Original Article

On the efficiency of risk measures for funds of hedge funds

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Falk Laube
is currently completing his PhD degree at the University of Luxembourg. He is a full-time research associate at the University of Luxembourg. His research fields comprise risk modelling, extreme risks and alternative investments.

Jang Schiltz
is associate professor in stochastic analysis and statistics at the Luxembourg School of Finance. His principal research interests comprise stochastic analysis, more precisely Mallivin Calculus, non-linear filtering and financial mathematics, as well as data analysis.

Virginie Terraza
is associate professor in finance at the University of Luxembourg, co-director of CREFI-LSF (2006–2008), the center of research in finance of the Luxembourg School of Finance. Her principal research interests focus on the analysis of the financial risks, portfolio management and econometric models. She participates in many research projects on the subject of fund performance in collaboration with the fund industry. She was consultant for Fortis Bank Luxembourg, specializing in the study of volatility of funds of funds.

Correspondence: Falk Laube, University of Luxembourg, Luxembourg School of Finance (LSF), 4 Rue Albert Borschette L-1246, Luxembourg
E-mail: falk.laube@uni.lu

ABSTRACT **The hedge fund industry has experienced some very troublesome periods in the recent past. In this study, we test the efficiency of simple and advanced risk measures during these difficult market periods according to the Basel II requirements. We concentrate on Fund of Hedge Fund (FoHF) data, as some studies propose that they suffer least from database and measurement biases, and are therefore likely to yield the most representative results compared to other alternative investment data. We examine model stability and risk measure efficiency using unconditional and conditional GMM-based and likelihood ratio tests, as well as independence tests. We find that model stability is very dependent on the successful specification of autoregressive and volatility models. In addition, custom quantile estimation is less susceptible to misspecification than volatility models. Further, we assess the hypothesis of market efficiency for the special case of FoHF. Finally, we find evidence of different level of managerial skill in terms of asset choice, allocation and market timing.**

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INTRODUCTION

The hedge fund industry has grown tremendously during the past 15 years. By the end of 2008, more than 10 700 hedge funds were listed in the HFR database. Hedge funds are private investment partnerships, in which both the investor and the manager make substantial personal investments. Hedge funds invest in long and short positions, leverage and derivatives, as well as illiquid markets such as real estate and concentrated portfolios. One of the fundamental goals for hedge funds is to reduce risk exposure to market cycles as far as possible.

Hedge funds[1] may not advertise in public and only a maximum of 500 sophisticated investors or offshore corporations are allowed to invest in them. Typically hedge fund investment involves a lock-up period for capital, as well as minimum investment thresholds that may range from several US$10 000 to several $million.

Hedge fund manager compensation is usually performance linked. The majority of hedge funds have a high-watermark provision that requires the manager to make up for previous losses before an incentive fee is paid. In addition, investors may sometimes ask for a rebate of previously charged management fees. These conditions provide a more powerful incentive scheme than those for mutual fund managers.

In this study, we investigate the efficiency and accuracy of risk measures in the context of FoHF. So far, current literature has focused on investigating the nature of the FoHF industry and FoHF portfolio-creation methods. In his overview of the FoHF industry, Ineichen[2] stipulates that FoHF have additional specific advantages compared to normal HF. Managers are 'both managers and advisors', corroborating the later argument by Fung and Hsieh[3] of FoHF being preferred by conservative investors. Amenc *et al*[4] conduct a survey, which indicates that the great majority of FoHF managers apply only simple, traditional risk indicators. As a consequence, FoHF risk properties appear to be largely opaque, even to their managers. According to Olszewski,[5] FoHF specifically add value through diversification of alternative assets that correlate only weakly with traditional markets, thus minimizing exposure to systemic risk. He further finds that FoHF portfolios comprising anti-persistent and quasi-random return processes display a persistent return profile and, at the same time, exhibit great persistence against extreme events. Denvir *et al*[6] show that different HF strategies are often significantly correlated and that the construction of efficient FoHF portfolios requires skill, experience and efficient risk monitoring. All authors use traditional dispersion measures or the classic VaR/CVaR measures for the assessment of FoHF volatilities, risk exposures or optimal FoHF portfolios.

Hence, our goal in this study is to assess the different parametric methods of risk quantification in the context of FoHF for their general efficiency under the Basel II conditions. In this article, we choose to implement parametric methods for VaR estimation in order to reduce the risk of data bias-induced errors of risk estimation. Each measure is applied to each fund of the sample with the goal of assessing the empirical mathematical robustness of the approach. Specifically, we investigate whether advanced coherent risk measures can improve the practise of risk management. For that, we analyse efficiency and robustness and evaluate the power of prediction of fund returns.

FUNDS OF HEDGE FUNDS DATA ANALYSIS

We extracted 10 years of price series data for the period of 31 December 1998 – 31 December 2008. During this period, financial markets have been subjected to several serious market corrections, which makes studying the efficiency of risk assessment tools a particularly interesting and current topic. Data were obtained from the Hedge Fund Research (HFR) commercial database, which is one of the most complete databases presently available. Under the conditions of monthly reporting and fund assets at inception amounting to at least US$ 5 Million, we extracted 2416 FoHF (of which 1805 were alive on 31 December 2008) return time series out a total of 10 761 hedge funds in the database. In this selection, we include defunct and alive funds in order to minimize the effect of survivorship bias. We then filter this pool by only including FoHF that have existed for consecutive 36 months or more, defining our final pool of 1465 FoHF (of which 1001 were alive on 31 December 2008).

All analysis has been carried out on log returns of the original price series:

$$r_t = \ln(X_t) - \ln(X_{t-1}) \qquad (1)$$

Return series have a monthly periodicity and are based on 12 months per year, while assuming identical lengths for each month. The rolling window size for all statistics is kept at 12 months length, as for dynamic assets market forces have changed significantly after a maximum of 24 months. For further discussions, see Blum[7] and others. Table 1 reports the general statistical properties of our FoHF sample.

Investigation of our sample properties reveals that average sample skewness is negative and spread narrowly and symmetrically about its mean, which indicates significant non-normality but also less fat tails than pure hedge funds.

Table 1: Synthesis of statistical data properties of the FoHF sample

	Mean	*Median*	*SD*	*Max.*	*Min.*
Size (US$)	232.88M	67.78M	565M	9.727M	0.016M
Age (months)	63.06	59.00	0.32	116.00	36.00
RETURN Statistics					
Mean	0.0050	0.0047	0.0029	0.0330	−0.0060
SD	0.0189	0.0169	0.0099	0.1123	0.0022
Skewness	−0.7641	−0.7398	0.9185	5.9910	−5.6793
Kurtosis	5.3025	4.0064	3.8517	42.7303	1.9022
JB-test (p-value)	0.586%	0.100%	1.109%	4.999%	0.000%
Max.	0.0454	0.0374	0.0324	0.5613	0.0109
Min.	−0.0548	−0.0484	0.0331	0.0030	−0.3388

Further, over 95 per cent of positive and negative extreme monthly returns are below the 10 per cent hurdle and cluster around the 5 per cent mark. This indicates more effective market de-correlation and less general sensitivity to market extreme events. Moreover, we find that the great majority of FoHF significantly reject the null of return normality, although few elements pass the Jarque–Bera test at the 5 per cent confidence level.

In unreported work, we find that most funds display statistically significant tail activity and some funds even exhibit clustering in the extremes of the left tail.

Next, we test our sample for the average levels of autocorrelation, moving average effects, volatility clustering and long-term persistence/anti-persistence. Table 2 reports the test results. We find persistent autocorrelation effects in returns similar to the case of general HF, using the Ljung-Box (1978)[8] Test. ARCH Tests indicate the existence of strong volatility clustering. Long-term persistence is determined by the Hurst (1951)[9] exponent. Empirically, we can state that FoHF are more likely to exhibit an anti-persistent (mean reverting) return process. Persistent FoHF are only weakly persistent. These results indicate that FoHF tend to be better diversified than HF, whose Hurst exponent may sometimes exceed 0.65, see Olszewski.[10]

NON-COHERENT AND COHERENT RISK MODELS

In this section, we will briefly outline our testing set of coherent and non-coherent risk measures. A coherent risk measure is a risk measure that fulfils coherency axioms as first proposed by Arditti[11] and then more recently improved by Arztner,[12] Föllmer and Schied,[13] Frittelli and Rosazza Gianin,[14] Acerbi *et al*,[15] Acerbi,[16] Cheridito and Stadje,[17] and Christofferson.[18] The coherency axioms of monotonicity, subadditivity, convexity, positive homogeneity, translation invariance and relevance ensure good behaviour, consistency and boundedness of the risk measure in the context of risk assessment and portfolio optimization.

The VaR

The VaR has rapidly become the standard quantitative benchmark for measuring the risk exposures of financial portfolios and has become

Table 2: Synthesis of tests for statistical time series effects

TEST statistics	*Mean (p-value)*	*Mean Q-statistics*	$X^2 0.10,15$
LB-Test (AR 1)	58,59%	14,41	22,31
LB-Test (MA 1)	64,55%	12,57	22,31
ARCH(1)-Test (*p-val*)	82,92%	9,85	22,31
	Mean	*Median*	*SD*
Hurst exponent	0.4511	0.4885	0.2458
	$0<H<0.5$	$0.5<H<1.0$	—
Hurst-sample	52.29%	47.71%	—

a standard concept in risk management, see Pichler and Selitsch[19] and Jorion.[20] Simply put, the VaR of a portfolio is the fraction of portfolio value being risked with some fixed probability. In other words, the VaR figure is a quantile loss function of the portfolio return distribution.

We first evaluate all FoHF using standard variance techniques for the simplest VaR measure, based on the assumption of return normality and homoscedasticity. This risk measure will then serve us as a benchmark for the remaining risk models. Formally, for our chosen Basel II 1 per cent coverage threshold, the classical Normal-VaR model is then written as:

$$VaR = \mu - \Phi_\alpha(x, \sigma^2) \cdot \sigma = \mu - 2.32 \cdot \sigma \quad (2)$$

Where μ is the mean, α is the VaR threshold (1 per cent) and $\Phi_\alpha(\cdot)$ is the Normal distribution. Many authors have shown that the hypothesis of normal return distributions is not valid for financial assets. We confirm this again for our sample of FoHF in the previous section. High tail activity and return dependencies induce fat tails and skewness, which cannot be modelled successfully under the normal distribution. Thus, the normal quantile systematically underestimates risk especially for VaR thresholds far into the tails. For this reason, we include the Cornish-Fisher (1937)-VaR, which takes into account higher moments by adjusting the Gaussian distribution quartile ratio according to excess kurtosis and skewness parameters using a point estimate derived through a fourth level Taylor Expansion. Although the quantile estimate now considers all first four moments, the underlying return distribution hypothesis remains Gaussian. Formally, we have:

$$VaR_{CF}(\alpha) = \mu - \Omega(\alpha) \cdot \sigma$$

with

$$\begin{aligned}\Omega(\alpha) = z(\alpha) &+ \frac{1}{6}(z(\alpha)^2 - 1)S \\ &+ \frac{1}{24}(z(\alpha)^3 - 3z(\alpha))K \\ &- \frac{1}{36}(2z(\alpha)^3 - 5z(\alpha))S^2 \quad (3)\end{aligned}$$

where $\Omega(\alpha)$ is the Cornish-Fisher Value, $z = \Phi^{-1}(\alpha, 0, 1)$ is the inverse of the standard Normal distribution and all remaining parameters remain as before. At present, these traditional measures are still the most widely used risk measures in financial institutions, and also form the basis for Basel II Agreements. Unfortunately, they are neither coherent, nor consistent with portfolio theory nor do they capture the dynamics of large losses. As we have seen in Section two 'Funds of hedge funds data analysis', our FoHF sample is heavily influenced by time series effects. This observation invalidates the assumption of constant means and variances. Different types of dynamics need to be modelled for both parameters.

Conditional VaR

As we can see from Table 2 in Section two 'Funds of hedge funds data analysis', all FoHF display significant degrees of autocorrelation in returns and heteroscedastic variance. More precisely, the latter displays significant levels of ARCH effects, persistence and asymmetry in the variance. This invalidates the hypotheses of independent, identically distributed (IID) returns and stationarity upon which the traditional VaR models have been based so far.

The family of GARCH-based VaR models address these problems by directly modelling the conditional mean and conditional variance processes of a return-generating process. The first

Autoregressive Conditional Heteroscedasticity (ARCH) model was developed by Engle (1982),[21] which was followed by the introduction of the generalized ARCH model (GARCH) by Bollerslev (1986)[22]. Presently, literature yields a vast refinement of this base model. In a survey of more than 400 variance models, Hansen and Lunde[23] and Theodossiou and Bali[24] find that the GARCH (1, 1) lag-1 coupled with ARMA (1, 1) models represent by far the best approximation of variance processes. For this reason, and because of restrictions in data availability, we limit ourselves to the use of first lag models only.

We extend the initial ARMA(1, 1) equation first by the symmetric GARCH(1, 1) model and then the EGARCH(1, 1) and GJR-GARCH(1, 1). EGARCH (Nelson, 1991)[25] allows for quantifying asymmetries in clusters over time, whereas GJR-GARCH (Glosten, Jagannathan and Runkle, 1993)[26] allows for quantifying the difference in impact on volatility for positive and negative returns.

ARMA:

$$r_t = c + a \cdot r_{t-1} + b \cdot \varepsilon_{t-1} + \varepsilon_t \tag{4}$$

GARCH:

$$\sigma_t^2 = \gamma + \alpha \cdot \varepsilon_{t-1}^2 + \beta \cdot \sigma_{t-1}^2 \tag{5}$$

EGARCH:

$$\begin{aligned} \sigma_t^2 &= \gamma + \alpha \cdot g(\varepsilon_{t-1}) + \beta \cdot \ln(\sigma_{t-1}^2) \\ g(\varepsilon_{t-1}) &= \theta\varepsilon_{t-1} + \omega[|\varepsilon_{t-1}| - E|\varepsilon_{t-1}|] \end{aligned} \tag{6}$$

GJR-GARCH:

$$\begin{aligned} &\sigma_t^2 = \gamma + \alpha \cdot \varepsilon_{t-1}^2 + \beta \cdot \sigma_{t-1}^2 + \phi \cdot I_{t-1}(\varepsilon_{t-1}^2) \\ &I_{t-1} = 1 \text{ for } \varepsilon_{t-1}^2 < 0, \text{ and } I_{t-1} = 0 \text{ otherwise.} \end{aligned} \tag{7}$$

With $\varepsilon_t \sim N(0, \sigma_t)$. Parameters α and β are regression coefficients, which satisfy $0 \leqslant \alpha + \beta \leqslant 1$, and σ_t and ε_t are the conditional variance and conditional mean terms, respectively. For a successfully defined model conditional variance residuals v should mimic a white noise process. We test this property using the Ljung-Box Q-Statistic Test. Implementing the conditional models into VaR, the new empirical model now becomes:

$$VaR_t = \mu - \sigma_t \cdot F_\alpha(\cdot) \tag{8}$$

where $F_\alpha(\cdot)$ is a distribution quantile. The next step in our study will be to assess the validity of the quantile estimation framework.

The quantile estimation framework

Now we expand our set of VaR measures further, based on both conditional variance models and custom-fitted quantiles. As we have shown above, the assumption of Gaussian-distributed returns is invalid for almost all FoHF as a consequence of high tail activity and variance clustering. We therefore choose to replace the normal distribution by the now popular Skewed-Generalized-T (SGT)[24–28] probability density function (PDF). It is well known that the SGT PDF is one of the most powerful analytic PDFs currently available in literature because of its high degree of flexibility: it nests eight well-known distributions. We choose this particular distribution function because of its high degree of scalability: next to skewness and kurtosis, the SGT has a fifth parameter controlling tail thickness. This feature makes it particularly useful for our purpose as we can model the geometry of the loss quantiles more precisely. Formally, the SGT is defined as follows:

$$\begin{aligned} &SGT(X|\mu, \sigma, n, k, \lambda) \\ &= \frac{C}{\sigma}\left(1 + \frac{|X - \mu + \delta\sigma|^k}{\left((n-2)/k\ (1 + sign(X - \mu + \delta\sigma)\lambda)\right)^k \theta^k \sigma^k}\right)^{-\frac{n+1}{k}} \end{aligned} \tag{9}$$

with

$$C = \frac{k}{2((n-2)/k)^{1/k} \cdot \theta \cdot B(1/k,\ n/k)}$$

$$\theta = \left(\frac{k}{n-2}\right)^{1/k} \cdot B(1/k, n/k)^{1/2} \cdot B(3/k, (n-2)/k)^{-1/2} \cdot S(\lambda)^{-1}$$

$$S(\lambda) = \sqrt{1 + 3\lambda^2 - 4A^2\lambda^2}$$

$$A = B(2/k,\ (n-1)/k) \cdot B(1/k,\ n/k)^{-1/2} \cdot B(3/k,\ (n-2)/k)^{-1/2}$$

$$\delta = 2\lambda A S(\lambda)^{-1}$$

where, μ is the fitted mean, σ the fitted standard deviation, n is the tail parameter, k the height parameter, λ the skewness parameter and $B(\cdot)$ the Beta Function, with $n>2$, $k>0$ and $-1<\lambda<1$. All other parameters are as before.

The SGT contains several nested probability density functions as special cases of the parameter configuration. Table 3 on the next page summarizes all nested distributions. For our experiment, we fit the SGT to our data set using Maximum Likelihood Estimation (MLE). From the resulting parameters, the $\alpha = 1$ per cent coverage quartile is determined as required by Basel II. The combination of custom quantiles and conditional variances will then be used to determine advanced VaR estimates. To test for the impact of difference between the traditional Gaussian quartile estimate approach and the customized-quantile model, we test both conditional-Gaussian and conditional-SGT-based VaR models.

The family of coherent VaR measures

We use different types of Coherent VaR (CVaR) measures, sometimes also referred to as Conditional VaR or Average VaR (AVaR). According to Rachev *et al*,[33] the *n-level* average of VaR violations is computed through the following integral:

$$CVaR_{\alpha}^{(n)} := \frac{1}{\alpha}\int_{0}^{\alpha} CVaR_{p}^{(n-1)}(X)dp \qquad (10)$$

Table 3: Synthesis of all probability density function nested in the SGT

Parameter configuration	*Description*	*Original Author(s)*
λ=0	Generalized T-distribution	McDonald and Newey (1988)[29]
K=2	Skewed-T distribution	Hansen (1994)[30]
$n=\infty$	Skewed generalized error distribution	Theodossiou (2004)[31]
$n=\infty$, λ=0	Generalized error distribution	Subbotin (1923)[32]
$n=\infty$, λ=0, k=1	Laplace distribution (double exponential)	Laplace
n=2, λ=0, k=0	Cauchy distribution	Cauchy
$n=\infty$, λ=0, k=2	Normal distribution	Gauss
$n=\infty$, λ=0, $k=\infty$	Uniform distribution	— none —

where α is the coverage threshold and VaR_p are the historical VaR values excessive to VaR_t and n is the order of CVaR. In our study, we also examine higher order CVaR that is the 'CVaR of CVaRs'. For the discrete case, for level 1 CVaR we have:

$$CVaR_{\alpha} := \frac{1}{\alpha}\sum(VaR_{t,\alpha} < \alpha) \qquad (11)$$

Literature also offers a large variety of variations of the CVaR measure. For our work, only the set of spectral risk measures was feasible because of stability issues during models estimation.

Spectral risk measures belong to the family of coherent risk measures and were first defined by Acerbi[15] and Artzner *et al.*[34] More precisely, the spectral risk measure is a special case of CVaR, where VaR measures are time-weighted using a *risk spectrum*, a non-constant averaging functional, instead of using the simple, constant arithmetic average. Formally, spectral risk measures are defined as:

$$\rho_{\phi}(X) = \int_0^1 VaR_p(X)\phi(p)dp \qquad (12)$$

Where $\phi(p)$ is the risk spectrum or the weighting functional. Acerbi[16] finds that models' risk spectra need to be calibrated individually to obtain the best risk performance. Acerbi,[16] Artzner *et al*[34] and Rachev *et al*[33] formally define and later refine the properties of risk spectra, namely positivity, a strictly non-increasing domain and full normalization of the weighing function.

We use only one single risk spectrum function, namely the widely known Exponentially Weighted Moving Average (EWMA), because it attributes more importance to recent tail events than a linear weighting model. According to Acerbi,[16] the choice of risk spectrum is purely subjective and there exist no intuitive reasons why one should be preferred to the other. The EWMA weighting function is algorithmically defined as follows:

$$\phi(p) = (1/\Sigma w_i) \cdot \bar{w}$$

with

$$\bar{w} = \sum_{i=1}^{l}(1-\theta)^{i-1};\ \theta = 2/(l+1) \qquad (13)$$

where $\phi(p)$ is the normalized risk spectrum, $\bar{w}$ the vector of non-normalized weights and θ the exponential decaying factor of the weighting function and l the length of the VaR vector to be weighted.

Performance of risk models

We perform several types of backtests in order to assess and quantify the accuracy and quality of the different risk assessment models, using methods by Kupiec,[35] Christofferson[36] and Candelon.[37] We construct VaR violation sequences and subsequently test for achievement of threshold $\alpha = 1$ per cent and conditional correlations in the sequences.

EMPIRICAL RESULTS

Model estimations

Here, we provide a brief overview of the VaR estimations, providing an impression of the empirical qualities and weaknesses of the different VaR estimation techniques. Table 4 below reports empirical model statistics for all 1465 FoHF.

Table 4: General overview of the results for different VaR estimates

	Mean	*SD*	*Max.*	*Min.(%)*	*Violations*	*LR(%)*	*(p)(%)*
Non-coherent risk measures							
VaR	−0.0178	0.0110	0.1107	0.0010	3.49	0.7843	74.96
CF-VaR	−0.0198	0.0166	0.2016	0.1640	4.30	8.8727	49.07
GARCH-normal-VaR	−0.0216	0.0191	0.2504	0.2278	2.24	8.2982	44.20
EGARCH-normal-VaR	−0.0215	0.0186	0.2449	0.1777	2.93	8.5748	40.71
GJR-GARCH-normal-VaR	−0.0215	0.0188	0.2408	0.1935	2.30	8.4281	41.18
GARCH-SGT-VaR	−0.0232	0.0168	0.1665	0.0098	2.79	10.3929	38.26
EGARCH-SGT-VaR	−0.0232	0.0168	0.1676	0.0100	3.49	10.5401	37.57
GJR-GARCH-SGT-VaR	−0.0230	0.0169	0.1796	0.0101	2.88	10.4615	37.98
Coherent risk measures							
CVaR (normal)	−0.0217	0.0147	0.1722	0.0010	2.66	8.1329	42.66
GARCH-normal-CVaR	−0.0314	0.0213	0.1723	0.0020	1.84	5.4239	33.86
EGARCH-normal-CVaR	−0.0335	0.0226	0.1771	0.0021	1.91	5.4463	31.92
GJR-GARCH-normal-CVaR	−0.0317	0.0216	0.1921	0.0021	1.84	5.4299	32.95
GARCH-SGT-CVaR	−0.0363	0.0247	0.1757	0.0007	1.53	4.1757	33.77
EGARCH-SGT-CVaR	−0.0395	0.0268	0.2866	0.0007	1.56	4.1841	31.98
GJR-GARCH-SGT-CVaR	−0.0370	0.0251	0.1993	0.0007	1.53	4.1857	33.04
GARCH-SGT-CVaR (ρ)	−0.0300	0.0205	0.1736	0.0026	1.83	5.4354	33.45
EGARCH-SGT-CVaR (ρ)	−0.0323	0.0217	0.1772	0.0026	1.90	5.4373	31.75
GJR-GARCH-SGT-CVaR (ρ)	−0.0305	0.0208	0.1942	0.0026	1.83	5.4592	32.79

From these results, we can state that non-coherent risk measures generally seem to be outperformed by coherent risk measures. Globally, all coherent risk measures have preferable VaR violation scores when compared to their non-coherent counterparts. Further, the general mean level of modelled risk is 50 per cent higher for coherent risk measures than for non-coherent ones. Classic VaR, with the highest violation score and the lowest average level of risk displays highest violation scores and very significant serial correlation of VaR events. As we proceed down the table from more sophisticated VaR measures towards coherent VaR measures, average score and serial correlation of VaR violation incidents declines.

Specifically, the introduction of conditional variance models contributes most to the significant improvement on model performance. Adding custom quantiles further improves that performance. From our results, it seems that successful volatility modelling is the most crucial factor for model performance, followed by coherency structure (∼25 per cent of model improvement) and finally by custom non-Gaussian quartiles (∼10–15 per cent of improvement).

The preferred volatility model by our sample data is the symmetric GARCH(1, 1) model as these risk measures display the most favourable LR values and the lowest number of violation events on average. It is directly followed by the GJR(1, 1) model, which performs only slightly worse. However, the EGARCH(1, 1) model performs significantly less well, indicating that temporal asymmetries of the volatility structure seems to be less important when constructing risk assessments than asymmetries caused by return signs.

Efficiency of VaR measures

Efficiency cannot only be traced back to the coherency axioms as postulated by Christoffersen.[36,18] We measure the efficiency of risk models by assessing numerical robustness of the estimation process. In addition, we look at the statistical quality of our results in order to ascertain the coherency of our risk measures with the theoretical framework provided by Artzner.[12]

Non-coherent risk measures

Comparisons among the non-coherent risk measures show that modelling volatility structure and fitting custom quartiles, which can take into account asymmetric tail thickness and skewness, are superior to simpler risk measures (see Table 5).

Clearly, advanced non-coherent risk measures have favourable violation sequences closer to the required threshold of $\alpha = 1$ per cent and also show lower levels of conditional correlation and inferior cost of violation during actual violation events.

However, we can also read that the specification of the asymmetry structure in the conditional volatility processes makes a significant difference: FoHF in our sample seem to display more asymmetry in returns

Table 5: Extract of comparisons of all non-coherent risk measures

Non-coherent risk measures	*VaR(classic)*	*CF-VaR*	*VaR-GARCH-normal*	*VaR-EGARCH-normal*	*VaR-GJR-normal*
Violation Test	3.6468	3.5997	1.4409	2.2103	1.5337
LR-CC	0.7873	3.1198	2.7864	3.0775	2.9806
p-values	0.7480	0.4907	0.4542	0.4180	0.4220
RMSE	1.19E-03	1.80E-03	1.02E-02	1.41E-03	1.56E-03
	VaR-GARCH-SGT	*VaR-EGARCH-SGT*	*VaR-GJR-SGT*		
Violation test	1.6062	2.3749	1.6998		
LR-CC	4.1079	4.2932	4.1940		
P-values	0.4003	0.3938	0.3977		
RMSE	1.75E-03	1.64E-03	1.71E-03		

Table 6: Comparisons of all coherent risk measures

Coherent risk measures	*CVaR-normal*	*CVaR(1)-GARCH-SGT*	*CVaR(1)-EGARCH-SGT*	*CVaR(1)-GJR-SGT*	*CVaR(2)-GARCH-SGT*
Violation Test	3.4927	1.2342	1.3263	1.2415	1.1276
LR-CC	0.9357	3.0569	3.0790	3.0676	2.7493
p-values	0.6264	0.3535	0.3343	0.3454	0.3510
RMSE	1.57E−06	1.53E−03	1.42E−03	1.49E-03	1.47E−03
	CVaR(2)-EGARCH-SGT	*CVaR(2)-GJR-SGT*	*CVaR(rho)-GARCH-SGT*	*CVaR(rho)-EGARCH-SGT*	*CVaR(rho)-GJR-SGT*
Violation Test	1.1711	1.1334	1.2321	1.3241	1.2444
LR-CC	2.7665	2.7565	3.0689	3.0887	3.0934
P-values	0.3324	0.3434	0.3496	0.3324	0.3430
RMSE	1.36E−03	1.53E−03	1.53E−03	1.41E−03	1.48E−03

than in volatility clusters. Classic VaR and CF-VaR significantly underperform risk assessments, indicating that the assessment of variance using the moving window method is inadequate. Unexpectedly, modelling custom quantiles does not necessarily improve the quality of the risk measure over time. A possible cause may be that, with as little data at hand as we have in this experiment, the observed return series may not be sufficiently representative of the true form of the underlying dynamics of the assets.

Therefore, among this class of risk measures the most preferable risk model is, on average, the VaR-GARCH-Normal model closely followed by the VaR-GJR-Normal model.

Coherent risk measures

Table 6 below presents the results of CVaR performance tests. From this table, it is clear that, generally, coherent risk measures assess risk levels more reliably than non-coherent measures. With exception of the CVaR-Normal measure, all risk measures come very close to the required $\alpha = 1$ per cent confidence threshold. Further, the performance discrepancies between different architectures of coherent risk measures are much smaller than with non-coherent risk measures.

Results indicate that coherent risk measures based on GARCH volatilities lead the performance for all CVaR model types, closely followed by GJR models. This implies that risks of monthly FoHF data are generally best assessed assuming no or some asymmetry in returns. Results for cluster asymmetry are relatively unfavourable.

Another important observation is that level-2 CVaR outperforms all other risk measures. Spectral risk measures are actually outperformed by their non-spectral counterparts. These observations indicate that greater care has to be taken when choosing the appropriate risk spectrum for an alternative asset.

The implementation of custom quantile estimates has a much stronger effect on coherent risk measures than on non-coherent ones. The reason for this behaviour may be in the fundamental structure of the risk measure: coherent risk measures also contain information of the loss magnitude beyond the tolerance threshold. Therefore, well-fit negative return tails provide better information about the entire loss structure. The CVaR measure can take this complementary information into account, which results in more robust estimates.

Therefore, the most recommended risk model structure for FoHF data with monthly frequency is the CVaR(2)-GARCH-SGT model followed very closely by CVaR(2)-GJR-SGT. In our experiment, CVaR-family risk measures showed the greatest robustness against outlier influence. Figure 1 on the next page further supports the hypothesis of advanced coherent risk measures being among the most preferable ones for risk exposure analysis. It contains four *p*-value graphs with simple, advanced and advanced coherent risk measures.

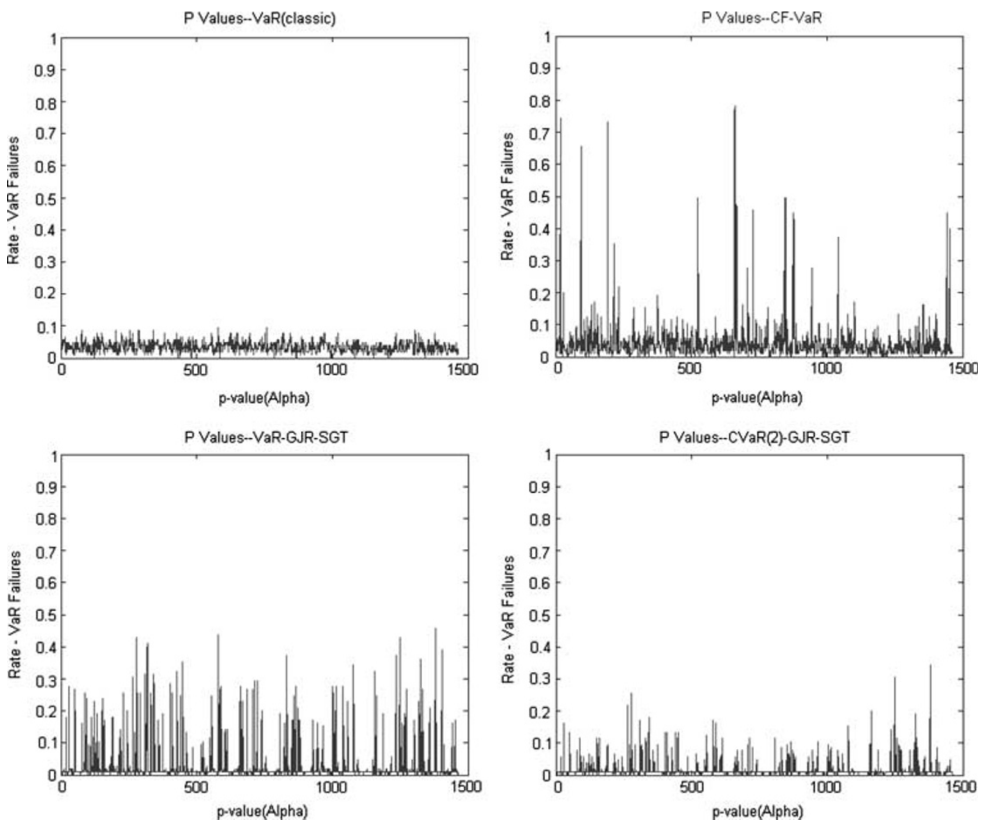

Figure 1: Plots of risk measure threshold success rates as risk measure go from simple to coherent advanced. Note that classic VaR does not display outliers, but is almost always far from the required confidence threshold. More advanced measures have large outliers where volatility or the custom quartile has not been modelled successfully, but in models converge towards the required confidence threshold.

From these graphs, clearly, the classic VaR measure does not converge towards the $\alpha = 1$ per cent confidence threshold. What is worse, CF-VaR shows the same bad convergence behaviour as VaR (classic), but additionally includes very large error outliers for some FoHF. This disqualifies it as the most unsuitable risk assessment model in our experiment and indicates that for some data series, the Cornish-Fisher expansion significantly and systematically severely underestimates the risk exposure of the underlying asset.

As we progress to advanced risk measures, we can see that all CVaR(2)-models converge closely towards the $\alpha = 1$ per cent confidence threshold. Risk underestimation is still statistically significant. However, the spread of difference in risk assessment performance is only small. This indicates that the impact of outliers is much less significant than for less sophisticated models. Under these circumstances, the CVaR(2)-model family clearly crystallizes as the best alternative for risk assessments with only little difference between alternative conditional volatility structures.

Robustness of models

In this section, we discuss our findings on the subject of the mathematical robustness of the different classes of risk measures. On closer inspection, we find that VaR measure outliers are created by model convergence problems. More precisely, our analysis shows that volatility models are more prone to misspecifications than quantile estimates: for very large outlier cases, risk models showed very low assessment performance regardless of class. The problem was concentrated around young FoHF most of the time, indicating that likely the amount of data was insufficient for stable convergence of the volatility model.

Further, in some cases (<1 per cent of the sample funds) we found convergence difficulties during quantile estimation, where SGT family risk measures systematically performed much worse than Gaussian risk measures. Again, we found that this problem is concentrated around young funds where only very little data are available. Quartile estimates for small return series may be mis-specified because the limited amount of real return data available may not yet be very representative of the true underlying return-generating process of the asset.

Next, we look at general robustness levels per risk measure class. Figure 2 below shows the maximum number of VaR estimation failures per risk quantification method. As can easily be seen, in the entire sample, classic VaR generally has the lowest number of VaR failures, whereas CF-VaR and GARCH family models show the highest failure rate. But does this mean that classic VaR is the most reliable risk measure? Certainly not: classic CVaR is the most stable risk measure as it does not model conditional variance, conditional mean or conditional quartiles. But it is also one of the most inefficient measures. In contrast, the very high rate of VaR prediction failures for advanced models can be traced back to singular cases where modelling the conditional variance process failed. For some rare data sets, GARCH models simply do not converge towards a meaningful solution. Complete failure of volatility convergence in our entire sample could be traced back to only two FoHF out of 1465. In general, the great majority of volatility models converge even if only little information is present. Nevertheless, these models may still carry the implicit risk of insufficient structural specification, as we restricted ourselves to the

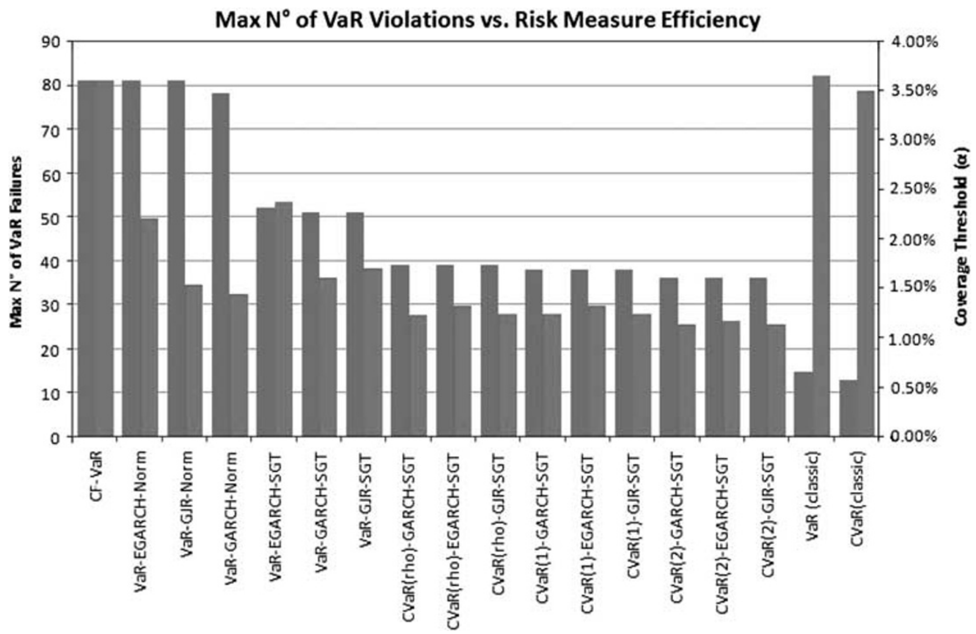

Figure 2: A graphical comparison of general risk model robustness versus risk model accuracy. The blue bars represent the maximum observed VaR violations per model on the entire sample. The red bars indicate the achieved confidence threshold. Classic models are numerically more robust, but fail to achieve the confidence threshold required by Basel II.

assumption that generating process followed an ARMA(1, 1)-GARCH(1, 1) process. This approach was chosen for reasons of parsimony and low data availability. Hence, before accepting volatility assessments for any FoHF data at monthly frequency model accuracy imperatively needs to be confirmed. We find further support for this conclusion in literature, for example Adam *et al*[38] conclude that VaR is as efficient a risk measure as moment-based and spectral risk measures, *provided the VaR measure is calibrated correctly.*

Correlation issues

FoHF are highly dynamic and unregulated investment vehicles and as such may be exposed to important degrees of leverage and risk factor concentration. It is thus natural to ask the question whether annualized returns are in any way correlated to the number of VaR failures, that is, underestimated risk exposure incidents, without primarily looking at failure magnitudes.

Figure 3 shows a set of scatter graphs that map annualized FoHF returns against the number of VaR failures for each risk measure. The first graph illustrates that classic-VaR model prediction failures cluster around 0 to 10 prediction failures for all return classes. For standard models, high and low return outliers display similar amounts of prediction failures without any discernible trends. However, the picture changes as soon as we start considering higher moments, conditional volatilities and

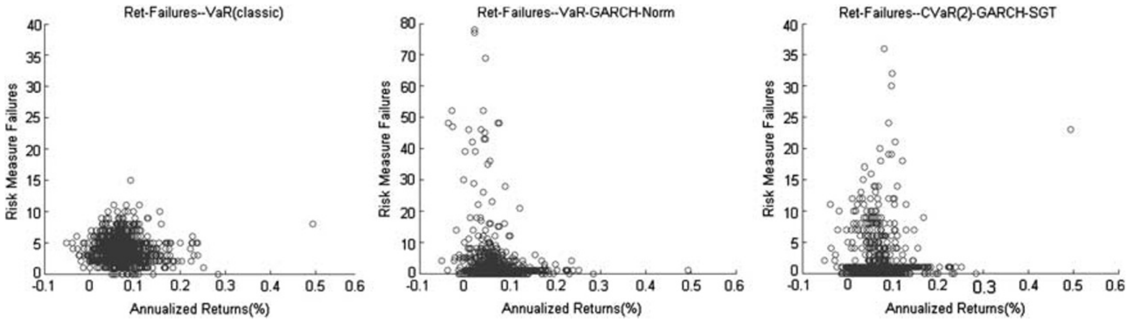

Figure 3: The evolution of classic risk models to recent advanced risk models: Classic VaR (left), VaR-GARCH-Normal and CVaR(2)-GARCH-SGT. Clearly, the most advanced models achieve $\alpha = 1$ per cent most consistently. However, some highly significant estimation outliers still persist.

custom quartiles. Risk measures then improve on accuracy at the expense of loss of some global numerical robustness.

Next, Figure 4 presents a risk–return distribution of all FoHF. From this figure, we can observe an interesting phenomenon: the apparent departure of the risk–return relationship originating from the Capital Asset Pricing Model (CAPM). In fact, this is not surprising: the universe of hedge funds and FoHF is notorious for its opacity and its subsequently highly asymmetric and incomplete information flow. One of the pillars of the CAPM assumes that information is accessible instantaneously and at no cost for every investor. This is not the case for the assets in our study. In fact, information access and control presents one of the key skills for successful asset management in the hedge fund industry. As a result, the market heterogeneity effects are more concentrated and pronounced than in any other asset class. Different ways of describing market dynamics must be explored, such as the Fractal Market Hypothesis (FMH), first introduced by Peters.[39]

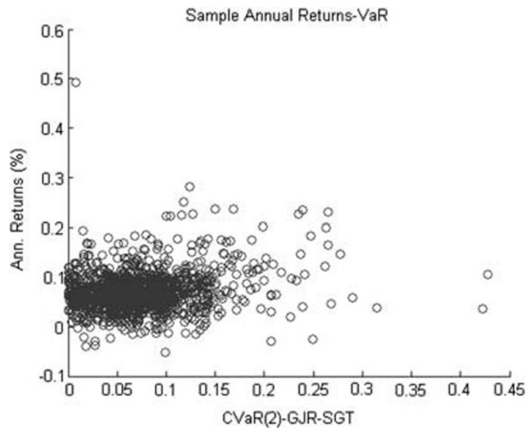

Figure 4: Annualized FoHF returns plotted against CVaR(2)-GJR-SGT risk measure.

We continue our analysis by briefly presenting a violation cost analysis. More precisely, Table 7 below compares the cost related to VaR measure failures for each one of the models tested in this study.

From the table, it is clear that classic risk measures fail most critically and thus pose the most serious threat of liquidation after faulty risk assessment for all FoHF. On the other end of extremes, we find the CVaR(2) family for which

Table 7: Résumé of the cost incurred by protection failure. In the event of a VaR threshold violation, advanced risk measures infer less than 50% of the cost of traditional measures. Further, violation costs for advanced measures are better behaved, meaning that if a VaR violation occurs, it is usually not far from the initial value proposed by the model. Nevertheless, for all models costs still remain statistically significant

Cost (annual % return)	*VaR (classic)*	*VaR-CF*	*VaR-GARCH-normal*	*VaR-EGARCH-normal*	*VaR-GJR-normal*	*VaR-GARCH-SGT*	*VaR-EGARCH-SGT*	*VaR-GJR-SGT*	*CVaR (classic)*
Total cost on portfolio	532.6	526.6	416.8	459.7	406.5	295.8	331.0	298.5	317.6
Avg. Cost per FoHF	0.2270	0.3595	0.2845	0.3138	0.2775	0.2019	0.2259	0.2037	0.2168
Mean (Avg.)	1.5E-04	2.5E-04	1.9E-04	2.1E-04	1.9E-04	1.4E-04	1.5E-04	1.4E-04	1.5E-04
Median (Avg.)	1.4E-04	1.3E-04	6.9E-05	9.5E-05	7.5E-05	7.1E-05	9.5E-05	7.3E-05	1.4E-04
SD (Avg.)	1.0E-04	1.4E-03	1.7E-03	1.5E-03	1.5E-03	2.4E-04	2.4E-04	2.4E-04	9.1E-05
Max (Avg.)	8.4E-04	4.5E-02	6.2E-02	4.8E-02	5.3E-02	4.9E-03	4.9E-03	4.9E-03	8.2E-04
Min (Avg.)	0	0	0	0	0	0	0	0	0

Cost (annual % return)	*CVaR(1)-GARCH-SGT*	*CVaR(1)-EGARCH-SGT*	*CVaR(1)-GJR-SGT*	*CVaR(2)-GARCH-SGT*	*CVaR(2)-EGARCH-SGT*	*CVaR(2)-GJR-SGT*	*CVaR(ρ)-GARCH-SGT*	*CVaR(ρ)-EGARCH-SGT*	*CVaR(ρ)-GJR-SGT*
Total cost on portfolio	247.0	251.5	246.0	233.6	234.8	232.2	246.8	250.4	245.6
Avg. Cost per FoHF	0.1686	0.1716	0.1679	0.1595	0.1603	0.1585	0.1685	0.1709	0.1677
Mean (Avg.)	1.2E-04	1.2E-04	1.1E-04	1.1E-04	1.1E-04	1.1E-04	1.1E-04	1.2E-04	1.1E-04
Median (Avg.)	6.9E-05	7.2E-05	6.9E-05	6.9E-05	7.0E-05	6.8E-05	6.9E-05	7.2E-05	6.9E-05
SD (Avg.)	1.6E-04	1.6E-04	1.6E-04	1.4E-04	1.4E-04	1.4E-04	1.6E-04	1.6E-04	1.6E-04
Max (Avg.)	2.7E-03	2.7E-03	2.7E-03	2.3E-03	2.3E-03	2.3E-03	2.7E-03	2.7E-03	2.7E-03
Min (Avg.)	0	0	0	0	0	0	0	0	0

costs do not greatly exceed the VaR threshold in the event of a threshold violation. Thus, although these measures exhibit a more conservative and therefore expensive nature, managers using advanced risk measures are much less exposed to liquidation risk.

These observations suggest that high return FoHF benefit from a more controlled risk exposure, as well as a higher risk-adjusted return. Hence, high and low return FoHF both tend to show much less prediction failures than medium range return FoHF. One possible explanation for this could be that the risk model does not succeed in estimating risk exposure correctly. Another could be that some fund managers may be less skilled than others and expose their fund to higher risks, willingly or unwillingly, while maintaining the same level of returns. For example, this can occur through overleveraging of the risky assets, thus overexposing the FoHF portfolio as a whole. Similarly, pursuing a static trading strategy while failing to frequently assess and correct risk exposures for portfolios invested in a dynamic asset sector would lead to the same situation. The low violation-return markers are low return funds that choose to accept lower returns for less exposure to risk factors, whereas low violation-high return markers represent high return funds displaying exceptional skill in quantifying and managing risk exposures.

We can interpret these groupings as evidence that managerial skill does matter and indeed different skill levels exist. Going one step further, we may venture the hypothesis that some of the medium return FoHF may only yield medium returns because their risk exposure is managed insufficiently and consequently best possible returns are reduced by inappropriate, because inefficient, hedging strategies.

The structure of VaR violation sequences

Next, we examine whether risk measures performing close to the confidence threshold $\alpha = 1$ per cent show particular patterns for correlations or dependences in prediction failure. More precisely, we attempt to determine whether risk models converging towards the intended confidence threshold *systematically* show preferable conditional coverage and dependence structure properties.

Results for the dependence structure of violation events indicate that, on average, for simple risk measures one can assume weak to medium correlation of violation events, independently of whether threshold α was achieved. For advanced measures, the picture is split in two. Measures that achieve threshold α exhibit very low or no correlation in the violation sequence. In contrast, cases that significantly fail to achieve threshold α always display weak to high degrees of correlations between consecutive violations.

This indicates that for coherent advanced risk measures, we can usually expect a more preferable conditional coverage and dependence structure, *on the condition that the confidence threshold is more or less achieved*.

These results imply that coherent advanced risk measures are generally more successful at ensuring conditional coverage of the VaR violation threshold than advanced and simple risk measures. Further they show weaker, and therefore preferable, dependence structures of violation events than simple risk measures. It is generally more recommendable to apply coherent risk measures when evaluating FoHF risk exposure as they appear to filter risk exposures more clearly, and show weaker dependence structures of violation events.

Table 8: Filtering the best models according to various quality criteria. The CVaR(2)-GARCH-SGT model is the most successful risk model, closely followed by the CVaR(2)-EGARCH-SGT model. Generally, the class of higher order advanced coherent risk models is the most preferable set of risk assessment tools for FoHF

Topic	*Conclusion*
Efficient models	CVaR(2)-GARCH-SGT / CVaR(2)-GJR-SGT
Non-coherent models	VaR-GARCH-Normal / VaR-GJR-Normal
Coherent models	CVaR(2)-GARCH-SGT / CVaR(2)-GJR-SGT
Robustness	CVaR-Normal / VaR-Normal
Model fit (RMSE)	CVaR(2)-EGARCH-SGT / CVaR(2)-GARCH-SGT
Violation cost	CVaR(2)-GARCH-SGT / CVaR(2)-GJR-SGT
Violation variance	CVaR(2)-GARCH-SGT / CVaR(2)-GJR-SGT
Violation threshold (99%)	CVaR(2)-GARCH-SGT / CVaR(2)-GJR-SGT
Christoffersen LR (CC)	CVaR(2)-EGARCH-SGT / CVaR(2)-GJR-SGT

To summarize, Table 8 briefly outlines the two best models for different test criteria.

CONCLUSION

In this article, we examine the efficiency of VaR-based risk measures in the context of the FoHF universe and under Basel II Accord stipulations. We assessed risk measure efficiency by testing VaR-violation sequences for the achievement of the unconditional confidence threshold α, for existence of autocorrelation up to several violation lags, and for numerical robustness, which is important for reliable risk assessment results.

We find that advanced coherent risk measures come closest to the targeted 99 per cent confidence threshold and further display weakest correlations of subsequent VaR violations.

During normal market periods, the best models, namely the CVaR(2)-model family, protect their underlying satisfactorily. Thus, provided no negative *extreme* events occur, this family of risk measures can provide very satisfactory risk protection and manage their exposure at economically acceptable costs.

However, results in this work indicate that no particular risk model can successfully protect managers from unfavourable *extreme* events.

In our experiments, even the CVaR(2) model family still fails to attain the critical confidence threshold on an empirical basis. Further, all models fail to protect their assets during critically abnormal market correction periods. All VaR measures only indicate high-risk market conditions *ex ante*, meaning only after extreme events have already occurred.

This systematic failure of risk models during critical market times leads us to postulate the existence of at least two different fundamental types of randomness: *mediocre* and *extreme* randomness. During times of mediocre randomness, market dynamics largely correspond to the descriptions offered by available data and the *exogenous* part of the volatility equations and the geometry of the return histogram. However, during abnormal times, the *residual* part of the volatility equations controls the price generation for a very short period of time. The investor is largely unaware of the dynamics of the process during this time and available data are very scarce. Therefore, he cannot, by definition, forecast such periods. From this follows that VaR models cannot, by definition, contribute valuable information, as the exogenous part of the equation has been calibrated to market dynamics present during 'normal' market times. Critical bear periods suffer systematically from data scarcity, so that the dynamics underlying the abrupt and extreme changes are very hard to model.

In light of these results, the imposed high confidence threshold of $\alpha = 1$ per cent induces significant error margin during model estimation because of the structural nature of the family of VaR models and the low frequency of the data available. Consequently, risk assessment techniques as imposed by the Basel II regulatory framework are generally insufficient for extreme risk management in the special case of FoHF.

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