Associate Professor, Dorel PARASCHIV, PhD
E-mail: dorel.paraschiv@ase.ro
Associate professor Cristiana TUDOR, PhD
International Business and Economics Department
The Bucharest Academy of Economic Studies
E-mail: cristiana.tudor@net.ase.ro

A BOOTSTRAPPING APPROACH FOR HEDGE FUNDS ALPHA INVESTIGATION

Abstract. *In this paper, we employ a robust bootstrap procedure to investigate whether hedge fund abnormal performance (alpha) can be attributed to superior active management skills or can it better be explained by luck, under a null hypothesis of zero abnormal performance. The resampling algorithm was thus used to generate cross-sectional distributions of alphas and t-statistics. We consider the bootstrap procedure relevant for this analysis as it does not rely on prior assumptions about the distributional properties from which individual fund alphas are drawn nor necessitates the estimation of the entire covariance matrix characterizing the joint distribution of individual funds and also allows us to deal with time-series dependencies that are due, for example, to heteroskedasticity or auto correlation in the residuals from performance multifactor models. In the estimation of excess returns we use a seven factors asset pricing model proposed by Fung and Hsieh (2004). After 1000 bootstrap iterations we can report that the performance of the top alpha hedge funds can solely be attributed to sampling variability. Our results are therefore in line with the classical view in finance that the top hedge funds are just lucky, and superior active management skills do not persist.*

Keywords*: Bootstrap, Hedge funds; Alpha; Factor models; Active management.*

JEL classification: G11; G12; G23

Introduction

The research conducted in this paper falls under a subject which has attracted an increasing interest in the aftermath of the recent global crisis – the investment funds' industry in general and the active portfolio management and financial innovations in particular - given its controversial role in the ignition and propagation of the late-2000s financial crisis.

Scientific research in evaluation, modeling and forecasting of portfolio risk and return has been stimulated to a large extent by the ever increased interest of capital market practitioners. The legislation of the financial markets, including the Basle Accords, has an important impact on institutional investors' portfolio strategy, and financial analysts, market regulators and investors allocate more and more time and resources in order to investigate the investment funds' industry, to evaluate portfolio performance, or to measure and monitor risk. The starting point for the majority of the portfolio risk adjusted performance evaluation methods is the CAPM model of Sharpe-Lintner-Mossin. The model brought first time a valid benchmark, in the sense that it offers an expected return the realized return can be compared with and we can in this way characterize their dynamics as being superior or inferior to this benchmark. Before the CAPM model became a reference, this function was allotted to the so-called tracking portfolios, which are portfolios that follow some indices considered relevant for the investment strategy for different investment funds. However, the moment the CAPM model was born, the comparison of the portfolio performance with this benchmark was nothing but the next natural step as the expected return of the portfolio was a superior reference point. A keystone of portfolio theory is that systematic risk is rewarded, which implies that in the long run investors expect compensation for bearing risk that they cannot diversify away and that a diversified portfolio's mean returns are reliably related to its systematic risk exposures. Geambasu et al. (2013) analyze the differences between the methods of measuring risk in the post-modern and modern portfolio theory, both from a theoretical and empirical perspective and conclude that the PMPT method generates better empirical results sustained by the theoretical approach presented in the paper, while F. Serban, V. Stefanescu and M. Ferrara (2013) discuss and compare the mean -variance approach with the mean -VaR approach. Other fundamentals of the modern portfolio theory, such as the homogeneity of expectations and rationality of decisions imply the existence of an efficient market – meaning a market where assets' prices coincide with their fundamental value. The subject of a stock market's efficiency has critical importance for portfolio managers (e.g. pension funds, mutual fund, asset management companies, insurance funds etc) as, on an inefficient market, the combination of information proved to impact future returns into a portfolio selection model will lead to higher profits on their investments. One important aspect of a market's inefficiency consists therefore in the empirical documentation of risk sources for stock returns, thus suggesting the existence of some explanatory factors for future stock returns which, if found, can be incorporated in a portfolio selection model that may achieve above-market returns.

Previously, Pele and Voineagu (2008) investigated the Romanian stock market's efficiency by using a model which decomposes the stock return into two components: a stochastic trend and a white noise component and could not reject the efficient market hypothesis for their data sample. Dragota et al. (2009) applied the Multiple Variance Ratio test to random walk hypothesis on the Romanian stock market data and found that there are not enough reasons to reject the Efficient Market Hypothesis in its weak form for the Bucharest stock exchange. Further, Tudor (2009) showed, by employing panel data regressions, that a portfolio selection model based on fundamental analysis of listed stocks helps in identifying those stocks that will bring a significant above-market rate of return, which in turn constitutes an indication that the Romanian stock market is inefficient. Therefore, previous studies on the subject of the Romanian stock market's efficiency reported mixed results.

In the context of the mutual funds' industry, the problem of market efficiency has an important and direct impact on portfolios' strategic asset allocation, which specifies the investor's desired exposures to systematic risk. An investment fund can theoretically adopt one of the following portfolio management strategies: passive, active or semi active. In passive management, the manager does not attempt to reflect his investment expectations through changes in security holdings. The dominant passive approach is indexing, which involves investing in a portfolio that attempts to match the performance of some specified benchmark. Passive investment philosophy has its roots in the history of equity indexing with the first indexed portfolio launched in 1971 by Wells Fargo. By contrast, an active manager seeks to outperform a given benchmark portfolio (the portfolio against which the manager's performance will be evaluated). Despite indexing growing popularity during the last few decades, active equity management still accounts for the overwhelming majority of equity assets managed. Statistics (2012) show that international small-capitalization investment funds provide an area where active management is rewarded: only 26.09% of actively managed international small-cap funds lagged their benchmark over past five years, and the one-year number is not considerably higher at 38.18%. These numbers suggest that active managers, as a group, need inefficient markets to excel. The final approach is semiactive management (also called enhanced indexing or risk-controlled active management) and is in reality a variant of active management. In a semiactive portfolio, the manager seeks to outperform a given benchmark, as do active managers in general. A semiactive portfolio manager, however, worries more about tracking risk than an active manager does and will tend to build a portfolio whose performance will have very limited volatility around the benchmark's returns.

On the other hand, Tactical asset allocation (TAA) involves making short-term adjustments to asset-class weights based on short-term predictions of relative performance among asset classes. In exchange for active risk, the manager using TAA hopes to earn positive active returns that sufficiently reward the investor after deducting expenses. TAA is an active investment strategy choice that has evolved into a distinct professional money management discipline. And is based on short-term expectations and perceived disequilibria.

The sector which has seen the fastest growth in the financial services industry is that of the hedge funds or alternative investments. Hedge funds manage to attract institutional investors like the pension funds of large corporations. Many hedge funds have generated 2-digit returns for investors, and in some cases, in a way that seemed uncorrelated with general market trends and also with relatively low volatility. Most funds reach this performance by maintaining both "long" and "short" positions in securities that, in principle, give investors an opportunity to take advantage of both positive and negative information, while ensuring degree neutrality towards the market due to this simultaneity.

Although in the attention of regulators, the term “hedge fund” does not have yet a legal definition. Hence there are different definitions, some contradictory, based on legal structures, investment strategies, returns, or risk taking/ risk hedging strategies. The first definition is given by Money Central Investor and defines the hedge fund as a risky investment in the form of a pool of money, generally opened to very wealthy investors seeking high returns by taking big risks. Sierra Capital Planning Inc. claims that a hedge fund is a private investment portfolio, structured as a private partnership opened to accredited investors and tax incentive-based, managed by a general partner.

About factors impacting on their performance, Liang (1999), Kazemi et al. (2002), De Souza and Gokcan (2003) and Koh et al. (2003) stated that both the period of capital immobilization and the period of the withdrawal notice can positively affect the performance of hedge funds.

Do (2005), Ackermann (1999) and Koh (2003) found no impact the age on the performance of hedge funds. Liang (1999) found a negative relationship between the two variables and argues that smaller funds, in their attempt to increase both the assets under management and their reputation in the industry have more incentives to achieve a better performance than older, consolidated funds do. On the other hand, Edwards and Caglayan (2001) argue that the age of a fund should have a positive impact on its performance. They base this statement on the assumption that, in an efficient and competitive market, the best performing funds will force funds with a more modest performance to close down. However, the authors did not find any strong empirical evidence for their predictions.

Another possible impact factor is the incentive fees of hedge fund managers. Among others, Ackermann (1999), Do (2005), Liang (1999), Edwards and Caglayan (2001) showed a positive relationship between incentive fees and fund returns.

The rest of the paper is structured as follows. Section 2 describes the data while Section 3 presents the methodology, including the seven factors model and the bootstrap procedure. Section 4 reports the empirical results of the bootstrap analysis, while Section 5 concludes.

Data

In this paper, we analyze the "abnormal" performance attained by three hedge funds, and try to determine whether this return is due to luck or to the fund manager’s investment skill. The hedge funds considered in this analysis have the tickers: QAI, MCRO and BHUE. The IQ Hedge Multi-Strategy Tracker ETF (QAI) is the first hedge fund style ETF (launched in 2009) and the industry’s largest alternative exchangetraded fund. QAI seeks to track, before fees and expenses, the performance of the IQ Hedge Multi-Strategy Index. The Index attempts to replicate the risk-adjusted return characteristics of hedge funds using various hedge fund investment styles, including long/short equity, global macro, market neutral, event-driven, fixed income arbitrage and emerging markets. The IQ Hedge Macro Tracker ETF (MCRO) was also launched in 2009 and seeks to track, before fees and expenses, the performance of the IQ Hedge Macro Index. The Index attempts to replicate the risk-adjusted return characteristics of a combination of hedge funds pursuing a macro strategy and hedge funds pursuing an emerging markets strategy. BlackRock UK Emerging Hedge SE (BHUE) fund was launched in 2009; it aims to maximize returns by investing primarily in shares of medium and small capitalization companies, while trying to reduce the correlation with the UK stock market by holding a short term portfolio. Annex 1A reflects performance data of QAI and MCRO, while Annex 1B shows the same information for BHUE.

In order to examine the abnormal performance of hedge funds, we use as performance benchmarks the seven-factor model developed by Fung and Hsieh (2004) which show that their seven factors model strongly explains variation in individual hedge fund returns. Table 1 is a correspondence table with the abbreviations used for the seven indices for the remainder of the paper.

The source of data is Yahoo Finance for funds' closing prices (further transformed in monthly continuous returns) and David A. Hsieh's Data Library for the seven factors employed in the asset pricing model. The analysis period covers the interval October 2009 - June 2013.

Table 1: Correspondence table

Factor Abbreviation	***Factor name***
SNPMRF	*S&P 500 return minus risk-free rate*
SCMLC	*Wilshire small cap minus large cap return*
BD10RET	*Change in the constant maturity yield of the 10-year Treasury*
BAAMTSY	*Change in the spread of Moody's Baa minus the 10-year Treasury*
PTFSBD	*Bond PTFS*
PTFSFX	*Currency PTFS*
PTFSCOM	*Commodities PTFS*

Methodology

The abnormal performance is investigated through a seven-factor model where the net-of-fee monthly excess return is the independent variable, in the following form:

$$r_t^i = \hat{\alpha}^i + \sum_{k=1}^{K} \hat{\beta}_k^i F_{k,t} + \hat{\varepsilon}_t^i \qquad (1)$$

where:

= excess return (above the risk-free rate) of fund *i* in month *t*.

= the alpha performance measure or the abnormal performance of hedge fund i over the regression time period

the factor loading of hedge fund i on factor k during the regression period

= the return for factor k for month t, where k is SNPMRF, SCMLC, BD10RET, BAAMTSY, PTFSBD, PTFSFX, PTFSCOM

= the error term.

Next, for the bootstrap procedure, for each fund i we measure the performance relative to the multifactor model in Eq. (1). We then save the coefficient estimates $\hat{\beta}_i$ şi $\hat{\alpha}_i$, alpha's t-statistic and the time series of estimated residuals . Similar to Kosowski et al.(2007), for the baseline residual-only resampling bootstrap we draw a sample with replacement from the fund—i residuals that are saved in the first step, thereby creating a time series of resampled residuals 1 , 2 ,..., , where b =1 (for bootstrap resample number one). The sample is drawn such that it has the same number of residuals (e.g., the same number of time periods Ti) as the original sample for each $i=\overline{1,3}$. This resampling procedure is repeated for the remaining bootstrap iterations b=2, b=3,.... B=1000. Next, for each bootstrap iteration b, we construct a time series of (bootstrapped) monthly net returns for this fund, imposing the null hypothesis of $\alpha_i = 0$ sau $t_{\alpha i} = 0$ (zero true performance).

$$r_{i,t}^b = \sum_{k=1}^{K} \hat{\beta}_k^i F_{k,t} + \hat{\varepsilon}_{i,t}^b , \qquad t = s_1^b, s_2^b, \ldots, s_{T_i}^b \qquad (2)$$

where: is the time reordering imposed by resampling the residuals in bootstrap iteration b.

Looking at the Eq. (2) we notice that this series of artificial returns has a true alpha (and t-statistic of alpha) of zero, since the residuals are drawn from a sample that is mean zero by construction. But when we regress the returns for a given bootstrap sample, b, on the multifactor model we can get a positive estimated alpha (and t-statistic) as that bootstrap may have drawn an abnormally high number of positive residuals, or, on the contrary, a negative alpha (and t-statistic) if an abnormally high number of negative residuals are drawn.

The bootstrap procedure is especially relevant for this kind of analysis as it does not rely on prior assumptions about the distributional properties from which individual fund alphas are drawn nor necessitates the estimation of the entire covariance matrix characterizing the joint distribution of individual funds and also allows us to deal with time-series dependencies that are due, for example, to heteroskedasticity or auto correlation in the residuals from performance regressions.

Repeating the above described steps for each fund *i*, $i=\overline{1,3}$ and for each bootstrap iteration *b=1,...,B*, we then build the cross-sectional distribution of the alpha estimates or their t-statistics , which result purely from sampling variation as we impose the null of no abnormal performance.

If we find that very few of the bootstrap iterations generate values of $\hat{\alpha}$ şi $\hat{t}_{\hat{\alpha}}$ that are as large as those that obtain in the actual data, this would suggest that sampling variation (luck) is not the source of performance, and thus that superior active management skills may exist.

Empirical results

After running Eq. (1) on our data sample, we find that only one fund (QAI) has positive abnormal performance over the analysis period, while MCRO and HUE could not achieve an above-market rate of return. All coefficients are statistical significant (Table 2).

Table 2: Coefficient estimation of abnormal performance after the seven factors model calibration

Hedge Fund	alpha	Alpha t-statistic	P-value
QAI	0.0898092	9.745865	2.24586E-11*
MCRO	-0.09258	-9.91366	1.45594E-11*
BHUE	-0.084687	-10.9767	1.02E-12*

*significant at 1%

Next, the bootstrapping procedure described in the previous section conducts to the alpha values reported in Table 3 after 1000 iterations.

Table 3: Bootstrapped Alpha values after 1000 iterations

Hedge Fund	Alpha min (bootstrapped)	Alpha average (bootstrapped)	Alpha max (bootstrapped)
QAI	-0.01643	0.000615	0.024318
MCRO	-0.01461	0.001146	0.013018
BHUE	-0.01006	0.001507	0.023071

The results in Table 3 indicate that the performance of the top alpha hedge funds can be attributed to sampling variability. Bootstrapped p-values for the top fund alphas are greater than 0.1, suggesting that we cannot reject the null hypothesis that their alphas are driven by sampling variability at the 10% level of significance.

Finally, we analyze the bootstrapped alpha t-statistics, which usually have superior statistical properties. Kosowski et. al (2007) explain that, by penalizing the high alpha funds, which have short investment histories and high standard deviations, the alpha t-statistic better discriminates between funds that generate superior performance through skill and funds that are simply lucky.

However, in our analysis, similar to the performance of top alpha hedge funds, the performance of the top alpha t-statistic hedge funds can be attributed again solely to sampling variability. Table 4 reveals that all estimated coefficients lack statistical significance.

Table 4: Bootstrapped Alpha t-statistics after 1000 iterations

Hedge Fund	t-statistic (bootstrapped)	P-value (bootstrapped)
QAI	0.105476	0.50514
MCRO	0.130851	0.462754
BHUE	0.268475	0.46641

Conclusions

The sector which has seen the fastest growth in the financial services industry is that of the hedge funds or alternative investments. In this paper we investigate the "abnormal" performance conducted by three hedge funds, namely QAY, MCRO and BHUE and use as performance benchmarks the seven-factor model developed by Fung and Hsieh (2004). In other words, we test whether the estimated alphas are due solely to luck or, at least in part, to genuine superior portfolio management skills. The resampling

algorithm was used to generate cross-sectional distributions of alphas and t-statistics, where the condition that the true alphas are zero was imposed.
Inference using the bootstrap (1000 iterations) showed that both bootstrapped alpha coefficients and bootstrapped alpha t-statistics lack statistical significance, and we can thus conclude that hedge funds do not generate superior performance through skill.
The advantages of our bootstrap approach include eliminating the need to rely on prior assumptions about the distributional properties from which individual fund alphas are drawn, and the need to estimate the entire covariance matrix characterizing the joint distribution of individual funds and also allows us to deal with time-series dependencies that are due, for example, to heteroskedasticity or auto correlation in the residuals from performance regressions.
Overall, our results are therefore in line with the classical view in finance that most funds show inferior performance relative to a particular benchmark, with even the highest-ranked fund having no statistical significant superior performance

Acknowledgements
This research was supported by CNCS-UEFISCDI, Project number IDEI 303, code PN-II-ID-PCE-2011-3-0593.

REFERENCES

[1] **Agarwal, V., N. Daniel, N. Naik (2009), *Role of Managerial Incentives and Discretion in Hedge Fund Performance***. *The Journal of Finance* 64:5, 2221-2256;
[2] **Barras, L., O. Scaillet, R. Wermers (2010), *False Discoveries in Mutual Fund Performance: Measuring Luck in Estimated Alphas***. *The Journal of Finance* 65:1, 179-216;
[3] **Brennan, M. J., Cao, H. H. (1997), *International Portfolio Investment Flows.*** *Journal of Finance*, 52(5), 1851–1880;
[4] **C. W. Li, A. Tiwari (2009), *Incentive Contracts in Delegated Portfolio Management***. *Review of Financial Studies* 22:11, 4681-4714;
[5] **Caplan, B. (2001), *Rational Ignorance vs Rational Irrationality***; *Kyklos,* Volume 54, Number 1, February 2001 , pp. 3-26(24)
[6] **Choe, H., Bong-Chan, K., Stulz, R. M. (2005), *Do Domestic Investors Have an Edge? The Trading Experience of Foreign Investors in Korea***. *Review of Financial Studies*, 18(3), 795 – 829;
[7] **Cooper, I., Kaplanis, E. (1994), *Home Bias in Equity Portfolios, Inflation Hedging and International Capital Market Equilibrium***. *Review of Financial Studies*, 7(1), 45-60;

[8] **Cremers, M., J. Driessen, P. Maenhout, D. Weinbaum (2009), *Does Skin in the Game Matter*? *Director Incentives and Governance in the Mutual Fund Industry. Journal*** *of Financial and Quantitative Analysis* 44:06, 1345;

[9] **Dedu, S.; Fulga, C. (2011), *Value-at-Risk Estimation Comparative Approach with Applications to Optimization Problems*** .*Economic Computation and Economic Cybernetics Studies and Research* 45, 127–142;

[10]**Douglas Cumming, Na Dai (2009), *Capital Flows and Hedge Fund Regulation***. *Journal of Empirical Legal Studies* 6:4, 848-873;

[11]**Dragota, V., A. Stoian, D. T. Pele, E. Mitrica, M Bensafta (2009), *The Development of the Romanian Capital Market: Evidences on Information Efficiency.*** *Romanian Journal of Economic Forecasting* 2: 147-160;

[12]**Dvořák, T. (2005), *Do Domestic Investors Have an Information Advantage? Evidence from Indonesia***. *Journal of Finance*, 60(2), 817–839;

[13]**Fulga, C. , Dedu, S., Şerban, F. (2009), *Portfolio Optimization with Prior Stock Selection*** . *Economic Computation and Economic Cybernetics Studies and Research* 43 (4), 157 -172;

[14]**Fung, W., Hsieh, D. (2001), *The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers***. *Review of Financial Studies* 14, 313–341;

[15]**Fung, W., Hsieh, D. (2004), *Hedge Fund Benchmarks: A Risk Based Approach***. *Financial Analyst Journal* 60, 65–80;

[16]**Geambasu, C., R. Sova, I. Jianu, L. Geambasu, (2013), *Risk Measurement in Post-modern Portfolio Theory: Differences from Modern Portfolio Theory*;** *Economic Computation and Economic Cybernetics Studies and Research* 1/2013, *ASE Publishing*;

[17]**Hsiu-lang Chen, George G. Pennacchi (2009), *Does Prior Performance Affect a Mutual Fund's Choice of Risk? Theory and Further Empirical Evidence***. *Journal of Financial and Quantitative Analysis* 44:04, 745;

[18]**Jagannathan, R., A. Malakhov, D. Novikov (2010), *Do Hot Hands Exist among Hedge Fund Managers? An Empirical Evaluation***. The *Journal of Finance* 65:1, 217-255;

[19]**Javier Gil-Bazo, Pablo Ruiz-Verdú (2009), *The Relation between Price and Performance in the Mutual Fund Industry***. *The Journal of Finance* 64:5, 2153-2183;

[20]**K. J. M. Cremers, A. Petajisto (2009), *How Active Is Your Fund Manager? A New Measure that Predicts Performance***. *Review of Financial Studies* 22:9, 3329-3365;

[21]**Kahneman, Daniel; Amos Tversky (1979), *Prospect Theory: An Analysis of Decision under Risk***, *Econometrica*, XLVII;

[22]**Kosowski, R., N. Y. Naik, M. Teo (2007), *Do Hedge Funds Deliver Alpha? A Bayesian and Bootstrap Analysis***; *Journal of Financial Economics* 84, 229–264;

[23]**M. Teo (2009), *The Geography of Hedge Funds***. *Review of Financial Studies* 22:9, 3531-3561;

[24]**Pele, D.T., V. Voineagu (2008), *Testing Market Efficiency via Decomposition of Stock Return. Application to Romanian Capital Market***; *Romanian Journal of Economic Forecasting* 3: 63-79*;*

[25]**Qiang Bu, Nelson Lacey (2010), *Smart Money Meets Smart Size***. *Journal of Asset Management* 10:6, 392-405;

[26]**Serban, F., V. Stefanescu, M. Ferrara (2013), *Portfolio Optimization in the Framework Mean – Variance – Var.*** *Economic Computation and Economic Cybernetics Studies and Research* 1/2013;

[27]**Stulz, René M.(2005), *The Limits of Financial Globalization*** ; *Journal of Finance* 60, 1595-1638;

[28]**Toma, A. (2012), *Robust Estimations for Financial Returns: An Approach Based on Pseudodistance Minimization*** ; *Economic Computation and Economic Cybernetics Studies and Research* 46, 117–131;

[29]**Tudor, C. (2009), *Price Ratios and the Cross-section of Common Stock Returns on BSE: Empirical Evidence***; *Journal for Economic Forecasting* 10 (2), 132-146, 2009.

Annex 1: Hedge funds' performance data

Annex 1A: QAI and MCRO performance data as of 06/30/2013

QAI

Index History (%)	**1 Month**	**3 Month**	**YTD**	**1 Year**	**3 Year**	**5 Year**	**Since Inception***
IQ Hedge Multi-Strategy Index	-1.91	-1.43	-0.41	2.55	3.49	--	4.20
Fund History (%)	**1 Month**	**3 Month**	**YTD**	**1 Year**	**3 Year**	**5 Year**	**Since Inception***

IQ Hedge Multi-Strategy Tracker ETF (NAV)	-1.95	-1.60	-0.83	1.77	2.81	--	3.53
IQ Hedge Multi-Strategy Tracker ETF (Price)	-2.78	-1.77	-0.50	1.74	2.92	--	3.57
MCRO							
Index History (%)	**1 Month**	**3 Month**	**YTD**	**1 Year**	**3 Year**	**5 Year**	**Since Inception***
IQ Hedge Macro Index	-2.34	-3.74	-5.53	-2.47	1.58	--	2.40
Fund History (%)	**1 Month**	**3 Month**	**YTD**	**1 Year**	**3 Year**	**5 Year**	**Since Inception***
IQ Hedge Macro Tracker ETF (NAV)	-2.39	-3.92	-5.93	-3.27	0.81	--	1.76
IQ Hedge Macro Tracker ETF (Price)	-2.69	-3.93	-6.20	-3.24	0.70	--	1.74

Source: IndexIQ

Annex 1B: BHUE performance data as of 07/13/2013

BHUE

	Fund / Benchmark	**Sep 09 - Jul 10**	**Jul 10 - Jul 11**	**Jul 11 - Jul 12**	**Jul 12 - Jul 13**
Price	BlackRock Hedge SE UK Emerging (Ordinary Share)	0.00%	25.99%	-5.31%	11.85%
NAV	BlackRock Hedge SE UK Emerging (Ordinary Share)	5.31%	19.51%	-0.75%	4.89%
Morningstar's Benchmark	FTSE World	4.65%	15.99%	-4.24%	29.59%

Source: http://markets.ft.com