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Generalized Runs Tests to Detect Randomness in Hedge Funds Returns

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Abstract

Using a large sample of hedge funds from the HFR universe over January 2000 to December 2012, we test and analyze the randomness, i.e. the lack of persistence, of absolute and relative returns using generalized runs tests. Our findings suggest that about 42% of the universe exhibit iid absolute returns, mainly found in proportions within the Macro and Equity Hedge strategies. A similar result holds for relative returns. Furthermore, funds having non-iid absolute or relative returns often exhibit ARCH effects and structural breaks. At last, using standard runs tests, a small percentage displays persistence in their relative performance (8.15% to 16.7% according to the benchmark), measured by their ability to produce clusters. Our work contributes to the hedge fund literature in terms of methodology, portfolio allocation, and performance measurement.

Key words:

Hedge Funds; Randomness; Persistence; Generalized Runs Tests

JEL: G14; G23; C14

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1. Introduction

The recent financial crisis has stressed the crucial role of hedge funds returns analysis in the selection process of managers. Indeed, due to the well known opacity of hedge funds, limiting access to information on implemented positions and on strategies, past performances analysis to detect positive persistence is often one of the main quantitative tools helping investors to pick the right manager. Apart from investors, analyzing performance persistence is also of interest for economists trying to study the market efficiency as in Fama and MacBeth (1973).

Performance persistence has been studied by many authors using parametric and non-parametric methods. Following Boyson (2008), this literature beginning with the early studies of Sharpe (1966) and Jensen (1968), has returned contradictory results, and drawing clear-cut conclusions is uneasy. Thus whether or not hedge funds are able to produce persistence remains an open question (see Eling, 2009 for a survey of this vast literature). Indeed, whereas early studies support short-term but not long-term persistence (see e.g. Agarwal and Naik, 2000a, 2000b, Baquero, ter Horst and Verbeek, 2005, Brown, Goetzman and Park, 2001 or Gyger, Gibson and Bares (2003), late studies suggest that long-term persistence is also likely (see e.g. Fung et al., 2008, Jagannathan et al., 2007 or Kosowski et al., 2007).

This literature has been extended in at least two ways. The first tries to link hedge fund performance persistence to fund characteristics (Amenc et al., 2003; Getmansky, 2012), whereas the other uses more advanced econometric tools, as the CPR (Agarwal and Naik, 2000a), the Chi-square test (Park and Staum, 1998, Carpenter and Lynch, 1999), the RIC (Herzberg and Mozes, 2003), the Kolmogorov-Smirnov goodness-of-fit test (Agarwal and Naik, 2000a) or the Hurst exponent as in De Souza and Gokcan (2004).

At last, recently, Kosowski, Naik and Teo (2007) have introduced a Bayesian approach to improve the accuracy of alpha estimates in parametric models.

Our paper clearly relates to this second branch, and one of our major contributions is to analyze performance persistence using the newly introduced generalized runs tests of Cho and White (2011). Generalized runs tests are simple and powerful tests that allow to check for the null of randomness, i.e. lack of persistence, against a broad and undefined alternative including first and second-order dependence or structural breaks. To our knowledge, it is the first time that generalized runs tests are used on financial data. The second contribution of the paper is to implement these tests on a selected sample of hedge funds extracted from HFR database (4759 funds) over the period January 2000 to December 2012. Both absolute and relative returns are analyzed. Concerning the latter, several benchmarks are used corresponding to either the hedge fund industry, or to an external market. Results are reported using a break down by primary strategies, i.e. Equity Hedge, Event-Driven, Macro and Relative Value. At last, since generalized runs tests are entirely based on the null, an incomplete mapping of the alternative is considered consisting in: i) AutoRegressive Conditional Heteroskedasticity (ARCH), ii) Structural breaks, and iii) Clustering, this latter being our measure of persistence.

Our main findings are: i) About less than half of the sample exhibit iid returns. A similar figure holds for relative returns, regardless of the benchmark used, ii) Under the alternative, most funds exhibit volatility clustering and/or structural breaks, whereas clustering, i.e. the ability to over-perform the market is found for between 8.15% and 16.7% of the funds, iii) In proportions, funds clustering are mainly found within the Relative Value and Event-Driven strategies, iv) Results are highly dependent on the benchmark and on the strategy, thus suggesting that the benchmark type (peer group average versus traditional) is a crucial step in the investment process. Our work has therefore direct implications in terms of methodology, portfolio allocation, and performance measurement.

This paper is structured as follows. In Section 2, we present the generalized runs tests. In Section 3, we implement the tests on HFR database. Section 4 goes deeper into the alternative, and Section 5 concludes and discusses our results.

2. Generalized runs tests

To analyze the randomness of absolute and relative returns we use Generalized Runs (GR) tests. Generalized runs tests have been introduced by Cho and White (2011) as a powerful mean to test the iid assumption against an unspecified broad alternative, including first and second order dependence or structural. This is a major difference with classical runs tests (Mood, 1940) in which the alternative is defined, i.e. clustering or mixing.

Define $\{r_{it}^j\}_{t=1}^T$ as a track record of absolute or relative returns of a hedge fund i having a strategy j computed as residuals of the linear model $r_{it}^j = h(X_t, \theta)$, where $X_t = (b_t, r_{it}^{oj})$, b_t is a benchmark of interest at time t, r_{it}^{oj} is the observed return, and θ is a parameter. The assumption we want to test is $\mathcal{H}_0 : \{r_{it}^j\}_{t=1}^T$ is an iid sequence, against the broad alternative that $\{r_{it}^j\}_{t=1}^T$ is not an iid sequence. Let $F(.)$ be the cumulative distribution function (cdf) of $\{r_{it}^j\}_{t=1}^T$, and first assume that both θ and $F(.)$ are perfectly known. Then using the notation in Cho and White (2011), the runs are defined in two steps. First, for a given probability p build the set $T_n(p) = \{t \in \{1, 2, ..., n\} | F(r_{it}^j) < p\}$, $n = 1, 2, ...$ that contains all indices such that the percentiles are less than the probability p. Let $M_n(p)$ be the number of elements in the set. Now, sort by ascending order $T_n(p)$, and let $t_{n,r}(p)$ be the element being at the rth position of the sorted set, $r = 1, ..., M_n(p)$. For a given p, the *p-runs* $R_{n,r}(p)$ are defined as follows:

$$R_{n,r}(p) = \begin{cases} t_{n,r}(p), & r = 1; \\ t_{n,r}(p) - t_{n,r-1}(p), & r = 2, ..., M_n(p). \end{cases} \tag{1}$$

To test for the null hypothesis and for a given $s \in \mathbb{S}$ compute the goodness-of-fit statistic $G_n(p, s)$:

$$G_n(p, s) = \frac{1}{\sqrt{n}} \sum_{r=1}^{M_n(p)} \left(s^{R_{n,r}(p)} - \frac{sp}{1 - s(1-p)} \right) \tag{2}$$

Various tests statistics are then derived by integrating $G_n(p, s)$ over s for a given p; integrating over p for a given s; integrating over both p and s, or taking the supremum of the function for some p or s.

In this paper, among all these statistics, we focus on $\mathcal{T}_{1,n}^p(\mathbb{S}_1) = \int_{\mathbb{S}_1} |G_n(p, s)|\, ds$, $\mathbb{S}_1 = [-0.99, 0.99]$ for $p \in \{0.1, 0.3, 0.5, 0.7, 0.9\}$, setting $n = T$. Testing for the null then amounts to computing $\mathcal{T}_{1,n}^p(\mathbb{S}_1)$ for various p and then comparing the computed values to critical values at a given threshold. Let $\mathbf{p}_{cv}$ be the (5×1) vector of critical values at a given threshold for the various p, and let $\boldsymbol{\tau}$ be the corresponding vector of $\mathcal{T}_{1,n}^p(\mathbb{S}_1)$ statistics. Then, we fail to reject the null if $\boldsymbol{\tau} << \mathbf{p}_{cv}$ (critical values are reported by Cho and White, 2011).

Now, if either $F(.)$ or θ, or both are unknown, they are replaced by their estimators $\widehat{F}(r_{it}^j) = \frac{1}{T} \sum_{t=1}^{T} 1_{(r_{it}^j \leq \bar{r}_{it}^j)}$ and $\widehat{\theta}$. In this case, Empirical Generalized Runs (EGR) tests are used in a similar fashion, replacing $T_n(p) = \{t \in \{1, 2, ..., n\} | F(r_{it}^j) < p\}$ by $\widehat{T}_n(p) = \{t \in \{1, 2, ..., n\} | \widehat{F}(r_{it}^j) < p\}$, $t_{n,r}(p)$ by $\widehat{t}_{n,r}(p)$, $M_n(p)$ by $\widehat{M}_n(p)$. Thus, (1) and (2) are re-defined as:

$$\widehat{R}_{n,r}(p) = \begin{cases} \widehat{t}_{n,r}(p), & r = 1; \\ \widehat{t}_{n,r}(p) - \widehat{t}_{n,r-1}(p), & r = 2, ..., \widehat{M}_n(p). \end{cases} \tag{3}$$

$$\widehat{G}_n(p,s) = \frac{1}{\sqrt{n}} \sum_{r=1}^{\widehat{M}_n(p)} \left(s^{\widehat{R}_{n,r}(p)} - \frac{sp}{1-s(1-p)} \right) \tag{4}$$

if $p \in (n^{-1}, 1)$ and $\widehat{G}_n(p,s) = 0$ otherwise.

Our test statistics then becomes $\widehat{\mathcal{T}}^p_{1,n}(\mathbb{S}_1) = \int_{\mathbb{S}_1} \left| \widehat{G}_n(p,s) \right| ds$. We next turn to empirical applications.

3. Data and results

In this section, we first present the HFR database. We then implement EGR tests to analyze the iid nature of absolute and relative returns.

3.1. HFR database

Growth in the hedge fund industry has resumed since the financial crisis of 2008. The increasing hedge funds data providers (Hedge Fund Research, Tass/Lipper, Bloomberg, Hennessee, Managed Accounts Reports) and the all time high of the asset under management show the renewed interest of investors.

In this paper, return series come from HFR database. The choice of this database relies on the following reasons: i) High coverage rate of the existing hedge funds universe, ii) HFR indices by strategy attenuated the survivorship bias as liquidated funds are taken into account in indices returns calculation, iii) The impact of the backfill bias is neglected in the HFRI indices. In fact, HFRI construction methodology ensures that constituents are selected as unique representative of redundant fund share classes and retains only funds with either \$50M or 12 months of track record. Beside this, it is clear that biases remain. For example, Fung and Hsieh (2000) estimated the backfill bias in the Tass database to be 1.4% annually. Brown et al. (1999) report a bias of 3%. By comparing the Tass and the HFR database, Liang (2000) examines this survivorship bias in hedge fund returns. He finds that the survivorship bias exceeds 2% per year in the Tass database, while the HFR database survivorship bias equals 0.6%. Caglayan and Edwards (2001) have highlighted the impact of survivorship bias by including in their research funds that have not survived and also excluded the first year of the track record to avoid the instant bias. Using data from 1990 to 1998, they confirmed the presence of persistence for both winners and losers (57%: 30%

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		

of losers and 27% of winners). They showed that funds which displayed more persistence are Global Macro (58 %) and Neutral Market (63%). At last, in a recent contribution, Joenväärä, Kosowski, and Tolonen (2014) make three suggestions in order to deal with biases. In particular they suggest rebuilding an aggregate database from the various providers, which is not done here.

In this paper, net-of-fee observed returns data between January 2000 and December 2012 are used[1]. The starting fund universe is constituted of 4759 funds classified within 4 primary strategies: 47% in Equity Hedge, 25% in Global Macro, 18% in Relative Value and 10% in Event-Driven. Table (1) provides the list of sub-strategies within each strategy, which associated proportions.

3.2. Results of EGR tests

We next implement EGR tests. As nothing is known about their power for a sample size less that $T < 100$, tests are implemented on funds having a track record of at least 100 observations. Also, following Joenväärä, Kosowski, and Tolonen (2014), funds exhibiting extreme realizations in their returns or relative returns are not considered. We run the EGR tests on absolute and on relative returns. For the former, series of median-adjusted returns are computed. For the latter, relative returns are computed using four different benchmarks, defined as:

$$r_{it}^{j} = \begin{cases} r_{it}^{oj} - rHFR_t^j, \\ r_{it}^{oj} - rHFRI_t, \\ r_{it}^{oj} - rSP500_t, \\ r_{it}^{oj} - med_t^j. \end{cases} \tag{5}$$

[1] In this paper, following the Liang (2000) study, we have also implemented tests taking into account the survivorship bias. Since results were not significantly altered compared to those obtained on the raw data, only the latter are reported.

where:

$rHFR_t^j$ is the return in period t computed using the class HFRI index corresponding to the main strategy j, where here the four main strategies are $j = 1$: Equity Hedge, $j = 2$: Macro, $j = 3$: Event-Driven, $j = 4$: Relative Value,

$rHFRI_t$ is the return in period t computed using the global overall HFRI index for all strategies,

$rSP500_t$ is the return in period t computed using the S&P500 index,

med_t^j is the median of the returns in period t for funds having a common strategy j,

r_{it}^{oj} is the observed return for hedge i having a strategy j at time t.

In definitions 1 to 4 we force $\theta = -1$. The tests are therefore to be interpreted as goodness-of-fit or adequation tests. Therefore, failing to reject the null leads to conclude that the discrepancy between the returns of a fund and a benchmark is at random, fund i behaving not differently from its benchmark. For definition 4 we search if among all funds having a common strategy j, a given fund is randomly distributed within the distribution of the returns or not.

Table 2: Proportions of funds (in %) for which we fail to reject the null of iid returns at 5 %, within the four main strategies.

	Equity Hedge	Event-Driven	Macro	Relative Value	Total
Percent[a]	44.18	19.61	64.64	21.14	.
Percent[b]	23.47	2.38	13.48	2.93	42.26

[(a)]: Proportions of funds within each strategy,

[(b)]: Proportions of funds with regard to the HFR universe.

Findings based on absolute returns. Table (2) reports the results of EGR tests. Main entries are the proportions of funds within each main strategy for which we fail to reject the null at five percent, and the total proportions regarding our hedge fund universe. We fail to reject the null for 42.26% of the funds included in our universe. In proportions, funds exhibiting iid returns are mainly to be found within the Macro (64.64%) and Equity Hedge (44.18%) strategies. For Event-Driven and Relative Value, the null is rejected for about 80% of the funds having these strategies.

Findings based on relative returns. Results are presented in Table (3). Main entries are the proportions of funds for which we fail to reject the null at 5% for each main strategy and by benchmarks, and the proportions of funds having iid relative returns for each benchmark. Focusing on the latter, regardless of the benchmark, about slightly less than half of the sample has iid relative returns. Concerning the former, results are benchmark and strategy-dependent, which is particularly clear for the Event-Driven, Macro and Relative Value strategies, but less for Equity-Hedge. For instance, focusing on the class index ($rHFR_t^j$), 60.08% of the funds having a Macro strategy do not perform differently from it,whereas for the Equity Hedge, the corresponding figure is 49.25 %. For Event-Driven and Relative Value, the proportion are quite different, with lower figures, respectively 33.99% and 21.71 %. Proportions are similar when one focuses on the global $HFRI$ index, except for the Relative Value strategy, with a much higher percentage. If we now look at an external market, i.e. the S&P500, respectively 41.64%, 54.90%, 34.98% and 53.71% of the funds having an Equity Hedge, Event-Driven, Macro or Relative Value strategy have iid relative returns. At last, using the median of the returns similar results of that of the class index. Thus, the two major conclusions are that i) about 50% of the funds does not behave differently from the benchmark, ii) In proportions, funds behaving as the benchmark are likely to be found within the Macro and Equity Hedge strategies.

Table 3: Proportions of funds (in %) for which we fail to reject the null of iid relative returns at 5 %, within the four main strategies.

	Benchmarks			
	$rHFR_t^j$	$rHFRI_t$	$rSP500_t$	med_t^j
Equity Hedge[a]	49.25	48.51	41.64	48.66
Event-driven[a]	33.99	39.87	54.90	28.76
Macro[a]	60.08	56.65	34.98	63.12
Relative value[a]	21.71	42.86	53.71	20.00
Percent[b]	46.01	48.37	43.53	45.28

[(a)]: Proportions of funds within each strategy,

[(b)]: Proportions of funds with regard to the HFR universe.

Table 4: Proportions of funds exhibiting non-iid returns, for which an ARCH effect or a structural break is found at 5%. Results given by main strategies.

	Equity Hedge	Event-Driven	Macro	Relative Value
ARCH	68.18	61.78	43.01	67.39
Structural Breaks	20.05	17.88	21.50	47.10
ARCH Alone	50.80	48.78	26.88	34.78
Structural Breaks Alone	2.67	4.88	5.38	14.49
ARCH and Structural Breaks	17.38	13.01	16.13	32.61

Proportions of funds within each strategy.

4. A deeper look into the alternative

EGR tests return a key information about the iid property of series. Nevertheless, since the alternative is not defined, when rejecting one can not know the reasons why. Hence the need for a deeper look into the alternative.

For the funds for which the null of randomness is rejected at five percent, we therefore consider an incomplete mapping consisting in three different possible rejection factors: i) First order dependence and especially clustering, ii) Second-order dependence, i.e. AutoRegressive Conditional Heteroskedasticity (ARCH), and iii) Structural breaks.

Table 5: Proportions of funds exhibiting clustering in their returns at 5%, for i) funds with no ARCH effects, and no structural breaks, ii) Funds with ARCH effects but no structural breaks, iii) For funds with and without ARCH effects but with no structural breaks.

	Equity Hedge	Event-Driven	Macro	Relative Value
Funds with no ARCH effects nor structural breaks				
Percent	40.37	58.54	39.58	76.01
Funds with ARCH effects but no structural breaks				
Percent	33.16	63.33	28.00	77.08
All funds but with no structural breaks				
Percent	35.79	61.39	35.62	76.71

Proportions of funds within each strategy.

To detect ARCH effects, we use a classical ARCH-LM test (Engle, 1982). For structural breaks, we use the Andrews and Ploberger (1994) SupF test, where the p-values are computed using the fixed regressors bootstrap of Hansen (2000) to deal with heteroskedasticity. At last, to analyze clustering, we use one-sided runs-based tests (see Gibbons and Chakraborti, 1992). Concerning the latter, define $\{d_{it}^{j}\}_{t=1}^{T}$ as:

$$d_{it}^{j} = \begin{cases} 1 \text{ if } r_{it}^{j} \geq 0, \\ 0 \text{ otherwise.} \end{cases} \tag{6}$$

and 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.

1 0 1 0 0 1 1 1 0 1 0 0 0 1

Table 6: Proportions of funds exhibiting non-iid relative returns, for which an ARCH effect or a structural break is found at 5%. Results given by main strategies.

	Benchmarks			
	$rHFR_t^j$	$rHFRI_t$	$rSP500_t$	med_t^j
Equity Hedge				
ARCH	60.88	0.29	75.19	21.80
Structural Breaks	22.94	22.03	30.43	59.30
ARCH Alone	43.24	0.29	52.17	41.57
Structural Breaks Alone	5.29	22.03	7.42	4.07
ARCH and Breaks	17.65	0.00	23.02	17.73
Event-driven				
ARCH	72.28	0.00	85.51	21.10
Structural Breaks	15.84	21.74	26.09	64.22
ARCH Alone	56.44	0.00	62.32	47.71
Structural Breaks Alone	0.00	21.74	2.90	4.59
ARCH and Breaks	15.84	0.00	23.19	16.51
Macro				
ARCH	38.10	0.00	69.59	21.65
Structural Breaks	15.24	14.91	11.11	36.08
ARCH Alone	28.57	0.00	60.82	23.71
Structural Breaks Alone	5.71	14.91	2.34	14.52
ARCH and Breaks	9.52	0.00	8.77	12.37
Relative value				
ARCH	62.77	1.00	87.65	47.86
Structural Breaks	32.85	36.00	18.52	62.14
ARCH Alone	39.42	1.00	71.60	26.43
Structural Breaks Alone	9.49	36.00	2.47	12.14
ARCH and Breaks	23.36	0.00	16.05	35.71

Proportions of funds within each strategy.

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 $r = 9$.

Focusing on the total of number of runs, the first and second moments are defined as:

$$E[r] = E[r_1] + E[r_0] = \frac{2T_1T_0}{T} + 1 \tag{7}$$

$$V[r] = V[r_1] + V[r_0] + 2cov[r_1, r_0] = \frac{2T_1T_0(2T_1T_0 - T)}{T^2(T-1)} \tag{8}$$

Using the above defined moments, to test for the null of randomness against clustering, a Z-stat is used. Using a continuity correction, this latter is given by:

$$Z_r = \frac{r + 0.5 - 2T_1T_0T^{-1} - 1}{\sqrt{\frac{2T_1T_2(2T_1T_0-T)}{T^2(T-1)}}} \tag{9}$$

which is asymptotically distributed as a normal standard deviate.

In this paper, we don't test for mixing, we thus implement the above test only if $r > E[r]$. For relative returns, focusing on clustering is of particular importance since it allows us analyzing the number of funds within each strategy able to significantly over-perform the market during large periods of time.

We first set the focus on structural breaks and ARCH effects. For the former test, we consider breaks in the intercept and in autoregressive coefficients (if any), where the lag is chosen according to the AIC criterion (Akaike, 1974). For the ARCH test, our test is based on 4 lags in the auxiliary regression, whereas the main regression includes an intercept, and also possibly autoregressive parameters, chosen here again using the AIC criterion. Since structural breaks may cause ARCH effects (see e.g. Russell, 2013) and also to analyze the impact of structural breaks on the variance of the series, we separately report the proportions of funds within each strategy exhibiting ARCH and structural breaks effects, and ARCH effects alone, i.e. without structural breaks, structural breaks alone, and both effects occurring together.

Findings based on absolute returns. Table (4) presents results of the ARCH and structural breaks analysis for the returns. Clearly, a large amount of

Table 7: Proportions of funds exhibiting clustering in their relative returns at 5%, for i) funds with no ARCH effects, and no structural breaks, ii) Funds with ARCH effects but no structural breaks, iii) For funds with and without ARCH effects but with no structural breaks.

	Benchmarks			
	$rHFR_t^j$	$rHFRI_t$	$rSP500_t$	med_t^j
Funds with no ARCH effects nor structural breaks				
Equity Hedge	25.22	30.22	14.71	30.95
Event-Driven	53.57	54.17	0.00	50.00
Macro	23.73	19.59	18.75	28.30
Relative Value	63.16	61.90	62.50	55.56
Funds with ARCH effects but no structural breaks				
Equity Hedge	31.29	100	18.14	32.87
Event-Driven	61.40	0.00	6.98	53.85
Macro	23.33	0.00	33.65	4.35
Relative Value	75.93	100	5.17	72.97
All funds but with no structural breaks				
Equity Hedge	28.63	31.23	18.38	34.75
Event-Driven	58.82	29.17	5.88	56.16
Macro	23.60	21.65	30.92	27.54
Relative Value	70.65	37.50	64.55	72.13

Proportions of funds within each strategy.

funds exhibits clustering in their variance. This is particularly true for funds having an Equity-Hedge, Event-Driven and Relative Value strategy. For this latter, around 50% of the funds also exhibit structural breaks. For the other strategies, structural breaks occur in approximately 20% of the cases. Having a look at the lower part of the table, except for Relative Value, structural breaks seldom appear alone, conversely to ARCH effects. Turning to clustering analysis, results are given by Table (5) and the upper part of Table (8). Table (5) reports the proportions of funds clustering within each strategy with a break down by ARCH/No-ARCH effects. We thus report

Table 8: Proportions of funds exhibiting clustering in their relative returns at 5%. Overall proportions

	Equity Hedge	Event-Driven	Macro	Relative Value	Total
			Returns		
	8.48	4.91	2.06	4.44	19.89
			Relative Returns		
$rHFR_t^j$	5.94	3.95	1.66	5.15	16.7
$rHFRI_t^j$	6.66	1.66	1.65	1.90	11.87
$rSP500_t$	3.96	0.23	3.72	0.24	8.15
med_t^j	6.50	3.64	1.50	3.48	15.12

Proportions of funds with regard to the HFR universe.

the proportions of funds clustering when no ARCH effects are found, when ARCH effects are present, and in both cases. When ARCH effects are found, tests for clustering are implemented on normalized series[2]. The upper part of Table (8) reports the proportions funds exhibiting some clustering in their returns with regard the whole HFR hedge fund universe. Clearly, about 20% of the funds of the HFR database exhibit clustering in their returns. Focusing on the last row of Table (5), funds exhibiting clustering are mainly to be found within Event-Driven and Relative Value strategies. For the two other strategies, about one third of the funds do cluster. Results can also be due to the illiquidity nature of the assets held, and the way the returns are reported in practice (Getmansky et al. 2004).

Findings based on relative returns. We next perform the same analysis but on relative returns. As for the returns, we first start by studying ARCH effects and structural breaks. Table (6) reports the proportions of funds within

[2]For this, we fit a simple Generalized Auto-Regressive Conditional Heteroskedastic (GARCH) model to the series, and divide the series by the estimated conditional standard error.

each strategy for which the null of randomness is rejected at 5% using EGR tests and exhibiting ARCH effects, structural breaks, ARCH effects alone (i.e. without structural breaks), structural breaks alone, and both effects. Interestingly, results are both benchmark and strategy-dependent, especially for ARCH effects. For instance, focusing on the HFR class index, 60.88 % of the funds having an Equity Hedge strategy exhibit volatility clustering in their returns, but when using the global HFRI index as a benchmark, this figure reduces to 0.29 %. Very similar results are found for all strategies for the two benchmarks, i.e. the ARCH effect vanishes when one considers the overall HFR index. Note that this result does not hold for structural breaks, since the proportions of funds remains very similar across the two benchmarks.

Considering now the S&P500 index results in a sharp increase in volatility clustering, up to 87.65% for the Relative Value. Still the structural breaks are very present. At last, when analyzing the position of a fund within the distribution of relative returns, all having the same strategy, the striking fact is the relatively high number of structural breaks, e.g. 62.14 % for the Relative Value, 64.22% for the Event-Driven. This means that the relative performances of a fund with regard to the other fund is not constant over time, which is deeply coherent with the reality.

Turning to clustering analysis as presented by Tables (7) and (8), the overall proportions of funds able to significantly over-perform the market vary from 8.15% when an external market is considered to 16.7% for the hedge fund industry. When focusing on proportions within each main strategy, it turns out that when the class index is considered, funds having Relative Value and Event-Driven strategies have the highest probability to produce cluster. When considering the external market (S&P500), only the Relative

Value do cluster.

5. Conclusion

In this paper, we have adopted runs statistics to analyze the statistical properties of both absolute and relative returns of hedge funds in terms of randomness. We have used a two-step methodology as follows i) Implement EGR tests to classify funds according to the assumption that returns are iid at 5% level. This will segment the hedge fund universe studied into two groups: One for which we fail to reject the null, and the complement one, for which the iid assumption does not hold, ii) For the second group, we have considered three possible rejection factors, i.e. ARCH effects, structural breaks and clustering.

Our main findings are: i) Less than 50% of the sample exhibit iid absolute or relative returns, ii) Most funds for which the null is rejected exhibit volatility clustering and/or structural breaks. Clustering in relative returns occurs between 8.15% and 16.7% of the cases, according to the benchmark, iii) Funds clustering, are mainly found within the Relative Value or Event-Driven strategies, iv) Results are highly dependent on the benchmark and on the strategy.

These empirical findings are important because they emphasize thumbs of these specific strategies. Concerning clustering, i.e. persistence, managers try to arbitrage upon inefficiencies and opportunities of the market and thus managing is dependent to the cycle's trends. This clustering can also be due to the illiquidity nature of these strategies (i.e. Relative Value or Event-Driven). In the contrary, fewer funds within Equity Hedge and Macro strategies do cluster. Our results cast some doubts on the ability of the hedge fund industry to over-perform the market, and have strong implications in terms of portfolio allocation. Also, they allow us to rearrange the universe of hedge funds into trend-following funds and mean-reversion one. According to the ARCH effects and structural breaks factors, 60.88 % of Equity Hedge strategy exhibit volatility clustering in their returns (when compared to the HFR Equity Hedge index). This strengthens the assumption that states that this style managing is based on long volatility strategies, in contrast to global macro strategies (43%). For structural breaks, 47% of Relative Value exhibits breaks. This could coincide with market crashes and correspond to substantial changes in the risk exposures of returns.

The contributions of our work are several. First, we have tested and analyzed a new framework to deal with randomness and persistence of hedge funds returns. Second, our methodology based on large sample of hedge funds, gives practical and theoretical answers to understand better the performance of certain hedge funds. Third, by investigating and testing clustering, ARCH and structural breaks, we pointed and investigate whether the risk exposures change with market conditions.

There are several avenues for future researches in this area. First, looking more closely to the impact of the recent financial crisis on results by dividing the period of test into: before and after crises. Also, exploring the differences in the risk exposures of the 4 main strategies analyzed. Finally, to enlarge factors to complete the mapping answers.

From an econometric point of view, we have presented results based on raw data, i.e. not biased-corrected. Testing the robustness of our results could therefore be of particular interest using for instance the methodology suggested by Joenväärä et al. (2014) or by Hentati and Prigent (2011). This is let for a future study.

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