FinAnalytica Quantitative Series – *Briefing 1*

Extreme Events on a Univariate Level:

Understanding the Fat-tails of a Risk Driver

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Briefing Series Overview

The global financial crisis that began in the fall 2007 is a profound reminder that black swans - those rare events which, until they occur, may have been thought impossible – do exist. Furthermore, history shows that these extreme events, fat tails, are not a once in a thousand year occurrence as modern portfolio theory leads us to believe. These events occur with regular frequency. Yet, time and time again, market participants are seemingly stunned by each event. The severity of the current crisis should result in serious reconsideration of "modern" risk management practices. Risk professionals must focus on the importance of accurately modelling tail risk and dynamic tail dependency. Only then can investors understand the actual nature of risk and make appropriate investment decisions based on the true probability of extreme loss.

From a general viewpoint, the notion of extreme events is generic and related to a number of phenomena. Possible reasons for tail events need to be looked at from several angles:

- Isolated, univariate, factor level
- Joint, multivariate, dependence level
- Asset class or strategy level

FinAnalytica has launched this briefing series to provide background and intuition on extreme events phenomena and the quantitative models explaining them. This first briefing studies and addresses fat tail risk on a univariate level.

A second paper will cover the extreme joint movement of groups of factors and assets in times of high market stress as compared to normal market conditions. Exploring this phenomenon of "asymmetric dependence structure", the paper will show how correlations alone are not sufficient to describe this dependence and will provide alternative approaches to more accurately model how extreme events are magnified by a sudden change in this structure.

Taking an asset class and strategy point of view, a third paper will examine breaks in market structure and demonstrate how major market dislocation, particularly in those markets based on derivatives, can be traced to the structure of the market at the time. It will describe how standard models relying on the efficient markets hypothesis failed during such discontinuities and will offer fat tailed models not depending on the hypothesis.

This briefing series highlights both the need for a fundamental paradigm shift in risk management and the fact that more accurate real world models and commercial risk management solutions are be utilized today to tackle these challenges.

> *"Designers of risk models have to shed the attitude 'don't let facts interfere with truth'. Risk models have to be based on market realities, since the converse is unlikely to happen. This will enable financial institutions to come up with both better risk mitigation strategies and internal incentive structures for more decentralized risk management processes.*
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> *"Also, regulators and policy makers should become more sensitive to the inadequacy of current risk modelling approaches. Their misleading risk assessment may not only jeopardize individual financial institutions but, due to the institutions' synchronization of misjudgment, will also be a destabilizing factor in national and international financial systems."*
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> **Dr. Svetlozar Rachev & Dr. Stefan Mittnik,**
> University of Karlsruhe, January 11, 2006
> Published interview www.risiko-manager.com
> *New Approaches for Portfolio Optimization: Parting with the Bell Curve*

Introduction

The occurrence of extreme events in financial markets is acknowledged in numerous academic studies, as well as by practitioners, all supporting the claim that financial returns have fat-tails. Still, quantitative models that can accommodate this profound phenomenon are not broadly accepted within the industry and the bell curve normal distribution remains the standard. In fact, the Financial Services Authority (FSA) cites wide-spread use of the normal distribution, underestimating potential losses, as one of the main reasons for the banking crisis in 2008-2009:

"Short-term observation periods plus assumption of normal distribution can lead to large underestimation of probability of extreme loss events."

Financial Services Authority
The Turner Review, pp 23, 2009

It should be noted that the shortcomings of the normal distribution and the existence of better alternatives were known and explored before the crisis:

"Despite the shortcomings of the bell (normal distribution) curve, reliance on it is accelerating, and widening the gap between reality and standard tools of measurement. The consensus seems to be that any number is better than no number – even if it is wrong. Finance academia is too entrenched in the paradigm to stop calling it an acceptable approximation.

…

We live in a world primarily driven by random jumps, and tools designed for random walks (geometric Brownian motion) address the wrong problem.

…

While scalable (stable distribution) laws do not yet yield precise recipes, they have become an alternative way to view the world, and a methodology where large deviation and stressful events dominate the analysis instead of the other way around. We do not know of a more robust manner for decision-making in an uncertain world."

Benoit Mandelbrot and Nassim Taleb,
A Focus on the Exceptions that Prove the Rule
Financial Times, March 23, 2006.

As noted earlier, the causes and implications of extreme events are complex and must be analyzed from various views. This briefing discusses the reasons for extreme events on a univariate level and, through empirical study, demonstrates how the current "normal distribution" standard is fully insufficient to deal with today's volatile markets.

Why Do Factor Tails Get Fat?

Considering fat tails in isolation on a factor by factor basis, there are many potential reasons for extreme events:

1. *Time-varying volatility is sometimes said to be the main cause for extreme events*. This phenomenon, as noted by Mandelbrot, concerns the fact that "large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes." To account for this volatility clustering effect, the class of Robert Engle's Nobel Prize winning *"autoregressive conditional heteroskedasticity"* (ARCH) models, their generalized (GARCH) extensions and the simpler exponentially weighted moving average (EWMA) volatility models are widely used.

GARCH models assume that the volatility on a given day depends on the volatilities and also on the squared residuals of the one or two previous days. Thus, when volatility starts increasing, this is captured by the model and the next-day volatility can be forecast.

Many studies, however, demonstrate that even after removing this time-varying effect, fat-tails, though smaller in magnitude, continue to be present.

2. *Changes in regulation, announcements of events (e.g. mergers, acquisitions, etc.), resulting in random and unpredictable jumps in the value of a given factor or variable.* A possible way to capture this phenomenon is through a Poissonian-type jump model. Note that the nature of these events is such that their exact occurrence cannot be predicted. However, a non-zero probability for such an event can be included in the model. This makes the risk

numbers more conservative and adequate should it occur.

FinAnalytica developed such a jump model to take into account this behaviour. It can identify isolated outliers and calculate the frequency of occurrence. Then, in the scenario generation phase, similar outliers are inserted into the scenarios.

3. *Market structure factors such as block trades, liquidity, market depth, concentration, etc.* All these characteristics are related to the idea of market timing – the fact that the market exhibits its own, non-physical time which depends on the intensity of the information arriving on the market. The information can be expressed in terms of trade order or news announcements. When there is no new information, trading is slow and the market time almost stops and thus the price process does not evolve. However, when new information arrives, market trading becomes more or less hectic depending on the intensity of the new information and the price process starts to progress quicker which leads to observing larger changes in magnitude (positive or negative) in the price for the same amount of physical time elapsed.

A simple approach to capture this idea is to consider a model with two states – one with low trading volume and one with high trading volume, which can be well distinguished especially for low liquidity assets. This is a simple form of an Embedded Markov Chain (EMC) model. This model can identify the two states and can calculate the transition probability matrix. Then, in the scenario generation phase, it can generate future states conditional on the current state. In each future state, we can generate representative scenarios.

Another approach is to employ the idea of subordinated processes according to which the returns of the variables are modelled as a random variable ranked lower than an unobservable additional variable, called market timing. This construction naturally leads to many of the fat-tailed models available in the academic literature, the most natural class of which is represented by the so called Stable Paretian models. Note that the fat-tailed models constructed in this way include the normal distribution as a special case and, therefore, nothing is lost by using a fat-tailed model. If financial returns do not exhibit fat-tails, then this is going to be recognized by the model and will be properly taken care of by using the normal model. FinAnalytica has deployed the only commercial implementation of Stable Paretian models in a risk management platform.

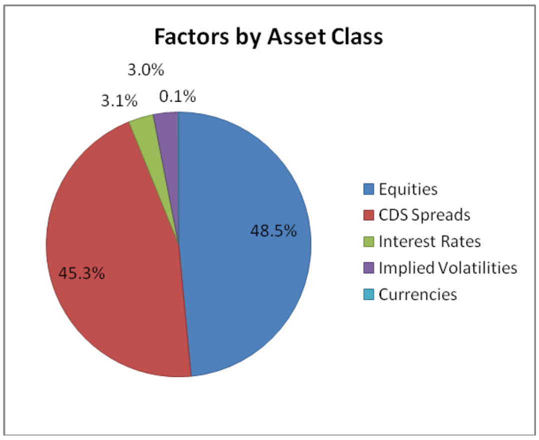
Fat Tails from Multiple Sources

The extreme events observed in returns may have different sources and may require the combining of different models in order to explain them. All models mentioned above can be combined into one model that best explains the data. For example, in order to explain the daily returns of an illiquid stock, the EMC model is needed to identify the corresponding two states and to calculate the transition probabilities. Then, in the state in which the stock is actively traded, clustering of volatility is observed and can be explained by a GARCH model. In the residuals of the GARCH model, typical outliers may be seen which can be filtered by the jump model. Finally, fat tails due to the market timing phenomenon can be captured by the class of stable distribution models.

Empirical Study: Single Factor Extreme Events

In order to explore the impact of the univariate extreme events, FinAnalytica, jointly with a client, regularly performs large-scale tests of financial returns data. Using 17,000 financial market factors, four of the distribution models available in the Cognity Risk Management and Portfolio Construction platform were tested. These four models correspond to the phenomena responsible for tail events as described above. The simplest model employed is the traditional normal model plus volatility clustering (VC). The second model extends the first one by incorporating jumps and the two-state EMCM liquidity model. The third model assumes stable Paretian distributions plus volatility clustering. The fourth model extends the third by incorporating Jumps and the EMCM overlays.

The tested factors included global equities, credit default swap spreads, interest rates and implied volatilities. The breakdown is shown below.



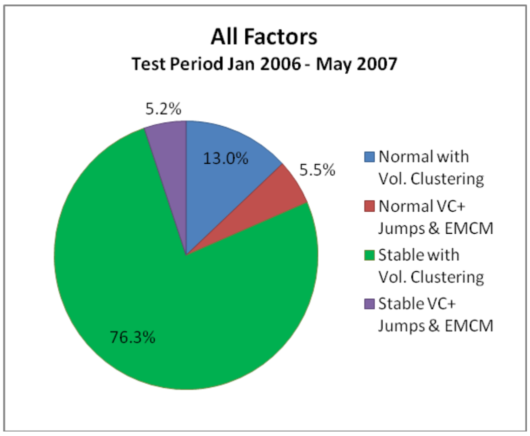
Factors Tested	Number	Percentage
Equities	8346	48.5%
CDS Spreads	7803	45.3%
Interest Rates	528	3.1%
Implied Volatilities	518	3.0%
Currencies	12	0.1%
Total	17207	100.00%

It should be noted that interest rates, spreads and implied volatilities have not been modelled directly but through appropriate models to accommodate for their particular structure in a given yield curve or volatility surface.

The experiment is based on out-of-sample VaR backtests using multiple confidence levels (85%, 95%, 97.5%, and 99%) for each the four models. The procedure starts with the simplest (Gaussian with constant volatility) model and checks if the actual loss is higher than the predicted VaR. If so, the day is recorded as a violation. If the violation is higher than the statistically acceptable number, then the model has underestimated the fat-tails and cannot explain them adequately. In such a case, the next model is considered and tested in the same way. When a simpler model is sufficient to describe the VaR at the corresponding confidence level, that model is accepted.

The first study was performed in May 2007, based on the period from January 2006 to May 2007 before the market crash. A rolling window analysis was used, and the time window for parameter estimation was 250 days. The study was most recently updated in December 2008.

In the first (pre-crisis) period, the normal distribution with volatility clustering failed in almost all cases. It accurately modelled only 13% of all variables. In contrast, as shown in the following chart, the fat-tailed stable distribution model enhanced with volatility clustering accurately modelled 76% of the total factors at all confidence levels.

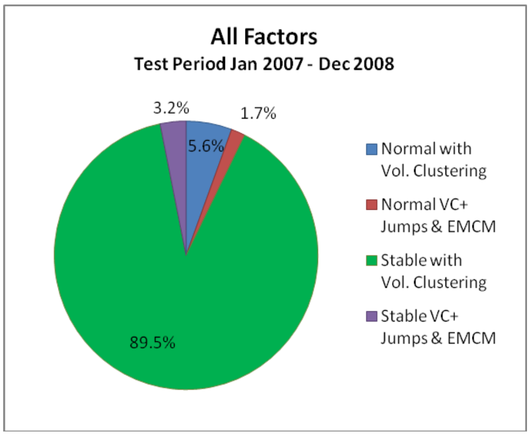


Adding jump and EMCM models had positive impact for about 10% of the factors. Those most probably correspond to the more illiquid assets. As already noted, the stable distribution family includes the normal distribution as a special end member. We see that the pure fat-tailed-volatility clustering model without further extensions (Stable with Vol. Clustering) is general enough to cover at least 90% of the variables.

These results also demonstrate that the full FinAnalytica model properly models all variables at all confidence levels tested.

The normal distribution greatest success was with global equities, where it was accurate in 20% of the cases, and its least success was with implied volatilities where only 3% were modelled accurately. Detailed breakdown by factor type is shown in Appendix 1.

The latest update of the study includes the period from May 2007 to December 2008 and the backtest period encompasses the entire period of the market crash. The data used in estimating the model is the most recent one year of daily returns before the VaR estimation day. In this test, the normal distribution fared significantly worse modelling only 6% of all factors with the rest requiring more sophisticated heavy tailed and asymmetrical distributions to accurately describe their behaviour. As shown in the next chart, the stable distribution with volatility clustering accurately modelled 89% of all factors. Strikingly, as seen in Appendix 1, the normal distribution accurately modelled only 7% of all equity factors.



This can be explained by the severe market turbulence which resulted from the most acute market crash in the past decade. It turned out that for this very turbulent period the fat-tailed model with volatility clustering again adequately represents the expected losses for all variables and at all confidence levels tested.

Conclusions

These findings prove that risk estimates based on the normal distribution, even with volatility clustering, systematically misrepresent the true nature of the risk being taken. More sophisticated modelling techniques are necessary in order to capture widely observed phenomena such as risk asymmetry and fat tails. They clearly highlight the requirement for commercial risk management platforms that integrate fat-tailed models across the risk measurement and portfolio construction workflow. This paper demonstrates how FinAnalytica's Cognity platform fulfils this need.

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University of Karlsrhue, January 11, 2006
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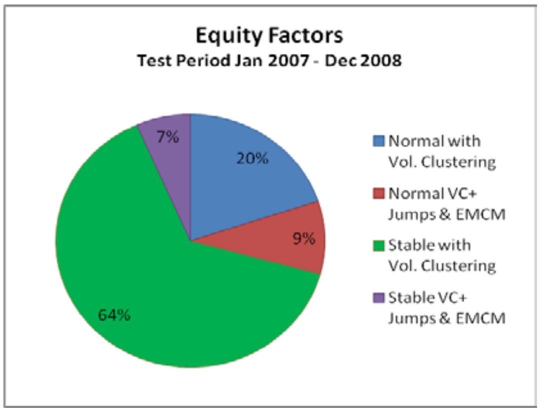
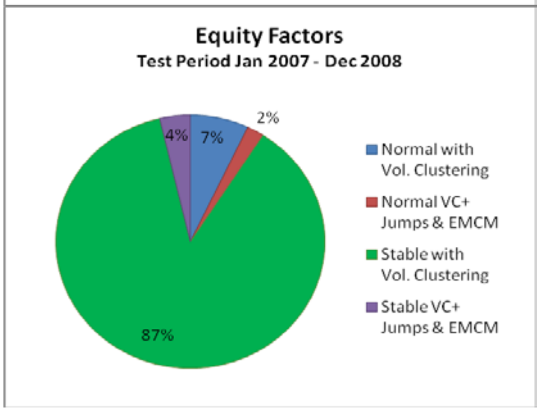
Appendix 1: Detailed Tests and Results

Global Equities

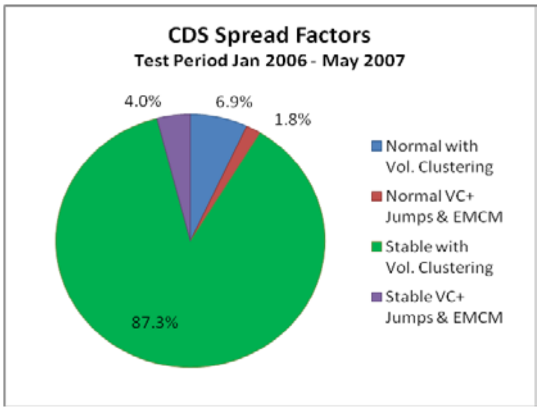
Equity factors from the U.S. accounted for 64% of the total number with another 14% from Japan, and 16% from Europe and the UK. Both test periods are shown for global equities.





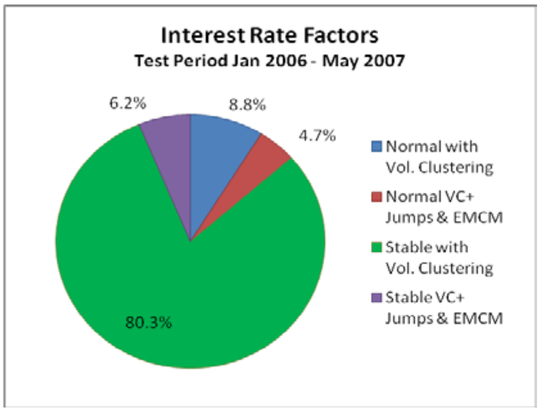
CDS Spreads

U.S. CDS spreads represented 82% of the total tested with the remaining being from Europe.



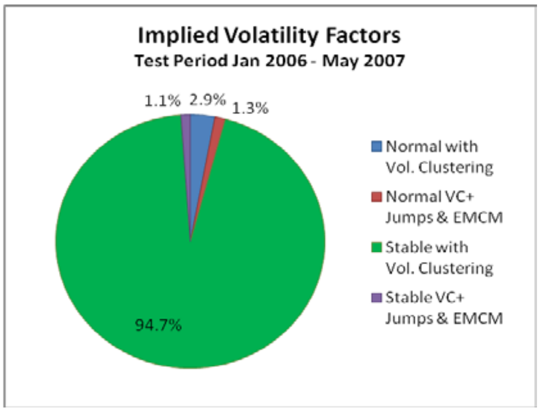
Interest Rates

By currency, interest rates are widely global with 42% USD, 16% EUR, 10% GBP and 4% JPY.



Implied Volatiltiies

Foreign exchange implied volatiltiies account for 86% of the total with another 10% fixed income and 3% treasury.



About FinAnalytica

FinAnalytica is a leading provider of post-modern portfolio and risk management solutions for quantitative analysts and portfolio managers. FinAnalytica's Cognity software suite incorporates the latest and most transparent advances in analytics, including comprehensive treatment of real world fat-tailed and skewed asset returns. FinAnalytica clients include leading fund of funds, hedge funds and asset management firms.

CognityFoF offers funds of hedge funds and other multi-manager firms with complete risk management and portfolio construction analytics. CognityFoF is the only risk platform offering fat-tailed, skewed VaR and Expected Tail Loss (ETL) risk measures. Its risk budgeting capabilities allow fund managers to maximize their expected returns per unit of allocated downside risk using Marginal Contribution to ETL, Percent Contribution to ETL and ETL-based Implied Return measures. Pro-actively managing their tail risk in a flexible, interactive and highly dynamic environment, CognityFoF users can optimize their returns from a true downside risk perspective.

CognityRisk is a global, multi-currency cross asset solution covering an extensive list of asset classes and instrument types. CognityRisk helps users to understand and correctly price risk asymmetry, improve investment decision making and build consensus through tail-risk budgeting, actively manage tail risk and communicate a structured investment process the impact of complex multidimensional stress scenarios on portfolio P&L.

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