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Idiosyncratic Risk Measurement for Financial Institutions

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Idiosyncratic Risk Measurement for Financial Institutions

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A B S T R A C T

Recent debacles in the financial industry are a reminder that although risk management tools have greatly developed over the past fifteen years, industry vulnerability has not declined proportionately. In our study, we build on (Allen and Bali, 2007), and infer extreme risk in financial institutions and its idiosyncratic component. Our contribution is twofold: first, extending the specification and estimation procedure for the model, and then estimating on a global dataset of European and American institutions, spanning major turmoil episodes in the past two decades.

Idiosyncratic risk is evaluated individually for each institution through initially regressing monthly stock returns on common factors underlying the returns in a panel comprising 1879 banks, life and non-life insurance companies traded on the stock exchanges in the United States, the UK, Germany, France, Italy, Austria, Belgium, Greece, the Netherlands, Norway and Spain. Using extreme value theory, the residuals are then employed to infer idiosyncratic VaR for financial companies, and risk is defined as the loss that shall not be exceeded over a given time horizon and at a specified confidence level. Our results suggest that systemic risk has doubled in 2008 compared to preceding years, while idiosyncratic risk has increased to a much lesser extent; and the impact on idiosyncratic risk is more pronounced in the US compared to Europe. We also find that the approach of Allen and Bali (2007) understates the true share of idiosyncratic risk; on the other hand, our study confirms their finding about the cyclicality of both idiosyncratic and overall catastrophic risk.

A R T I C L E I N F O

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Idiosyncratic risk, Operational risk,

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1. Introduction

Modern financial theory is built upon the fundamental contributions of Markowitz (1952), Sharpe (1964) and Lintner (1965a, 1965b), and answers the question about the pervasive factors driving asset returns. There have been few articles, however, studying idiosyncratic risk, e.g. (Levy, 1978), and one of the reasons is that models of idiosyncratic risk rarely produce testable predictions. In a recent study, Campbell *et al.* (2001) revive the interest to both the theoretical foundations of idiosyncratic risk and its empirical properties. They use stock returns from NYSE, AMEX and NASDAQ, over the period from 1962 to 1997, and report that systemic and industry volatility remain relatively stable while idiosyncratic and total risk are on an uptrend. Similar findings are reported by Wei and Zhang (2006), who study the drivers of idiosyncratic volatility and suggest that its trend is driven by diminishing return on equity (ROE) and increased ROE volatility. Interestingly, firm size, price-book value ratios, firm age and leverage, are not found to be significant drivers of idiosyncratic volatility. Reportedly, the increased ROE volatility is next linked to the raising number of listed companies, due to enhanced accessibility of stock markets.

The predictability of stock market returns using the volatility of idiosyncratic risk is further explored by Goyal and Santa-Clara (2003), who find that average volatility calculated from individual stock returns helps explain market returns. Their results are subsequently challenged by other authors, who argue that the detected predictability is an artefact of a short turbulence episode and the bull market in the 1990's (Wei and Zhang, 2005), or of institutional ownership, and volatility induced by low liquidity or volatile fundamentals (Brandt *et al.*, forthcoming). Additional arguments indicate the inclusion of smaller stocks in the calculation of the equally-weighted average volatility, and further point to the liquidity premium (Bali *et al.*, 2005). On the other hand, Gaspar and Massa (2006) present evidence that market power of companies effectively reduces their exposure to idiosyncratic shocks, so the increase of volatility could be attributed to deregulation and globalisation. Also recently, Bennett and Sias (2006) suggest that changes in idiosyncratic risk are largely explained by changes in the baskets of stocks used to measure average idiosyncratic risk. Their results demonstrate that changes in average idiosyncratic risk are due to changes in the relative importance of both riskier industries and small-cap stocks, and due to changes in industry concentration that result in measurement differences for company-specific risk estimates.

An interesting approach to total and idiosyncratic risk is explored in two recent articles by Allen and Bali (2007) and Allen *et al.* (2004), where total risk is termed "catastrophic" and idiosyncratic risk is labelled "operational". The risks are measured as the maximum change in market value of a single company, based on cross section of returns within a homogenous sample of companies. Advantageously, their approach to risk measurement allows for a comprehensive evaluation of total risk and its decomposition into contributing factors, and accounts for fat tails in asset returns. However, one should acknowledge as a debatable issue whether operational risk can be measured through idiosyncratic risk. In that respect, Moosa (2006) argues that operational risk needs not be idiosyncratic risk. The author provides examples that an internal fraud event in bank A, like the one at Bearings, could result in insolvency of the affected bank A, and subsequently, in losses for its counterpart banks B and C. From the perspective of the bank's counterparts, therefore, the default of bank A is credit risk and not operational one. Even in case bank B has been overexposed to bank A and thus has had unreasonable exposure limits to counterparts, then there is not one but two separate operational events – an internal fraud in bank A and a failed process in bank B.

Another issue raised in (Moosa, 2006) is that in the presence of 'group think', i.e. uncritical acceptance of a prevailing point of view, operational losses could hit the whole industry rather than individual financial institution. In our view, this point is more interesting as most of the largest operational losses reported by credit institutions arguably reflect such 'group think'. Indeed, the industry has considered uncritically the models used for valuation of various types of exotic derivatives, and the terms and conditions for a variety of products. The recent crisis has highlighted that such products accounted for tail risks and triggered a wave of write-downs – some under the heading of market or credit risks, but some under the title of inappropriate clients, products and business practices. Therefore, operational risk is not always idiosyncratic risk but also part of the systemic risk. In the context of the present discussion, we should add that not all idiosyncratic risk is operational, since the Basel definition of operational risk does not include business, strategic and reputational losses. Of these, reputational losses can be viewed as substantially operational, but were excluded from the Basel II definition due to the significant problems with their quantification. On the other hand, most business and strategic risks should not be considered operational by definition. For example, decisions about how to position a company, what product mix to offer and how to raise funding, and merger and acquisition decisions, should hardly be covered by the operational risk capital requirement. In order to avoid misinterpretation, throughout this paper and the introduced mesaurement approach, we shall refer to idiosyncratic risk rather than operational risk.

Despite the intuitive appeal of the procedure for measuring idiosyncratic risk in (Allen and Bali, 2007), the estimation technique has limitations that weaken the validity of conclusions. The use of ordinary least squares (OLS) to estimate regressions of stock returns on a set of 27 apparently correlated variables, with a 50-month rolling window, could produce overfitted results and underestimate the true share of idiosyncratic risk within the overall risk of financial institutions. Another issue is the choice of proxy variables. Indeed, some of the variables represent sources of particular type of risk, e.g. interest rates, foreign exchange rates, capital market returns. However, the firm-specific credit risk variables, i.e. market value of equity to book value of assets, net income to sales, and log of book value of total assets, are not credit risk measures but proxies of the risk the particular issuer presents to its investors and counterparts. The first ratio approximates the leverage, the second one measures the income margin, and the third – the company size. The sign of the correlation with some of the variables is not clear, either. A high ratio of market value of equity to total assets could be considered as indicative of lower risk if it reflects high capitalisation, but could also indicate higher risk if it is due to higher price-to-book value ratio. In this article, we refine the estimation methodology and benchmark the resulting measurements for European financial institutions against their American peers. We investigate the capacity of maximum likelihood factor analysis and extreme value theory for quantifying total and idiosyncratic risk. Factor analysis is used in order to decompose asset returns into common and idiosyncratic components; then idiosyncratic risk is analysed by means of extreme value theory to evaluate the maximum idiosyncratic loss that can be realised over a given time horizon. Our results suggest that idiosyncratic risk comprises a larger proportion of overall risk than the one reported by Allen and Bali (2007). On the other hand, we confirm their finding about risk cyclicality. However, we disagree that their idiosyncratic risk is a useful guideline in measuring operational risk capital for financial institutions. Finally, the focus in this article is on investigating the risk profiles of financial institutions, though the approach is directly applicable to other sectors.

2. Estimating idiosyncratic risk

2.1. Generalised Pareto distribution

Extreme value theory (EVT) as a branch of statistics studying the probability distribution of rare, extreme events. There are two approaches to modelling the distribution of such events – the block maxima method and the peaks over threshold (POT) technique. In this paper, we employ the latter in order to estimate the high quantiles of monthly total and idiosyncratic losses. Suppose that $F(X)$ is the distribution of a random variable X, and let us denote the conditional distribution of the excesses $(X - u)$ over a threshold u as $F_u(y) = P(X - u < y | X > u)$. The major proposition in the POT approach (Pickands, 1975) is that when $u \to \infty$ then $F_u(y) \to G(y)$, where $G(y)$ is a member of the (two-parameter) generalised Pareto distribution (GPD) family:

$$G_{\xi,\sigma}(y) = \begin{cases} 1 - \left(1 + \frac{\xi y}{\sigma}\right)^{-1/\xi}, & \text{if } \xi \neq 0; \\ 1 - \exp\left(-y/\sigma\right), & \text{if } \xi = 0. \end{cases}$$

Here $y = X - u$ is the excess over the threshold u, ξ is the tail parameter, and σ is the scale parameter. Furthermore, ($\sigma > 0$, $y > 0$) when $\xi > 0$, and $0 \leq y < -\sigma/\xi$ when $\xi < 0$, and $(1 + \xi y/\sigma) > 0$ (refer to Embrechts *et al.* (2003) for a detailed exposition). The three-parameter GPD is obtained by including a location parameter μ, and is defined as $G_{\xi,\sigma}(y - \mu)$. When $\xi < 0$, the GPD maximum value is $u - \sigma/\xi$; when $\xi \geq 0$, the values of threshold excesses are unconstrained. Among the parameters of the GPD, ξ is of particular interest, since it controls the thickness of the tail. In financial applications, we usually find $\xi \in (0, 0.5)$, which corresponds to a heavy-tailed distribution ($\xi > 0$) with a finite variance ($\xi < 0.5$). This result is formulated in terms of the right tail of the distribution, while a similar result holds for the left tail. We adopt the convention of considering losses as positive numbers.

The result holds asymptotically, i.e. the larger the threshold u, the better approximation is achieved. Therefore, the choice of threshold is a fine balance between bias and standard error. If the threshold is too low, there would be more observed exceedances over the threshold, hence a lower standard error. However, the low threshold would not allow the distribution of the maxima to converge to GPD, resulting in biased estimates. Too high a threshold would reduce the bias, but the small number of exceedances would increase the error of the estimates. There is no generally accepted method for choosing the

Table 1
Dataset Summary

Country	Banks		Life insurance		Non-life insurance		Total	
	no. issuers	no. returns	no. issuers	no. returns	no. issuers	no. returns	no. issuers	no. returns
US	1,285	144,018	77	9,430	212	27,354	1,574	180,802
Austria	17	1,656	–	–	4	542	21	2,198
Belgium	9	1,104	–	–	2	148	11	1,252
France	6	437	1	71	4	342	11	850
Germany	28	2,565	2	232	19	1,889	49	4,686
Italy	52	6,100	4	610	13	1,978	69	8,688
Norway	31	3,159	2	280	6	295	39	3,734
Spain	25	3,727	1	89	2	358	28	4,174
UK	16	2,404	12	1,697	49	4,611	77	8,712
Total	1,469	165,170	99	12,409	311	37,517	1,879	215,096

threshold. Analytical methods for optimal threshold selection do exist (Lang *et al.*, 1999), though there is no consensus on their performance in terms of speed of convergence to GPD. A common approach, particularly in finance, is to rely on visual inspection of the plot of mean exceedances over different thresholds, and choose the lowest threshold over which the mean exceedances are approximately linear (Embrechts *et al.*, 2003).

A number of methods have been developed for fitting GPD to data, the two most popular being the method of maximum likelihood and the method of probability-weighted moments. The maximum likelihood estimator (MLE) is a common choice for fitting GPD; it is asymptotically normal and asymptotically efficient, provided that $\xi > -0.5$ (refer to Grimshaw (1993) for a numerical MLE algorithm). The method of probability-weighted moments (PWM) is develop by Hosking and Wallis (1987), whose simulation results suggest that although the estimator is biased, the bias quickly decreases with the increase of the sample size. The variance of the estimator is similar to that of the MLE, and simulation studies suggested that PWM significantly outperforms MLE when the sample size of exceedances is smaller than 100 and $\xi > -0.2$. Since both conditions apply to our dataset, we employ PWM estimators for this study. Once the parameters of the distribution are estimated, the unconditional distribution of losses is constructed by multiplying the probability of observing losses beyond the threshold u times the distribution of excess losses as approximated by the GPD. The natural estimate for the probability of threshold exceedances is k/n, where n is the total number of observations in the dataset, and $k = card\{i : i = 1, 2, \ldots, n, X_i > u\}$ is the number of threshold exceedances. Finally, the unconditional distribution of losses is used to derive the quantile function, and thus the value at risk (VaR) is obtained for a given confidence level.

2.2. Data

Our dataset comprises all shares and deposit receipts of banks, life and non-life insurance companies traded on the stock exchanges in the United States, the UK, Germany, France, Italy, Austria, Belgium, Greece, the Netherlands, Norway and Spain. Share prices and sectoral classification are collected from the Thompson's Datastream database. The dataset spans the period from January 1987 until December 2008. An essential assumption in the approach is that returns are drawn independently from an identical distribution. Therefore, we have limited our attention in this study to banks and insurance companies, since these are more homogeneous in terms of exposures to risk factors and risk management practices. Furthermore, in order to mitigate inasmuch as possible non-independence between observations, we have removed from the dataset companies that are listed simultaneously at more than one stock exchange or which are known to be related or under common control. Next, in order to ensure that there is sufficient history for each stock allowing to establish its exposure to risk factors, we have required that price data should be available for at least 36 months, though gaps are allowed. Liquidity is another concern when implementing the proposed approach. We have not opted to include every European country and stock exchange, since markets with lower liquidity or less mature regulation could result in more significant price changes that are not driven by fundamental factors. Therefore, a subset of European stock exchanges have been included in the sample. Finally, price quotes in months when there has been no trading are removed from the sample.

After applying the filters described in the preceding paragraph, a total of $1,879$ financial institutions remain in the sample. At any point in time a subset of those institutions are actually traded, and the number of listed financial institutions has increased over time. Table 1 provides summary information on the dataset - number of instruments, monthly stock returns available, and distribution by sectors and countries. Furthermore, a practical guideline to whether the sample is homogeneous is to verify if the probability of exceeding a threshold u does not depend on the sector or country. We have examined how the empirical probability of exceeding a 10% threshold varies across sectors and countries. The exceedances of the common threshold are 6.7% for banks, 8.1% for life insurers, and 9.3% for nonlife insurers. Across countries, the corresponding rates are similar too – 7.3% for the United States, 7.9% for the United Kingdom, and 6.3% for the remaining European markets. The slightly lower volatility for banks could be explained by the stronger risk management culture, closer supervision and presumably better transparency.

2.3. Estimation Procedure

We use a two step procedure in order to estimate idiosyncratic risk VaR for financial companies. As a first step, an overall loss measure for each company is obtained, using monthly data and estimating a generalised Pareto distribution on cross-sectional stock returns, similarly to (Allen and Bali, 2007). The total "catastrophic" risk is quantified by fitting the excess returns for all institutions to a GPD. In this study, we estimate catastrophic risk by fitting the 10% largest losses in each month to a GPD. As a second step, we explore the use of heteroscedastic factor analysis (Jones, 2001), in order to extract a set of K common factors underlying observed volatility. The common factors are estimated hierarchically. Initially, one global factor is identified, underlying volatility in all markets. Next, further 20 factors are identified from US stocks, and another 20 factors are estimated for European stocks. Then for each stock, factor loadings are estimated as the coefficients in an OLS regression of monthly returns on a subset of the 21 common

Table 2
Number of Factors in Idiosyncratic Risk Regressions

Number of factors	Share of returns
0	16,206
1	44,074
2	59,574
3	48,520
4	30,987
5	15,762
6	7,012
7	3,344
8	1,265
9	444
10	380
11	328
12	239
13	60
14	17
15	10
16	1

factors (1 global + 20 regional). The subset is selected using stepwise elimination of redundant factors.

Let R^n denote the $n \times T$ (corresponding sample size $\times$ time periods) matrix of observed excess returns, and H stand for the matrix of (unobservable) factor realisations. Let B^n stand for the matrix of factor loading, and E^n denotes idiosyncratic returns. Then the model of observed returns is assumed in the following form:

$$R^n = B^n H + E^n.$$

Further, let $F \equiv M^{-1/2}H$ stand for the matrix of rotated factor realisations, introduced to simplify notation, and D denote the diagonal matrix of average idiosyncratic variances. As shown in (Jones, 2001), the average variance $(1/n)R^{n\prime}R^n$ converges to $F'F + D$ and can be estimated using the Jöreskog's procedure:

i. Compute $C = (1/n)R^{n\prime}R^n$.

ii. Initialise D as $D = 0.5C$.

iii. Obtain the K largest eigenvalues of $D^{-1/2}CD^{-1/2}$ and create a diagonal matrix Λ having the largest eigenvalues along its main diagonal; then create a matrix V of their corresponding eigenvectors.

iv. Estimate the factor matrix as $F = D^{1/2}V(\Lambda - I)^{1/2}$.

v. Compute a new estimate of $D = C - F'F$ and return to (iii) until the algorithm has converged.

vi. Estimate factor loadings using OLS regressions of observed excess stock returns on identified factors, and obtain residual idiosyncratic errors ϵ.

An important issue in factor analysis is the choice of appropriate number of factors, and there is no commonly accepted approach. Such techniques overall aim to measure whether an additional factor would have additional explanatory power (Kandel and Stambaugh, 1989; Connor and Korajczyk, 1993; Bai and Ng, 2002). In this paper, we are guided by the explanatory power of each factor, and for each individual company the appropriate number of factors during a given horizon is selected by a backward stepwise elimination. The number of factors typically does not exceed 5, compared to 27 variables used in (Allen and Bali, 2007). A detailed breakdown is provided in Table 2. Finally, the idiosyncratic VaR is estimated by fitting regression residuals to GPD, and estimating the quantiles of the idiosyncratic loss distribution.

3. Empirical results

3.1. Total and idiosyncratic risk

The results of fitting monthly stock returns to GPD are summarized in Figure 1, where the estimated tail and scale parameters can be considered as fairly stable. One reason is the larger number of US issues, which results in a larger dataset on which estimates are based. The tail parameter ξ of the GPD controls tail thickness, and the median value of ξ is 0.185, while the 1st and 3rd quartiles are 0.068 and 0.286, correspondingly. These values imply a fat-tailed distribution of overall catastrophic losses, as $\xi > 0$, with a finite variance, as $\xi < 0.5$. Therefore, tail thickness has not been materially affected by the recent turmoil. The scale parameter σ, on the other hand, has a median value of 0.044, and 1st and 3rd quartiles equal to 0.033 and 0.056, respectively. Distinctively, the parameter has more than doubled since mid-2007, reflecting an increased dispersion of asset returns. Now based on the GDP parameter estimates, the catastrophic VaR can be evaluated using the approach outlined in the preceding section. The values presented in Figure 1 measure the maximum loss of capitalisation that a company could experience over 1-month horizon with a confidence level of 99%. The median 99% monthly catastrophic VaR is 0.203, where the quartiles are respectively 0.159 and 0.257. The evaluated catastrophic risk increases significantly in the second half of 2007 and through 2008, averaging 0.446 in 2008 compared to 0.200 during 1987-2006. The comparison in Figure 2 further reveals that though the recent turmoil in financial markets has spread to Europe, it has been more contained and the 99% VaR in 2008 averages at 0.291, as opposed to 0.477 for the United States. Another detail here is that the estimates for Europe are more volatile due to the lower number of financial institutions in the sub-sample.

Next, idiosyncratic VaR is estimated by fitting regression residuals to GPD, and evaluating the quantiles of the idiosyncratic loss distribution. The results are presented in Figure 3. The estimated GPD parameters suggest that tail thickness is lower compared to the catastrophic loss distribution. The median ξ value is 0.125, with 1st and 3rd

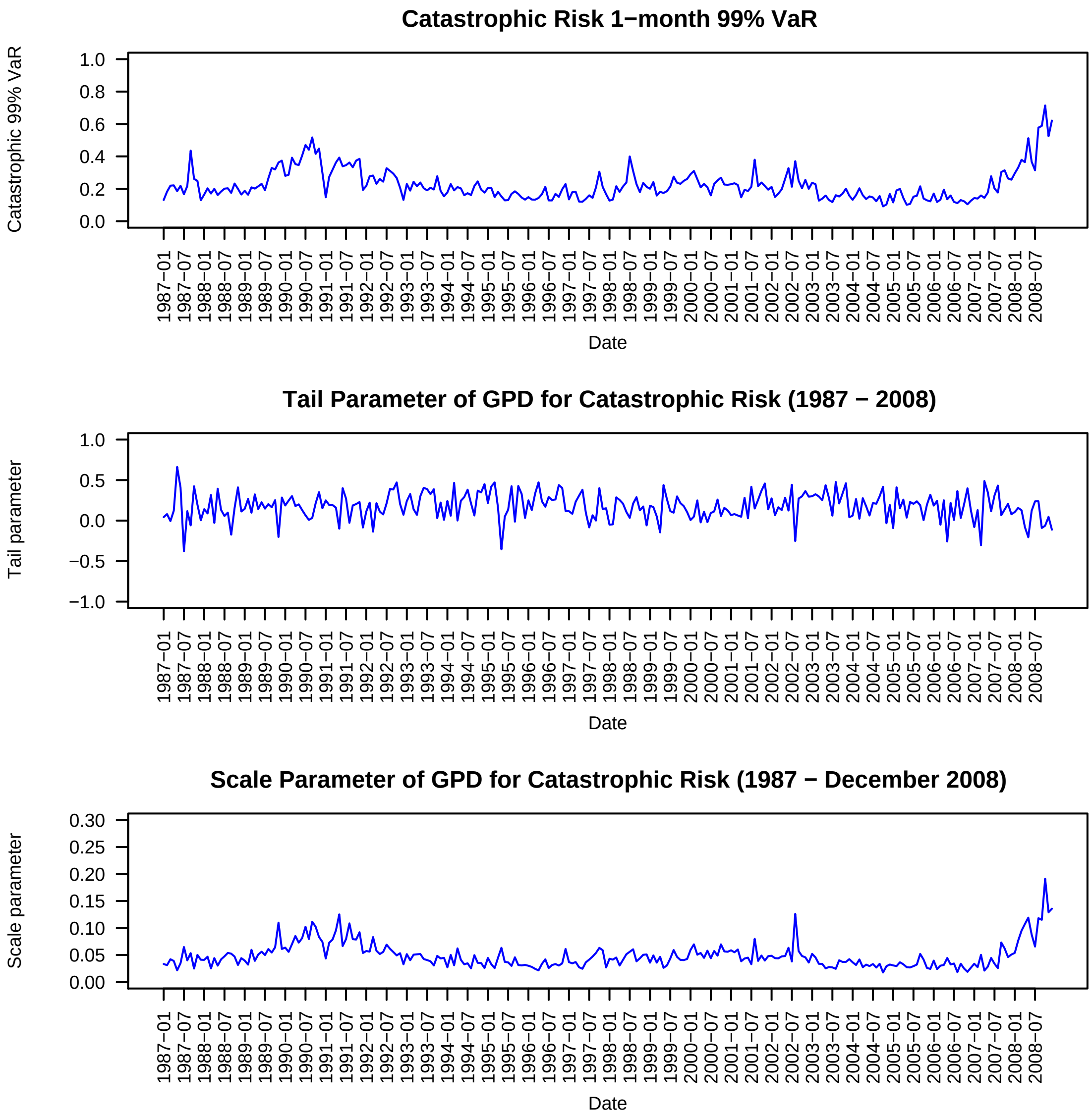

Figure 1. *Monthly 99% Catastrophic VaR and Generalised Pareto Distribution Parameters.* Panel A presents the quantiles of catastrophic risk VaR – the maximum loss of market capitalisation that a company is likely to exceed with probability 1%. The distribution is estimated using the method of probability-weighted moments and the 10% largest losses. The tail is estimated using the two-parameter generalised Pareto distribution. The median of the estimated VaR is 20.3%, however since mid-2007 catastrophic risk has soared and average VaR has more than doubled compared to pre-June 2007 period. Panels B and C present the estimates for the GPD parameters. The tail parameter controls tail thickness and has a median of 0.185, corresponding to a fat-tailed distribution. The scale parameter controls the overall dispersion of GPD, and its sample median value is 0.044. Estimated catastrophic risk has increased significantly in the second half of 2007 and 2008, and in 2008 it averages 0.446 compared to 0.200 during 1987-2007.

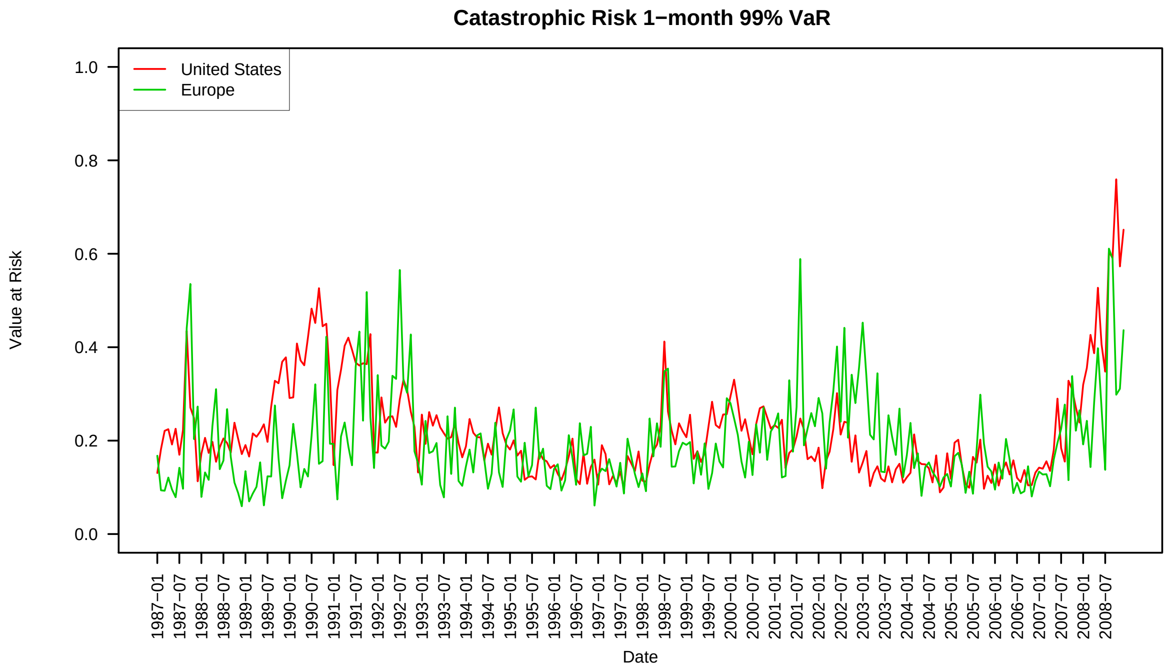

Figure 2. *Monthly 99% Catastrophic VaR by region.* Catastrophic risk in Europe has been similar to that in the US for most of the sample period. Considering the recent turmoil phase, the estimates in 2008 increase significantly for both the US and Europe. The 99% VaR in 2008 averages at 0.477 for the US, and at the notably lower 0.291 for Europe. Another empirical evidence revealed in the graphics is that prior to 1993, the US financial services are found riskier than their European counterparts, a consequence of the savings and loans crisis in the 1980's and early 1990's.

quartiles equal to 0.008 and 0.215, compared to a median value of 0.185 for catastrophic risk, with quartiles of 0.068 and 0.286. Furthermore, the median σ value for idiosyncratic risk is 0.039, with quartiles of 0.032 and 0.047, while the corresponding scale parameter values for catastrophic risk are 0.044, 0.033 and 0.056. Based on the parameter estimates and following the procedure, we can now produce the monthly 99% idiosyncratic value-at-risk and display in Figure 4. The median VaR is 0.179, with quartiles at 0.153 and 0.210, implying that idiosyncratic risk is the major constituent part of catastrophic risk under normal market conditions. The reason is that during calm periods, sudden losses of market value are due to a situation or event specific to the particular issuer. During crisis periods, however, the share of idiosyncratic risk declines, partly due to the presence of 'group think'. Thus in 2008, both catastrophic and idiosyncratic risk increase substantially compared to the 1987–2007 period. However, catastrophic risk has more than doubled, with the median VaR reaching 0.446 in 2008 compared to 0.200 in 1987–2007. On the other hand, the median idiosyncratic VaR has risen from 0.178 in 1987–2007 to 0.242 in 2008, an increase of 36%.

The quality of estimates can be further enhanced by pooling monthly returns by years and then using those to evaluate catastrophic and idiosyncratic VaR. That approach would

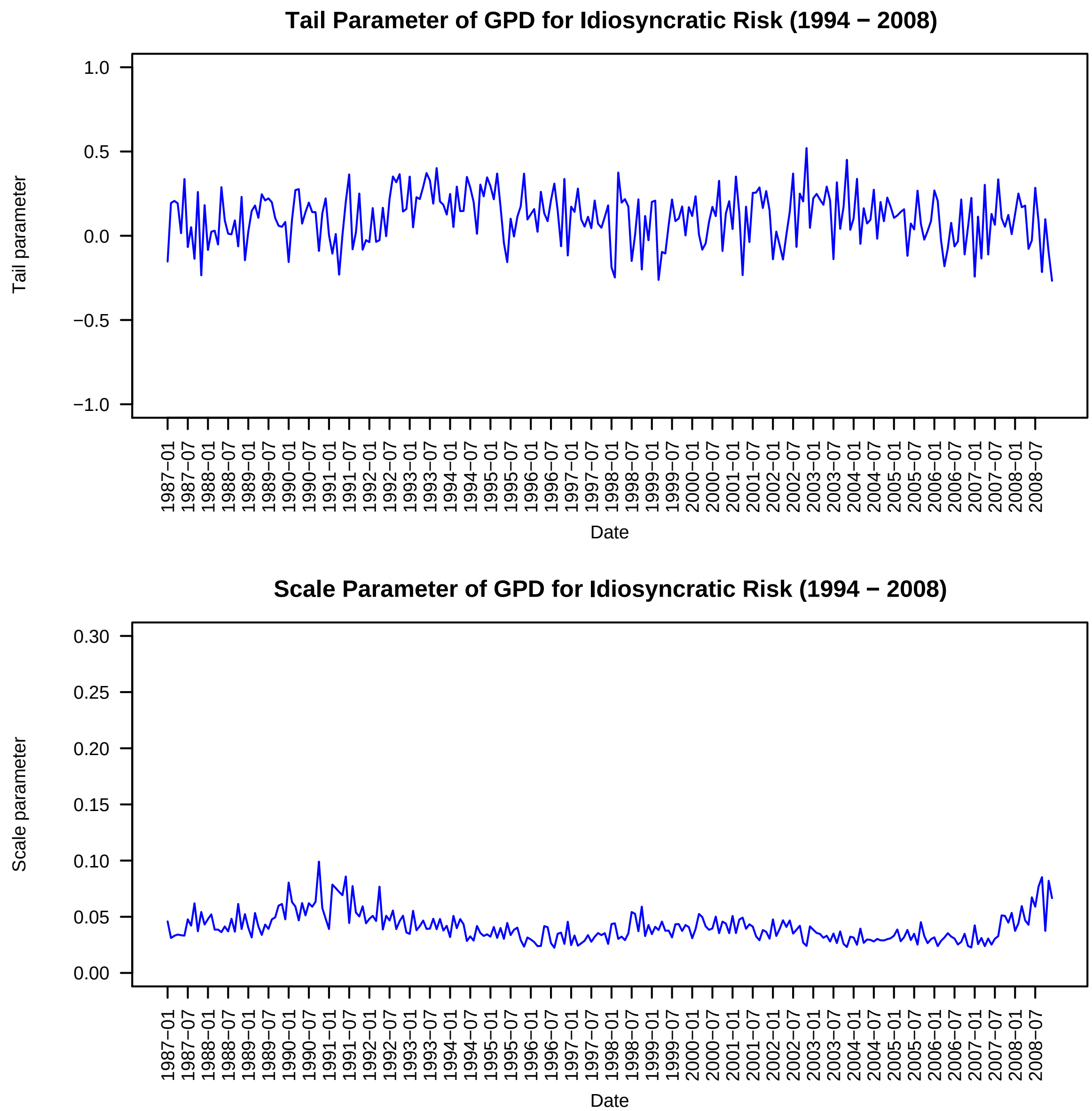

Figure 3. *Parameters of the Generalised Pareto Distribution for Idiosyncratic Value at Risk.* Parameter estimates are obtained through the method of probability-weighted moments, using the largest 10% of idiosyncratic losses. The median tail parameter is 0.125, corresponding to medium-tailed idiosyncratic loss distribution. The median scale parameter is 0.039.

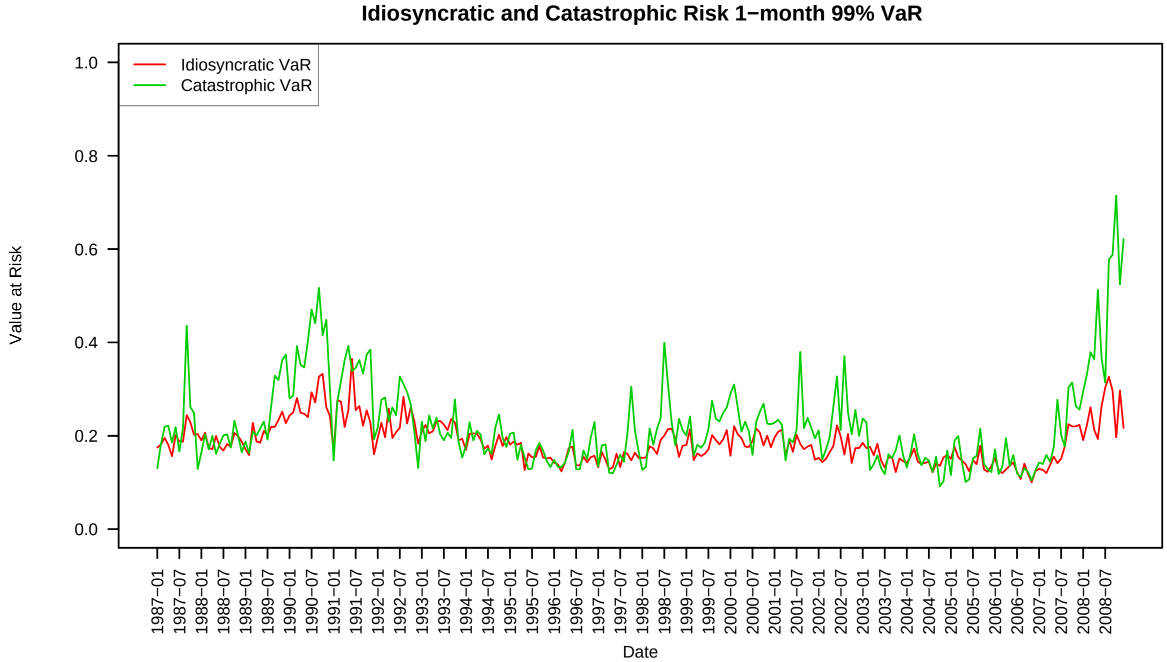

Figure 4. *Monthly 99% Idiosyncratic Value at Risk.* The panel presents the idiosyncratic loss that a company is likely to exceed with probability of 1%. The median VaR in terms of market capitalisation is 17.9%. The ratio of idiosyncratic to overall catastrophic VaR has a median value of 0.899. The increase of catastrophic risk has been driven by market-wide factors. Idiosyncratic risk has also increased, however its share in the catastrophic risk has declined.

allow producing more robust estimates of catastrophic and idiosyncratic risk, and the technique is warranted as long as the monthly loss distributions are similar for all months in the respective year. To test if that is the case, we have bootstrapped the confidence intervals for the GPD parameters in each month. Then for each year, it is examined whether there is a non-empty intersection of these intervals, implying that we cannot reject the hypothesis that all observations in the corresponding year come from a common return distribution whose parameters lie in the intersection of these intervals. Table 3 presents parameter estimates and 95% bootstrapped confidence intervals, confirming a non-empty interval intersection for each year. Therefore, we proceed with evaluating catastrophic and idiosyncratic risk through pooling monthly returns by years. Resulting quantile estimates from that exercise are presented in Figure 5. Based on the diagnostic mean residual plots shown in Figures 6 and 7, a fixed threshold of 12% is used for both catastrophic and idiosyncratic GPD evaluation.

Figure 5 suggests that idiosyncratic risk of financial institutions has converged to a similar level during most of the 1990's and 2000's. The financial turmoil in 2007 and 2008 though has resulted in a notable increase of idiosyncratic risk, and more so in the US compared to Europe. While much of the losses caused by subprime lending have been transferred to European financial institutions, the larger part of such losses has been

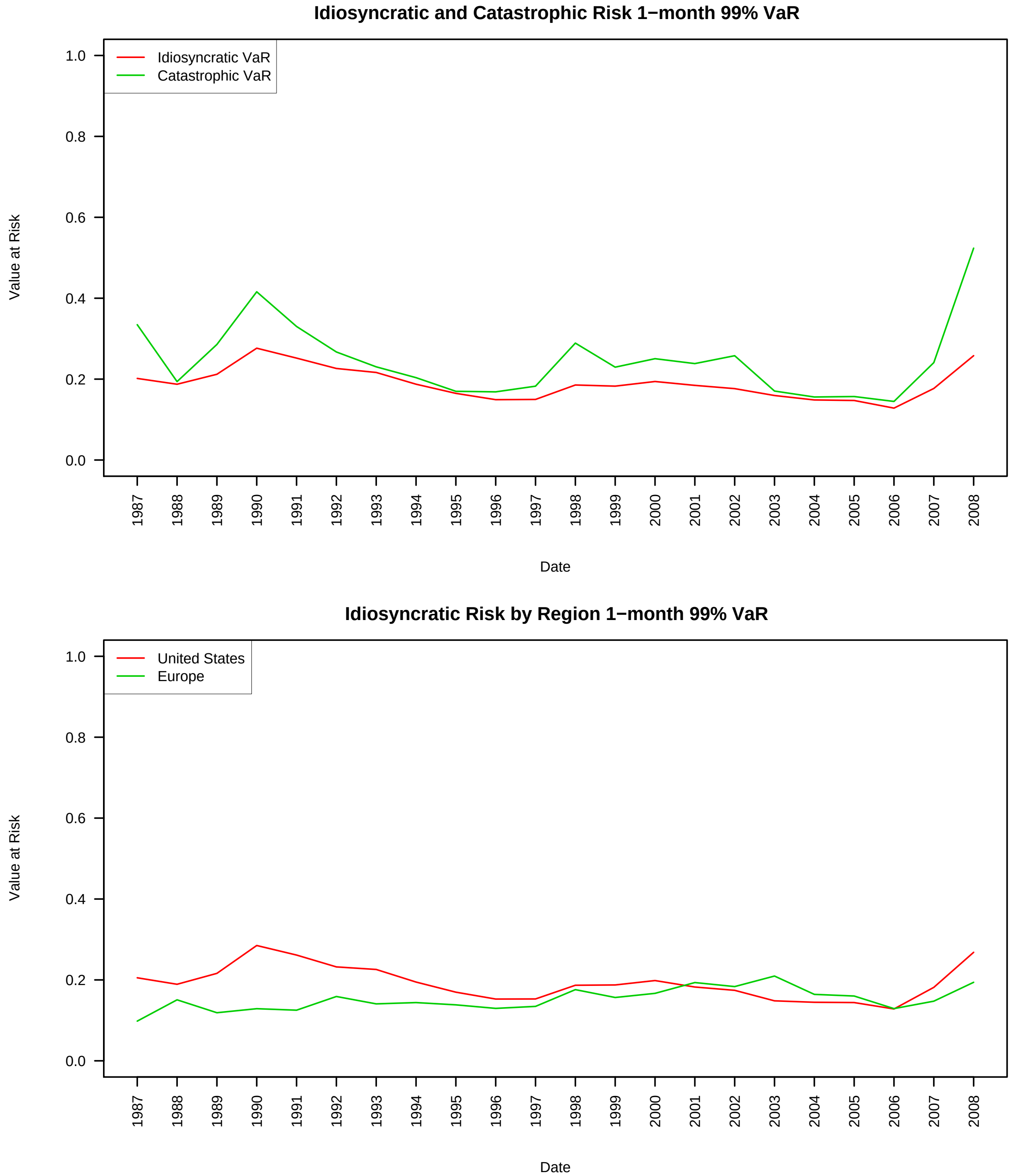

Figure 5. *99% Idiosyncratic Value at Risk and Breakdown by Regions.* The panels present the estimated idiosyncratic VaR using generalised Pareto distribution and losses larger than 12%. Panel A plots the estimates for idiosyncratic VaR using all monthly returns from the respective year. The median ratio of idiosyncratic to catastrophic VaR is 0.808. Panel B presents estimates obtained separately for the United States and Europe.

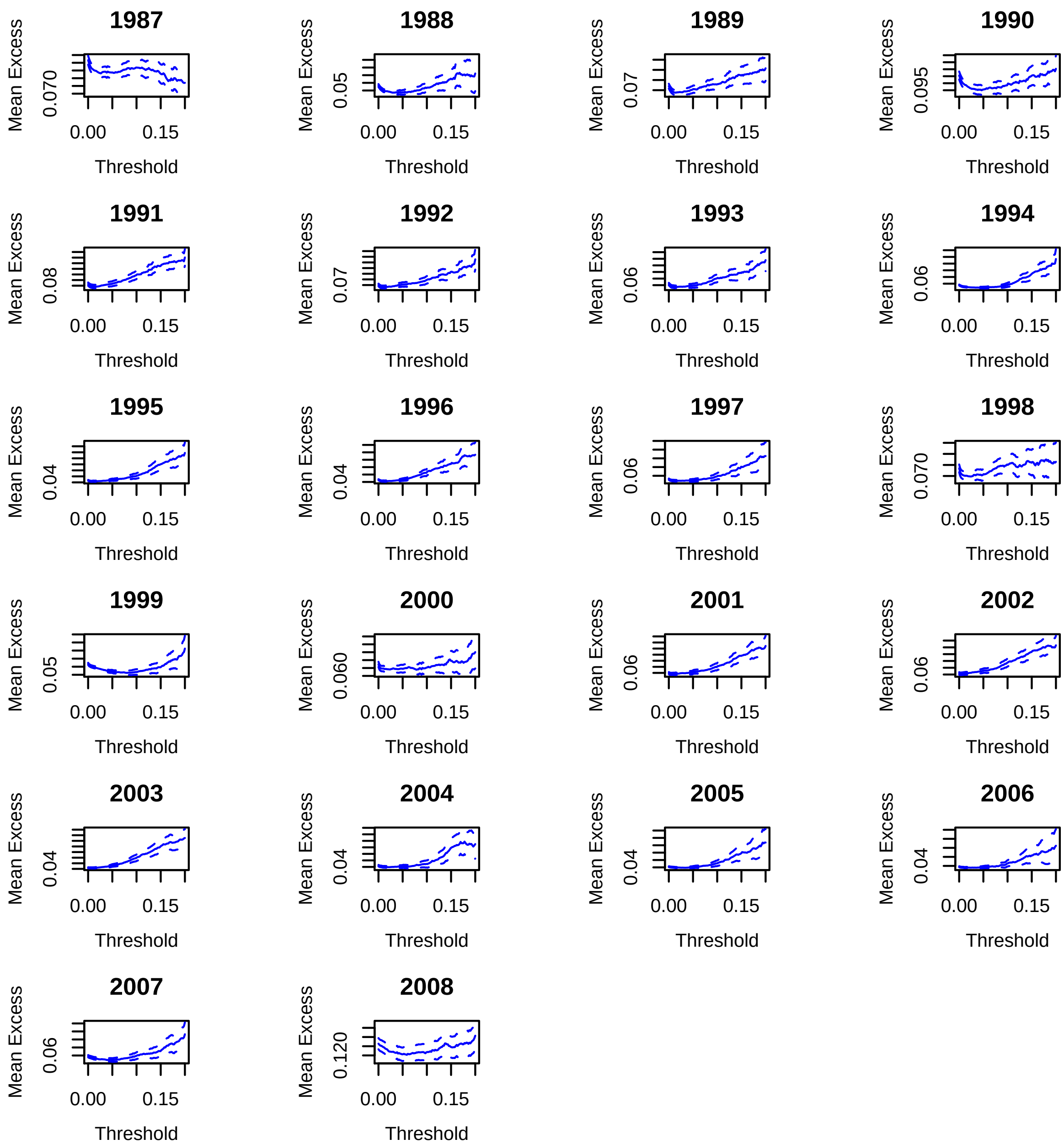

Figure 6. *Mean Residual Life Plot for Catastrophic Loss Distributions.* A good choice of threshold for estimating GPD is the lowest threshold beyond which the mean residual life plot is linear. We employ a threshold of 12% to estimate overall catastrophic VaR pooling all monthly returns in a given year.

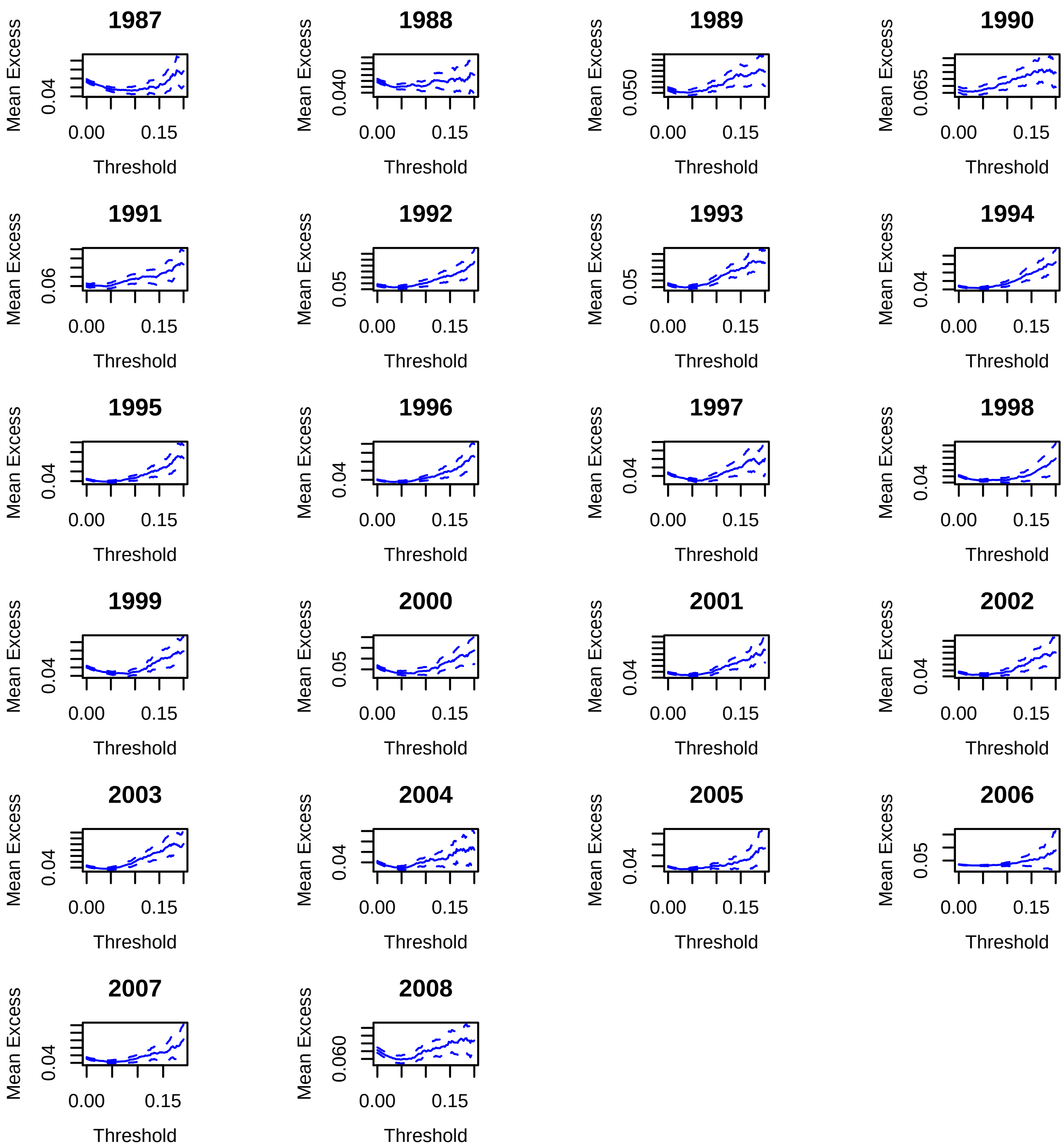

Figure 7. *Mean Residual Life Plot for Idiosyncratic Loss Distributions.* A good choice of threshold for estimating GPD is the lowest threshold beyond which the mean residual life plot is linear. We employ a threshold of 12% to estimate idiosyncratic VaR pooling all monthly returns in a given year.

Table 3

Point and 95% Confidence Interval Estimates for GPD Parameters

	Catastrophic risk				Idiosyncratic risk			
Year	Tail	Conf. interval	Scale	Conf. interval	Tail	Conf. interval	Scale	Conf. interval
1987	-0.164	(-0.291 , -0.058)	0.098	(0.087 , 0.111)	0.089	(-0.033 , 0.179)	0.042	(0.038 , 0.048)
1988	0.146	(0.061 , 0.220)	0.043	(0.039 , 0.048)	0.067	(-0.026 , 0.139)	0.042	(0.039 , 0.048)
1989	0.137	(0.071 , 0.199)	0.066	(0.060 , 0.073)	0.122	(0.050 , 0.190)	0.048	(0.043 , 0.053)
1990	0.087	(0.018 , 0.165)	0.098	(0.087 , 0.106)	0.106	(0.036 , 0.180)	0.065	(0.059 , 0.073)
1991	0.226	(0.151 , 0.272)	0.076	(0.070 , 0.087)	0.089	(0.008 , 0.161)	0.062	(0.055 , 0.067)
1992	0.214	(0.135 , 0.279)	0.06	(0.055 , 0.065)	0.178	(0.093 , 0.255)	0.049	(0.044 , 0.054)
1993	0.189	(0.127 , 0.255)	0.052	(0.047 , 0.057)	0.268	(0.196 , 0.321)	0.041	(0.037 , 0.045)
1994	0.287	(0.218 , 0.357)	0.037	(0.034 , 0.039)	0.23	(0.135 , 0.302)	0.037	(0.034 , 0.041)
1995	0.237	(0.152 , 0.299)	0.037	(0.035 , 0.041)	0.204	(0.117 , 0.269)	0.032	(0.030 , 0.036)
1996	0.305	(0.218 , 0.369)	0.033	(0.031 , 0.036)	0.179	(0.105 , 0.253)	0.03	(0.027 , 0.033)
1997	0.189	(0.102 , 0.262)	0.041	(0.038 , 0.045)	0.166	(0.080 , 0.222)	0.029	(0.027 , 0.032)
1998	0.022	(-0.047 , 0.110)	0.074	(0.066 , 0.080)	0.075	(-0.018 , 0.162)	0.041	(0.037 , 0.045)
1999	0.141	(0.061 , 0.209)	0.046	(0.043 , 0.050)	0.142	(0.065 , 0.209)	0.037	(0.034 , 0.040)
2000	0.07	(0.005 , 0.132)	0.061	(0.055 , 0.066)	0.087	(0.022 , 0.149)	0.044	(0.040 , 0.047)
2001	0.223	(0.172 , 0.291)	0.052	(0.046 , 0.055)	0.19	(0.120 , 0.250)	0.038	(0.035 , 0.042)
2002	0.226	(0.163 , 0.273)	0.057	(0.052 , 0.062)	0.142	(0.055 , 0.219)	0.038	(0.034 , 0.042)
2003	0.309	(0.244 , 0.369)	0.036	(0.033 , 0.038)	0.208	(0.130 , 0.271)	0.032	(0.029 , 0.035)
2004	0.126	(0.054 , 0.194)	0.035	(0.032 , 0.038)	0.139	(0.073 , 0.195)	0.031	(0.028 , 0.034)
2005	0.195	(0.098 , 0.281)	0.034	(0.031 , 0.037)	0.092	(0.005 , 0.163)	0.033	(0.030 , 0.036)
2006	0.094	(0.010 , 0.190)	0.035	(0.031 , 0.037)	0.097	(-0.019 , 0.179)	0.028	(0.026 , 0.031)
2007	0.139	(0.059 , 0.206)	0.052	(0.048 , 0.057)	0.161	(0.063 , 0.229)	0.036	(0.033 , 0.040)
2008	0.011	(-0.057 , 0.071)	0.129	(0.118 , 0.141)	0.079	(0.008 , 0.137)	0.06	(0.055 , 0.066)

incurred by American institutions, which results in higher catastrophic risk but also in higher idiosyncratic risk. We could further hypothesize that differences in the structure of financial systems in the US and Europe have played a complementary role. The US financial system, and therefore the US sample, features a larger number of smaller financial institutions, in comparison to Europe. In time of turmoil, smaller institutions are less likely to be able to raise additional capital or liquidity, or to be bailed out from the government, as opposed to larger institutions. Consequently, as the approach treats equally smaller and larger institutions, the catastrophic and idiosyncratic risk for the region with a more fragmented financial system is expected to be higher.

3.2. Cyclicality

In this section, we test for the existence of correlation between the quarterly catastrophic and idiosyncratic risk measures on the one side, and a set of macroeconomic variables on the other side. Allen and Bali (2007) and Allen *et al.* (2004) report statistically significant correlations between their risk measures (based on US data) and a broad set of macroeconomic factors. Here, we use the alternative risk measures introduced in the previous section, and next consider time series including measures from monetary accounts, foreign exchange rates, inflation, national accounts, market yields, interest rates and bond yields, as listed in Tables 4 and 5. The cyclicality analysis is focused on US data, since there are no consolidated accounts for the group of European countries in our sample. If Euro area macroeconomic indicators are used as proxies, they would not account for the developments in the UK, and there are countries in the Euro area that are not part of our sample.

The analysis measures correlation in terms of Pearson's correlation coefficient and uses the test statistic $\rho\sqrt{\frac{N-2}{1-\rho^2}}$, where ρ is the correlation coefficient and N is the number of data points. The test statistic follows t-distribution with $N-2$ degrees of freedom. We find that both idiosyncratic and catastrophic VaR are significantly correlated with most of the macroeconomic variables used in the test (refer to Tables 4 and 5). The σ parameters, which control the overall dispersion of GPD, are also significantly correlated with most macroeconomic variables, for both idiosyncratic and catastrophic risk distributions. The tail parameter ξ, which controls tail thickness, is not correlated with macroeconomic variables except with changes of M2, for catastrophic and idiosyncratic risk, and with industrial production, for idiosyncratic risk. The finding of cyclicality of idiosyncratic risk could be viewed as consistent with the observation of (Moosa, 2006) that operational risk is likely to be cyclical since some operational losses are more likely to occur in specific macroeconomic environments.

4. Conclusions

We have explored the implications of methodologies for quantification of idiosyncratic risk and proposed an alternative approach. First, overall catastrophic risk is quantified by fitting the largest negative stock returns to generalized Pareto distribution, using the technique of probability-weighted moments. Next, we employ hierarchical factor analysis to identify the common factors underlying stock returns. Idiosyncratic risk is thus associ-

Table 4

Correlations between Catastrophic VaR and GPD Parameters, and Selected Macroeconomic Variables

	Correlation			N	Test statistic			P-value		
Series	VaR	σ	ξ		VaR	σ	ξ	VaR	σ	ξ
M1 SA	0.477	0.46	-0.069	89	5.058	4.829	-0.644	0	0	0.519
M2 SA	0.15	0.163	-0.293	89	1.42	1.538	-2.86	0.156	0.124	0.004
M3 SA	-0.33	-0.354	-0.211	77	-3.03	-3.274	-1.874	0.002	0.001	0.061
GNI	-0.427	-0.473	0.087	89	-4.399	-5.01	0.819	0	0	0.413
GDP	-0.382	-0.393	0.032	89	-3.853	-3.988	0.301	0	0	0.764
Bank Prime Loan Rate	-0.372	-0.381	0.074	89	-3.741	-3.845	0.688	0	0	0.492
Mortgage Rate	-0.076	-0.09	-0.004	89	-0.712	-0.847	-0.041	0.476	0.397	0.967
Govt Bond Yield: 10 Year	-0.16	-0.179	-0.002	89	-1.51	-1.697	-0.023	0.131	0.09	0.982
Govt Bond Yield: 3 Year	-0.287	-0.304	0.078	89	-2.79	-2.972	0.725	0.005	0.003	0.468
Share Prices	-0.435	-0.396	0.023	89	-4.504	-4.017	0.213	0	0	0.831
Nasdaq Composite	-0.284	-0.29	0.103	89	-2.762	-2.827	0.963	0.006	0.005	0.336
S&P Industrials	-0.39	-0.375	0.033	89	-3.948	-3.77	0.303	0	0	0.762
Amex Average	-0.467	-0.445	0.04	89	-4.926	-4.635	0.374	0	0	0.708
PPI / WPI	-0.153	-0.161	-0.073	89	-1.44	-1.518	-0.682	0.15	0.129	0.495
CPI All Items City Average	-0.005	0.005	-0.16	89	-0.042	0.045	-1.514	0.966	0.964	0.13
Industrial Production NSA	-0.374	-0.436	0.102	89	-3.758	-4.519	0.957	0	0	0.339
Industrial Production SA	-0.438	-0.498	0.144	89	-4.546	-5.35	1.361	0	0	0.173
Unemployment Rate	0.17	0.174	-0.028	89	1.606	1.65	-0.265	0.108	0.099	0.791
NEER From INS	0.198	0.26	-0.154	89	1.886	2.511	-1.456	0.059	0.012	0.145
NEER From ULC	0.094	0.162	-0.139	89	0.879	1.533	-1.31	0.38	0.125	0.19
REER Based On RNULC	0.124	0.173	-0.156	89	1.161	1.641	-1.477	0.246	0.101	0.14
US Dollars Per SDR, eop	0.088	0.033	-0.015	89	0.82	0.309	-0.139	0.412	0.758	0.89

Table 5

Correlations between Idiosyncratic VaR and GPD Parameters, and Selected Macroeconomic Variables

	Correlation			N	Test statistic			P-value		
Series	VaR	σ	ξ		VaR	σ	ξ	VaR	σ	ξ
M1 SA	0.416	0.385	0.008	89	4.261	3.891	0.071	0	0	0.944
M2 SA	-0.075	-0.002	-0.235	89	-0.697	-0.023	-2.258	0.486	0.982	0.024
M3 SA	-0.439	-0.365	-0.209	77	-4.236	-3.395	-1.855	0	0.001	0.064
GNI	-0.283	-0.297	0.032	89	-2.755	-2.896	0.297	0.006	0.004	0.766
GDP	-0.214	-0.183	-0.043	89	-2.042	-1.739	-0.399	0.041	0.082	0.69
Bank Prime Loan Rate	-0.294	-0.328	0.114	89	-2.867	-3.243	1.066	0.004	0.001	0.286
Mortgage Rate	-0.107	-0.066	-0.111	89	-1.007	-0.62	-1.044	0.314	0.535	0.296
Govt Bond Yield: 10 Year	-0.156	-0.103	-0.15	89	-1.478	-0.965	-1.412	0.139	0.335	0.158
Govt Bond Yield: 3 Year	-0.24	-0.185	-0.128	89	-2.304	-1.755	-1.201	0.021	0.079	0.23
Share Prices	-0.304	-0.259	-0.054	89	-2.975	-2.5	-0.505	0.003	0.012	0.613
Nasdaq Composite	-0.166	-0.15	0.003	89	-1.568	-1.418	0.026	0.117	0.156	0.979
S&P Industrials	-0.258	-0.222	-0.046	89	-2.486	-2.123	-0.429	0.013	0.034	0.668
Amex Average	-0.341	-0.295	-0.059	89	-3.378	-2.874	-0.554	0.001	0.004	0.58
PPI / WPI	-0.044	-0.029	-0.04	89	-0.41	-0.269	-0.372	0.682	0.788	0.71
CPI All Items City Average	0.176	0.21	-0.122	89	1.663	2	-1.147	0.096	0.045	0.252
Industrial Production NSA	-0.238	-0.327	0.189	89	-2.283	-3.228	1.792	0.022	0.001	0.073
Industrial Production SA	-0.307	-0.402	0.207	89	-3.009	-4.099	1.976	0.003	0	0.048
Unemployment Rate	0.172	0.196	-0.011	89	1.631	1.859	-0.099	0.103	0.063	0.921
NEER From INS	0.156	0.169	-0.01	89	1.471	1.601	-0.097	0.141	0.109	0.923
NEER From ULC	0.018	0.054	-0.07	89	0.173	0.503	-0.651	0.863	0.615	0.515
REER Based On RNULC	0.011	0.044	-0.104	89	0.106	0.41	-0.98	0.915	0.682	0.327
US Dollars Per SDR, eop	0.063	0.035	0.003	89	0.586	0.331	0.027	0.558	0.74	0.979

ated with the residual from OLS regressions of stock returns on subsets of common factors, identified through backward stepwise elimination. We find that the average financial institution is exposed to 3 or 4 factors. Idiosyncratic risk is then quantified through fitting residual losses to GPD.

We evaluate idiosyncratic and catastrophic VaR, implied by the GPD-parameter estimates, and corresponding to an overall or idiosyncratic loss that a company is likely to exceed with 1% probability. Thus the empirical analysis produces a median ratio of idiosyncratic to total VaR for financial institutions as standing at 80.8%, compared to 52% reported by Allen and Bali (2007) . However, our results show that the ratio varies significantly over time. *During calm periods, idiosyncratic risk is the major risk for financial institutions. While throughout more turbulent episodes, like the late 1980's and the recent 2007-2008, the co-dependency between stocks increases and the ratio of idiosyncratic to catastrophic VaR diminishes. Finally, we find that idiosyncratic risk has significantly increased in 2007 and 2008, and the impact on the risk profile of US financial institutions has been considerably more pronounced.*

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