Detecting Performance Persistence of Hedge Funds : A Runs-Based Analysis

Rania Hentati Kaffel, Philippe De Peretti

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Rania Hentati-Kaffel*

Centre d'Economie de la Sorbonne, Université Paris1 Panthéon-Sorbonne

Philippe de Peretti†

Centre d'Economie de la Sorbonne, Université Paris1 Panthéon-Sorbonne

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Abstract

In this paper, we use nonparametric runs-based tests to analyze the randomness of returns and the persistence of relative returns of hedge funds. Runs tests are implemented on a universe of hedge extracted from HFR database over the period spanning January 2000 to December 2012. Our findings suggest that i) For about 80% of the

*Contact author. Centre d'Economie de la Sorbonne, Université Paris1 Panthéon-Sorbonne, Maison des Sciences Economiques, 106-112 Boulevard de l'Hôpital 75013 Paris, France. Phone: 00 33 1 44 07 87 45, Email: rania.kaffel@univ-paris1.fr

†Centre d'Economie de la Sorbonne, Université Paris1 Panthéon-Sorbonne, Maison des Sciences Economiques, 106-112 Boulevard de l'Hôpital 75013 Paris, France. Phone: 00 33 1 44 07 87 46, Email: philippe.de-peretti@univ-paris1.fr

funds, we fail to reject the null of randomness of returns, ii) A similar figure is found out when focusing on relative returns, iii) Hedge funds that do present clustering in their relative returns are mainly found within Event Driven and Relative Value strategies, iv) For relative returns, results vary with the benchmark nature (hedge or traditional). The paper also emphasizes that runs tests may be a useful tool for investors in their fund's selection process.
Keywords: Hedge Funds ; Runs Tests ; Persistence ; Clustering
JEL classification: G1 ; G110 ; C1

1 Introduction

The hedge funds industry has long been, naively, seen as being able to generate "all weather" positive returns, no matter what the market conditions were. Nevertheless, the recent financial crisis has cast some doubts on this opinion, leading investors to question whether this industry was significantly able to over-perform the traditional management (Gupta et al., 2003). The question of over-performances, or equivalently of the persistence of relative returns, is of key importance for investors. Indeed, assessing persistence is a milestone in the decision making process. For instance, one of the main strategies used by investors, e.g. funds of hedge funds strategy, to pick-up top hedge funds, relies on realized relative returns (versus HFR representative strategy index or traditional indices) momentum. Thus, selecting a hedge fund for its ability to significantly over-perform the market during large periods may be a very useful tool.

Persistence has been studied by many authors using various methodologies[1] as the Cross-Product Ratio (CPR) (DeSouza and Gokcan, 2004), Chi-square tests (Carpenter and Lynch, 1999), regression models (Fama-MacBeth, 1973; Agarwal and Naik, 2000a), or the test of Hurst (Amenc et al., 2003; De Souza and Gokcan, 2004; Edwards et al., 2001; Eling, 2008). Clearly, three conclusions are to be drawn: *i*) Results vary with both the database (TASS, HFR, Tremont, ...) and the methods *ii*) Most studies agree to find a persistence for a one to a six-month horizon (short-term) (Barès et al., 2003; Boyson and Cooper, 2004; Brorsen and Harri, 2004; Herzberg and Mozes, 2003), but results are contradictory for longer periods, *iii*) There is no agreement whether the persistence is related to the nature of the strategy of the hedge fund.

The goal of this paper is to re-examine the questions of persistence ,and randomness of returns for a given hedge fund firstly in absolute term and then relatively to a set of indices. For both analyses, we use the HFR data base, with a universe spanning more than 4000 hedge over the period spanning January 2000 to December 2012. Relative returns are computed using a blend of traditional and alternative indices: *i*) The median of the returns of funds having a common primary strategy, *ii*) An HFRI index computed for each primary strategy, *iii*) An overall index for the hedge fund market, and *iv*) The S&P500 index. Performances of hedge funds are thus analyzed with regard to peer groups, the whole hedge fund universe, and an external market.

To extract information about randomness and persistence, we use tests

[1] See also Edwards and Caglayan (2001), Harri and Brorsen (2004), Brown, Goetzmann and Ibbotson (1999), Kat and Menexe (2003), Koh, Koh and Teo (2003), Baquero, the Hurst and Verbeek (2005), Kouwenberg (2003), Jagannathan et al.(2006).

based on runs (Wald and Wolfowitz, 1940; Mendenhall, Scheaffer, and Wackerly, 1986; Gibbons and Chakraborti, 1992). Runs tests are very versatile and powerful tools. Used as two-sided tests, they allow to check for randomness. Used as a one-sided test, they allow to test for randomness against a pre-specified alternative: Either clustering, i.e. persistence, implying the ability for a fund to significantly over (under)-perform a given market, or mixing, i.e. systematically alternating over and under performances.

Our main findings suggest that *i*) Using two-sided tests, about 80% of the studied universe has returns at random, *ii*) A similar outcome is obtained when relative returns are used, *iii*) Hedge fund strategies displaying the highest percentage of funds generating clusters are Event-Driven and Relative Value, emphasizing the link between the strategy and the persistence, *iv*) For the relative returns, results deeply vary with the benchmark.

This paper is organized as follows. In Section 2, we details how our series are computed, and introduce runs-based tests. An empirical application is also presented. In Section 3, we implement the tests on the HFR database, and present results in contingency tables crossing the results on runs tests with strategies. On Section 4, we split our sample into two sub-samples, before and after the 2007 crisis, and re-run the tests. Finally Section 5 discusses our main results and concludes.

2 Runs-based tests

Let $\{r_{it}^j\}_{t=1}^T$, be an observed track record of T observations of returns for fund i having a main strategy j, $j \in (1,4)$, where $j = 1$ corresponds to Equity

Hedge, $j = 2$ to Event-Driven, $j = 3$ to Macro, and $j = 4$ to Relative Value.

Now, define $\{d_{it}^j\}_{t=1}^T$ $j \in (1, 4)$ as follows:

$$d_{it}^j = \begin{cases} 1 \text{ if } r_{it}^j \geq b_{it}^j, \\ 0 \text{ otherwise.} \end{cases} \tag{1}$$

where b_{it}^j is either defined as:

$$b_{it}^j = b_i^j = \text{median } (r_{i1}^j, r_{i2}^j, ..., r_{iT}^j)', j \in (1, 4). \tag{2}$$

or:

$$\begin{aligned} b_{it}^j &= b_t^j = \text{median } (r_{it}^j, r_{kt}^j, ..., r_{lt}^j)', j \in (1, 4), t = 1, ..., T. && (3) \\ b_{it}^j &= b_t^j = HFRI_t^j, j \in (1, 4), t = 1, ..., T. && (4) \\ b_{it}^j &= b_t = HFRGI_t, t = 1, ..., T. && (5) \\ b_{it}^j &= b_t = SP500_t, t = 1, ..., T. && (6) \end{aligned}$$

where:

$r_{it}^j, r_{jt}^j, ..., r_{lt}^j$ are the returns of funds having a common main strategy j,

$HFRI_t^j$ is a performance index corresponding to the primary strategy j,

$HFRGI_t$ is the HFRI global performance index at time t, $t = 1, ..., T$.

$SP500_t$ is the S&P500 index at time t, $t = 1, ..., T$.,

Remark 1 *Definition (2) allows us to analyze the randomness of the series, whereas definitions of b_{it}^j given by (3) to (6) return an information about the relative performance of the fund, i.e. the possible persistence of the returns with regard to a benchmark, indicated by large clusters of 1's or 0's. Using (3)* *to compute b_{it}^{j} returns a straightforward information about the location of the return of the fund i in the distribution of the returns of a main strategy,.i.e. if the returns are located in the right (left) tail of the distribution during large periods of times, or is randomly distributed on the right or left tail.*

Remark 2 *In our opinion, the definition of a skilled manager should emphasize its ability to outperform its peers (representative HFRI hedge index), as well as the overall sample (HFRI Global Hedge index). Comparing performance to the overall sample attenuates the selection bias effects (Databases have their own classification criteria which could differ from one provider to another).Thus, the second and third benchmarks, (3) and (4) are used to study how a fund performs compared to its peers (funds classified in the same class), whereas the fourth, (5), is used to study the relative performance of the fund with regard to whole hedge fund sample. The last benchmark, (6), is used as an external reference, to see if funds are able to outperform traditional market (equity in our case).*

We next use runs-based tests to analyze the information returned by the $d_{it}^{j}s$. Define a run of one kind of element, say of $1's$, as a successions of $1^{'}s$ immediately preceded or followed by at least one 0, or nothing. Let T_1 be the number of $1's$ and T_0 be the $0's$ with $T_1 + T_0 = T$, and let r_{1j} be the number of runs of $1's$ of length j and r_{0j} be the number of runs of $0's$ of length j. Let $r_1 = \sum_j r_{1j}$ be the total number of runs of $1's$, and $r_0 = \sum_j r_{0j}$ the total number of runs of $0's$. At last let $r = r_1 + r_0$ be the total number of runs of both kinds. For instance assuming that $\{d_{it}\}_{t=1}^{14}$ takes the following values:

$$1\ 0\ 1\ 0\ 0\ 1\ 1\ 1\ 0\ 1\ 0\ 0\ 0\ 1$$

we have $r_{11} = 4, r_{01} = 2, r_{12} = 0, r_{02} = 1, r_{13} = 1, r_{03} = 1, r_1 = 5, r_0 = 4$ and $r = 9$.

Testing for randomness amounts to testing if we have either too few runs or two many runs by using a two-sided test, whereas testing for the null of randomness against the alternative of clustering i.e. persistence, amounts to using a one-sided test (focusing on the left tail of the distribution), testing for too low values of r_1 (or r).

Following Gibbons and Chakraborti (1992), exact and approximate distributions can be used to test for the null. Concerning the former, using combinatorial, the marginal (exact) distribution function of r_1 is given by:

$$P(r_1) = \frac{\binom{T_1-1}{r_1-1}\binom{T_0+1}{\mathbf{r}_0}}{\binom{T}{T_1}} \tag{7}$$

where $\binom{T_1-1}{r_1-1}$ is a binomial coefficient.

Similarly, the (exact) distribution function of r is given by:

$$P(r) = \begin{cases} 2\frac{\binom{T_1-1}{\frac{1}{2}r-1}\binom{T_0-1}{\frac{1}{2}r-1}}{\binom{T}{T_1}} \text{ if } r \text{ is even,} \\ \frac{\binom{T_1-1}{\frac{1}{2}r-\frac{1}{2}}\binom{T_0-1}{\frac{1}{2}r-\frac{3}{2}}}{\binom{T}{T_1}} + \frac{\binom{T_1-1}{\frac{1}{2}r-\frac{3}{2}}\binom{T_0-1}{\frac{1}{2}r-\frac{1}{2}}}{\binom{T}{T_1}} \text{ if } r \text{ is odd.} \end{cases} \tag{8}$$

Among many other, Gibbons and Chakraborti (1992) provide tabulations for small values of T_0 and T_1, i.e. for $T_0 \leq T_1 \leq 12$, such that (7) and (8) can be used to build one or two-sided tests.

For 'large' values of T_1 and T_0, i.e. for $T_0 > 12$ and $T_1 > 12$ a normal approximation can be used. Define the first two moments of r_1

and r as:

$$E[r_1] = \frac{T_1(T_0+1)}{T} \tag{9}$$

$$V[r_1] = \frac{(T_0+1)^{[2]}(T_1)^{[2]}}{T(T)^{[2]}} \tag{10}$$

where $x^{[a]} = x(x-1)(x-2)...(x-a+1)$,

$$E[r] = E[r_1] + E[r_0] = \frac{2T_1T_0}{T} + 1 \tag{11}$$

$$V[r] = V[r_1] + V[r_0] + 2cov[r_1, r_0] = \frac{2T_1T_0(2T_1T_0 - T)}{T^2(T-1)} \tag{12}$$

Then, using a continuity correction, the corresponding *Z-stats* are defined as:

$$Z_{r_1} = \frac{r_1 + 0.5 - T_1(T_0+1)T^{-1}}{\sqrt{\frac{(T_0+1)^{[2]}(T_1)^{[2]}}{T(T)^{[2]}}}} \tag{13}$$

and:

$$Z_r = \frac{r + 0.5 - 2T_1T_0T^{-1} - 1}{\sqrt{\frac{2T_1T_2(2T_1T_0-T)}{T^2(T-1)}}} \tag{14}$$

Thus, for a one-sided test of clustering ($r \leq E(r)$ and/or $r_1 \leq E(r_1)$) one is thus to compare (13) and (14) to a standard normal deviate at α. Similarly, if one suspects the series to have a tendency to mix, i.e. having too many runs, the right-tail of the standard normal must be considered and the corresponding statistics are given by:

$$Z_{r_1} = \frac{r_1 - 0.5 - T_1(T_0+1)T^{-1}}{\sqrt{\frac{(T_0+1)^{[2]}(T_1)^{[2]}}{T(T)^{[2]}}}} \tag{15}$$

and:

$$Z_r = \frac{r - 0.5 - 2T_1T_0T^{-1} - 1}{\sqrt{\frac{2T_1T_2(2T_1T_0 - T)}{T^2(T-1)}}} \tag{16}$$

Two-tailed tests are a combination of the above statistics with $\alpha/2$ as threshold.

In this paper, for $T \leq 100$, we re-tabulate (7) and (8), and build significance tests on exact probabilities. For $T > 100$, we base our tests on the normal approximation. Note, that on simulations we performed, the normal approximation appeared to be quite accurate for $T \geq 25$ (see also the three filters we apply, in the next section).

To pick up an exemple, consider three funds (fund #1, fund #2 and fund #3), all having an Equity Hedge strategy, with relative monthly performance $\mathbf{d}_1, \mathbf{d}_2$ and $\mathbf{d}_3$ computed using (4). Figure (**??**) plots the returns of the three funds together with the corresponding HFRI Equity Hedge index. A visual inspection reveals that fund #1 has too many runs, and alternates, too often, successes and failures. This is indicative of a tendency to mix. Conversely, fund #2 has a tendency to produce clusters of both successes and failures, especially after the end of 2007. Turning to statistical analysis, for fund #1, we have $r_{11} = 17$, $r_{12} = 7$, $r_{13} = 1$ and $r_{15} = 1$, $r_{01} = 15$, $r_{02} = 7$, $r_{03} = 3$, $r_{04} = 1$ and therefore $r_1 = 26$ and $r_0 = 26$ and $r = 52$. Since $E[r_1] = 20.74$ and $E[r] = 41.44$, we have too many runs of lengths 1 and 2 of $1's$. This suggests that the arrangements of the $1's$ and of the $0's$ are not at random. The (exact) one-sided statistics (right-tail) are $P(r \geq 52) = 0.0119$ and $P(r_1 \geq 26) = 0.0168$ and the corresponding asymptotic p-values are respectively 0.0121 and 0.0177 . This leads to reject the null, concluding to a tendency to mix for fund #1. Concerning fund #2, we have $r_{11} = 5$, $r_{12} = 4$, $r_{13} = 2$, $r_{14} = 2$ and $r_{15} = 2$. For the runs of $0's$ we have $r_{01} = 6$, $r_{02} = 3$, $r_{03} = 2$, $r_{04} = 1$ and $r_{08} = 3$, with $r = 30$ and $r_1 = r_0 = 15$. The expected values are $E[r] = 42.01$ and $E[r_1] = 20.95$ suggesting clustering, and the associated exact (one-sided) probabilities are $P(r \leq 30) = 0.0048$ and $P(r_1 \leq 15) = 0.0074$ (corresponding asymptotic p-values are 0.005 and 0.0078). The null is therefore rejected in favor of clustering.

Turning next to the analysis of fund #3, no clear pattern appears in the graph. Turning to the runs analysis, we have $r_{01} = 15$, $r_{02} = 6$, $r_{03} = 2$, $r_{04} = 2$ and $r_{11} = 13$, $r_{12} = 3$, $r_{13} = 5$, $r_{14} = 1$, $r_{15} = 2$, and $r_{19} = 1$ with $r_0 = r_1 = 25$ and $r = 50$. With $E[r] = 48.69$ and $E[r_1] = 24.52$, the exact probabilities are $P(r \geq 50) = 0.43$ and $P(r_1 \geq 25) = 0.48$. The corresponding two-sided asymptotic tests return a p-value of 0.8663 and 0.9765. Clearly the arrangements are at random. Thus the performance of this fund is not significantly different from the Equity Hedge index.

3 Implementing runs-based tests

3.1 Data description: The HFR database

With the growth of the hedge fund industry, the number of publicly available hedge fund databases has increased. The main data providers are Hedge Fund Research (HFR), Managed Account Reports (MAR) and Tremont Advisory

Shareholders Services (TASS). Each one has its own biases [2], and therefore the choice of a database is likely to have some impacts on the results. In this study, we use monthly[3] data from HFR database, over a period spanning January 2000 to December 2012. HFR may be considered to suffer the least from the biases mentioned below

It's well known that database start date affects its indices performance. Indeed returns calculation takes into account of only still alive (resulting in a survivorship bias). Thus anteriority of databases is key for statistics relevancy. This is the case of HFR and CISDM database (start in 1994) compared to CSFB (start in 2000). Brown, Goetzmann, and Ibbotson (1999) valued the average impact of the survivorship bias at 2.6%, compared to 3% for Fung and Hsieh (2000) and 2.43% for Liang (2001).

Obviously, the bias amplitude varies from one database to another. For example, data providers on hedge funds have their own criteria to include and exclude one fund from their databases. The more criteria come into play the higher is the bias amplitude. For illustration TASS database has a higher survivorship bias than the HFR database and a higher attrition rate, which in turn is due to different criteria for adding and removing funds. Also, the funds have selection criteria that can be very diverse, and the data provided will not be representative of the same management universe. This is referred to as "selection

bias". For instance, HFR doesn't cover managed futures unlike TASS

[2] Some authors use the databases in combination, e.g. Ackermann et al. (1999) and Capocci et al. (2005).

[3] For studies estimating the impact of the different frequencies on the results, see Harri and Brorsen (2004), Henn and Meier (2004) and Koh et al. (2003).

and CISDM.

HFR may be considered to suffer the least from the biases mentioned below. HFR is a leading data provider on hedge funds. It covers a higher percentage of existing hedged funds in the industry. Information contained in the HFR database is quantitative (monthly returns, assets under management, net asset value,...) or qualitative (name of the fund, primary strategy, secondary strategy,...). The starting fund universe is constituted of 4759 funds classified within 4 primary strategies: 47.44 % in Equity Hedge, 24.79% in Global Macro, 18.28% in Relative Value and 9.47% in Event-Driven. Readers would find, for each primary strategy, a split by secondary strategy in Table 1.

Table 2 returns summary statistics for funds having a common primary strategy. At first glance, it appears that mean returns are quite insensitive to the HFR classification. Indeed, the four strategies delivered close average return over the period. Differentiation is notable only through moment greater than 1. All distributions are positively skewed with an unexpectedly high kurtosis for Equity Hedge. For a comparison purpose, summary statistics for the S&P500 index is also provided[4].

Before implementing the tests, the database is first filtered. In particular, three filters are applied:

i) Track record size: We focus on hedge funds having more than 24 months

[4]It is well known that biases may cause the underlying indexes to be over-estimated. Some study (e.g. Malkiel and Saha, 2005; Posthuma van der Slui, 2004), report a biais of about 4%. To analyze the robustness of the results we re-run the tests exluding the hedge with returns no different than a margin of plus/minus 4% of the indices. Conclusions are not altered. Results not reported, avalaible under request.

of track record on **December 2012**, i.e.$T \geq 24$,

ii) Minimal number of occurrence of failures and successes: We select hedge funds with $T_1 > 10$ and $T_0 > 10$,

iii) Relative size : The last filter concerns the proportion of $1\prime s$ and $0\prime s$, and we apply the condition $max(T_1, T_0)/min(T_1, T_0) \leq 1.5$.

The three filters ensure a minimal number of observations, as a well a balanced number of both events, since what we search is to test for random arrangements.

Although database biases are not directly addressed in this paper, these "rules of thumb" are taken into account to limit their impacts. Also, the use of HFRI sub-strategy indices, which take account of all funds existing at one date, attenuates some biases, principally the survivorship bias.

3.2 Testing for randomness of returns

We begin by testing the randomness of the series using two-sided runs tests based on $P(r)$ and $P(r_1)$. These runs tests return a crucial information about the predictability of returns, and maybe about the (temporary) efficiency of the market. The benchmark is computed as the median of each series. For small samples ($T \leq 100$) we use exact statistics based on (8) and (7), and for $T > 100$ asymptotic ones. Table 3 returns the results of runs tests. Results are twofold:

i) For about 82% of the funds, we fail to reject the null of randomness. Thus, the vast majority of funds have returns distributed at random.

ii) The row percents, returning the proportions of funds at random or not, within each primary strategy, show that the proportions of funds having non-random returns are highest for Event-Driven (39.15%) and Relative Value (34.00%).

Refining the analysis, we also implement one-sided tests, i.e. randomness against clustering or mixing (one sided tests). Table 4 returns the results. Clearly, 48.88 % of the Event-Driven funds and 41.14% of the Relative Value have a tendency to cluster, i.e. have positive autocorrelations in their returns. Conversely, very few Macro funds do cluster. Finally, the percent of funds having a tendency to mix is very low. Results are in sharp contrast with Brooks and Kat (2002) who, working only on indices found out an autocorrelation in returns (Lo and MacKinlay, 1988).

We next focus on one-sided tests of randomness, when the alternative is either clustering or mixing.

3.3 Analysing relative returns

3.3.1 Relative returns with respect to peers group

We now perform the tests on relative returns calculated either with regard to peers group, using either (3) or (4), i.e. the median of returns at time t for a primary strategy, or the corresponding HFRI index, or globally using (5), i.e. the HFRI Global index.

Table 5 contains the results of runs tests when the benchmark is computed, each period, as the median of the returns of the funds having the same primary strategy. 2878 funds matched the filters described previously.

Focusing on the number of runs of success based on $P(r_1)$, (7), (13) or (15), on 2878 funds, only 15.18 % (437 funds) have a tendency to cluster, i.e. to be during large periods of time in the right tail of the distribution of the returns. Only 0.76% (22 funds) have a tendency to mix. Among these 437 funds, 42.33% are Equity Hedge, 31.35% Relative Value, 16.70% Event-Driven and 9.61% Macro. Nevertheless, the proportions of funds showing clusters within each primary strategy are: 35.22% for Relative Value, and by decreasing order, 27.04% for Event Driven, 12.56% for Equity Hedge and 5.63% for Macro. Hence, funds following Relative Value or Event-Driven strategy have the highest probability to generate clusters in their relative returns.

Next, benchmarks are calculated as average of peer's group (same primary strategy) returns per period, using primary indices. Results are summarized in Table 6. It turns out that only 16.69% present clustering in their relative returns. In proportions, returned by the row percents, again, the Relative Value and the Event Driven strategies have the highest probability to cluster (34.34% and 30.00%). Fewer funds within Equity Hedge and Macro strategies do cluster.

As a reminder, Relative Value strategy covers a very diverse set of strategies which have all as common goal to take advantage upon inefficiencies and opportunities of the market. Arbitrage may be conditioned in some cases by the directional evolution of the market or the realization of a particular event so that the expected convergence is achieved.

A second explanation for this persistence arises from the fact that for certain trading strategies such as convexity trading (gamma trading), arbitrageurs choose not to systematically adjust their portfolios when the stock price changes and prefer to do rather according to their expectations based on the existence of cycles trends (upward or downward) of the prices. Thus, in this type of strategy, model the convertible bond as a portfolio of options implies less liquidity and therefore it forced the managers in some cases stick with their positions for a certain number of months (that is to say, to redeem the bond).

Moreover, Fixed Income-Sovereign strategy (as defined by HFR) includes strategies in which the investment thesis is predicated on realization of a spread between related instruments in which one or multiple components of the spread is a sovereign fixed income instrument. The presence of clusters can be explained by the fact that interest rate risk is linked to yield curve movement. This is very important in the case of in and out of the money convertible bonds. In this context, the interest rate risk is often related to the yield curve swaps or bonds. The latter could explain why in this class clustering percentage is lowered to 8.02%. (The S&P500 index does not affect the Relative Value class generally).

When relative returns are calculated relative to the HFRI Global index, results are quite different. As shown by Table 7, only 12.29% attempt to cluster. 47.68% of which are in the Equity Hedge peer group, 23.43% in the Relative Value, 19.35% in Macro and only 9.54% in Event-Driven. Here again, the highest probability to cluster is within the Relative Value (19.35%), followed by the Equity-Hedge (11.90%), the Event-Driven (11.55%) and The Macro (9.26%).

Our results are therefore in line with Eling (2008), Brown and Goetzmann

(2003) and Harri and Brorsen (2004), who concluded that persistence was related to the kind of hedge fund strategy, and therefore in sharp contrast with Agarwal and Naik (2000b), finding out that persistence was not related to a primary strategy.

Remark 3 *At some degree, HFR classification of hedge funds by primary strategy is relevant and it gives hedge fund allocator with some guidelines on needed effort to pick-up good candidate capable to replicate past returns. Indeed, hedge fund selection is more challenging for Macro and Equity hedge strategies than Relative value and Event driven. In other words, "top in class" funds tend to maintain their 1st half ranking when the main strategy is Event driven or Relative value. For an investor, for instance a fund of hedge funds manager targeting to outperform an index representing a certain hedge strategy, or the industry as a whole had better to consider differently the four HFR strategies. Tools needed to select top performing hedge funds should be adapted to the strategy (Event driven/Relative value versus Equity Hedge/Macro).*

3.3.2 Relative performance with regard to the S&P500 index

Here, randomness is assessed relative to a traditional equity index, the S&P 500 index. The tested universe is composed of 3378 funds.

Results are given by Table 8. Only 11.16% (377 funds) of the funds of the universe have a tendency to cluster and 0.56% to mix. 54.91% of these funds are Equity Hedge, 27.59% Macro, 10.88% Relative Value and finally 6.63% Event-Driven. Focusing on row percents, 13.32% of the Macro funds present a tendency to cluster, against 12.53%, 6.83% and 7.08% for respectively the Equity Hedge, Event-Driven and Relative Value. Clearly, this is in sharp contrast with preceding results, and emphasize that the choice of a benchmark to analyze the relative performance is crucial.

Remark 4 *As classified by the HFR database, Macro strategy classification includes the following sub-strategies: Active Trading, Macro: Commodity - Agriculture, Macro: Commodity - Energy, Macro: Commodity - Metals Sector: Technology / Healthcare, Systematic Diversified Discretionary Thematic). These strategies are directional, with a high leverage. Trading ideas of these strategies are generated from the economic environment in general (top-down approach) and the alpha of the manager hold on his real ability to choose the right moment to implement his views (market timing). Thus, the corrections related to imbalances in markets can last several months and thereby explains the presence of trend and persistence in returns.*

Remark 5 *When a representative index of the most liquid stock in the US is used, then the global picture changes completely. Here, the more liquid strategy (in terms of traded assets) become leading (the reverse of the previous section). This raised the question of "prices manipulation" by hedge fund managers deploying Event driven or Relative value strategies in their portfolio. In their effort to smooth returns, those hedge fund managers use price to reflect their valuation rather than market prices.*

Fund of hedge fund manager targeting to beat traditional markets should therefore consider a different framework in his portfolio construction process. Macro and Equity hedge strategies require less effort to select good candidate than Event driven and Relative value ones.

4 Before and after the 2007 crisis

Financial crisis started in 2007 has revealed the vulnerability of the hedge fund industry; at epicenter, Relative Value funds group had the highest blow-up rate. Has the crisis changed the hedge fund relative returns profile? To answer this question, we split into two sub-periods by choosing August 2007 as a breaking point. The results of tests carried out over the 2 periods are displayed in Tables 9 and 10.

At first glance, almost all proportions of funds (row percent) clustering on each sub-period are lower compared to the whole period. Also, the impact of the crisis on persistence deeply depends on the type of benchmark considered:

i) It is positive (increased clustering), in the case of a traditional external index (S&P 500), and independently of the strategy

ii) It is negative (decreased clustering), when HFR indices are used, except for Event Driven peer group

The positive effect in *i*) could be mainly explained by a behavioral change in the industry priority to generate returns. After the financial crisis of 2007, hedge funds return objective was indexed in absolute term rather than relative to a traditional benchmark.

In *ii*), the discrepancy between Event Driven and the rest of strategies may be due to the heterogeneity of the former. The returns spread, between sub-strategies within Event Driven, have been amplified through the crisis. Apart from Event Driven, the negative impact of the crisis resulted from the returns profile similarity of the underlying hedge fund after the crisis.

5 Conclusion and discussion

In this paper, we have used runs based tests to test for randomness in both returns, and relative performances. Clearly, concerning the former test, more than 80% of the funds have returns distributed at random. For relative performances, few funds have a tendency to cluster. But the key information is that, focusing on row percent, about one third of the firms having a Relative Value strategy present clustering, and 30% for the Event-Driven strategy, when one uses the median or indices by classes as benchmarks. Using the HFRI global index as a benchmark, only 12.29 % of the firms have a tendency to cluster in the their relative performances. Still, at the sub-class index level, hedge funds having a Relative Value strategy have the highest probability to cluster (19.33 %). At last, concerning an external market, given by the S&P500 index, only 11% do cluster, but here, the highest proportion is found within the Macro strategy. At last, the 2007 financial crisis has increased the proportion of fund with the Event Driven strategy that do cluster. Our results show that few funds are able to significantly over-perform the market during given periods.

In addidion to that, "Smart money" effect consists in investing in funds that will outperform in the future. We believe that our work could provide smart investors with robust tools to assess its challenging mandate.

There is an avenue for future researches in this area. Once selected the hedge clustering, a natural development would be finding external factors explaining persistence, thus leading to a possible forecasting of relative returns. Also, of primary importance as the manageurial skills (Caglayan and Edwards, 2001).

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Table 1: Repartition by secondary strategies for Equity Hedge, Event-Driven, Macro and the Relative Value primary strategies

Main Strategy			
Equity Hedge Strategy		Event Driven Strategy	
Sub-Strategy	Percent	Sub-Strategy	Percent
Equity Market Neutral	11.34	Activist	4.88
Fundamental Growth	29.48	Credit Arbitrage	6.87
Fundamental Value	38.09	Distressed-Restructuring	27.93
Multi-Strategy	4.52	Merger Arbitrage	12.19
Quantitative Directional	4.96	Multi-stategy	14.19
Sector Energy-Basic Materials	5.85	Private issue-Regulating	1.33
Sector technology-Health care	4.38	Special Situation	32.59
Short Bias	1.06		
Main Strategy			
Macro		Relative Value	
Sub-Strategy	Percent	Sub-Strategy	Percent
Active Trading	4.66	Fixed Income-Asset Backed	17.47
Commodity-Agriculture	2.20	Fixed Income-Arbitrage Convertible	9.31
Commodity-Energy	1.39	Fixed Income-Corporate	19.77
Commodity Metal	3.30	Fixed Income-Sovereign	7.47
Commodity-Multi	9.49	Muti-Strategy	27.59
Currency-Discretionary	4.15	Volatility	9.19
Currency-Systematic	6.52	Yield Alternatives-Energy Infrastructure	4.25
Discretionary Thematic	18.05	Yield Alternatives-Real Estate	4.94
Multi-Strategy	16.19		
Systematic Diversified	34.04		

Table 2: Distribution of returns by kind of primary strategies. The distribution of the S&P500 index is also given.

	Equity Hedge	Event-Driven	Macro	Relative Value	S&P500
Mean	0.72	0.80	0.78	0.77	0.69
Variance	33.45	19.35	27.83	20.07	19.18
Skweness	12.73	1.84	0.71	2.89	-0.57
Kurtosis	1413.27	43.69	20.74	225.36	1.03

Table 3: Two-sided tests for randomness of returns. Results based on $P(r)$, given at the 5% threshold (Number of hedge funds: 3947)

Equity Hedge	Not Random	Random	Total
Frequency	242	1656	1898
Percent	6.13	41.96	48.09
Row percent	12.75	87.25	
Col. percent	33.89	51.22	
Event-driven			
Frequency	157	244	401
Percent	3.98	6.18	10.16
Row percent	39.15	60.85	
Col. percent	21.99	7.55	
Macro			
Frequency	77	871	948
Percent	1.95	22.07	24.02
Row percent	8.12	91.88	
Col. percent	10.78	26.94	
Relative value			
Frequency	238	462	700
Percent	6.03	11.71	17.73
Row percent	34.00	66.00	
Col. percent	33.33	14.29	
Total			
Frequency	714	3233	3947
Percent	18.09	81.91	100.00

The table is to be interpreted as follows: The Frequency returns the number of funds having returns at random or not within each main strategy. The Percent returns the number of funds having returns at random or not, divided by the total number of funds. The Row Percent returns the number of funds having returns at random or not, within a main strategy divided by the total number of funds in this strategy. The Column Percent returns the number of funds having returns at random or not in a main strategy divided by the total number of funds having returns at random or not.

Table 4: One-sided tests for randomness of returns against clustering or mixing. Results based on $P(r)$ and $P(r_1)$ given at the 5% threshold (Number of hedge funds: 3947)

	Results based on $P(r)$		Results based on $P(r_1)$		
Equity Hedge	Clustering	Mixing	Clustering	Mixing	Total[1]
Frequency	353	9	316	7	1898
Percent	8.94	0.23	8.01	0.18	48.09
Row percent	18.60	0.47	16.65	0.37	
Col. percent	38.08	19.57	37.00	25.93	
Event-driven					
Frequency	196	0	184	0	401
Percent	4.97	0.00	4.66	0.00	10.16
Row percent	48.88	0.00	45.89	0.00	
Col. percent	21.14	0.00	21.55	0.00	
Macro					
Frequency	90	30	76	20	948
Percent	2.28	0.76	1.93	0.51	24.02
Row percent	9.49	3.16	8.02	2.11	
Col. percent	9.71	65.22	8.90	74.07	
Relative value					
Frequency	288	7	278	0	700
Percent	7.30	0.18	7.04	0.00	17.73
Row percent	41.14	1.00	39.71	0.00	
Col. percent	31.07	15.22	32.55	0.00	
Total					
Frequency	927	46	854	27	3947
Percent	23.49	1.17	21.64	0.68	100

The table is to be interpreted as follows: The Frequency returns the number of funds clustering or mixing within each main strategy. The Percent is the number of funds clustering or mixing divided by the total number of funds. The Row Percent returns the number of funds clustering or mixing within a main strategy, divided by the total number of funds in this strategy. The Column percent returns the number of funds clustering or mixing in a main strategy divided by the total number of funds clustering or mixing.

Table 5: One-sided tests for randomness of relative performances against clustering or mixing. Relative performances computed using the median of returns. Results given at the 5% threshold by primary strategies (Number of hedge funds: 2878)

	Results based on $P(r)$		Results based on $P(r_1)$		
Equity Hedge	Clustering	Mixing	Clustering	Mixing	Total
Frequency	212	10	185	8	1473
Percent	7.37	0.35	6.43	0.28	51.18
Row percent	14.39	0.68	12.56	0.54	
Col. percent	41.33	38.46	42.33	36.36	
Event-driven					
Frequency	92	2	73	1	270
Percent	3.20	0.07	2.54	0.03	9.38
Row percent	34.07	0.74	27.04	0.37	
Col. percent	17.93	7.69	16.70	4.55	
Macro					
Frequency	56	14	42	13	746
Percent	1.95	0.49	1.46	0.45	25.92
Row percent	7.51	1.88	5.63	1.74	
Col. percent	10.92	53.85	9.61	59.09	
Relative value					
Frequency	153	0	137	0	389
Percent	5.32	0.00	4.76	0.00	13.52
Row percent	39.33	0.00	35.22	0.00	
Col. percent	29.82	0.00	31.35	0.00	
Total					
Frequency	513	26	437	22	2878
Percent	17.82	0.90	15.18	0.76	100

Table 6: One-sided tests for randomness of relative performances against clustering or mixing. Relative performances computed using HFRI indices for each primary strategies. Results given at the 5% threshold by primary strategies (Number of hedge funds: 2954)

	Results based on $P(r)$		Results based on $P(r_1)$		
Equity Hedge	Clustering	Mixing	Clustering	Mixing	Total
Frequency	236	20	216	13	1497
Percent	7.99	0.68	7.31	0.44	50.68
Row percent	15.76	1.34	14.43	0.87	
Col. percent	43.95	54.14	43.81	48.15	
Event-driven					
Frequency	97	4	93	3	310
Percent	3.28	0.14	3.15	0.10	10.49
Row percent	31.29	1.29	30.00	0.97	
Col. percent	18.06	10.81	18.86	11.11	
Macro					
Frequency	57	13	48	10	751
Percent	1.93	0.44	1.62	0.34	25.42
Row percent	7.59	1.73	6.39	1.33	
Col. percent	10.61	35.14	9.74	37.04	
Relative value					
Frequency	147	0	136	1	396
Percent	4.98	0.00	4.60	0.03	13.41
Row percent	37.12	0.00	34.34	0.25	
Col. percent	27.37	0.00	27.59	3.70	
Total					
Frequency	537	37	493	27	2954
Percent	18.18	1.25	16.69	0.91	100

Table 7: One-sided tests for randomness of relative performances against clustering or mixing. Relative performances computed using the HFRI global index. Results given at the 5% threshold by primary strategies (Number of hedge funds: 2985)

	Results based on $P(r)$		Results based on $P(r_1)$		
Equity Hedge	Clustering	Mixing	Clustering	Mixing	Total
Frequency	210	13	175	13	1470
Percent	7.04	0.44	5.86	0.44	49.25
Row percent	14.29	0.88	11.90	0.88	
Col. percent	48.84	56.52	47.68	76.42	
Event-driven					
Frequency	38	2	35	0	303
Percent	1.27	0.07	1.17	0.00	10.15
Row percent	12.54	0.66	11.55	0.00	
Col. percent	8.84	8.70	9.54	0.00	
Macro					
Frequency	88	7	71	4	767
Percent	2.95	0.23	2.38	0.13	25.70
Row percent	11.47	0.91	9.26	0.52	
Col. percent	20.47	30.43	19.35	23.53	
Relative value					
Frequency	94	1	86	0	445
Percent	3.15	0.03	2.88	0.00	14.91
Row percent	21.12	0.22	19.33	0.00	
Col. Percent	21.86	4.35	23.43	0.00	
Total					
Frequency	430	23	367	17	2985
Percent	14.41	0.77	12.29	0.57	100

Table 8: One-sided tests for randomness of relative performances against clustering or mixing. Relative performances computed using the S&P500 index. Results given at the 5% threeshold by primary strategies (Number of hedge funds: 2985)

	Results based on $P(r)$		Results based on $P(r_1)$		
Equity Hedge	Clustering	Mixing	Clustering	Mixing	Total
Frequency	233	12	207	13	1652
Percent	6.90	0.36	6.13	0.38	48.90
Row percent	14.10	0.73	12.53	0.79	
Col. percent	54.82	52.17	54.91	68.42	
Event-driven					
Frequency	30	4	25	2	366
Percent	0.89	0.12	0.74	0.06	10.83
Row percent	8.20	1.09	6.83	0.55	
Col. percent	7.06	17.39	6.63	10.53	
Macro					
Frequency	115	6	104	3	781
Percent	3.40	0.18	3.08	0.09	23.12
Row percent	14.72	0.77	13.32	0.38	
Col. percent	27.06	26.09	27.59	15.79	
Relative value					
Frequency	47	1	41	1	579
Percent	1.39	0.03	1.21	0.03	17.14
Row percent	8.12	0.17	7.08	0.17	
Col. Percent	11.06	4.35	10.88	5.26	
Total					
Frequency	425	23	377	19	3378
Percent	12.58	0.68	11.16	0.56	100

Table 9: One-sided tests for randomness of relative performances, against clustering or mixing. Tests are performed before and after the 2007 financial crisis. Relative performances are computed using i) the median of the returns, ii) a primary HFRI index, iii) the HFRI global index. The results are given at the 5 % threshold

	Before the 2007 crisis						After the 2007 crisis					
	Median of the Returns		Class Indices		HFR Global Index		Median of the Returns		Class Indices		HFR Global Index	
Equity Hedge	Clustering	Mixing	Clustering	Mixing	Clustering	Mixing	Clustering	Mixing	Clustering	Mixing	Clustering	Mixing
Row percent[1]	12.27	2.16	11.78	3.16	12.05	2.23	10.05	0.71	11.08	1.04	10.82	0.60
Col. percent[2]	41.87	68.18	41.00	88.00	47.37	75.00	40.41	36.67	42.33	48.48	53.11	39.13
Event-driven												
Row percent[1]	20.14	0.00	12.35	0.00	6.71	0.61	26.09	0.33	27.96	1.22	11.21	1.25
Col. percent[2]	13.79	0.00	10.00	0.00	6.43	5.00	20.21	3.33	22.77	12.12	11.80	17.39
Macro												
Row percent[1]	7.26	1.40	10.19	0.80	8.80	1.07	5.40	2.37	4.50	1.67	9.46	0.91
Col. percent[2]	12.81	22.73	19.00	12.00	19.30	20.00	10.62	60.00	8.66	39.39	23.93	30.43
Relative value												
Row percent[1]	35.75	1.12	36.14	0.00	23.00	0.00	26.18	0.00	25.42	0.00	7.83	0.69
Col. percent[2]	31.53	9.09	30.00	0.00	26.90	0.00	28.76	0.00	26.24	0.00	11.15	13.04
Total												
Percent[3]	14.83	1.61	14.32	1.79	12.12	1.42	12.72	0.99	13.17	1.08	10.09	0.76

[1]: Proportion of funds having a tendency to cluster or to mix within a given main strategy.

[2]: Proportion of funds having a tendency to cluster or to mix by main strategy.

[3]: Total proportion of funds having a tendency to cluster or to mix.

Table 10: One-sided tests for randomness of relative performances, against clustering and mixing. Tests are performed before and after the 2007 financial crisis. Relative returns computed using the S&P500 index. The Results are given at the 5% threshold by primary strategies (Number of hedge funds: 2985)

	Before the 2007 crisis		After the 2007 crisis	
Equity Hedge	Clustering	Mixing	Clustering	Mixing
Row percent	6.75	2.25	9.75	0.76
Col. percent	50.53	59.26	41.29	50.00
Event-driven				
Row percent	3.26	2.17	8.09	0.78
Col. percent	6.32	14.81	7.71	11.54
Macro				
Row percent	8.31	0.78	18.28	0.98
Col. percent	33.68	11.11	37.06	30.77
Relative value				
Row percent	3.86	1.71	8.82	0.31
Col. percent	9.47	14.81	13.93	7.69
Total				
Percent	6.27	1.78	11.37	0.74

The table is to be interpreted as follows: The Row Percent returns the number of funds having clustering or mixing within a main strategy divided by the total number of funds in this strategy. The Column Percent returns the number of funds clustering or mixing divided by the total number of funds clustering or mixing