Original Article

Boost your traditional portfolio: Activate traditional asset classes with alternative investments

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ABSTRACT We propose a new methodology to include hedge funds in a traditional portfolio. The concept of ‘substitution’ consists of activating a passive traditional investment strategy in a given asset class by adding active hedge fund strategies focusing on the same asset class. Our analysis, based on long-term data, shows that activated asset classes outperform the passive investments in terms of total performance, risk-adjusted performance and downside protection. Aggregating activated asset classes into an overall portfolio improves the efficiency of the initial portfolio without deteriorating its fat tail risk. Finally, we show that the ‘substitution’ approach leads to similar results as an optimisation approach in which the hedge fund portfolio is optimised as a stand-alone investment class and then added to the traditional portfolio. These findings validate an alternative solution for institutions that want to invest in hedge fund strategies, a solution that may be closer to their approach of portfolio management.

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INTRODUCTION

The year 2008 saw a huge collapse of financial markets. In such a context, dynamic strategies suffered significantly less than most of the traditional long-only strategies because they were able to partially adjust their risk exposures

to the underlying market conditions. It is therefore interesting to think about ways to ‘activate’ traditional asset classes or passive (buy-and-hold) investment strategies. Long-short strategies behave dynamically, and thus they are able to mitigate their dependence

on turnarounds in financial markets. Hedge funds constitute the most common access to dynamic strategies. The standard way to invest in hedge funds is through a diversified hedge fund portfolio that fits more or less the traditional part of the overall portfolio.

Academic literature has covered the characteristics of hedge funds, as well as the properties of their return distribution. It has also proposed several optimisation models that accommodate for these characteristics. Models based on Modified Value-at-Risk¹, on Conditional Value-at-Risk^{2,3}, on Omega measure⁴, on Extreme Value Theory⁵ and on higher moments optimisation⁶ have proven to outperform the traditional mean-variance optimisation framework. They all rely on different risk measures that take into account the non-normality of hedge fund returns. Another stream of research looks into the generation of hedge fund returns. Authors like Fung and Hsieh,⁷⁻⁹ Agarwal and Naik,⁴ and Agarwal, Fung, Loon and Naik¹⁰ have shown the importance of alternative risk factors in explaining hedge fund returns. On the basis of a factor approach, Alexander and Dimitriu¹¹ rank hedge fund managers with respect to their alpha. They construct outperforming portfolios with a selection of the highly ranked hedge funds. Martellini, Vaissié and Ziemann¹² propose an active style allocation methodology to improve the performance of their hedge fund portfolio. They claim that the allocation to hedge funds in the investor's overall portfolio is low (5–15 per cent). Therefore, all the effort should focus on improving the performance of the hedge fund component rather than looking at it from a global portfolio perspective. This approach is not followed by French¹³ who examines how hedge funds interact with a portfolio of traditional

assets (equities and bonds). He finds that the efficient frontier constructed from portfolios including hedge funds dominates the one restricted to equities and bonds. Amin and Kat¹⁴ corroborate this evidence showing that hedge funds improve the mean-variance characteristics of traditional portfolios, but that they also lead to lower skewness and higher kurtosis, mitigating therefore their added value. Analysing hedge fund allocations in an asset and liability framework, Otruba, Quesada and Scholz¹⁵ suggest that hedge funds add value by improving the risk-return profile of the portfolio in a surplus context and help lower the probability of underfunding.

In all the previously mentioned studies, hedge funds are considered first as a portfolio – some authors (for example, French¹³) would even say as a stand-alone asset class – that is managed as a stand-alone investment or in a global portfolio context. If the mix of hedge fund styles may be influenced by the asset allocation of the traditional portfolio (for example, Bacmann and Gawron⁵), it is always viewed as one investment bucket. In the universe of traditional equities, an innovative approach has emerged that combines buy-and-hold investment (long-only) with an active component (long-short). The approach is known as the 130/30 strategy where a manager can short sell 30 per cent of identified 'underperformers' to leverage up the weights on the long side of the portfolio either by identifying 'outperformers' or by considering all stocks that are not 'underperformers'. This approach looks like a long-short equity hedge fund, but in reality the 130/30 equity manager is constrained in terms of beta, tracking error, liquidity requirements and so on. Nevertheless, 130/30 managers are found to outperform the buy-and-hold managers in the United States

(Sorensen, Hua and Qian¹⁶; Armfelt and Somos¹⁷), in EAFE countries (Johnson, Ericson and Srimurthy¹⁸) and in Australia (Das, Frino and Jarnecic¹⁹). Agarwal, Boyson and Naik²⁰ analyse 'hedged mutual funds' that implement 130/30 type of strategies. They observe that these funds on average outperform traditional buy-and-hold funds by 4.8 per cent per annum, but they underperform hedge funds on a net of fee basis by 3.3 per cent per annum. They explain the overperformance of hedge funds by the fact that they are less constrained and/or regulated. The interesting point of the 130/30 approach is that an investor can add value to his portfolio if he combines his buy-and-hold investment with an actively managed component. Empirical evidence shows that it tends to work for equities. Why should it not work for other traditional asset classes? And why should we not use hedge funds as the active component?

In this article, we propose a methodology to combine long-only traditional asset classes with an active component directly linked to their investment focus and made of hedge funds. A straightforward example is long-short equity to boost the long-only equity piece of the portfolio. We name this approach 'substitution' of traditional asset classes. The blending of dynamic strategies with buy-and-hold ones is specific to one asset class and differentiated across the overall portfolio. The 'substitution' approach looks at hedge funds in the context of the underlying markets in which they operate and no longer as a single investment block in the overall portfolio. We do not argue that the 'substitution' approach is better than the standard approach. It rather constitutes an alternative solution for investors in their search for their optimal overall portfolio.

The remainder of the article is organised as follows: In the first section, we present the traditional asset classes and the active components that are linked to them. We show their risk-return, correlation and beta characteristics. We also define a traditional portfolio that will be used as a reference throughout the analysis. The next section is dedicated to the construction of activated portfolios for the appropriate asset classes. We look at efficiency, tracking error and the allocation to hedge funds. We then compare the 'activated' portfolio to the traditional portfolio. Adding a directional hedge fund portfolio following the same 'substitution' principle is presented in the subsequent section. We especially focus on the attractiveness of directional hedge fund strategies from an efficiency improvement perspective. The penultimate section compares the 'substitution' approach to the more conventional optimisation approach. Optimal hedge fund portfolios are constructed, which have similar risk levels as 'activated' ones. They are then analysed in terms of efficient frontier, hedge fund asset allocation and risk-return characteristics in a global portfolio context (including the traditional part of the portfolio). Finally, we present our concluding remarks in the final section.

TRADITIONAL ASSET CLASSES AND THEIR ACTIVE COMPONENT

We base our analysis on six asset classes: bonds, credit, equities, commodities, real estate and emerging markets. We aim to activate five of them with related hedge fund investments. Bonds represent Government bonds and therefore cannot be activated by a hedge fund

strategy active in the same underlying markets and with risk characteristics that are close enough. The list of traditional and alternative indices used throughout the study is presented in Table 1. The alternative counterpart for long-only credit is the HFRI ED: Distressed Restructuring Index. It includes hedge funds active in corporate fixed income instruments and primarily in corporate credit instruments of companies trading at significant discounts to their value at issuance or obliged (par value) at maturity as a result of either formal bankruptcy proceeding or financial market perception of near-term proceeding.

Equity long-short strategies as represented by the HFRI Equity Hedge (Total) Index serve as the active equity benchmark. Equity hedge managers maintain positions both long and short in equity and equity derivative securities. They dynamically manage their exposure to long-only equity indices in order

to be less dependent on the direction of equity markets.

For commodities and real estate, there are plenty of proxies available on the traditional side. We select the S&P/GSCI Index for commodities and the GPR 250 Global REIT Index for real estate. However, there does not exist any publicly available hedge fund index to represent these two asset classes. We construct our own indices by equally weighting all funds in HFRI, TASS and TASS Graveyard databases with an investment focus either on commodities or on real estate. Using graveyard data allows us to mitigate the survivorship bias. The Commodity HF Index includes a total of 94 funds over the whole period with at least two funds and with a maximum number of 67 managers at any point in time. Commodity hedge fund managers invest in a wide variety of trades: Directional trades based on their opportunistic view about commodity prices; equity trades based on

Table 1: List of traditional and alternative indices

	<i>Traditional index</i>	<i>Alternative index</i>
Bonds	Citigroup World Government Bond Index all maturities (Citigroup WGBI)	None
Credit	Credit Suisse High Yield Index II (CS High Yield)	HFRI ED: Distressed Restructuring Index (HFRI Distressed)
Equities	MSCI World Total Return USD (MSCI World)	HFRI Equity Hedge (Total) Index (HFRI Equity Hedge)
Commodities	S&P/GS Commodity Index Total Return (S&P/GSCI)	Commodity Hedge Fund Index (HF Commodity Index)
Real estate	GPR 250 Global REIT Index (GPR 250 Global)	Real Estate Hedge Fund Index (Real Estate HF Index)
Emerging markets	MSCI Emerging Market Total Return USD (MSCI EMMA)	HFRI Emerging Markets (Total) Index (HFRI EMMA)

commodity-linked equities; relative value trades based spreads observed on commodity markets. The Real Estate HF Index includes a total of 23 funds over the whole period and the number of managers present at any point in time ranges between 2 and 20. Real estate hedge fund managers mostly invest in long-short equity trades linked to the real estate sector.

The traditional emerging market index is an equity index. We do not consider emerging market bonds for the sake of simplicity. However, switching to, or adding, an emerging market debt index would not modify our findings. The alternative index for emerging markets (HFRI Emerging Markets (Total) Index) is not related to a specific investment

strategy but only considers the geographical focus of the included hedge fund managers. Nevertheless, it is safe to say that most emerging market hedge funds are mainly trading emerging market equities.

We base our analysis on historical performance. Therefore, we consider a long-term time period to take into account several cycles in all of the asset classes. Our analysis covers the period from January 1994 to September 2009.²¹

Looking at the risk-return characteristics of traditional indices (Panel A of Table 2) and alternative indices (Panel B of Table 2), we observe that alternative indices outperform their traditional counterparts (except for real estate)

Table 2: Risk-return characteristics per asset class

<i>January 1994 to September 2009</i>	<i>Bonds</i>	<i>Credit</i>	<i>Equities</i>	<i>Commodities</i>	<i>Real estate</i>	<i>Emerging markets</i>
<i>Panel A: Traditional indices</i>						
Return ann. (%)	6.53	6.96	6.28	4.48	9.19	5.91
Volatility ann. (%)	6.85	8.74	15.43	22.75	17.62	24.94
Downside dev (Libor) ann. (%)	4.24	6.51	11.51	16.14	13.18	18.38
Maximum drawdown (%)	−8.96	−31.84	−53.65	−67.64	−67.23	−61.44
Sharpe (Libor) ann.	0.35	0.34	0.21	0.13	0.36	0.19
Sortino (Libor) ann.	0.57	0.46	0.28	0.18	0.48	0.26
Skewness	0.31	−1.60	−0.89	−0.36	−1.56	−0.77
Excess kurtosis	0.36	11.26	1.99	1.58	9.48	1.89
<i>Panel B: Alternative indices</i>						
Return ann. (%)	—	9.84	11.52	7.13	7.43	9.72
Volatility ann. (%)	—	6.42	9.48	15.02	9.39	14.68
Downside dev (Libor) ann. (%)	—	4.53	5.85	10.47	6.33	10.59
Maximum drawdown (%)	—	−27.42	−30.57	−58.83	−20.26	−43.37
Sharpe (Libor) ann.	—	0.85	0.77	0.26	0.37	0.42
Sortino (Libor) ann.	—	1.21	1.24	0.37	0.55	0.59
Skewness	—	−1.58	−0.20	−0.39	−0.10	−0.97
Excess kurtosis	—	6.24	2.27	7.64	0.80	4.11

and present lower risk figures (standard deviation, downside deviation below Libor and maximum drawdown). In contrast to Amin and Kat¹⁴, the tail behaviour of alternative indices is not that different from that of traditional indices. Overall, skewness is comparable and the excess kurtosis is well above zero for all indices. In other words, alternative indices show negative fat tail risk but so do traditional indices²². Only bonds present a return distribution that is close to normal with a slightly positive skewness and a very mild excess kurtosis.

One advantage of alternative strategies compared with long-only ones is their dynamics. We examine the dynamics of alternative indices by looking at their rolling correlations to traditional indices (Figure 1a) and their rolling beta to traditional indices (Figure 1b). Rolling correlations are time varying for credit, commodities and real estate, whereas they are more static for equities and emerging markets. Correlations only measure the probability of both returns to evolve in the same direction. Hedge fund managers in the long-short equity space for instance also time their volatility, which is reflected in a time-varying beta even when correlation remains high.

Looking at the black line in Figure 1b, we see that the rolling beta of HFRI Equity Hedge evolves in line with the underlying equity environment: Increasing when equity markets are bullish and decreasing when bearish. These dynamics add value to the hedge fund strategy, allowing it to outperform in the long run (see performance figures in Table 2).

Figures 1a and 1b support the evidence that alternative indices are, at the same time, active in the same markets as their underlying indices but in a different manner. In that sense, they

constitute interesting complements to traditional long-only portfolios.

CONSTRUCTING THE 'ACTIVATED' PORTFOLIOS

Our methodology for constructing 'activated' portfolios per asset class is based on the tracking error of the 'activated' portfolio with respect to its traditional component. We analyse the five asset classes we want to activate separately, determining for each of them the maximum level of divergence we can tolerate in order to set the allocation to the hedge fund component. In short, the level of divergence is measured by the tracking error, which is defined as the annualised volatility of the difference in returns between the 'activated' portfolio and the traditional portfolio. Simultaneously, we look at the efficiency of adding hedge funds to the traditional index in terms of risk–return reward. Owing to the asymmetry of hedge fund returns, we use the downside deviation below Libor as the risk measure.

Figure 2 depicts the tracking error charts and the allocation to hedge funds for all asset classes to be activated. Two tracking error thresholds are used: TE 1 per cent and TE 2 per cent. Each chart in Exhibit shows the allocations for a given threshold (TE 1 per cent in the upper chart and TE 2 per cent in the lower) (Figure 2)

On the one hand, HFRI Distressed is an active component that does not diverge much from the CS High Yield Index (the long-only credit index). Thus, the allocation to hedge funds even at low levels of tracking error is material and the highest for all asset classes: 16 per cent for TE 1 per cent and 32.5 per cent for TE 2 per cent. On the other hand, the Commodity HF Index diverges considerably

Figure 1: (a) 24 M rolling correlations per asset class: Traditional to alternative. (b) 24 M rolling betas per asset class: alternative regressed on Traditional.

from its underlying long-only index. Therefore, allocations to Commodity HF Index are the lowest of all asset classes: 5 per cent for TE 1 per cent and 8 per cent for TE 2 per cent. This finding is not surprising as strategies implemented by commodity hedge funds differ the most from long-only passive investments. The remaining asset classes range in between,

with very close allocations to the Real Estate HF Index and HFRI Emerging Markets (7.5 per cent for TE 1 per cent and 15 per cent for TE 2 per cent), and slightly higher allocations to HFRI Equity Hedge (10 per cent for TE 1 per cent and 20 per cent for TE 2 per cent).

As presented in Figure 3, adding a dynamic component to the long-only asset classes

Figure 2: Tracking error chart and allocations to hedge funds in the 'activated' asset classes.

improves efficiency. The square indicates the starting point with 100 per cent allocated to the long-only index. Triangles represent the portfolios with allocations derived from the TE 1 per cent threshold, whereas diamonds illustrate the portfolios with allocations derived from the TE 2 per cent threshold.

For all asset classes, but real estate, adding the alternative component improves both risk and return of the respective traditional index. Even for low allocations such as those in the commodity asset class, the efficiency gains are noticeable. Real estate presents a slightly different pattern. Efficiency is improved only on

Figure 3: Efficiency analysis at the asset class level.

the risk side, and thus ‘incomplete’ compared with other asset classes. Nevertheless, ‘activating’ the real estate portfolio is beneficial from a diversification perspective.

All five asset classes have been activated with respect to the tracking error methodology. The next step is to aggregate all asset classes into a portfolio. Our starting point is a traditional portfolio containing the traditional asset classes defined in Table 1. The top chart in Figure 4 shows the initial asset allocation of the traditional portfolio. Its main component is bonds that are not activated but the remaining five asset classes are activated. The middle chart in Figure 4 presents the allocation in the ‘activated portfolio TE 1 per cent’, which includes activated asset classes with a tracking error of 1 per cent. Allocations to asset classes are unchanged. For all activated asset classes, the allocation to the traditional component is reduced to take into account the allocation to the active component determined by the ‘substitution’ process previously described. Figure 4 represents the aggregated hedge fund allocation, whereas the small pie chart details the hedge fund allocations within the five traditional asset classes. The

bottom chart in Figure 4 shows the allocations for the ‘activated portfolio TE 2 per cent’, which includes activated asset classes with a tracking error of 2 per cent. If the aggregated allocation to hedge funds increases from a tracking error of 1 per cent to a tracking error of 2 per cent, the repartition within the hedge fund buckets remains fairly similar. The relative allocation to distressed (alternative credit) is very large compared with the other hedge fund strategies that are more or less in line with the initial traditional allocation.

In Table 3, we present the risk–return characteristics of the portfolios illustrated in Figure 4. Activating the traditional asset classes improves the performance, reduces the risk and thus generates higher risk-adjusted figures. An interesting feature is the overall tracking error of the activated portfolios with respect to the traditional portfolio. They are markedly below the tracking error threshold at the asset class level. For instance, the tracking error of the ‘activated portfolio TE 1 per cent’ equals 0.43 per cent, which is less than half of the 1 per cent threshold. A similar proportion applies to the ‘activated portfolio 2 per cent’. These results outline the diversification benefits of hedge fund strategies.

We can clearly see the diversification benefit in terms of tracking error, which is linked to the normality assumption that hedge funds breach. However, the skewness and excess kurtosis of the ‘activated’ portfolios are slightly better than those of the traditional portfolio. This finding is in line with what is already observed at the asset class level. Our analysis includes the year 2008, which was the worst ever for the hedge fund industry. Consequently, we are reasonably confident in the tail behaviour of the ‘activated’ portfolios.

Figure 4: Asset allocation – Traditional portfolio and 'activated' portfolios.

Figure 5: Adding HF Directional portfolio to the 'activated' portfolios – Tracking error.

ADDING A DIRECTIONAL HEDGE FUND (HF DIRECTIONAL) PORTFOLIO

Directional hedge fund strategies such as global macro and managed futures cannot be related to a specific asset class. They are active on global markets. Global macro managers analyse shifts in macro-economic trends to capitalise on upward and downward directional opportunities across the spectrum of markets, asset classes and financial instruments. Managed futures trade futures and derivatives in financial assets and

tangible commodities worldwide. Their dynamic trading strategies help them to rapidly adjust to underlying market conditions. Thus, directional strategies have interesting correlation features with respect to a portfolio of traditional asset classes. Given the reduced tracking error observed at the portfolio level, directional hedge fund strategies could constitute an interesting and efficient way to bring back the tracking error level to its initial threshold.

We construct an HF Directional portfolio having a 60 per cent allocation to the HFRI Macro (Total) Index (proxy for global macro strategies) and a 40 per cent allocation to the Stark 300 Trader Index (proxy for managed futures strategies). The tracking error is computed with respect to the ‘activated’ overall portfolios. Consequently, the allocation to the HF Directional portfolio is determined on the basis of the overall tracking error level, including the sum of all allocations to hedge funds. We perform the analysis starting with the two activated portfolios: ‘Activated portfolio TE 1 per cent’ and ‘activated portfolio TE 2 per cent’. Figure 5 shows the tracking error chart with each line representing a different starting ‘activated’ portfolio. For the sake of brevity, we only show allocations to HF Directional that target an overall tracking error of 1 per cent with respect to the traditional portfolio as they illustrate two different cases: A relatively large allocation to HF Directional (starting from ‘activated portfolio TE 1 per cent’) and a relatively small allocation to HF Directional (starting from ‘activated portfolio TE 2 per cent’).

Raising the overall tracking error from 0.43 per cent to 1 per cent for the ‘activated’ portfolio TE 1 per cent allows for an allocation of 7.5 per cent to HF Directional. The overall tracking

error of 0.87 per cent of the ‘activated’ portfolio TE 2 per cent only allows for an allocation of 2.5 per cent to HF Directional. The remaining allocations in the ‘activated’ portfolios are scaled down on a *pro rata* basis to account for the allocation to HF Directional. The efficiency analysis for adding HF Directional to the ‘activated’ portfolios is shown in Figure 6. As previously, the square box represents the starting point with a 100 per cent allocation to the ‘activated’ portfolio. The triangle and the diamond represent the ‘activated’ portfolio TE 1 per cent with 7.5 per cent allocated to HF Directional and the ‘activated’ portfolio TE 2 per cent with 2.5 per cent allocated to HF Directional, respectively.

Adding HF Directional improves both risk and return of the ‘activated’ portfolios. It is interesting to notice that the risk level of the two new portfolios (‘activated TE 1 per cent with HF Directional’ and ‘activated TE 2 per cent with HF Directional’) is very close. In terms of performance, ‘activated’ TE 2 per cent with HF Directional benefits from its higher allocation to the active components in the various asset classes to exhibit a higher return than its TE 1 per cent correspondent portfolio.

Figure 6: Adding HF Directional portfolio to the ‘activated’ portfolios – Efficiency analysis.

For the sake of brevity, we restrict our analysis to these two portfolios combining activated asset classes with directional hedge fund strategies.²³ The choice of these two specific portfolios from all possible combinations of basis portfolios and overall tracking error thresholds is guided by the characteristics of the allocations to hedge funds. Figure 7 provides the detailed allocations of both portfolios.

The overall tracking error threshold of 1 per cent leads to total allocations that are of the same magnitude: 13.3 per cent for the ‘activated portfolio TE 1 per cent with HF Directional’ (see left-hand chart in Figure 7) and 14.7 per cent for the ‘activated portfolio TE 2 per cent with HF Directional’ (see right-hand chart in Figure 7). However, the allocation within the hedge fund ‘bucket’ varies from one portfolio to the other. On the one hand, the allocation to HF Directional in the ‘activated portfolio TE 1 per cent with HF Directional’ represents

more than 50 per cent of the entire allocation to hedge funds. On the other hand, the allocation to HF Directional in the ‘activated portfolio TE 2 per cent with HF Directional’ represents less than 20 per cent of the entire allocation to hedge funds. These characteristics make these two portfolios particularly interesting to analyse (Table 3).

The risk–return characteristics of the HF Directional portfolio (second column in Table 4) are very attractive compared with those of the traditional portfolio, especially in terms of downside risk and maximum drawdown. Adding HF Directional to the activated portfolios slightly improves the risk-adjusted performance, the skewness and the excess kurtosis. The two portfolios including HF Directional (the two highlighted columns in Table 4) are quite similar in terms of risk–return characteristics despite their specific allocation within the hedge fund bucket.

Figure 7: Portfolio allocation – Adding HF Directional to activated portfolios.

Table 3: Risk-return characteristics of traditional and 'activated' portfolios

<i>January 1994 to September 2009</i>	<i>Traditional portfolio</i>	<i>Activated portfolio TE 1%</i>	<i>Activated portfolio TE 2%</i>
Return ann. (%)	7.13	7.34	7.54
Volatility ann. (%)	8.82	8.48	8.15
Downside dev (Libor) ann. (%)	6.46	6.17	5.90
Maximum drawdown (%)	−32.21	−31.06	−29.95
Sharpe (Libor) ann.	0.36	0.39	0.42
Sortino (Libor) ann.	0.49	0.54	0.59
Skewness	−1.18	−1.17	−1.16
Excess kurtosis	5.10	4.95	4.80
Tracking error ann. (%)	0.00	0.43	0.87

Table 4: Risk-return characteristics of portfolios involving HF Directional portfolio

<i>January 1994 to September 2009</i>	<i>Traditional portfolio</i>	<i>HF Directional portfolio</i>	<i>Basis portfolio:</i>		<i>Basis portfolio:</i>	
			<i>Activated portfolio</i>	<i>TE 1%</i>	<i>Activated portfolio</i>	<i>TE 2%</i>
			<i>Without HF Directional</i>	<i>With HF Directional</i>	<i>Without HF Directional</i>	<i>With HF Directional</i>
Return ann. (%)	7.13	8.51	7.34	7.46	7.54	7.58
Volatility ann. (%)	8.82	6.69	8.48	7.99	8.15	7.99
Downside dev (Libor) ann. (%)	6.46	3.93	6.17	5.74	5.90	5.76
Maximum drawdown (%)	−32.21	−6.76	−31.06	−28.92	−29.95	−29.26
Sharpe (Libor) ann.	0.36	0.64	0.39	0.42	0.42	0.44
Sortino (Libor) ann.	0.49	1.09	0.54	0.59	0.59	0.61
Skewness	−1.18	0.16	−1.17	−1.08	−1.16	−1.13
Excess kurtosis	5.10	0.13	4.95	4.36	4.80	4.60
Tracking error ann. (%)	0.00	9.64	0.43	1.06	0.87	1.04

LINK TO OPTIMAL HEDGE FUND PORTFOLIOS

In the previous sections, we have shown that the 'substitution' methodology based on tracking error to determine the allocation to hedge fund strategies adds value to a traditional portfolio. In this section, we reconcile the 'substitution'

approach with an optimisation approach. We compute optimal hedge fund portfolios that have similar characteristics as the activated portfolios in terms of risk.

The optimisation framework we use is relatively simple and easy to explain. It is a single-period mean-downside deviation model

with constraints on minimum and maximum allocations to single hedge fund strategies. We select the downside deviation below Libor as the risk measure in order to better take the non-normality of hedge fund returns into account. We add constraints on allocations to single strategies to ensure a relatively diversified optimal portfolio along the efficient frontier.²⁴ The minimum allocation is set to 5 per cent, whereas the maximum allocation is fixed at 60 per cent. Figure 8 presents the outcome of the optimisation. The optimal asset allocation along the efficient frontier is shown in the upper chart. The lower chart displays the efficient frontier (black line). The two ‘activated

portfolios including HF Directional’ are represented by grey squares.

Only four hedge fund strategies get allocations higher than 5 per cent. Global macro represents the main bulk in the central part of the efficient frontier. There is a trade-off between distressed securities/managed futures and equity hedge as we move up the frontier. The activated portfolios are located below but very close to the efficient frontier. A pragmatic analysis would say that they are still in the grey zone where portfolios are no longer on the efficient frontier but not materially different.

In Figure 9, we compare the allocations of the hedge fund bucket between the activated

Figure 8: Optimal hedge fund allocation and efficient frontier.

Figure 9: Difference in asset allocation between activated HF and optimal HF portfolios.

portfolios including HF Directional and their corresponding optimal HF portfolios. A corresponding optimal HF portfolio is a portfolio located on the efficient frontier at the same level of risk as the activated portfolio. A striking result is that the asset allocations differ greatly even though activated portfolios and optimal HF portfolios are very close to each other in the mean-downside deviation framework. 'Activated portfolio TE 1 per cent with HF Directional' over-allocates to HFRI EH and Stark 300, whereas it under-allocates to HFRI Distressed. 'Activated portfolio TE 2 per cent with HF Directional' over-allocates to HFRI Distressed and to HFRI EMMA, whereas it under-allocates to HFRI EH and HFRI Macro. Comparing allocations to other strategies is less relevant as they are hitting the minimum allocation constraints in the optimal HF portfolios.

The next step involves measuring the impact of switching from the activated HF portfolio to the optimal HF portfolio in the overall portfolio context, including the traditional components. We do that from two perspectives: The first one consists of replacing the activated hedge fund bucket by its corresponding optimal HF portfolio leaving the total allocation to hedge funds unchanged. The second one relies on the tracking error concept. We add the optimal HF portfolio to the traditional portfolio in order to reach the 1 per cent overall tracking error level. The traditional portfolio is replaced by the optimal HF portfolio on a *pro rata* basis.

Risk-return characteristics of both approaches are presented in Table 5. The first two columns show the statistics of the overall activated portfolios. The two columns in the middle exhibit the statistics of the optimised portfolios, leaving the total allocation to hedge funds

Table 5: Risk-return characteristics of portfolios including optimal HF or activated components

January 1994 to September 2009	Activated portfolios		Optimal HF components matching total HF allocation		Optimal HF components matching tracking error	
	Activated TE	Activated TE	Optimal HF	Optimal HF	Optimal HF	Optimal HF
	1% with HF Directional	2% with HF Directional	TE 1% with traditional portfolio	TE 2% with traditional portfolio	TE 1% with traditional portfolio	TE 2% with traditional portfolio
Return ann. (%)	7.46	7.58	7.46	7.64	7.52	7.74
Volatility ann. (%)	7.99	7.99	8.13	8.34	8.01	8.26
Downside dev (Libor) ann. (%)	5.74	5.76	5.88	6.03	5.77	5.95
Maximum drawdown (%)	-28.92	-29.26	-29.83	-30.47	-29.35	-30.11
Sharpe (Libor) ann.	0.42	0.44	0.41	0.45	0.43	0.46
Sortino (Libor) ann.	0.59	0.61	0.59	0.62	0.60	0.64
Skewness	-1.08	-1.13	-1.15	-1.16	-1.14	-1.15
Excess kurtosis	4.36	4.60	4.74	4.66	4.65	4.55
Tracking error ann. (%)	1.06	1.04	0.88	0.86	1.06	1.04
Total hedge fund allocation (%)	13.30	25.65	13.30	14.71	15.98	17.72

constant. Finally, the last two columns display the statistics of the optimised portfolios achieving similar tracking error level as their activated counterparts.

The risk-adjusted performance is similar across all portfolios in Table 5. Keeping the total allocation to hedge funds constant, the tracking error of the optimised portfolios is lower than that of the activated portfolios. Consequently, by fixing the overall tracking error level, the total allocation to hedge funds increases for the optimised portfolios. Therefore, the risk-adjusted performance of the latter portfolios is slightly higher than that of their activated counterparts. The differences in asset allocations observed in Figure 9 have some impact on the overall portfolios. The optimised portfolios have a higher return but also a higher risk. Skewness and excess kurtosis figures are also slightly worse for optimised portfolios. Therefore, activating portfolios may have some advantage in keeping the overall risk characteristics lower than their optimised counterpart, although the differences are very small.

CONCLUSION

We propose an alternative solution to include hedge funds in a traditional portfolio. On the basis of the observation that dynamic or active strategies typical for hedge funds should complement passive investments in traditional asset classes, we develop a 'substitution' approach in which traditional asset classes are activated by active strategies applied to the same asset classes. A tracking error methodology is used to determine the allocation to the active strategies per asset class. Owing to diversification benefits, the tracking error of the overall portfolio containing all activated asset classes is below the

initial threshold. Therefore, supplementary investments into directional hedge fund strategies active on global markets are available. Directional hedge fund strategies display diversification benefits to the overall portfolio. Using the tracking error methodology, we add directional hedge fund strategies to the activated portfolios gaining additional improvement in efficiency and risk-return characteristics.

On the basis of a long-term time period involving several complete cycles for all asset classes considered, our results outline that the 'substitution' approach improves the total performance, the risk-adjusted performance and the downside risk at all levels: For individual asset classes, as well as for overall portfolios mixing traditional and active strategies. The non-normality of hedge fund returns does not increase the asymmetry of the distribution of returns in activated portfolios, mainly because traditional asset classes exhibit non-normality in their return distributions that is at least as pronounced as that of active strategies.

Overall, we show in our analysis that the 'substitution' approach leads to similar benefits of investing in hedge funds as the optimisation approach. The main advantage of the 'substitution' approach is that it relies on concepts that are well known in the traditional investment universe such as indexing and tracking error. From a quantitative and empirical perspective, it is impossible to say that one approach is better or worse than the other. The 'substitution' approach offers an alternative solution to the optimisation framework, as attractive in terms of performance and risk management but maybe easier to understand because it does not depend on sophisticated optimisation frameworks to deal with non-normality of hedge fund returns.

REFERENCES AND NOTES

- 1 Favre, L. and Galeano, J.A. (2002) Mean-modified value-at-risk optimisation with hedge funds. *Journal of Alternative Investments* 5: 21–25.
- 2 De Souza, C. and Gokçan, S. (2004) Allocation methodologies and customising hedge fund multi-manager multi-strategy products. *Journal of Alternative Investments* 6: 7–21.
- 3 Agarwal, V. and Naik, N.Y. (2004) Risks and portfolio decisions involving hedge funds. *Review of Financial Studies* 17: 63–98.
- 4 Favre Bulle, A. and Pasche, S. (2003) The Omega Measure: Hedge Fund Portfolio Optimisation. Working Paper available at SSRN: <http://ssrn.com/abstract=365740>.
- 5 Bacman, J.F. and Gawron, G. (2005) Fat-tail risk in portfolios of hedge funds and traditional investments. In: G.N. Gregoriou, G. Hübner, N. Papageorgiou and F.D. Rouah (eds.) *Hedge Funds: Insights in Performance Measurement, Risk Analysis and Portfolio Allocation*. Hoboken, NJ: John Wiley and Sons.
- 6 Anson, M.J.P., Ko, H. and Silberstein, K. (2007) Building a hedge fund portfolio with kurtosis and skewness. *Journal of Alternative Investments* 10: 25–34.
- 7 Fung, W. and Hsieh, D.A. (2001) The risk in hedge fund strategies: Theory and evidence from trend followers. *Review of Financial Studies* 14: 313–341.
- 8 Fung, W. and Hsieh, D.A. (2002) Asset-based style factors for hedge funds. *Financial Analyst Journal* 68: 16–27.
- 9 Fung, W. and Hsieh, D.A. (2004) Hedge fund benchmarks: A risk based approach. *Financial Analyst Journal* 60: 65–80.
- 10 Agarwal, V., Fung, W., Loon, Y.C. and Naik, N.Y. (2007) Risk and Return in Convertible Arbitrage: Evidence from the Convertible Bond Market. Working Paper available at SSRN: <http://ssrn.com/abstract=885945>.
- 11 Alexander, C. and Dimitriu, A. (2004) The art of investing in hedge funds: Fund selection and optimal allocations. In: B. Schachter (ed.) *Intelligent Hedge Fund Investing*. London: Risk Books.
- 12 Martellini, L., Vaissie, M. and Ziemann, V. (2005) Investing in Hedge Funds: Adding Value through Active Style Allocation Decisions. Working Paper: Edhec Risk and Asset Management Research Centre Publication.
- 13 French, C.W. (2005) Portfolio Selection with Hedge Funds. Working Paper available at SSRN: <http://ssrn.com/abstract=757892>.
- 14 Amin, G.S. and Kat, H.M. (2002) Stock, Bonds and Hedge Funds: Not a Free Lunch! Working Paper available at SSRN: <http://ssrn.com/abstract=310224>.
- 15 Otruba, S., Quesada, C. and Scholz, S. (2006) The added value of hedge funds in an asset-liability framework. *Journal of Asset Management* 6: 433–444.
- 16 Sorensen, E.H., Hua, R. and Qian, E. (2007) Aspects of constrained long-short equity portfolio. *Journal of Portfolio Management* 33: 12–22.
- 17 Armfelt, C. and Somos, D. (2008) Performance, Benefits and Risks of Active-Extension Strategies. Working Paper available at Stockholm School of Economics: <http://arc.hhs.se/download.aspx?MediumId=474>.
- 18 Johnson, G., Ericson, S. and Srimurthy, V. (2007) An empirical analysis of 130/30 strategies: Domestic and international 130/30 strategies add value over long-only strategies. *Journal of Alternative Investments* 10: 31–42.
- 19 Das, A., Frino, A. and Jarnecic, E. (2008) The Performance of the 130/30 Strategy in the Australian Equities Market. Working Paper available at SSRN: <http://ssrn.com/abstract=1181363>.
- 20 Agarwal, V., Boyson, N.M. and Naik, N.Y. (2009) Hedge funds for retail investors? An examination of hedged mutual funds. *Journal of Financial and Quantitative Analysis* 44: 273–305.
- 21 January 1994 is the inception date of the Hedge Fund Research database. Hedge Fund Research shows performance figures from January 1990 but data are backfilled before January 1994.
- 22 We used additional measures to examine the distributions of returns such as Omega (see Keating, C. and Shadwick, W. (2002) A Universal Performance Measure. *Journal of Performance Measurement*, Spring: 59–84). They support the evidence that hedge funds do not skew the distribution of returns to the left when combined with traditional asset classes (results available from the authors upon request).
- 23 Results for all the possible combinations of basis portfolios and overall tracking error thresholds are available from the authors upon request. We restrict the number of portfolios analysed in this study for the sake of brevity. The findings presented here are supported by any other combination of basis portfolios and overall tracking error thresholds.
- 24 We also run an unconstrained optimisation. The optimal portfolio only allocates to two or three hedge fund strategies but the overall findings remain valid.