RISK MANAGEMENT SOLUTIONS FOR SUSTAINABLE INVESTMENT GROWTH

The information contained in this document is related to proprietary technology and commercial data. By accepting and reading it, you acknowledge that the content of this document is provided for your sole information. You do not obtain any ownership interest in such content, nor any right to copy, modify, or transfer to a third party. Ownership of all such content shall at all times remain with Riskdata. Riskdata reserves all rights not expressly granted to you.
Extreme Risk Management
Poly-models and the Stress VaR
A New Risk Concept for Superior Fund Allocation

Raphael Douady
Research Director, Riskdata

Bachelier Finance Society
6th World Congress
June 23, 2010
Toronto Hilton - Fields Institute
Agenda

1. What is extreme/crisis risk?
2. Performance analysis missed hidden risks
3. Factor analysis
4. Models that don’t work
5. Poly-models and the StressVaR
6. Conclusion
What is Crisis / Extreme Risk?
Risk is not what happened or what is currently happening. It is what may happen in the future. This is why credit risk is part of market risk because future prices of defaultable assets are driven by future default probability. Liquidity risk is both direct market risk – as potential loss due to slippage – and potential liquidity shift. To this extent a corporate bond can be thought to have a much higher liquidity risk than a private equity fund because the liquidity of the first can dramatically change overnight while the one of the second is in fact quite stable.

<table>
<thead>
<tr>
<th>What is Risk?</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Market Risk</strong></td>
</tr>
<tr>
<td>Max Draw Down</td>
</tr>
<tr>
<td>Potential loss due to market variables</td>
</tr>
<tr>
<td>Potential loss due to change of asset underlying pricing factors (market variables, bid-ask spreads or credit spread)</td>
</tr>
</tbody>
</table>
Performance Analysis Missed Hidden Risks
What Is “Hidden Market Risk”?

> **Ex Post:**

  • Hidden risk appears when observed **losses exceed** anything that could have been extrapolated from **past performance** metrics, merely by using simple performance analysis tools

> **Ex Ante:**

  • Possible sources of hidden risk:
    > **Return smoothing**, fraud, etc.
    > ‘Time bombs’: **liquidity traps** and correlation breaks
    > ‘Time bombs’: **Market disruption**
    > **Leverage**, downside bubbles, illiquid assets…
Hidden Market Risks

This fund seems to display all possible green lights for an investor… But will the performance last?
Hidden Market Risks

NO! Losses during the crisis exceeded 4 times the Max Drawdown... The fund? = The HFR Fund of Funds index!

HFRI FoF Composite Index

Performance: 3.21%
Volatility: 6.84%
Downside Vol: 9.35%
Max Draw Down: -18.69%
Sharpe: -0.10
Sortino: -0.07
**Ex-Post Statistics on Hidden Risk Materialization**

We consider that a fund has materialized its hidden risks if the fund’s cumulated loss during Sep-Oct 08 exceeds twice its past Max Drawdown. In a sample of over 3000 funds and FoFs from the HFR database, we found that 40% had materialized hidden risks. By category, 64% of Funds of Funds, 53% of Relative Value, 42% of Event Driven, 26% of Equity Hedge, 9% of Macro.

Prior to the crisis, funds whose hidden risks would subsequently materialize during the crisis tended to exhibit lower volatility (precisely because the crisis was a surprise). Therefore, these funds paradoxically sported the majority of losses. Other funds, for instance those with more systematic volatility, encountered significantly lower losses during the fall of 2008.
Still using the same sample of 3,098 funds, the X axis is the Sharpe Ratio over the period Jan 04 – Dec 07, the Y axis is the performance during Sep-Oct 08 divided by the volatility prior to the crisis. Clearly, the Sharpe ratio is a very poor predictor of losses during the crisis!
### Why Traditional “Return-Based” Methods Miss Hidden Risks

<table>
<thead>
<tr>
<th>Source of Hidden Risk</th>
<th>Example</th>
<th>Effect on Sharpe Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Return Smoothing</strong></td>
<td>Illiquid Securities</td>
<td>+++ High Sharpe Ratio</td>
</tr>
<tr>
<td><strong>Fraud</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Time Bomb</strong></td>
<td>Event Driven</td>
<td>+++ High Sharpe Ratio</td>
</tr>
<tr>
<td><strong>Short Gamma</strong></td>
<td>Sub-Prime</td>
<td></td>
</tr>
<tr>
<td><strong>Surf the Trend</strong></td>
<td>Event Driven</td>
<td>+++ High Sharpe Ratio</td>
</tr>
<tr>
<td></td>
<td>Relative Value...</td>
<td></td>
</tr>
</tbody>
</table>

Practically all sources of hidden risks have the effect of boosting the Sharpe ratio. This explains why past performance is not indicative of future results!

“Time Bombs” refer to typical characteristics of certain trading strategies – those producing small profits a vast majority of the time, but whose occasional extreme losses cancel out years of profits.

For example: Funds that are “short gamma” resemble a strategy that consists of selling a put option on an index and then rolling this position (over years).
Optimizers, however sophisticated, simply maximize expected return while minimizing *measured* risk. Therefore, by design, optimizers maximize the proportion of unmeasurable risk – i.e. hidden risk – leading automatically to portfolios which eventually deliver very nasty surprises….
Factor Analysis
What Are You Looking For?

Did you lose your key there?

No, on the other side, but here I have light!
Pure Performance Analysis

Credit driven fund:
- Long AAA bonds, Short T-bonds, duration 10Y

Could such a loss be anticipated by looking only at the past fund performances?
> Credit driven fund vs. AAA spread over T-Bonds:

- The driving factor experienced in many past jumps comparable to the crisis

The fund returns mostly depend on the AAA credit spread, in a nonlinear (optional) way. The grey curve is obtained by cumulating this nonlinear function of the credit spread changes over the years.

This leads us to the way extreme risk can be anticipated through the concept of STRESS VAR. One can see that the loss experienced in 2007 had several similar precedents. The loss of the fund is in line with its Stress VaR, which itself is derived from “extrapolated” losses of the fund, prior to its actual track record.
Models That Don’t Work
The Delusion of Fat Tails

> Principle of “Fat Tail” Models

- Revise the relation: “# of sigmas” $\leftrightarrow$ “probability of event”
- Stretch probability distribution to fit actual frequency of large events
- Examples: Extreme Value Theory, Pareto-Levy, Power Laws, etc.

![Graph showing Gauss and Levy distributions with annotations for weaker and stronger probability of medium and large events.](image-url)
The Delusion of Fat Tails

> Flaws

- Ignore *special behavior* during crises and liquidity traps
- Ignore changing correlations between asset classes: Alpha → Beta
- Ignore “change of regime” when a crisis occurs
- Mostly calibrated on “business-as-usual” periods ⇒ *Unstable VaR measure*
- Doesn’t inform on which *market scenario* causes extreme portfolio losses
  ⇒ *Not manageable*

> Robust Statistics

- *Even worse:* decreases the weight of extreme observations!
The Delusion of Linear Models

> Linear Models
  • Assume fixed correlations
  • Beta is the same whatever the regime

> Flaws
  • Upside and downside correlations are different
  • Under crises, correlations are even more “broken” → close to 100%

> Impact on Portfolios
  • Optimization based on erroneous assumptions
  • Negative skew of portfolios, funds of funds, indices, etc.
  • “Bad surprises” destroy long-term performances
The Delusion of Linear Models

Event-driven hedge funds are uncorrelated to markets in “business-as-usual” periods, but strongly correlated when the stock market is falling.
Sources of Nonlinearity

Sources of Nonlinearities in Order of Importance:

> **1** Liquidity Gaps
  - They are **SYSTEMATIC**
  - Create **CORRELATION BREAKS**

> **2** Dynamic Trading
  - Positions change with market
  - Mimic **OPTION REPLICATION**

> **3** Nonlinear Relation Between Assets
  - 3.1 **BONDS vs. STOCKS**
    (credit spreads increase when the stock declines)
  - 3.2 Options…

Options are commonly considered as being responsible for nonlinearities. However, this is only the least cause of nonlinearities. Rather, the first cause of correlations-in-flux is the impact of liquidity gaps.
Quantitative Long-Short Equity US: the fund experienced, like most of its peers, a strong drop on Aug 13 2007
Are You Short a Put Without Noticing?

FOFiX analysis of the fund demonstrates that what looked like pure Alpha was, in fact, the premium of a put option.
Models That Work
The Data Wall

> 10,000+ Hedge Funds
  • A few years of history => only a few 10’s of returns
  • Position info: unreliable, incomplete, delayed, fast changing
  • Large variety of strategies and trading universe

> 10,000’s Market Factors
  • All asset classes
  • Long term history, including many crises, cycles
  • Hedge Funds often uncorrelated to markets: need exotic factors
  • Correlations only appear during crises: need nonlinear models

> Too many models, too little information

> IMPOSSIBLE TO SELECT AND CALIBRATE A MODEL
Poly-Models

A Collection of Single-Factor Models

> **Step 1:** Identify a **LARGE** Set of Factors
  - **LONG HISTORY** (20 Yrs incl. crises)
  - As many factors as potential **risk sources** ⇒ *Several 100’s*

> **Step 2:** Scan Factors One at a Time
  - Select only factors with a strong statistical relationship to the fund ⇒ *Score*
  - Focus on **EXTREME MOVES** ⇒ *Nonlinear Models*

> **Step 3:** Stress Selected Factors
  - Compute Information Ratio
    \[
    \text{Information Ratio} = \frac{\text{Impact of Factor}}{\text{Uncertainty}}
    \]
  - Merge single-factor models to maximize Information Ratio

---

Poly-models are aimed at breaking the “data wall”. Here, the major innovation is in the way that the distribution of future returns is estimated; using a very long history of markets in order to include past crises, a large number of factors in order to account for all possible risk sources and a collection of nonlinear models in order to account for extreme risks – in particular, the impact of liquidity gaps. Short fund historical records are utilized in an optimal way.
Poly-Models

> Multi-Factor Model

\[ \text{Fund} = \lambda_1 \text{Fact}_1 + \ldots + \lambda_n \text{Fact}_n + \alpha \]

- Coefficient \( \lambda_i \) are fixed
- Factor set \{\text{Fact}_1, \ldots, \text{Fact}_n\} is frozen

> Poly-Model: Collection of models:

- Linear:
  \[
  \text{Fund} = \beta_i \text{Fact}_i + \alpha_i \quad i = 1 \ldots n
  \]

- Nonlinear + lags:
  \[
  \text{Fund} = \varphi_i(\text{Fact}_t) + \psi_i(\text{Fact}_{t-1}) + \rho_i \text{Fund}(t-1) + \alpha_i \quad i = 1 \ldots n
  \]

- Score each model by relevance in extreme scenarios
Poly-Models

> Relation with Multi-factor Models: the **Linear** case

- Fund = $\beta_i \text{Fact}_i + \alpha_i \quad i = 1 \ldots n$
- Fund = $\lambda_1 \text{Fact}_1 + \ldots + \lambda_n \text{Fact}_n + \alpha$
- $\langle \text{Fund}, \text{Fact}_i \rangle = \beta_i \text{Var(Fact}_i) = \sum \lambda_j \langle \text{Fact}_i, \text{Fact}_j \rangle$
- $(\lambda_1, \ldots, \lambda_n) = \text{Cov(Fact)}^{-1} (\beta_1 V_1, \ldots, \beta_n V_n)$ \quad $V_i = \text{Var(Fact}_i)$
- The uncertainty on $\lambda$’s depends on colinearity of factors
- Badly conditioned covariance matrix $\Rightarrow$ Low Information Ratio

> **Nonlinear** Modelling

- Hermitte Polynomials $H_k$: $\varphi_i(\text{Fact}_i) = \sum \beta_i^k H_k(\text{Fact}_i) + \alpha_i$
- Nonlinear Multi-factor model by inverting Cov($H_k(\text{Fact}_i)$)
- Improve Information Ratio with LOESS Regression
Poly-Models

> Model Selection

- For each subset of indices $I = (i_1, \ldots, i_q)$, merge models as above
- Compute the Information Ratio = Merged Impact / Uncertainty
- Find the subset $I$ with the highest Information Ratio

> Stepwise Regression

- Find the factor $i_1$ with highest Information Ratio
- Take this factor as given. Find the second factor $i_2$ such as, jointly with $i_1$, the Information Ratio is maximum
- Repeat until the Information Ratio cannot be increased
- Try to remove factors while increasing the Information Ratio
- Stop when it is not possible to add – or remove – factors
Poly-Models: Information Ratio

• Given $I = (i_1, \ldots, i_q)$ and factor stress values $(x_{i1}, \ldots, x_{iq})$ we compute the joint impact by merging single factor models:

\[
\text{Impact} = \sum_{i \in I} \lambda_i^k H_k(x_i) + \alpha_I
\]

where $\lambda_i^k$ are the coefficients of the merged multi-factor nonlinear model.

• The uncertainty of the estimate is given by the covariance matrix of coefficients $(\lambda_i^k, \alpha_I)$, which can be redeemed from the inverse Hessian of the log-likelihood function.

\[
\text{Info Ratio} = \frac{\text{Impact} - E(\text{Fund})}{\sigma(\text{Impact})}
\]

• Account for small sample bias and non-gaussian input distributions

\[
p\text{-value} = \text{Percentile of } E(\text{Fund}) \text{ in the distribution of Impact}
\]

• LOESS Regression: Weighted linear model $\Rightarrow$ Better Information Ratio when history contains large events, but lack of consistency for portfolio aggregation
StressVaR Three Step Process

Combine STRESS TESTS and Value-At-Risk

> **Step 1:** Identify a LARGE set of factors
  
  • 99% confidence interval of each factor based on LONG HISTORY (20 Yrs)

> **Step 2:** Scan factors, one at a time
  
  • Select only factors with a strong statistical relationship to the fund
  
  • Focus on EXTREME MOVES

> **Step 3:** Stress each selected factor $X_i$
  
  • Measure the worst impact on the fund over the 99% interval $S_i$
  
  • Measure the standard deviation of residuals of the model calibration $\sigma_i$
  
  • Use NONLINEAR model

\[
99\% \text{ StressVaR} = \max_{\text{Selected Factors}} \sqrt{S_i^2 + 2.33^2 \sigma_i^2}
\]

Stress VaR is a risk measure that combines stress tests and value-at-risk. It relies on “poly-models” for the estimation of the distribution of future returns. It is generated from market histories that include past crises, and draws on a sufficient volume of factors, so as to account for all possible risk sources. Nonlinear models capture extreme risks – in particular, the impact of liquidity gaps. Therefore, the Stress VaR unveils hidden risks by identifying drivers of returns.
FOFIX® interface shows the implementation of the 3-steps StressVaR process.

List of Market Factors
Relevance of Factors
Stress Test of each factor
Stress VaR and Poly-Models

> Handle hundreds of risk sources

> Model rare events ("Black Swans")

> More accurate when needed than when not needed!
  
  • Tail concentration effect

> Suited for risk measurement and stress scenarios
  
  • Prediction from individual factors can be merged
  
  • Risk measure = StressVaR (worst case) includes hidden risks

> Can be aggregated for a portfolio
  
  • Risk contributions involve extreme correlations
  
  • Superior allocation and optimization
Can We Anticipate the **Impact** of Time Bombs?

This graph compares the actual performance of hedge funds during Sep-Oct 08 with the pattern of what could have been predicted by FOIfX’s nonlinear factor analysis (using fund data until Mar 08 only).

Assuming an investor anticipated the market crisis, the set of funds that appeared to be actual losers and winners was quite predictable.

In the following slides we will see the techniques put in place to generate such a result.
When, ex ante – as of Dec 07 – eliminating funds whose Stress VaR exceeded their Max Drawdown, the percentage of funds that subsequently materialized hidden risks during the Fall 08 is then divided by 2!

Let us now build a portfolio in which funds with Stress VaR > Max Drawdown as of Dec 07 are eliminated and, on the remaining funds, the weight of each investment is inversely proportional to its risk – measured by the dec 07 Stress VaR. Compared to the equally weighted portfolio on all the funds, the loss during the crisis is strongly reduced.
Manage with Constant Extreme Risk Budgets Rather Than Static Allocation or Constant Volatility

<table>
<thead>
<tr>
<th>Capital Allocation</th>
<th>Medium Performance</th>
<th>Medium Risk Control</th>
</tr>
</thead>
<tbody>
<tr>
<td>Risk Allocation</td>
<td>Weak Performance</td>
<td>Risk Control OK</td>
</tr>
<tr>
<td>Markowitz</td>
<td>Performance OK</td>
<td>Bad Risk Control</td>
</tr>
<tr>
<td>FOFiX</td>
<td>Performance OK</td>
<td>Good Risk Control</td>
</tr>
</tbody>
</table>

Track Record of Quant Driven Portfolios With a 3% Tail Risk Budget
Ex-Ante Fund Selection by Convexity

Discard funds which exhibit negative convexity (gamma) with respect to critical risk factors

Number of bad surprises is divided by almost 3

When a crisis is announced (even when it is only a possibility), funds mimicking the shorting of an option should be avoided. If one eliminates funds with negative Gamma (in respect to at least one of the 3 most significant explanatory factors), the total number of funds that materialized their hidden risks during the crisis is divided by 3. With the same selection, average losses are practically brought to 0. Filtering out funds that display a negative Gamma should not be done systematically, but only when markets are unstable and unpredictable.
Conclusion: Quantifying Hidden Risk

> Returns are used to identify RISK SOURCES
  • DO NOT confuse: PERFORMANCE ANALYSIS ≠ RISK ANALYSIS

> Use LONG HISTORY of market factors to anticipate near-future moves and possible EXTREME SHIFTS

> Run systematic STRESS TESTS, consider Worst Case
  • Stress VaR = Worst Stress Test from factors hitting their VaR
  • HIDDEN RISK when Stress VaR > Past Worst Case

> Use StressVaR for portfolio construction under EXTREME RISKS

> When crisis is PROBABLE, run away from NEGATIVE GAMMA
  • DO NOT « sell a put » without noticing: OPTION PREMIUM ≠ TRUE ALPHA !
Conclusion: Budget the Next Crisis

> Budget for the next crisis to secure long-term returns

> In extreme market conditions, monitoring credit and liquidity risk ⇔ **Hidden** Market Risks

> Measuring “hidden” market risk means integrating gamma, long-term factor risk and return smoothing

> Monitoring “hidden” market risk budget implies shifting from static allocations to stable risk budgets per factors, reflecting ALM constraints & long-term views

> This all helps discriminate between “lucky” managers, generating returns based on hidden risks, and the talented ones!