Style Analysis and Value-at-Risk of Asia-Focused Hedge Funds

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ABSTRACT

In this paper we identify risk factors for Asia-focused hedge funds through a modified style analysis technique. Using an Asian hedge fund index, we find that Asian hedge funds show significant positive exposures to emerging equity marketsand also hold significant portion of portfolio in cash and high credit rating bonds while they take short positions in world government and emerging market bonds. A rolling window style analysis is further employed to analyse the time-varying risk exposure of Asian hedge funds. For both a static and rolling period style analysis, our model provides a high explanatory power for returns of the considered hedge fund index. We further conduct a Value-at-Risk analysis using the results of a rolling window style analysis as inputs. Our results indicate that the accuracy of VaR models is dominated by their ability to capture the tail distribution of the hedge fund returns. Moreover, the distributional assumption seems to be more important than the chosen volatility model for the performance of the models in VaR prediction. Our findings further suggest that the considered parametric models outperform a simple historical simulation that is purely based on past return observations.

Keywords: Hedge fund; 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 for capital allocation in Asia focused hedge funds. The expansion of the sector results in over 1,000 hedge funds 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 significant growth rates of the Asia-focused hedge fund industry over the past years has also drawn the attention of the research community.

A number of studies concerned with measuring the performance and risk of hedge funds have been conducted in the literature already. In many of these studies, the performance of hedge funds, as alternative investments, is compared to traditional funds or asset classes (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 studies cast doubt on the persistence of the superior performance of 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 the presence of various biases in hedge fund indices as pointed out by 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 many hedge funds 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. While the conventional return-based Sharpe's (1992) style analysis is commonly used in mutual fund analysis, Agarwal and Naik (2000) firstly conduct a generalised style analysis of various hedge fund strategies by allowing negative style weights and relaxing the constraint that the sum of the style weights has to be one. They examine the significance of style weights by employing a two-step procedure initially proposed by Lobosco and DiBartolomeo (1997). Similarly, Dor et al. (2003) modify Sharpe's return based style analysis 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. More recently, Teo (2009) suggests to augment 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 Agarwal and Naik (2000) and Dor et al. (2003) 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 to apply this technique to the Asian hedge fund industry. Our model also differs from Teo (2009) who follows an approach similar to an APT (arbitrage pricing theory) model. In contrast, our approach is based on Sharpe's (1992) return based style analysis, in which there is no intercept term and the sum of coefficients is equal to one. Further, instead of averaging individual hedge fund returns as in Teo (2009), we adopt the HFRI Emerging Markets: Asia ex-Japan Index to represent the universe of Asia-focused hedge funds. Another contribution to the literature of this paper is the focus on backtesting the proposed models in an extensive out-of-sample forecasting and risk analysis. We apply both parametric and non-parametric models and apply a variety of performance measures using VaR and density forecasts in combination with loss functions to examine the ability of the models to give an appropriate quantification of the risk for the considered hedge fund index.

Conventional style analysis usually includes the broad range of traditional asset classes across the world. Since our focus is on Asian hedge funds, we augment the considered style factors by including the MSCI emerging markets Asia index, the MSCI Pacific excluding Japan index (developed markets in pacific region exclude Japan) and the MSCI Japan index in the return based style analysis for better explaining returns 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). Reasons for this are that hedge fund managers trade dynamically and are not limited to investing in a specific class of assets 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 based style analysis, the literature suggests using actively traded index options as nonlinear factors for the mapping of hedge fund returns; see e.g. Fung and Hsieh(2001), Agarwal and Naik (2004) and Teo (2009). Other studies suggest augmenting the return of traditional asset classes with the returns of synthetic options on these traditional asset classes, see e.g. Loudon et al. (2006). In this paper, we augment the trend-following factors created by Fung and Hsieh (2001) in style analysis to capture the option-like payoff of hedge fund's dynamic trading. The trend-following factors are created by using combinations of exchanged-traded put and call options in stock, bond, short term interest rate, currency and commodity. In summary, the selected style factors in this paper include global asset indices to cover the broad range of asset classes that Asian hedge fund managers can invest and trend-following style factors to capture the option-like payoff resulting from hedge fund managers' dynamic trading activities.

Similar to Agarwal and Naik (2000) and Dor et al (2003), we relax the style analysis conditions by allowing negative weights of style factors since hedge fund managers often take short positions to exploit arbitrage opportunities or hedge the portfolio against market movements. Ideally, the factors used in the style analysis are independent; however, in practise, the chosen factors will fall short of ideal and sometimes will have high correlations with other factors. Therefore we need to eliminate the redundant factors which can be replicated by others and keep the remaining factors independent as much as possible. To address this issue, we further employ the two-step procedure proposed by Lobosco and Dibartolomeo (1997) to determine the statistical significance of factor weights. Finally, as shown by many researchers (e.g. Fung and Hsieh 2004; Bollen and Robert 2008), hedge fund managers change trading strategies over time; therefore we perform style analysis using rolling estimation to provide insights of time variation of hedge fund exposures.

Our findings suggest that Asian hedge funds show significant positive exposures to emerging equity markets, especially emerging markets in Asia, and also hold significant portion of portfolio in cash and high credit rating bonds while short sell world government bond and high yield emerging market bonds. Further, small but statistically significant exposures to trend-following factors show the option-like payoff pattern of Asian hedge funds. In general, the style analysis can explain up to 82% of the variance of hedge fund returns, indicating a high explanatory power of our model. Finally, the style analysis on rolling window sheds light on how hedge fund managers change risk exposures over time in response to changing market conditions and arbitrage opportunities .

Second, the ultimate goal for identifying the underlying risk exposures of the hedge fund is to evaluate the risk of the hedge 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 leads 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.

Many methods have been proposed to calculate VaR (see Duffie and Pan 1997, Hull and White 1998, Jorion 2000). In general, they can be categorised as non-parametric and parametric approaches. Historical simulation as a non-parametric method assumes that historical returns can provide an appropriate evaluation of the risk and therefore estimates the VaR based on the empirical distribution of past observations. On the other hand parametric methods usually apply a two-step approach: first, it is assumed that the portfolio variance is governed by certain specifications, such as a covariance matrix specification of the underlying assets, or a time-varying variance of the aggregate portfolio. It further makes distributional assumption about the portfolio returns and then calculates the VaR based on the estimated parametric dependence structure and return distributions. For example, portfolio variance can be modelled as a GARCH process or exponential weighted moving average (EWMA) specification. The distribution of portfolio returns is often assumed to be normal or from the Student's t distribution.

In this paper, we examine VaR for the considered hedge fund index using both parametric and non-parametric techniques. For the parametric approach, two methods are used to estimate the time-dependent portfolio variance: covariance matrix forecasts estimated from a wide variety of multivariate volatility models and aggregate portfolio variance forecasts. Loss functions are employed to evaluate the quality of the competing volatility models. Portfolio returns are assumed to be either from the normal or Student t distribution. For the non-parametric approach, VaR is calculated using historical simulation with a rolling window including 100 months of observations. To evaluate the different approaches with respect to their ability to appropriately quantify the risk, we employ different methods to determine the accuracy of the VaR forecasts. Next to examining the coverage and numbers of exceptions for the considered VaR models, we also investigate density forecasts and the magnitude of the occurred exceptions. Practitioners and researchers are interested not only in the frequency of the VaR exceptions, but also in the magnitude of the loss when the VaR is violated. Therefore, we employ a hypothesis test initially proposed by Berkowitz (1999) to examine whether the magnitudes of the observed violations are consistent with those implied by the proposed VaR models.

Our empirical results show that in general, the direct hedge fund index variance forecast (H-EWMA and H-GARCH models) outperform the forecast based on covariance matrix specification in term of hedge fund variance forecasting. However, under the VaR loss functions, the results show that VaR model based on the Student t distribution outperform those based on a normal distribution regardless of the chosen model for the volatility. These results suggest that the distributional assumption for the returns might be of greater importance than the model that is used for volatility dynamics. Because our out-of-sample data covers the Global Financial Crisis period when hedge funds also suffered from significant negative returns, it indicates that in this paper the performance of a VaR model is dominated by its ability to capture the tail distribution of hedge fund returns correctly. Moreover, we find that most of the considered VaR Models perform well with respect to the magnitude of VaR exceptions.

The remainder of the paper is structured as follows. Section two describes the hedge fund data used in this paper. Section three presents the style analysis technique used in this paper as well as the empirical results for the considered style factors. Section four presents the examined approaches for our risk analysis and evaluates the out-of-sample Value-at-Risk forecasts for the considered models. Finally, section five concludes.

2. Data

When performing analysis of hedge funds, data can be collected by either averaging individual hedge fund returns or using hedge fund indices directly. It is important to keep in mind that hedge fund indices can inherit biases existing in the hedge fund databases. Hedge fund data are susceptible to selection bias, survivorship bias and instant history bias as discussed by Fung and Hsieh (2004). Hedge fund managers voluntarily report the returns to the data vendors, so selection bias can arise if the hedge fund data collected in the database can not represent the whole universe of the hedge funds. Survivorship bias occurs if the database only contains information on operating funds. Defunct funds may stop reporting to the database because of bad performance, termination or other reasons like e.g. mergers. When a fund is included in a database, its past track record is appended to the database, which creates instant history bias. Funds often undergo an incubation period before reporting to the database. Funds with good performance then go on to list in various databases for seeking new investors, while unsuccessful funds will not enter the databases. Thus backfilling the past performance into the database may generate an upward bias. Recognizing these biases, some database vendors construct the indices with the care to mitigate the effects of these errors inherited from the databases. When working with hedge fund indices, it is essential to choose those indices that are less prone to these biases.

In this paper, we choose to work with an Asian hedge fund index rather than individual hedge fund returns. There are two major providers for Asian hedge fund indices: Eurekahedge and Hedge Fund Research (HFR). The Eurekahedge database mainly includes funds with investments in the Asia-Pacific region, while HFR is a large global hedge fund database. Eurekahedge provides the explicit information on the fund main investment region; in contrast, HFR classifies a fund as Asian hedge fund if the fund has more than 50% of its investments in the Asia ex-Japan region. Eurekahedge and HFR started to collect hedge fund return data from January 2000 and January 1990, respectively. There are some differences in constructing the indices between the two databases. For example, unlike Eurekahedge, HFR has a requirement that included funds have at least $50 Million under management or have been actively traded for at least twelve months. In the HFR index, the historical performance of a new constituent fund will not affect the finalized historical performance of the index. In contrast, Eurekahedge backfills the new constituent funds with past performance and rebalances the index value, which is prone to instant history bias. Considering that the HFR has a longer performance history and is less prone to instant history bias, we decide to use a HFR Asia index (HFRI Emerging Markets: Asia ex-Japan Index) as a proxy to investigate the style factors and risk of Asia-focused hedge funds. We consider monthly returns of the index for the period January 1990 to April 2010.

3. Style Analysis of Asia-Focused Hedge Funds

This section provides empirical results on the conducted style factor analysis on Asia-focused hedge funds. In a first step we identify appropriate style factors to use in the style analysis. In a second step we apply the style analysis framework proposed by Sharpe (1992) to identify the risk exposures of Asia-focused hedge fund managers. Furthermore, we employ the two-step procedure proposed by Lobosco and Dibartolomeo (1997) to determine the statistical significance of factor weights. Finally, we perform the style analysis using a rolling estimation framework in order to examine the time variation of the factor weights and hedge fund exposures.

3.1 Style factors of Asian Hedge Funds

It has been noted by many researchers that hedge fund returns are related to returns from traditional asset classes (e.g. Fung and Hsieh 2001, 2002, 2003; Agarwal and Naik 2000, 2004; Mitchell and Pulvino 2001; Dor et al. 2003). Fung and Hsieh (2002) find that fixed income hedge funds are typically exposed to interest rate spreads. 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. Further, Fung and Hsieh (2003) show that equity long/short hedge funds tend to take long positions in low capitalization stocks and short positions in large capitalization stocks, such that hedge fund returns are typically exposed to the spread between large cap and small cap stocks. In an extension of their prior work, Fung and Hsieh (2004) propose a model of hedge fund returns using seven identified asset based style (ABS) factors. For diversified hedge fund portfolios, the seven ABS factors can explain up to 80 percent of monthly return variations. The seven ABS factors include two equity ABS factors (equity market return and spread between small-cap stock returns and large-cap stock returns), two fixed income ABS factors (change in 10 year Treasury yields and change in the yield spread between 10 year T-bonds and Moody's Baa bonds) and three trend following ABS factors (lookback straddles on bonds, currencies and commodities).

Agarwal and Naik (2000) conduct a generalised style analysis of various hedge fund indices. To cover the broad range of the asset classes hedge fund managers may invest in, they use the S&P 500 composite index, the MSCI world index excluding US and MSCI emerging market index to proxy the global equity market exposures. They further choose the Salomon Brothers (SB) Government and Corporate Bond index, the SB World Government Bond index and the Lehman High Yield index to assess the bond market exposure. Finally, they include a number of commodity and currency indices to account for the hedge funds' exposure to these variables.

Similarly, Dor et al. (2003) perform a return-based style analysis to examine the effective style of hedge fund managers by using traditional asset classes and index options. They select the asset classes aiming to cover the equity and fixed income investment in the US and outside the US. For instance, they use 3-month Treasury bills as cash equivalent, intermediate and long term bonds and US corporate bonds to represent fixed income investment in the US, the Russell 1000 and 2000 index to represent equity investment in US as well as four global equity and fixed income indices to represent foreign investments. Applying principal component analysis, Teo (2009) shows that the Asia exclude Japan equity market index and Japan equity market index both are highly correlated with the returns of Asia equity hedge funds.

In addition to an exposure to traditional asset classes, many researchers argue that due to dynamic trading, hedge fund returns often exhibit non-linear option-like exposures to standard asset classes (Fung and Hsieh 1997, 2001; Agarwal and Naik 2004). Further, Agarwal and Naik (2004) illustrate that the payoffs of a large number of equity-oriented hedge funds actually resemble a short position of a put option on the market index. To capture this option-like feature of hedge fund returns, Fung and Hsieh (2001) create style factors by using combinations of exchanged traded put and call options in stocks, bonds, interest rates as well as currency and commodity markets. Similarly, 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 to capture the option-like features of hedge fund returns. Hereby, 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 and then sold at its expire day. This strategy is repeated for each month and hence the returns of this strategy are recorded. A similar procedure provides the returns on buying put options. The ATM option is the option whose strike price is closest to the current index value and the OTM call (put) option is the one with the next 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 for the option trading strategy in a similar way. Given 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 index factors to model the nonlinear exposures that fixed income hedge funds may face.

In this paper, we select global asset indices to cover the investment regions including Asia and the rest of the world and employ the five trend-following factors used in Fung and Hsieh (2001) to capture the option-like payoff of hedge fund dynamic trading strategies. The global asset indices included in our style analysis cover cash, equities and bonds markets. In particular, we use 3-month Treasury bills as cash equivalent. To proxy the exposure to Asia and global equities, we include the MSCI emerging markets Asia index, the MSCI Pacific excluding Japan index (developed markets in the pacific region excluding Japan), the MSCI Japan index, the S&P 500 index, the MSCI Europe index (developed markets in Europe) and the MSCI emerging markets excluding Asia index. To capture the exposures to bonds, we consider the Bank of America Merrill Lynch US High Bond index, the JP Morgan emerging markets bond Asia index, the CGBI broad investment grade (BIG) index and the CITI world government bond index. The five trend following factors are the returns of a private trend following strategy (PTFS) lookback straddles in bonds, currencies, short term interest rates, commodities and stocks. In total, we use eleven asset indices and five trend-following factors. Appendix A provides a more detailed description of the selected style factors.

3.2. Style Analysis

After having identified the style factors, we can conduct a return based style analysis for the hedge fund returns. Sharpe (1992) 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 fund. The style analysis framework for modelling the fund return is as follows:

$$r_t = \sum_{i=1}^{N} w_i F_{i,t} + e_t \tag{1}$$

where r_t is the fund return at time *t*, $F_{i,t}$ is the return of the i^{th} style factor at time *t*, $i = 1, \ldots, N$, w_i is the corresponding factor weight, and e_t represents the error term.

Style analysis has been initially proposed to analyse mutual funds. Because the weights of the replicated asset classes should add up to unity and mutual fund managers are not allowed to take short positions, Sharpe (1992) imposed two constraints on the coefficients w_i:

$$\sum_{i=1}^{N} w_i = 1, \ \forall i \tag{2a}$$

$$w_i \geq 0, \ \forall i \tag{2b}$$

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 in the various asset classes (Agarwal and Naik 2000; Dor et al 2003).

Based on Eq. (1), the excess return of the hedge fund over the sum of the weighted factor returns can be expressed as $e_t = r_t - \sum_{i=1}^{N} w_i F_{i,t}$. Sharpe (1992) suggests choosing the optimal weights for w_i through minimising the term e_t or rather the variance of e_t subject to constraint (2). This can be achieved for example by quadratic programming. To evaluate the effectiveness of the style analysis, we use the adjusted coefficient of determination (R^2 or adjusted R^2) given by $R^2 = 1 - \frac{var(e_p)}{var(r_p)}$ and $R_{adj}{}^2 = 1 - \frac{T-1}{T-N} \times \frac{var(e_p)}{var(r_p)}$, where *N* is the number of style factors, *T* the number of observations, $var(e_p)$ the variance of the residuals and $var(r_p)$ is variance of the hedge fund returns. Often, for hedge fund analysis these measures are interpreted as R^2 indicating the proportion of return variance attributable to investment styles while the unexplained part $(1 - R^2)$ is attributable to the fund manager's skill. In contrast to R^2, the adjusted R^2 has the advantage of imposing a penalty an increased number of style factors.

Ideally, the factors used in style analysis need to be independent; however, in practise, the chosen factors will fall short of the ideal and sometimes will have high correlations with other factors. To address this issue, we therefore employ a two-step procedure initially proposed by Lobosco and Dibartolomeo (1997) to determine the statistical significance of the factor weights. In a first step we conduct the analysis using all style factors and then calculate the standard deviation of the residuals (σ_e). Then we perform a style analysis for each style factor using the remaining style factors as explanatory variables calculating the standard deviation of the residuals (σ_i) for style factor i. The latter style analysis is estimated with the constraint that the sum of weights is one. The standard error for the weight of style factor i is given by $\frac{\sigma_e}{\sigma_i\sqrt{N-k-1}}$, where N is the number of observations and k is the number of style factors with non-zero weight. A low standard error indicates that the factor is difficult to be replicated by other style factors. The *t*-statistic for each factor is given by $\frac{w_i\sigma_i\sqrt{N-k-1}}{\sigma_e}$, where w_i is the weight for factor i . Based on the calculated *t*-statistics, using a 5% significance level non-significant factors are excluded from the model. This two-step procedure is repeated until the remaining factors are all statistically significant.

3.3 Empirical Results for the Style Analysis

As mentioned above we investigate monthly returns of the HFRI Emerging Markets: Asia ex-Japan Index obtained from the HFR database. The style factors including eleven asset indices and five trend-following factors are obtained from Datastream and David Hsieh's Hedge Fund Data Library. Both hedge fund and style factor returns are considered for the period January 1994 to December 2009 including a total of 192 observations. Table 1 reports the descriptive statistics for the hedge fund and style factors returns. The average monthly hedge fund index return is 0.62% while the standard deviation of monthly returns is 3.79%. The bond factors, in general, appear to have positive mean, negative skewness and high kurtosis. Among these, the Asia bond index has the highest return but also exhibits the highest negative skewness and kurtosis indicating that the lower tail of the distribution is longer than the upper tail, as well as a heavy-tailed distribution. Similar results are obtained for the equity factors apart from the Japanese equity index, that yields a negative mean, positive skewness and low kurtosis during the considered time period. The five trend-following factors appear to have the largest standard deviation among all the style factors. We further note that the Asian hedge fund, world government bond index and Japan equity index are normally distributed during the sample period.

Table 2 provides the results for the conducted style analysis: the first column shows the weights with standard errors for all style factors. The second column shows the results of the style analysis after dropping the insignificant factors using the recursive procedure described above. We find that Asian hedge funds show significant style weights on the three-month T-bill, the world government bond index, the US broad investment grade index, the Asian bond index, Japan equity, emerging market (Asia and the rest of emerging market) equity, and three trend-following indices on short term interest rates, currencies and stocks. In particular, Asian hedge funds show a significant positive exposure to emerging equity markets with 34.5% to the Asia market index and 10.3% to the MSCI emerging markets excluding Asia index and a small positive exposure to the Japanese equity index. Since the hedge fund index studied in this paper includes hedge funds investing in emerging markets with primary focus on Asia and typically less than 10% exposure to Japan, our finding is consistent with the classification of the fund index. The long position in emerging equity is also consistent with the typical short selling restrictions in emerging equity markets. The Asian hedge funds also show positive style weight on three-month T-bill and US corporate bond index, but negative style weights on world government bond and emerging market bond Asia indices. The net exposure to the bond market is approximately 45%. This suggests that Asian hedge funds hold significant portions of portfolio in cash and high credit rating bonds while they short sell world government bonds and high yield emerging market bonds. Further, small but statistically significant exposures to trend-following factors show the option-like payoff pattern of Asian hedge funds. The style analysis can explain up to 82% of the variance of hedge fund returns, the remaining unexplained variance being attributed to managers' trading skill. Moreover, the explanatory power of the regression model remains almost unchanged after eliminating the insignificant style factors.

Unlike mutual funds that follow a defined investment strategy and therefore are not allowed to change their investment styles, hedge funds are generally free to change trading strategies and asset allocation to different asset classes. Assuming the style weights are constant, the above style analysis shows an average risk exposure of Asian hedge funds over the sample period from January 1994 to December 2009. To investigate the hedge funds' dynamic risk exposure over time, we perform the style analysis using a rolling window of 72 months. Figure 1 shows the style changes for the HFRI Emerging Market-Asia exclude Japan index over time. We find that Asian hedge funds experience significant shifts in risk exposure over time. Furthermore, the major style factors are the three-month T-bill, emerging market Asia bond index, emerging market equity and Japan equity. Figure 2 shows the adjusted R^2 when factors weights change over time. The adjusted R^2 is 80% on average, indicating a high explanatory power of the rolling-period style analysis. In the next section, the results of the rolling period style analysis will be used as inputs for an extensive risk analysis of the considered hedge fund index.

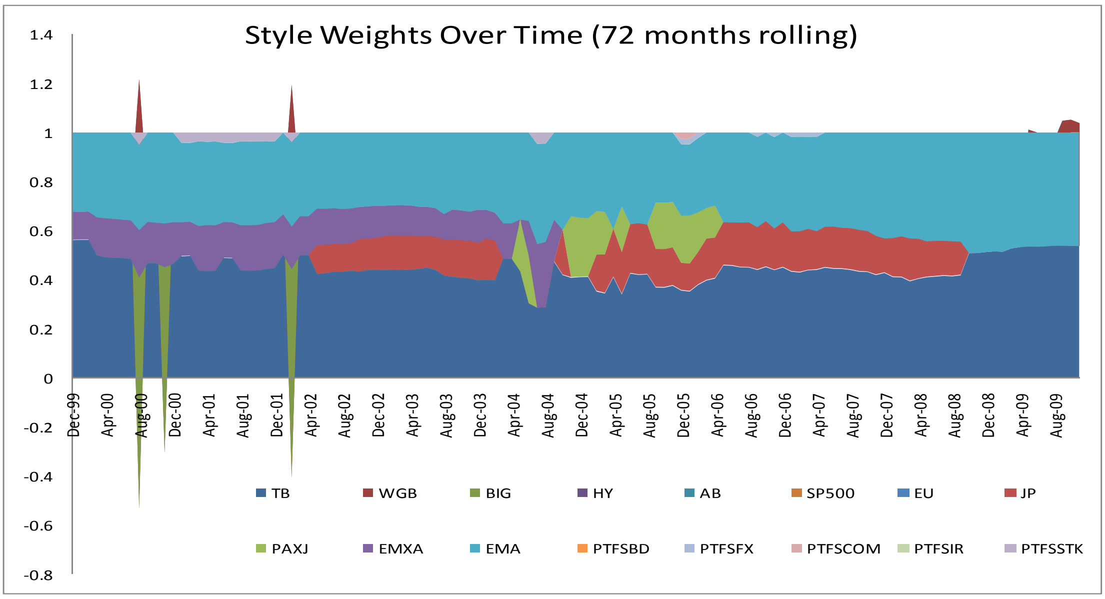

Fig.1. The dynamic exposure to the considered style factors of the HFRI emerging markets Asia excluding Japan index based on a rolling window approach with length of 72 months

Table 1 Descriptive statistics of hedge fund and style factor returns

The table shows the mean, median, standard deviations, minimum and maximum returns, skewness, kurtosis and results for a normality test for the hedge fund index and selected style factors during the period January 1994 to December 2009. The hedge fund index is the HFRI emerging markets Asia excluding Japan (HF). The style factors are three-month T-bill (TB), CITI world government bond index (WGB), CGBI broad investment grade index (BIG), Bank of America Merrill Lynch US High Bond index (HY), JP Morgan emerging markets bond Asia index (AB), S&P 500 index (SP500), MSCI Europe index (EU), MSCI Japan index (JP), MSCI Pacific excluding Japan index (PAXJ), MSCI emerging markets excluding Asia index (EMXA), MSCI emerging markets Asia index (EMA), bond PTFS (PTFSBD), currency PTFS (PTFSFX), commodities PTFS (PTFSCOM), short term interest rate PTFS (PTFSIR) and stock PTFS (PTFSSTK). The normality test is the Jarque-Bera Test which has a χ^2 distribution with 2 degree of freedom under the null hypothesis of normal distribution. The 5% critical value is 5.99. The asterisk indicates statistical significance at 5%

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	Mean	Median	Max	Min	Standard Deviation	Skewness	Kurtosis	Normality Test
HF	0.62	0.72	12.37	-11.02	3.79	-0.07	3.43	1.68
TB	0.29	0.36	0.51	0.00	0.15	-0.50	1.78	19.89*
WGB	0.42	0.49	3.38	-1.91	0.89	-0.05	3.36	1.13
BIG	0.51	0.61	4.44	-3.44	1.14	-0.17	4.17	11.95*
HY	0.54	0.85	7.15	-15.42	2.54	-1.63	11.94	724.69*
AB	0.72	0.85	9.10	-17.64	2.80	-2.42	17.42	1,851.24*
SP500	0.45	1.14	9.23	-18.56	4.54	-0.95	4.70	51.84*
EU	0.44	1.08	12.36	-23.98	5.09	-1.09	6.05	112.59*
JP	-0.12	-0.31	15.43	-16.00	5.63	0.07	2.89	0.24
PAXJ	0.22	0.85	17.43	-28.90	6.45	-0.88	5.82	88.78*
EMXA	0.60	1.96	17.55	-40.82	8.06	-1.46	7.87	257.50*
EMA	-0.02	0.05	19.44	-27.65	7.83	-0.47	3.69	10.71*
PTFSBD	-1.38	-4.82	68.86	-25.36	14.73	1.46	6.00	140.13*
PTFSFX	0.19	-4.31	90.27	-30.13	19.82	1.37	5.63	114.86*
PTFSCOM	-0.30	-2.90	64.75	-23.04	13.92	1.26	5.54	102.62*
PTFSIR	3.12	-3.14	221.92	-30.60	28.89	4.09	25.57	4,609.18*
PTFSSTK	-4.73	-6.32	46.15	-30.19	12.84	0.98	4.88	59.08*

Table 2 Style analysis of Asian hedge fund index

This table shows the results for style analysis of the Asian hedge fund index from January 1994 to December 2009. The first column shows the weights with standard errors for all style factors. Standard errors for style weight are in parentheses. The weights significant at 5% level are expressed in bold font. The second column shows the results of the style analysis after dropping the insignificant factors through repeated procedure. All data are in percentage. The adjusted coefficient of determination R^2 is reported as well.

	HF	HF
TB	**78.3**	**74.2**
	(15.4)	(14.7)
WGB	**-64.2**	**-64.1**
	(28.6)	(28.3)
BIG	**50.1**	**51.3**
	(22.9)	(22.3)
HY	1.0	
	(6.4)	
AB	**-17.6**	**-16.6**
	(6.4)	(6.1)
SP500	-2.5	
	(5.1)	
EU	-6.0	
	(4.8)	
JP	**7.8**	**7.4**
	(2.7)	(2.6)
PAXJ	6.6	
	(4.4)	
EMXA	**10.4**	**10.3**
	(2.8)	(2.3)
EMA	**33.0**	**34.5**
	(3.0)	(2.3)
PTFSBD	-1.0	
	(0.9)	
PTFSFX	**1.3**	**1.5**
	(0.7)	(0.6)
PTFSCOM	1.3	
	(0.9)	
PTFSIR	**-1.1**	**-1.0**
	(0.5)	(0.5)
PTFSSTK	**2.5**	**2.5**
	(1.0)	(1.0)
Adjusted R^2	82.64	82.49

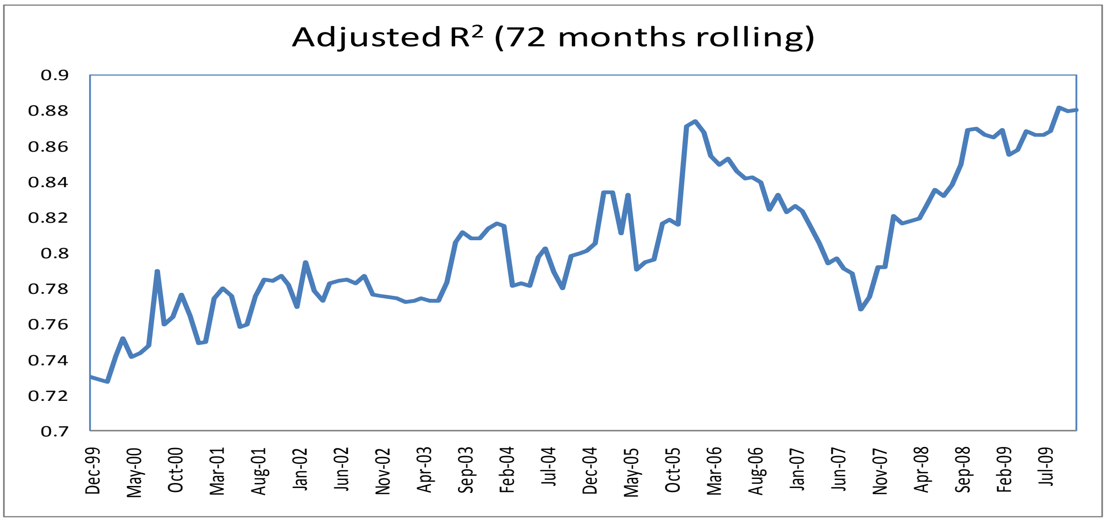

Fig. 2. Adjusted R^2 of the rolling window style analysis.

4. Value-at-Risk Analysis

In the previous section we have identified risk factors for the considered Asian hedge fund index and examined the dynamic nature of the risk exposure to the identified factors. In this section we conduct a thorough Value-at-Risk analysis for the considered hedge fund index using various benchmark models and back-testing techniques. In particular the performance of different approaches to modelling the volatility of the index and the style factor returns are considered.

4.1 Modelling the conditional volatility

In order to evaluate the performance of the style factor analysis with respect to risk quantification, an adequate approach for modelling the conditional variance of the index and factor returns is required. Therefore, we start our analysis with a description of the considered models for volatility in the empirical analysis. Let y_t and $r_{i,t}$ denote the return of the hedge fund index and style factor i at time t. Investigating the autoregressive nature of returns, we find that, generally, the considered time series do not indicate significant ARMA dynamics. An exception is the return series of the three-month T-bill, which yields significant first-order autocorrelation. Further, we conduct augmented Dickey-Fuller unit root tests for the three-month T-bill to test the stationarity of the data series, and find that it has a unit root such that the series is non-stationary. Therefore, we express the returns of the three-month T-bill as

$$r_{b,t} = r_{b,t-1} + \varepsilon_{b,t} = r_{b,t-1} + \eta_t \sqrt{h_{b,t}} \tag{3}$$

Since our focus is on volatility forecasting, we model the hedge fund index and the style factors using the following model:

$$y_t = u_t + \epsilon_t = u_t + \eta_t \sqrt{h_t} \tag{4}$$

$$r_{i,t} = \mu_{i,t} + \varepsilon_{i,t} = \mu_{i,t} + \eta_t \sqrt{h_{i,t}} \tag{5}$$

where u_t and $\mu_{i,t}$ are the conditional mean for the hedge fund index and factor *i* at time *t*. Further, h_t and $h_{i,t}$ are conditional variance for hedge fund index and factor *i* at time *t*, and η_t is an *iid* process with zero mean and unit variance. Using a rolling window analysis, therefore, the conditional mean for the three-month T-bill is its past return at time $t-1$, while the conditional mean for the hedge fund index and the other style factors is equal to the mean return over the past 72 months. Let further $w_t = [w_{1,t}, w_{2,t}, \dots, w_{n,t}]$ denote the style weights vector at time *t* estimated from the rolling window style analysis, such that the forecasted hedge fund conditional variance at time $t+1$ in covariance matrix specification is given by

$$h_{t+1} = w_t \times H_{t+1} \times w_t' + h_{e,t} \tag{6}$$

where H_t is a *n*x*n* matrix with *n* being the number of significant non-zero style factors. Taking $n = 2$, for example, $H_{t+1} = \begin{bmatrix} h_{11,t+1} & h_{12,t+1} \\ h_{21,t+1} & h_{22,t+1} \end{bmatrix}$, while $h_{e,t}$ is the conditional variance of the corresponding residuals of the rolling window style analysis, which is assumed to be normally distributed with variance $\sigma_{e,t}^2$.

To generate appropriate covariance matrix forecasts, we then apply equally weighted moving average, exponentially weight moving average (EWMA) and GARCH-BEKK models.

The equally weighted moving average (MA) model puts equal weights on the past priod observations, taking the form:

$$H_{t+1} = \sum_{k=0}^{72} \varepsilon_{t-k}\, \varepsilon_{t-k}' \tag{7}$$

where $\varepsilon_t = [\varepsilon_{1,t}, \varepsilon_{2,t}, \dots, \varepsilon_{n,t}]$ is the vector containing the style factor's innovations at time *t*. In contrast, the exponentially weight moving average (EWMA) model is based on exponentially decreasing weights, i.e., more weight is given to more recent observations:

$$H_{t+1} = \sum_{k=0}^{72} (1-\lambda)\lambda^k \varepsilon_{t-k}\, \varepsilon_{t-k}' \tag{8}$$

where λ is the decay factor that is set equal to 0.97 following the weight suggested by RiskMetrics (JP Morgan 1996).

The third method used in this paper for forecasting the covariance matrix is a multivariate GARCH model. 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 VECH, 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 some of the difficulties of the VECH model by ensuring that the conditional variance-covariance matrix is always positive definite. The model has the form

$$H_{t+1} = CC' + \sum_{j=1}^{p} \sum_{k=1}^{K} A_{kj}' H_{t+1-j} A_{kj} + \sum_{j=1}^{q} \sum_{k=1}^{K} B_{kj}' \varepsilon_{t+1-j} \varepsilon_{t+1-j}' B_{kj} \quad (9)$$

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 conducted to ensure the positive definiteness of the conditional variance-covariance matrix (H_{t+1}). For example, for $q = p = K = 1$ the BEKK model becomes

$$H_{t+1} = CC' + A' H_t A + B' \varepsilon_t \varepsilon_t' B \quad (10)$$

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

$$H_{t+1} = \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{bmatrix} + \begin{bmatrix} a_{11} & 0 \\ 0 & a_{22} \end{bmatrix}' H_t \begin{bmatrix} a_{11} & 0 \\ 0 & a_{22} \end{bmatrix} + \begin{bmatrix} b_{11} & 0 \\ 0 & b_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon_{1,t}^2 & \varepsilon_{1,t}\varepsilon_{2,t} \\ \varepsilon_{2,t}\varepsilon_{1,t} & \varepsilon_{2,t}^2 \end{bmatrix} \begin{bmatrix} b_{11} & 0 \\ 0 & b_{22} \end{bmatrix} \quad (11)$$

In our analysis, we employ a GARCH(1,1)-BEKK model in order to generate forecasts of the covariance matrix through time. Then the conditional variance of the hedge fund index at time t can be forecasted using the covariance matrix forecast of the underlying style factors in combination with the estimated weights.

An alternative approach would be to estimate the conditional variance of the hedge fund index directly from its historical return observations. This approach reduces the computational effort provided that the historical observations are sufficient for estimation. In this paper, we employ EWMA and GARCH(1,1) models to forecast the hedge fund conditional variance, taking the following forms:

$$h_{t+1} = \sum_{k=0}^{72}(1-\lambda)\lambda^k \epsilon_{t-k}\, \epsilon_{t-k}{}' \tag{12}$$

$$h_{t+1} = \alpha_0 + \alpha_1 \epsilon_t^2 + \beta h_t \tag{13}$$

where ϵ_t denotes the innovation of the hedge fund index at time t and λ is equal to 0.97.

In summary, we use two approaches to estimate the hedge fund conditional variance: a covariance matrix forecast based on the style factors and a forecast being only based on histrorical returns of the hedge fund. As mentioned above for the covariance matrix specification based on the style factors we employ three different methods: equally weighted moving average (henceforth F-MA); exponentially weighted moving average (henceforth F-EWMA) and GARCH-BEKK (henceforth F-BEKK) models. To derive forecasts based on historical returns only, we apply two approaches: the EWMA approach (henceforth H-EWMA) and a GARCH(1,1) model (henceforth H-GARCH).

4.2 Statistical loss functions for volatility models

To evaluate the out-of-sample performance of the considered forecast models, we adopt a variety of statistical loss functions that have different interpretations and therefore provide a more complete evaluation of the competing models; see e.g. Bollerslev and Ghysels (1996) for more details on the choice of appropriate loss functions. The loss functions considered in our empirical analysis are:

$$MSE_1 = \frac{1}{T}\sum_{i=1}^{T}\left(\sigma_{t+1} - h_{t+1}^{1/2}\right)^2 \tag{14}$$

$$MSE_2 = \frac{1}{T}\sum_{i=1}^{T}(\sigma_{t+1}^2 - h_{t+1})^2 \tag{15}$$

$$MAE_1 = \frac{1}{T}\sum_{i=1}^{T}\left|\sigma_{t+1} - h_{t+1}^{1/2}\right| \tag{16}$$

$$MAE_2 = \frac{1}{T}\sum_{i=1}^{T}|\sigma_{t+1}^2 - h_{t+1}| \tag{17}$$

$$GMLE = \frac{1}{T}\sum_{i=1}^{T}\left(\ln(h_{t+1}) + \frac{\sigma_{t+1}^2}{h_{t+1}}\right) \tag{18}$$

$$LL = \frac{1}{T}\sum_{i=1}^{T}(\ln(\sigma_{t+1}^2) - \ln(h_{t+1}))^2 \tag{19}$$

$$HMSE = \frac{1}{T}\sum_{i=1}^{T}\left(\frac{\sigma_{t+1}^2}{h_{t+1}} - 1\right)^2 \tag{20}$$

Where σ_{t+1}^2 is the realised hedge fund variance at time $t+1$ given by $(y_{t+1} - \bar{y})^2$, y_{t+1} the hedge fund return at time $t+1$ and $\bar{y}$ is the mean hedge fund return during the out-of-sample period. Note that the mean-squared error (MSE) in (14) and (15) and mean absolute error (MAE) in (16) and (17) penalise the errors symmetrically, while logarithmic loss function (LL) in (19) and the heteroscedasticity -adjusted MSE in (20) have the particular features of penalising forecast errors asymmetrically. Further, GMLE in (18) corresponds to the loss implied by a Gaussian quasi-maximum likelihood function. Theoretically, the volatility model that yields the minimum value for a particular loss function is considered to be the best model. However, as pointed out by Bollerslev et al. (1994), the criteria being used to select the best model are not always straightforward when several loss functions are being considered. Once the volatility model that generates the lowest value under a given loss function is said to be the best model, the Diebold-Mariano test (1995) can be applied to test for significant differences between the models. This is a pairwise test of equal predictive ability (henceforth EPA) of two competing models, to find out whether the competing model has the same predictive power as the best model. Under the null hypothesis of equal forecasting accuracy of two competing models, the

Diebold-Mariano statistic given by $\frac{\bar{d}}{\sqrt{\hat{V}(\bar{d})}}$ is asymptotically normally distributed. Hereby, $\bar{d}$ denotes the sample mean of the loss difference between the two competing models and $\hat{V}(\bar{d})$ is an estimate of the asymptotic variance of $\bar{d}$.

4.3 Empirical results for the considered volatility models and loss functions

Table 3 reports the out-of-sample evaluation of the competing volatility models, according to the statistical loss functions introduced in Section 4.2. The evaluation of the one month ahead volatility forecasts is based on 120 out-of-sample observations and a rolling window of 72 months. As indicated in Table 3, the H-EWMA model performs best with respect to the MSE, MAE and LL loss functions, while the H-GARCH model performs best with respect to the GLME and HMSE loss functions. The F-EWMA is the second best model for the MSE, MAE and LL loss functions, while the H-EWMA and F-BEKK model are the second best for the GMLE and HMSE loss functions, respectively. Although the H-EWMA is not consistently the best model for all of the considered loss functions, we decided to choose it as the benchmark model for the conducted Diebold-Mariano test since it provided the best results for five out of the seven considered loss functions. Table 4 reports the results for the Diebold-Mariano tests where the H-EWMA is tested against the other competing models under the null hypothesis of equally predictive ability. We find that the H-EWMA and H-GARCH models provide the same level of forecast accuracy except for the MAE criterion where the H-EWMA is significantly better. In general, the hedge fund index variance forecasts being based on past returns (H-EWMA and H-GARCH models) seem to outperform the forecasts based on the covariance matrix specification. This is probably due to the difficulties in modeling the conditional variance of the regression residuals, which is attributable to the hedge fund managers' skills. However, also the F-EWMA model that used the style factors to forecast the conditional variance of the hedge fund index returns provides appropriate results and comes second for most of the considered loss functions. To apply this technique might of particular interest for risk managers when newly created funds with a short history of return observations are being considered. In such cases the estimation of conditional variance EWMA or GARCH models may not be feasible due to lack of data.

Table 3 Out-of-sample evaluation of volatility models

Evaluation of one month ahead volatility forecasts based on 120 out-of-sample observations and a rolling window of 72 months. The minimum value for each loss function is in bold font and underlined, and the second smallest value is just in bold font.

Model	MSE_1	MSE_2	LL	GMLE	MAE_1	MAE_2	HMSE
F-MA	10.0106	753.5978	9.0383	6.2431	3.4162	23.8276	4.9643
F-EWMA	**9.4507**	**728.2086**	**8.6407**	6.2236	**3.3130**	**23.0510**	5.0119
F-BEKK	11.8436	931.5314	9.3659	6.2715	3.6962	27.1971	**4.1585**
H-EWMA	**<u>9.1445</u>**	**<u>713.4914</u>**	**<u>8.4755</u>**	**6.1584**	**<u>3.2408</u>**	**<u>22.5607</u>**	4.4970
H-GARCH	10.9369	794.8419	9.1468	**<u>6.1323</u>**	3.5280	25.7920	**<u>2.9251</u>**

Table 4 Diebold-Mariano test (benchmark model: H-EWMA)

This table shows the statistics and corresponding p-values (in parentheses) for the conducted Diebold-Mariano test. Other competing models are tested against H-EMWA model under the null hypothesis of equal predictive ability. * and ** represent the rejection of the null hypothesis at 5% and 1% respectively.

Model	MSE_1	MSE_2	LL	GMLE	MAE_1	MAE_2	HMSE
F-MA	-2.06*	-2.19*	-1.49	-1.99*	-1.85	-1.82	-0.63
	(0.040)	(0.028)	(0.136)	(0.047)	(0.065)	(0.069)	(0.529)
F-EWMA	-2.10*	-2.00*	-2.67**	-1.51	-2.32*	-2.24*	-1.80
	(0.035)	(0.045)	(0.008)	(0.130)	(0.020)	(0.025)	(0.071)
F-BEKK	-1.97*	-1.39	-1.92	-2.95**	-2.43*	-2.08*	1.27
	(0.049)	(0.166)	(0.054)	(0.003)	(0.015)	(0.038)	(0.205)
H-GARCH	-1.86	-0.96	0.30	-1.89	-2.00*	-2.10*	1.37
	(0.063)	(0.338)	(0.768)	(0.059)	(0.046)	(0.036)	(0.171)

4.4 Value-at-Risk framework and loss functions

The derived forecasts for the volatility of the considered hedge fund index can also be used as an input for a Value-at-Risk (VaR) analysis. The one-month ahead hedge fund index VaR at the α% confidence level of model *i* can then be denoted by:

$$VaR^{i}(\alpha) = u_{t+1}^{i} + \Phi(\alpha)\sqrt{h_{t+1}^{i}} \tag{21}$$

where u_{t+1} and h_{t+1} are the forecasted conditional mean and variance estimated at time t with model i; $\Phi(\,)$ is a cumulative distribution function, which is often assumed to be the Gaussian or Student t distribution. Using the style factor covariance matrix specification, u_{t+1} is given by $w_t \times \mu_t{}'$, where $w_t = [w_{1,t}, w_{2,t}, \dots, w_{n,t}]$ and $\mu_t = [\mu_{1,t}, \mu_{2,t}, \dots, \mu_{n,t}]$ are the vectors containing the weights and the conditional means of the significant style factors at time *t*. On the other hand, when only considering historical hedge fund index returns, u_{t+1} is simply equal to u_t, the conditional mean of the hedge fund index at time *t*. In this paper, using the techniques described in the previous sections, we use a normal and Student t distribution in order to estimate the hedge fund VaR at the 1% and 5% confidence level.

Generally, the normal distribution is the most commonly used distribution in VaR estimation. However, empirical distributions of hedge fund returns are usually fat-tailed, i.e., great losses have a higher likelihood than suggested by the Gaussian distribution. Therefore, we also employ a Student t distribution for the VaR estimation of the considered index. The t-distribution has the form

$$f(\epsilon_t) = \frac{\Gamma\left(\frac{v+1}{2}\right)}{\sqrt{\pi}\Gamma\left(\frac{v}{2}\right)}[h_t(v-2)]^{-0.5}[1 + \frac{\epsilon_t^2}{h_t(v-2)}]^{-\frac{v+1}{2}} \tag{22}$$

where $v > 2$ is the degree of freedom that affects the tail thickness of the distribution, and $\Gamma(\,)$ denotes the Gamma function. Using the residuals of the considered volatility models during the in-sample period, we estimate the degree of freedom parameter as $v = 6$. In the following we compare the VaR results for the considered models in combination with the assumption of a Gaussian or Student t distribution for the hedge fund index returns.

When investigating the appropriateness of different VaR models, another common approach is to estimate VaR based on historical simulation. In this case the VaR is calculated from the empirical distribution of historical returns only, not assuming any parametric model for the returns or volatility. Historical simulation is a particularly popular approach in the industry such that we decided to compare our results for VaR quantification based on the considered parametric models also to a non-parametric approach. Hereby, we use a rolling window of the past 100 return observations in order to construct the non-parametric empirical distribution of hedge fund returns and subsequently estimate the VaR.

To evaluate the different VaR models in their ability to forecast extreme losses at a specified confidence level, we thus employ the historical simulation approach, parametric models for the index returns as well as models based on the estimated style factors in order to determine the accuracy of the VaR forecasts. This is done by using a three-step procedure initially proposed by Christoffersen (1998).

The first step is to evaluate the VaR estimation based on the unconditional coverage. Here the null hypothesis is that the unconditional coverage $\hat{\alpha} = x/T$ is equal to p, with x being the number of VaR exceptions at a given confidence level p and T the total number of VaR forecasts in the out-of-sample period. Then the test statistics is given by $LR_{uc} = -2\ln\left[\frac{p^x(1-p)^{T-x}}{\alpha^x(1-\alpha)^{T-x}}\right]$, follows a $\chi^2(1)$ distribution. The second step is to test for independence of VaR exceptions in order to examine whether exceptions are spread evenly through the period used for back-testing. The statistics for the test of independence LR_{ind} also follows a $\chi^2(1)$ distribution. Note that when hedge fund returns exhibit heteroskedasticity, evaluation of VaR models based on the test for unconditional coverage only may not be sufficient, because a VaR model providing an appropriate unconditional coverage may still yield an incorrect conditional coverage. Thus, the third step is to test the conditional coverage by using the statistics $LR_{cc} = LR_{ind} + LR_{uc}$ that follows a $\chi^2(2)$ distribution. As pointed out by Christoffersen (1998), a model that passes both the unconditional and conditional coverage test can be considered as adequate for VaR estimation.

4.5 Empirical results for Value-at-Risk quantification

Table 4 presents the unconditional coverage (UC), i.e., the percentage of exceptions, the LR statistics for unconditional coverage test (LR_{uc}), the independence test (LR_{ind}) and the conditional coverage test (LR_{cc}) for both 95% and 99% VaR one month ahead forecasts. If the fraction of empirically observed exceptions is greater than the theoretical number of exceptions at the 1% and 5% significance level, it indicates that the model is inadequate. From the table, the results show that VaR models based on t-distribution assumption clearly outperform those based on a normal distribution assumption. Recall that for volatility forecasting, the H-EWMA and H-GARCH models performed best for most of the considered loss functions. However, for the conducted VaR analysis we find that with respect to unconditional coverage during the out-of-sample period in particular the H-GARCH and F-BEKK models combined with the assumption of a t-distribution for the returns yield the best results. For these models, the number of exceptions is usually equal or even lower than the corresponding probability level while all three LR tests fail to reject the null hypothesis of adequate model specification. In contrast to these parametric methods, the non-parametric historical simulation approach performs rather poorly. In Section 4.3, the empirical results indicated that the H-GARCH and F-BEKK models rank among the two best models with respect to volatility forecasting for the HMSE loss function. This function assigns higher weight to an incorrect low variance forecast when the actual realised variance is high. Hence, the volatility model that closely captures the tail features of the distribution should perform best for HMSE loss criterion. Moreover, we find that the Student t distribution is significantly more suitable than the normal distribution to capture the fat-tailed distribution of hedge fund returns. Taking into account that our out-of-sample data covers the Global Financial Crisis period during the years 2008 and 2009 when also hedge funds suffered significant losses, the empirical results indicate that the performance of VaR models is particularly dominated by its ability to capture the tail of the return distribution.

Table 4 VaR out-of-sample evaluation: 95% and 99% VaR

Unconditional coverage (UC), i.e., the percentage of exceptions as well as the LR statistics for unconditional coverage test (LR_{uc}), independence test (LR_{ind}) and conditional coverage test (LR_{cc}) for both 95% and 99% VaR estimates. * indicates rejection of the null hypothesis at the 5% significance level. The minimum value of the unconditional coverage is highlighted in bold letters.

	95% VaR				99% VaR			
Model	UC	LR_{uc}	LR_{ind}	LR_{cc}	UC	LR_{uc}	LR_{ind}	LR_{cc}
H-EWMA-n	7.50	1.38	0.16	1.54	4.17	6.79*	1.82	8.62*
H-EWMA-t	**5.00**	0.00	1.18	1.18	1.67	0.45	0.07	0.52
H-GARCH-n	7.50	1.38	0.16	1.54	**0.83**	0.04	0.02	0.05
H-GARCH-t	**5.00**	0.00	1.18	1.18	**0.83**	0.04	0.02	0.05
F-MA-n	8.33	2.36	0.04	2.39	5.00	9.91*	1.18	11.09*
F-MA-t	5.83	0.17	0.71	0.88	**0.83**	0.04	0.02	0.05
F-EWMA-n	9.17	3.56	0.00	3.56	5.00	9.91*	1.18	11.09*
F-EWMA-t	**5.00**	0.00	1.18	1.18	1.67	0.45	0.07	0.52
F-BEKK-n	9.17	3.56	0.00	3.56	3.33	4.10*	2.71	6.81*
F-BEKK-t	**5.00**	0.00	1.18	1.18	**0.83**	0.04	0.02	0.05
Historical Simulation	6.67	0.64	0.38	1.02	3.33	4.10*	2.71	6.81*

for the considered out of sample period January 2000 to December 2009. The graph also compares the computed 95% VaR for the H-GARCH-t model (green dotted line) and F-BEKK-t model (red dotted line).

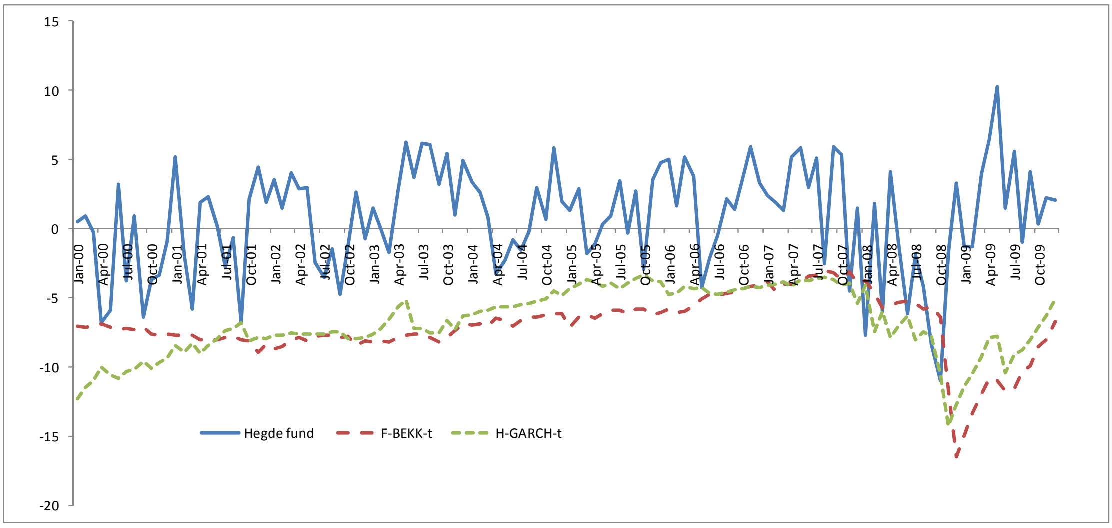

Fig.3. Returns of HFRI Emerging Market-Asia exclude Japan index and 95% VaR forecasts for the considered out of sample period January 2000 to December 2009. The graph compares the computed 95% VaR for the H-GARCH-t model (green dotted line) and F-BEKK-t model (red dotted line).

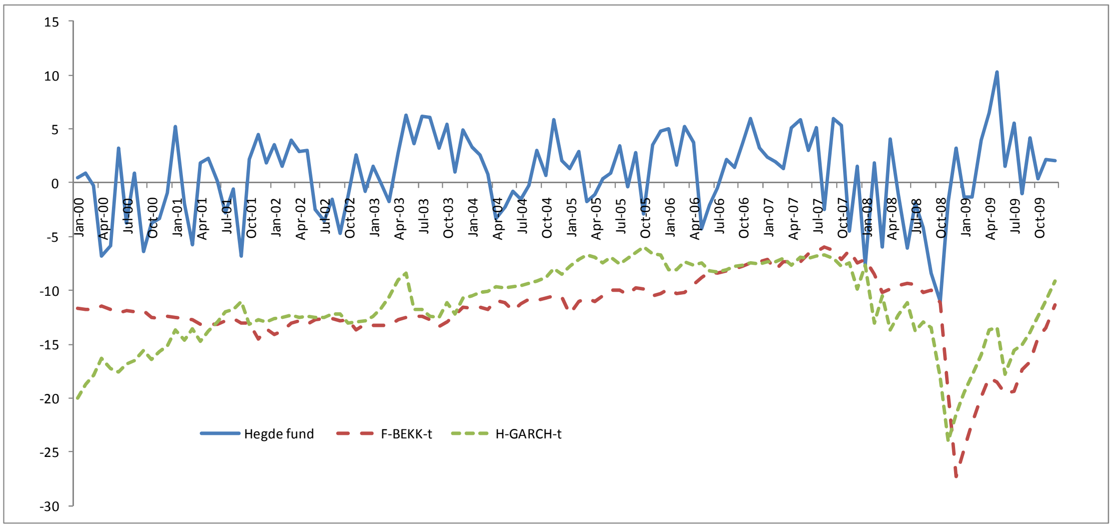

Fig.4. Returns of HFRI Emerging Market-Asia exclude Japan index and 99% VaR forecasts for the considered out of sample period January 2000 to December 2009. The graph compares the computed 99% VaR for the H-GARCH-t model (green dotted line) and F-BEKK-t model (red dotted line).

In Figure 3 and 4 we also provide a plot of the actual hedge fund returns and the 95% and 99% VaR estimates based on the considered H-GARCH-t and F-BEKK-t models. Both models react quite significantly to the change in market condition during the Global Financial Crisis. However, the H-GARCH-t model seems to respond even quicker to the changes than the F-BEKK-t model

4.6 Magnitude of VaR exceptions

Generally, in the academic literature and practice, most evaluations of VaR estimates are based on the frequency of the VaR exceptions. However, also the magnitude of VaR exceptions is of particular interest to risk managers and financial institutions. This is even of higher importance when risk management practices focus also on expected shortfall instead of VaR only. In this section, we employ a hypothesis test proposed by Berkowitz (2001) focussing on the expected loss in comparison to the actually observed loss when the VaR is exceeded.

A difficulty in evaluating the performance of VaR models is the small number of observed violations. For example, a 99% VaR should provide only approximately one violation in every 100 observations if it is correctly specified. Therefore, as stressed by Kupiec (1995), a large sample size is required to verify the accuracy of a VaR model. An alternative to focusing on the low frequency of VaR exceptions only, is to apply the Rosenblatt (1952) transform to the predicted return distribution

$$\hat{F}(y_t) = \int_{-\infty}^{y_t} \hat{f}(x)dx \qquad (22)$$

where y_t is the realised return at time *t* and $\hat{f}(x)$ is the loss density function generated by the model used for forecasting. Rosenblatt shows that if the distribution is correctly specified this will transform the o bserved returns into a series of *iid* random variables. Thus, the accuracy of the VaR model can be tested under the null hypothesis that the probability integral transforms $\hat{F}$ are *iid* and distributed uniformly on [0,1]. As suggested by Crnkovic and Drachman (1996), the Kuiper statistic based on the distance between the empirical and the theoretical cumulative distribution function of the uniform distribution can be used in order to test for uniformity. However, a small sample size is not suitable for this test since a large number of points is required to calculate the distance. Therefore, instead of testing the uniformity, Berkowitz (2001) transforms $\hat{F}$ into standard normal series and tests the accuracy of VaR models by constructing likelihood-ratio (LR) tests. Focusing on the magnitude of the VaR exceptions, Berkowitz proposes a LR test based on the censored likelihood, such that the shape of realised lower tail is compared with the forecasted lower tail so as to determine whether the observed VaR exceptions are in line with the underlying VaR model. Moreover, Berkowitz points out that the proposed likelihood-ratio test is well suited for sample sizes as small as 100. Let $z_t = \Phi^{-1}\left(\hat{\mathrm{F}}(\mathrm{y_t})\right)$ denote the inverse of the standard normal distribution function of $\hat{\mathrm{F}}(\mathrm{y_t})$, $VaR = \Phi^{-1}(\alpha)$ denote the cut-off point, i.e., VaR=-1.96 for 5% lower tail of standard normal distribution and z_t^* denote the further transformation of z_t given by

$$z_t^* = \begin{cases} VaR \ if \ z_t \geq VaR \\ z_t \quad if \ z_t < VaR \end{cases}.$$

Then the log-likelihood function can be expressed as

$$L = \sum_{z_t^*=VaR} Log\left(1 - \Phi\left(\frac{\mathrm{VaR}-\mu}{\sigma}\right)\right) + \sum_{z_t^*<VaR}\left(-\frac{1}{2}log(2\pi\sigma^2) - \frac{(z_t^*-\mu)^2}{2\sigma}\right) \tag{23}$$

where μ and σ denote the mean and standard deviation of the transformed standard normal series z_t. Under the null hypothesis that $\mu = 0$ and $\sigma = 1$, the likelihood-ratio test statistic is given by $LR = 2\big(L(\mu,\sigma) - L(0,1)\big)$, which is approximately $\chi^2(2)$ distributed.

The test statistics for the LR test are reported in Table 5. Interestingly, for none of the models the null hypothesis that $\mu = 0$ and $\sigma = 1$ can be rejected, indicating that the mean and the variance of the observed violations is consistent with those implied by the considered VaR models. That is, all the models appear to perform well regarding to the magnitude of VaR exceptions.

Table 5 Magnitude of VaR exceptions

LR statistics for magnitude of VaR exception test for both 95% and 99% VaR. * indicates the rejection of the null hypothesis at 5% significance level.

Model	95% VaR	99% VaR
H-EWMA-n	-1.18	0.68
H-EWMA-t	1.11	0.13
H-GARCH-n	-1.04	-0.20
H-GARCH-t	2.69	0.76
F-MA-n	0.52	2.15
F-MA-t	1.97	0.48
F-EWMA-n	-0.74	1.36
F-EWMA-t	0.95	0.10
F-BEKK-n	-0.11	0.50
F-BEKK-t	2.19	0.77
Historical Simulation	-0.22	-0.38

5. Conclusion

In this paper, we identify style factors for Asia-focused hedge funds represented by the HFRI Emerging Market-Asia exclude Japan index. Hereby, we make use of the style analysis framework initially suggested by Agarwal and Naik (2000) and Dor et al. (2003). Furthermore, we employ the two-step procedure proposed by Lobosco and Dibartolomeo (1997) to test for the significance of the considered style factors. A rolling window style analysis is performed to provide further insights into the dynamic structure of style factor weights and risk exposures. This is one of the first empirical studies applying these techniques with particular focus on the Asian hedge fund industry.

The empirical results show that the most significant equity factors relating to the

HFRI Emerging Market-Asia exclude Japan index are emerging equity markets, especially emerging markets in Asia. The two factors together account for a weight of approximately 45% on average. The risk exposures are consistent with the investment objective of the hedge fund strategy. With respect to the fund's exposure to bond markets, we find that Asia-focused hedge funds indicate positive exposures to cash and high credit rating bonds but negative exposures to world government and emerging market bonds. In general, these fixed income factors account for a weight of 45%. The rolling window style analysis captures the hedge fund managers' style drift in responding to dynamic trading and changing market situations. For both static and rolling period style analysis, our model provides a high explanatory power for returns of the hedge fund index.

We further conduct an extensive Value-at-Risk analysis using the results of the rolling window style analysis as inputs and compare them to alternative approaches including historical simulation, EWMA models and parametric approaches that use only the returns of the considered index to forecast volatility. We evaluate the different forecasting models based on comparing the observed and predicted volatility using a set of loss functions. Based on these loss functions, we further evaluate the performance of the considered approaches with respect to different assumptions for the return distribution. Finally, the magnitude of the observed VaR exceptions is compared to those implied by the estimated VaR models. Our results indicate that the accuracy of VaR models is dominated by its ability to capture the tail distribution of the hedge fund returns. Moreover, the distributional assumption seems to be more important than the chosen volatility model for the performance of the model in VaR prediction. Our findings further suggest that the parametric models outperform a simple historical simulation approach that is purely based on past return observations. Finally, all of the considered VaR models perform reasonably well in forecasting the magnitude of the loss conditional on a VaR exception.

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Appendix A: Description of considered style factors for the style analysis of Asian-focused hedge funds

Factors	Description
3-month Treasury Bill	Monthly yield on U.S. Treasury securities at 3-month constant maturity.
Bank of America Merrill Lynch US High Bond	Index for US high yield bonds (below investment grade).
CGBI Broad Investment Grade	Index for US investment grade bonds. The index includes treasuries, agency debt, corporate, non-corporate credit, mortgage-backed securities, and asset-backed securities.
CITI World Government Bond	A market capitalization weighted bond index consisting of the government bond markets of the multiple countries.
S&P 500	The S&P 500 is a free-float capitalization-weighted index of the prices of 500 large-cap common stocks actively traded in the United States
MSCI Europe	The market capitalization weighted index measures the equity market performance of the 16 developed markets in Europe.
MSCI Japan	MSCI Japan measures the performance of the Japanese equity market.
MSCI emerging markets excluding Asia	The market capitalization weighted index measures the equity market performance of the emerging markets excluding Asia. There are 13 emerging market countries included in this index.
MSCI emerging markets Asia	The market capitalization weighted index measures the equity market performance of the emerging markets in Asia. The index consists of the following emerging market countries: China, India, Indonesia, Korea, Malaysia, Philippines, Taiwan, and Thailand.
MSCI Pacific excluding Japan	The market capitalization weighted index measures the equity market performance of the developed markets in the Asia Pacific region excluding Japan. The index consists of the following developed market countries: Australia, Hong Kong, New Zealand and Singapore.
Trend-Following Risk Factors	The returns of private trend following strategy (PTFS) lookback straddles in bond, currency, short term interest rate, commodity and stock.