Simulating Hedge Fund Strategies
Generalising Fund Performance

This note summarises the research Scope has carried out to estimate the downside risk of portfolios of hedge funds and funds of hedge funds. We show that a carefully selected set of market indices is sufficient to capture most features of hedge fund return distributions. In a second step we generalise this mapping to the projection of hedge fund strategies onto the market indices. We calibrated asymmetric GARCH processes to the indices and ran out-of-sample tests for the combined model. The resulting distributions are shown to capture the downside risk of hedge funds in 21 out of the 23 strategies for which we had sufficient data to carry out the tests. The approach can easily be extended to test the strategy classification of a hedge fund or check for persistent changes in its investment strategy.

Estimating hedge fund returns matters

Estimating hedge fund returns is important when assessing the credit risk for collateralised hedge fund obligations (CFO) and similar securitisations that were developed in the market in order to provide direct funding to hedge funds and alternative investment funds. These transactions are typically low loan-to-value credit products, e.g. notes, secured by a portfolio of hedge fund shares. The structures expose investors to market value risk related to the liquidation of fund shares to cover interest and principal payments to investors. Typical transactions[2] require the regular assessment of the share's net asset value (NAV) and protect investors by defining dynamic triggers on the NAV of a fund's shares. For example, if NAV falls below any predefined level for a given period of time, the fund's shares are liquidated to cover the notes' principal and interest. Understanding the return distribution of the portfolio of hedge fund shares is therefore a central element of judging risks in CFOs.

Challenges of applying statistical analysis to hedge fund returns

Hedge fund managers are paid by investors to provide a bespoke investment strategy with a specific risk profile generally uncorrelated to plain vanilla financial investments. The development of the funds' asset values is therefore very idiosyncratic and does not follow any regular financial market indicators. Other key characteristics of hedge funds add to the challenge: they operate under limited regulation and provide very little transparency over their operations. Additionally, the investment guidelines are highly flexible; they allow for drifts in management style, the adoption of long and short positions, the use of derivatives, and added exposure to a wide range of highly illiquid instruments. Past history has also shown that market events can lead to a sudden regime change that forces fund returns into a parallel movement (see Billio, Getmansky, and Pelizzon, 2010). Assessing the downside risk of a hedge fund portfolio therefore requires us to parameterise the stochastic nature of the individual fund as well as the co-movement of funds.

Furthermore, hedge fund managers have limited reporting constraints. As a consequence, data of past hedge fund returns is often either very limited or not available at all. The data is mainly reported to attract investors. Given this, managers have limited incentive to report results for underperforming funds or large P&L swings.

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1 This study greatly benefitted from the contributions of Adrien Becam and Martin Marquardt, both working students at Scope when this research was carried out
2 For example the debt issuance programme by Amathea Funding PLC listed on ISE

It is therefore almost impossible to fit a stochastic process to each individual hedge fund for such a sparse data set. Even if we were able to accomplish this, we would be faced with the daunting task of fitting a (dynamic) dependency structure among the funds. In the past, researchers have sought to overcome these problems by mapping the time series of individual hedge funds to specially constructed indices that synthesise common risk drivers of hedge fund performances. Over the years a large set of explanatory indices has emerged.

Mapping the hedge fund performance to indices has several practical advantages:

- The estimation of a large number of pairwise correlations (or other dependencies) is avoided. This procedure is numerically challenging and in most cases leads to inconsistent dependency structures.
- The resulting factor model creates clear dependencies between funds.
- The universe of risk factors that need to be jointly simulated is vastly reduced.
- The indices have a long time series that simplifies the calibration of a stochastic process.

In this paper we follow a variant of the index-projection approach. We chose a subset of indices proven to be particularly efficient at explaining hedge fund performance. We reduced the set with a search algorithm to retain only the most relevant explanatory factors and to avoid the problem of spurious factors due to the limited data set ('overfitting'). The chosen indices lend themselves well to the calibration of standard GARCH stochastic processes.

Data used for our research

Scope used hedge fund return data from eVestment's database[3] for the present study. The data covers the period from January 1998 through September 2015 and contains monthly returns (net of fees) and trading costs. It is a comprehensive commercial database that also provides data on assets under management as well as basic descriptions of the fund for individual hedge funds and the fund of hedge funds. The database has many cross-sectional observations and provides a fine-grained categorisation schema, differentiating between 31 strategies (see Appendix: The eVestment hedge fund strategies). The database contains both 'live' and 'dead' funds, thereby considerably reducing the tendency towards a survivorship bias. Nevertheless, it should be kept in mind that the data still suffers from other biases, generally due to the industry's unregulated nature, as Getmansky, Lee, and Lo (2015) discuss in detail.

Performance indices

We show in the following research that only a few performance indices are needed to explain a very high proportion of hedge fund returns. However, the composition of the explanatory portfolio changes with the nature of the funds. We therefore decided to use a large basis set of 12 explanatory factors from which we removed less significant components by means of a search algorithm. We build the basis portfolio from indices with both academic and non-academic origins[4]. Our starting point was the index set used in Fung and Hsieh (2001), from which we proceeded to include two indices introduced by hedge fund managers to facilitate automated trading as well as two indices to capture interest differentials and market liquidity. We introduce the indices here and refer to the original papers for a detailed discussion of their construction.

3 www.evesetment.com
4 For a detailed overview of linear models used to explain hedge fund performances see Getmansky, Lee, and Lo (2015), chapter 6.2 and references therein.

We start with the eight indices of Fung and Hsieh[5]:

- Three trend-following indices, derived from the price change of straddle options written on bonds, currencies and commodities; the straddle options are chosen to replicate lookback options, which reflect the idealised performance of trend-following hedge funds;
- An equity risk index, the return of the S&P500;
- A size index, the difference of returns between the Russell 2000 and the S&P 500;
- A bond-oriented index, the change in the 10-year treasury yield;
- A credit risk index, the change in the Moody's Baa yield minus the 10-year treasury yield; and
- An emerging market risk factor, the MSCI emerging-market index.

These indices are widely used in hedge fund literature. We added:

- The Betting-Against-Beta (BAB) index of Frazzini and Pedersen (2014). Eisele (2012) showed that this index explains some of the cross-sectional differences of hedge fund returns and that beta arbitrage strategies are actively followed.
- The Quality-Minus-Junk (QMJ) of Asness, Frazzini and Pedersen (2013), a factor mimicking investors seeking 'quality' stocks, a popular strategy among value funds.
- The carry trade index, based on the portfolios of Lustig and Roussanov (2011). The carry trade is a popular strategy among macro funds.
- A liquidity level factor. Sadka (2010) showed that liquidity is one of the most useful factors to explain the difference in hedge fund performance. We use the liquidity levels developed by Pastor and Stambaugh (2013).

Mapping hedge fund performance to indices

We follow a linear regression ansatz to fit the hedge fund performance, using the indices of the full set as independent factors. We proceed to reduce the model with a general-to-specific (GETS) algorithm in order to identify the most relevant risk drivers. This is particularly important as most hedge funds will only be exposed to a few risk factors and not to the whole set. By reducing the dimensionality we avoid overfitting and get a better estimate for the correlation between the funds. The process will also help to identify the most important risk drivers of hedge fund strategies (as detailed below). In the following section we introduce the GETS algorithm, state the model, and propose a mapping approach to capture hedge fund strategy performance.

General-to-specific (GETS) algorithm

The GETS approach starts from the largest-possible model specification, the general unrestricted model (GUM), and proceeds to remove non-relevant variables from this model. The process begins by eliminating the statistically least significant variable and checks whether the new regression model passes the encompassing model test and whether residuals are showing autocorrelation or heteroscedasticity. If any of these tests are not passed, the elimination is rejected and the algorithm proceeds with the next non-significant variable. The process continues until a parsimonious model has been found that minimises the Akaike information criterion[6].

5 Data available at http://faculty.fuqua.duke.edu/~dah7/DataLibrary/TF-FAC.xls.
6 We used the R package GETS in the present analysis. More details about the algorithm can be found in (Sucarrat, Pretis, & Reade, 2016).

Applying GETS to hedge fund data

The hedge fund time-series data is known to have considerable autocorrelation. This is because hedge fund managers prefer to smooth their P&L (Getmansky, Lee, and Lo (2015)). We therefore include an autocorrelation term in the linear model. Our GUM for the logarithmic returns of hedge funds r_t takes the form.

$$r_t = \phi_0 + \phi_1 r_{t-1} + \sum \beta_i x_t^i + \sigma \epsilon_t \qquad (1)$$

where ϕ_0 denotes the intercept; ϕ_1 the first order auto-regression term; x_t^i the returns of the independent variables; β_i the regression factor parameters; ϵ the standard normal distributed residuals; and σ the volatility.

We limited the study to funds with time series longer than 25 data points. We chose this number not only to have enough observations to make the fitting process meaningful, but also to avoid the inclusion of data with too much incubation and liquidation bias. The GETS algorithm found a valid parsimonious model for about 80% of the funds. The reminder failed mostly because the residuals of the GUM model did not pass the autocorrelation and heteroscedasticity tests. Our final model specification includes autocorrelation and heteroscedasticity, by way of the indices, so we decided to remove the corresponding checks from the GETS search. With this simplified assumption, we found a parsimonious model for more than 90% of the funds, of which about 10% miss potentially[7] heteroscedasticity and longer autocorrelation lags in the model specification. In a forthcoming paper we will suggest a more rigorous solution to this issue (Becam, Marquardt, & Nonas).

From hedge funds to strategies

Under most circumstances, it is impractical to map all the hedge fund returns of a portfolio to indices: very often, an adequate time series is unavailable. Therefore, instead of looking at individual funds, we apply the above approach to hedge fund strategies. This approach has limits, because a broad strategy classification lumps several heterogeneous individual management styles together. Nevertheless we find that the strategy classifications are in many cases very characteristic and sufficient for our purposes. Our regression model clearly identifies common factors between most of the funds that belong to a particular strategy. However, the ad-hoc approach to define the strategy return as the sum of fund returns and then run the GETS algorithm proved to be insufficient. The individual funds' performances within a strategy are different enough to average out a large amount of information. Instead we determine the regression model of the strategy as the average of the factor loadings of individual funds' regressions.

Having identified the most relevant factors for each strategy allows us in principle to turn this process on its head and garner information about the strategic alignment of a hedge fund based on the decomposition of its performance into market indices.

7 Some will be introduced into the simulated time series by the indices.

Stochastic index model

Fitting the index model has reduced the high dimensional simulation problem to a system of 12 risk drivers. Whilst this model is still not trivial to simulate, it is certainly manageable. Its performance will depend on the model specification of the indices. We proceed in two steps. First, we identify a reasonable stochastic model for each individual index and show that it not only replicates the input distribution but also performs well in out-of-sample testing. In the second step, we link the individual indices together with a standard correlation assumption.

Fitting the indices

The indices show strong autoregressive and heteroscedastic properties. Therefore, we decided to fit to the asymmetric ARMA(1,1)-GJR GARCH(1,1) model introduced by (L.R. Glosten, 1984) using either normally or t-distributed innovations:

$$\sigma_t^2 = \omega + \alpha_1 \sigma_{t-1}^2 \epsilon_{t-1}^2 + \gamma_1 I_{\{\epsilon_{t-1}<0\}} \sigma_{i-1} + \beta_1 \sigma_{t-1}^2$$

$$x_t = \mu + ar_1\, x_{t-1} + ma_1\, \sigma_{t-1}\, \epsilon_{t-1} + \sigma_t\, \epsilon_t \qquad (2)$$

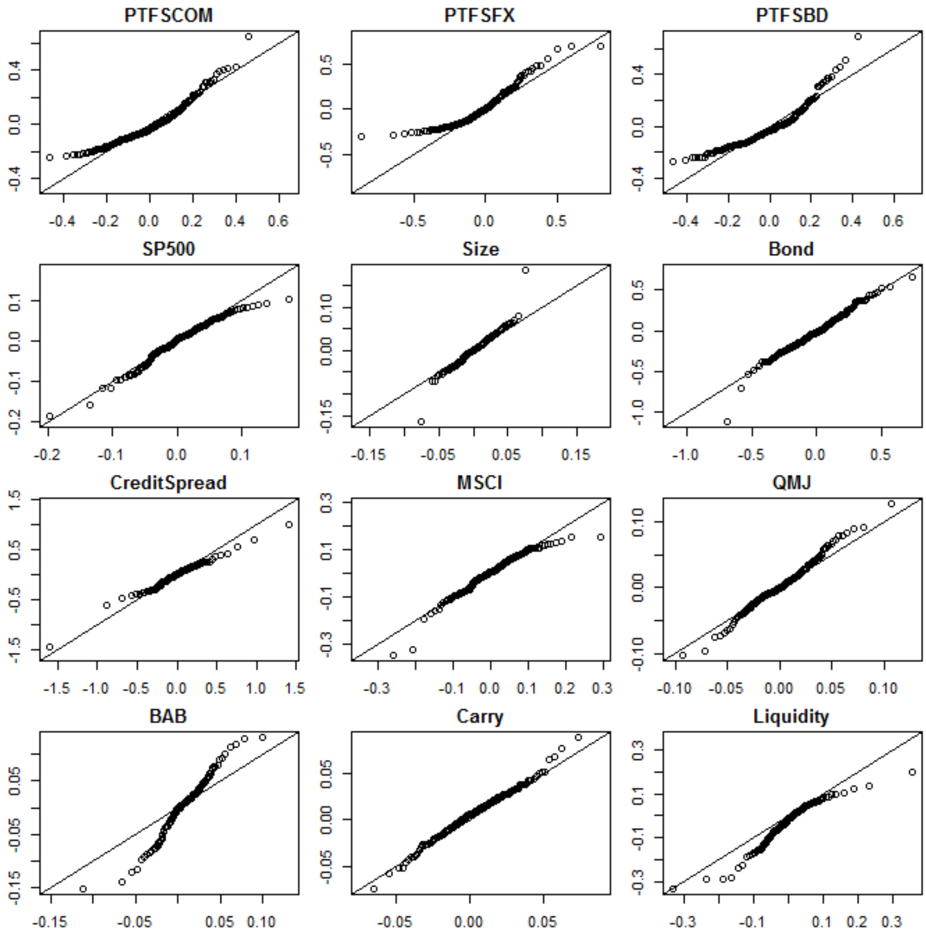
where σ_t^2 denotes the variance; x_t the return of the process at time t; ϵ_t the normal or t-distributed innovations; $I_{\{\epsilon_{t-1}<0\}}$ the indicator function that takes the value of 1 if the last innovation was negative and zero otherwise. The model-determining constants $(\omega, \alpha_1, \gamma_1, \beta_1, ar_1, ma_1)$ and the distribution of the residuals are fitted to the data by optimising the log-likelihood function[8]. We manually modified the model specification (excluding certain components, changing the distribution of the innovation) to minimise the Akaike information criterion value. For the fit we used a time series consisting of 102 monthly observations of the indices. This provides enough data for the calibration algorithm and includes the relevant events for the current business cycle.

Goodness of fit

As a first test of our model specification, we compare the quantile-quantile (QQ) plots of the simulated returns against the index returns.

8 We used the R package rugarch to obtain the best fit (Ghalanos, 2015).

Figure 1: QQ plots of observed hedge fund index returns against simulation

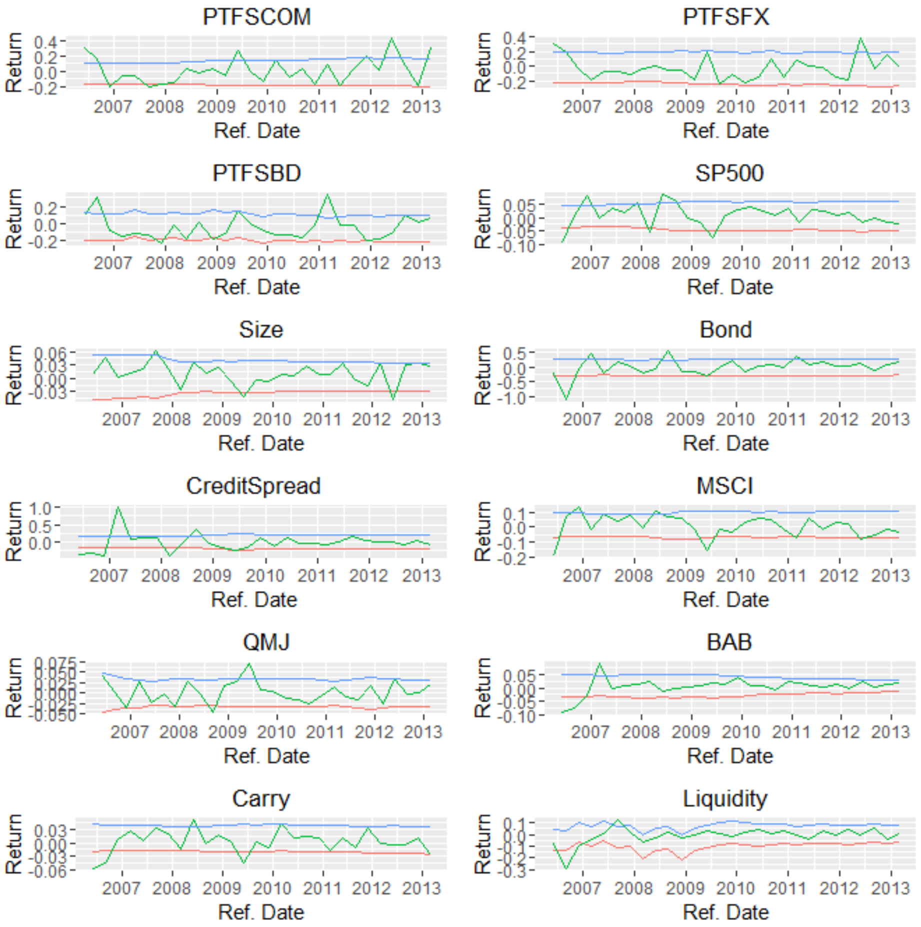


Quantiles of the simulated index distribution (x axis) against observed distributions. Points below the x=y line at either end indicate that the observed distribution is wider and vice versa.

The models were calibrated with the 102 monthly observations of the indices before 1 June 2015. The plots in Figure 1 compare the quantiles of the simulated returns against the observed index returns between 1998 and 2015. Overall, the model distributions fit the data quite well, despite the fact that the model has only been calibrated to a subset of the data time series. In some cases the tails are slightly over- or underestimated.

To further test the predictive power of the model, we ran a backtesting calculation (out-of-sample test), in which we compared the simulated and realised one-month return distributions 27 periods after the reference date. In Figure 2 we report results of quarterly calculations, comparing the 10th and 90th percentiles of the simulated distribution against the realised index values. For most of the indices we see the statistically-expected two exceedances of each percentile in the set of 28 observations. The results indicate that the model fit reflects the stochastic properties of the indices very well.

Figure 2: Out-of-sample backtesting results for indices



Backtesting results for hedge fund indices.
The 10th percentile (blue) and the 90th percentile (red) of the simulated distribution plotted against the observed index return (green) 27 months after the simulation start date (reference date).

Correlation

Correlations of financial time series are usually quite difficult to determine, as values tend to vary greatly with the selected time interval. The correlation of hedge funds in particular is known to undergo regime shifts upon market events. In the GARCH context, several proposals have been made to account for dynamic correlation matrices (Bauwens, Laurent, & Rombouts, 2006). However, we were unable to find a stable fit for our index set; therefore we settled for the standard approach of a Gaussian copula with a constant correlation matrix. It should be emphasised, however, that this determines the correlation between the indices, not between the funds themselves. The latter is constructed from their mapping to the indices (see below). We calculated the correlation matrix using the multivariate GARCH package rmgarch in R (Ghalanos, 2015).

Hedge fund return modelling

We proceeded to combine the results of the previous sections to a simulation framework for hedge fund returns. The search algorithm has allowed us to effectively map the hedge fund strategy returns to the index returns. The dynamics of the index returns themselves were shown to be well captured by fitting appropriate GARCH processes.

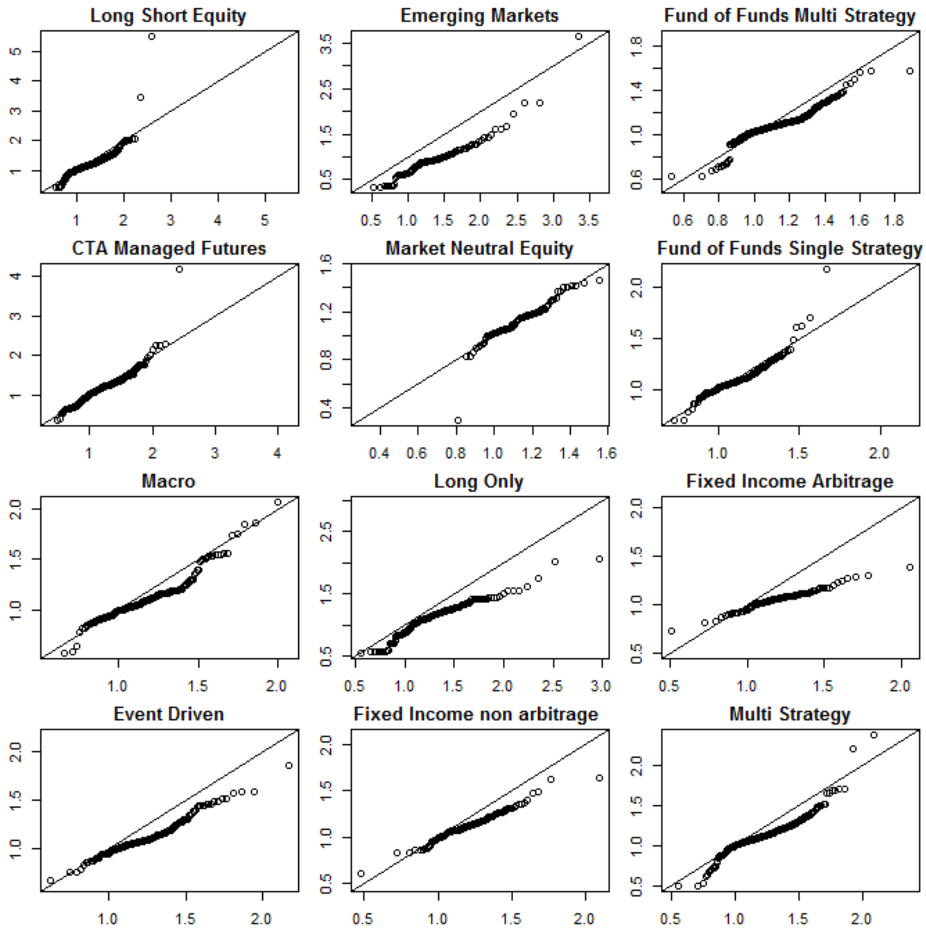
We simulated the hedge fund returns using equation (1), with parameters that result from the average of regression parameters of funds belonging to the corresponding strategy. The index returns x_i are calculated from the GARCH equation (2) with the normal or t-distributed innovations ϵ_t correlated by a Gaussian copula. The correlation matrix is estimated from the full time series of the indices. The δ_t innovations of the fund returns are uncorrelated and drawn from a standard normal distribution. We start the recursive processes with the volatility of the index time series and the last observed return of the index or strategy respectively. Note that each individual fund performance is still simulated with idiosyncratic innovations δ_t but uses the same regression parameters as any other fund with the same strategy.

Model test

The litmus test for any predictive model is its out-of-sample performance. To that end we compared against each other: i) the return distribution after 27 months of a strategy generated by a Monte Carlo simulation and ii) the observed returns of hedge funds that follow this particular strategy. For the calibration of the model parameters we used only the time series and index data available up to the reference date. We compare the distribution of the total return over the relevant number of periods (as the sum of simulated log returns) and the realised returns of the corresponding hedge funds. As some of the strategies have only a limited number of funds with a full reporting history in the observation period, we had to exclude them to arrive at meaningful comparisons. We decided to only show results for strategies with more than 60 funds with full reporting histories during the backtest period. We have performed tests for two periods: one for the recent history, with 1 July 2013 as a reference date, and one covering the financial crisis, using 1 July 2008 as a reference date.

Test with data from recent history Figure 3 compares the quantiles of the simulated returns against the observed return distribution. For most strategies the fit is very good.

Figure 3: QQ plots for out of sample testing – recent history



QQ plots of simulated strategy total returns (x-axis) against observed distribution of fund returns 27 months after the reference date, 01.07.2013. The calibration data set includes the data available before the reference date.

The results in Table 1 (left-hand side columns, labelled 'full set') corroborate the visual impression; the number of observations in the upper and lower tails are within the limits for many of the strategies. However, for some strategies, e.g. Long Only, Merger/Risk Arbitrage or Market-Neutral Equity, the fit is not perfect, leaving more returns in the lower percentile than expected. We therefore proceeded to amend the specification of the strategy slightly: instead of averaging over all funds, we ordered them by their average return over the observation period and considered only funds with returns in the lower percentiles. Figure 4 shows some QQ plots when funds from the 20th percentile are used[9]. The simulated distributions are shifted to the left, which is also evident in the '20th percentile set' column in Table 1. Occasionally we found only a very low number of observable funds in the time windows. In those cases we used a minimum of 15 funds to ensure that averaging was not completely meaningless. For many of the strategies we see an increase not only in the left tail but also in the upper end of the distribution. The selection of lower-performing funds in the calibration set results in much higher volatility, thereby widening the full distribution. This is not ideal, as the simulation might overestimate returns from well-performing funds and could therefore overestimate the portfolio return.

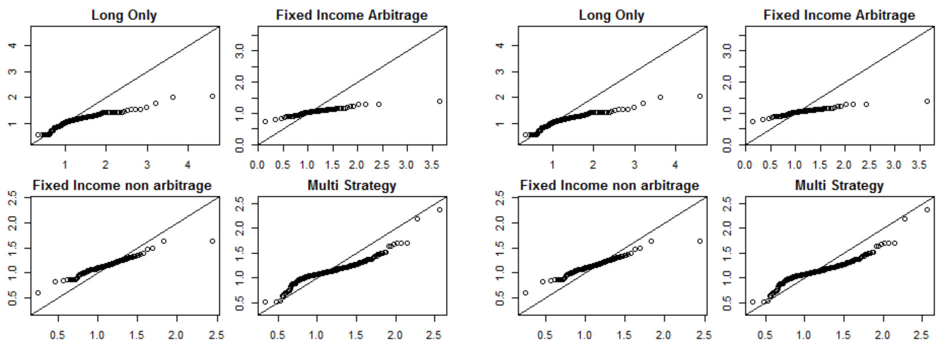
9 The decision to look at the 20th percentile is data-driven: we want to capture tail risk but also need a minimum number of funds in the calibration set.

Table 1: Backtesting results, recent period

		Full set		20th-percentile set	
	Observations	Lower	Upper	Lower	Upper
CTA/Managed Futures	459	15.7%	5.4%	12.6%	3.5%
Convertible Arbitrage	40	5.0%	2.5%	2.5%	0.0%
Distressed	53	9.4%	0.0%	5.7%	0.0%
Emerging Markets	97	35.1%	3.1%	21.6%	1.0%
Energy Sector	23	26.1%	0.0%	17.4%	0.0%
Event-Driven	179	15.6%	2.2%	2.2%	8.9%
Finance Sector	49	6.1%	2.0%	4.1%	2.0%
Fixed Income (non-arbitrage)	157	12.1%	2.5%	0.6%	3.2%
Fixed-Income Arbitrage	103	13.6%	0.0%	0.0%	0.0%
Fund of Funds – Multi-Strategy	694	5.3%	2.6%	1.9%	1.0%
Fund of Funds – Single-Strategy	179	6.1%	5.6%	1.7%	2.8%
Healthcare Sector	33	3.0%	6.1%	3.0%	12.1%
Long Only	130	20.0%	1.5%	10.0%	0.0%
Long/Short Equity	827	6.4%	2.9%	2.2%	2.8%
Macro	226	6.6%	8.0%	1.3%	8.0%
Market-Neutral Equity	89	10.1%	9.0%	2.2%	10.1%
Merger/Risk Arbitrage	45	28.9%	0.0%	6.7%	13.3%
Mortgages	38	26.3%	0.0%	0.0%	2.6%
Multi-Strategy	444	9.7%	2.7%	2.9%	1.8%
Small/Micro Cap	32	3.1%	0.0%	3.1%	0.0%
Special Situations	55	21.8%	0.0%	5.5%	0.0%
Statistical Arbitrage	32	9.4%	12.5%	6.2%	18.8%
Value	39	15.4%	2.6%	2.6%	0.0%

Results for out-of-sample test: Lower/upper denote the observed exceedances of the 10th and 90th percentiles. The columns differ by the set used for calibration. The 20th percentile run used only funds with average returns in the corresponding lower percentile whereas all funds were used for the full set calculation. Numbers exceeding the expected observations are marked in yellow.

Figure 4: QQ plots for out-of-sample testing – recent history – using 20th-percentile calibration



Source: QQ plots of simulated strategy total returns (x axis) against observed distribution of fund returns 27 months after the reference date, 1 June 2013. The calibration data set includes only the data available before the reference date. The index weights of the strategies are calculated from funds with an average return lower than the 20th percentile of the average return of all funds conforming to that strategy.

Test through the financial crisis

Complementing the results from the previous paragraph and to guard against 'data snooping' by adjusting the method after looking at the backtesting results, we show here the out-of-sample model performance for the crisis period. Not surprisingly, the model calibrated on the full set fails to predict the tail end of the return distribution. The calibration data does not contain enough extreme events to incorporate the returns observed during the crisis. However, the model with the proposed modification of looking at lower-than-average performing funds performs reasonably well and captures the downside risk for most strategies – albeit in a conservative manner, as the upper quantile is almost consistently underestimated.

Table 2: Backtesting results, financial crisis period

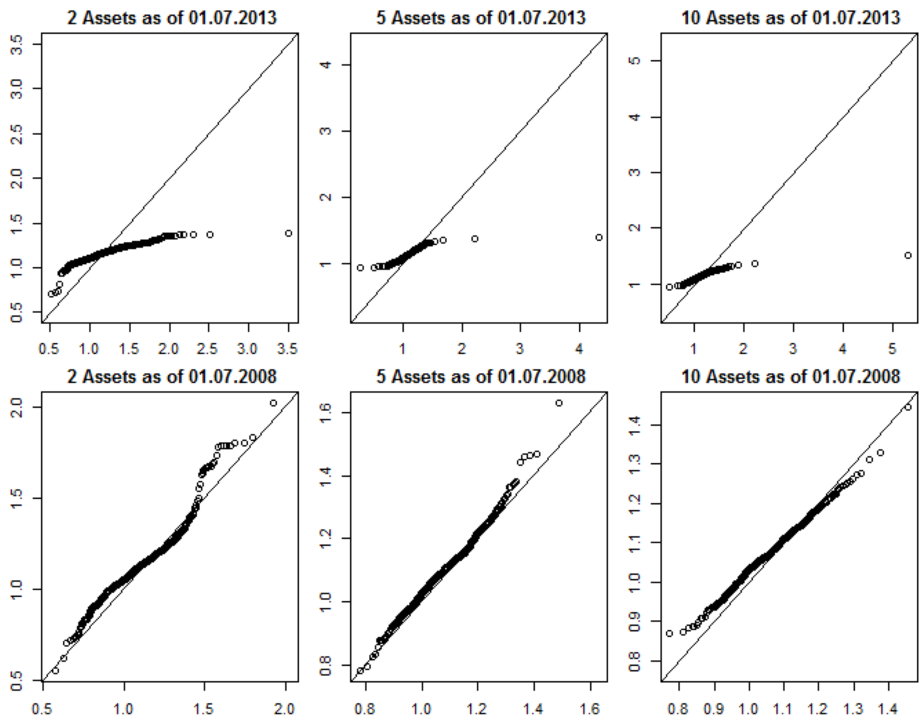
		Full set		20th percentile set	
	Observations	Lower	Upper	Lower	Upper
Asset-Based Lending	33	66.7%	0.0%	45.5%	33.3%
CTA/Managed Futures	687	17.6%	3.5%	14.0%	12.8%
Convertible Arbitrage	70	4.3%	27.1%	1.4%	61.4%
Distressed	106	25.5%	9.4%	12.3%	16.0%
Emerging Markets	243	32.1%	0.0%	30.9%	8.2%
Energy Sector	65	46.2%	0.0%	32.3%	1.5%
Event-Driven	212	18.4%	5.2%	4.2%	7.5%
Finance Sector	58	6.9%	1.7%	5.2%	0.0%
Fixed Income (non-arbitrage)	179	8.9%	24.0%	2.2%	43.6%
Fixed-Income Arbitrage	131	11.5%	22.9%	4.6%	35.1%
Fund of Funds – Market-Neutral	37	94.6%	0.0%	75.7%	0.0%
Fund of Funds - Multi-Strategy	1687	64.4%	1.2%	44.1%	2.1%
Fund of Funds – Single-Strategy	391	46.5%	0.8%	20.5%	1.5%
Healthcare Sector	41	9.8%	2.4%	2.4%	14.6%
Long Only	181	22.1%	2.8%	5.0%	7.7%
Long/Short Equity	1548	21.2%	4.3%	9.6%	9.4%
Macro	331	12.4%	5.7%	5.1%	35.3%
Market-Neutral Equity	228	42.5%	3.9%	18.0%	20.2%
Merger/Risk Arbitrage	34	14.7%	5.9%	2.9%	52.9%
Mortgages	31	6.5%	64.5%	0.0%	77.4%
Multi-Strategy	433	31.6%	5.3%	11.8%	12.5%
Options Strategies	86	30.2%	3.5%	4.7%	16.3%
Short Bias	32	18.8%	3.1%	6.2%	3.1%
Small/Micro Cap	61	11.5%	1.6%	6.6%	3.3%
Special Situations	67	28.4%	1.5%	16.4%	19.4%
Statistical Arbitrage	31	22.6%	16.1%	3.2%	45.2%
Value	89	16.9%	3.4%	11.2%	6.7%

Results for out-of-sample test: Lower/upper denote the observed exceedances of the 10th and 90th percentiles. The columns differ by the set used for calibration. The 20th-percentile run used only funds with average returns in the corresponding lower percentile whereas all funds were used for the full set calculation. Numbers exceeding the expected observations are marked in yellow.

Portfolios

We showed in the previous paragraph that we can construct a simulation model that fits the distribution of most funds reasonably well. We further demonstrated how a change in the calibration set can yield a model that captures the downside of funds' returns even better but that potentially creates an artificially high upside. The aim of this study is to estimate the downside risk of a portfolio of hedge funds. An increased upside could obviously invalidate the approach for this purpose. In the following we look at out-of-sample tests for portfolios of hedge funds with a variable number of assets.

.Figure 5: QQ plots for out-of-sample portfolio testing



QQ plots of simulated (x-axis) vs. observed total returns 27 months after the reference date for random portfolios of hedge funds with varying number of assets and reference dates. The number of assets in the portfolio varies from two to 10. Reference dates are summer 2013 for the most recent period (top) and summer 2008 at the start of the financial crisis (bottom). The calibration data set includes the data available before the reference date.

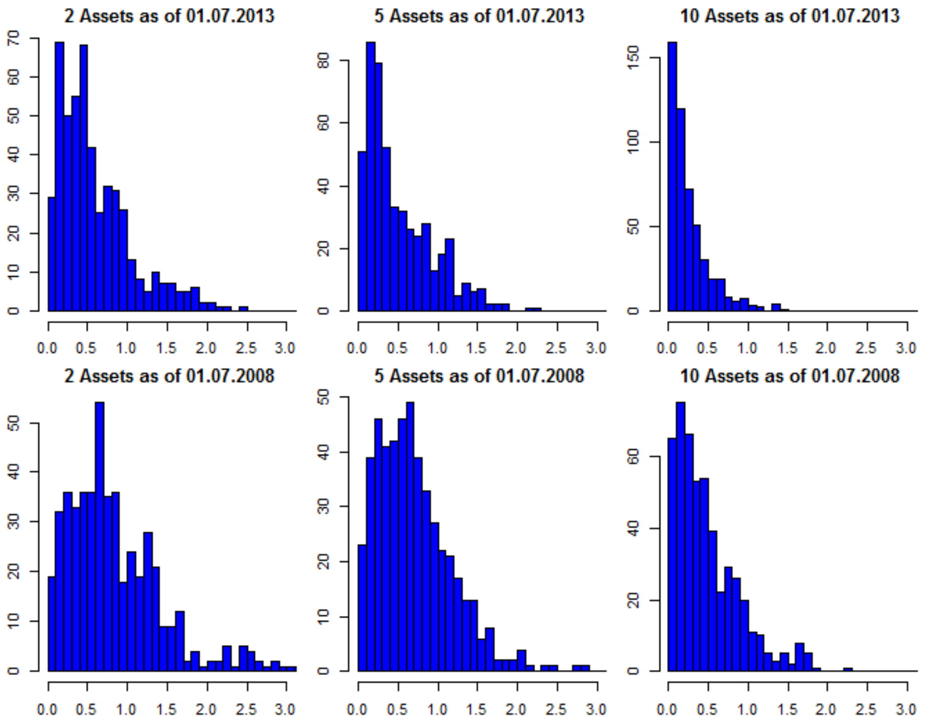
We created the benchmark distribution of realised returns for a given portfolio of strategies by randomly selecting funds of the corresponding strategies from the data set. The QQ plots for random portfolios with randomly selected strategies (Figure 5) show that the model continues to overestimate the up- and down-sides consistently as it did for the individual funds. This is due to the dependency framework introduced by the indices that strongly couple the funds' performances. Indeed we observed in our calculations that the absolute pairwise correlations of the simulated funds were much larger than the correlations in the data set when estimated over several years[10]. The plots show quite clearly how the calibration to the post-crisis period (summer 2013) increases the width of the simulated distribution.

The plots in Figure 5 show results for single randomly constructed portfolios. In the following we compare the simulated distributions for 500 random portfolios for likelihood of losses and their severity. To that end we randomly selected a portfolio of hedge funds from the set of strategies with no more than two funds following the same strategy. We calculated the probability ratio of losses (total return less than one) in observations and

10 This was only possible for a very limited number of funds due to the lack of long time series in the data.

simulations. A ratio of less than one indicates that the simulation predicts a loss more often than is observed in the data and thus points to a conservative simulation model (note that we are not comparing the severity of the losses here). The histograms in Figure 6 show clearly that the simulation underestimates the probability of a loss only occasionally. In all cases we could trace the misestimate back to portfolios composed of funds for which the model underestimates the losses as shown in Table 1. The frequency of observed underestimations reduces with increasing number of assets and with inclusion of the financial crisis data into the calibration set.

Figure 6: Ratio of observed to simulated probabilities of observing a portfolio loss

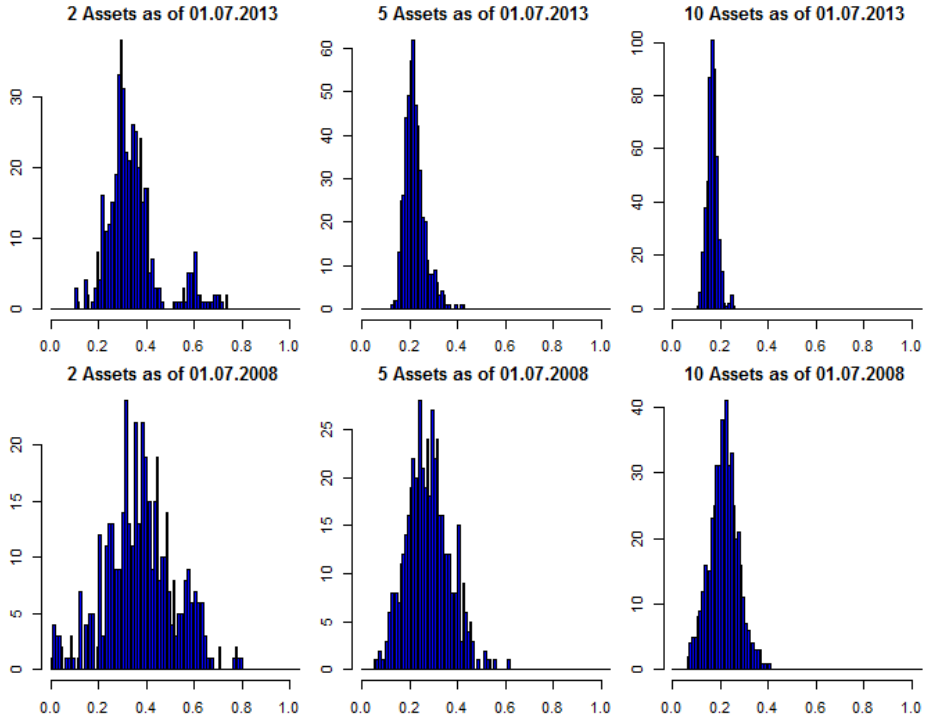


Ratio of observed to simulated probabilities of seeing a total return of less than one after 27 periods for 500 randomly selected portfolios. A ratio value smaller than one indicates that the probability of seeing a loss is higher in the simulation than in the observed portfolios.

The increased width of the return distribution is already evident from the QQ plots. The simulated losses should therefore not only be more likely but also more severe. We compared the loss severity by looking at the 5% quantile of the returns. Once again we compare the simulated and observed values by taking the ratio. However, when considering the quantiles, it is now the lower number (the corresponding return) that indicates a more conservative model. We therefore plot in Figure 7 the ratio of the simulated to the observed quantiles. The observed patterns follow the now familiar trend of more pronounced shapes with an increased number of assets in the portfolio and with the inclusion of the financial crisis data into the calibration set.

We can conclude here that the constructed simulation model is conservative on a portfolio level as was intended. Choosing the less-performant calibration set increases the width of the simulated distribution and makes the observation of higher funds' returns unrealistically more likely. However, this does not lead to cancellation effects in the simulation of a portfolio of hedge funds. Instead, the strong correlation between the funds results in an increased probability of observing losses for most portfolios. Furthermore the losses are of higher severity.

Figure 7: Ratio of simulated to observed fifth percentiles



Ratio of simulated to observed 5% quantiles of a total return distribution after 27 periods for 500 randomly selected portfolios. A ratio value smaller than one indicates a fatter left tail in the simulated return probability and correspondingly higher losses.

Conclusion

We presented a calibration and simulation framework to estimate the return distribution of hedge fund portfolios over a horizon of 27 months. The model uses a set of 12 indices to capture the most important risk drivers of the hedge fund industry. We introduced an efficient model-selection algorithm to identify the relevant drivers for individual hedge fund performances and proposed a mapping procedure to create representative performances of hedge fund strategies. We showed in QQ plots and backtesting calculations that an ARMA(1,1)-GJRGARCH(1,1) process is rich enough to capture the most significant features of the index distributions. We used out-of-sample tests to demonstrate that the proposed simulation of hedge fund strategies matches the observed return distributions of funds to a very high degree. Finally, we suggested a modification to explicitly capture tail risk. Such an adjustment, however, comes at the expense of a worse overall fit of the model. We showed that the modified model is conservative on a portfolio level and would still have worked reasonably well for most portfolios during the 2008-2009 financial crisis.

The suggested model is adequate to estimate the returns of a diversified portfolio, i.e. for a set of hedge funds selected in proportion to the sample available for this study. Analysing single hedge funds or highly concentrated portfolios would require additional analysis to account of idiosyncratic risks not adequately captured under the suggested model.

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I. Appendix: The eVestment hedge fund strategies

We list here the 31 categories of investment strategies that are used in the eVestment database:

- Fund of Funds – Single Strategy (funds investing in other hedge funds and specialising in a single strategy)
- Fixed-Income (funds investing primarily in the fixed-income market)
- Long/Short Equity (funds getting long and short positions on the equity market)
- Technology Sector (hedge funds investing in technology-related financial securities)
- Multi-Strategy (hedge funds pursuing multiple strategies)
- Fund of Funds - Market Neutral (funds investing in other hedge funds and specialising in the market-neutral strategy)
- Risk Arbitrage (hedge funds undertaking arbitrage on mergers and acquisitions)
- Regulation D (hedge funds investing in penny stocks)
- Market-Neutral Equity (hedge funds investing in the equity markets with a full hedging on global market moves)
- Statistical Arbitrage (hedge funds undertaking statistical arbitrage trades, such as co-integration and pairs trading)
- CTA/Managed Futures (hedge funds investing primarily in futures and pursuing trend-following and momentum strategies)
- Convertible Arbitrage (hedge funds doing statistical arbitrage in the convertible bonds market)
- Healthcare (hedge funds investing in healthcare-related financial securities)
- Value (hedge funds following a value-oriented strategy, mostly stock picking)
- Funds of Funds (funds investing in other hedge funds)
- Short Bias (funds getting long and short positions on the equity market, with more short positions)
- Small/Micro Cap (hedge funds focusing on small caps to earn a size premium)
- Fixed-Income Arbitrage (hedge funds undertaking statistical arbitrage in the fixed-income market)
- Funds of Funds – Multi-strategy (funds investing in multi-strategy hedge funds)
- Event-Driven (hedge fund trading on firms affected by special events such as mergers, spin-offs, bankruptcies...)
- Options (hedge funds trading in the option markets)
- Emerging Markets (hedge funds focusing on emerging stock and bond markets)
- Long Only (hedge funds taking only long equity positions)
- Macro (hedge funds investing according to macroeconomic news and analysis)
- Special Situations (hedge funds trading on firms affected by special events)
- Finance (hedge funds investing in securities of firms from the financial sector)
- Distressed (hedge funds investing in firms having filed for Chapter 11)
- Energy (hedge fund investing in energy firms and energy derivatives)
- Asset-Based Lending (hedge funds lending to struggling companies)
- Mortgages (hedge funds investing in mortgages)
- Capital Structure Arbitrage (hedge funds arbitraging between the relative value of equity and debt)

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