Original Article

Are investable hedge fund indices holding their promise?

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ABSTRACT **The goal of this article is to assess whether investable hedge fund indices represent a worthwhile addition to an alternative investment portfolio. Adjusting index returns for liquidity (staleness and smoothing) and using standard performance measures, we found that investable indices perform worse than their corresponding hedge fund benchmarks, regardless of the sample period studied. Using only risk metrics that allow for more aggressive risk tastes, some selected investable hedge fund strategies may appear worthwhile. Moreover, these best strategies have the additional benefit to offer a low exposure to systematic risk factors.**

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INTRODUCTION

Investable hedge fund indices are, according to their providers, the industry's most representative and fully investable strategy-based hedge fund indices. Investors who are looking for hedge fund-like returns, and are not willing, able or allowed to invest directly into hedge funds can opt to seek exposure to these investable hedge funds indices through Tracker Funds.[1]

The literature has long discussed hedge fund indexing, its benefits and drawbacks; see Amin and Kat (2003), Kat and Lu (2002), Goltz *et al* (2007), Switzer and Omelchak (2009). Among the shortcomings of the available indices, analysts generally point out the lack of representativeness, the overlapping reporting period (some funds report to multiple index providers), the sometimes non-audited data that are provided and the numerous biases hedge fund performance data exhibit (to name a few: self-selection, backfilling, survivorship biases). Gehin and Vaissié (2004) were the first to wonder whether some of the bias is mitigated in the construction of investable hedge fund indices. More recently, Heidorn *et al* (2010) argued that investable funds did not suffer from survivorship or backfilling bias. Hence, investable hedge fund indices may be seen as more indicative and suitable hedge fund benchmarks as they reduce the biases that tend to overstate their performance (see Amin and Kat, 2003).

On the other hand, some drawbacks may still persist, such as size and selection bias. Indeed, investable indices only contain a fraction of funds included in the benchmark indices, and as such may exhibit greater volatility during turbulent times. Moreover, most providers only include funds that are liquid as well as open to new investments. Although these features are more appealing to investors, given that the lack of liquidity may interfere with risk management, this could also damage the representativeness of the index and artificially increase its exposure towards more conservative funds.

However, above all, the major concern with investable indices is their performance. Since their creation, they underperformed significantly their corresponding benchmarks according to standard (naïve) performance metrics (see Heidorn *et al*, 2010). Worse, they also tend to underperform synthetic benchmarks (or hedge fund 'clones'), which are based on the replication of (non-investable) hedge fund strategies with underlying investable risk factors (see Jaeger and Wagner, 2005; Wallerstein *et al*, 2010).

The first goal of this article is to reassess how investable indices performed during the last decade relatively to their non-investable relatives for a wide range of performance metrics. Unlike previous literature, we first unsmooth reported returns that result from general partner's valuation conventions from both sets of indices to recover the true economic returns, following Getmansky *et al* (2004) (hereafter GLM). We then use these true returns to compute several risk-adjusted measures of performance suited to hedge fund returns, including the modified Sharpe ratio (Getmansky *et al*, 2004), the Omega ratio (Keating and Shadwick, 2002) and the Farinelli-Tibiletti ratio (Farinelli and Tibiletti, 2003).

In a second step, we analyse the exposure of both investable and non-investable indices to economic and financial factors following the work of Hasanhodzic and Lo (2007) and Amenc *et al* (2010) on hedge fund replications. Following their methodology, each hedge fund style is assigned factors consistent with its underlying investment strategy. This method allows us to assess objectively to which extent economic factors can explain the returns on non-investable as well as investable indices.[2]

DATA DESCRIPTION

Two of the most reputable hedge fund data providers, Hedge Fund Research (HFR) and Dow Jones Credit Suisse (DJCS), offer benchmarking indices as well as investable hedge fund indices. The DJCS composite indices are assembled from

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10 sub-strategies that track individual hedge fund strategies. The Dow Jones Credit Suisse AllHedge Index,[3] an investable fund index compiled by DJCS, is constructed from the set of funds that meet specified eligibility conditions. Notably, its member funds hold in aggregate 70 per cent of all Assets Under Management for the eligible funds in the investable universe for that sector. The AllHedge Index requires its strategy indices to include a minimum of 10 but a maximum of 25 individual hedge funds. DJCS also states that the investable AllHedge indices are not designed to track the DJCS benchmark indices, but are constructed as 'investable, liquid, strategy-specific indices with their own characteristics, and thus performance may be significantly different'. The DJCS indices are asset-weighted. Although DJCS provide data from 1994, investable indices are only available from 2004. For the sake of comparison, our sample study starts in September 2004 and ends in April 2010.

The HFR composite indices contain five main strategy sub-indices. The benchmark index, the HFRI, is constructed from more than 2000 funds, whereas the investable counterpart, HFRX, consists of about 250 funds.[4] Further differences include the requirements of a 24-month track record for the HFRX versus the HFRI's 12 months. In comparison with the asset-weighted DJCS indices, the HFR indices are equally weighted. The indices start in January 1998 and end in April 2010.[5]

PERFORMANCE OF NON-INVESTABLE AND INVESTABLE HEDGE FUND INDICES

Tables 1 and 2 show the distributional characteristics of the two data sets. The monthly average performances do not differ significantly

Table 1: Moments of the DJCS benchmarks and AllHedge investable indices (monthly basis)

Strategy	*DJCS benchmark*					*DJCS AllHedge*				
	μ	σ	*Skew*	*Kurtosis*	*Ljung-Box*	μ	σ	*Skew*	*Kurtosis*	*Ljung-Box*
Composite	0.63	1.90	−1.46	6.33	0.00	0.35	2.18	−2.49	12.07	0.00
Convertible Arbitrage	0.46	2.81	−2.33	12.55	0.00	0.22	3.82	−3.33	18.13	0.00
Dedicated Short	−0.52	4.53	0.24	2.66	0.34⋆	−0.56	4.54	−0.00	3.96	0.61⋆
Emerging Markets	0.87	3.12	−1.64	8.34	0.00	0.64	4.14	−2.04	10.85	0.00
Equity Market Neutral	−0.04	4.79	−7.75	65.80	0.70⋆	−0.12	3.05	−3.04	20.02	0.37⋆
Event Driven	0.74	1.85	−1.13	4.81	0.00	0.63	2.20	−0.99	5.49	0.00
Fixed Income Arbitrage	0.29	2.36	−3.57	20.26	0.00	−0.26	3.25	−3.48	23.23	0.00
Global Macro	0.83	1.75	−1.30	7.31	0.05	0.25	2.80	−1.85	11.29	0.00
Long/Short Equity	0.68	2.43	−1.03	4.59	0.01	0.36	2.63	−1.78	7.36	0.00
Managed Futures	0.69	3.24	−0.09	1.82	0.97⋆	0.64	2.95	−0.06	2.08	0.54⋆
Multi-Strategy	0.57	1.93	−1.78	7.97	0.00	0.24	2.51	−2.51	14.91	0.00
MSCI World	—	—	—	—	—	0.49	5.02	−1.03	5.24	0.01

Note: ⋆indicates that the presence of autocorrelation is rejected at the 5 per cent level.

Table 2: Moments of the HFRI benchmarks and HFRX investable indices (monthly basis)

Strategy	*HFRI*					*HFRX*				
	μ	σ	*Skew*	*Kurtosis*	*Ljung-Box*	μ	σ	*Skew*	*Kurtosis*	*Ljung-Box*
Composite	0.68	2.17	−0.66	5.79	0.00	0.44	1.49	−2.86	18.60	0.00
Event Driven	0.74	2.08	−1.40	7.23	0.00	0.49	1.98	−1.59	8.04	0.00
Equity Hedge	0.78	2.83	−0.16	5.12	0.00	0.63	2.49	−0.35	6.41	0.00
Emerging Markets	0.91	3.74	−1.22	6.30	0.00	0.86	2.82	−1.20	6.54	0.04
Macro	0.68	1.72	0.40	3.82	0.53⋆	0.63	2.62	0.23	3.91	0.24⋆
Relative Value	0.64	1.36	−2.96	18.14	0.00	0.43	2.16	−2.83	18.67	0.00
MSCI World	—	—	—	—	—	0.36	5.07	−0.97	5.11	0.01

Note: ⋆indicates that the presence of autocorrelation is rejected at the 5 per cent level.

between the DJCS and the HFRI benchmarks, despite the different sample periods. The best performing strategy, that is, with the highest average returns, is Emerging Markets for both providers. The investable indices appear more dissimilar: the composite HFRX underperforms the composite AllHedge on average by 1 percentage point per year. More importantly, both investable sets show a lower mean return than their non-investable counterparts across the board. On the other hand, the volatilities (standard deviations) appear lower for the HFRX indices than for the non-investable benchmarks. However, this trade-off between return and risk is not present in the DJCS data, the volatility of the investable indices being on average slightly higher. The higher moments are also quite different: the investable indices present both a higher level of (negative) skewness and kurtosis.[6] We also document the presence of autocorrelation in returns for each hedge fund strategy. Most of the indices exhibit autocorrelation (as evidenced by the Ljung-Box *P*-values). We find evidence of no autocorrelation only for four strategies: Dedicated Short, Equity Market Neutral, Managed Futures for DJCS and Global Macro for HFR.

UNSMOOTHING HEDGE FUND RETURN SERIES

The presence of autocorrelation in hedge fund returns was first reported by Asness *et al* (2001), and its implication for risk measurement was stressed earlier in the hedge fund literature by GLM. GLM argues that the sources of autocorrelation in hedge fund returns are mainly stale values reported for illiquid assets used by alternative investments and by return smoothing practices. To recover the true returns, GLM use a moving average process of order 2, MA(2), where the observed returns are equal to a weighted average of past 'true' unobserved returns.[7] However, GLM, and subsequent papers, also assume that the true returns are normally distributed, which may not be appropriate, given the peculiar investment

Table 3: Best-fitting distribution and Jarque-Bera test for DJCS benchmarks and AllHedge investable indices

Strategy	*DJCS*			*AllHedge*		
	Distribution	*Chi-square p-value*	*JB p-value*	*Distribution*	*Chi-square p-value*	*JB p-value*
Composite	Skew Student	0.09	0	Skew Student	0.33	0
Convertible Arbitrage	Skew Student	0.10	0	Skew Student	0.11	0
Dedicated Short	Normal	0.57	0.71[b]	Normal	0.11	0.18[b]
Emerging Markets	Skew Student	0.10	0	Student	0.05	0
Equity Market Neutral	Skew Student	0[a]	0	Skew Student	0[a]	0
Event Driven	Student	0.05	0	Skew Student	0.06	0
Fixed Income Arbitrage	Skew Student	0.02[a]	0	Skew Student	0[a]	0
Global Macro	Student	0.53	0	Skew Student	0.20	0
Long/Short Equity	Normal	0.01[a]	0	Skew Student	0.05	0
Managed Futures	Normal	0.27	0.12[b]	Normal	0.27	0.29[b]
Multi-Strategy	Skew Student	0.32	0	Skew Student	0.50	0

Notes: [a]indicates that the Chi-square null hypothesis is rejected at the 5 per cent level; [b]indicates that the Normality assumption is not rejected at the 5 per cent level.

strategies used by hedge funds. Thus, we improve on the earlier approach and estimate the moving average model with the best-fitting distribution for each index. We allow the errors to be distributed by one of the following distributions: Normal, Student and Skew Student.[8] In order to select the best-fitting distribution, we conduct a chi-square goodness-of-fit test where the null hypothesis assumes that the data are randomly sampled from one of the distributions. Tables 3 and 4 show the best-fitting distribution for each strategy along with the *P*-value associated with the test as well as the *P*-value of a Jarque-Bera test for normality. The 'best' null hypothesis is rejected at the 5 per cent level for three strategies only: Fixed Income Arbitrage, Equity Market Neutral and Long-Short Equity for the DJCS data. Interestingly, for this same data set, the Skew Student is most often the best-fitting, whereas the Normal distribution is not rejected for two strategies: Dedicated Short and Managed Futures. This result may arise from the sample period, which includes the large negative performances seen during the last financial crisis and excludes the large positive returns seen at the end of the 1990s.

Figure 1 shows the empirical distribution for the four composite indices along with the best-fitted distribution computed with the same mean and standard deviation as the corresponding data.

Given the best-fitting distribution, we then estimate the smoothing parameters and the smoothing profile for all indices, reported in Tables 5 and 6. In line with the Ljung-Box test, there are 26 indices and

Table 4: Best distribution and Jarque-Bera test for HFRI benchmarks and HFRX investable indices

Strategy	*HFRI*			*HFRX*		
	Distribution	*Chi-square p-value*	*JB p-value*	*Distribution*	*Chi-square p-value*	*JB p-value*
Composite	Student	0.29	0	Skew Student	0.27	0
Equity Hedge	Student	0.55	0	Student	0.40	0
Event Driven	Skew Student	0.20	0	Skew Student	0.28	0
Emerging Markets	Skew Student	0.06	0	Student	0.72	0
Macro	Student	0.74	0.01	Skew Student	0.27	0.03
Relative Value	Student	0.35	0	Skew Student	0.17	0

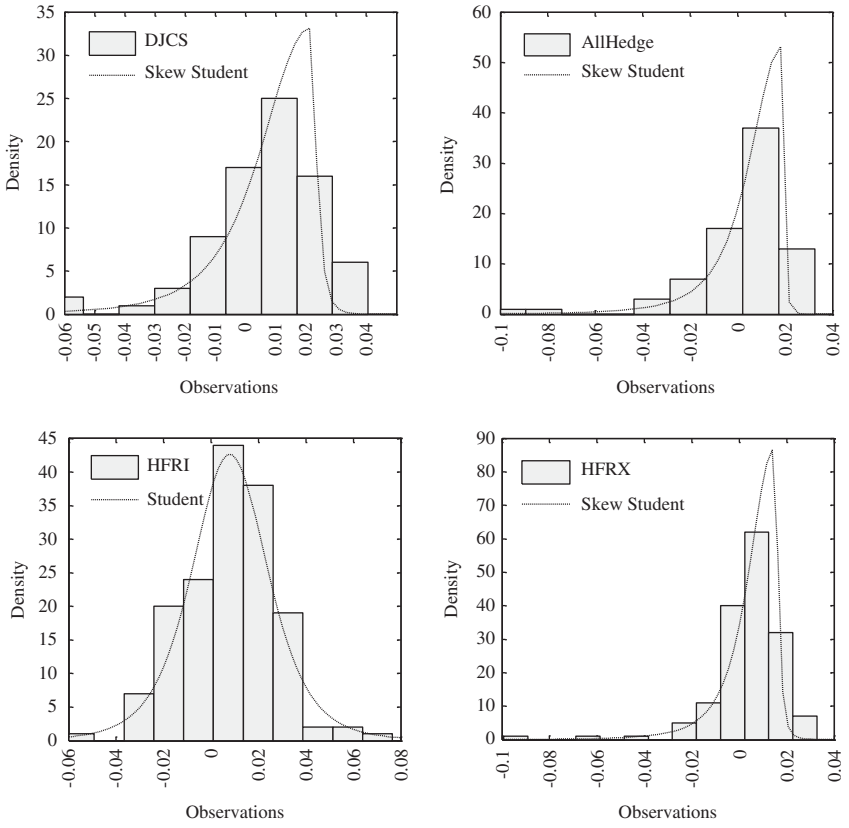

Figure 1: Best-fitting distribution of the DJCS and HFR composite indices.

sub-indices out of 34, for which a moving average process can be applied. Overall, the ranking of the different strategies according to their smoothing index seems consistent, given that the strategies expected to be relatively illiquid corresponding to those

Table 5: Smoothing parameters of DJCS benchmarks and AllHedge investable indices

Strategy	*DJCS benchmark*				*DJCS AllHedge*			
	θ_0	θ_1	θ_2	*Smoothing index*	θ_0	θ_1	θ_2	*Smoothing index*
Multi-Strategy	0.547	0.302	0.151	0.413	0.562	0.328	0.110	0.436
Fixed Income Arbitrage	0.533	0.353	0.114	0.421	0.517	0.389	0.094	0.427
Convertible Arbitrage	0.536	0.356	0.108	0.426	0.479	0.382	0.139	0.395
Composite	0.630	0.241	0.129	0.471	0.602	0.286	0.112	0.457
Event Driven	0.671	0.205	0.124	0.508	0.716	0.156	0.128	0.553
Emerging Markets	0.701	0.223	0.077	0.546	0.67	0.201	0.127	0.509
Long/Short Equity	0.712	0.187	0.101	0.552	0.706	0.251	0.043	0.563
Global Macro	0.773	0.176	0.051	0.631	0.648	0.188	0.164	0.482
Equity Market Neutral	1			1	1			1
Dedicated Short	1			1	1			1
Managed Futures	1			1	1			1

Note: The smoothing index is calculated as the sum of the squared θ_s.

Table 6: Smoothing parameters of HFRI benchmarks and HFRX investable indices

Strategy	*HFRI benchmark*				*HFRX*			
	θ_0	θ_1	θ_2	*Smoothing index*	θ_0	θ_1	θ_2	*Smoothing index*
Relative Value	0.595	0.289	0.116	0.451	0.538	0.308	0.154	0.408
Emerging Markets	0.650	0.218	0.133	0.487	0.770	0.108	0.122	0.620
Event Driven	0.670	0.265	0.065	0.523	0.665	0.252	0.084	0.512
Composite	0.738	0.191	0.071	0.586	0.612	0.289	0.099	0.468
Equity Hedge	0.753	0.180	0.067	0.604	0.734	0.180	0.087	0.578
Macro	1	—	—	1	1	—	—	1

with the lowest smoothing parameters. Indeed, Fixed Income Arbitrage, Convertible Arbitrage and Emerging Markets (HFRX) are well known to hold the most illiquid assets among all hedge fund strategies. Moreover, although they are in principle more liquid, the investable indices appear as smoothed as their non-investable counterparts. Smoothing practices, and even possibly illiquidity and/or non-synchronous trading issues, appear to be present in the investable return series, despite the constraints imposed during the selection of funds in them.

PERFORMANCE AND RISK MEASURES

Tables 7 and 8 report the Sharpe ratios for the composite and strategy indices.

This reward-to-variability ratio is a measure of the excess return per unit of risk of each index, where the excess returns are calculated assuming that the risk-free rate is represented by the average QJ;3-month US Treasury Bill rate over the sample period. Overall, with the exception of Managed Future indices, the non-investable benchmarks show a higher Sharpe ratio than the investable indices. Yet the investable indices do not exhibit the same rankings as their non-investable benchmark indices.

The performance of these hedge fund strategies is significantly altered when their return series are unsmoothed. In the reported (smoothed) returns, the 'true' risk level of the hedge fund strategies is masked by the smoothing process. Figures 2 and 3 display the

Table 7: Sharpe ratio of DJCS benchmarks and AllHedge investable indices

Strategy	*DJCS*		*AllHedge*	
	Original series	*Unsmoothed*	*Original series*	*Unsmoothed*
Global Macro	1.30	1.15	0.10	0.09
Event Driven	1.08	0.67	0.73	0.47
Composite	0.83	0.55	0.29	0.18
Emerging Markets	0.77	0.55	0.40	0.27
Long/Short Equity	0.73	0.58	0.25	0.18
Multi-Strategy	0.71	0.44	0.10	0.05
Managed Futures	0.56	0.56	0.56	0.56
Convertible Arbitrage	0.36	0.23	0.05	0.03
Fixed Income Arbitrage	0.18	0.12	−0.45	−0.35
Equity Market Neutral	−0.15	−0.15	−0.51	−0.51
Dedicated Short	−0.53	−0.53	−0.55	−0.73

Table 8: Sharpe ratio of HFRI benchmarks and HFRX investable indices

Strategy	*HFRI*		*HFRX*	
	Original series	*Unsmoothed*	*Original series*	*Unsmoothed*
Relative Value	1.20	0.82	0.42	0.25
Macro	1.03	1.03	0.61	0.61
Event Driven	0.95	0.68	0.56	0.40
Composite	0.82	0.65	0.63	0.40
Equity Hedge	0.74	0.56	0.65	0.45
Emerging Markets	0.69	0.47	0.84	0.63

time series plots of the reported versus unsmoothed cumulative returns for our four composite indices.

The Sharpe ratio naively computed from returns as reported significantly overestimates the true risk-adjusted performance of hedge funds on average by 30 per cent for both data sets.[9]

Consequently, the gap between investable and non-investable is lower for the unsmoothed returns compared with the reported returns, because the correction factor has a bigger impact, the higher the initial Sharpe ratio.

The Sharpe ratio measures the risk of an investment based on the second moment only and thus may give an incomplete and misleading picture of true risk because of the asymmetric strategies deployed by hedge funds. Consequently, a risk measure that takes higher moments into account is called for, such as the Omega Ratio developed by Keating and Shadwick (2002).

The Omega risk measure is the ratio of the probability of having a gain by the probability of having a loss relative to a threshold.[10] When two investments are compared, the

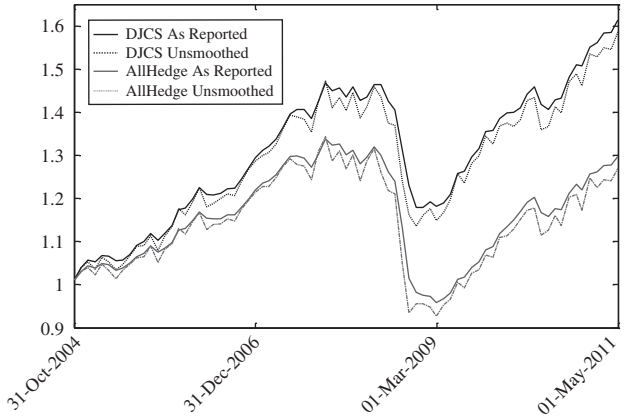

Figure 2: DJCS and AllHedge as reported versus unsmoothed cumulative returns.

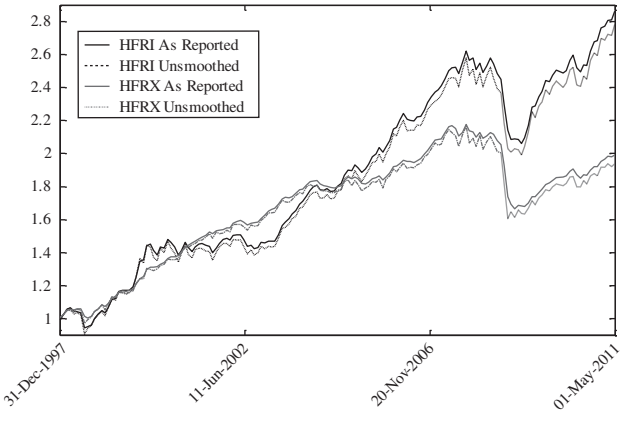

Figure 3: HFRI and HFRX as reported versus unsmoothed cumulative returns.

one exhibiting the higher Omega ratio is the superior investment. This non-negative ratio reflects all the moments of the probability density function into its calculation and is therefore considered a more useful risk measure for hedge fund returns. The formula for the Omega ratio is the following:

$$Omega(r_f) = \frac{\int_{r_f}^{\infty} [1 - F(R)]\mathrm{d}R}{\int_{-\infty}^{r_f} F(R)\mathrm{d}R}$$

Once again, as reported in Tables 9 and 10, the benchmark strategy indices still outperform the investable indices on a risk-adjusted basis. Interestingly, in line with previous findings (Eling and Schuhmacher, 2007; Eling *et al*, 2011), the rankings given by Omega index are highly correlated with those given by the Sharpe ratio, the smoothed Macro indices performing best for both sets of data. However, one may wonder whether this result is influenced by the specifics of the Omega ratio, which gives equal weights to all excess returns, and thus does not account for extreme distribution tail risks. Thus, the Omega ratio may not suit investors who are more risk-averse, such as the ones who invest in hedge funds.

Therefore, we finally explore the Farinelli-Tibiletti ratio (Farinelli and Tibiletti, 2003) computed as:

$$\Phi_{r_f}^{p,q} = \frac{E^{1/p}\left(\left\{(R - r_f)^+\right\}^p\right)}{E^{1/q}\left(\left\{(R - r_f)^+\right\}^q\right)}$$

This ratio can be interpreted as the price of one unit of return for one unit of loss, where returns and losses are computed with regard to a reference point, or target, and weighted by the parameters p and q, respectively. Zakamouline (2011) shows that the Farinelli-Tibiletti ratio is the performance measure of an investor with the following utility function:

$$U(R) = \left\{ \begin{array}{ll} (R - r_f)^p & \text{when } R \geqslant r_f \\ -\gamma(R - r_f)^q & \text{when } R < r_f \end{array} \right\}$$

Table 9: Omega ratio of DJCS benchmarks and AllHedge investable indices

Strategy	*DJCS*		*AllHedge*	
	Original series	*Unsmoothed*	*Original series*	*Unsmoothed*
Global Macro	2.39	1.95	0.94	0.93
Event Driven	1.98	1.59	1.55	1.35
Composite	1.70	1.39	1.13	1.05
Emerging Markets	1.61	1.40	1.24	1.13
Multi-Strategy	1.57	1.28	0.92	0.90
Long/Short Equity	1.54	1.35	1.10	1.05
Managed Futures	1.38	1.38	1.37	1.37
Convertible Arbitrage	1.22	1.05	0.90	0.86
Fixed Income Arbitrage	1.01	0.94	0.41	0.58
Dedicated Short	0.64	0.64	0.62	0.62
Equity Market Neutral	0.55	0.55	0.37	0.37

Table 10: Omega ratio of HFRI benchmarks and HFRX investable indices

Strategy	*HFRI*		*HFRX*	
	Original series	*Unsmoothed*	*Original series*	*Unsmoothed*
Relative Value	2.53	1.89	1.34	1.19
Macro	2.09	2.09	1.52	1.52
Event Driven	1.93	1.58	1.46	1.29
Composite	1.75	1.51	1.57	1.33
Equity Hedge	1.66	1.47	1.57	1.39
Emerging Markets	1.51	1.31	1.70	1.48

Table 11: Farinelli-Tibiletti ratio of DJCS benchmarks and AllHedge investable indices

Strategy	*DJCS*		*AllHedge*	
	Original series	*Unsmoothed*	*Original series*	*Unsmoothed*
Managed Futures	2.20	2.20	3.10	3.10
Dedicated Short	1.24	1.24	0.64	0.64
Long/Short Equity	0.27	0.34	0.04	0.11
Event Driven	0.27	0.32	0.28	0.28
Global Macro	0.23	0.27	0.12	0.31
Composite	0.16	0.23	0.02	0.07
Emerging Markets	0.10	0.14	0.04	0.04
Multi-Strategy	0.09	0.14	0.05	0.19
Convertible Arbitrage	0.04	0.09	0.01	0.02
Fixed Income Arbitrage	0.01	0.10	0.04	0.18
Equity Market Neutral	0.00	0.00	0.06	0.06

The Farinelli-Tibiletti ratio is then very flexible with respect to defining risk preferences. In order to have a more 'aggressive' ratio compared with the Omega ratio ($p = q = 1$), we set $p = q = 4$. Therefore, compared with the Omega ratio, our measure puts more weight on big gains and big losses, reflecting an investor risk-averse below her target r_f and risk-seeking above.[11]

Tables 11 and 12 illustrate that the rankings given by the Farinelli-Tibiletti ratio is rather different from those given by the Sharpe and Omega ratios. Interestingly, the smoothed and unsmoothed returns now show more consistent ranking results compared with our previous findings. For the DJCS data set, the two strategies best by the Farinelli-Tibiletti ratio are not even among the top five given by the Sharpe ratios. For the HFR data, the best strategy given by the Sharpe ratio, that is, Relative Value is now ranked last according to

Table 12: Farinelli-Tibiletti ratio of HFRI benchmarks and HFRX investable indices

Strategy	*HFRI*		*HFRX*	
	Original series	*Unsmoothed*	*Original series*	*Unsmoothed*
Macro	6.61	6.61	2.59	2.59
Equity Hedge	1.17	1.52	0.82	0.67
Composite	0.53	0.53	0.03	0.07
Emerging Markets	0.17	0.13	0.21	0.11
Event Driven	0.16	0.19	0.11	0.09
Relative Value	0.04	0.07	0.03	0.10

the Farinelli-Tibiletti ratio. Our findings corroborate the conclusions in Eling *et al* (2011) on the weaker link between the Sharpe ratio and the Farinelli-Tibiletti ratio. Our results also reinforce the fact that an investor downside-risk-averse may require (or be more sensitive to) different performance metrics in the presence of non-normal investments returns (Zakamouline, 2011).

The best DJCS strategy is the AllHedge Managed futures, whereas several other investable strategies (Global Macro, Event driven and Fixed Income Arbitrage) are on par with the non-investable indices. The HFRX data tend to diminish this last result though, as the difference between the two sets is more noticeable.

EXPOSURE TO RISK FACTORS

Finally, we carry out some multiple regression models, based on the factors proposed by Hasanhodzic and Lo (2007) and Amenc *et al* (2010) (see Table B1 for details). Notably, each hedge fund style is assigned only factors that are in accordance with its underlying investment strategy, statistically significant and maximize the adjusted *R*-square. As shown in Tables 13-16, investable and non-investable style indices are generally exposed to the same economic factors, implying that investable indices are representative of their benchmarks. Surprisingly, the non-investable indices are, on average, more exposed to common factors as measured by the adjusted *R*-square. Moreover, some strategies returns are well explained by a limited number of factors; notably, the Emerging Markets, Long/Short Equity and Event Driven strategies have an adjusted *R*-square above 0.6. On the other hand, some investment styles, Managed Futures and Global Macro, are little related to the selected economic factors with an adjusted *R*-square, on average, well below 0.2. Although this exercise does not yield an exact view regarding the replicability of the index, it still indicates how hedge fund indices are exposed to common risk premiums, and provide a first idea on how difficult/easy it would be for an investor lambda to reach that type of performance.[12]

In terms of alpha returns, the results are rather different. Although we found significant alpha coefficients for more than half of the non-investable indices (eight out of 14), only three investable indices show positive and

Table 13: Exposure of DJCS indices to selected economic factors

DJCS indices	*Asset class factor*	*Beta (alpha)*	*t-value*	*Adj R^2*
Emerging Markets	IFC	0.50	18.7	0.82
		0.00	0.36	
Long/Short Equity	MSCI	0.61	16.6	0.79
	Value_Spread	−0.72	3.05	
	UMD	0.09	2.36	
		0.003*	1.84	
Event Driven	MSCI	0.42	12.9	0.68
	Value_Spread	−0.70	3.59	
		0.005*	2.83	
Dedicated Short	S&P500	−0.37	5.13	0.47
	S-L	−0.84	4.75	
		−0.00	0.40	
Fixed Income Arbitrage	CSHY	0.74	7.57	0.42
	Bond	0.60	1.80	
		−0.00	0.77	
Convertible Arbitrage	CSHY	0.76	5.73	0.40
	CONV	0.086	0.99	
		−0.00	0.37	
Macro	CONV	0.13	2.50	0.23
	USD	−0.24	2.49	
		0.007*	3.18	
Equity Market neutral	S&P	0.37	−3.87	0.15
		−0.00	0.35	
Managed Futures	USD	−0.19	2.60	0.07
		0.007*	3.59	

Note: *indicates that the alpha coefficient is significant at the 5 per cent confidence level.

significant alpha; Managed Futures investable strategy is the only one significant for both index providers. On the one hand, one might argue that whether investable indices are less prey to the numerous hedge fund biases, and hence represent a more accurate representation of the achievable performance of hedge funds, they may generate their returns mainly through exposure to systematic risk and only secondarily by exploiting inefficiencies in markets. On the other hand, Fung and Hsieh (2009) observe that close to 40 per cent of the top hedge fund firms do not report to databases, which could then represent a sizable bias in the opposite direction. If the non-reporters are open to new investments, the alphas of investable indices may not be an accurate portrayal of the opportunity set for potential investors.

Table 14: Exposure of DJCS AllHedge indices to selected economic factors

DJCS AllHedge indices	*Asset class factor*	*Beta (alpha)*	*t-value*	*Adj R^2*
Long/Short Equity	MSCI	0.65	16.0	0.77
	UMD	0.12	2.87	
	Value_Spread	−0.61	2.32	
		0.00	0.03	
Emerging Markets	IFC	0.65	15.1	0.74
		−0.00	1.13	
Event Driven	MSCI	0.46	11.4	0.63
	Value_Spread	−0.95	3.96	
		0.003	1.53	
Equity Market neutral	S&P	0.37	6.90	0.37
		−0.00	0.89	
Fixed Income Arbitrage	CSHY	0.97	6.50	0.34
	Bond	0.73	1.43	
		−0.01*	2.01	
Convertible Arbitrage	CSHY	0.73	3.62	0.30
	CONV	0.29	2.18	
		−0.00	0.86	
Dedicated Short	S-L	−0.80	4.71	0.29
	S&P500	−0.13	1.88	
		−0.00	0.84	
Macro	CONV	0.29	3.06	0.23
	USD	−0.32	1.88	
		0.00	0.02	
Managed Futures	USD	−0.22	2.95	0.09
	CMDTY	−0.05	2.20	
		0.007*	4.10	

Note: *indicates that the alpha coefficient is significant at the 5 per cent confidence level.

CONCLUSION

We find that investable hedge fund indices perform worse than their corresponding hedge fund benchmarks (which include funds that are closed to new investors) regardless of the sample periods studied. We conclude this after recovering the true economic returns via an unsmoothing process and analysing the true returns by several performance and risk metrics (Sharpe, Omega ratio and Farinelli–Tibiletti ratio). Nonetheless, for some aggressive risk tastes, some of the portfolios represented by investable indices may be desirable investments, namely, Managed futures and Global Macro investable indices exhibit risk-adjusted

Table 15: Exposure of HFRI indices to selected economic factors

HFRI indices	*Asset class factor*	*Beta (alpha)*	*t-value*	*Adj R^2*
Emerging Markets	IFC	0.65	24.6	0.89
		−0.00	0.08	
Equity Hedge	MSCI	0.61	21.8	0.82
	S-L	0.34	8.40	
	Value_Spread	−0.47	4.36	
	UMD	0.08	3.42	
		0.004⋆	3.46	
Event Driven	MSCI	0.36	11.4	0.74
	S-L	0.27	7.01	
	CSHY	0.21	3.53	
		0.004⋆	3.50	
Relative Value	CSHY	0.52	12.7	0.50
	BOND	0.21	1.95	
		0.003⋆	2.85	
Macro	USD	−0.16	2.91	0.11
	CMDTY	0.04	2.27	
		0.006⋆	5.18	

Note: ⋆indicates that the alpha coefficient is significant at the 5 per cent confidence level.

Table 16: Exposure of HFRX indices to selected economic factors

HFRX indices	*Asset class factor*	*Beta(alpha)*	*t-value*	*Adj R^2*
Emerging Markets	IFC	0.42	17.0	0.79
		0.00	1.39	0.56
Equity Hedge	MSCI	0.50	13.1	
	UMD	0.12	3.98	
	S-L	0.18	3.23	
		0.004⋆	2.02	
Event Driven	MSCI	0.30	7.44	0.55
	S-L	0.16	3.36	
	CSHY	0.22	3.01	
		0.002	1.37	
Relative Value	CSHY	0.83	11.6	0.46
		−0.00	0.37	
Macro	CMDTY	0.05	2.10	0.05
	RUSSELL 2000	0.06	1.83	
		0.006⋆	2.88	

Note: ⋆indicates that the alpha coefficient is significant at the 5 per cent confidence level.

performance measures superior to their non-investable counterparts and also outperform all the other investable strategies. Moreover, these two indices have the additional benefit to offer little exposure to systematic risk factors.

NOTES

1. It is indeed important to note that these investable 'products' are only available through investment vehicles, ETFs or trackers. Thus, the performance data shown in this article are only 'a model output' and do not reflect the true performance of the investment vehicles. Moreover, the data do not take into account the investment vehicle fee.
2. Amenc *et al* (2010) emphasize the limits of replication; hence, the difference between 'explaining' and replicating hedge fund returns.
3. Formerly known as the Credit Suisse/Tremont Hedge Fund Index.
4. HFR states that 'the HFRX Global Hedge Fund Index is designed to be representative of the overall composition of the hedge fund universe' and 'HFRX Indices utilize state-of-the-art quantitative techniques and analysis; multi-level screening, cluster analysis, Monte-Carlo simulations and optimization techniques ensure that each index is a pure representation of its corresponding investment focus' (Hedge Fund Research, 2011).
5. Emerging markets indices only start in January 2005.
6. As the investable indices are characterized by a lower number of hedge funds, our result somewhat validates the law of large numbers. A Kolmogorov-Smirnov test for normality is rejected for both composite indices though (see Table 3).
7. As shown by Cavenaile *et al* (2011), the results are very similar to those obtained with the adjustment proposed by Okunev and White (2003). Moreover, given that the essence of the GLM approach is illiquidity driven, we decided to focus on this methodology only.
8. The estimation method is based on a maximum likelihood estimation of a moving average process. See Appendix A for more details.
9. This is because of the downward bias in the variance of the smoothed returns compared with the true variance. Moreover, for the calculation of the Sharpe ratio, we use the small sample bias corrected estimator (see Getmansky *et al*, 2004).
10. As before, we use the average risk-free rate over the sample period.
11. As Eling *et al* (2011) computations have also been carried out for $p = q = 10$, and $p = 1.5$, $q = 2$ as in Zakamouline (2011), and showed similar results. Moreover, the case where the investor is risk-averse below and above the target also showed similar results (available upon request).
12. According to Wallerstein *et al* (2010), implementing a sophisticated version of factor analysis should be possible with 6 months of work.

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APPENDIX A

The GLM (2004) methodology rests on a particular assumption regarding the structure of reported returns, which are equal to a weighted average of past 'true' unobserved returns. The model is the following:

$$r_t^o = \theta_0 r_t + \theta_1 r_{t-1} + \cdots + \theta_k r_{t-k} \quad (1)$$

Such that:

$$\theta_j \in [0,1], j = 0, \ldots, k \quad (2)$$

$$\theta_0 + \theta_1 + \cdots + \theta_k = 1 \quad (3)$$

where r_t^0 is the observed return at time t, r_t is the 'true' unobserved return at time t, and each theta is interpreted as a 'smoothing parameter'. The approach then consists in computing the demeaned observed returns and estimate the following MA(k) process:

$$X_t = \theta_0 \eta_t + \theta_1 \eta_{t-1} + \cdots + \theta_k \eta_{t-k} \quad (4)$$

With

$$X_t = r_t - \bar{r} \quad (5)$$

where $\bar{r}$ is the average over the sample period, and the errors are assumed to be Normal.

In this article, we relax the last assumption and allow the errors to follow one of the following distributions:

(1) Normal distribution:

$$\eta_t \sim N(\mu, \sigma^2).$$

(2) Student distribution:

$$\eta_t \sim T(\mu, \sigma^2, \upsilon),$$

where v represent the tails of the distribution.

(3) Skew Student distribution:

$$\eta_t \sim ST(\mu, \sigma^2, \upsilon, \alpha),$$

where the skewness is regulated by the shape parameter α and the tails of the distribution are controlled by v.

To select the best-fitting distribution, we conduct a chi-square goodness-of-fit test. We then estimate a MA(k) process with Maximum Likelihood. ML estimates have been shown to converge to clearly defined quantities, namely the parameters of the specified distribution. However, as indicated by Azzalini and Genton (2008), the likelihood function of the distribution may sometimes reach its maximum at the boundary of the parameters space. In order to deal with this issue, we decide to first estimate the parameters of the distribution, namely, the shape α and the tail v for each hedge fund index (via Maximum likelihood) and plug them as fixed coefficients in the MA(k) process.

Once the θ_i are estimated, we follow Gallais-Hamonno and Nguyen-Thi-Thanh (2008) and compute the 'true' returns by 'inverting' equation (1) as follows:

$$r_t = \frac{r_t^o - \hat{\theta}_1 r_{t-1} - \cdots - \hat{\theta}_k r_{t-k}}{\hat{\theta}_0} \qquad (6)$$

A recurring application of the above formula on the observed returns provides a series of corrected returns, which is free of serial correlation.

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APPENDIX B

Table B1: List of economic factors from Hasanhodzic and Lo (2007), and Amenc et al (2010)

	Economics factors
SP500	S&P 500 index
MSCI	MSCI World index
RUSSELL 2000	RUSSELL 2000 index
USD	USD index
BOND	Barclays US Aggregate Intermediate AAA index
CMDTY	Goldman Sachs Commodity index
S-L	Spread between the RUSSELL 2000 Small Cap index and the RUSSELL 3000 index
Value_Spread	Spread between the MSCI Value index and the MSCI World index
UMD	Up minus Down factor or Momentum Fama-French factor
CONV	Merrill Lynch 300 Global Convertible Bond index
CSHY	Credit Suisse High Yield Bond index
IFC	IFC Emerging Markets index
DEF	Difference between Barclays US Aggregate Intermediate BAA index and the Barclays US Aggregate Intermediate AAA index
MOR	Excess return of the GNMA index over the Barclays US Treasury index
CREDIT	Spread between Barclays US Aggregated Long Credit BAA index and the Barclays US Treasury index