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**Haijie Weng and Stefan Trück**

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Return Based Style Factors and Value-at-Risk of Asia-Focused Hedge Funds

Haijie Weng* and Stefan Trück

ABSTRACT

In this paper, we identify return based style factors for Asia-focused hedge funds represented by the HFRI Emerging Market-Asia exclude Japan index. This hedge fund index has a particularly strong exposure to Asian equity markets and bond indices. Next to linear fixed income and equity factors, we also include non linear equity factors based on hypothetical option positions, in order to model the often reported nonlinear exposures of hedge funds. Our model provides a high explanatory power for returns of the hedge fund index, both for in sample and out of sample periods. The inclusion of non-linear factors results in a marginal increase in explanatory power for the considered index indicating that small positions in options provide protection against extreme losses of the market. We further conduct a Value-at-Risk analysis using the identified return based style factors. We propose a parametric approach using Monte Carlo simulation in combination with a multivariate GARCH BEKK model to forecast the Value-at-Risk. Our results suggest that this approach provides an appropriate quantification of the risk and yields a more plausible estimation of Value-at-Risk than a simple bootstrap method.

Keywords: Hedge fund, Return based style analysis, Value-at-risk, Emerging markets

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1. Introduction

In the past decade, significant growth rates in Asian financial markets have attracted global investors’ strong interest also for capital allocation in Asia focused hedge funds. The expansion of the sector results in over 1,000 hedge funds now focusing on Asian markets, representing over 15 percent of the total number of funds in the global industry. Although Asia-focused funds are characteristically smaller, accounting only for 4.9 percent of total industry assets, the fast growth of the Asia-focused hedge fund industry over the past years has also drawn the attention of the research community.

A number of studies have been conducted on hedge fund performance and risk management. Often, in these studies, hedge funds, as an alternative investment, are compared with traditional asset classes in terms of performance (Ackermann et al., 1999; Brown et al., 1999; Liang, 1999; Agarwal and Naik, 2004). Some of the results suggest that hedge funds can outperform equity markets due to superior investment skills of hedge fund managers (Brown et al., 1999; Liang, 1999), while other results cast doubt on the persistence of the outperformance of the hedge funds (Ackermann et al., 1999; Agarwal and Naik, 2004). From a risk management perspective, hedge funds are exposed to market risk, liquidity risk and credit risk (Amenc et al., 2002). The performance and risk analysis of hedge funds may also be underestimated due to presence of various biases in hedge fund indices (Fung and Hsieh, 2000). There are several difficulties as it comes to investigating the performances and risks of the hedge fund industry. The short data history of hedge funds available makes it difficult to compare the returns with those of traditional asset classes. Also dynamic and less transparent investment strategies applied by hedge fund managers make it difficult to capture the effective style components for this asset class. Finally, hedge fund returns usually exhibit nonlinearities when being regressed on returns of traditional asset classes.

In order to explore the risk exposures of hedge funds, many researchers have attempted to map the returns onto a set of external factors. Dor et al. (2003) modify Sharpe’s return based style analysis (Sharpe, 1988) in order to examine the effective style of hedge funds. Hereby, the return based style analysis using traditional asset classes is augmented by index options to more appropriately characterize the risk of the hedge funds. Fung and Hsieh (2004) propose an asset based style factor model that can explain up to 80 percent of the monthly variation in hedge fund portfolios. Teo (2009) augments the factor model of Fung and Hsieh (2004) with broad Asian equity indexes to study Asian focused hedge funds.

This paper aims to contribute to the literate in several dimensions. First, we make use of the return based style analysis framework suggested by Dor et al. (2003) in order to identify the effective style factors for Asia-focused hedge funds. To our knowledge, next to Teo (2009) this is one of the first empirical studies applying this technique to the Asian hedge fund industry. Teo (2009) performs a principal component analysis of Equity Long/Short hedge funds grouped by investment regions and identifies two additional equity asset based factors for the explanation of Asia-focused hedge fund returns: the Asia ex Japan equity market index and the Japan market equity index. Similarly, we augment the factors by including the Asia ex Japan equity index, Japan
equity index and the Asia emerging market index in the return based style analysis to better explain returns of Asia-focused hedge funds. In this paper, the HFRI Emerging Markets: Asia ex-Japan Index is chosen to represent the universe of Asia-focused hedge funds. Further, we identify three fixed-income styles and five equity styles as the underlying risk factors for Asia-focused hedge funds.

Second, we include hypothetical out-of-the money call and put options on a subset of equity styles in order to model the nonlinear exposures of Asia-focused hedge funds. Several studies on hedge funds show that the returns exhibit option-like features (Glosten and Jagannathan, 1994; Mitchell and Pulvino, 2001; Fung and Hsieh, 2001). Hedge fund managers trade dynamically and are not limited by investing in a specific class of asset only. Hence the nonlinear payoff of a hedge fund may result from explicitly investing in derivatives or implicitly trading dynamically. In order to include the nonlinearity in hedge fund returns in the return base style analysis, the literature suggests using actively traded index options as nonlinear factors for the mapping of hedge fund returns, see e.g. Agarwal and Naik (2004) and Teo (2009). Other studies suggest to augment the return of traditional asset classes with the returns of the synthetic options on these traditional asset classes (Loudon et al., 2006). In this paper, we choose the latter approach: including hypothetical out-of-the money call and put options, we are able to identify a relationship between out-of-the money put and call option positions and returns from Asia-focused hedge funds. It is reasonable to assume that these positions are constructed by Asia-focused hedge fund managers through active trading strategies in order to hedge the risk exposure from equity markets.

Finally, the ultimate goal for identifying the underlying risk exposures of the hedge fund is to evaluate the risk of the hedge funds. Many hedge funds exhibit significant lower tail risks, i.e., the funds face great loss in some extreme events. Unfortunately, the data history of hedge fund returns is usually quite short, especially for Asia-focused hedge funds. Therefore, rather rare events like extreme losses may not have happened since the inception of the funds what makes the quantification of risk more difficult. Once the effective styles of the hedge funds are identified, the risks of these styles can be evaluated with a longer time series of data. Since the effective styles normally had been exposed to extreme events in the past, modelling hedge fund returns as a linear combination of effective styles’ returns, it is possible to provide a more adequate estimation of the actual risk for these funds.

In our analysis we use the Value-at-Risk (VaR) measure, defined as the maximum loss with a given confidence level over a given period of time. VaR can provide information about the risk in the extreme tails of a distribution. This is of particular importance, since many hedge funds exhibit a non linear payoff structure, that is, hedge funds may face great losses under certain extreme events although they have an average low standard deviation. The nonlinear exposures also lead to a situation where the normality assumption of expected returns that suggests the use of the standard deviation as the only risk measure is no longer justified. Therefore, for hedge funds, VaR, as a complementary tool for measurement of the risks, can better capture the behaviour of hedge funds in some extreme events. We conduct our risk analysis using the identified effective styles and compare the VaR estimated through Monte Carlo simulation and historical simulation.
In an out-of-sample analysis for the period from January 2005 to April 2009, we find that Monte Carlo simulation provides a better evaluation of the hedge fund risk for such extreme market situations.

The remainder of the paper is structured as follows. Section two discusses the theoretical framework. Section three presents the results of the return-based style analysis. Section four provides an out-of-sample risk analysis for the considered Asian-focused hedge funds using the VaR measure and generates density forecasts for the considered hedge fund index. Finally, section five concludes.

2. Theoretical Framework

This section illustrates the chosen theoretical framework for the analysis. As mentioned above, we will consider the return based style analysis framework suggested by Dor et al. (2003) in order to examine the effective style factors for Asia-focused hedge funds. For modelling the nonlinear exposures of these funds, we also include option-based risk factors next to the traditional linear risk factors generally suggested in the literature. Finally, a risk analysis using the identified effective styles will be conducted. Hereby, both a parametrical approach including Monte Carlo simulation and a simple historical simulation approach will be implemented in order to estimate VaR and generate density forecasts for the index.

2.1. Return Based Style Factors

Fung and Hsieh (2002) find that fixed income hedge funds are typically exposed to interest rate spread. This is a result of many fixed income hedge funds rather holding long positions in high yield bonds and hedging the interest rate risk by shorting treasury bills or bonds. Overall, Fung and Hsieh (2002) identify three major fixed income styles: three month treasury bills, ten year treasury bonds and Moody’s Baa bonds. Further, Fung and Hsieh (2003) showed that equity long/short hedge funds tend to take long positions in low capitalization stocks and short positions in large capitalization stocks, thus the returns are typically exposed to the spread between large cap and small cap stocks. In this paper, we include both fixed income styles and equity styles as return based style factors since the major investment tools used by Asia-focused hedge fund managers are fixed income and equity. Although the focus of this paper is on Asia-focused hedge funds, we decided to include US equity indices as selected style factors because the movement of US equity market has great influence on other equity markets all over the world also including Asian equity markets. Teo (2009), using principal component analysis, found that both the Asia exclude Japan equity market index and Japan equity market index have a high correlation with the performance of Asia equity hedge funds. Based on these results, next to the factors suggested by Fung and Hsieh (2002, 2003), we decided to also include an index representing the Japanese market, an index representing the Asian equity market excluding Japan as well as an index representing Asia emerging markets. Overall, we select eight factors: three fixed income factors, two US equity market indices and three Asian equity market indices as the return based style factors for Asia-focused hedge funds. In detail the eight factors are: yields on three month treasury bills, ten year treasury bonds, Moody’s Baa bonds, returns on Russell 1000 index, Russell
2000 index, MSCI Japan index, MSCI Asia Pacific exclude Japan index and MSCI Emerging market Asia index. Appendix A provides a detailed description of the selected return based style factors.

2.2. Non Linear Equity Factors

Agarwal and Naik (2004) show that hedge funds often exhibit non-linear option-like exposures to standard asset classes. They illustrate that the payoffs of a large number of equity-oriented hedging strategies actually resembles a short position in a put option on the market index. Under these circumstances, models using traditional linear factors only, provide limited help in capturing the actual risk-return relationship and are not appropriate. Hedge funds may bear significant left-tail risk that will be ignored by linear factor models and the commonly used mean-variance framework. With respect to these results, in our analysis we augment the traditional linear factor model approach with option-based risk factors.

Agarwal and Naik (2004) use actively traded at-the-money (ATM) and out-of-the-money (OTM) European call and put options on the S&P 500 composite index as option based risk factors in order to capture the option-like features of hedge fund returns. The long call option strategy is constructed as follows: on the first trading day of the month, a call option on the S&P 500 index that expires at the end of the month is bought, held during the entire month and being sold at its expiration date. This strategy is repeated for each month while the returns of this strategy are recorded. A similar procedure then provides the returns on buying put options. The at the money (ATM) option is the option with strike price closest to the current index value while an out-of-the-money (OTM) call (put) option is one with a higher (lower) strike price. Following Agarwal and Naik (2004), Teo (2009) uses OTM European call and put options on the Nikkei225 traded on the Singapore Stock Exchange and calculates the time series of returns of the above-mentioned option trading strategy for Asian equity hedge funds. Due to the lack of actively traded options for the identified index factors, Loudon et al. (2006) create pseudo option-like payoff profiles for a subset of the index factors to model the nonlinear exposures that fixed income hedge funds may face. Similarly, in this paper, in contrast to using actively traded options, we construct hypothetical OTM call and put options on a subset of equity indices in order to model the nonlinear exposures of Asia-focused hedge fund returns. The reasons for the use of hypothetical instead of actually observed option prices are as follows: unfortunately, the Asian stock index option market is less developed than similar markets in the US or Europe. By volume and turnover, the most actively traded stock index option is available in Korea. According to the World Federation of Exchanges, stock index option traded on the Korea Exchange (KRX) accounted for 86.8% of the region’s volume in 2009. Due to the illiquidity of traded stock index options in Asian markets, usually these options only account for a small weight in the portfolio of Asian hedge funds. Thus, the option-like features of Asian hedge fund returns are probably due to the hedge fund managers’ active trading strategy. Compared with the traded option, the hypothetical option is less realistic since the option price is calculated based on the Black-Scholes model with a number of simplifying assumptions. However, in the absence of actively traded options on Asian equity indices, constructing hypothetical options on an index is an appropriate approach to study the option-like features of Asian hedge fund returns.
The hypothetical option strategy is constructed as follows: we create out-of-the-money call and put options with exercise prices set at two monthly standard deviations out-of-the-money from the current price of the equity style factors. We assume that each option has a maturity of one month and is held until maturity. If the call option expires in the money, the return is computed as \((S_T - K_c - c)/c\), where \(S_T\) is the underlying asset price at maturity, \(K_c\) is the strike price of the call option set at \(S_0 - 2\sigma S_0\), \(c\) is the call option price calculated using the Black-Scholes formula, \(S_0\) is the initial underlying asset price, \(\sigma\) is the monthly volatility of the underlying asset estimated by a trailing 24 month standard deviation. If the put option expires in the money, the return is computed as\((K_p - S_T - p)/p\), where \(p\) is the put option price, \(K_p\) is the strike price of the put option set at \(S_0 + 2\sigma S_0\). If the option expires out of the money, the return is -100%. The payoff of the short position is assumed to be the inverse to that of the long position.

Because the equity indices are highly correlated, we only create hypothetical out-of-the-money call and put options for the MSCI Asia Pacific排除 Japan Index and the MSCI Emerging market Asia Index since the investment region for the HFRI Emerging Market-Asia exclude Japan index is mainly the Asia Pacific excluding Japan.

2.3. Return Based Style Analysis

After having identified the return based style factors and the non linear equity factors, we conduct a return based style analysis for the hedge fund returns following Dor et al. (2003). As mentioned above, usually there is only a short data history available for returns of Asia-focused hedge funds. Therefore, in particular for a risk analysis it will be helpful to represent the returns of the funds by a number of style factors with longer history available. Sharpe (1988) proposed an econometric technique to determine the mutual fund’s investment style which requires a time series of historical fund returns. This technique involves a constrained regression that uses \(N\) asset classes to replicate the historical return pattern of a portfolio. The basic econometric framework is as follows:

\[
r_{t,t} = \alpha_{t,1}f_{1,t} + \alpha_{t,2}f_{2,t} + \cdots \alpha_{t,N}f_{N,t} + \epsilon_{t,t} \quad (1)
\]

Because the weights of the replicated asset classes should add up to unity and mutual fund managers are not allowed to take short positions, two constraints are imposed on the coefficients \(\alpha_{i,j}\):

\[
\sum_{j=1}^{K} \alpha_{i,j} = 1, \quad \forall i \quad (2a)
\]

\[
\alpha_{i,j} \geq 0, \quad \forall i, j \quad (2b)
\]

When applying return based style analysis to hedge funds, the constraint of nonnegative coefficients is usually released to allow hedge fund managers also to take short positions. Using the identified return based style factors and non linear equity factors, the returns of the HFRI Emerging Market-Asia excluding Japan index can therefore be represented as:

\[
r_t = \sum \alpha_{i}f_{i,t} + \sum \beta_{j}k_{j,t} + \epsilon_t \quad (3)
\]
\[ \sum_{i=1}^{M} \alpha_i + \sum_{j=1}^{N} \beta_j = 1, \forall i, j \quad (4) \]

where \( f_i \) are the returns of the return based style factors, \( k_j \) are the returns of the option on the equity index, \( \alpha_i \) and \( \beta_j \) are the estimated coefficients.

Based on Eq. (3), the excess return of the hedge fund index over the sum of the weighted factor returns can be expressed as

\[ \varepsilon_t = r_t - \sum \alpha_i f_{i,t} + \sum \beta_j k_{j,t} \quad (5) \]

Sharpe (1988) suggests choosing the optimal weights for \( \alpha_i \) and \( \beta_j \) in order to minimize the term \( \varepsilon_t \) or rather the variance of \( \varepsilon_t \) subject to constraint (4). This can be achieved for example by quadratic programming. To evaluate the effectiveness of the style analysis, we use the adjusted coefficient of determination (adjusted \( R^2 \)) as follows:

\[ Adjusted \ R^2 = 1 - \frac{T-1}{T-N} \times \frac{\text{var}(e_p)}{\text{var}(r_p)} \quad (6) \]

where \( N \) is the number of the style factors and \( T \) is the number of observations, \( \text{var}(e_p) \) is the variance of the residuals and \( \text{var}(r_p) \) is the variance of the hedge fund index returns. The adjusted \( R^2 \) has the advantage of imposing a penalty on the increase of style factors.

2.4. Value-at-Risk Analysis

After the style analysis has been completed, we can proceed with a risk analysis for the considered hedge fund index. Popular approaches for determining the Value-at-Risk of a portfolio are for example Monte Carlo simulation or historical simulation, see e.g. Duffie and Pan (1997), Hull and White (1998), Jorion (2000) or Loudon et al. (2006). In the latter approach, the distribution of future hedge fund returns is simulated by randomly selecting the historical returns of identified effective style factors and generating random variables for the errors. The distributions of the errors are usually assumed as being from the Gaussian or Student-t distribution. Hence, the hedge fund returns can be computed through Eq. (3). Since the history of the style factors is substantially longer than that of hedge fund returns, we can use the longer history of the style factors to produce a more accurate risk analysis for the hedge funds. The hedge fund index studied in this paper is the HFRI Emerging Market-Asia exclude Japan index with available data on returns starting from January 1990. In contrast, data on the underlying effective style factors is available starting from January 1988, which is two years earlier than the considered hedge fund index. In fact, many hedge fund indices have a significantly shorter history, such that the risk estimation using bootstrapping of the indentified effective style factors instead of the actual hedge fund returns will become even more appealing. In particular, many of the newly established hedge fund indices have not experienced a history of extreme events. In particular, using scenario analysis techniques one could examine how the hedge funds performs given unexpected extreme events by using the performance data of the style factors during such events. Finally, also the nonlinearity of the hedge fund performance can be better estimated.
using a longer time series.

However, a potential weakness of the historical simulation or bootstrap approach is that the Value-at-Risk is estimated based on actual historical observations of the style factors only. Therefore, we decided to also use Monte Carlo simulation that generates correlated random style factor returns based on an estimated conditional covariance matrix for the style factors. Unlike historical simulation, due to the parametric approach of Monte Carlo simulation, it can provide results for the tails of the return distribution, even when such events have not been historically observed yet.

Therefore, we model the identified return based style factors as autoregressive progresses of order \( p \)

\[
y_t = c + \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \cdots + \varphi_p y_{t-p} + \mu_t, \quad \mu_t \sim N(0, \sigma_t^2) \quad (7)
\]

where \( \mu_t \) denotes the error term. After estimation of the AR model, a forecast of the style factor for the next period can be determined by:

\[
y_{t+1} = c + \varphi_1 y_t + \varphi_2 y_{t-1} + \cdots + \varphi_p y_{t-p+1} + \mu_{t+1} \quad (8)
\]

In this paper, we identify five equity style factors. The volatility spillovers between equities markets, that is, a tendency for volatility to change in one equity market following a change in the volatility of another, are well observed by practitioners and researchers. Multivariate GARCH models provide estimates for the conditional covariances as well as the conditional variances in contrast to univariate models and have gained high popularity in modelling and forecasting multivariate time series. For example, Gibson and Boyer (1998) compare the correlation forecasting ability of three sophisticated models (two GARCH models and a two-state Markov switching model) and two simple moving average models and find that the sophisticated models (a diagonal GARCH and a Markov switching approach) produce better correlation forecasts than the simple moving averages. Multivariate GARCH models specify equations for the behaviour of the variance covariance matrix through time. Several different multivariate GARCH formulations have been proposed in the literature, including the VEC, the diagonal VECH and the BEKK model, see e.g. Bauwens et al. (2006) for a survey on the most important developments in multivariate GARCH modelling. In our analysis we suggest to use a GARCH BEKK (Baba-Engle-Kraft-Kroner) model (Engle and Kroner, 1995). This model overcomes the difficulties of the VEC model of ensuring that the conditional variance-covariance matrix is always positive definite. The model has the form

\[
H_t = C C' + \sum_{j=1}^{p} \sum_{k=1}^{K} A_{kj}' H_{t-j} A_{kj} + \sum_{j=1}^{q} \sum_{k=1}^{K} B_{kj}' u_{t-j} u_{t-j}' B_{kj} \quad (9)
\]

where \( A_{kj}, B_{kj} \) are parameter matrices and \( C \) is a lower triangular matrix. The decomposition of the constant term into a product of two triangular matrices \((CC')\) is to ensure the positive definiteness of the conditional variance-covariance matrix \((H_t)\). For example, for \( q = p = K = 1 \) the BEKK model becomes
\[ H_t = C C' + A'H_{t-1}A + B'u_{t-1}u_{t-1}'B \] (10)

The diagonal BEKK model is a further simplified version of (10) where \(A\) and \(B\) are diagonal matrices. It is a restricted version of the diagonal VEC model such that the parameters of the covariance equations (equations for \(h_{i,j}, i \neq j\)) are products of the parameters of the variance equations (equations for \(h_{i,i}\)). To illustrate the diagonal BEKK model, consider the simple GARCH(1,1) model in a bivariate case, where the diagonal BEKK model becomes:

\[
H_t = \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{bmatrix} + \begin{bmatrix} a_{11} & 0 \\ 0 & a_{22} \end{bmatrix} H_{t-1} \begin{bmatrix} a_{11} & 0 \\ 0 & a_{22} \end{bmatrix} + \begin{bmatrix} b_{11} & 0 \\ b_{22} & 0 \end{bmatrix} \begin{bmatrix} u^2_{t-1} & u_{1,t-1}u_{2,t-1} \\ u_{2,t-1}u_{1,t-1} & u^2_{2,t-1} \end{bmatrix} + \begin{bmatrix} b_{11} & 0 \\ 0 & b_{22} \end{bmatrix} (11)
\]

To model the conditional covariances and variances among the five equity styles over time, we use a multivariate GARCH (1,1) diagonal BEKK model represented by

\[ H_t = W + A'H_{t-1}A + B'u_{t-1}u_{t-1}'B, u_t \sim N(0,H_t) \] (12)

where \(A\) and \(B\) are 5x5 diagonal matrices, \(W\) is a 5x5 upper triangular matrix, \(H\) a 5x5 upper triangular conditional variance-covariance matrix and \(u\) is a 5x1 residual vector. Hence, we can forecast the conditional variance-covariance matrix for time \(t+1\) as

\[ H_{t+1} = W + A'H_tA + B'u_tu'_tB \] (13)

Once the conditional variance-covariance matrix is estimated for time \(t+1\), Monte Carlo simulation coupled with Cholesky decomposition is applied to generate correlated random variables \((u_{t+1})\) and thus the return of each style factor can be forecasted through Eq. (8). The payoff of the option on the considered equity indices can be easily calculated based on the simulated equity index values. We assume that the error term in Eq. (3) is normally distributed, thus generate random variables which are normally distributed with mean and variance estimated from the error terms. Finally, a forecast for the probability density distribution for the hedge fund returns can be simulated through Eq. (3). Then the point forecast for the return of the hedge fund over the next month is simply the mean of all simulated hedge fund returns while the Value-at-Risk at different level of confidence can be derived from the forecasted return distribution.

3. Results for the Multi-Factor Model

In this section, we describe the results for mapping the selected return based style factors and non linear equity factors into the returns on HFRI Emerging Market-Asia exclude Japan index. We consider the HFRI Emerging Market-Asia exclude Japan index over the period January 1990 through April 2009. Fig. 1 provides a plot of the returns of the HFRI Emerging Market-Asia exclude Japan index over the period from January 1990 through April 2009. We chose the period January 1990 through December 2004 as in sample period for estimation of the coefficients and the period from January 2005 through April 2009 as out of sample period for model testing and
risk forecasting. We decided to concentrate on the HFRI index rather than investigating individual hedge funds, in order to represent the general characteristics of the Asian hedge fund industry. Further, for an index often the identification of the underlying return based style factors is more straightforward.

Fig.1. Monthly returns (Left Panel) and Cumulative Return (Right Panel) of HFRI Emerging Market-Asia exclude Japan index over the period from January 1990 to April 2009

We adapt the return based style analysis as in Dor et al. (2003) in order to determine the weights of return based style factors for the hedge fund returns. Recall that we include eight linear factors, three fixed income factors (yields on three month treasury bills, ten year treasury bonds, Moody’s Baa bonds), two US equity market indices (Russell 1000 index, Russell 2000 index) and three Asian equity market indices (MSCI Japan index, MSCI Asia Pacific exclude Japan index and MSCI Emerging market Asia index). Besides, we included the created nonlinear equity factors described in section 2.2, the out-of-the-money call and put options for MSCI Asia Pacific exclude Japan Index and the MSCI Emerging market Asia Index.

The results for the analysis are presented in Table 1. The table also reports the adjusted coefficient of determination both for the in sample period, January 1990 to December 2004 and out of sample period from January 2005 to April 2009. Results for the out of sample period are of particular interest, since they indicate how good the determined style factors represent the hedge fund index returns after the calibration period.
Table 1
Mapping of HFRI Emerging Market-Asia exclude Japan index using return based style analysis for the in sample period from January 1990 – December 2004. The adjusted coefficient of determination $R^2$ is reported both for the in sample period and the out of sample period.

<table>
<thead>
<tr>
<th>Underlying Risk Factors</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>3m US T-bill</td>
<td>22.78%</td>
</tr>
<tr>
<td>10 year US treasury</td>
<td>10.45%</td>
</tr>
<tr>
<td>BAA corporate bond</td>
<td>10.47%</td>
</tr>
<tr>
<td>Russell 1000</td>
<td>-4.13%</td>
</tr>
<tr>
<td>Russell 2000</td>
<td>4.93%</td>
</tr>
<tr>
<td>MSCI Japan</td>
<td>7.18%</td>
</tr>
<tr>
<td>MSCI Asia Pacific exclude Japan</td>
<td>17.17%</td>
</tr>
<tr>
<td>MSCI Emerging market Asia</td>
<td>31.14%</td>
</tr>
<tr>
<td>OTM call on MSCI Asia Pacific exclude Japan</td>
<td>0.03%</td>
</tr>
<tr>
<td>OTM call on MSCI Emerging market Asia</td>
<td>-0.01%</td>
</tr>
<tr>
<td>OTM put on MSCI Asia Pacific exclude Japan</td>
<td>0.01%</td>
</tr>
<tr>
<td>OTM put on MSCI Emerging market Asia</td>
<td>0.00%</td>
</tr>
</tbody>
</table>

In sample period (January 1990-December 2004, adjusted $R^2$) 76.84%
Out of sample period (January 2005-April 2009, adjusted $R^2$) 79.02%

Table 1 clearly shows that the most significant equity factors relating to the HFRI Emerging Market-Asia exclude Japan index are returns on MSCI Asia Pacific exclude Japan index and MSCI Emerging market Asia index. As equity is still the major investment tool used by many Asia-focused hedge fund managers, it is not surprising that the above two Asian equity indices are determined as highly significant factors for Asia-focused hedge fund returns. The two factors together account for a weight of 48.3%. We also observe a significantly smaller exposure of the returns to the Japanese equity market with a factor weight of 7.2%. This result could be expected, since the HFRI Emerging Market-Asia exclude Japan index does not include the Japan-focused hedge funds. In addition, we find a positive influence of the small cap Russell 2000 index returns with a weight of 4.9% and a negative influence of the Russell1000 index with an absolute weight of 4.1%. This is consistent with Fung and Hsieh (2003)’s finding that equity long/short hedge funds have exposure to the spread between large and small cap stocks.

With respect to the fixed income factors, we find that Asia-focused hedge funds indicate a strong linear relationship with the three considered factors. The highest weight with 22.8% can be observed for the 3m US T-bill, while the 10 year US treasury and BAA corporate bond returns have approximately equal weights of 10.5%. Overall, the fixed income factors account for a weight of 43.7%. The exposure to fixed income factors can be explained by the fixed income strategies that are used by some of the Asia-focused hedge fund managers.

With respect to the considered non linear equity factors, the inclusion resulted only in a marginal increase of the explanatory power of the model. We obtain an adjusted $R^2$ of 75.5% for using return based linear style factors only and 76.8% with the inclusion of nonlinear equity factors. The results indicate only a small weight of option positions on equity indices, for example, a
weight of 0.01% for the out-of-the-money put on MSCI Asia Pacific exclude Japan. However, note that this small position can have significant amount of sensitivity to tail events. To illustrate this, consider the following example: assume that on August 29, 2008, a hedge fund manager buys an out-of-the-money put on MSCI Asia Pacific exclude Japan index with strike price set at two monthly standard deviations out-of-the-money from the current index price. Further assume that the option had a maturity of one month and was held until maturity, the interest rate was 4% per year and the index volatility was 19.66% per year based on trailing 24 month returns. The closing index price on 29 August 2008 was 1157. Then the strike price according to our specification was 1026 and the Black-Scholes put option value was 0.32. On 30 September 2008, the index closed at 955, thus a long position in put options as small as 0.01% would result in a 2.21% positive gain to the portfolio. Hence, a long position in an out-of-the-money put option can provide significant positive returns during extreme market drops. It serves as a protection of portfolio wealth against severely depreciating markets. Further, we observe a weight of -0.01% on the OTM call options on the MSCI Emerging market index. This short call position is hedged by the significant exposure to MSCI Emerging market Asia index.

A standard way to examine the usefulness of a model is to test it during an out of sample period that has not been used for model calibration. Specifically, we use the coefficients estimated from the in sample period (January 1990 to December 2004), along with the realized out of sample data (January 2005 to April 2009), to compare the forecasted returns of the model with the actually realized returns of hedge fund index during the out of sample period. If the model correctly captures the underlying risk factors of the hedge fund index, an adjusted coefficient of determination R² similar to the in-sample period could be expected. We obtain an adjusted R² of 79.2% for the out of sample period, which is approximately equal to that for the in sample period, indicating a reasonable representation of the hedge fund returns by the considered style factors.

Further, we repeat the style analysis by extending the in sample period by one month at each time step and recalculate the weights of the indentified factors. So the in sample period grows from 180 months to 231 month at the last time step. Fig. 2 shows the changes of the factors weights for the different estimation periods. We observe that the factor weights are fairly constant through time with the maximum standard deviation among all factors being less than 0.4%. However, we observe slightly more pronounced changes in the estimated factor weights for the last 6 months of the out of sample period possibly indicating the effects of the Global Financial Crisis on the hedge fund index behaviour.
In this section we conduct a risk analysis consisting of an in sample model calibration and out of sample forecasting analysis for the returns of the HFRI Emerging Market-Asia exclude Japan index.

4.1. In Sample Model Calibration

In the following we discuss the estimation and in-sample results for the suggested models described in Section 2.4. To test the stationarity of the data series, we conduct augmented Dickey-Fuller unit root tests for the monthly returns of the eight identified return based style factors from January 1990 to December 2004 and find that all three fixed income style factors have a unit root at 95% significance, that is, the data series are non-stationary. Hence we express the yields on fixed income factors as

\[ y_{b,t} = y_{b,t-1} + \mu_{b,t} \quad \mu_{b,t} \sim N(0, \sigma_{b,t}^2) \] (14)

The returns of the considered equity indices pass the stationarity test and are modelled as being from a normal distribution:
\[ y_{e,t} = c + \mu_{e,t}, \mu_{e,t} \sim N(0, \sigma^2_{e,t}) \] (15)

For simplicity, we assume that residuals of bond factors (\( \mu_{b,t} \)) and residuals of equity factors (\( \mu_{e,t} \)) are uncorrelated. Hence we only need to generate the conditional variance-covariance matrix for the five equity styles such that the computational efforts are reduced significantly. We adapt the diagonal BEKK model to estimate the conditional variances and covariances between the five equity indices with in sample data from January 1990 to December 2004. The estimated model parameters are reported in Table 2. We find that apart from \( B(3,3) \) all estimated parameters are significant at the 10% level and show the expected signs.

### Table 2

Estimated parameters for diagonal BEKK model, where \( A \) and \( B \) are 5x5 diagonal matrices of parameters, \( W \) is a 5x5 upper triangular matrix of parameters, \( H \) is 5x5 upper triangular conditional variance-covariance matrix and \( u \) is a 5x1 residual vector (data period from January 1990 to December 2004).

<table>
<thead>
<tr>
<th>Covariance specification: Diagonal BEKK</th>
</tr>
</thead>
<tbody>
<tr>
<td>( H_t = W + A'H_{t-1}A + B'u_{t-1}u_{t-1}'B )</td>
</tr>
<tr>
<td>Coefficient</td>
</tr>
<tr>
<td>-------------</td>
</tr>
<tr>
<td>W(1,1)</td>
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<tr>
<td>W(1,2)</td>
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<tr>
<td>W(1,3)</td>
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<tr>
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<tr>
<td>A(4,4)</td>
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<tr>
<td>A(5,5)</td>
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</tbody>
</table>
4.2. Forecasting VaR

We conduct an out-of-sample forecast analysis for the HFRI Emerging Market-Asia exclude Japan index returns for the period from January 2005 to April 2009 using the proposed parametric approach and bootstrapping of the historical data. The parameters are estimated using a recursive window technique. For the recursive window approach, the initial estimation date is fixed and additional observations are added once at a time to the in-sample estimation period. Due to the monthly data available for the hedge fund index returns, one time step equals one month. We simulate 30,000 hedge fund returns for each month in order to construct a distribution of future hedge fund returns.

The simulated 99% and 95% VaR as well as the actual observations of index returns for the considered out of sample period are plotted in Fig. 3 and 4. For comparison, we also provide the VaR computed using a non-parametric bootstrap approach for the style factors. We can observe that the VaR computed by the bootstrap method is almost constant through the considered out of sample period, since it is computed from historical observations only. On the other hand, based on the chosen parametric approach, the estimates for VaR change significantly over time. This is due to the changing structure of the estimated variance-covariance matrix for the equity style factors.

![Fig.3. Returns of HFRI Emerging Market-Asia exclude Japan index and 95% VaR forecasts for the considered out of sample period January 2005 to April 2009. The graph also compares the computed 95% VaR for the proposed parametric approach (black line) and a nonparametric bootstrap approach (green line). The parameters are estimated using recursive window approach.](image-url)
Fig. 4. Returns of HFRI Emerging Market-Asia exclude Japan index and 99% VaR forecasts for the considered out of sample period January 2005 to April 2009. The graph also compares computed 99% VaR for the proposed parametric approach (black line) and a nonparametric bootstrap approach (green line). The parameters are estimated using recursive window approach.

The figures also illustrate that under a normal market scenario, the bootstrap method seems to overestimate the risk in comparison to the parametric approach. However, during the times of the Global Financial Crisis, the parametric approach forecasts indicate a more significant and quicker reaction to the changing business environment and provide significantly higher estimates for the risk during the period from October 2008 to January 2009. Further, we observe that after the financial crisis, the risk forecasted using the parametric approach rapidly returns to a normal level while the bootstrap method will take a longer time to respond, which might cause an overestimation of the risk. Overall, the parametric approach shows an advantage with respect to a timely adjustment of the risk level.

In a second step, we also investigate the effect of the nonlinear equity factors on VaR estimates. Fig. 5 and 6 plot the index returns as well as the computed 95% and 99% VaR for the out of sample period with and without the inclusion of the nonlinear factors. We find that the VaR computed excluding the nonlinear factor, on average is slightly higher than when these factors are included into the model. Overall, this confirms our results from section 3. Recall that the estimated weight of the nonlinear factors was rather small while the inclusion of these factors resulted only in a marginal increase of the explanatory power of the model. However, as illustrated in our example even a small weight for these factors can have an important impact on the risk of the hedge fund.
Further, we also conduct a distributional test to evaluate the accuracy of the density forecasts following Crnkovic and Drachman (1996) and Diebold et al. (1998). We are interested in the distribution of the hedge fund index return $r_{t+1}$, which is forecasted at time $t$. Further we denote $f(r_{t+1})$ as the probability density function and $F(r_{t+1}) = \int_{-\infty}^{r_{t+1}} f(x) dx$ as the cumulative distribution of $r_{t+1}$. To conduct the test, $\hat{F}(r_{t+1})$ is determined by using the parameters estimated from the in-sample period and the observations $r_s, s = 0, \ldots, t$. Rosenblatt (1952) shows that if $\hat{F}$ is the correct distribution, the transformation of $r_{t+1}$, namely
\[ u_{t+1} = \int_{-\infty}^{x_{t+1}} f(x)dx = F_x(r_{t+1}) \] is i.i.d. uniformly on [0,1].

In order to investigate the assumption of uniformity, Crnkovic and Drachman (1996) then suggest a test that is based on the distance between the empirical and the theoretical cumulative distribution function of the uniform distribution. This may be done using the Kolmogorov-Smirnov (KS) statistic. The KS statistic is usually denoted by \( D_{ks} = \max(D^+, D^-) \), with \( D^+ = \sup \{ F_n(u) - \hat{F}(u) \} \) and \( D^- = \sup \{ \hat{F}(u) - F_n(u) \} \). Hereby \( F_n(u) \) denotes the empirical distribution function for the probability integral transforms of the one-month ahead forecasts and \( \hat{F}(u) \) is the \( cdf \) of the uniform distribution. Table 3 provides results for the proposed parametric approach and the bootstrap method. We find that, for both models, the assumption of uniformity cannot be rejected even at the 10% significance level. From the results of KS test, the parametric approach slightly outperforms the bootstrap method.

| Table 3 |
|-----------------|-----------------|
|                | KS Statistic    | P Value       |
| Proposed Parametric Approach | 0.1016          | 0.6448        |
| Bootstrap Method             | 0.1113          | 0.5162        |

Overall, the results suggest the superiority of a parametric approach using Monte Carlo simulation in combination with a multivariate GARCH (1,1) model to capture the dependence and dynamics between the risk factors. In contrast to the bootstrap method that overestimates the hedge fund risk during a normal market situation, the proposed parametric approach provides more timely and appropriate forecast of the Value-at-Risk. Further, the parametric approach incorporates extreme market movement better than the bootstrap method, thus providing a more realistic and satisfactory measure of the hedge fund risk. In terms of providing density forecasts, the parametric approach also slightly outperforms the bootstrap method.

5. Summary and Conclusion

In this paper, we identify return based style factors for Asia-focused hedge funds represented by the HFRI Emerging Market-Asia exclude Japan index. Hereby, we make use of the return based style analysis framework initially suggested by Dor et al. (2003). In our analysis, we also include non linear equity factors based on hypothetical option positions, in order to model the often reported nonlinear exposures of hedge funds. This is one of the first empirical studies applying these techniques with particular focus on the Asian hedge fund industry.

Our model provides a high explanatory power for returns of the hedge fund index, both for in sample and out of sample periods. The most significant equity factors relating to the HFRI Emerging Market-Asia exclude Japan index are returns on MSCI Asia Pacific exclude Japan index and MSCI Emerging market Asia index. The two factors together account for a weight of 48.3%. With respect to fixed income factors, we find that Asia-focused hedge fund returns can be related to the 3m US T-bill, 10 year US treasury and BAA corporate bond returns. Overall, these three
fixed income factors account for a weight of 43.7%. The inclusion of non-linear equity factors results in a marginal increase of the explanatory power of the model. The estimated small portions of options can be interpreted as providing protection for the funds against unexpected severely depreciating markets.

We further conduct a Value-at-Risk analysis using the identified return based style factors. We propose a parametric approach using Monte Carlo simulation in combination with a multivariate GARCH BEKK model to forecast the Value-at-Risk. The results are also compared to the standard industry approach of bootstrapping using historical observations for the style factors only. Overall, our results suggest the superiority of the parametric approach. Since the suggested model also captures the dependence and dynamics between the risk factors, it provides a better quantification of the risk for the considered hedge fund index.

Acknowledgements

References


**Appendix A: Description of considered Return Based Style Factors**

<table>
<thead>
<tr>
<th>Asset class</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>3-month Treasury bill</td>
<td>Market yield on U.S. Treasury securities at 3-month constant maturity.</td>
</tr>
<tr>
<td>10-year Treasury bond</td>
<td>Market yield on U.S. Treasury securities at 10-year constant maturity.</td>
</tr>
<tr>
<td>Corporate bond</td>
<td>Moody’s yield on Baa Corporate bonds-all industries. Source: <a href="http://www.federalreserve.gov">www.federalreserve.gov</a></td>
</tr>
<tr>
<td>Russell 1000</td>
<td>The Russell 1000 index measures the performance of the 1000 largest US companies based on total market capitalization. It represents approximately 90% of the investable US equity market. Source:www.russell.com</td>
</tr>
<tr>
<td>Russell 2000</td>
<td>The Russell 2000 index represents the small-cap segment of the U.S. equity universe. It measures the performance of the 2000 smallest companies in the Russell 3000 index, representing approximately 8% of the total market capitalisation of that index. The Russell 3000 index measures the performance of the 3000 largest US companies based on total market capitalization, which represents approximately 98% of the investable US equity market. Source:www.russell.com</td>
</tr>
<tr>
<td>MSCI Japan</td>
<td>MSCI Japan measures the performance of the Japanese equity market. It is a capitalization-weighted index that aims to captures 85% of the market capitalization.</td>
</tr>
<tr>
<td>MSCI Asia Pacific</td>
<td>The market capitalization weighted index measures the equity market.</td>
</tr>
</tbody>
</table>
exclude Japan performance of the developed and emerging markets in the Asia Pacific region excluding Japan. The index consists of the following developed and emerging market countries: Australia, China, Hong Kong, Indonesia, Korea, Malaysia, New Zealand, Philippines, Singapore, Taiwan, and Thailand.

| MSCI Emerging market Asia | The market capitalization weighted index measures the equity market performance of the emerging markets in the Asia Pacific region excluding Japan. The index consists of the following emerging market countries: China, India, Indonesia, Korea, Malaysia, Philippines, Taiwan and Thailand. |