to a blend of sophisticated active management strategies subject to high liquidity and transparency constraints, which are ensured by regulatory oversight. The introduction of alternative UCITS funds under the UCITS III Product Directive fits in the so-called "retail alternatives phenomenon". The client base of alternative investments (apart from long-only allocations to equity and bonds) is increasingly composed of retail investors seeking absolute return investments characterized by low volatility, decorrelation with broad market movements [Angana, 2016; SEI, 2013; Wiedemeijer and Keller, 2013] and exposure to alternative risk premia [Hamdan, Pavlowsky, Roncalli, and Zheng, 2016; Roncalli, 2017]. Accordingly, the combined effect of strong efforts in investor-favourable regulation when investing in the hedge fund industry and a thematic shift in the mindset of the investor desiring hedge fund-like returns, led to a substantial increase in terms of the number of alternative UCITS funds, assets under management and market depth. In March 2017, the LuxHedge database reports a UCITS universe of €420 billion Assets under Management (AuM) across 1,380 funds operating under 16 distinct strategies.

Realistic portfolios invested in alternative UCITS funds are composed of a diversified set of at least 20 funds. Consistent with the *adaptive markets hypothesis* of Lo [2004], we expect the set of outperforming funds to be time-varying. In this book chapter, we therefore investigate the use of momentum strategies to detect the funds whose strategies are best adapted to the current market regime. Our approach builds on the hypothesis set in Blitz, Huij, and Martens [2011] that the performance of standard momentum strategies based on rolling averages of past returns can be improved by the use of residual return (alpha). We will use factor models in order to isolate the manager-specific component from common-factor performance using a peer return style factor or a portfolio invested in rule-based strategies capturing the asset-based risk factors. These results are also in line with the presence of a *hot hands* effect in fund performance [Hendricks, Patel, and Zeckhauser, 1993] and the time-variation in the alpha of hedge fund managers [Avramov, Kosowski, Naik, and Teo, 2011; Criton and Scaillet, 2014].

Our research contributes to the recent research agenda of understanding the sources of performance of alternative UCITS funds. At present, academic research is still scarce. Notable exceptions include the recent papers by Tuchschmid, Wallerstein, and Zanolin [2010], Zanolin [2012], Gregoriou, Kaisery, and Pascalau [2013], Tuchschmid and Wallerstein [2013], Dewaele, Markov, Pirotte, and Tuchschmid [2013], Darolles [2014] and Busack, Drobetz, and Tille [2014, 2015]. Understanding the performance of alternative UCITS funds is of utmost importance in fund selection and optimizing the portfolio allocation. Consistent with the mainstream use of factor models to evaluate the performance of mutual funds and hedge funds, we make a distinction between investment style and asset-based return factors. On the part of complementing academic and practitioner literature, we extend the studied time interval and acknowledge the heterogeneity of the UCITS universe by applying factor models to disentangle the fund-specific (instead of strategy-specific) residual performance (alpha) from the joint return that can be explained by common style and asset-based factors (beta). The decomposition of the universe indicates heterogeneity across funds in terms of exposure to the factors and obtained residual performance. We find that only a small subset of funds shows evidence of statistically significant alpha surplus. Finally, we evaluate the informativeness of the residual return component by means of a portfolio sorting strategy. When the fund-of-fund allocation is momentum-based, we show that there is economic value in using factor models. We find that the performance of a systematic monthly rebalanced momentum-based investment scheme is improved when ranking the funds using the fund's residual performance after correcting for false discoveries, as compared to the traditional use of rolling averages of past returns. We obtain this result through a detailed analysis of the equity hedge UCITS funds' net returns using both the peer return style factor and asset-based risk factor models over the period 2010-2016.

The rest of this chapter is organized as follows. Section 2 provides a review of the alternative UCITS market and the basic constructs used in a factor modelling approach. Section 3 describes the methodology and the data used in our empirical analysis. In particular, we describe the subuniverse of equity hedge UCITS funds and discuss factor selection. Section 4 describes our findings on disentangling the fund-specific residual performance from common style and asset-based factors. Section 5 then tests the out-of-sample performance of momentum-based fund-of-fund allocation based on residual returns. Finally, Section 6 concludes.

2 Literature review

Alternative UCITS funds occupy a place in the investment space in between mutual funds and hedge funds. In this literature review, we first present a detailed definition of these investment vehicles. We then revisit important themes examined in prior research, such as risk-adjusted performance evaluation and biases that may arise when analyzing data sets of historical UCITS funds' net returns.

2.1 UCITS fund structure

The European UCITS or "Undertakings for Collective Investment in Transferable Securities" is a pan-European regulation with the objective to harmonize a regulatory regime across the European market, establish a minimum level of investor protection requirements and facilitate cross-border marketing. The regulation encompasses the management and sale of retail investment funds that offer the unique return characteristics of hedge funds in an on-shore regulated vehicle with high liquidity and transparency. The format provides retail investors with access to a diverse range of underlying hedge fund strategies, such as long/short or momentum trading through managed futures [Busack et al., 2014; SEI, 2013; Tuchschmid et al., 2010].

UCITS was introduced in 1985 (85/611/EEC) to facilitate cross-border marketing and harmonize investor protection through product regulation (viz. transparancy, investment guidelines and liquidity). The original UCITS directive only allowed for *transferable securities* (i.e. publicly traded equities or bonds listed on traditional stock exchanges). As a result from an industry call, the joint efforts in the UCITS III Directive (adopted in 2001), the commission recommendation in 2004 (2004/383/EC) and the Eligible Assets Guidelines in 2007 (CESR 07-044), allowed for a greater latitude in the investment spectrum and for sophisticated active management strategies to be packaged as UCITS [Arendt & Medernach, 2013; Busack et al., 2014]. Drafted in two parts, the Product Directive (2001/108/EC) – in combination with the Eligible Assets Guidelines – broadened the type and range of investments that UCITS can hold (financial derivatives for investment purposes, money instruments, cash deposits, etc.). One of the key characteristics of the directive permitted for a number of hedge fund strategies to be accommodated within the UCITS format. The *Management Directive* (2001/107/EC) provides funds with a European passport which enables them to operate throughout Europe once the investment fund is authorized in one member state.[1]

In general, UCITS-compliant funds can offer non-linear, hedge fund-like strategies in an regulated envelope, which is generally defined as an alternative UCITS fund. The fund structure is more constrained than a traditional hedge fund and simultaneously offers more flexibility than long-only vehicles. The main difference with traditional hedge funds is that they are subject to a number of strict guidelines related to risk management (e.g. investment restrictions, concentration limits and portfolio liquidity) and regulatory oversight. For example, UCITS-compliant funds are legally required to limit their leverage, they are prohibited from making large undiversified bets, they should focus on eligible instruments and investors can withdraw their money on – at least – a biweekly basis. Aside from being a stand-alone product, the structure also allows access to multiple underlying managers using an umbrella or a fund-of-fund structure. The popularity of the self-imposed constraints under the UCITS-framework is closely related to its perceived asset safety and transparency [Wiedemeijer and Keller, 2013].

2.2 Prior research on alternative UCITS

A key research question in previous studies is focused on the cost of regulation. Or in other words, does UCITS-compliance lead to differences in risk-return characteristics between alternative UCITS funds and their off-shore unrestricted counterparts? Intuitively we could expect that the impact of regulation limits the flexibility of the manager. However recent empirical work on the performance of the alternative UCITS fund manager provides mixed results.

In terms of risk-adjusted performance, Tuchschmid et al. [2010]; Tuchschmid and Wallerstein [2013] posit that UCITS funds should be less likely to show extreme returns under the common legal and regulatory framework. Tuchschmid et al. [2010] look into cross-sectional differences between alternative UCITS indices and traditional hedge funds. Although they do not find conclusive evidence that orthodox hedge funds outperform alternative UCITS funds on a risk-adjusted basis, they do observe differences in risk, with UCITS funds showing a lower volatility. The authors attribute this to limitations on risk and leverage, higher liquidity and a lower attrition rate under the UCITS format. Busack et al. [2014] compare equally-weighted UCITS indices to matched hedge fund indices and asset-based factor models. They conclude that alternative UCITS are not perfect substitutes for hedge funds and show different risk profiles based on different loadings on systematic risk factors, a lower standard deviation and smaller tail risk. Additionally, Tuchschmid and Wallerstein [2013] do not find statistically significant differences in mean performance compared to unrestricted funds. Yet, they do find that alternative

[1]For a more complete description on eligible assets, we refer to the council directives 85/61/EEC, 2001/108/EC, 2009/65/EC and 2012/832/ESMA and Chapter II: *The UCITS Framework* in Busack et al. [2014]. For a comprehensive discussion on risk management, leverage, concentration, counterparty and liquidity risk of alternative UCITS funds, we refer to Tuchschmid et al. [2010].

UCITS funds have a lower exposure to illiquid assets than hedge funds. The dispersion of returns is investigated in Tuchschmid et al. [2010], who suggest that performance in hedge funds is scattered over a more extensive range than in alternative UCITS. It is important to note that the authors inferred their conclusions on UCITS performance for the period between 2006 and 2010, when the investment vehicles were small in number.

2.3 Data biases of alternative UCITS

Our investigation of the performance of equity hedge alternative UCITS funds is empirical. An important caveat is that the data analyzed may be affected by a number of irregularities and biases, that are often mentioned in the case of hedge fund data [Fung and Hsieh, 1997, 2001, 2004; Jagannathan, Malakhov, and Novikov, 2010]. We summarize the most prominent database biases and discuss how they may also affect the reliability of alternative UCITS data.

First, a common cited problem when dealing with fund data is the end-of-life reporting bias, which occurs when a loss-making fund stops reporting its performance to database providers. This is similar to the self-selection bias inherent in hedge funds, where unregulated managers only have an incentive to report if the fund has done well. In the case of UCITS funds this should be of little effect since UCITS requires reporting on a consistent basis.

Second, backfill bias or instant-history bias arises when a UCITS manager, entering a database, retrospectively backfills the fund's acquired performance track record. An inclusion of (non-representative) data prior to UCITS-conformance can distort overall performance with favourable returns [Busack et al., 2014] or overestimation of managerial alpha in early years of the sample [Jagannathan et al., 2010]. Still, the regulator allows past performance disclosure if there is no considerable difference [Busack et al., 2014]. It should also be taken into account that the associated history of UCITS is relatively short, as most UCITS funds were launched in the wake of the late-2000s crisis. Hence, an elimination of prior non-UCITS history would lead to a loss of (already scarce) data points and thus low power in testing [Busack et al., 2014; Fung and Hsieh, 2009].

Finally, survivorship bias implies that a database only reflects the returns generated by surviving funds, since poor performance (originating from dead funds) will be excluded from the study. Within hedge funds this seems to be a major issue. The market segment is characterized by high attrition rates as unsuccessful funds quickly liquidate [Busack et al., 2014]. Per contra, in alternative UCITS research some authors assume non-existence following the notion that funds are obliged to report their performance [Dewaele et al., 2013; Tuchschmid et al., 2010; Tuchschmid and Wallerstein, 2013] or provide an additional estimate of the magnitude of survivorship bias to account for potential malpractices [Busack et al., 2014].[2] In this chapter, we address the potential presence of a survivorship bias by collecting data for both extinct and alive funds in our sample of UCITS funds.

[2] Busack et al. [2014] measure the difference in performance between two buy-and-hold portfolios, one which invests solely in the surviving funds and one which allocates funds equally to the union of dead and surviving funds. The difference between the two portfolio is interpreted as the overestimated return resulting from a survivorship bias.

2.4 Review of the factor model approach to study fund performance

A central problem in fund selection is the evaluation of the risk-adjusted performance of a fund. The most common approach consists of estimating the risk-adjusted performance of a fund by calculating the intercept of a least squares regression of the fund returns on a series of risk factors, such as the equity risk factors in Carhart [1997] or the hedge fund risk factors put forward by Fung and Hsieh [2001, 2004].[3]

More precisely, let $\mathbf{f}_t$ be the $(K \times 1)$ vector of factors at time t and denote by $r_{i,t}$ the fund's i excess return at time t. The factor model approach then estimates the following regression:

$$r_{i,t} = \alpha_i + \boldsymbol{\beta}_i' \mathbf{f}_t + \varepsilon_{i,t} \,, \tag{2.1}$$

where the intercept α_i is usually interpreted as a measure of talent, $\boldsymbol{\beta}_i$ is the $(K \times 1)$ vector of factor exposures and $\varepsilon_{i,t}$ is the corresponding error term, for $t = 1, \ldots, T$. The alpha and beta parameters in (2.1) are typically estimated using ordinary least squares. When the estimated alpha is significantly different from zero, the fund is classified as talented. This test is usually implemented using the heteroscedasticity and autocorrelation robust (HAC) standard error estimators of Andrews [1991] and Andrews and Monahan [1992]. We refer the reader to Subsection 3.2 for the exact factor specification.

3 Data and methodology

We analyze the performance of the equity hedge UCITS funds over the period January 2010 to September 2016. This section describes the composition of the universe and zooms in on the factor models under consideration.

3.1 Data

For the composition of the alternative UCITS universe we use the LuxHedge database, which provides us with a unique list of 1,434 funds.[4] The net asset values (NAV) and Assets under Management (AuM) were collected from Bloomberg.

In order to obtain a universe which is representative for the investable equity hedge UCITS universe, we applied a set of screening criteria. First, it is common that funds launch different share classes addressed to different classes of investors [Busack et al., 2014; Cogneau, Debatty, and Hübner, 2013]. We only keep one share class per fund. Second, non-Euro denominated share classes are converted into the same base currency using the end-of-month exchange rate to analyze the universe from the viewpoint of a European investor [Busack et al., 2014, 2015;

[3] For presentation purposes, we focus on the fund's alpha as the risk-adjusted performance measure. However, it is straightforward to apply the regression in a peer performance evaluation framework with other risk-adjusted performance measures, such as the fund's (modified) Sharpe ratio, by using the equal-performance test of Ledoit and Wolf [2008] and Ardia and Boudt [2017].

[4] The LuxHedge alternative UCITS database is one of the largest sources available on alternative UCITS funds. The Luxembourg-based data provider was established in 2012 and collects data on funds with inception dates going back to 1998. They collect qualitative data for alternative UCITS funds such as fund names, ISINs, share class, reported strategies, etc. We refer the interested reader do http://www.luxhedge.com for more details.

Tuchschmid et al., 2010]. Third, studies on hedge fund performance require at least 24 months of data [Ackermann, McEnally, and Ravenscraft, 1999; Fung and Hsieh, 2000]. Given that alternative UCITS-compliant funds are a relatively young market segment, the elimination of return histories is a costly loss of observations [Busack et al., 2014] and can introduce other biases [Fung and Hsieh, 2009]. We follow Busack et al. [2014, 2015] and require a shorter minimum return history of 12 months of compliance under the UCITS-format. For the ex-post performance evaluation of funds, we only retain those funds that have at least a track record of 5 years. As mentioned before, the exclusion of dead funds can lead to an overestimation of average performance [Jagannathan et al., 2010]. We use the union of active and inactive funds to mitigate any survivorship biasing influences in our sample. Finally, we exclude duplicates, funds lacking consecutive returns and consider only funds with an inception data before January 2014. The resultant sample is composed of 618 funds with daily returns spread over 16 different strategies. For the ex-post and ex-ante performance evaluation using factor analysis, we consider discrete end-of-month total returns on the funds' net asset values. Our sample period spans from January 2010 to September 2016, which coincides with the European sovereign debt crisis and shows partial overlap with previous studies on alternative UCITS performance [Busack et al., 2014, 2015; Dewaele et al., 2013; Tuchschmid et al., 2010; Tuchschmid and Wallerstein, 2013].

Table 1 reports the number of funds in the total universe per style and per strategy available in the LuxHedge database. We also report the growth of the universe of the studied time period. In growth rates not reported in this study, we examine that the Assets under Management showed consistent growth, while the increase in the number of funds stalled in the later years of the sample (Panel C).

Recall that in our study, we focus on equity hedge-inspired strategies. These strategies invest in liquid instruments with (in most cases) a daily pricing. They can invest in any sector, market capitalization, region or country. As a result, it is relatively practicable to accommodate them in a UCITS-format [Angana, 2016]. We focus on a Long/Short UCITS aggregate index (viz. Equity Hedge), Long/Short Global, Long/Short Europe, Long/Short U.S. and Long/Short Emerging Markets. We also identify an Equity Market Neutral strategy. The main difference between a long/short and a market neutral strategy is that the first does not seek a neutral position in terms of market risk (beta neutral) and generally has a long bias. Consistent with previous studies we construct equally-weighted portfolios to represent the respective styles and strategies. We assume that investors allocate funds equally to all surviving funds in a buy-and-hold portfolio for the total sample period. As a reference group we select the Hedge Fund Research (HFR) UCITS indices, which represents the overall composition of the UCITS-compliant universe.[5]

We proceed by examining cross-sectional performance differences. The risk-return scatter plot presented in Figure 1 suggests a degree of heterogeneity in terms of risk and return when we consider the equity hedge style funds represented by their equally-weighted portfolios. This becomes more clear if we look at Table 2, which presents summary statistics for the location, scale and shape of the equally-weighted strategies and the the matched HFRU strategies over the total sample period (2010-2016). For the equity hedge strategies, the annualized returns range

[5]The Hedge Fund Research indices are comprehensive performance benchmarks for the total UCITS universe and include a composite index and four strategies, i.e. Equity Hedge, Event Driven, Macro and Relative Value arbitrage. The indices are rebalanced on a quarterly basis (http://www.hedgefundresearch.com).

Table 1: **LuxHedge alternative UCITS subuniverse (October 2016)**

***Panel A* – Composition of alternative UCITS universe**

Style	# Funds	% Universe
All	618	-
Equity Hedge	178	28.8
Relative Value	149	24.1
Multi-Asset	147	23.8
Macro	124	20.1
Event Driven	20	3.2

***Panel B* – Style breakdown**

Strategy	# funds	% universe
Fixed Income Arbitrage	134	21.7
Global Macro	79	12.8
Multi-Strategy	64	10.4
Fund of Funds	59	9.5
Equity Market Neutral	59	9.5
Long/Short Europe	58	9.4
Long/Short Global	36	5.8
CTA/Managed Futures	34	5.5
Volatility Arbitrage	16	2.6
Convertibles Arbitrage	15	2.4
Long/Short Em. Markets	14	2.3
Merger Arbitrage	13	2.1
Long/Short US	11	1.8
Currency Arbitrage	11	1.8
Commodity Arbitrage	8	1.3
Event Driven	7	1.1

***Panel C* – Growth of alternative UCITS universe**

Month – Year	# funds	% Growth
January 2010	260	-
January 2011	337	29.6
January 2012	435	29.1
January 2013	516	18.6
January 2014	598	15.9
January 2015	616	3.0
January 2016	616	0.0

Notes: Table 1 gives an overview of our constrained set of alternative UCITS funds. Panel A presents the breakdown per Style, in which Multi-Asset represents strategies that did not have a appropriately matched HFRU strategy (i.e. Commodity Arbitrage, Fund of Funds, Volatility Arbitrage and Multi-Strategy). Panel B presents the breakdown per self-reported strategy in descending order. Panel C presents the year-on-year growth of funds for the total sample period. The input data for this table was retrieved in October 2016.

from 2.17 to 4.61 percent. In addition, we observe varying degrees of risk, measured in terms of standard deviation. For example, we find a smaller volatility for Equity Market Neutral (1.97%) as compared to Long/Short Europe (4.93%). Typical stylized facts for the return distribution of a hedge fund are asymmetry and heavy tails. Differently, for alternative UCITS we observe that the average fund has a negative skewness and a leptokurtic distribution. We refer to Scott and Horvath [1980], who discuss the positive preference for odd moments (mean, skewness) and aversion to even moments (variance, kurtosis). In most cases we reject the null hypothesis of normality based on significant p-values for the Jarque-Bera test.

3.2 Factor model specification

In the sequel, we adjust returns for their factor exposure. Following the terminology of Fung and Hsieh [1997], our work is based on the notion that a manager's return can be characterized by three determinants, i.e. returns from assets in the portfolio, trading strategies and the use of leverage. Accordingly, a style-factor model is focused on a so-called location component (asset categories a manager invests in) and the asset-based risk factor approach refers to the strategy component (exposure to an asset class, direction and leverage).

The standard approach to model fund risk is to use broad-based indices as factors [Fung and Hsieh, 2004]. First, we identify the style benchmark market factors and look at excess return

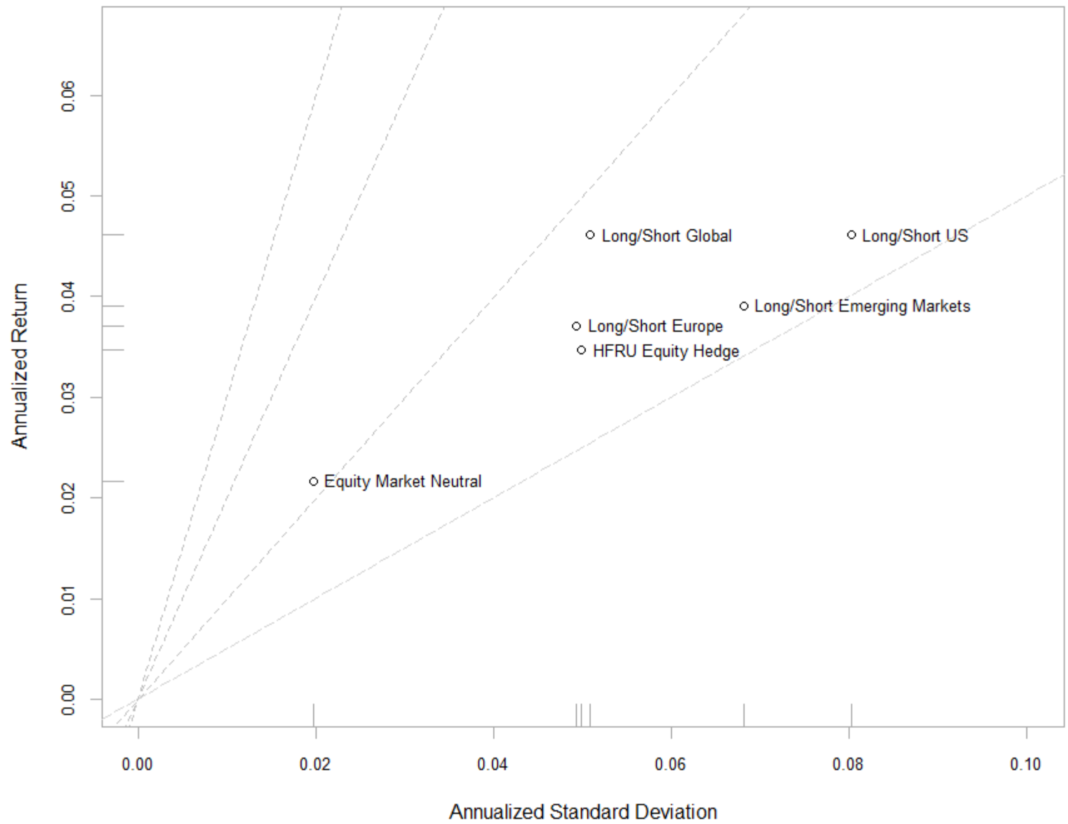

Figure 1: Annualized Return and Standard Deviation for Equity Hedge UCITS (2010 – 2016)
Notes: Figure 1 presents a risk-return scatterplot of the equally-weighted long/short strategies versus their style benchmark (i.e. HFRU Equity Hedge). The slope of the diagonal lines represent the Sharpe ratio for increasing values (i.e. 0.5, 1, 2 and 3).

versus self-reported benchmarks. Next, we apply two baseline asset pricing models to separate the managerial alpha from identifiable risk factors: the common equity risk factors as proposed by Fama and French [1993], Carhart [1997] and the dynamic risk factors of Fung and Hsieh [2004]. The alpha describes the average performance of the fund above the return explained by the exposure to the systematic factors. All factors that we use in this chapter can be interpreted as the returns on passive, zero-investment factor-mimicking portfolios [Bauer, Koedijk, and Otten, 2005].

We evaluate the factor models at the level of synthetic indices, which pool all funds belonging to the same category, but also at the individual fund level. The relative performance of the former is affected by the variety in universe composition, since, as can be seen in Table 1, the number of constituents is not equal over different strategies, which can lead to extreme values and increased volatility measures [Zanolin, 2012]. In their analysis, Busack et al. [2014] report poor risk-

Table 2: **LuxHedge UCITS subuniverse: Descriptive performance statistics**

	(1) Ann. Return	(2) Ann. StDev	(3) Skewness	(4) Excess kurtosis	(5) Sharpe ratio	(6) Maximum drawdown	(7) JB p-value
***Panel A* – Alternative UCITS universe**							
Alternative UCITS	2.649	3.034	−0.423	1.025	0.873	5.001	0.053
Equity Hedge	3.345	3.650	−0.725	1.121	0.917	6.384	0.004
***Panel B* – Non-investable HFRU alternative UCITS indices**							
HFRU Composite	2.309	3.474	−0.771	0.891	0.671	6.226	0.005
HFRU Equity Hedge	3.474	4.993	−0.805	0.941	0.676	8.134	0.003
***Panel C* – Alternative UCITS equity hedge strategies**							
Equity Market Neutral	2.168	1.970	−0.516	1.259	1.100	2.675	0.014
Long/Short Global	4.615	5.092	−0.678	1.248	0.906	8.099	0.004
Long/Short Europe	3.707	4.928	−0.661	0.850	0.752	8.627	0.020
Long/Short US	4.607	8.021	−0.288	−0.380	0.574	15.353	0.471
Long/Short EM	3.908	6.812	−0.803	2.409	0.574	13.692	0.000

Notes: Table 2 presents the summary statistics over the total time interval (2010-2016) for our sample universe. For comparison, we also include the HFRU Composite index as representative of the total UCITS universe. We report the annualized return (%), the standard deviation (%), sample skewness, sample excess kurtosis, Sharpe ratio, maximum drawdown (%) and the Jarque-Bera p-value. Panel A presents the results for two synthetic equally-weighted Composite and equity hedge portfolio. Panel B presents the results for the matched HFRU indices. Panel C presents the results for the equity hedge substrategies available in the LuxHedge database.

adjusted performance in the form of alphas indistinguishable from zero (either statistically or economically) for the synthetic buy-and-hold portfolios. It is important to note that conclusions using the aggregate view cannot be generalized across the total population of managers, since the average of all fund returns is essentially the same as the benchmark [Angana, 2016]. Within alternative UCITS, Wiedemeijer and Keller [2013] note that the quality of the operational set-up (for UCITS-compliance) and talent of managers may vary. Hence, fund selection within a heterogeneous universe is important. The focal point in this book chapter is to consider the risk-adjusted performance on a per-fund basis.

3.2.1 Peer return style-based factor model

Jagannathan et al. [2010] define a fund's relative alpha as the intercept in the regression of fund returns on the investment style returns to account for the common factors that affect all managers in the peer category. However, for the estimation of the peer alpha, we do not follow the methodology of these authors, who estimate the intercept with an aggregate U.S. market factor, the self-reported style factor and an auxiliary factor based on statistical model selection. Instead, we will focus on the self-reported style index as an explanatory variable. In measuring the relative fund performance versus the self-reported style, we use Equation 3.1:

$$r_{i,t} = \alpha_i + \boldsymbol{\beta}_i r_{s,t} + \varepsilon_{i,t} \, , \tag{3.1}$$

where $r_{i,t}$ denotes the return in excess of the risk-free rate and $r_{s,t}$ is the self-reported style factor return.

In order to set up our style-factor model, we define our regressand as the equally-weighted average return for all alternative UCITS funds within the same strategy. We choose the HFR indices for the representation of the alternative UCITS peer category. Brown and Goetzmann [2003] note that the associated fund style is a strong determinant of the cross-sectional distribution in fund performance. This is also consistent with the observation in Hunter, Kandel, Kandel, and Wermers [2014], who show that controlling for funds that operate under similar strategies tends to improve fund selection. Therefore, we consider these style indices as good proxies for non-linear strategies of funds. We will first match the UCITS funds with their respective style axes to represent the market premium factor and the peer alpha. We acknowledge the matching will be imprecise in some cases, since funds self-report their strategies. Next to assessing overall management skills, we want determine whether there are stylistic differences. Or in other words: are the styles funds report consistent with their return data? In that connection it is important to look at the goodness of fit (R^2). We refer to the substitution effect reported in Busack et al. [2014], mutual fund selectivity in Amihud and Goyenko [2013] and managerial talent in Titman and Tiu [2011]. Suppose that the R^2 value is close to 1. In this case, the fund does not deliver any additional return and is fully exposed to the risk drivers of its representative benchmark.

3.2.2 Asset return-based multi-factor model

A second approach consists of regressing the alternative UCITS fund returns onto a common risk factor space. The concept of factor investing is generally associated to long-only exposures to traditional equity risk factors, such as the value equity strategy [Hamdan et al., 2016]. When we use equity risk factors of the Carhart [1997] model, we obtain the following linear factor model:

$$r_{i,t} = \alpha_i + \boldsymbol{\beta}_i^{mkt} r_{mkt,t} + \boldsymbol{\beta}_i^{smb} r_{smb,t} + \boldsymbol{\beta}_i^{hml} r_{hml,t} + \boldsymbol{\beta}_i^{wml} r_{wml,t} + \varepsilon_{i,t} \, , \tag{3.2}$$

where $r_{i,t}$ denotes the return in excess of the risk-free rate, $r_{mkt,t}$ is the market return in excess of the risk-free rate, $r_{smb,t}$ is the return on small stocks minus return on large stocks, $r_{hml,t}$ is the return on high book-to-market values stocks minus return low book-to-market values, $r_{wml,t}$ is the return on winner stocks minus losers stocks over the last year. The data is provided on the Data Library of Kenneth French.[6] The risk-free rate is the local one-month interbank offered rate.

Alternative risk premia are investments apart from long-only allocations to equity and bonds. These non-traditional risk premia correspond to non-linear, long-short portfolios in equities, cur-

[6] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

rencies, commodities or credit [Hamdan et al., 2016]. An alternative approach is to include non-linear exposures in the set of risk factors with the objective to enhance the risk-return analysis of funds and increase our understanding of the strategies implemented by these fund managers (viz. location, strategy and leverage).[7] One could use the three option profiles put forward in Fung and Hsieh [2001] as regressors in the risk factor space to proxy the returns of dynamic trading strategies. In a follow-up study, Fung and Hsieh [2004] proposed a seven-factor model, which includes two equity factors, two bond factors and three non-linear, trend-following strategies. These factors are generally accepted as the systematic sources of alternative risk premia for a balanced hedge fund:

$$
\begin{aligned}
r_{i,t} = \alpha_i &+ \boldsymbol{\beta}_{i,1} r_{mkt,t} + \boldsymbol{\beta}_{i,2} r_{smb,t} + \boldsymbol{\beta}_{i,3} r_{ge10y,t} + \boldsymbol{\beta}_{i,4} r_{spread,t} \\
&+ \boldsymbol{\beta}_{i,5} r_{ptfsbd,t} + \boldsymbol{\beta}_{i,6} r_{ptfsfx,t} + \boldsymbol{\beta}_{i,7} r_{ptfscom,t} + \varepsilon_{i,t}.
\end{aligned}
\tag{3.3}
$$

Specifically for equity-oriented factors, we note that alternative UCITS funds invest in a regulated and a sufficiently liquid asset universe. Busack et al. [2014] use the Fama and French [2012] global market (mkt) and global size (smb) factors instead of the excess returns of the S&P 500 (U.S. aggregated market factor) and the difference between the Russel 2000 index and the S&P 500 index (size spread). The latter factors are commonly used in other papers as a reference to the original form of the seven-factor model. Following Busack et al. [2014], we will use the international proxies for the respective factors and add back the one-month U.S. Treasury bill to adjust the excess returns. In order to capture a risk factor that is directed to fixed income instruments, we use the change in the iBoxx Germany 7-10 Government bonds ($ge10y$). For the credit risk factor in bond markets, we calculate the change in European credit spreads ($spread$), which is the difference between the yield of liquid investment grade bonds (i.e. iBoxx Euro Corporate Bond Euro AA 7-10 Year Index) and German government bond index. Regarding non-linear strategies, there is strong empirical evidence on the time-variation in hedge fund returns. These funds change their investment bets conditional on changing market conditions and risk exposures [Fung and Hsieh, 2004; Patton and Ramadorai, 2013]. In order to capture the non-linear pay-off structure of equity-hedge strategies, we draw insights from trend-following strategies. Fung and Hsieh [2001, 2004] posit that momentum strategies behave like a long position in a lookback straddle and propose the Primitive Trend-Following Strategy (PTFS) on various asset classes to capture the essential features in trend-following funds' trading strategies, such as strong positive skewness and positive returns during market downturns.[8] The authors propose three drivers to proxy alternative risk premia: the $ptfsbd$ is the excess return on a bond lookback straddle, $ptfsfx$ is the excess return on a currency lookback straddle and $ptfscom$ is the excess return on a commodity lookback straddle. The data can be retrieved from the Data Library of David Hsieh.[9] Finally $\epsilon_{i,t}$ is a mean zero error term. Contrary to Busack et al. [2015], the relevant factors in the model are converted to the same base currency using end-of-month exchange rates in EUR.

[7] For a comprehensive elaboration on the mechanisms of alternative risk premia and market anomalies, we refer to Hamdan et al. [2016]; Roncalli [2017].

[8] Trend followers face frequent small losses and large gains. For a further discussion, we refer to Hamdan et al. [2016].

[9] https://faculty.fuqua.duke.edu/~dah7/HFData.htm

4 The cross-section of factor exposures and residual performance

Before we can start selecting funds, we need to isolate the manager-specific component from common-factor performance using a peer return style factor or a portfolio invested in rule-based strategies capturing the asset-based risk factors. We study alpha characteristics – ex-post – for the collective equity hedge subuniverse for the period 2010-2016.

4.1 Style-based analysis

We analyze the alternative UCITS fund returns at different levels of granularity, starting with synthetic indices aggregating the returns over pools of funds, and then proceed with individual fund performance.

4.1.1 Collective UCITS performance

Recall that we have constructed equally-weighted portfolios to represent the respective styles and strategies in our UCITS-compliant subuniverse (cf. Subsection 3.1). We will use these synthetic indices as a proxy for the performance of the average UCITS-compliant fund. In what follows, we will focus on equity hedge UCITS strategies and regress synthetic buy-and-hold portfolios on a non-investable HFRU style benchmark. For comparison, we also include a buy-and-hold portfolio for all alternative UCITS funds in our subuniverse (All UCITS) and perform a regression on the HFRU Composite index. We report our regression results in Table 3.

The α_i in column (1) is the mean residual return of the screened subuniverse over the HFRU style benchmark. Since we are mainly concerned with the accurate estimation of the intercepts, we should also estimate the associated HAC standard errors [Newey and West, 1987]. The evidence in Panel A indicates that the alternative UCITS screened subsample was able to generate a positive (economically and statistically) significant monthly alpha equal to 0.066 percent. While the overall equity hedge style (i.e. over all strategies and all funds) was *on average* not able to provide additional performance on top of the broad-based style portfolio. Panel B shows us the results of the regression of two non-overlapping periods, i.e. time-varying alpha. We see that for both the total UCITS universe and the equity hedge style, significance disappears in the second half of our sample. On a strategy level (Panel C), all the strategies - with the exception of Equity Market Neutral - produced alphas that are indistinguishable from zero. Meaning that a different geographic focus was not able to deliver a significant alpha surplus. While an equity market neutral strategy (a strategy that seeks a neutral position in the market) is able to deliver additional performance as compared to its overall peer category.

The coefficient of determination R^2 in column (5) indicates for the equity hedge style that the style index tends to fit our subsample data closely and makes up a considerable portion of our returns (70.4%). On a strategy level, the Long/Short Europe and Long/Short Global strategies seem to move closely with the equity hedge peer category, showing a significantly positive β_i-coefficient (column 3) and high R^2. However, the difference in R^2 also shows us that there are stylistic differences between managers versus a peer benchmark. In other words, the equity hedge style benchmark is not able to capture all the nuances of the strategies. However, it is important to note that a low value for R^2 in the case of the Long/Short U.S. and Long/Short

Table 3: **Regression results style-based factor model: Synthetic portfolios (2010-2016)**

		(1) $\alpha_i(\%)$	(2) $t(\alpha_i)$	(3) β_i	(4) $t(\beta_i)$	(5) R^2
Panel A **– UCITS Composite and Equity Hedge versus non-investable style indices**						
All UCITS		0.066*	[1.740]	0.800***	[17.180]	0.821
Equity Hedge		0.099	[1.480]	0.613***	[10.490]	0.704
Panel B **– UCITS Composite and Equity Hedge: Two-period analysis**						
All UCITS	2010 − 2013	0.123**	[2.630]	0.743***	[13.450]	0.814
	2013 − 2016	0.012	0.190	0.834***	13.770	0.832
Equity Hedge	2010 − 2013	0.134*	[1.770]	0.840***	[8.810]	0.725
	2013 − 2016	0.072	[0.730]	0.973***	[10.680]	0.778
Panel C **– Equity Hedge UCITS strategies versus non-investable Equity Hedge style index**						
Equity Market Neutral		0.123**	[2.214]	0.196***	[4.909]	0.247
Long/Short Global		0.134	[0.140]	0.859***	[12.707]	0.709
Long/Short Europe		0.065	[0.486]	0.841***	[12.872]	0.726
Long/Short U.S.		0.248	[0.343]	0.524**	[2.550]	0.106
Long/Short E.M.		0.057	[0.289]	0.955***	[5.337]	0.489

Notes: Table 3 reports the results of the style factor regressions of synthetic equally-weighted alternative UCITS portfolios versus the matched HFRU style indices. We use the HFRU Composite for the synthetic composite index (All UCITS) and the HFRU Equity Hedge for the equity hedge style index and the long/short substrategies. The results in Panel A and C are measured over the entire sample period (January 2010 - September 2016). Panel B reports results for two non-overlapping samples: 1) January 2010-May 2013; 2) June 2013 to September 2016. Column 1 presents the estimated monthly alphas in percentages. Column 2 contains the t-statistics of two-sided tests of alpha, where the null hypothesis is that the alpha is zero. Column 3 presents the estimated betas against the respective HFRU style indices. Column 4 containts the t-statistics of the test that beta is zero. Column 5 shows the coefficient of determination (R^2). *, ** and *** denote statistical significance at the 10%, 5% and 1% level using heteroscedasticity- and autocorrelation consistent Standard Errors following Newey and West [1987].

Emerging Markets strategy is most likely due to a limited number of funds operating under the respective strategies (see Table 1). On average, the equity hedge style has a diminished beta, as indicated by an estimated β_i-coefficient of 0.613. The same observation holds for the other strategies.

4.1.2 Individual UCITS funds

In the previous section, we inferred that our regression intercepts are (in most cases) indistinguishable from zero for the average equity hedge UCITS fund. Nonetheless, it is possible that good managers cancel out bad managers or that the synthetic portfolios may be subject to measurement errors in the independent variable (synthetic portfolio return), which makes that the (average) alphas reported in our own and previous studies are close to zero. In other words, a portfolio considering all managers may be inefficient as it ignores heterogeneity in the talent of fund managers. Individual managers may show traits that differ from the population. Moreover, descriptive statistics in Table 2 also point to non-normality (Jarque-Bera p-value), negative skewness and positive excess kurtosis in the fund returns, which jointly provide strong motivation for assessing individual fund performance and the role of talent in the industry. Table 4 summarizes the frequencies of significant alphas. We divide the observations into positive and negative significant excess returns at the 5% and 10% level. A positive and significant estimation for alpha signals a fund with superior talent compared to its peer category [Jagannathan et al., 2010].

We observe a small number of funds that are able to generate significant excess returns compared to peers. Out of 101 equity hedge funds, 15 funds are positively significant at the 5% significance level and 20 at the 10% level. The analysis shows that we can select funds that demonstrate superior performance over the total sample period.

Table 4: **Alpha frequencies style-factor model: Equity Hedge funds (2010-2016)**

	(1) N	(2) $\overline{\beta_i}$ $[\overline{SE_\beta}]$	(3) # significant α_i at 5%	(4) # significant α_i at 10%	(5) $\overline{R^2}$
Equity Hedge	101	0.618	15^+	20^+	0.229
		[0.168]	4^-	7^-	
Equity Market Neutral	35	0.214	8^+	8^+	0.093
		[0.132]	2^-	2^-	
Long/Short Global	14	0.998	2^+	3^+	0.328
		[0.229]	1^-	1^-	
Long/Short Europe	39	0.808	3^+	5^+	0.333
		[0.157]	1^-	4^-	
Long/Short U.S.	6	0.488	1^+	3^+	0.120
		[0.231]	0^-	0^-	
Long/Short Em. Markets	7	0.882	1^+	1^+	0.217
		[0.221]	0^-	0^-	

Notes: Table 4 reports the significant alpha frequencies of the single style-factor regressions on individual alternative UCITS funds versus the peer group, i.e. the non-investable HFRU Equity Hedge. The results are measured over the entire sample period (January 2010 - September 2016). Column 1 contains the number of constituents per strategy. Column 2 presents the average of estimated beta versus the HFRU Equity Hedge style index. The second row reports an average of the estimated standard error. Column 3 and 4 present the number of statistically significant alphas at the 5% and 10% level. The first row depicts the number of significantly positive alphas, the second row the significantly negative alphas. Column 5 presents the average R^2 of the style-factor model. The null hypothesis is that the alphas are zero is tested using heteroscedasticity- and autocorrelation consistent Standard Errors following Newey and West [1987]. We retained funds that had at least a track record of 5 years.

4.2 Risk factor analysis

In order to obtain more information on the relation between alternative UCITS and the equity market, we perform a risk-based analysis using equity risk factors. Compared to the previous section, we consider an asset-based factor model instead of a return-based approach. Table 5 presents the risk-adjusted returns of synthetic UCITS portfolios using the Carhart [1997] four-factor model that considers to equity-market factors (viz. market, size, value and momentum).

4.2.1 Collective UCITS performance

The results in Table 5, show no evidence to reject the null hypothesis of an alpha indistinguishable from zero (column 1). In terms of $adj.R$ (column 6), we observe that the factors explain a high portion of the average returns of synthetic indices. To the extent that there are common factors that affect all managers in the UCITS universe, we find strong significance for the equity market factor (mkt) and the equity size factor (smb) in the total UCITS universe and the equity hedge funds. Moreover, all equity hedge substrategies load significantly on the equity market factor (mkt) and in most cases on the equity size factor (smb). The Long/Short US strategy also shows exposure to the value (hml) and momentum factor (wml).

Table 5: **Regression results Carhart four-factor model: Synthetic portfolios (2010-2016)**

	(1) $\alpha_i(\%)$	(2) β_{mkt}	(3) β_{smb}	(4) β_{hml}	(5) β_{wml}	(6) $adj.R^2$
***Panel A* – UCITS styles**						
All UCITS	-0.051	0.242***	0.056**	0.006	-0.006	0.789
	[1.216]	[16.421]	[2.099]	[0.32]	[0.355]	
Equity Hedge	-0.045	0.288***	0.091***	-0.023	-0.010	0.763
	[0.794]	[15.085]	[2.77]	[0.78]	[0.447]	
***Panel B* – Equity Hedge UCITS strategies**						
Equity Market Neutral	0.047	0.098***	0.107***	-0.023	-0.006	0.518
	[1.092]	[7.513]	[3.929]	[1.11]	[0.283]	
Long/Short Global	-0.109	0.420***	0.064	-0.050	0.031	0.811
	[1.411]	[15.763]	[1.318]	[1.161]	[1.429]	
Long/Short Europe	-0.060	0.377***	0.062	-0.044	-0.042	0.658
	[0.68]	[11.536]	[1.083]	[1.016]	[1.022]	
Long/Short U.S.	-0.175	0.338***	0.287***	0.196***	0.081**	0.800
	[1.323]	[8.162]	[3.772]	[3.748]	[2.095]	
Long/Short Em. Markets	-0.090	0.396***	0.205***	-0.034	-0.059	0.416
	[0.375]	[5.696]	[2.75]	[0.435]	[0.852]	

Notes: Table 5 reports the results of the regressions of synthetic equally-weighted alternative UCITS portfolios versus the Global Carhart factor model which includes: market, size, value and momentum. The results in Panel A and B are measured over the entire sample period (January 2010 - September 2016). Column 1 presents the estimated monthly alphas in percentages. Column 2 presents the estimated betas versus the equity market factor [Fama and French, 2012]. Column 3 presents the estimated betas versus the equity size factor [Fama and French, 2012]. Column 4 presents the estimated betas versus the equity value factor [Fama and French, 2012]. Column 5 presents the estimated betas versus the equity momentum factor [Carhart, 1997]. Column 6 shows and adjusted coefficients of determination (R^2). We present the t-statistics of the two-sided tests, in which the null hypothesis is that the coefficients are zero, in the second row of each regression. *, ** and *** denote statistical significance at the 10%, 5% and 1% level using heteroscedasticity- and autocorrelation consistent Standard Errors following Newey and West [1987].

In another way, we can look at the relation of synthetic UCITS portfolios and the Fung and Hsieh [2004] factor model. We control for the relation to the global equity market (mkt), the global size factor (smb), the European bond market, the European credit spread and three trend-following, alternative risk premia represented by lookback straddles on bonds ($ptfsbd$), foreign exchange ($ptfsfx$) and commodities ($ptfscom$). The statistical results of the excess returns over the full sample period can be found in Table 7.

For the overall UCITS market, the most informative variables are the global equity market risk (mkt), global size (smb), the European bond factor ($ge10y$) and the European credit spread ($spread$), which validates our choice of focusing on global market factors instead of the traditional U.S.-based factors. The significant loading on the European bond market may be due to the home bias discussed in Bauer et al. [2005]. It may be the case that UCITS-compliant funds – as a European format – overweight their positions in Europe. We do not find any evidence of significant factor loadings on the non-linear factors across strategies. This observation is consistent with previous findings in Agarwal, Boyson, and Naik [2009]; Busack et al. [2014]; Tuchschmid and Wallerstein [2013], who note that alternatives are less exposed to classical alternative risk premia targeted by hedge funds. We also confirm previous observations of an alpha that is indistinguishable from zero, with the exception of the overall UCITS index.

When comparing Table 5 and 7, we notice that the Fung and Hsieh factors explains a higher portion of the variance in returns ($adj.R^2$) and possibly a better estimation of the intercept compared to the Carhart model. We report an improvement of the in-sample adjusted R^2 from 0.780 in the Carhart model (Table 5, column 6) to 0.827 in the Fung & Hsieh model (Table 7, column 9). Yet, we detect a deterioration for the equity hedge style and individual substrategies , with the exception of Equity Market Neutral. Altogether, the analysis of both models does not present us with a conclusive picture on the incremental improvement of using the Fung & Hsieh alternative risk premia.

4.2.2 Individual funds

In the previous section we applied the Carhart four-factor model on synthetic equally-weighted portfolios. For the average equity hedge UCITS fund, we did not find evidence to reject the null hypothesis of alphas indistinguishable from zero after accounting for the equity risk-factors of the Carhart model. This observation remains consistent across substrategies. Next, we perform the regressions on a per-fund basis and thus investigate potential superior skill of individual funds after adjusting for market-wide equity risk factors. We report regression results in Table 6. We find that only a small number managers produce significant alphas on top of the Carhart [1997] asset-based factors over the total sample period. Within equity hedge, 10 funds out of 101 are able to produce a significantly positive alpha at the 5% level, 14 at the 10% level, which is thus only slightly higher than the expected number of type I errors. The average estimates for β show that the equity hedge and equity market neutral strategy deliver almost beta neutral loadings to the market factor, resp. 0.287 and 0.101.

In the analysis of the Fung and Hsieh [2004] model on synthetic buy-and-hold portfolios, we did not reject the zero-alpha hypothesis. Table 8 presents managerial performance after unbundling the returns using alternative risk factors inherent in hedge funds. We find evidence of statistical significant alphas for a small number of funds. This means that only a limited subset of managers show superior performance on top of the passive replicated portfolios that are augmented with the non-linear Fung and Hsieh factors. Within equity hedge 13 funds out of

Table 6: **Alpha frequencies Carhart four-factor model: Equity Hedge funds (2010-2016)**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	N	β_{mkt}	β_{smb}	β_{hml}	β_{wml}	# significant α_i		$adjR^2$
		$[SE_\beta]$	$[SE_\beta]$	$[SE_\beta]$	$[SE_\beta]$	at 5%	at 10%	
Eq. Hedge	101	0.287	0.108	-0.004	-0.032	10^+	14^+	0.320
		[0.069]	[0.123]	[0.108]	[0.077]	7^-	11^-	
EM. Neutral	35	0.101	0.127	-0.022	-0.022	7^+	10^+	0.178
		[0.051]	[0.097]	[0.087]	[0.06]	2^-	2^-	
L/S Global	14	0.493	0.115	-0.010	-0.019	1^+	1^+	0.437
		[0.092]	[0.147]	[0.143]	[0.097]	1^-	3^-	
L/S Europe	39	0.360	0.038	-0.026	-0.053	2^+	2^+	0.357
		[0.073]	[0.132]	[0.132]	[0.082]	4^-	5^-	
L/S U.S.	6	0.352	0.267	0.253	0.119	0^+	0^+	0.678
		[0.054]	[0.114]	[0.1]	[0.064]	0^-	1^-	
L/S Em. Mar.	7	0.374	0.221	0.002	-0.047	0^+	1^+	0.308
		[0.097]	[0.097]	[0.157]	[0.109]	0^-	0^-	

Notes Table 6 reports the significant alpha frequencies of the Carhart four-factor regressions on individual alternative UCITS funds. The results are measured over the entire sample period (January 2010 - September 2016). Column 1 contains the number of constituents per strategy. Column 2 presents the average of estimated beta versus the global equity market [Fama and French, 2012]. The second row reports an average of the estimated standard error. Column 3 presents the average of estimated beta versus the global size factor [Fama and French, 2012]. Column 4 presents the average of estimated beta versus the global value factor [Fama and French, 2012]. Column 5 presents the average of estimated beta versus the global momentum factor [Fama and French, 2012]. Column 6 and 7 present the number of statistical significant alphas at the 5% and 10% level. The first row depicts the number of significantly positive alphas, the second row the significantly negative alphas. Column 8 presents the average R^2 of the Carhart four-factor model. The null hypothesis that the alphas are zero is tested using heteroscedasticity- and autocorrelation consistent Standard Errors following Newey and West [1987]. We retained funds that had at least a track record of 5 years.

Table 7: **Regression results Fung and Hsieh seven-factor model: Synthetic portfolios (2010-2016)**

	(1) $\alpha_i(\%)$	(2) β_{mkt}	(3) β_{smb}	(4) β_{ge10y}	(5) β_{spread}	(6) β_{ptfsbd}	(7) β_{ptfsfx}	(8) $\beta_{ptfscom}$	(9) $adj.R^2$
***Panel A* – UCITS styles**									
All UCITS	−0.089**	0.224***	0.057***	0.106***	0.147***	0.000	0.003	0.000	0.827
	[1.899]	[12.834]	[3.613]	[3.2]	[3.807]	[0.01]	[0.82]	[0.285]	
Equity Hedge	−0.041	0.275***	0.077***	−0.001	0.040	−0.001	0.000	−0.002	0.753
	[0.638]	[11.681]	[3.474]	[0.023]	[0.683]	[0.173]	[0.096]	[0.612]	
***Panel B* – Equity Hedge UCITS strategies**									
Equity Market Neutral	0.049	0.087***	0.102***	−0.014	0.047	0.001	−0.004	0.001	0.511
	[1.022]	[5.109]	[6.246]	[0.359]	[0.911]	[0.377]	[1.225]	[0.296]	
Long/Short Global	−0.086	0.402***	0.071**	0.042	0.034	−0.004	0.003	−0.007	0.804
	[1.084]	[12.188]	[1.942]	[0.819]	[0.342]	[0.55]	[0.737]	[1.338]	
Long/Short Europe	−0.041	0.351***	0.021	−0.060	0.037	−0.004	0.001	−0.004	0.640
	[0.413]	[8.798]	[0.534]	[0.751]	[0.38]	[0.499]	[0.103]	[0.707]	
Long/Short U.S.	−0.258	0.410***	0.420***	0.148	−0.179	0.009	−0.004	0.002	0.769
	[1.635]	[8.188]	[6.704]	[1.292]	[1.1]	[0.796]	[0.355]	[0.272]	
Long/Short Em .Markets	−0.150	0.373***	0.104	0.149	0.109	−0.007	0.014	−0.007	0.408
	[0.571]	[4.129]	[1.588]	[1.183]	[0.618]	[0.585]	[1.638]	[0.628]	

Notes: Table 7 reports the results of the Fung and Hsieh seven-factor regressions of synthetic equally-weighted alternative UCITS portfolios versus the [Fung and Hsieh, 2004] factors: global equity market, global size factor, European bond market, European credit spread and three trend-following lookback bond straddles (bond, foreign exchange and commodities) The results in Panel A and B are measured over the entire sample period (January 2010 - September 2016). Column 1 presents the estimated monthly alphas in percentages. Column 2 presents the estimated betas versus the Global equity market factor [Fama and French, 2012]. Column 3 presents the estimated betas versus the Global equity size factor [Fama and French, 2012]. Column 4 presents the estimated betas versus a European bond-market factor. Column 5 presents the estimated betas versus a European bond credit spread factor. Column 6,7, and 8 present the estimated betas versus the Fung and Hsieh [2004] trend-following factors in resp. bonds, foreign exchange and commodity. Column 9 shows and adjusted coefficients of determination ($adj.R^2$). We present the t-statistics of the two-sided tests, in which the null hypothesis is that the coefficients are zero, in the second row of each regression. *, ** and *** denote statistical significance at the 10%, 5% and 1% level using heteroscedasticity- and autocorrelation consistent Standard Errors following Newey and West [1987].

Table 8: **Alpha frequencies Fung & Hsieh seven-factor model: Equity Hedge funds (2010-2016)**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	N	β_{mkt}	β_{smb}	β_{ge10y}	β_{spread}	β_{ptfsbd}	β_{ptfsfx}	$\beta_{ptfscom}$	# significant α_i		$adj R^2$
		$[SE_\beta]$	$[SE_\beta]$	$[SE_\beta]$	$[SE_\beta]$	$[SE_\beta]$	$[SE_\beta]$	$[SE_\beta]$	at 5%	at 10%	
Equity Hedge	101	0.280	0.095	-0.021	0.013	-0.004	-0.001	-0.001	13^+	15^+	0.305
		[0.083]	[0.09]	[0.16]	[0.249]	[0.016]	[0.014]	[0.013]	7^-	11^-	
Equity Market Neutral	35	0.099	0.106	-0.045	-0.003	0.000	-0.009	0.003	8^+	8^+	0.176
		[0.063]	[0.065]	[0.122]	[0.179]	[0.013]	[0.011]	[0.01]	2^-	2^-	
L/S Global	14	0.475	0.091	0.040	0.058	-0.004	0.007	-0.004	0^+	1^+	0.393
		[0.102]	[0.118]	[0.183]	[0.324]	[0.021]	[0.018]	[0.017]	1^-	4^-	
L/S Europe	39	0.334	0.007	-0.061	0.029	-0.008	-0.001	-0.002	4^+	5^+	0.352
		[0.087]	[0.093]	[0.168]	[0.263]	[0.017]	[0.014]	[0.013]	4^-	5^-	
L/S U.S.	6	0.388	0.518	0.113	-0.052	0.001	0.001	0.008	0^+	0^+	0.611
		[0.074]	[0.092]	[0.172]	[0.277]	[0.017]	[0.015]	[0.013]	0^-	0^-	
L/S Em. Markets	7	0.365	0.142	0.080	-0.024	-0.011	0.018	-0.008	1^+	1^+	0.235
		[0.128]	[0.128]	[0.234]	[0.335]	[0.022]	[0.018]	[0.02]	0^-	0^-	

Notes Table 8 reports the significant alpha frequencies of the Fung and Hsieh seven-factor regressions on individual alternative UCITS funds. The results are measured over the entire sample period (January 2010 - September 2016). Column 1 contains the number of constituents per strategy. Column 2 presents the average of estimated beta versus the global equity market [Fama and French, 2012]. The second row reports an average of the estimated standard error. Column 3 presents the average of estimated beta versus the global size factor [Fama and French, 2012]. Column 4 presents the average of estimated beta versus a European bond market factor. Column 5 presents the average of estimated beta versus a bond European bond credit spread factor. Column 6,7,8 presents the average of estimated beta versus [Fung and Hsieh, 2004] trend-following factors in resp. bonds, foreign exchange and commodities. Column 9 and 10 present the number of statistically significant alphas at the 5% and 10% level. The first row depicts the number of significantly positive alphas, the second row the negative significant alphas. Column 11 presents the average R^2 of the Fung & Hsieh four-factor model. The null hypothesis that the alphas are zero is tested using heteroscedasticity- and autocorrelation consistent Standard Errors following Newey and West [1987]. We retained funds that had at least a track record of 5 years.

101 produce a significantly positive alpha at the 5% level, 15 at the 10% level.

Our decomposition of the universe reveals that the majority of the equity hedge UCITS funds are zero-alpha funds. We observe that less than 15% of managers (both at the 5% and 10% significance level) have managerial talent (α>0), while around 10% of managers are unskilled (α<0). However, a finding in which the majority of the funds is at par with systematic return sources is consistent with the findings in Barras, Scaillet, and Wermers [2010] for mutual funds.

However, we need to consider our results in the light of the statistical power of these tests. The analysis of simply counting the number of funds exceeding a preset significance level has the drawback that, when testing on multiple funds, it is prone to type I errors. In fact, when we use the usual significance levels of 5% (or 10%), we would expect that 5% (or 10%) of the cases the zero-alpha funds will have a significant alpha measure. Conversely, in case of "bad" luck, funds with true significant alphas can have a test statistic in the region of non-rejection of the zero-alpha test [Barras et al., 2010]. In summary, significant residual performance is rare, but does exist.

4.3 Peer performance

When the objective is to invest in quintile portfolios, the question of interest is not the number of funds with significant alpha, but to detect the funds that outperform their peers. The industry standard approach to evaluate an investment fund compared to its peers consists of two steps. First, we evaluate the focal fund using a standard performance measure, such as the Sharpe ratio or alpha. Next, the fund is ranked and percentiles are used to classify peer performance as either "outperforming" or "underperforming". Without regard to the possibility that funds show similar performance, this method may be prone to false discoveries. As a consequence, the performance evaluation may exhibit significant (estimated) alpha differentials between funds, while the true alpha is identical [Ardia and Boudt, 2017].[10]

To address this problem, we propose to evaluate the funds using the framework of peer performance, as proposed by Ardia and Boudt [2017]. The building block of this method is the "False Discovery" methodology by Storey [2002] to obtain estimates of equal performance that are robust to false positives. We refer to Barras et al. [2010] who provides an explicit form for estimators which are based on the false discovery rate and assesses the proportion of talented mutual funds. Ardia and Boudt [2017] provide an application in the hedge fund industry. The method evaluates an investment fund's performance by applying an evaluation framework which categorizes peer performance in three types: (a) equal performance ($\hat{\pi}^0$): the percentage composition of the peer group that perform equally well as the fund of interest; (b) outperformance ($\hat{\pi}^+$): the percentage composition in the peer category the focal fund outperforms; and (c) underperformance ($\hat{\pi}^-$): the percentage of peer funds that outperform the focal fund.

In Figure 2, we show a two-panel diagnostic plot that examines the distribution of peer performance across funds. In the left plot, we ranked our universe by the average (annualized) monthly style-factor alpha. For example, Bucket 1 corresponds to average of the best performing funds in terms of their style alpha. In the right barplot, we present for the corresponding buckets the

[10] The same authors make the comparison with the percentile-rank rate of outperformance and note that, in the extreme case of equal performance between all funds, the percentile-rank will be purely driven by noise.

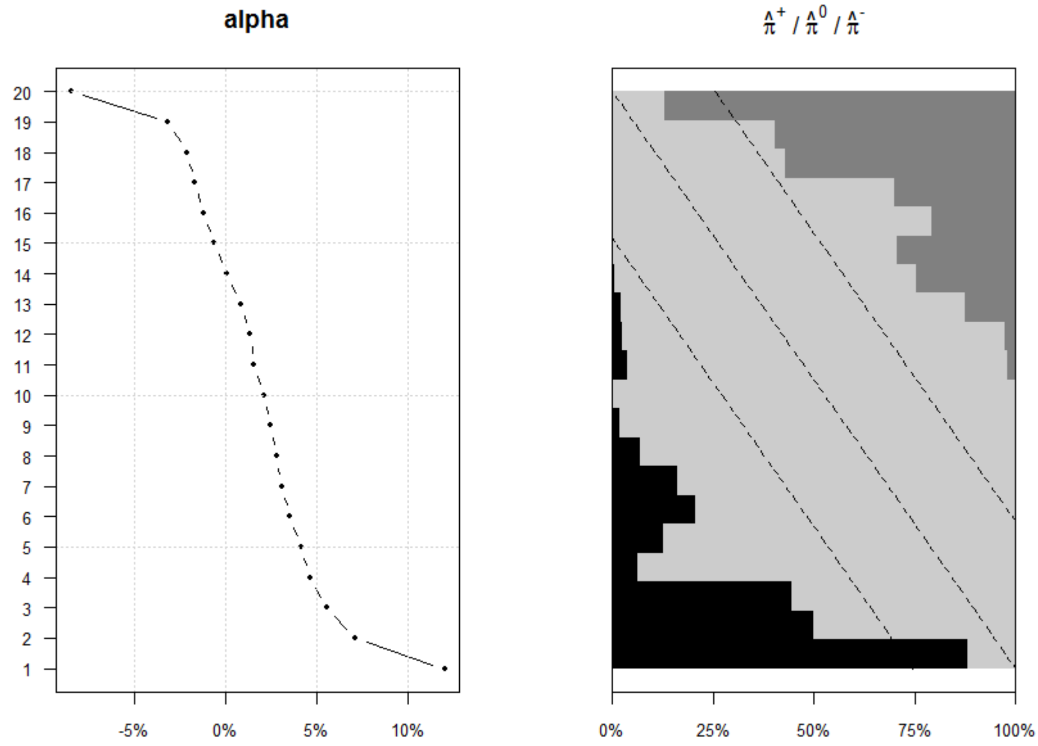

Figure 2: Screening Plot (2010-2016)

Notes: A screening plot is a two-panel plot which examines the distribution of peer performance across funds. In the left plot, we rank the universe by (annualized) monthly style-alpha and group them in 20 buckets. In the right plot, we show, for each of the corresponding buckets, the average outperformance $\hat{\pi}^+$ (black), equal-performance $\hat{\pi}^0$ (light gray) and underperformance $\hat{\pi}^-$ (dark gray).

average of estimated outperformance π^+ (black), equal-performance π^0 (light gray) and underperformance π^- (dark gray). While most funds show high values of equal performance to their peers, we still detect heterogeneity in the out- and underperformance ratios. Moreover, the alpha and peer performance outperformance ratio are in most cases positively non-linearly dependent. This can be seen by the diagonal lines that accentuate the non-linear relationship. For example, a decrease of a 1% in monthly alpha has a larger impact on the outperformance ratio for a top performing fund than a mediocre fund. In results not included in this study, we observed that the average downward correction for false discoveries is 37.2 percent for outperformance and 33.7 for underperformance as compared to a standard rank approach. It follows that the peer performance parameters account for estimation uncertainty in the associated performance measures.

Table 9 shows the ranking of funds based on their style factor alpha in column (1). Between brackets we show the outperformance and underperformance ratio for each focal fund. The last

Table 9: **Peer performance & fund rankings**

Fund	(1) Strategy	(2) Style	(3) Carhart	(4) Fung & Hsieh
A	Long/Short Em. Markets	1[0.98; 0.00]	1[0.97; 0.00]	1[0.98; 0.00]
B	Long/Short Europe	2[0.93; 0.00]	2[0.67; 0.00]	2[0.46; 0.00]
C	Long/Short Global	3[0.85; 0.00]	60[0.00; 0.00]	10[0.00; 0.00]
D	Long/Short US	4[0.77; 0.00]	50[0.00; 0.05]	20[0.06; 0.18]
E	Long/Short US	5[0.86; 0.00]	64[0.00; 0.19]	32[0.10; 0.00]
...	...	...	...	...
K	Long/Short Global	50[0.00; 0.00]	57[0.00; 0.19]	42[0.00; 0.00]
L	Equity Market Neutral	51[0.00; 0.00]	43[0.00; 0.00]	34[0.15; 0.00]
M	Long/Short Europe	52[0.00; 0.00]	58[0.00; 0.00]	43[0.00; 0.00]
N	Long/Short Europe	53[0.09; 0.00]	46[0.38; 0.01]	31[0.33; 0.00]
O	Long/Short Europe	54[0.00; 0.00]	17[0.26; 0.00]	55[0.00; 0.00]
...	...	...	...	...
V	Long/Short Europe	99[0.00; 0.84]	102[0.00; 0.97]	98[0.00; 0.86]
W	Long/Short Global	100[0.00; 0.82]	103[0.00; 0.87]	102[0.00; 0.82]
X	Long/Short Global	101[0.00; 0.83]	99[0.00; 0.74]	103[0.00; 0.87]
Y	Long/Short Europe	102[0.00; 0.93]	101[0.00; 0.82]	100[0.00; 0.86]
Z	Equity Market Neutral	103[0.00; 1.00]	100[0.00; 0.91]	101[0.00; 0.91]

Notes Table 9 reports the alternative UCITS fund rankings for the fund's alpha with respect to the different factor models. We report the 5 best, 5 central and 5 worst funds in terms of the respective alphas. We report the ranking within the universe. In between brackets we show the outperformance and underperformance ratios with respect to different factor models. The alphas are calculated over the entire sample period (January 2010-September 2016). We retained funds that had at least a track record of 5 years (103 funds).

two columns show a comparison in ranking using the models proposed by Carhart [1997] and Fung and Hsieh [2004]. First, we note the fairly broad scope in investment strategies that are in the top, middle or worst performers. It doesn't seem that a particular strategy has the upper hand when we use the style-factor alpha. Second, the factor models under consideration do not tend to give comparable rankings for the best and mediocre funds, with the exception of two best funds which resp. follow a Long/Short Emerging Markets strategy and a Long/Short Europe strategy. Thus, the standard approach for estimating residual performance may be too optimistic about the outperformance of the focal fund. With regards to the worst funds the models give consistent results.

In results not reported in this study, we computed the conditional probability of fund selection. While the factor models show comparable coefficients of determination on a collective level (see Tables 3, 5 and 7), they show different amounts of coverage. Bearing on the fact that the factor models' intercepts proxy the fund's talent, they show different results in their ranking. For the style factor model, we find the probability (conditional on a top ranking in the style factor model) for the Carhart model and Fung & Hsieh model to be 62.0% and 49.4% respectively.

Table 10: **Out-of-sample performance of quintile portfolios (2013-2016)**

		Equally-weighted portfolios				Value-weighted portfolios			
P	Q	Mean	Std	Sharpe	Alpha	Mean	Std	Sharpe	Alpha
***Panel A* – Benchmark Portfolios**									
S	–	3.877	4.063	0.893	–	3.192	3.777	0.780	–
***Panel B* – Portfolio sorts rolling using averages of past returns**									
M	Top	4.268	6.715	0.599	0.000	3.656	6.599	0.517	0.004
	Bottom	1.791	2.872	0.539	−0.020	2.887	2.417	1.093	0.113
MV	Top	3.210	4.400	0.674	0.030	2.627	4.070	0.586	0.006
	Bottom	1.320	2.929	0.368	−0.062	2.062	2.325	0.782	0.046
***Panel C* – Portfolio sorts using alpha**									
P	Top	6.240	5.778	1.036	0.298	5.210	5.951	0.834	0.238
	Bottom	1.977	5.496	0.316	−0.169	2.871	5.622	0.467	−0.089
C	Top	5.759	4.340	1.269	0.258*	4.966	4.554	1.036	0.198
	Bottom	3.710	6.866	0.504	−0.095	4.298	7.126	0.568	−0.049
F	Top	5.261	4.379	1.144	0.216	4.778	4.539	0.998	0.208
	Bottom	3.498	5.938	0.548	−0.075	4.693	6.125	0.726	0.024
***Panel D* – Portfolio sorts using t-statistic**									
P	Top	5.810	4.281	1.299	0.308*	5.250	4.604	1.086	0.268
	Bottom	1.432	5.227	0.228	−0.195*	2.203	4.727	0.414	−0.094
C	Top	6.203	3.581	1.662	0.334***	5.887	3.548	1.588	0.308***
	Bottom	2.978	5.915	0.462	−0.091	3.718	6.277	0.553	−0.039
F	Top	5.122	3.259	1.495	0.268**	4.983	3.271	1.447	0.268**
	Bottom	2.950	5.641	0.480	−0.095	4.100	5.487	0.702	0.017
***Panel E* – Portfolio sorts using out- and underperformance ratio**									
P	Top	5.963	5.500	1.038	0.301	4.757	5.508	0.819	0.205
	Bottom	1.427	4.733	0.250	−0.167	1.560	4.201	0.314	−0.126
C	Top	6.738	3.795	1.709	0.374***	6.413	3.864	1.595	0.349**
	Bottom	3.547	6.358	0.519	−0.075	4.781	6.697	0.677	0.013
F	Top	5.614	4.012	1.337	0.264**	5.317	4.135	1.225	0.266*
	Bottom	3.214	5.725	0.518	−0.075	4.014	5.738	0.656	0.005

Notes Table 10 reports the results for an out-of-sample performance test of quintile portfolios using systematic momentum investment strategies based on style-factor model, the Carhart four-factor model and the Fung & Hsieh seven-factor model. We use equally-weighted and value-weighted quintile portfolios. The evaluation period spans from December 2012 to September 2016. Panel A reports the results for synthetic benchmark portfolio (S) in which we include all the funds in our equity hedge universe. Panel B reports two systematic momentum strategies using only the return series of the fund. First, we look at a standard 36-month momentum strategy (M). We also include a momentum strategy which is scaled by volatility (MV). Panel C reports the alpha-sorted portfolios that selects funds based on the conditionally estimated intercepts by comparing fund returns with a factor space, respectively, the style or peer factor (P), Carhart four-factor model (C) and Fung & Hsieh's seven-factor model (F). Panel D reports the HAC alpha-t statistic portfolios that selects funds based on the significant HAC t-statistics of the estimated alphas in respective factor models. Panel E reports the out- and underperformance portfolios that selects funds based on the the peer performance ratios by Ardia and Boudt [2017] of the estimated alphas in respective factor models. We evaluate the quintiles based on annualized return (Mean, in %), annualized volatility (Std, in %), Sharpe ratio (Sharpe) and style-factor alpha (Alpha). *, ** and *** denote statistical significance at the 10%, 5% and 1% level using HAC standard errors.

5 Persistence of equity hedge UCITS managers

We now turn to our main research question regarding the equity hedge UCITS funds' alpha: Is there added value in factor model based estimation of residual performance for fund selection? This question is relevant since investors tend to shift their portfolio allocation to outperforming funds [Fung, Hsieh, Naik, and Ramadorai, 2008]. Therefore, we want to a adopt a ranking criterion with a reliable signal of superior (relative) ability of a fund manager that integrates the use of risk premia in the bottom-up selection of fund managers [Hamdan et al., 2016]. The aim of this section is to verify the hypothesis of short-run persistence in performance using the residual return as a measure of managerial skill. This is related to the positive autocorrelation in monthly and quarterly mutual and hedge fund returns, which is known in the literature as the *hot hands* effect [see.e.g., Ardia and Boudt, 2013; Hendricks et al., 1993; Jagannathan et al., 2010]. We expect the set of outperforming funds to be time-varying [Avramov et al., 2011; Criton and Scaillet, 2014], which is consistent with the *adaptive market hypothesis* of Lo [2004]. We don't consider the conditional nature of the alphas [Jagannathan et al., 2010]. Still, we intend to show the practical relevance of common style and risk factors in the estimation using the standard approach discussed in Carhart [1997], Capocci and Hübner [2004] and Blitz et al. [2011], compared to systematic momentum techniques based on raw returns. We also address the question of informativeness of the considered ranking criteria in peer performance evaluation. Of course, precise fund selection increases our odds to achieve persistent outperforming portfolios.

We proceed by analyzing whether past alpha is a predictor of future superior performance in the following way. On every selection date t we set up managed portfolios of alternative UCITS funds based on a ranking criterion in $t-1$. We account for the time-variation in the distribution of monthly alphas by using three-year rolling samples.[11] The out-of-sample evaluation ranges from December 2012 to September 2016, for a total of 46 rebalancing dates. The backtest considers 36 months of data to compute the alpha measures using the model discussed in Equation 2.1. The ranking criteria under consideration are the unconditional alpha and two alternative ranking criteria. For the unconditional alpha we assume that skilled funds are concentrated in the extreme tails. Thus, we infer that a high alpha gives a signal of fund manager skill. Nonetheless, unconditional alpha can be prone to measurement errors [Jagannathan et al., 2010]. In implementing such a procedure, we would mistakenly assign superior ability to managers, we also use the relative alpha t-statistic sorted strategy and the "false discovery"-robust peer performance ratio. We proceed by composing equally-weighted and value-weighted monthly rebalanced portfolios of the UCITS funds invested in the top and bottom quintile.

In order to assess the economic gains of selecting funds based on ranking criteria, we evaluate our portfolios using the annualized return, annualized standard deviation, Sharpe ratio and the style-factor alpha. To answer the relevant questions: Are we able to detect skilled funds over time and do we capture their superior alphas. And, how do we perform versus a a synthetic market index and a systematic momentum strategy? We report our results in Table 10.

First, we verify that -across all sorting criteria, factor models and weighting method- the difference in out-of-sample performance between the top quintile portfolio and bottom quintile

[11] We note that the previous analysis based on longitudinal time series may be unbalanced since the universe composition grows over time.

portfolio is as we expected: the top quintile delivers a higher absolute return and higher risk-adjusted return as compared to the bottom quintile. We have to note that this is not the case for the value-weighted counterpart of a noise-driven momentum strategy, which shows a rather high standard deviation and a lower Sharpe ratio than the corresponding bottom portfolio.

Second, a monthly-rebalanced portfolio invested in the top quintile in terms of the alpha t-statistic and the outperformance ratio significantly outperforms the investing strategy based on the historical alpha. From a raw performance alpha perspective we find that the winner (loser) quintile has a total return of 6.240 (1.977) percent and a Sharpe of 1.036 (0.316) for the alpha-sorted strategy. Comparable discrepancies can be found in the Carhart alpha and the Fung and Hsieh alpha. While, investing in past winners using the t-statistics as a sorting criterion leads to a Sharpe ratio up to 1.662 with a corresponding significant style-alpha. In relation to the outperformance ratio, we find a Sharpe ratio up to 1.709. It is interesting to see that the standard deviation is reduced when we use the alpha t-statistic or the outperformance ratio. Similar results are obtained in the case of alternative value-weighted scheme, which is more in line with an investable fund-of-funds strategy. We note a minor decrease in risk-adjusted performance, which indicates that our results our not driven by non-investable small funds.

Third, we detect a risk/return trade-off when using the t-statistic and outperformance ratio measures for selection: we can achieve a higher annualized return using the outperformance ratio at the cost of a higher standard deviation as compared to the alpha t-statistic. A finding which is consistent over all factor models.

Fourth, to the extent that we account for common factors that affect all funds in the universe, we examine that we improve accuracy by controlling for the factors introduced by Carhart [1997] and Fung and Hsieh [2004] as compared to the style factor model. However, we do not find that the maximally expanded factor space delivers the highest performance. In all cases, the equity-inspired Carhart four-factor model delivers a higher risk-adjusted performance as compared to the Fung & Hsieh model. The observed performance further validates our use of factor models in performance persistence analysis.

6 Concluding remarks

The UCITS market is a fast-growing market segment within the fund-management industry. In this chapter, we study the problem of identifying truly skilful managers. Despite the relevance of the topic, there are only a few empirical studies on role of talent and the alternative risk premia in the UCITS industry. We contribute by reviewing the general characteristics of alternative UCITS funds, and then zoom in on the performance of funds within a particular style, namely the equity hedge UCITS funds.

Foremost, it is important to consider the risk-return relationship. We examine the ex-post risk-adjusted performance of alternative UCITS funds taking into account a portfolio of systematic return sources (beta). At the aggregate index level, we report results consistent with previous research. We observe that studying average fund performance relative to the HFR style benchmark provides insights on the prevalence of talent in the UCITS-compliant universe. We find that the style index performs well in capturing the variance of the strategies operating under a common header. Furthermore, we observe time-varying UCITS funds' alpha using two non-overlapping periods. Conversely, the analysis using the multi-factor framework is less conclusive in explaining the main drivers of the UCITS industry. Busack et al. [2014] conclude that the returns of alternative UCITS are less exposed to hedge fund risks. We support their finding by observing that the non-linear, trend-following strategies of Fung and Hsieh [2004] don't show any incremental usefulness when considering the UCITS-compliant universe. Altogether, we believe more research is needed in the unbundling of returns using non-linear strategies with different risk profiles and pay-outs [Hamdan et al., 2016].

The long-standing puzzle of active management skill is equally relevant in the UCITS universe. In order to complement literature we also acknowledge the heterogeneity of the equity hedge UCITS universe by breaking down our returns in alpha and beta on a per-fund basis. Our decomposition of the universe reveals that a limited subset shows statistically significant alpha surplus after isolating the manager-specific component from the common-factor performance. The large proportion of unskilled zero-alpha funds might indicate that they are at par with the passive systematic betas. Based on standard significance tests, we find that significantly positive residual performance is rare in the analyzed equity hedge UCITS funds universe, but does exist. Considering that the standard alpha significance test may not adjust for the possibility that performance may be due to chance, we apply a peer performance evaluation framework to adjust our findings for false discoveries. The adjustment can thus be considered as a reliable signal for fund-of-fund portfolio allocation. Further, while the intercepts of the factor models share a common goal, i.e. proxy the managerial talent of a particular fund, we find disagreement in fund ranking results across factor models.

Finally, we used an out-of-sample portfolio sort to detect performance persistence, following the notion that the choice of the skilled fund manager is based on his ability to reproduce superior past performance [Jagannathan et al., 2010]. Using portfolio sorts, we show economic value in terms of a risk-return trade-off: we can achieve higher risk-adjusted returns when we control for false discoveries. However, the use of alpha t-statistics leads to lower-risk portfolios across both weighting schemes and factor specifications. Another takeaway is less noise when using factor models in fund selection, which is supportive of our view to control for systematic return sources. It is important to consider that we are looking at relative performance persistence in the equity hedge universe. Altogether, the empirical results support our view that the proposed factor spaces and alternative ranking criteria are useful in the ex-post evaluation of UCITS funds and the ex-ante fund-of-fund investment strategies.

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