Measures of Extreme Loss Risk – An Assessment of Performance During the Global Financial Crisis

Jamshed Y. Uppal
Catholic University of America

The paper evaluates the performance of various Value-at-Risk (VaR) measures during the Global Financial Crisis (GFC) period in five developed and five emerging markets. The models based on the Extreme Value Theory (EVT) fit the observed distribution of extreme values well, in both pre-crisis and the crisis periods, with the exception of the US market during the crisis period. However, the extreme loss estimates based on pre-GFC period were not a reliable guide to the risk of actual losses during the financial crisis. The back-testing procedure shows that while the dynamic EVT-VaR model performed better than the competing models, the results are mixed for different markets and quintile levels.

INTRODUCTION

Measurement of market risk is important for all market participants, in particular for financial institutions for devising risk management strategies. Value at Risk (VaR) approach has gained acceptance as the standard measure of market risk, which is defined as the maximum possible loss to the value of financial assets with a given probability over a certain time horizon. However, the task of implementing the VaR approach still remains a challenge. The main issue is of accurately modeling the return distributions which in empirical research are found to be fat tailed and skewed in contrast to the normal distribution as assumed. There is an extensive literature in finance (highlighted by Nassim Taleb's, *The Black Swan*, 2010) that underscores the importance of rare events in asset pricing and portfolio choice. The rare events may materialize as large positive or negative investment returns, a stock market crash, major defaults, or the collapse of risky asset prices.

An understanding of the tails of return distributions has, therefore, been advocated as the key to sound management of financial exposures. In response, VaR risk measures based on the *Extreme Value Theory* (EVT) have been developed to model tail risk which allows one to estimate the probabilities of the extreme movements in financial markets. The basic idea behind EVT is that in applications where one is concerned about the risk of extreme loss, it is more appropriate to separately model the tails of the return distribution. At a more fundamental level, the issue is whether or not the return distributions remain stable over time. EVT's usage to model risk, however, assumes that the probability distribution parameters extracted from the historical data are stable.

EVT uses extreme observations to model the tails of a random variable, which are typical only a handful in a given period. The backdrop of the global financial crisis of 2007-09 (GFC) provides us with an historical experiment to examine the tails of stock return distributions. The GFC has had widespread and severe impact on the financial markets across countries. Stock market volatility increased many folds during the period of crisis, most markets experiencing extreme returns. Large swings in the stock prices were observed with unprecedented frequencies which provide us with a rich data set for evaluating EVT based risk models.

Up till now only a few studies have examined the impact of GFC on the stock market behavior. Uppal and Mangla (2012) have documented shifts in distributional parameters in financial turbulence. There have, however, been a number of studies using EVT following previous stock markets crashes and periods of high volatility in the developed as well as the emerging markets. For example, Gencay and Selcuk (2004) employ VaR models using EVT to a sample of emerging markets after the Asian financial crisis of 1998. Onour (2010) presents estimation of extreme risk in three stock markets in the Gulf Cooperation Council (GCC) countries, Saudi, Kuwait, and United Arab Emirates, in addition to the S&P500 stock index, using the Generalized Pareto Distribution (GPD). Djakovic et al. (2011) investigate the performance of extreme value theory with the daily stock index returns for four different emerging markets, the Serbian, Croatian, Slovenian and Hungarian stock indices. Bhattacharyya and Ritolia (2008) suggest a Value-at-Risk (VaR) measure for the Indian stock markets based on the Extreme Value Theory (EVT) for determining margin requirements for traders.

The objective of this study is to examine the performance of the market risk measures based on the Extreme Value Theory in the major developed and emerging markets. Our study addresses, firstly, the issue of the stability of parameters and finds that the pre-crisis and the GFC periods are characterized by tail-distributions with significantly different parameters. Secondly, we compare the performance of four different EVT models in predicting the incidence of extreme losses during the GFC period by employing a dynamic back-testing procedure. We find that while the dynamic EVT based VaR model performed better than the competing models, the results are mixed for different markets and quintile levels. Our results suggest that the usefulness of EVT in assessing market risk in times of extreme turbulence such as the GCF may be rather limited.

EVT MODELS OF DISTRIBUTION TAILS

Value at Risk (VaR) is a high quintile (typically the 95th or 99th percentile) of the distribution of negative returns and provides an upper bound on the losses with a specified probability. However, classical VaR measures based on the assumption of normal distribution of the stock returns underestimate risk as the empirical return distributions exhibit heavier tails. One alternative for dealing with the non-normality of the financial asset distributions has been to employ historical simulation methodology which does not make any distributional assumptions, and the risk measures are calculated directly from the past observed returns. However, the historical approach sill assumes that the distribution of past stock prices will be stable in the future.

Another approach is to use Extreme Value Theory to construct models which account for such thick tails as are empirically observed. According to EVT, the form of the distribution of extreme returns is precisely known and independent of the process generating returns; see for example, Longin (1996), Longin and Solnik (2001) and Chou (2005), and Diebold et al. (2000) for a note of caution. The family of extreme value distributions can be presented under a single parameterization, known as the Generalized Extreme Value (GEV) distribution.

There are two ways of modeling extremes of a stochastic variable. One approach is to subdivide the sample into m blocks and then obtain the maximum from each block, the *block maxima method*. The distribution of block maxima can be modeled by fitting the GEV to the set of block maxima. The alternative approach takes large values of the sample which exceed a certain threshold u, the peak-over-threshold (POT) approach. The distribution function of these *exceedances* is then obtained by employing fat-tailed distributions models such as the Generalized Pareto Distribution (GPD). The POT approach is the preferred approach in modeling financial time series.

Fisher and Tippett (1928) developed the theory describing the limiting distribution of sample maxima and the distribution of *exceedances* above a threshold. Building on their work, Pickands (1975), Balkema and de Haan (1974) state the following theorem regarding the conditional excess distribution function.

Theorem: For a large class of underlying distribution functions the conditional excess distribution function F_u (y) for a large value of μ, is well approximated by:

$$F_{\mu}(y) \simeq G_{\beta,\xi}(y) \; ; \; \mu \rightarrow \infty$$

$$G_{\beta,\xi}(y) = 1 - (1 + \xi y/\beta)^{-1/\xi} , \xi \neq 0$$

$$= 1 - e^{-y/\beta}, \xi = 0 \tag{1}$$

for y $\in[0, x_F - \mu]$ if $\xi>0$, and $y\in[0,- \beta/\xi]$ if $\xi<0$. $y = (x - \mu)$, and μ is the threshold; $x_F\leq\infty$ is the right endpoint of F. $G_{\beta,\xi}(y)$ is known as the Generalized Pareto Distribution (GPD). $F_{\mu}(y)$ can also be reformulated in terms of F(x) describing the entire time series X_t to construct a tail estimator for the underlying distribution. Using the ratio $(n - N_u)/n$ as an estimator of F(u) where n is the total number of observations and N_u is the number of observations above the threshold, the tail estimator is defined as:

$$F(x) = 1 - N_u/n(1 + \xi(x-\mu)/\beta)^{-1/\xi} \tag{2}$$

for $x>u$. For a given probability, $q>F(u)$, the VaR estimate is obtained by inverting the tail estimation formula above to get (see Embrechts et al., 1997).

$$VaR_q = \mu + \beta/\xi\ ((n/N_u(1 - q)^{-\xi} - 1) \tag{3}$$

The estimation of the GPD parameters, ξ and β, is made using the method of maximum likelihood. Alternatively, Hill's tail index estimator is calculated as:

$$\xi = \frac{1}{N_{\mu}} \sum_{i=1}^{i=n} \left(\ln X_{n-i+1} + \ln X_{n-N_{\mu}} \right) \tag{4}$$

DYNAMICS OF VOLATILITY

Although EVT is an appropriate approach for modeling the tail behavior of stock returns, the assumption of constant volatility is contradicted by the well documented phenomenon of volatility clustering i.e., large changes in assets values are followed by large changes in either direction. In the presence of the GARCH effects applying EVT to the unadjusted return series would not be appropriate. VaR calculated in a period of relative calm may seriously underestimate risk in a period of higher volatility. Therefore, VaR models employ various dynamic risk measures such as the Random Walk model, the GARCH, and the Exponentially Weighted Moving Average (EWMA); see (Hull and White, 1998). The time varying volatility was first modeled as an ARCH (q) process (Bollerslev et al., 1992) which relates time t volatility to past squared returns up to q lags. The ARCH (q) model was expanded to include dependencies up to p lags of the past volatility. The expanded models, GARCH (p,q) have become the standard methodology to incorporate dynamic volatility in financial time series (see Poon & Granger (2003). In addition the return series may be auto-correlated. Therefore, we employ an AR(1)-GARCH (1,1) model in this paper with the following specification:

$$X_t = \phi X_{t-1} + \sigma_t Z_t \tag{5}$$

$$\sigma^2_t = w + \alpha(X_{t-1} - \mu_{t-1})^2 + \beta\ \sigma^2_{t-1} \tag{6}$$

where σ_t is the volatility of the return on day t, μ_t is the expected return and X_t is the actual return. The stochastic variable, Z_t, represents the residuals or the innovations of the process, and is assumed to be independently and identically distributed. A condition of stability is that w, α, $\beta>0$, and $\alpha + \beta < 1$.

HYPOTHESIS, DATA AND METHODOLOGY

In this paper we focus on the extreme returns experienced for a set of 10 countries, including the G5 countries - France, Germany, Japan, the United Kingdom, and the United States and the five leading emerging economies - Brazil, People's Republic of China, India, Mexico, and South Africa. Parameters of the Extreme Value Distribution for each country are estimated for the pre- and the GFC period. We hypothesize as null that the parameters of the *extremal distributions* have the same values in the pre-crisis and the crisis periods.

Considering the time-line of the progression of the GFC, we mark the onset of the downturn in the stock markets as the first of July, 2007. We go back about four years to establish a base case. Although, the economic recession was formally declared to have ended in July 2009, the markets continued to be volatile mainly due to European sovereign debt crisis till towards the end of 2011, when the volatility seems to have subsided. Therefore, our study spans a time period from January, 2003 to December, 2011, evenly divided in two sub-periods of 1175 observations each, as follows:

1. Pre Crisis Period: 12/30/2002 to 06/29/2007
2. Crisis Period: 07/02/2007 to 12/30/2011

Following the approach suggested by McNeil and Frey (2000), we apply EVT to the residuals from an AR-GARCH model. We then apply the GPD tail estimation procedure described in the previous section. Our estimation procedure can be summarized as a two-step procedure: (i) An AR(1)-GARCH(1,1) model is fitted to the historical return data by pseudo maximum likelihood method. The residuals of this model are extracted; (ii) Hill's tail estimation procedure is employed on the standardized residuals and $VaR(Z)_q$ is calculated using equation (3).

The first step in applying the POT procedure is to determine a threshold for identifying the tail region. It involves a trade-off: a very high threshold level may provide too few points for estimation, while a low threshold level may render GPD a poor approximation, as the GPD is a limiting distribution when $\mu \to \infty$. Several researchers, e.g., McNeil (1997, 1999), suggest employing a high enough percentile as the threshold. Following other researchers we use a 95% quintile to define the threshold (negative) return, μ, taking extreme 60 observations (about 5%) to estimate the GPD parameters in both the pre-crisis and the crisis periods. We also employ an approach suggested by Kluppelberg (2001) for determining the threshold value by examining the mean excess function of X_t over the threshold for linearity (not reported here), which confirms the appropriateness of the selecting the number of extreme observations (N_u).

We further back-test the method on the historical series of negative log-returns $\{x_1, x_2, ..., x_n\}$ starting from January 2003. We calculate $\hat{x}^t_q$ on day t in the set $T=\{m, m+1, \ldots, n-1\}$ using a time window of m days each time. Similar to McNeil and Frey (2000), we set m=1175, and consider 60 extreme observations (about 5%) from the upper tail of the innovation distribution i.e., we fix k=60 each time. On each day $t \in T$, we fit a new AR(1)-GARCH(1,1) model and determine a new Hill tail estimate. The dynamic or conditional VaR is estimated as: $\hat{x}^t_q = \mu_{t+1} + z_q \sigma_{t+1}$, where z_q denotes the qth quintile of the noise variable Z_t. We compare $\hat{x}^t_q$ with x_{t+1}, for $q \in \{0.995, 0.99, 0.975, 0.95\}$. A violation is said to occur whenever $\hat{x}^t_q > x_{t+1}$. We then apply a one-sided binomial test based on the number of violations for evaluating the model's adequacy.

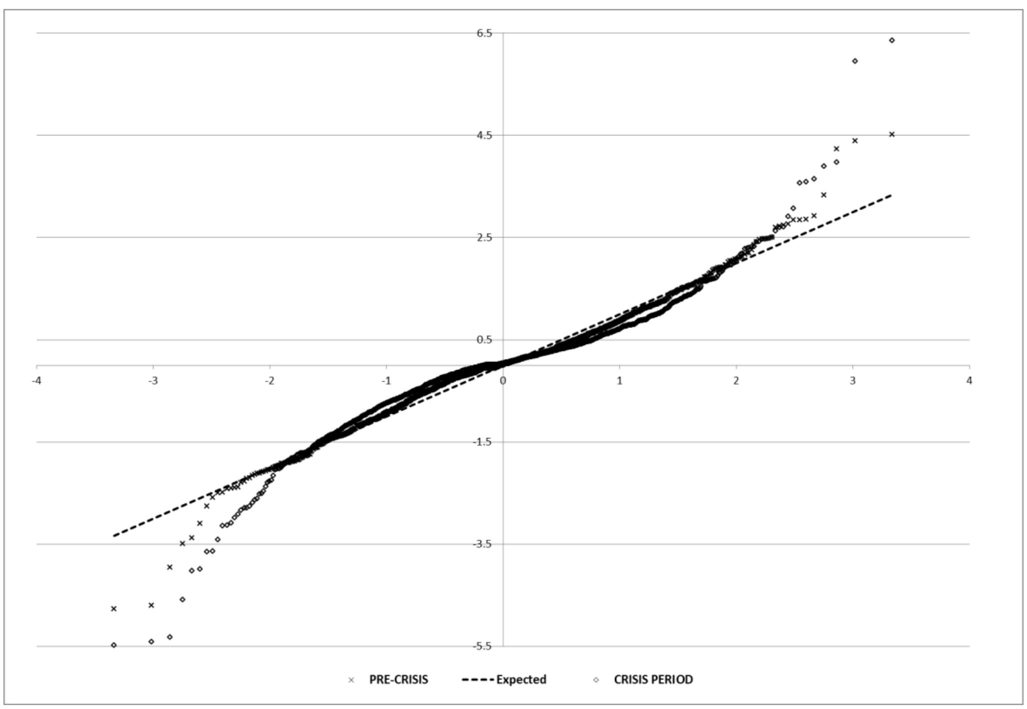
In the back-testing procedure we compare the Dynamic EVT model as described above with three other well-known parametric methods of VaR estimation. The first one is the Static Normal method in which returns are assumed to be normally distributed and the VaR is calculated as the *qth* upper quintile from the normal distribution. Second one is the Dynamic or Conditional Normal in which AR(1)-GARCH(1,1) model with normal innovations is fitted by the method of maximum likelihood to the return data and VaR_q is estimated. The third is the Static EVT method in which returns are assumed to have fat-tailed distribution and extreme value theory is applied to the left tail of the returns.

RESULTS

Table 1 provides descriptive statistics for the ten stock markets covered in this study, both for the pre-GFC and the crisis period, computing market returns as first log differences in the index values; $R_t = ln(Index_t/Index_{t-1})$. The descriptive statistics of the stock returns clearly show that the return distributions have heavier tails than of a normal distribution. The Jarque-Bera statistic is significant even at very low levels. High values of the Kurtosis statistics indicate that the distributions have fat tails. The negative value of skewness indicates that the left tail (the tail of interest for VaR calculation) is particularly thick. Hence, we reject the null hypothesis that the stock returns follow a normal distribution.

In order to compare the pre-crisis statistics with those of the crisis period, we conduct tests for equality of means and variances. The tests fail to reject the null of equality of means in all markets except Japan and Mexico, while the equality of variances is strongly rejected for all markets. For these two countries, we observe a strong bullish trend in the pre-crisis period which was broken by the on-set of GFC. There is a marked increase in the standard deviations in the crisis period as compared to the pre-crisis period. The skewness statistic in the pre-crisis period is generally negative contrary to the expected positive sign for all markets except UK. However, skewness has mixed signs for different countries during the crisis period. Comparing Kurtosis statistic for the pre- and crisis period, we see an increase in its value for the sample countries, except for China, India and South Africa. In some cases kurtosis increased dramatically, for example, in the US market, its value jumped from 4.97 to 9.19. For illustration, Figure 1 below is a QQ-plot for S&P500 index for the pre-GFC and the crisis period, which clearly shows the departure from normality in the pre-crisis period which was exacerbated in the crisis period.

FIGURE 1
QQ-PLOT (NORMAL DISTRIBUTION) – S&P500



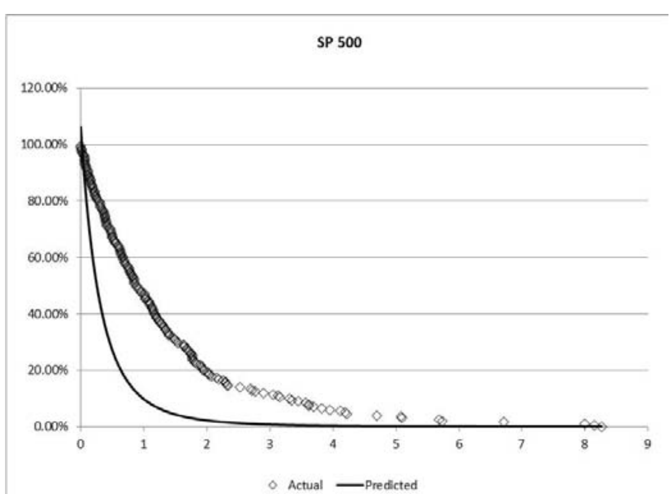
The descriptive statistics show that the returns distributions were fat tailed even in the base period; the tails became dramatically fatter during the crisis period. Therefore, the nature of distributions provides support for modeling the tails of the distribution using EVT.

The next step was to extract residuals from applying AR(1)-GARCH(1,1) model to each market. The results of the estimation procedure are given in Table 2. All the coefficients of the volatility equations are significant for all 10 stock markets, both for the pre- as well for the crisis period. The Durbin-Watson statistics are within the acceptable range implying that the model's specification is tenable and the residuals are iid.

Table 3 provides results for the estimation of GPD parameters and distribution fit tests for the left tails of the return distributions. The first two column panels, "Estimation of Empirical Distribution," report the estimated parameters as well as the test values and the achieved p-values for the Kolmogorov-Simirnov (D), Cramer-von Mises (W^2) and Anderson-Darling (A^2) criteria for judging the goodness of fit of the cumulative distribution function for the GPD compared to the empirical distribution function. For all markets, except for the USA for the crisis period, the tests fail to reject the null hypothesis that the fitted GPD distribution parameters are the same as the true parameters. Therefore, these provide statistical evidence that the GPD is a good fit for the empirical probability distribution of the extreme returns, both in the pre-crisis as well as in the crisis period. It is noteworthy, however, that the US market return distribution in the crisis period does not seem to conform to the GDP as per the Extreme Value Theory. The panel also provides the estimated values for the tail index (inverse of ξ in the GPD function, $G_{\beta,\xi}(y)$) and the threshold value, μ, for the sample countries. These tail index estimates are statistically significant at very high levels as indicated by the low achieved *p*-values. Comparing the index values for the pre-crisis and the crisis period one can observe that the tail index values are substantially higher in the crisis period than in the pre-crisis period (except for China and Mexico) indicating much fatter tails in the crisis period.

Next, we test whether the parameters estimated over the pre-crisis period would also provide a good fit for the distribution of extreme values in the crisis period. The results of the tests are shown in the third column panel of Table 3, "Test of Distribution." The goodness of fit statistics mentioned above (D, W^2, A^2) tests are reported which strongly reject the null hypotheses that the sample observations arose from the GPD distributions with the parameters values estimated over the pre-crisis period. It appears that although the extreme values (left tails) in each period is well described by the General Pareto Distribution in accordance with the extreme value theory, the parameters of the distributions in each period are quite different from one period to the other.

FIGURE 2
ACTUAL VS PREDICTED LOSS DISTRIBUTION OF EXCEEDANCES – S&P500



As an illustration Figure 2 shows, for the S&P500 index, the extreme distribution predicted on the basis of the parameters estimated over the pre-crisis period. The horizontal axis shows the percentage (negative) returns over the threshold. The vertical axis shows the percentage of observations that exceeded the thresh-hold. The divergence of predicted losses from the actual losses is indicative of the intrinsic problem of instability of parameters.

Table 4 provides the back testing results with theoretically expected number of violations and the number of violations using the Dynamic EVT (or GARCH-EVT model), the Static EVT model, the Dynamic Normal model (GARCH-model with normally distributed innovations) and the Static Normal model in which returns are assumed to be normally distributed. The various VaR estimation methods are tested by comparing one-day ahead forecasted losses with the actual losses; a violation occurs when the actual loss exceeds the estimated loss. Tests of violation counts against the expected number of violations based on the binomial distribution can show if there has been a systematic under- or over-estimation. The table reports the number of violations that occurred during the crisis period under various VaR methods and the corresponding achieved *p*-values. The tests are conducted for four different quintiles, i.e., $q \in \{.995, .99, .975, .95\}$. Reported *p*-values of less than 0.10, 0.05 and .01 implies a failure of the method at 10%, 5%, and 1% significance levels (indicated by *,**, and ***) respectively.

The results show that the two methods not employing EVT, the Static Normal and the Dynamic Normal, failed remarkably; only in two out of 40 cases (ten markets and four quintile levels), the realized number of violations were statistically close to the predicted at 10% or better significance level. The Static EVT method performs slightly better, but fails in 30 out of 40 cases. The VaR measure based on the Dynamic EVT procedure seems to have performed the best of the four methods. However, it still fails in the majority of the cases (21 out of 40), doing particularly poor for the 0.975 and 0.95 quintiles, failing in 8 and 6 markets respectively at the 10% significance level.

SUMMARY AND CONCLUSIONS

A major short coming of the various VaR measures has been that the actual return distributions exhibit much fatter tails than the normal distribution would specify. As a remedy EVT has been employed to explicitly incorporate extreme values, and modifying VaR accordingly. Typically, there would be limited number of extreme observations during a given period, which makes it hard to test and apply EVT as parameters are estimated with low levels of confidence. The global financial crisis provides an opportunity to test the EVT more rigorously as the period is characterized by an abundance of extreme returns.

We apply the EVT to five developed and five emerging markets in the pre-crisis and crisis periods. We find that the GPD model fits the observed distribution of extreme values well, in both pre-crisis and the crisis periods, with the exception of the US market during the crisis. It appears that the financial crisis which originated in the US markets, affected the stock return distributions in a peculiar way which is not accurately captured by the extreme value theory. We note that the estimated tail-indices of the GPD distribution are quite different in the two periods. The implication is that the extreme loss estimates based on one period may not be a reliable guide to the risk of actual losses during a period of financial turbulence and crisis. Our back-testing procedure shows that while the dynamic EVT based VaR performed better than the competing models, the results are mixed for different markets and quintile levels.

The study underscores the fundament problem of dealing with uncertainty; the parameters of the empirical distribution may unexpectedly shift in times of financial turbulence and may render quantitative models of risk assessment unhelpful.

REFERENCES

Balkema, A., & de Haan, L. (1974). Residual Life Time at Great Age. *Annals of Probability*, 2, 792-804.

Bhattacharyya, M. & Ritolia, G. (2008). Conditional VaR Using EVT - Towards a Planned Margin Scheme. *International Review of Financial Analysis*, 17, 382-395.

Bollerslev, T., Chou, R., & Kroner, K. (1992). ARCH Modeling in Finance. *Journal of Econometrics*, 52, 5-59.

Chou, R. Y. (2005). Forecasting Financial Volatilities with Extreme Values: The Conditional Autoregressive Range (CARR) Model. *Journal of Money, Credit and Banking*, 37, (3), 561-582.

Diebold, F. X., Schuermann T. & Stroughair, J.D. (2000). Pitfalls and Opportunities in the Use of Extreme Value Theory in Risk Management. *Journal of Risk Finance*, 1, 30-36.

Djakovic, V., Andjelic, G. & Borocki, J. (2011). Performance of Extreme Value Theory in Emerging Markets: An Empirical Treatment. *African Journal of Business Management*, 5, (2), 340-369.

Embrechts, P., Kluppelberg C., & Mikosch T. (1997). Modeling Extreme Events for Insurance and Finance. Berlin: Springer.

Fisher, R. & Tippet, L. (1928). Limiting Forms of the Frequency Distribution of the Largest or Smallest Member of a Sample. *Proceedings of the Cambridge Philosophical Society*, 24, 180-190.

Gencay R. & Selcuk, F. (2004). Extreme Value Theory and Value-at-Risk: Relative Performance in Emerging Markets. *International Journal of Forecasting*, 20, 287-303.

Hull, J. & White, A. (1998). Incorporating Volatility Updating Into the Historical Simulation Method for Value At Risk. *Journal of Risk*, 1(1), 5-19.

Kluppelberg, C. (2001). Development in Insurance Mathematics. In B. Engquist, & W. Schmid (Eds.), *Mathematics Unlimited - 2001 and Beyond* (pp. 703−722). Berlin: Springer.

Longin, F. & Solnik, B. (2001). Extreme Correlation of International Equity Markets. *The Journal of Finance*, 56, (2), 649-676.

Longin, F. M. (1996). The Asymptotic Distribution of Extreme Stock Market Returns. *The Journal of Business*, 69(3), 383-408.

McNeil, A. (1997). Estimating the Tails of Loss Severity Distributions Using Extreme Value Theory. *ASTIN Bulletin*, 27,117−137.

McNeil, A., & Frey, R. (2000). Estimation of Tail-Related Risk Measures for Heteroscedastic Financial Time Series: An Extreme Value Approach. *Working Paper*, ETH Zürich, Switzerland.

McNeil, A. J. (1999). Extreme Value Theory for Risk Managers. *Unpublished manuscript*, ETH, Zürich, Switzerland.

Morgenstern, O. (1959). International Financial Transactions and the Business Cycle. Princeton N, J: Princeton University Press.

Nassim, N. T. (2010). *The Black Swan: The Impact of the Highly Improbable*, Random House.

Onour, I. A. (2010). Extreme Risk and Fat-Tails Distribution Model: Empirical Analysis. *Journal of Money, Investment and Banking*, 13, 27-34.

Pickands, J. (1975). Statistical Inference Using Extreme Order Statistics. *The Annals of Statistics*, 3, 119-131.

Poon, S., & Granger, C. (2003). Forecasting Volatility in Financial Markets. *Journal of Economic Literature*, 41, 478−539.

Uppal J.Y. & Mangla I.U. (2012). Extreme Loss Risk in Financial Turbulence - Evidence from Global Financial Crisis. *Journal of Financial Issues, forthcoming*.

APPENDIX

TABLE 1
DESCRIPTIVE STATISTICS

A: Developed Markets	**FRANCE MSCI**		**GERMANY MSCI**		**JAPAN MSCI**		**UK FTSE100**		**USA SPCOMP**	
Statistic	**PRE-GFC**	**GFC PERIOD**	**PRE-GFC**	**GFC PERIOD**	**PRE-GFC**	**GFC PERIOD**	**PRE-GFC**	**GFC PERIOD**	**PRE-GFC**	**GFC PERIOD**
Mean	0.059	-0.051	0.079	-0.041	0.064	-0.079	0.046	-0.015	0.046	-0.015
Median	0.062	0.000	0.086	0.000	0.041	0.000	0.041	0.000	0.059	0.048
Maximum	6.571	10.363	6.960	11.125	3.660	13.062	5.903	9.384	3.481	10.957
Minimum	-5.965	-9.306	-6.102	-7.386	-5.112	-10.435	-4.918	-9.266	-3.587	-9.470
Std. Dev.	1.038	1.792	1.193	1.733	1.064	1.747	0.821	1.586	0.762	1.725
Skewness	-0.092	0.117	-0.073	0.157	-0.416	-0.293	0.007	-0.072	-0.034	-0.225
Kurtosis	7.620	7.632	6.896	8.079	4.699	9.991	7.813	8.292	4.973	9.186
Jarque-Bera	1046.49	1053.21	744.19	1267.61	175.12	2409.95	1134.22	1372.01	190.87	1883.62
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Test for Equality	*Value*	*Prob*	*Value*	*Prob*	*Value*	*Prob*	*Value*	*Prob*	*Value*	*Prob*
T-Test for Means	1.817	0.069	1.240	0.215	2.394	0.017	1.170	0.242	1.113	0.266
F-Test for Variances	2.98	0.0000	2.11	0.0000	2.70	0.0000	3.74	0.0000	5.13	0.0000
B: Emerging Markets	**BRAZIL BOVESPA**		**CHINA SHANGHAI**		**INDIA SENSEX30**		**MEXICO IPC (BOLSA)**		**S. AFRICA MSCI**	
Statistic	**PRE-GFC**	**GFC PERIOD**	**PRE-GFC**	**GFC PERIOD**	**PRE-GFC**	**GFC PERIOD**	**PRE-GFC**	**GFC PERIOD**	**PRE-GFC**	**GFC PERIOD**
Mean	0.134	0.004	0.086	-0.047	0.124	0.005	0.138	0.015	0.079	0.016
Median	0.115	0.022	0.000	0.000	0.146	0.000	0.157	0.035	0.099	0.000
Maximum	5.159	13.679	7.890	9.034	7.931	15.990	6.510	10.441	5.610	5.962
Minimum	-6.856	-12.096	-9.256	-8.044	-11.809	-11.604	-5.978	-7.266	-6.479	-7.907
Std. Dev.	1.560	2.092	1.411	1.911	1.365	1.901	1.093	1.581	1.133	1.459
Skewness	-0.272	0.007	-0.309	-0.191	-0.847	0.261	-0.179	0.194	-0.350	-0.048
Kurtosis	3.943	9.150	7.706	5.657	10.617	9.805	6.050	8.325	5.711	5.320
Jarque-Bera	58.01	1851.68	1103.18	352.83	2980.68	2280.43	461.80	1395.50	383.83	264.00
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Test for Equality	*Value*	*Prob*	*Value*	*Prob*	*Value*	*Prob*	*Value*	*Prob*	*Value*	*Prob*
T-Test for Means	1.716	0.086	1.927	0.054	1.755	0.079	2.204	0.028	1.166	0.244
F-Test for Variances	1.80	0.0000	1.83	0.0000	1.94	0.0000	2.09	0.0000	1.66	0.0000

TABLE 2
RESULTS OF GARCH ESTIMATION

	DEVELOPED MARKETS						EMERGING MARKETS					
	FRANCE						BRAZIL					
	PRE CRISIS			CRISIS PERIOD			PRE CRISIS			CRISIS PERIOD		
	Coeff	z-Stat	Prob.	Coeff	z-Stat	Prob.	Coeff	z-Stat	Prob.	Coeff	z-Stat	Prob.
AR(1)	-0.046	-1.490	0.1362	-0.025	-0.743	0.4573	0.107	3.214	0.0013	0.058	1.735	0.0827
Variance Equation												
Constant, ω	0.020	3.903	0.0001	0.057	3.309	0.0009	0.091	4.046	0.0001	0.017	3.132	0.0017
RESID(-1)^2, α	0.066	5.960	0.0000	0.117	7.728	0.0000	0.092	4.468	0.0000	0.094	9.116	0.0000
GARCH(-1), β	0.910	65.574	0.0000	0.869	55.336	0.0000	0.829	22.473	0.0000	0.903	98.377	0.0000
Adjusted R-squared	-0.005			-0.002		1.7923	-0.006			0.002		1.5819
Durbin-Watson stat	1.960			2.025			0.107	3.214	0.0013	0.058	1.735	0.0827
	GERMANY						CHINA					
	PRE CRISIS			CRISIS PERIOD			PRE CRISIS			CRISIS PERIOD		
	Coeff	*z-Stat*	*Prob.*	*Coeff*	*z-Stat*	*Prob.*	*Coeff*	*z-Stat*	*Prob.*	*Coeff*	*z-Stat*	*Prob.*
AR(1)	-0.023	-0.735	0.4623	-0.017	-0.482	0.6296	-0.009	-0.302	0.7627	-0.004	-0.124	0.9015
Variance Equation												
Constant, ω	0.020	3.646	0.0003	0.045	3.582	0.0003	0.024	3.429	0.0006	0.024	3.159	0.0016
RESID(-1)^2, α	0.066	5.432	0.0000	0.114	7.486	0.0000	0.056	6.908	0.0000	0.045	6.669	0.0000
GARCH(-1), β	0.914	61.223	0.0000	0.874	58.098	0.0000	0.935	108.1	0.0000	0.947	124.7	0.0000
Adjusted R-squared	-0.005			-0.004		1.7340	-0.007			-0.003		1.9115
Durbin-Watson stat	2.051			1.959			1.981			2.013		
	JAPAN						INDIA					
	PRE CRISIS			CRISIS PERIOD			PRE CRISIS			CRISIS PERIOD		
	Coeff	*z-Stat*	*Prob.*	*Coeff*	*z-Stat*	*Prob.*	*Coeff*	*z-Stat*	*Prob.*	*Coeff*	*z-Stat*	*Prob.*
AR(1)	0.052	1.553	0.1205	-0.015	-0.439	0.6604	0.100	3.324	0.0009	0.057	1.845	0.0651
Variance Equation												
Constant, ω	0.027	3.027	0.0025	0.087	3.773	0.0002	0.086	4.023	0.0001	0.038	3.745	0.0002
RESID(-1)^2, α	0.076	5.357	0.0000	0.135	8.461	0.0000	0.130	8.729	0.0000	0.099	8.610	0.0000
GARCH(-1), β	0.902	48.408	0.0000	0.835	41.486	0.0000	0.820	34.678	0.0000	0.895	77.686	0.0000
Adjusted R-squared	-0.005			-0.005		1.7478	-0.009			0.000		1.9017
Durbin-Watson stat	2.031			1.964			2.068			2.010		
	UK						MEXICO					
	PRE CRISIS			CRISIS PERIOD			PRE CRISIS			CRISIS PERIOD		
	Coeff	*z-Stat*	*Prob.*	*Coeff*	*z-Stat*	*Prob.*	*Coeff*	*z-Stat*	*Prob.*	*Coeff*	*z-Stat*	*Prob.*
AR(1)	-0.073	-2.385	0.0171	-0.040	-1.215	0.2242	0.016	0.496	0.6196	-0.040	-1.230	0.2186
Variance Equation												
Constant, ω	0.016	3.128	0.0018	0.043	3.226	0.0013	0.102	2.152	0.0314	0.061	4.285	0.0000
RESID(-1)^2, α	0.083	5.723	0.0000	0.109	7.075	0.0000	0.041	3.514	0.0004	0.094	8.555	0.0000
GARCH(-1), β	0.888	44.948	0.0000	0.875	52.628	0.0000	0.916	31.935	0.0000	0.892	84.447	0.0000
Adjusted R-squared	0.003			-0.001		1.5870	-0.010			-0.001		2.0923
Durbin-Watson stat	2.033			2.010			1.987			1.994		
	USA						SOUTH AFRICA					
	PRE CRISIS			CRISIS PERIOD			PRE CRISIS			CRISIS PERIOD		
	Coeff	*z-Stat*	*Prob.*	*Coeff*	*z-Stat*	*Prob.*	*Coeff*	*z-Stat*	*Prob.*	*Coeff*	*z-Stat*	*Prob.*
AR(1)	-0.058	-1.823	0.0683	-0.094	-2.582	0.0098	0.092	2.864	0.0042	0.053	1.734	0.0830
Variance Equation												
Constant, ω	0.008	3.280	0.0010	0.031	3.672	0.0002	0.050	3.959	0.0001	0.027	2.559	0.0105
RESID(-1)^2, α	0.021	3.327	0.0009	0.102	8.026	0.0000	0.097	6.373	0.0000	0.096	5.984	0.0000
GARCH(-1), β	0.962	93.469	0.0000	0.888	66.035	0.0000	0.864	44.438	0.0000	0.892	52.534	0.0000
Adjusted R-squared	0.000			0.013		1.7256	-0.007			0.000		1.4598
Durbin-Watson stat	2.048			2.088			2.085			1.992		

Note: Method ML - ARCH (BHHH) - Normal distribution

TABLE 3
RESULTS OF GPD DISTRIBUTION ESTIMATION

	PRE-CRISIS PERIOD			CRISIS PERIOD				
FRANCE	Estimation of Empirical Distribution						Test of Dist.	
Parameter	*Value*	*z-Stat*	*Prob.*	*Value*	*z-Stat*	*Prob.*	*Value*	*Prob.*
Threshold	1.613	192.99	0.000	1.788	295.97	0.000	1.613	*n.a.*
Tail Index	3.250	7.30	0.000	4.966	7.30	0.000	3.250	*n.a.*
Goodness of Fit Test								
Kolmogorov (D)	0.978		0.294	0.931		0.352	2.236	0.000
Cramer-von Mises (W2)	0.140		0.409	0.139		0.411	1.178	0.001
Anderson-Darling (A2)	0.791		0.487	0.816		0.469	6.464	0.001
GERMANY								
Parameter	*Value*	*z-Stat*	*Prob.*	*Value*	*z-Stat*	*Prob.*	*Value*	*Prob.*
Threshold	1.628	200.84	0.000	1.830	317.75	0.000	1.628	*n.a.*
Tail Index	3.381	7.30	0.000	5.329	7.30	0.000	3.381	*n.a.*
Goodness of Fit Test								
Kolmogorov (D)	0.818		0.515	0.580		0.889	2.572	0.000
Cramer-von Mises (W2)	0.119		0.483	0.072		0.710	1.380	0.000
Anderson-Darling (A2)	0.790		0.489	0.513		0.734	7.193	0.000
JAPAN								
Parameter	*Value*	*z-Stat*	*Prob.*	*Value*	*z-Stat*	*Prob.*	*Value*	*Prob.*
Threshold	1.630	191.37	0.000	1.744	245.14	0.000	1.630	*n.a.*
Tail Index	3.223	7.30	0.000	4.119	7.30	0.000	3.223	*n.a.*
Goodness of Fit Test								
Kolmogorov (D)	1.242		0.092	0.420		0.995	1.546	0.017
Cramer-von Mises (W2)	0.288		0.145	0.025		0.972	0.389	0.077
Anderson-Darling (A2)	1.507		0.175	0.256		0.967	2.617	0.043
UK								
Parameter	*Value*	*z-Stat*	*Prob.*	*Value*	*z-Stat*	*Prob.*	*Value*	*Prob.*
Threshold	1.652	214.44	0.000	1.755	237.62	0.000	1.652	*n.a.*
Tail Index	3.607	7.30	0.000	3.994	7.30	0.000	3.607	*n.a.*
Goodness of Fit Test								
Kolmogorov (D)	0.831		0.494	0.757		0.615	1.555	0.016
Cramer-von Mises (W2)	0.088		0.624	0.120		0.479	0.837	0.006
Anderson-Darling (A2)	0.590		0.657	1.015		0.349	4.515	0.005
USA								
Parameter	*Value*	*z-Stat*	*Prob.*	*Value*	*z-Stat*	*Prob.*	*Value*	*Prob.*
Threshold	1.586	214.79	0.000	1.901	255.51	0.000	1.586	*n.a.*
Tail Index	3.613	7.30	0.000	4.292	7.30	0.000	3.613	*n.a.*
Goodness of Fit Test								
Kolmogorov (D)	0.859		0.452	1.633		0.010	3.787	0.000
Cramer-von Mises (W2)	0.202		0.258	0.413		0.067	5.066	0.000
Anderson-Darling (A2)	1.253		0.248	1.912		0.103	22.737	0.000

… Table continued next page

TABLE 3
RESULTS OF GPD DISTRIBUTION ESTIMATION – *Continued*

	PRE-CRISIS PERIOD			CRISIS PERIOD				
BRAZIL	Estimation of Empirical Distribution						Test of Dist.	
Parameter	*Value*	*z-Stat*	*Prob.*	*Value*	*z-Stat*	*Prob.*	*Value*	*Prob.*
Threshold	1.609	218.51	0.000	1.741	237.42	0.000	1.609	*n.a.*
Tail Index	3.675	7.30	0.000	3.990	7.30	0.000	3.675	*n.a.*
Goodness of Fit Test								
Kolmogorov (D)	0.794		0.555	0.613		0.847	2.015	0.001
Cramer-von Mises (W2)	0.163		0.342	0.022		0.983	1.195	0.001
Anderson-Darling (A2)	1.228		0.257	0.330		0.914	6.221	0.001
CHINA								
Parameter	*Value*	*z-Stat*	*Prob.*	*Value*	*z-Stat*	*Prob.*	*Value*	*Prob.*
Threshold	1.577	224.41	0.000	1.779	195.51	0.000	1.577	*n.a.*
Tail Index	3.773	7.30	0.000	3.292	7.30	0.000	3.773	*n.a.*
Goodness of Fit Test								
Kolmogorov (D)	0.763		0.605	1.085		0.190	3.463	0.000
Cramer-von Mises (W2)	0.074		0.700	0.255		0.179	4.395	0.000
Anderson-Darling (A2)	0.579		0.669	1.607		0.153	20.401	0.000
INDIA								
Parameter	*Value*	*z-Stat*	*Prob.*	*Value*	*z-Stat*	*Prob.*	*Value*	*Prob.*
Threshold	1.506	166.25	0.000	1.622	210.21	0.000	1.506	*n.a.*
Tail Index	2.804	7.30	0.000	3.537	7.30	0.000	2.804	*n.a.*
Goodness of Fit Test								
Kolmogorov (D)	0.947		0.331	0.717		0.684	1.477	0.025
Cramer-von Mises (W2)	0.115		0.499	0.095		0.588	0.549	0.030
Anderson-Darling (A2)	0.811		0.474	0.866		0.436	3.373	0.018
MEXICO								
Parameter	*Value*	*z-Stat*	*Prob.*	*Value*	*z-Stat*	*Prob.*	*Value*	*Prob.*
Threshold	1.612	225.03	0.000	1.673	178.94	0.000	1.612	*n.a.*
Tail Index	3.784	7.30	0.000	3.016	7.30	0.000	3.784	*n.a.*
Goodness of Fit Test								
Kolmogorov (D)	0.872		0.432	0.810		0.528	1.882	0.002
Cramer-von Mises (W2)	0.187		0.287	0.187		0.288	1.680	0.000
Anderson-Darling (A2)	1.095		0.311	1.229		0.257	8.691	0.000
SOUTH AFRICA								
Parameter	*Value*	*z-Stat*	*Prob.*	*Value*	*z-Stat*	*Prob.*	*Value*	*Prob.*
Threshold	1.586	200.06	0.000	1.736	299.07	0.000	1.586	*n.a.*
Tail Index	3.368	7.30	0.000	5.018	7.30	0.000	3.368	*n.a.*
Goodness of Fit Test								
Kolmogorov (D)	0.735		0.652	0.539		0.933	2.066	0.000
Cramer-von Mises (W2)	0.095		0.587	0.058		0.791	0.931	0.004
Anderson-Darling (A2)	0.768		0.505	0.474		0.773	5.345	0.002

TABLE 4
BACK-TESTING RESULTS – NO OF VIOLATIONS AND *p*-VALUES

MARKET	Static Normal #	Static Normal *p*-value	Dynamic-Normal #	Dynamic-Normal *p*-value	Static EVT #	Static EVT *p*-value	Dynamic EVT #	Dynamic EVT *p*-value
PANEL A: quintile = 0.995, Expected # Violations = 5.875								
FRANCE	41	0.0000***	12	0.0074***	11	0.0172**	4	0.3015
GERMANY	33	0.0000***	14	0.0011***	15	0.0004***	3	0.1620
JAPAN	32	0.0000***	16	0.0001***	14	0.0011***	6	0.3736
UK	40	0.0000***	19	0.0000***	16	0.0001***	5	0.4656
USA	54	0.0000***	28	0.0000***	26	0.0000***	8	0.1396
MEXICO	27	0.0000***	25	0.0000***	7	0.2386	10	0.0373**
CHINA	24	0.0000***	19	0.0000***	4	0.3015	5	0.4656
INDIA	25	0.0000***	16	0.0001***	4	0.3015	4	0.3015
BRAZIL	21	0.0000***	14	0.0011***	11	0.0172**	7	0.2386
S. AFRICA	20	0.0000***	12	0.0074***	4	0.3015	2	0.0673*
PANEL B: quintile =0.99, Expected # Violations= 11.75								
FRANCE	55	0.0000 ***	25	0.0002 ***	31	0.0000***	10	0.3730
GERMANY	44	0.0000 ***	23	0.0011 ***	27	0.0000***	12	0.3953
JAPAN	35	0.0000 ***	20	0.0090 ***	24	0.0005***	15	0.1370
UK	51	0.0000 ***	30	0.0000 ***	29	0.0000***	16	0.0872*
USA	62	0.0000 ***	39	0.0000 ***	41	0.0000***	24	0.0005***
MEXICO	34	0.0000 ***	29	0.0000 ***	24	0.0005***	24	0.0005***
CHINA	40	0.0000 ***	28	0.0000 ***	16	0.0872*	15	0.1370
INDIA	32	0.0000 ***	23	0.0011 ***	14	0.2049	11	0.4900
BRAZIL	29	0.0000 ***	24	0.0005 ***	19	0.0170**	15	0.1370
S. AFRICA	27	0.0000 ***	16	0.0872 *	15	0.1370	12	0.3953
PANEL C: quintile = 0.975, Expected # Violations=29.375								
FRANCE	81	0.0000***	56	0.0000 ***	68	0.0000***	47	0.0008***
GERMANY	66	0.0000***	55	0.0000 ***	54	0.0000***	48	0.0005***
JAPAN	61	0.0000***	38	0.0488 **	47	0.0008***	29	0.5211
UK	73	0.0000***	47	0.0008 ***	63	0.0000***	40	0.0230**
USA	86	0.0000***	64	0.0000 ***	77	0.0000***	54	0.0000***
MEXICO	50	0.0002***	42	0.0099 ***	43	0.0063***	37	0.0687*
CHINA	50	0.0002***	51	0.0001 ***	44	0.0039***	43	0.0063***
INDIA	50	0.0002***	42	0.0099 ***	36	0.0947*	38	0.0488**
BRAZIL	50	0.0002***	41	0.0153 **	41	0.0153**	37	0.0687*
S. AFRICA	41	0.0153**	41	0.0153 **	33	0.2168	32	0.2731
PANEL D: quintile = 0.95, Expected # Violations = 58.75								
FRANCE	111	0.0000***	91	0.0000 ***	113	0.0000***	80	0.0027***
GERMANY	92	0.0000***	88	0.0001 ***	95	0.0000***	79	0.0039***
JAPAN	87	0.0001***	74	0.0203 **	86	0.0002***	58	0.4947
UK	108	0.0000***	80	0.0027 ***	111	0.0000***	72	0.0361**
USA	113	0.0000***	87	0.0001 ***	118	0.0000***	76	0.0109**
MEXICO	71	0.0472**	70	0.0610 *	66	0.1500	67	0.1220
CHINA	75	0.0150**	67	0.1220	76	0.0109**	65	0.1820
INDIA	63	0.2586	62	0.3026	58	0.4947	65	0.1820
BRAZIL	77	0.0078***	78	0.0056 ***	69	0.0778*	69	0.0778*
S. AFRICA	64	0.2183	73	0.0273 **	63	0.2586	68	0.0981*