Evaluating the performance of hedge funds using two-stage peer group benchmarks

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ABSTRACT This article proposes a two-stage peer group benchmarking approach to evaluate the performance of hedge funds. We present different ways of orthogonalizing the peer group benchmarks and discuss their general properties. We then orthogonalize the relevant benchmarks against predetermined exogenous factors. For a broad dataset we show that this approach captures much more commonalities in hedge funds returns when compared with the standard methodology of using exogenous factors only.

As a consequence, the empirical rankings of hedge funds, on the basis of alphas, change considerably. Therefore, the proposed two-stage peer group benchmark allows us to identify which hedge fund managers outperformed their cohorts.

Keywords: hedge funds; performance measurement; factor models; peer group benchmarks

INTRODUCTION

Ever since Alfred Winslow Jones started the first hedge fund in 1949, hedge funds have attracted much attention from both academics and practitioners. The rising interest in the hedge funds industry is a direct consequence of some prominent incidents, such as the successful bets of Soros' *Quantum Fund* against the British pound in 1999, the collapse of *Long Term Capital Management* in 2000, and also the multi-billion dollar profits of *Paulson & Company* during the recent financial crisis (cf. report on New York Times, 2011).
In recent years, the hedge funds sector has attracted some major institutional investors, such as pension funds, insurance companies and university endowments. There were approximately 22 000 active hedge funds globally by 2010 and by 2013 the assets under management amounted to about US$2.7 trillion (Brown, 2013).

Most empirical studies measure the past performance of hedge funds using different specifications of multi-factor models on the basis of exogenous factors to estimate the excess risk adjusted returns (alphas). However, these approaches have significant limitations when adopted for hedge fund performance measurement.

First, as hedge funds invest across a huge variety of asset classes and their positions are usually leveraged, the dynamics of their risks and returns differ from traditional investment vehicles. Some researchers have argued that hedge fund risk-return payoffs are non-linear and in addition equity-oriented hedge fund strategies exhibit a put option-like payoff (Fung and Hsieh, 2001; Mitchell and Pulvino, 2001; Agarwal and Naik, 2004). Second, because of their dynamic trading strategies, hedge funds potentially contain certain systematic risks that are not readily observable. Though the factor models have evolved from a single market-factor model, to the Fama-French three-factor, to Carhart's four-factor model, and to the more recent Fung and Hsieh seven-factor model, the search for additional risk factors in hedge funds investment is open ended because of the wide range of investments and investment strategies adopted by hedge funds. Thus, the multi-factor model with the standard asset benchmarks will never be sufficient to capture the complete risk-return relationships in hedge funds.

Since many hedge funds employ similar strategies, the residuals produced from standard factor models are inherently correlated with each other. This 'commonality' problem within hedge funds strategies makes it difficult to assess the performance of individual hedge funds. That is, it is hard to distinguish whether the superior performance of a fund is a result of an individual manager's unique skill or just a reflection of the particular investment strategies adopted.

Fund performance measurement using benchmarks has been a standard practice in the fund management industry, especially within pension funds and mutual funds. Many institutional investors use their own customized benchmarks to reflect their specific objectives of investment. The common benchmarks utilized are based on specific asset classes and market indices.

Consequently, single index or multi-index models serve as the basis for this kind of benchmarking. In this respect, some companies have started to provide 'peer group benchmarks' to facilitate performance measurement across similar pension funds, life funds, unit trusts and investment trusts. In particular, companies in the United Kingdom who provide peer group benchmarks include Combined Actuarial Performance Limited, Micropal, Morningstar Europe and World Markets Company (Blake and Timmermann, 2001). However, in other countries, such services are limited, non-existent or not yet available for the corresponding country-based hedge funds. This underlines the practical relevance of our article in providing an overarching approach for creating and using 'peer group benchmarks' for the evaluation of the performance of hedge funds in general.

In this regard we are the first to introduce the concept of a two-stage peer group benchmark to improve the performance measurement of hedge funds. We suggest that individual hedge fund performance should be measured not only against the common risk factors but also against its peer group benchmarks or 'commonalities'. An intuitive peer group classification approach is to adopt the group strategy declared by the funds themselves. Thus we augment the approach of Hunter *et al* (2014) to form both main-strategy and sub-strategy peer group benchmarks and to combine them with our predetermined exogenous risk factors. In addition, we orthogonalize these peer group benchmarks (main-strategy and sub-strategy) separately for every fund in our sample with respect to the life time of the fund. By doing so, we eliminate distortions which otherwise would be caused by the variation of correlations between exogenous and peer group benchmarks over the total sample period.

Our study finds that the use of a two-stage orthogonal peer group benchmark facilitates a more parsimonious and precise identification of superior hedge funds. Our findings indicate that two-stage peer group benchmarks should be included when examining individual hedge fund performance. These benchmarks should be orthogonalized against all the exogenous risk factors in the factor model. However, it must also be noted that the form of orthogonalization affects the rankings of the hedge funds studied at the sub-group level. In particular, the orthogonalization 'without group alphas' only ranks the funds with reference to the exogenous factors considered, whereas the orthogonalization 'with group alphas' ranks the funds with reference to both the peer group benchmarks and the exogenous factors. Thus, depending on the evaluator's needs, a proper form of orthogonalization needs to be chosen when our two-stage peer group benchmark approach is adopted.

The article is organized as follows. The next section describes our research design. The section after that contains information about the data. The empirical results are presented in the penultimate section. The final section concludes.

RESEARCH METHODOLOGY

Introducing two-stage peer group benchmark

The usual multi-factor models employed in performance measurement utilize exogenously determined risk factors. They explain a significant part of the variance of hedge fund returns. However, hedge funds invest in a variety of asset classes. The private nature and a diversity of strategies that hedge fund managers employ impede the detection of further exogenous factors that significantly influence fund performance. These hedge fund specific strategies introduce fund-specific risk factors which are difficult to proxy and hence are left unaccounted for in the performance management studies to date.

The basic idea of using peer group factors for performance measurement is not new.

The essence of the idea is to evaluate the 'relative' performance of the fund managers to her peer groups. The spirit of peer evaluation has been adopted by Elton *et al* (1997) and Cohen *et al* (2005) in assessing mutual funds' performance and in a more recent work on hedge funds by Jagannathan *et al* (2010). Hunter *et al* (2014) are the first to explicitly use the term 'peer group benchmark' in this context. It is based on the idea that performance measurement does not necessarily require the exact identification of all exogenous factors. In fact, taking advantage of the information by groupings or classifications of investment funds naturally creates an explanatory proxy. The incorporation of peer group benchmarks offers several advantages at better measuring and identifying top performing funds and its fund managers.

First of all, hedge fund managers tend to conceal their investment strategies. Even if an evaluator or investor was able to identify additional explanatory risk factors for single funds or fund classes, she still has to assume that these assets underlie other 'hidden' factors. Endogenous benchmarks allow controlling for these factors without requiring any specific knowledge or information on these factors.

Second, investors are able to diversify their wealth by investing in various assets. Even if they aim for one certain investment strategy, they still can spread their money over many different funds pursuing this strategy. By promising a superior performance, fund managers naturally compete with returns that can be gained by pursuing diversified investments in other funds of the same strategy. Hence, individual managers implicitly compete within the peer group of their strategy and therefore should be benchmarked against this peer group.

In addition, fund managers within the same category of funds may well-apply similar models, behave similarly and invest capital in the same asset categories. Thus, a high correlation between the residuals from regressions of single funds' returns to market returns is usually expected and encountered. Further benchmarking the individual funds against its peer group will reduce the high correlation across residuals. If benchmarking leads to no increases in explanatory power, this finding is valuable as it indicates that a fund may have been incorrectly allocated or may have additional risk exposures which are not yet identified.

Thus, the peer group benchmark approach proposed by Hunter *et al* (2014) for mutual funds represents a promising approach to solve the 'missing variables' problem in risk factor identification as well as the 'commonality' problem in assessing individual hedge fund's performance. A huge advantage of this method is that it does not require a deep understanding of underlying factors – it is sufficient to know that such unidentified influences exist, which similarly affect the performance of hedge funds pursuing comparable strategies.

However, the Hunter *et al* (2014) approach is not directly applicable to hedge funds because of distinct differences in the nature of hedge funds and mutual funds. Applying the method requires the knowledge of the investment objectives of all considered funds, which is quite straightforward in the case of mutual funds. The actual allocation is done by the fund managers themselves who, by choosing a strategy or investment objective, determine their own benchmark.

In contrast to mutual funds, which can be categorized very precisely because of restrictive regulatory requirements, hedge funds are not obligated to disclose the details of their investment activity. In addition, as the definitions of many strategies are imprecise and inconsistent the allocation of individual funds into an aggregated strategy group is less obvious. Furthermore, it is common for hedge fund managers to conceal their strategies, or to pursue several different strategies at the same time (Fung and Hsieh, 1997; Fung and Hsieh, 2002; Mader, 2008). Thus, the categorization of each fund into a strategy group is more complex for hedge funds than for mutual funds.

In order to cope with these problems, we extend the approach of Hunter *et al* (2014) by using a two-stage peer group benchmark regression. We compute peer group benchmarks for all hedge funds according to their main- and sub-strategies in our sample which allows us to benchmark single funds against a relatively homogenous group. This design helps us to add explanatory power to our model in particular with respect to funds which cannot be allocated directly or which were categorized wrongly.

In addition to equally-weighted peer group benchmarks, we also use value-weighted peer group benchmarks. Since size has been identified as an important factor in hedge fund performance (cf. Gregoriou and Rouah, 2002), computing the value-weighted benchmark is able to serve as a robustness test here.

For creating equally-weighted peer group benchmarks we consider all funds included in our *sample*. The computing process for calculating the peer group benchmarks for the main- and sub-strategies is based on

$$EB^{ew}_{Strat,\,t} = \frac{\sum_{i=1}^{n_{Strat,t}} \left(r_{it} - r_{ft}\right)}{n_{Strat,\,t}} \tag{1}$$

with $EB^{ew}_{Strat,t}$ representing the equally-weighted peer group (endogenous) benchmark as the excess return of all funds belonging to the respective main- or sub-strategy *Strat* in month *t*. The variable r_{it} represents the return of the hedge fund *i*, which is allocated to strategy *Strat*, and r_{ft} represents the risk-free rate in month *t*. $n_{Strat,t}$ stands for the number of all funds which belong to *Strat* in *t*.

The value-weighted peer group benchmark is computed similarly. However, here we do not consider all funds in our sample. If the sample does not contain any information about the capitalization of certain hedge funds, these funds are not incorporated in our value-weighted peer group benchmark. If the data are incomplete, we compute the missing values for the assets under management (*AuM*) by interpolation.

$$EB^{vw}_{Strat,\,t} = \frac{\sum_{i=1}^{n} \left(r_{it} - r_{ft}\right) AuM_{it}}{\sum_{i=1}^{n} AuM_{it}} \tag{2}$$

$EB^{vw}_{Strat,t}$ in equation (2) represents the value-weighted peer group (endogenous) benchmark as the value-weighted monthly excess return of the main- or sub-strategy *Strat*. For each month *t*, we multiply the monthly excess returns $r_{it}-r_{ft}$ of hedge fund *i,* allocated to the group *Strat,* by the value of its own assets under management (AuM_{it}). Then we divide the sum of all value-weighted returns in *t* by the sum of all *AuM* of the respective main- or sub-strategy in *t*.

Base factor model

The standard multifactor model serves as our base model, where we utilize the three Fama-French Factors, namely the *Market Factor* (*MMRF*), the *Small Minus Big Factor* (*SMB*) and the *High Minus Low Factor* (*HML*) supplemented by Carhart's (1997) *Momentum Factor* (*MOM*). As our US sample contains hedge funds which are actively investing in domestic as well as international markets (including emerging markets), we augment our model in line with Agarwal and Naik (2004) to include more risk factors. The first additional factor is the return of the *MSCI Emerging Markets Index* (*EMI*). However, since this index exhibits high correlations with the market factor *MMRF*, we orthogonalize this factor against *MMRF.* We use the superscript $factor^O$ to indicate the orthogonalization of a factor against all others; for example EMI^O.

In addition, we integrate the return of the *Lehman* (now *Barclays*) *High Yield Index* (*HYI*) into our model which allows a better explanation of returns gained by fixed income strategies. As this factor exhibits no significant correlations with other benchmarks, we do not orthogonalize this factor.

One problem with hedge fund performance evaluation is to deal with non-linear factors. An effective measure for extending the benchmark portfolio from linear to non-linear is to integrate the orthogonalized returns from call and put options ($Call^O$ *and* Put^O) on market factors (Amin and Kat, 2003). This approach was first applied by Glosten and Jagannathan (1994) based on earlier work of Merton (1981) and Connor and Korajczyk (1986). By applying this approach to hedge funds, Fung and Hsieh (2001) and Mitchell and Pulvino (2001) show that there is a relation between some hedge fund strategies and option payoffs. However, Agarwal and Naik (2004) discover that the explanatory power of option return is not limited to these strategies. They show that improvements in performance measurement can be achieved for many other hedge fund strategies.

Building on previous research, we use the following regression as our base model:

$$\begin{aligned} r_{it} - r_{ft} = \alpha_i + \beta_{i,MMRF} MMRF_t + \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t \\ + \beta_{i,MOM} MOM_t + \beta_{i,EMI} EMI_t^o + \beta_{i,HYI} HYI_t \\ + \beta_{i,Call} Call_t^o + \beta_{i,Put} Put_t^o + \epsilon_{it} \end{aligned} \tag{3}$$

with r_{it} representing the return of hedge fund i in month t and r_{ft} representing the risk-free rate at time t. $MMRF_t$, SMB_t, HML_t, MOM_t, EMI_t^o, HYI_t, $Call_t^o$ and Put_t^o represent the exogenous risk factors for the corresponding month t. In the following, exogenous factors will be referred to as standard factors $SF_{t,x}$ with x representing the respective consecutively numbered factor. The intercept α_i and the residuals ϵ_{it} represent the outputs of the regression. In addition, the regression yields a beta $\beta_{i,x}$ for every risk factor x and every fund i.

For simplicity equation (3) will be expressed as:

$$r_{it} - r_{ft} = \alpha_i + \sum_{x=1}^{8} \beta_{i,x} SF_{t,x} + \epsilon_{it} \tag{4}$$

Models with orthogonalized peer group benchmarks

We introduce the peer group benchmark as an additional explanatory factor. The peer group benchmarks are formed from the sample set and augmented into our standard multi-factor model to capture otherwise non-explained variances. Depending on the exact form of the peer group benchmark, the estimated alphas will be adjusted accordingly. To make sure that the peer group benchmarks do not distort the coefficients estimated from our base model, the peer group benchmarks can be orthogonalized against all exogenous factors. As we do not want to pre-justify which orthogonalization approach will yield the most meaningful results, we consider two different approaches.

We begin with the orthogonalization of the equally- and value-weighted peer group benchmarks (index O applies to both equally- and value-weighted benchmarks) for the respective main-strategies against the exogenous factors from equation (3). For this purpose we apply the following linear OLS-multi-factor regression to either definitions in equations (1) or (2):

$$EB_{Mainstrat,t} = a_{Mainstrat} + \sum_{x=1}^{8} b_{Mainstrat,x} SF_{t,x} + e_{Mainstrat,t} \tag{5}$$

From this we get the first orthogonalized peer group benchmark:

$$EB^{O,a+e}_{Mainstrat,t} = \hat{a}^O_{Mainstrat} + \hat{e}^O_{Mainstrat,t} \tag{6}$$

where we use $\hat{a}$, $\hat{e}$ to represent the estimated values. Hunter *et al* (2014) modify this further by dropping the $\hat{a}^O_{Mainstrat}$ from equation (6). The second orthogonalized peer group benchmark thus obtained is:

$$EB^{O,e}_{Mainstrat,t} = \hat{e}^O_{Mainstrat,t} \tag{7}$$

According to Hunter *et al* (2014) this approach allows for a better identification of management skills. Later we discuss which of these two approaches is more appropriate for hedge funds.

In the second stage, we additionally augment the orthogonalized peer group benchmarks in our factor model based on the sub-strategies. This is carried out by orthogonalizing the equally- and value-weighted sub-strategy benchmarks against all exogenous factors and the respective main-strategy benchmark. Thus we get:

$$EB_{Substrat,\,t} = a_{Substrat} + \sum_{x=1}^{8} b_{Substrat,x} SF_{t,\,x} + b^{O}_{Substrat} EB^{O,\,a+e}_{Mainstrat,\,t} + e_{Substrat,\,t} \quad (8)$$

respectively

$$EB_{Substrat,\,t} = a_{Substrat} + \sum_{x=1}^{8} b_{Substrat,\,x} SF_{t,\,x} + b^{O}_{Substrat} EB^{O,\,e}_{Mainstrat,\,t} + e_{Substrat,\,t} \quad (9)$$

From this we get the results for the orthogonalized peer group sub-strategy benchmark:

$$EB^{O,\,a+e}_{Substrat,\,t} = \hat{a}^{O}_{Substrat} + \hat{e}^{O}_{Substrat,\,t} \quad (10)$$

respectively

$$EB^{O,\,e}_{Substrat,\,t} = \hat{e}^{O}_{Substrat,\,t} \quad (11)$$

Finally, we augment the orthogonalized main- and sub-strategy peer group benchmarks into our multi-factor-models:

$$r_{it} - r_{ft} = \alpha_i + \sum_{x=1}^{8} \beta_{i,\,x} SF_{t,\,x} + \beta_{i,\,Mainstrat} EB^{O,\,a+e}_{Mainstrat,\,t} + \beta_{i,\,Substrat} EB^{O,\,a+e}_{Substrat,\,t} + \epsilon_{it} \quad (12)$$

and

$$r_{it} - r_{ft} = \alpha_i + \sum_{x=1}^{8} \beta_{i,\,x} SF_{t,\,x} + \beta_{i,\,Mainstrat} EB^{O,\,e}_{Mainstrat,\,t} + \beta_{i,\,Substrat} EB^{O,\,e}_{Substrat,\,t} + \epsilon_{it} \quad (13)$$

respectively, with $\beta_{i,Mainstrat}$ representing the factor loading for the respective main-strategy for each fund i and $\beta_{i,Substrat}$ representing the factor loading for the respective sub-strategy for each fund i.

All peer group benchmarks in all variations are separately calculated for the equally- and value-weighted cases.

DATA

Hedge funds data

Our dataset covers a 20-year period between the 1 January 1990 and the 2 January 2010 that exceeds the sample period of most previous studies. In addition, this time frame covers several different market conditions, including the bull market of the 1990s when the S&P500 index increased from 379 to 2002 points and where the total return of the S&P500 more than quintupled between January 1990 and January 2000, and the subsequent crisis-ridden decade, characterized by the bursting of the dotcom bubble and the global financial crisis.

Hence, in contrast to most other studies which are restricted to the 90s and late 80s, we analyze the performance of hedge funds during a period of serious crisis. Fung and Hsieh (2004) and Agarwal and Naik (2004) note that the 90s do not offer a sufficiently varied market environment to reasonably measure hedge fund performance in different market phases. For evaluating hedge funds' performance, considering periods of negative market performance is essential, since the term *hedge fund* implicitly assumes the use of hedging to minimize market risk.

In accordance with previous studies we use monthly returns for our study. All relevant information, such as the funds' monthly returns, the *AuM*, the currency denomination, as well as funds' main- and sub-strategies, are obtained from the *Life Fund* and *Dead Fund* databases from *Hedge Funds Research (HFR)*. The *Life Fund* only contains funds which report to *HFR* by the end of our sample period. The latter includes all funds which stopped reporting data to *HFR* before the end of our sample period either because of the tactical closure or liquidation. After screening the database for redundant indices and duplications our *base sample* encompasses 14 816 funds, with 4418 identified as *liquidated*, 4101 classified as *not reporting* and 6297 classified as *live*.

We further screen the data to make sure that we only consider funds reporting all of their returns in USD monthly. Furthermore, we only consider funds which provide detailed information about the fees charged. By removing all other funds from our sample we obtain our *benchmark sample* that we used to calculate the peer group benchmarks. Further, we also eliminate all funds which did not report more than 36 monthly returns to *HFR,* which leaves us with a *study sample* of 7559 funds.

Table 1 gives an overview of the strategy allocations in the *HFR*-database and the number of monthly return observations for all funds included in the *study sample*.

The *study sample* we use for our performance evaluation might embody several biases, which we had to consider in order to control for potential distortions of our findings. Studies working with any kind of performance data are often affected by *survivorship biases*, which occur when underperforming 'dead' funds are not sufficiently considered in the evaluation process. Previous studies on hedge fund performance observe positive distortions in yearly returns from 0.16 per cent (Ackermann *et al*, 1999) up to 3 per cent (Brown *et al,* 1999; Liang, 2000; Amin and Kat, 2001, 2003; Capocci, 2001), which are caused by yearly hedge fund liquidation rates of up to 20 per cent (Brown *et al*, 1999). We can however control for these biases by including both 'live' and 'dead' funds in our sample.

There is another group of agency caused biases, which are more difficult to rule out and which are particularly relevant in the context of the comparably unregulated hedge fund industry, in which managers are able to strategically decide whether and how to report performance to data base providers. This group includes, (i) *self-selection biases,* occurring when sufficiently capitalized funds decide to cease reporting returns to data providers (Ackermann *et al,* 1999), (ii) *liquidation biases*, occurring when in the face of liquidation managers stop reporting (Fung and Hsieh, 2011), (iii) *instant history* or

Table 1: Strategy allocation of hedge funds

	#	*share (%)*	*ø obser. per fund*		#	*share (%)*	*ø obser. per fund*
Event Driven	**600**	**7.94**	**120.0**	*Macro*	**1192**	**15.77**	**116.6**
Activist	22	0.29	119.2	Active Trading	36	0.48	109.3
Credit Arbitrage	22	0.29	79.3	Commodity – Agriculture	19	0.25	145.8
Distressed/Restructuring	178	2.35	119.0	Commodity – Energy	4	0.05	124.0
Merger Arbitrage	92	1.22	131.0	Commodity – Metals	17	0.22	75.4
Multi-Strategy	12	0.16	172.6	Commodity – Multi	48	0.64	111.5
Private Issue/Regulation D	39	0.52	81.7	Currency – Discretionary	17	0.22	135.1
Special Situations	235	3.11	119.1	Currency – Systematic	140	1.85	118.1
				Discretionary Thematic	252	3.33	107.9
Equity Hedge	**2859**	**37.82**	**108.8**	Multi-Strategy	96	1.27	105.6
Equity Market Neutral	353	4.67	103.8	Systematic Diversified	563	7.45	121.3
Fundamental Growth	697	9.22	112.8				
Fundamental Value	1128	14.92	111.6	*Relative Value*	**1003**	**13.27**	**102.0**
Multi-Strategy	54	0.71	120.0	Fixed Income – Asset Backed	135	1.79	105.4
Quantitative Directional	246	3.25	101.5	Fixed Income – Convertible A.	179	2.37	120.9
Sector – Energy/Basic Mat.	101	1.34	87.7	Fixed Income – Corporate	188	2.49	91.5
Sector – Technology/HC	235	3.11	97.5	Fixed Income – Sovereign	32	0.42	100.8
Short Bias	45	0.60	123.9	Multi-Strategy	338	4.47	100.8
				Volatility	73	0.97	81.3
Fund of Funds	**1905**	**25.20**	**113.6**	Yield A. – Energy Infra.	29	0.38	62.8
Conservative	425	5.62	113.4	Yield A. – Real Estate	29	0.38	93.0
Diversified	783	10.36	116.1				
Market Defensive	92	1.22	135.7				
Strategic	605	8.00	106.3	*Total*	**7559**	**100**	**111.4**

This table gives an overview of the strategy allocations in the *HFR*-database and the number of monthly return observations for all funds included in the sample.

backfill biases that can be observed when funds are able to report returns ex post (Fung and Hsieh, 2000), thereby allowing managers to only report successful performances in order to attract more capital (Capocci, 2001), as well as, (iv) *stale price biases*, occurring when hedge funds report assets based on non-liquid OTC-securities, which cannot be priced precisely, therefore allowing managers to overstate and understate performance (Asness *et al*, 2001; Schneeweis *et al*, 2001).

However, in our study these influences can be mitigated. The focus of the present study lies on exploring a new methodology. This methodology may actually help overcome the presented problems. It is likely that specific hedge fund strategies are more strongly affected by some of the previously mentioned biases than others (for example, because of differences in OTC exposure or liquidation rates). By comparing individual hedge funds to other hedge funds with a similar risk exposure, we can control for systematic differences between strategies, which could for instance be caused by strategy specific biases. If hedge fund managers within a specific category strategically report data in order to improve their alpha, this will lead to an overestimated performance for the whole benchmark, on which individual fund performances are regressed. If all individual funds pursuing a strategy are similarly affected by these biases, the distortions cancel out in the multi-factor-model. A potential problem with this approach is that individual funds which are not subject to any agency caused biases may be compared with a biased benchmark. To control for this, in equations (7) and (11) we presented orthogonalization options, in which benchmark alphas are eliminated from the multi-factor-model. These approaches may be more useful, when individual funds within categories are likely to be heterogeneously affected by agency caused biases.

However, albeit in reference to such biases the quality of hedge funds data has often been questioned, a recent study by Edelman *et al* (2013) provides some credence to the reliability of the data provided by commercial data vendors. Examining a group of mega hedge funds which have never reported to commercial data vendors they show that these funds have many similarities with reporting mega funds. They compare the performance of mega funds that chose not to report to commercial databases with the performance of reporting mega funds and find no significant differences in average returns and volatilities.

Exogenous factors

For calculating the excess returns we use the risk-free interest rate provided by French (mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html). In addition, we also obtain *market returns (MMRF), SMB, HML* and Carhart's *momentum factor (MOM)* from French's website. All other exogenous factors (EMI^O, *HYI*, $Call^O$, Put^O) were obtained from *Datastream* or computed by ourselves.

We construct our option factors analogously to Agarwal and Naik (2004).
We use European call and put options on the *S&P 500*. We compute the option prices in-house, applying the pricing model of Black and Scholes (1973) and Merton (1973). For computing the prices of put and call options, we use the *S&P 500* price index as well as its implicit volatilities, which are tracked by the *Chicago Board Options Exchange Market Volatility Index (VIX)*. For the risk-free rate we use the monthly US Treasury Bill rates. As the earliest *VIX* time series only goes back to the first of January 1990 and we need the option price of the previous month to calculate a month's return, the available information does not allow the calculation of option returns for the month of January 1990. Hence, in all our examinations, we neglect the option factors for January 1990. Table 2 lists the correlations between all exogenous factors for the 20-year period investigated.

EMPIRICAL RESULTS

Since there is no theoretical rule as to whether and how to orthogonalize the peer group

Table 2: Correlations of exogenous factors

	HYI	*EMI*	*Call*	*Put*	*MMRF*	*SMB*	*HML*	*MOM*
HYI	1.000							
EMI	0.301	1.000						
Call	0.303	0.511	1.000					
Put	−0.303	−0.616	−0.789	1.000				
MMRF	0.296	0.713	0.806	−0.855	1.000			
SMB	0.146	0.289	0.021	−0.127	0.198	1.000		
HML	−0.020	−0.212	−0.251	0.249	−0.269	−0.354	1.000	
MOM	−0.069	−0.226	−0.208	0.233	−0.281	−0.126	−0.046	1.000

This table reports the correlations between all exogenous factors for the total evaluation period from 1 January 1990 to 31 February 2010.

benchmark, we first clarify the common and distinctive features of all alternative approaches. We do this on the basis of a one-stage peer group benchmark for multiple exogenous factors. The respective regressions are estimated using OLS as usual.

There are four main options considered:

1. Non-inclusion of any peer group benchmark (‘*no EB*’), corresponding to equation (4).
2. Inclusion of a non-orthogonalized peer group benchmark (‘*EB non-orth*’).
3. Inclusion of an orthogonalized peer group benchmark – Use of epsilons *e* plus benchmark-alphas *a* (‘*EB a+e*’), that is, corresponding to equation (12).
4. Inclusion of an orthogonalized peer group benchmark without the benchmark-alphas – Use of the epsilons *e* only (‘*EB e*’), that is, corresponding to equation (13).

In the following we present and interpret the findings of our examinations. We focus on the different variations of the peer group benchmark, as it is our aim to examine to which extent the alternative peer group benchmarks can improve performance measurement.

Performance measurement of individual funds

Table 3 presents regression results from the base model as well as three alternatives with various forms of endogenous benchmarks (*EB*). The top panel gives the estimated means of alphas and associated statistics and the bottom panel lists the estimated means of factor loadings and their statistics. The results when only using exogenous factors are summarized in row one (‘*no EB*’). The results from the base model with non-orthogonalized benchmark (‘EB non-orth’) are in row two. The rows three and four present the results with two forms of orthogonalized benchmarks (‘EB a+e’ and ‘EB e’) respectively.

First, it is striking that the mean alpha for hedge funds is significantly positive when using the exogenous factors only. This suggests that the hedge fund managers outperformed the market on average by approximately 3.7 per cent per annum (0.267 per cent per month.) over the study period. Of the 7559 hedge funds under consideration, 1444 (19 per cent) hedge funds significantly outperformed the market, measured by positively significant alphas, whereas only 293 (4 per cent) significantly underperformed the market (measured by negatively significant alphas).

With the non-orthogonalized peer group benchmark (Option 2) we obtain a significantly negative mean alpha of −0.024. It is not surprising that after implementing a non-orthogonalized peer group benchmark (Option 2), the model results in different estimates for the alphas. Because of the inclusion of the non-orthogonalized benchmarks under Option 2, all common factor loadings are expected to be shifted to the peer group benchmark. Therefore the information about

Table 3: Performance with equal-weighted peer group benchmarks

	Mean	*Standard deviation*	*Minimum*	*Maximum*	*Mean P-value P>|t|*	*Number of positive*	*Number of negative*	*** Number of sig.*	*** Number of pos sig.*	*** Number of neg sig.*	*** Number of pos not sig.*	*** Number of neg not sig.*
alpha												
1. no EB	***0.267	0.920	−7.589	12.508	0.357	4927	2632	1737	1444	293	3483	2339
2. EB non-orth	**−0.024	0.918	−12.259	12.423	0.358	3764	3795	1702	900	802	2864	2993
3. EB a+e	**−0.024	0.918	−12.259	12.423	0.358	3764	3795	1702	900	802	2864	2993
4. EB e	***0.267	0.920	−7.589	12.508	0.307	4927	2632	2354	1820	534	3107	2098
	Mean	*Standard deviation*	*Minimum*	*Maximum*	*Mean P-value P>|t|*			*Mean*	*Standard deviation*	*Minimum*	*Maximum*	*Mean P-value P>|t|*
β-MMRF						*β-EMI[O]*						
1. no EB	***0.335	0.448	−3.012	7.742	0.132	*1. no EB*		***0.153	0.279	−2.261	2.734	0.307
2. EB non-orthogonalized	−0.007	0.456	−12.470	4.345	0.319	*2. EB non-orthogonalized*		**−0.005	0.228	−4.291	2.616	0.424
3. EB a+e	***0.335	0.448	−3.012	7.742	0.120	*3. EB a+e*		***0.153	0.279	−2.261	2.734	0.273
4. EB e	***0.335	0.448	−3.012	7.742	0.120	*4. EB e*		***0.153	0.279	−2.261	2.734	0.273
β-HML						*β-Call[O]*						
1. no EB	***0.018	0.318	−4.931	2.594	0.341	*1. no EB*		***−0.001	0.030	−0.956	0.271	0.359
2. EB non-orthogonalized	***0.011	0.286	−3.489	2.376	0.386	*2. EB non-orthogonalized*		0.000	0.024	−0.801	0.244	0.407
3. EB a+e	***0.018	0.318	−4.931	2.594	0.297	*3. EB a+e*		***−0.001	0.030	−0.956	0.271	0.316
4. EB e	***0.018	0.318	−4.931	2.594	0.297	*4. EB e*		***−0.001	0.030	−0.956	0.271	0.316
β-SMB						*β-Put[O]*						
1. no EB	***0.049	0.288	−3.256	3.233	0.411	*1. no EB*		***0.002	0.018	−0.158	0.274	0.450
2. EB non-orthogonalized	−0.004	0.298	−11.137	3.146	0.418	*2. EB non-orthogonalized*		**−0.001	0.016	−0.177	0.285	0.448
3. EB a+e	***0.049	0.288	−3.256	3.233	0.356	*3. EB a+e*		***0.002	0.018	−0.158	0.274	0.394
4. EB e	***0.049	0.288	−3.256	3.233	0.356	*4. EB e*		***0.002	0.018	−0.158	0.274	0.394
β-MOM						*β-Mainstrat*						
1. no EB	0.053	0.204	−2.833	2.552	0.307	*1. no EB*		—	—	—	—	—
2. EB non-orthogonalized	**−0.005	0.183	−3.517	1.650	0.368	*2. EB non-orthogonalized*		**0.054	2.015	−23.627	23.639	0.340
3. EB a+e	***0.053	0.204	−2.833	2.552	0.270	*3. EB a+e*		***1.004	1.114	−17.618	23.922	0.136
4. EB e	***0.053	0.204	−2.833	2.552	0.270	*4. EB e*		***1.004	1.114	−17.618	23.922	0.136
β-HYI						*β-Substrat*						
1. no EB	***−0.069	0.928	−14.408	10.879	0.418	*1. no EB*		—	—	—	—	—
2. EB non-orthogonalized	0.013	0.824	−10.903	15.884	0.436	*2. EB non-orthogonalized*		***0.955	2.005	−12.124	34.051	0.258
3. EB a+e	***−0.069	0.928	−14.408	10.879	0.371	*3. EB a+e*		***0.955	2.005	−12.124	34.051	0.258
4. EB e	***−0.069	0.928	−14.408	10.879	0.371	*4. EB e*		***0.955	2.005	−12.124	34.051	0.258
Number observations: 7559		Mean R^2:	*no EB*	0.399	—	*EB non–orthogonalized = EB a+e = EB e:*				0.563	—	—

This table reports the mean alphas and the mean R^2 of all hedge funds in the study sample as well as the mean estimated coefficients for all exogenous factors and equally-weighted endogenous main- and sub-strategy benchmarks. For the alphas and the coefficients the standard deviation, the minimum and the maximum values as well as the mean *P*-values are reported. In addition, this table reports the number of positive and negative alphas, the number of significant alphas and further details about the algebraic signs of estimated significant and non-significant alphas. The results are shown separately for four different Options: (1) The use of no endogenous benchmark at all (*no EB*), (2) the use of non-orthogonalized endogenous benchmarks (*EB non-orthogonalized*), (3) the use of orthogonalized endogenous benchmarks which comprise the estimated intercepts *a* as well as the residuals *e* (*EB a+e*), (4) the use of orthogonalized endogenous benchmarks which only comprise the estimated residuals *e* (*EB e*). ***/** denote significance (sig.) of being different from 0 at the 1%/5% level.

how the funds perform against the exogenous factors – in other words the market – is not visible any more. By construction this leads to the result that the mean alpha and the mean betas for all exogenous factors over all funds become 0.

However, in our study sample the group alpha with a value of −0.024 differs from 0. This is because of the different time frames the single funds had when constructing the fund dependent peer group benchmarks. Therefore this group alpha cannot be interpreted in the way that the hedge funds underperformed the market on average and is therefore unique to the study sample. However, the single alphas can be used to rank the individual funds relative to their intra-fund risks. We find that 900 (12 per cent) of the funds significantly outperformed their peer group, whereas 802 (11 per cent) significantly underperformed their peer group.

In specification of Option 3, when the model includes the orthogonalized benchmark $a+e$, the mean of the estimated alpha as well as its t-statistics are the same as the ones under Option 2. The results here suggest that implementing the benchmark affects the estimates of alphas; however, there is no difference in estimated alphas when using a non-orthogonalized benchmark or orthogonalized with a group alpha. Consequently, under Option 2, we find the number of funds outperformed the market drops to 900 while the number of funds underperformed the market increases to 802. This is not surprising as in Option 2 the individual funds are evaluated to its peer group average as well as exogenous factors. However, since the regression model in Option 2 is spurious, the results from Option 3 offer more reliable information on outperformed/ underperformed funds relative to Option 1.

When the orthogonalized benchmark with residuals only is used (Option 4), the estimated mean of alphas is the same as in Option 1. However, the t-statistics improve in Option 4, with a lower mean P-value. Consequently, the number of funds with positive significant alphas increases to 1820 (previously at 1444) while funds with negative significant alphas increase to 534 (previously at 293).

The Option 4 combines the 'original' alphas (from the base model) and exogenous factor loadings with the new peer group benchmarks, in expectation of better test-statistics for the coefficients as per Hunter *et al* (2014). Therefore this approach makes sense if one is interested in the performance of the hedge funds against all exogenous factors.

The bottom panel of Table 3 provides the estimated mean coefficients as well as their t-statistics for all selected risk factors including the peer group benchmark. As to the eight exogenous factors considered, across all four options the mean P-value is the lowest for the market returns indicating that this is the most important exogenous factor for hedge funds regardless whether a group benchmark is included in the model or in what form it is implemented.

When the peer group benchmarks are orthogonalized under Options 3 and 4, there is no change in the mean estimates of factor loadings, but we get lower P-value on average compared with the base model. However, the mean P-values of most of the exogenous factors increase when the peer group benchmarks are not orthogonalized as in Option 2. This is because the implemented benchmark correlates with other risk factors to some degree.

The results for the factor loadings demonstrate that the implementation of orthogonalized group benchmark does not change the coefficient estimates but improves the t-statistics of the estimates. This can also be confirmed by the increased R-squared estimates. The R-squared statistics increases from 0.399 in the base model to 0.563 when a group benchmark is included regardless of the form of implementation. Thus, the results here support the implementation of a group benchmark.

The economic interpretation of different specifications offers some useful insights when evaluating hedge fund performances. The base model measures the performance of the fund relative to all identified exogenous risk factors while in Option 2 the fund is also measured against its peer group. Assuming that not all exogenous factors are captured in the standard model this approach thus is sensible, especially, when one is interested in choosing one fund out of the available funds within one peer group. However, as the benchmark variable is correlated with the funds return, the regression is spurious.

To prevent changes in factor loadings of the exogenous factors the orthogonalized peer group benchmark (Option 3) is used. Now the estimated alphas including the test-statistics are by construction the same as in Option 2. The betas for the exogenous factors are by construction the same as in Option 1. Therefore the overall economic interpretation of these results – especially the alphas – is analogous to Option 2. From an econometric perspective, both Option 3 and Option 4 improve the estimates of alpha thus are superior to the specification of Options 1 and 2.

To briefly summarize the findings from Table 3, the adoption of peer group benchmark regardless the form of benchmarking improves the estimation of the individual fund alpha. As suggested by Hunter *et al* (2014), if the source of a fund's performance comes from unique skills that are unrelated to co-movement, the alpha should be strong in both Options 3 and 4. But this is not the case here. Among 1444 top performing funds identified by the factor model, only 900 of them stay top performing when the group alpha is included in the benchmark and there are also more poor performing funds of 802 compared with 293 in the base model. If the peer group benchmark does not include the group alpha (Option 4), more funds are identified as outperforming (1820 compared with 1444 in the factor model), which is because some funds either have highly correlated skills or load on a common missing risk factor.

Overall, depending on the aim of the performance analysis, the Option 3 (*EB* $a+e$) and Option 4 (*EB* e) deliver richer and more comprehensive performance information than Option 2 and Option 1, respectively. Therefore we limit our discussions to these of Options 3 and 4 in our subsequent analyses.

Performance measurement of strategies

In Table 4 we summarize the mean alphas, test-statistics and R-squared statistics for the different main- and sub-strategies when using the peer group benchmarks $a+e$ (Option 3) and the peer group benchmark e (Option 4). We also rank the performances of funds in our sample according to their main- and sub-strategies under two options. The rankings are provided in the first two columns and the mean R-squared of two options are provided in the last column, as previously stated, these two options provide same R-squared numbers.

At the main-strategy level, four out of five strategies, 'Event Driven', 'Equity Hedge', 'Macro', 'Relative Value' have significant positive alphas between 0.16 and 0.67. It is not surprising that the 'Fund of Funds' group is the only one which has no significant alpha because of its 'passive' nature. The most outperforming strategy is 'Macro'. The rankings of five main-strategies are quite consistent regardless of the form of the benchmark. Similar to the results in Table 3, the mean alphas under Option 3, which is the '*EB* $a+e$' are a lot lower than Option 4 (*EB* e). This is because of the fact that in Option 3 the funds' group average is considered as the benchmark. Interestingly, only 'Fund of Funds' appears to be significant but negatively. This again suggests that the 'Fund of Funds' is the worst performing strategy. Within each main-strategy, the number of funds with significant positive alphas are 218 (36 per cent) for 'Event Driven', 673 (24 per cent) for 'Equity Hedge', 635 (33 per cent) for

Table 4: Regression alphas with equal-weighted peer group benchmarks for different strategies

	Rank		*Mean alpha*		*Mean P-Value P>|t|*		*Observations*	*# positive alpha*		*** # sig. alphas*		*Mean R^2*
	Left: EB e	*Right: EB a+e*	*EB e*	*EB a+e*	*EB e*	*EB a+e*	*both Cases*	*EB e*	*EB a+e*	*EB e*	*EB a+e*	*EB e = EB a+e*
Event Driven	**2**	**2**	***0.374	0.041	0.276	0.344	600	439	264	218	174	0.535
Activist	*31*	*4*	0.033	0.117	0.332	0.351	22	11	10	5	8	0.616
Credit Arbitrage	*26*	*32*	0.171	–0.141	0.131	0.183	22	15	9	12	10	0.614
Distressed/Restructuring	*21*	*24*	***0.268	–0.035	0.302	0.370	178	127	84	55	48	0.527
Merger Arbitrage	*23*	*20*	***0.248	–0.027	0.278	0.318	92	70	36	37	34	0.509
Multi-Strategy	*10*	*10*	**0.526	0.033	0.117	0.415	12	10	4	7	4	0.509
Private Issue/Regulation D	*1*	*36*	***1.170	–0.461	0.129	0.266	39	37	19	23	10	0.426
Special Situations	*16*	*12*	***0.413	0.009	0.296	0.357	235	169	102	79	60	0.556
Equity Hedge	**3**	**4**	***0.292	–0.032	0.343	0.386	2859	1903	1486	673	487	0.532
Equity Market Neutral	*25*	*15*	***0.185	–0.003	0.370	0.360	353	239	180	81	82	0.384
Fundamental Growth	*20*	*29*	***0.291	–0.104	0.346	0.390	697	464	350	151	118	0.572
Fundamental Value	*19*	*11*	***0.299	0.014	0.328	0.390	1128	746	604	285	174	0.532
Multi-Strategy	*14*	*3*	***0.479	**0.252	0.233	0.368	54	43	35	20	14	0.446
Quantitative Directional	*22*	*34*	***0.259	–0.152	0.402	0.393	246	149	117	45	38	0.560
Sector – Energy/ Basic Materials	*27*	*35*	0.162	–0.197	0.350	0.343	101	55	44	21	20	0.655
Sector – Technology/Healthcare	*11*	*7*	***0.513	0.064	0.330	0.404	235	180	133	64	33	0.544
Short Bias	*30*	*31*	0.059	–0.125	0.336	0.426	45	27	23	6	8	0.676
Fund of Funds	**5**	**3**	0.004	***–0.029	0.297	0.331	1905	995	924	635	494	0.727
Conservative	*35*	*22*	0.010	–0.029	0.238	0.299	425	228	204	186	136	0.710
Diversified	*33*	*17*	**0.029	–0.017	0.290	0.323	783	421	381	258	213	0.734
Market Defensive	*17*	*28*	***0.381	–0.091	0.217	0.357	92	75	42	48	23	0.625
Strategic	*37*	*23*	***–0.091	–0.035	0.361	0.359	605	271	297	143	122	0.744
Macro	**1**	**1**	***0.664	0.042	0.288	0.400	1192	945	606	404	205	0.443
Active Trading	*4*	*19*	***0.771	–0.018	0.245	0.489	36	33	25	14	7	0.394
Commodity – Agriculture	*5*	*2*	***0.725	0.269	0.257	0.250	19	16	10	6	5	0.570
Commodity – Energy	*6*	*37*	0.619	–0.753	0.413	0.284	4	2	1	1	0	0.609
Commodity – Metals	*12*	*27*	0.492	–0.090	0.282	0.328	17	11	7	3	4	0.683
Commodity – Multi	*2*	*1*	***0.952	0.446	0.250	0.379	48	41	28	15	6	0.474
Currency – Discretionary	*9*	*26*	***0.532	–0.065	0.295	0.559	17	16	9	6	0	0.395
Currency – Systematic	*15*	*16*	***0.456	–0.008	0.326	0.324	140	100	68	34	24	0.344
Discretionary Thematic	*18*	*14*	***0.311	0.005	0.365	0.424	252	178	131	58	47	0.427
Multi-Strategy	*8*	*5*	***0.583	0.098	0.298	0.402	96	75	49	34	17	0.417
Systematic Diversified	*3*	*9*	***0.864	0.036	0.250	0.407	563	473	278	233	95	0.468
Relative Value	**4**	**5**	***0.159	–0.056	0.265	0.289	1003	645	484	424	342	0.498
Fixed Income – Asset Backed	*13*	*6*	***0.487	0.074	0.211	0.206	135	106	81	76	76	0.369
Fixed Income – Convertible Arb.	*29*	*13*	0.076	0.006	0.227	0.284	179	111	87	93	56	0.607
Fixed Income – Corporate	*36*	*33*	–0.078	–0.142	0.317	0.336	188	93	82	64	52	0.523
Fixed Income – Sovereign	*32*	*18*	0.032	–0.017	0.239	0.240	32	20	18	13	14	0.487

Table 4: (Continued)

	Rank		Mean alpha		Mean P-Value P>|t|		Observations	# positive alpha		** # sig. alphas		Mean R^2
	Left: EB e	Right: EB a+e	EB e	EB a+e	EB e	EB a+e	both Cases	EB e	EB a+e	EB e	EB a+e	EB e = EB a+e
Multi-Strategy	24	30	***0.213	**−0.108	0.273	0.309	338	237	149	138	106	0.467
Volatility	34	25	0.013	−0.057	0.254	0.250	73	37	36	26	26	0.477
Yield Alternatives – Energy Infra.	7	21	**0.601	−0.028	0.389	0.290	29	21	14	8	7	0.661
Yield Alternatives – Real Estate	28	8	0.129	0.042	0.251	0.322	29	20	17	6	5	0.529
Number of Observations: 7559	—	—	Mean R^2 total: *EB a+e = EB e*:				0.563	—	—	—	—	—

This table reports the mean alpha and the mean R^2 for all main- and sub-strategies in the HFR-database. The results are shown separately for the two orthogonalization options *EB a+e* and *EB e*. For each strategy the mean *P*-values of the estimated alphas, the number of positive alphas as well as the number of significant alphas are reported. The table additionally includes rankings which show the relative performance of individual strategies in relation to the other strategies. There are separate rankings for main- and sub-strategies and for the two orthogonalization options respectively. ***/** denote significance of being different from 0 at the 1%/5% level.

'Fund of Funds', 404 (34 per cent) for 'Macro' and 424 (42 per cent) for 'Relative Value'. However, when measured against the peer group alphas, that is, under Option 3 (*EB a+e*), the outperforming funds drop in both numbers and proportions.

At the sub-strategy level, most subgroups have significant positive mean alphas under Option 4 (*EB e*), however, most of them lose their significance under Option 3 (*EB a+e*), except the 'Multi-Strategy' in 'Equity Hedge' and 'Multi-Strategy' in 'Relative Value' that appears to be negatively significant.

As we get considerably deviating values for the estimated alphas from the orthogonalized peer group benchmark *a+e* (Option 3) and the orthogonalized peer group benchmark *e* (Option 4), we consider whether the rankings of individual funds and additionally groups of funds diverge, depending on the peer group benchmarks used. We started with calculating the rankings of the mean alphas of all funds within one main-strategy and one sub-strategy respectively (column 'rank' in Table 4). We notice that at the main-strategy level, rankings by Options 3 or 4 are similar. The strategy 'Macro' comes first, the second is 'Event Driven', which is followed by the remaining three strategies. However, at the sub-strategy level, there is a huge variation in rankings among most of the cases. Only four sub-strategies are ranked same or similarly, namely 'Multi-Strategy', 'Short Bias', 'Commodity-Multi' and 'Currency-Systematic'. Rankings of other sub-strategies are considerably different with respect to different ways of orthogonalizing the peer group benchmark. For instance, the sub-strategy *Private Issue/Regulation D* is ranked 1 of 37 for the orthogonalized peer group benchmark *e* (Option 4), but when we apply the orthogonalized peer group benchmark *a+e* (Option 3), the same sub-strategy clearly underperforms (rank 36 of 37 sub-strategies).

To further examine to what extent the rankings of single hedge funds depend on the applied orthogonalization method, we also rank the calculated alphas of all individual funds in our study sample for both the peer group benchmarks, Options 3 (*EB a+e*) and 4 (*EB e*). In both rankings the fund with the highest alpha is ranked first and the fund with the lowest alpha is ranked 7559th. We observe considerable differences between the two rankings (for the brevity of the presentation, the results are not provided here). We find that the mean change in ranking is 1098 with a standard deviation of 1150. Hence, the peer group benchmark adopted exerts an influence on the relative performance evaluation of individual fund managers. The correlation of the two types of rankings is only 0.73 that is considerably low and suggests that rankings clearly change radically for the different peer group benchmark of Option 3 (*EB a+e*) versus Option 4 (*EB e*).

Table 5 presents the estimated coefficients for models with Options 3 (*EB a+e*) and 4 (*EB e*). As shown in Table 3, these two specifications provide same results for factor loadings. It can be seen that the factor loadings of the peer group benchmark $\beta_{i,mainstrat}$ and $\beta_{i,substrat}$, shown by the last four columns, are in most cases significantly different from 0, which again highlights the importance of implementing the peer group benchmarks. Among all other risk factors, the excess market return is still the most significant variable in explaining funds' performance. It might be surprising that the mean factor loadings on the peer group benchmarks are not one. However, this is because of the different time-frames the individual funds existed.

To verify our results using the equally-weighted group returns, we also repeat all tests using the value-weighted group returns as the peer group benchmarks. The results in Table 6 are comparable to those in Table 3 and basically similar from an economical point of view, which provides support to the robustness of our approach.

Overall, our results confirm that implementing the group return as a peer group benchmark in the standard risk factor model improves the estimates of the funds' alpha. In addition, implementing the orthogonalized peer group benchmark does not change the estimates of factor loadings, but increases the explanatory power of the model. The rankings and therefore the relative performance of individual funds deviate according to the different specification of benchmarks.

CONCLUSION

To the best of our knowledge this article is the first in adopting the concept of a two-stage peer group benchmark to measure the performance of hedge funds. The main purpose of using the endogenous peer group benchmarks is to obtain an improved assessment of the relative performance of hedge funds as the exogenous factors alone do not capture all the implicit commonalities and explicit strategies of various funds.

Expanding the concept of peer group benchmarks by Hunter *et al* (2014), who measure the performance of mutual funds, we show that two-stage peer group benchmarks are a simple but effective way to avoid the 'missing factors' and 'commonality' problem when assessing individual hedge funds performances.

In summary, we find that the hedge funds in our data sample exhibit a significantly positive alpha of about 3.7 per cent per annum on average against the exogenous factors. When using the non-orthogonalized peer group benchmark (Option 2) or the orthogonalized peer group benchmark including the benchmark-alpha (Option 3), the alphas reflect the relative performance against both exogenous factors as well as peer groups of funds, which allows identifying the top/bottom performing funds relative to their group averages. By this way individually added value to fund performance can be isolated from the value added by common investment strategies used by the whole peer group. When using the orthogonalized peer group benchmark (Option 4) without the benchmark-alpha, the significance in results increased, without

Table 5: Regression betas with equal-weighted peer group benchmarks for different strategies

The results for EB e and EB a+e are the same	$\varnothing\,\beta$ *MMRF*	$\varnothing\,\beta$ *HML*	$\varnothing\,\beta$ *SMB*	$\varnothing\,\beta$ *MOM*	$\varnothing\,\beta$ *Put*^{O}	$\varnothing\,\beta$ *Call*^{O}	$\varnothing\,\beta$ *HYI*	$\varnothing\,\beta$ *EMI*^{O}	$\varnothing\,\beta$ *mainstrat*	$\sigma\,\beta$ *mainstrat*	$\varnothing\,\beta$ *substrat*	$\sigma\,\beta$ *substrat*
Event Driven	0.316***	0.071***	0.111***	0.011	−0.001	−0.005***	−0.118***	0.072***	1.021	0.828	1.026***	1.806
Activist	0.747***	0.140	0.245***	0.000	−0.003	−0.005	−0.134	0.239	1.265***	1.047	1.216***	1.499
Credit Arbitrage	0.239***	−0.011	0.074**	−0.036	−0.001	−0.013**	−0.423***	−0.020	0.974***	0.661	1.029***	1.178
Distressed/Restructuring	0.293***	0.088***	0.108***	0.017**	−0.002**	−0.008***	−0.201***	0.050	1.221***	0.777	1.016***	1.324
Merger Arbitrage	0.147***	0.060***	0.040***	0.009	−0.001	−0.001	0.032	0.033***	0.456***	0.345	0.953***	0.429
Multi-Strategy	0.243***	0.044	0.019	−0.018	−0.003	−0.004	−0.289	0.128	1.048***	0.868	0.783**	1.039
Private Issue/Regulation D	0.187***	0.055	0.114	0.106***	−0.007**	−0.002	−0.387***	0.071	1.002***	0.977	1.327***	1.623
Special Situations	0.391***	0.067***	0.136***	−0.002	0.002	−0.003**	−0.030	0.093***	1.074***	0.873	1.008***	2.475
Equity Hedge	0.502***	0.015**	0.084***	0.063***	0.003***	−0.003***	−0.126***	0.205***	1.033***	1.322	1.028***	2.119
Equity Market Neutral	0.084***	0.065***	0.024***	0.064***	0.000	0.000	−0.025	0.036***	0.420***	0.668	0.890***	1.437
Fundamental Growth	0.723***	0.008	0.055***	0.082***	0.006***	−0.001	−0.234***	0.414***	1.406***	1.390	1.054***	2.182
Fundamental Value	0.473***	0.063***	0.100***	0.037***	0.003***	−0.001	−0.080***	0.153***	0.925***	1.066	1.145***	2.443
Multi-Strategy	0.392***	0.015	0.066**	0.016	0.004	−0.001	−0.099	0.190***	0.518***	0.854	0.297	1.354
Quantitative Directional	0.704***	−0.017	0.237***	0.070***	0.003	−0.006	−0.144**	0.120***	1.088***	2.029	0.977***	2.572
Sector – Energy/Basic Materials	0.784***	0.068	0.159***	0.123***	0.005**	−0.013***	−0.473***	0.511***	2.119***	1.575	1.017***	0.757
Sector – Technology/Healthcare	0.576***	−0.269***	0.071***	0.123***	0.004***	−0.010***	−0.114	0.087***	1.213***	1.328	0.836***	0.955
Short Bias	−0.929***	0.075	−0.300***	−0.040	−0.008**	−0.008	0.395***	−0.018	−0.266	0.999	0.944***	0.746
Fund of Funds	0.309***	0.003	0.028***	0.074***	0.002***	−0.002***	−0.160***	0.158***	1.012***	0.542	0.932***	2.008
Conservative	0.190***	0.016**	0.011***	0.023***	0.000	−0.004***	−0.209***	0.076***	0.816***	0.412	1.101***	1.127
Diversified	0.294***	0.006	0.035***	0.073***	0.002***	−0.002***	−0.173***	0.144***	0.990***	0.455	0.897***	2.212
Market Defensive	−0.002	0.081***	−0.018	0.076***	0.007***	0.011***	0.161***	0.114***	0.978***	0.590	1.006***	0.855
Strategic	0.459***	−0.022**	0.038***	0.109***	0.003***	−0.004***	−0.156***	0.238***	1.182***	0.655	0.847***	2.313
Macro	0.091***	0.028***	−0.010	0.075***	0.007***	0.012***	0.246***	0.144***	0.894***	1.228	0.889***	1.690
Active Trading	−0.005	−0.093	−0.073	−0.019	0.002	−0.015	0.202	0.083***	−0.378	3.051	1.282	5.636
Commodity – Agriculture	0.240***	0.044	0.032	0.192***	0.007**	−0.003	0.166	0.158***	1.164***	1.329	1.105***	0.975
Commodity – Energy	0.407	0.129	−0.036	0.229	0.004	−0.023	−0.276	0.498	1.335	0.840	0.822**	0.486
Commodity – Metals	0.531**	0.138	0.010	0.132**	0.018	−0.016	−0.556	0.907***	1.491***	1.665	0.875***	0.533
Commodity – Multi	0.097**	0.106**	−0.116**	0.113***	0.011***	0.008	−0.046	0.118	1.189***	1.204	1.036***	0.945
Currency – Discretionary	0.018	0.031	0.070	−0.004	0.000	0.002	−0.064	0.063	0.268***	0.332	1.092**	1.962
Currency – Systematic	−0.016	0.016	0.007	0.048**	0.002	0.010***	0.179**	0.022	0.565***	0.840	0.872***	1.057
Discretionary Thematic	0.303***	0.078***	0.036	0.039**	0.005***	0.004**	0.132	0.226***	0.431***	0.721	0.938***	1.211
Multi-Strategy	0.204***	0.009	0.010	0.053***	0.004***	0.006**	0.097	0.183***	0.621***	0.692	0.473***	1.045
Systematic Diversified	−0.010	0.008	−0.030**	0.099***	0.010***	0.022***	0.406***	0.114***	1.275***	1.203	0.893***	1.640
Relative Value	0.208***	0.009	0.026***	−0.017***	−0.003***	−0.011***	−0.081***	0.057***	1.028***	1.261	0.827***	2.111
Fixed Income – Asset Backed	0.054***	0.061***	0.016	−0.004	−0.001	−0.005***	0.028	0.000	0.521***	0.970	0.815***	1.167
Fixed Income – Convertible Arb.	0.227***	−0.003	0.039***	−0.032***	−0.001**	−0.008***	−0.005	0.092***	1.602***	1.072	0.922***	0.825
Fixed Income – Corporate	0.244***	0.063**	0.001	−0.024**	−0.003***	−0.012***	−0.217***	0.000	1.176***	1.308	1.324***	3.388
Fixed Income – Sovereign	0.158***	−0.043	−0.039	−0.009	−0.002	−0.014***	0.113	0.077***	0.583***	1.040	0.846***	0.902
Multi-Strategy	0.203***	0.012	0.039**	−0.031**	−0.002**	−0.008***	−0.061	0.082***	1.046***	1.066	0.429***	2.182
Volatility	0.232***	−0.150**	0.020	0.065	−0.016***	−0.040***	−0.169	0.080**	0.295	1.937	1.176***	1.860
Yield Alternatives – Energy Infra.	0.559***	−0.277***	0.025	−0.001	−0.004**	−0.011**	−0.526***	0.090**	1.697***	1.500	0.790***	0.676
Yield Alternatives – Real Estate	0.292***	0.182***	0.085**	−0.005	0.002	−0.004	0.039	0.052	0.341	0.915	0.848***	0.658

This table reports the coefficients for all exogenous factors and for the endogenous main- and sub-strategy benchmarks for the two orthogonalization options *EB a+e* and *EB e*. The results are reported separately for all main- and sub-strategies in the HFR-database. The table additionally reports the standard deviations of the endogenous benchmark coefficients. ***/** denote significance of being different from 0 at the 1%/5% level.

Table 6: Performance with value-weighted peer group benchmarks

	Mean	*Standard-deviation*	*Minimum*	*Maximum*	*Mean P-value P>|t|*	*Number of positive*	*Number of negative*	*** Number of sig.*	*** Number of positive sig.*	*** Number of negative sig.*	*** Number of pos. not sig.*	*** Number of neg. not sig.*
alpha												
1. no EB	***0.267	0.920	−7.589	12.508	0.357	4927	2632	1737	1444	293	3483	2339
2. EB non-orthogonalized	**0.025	0.891	−9.200	12.499	0.361	3798	3761	1669	934	735	2864	3026
3. EB a+e	**0.025	0.891	−9.200	12.499	0.361	3798	3761	1669	934	735	2864	3026
4. EB e	***0.267	0.920	−7.589	12.508	0.312	4927	2632	2295	1782	513	3145	2119

	Mean	*Standard-deviation*	*Minimum*	*Maximum*	*Mean P-value P>|t|*
β-MMRF					
1. no EB	***0.335	0.448	−3.012	7.742	0.132
2. EB non-orthogonalized	***0.078	0.437	−11.285	5.234	0.296
3. EB a+e	***0.335	0.448	−3.012	7.742	0.121
4. EB e	***0.335	0.448	−3.012	7.742	0.121
β-HML					
1. no EB	***0.018	0.318	−4.931	2.594	0.341
2. EB non-orthogonalized	***0.017	0.303	−6.753	2.068	0.368
3. EB a+e	***0.018	0.318	−4.931	2.594	0.301
4. EB e	***0.018	0.318	−4.931	2.594	0.301
β-SMB					
1. no EB	***0.049	0.288	−3.256	3.233	0.411
2. EB non-orthogonalized	***0.028	0.279	−5.860	3.213	0.411
3. EB a+e	***0.049	0.288	−3.256	3.233	0.360
4. EB e	***0.049	0.288	−3.256	3.233	0.360
β-MOM					
1. no EB	***0.053	0.204	−2.833	2.552	0.307
2. EB non-orthogonalized	***−0.013	0.195	−5.825	1.907	0.377
3. EB a+e	***0.053	0.204	−2.833	2.552	0.274
4. EB e	***0.053	0.204	−2.833	2.552	0.274
β-HYI					
1. no EB	***−0.069	0.928	−14.408	10.879	0.418
2. EB non-orthogonalized	0.002	0.854	−11.542	14.956	0.438
3. EB a+e	***−0.069	0.928	−14.408	10.879	0.376
4. EB e	***−0.069	0.928	−14.408	10.879	0.376
Number observations: 7559	Mean R^2:	*no EB*	0.399	—	

	Mean	*Standard-deviation*	*Minimum*	*Maximum*	*Mean P-value P>|t|*
β-EMI^O					
1. no EB	***0.153	0.279	−2.261	2.734	0.307
2. EB non-orthogonalized	***0.018	0.236	−4.760	3.648	0.417
3. EB a+e	***0.153	0.279	−2.261	2.734	0.277
4. EB e	***0.153	0.279	−2.261	2.734	0.277
β-Call^O					
1. no EB	***−0.001	0.030	−0.956	0.271	0.359
2. EB non-orthogonalized	***−0.002	0.027	−1.098	0.210	0.408
3. EB a+e	***−0.001	0.030	−0.956	0.271	0.320
4. EB e	***−0.001	0.030	−0.956	0.271	0.320
β-Put^O					
1. no EB	***0.002	0.018	−0.158	0.274	0.450
2. EB non-orthogonalized	***−0.001	0.016	−0.162	0.285	0.443
3. EB a+e	***0.002	0.018	−0.158	0.274	0.399
4. EB e	***0.002	0.018	−0.158	0.274	0.399
β-Mainstrat					
1. no EB	—	—	—	—	—
2. EB non-orthogonalized	***0.357	1.744	−21.145	26.691	0.335
3. EB a+e	***0.831	0.995	−19.853	15.101	0.149
4. EB e	***0.831	0.995	−19.853	15.101	0.149
*β-*Substrat					
1. no EB	—	—	—	—	—
2. EB non-orthogonalized	***0.491	1.539	−18.247	19.724	0.279
3. EB a+e	***0.491	1.539	−18.247	19.724	0.279
4. EB e	***0.491	1.539	−18.247	19.724	0.279
EB non-orthogonalized = EB a+e = EB e:			0.548	—	—

This table reports the mean alpha and the mean R^2 of all hedge funds in the study sample as well as the mean estimated coefficients for all exogenous factors and value-weighted endogenous main- and sub-strategy benchmarks. For the alphas and the coefficients the standard deviation, the minimum and the maximum values as well as the mean *P*-values are reported. In addition, this table reports the number of positive and negative alphas, the number of significant alphas and further details about the algebraic signs of estimated significant and non-significant alphas. The results are shown separately for four different options: (1) The use of no endogenous benchmark at all (*no EB*), (2) the use of non-orthogonalized endogenous benchmarks (*EB non-orthogonalized*), (3) the use of orthogonalized endogenous benchmarks which comprise the estimated intercepts *a* as well as the residuals *e* (*EB a+e*), (4) the use of orthogonalized endogenous benchmarks which only comprise the estimated residuals *e (EB e)*. ***/** denote significance of being different from 0 at the 1%/5% level.

isolating fund managers' individual alphas from peer group alphas.

We further show that the rankings of single funds change significantly when employing the two-stage peer group benchmarks. Therefore, investors and portfolio managers should not only consider the common but also the specific strategies when evaluating the performance of hedge funds and hedge fund managers.

In addition, we investigate different specifications of peer group benchmarks to address potential distortions in the data set. We argue that especially hedge fund data is likely to be biased because of the strategic reporting of performance. This is expected to lead to overestimations of hedge fund alphas. If this affects many hedge funds within a category, the endogenous benchmark itself may be biased. However, as such biases may be present in the individual as well as in the benchmark performance, the endogenous benchmark may actually help cancelling out systematic distortions in the data. The endogenous benchmark may thus help overcome some of the presented biases that homogenously affect hedge funds within a similar category. The presented biases may however become problematic, if the actual performance is benchmarked against overstated performance, and vice versa. To account for those situations we present an orthogonalization option that excludes benchmark alphas (Option 4). Of course, the rankings of individual 'biased funds' will then be affected similarly as by using traditional performance measures. However, Edelman *et al* (2013) document that hedge funds which do not report data perform similarly to those reporting data, which suggests that the presented biases may be mitigated and which thus supports the use of benchmarks that include alphas (Option 3).

Endogenous benchmarks may not only help to mitigate biases resulting from strategic reporting of performance data, they may also help to deal with misleading strategy declarations. A crucial point with hedge fund data is that funds might not follow their announced strategies. This can lead to inappropriate alpha estimates for the respective hedge funds and to biased endogenous benchmarks. However, if funds do not follow their announced strategy one can expect lower *t*-statistics for the respective benchmark betas. This information in turn may be used iteratively to choose only those funds for constructing the endogenous benchmark that show highly correlated performance, and therefore are assumed to follow their announced common strategy. It is left to further research to refine the presented methodology, for example, by basing benchmarks on performance correlations rather than on self-reported strategies.

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