The Fund of Hedge Fund Selection Puzzle: A Pragmatic Approach to Identify the X-Factor

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Abstract
We use the regime switching approach introduced in Pelletier (2006), and adapted by Giamouridis and Vrontos (2007) to the context of hedge fund portfolios, to design a new tactical style allocation factor. We then propose to leverage on this factor to identify fund of hedge fund managers who turn out to be good at capturing the upside while controlling for the downside risk. By so doing, we provide investors with a pragmatic though robust approach to address the fund of hedge fund selection puzzle. We show in the empirical analysis that funds of hedge funds showing the strongest loading on our factor outperform their peers materially. Very interestingly, we find persistence for both the highest and the lowest loadings. In the end, 11% of the funds of hedge funds in our sample systematically appear in the 1st tier.

Keywords: Fund of hedge fund selection, Dynamic portfolio construction, Regime switching model, Benefits of active portfolio management.

JEL classification: C23, G11.

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1. Introduction
The world has undergone dramatic changes since Harry Markowitz laid the foundations for Modern Portfolio Theory, back in the early 1950s (Markowitz (1952)). Technological breakthroughs, together with financial innovation, have made it possible for investors to gain exposure, at lightning speed, to an increasing number of markets, via a wider range of instruments. The asset allocation puzzle is therefore more complex today than it has ever been.

Investors have adjusted their practices to keep abreast of these changes and improve the long-term risk-adjusted performance of their portfolio. They started by allocating their capital across an increasing number of asset classes, and then progressively drilled down to geographical areas (i.e., developed, developing, frontier countries) and styles (e.g., value, growth, small cap, large cap). More recently, investors have turned to alternative investment strategies in an attempt to improve the resilience of their portfolio during episodes of stress. But experience shows that maximising the benefits of alternative diversification is not trivial. The alternative arena is populated by a myriad of strategies with heterogeneous return-enhancing and/or risk-reducing properties and identifying the best managers in a universe made up of 8,000+ active funds is a bit like looking for a needle in a haystack. It is all the more true in that transparency can (still) not be taken for granted in the hedge fund world. Many traditional investors have therefore naturally decided to take the “fund of hedge fund” route. But even if the recent crisis has fostered a consolidation process, and the number of funds of hedge funds is now close to its lowest level since 2005—separating the wheat from the chaff remains tricky. There are still close to 2,000 funds of hedge funds that are up and running according to the latest industry reports published by Hedge Fund Research Inc., and selecting the best ones just by looking at their track records is all but straightforward.

In order to help investors better understand the determinants of fund of hedge fund returns, we introduced in Darolles and Vaissié (2012) a return-based attribution model allowing for a full decomposition of their performance. We showed that funds of hedge funds are funds of funds like others, in that strategic allocation turns out to account for the bulk of the variation, and of the level of their performance. Fund picking also turns out to be a potential source of enhanced returns though more difficult to capture, as illustrated by a significant cross-sectional dispersion. Tactical Allocation, on the other hand, appears to have a marginal impact on the performance of funds of hedge funds.

A limitation of the aforementioned performance attribution model is however to assume that the strategic allocation of funds of hedge funds remains unchanged over the long-term, which is not necessarily the case, and may lead to a biased estimation of the value added both at the tactical allocation and at the fund picking levels (Darolles and Vaissié (2012)). Moreover, the poor contribution of tactical allocation that we evidenced could very well be partly explained by the limited level of liquidity offered by hedge funds in the past. Finally, one may argue that decomposing ex-post the performance of funds of hedge funds is one thing; identifying ex-ante the managers having the “X-factor” another. The former is important; the latter is crucial.

In an attempt to kill three birds with one stone, we propose to build on the model first introduced in Pelletier (2006) and advocated in Giamouridis and Vrontos (2007) in the context of hedge fund portfolios, to design a tactical style allocation strategy. In order to make the analysis less theoretical and obtain results that are as close as practically possible to investors’ actual experience, we consider in the first section a range of highly liquid investment vehicles that track the most popular hedge fund strategies. As we shall see, when the dynamics of the variance and correlation terms are properly taken into account, downside risk can be mitigated without compromising long-term growth prospects. Unfortunately, the practical implementation of this tactical allocation strategy turns out to be hardly possible over the long-term. Nevertheless, we
then propose to leverage on it to design a pseudo risk factor that we subsequently use to identify those fund of hedge fund managers who turn out to be good at capturing the upside while controlling for the downside risk.

Our main contribution is therefore to provide investors with a pragmatic though robust approach to address the fund of hedge fund selection puzzle. It is indeed, to the best of our knowledge, the first article to propose a pseudo risk factor making it possible to measure the capacity of a fund of hedge fund manager to manage risk efficiently. This article is aiming at traditional investors willing to dip a first toe in the hedge fund ocean and/or at those investors who have been disappointed by the behaviour of their fund of hedge fund investments throughout the recent crisis but (still) do not have the expertise and/or the resources to do the hedge fund picking and/or the portfolio construction on their own.

The remainder of this article is organised as follows. In Section 2, we investigate whether an optimal tactical style allocation strategy can actually help investors mitigating the (downside) risk of a hedge fund portfolio. We then figure out in Section 3 how to leverage on a dynamic portfolio construction approach to design a pseudo risk factor that will prove to be very useful in the fund of hedge fund selection process. Section 4 ends this article with some concluding remarks and suggestions for future research.

2. Assessing the Actual Benefits of Dynamic Portfolio Construction

The risk factor exposures of the different hedge fund strategies, and as a result their risk/return profiles, depend not only on market changes, but also on the underlying managers' idiosyncratic views (Billio et al. (2012)). The level of risk of the different funds, as well as their relationship with the other funds (within the same strategy or not) is therefore likely to change constantly. Adopting a dynamic portfolio construction approach at the fund of hedge fund level therefore appears to be relevant - if not necessary - to deal with such a parameter time-dependence.

The objective of this section is to find out whether an optimal tactical style allocation strategy can actually help investors mitigating the (downside) risk of a hedge fund portfolio without compromising its long-term growth prospects, knowing that the world is in constant evolution.

2.1. Data

Two practical challenges are faced when manipulating hedge fund data. First and foremost, the quality of the publicly-available information can, more often than not, be questionable. There is ample evidence in the academic literature that the information provided by commercial databases is considerably impacted by performance measurement biases (i.e., survivorship, selection, instant history, etc.). Some of these biases are inherent in the very nature of the hedge fund industry (i.e., “natural biases”), and others result from the way information is processed (i.e., “spurious biases”). While the estimation of these biases strongly depends on the sample and the observation period, most studies conclude that the impact on performance, as well as on the risk dimension, is very significant (see, among other examples, Fung and Hsieh (2000 & 2002)). In sum, hedge fund performance data is not always representative of the performance an investor would actually have obtained. This is all the more true today as information available on funds that were shut down or created side pockets in the wake of the Lehman Brothers collapse is scarce.

Secondly, hedge funds typically calculate net asset value on a monthly basis. It therefore takes years to collect a meaningful amount of data points. Since most hedge funds have a short history, empirical studies are frequently conducted on a very limited number of observations. The estimation risk is therefore exacerbated.
In order to tackle these two issues, we will use the hedge fund strategy indices provided by Lyxor. The specificity of these indices is that they comprise only managed accounts.\(^1\) Firstly, independent pricing of all the underlying positions and independent risk management ensure that the official net asset values published on a weekly basis, offer a true and fair representation of the performance of the constituent funds. The performance of the indices is subsequently calculated by an independent calculation agent, namely Standard & Poor’s. The quality of the data is, as a result, as good as it can be. Secondly, the constituent funds, and in turn, the indices, are truly investable. Subscription and redemption frequency is the same for the indices and their constituents, namely weekly, not to mention the fact that there is no entry/exit fee for institutional investors. Market frictions are therefore expected to be minimal. This is all the more important in that the dynamic portfolio construction approach that we apply in this section is liable to imply a significant turnover. Finally, the 14 strategy indices are mutually exclusive and collectively exhaustive. This collection of indices is thus a perfect allocation toolbox.

It should be noted at this stage that due to our focus on a highly liquid investment universe, the results that we obtain in this empirical analysis might not be generalised to the whole hedge fund universe. This is however not our goal; the primary objective of this section being a realistic implementation of the portfolio construction technique advocated in Giamouridis and Vrontos (2007).

Our sample comprises the weekly returns of the 14 Lyxor hedge fund strategy indices,\(^2\) from 4 January 2005 to 31 December 2012. We therefore have 418 weekly observations available. Thirty five years of track record would have been needed to have the same number of observations with traditional hedge funds. Although necessary, having a significant number of data points is not sufficient. The information content is also essential. In this respect, our sample covers the most eventful period since the Great Depression, with a series of bull markets and significant corrections, a "risk on/risk off" environment, a banking crisis, a sovereign debt crisis, etc.

2.2. Methodology

Several models have been introduced in the literature to try and capture the dynamics of the variance and the correlation of asset returns. Engle (2002) proposes, for example, a generalisation to multivariate time series of the ARCH/GARCH approach first introduced in Engle (1982). However, this approach is anything but straightforward and generally leads to an acute dimensionality problem. This explains why the most popular multivariate volatility model is certainly the constant conditional correlation (CCC) model introduced in Bollerslev (1990). Once the covariances of the asset returns are broken down into standard deviations and correlations, the constant correlation hypothesis allows factoring of the likelihood function and uses a two-step estimation procedure. Thus, only univariate dynamic volatility models have to be estimated asset by asset in the first step. The constant correlation estimator is computed in the second step. However, the hypothesis of constant correlations is rarely supported by the data. Pelletier (2006) therefore extends the initial CCC specification by introducing a regime switching dynamic correlation (RSDC) model. Starting with the same decomposition of covariance matrices, Pelletier (2006) specifies a dynamic process for the correlation matrices. These matrices are set to follow a regime switching model; correlations are constant within a regime but different across regimes. The transitions between the regimes follow a Markov chain. The CCC model thus appears to be a special case of the RSDC model, with just a single regime on the correlation matrices. Giamouridis and Vrontos (2007) test different static and dynamic covariance/correlation models and compare the out-of-sample performance of the optimised portfolios in the context of hedge fund portfolios. They find that the RSDC model both reduces portfolio risk and improves the out-of-sample risk-adjusted performance. Empirical studies covering the recent crisis gave further credence to these results (Harris and Mazibat (2010), Bruder et al. (2011)). Building on Giamouridis and Vrontos (2007), we will thus put the RSDC model on the grill in the remainder of this section.

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1 - For technical details on managed accounts please refer to Siraud (2005).
2 - Please visit www.lyxorhedgeindices.com for greater details on the construction methodology and the composition of the 14 strategy indices.
In order to isolate the benefits of the RSDC model (see Appendix I for the technical details), we focus on the one portfolio on the efficient frontier for which no information on expected returns is required, that is, the portfolio with the minimum amount of risk. For the sake of simplicity and in an attempt to control for the estimation risk, we will opt for the mean/variance framework and consider the minimum variance portfolio. The risk dimension is therefore assumed to be fully defined by the covariance matrix.

In the empirical analysis, we use the weekly returns of the 14 Lyxor hedge fund strategy indices, from 4 January 2005 to 31 December 2012, to run the optimisation and obtain the weightings of the minimum variance portfolio. We only impose two constraints on the optimisation, namely the portfolio constraint (i.e., weightings have to add up to 1), and the short sale constraint (i.e., weightings must be positive). We do so to construct a series of three portfolios. First of all, we assume that the volatility and correlation terms are constant over time, and compute the static minimum variance portfolio (referred to below as the “STATIC portfolio”). Secondly, we allow for volatility to be time-varying; we thus filter the volatility of the 14 Lyxor hedge fund strategy indices using a GARCH (1,1) model, and compute a first dynamic minimum variance portfolio (the “GARCH portfolio”). Thirdly, we allow both the volatility and the correlation terms to be time-varying; we thus filter the volatility of the 14 Lyxor hedge fund strategy indices, model the correlation matrix with a switching regime model, and compute a second dynamic minimum variance portfolio (the “SRM portfolio”). Lastly, we consider the equally-weighted portfolio (the “1/N portfolio”) to see how optimal diversification compares to naïve diversification. We therefore end up with four portfolios, with weekly returns from 4 January 2005 to 31 December 2012.

2.3. Empirical analysis

As suggested in Amenc and Martellini (2002), by focusing on the minimum variance portfolio, we may expect the optimal portfolio to be over allocated to low-volatility strategies. This is definitely true for the STATIC portfolio. Relative value strategies are given the lion’s share. As much as 27% is allocated to L/S Equity Market Neutral (14% to Fixed Income Arbitrage and 6% to Statistical Arbitrage). With 3%, Convertible Arbitrage is considerably behind, which does not come as a big surprise, given the behaviour of the strategy throughout 2008. As one could have expected, CTA Short-Term is granted a nice chunk of the capital, namely 14%. Conversely, strategies such as CTA Long-Term, L/S Credit Arbitrage or Special Situations, with higher risk/return profiles, are purely and simply ruled out. The only real exception is the L/S Equity Short Bias strategy, which obtains an 11% allocation despite its high volatility; this is easy to understand once we factor in its genuine diversification properties. All in all, the STATIC portfolio remains fairly diversified though, with a normalised Herfindahl index (NHI) of 9%. Turnover is obviously nil.

The optimal portfolio may be expected to be more diversified on average when the volatility of the hedge fund strategy indices is time-varying. The reason is that even high-octane strategies can at times be less volatile. They might as a result find their way into the optimal portfolio from time to time. But this greater diversification is likely to come at the cost of significantly higher turnover. To find out whether all this proves to be true we filter the volatility of the hedge fund strategy indices using a GARCH (1,1) model.

As can be seen from Figure 1, some strategies, such as L/S Equity Short Bias, show the highest levels of volatility almost systematically. Others, like CTA Long-Term, Special Situations or L/S Equity Long Bias, rank on average among the most volatile strategies, but can under certain circumstances show a lower level of volatility relative to the other strategies (essentially as a result of other strategies experiencing an increase in volatility). Conversely, some strategies, such as Convertible Bond Arbitrage, Merger Arbitrage, Fixed Income Arbitrage or Statistical Arbitrage exhibit on average, a fairly low level of volatility, but can at times experience spikes of volatility. Finally, some rare strategies, such as L/S Equity Market Neutral, appear to end up with one of the lowest levels of volatility almost on a systematic basis.

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3 - The Herfindahl Index is a measure of concentration that is defined as the sum of the squared weightings of the portfolio. The normalised Herfindahl Index is equal to: H* = (H - 1/N) / (1 - 1/N). The index thus ranges from 0% (maximum diversification) to 100% (maximum concentration).
In line with our hypothesis, new strategies appear in the optimal mix when we use GARCH-filtered volatilities. This is the case of Convertible Bond Arbitrage and to a lesser extent of L/S Credit Arbitrage. L/S Equity Market Neutral and CTA Short-term, the two largest positions in the STATIC portfolio are, unsurprisingly, the main losers. L/S Equity Long Bias also sees its allocation decrease materially. The NHI calculated on the average strategy weightings of the GARCH portfolio ends up at 6%, versus 9% for the STATIC portfolio.

Apart from the Lehman Brothers collapse that triggered a systemic crisis and impacted all hedge fund strategies concomitantly, market events of a different nature seem to impact the various strategies in diverse ways (for example, the spike in volatility of L/S Equity Variable Bias when the markets turned down swiftly in mid-2006, or of Long-Term CTA at the onset of the subprime crisis early 2007, or of Statistical Arbitrage during the Quant Crisis in the summer of 2007, or of Fixed Income Arbitrage when Bear Stearns got into trouble early in 2008). The allocation of the optimal portfolio is therefore likely to change frequently. We do indeed observe as much as 13% of turnover on a weekly basis. As a comparison, allocators’ portfolio turnover reached a maximum of 29% per annum in 2008.

4 - Please refer to Goldman Sachs Prime Brokerage Eleventh Annual Global Hedge Fund Investor Survey 2011 for more detail. Note, however, that the indices used in this experiment offer weekly liquidity, whereas hedge funds typically have a redemption frequency of monthly to annually.
The marginal impact of regime switching correlations on the concentration and turnover of the optimal portfolio is less straightforward. To find out whether it magnifies or counterbalances the effect of GARCH-filtered volatility, we implement the two-step procedure presented in Appendix I, and compare the characteristics of the GARCH and SRM portfolios. We start by identifying the different regimes and estimate the associated probabilities.

Table 1: Transition matrix

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<th>Normal market regime</th>
<th>Stressed market regime</th>
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<tbody>
<tr>
<td>Normal market regime</td>
<td>97%</td>
<td>3%</td>
</tr>
<tr>
<td>Stressed market regime</td>
<td>40%</td>
<td>60%</td>
</tr>
</tbody>
</table>

Given the high probability associated with the "Normal" regime, and the high degree of stability (see Figure 2 and Table 1), it is not surprising to observe that the correlation matrix obtained in this regime is very close to that based on the full observation period. As can be seen from Table 2C, the average difference between the two matrices is as low as 4%. We observe a low average correlation between hedge fund strategies (i.e., 21%), but with a large dispersion (i.e., from +85% between Special Situations and L/S Equity Long Bias to -73% between L/S Equity Long Bias and L/S Equity Short Bias). The picture is somewhat different when it comes to the "Stressed" regime. In this case, the correlation matrix is very different. Interestingly, contrary to conventional wisdom, correlations do not move in lockstep in the "Stressed" regime, and more importantly, they do not necessarily increase. As can be seen from Table 2E, the average difference between the correlation matrices of the "Normal" and "Stressed" regimes turns out to be negative (i.e., -10%). This result can be explained by the fact that the impact of the standard deviation terms has already been filtered out. We therefore capture changes in the market structure as opposed to market shocks. We still find a low average correlation between the different strategies (i.e., 14%), again with a large dispersion (i.e., from +77% between L/S Equity Market Neutral and L/S Equity Short Bias to -72% between L/S Equity Long Bias and L/S Equity Market Neutral). Surprisingly, the average correlation of L/S Equity Short Bias with the other strategies increases significantly (i.e., from -42% in the "Normal" regime to +17% in the "Stressed" regime) - as if its diversification properties vanish precisely when investors are most in need of them. Although unexpected, this is consistent with the findings of previous studies (Billio et al. (2012)).

Table 2A: Correlation matrix — normal market regime (1)

Table 2B: Correlation matrix — normal market regime (2)
Despite the fairly low probability associated with the "Stressed" regime, and the poor stability, it turns out that it plays a significant role in the portfolio construction process. The average exposure to L/S Equity Market Neutral (which was strongly reduced after volatility filtering) is higher than it is for the GARCH portfolio. The Convertible Bond Arbitrage strategy (which was significantly increased after volatility filtering) sees the largest average reduction. Massive swings are also observed around market events for many other strategies.

We note that, at the onset of the subprime crisis, Convertible Bond Arbitrage is trimmed in favour of L/S Equity Market Neutral. In the same vein, ahead of the Lehman Brothers collapse we observe a massive reduction in Convertible Bond Arbitrage and Fixed Income Arbitrage, while CTA Short-Term, Global Macro, L/S Credit Arbitrage and Statistical Arbitrage see their weighting increase substantially. All in all, we obtain an NHI of 7% and turnover of 16%.

Now that we have the weightings of the different portfolios, we can compare and contrast their behaviour. As can be seen from Figure 3, the outperformance of the SRM portfolio relative to the STATIC portfolio is considerable. The dynamic approach not only better captures the upside, but more importantly, it dramatically reduces the downside risk. The compounded annual growth return increases by as much as 77%. This result does not come as a big surprise. By focusing on strategies with a low level of volatility, the STATIC portfolio completely ruled out strategies such as Special Situations, which performed very well during the different bull markets, Long-Term CTA, which did well through the storm of 2008, and finally L/S Credit, which rebounded massively in 2009 when markets normalised. As can be seen from Figure 3, the outperformance relative to the GARCH portfolio is also significant. This confirms that despite its low probability and high instability, the “Stressed” regime plays a key role in the portfolio construction process,
especially when there are multiple structural changes in market conditions. The result is a similar performance in the final stage of the bull market of 2007, a similar resilience during the first part of the crisis, but better behaviour during the second part of the crisis, and greater upside potential when market conditions normalise (i.e., when the correlation component kicks in). The compounded annual growth return increases by as much as 30%. Lastly, the SRM portfolio outperforms the naïve 1/N portfolio quite substantially. Here again, the key determinant of the performance gap is the dramatically lower downside risk. In spite of lower returns during normal market conditions, the SRM portfolio ends up with a compounded annual growth return 41% higher. This confirms that the best way to make money over the long run is to avoid losing money in the first place. It is worth noticing that the naïve diversification strategy fared better than the STATIC portfolio. This result may, however, be largely attributed to the V-shape of the crisis (i.e., freefall followed by a sharp rebound). If the market turmoil had lasted longer, more funds in strategies such as Convertible Bond Arbitrage, L/S Credit Arbitrage, Special Situations or even Global Macro would have imploded, so the drawdown of the 1/N portfolio would have been significantly worse, and the upside potential massively reduced.

In practice lightning rarely strikes twice in the same place, and every new crisis comes with its share of novelty. One may therefore argue that such appealing results can only be obtained on an in-sample basis. But very interestingly qualitatively similar results are obtained when investors do not already have all the relevant information sets, and they are receiving new information randomly (see Appendix II). However, it turns out that these benefits only hold true for fast-moving investors dealing with liquid instruments, as significant and unforeseen events may necessitate swift and potentially major adjustments of the portfolio structure (see Appendix III). Implementing such a tactical style allocation strategy may thus be problematic over the long-term as the underlying fund managers (and their investors) may sooner than later be reluctant to accept money from (co-invest with) such unstable investors.

3. Identifying the X-Factor
We have seen in the first section of this article that the RSDC model advocated in Giamouridis and Vrontos (2007) lived up to investors' expectations, in that it helped mitigating the downside risk without sacrificing on the upside potential. Unfortunately, such a tactical style allocation strategy can hardly be implemented in practice—at least over the long-term. We argue that it remains very interesting for investors though. As we shall see in this section, one can leverage on this dynamic portfolio construction approach to design a pseudo risk factor that will prove to be very useful in the fund of hedge fund selection process.
3.1. Data
We will make use of two sets of data in this section. On the one hand, the weekly returns of the hedge fund indices provided by Lyxor (including the composite index), so that we can build the track record of the tactical style allocation strategy that we put under the microscope in the first section, and in turn, so that we can design our pseudo risk factor. On the other hand, a representative sample of funds of hedge funds; we used to this end the database provided by Morningstar. This database contains information on 7,000 actively reporting funds from more than 3,700 managers, 1,925 of which fall into the fund of funds category. For the sake of consistency, and in order to have sufficient meaningful information, we only considered the funds of hedge funds denominated in USD, showing a minimum of $5 million of assets under management, and with a continuous track record from January 2005 through December 2012. Finally, in an attempt to mitigate the double-counting issue, we identified the funds of hedge funds with a similar name showing a correlation superior or equal to 0.95, and we only kept the one with the longest track record and/or the institutional share class when a distribution share class was also available. We therefore ended up with a sample of 262 funds of hedge funds with 96 months of continuous return streams.

While hedge fund data is seriously flawed by a series of performance measurement biases, fund of hedge fund data provides a much cleaner estimation of investors’ actual performance (Fung and Hsieh (2000)). Fund of hedge fund returns are for example immune to the so-called self-reporting bias, which is liable to be severe in hedge fund data bases (Agarwal et al. (2013), Aiken et al. (2013), Hodder et al. (2013)). The impact of the aforementioned biases on the results of the following empirical study should therefore be limited.

3.2. Methodology
While risk (e.g., volatility) can fairly easily be mitigated with a properly diversified portfolio, investors have much more difficulty coping with uncertainty (i.e., volatility of volatility). One could even argue that traditional investors, who typically follow buy-and-hold strategies and manage more often than not cumbersome portfolios, are structurally ill-suited to the new complexity of financial markets. It is precisely to try and bridge the gap that many made their first foray into alternative investment strategies. More than alpha, which is difficult to identify and typically lacking persistence (Agarwal and Naik (2000), Baquero et al. (2005), Kosowski et al. (2007), Eling (2009)), what these investors are expecting from funds of hedge funds are asymmetric risk factor exposures so that they can enhance their expected return without taking additional (downside) risk. Those non-linear risk factor exposures can be obtained at the strategic allocation level, through the selection of strategies showing non-linear exposures (Giannikis and Vrontos (2011)), at the tactical allocation level, through a dynamic allocation across strategies and eventually at the fund selection level (Ter Horst and Salganik (2014)).

Numerous factor models have been introduced in the literature to assess the performance of mutual funds (Sharpe (1964), Fama and French (1992), Carhart (1997), Pastor and Stambaugh (2003), Baker and Würgler (2006), etc.), or hedge funds (Agarwal and Naik (2004), Fung and Hsieh (2004), Hasanhodzic and Lo (2007), etc.). Moreover, different return-based approaches have been proposed in the literature to capture the benefits of active risk management. Treynor and Mazuy (1966) for example proposed very early on to augment the linear Capital Asset Pricing Model (hereafter CAPM) with a quadratic term. Henriksson and Merton (1981) argued a few years later that perfect market timing was equivalent to a fully covered buy-and-hold strategy in the market. They therefore proposed to augment the CAPM with the price of a put option on the market with a strike set at the risk-free rate. But as stressed in Darolles and Vaissié (2012) very little has been done so far for funds of hedge funds specifically, leaving many traditional investors at a loss.
In an attempt to have an explicit return-based measure of the benefits of active risk management, and in turn make the interpretation for funds of hedge funds straightforward, we propose to leverage on the tactical style allocation strategy analysed in the first section of this article to design a pseudo risk factor. More specifically, we propose to decompose the performance of funds of hedge funds in three components. First of all, following Aglietta et al. (2012) we isolate the market component. We will use in this respect the Lyxor Composite index as a proxy for the hedge fund industry. Secondly, we consider the return derived from an active management of the underlying risk factor exposures. We will use as a proxy the excess return of the tactical style allocation strategy over the market return. As previously mentioned, we may at this stage capture decisions made by the fund of hedge fund manager at the strategic allocation, tactical allocation and/or fund selection levels. As evidenced in Ter Horst and Salganik (2014) investors do indeed actively allocate capital across and within hedge fund styles. Finally, we will define the residual return as the outperformance stemming from idiosyncratic risks. We therefore obtain the following equation:

$$R_i = \alpha_i + \beta_i R_{COMP} + \gamma_i (R_{TSA} - R_{COMP}) + \varepsilon$$

Where $R_i$ denotes the return of the fund of hedge fund $i$, $R_{COMP}$ the return of the Lyxor composite index, and $R_{TSA}$ the performance of the tactical style allocation strategy building on the RSDC model (i.e., the "SRM portfolio" in Section 2). The error term $\varepsilon$ is assumed to be an independently identically distributed (i.i.d.) zero-mean white noise.

Differently put, we propose to augment the CAPM with the X-Factor, which simply consists in the outperformance generated by a fund of hedge fund manager managing his aggregated risk factor exposures efficiently.

The following empirical study therefore involves regressing the monthly returns of the 262 funds of hedge funds in our sample on the market risk, and on the so-called X-Factor. By doing so, we can not only identify the fund of hedge fund managers having the highest loadings on the X-Factor, but we can also have a sense of the underlying structure of risk implicitly or explicitly taken by this manager.

3.3. Empirical analysis
We first carry out the regression analysis over the whole observation period, i.e., from January 2005 through December 2012. In order to assess the impact of the X-Factor, we ranked all the funds of hedge funds based on their factor loading, and formed five quintiles made up of approximately 50 funds of hedge funds each. The funds of hedge funds exhibiting the lowest (respectively highest) loading are classified in the 1st (respectively 5th) quintile, Q-1 (respectively Q-5).

The identikit picture of the fund of hedge funds entering into the composition of the 5 quintiles is presented in the Table 2A and 2B. First observation, 4 out of 5 Quintiles show a negative average loading on the X-Factor. We then observe that a higher exposure to the X-Factor tends to be associated with a greater liquidity at the fund of hedge fund level (higher redemption frequency together with lower notice period), and a slightly higher level of fees (the variable fees in particular). The first point is consistent with the fact that the funds of hedge funds offering the greatest level of liquidity tend to invest in the most liquid underlying funds to try and mitigate the risk of a liquidity mismatch; they therefore have more flexibility to adjust their exposures dynamically. The second point shows that paying higher fees is not always a bad thing. It suggests that instead of focusing on lower fees, investors would probably be better off making sure that they get value for money. Our X-Factor is a pragmatic way to do so. Another interesting result is the fact that the length of the track record, and the size of the assets under management, which typically rank highly in the check lists of fund selectors do not seem to really matter. They do
indeed appear to be roughly the same across the board. Finally, a higher exposure to the X-Factor tends to be associated with a higher (respectively lower) exposure to the Macro/Systematic and Multi-strategy (respectively directional) investment styles. This is here again consistent with the nature of the underlying strategies.

Table 2A: Fund of Hedge Fund Average Characteristics

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<td>-0.5</td>
<td>120</td>
<td>1.2</td>
<td>6</td>
<td>168</td>
<td>59</td>
<td>15</td>
</tr>
<tr>
<td>Q3</td>
<td>-0.4</td>
<td>302</td>
<td>1.2</td>
<td>6</td>
<td>93</td>
<td>54</td>
<td>13</td>
</tr>
<tr>
<td>Q4</td>
<td>-0.3</td>
<td>130</td>
<td>1.2</td>
<td>7</td>
<td>65</td>
<td>40</td>
<td>13</td>
</tr>
<tr>
<td>Q5</td>
<td>0.0</td>
<td>254</td>
<td>1.3</td>
<td>8</td>
<td>51</td>
<td>33</td>
<td>13</td>
</tr>
<tr>
<td>ALL</td>
<td>-0.4</td>
<td>208</td>
<td>1.2</td>
<td>7</td>
<td>95</td>
<td>47</td>
<td>13</td>
</tr>
</tbody>
</table>

Table 2B: Fund of Hedge Fund Classification

<table>
<thead>
<tr>
<th>Investment Style</th>
<th>Q1</th>
<th>Q2</th>
<th>Q3</th>
<th>Q4</th>
<th>Q5</th>
<th>ALL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Equity</td>
<td>51%</td>
<td>31%</td>
<td>58%</td>
<td>23%</td>
<td>17%</td>
<td>36%</td>
</tr>
<tr>
<td>Event</td>
<td>2%</td>
<td>8%</td>
<td>2%</td>
<td>12%</td>
<td>2%</td>
<td>5%</td>
</tr>
<tr>
<td>Debt</td>
<td>4%</td>
<td>2%</td>
<td>8%</td>
<td>0%</td>
<td>0%</td>
<td>3%</td>
</tr>
<tr>
<td>Relative Value</td>
<td>4%</td>
<td>6%</td>
<td>6%</td>
<td>6%</td>
<td>6%</td>
<td>5%</td>
</tr>
<tr>
<td>Multi-strategy</td>
<td>40%</td>
<td>52%</td>
<td>25%</td>
<td>52%</td>
<td>47%</td>
<td>43%</td>
</tr>
<tr>
<td>Macro/Systematic</td>
<td>0%</td>
<td>2%</td>
<td>2%</td>
<td>8%</td>
<td>28%</td>
<td>8%</td>
</tr>
</tbody>
</table>

We then obtained the performance of the 5 groups of funds of hedge funds by computing the arithmetic average of the constituents’ performance. The behaviour of the 5 quintiles is displayed in Figure 4. As one could have expected, the funds of hedge funds showing the highest exposure to the X-Factor tend to lag behind their peers during strong bull markets. Staying put and surfing the wave is indeed a more rewarding strategy under these circumstances. This translates into a slight underperformance of Q-5 from 2005 through 2007. But as soon as the market conditions become more unstable, the ones managing risks efficiently stand out from the crowd and post substantial excess returns relative to their peers. This is clearly evidenced by the behaviour of Q-5 from 2008 onward. Differently put, an investor able to identify the fund of hedge fund managers with the highest exposure to the X-Factor turn out to benefit from an (implicit) option on the stability of the market environment. There is a little premium to pay when market conditions are stable; but it pays off a lot sooner as uncertainty arises.

Figure 4: Cumulative returns

6 - Differences in terms of Size are due to a few outliers.
Funds of hedge funds with a high exposure to the X-Factor tend to do materially better over the long-run. Unfortunately, many are called, but very few are chosen. As can be seen from Figure 5, only 20 funds of hedge funds out of 262 (i.e., 8% of the population) exhibit a positive loading. Finding fund of hedge fund managers, which are good at capturing the upside while mitigating the downside risk does indeed turn out to be like looking for a needle in a haystack. Interestingly, 80% of the funds of hedge funds with a positive loading on the X-Factor also exhibit an above average alpha (vs. only 43% for the rest of population). This is a further confirmation that the X-Factor is a very useful tool to identify skilled fund of hedge fund managers.

Figure 5: Cross-sectional Analysis

To dig into greater detail, we subsequently carried out the very same regression analysis on overlapping 3-year rolling windows, each observation period starting in January of year Y, and ending in December of year Y+2. We therefore end up with 6 observation periods (2005-2007, 2006-2008, 2007-2009, 2008-2010, 2009-2011, 2010-2012). The behaviour of the 5 quintiles is presented in Figure 6A through 6F. We find here again that Q-5 slightly underperforms Q-1 when there is a bull market (2005-2007, 2009-2011). The results are more mixed when the market is trending upward, but with significant uncertainty (i.e., volatility of volatility). Q-5 shows on the other hand a strong outperformance when there is a clear regime switch (2006-2008, 2007-2009, 2008-2011). This is a further confirmation that funds of hedge funds showing a high loading on the X-Factor are better off with an implicit option on the stability of the market environment.

In order to know whether investors can actually take advantage of the outperformance of Q-5, by identifying and investing with the funds of hedge funds entering into its composition, we need to check whether the fund of hedge funds exhibiting the highest sensitivity to the X-Factor in a given period keep on doing so in the subsequent period. We thus estimated the probability for a fund of hedge fund to fall into Q-i in period t, knowing that it was in Q-j in period t-1. The conditional probabilities are presented in Figure 7. We observe that the probability of staying in the same quintile from one period to another is materially higher for extreme quintiles. The funds of hedge funds exhibiting the greatest (respectively lowest) sensitivity to the X-Factor have a 70% (respectively 68%) probability of staying at the top (respectively bottom) the next period. The funds of hedge funds falling into Q-2 to Q-4 on the other hand, have approximately a 50% chance of seeing their ranking change from one period to another. It turns out that investors can indeed leverage on the X-Factor to try and separate the wheat from the chaff.
The fund of hedge fund process remains challenging though. The number of funds of hedge funds falling into Q-5 systematically appears out to be very limited. Only 9 out of 262 (i.e., slightly more than 3% of the population) do so. If we broaden the selection to funds of hedge funds with an average ranking greater than or equal to 4.5, we obtain a list of 29 names (i.e., 11% of the population). The identikit picture of these funds of hedge funds is presented in Table 3A and 3B.
We find here again that the funds of hedge funds showing the highest exposure to the X-Factor tend to be more liquid than the average; they also turn out to be smaller and slightly older. But, this time around fees are in line with the population average. As one could have expected, multi-asset strategies dominate (e.g., Multi-strategy and Macro/Systematic). Interestingly the Relative Value strategy only shows up in the extended selection. This confirms that controlling the risk of relative value positions is not trivial and, more generally, that a low average volatility is not a guarantee of efficient risk management.

4. Concluding remarks
Alternative investment strategies are slowly but surely becoming mainstream. The hedge fund road remains long and bumpy though, and many traditional investors still have to pay the fund of hedge fund toll to take the ride. But selecting the good fund of hedge fund is not a piece of cake either. Our objective in this article was twofold.
On the one hand, we aimed to assess the extent to which one could mitigate the downside risk of a hedge fund portfolio by making a more efficient use of the available information set, and by adopting a dynamic investment policy. The results of the empirical study are unambiguous. Building on Giamouridis and Vrontos (2007) we show that with an optimal tactical style allocation strategy one can dramatically reduce the peak-to-valley during periods of market stress, and still capture a significant share of the upside when the situation normalises. There is, however, a caveat emptor. These very appealing results are obtained at the cost of high turnover and they rely heavily on investors’ capacity to collect the information, process it, and implement the resulting allocation changes swiftly. If the implementation of very dynamic strategies should not be a major hurdle for fast-moving investors dealing with liquid instruments, this might be more problematic for investors with a long decision-making process and/or somewhat less liquid positions. Controlling the portfolio activity may therefore prove crucial. This is particularly true when it comes to hedge fund investing.

Three pragmatic and complementary solutions can be imagined to tackle this issue. The first solution addresses the causes. Most strategies are implicitly or explicitly short volatility, which makes them sensitive to very unstable market sentiment. The introduction of an asset with a structurally long exposure to volatility would bring additional diversification and help smoothing the risk profile of the overall allocation. A series of investment vehicles (e.g., options, futures, ETFs) has been launched over the last few years and some of these now provide enough liquidity to make them a viable option (Hill (2013)). The second solution addresses our reading of the causes; it consists of introducing active views into the transition matrix. In certain market environments, investors might be willing to reduce the turnover of their portfolios in order to mitigate the impact of market whipsaws, while in others they might be looking for more reactivity to adapt to a new market regime more quickly. In this respect, combining historical probabilities together with investors’ unique forward-looking views might be a more efficient way to build the transition matrix. The third solution addresses the symptoms; it consists of partially adjusting the aggregate portfolio factor exposures through an overlay solution. The objective of investors is to control for the optimality of their portfolios over time. Should the liquidity of the underlying assets or the length of the decision-making chain prevent them from doing so, a systematic hedging strategy based on very liquid instruments could be a cost-efficient way of partially bridging the gap. An in-depth analysis of the three aforementioned solutions is out of the scope of this article and left for further research.

On the other hand, we aimed to check whether the aforementioned tactical style allocation strategy could be used to design a pseudo risk factor, and in turn, identify the fund of hedge fund managers that manage risk efficiently. We therefore proposed to augment the CAPM with the X-Factor, which simply consists in the outperformance generated by a fund of hedge fund manager managing risk efficiently. We found that the fund of hedge funds exhibiting the highest sensitivity to the so-called X-Factor outperform their peers materially. A closer look at their behaviour over different market configurations, suggests that these funds of hedge funds are better off with an implicit option on the stability of the market environment. The funds of hedge funds exhibiting a high sensitivity to the X-Factor slightly do indeed underperform when the market is enjoying a strong momentum (i.e., premium of the option), and they strongly outperform when there is a regime switch (i.e., option pay-off). Our approach is in this respect close to the model proposed by Henriksson and Merton (1981). The main difference is that we are in a multi-factor setting and consider as skilled a fund of hedge fund manager who is good at dealing with the instability of the variance/co-variance matrix, as opposed to capturing the ups and downs of the market. Very interestingly we find significant persistence in both the highest and the lowest loadings to the X-Factor, suggesting that investors can leverage on our pseudo risk factor to separate the wheat from the chaff. It is consequently a pragmatic though robust approach to tackle the fund of hedge fund selection puzzle. The very same approach could be used in the hedge fund selection process. This is left for further research.
Appendix I. Theoretical Framework of the Regime Switching Dynamic Correlation Model

We present in this appendix the technical details of the Regime Switching Dynamic Correlation model (hereafter RSDC) introduced in Pelletier (2006) and applied in Giamouridis and Vrontos (2007) in the context of hedge fund portfolio optimisation, to take better account of the time-varying nature of asset returns risk parameters. Let us denote by $R_t$, the $n \times 1$ vector of asset returns at time $t$. This vector satisfies the following equation:

$$R_t = \mu + \varepsilon_t,$$

where $\mu$ is the $n \times 1$ vector of expected returns and $\varepsilon_t$ a $n \times 1$ the vector of innovations satisfying the following property:

$$\varepsilon_t | I_{t-1} \sim N(0, V_t),$$

where $I_{t-1}$ denotes the information available at time $t-1$, and $V_t$ is an $n \times n$ covariance matrix with the following decomposition:

$$V_t = \Sigma_t C_t \Sigma_t.$$

$\Sigma_t$ is a diagonal matrix, with the standard deviation/volatility $\sigma_{i,t}, i = 1, ..., n$, terms on the diagonal, and $C_t$ is the $n \times n$ asset returns correlation matrix. These two matrices are time-varying to take into account the possible time-varying nature observed on both standard deviations and correlations of asset returns. In a first step, we filter the individual asset volatility using a GARCH (1,1) model. Diagonal terms of $\Sigma_t$ are then assumed to follow the univariate dynamics:

$$\sigma^2_{i,t} = \alpha_i + \beta_i \varepsilon^2_{i,t-1} + \gamma_i \sigma^2_{i,t-1},$$

where $\beta_i$ captures the effects of lagged shocks and $\gamma_i$ captures the effect of lagged conditional variance. Parameters are estimated separately for the different assets and correspond to the terms of the matrix $\Sigma_t$.

In a second step, a time-dependent correlation matrix is modelled in a dynamic framework by using the following regime switching specification:

$$C_t = \sum_{k=1}^{K} 1\{S_t = k\} C_k,$$

where $1$ is the indicator function, $S_t$ is an unobserved Markov chain process independent of $\varepsilon_t$, which can take $K$ possible values ($S_t = 1, 2, ..., K$), and $C_k$ are correlation matrices with $C_k \neq C_{k'}$ for $k \neq k'$. Regime switches in the state variable $S_t$ are assumed to be governed by the transition probability matrix $\Pi = (\pi_{i,j})$. The transition probabilities between states follow a first order Markov chain:

$$Pr\{S_t = j | S_{t-1} = i\} = \pi_{i,j}$$

to model persistence in each state. As in Pelletier (2006) and Giamouridis and Vrontos (2007), we assume that $K = 2$.

The estimation of the RSDC model can be achieved by using a two-step procedure (Engle (2002)). In the first step, we estimate the univariate GARCH model parameters by asset. In the second step, we estimate the parameters in the correlation matrix and the transition probabilities $\Pi = (\pi_{i,j})$ conditional on the standardised residuals of step 1. The likelihood function can be computed iteratively using a direct adaptation of the EM algorithm. This gives an estimator of the matrices $C_k, k = 1, ..., K$ and the transition matrix $\Pi = (\pi_{i,j})$. Smoothed inference of the regime is obtained using Kim’s algorithm.
Appendix II. Stress-Test Analysis

The results of the in-sample analysis confirm that when the investor already has all the relevant information sets, and the dynamic of the standard deviation and correlation terms is taken into account, it is possible to materially reduce the downside risk of the portfolio without harming its upside potential. But, in practice, lightning rarely strikes twice in the same place, and every new crisis comes with its share of novelty. The objective of the stress test analysis is to assess the behaviour of the different approaches when the investor is receiving new information randomly.

In order to challenge our approach, we use an initial calibration period characterised by abundant liquidity and rising prices for risky assets all over the world (i.e., from 4 January 2005 to 25 December 2007). This calibration period contains a series of market corrections but no major accident. The investor therefore starts the out-of-sample period with a very positive view of the world, without knowing that he is heading into the perfect storm - and without even knowing what a real storm might look like. In other words, the definition of the market regimes used by the investor to build the SRM portfolio will be dramatically different at the beginning and at the end of the out-of-sample observation period (1 January 2008 and 31 December 2012, respectively). The allocation of the STATIC portfolio is similar to that obtained in the in-sample analysis, with a strong concentration in Relative Value strategies. The average weighting of L/S Equity Market Neutral and Fixed Income Arbitrage is even higher (i.e., 43% and 23% respectively). This increase is essentially financed with a lower exposure to equity-linked strategies (i.e., L/S Equity Long Bias, L/S Equity Short Bias, Merger Arbitrage, Statistical Arbitrage). The portfolio turns out to be more concentrated, with an NHI of 22%. This is consistent with the fact that market conditions did not change much over the in-sample period. Turnover, meanwhile, is nil.

A simple way to allow the parameters to be time-dependent is to run the optimisation on rolling-windows. We start with the same allocation as the STATIC portfolio, but as market conditions change and the behaviour of the different strategies evolves, the optimal weightings diverge. As a matter of fact, the weighting of credit-oriented strategies such as Convertible Arbitrage or L/S Credit Arbitrage decreases in the wake of the Lehman Brothers collapse or the sovereign debt crisis, while strategies such as CTA Short-Term or L/S Equity Short Bias benefit from the turmoil. Conversely, as market conditions normalise strategies such as Merger Arbitrage, Distressed Securities or L/S Equity Long Bias benefited from tailwinds. As could have been expected, Relative Value strategies appear to be less represented.

L/S Equity Market Neutral accounts on average for 14% of the allocation, while Fixed Income Arbitrage falls below the 10% mark. The consequence of the aforementioned allocation changes is greater diversification (i.e., NHI of 5%), but also greater turnover (i.e., 7% per week on average) than the STATIC portfolio.

Though interesting, the rolling-window approach is known to make sub-optimal use of available information. New information tends to be incorporated with a time lag, preventing allocation changes from being implemented in a timely manner. Using GARCH-filtered volatility is a first step in attempting to tackle this issue. The average strategy weightings that we obtain are close to those resulting from the rolling-window approach. Major allocation differences can, however, be observed around market events (e.g., the Bear Stearns takeover, the collapse of Lehman Brothers, European sovereign debt worries, etc.). The concentration of the GARCH portfolio is similar (i.e., 4%) but the turnover is much more significant (i.e., 16% per week on average) than in the case of the ROLLING portfolio.

Interestingly, the average strategy weightings of the GARCH and the SRM portfolios are similar. Statistical Arbitrage and to a lesser extent Merger Arbitrage or L/S Equity Long Bias show slightly
lower weightings, while Distressed Securities and to a lesser extent CTA Short-term or L/S Equity Market Neutral exhibit slightly higher allocations. However, these minor discrepancies in average exposures mask major differences in specific dates (generally related to one of the aforementioned events). The SRM portfolio is slightly less diversified than the GARCH portfolio (i.e., NH1=5%), and turnover somewhat higher (i.e., 18%). It is worth pointing out that portfolio activity spikes slightly earlier for the SRM portfolio than for the GARCH and to an even greater extent than for the ROLLING portfolios, suggesting a greater reactivity to market events.

Now that we have the weightings of the different portfolios, we can compare and contrast their cumulative returns. As can be seen from Figure II.1, the outperformance of the SRM portfolio relative to the other approaches is substantial. Despite the very different nature of the initial calibration and the out-of-sample periods, the capacity of the optimal diversification strategy to mitigate downside risk remains intact; the peak-to-valley of the SRM portfolio is as much as 56% lower than that of the 1/N portfolio. Indeed, although very good at capturing market upside potential, the 1/N shows a poor downside risk control, and as a result, a somewhat disappointing compounded return in very unstable market environments. Interestingly the STATIC portfolio turns out to dominate the ROLLING portfolio, which confirms that more information is not always a warranty of a better outcome. In other words, the dynamics of the standard deviation and correlation terms needs to be taken into account properly, for optimal diversification to dominate the naïve 1/N strategy on an out-of-sample basis.

Figure II.1: Cumulative returns

Appendix III. Robustness Checks
In both the in-sample and the stress test analysis we made the assumption that investors could change their allocation on a weekly basis, with no limitations. But in practice, rotating a portfolio implies visible (e.g., entry/exit fees, market impact) and invisible (e.g., relationship with the hedge fund manager) costs. Investors therefore control the turnover of their portfolios carefully. Our first robustness check focuses on the impact of such control, and on the benefits expected to derive from the SRM approach (i.e., lower downside risk together with higher performance). To this end, we simulate the allocation changes an investor subject to a 5% / 10% / 15% / 20% weekly portfolio turnover limit would have implemented and compare the outcome with the results for the unconstrained strategy. We have seen in the previous section that the turnover of

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8 It is worth pointing out that in the real world no transaction costs are charged to institutional investors for subscriptions and/or redemptions in the Lyxor hedge fund strategy indices. Moreover, independent risk management at the managed account platform level mitigates the risk of having a liquidity mismatch between assets and liabilities, and in turn, reduces market impact should a fund experience massive outflows. Frictions therefore tend to be minimal in our case.
the SRM portfolio was particularly high, especially around market events; the cost of imposing constraints on the turnover is therefore liable to be material. Indeed, as can be seen from Figure III.1 the peak-to-valley increases by 68% versus the unconstrained strategy, and the average return decreases by as much as 129% for a 5% limit. This first robustness check clearly shows that the ability to rebalance the portfolio to a large extent is essential for investors to mitigate downside risk without compromising long-term growth prospects. While this might not be problematic with liquid instruments such as futures, it could be more of an issue with hedge funds.

So far, we have also made the assumption that investors are able to rotate their portfolios on a weekly basis. But the liquidity terms of the Lyxor hedge fund indices are quite unusual, and investors rarely have the option to rebalance their portfolios so frequently. Our second robustness check consists of assessing the impact of rebalancing frequency on the portfolio risk/return trade-off. To this end, we simulate the behaviour of an investor able to change allocation every two to twelve weeks, and compare the outcome with the unconstrained strategy. As can be seen from Figure III.2, the impact is somewhat limited at up to four to five weeks, but it tends to be significant above that time frame. Unsurprisingly, the loss function is somewhat less linear than for the first robustness check. The peak-to-valley increases by 68% versus the unconstrained strategy, and the average return decreases by 82%, for a portfolio rebalanced every six weeks. Notice periods and settlement issues make it fairly difficult in practice to reallocate a fund of hedge fund portfolio every four to five weeks, the rebalancing frequency might thus also be of an issue.

Figure III.1: Impact of portfolio turnover

Figure III.2: Impact of rebalancing frequency
Finally, in the previous experiments we considered that investors react to new information in a timely manner, adjusting their strategy allocation as soon as practically possible. But in practice, investors tend to react with a certain delay, essentially as a result of a sub-optimal decision-making process. Our third robustness check consists of assessing the impact of time-to-market on the portfolio risk/return trade-off. To this end, we simulate the behaviour of an investor who incorporates new information with a delay of one to twelve weeks. In other words, instead of implementing the optimal weightings obtained week W, the following week, we do it (W+2) to (W+13). We then compare the outcome with the optimal strategy. As can be seen from Figure III.3, the cost of reacting with a one-week delay is reasonable, but it becomes significant with a two-week delay, and very substantial above that threshold. The peak-to-valley increases by 48% versus the unconstrained strategy, and the average return decreases by as much as 85%, for a portfolio rebalanced with a two-week lag.

Figure III.3: Impact of time-to-market

References

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