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Using Two-stage Peer Group Benchmarks

Abstract

This paper is the first to present a two-stage peer group benchmarking approach to evaluate the performance of hedge funds. We present different ways of orthogonalizing the peer group benchmark and discuss their properties in general. We propose to orthogonalize the benchmark against all other exogenous factors. For a broad dataset we show that this approach captures much more commonalities in hedge funds returns compared to the standard methodology if only classical exogenous factors are used. As a result the empirical rankings of hedge funds on the basis of alphas received by this new approach change heavily. Therefore, the proposed two-stage peer group benchmark allows us to better determine which hedge fund managers outperformed the others in the past.

Keywords: Hedge Funds, Performance Measurement, Factor Model, Peer Group Benchmark

JEL Classification: G11, G12, G15

1 Introduction

Since 63 years ago when Alfred Winslow Jones founded the first hedge fund in 1949, this investment vehicle has attracted much attention from both academics and the general investment community. The rising interest in hedge funds industry might be a direct consequence of some prominent incidents, such as the successful bets of Soros' *Quantum Fund* against the British pound in 1999, however, later the collapse of *Long Term Capital Management* in 2000, and also the multi-billion dollar profits of *Paulson & Company* during the recent financial crisis (see 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 are approximately 21,999 active hedge funds globally by 2010 with 14,000 of them single strategy ones and 7,000 fund of hedge funds and the asset under management is about $2.7 trillion (Brown, 2013).

Most of empirical studies measure the past performance of hedge funds using different kinds of multi-factor models. The estimated alpha then represents the excess risk adjusted returns of hedge funds. Though the multi-factor model has been the dominant approach applied in asset pricing literature, it has significant difficulties when adopted in hedge funds performance measurement.

Firstly, as hedge funds invest across a huge variety of asset classes and their positions are usually leveraged, the dynamics of risk-return payoff in hedge funds differ from traditional investment vehicles. Some researchers have argued that the hedge fund risk-return payoffs are nonlinear; in particular, the equity-oriented hedge fund strategies exhibit a put option-like payoff (Fung and Hsieh 2001, Mitchell and Pulvino 2001, and Agarwal and Naik 2004). Secondly, due to their dynamic trading strategies, hedge funds potentially contain certain systematic risks that are not observable. Though the risk factor model has been developed from single market-factor model, to Fama-French three-factor, and to Carhart four-factor model, and to more recent Fung and Hsieh seven-factor model, the search for additional risk factor in hedge funds investment can never end due to the wide range of investments and investment strategies by hedge funds.

Thus the linear-factor model with standard asset benchmarks will not be sufficient to capture the risk-return relationship of hedge funds.

Additionally, though some studies have agreed that in general the hedge funds outperform the mutual funds, it is not clear how funds should be ranked relatively. Empirically, while many hedge funds employ similar strategies, the residuals produced from standard factor models are correlated with each other. This "commonality" problem within hedge funds strategies makes it difficult to assess the performance of individual funds. That is, it is hard to distinguish whether the superior performance of a fund is a result of individual manager's unique skills or just an average reflection of particular investment strategies.

In this regards we introduce a concept of two-stage peer group benchmark for hedge funds to improve their performance measurement. We propose that the individual hedge funds performance should be measured not only against the common risk factors but also against a peer group benchmark. The most intuitive peer group is the strategy group identified by funds themselves. Thus we augment the approach of Hunter et al. (2013) to derive both main strategy and sub-strategy peer group benchmark and combine them with our selected common risk factors. Furthermore, we orthogonalize the respective benchmarks (main-strategy and sub-strategy) separately for every fund in our sample with respect to the life time of the funds. By doing this we get more precise results as 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 employment of a two-stage orthogonal peer group benchmark facilitates a more parsimonious and in-depth identification of superior hedge funds. Our findings indicate that two-stage peer group benchmarks should be implemented in examining the individual hedge funds performance. The benchmarks should be orthogonalized against all exogenous factors in a common risk factor model. However, the form of orthogonalization affects the rankings of the hedge funds studied at the sub-group level. In particular, the orthogonalization 'without alphas' option only ranks the funds with reference to the exogenous factors considered, whereas the orthogonalization 'with alphas' option ranks the funds with reference to both the peer group benchmarks and exogenous factors. Thus, depends on the examiner's need, a proper form of orthogonalization needs to be chosen when the peer group benchmark is adopted.

The paper is organized as follows. Section 2 provides a literature review. Section 3 describes our research design. Section 4 contains information about the data and the empirical results are presented in Section 5. Section 6 concludes.

2 Literature review

There is an extensive literature on hedge funds performance. Most of earlier literature suggests that hedge funds perform better than mutual funds in regards to delivering a positive risk-adjusted return, measured by alpha. Liang (1999) claims that compare to mutual funds, hedge funds offer better risk-return trade-offs, in particular, higher Share ratio, lower market risk and higher abnormal returns from 1994 to 1996. Thus, hedge funds provide a more efficient investment opportunity set for investors. Similarly, Ackerman, McEnally and Ravenscraft (1999) find that hedge funds outperform mutual funds from 1988-1995 and the average Sharpe ratio of hedge funds was higher than that of mutual funds, but not standard market indices. Brown, Goetzmann and Ibbotson (1999) examine the performance of the off-share hedge fund over the period of 1989 to 1995. Their results also show that there where positive risk-adjusted returns despite the fact that hedge funds had high attrition rates and low covariation with the US stock market. However, they found little evidence of differential manager skill. Capocci, Corhay and Hübner (2005) show that due to high adaptability and active investment behaviour, most hedge funds in their databases significantly outperformed the market during their sample period, especially during the bullish period. The performance persists during the bullish period as well. Other studies supporting the outperformance of hedge funds include Fung and Hsieh (2011), Chincarini (2010) and Ibbotson, Chen and Zhu (2010).

Another stream of research however questions the performances of hedge funds by addressing some "hidden" risk factors by previous work, such as volatility, capital flows and liquidity. Liang (2001) study hedge fund performance and risk from 1990 to 1999. His results show that hedge funds returned 14.2% annually compared to 18.8% of the S&P 500 index. However, the S&P 500 index is more volatile than hedge funds.

Yu and Dichev (2011) argue that the returns of hedge fund investors are not as good as previously documented when taking into consideration of the capital flows in and out of the funds. Using a measure of dollar-weighted returns they find that the hedge fund returns are 3 to 7 percent lower than the corresponding buy-and-hold strategy. Using factor models of risk and estimated dollar-weighted performance gap, they find that the real alphas of hedge funds are close to zero. In absolute terms, dollar-weighted returns are lower than the return on S&P 500 index and are only marginal higher than the risk-free rate. The result of Yu and Dichev (2011) is consistent with earlier work of Baquero and Verbeek (2009) and Fung et al. (2008).

More recently literature concerns the missing factors from earlier work, and one of them is the liquidity risk of hedge funds. Aragon (2007) examines the relationship of hedge fund returns and share restrictions imposed by funds. His study finds that the excess returns of funds with lockup restrictions are approximately 4-7% per year higher than those of non-lock up funds. The average alpha of all funds is negative or insignificant after controlling for lockups and other share restrictions. Sadka (2010) claims that funds load on liquidity risk subsequently outperform low-loading funds by about 6% annually from 1994 to 2008.

Besides the liquidity is considered as an additional risk factor, the search for external risk factors seems to continue as there are other factors being discovered which influence the hedge fund performance, such as the managerial skills and macroeconomic variables (Avramov, et al. 2011). Though many research works have been devoted to study the performance of hedge funds relative to other asset classes, the relative performance of individual funds are less studied. Some empirical studies such as Kosowaski, Naik and Teo (2007), find that the top hedge funds performance is not by luck. Performance persists at annual horizons; in particular, performance persistence is stronger within certain strategies. The performance persistence of funds might imply the possible unique skills among certain group of fund managers. To further identify managers' skills, Jagannathan, Malakhov and Novikov (2010) developed a statistical model to relate the fund performance to its decision to liquidate or close in order to infer the performance of a hedge fund that left the database. They also confirmed that there is significant performance persistence among superior funds.

In general, the literature agrees that trading strategies of HFs differ from traditional investment vehicles, such as mutual funds. The distinct features of hedge funds make the performance measurement a challenging task. Though earlier literature claims that hedge funds were able to deliver a positive significant excess return, measured by alpha, the conventional multi-risk factor model with the standard asset benchmarks appear to be weak, especially in assisting identification of superior funds at individual level.

3 Research design

3.1 Introducing Two-stage Peer Group Benchmark

The standard multi-factor models employed in performances 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 which 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 extant performance management studies to date.

The basic idea of using peer group factor for performance measurement is not new. The essence of the idea is to evaluate the "relative" performance of the fund managers to his/her peer groups. The spirit of peer evaluation has been adopted by Elton, Gruber and Blake (1997) and Cohen, Coval and Pástor (2005) in assessing mutual funds performance and a more recent work in hedge funds by Jagannathan, Malakhov and Novikov (2010). Hunter et al. (2013) is the first to explicitly using the term of "peer group benchmark". It is based on the idea that performance measurement does not necessarily require the exact identification of all influencing exogenous factors. In fact, taking advantage of the information by groupings or classifications of mutual funds naturally leads an explanatory proxy, which is called the peer group benchmark.

The incorporation of peer group benchmarks has a few advantages in better measuring and identifying the top performing funds or the fund managers. First of all, even if an exemplary examiner was able to identify additional explanatory risk factors for single funds or fund classes, he/she still has to assume that these assets underlie other "hidden" factors. If these unidentified factors significantly influence the returns of several individual funds within one group, they consequently influence the performance of the group as a whole.

Secondly, investors are able to diversify their wealth by investing in various assets. Even if they aim for one certain investment strategy, they still can disperse 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.

Additionally, fund managers within the same category of funds apply similar models, behave similarly and invest capital in the same asset categories. Thus, a high correlation between the residuals from regression of single fund returns to market returns is usually expected. Further benchmarking the individual funds again its peer group will reduce the high correlation of residuals.

Thus, the peer group benchmark approach proposed by Hunter et al. (2013) for mutual funds represents an even more 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. However, the Hunter et al. (2013) approach is not directly applicable in hedge funds study due to the distinct difference in nature of hedge funds and mutual funds.

Hunter et al. (2013) 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. 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 affect the performance of individual strategies to varying degrees.

However, there are some problems when applying this method to hedge funds. In contrast to mutual funds which can be categorized very precisely due to restrict regulatory requirement, 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; Mader, 2008; Fung and Hsieh, 2002). Thus, categorize each hedge funds into a strategy group is a more complicated case.

In order to cope with these problems, we extend the approach of Hunter et al. (2013) by using a two-stage peer group benchmark regression. We compute peer group benchmarks for all hedge funds 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 the funds which cannot be allocated directly or which were categorized wrongly.

In addition to equally-weighted peer group benchmarks, we also consider using value-weighted peer group benchmarks. Since size has been identified as an important factor in hedge funds' performance (see Gregorious 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

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

with $EB^{ew}_{Strat_t}$ representing the equally-weighted peer group benchmark as the excess return of all funds belonging to the respective main- or sub-strategy $Strat$ in month t, 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, they are not incorporated in our value-weighted peer group benchmark. If the data is incomplete, we compute the missing values for the assets under management *(AuM)* by interpolation.

$$EB_{Strat_t}^{vw} = \frac{\sum_{i=1}^{n}(r_{it} - r_{ft})\, AuM_{i_t}}{\sum_{i=1}^{n} AuM_{i_t}} \qquad (2)$$

$EB_{Strat_t}^{vw}$ in Equation (2) represents the value-weighted peer group 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_{i_t}). 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.

3.2 Base factor model

The standard multifactor model serves as our base model which utilizes 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 *MSCI Emerging Markets Index* (*EMI*). However, since this index exhibits high correlations with the market factor *MMRF*, we orthogonalize this factor with regard to *MMRF*. We use the superscript $factor^0$ to indicate the orthogonalization of a factor against all others, here EMI^O.

Additionally we integrate the return of *Lehman* (now *Barclays*) *High Yield Index* (*HYI*) into our model which allows better explanations 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 funds performance evaluation is to deal with the nonlinear 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 firstly 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 (2001b) and Mitchell and Pulvino (2001) show that there is a relation between 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 hedge fund strategies.

Building on previous research, we use the following equation 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 residual ϵ_{it} represent the output parameters of the regression. Additionally, 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:

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

3.3 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 same sample set and augmented into our standard multi-factor model to capture otherwise non-explained variances, and depending on the concrete form of the peer group benchmark, to adjust the alphas measured. 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:

$$EB^{O}_{Mainstrat_t} = a^{O}_{Mainstrat} + \sum_{x=1}^{8} b^{O}_{Mainstrat,x} SF_{t,x} + e^{O}_{Mainstrat,t} \quad (5)$$

From this we get the first orthogonalized peer group benchmark:

$$EB^{O,a+e}_{Mainstrat_t} = a^{O}_{Mainstrat} + e^{O}_{Mainstrat,t} \quad (6)$$

Hunter et al. (2013) modify this further by dropping the $a^{O}_{Mainstrat}$ from Equation (6). The second orthogonalized peer group benchmark thus obtained is:

$$EB^{O,e}_{Mainstrat_t} = e^{O}_{Mainstrat,t} \quad (7)$$

According to Hunter et al. (2013) this approach allows better identification of management skills. We discuss later which of these two approaches is 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:

$$EB^{O}_{Substrat_t} = a^{O}_{Substrat} + \sum_{x=1}^{8} b^{O}_{Substrat,x}\, SF_{t,x} + b^{O}_{Substrat}\, EB^{O,a+e}_{Mainstrat_t} + e^{O}_{Substrat,t} \tag{8}$$

respectively

$$EB^{O}_{Substrat_t} = a^{O}_{Substrat} + \sum_{x=1}^{8} b^{O}_{Substrat,x}\, SF_{t,x} + b^{O}_{Substrat}\, EB^{O,e}_{Mainstrat_t} + e^{O}_{Substrat,t} \tag{9}$$

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

$$EB^{O,a+e}_{Substrat_t} = a^{O}_{Substrat} + e^{O}_{Substrat,t} \tag{10}$$

respectively

$$EB^{O,e}_{Substrat_t} = e^{O}_{Substrat,t} \tag{11}$$

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

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

respectively

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

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

3.4 Models with different forms of peer group benchmarks

Since there is no theoretical rule as to whether and how to orthogonalize the peer group 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. We assume that 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*")
2. Inclusion of a non-orthogonalized peer group benchmark ("*EB non-ortho*.")
3. Inclusion of an orthogonalized peer group benchmark – Use of epsilons *e* plus benchmark-alphas *a* ("*EB* = *a*+*e*"), i.e. the residuals plus intercept
4. Inclusion of an orthogonalized peer group benchmark without the benchmark-alphas – Use of the epsilons *e* only ("*EB* = *e*"), i.e. the residuals only

It is not surprising that using no peer group benchmark at all (Option 1) and using a non orthogonalized peer group benchmark (Option 2) will result in different estimates for the alphas and betas for the exogenous factors as well as the respective test-statistics and the R^2. Due to the inclusion of the non-orthogonalized benchmarks under Option 2, all common factor loadings are shifted to the peer group benchmark. Therefore the information about 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 zero. Note that also the rankings of the funds on the basis of the alphas within each group can change. In general, adding the peer group benchmark will increase the (adjusted) R^2 in most cases. The economic interpretation of the results of Option 2 is the performance of the single funds against its peer group. Assuming that not all exogenous factors are captured in the standard model this approach can be seen as to be 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) can be 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 Option 1. Therefore the overall economic interpretation of these results – especially the alphas – is analogous to Option 2.

To obtain also the same values for the alphas as in Option 1, the orthogonalized peer group benchmark with residuals only (Option 4) can be used. However, the test-statistics for the alphas changes in comparison to the other approaches. Therefore this approach 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. (2013) argues. Therefore this approach makes sense if one is interested in the performance of the hedge funds against all exogenous factors.

To summarize, using peer group benchmarks can result in different rankings of funds within the peer group when using Options (2) and (3). The test-statistics improve with respect to Option 1 which enables us to better identify which funds out- or under-performed the market relative to their peer group. In addition, the rankings against the market and other extra-market factors change when using the peer group benchmarks in Options (2) and (3), but is the same for Options (1) and (4). The same holds within the sample of hedge funds when the hedge funds are attributed to different peer group benchmarks. Not surprisingly, the regression results for Option 4 mimic that of Option 1 and the regression results for Option 2 are spurious due to strong multi-collinearities between the exogenous and peer group regressors. As such, we shall focus only on Options (3) and Option (4) for the rest of the paper.

4 Data

4.1 Hedge funds data

Our dataset covers a 20-year period between the first of January 1990 and the second of January 2010 which 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 2,002 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 dot-com 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 risks.

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 due to the tactical closure or liquidation. After screening the database for redundant indices and duplications our *base sample* encompasses 14,816 funds, with 4,418 identified as *liquidated*, 4,101 classified as *not reporting* and 6,297 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* which 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 7,559 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.*

(Insert Table 1 about here)

The *study sample* we use for our performance evaluation might embody several biases. The *survivorship bias* occurs when underperforming "dead" funds are not sufficiently considered in the evaluation process. With respect to the *survivorship bias*, previous studies on hedge fund performance observed a positive impact on yearly returns from 0.16% (Ackermann, McEnally and Ravenscraft, 1999) up to 3% (Amin and Kat, 2003; Amin and Kat, 2001; Brown, Goetzmann and Ibbotson, 1999; Capocci, 2001; and Liang, 2000). This clear distortion is caused by yearly hedge fund liquidation rates of up to 20% (Brown, Goetzmann and Ibbotson, 1999). However, as our sample includes both "life" and "dead" funds, we expect our *benchmark* and *study samples* not to be significantly affected by this bias. But due to the criteria of eliminating all funds with 36 or less reported returns, there might be a mild bias.

In addition, s*elf-selection bias* occurs when well performing and sufficiently capitalized funds decide to cease reporting returns to data providers (Ackermann, McEnally and Ravenscraft, 1999). The *instant history* or *backfill bias* can be observed when funds are allowed to report returns ex post (Fung and Hsieh, 2000). This allows the fund management to report only if they have performed successfully in the past. As the fund managers use data bases for marketing purposes there is an incentive to manipulate the reported returns (Capocci, 2001).

Furthermore, the study sample could also be affected by the so called *stale price bias* which occurs when hedge funds trade non-liquid OTC-securities which cannot be priced precisely at any time. This leads to price distortions and as the change in asset value decisively influences fund returns, managers might have an incentive to take advantage of this effect (Asness, Krail and Liew, 2001; and Schneeweis, Kazemi and Martin, 2001).

Finally, we would like to mention the *liquidation bias* which can be observed in the context of fund liquidations. When realizing that their fund will be liquidated (due to bad performance), managers might lose the incentive to report fund information to data bases (Fung and Hsieh, 2011). This might lead to an upward distortion of our results.

4.2 Exogenous factors

For calculating the excess returns we use the risk-free interest rate provided by French (http://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. The earliest *VIX* time series only goes back to the first of January 1990. As we need the option price of the previous month to calculate a month's return, the available information does not allow calculating option returns for January 1990. Hence in all our examinations, we neglect the option factors for this month.

(Insert Table 2 about here)

5 Empirical results

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.

5.1 Results using exogenous factors only

Table 3 presents regression results from base model as well as various forms of employed peer group benchmarks (EB). The top panel gives the estimates of alpha and associated statistics and the bottom panel lists the estimated factor loadings and their statistics. The results when using exogenous factors only are summarized in row one ("no EB"). Firstly, it is striking that the mean alpha for hedge funds is significantly positive when using the exogenous factors. This suggests that the hedge funds managers outperformed the market on average by approximately 4% p.a. (0.267% p.m.) over the study period. Of the 7,559 hedge funds under consideration, 1,444 (19.103%) hedge funds significantly outperformed the market, whereas only 293 (3.876%) significantly underperformed the market (with a level of significance of 5%). The P-values for the exogenous factors differ from factor to factor and fund to fund. The mean P-value is the lowest for the market returns indicating that this is also the most important exogenous factor for hedge funds. However, for the base model "no EB", the mean R^2 is only 0.40 which is relatively low.

(Insert Table 3 about here)

5.2 Results using equal-weighted peer group benchmarks

Table 3 also summarizes the respective results when using the equally weighted two-stage peer group benchmarks, respectively for the three alternative orthogonalization approaches in row 2 to 4.

With the non-orthogonalized peer group benchmark (Option (2)) we obtain – as expected – different alphas for the single funds but one might have expected to get the group alpha of zero. However, in our study sample the group alpha with a value of -0.024 which differs from zero. This is due to 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 (11.906%) of the funds significantly outperformed their peer group whereas 802 (10.609%) significantly underperformed their peer group. Due to the fact that we did not orthogonalize this peer group benchmark we get different loadings against the exogenous factors. The mean R^2 increases to 0.56 (compared to the R^2 of 0.4 previously), supporting the relevance of applying the concept of peer group benchmarks. The bottom panel of Table 3 provides the estimated mean coefficients for all risk factors include peer group benchmarks. We can see that as expected, when the peer group benchmarks are orthogonalized, there is no change in the mean estimates of factor loadings, but lower P-value on average compared to the base model. Note that the mean P-values of most of the exogenous factors increase when the peer group benchmarks are not orthogonalized. This is because the implemented benchmark correlates with other risk factors to some degree.

To retain the same factor loadings as in the case of not using peer group benchmark we use the orthogonalized peer group benchmark $a+e$ (Option 3). By construction the factor loadings remain the same as in Option 1 whereas we get the same alphas and R^2 as in the case where we did not orthogonalize the peer group benchmark (Option 2). Therefore the economic interpretation of these results with respect to the alphas is the same to those did not include any peer group benchmarks (Option 1). Note that the mean P-values of all of the exogenous factors now decrease and are even lower than in the case of not using any peer group benchmark.

When using the orthogonalized peer group benchmark e (Option 4) we receive by construction the same alphas and betas as in the case of not using any peer group benchmark (Option 1). The R^2 is again 0.56, as a consequence of the methodology. However, the test statistics for the alphas change and consequently the number of funds significantly out- and under-performing the market with respect to their peer group changes too. In total we find 1,820 funds (previously 1,444 funds) significantly outperforming and 534 funds (previously 293 funds) significantly underperforming the market with respect to their peer groups. The mean P-values are at the same low levels as for Option 3.

To briefly summarize the findings from Table 3, the adoption of peer group benchmark regardless in the form of Option 3 or Option 4 improves the estimation of the individual funds alpha. As suggested by Hunter et al. (2013), 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, this is not the case here. Among 1,444 top performing funds identified by factor model, only 900 of them stay top performing when group alpha is included in benchmark and there are also more poor performing funds of 802 compared with 293 in factor model. If the peer group benchmark does not include group alpha, that is, in Option 4, more funds are identified being out-performing, which is 1,820 compare to 1,444 in factor model, this 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 Options 3 (*EB* a+e) and Option 4 (*EB e*) deliver richer and more comprehensive performance information as compared to the Option 2 and Option 1, respectively. Even though Option 3 seem to provide same estimates of alphas as Option 2, by construction Option 2 is spurious. Therefore we limit our discussions to these Options 3 and 4 in our subsequent analyses.

In Table 4 we summarize the mean alphas, test-statistics and R^2 respectively for the different main- and sub-strategies when using the peer group benchmark 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 squares of two options are provided in the last column, as previously stated, these two options provide same R squares.

(Insert Table 4 about here)

At the main strategy level, four out of five strategies have significant positive alphas between 0.16 and 0.67 under Option 4 (*EB e)* the most out-performing strategy is "Macro". Interestingly, the "Fund of Funds" has no significant alpha. 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*). With Option 4 (*EB e*), among five main categories, 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 funds with significant positive alphas are 218 (36%) for "Event Driven", 673 (24%) for "Equity Hedge", 635 (33%) for "Fund of Funds", 404 (34%) for "Macro" and 424 (42%) for "Relative Value". However, under Option 3 (*EB* a+e), all out-performing funds drop in both numbers and proportions. At the sub-strategy level, most of 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" which 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 if 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 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 the "Event Driven", than followed by the other three. 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 closely which are "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 employed peer group benchmark Options 3 (*EB* $a+e$) and 4 (*EB* e). There are 7,559 funds in total. In both rankings the fund with the highest alpha is ranked 1^{st} and the fund with the lowest alpha is ranked $7{,}559^{th}$. We observe considerable differences between the two rankings[1]. We find that the mean change of rankings is 1,098 with a standard deviation of 1,150. Hence, the peer group benchmark adopted exerts an influence on the relative performance evaluation of individual fund managers. The correlation of two types of rankings is only 0.73 which is considerably low and suggests that rankings clearly change radically for the different peer group benchmarks Option 3 (*EB* $a+e$) versus Option 4 (*EB* e).

(Insert Table 5 about here)

Table 5 presents the estimated coefficients for models with Options 3 (E*B* $a+e$) and 4 (*EB* e), as shown in Table 3, these two specifications provides 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 zero, which again highlights the importance of implementing the

[1] For brevity of presentation, the results are not provided here.

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. But this is again due to 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 are presented in Table 6.

As we can see that the results in Table 6 is comparable to Table 3. The results are basically similar from an economical point of view and therefore this suggests the robustness of our approach.

(Insert Table 6 about here)

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. Additionally implementing the orthogonalized peer group benchmark doesn't change the estimates of factor loadings, but increase the explanatory power of the model. When the relative performance of funds considered, the rankings of individual funds deviate according to the different specification of benchmarks.

6 Conclusion

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

Expanding the concept of peer group benchmarks from Hunter et al. (2013), where the performance of mutual funds was measured, we show that a two-stage peer group benchmark is a simple but effective way to avoid the "missing variable" and "commonality" problem when assessing individual hedge funds performances. Furthermore, we investigate different specification of peer group benchmark.

We find that on average, hedge funds in our data sample exhibit a significantly positive alpha of about 4% p.a. against the market wide or exogenous factors, however, implementing the peer group benchmarks with group alpha could reduce this estimated values significantly. When using the non-orthogonalized peer group benchmark (Option 2) or the orthogonalized peer group benchmark including the benchmark-alpha (Option 3) the new alphas reflect the relative performance against the both exogenous factors as well as the peer groups of funds, which enable to identify the top/bottom performing funds relative to their group averages.

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

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Tables

Table 1: Strategy allocation of hedge funds

	#	share	⌀ obs. per fund		#	share	⌀ obs. per fund
Event Driven	**600**	**7.94%**	**120.0**	**Macro**	**1,192**	**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	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	**2,859**	**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	1,128	14.92%	111.6	**Relative Value**	**1,003**	**13.27%**	**102.0**
Multi-Strategy	54	0.71%	120.0	Fixed Income - Asset Backe	135	1.79%	105.4
Quantitative Directional	246	3.25%	101.5	Fixed Income - Convertible	179	2.37%	120.9
Sector - Energy/Basic M	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	**1,905**	**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**	**7,559**	**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 study sample.

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 01.01.1990 to 31.02.2010.

Table 3: Performance with equal-weighted peer group benchmarks

	Mean	Std. dev.	Min.	Max.	Mean P-value P>|t|	# positive	# negative	** # sig	** # pos sig.	** # neg sig.	** # pos not sig.	** # neg not sig.
Alpha												
1. no EB	***0.267	0.920	-7.589	12.508	0.357	4,927	2,632	1,737	1,444	293	3,483	2,339
2. EB no orth.	**-0.024	0.918	-12.259	12.423	0.358	3,764	3,795	1,702	900	802	2,864	2,993
3. EB a+e	**-0.024	0.918	-12.259	12.423	0.358	3,764	3,795	1,702	900	802	2,864	2,993
4. EB e	***0.267	0.920	-7.589	12.508	0.307	4,927	2,632	2,354	1,820	534	3,107	2,098

	Mean	Std. dev.	Min.	Max.	Mean P-value P>|t|		Mean	Std. dev.	Min.	Max.	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 no orth.	-0.007	0.456	-12.470	4.345	0.319	*2. EB no orth.*	-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 no orth.	0.011	0.286	-3.489	2.376	0.386	*2. EB no orth.*	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 no orth.	-0.004	0.298	-11.137	3.146	0.418	*2. EB no orth.*	-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 no orth.	-0.005	0.183	-3.517	1.650	0.368	*2. EB no orth.*	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 no orth.	0.013	0.824	-10.903	15.884	0.436	*2. EB no orth.*	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: 7,559 Mean R^2: *no EB* 0.399 *EB no orth. = EB a+e = EB e* 0.563

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 equally-weighted endogenous main- and substrategy 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 signficant 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 not orthogonalized endogenous benchmarks (EB no orth.), 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 zero at the 1%/5% level.

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

	Rank		Mean Alpha		Mean P-Value P>|t|		Obs.	# pos. Alphas		** # 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	2,859	1,903	1,486	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	1,128	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	1,905	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	1,192	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	1,003	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
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

Num. Observations: 7,559 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 zero at the 1%/5% level.

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	Ø Beta MMRF	Ø Beta HML	Ø Beta SMB	Ø Beta MOM	Ø Beta Put[O]	Ø Beta Call[O]	Ø Beta HYI	Ø Beta EMI[O]	Ø Beta Mainstrat	σ Beta Mainstrat	Ø Beta Substrat	σ 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 additonally reports the standard deviatons of the endogenous benchmark coefficients. ***/** denote significance of being different from zero at the 1%/5% level.

Table 6: Performance with value-weighted peer group benchmarks

	Mean	Std. dev.	Min.	Max.	Mean P-value P>|t|	# positive	# negative	** # sig	** # pos sig.	** # neg sig.	** # pos not sig.	** # neg not sig.
Alpha												
1. no EB	***0.267	0.920	-7.589	12.508	0.357	4,927	2,632	1,737	1,444	293	3,483	2,339
2. EB no orth.	**0.025	0.891	-9.200	12.499	0.361	3,798	3,761	1,669	934	735	2,864	3,026
3. EB a+e	**0.025	0.891	-9.200	12.499	0.361	3,798	3,761	1,669	934	735	2,864	3,026
4. EB e	***0.267	0.920	-7.589	12.508	0.312	4,927	2,632	2,295	1,782	513	3,145	2,119

	Mean	Std. dev.	Min.	Max.	Mean P-value P>|t|		Mean	Std. dev.	Min.	Max.	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 no orth.	0.078	0.437	-11.285	5.234	0.296	*2. EB no orth.*	0.018	0.236	-4.760	3.648	0.417
3. EB a+e	0.335	0.448	-3.012	7.742	0.121	*3. EB a+e*	0.153	0.279	-2.261	2.734	0.277
4. EB e	0.335	0.448	-3.012	7.742	0.121	*4. EB e*	0.153	0.279	-2.261	2.734	0.277
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 no orth.	0.017	0.303	-6.753	2.068	0.368	*2. EB no orth.*	-0.002	0.027	-1.098	0.210	0.408
3. EB a+e	0.018	0.318	-4.931	2.594	0.301	*3. EB a+e*	-0.001	0.030	-0.956	0.271	0.320
4. EB e	0.018	0.318	-4.931	2.594	0.301	*4. EB e*	-0.001	0.030	-0.956	0.271	0.320
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 no orth.	0.028	0.279	-5.860	3.213	0.411	*2. EB no orth.*	-0.001	0.016	-0.162	0.285	0.443
3. EB a+e	0.049	0.288	-3.256	3.233	0.360	*3. EB a+e*	0.002	0.018	-0.158	0.274	0.399
4. EB e	0.049	0.288	-3.256	3.233	0.360	*4. EB e*	0.002	0.018	-0.158	0.274	0.399
β-MOM						β-Mainstrat					
1. no EB	0.053	0.204	-2.833	2.552	0.307	*1. no EB*					
2. EB no orth.	-0.013	0.195	-5.825	1.907	0.377	*2. EB no orth.*	0.357	1.744	-21.145	26.691	0.335
3. EB a+e	0.053	0.204	-2.833	2.552	0.274	*3. EB a+e*	0.831	0.995	-19.853	15.101	0.149
4. EB e	0.053	0.204	-2.833	2.552	0.274	*4. EB e*	0.831	0.995	-19.853	15.101	0.149
β-HYI						β-Substrat					
1. no EB	-0.069	0.928	-14.408	10.879	0.418	*1. no EB*					
2. EB no orth.	0.002	0.854	-11.542	14.956	0.438	*2. EB no orth.*	0.491	1.539	-18.247	19.724	0.279
3. EB a+e	-0.069	0.928	-14.408	10.879	0.376	*3. EB a+e*	0.491	1.539	-18.247	19.724	0.279
4. EB e	-0.069	0.928	-14.408	10.879	0.376	*4. EB e*	0.491	1.539	-18.247	19.724	0.279

Number observations: 7,55 Mean R^2: *no EB* 0.399 *EB no orth. = 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 substrategy 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 detail about the algebraic signs of estimated signficant 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 not orthogonalized endogenous benchmarks (EB no orth.), 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 zero at the 1%/5% level.

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