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# RISK MANAGEMENT SOLUTIONS FOR SUSTAINABLE INVESTMENT GROWTH

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# Extreme Risk Management

## Poly-models and the Stress VaR

### A New Risk Concept for Superior Fund Allocation

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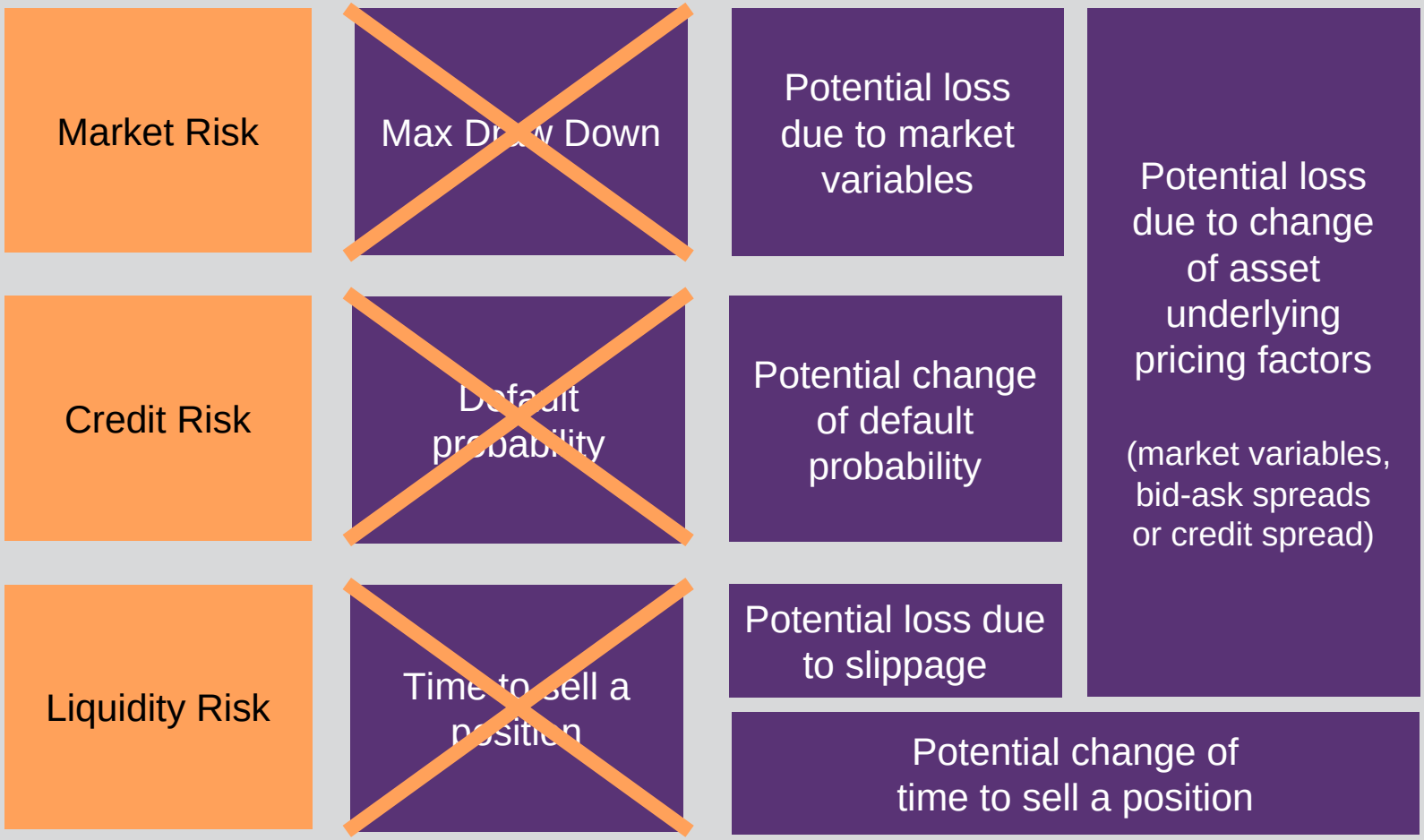
Toronto Hilton - Fields Institute

# 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?

# What is Risk?



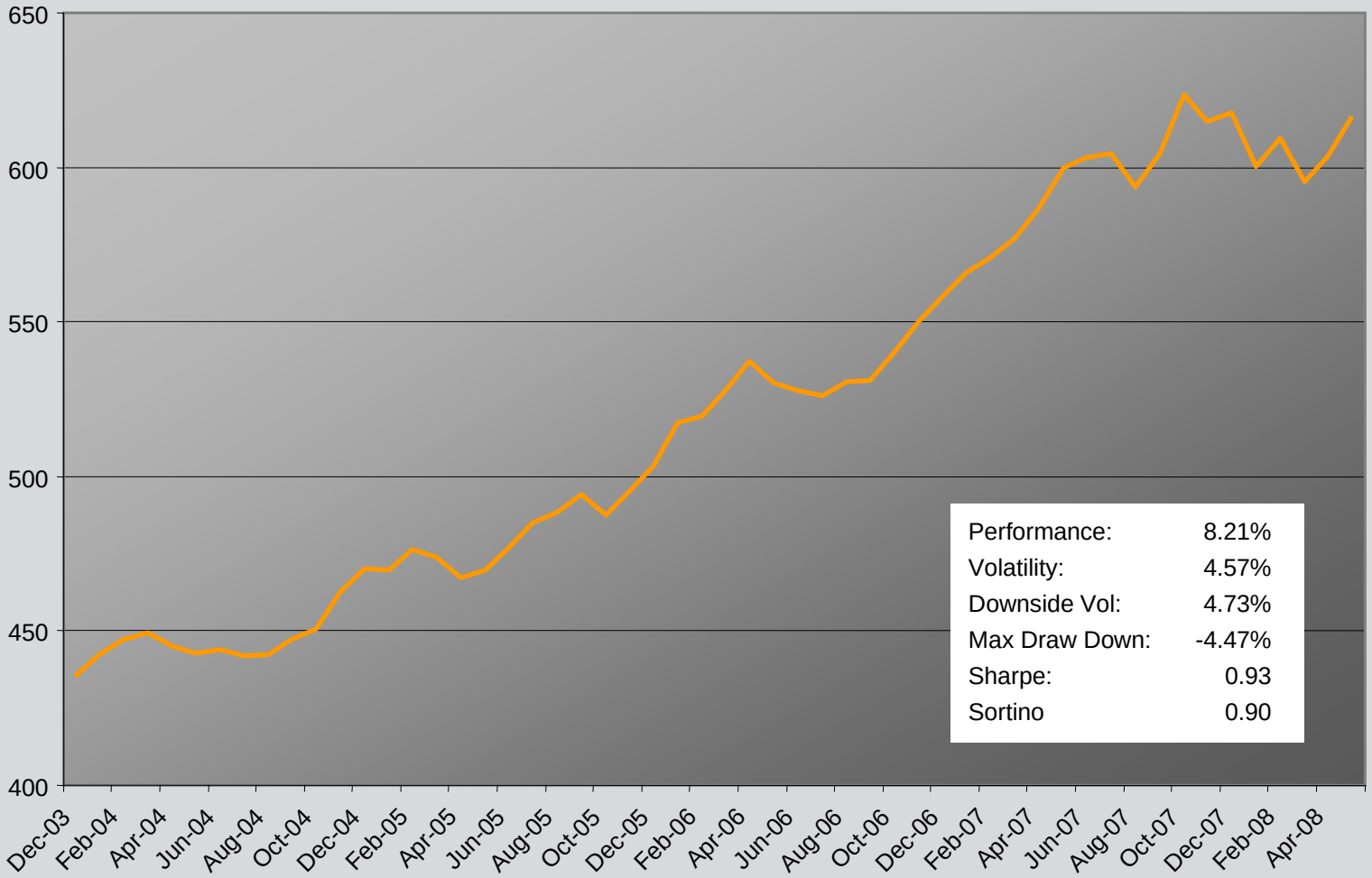

**Risk is not what happened or what is currently happening. It is what may happen in the future. This is why credit risk is part of market risk because future prices of defaultable assets are driven by future default probability. Liquidity risk is both direct market risk – as potential loss due to slippage – 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.**

# Performance Analysis Missed Hidden Risks

# What Is “Hidden Market Risk”?

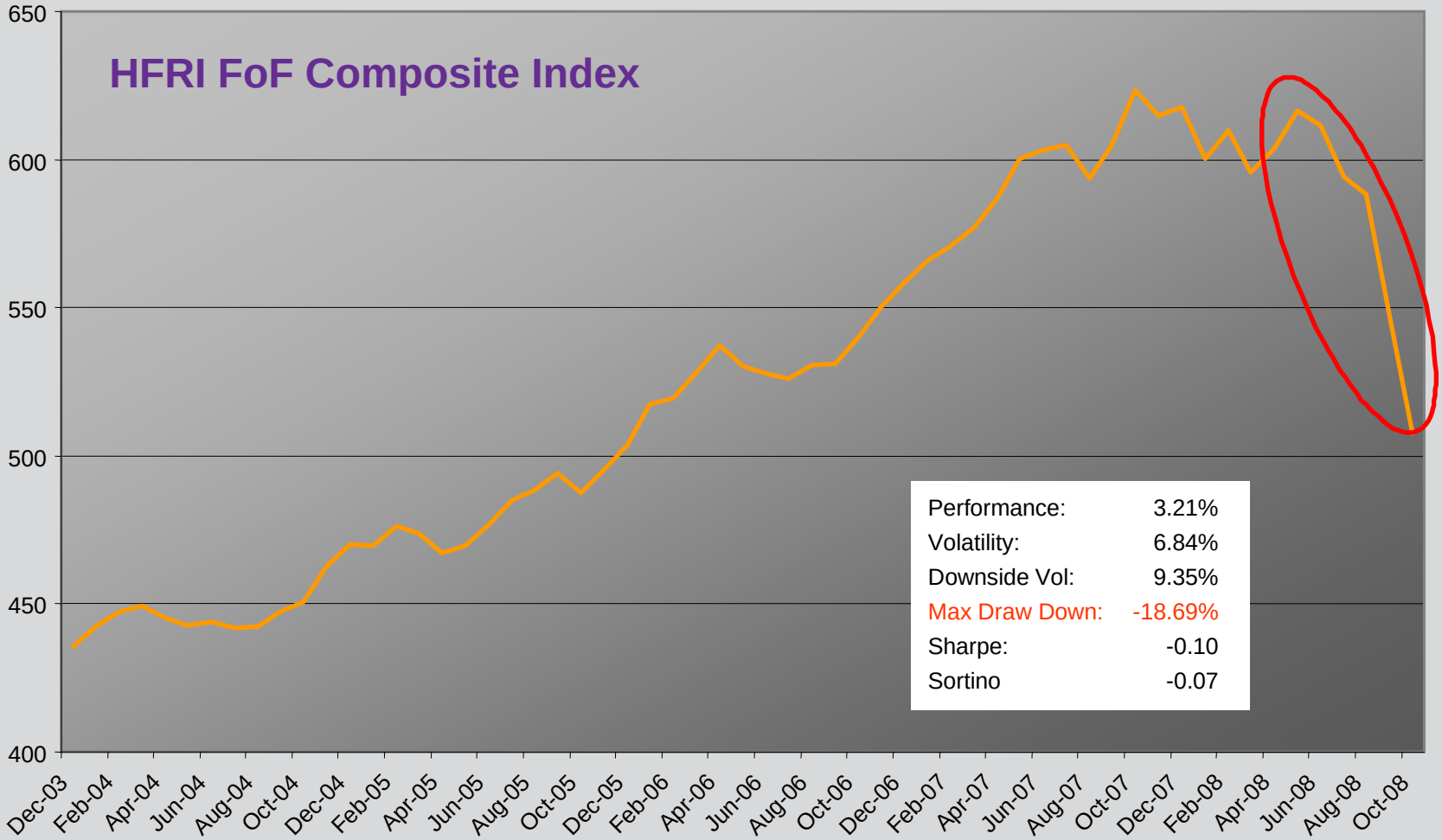
- **Ex Post:**
  - Hidden risk appears when observed **losses exceed** anything that could have been extrapolated from **past performance** metrics, merely by using simple performance analysis tools
- **Ex Ante:**
  - Possible sources of hidden risk:
    - **Return smoothing**, fraud, etc.
    - ‘Time bombs’: **liquidity traps** and correlation breaks
    - ‘Time bombs’: **Market disruption**
    - **Leverage**, downside bubbles, illiquid assets…

# Hidden Market Risks



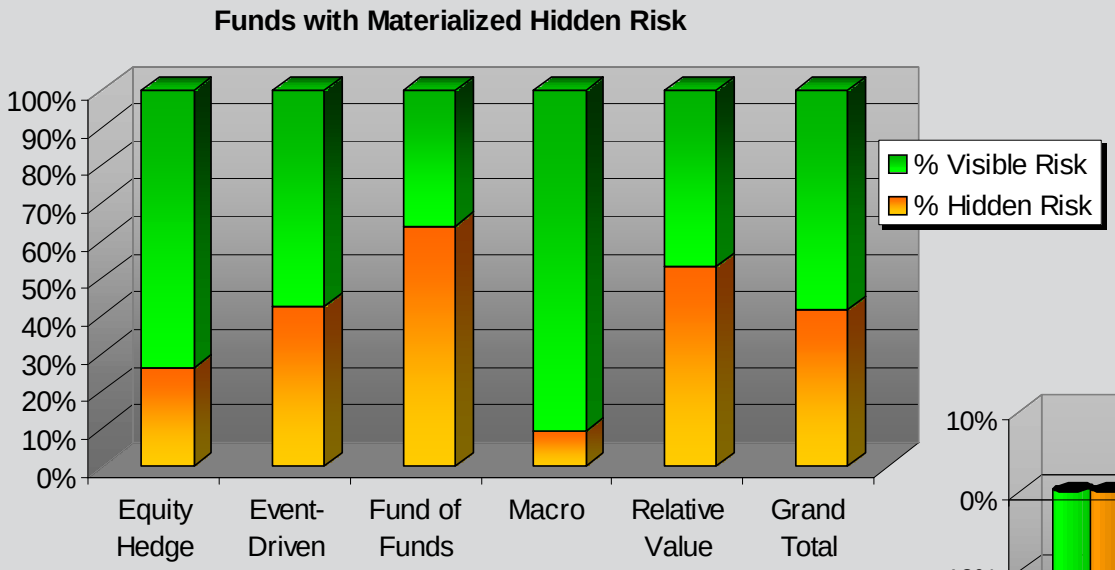

**This fund seems to display all possible green lights for an investor… But will the performance last?**

# Hidden Market Risks



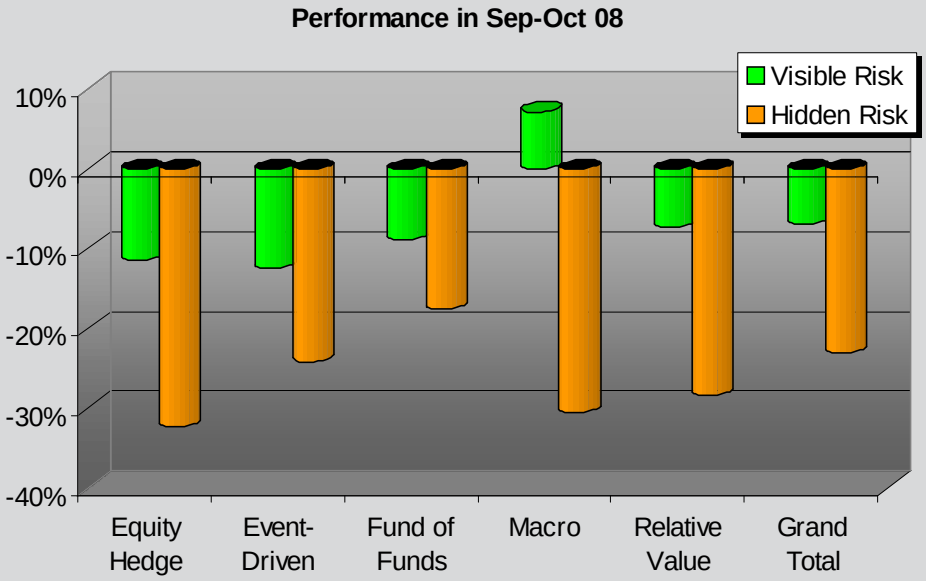

**NO! Losses during the crisis exceeded 4 times the Max Drawdown… The fund? = The HFR Fund of Funds index!**

# Ex-Post Statistics on Hidden Risk Materialization




**Hidden Risks:**

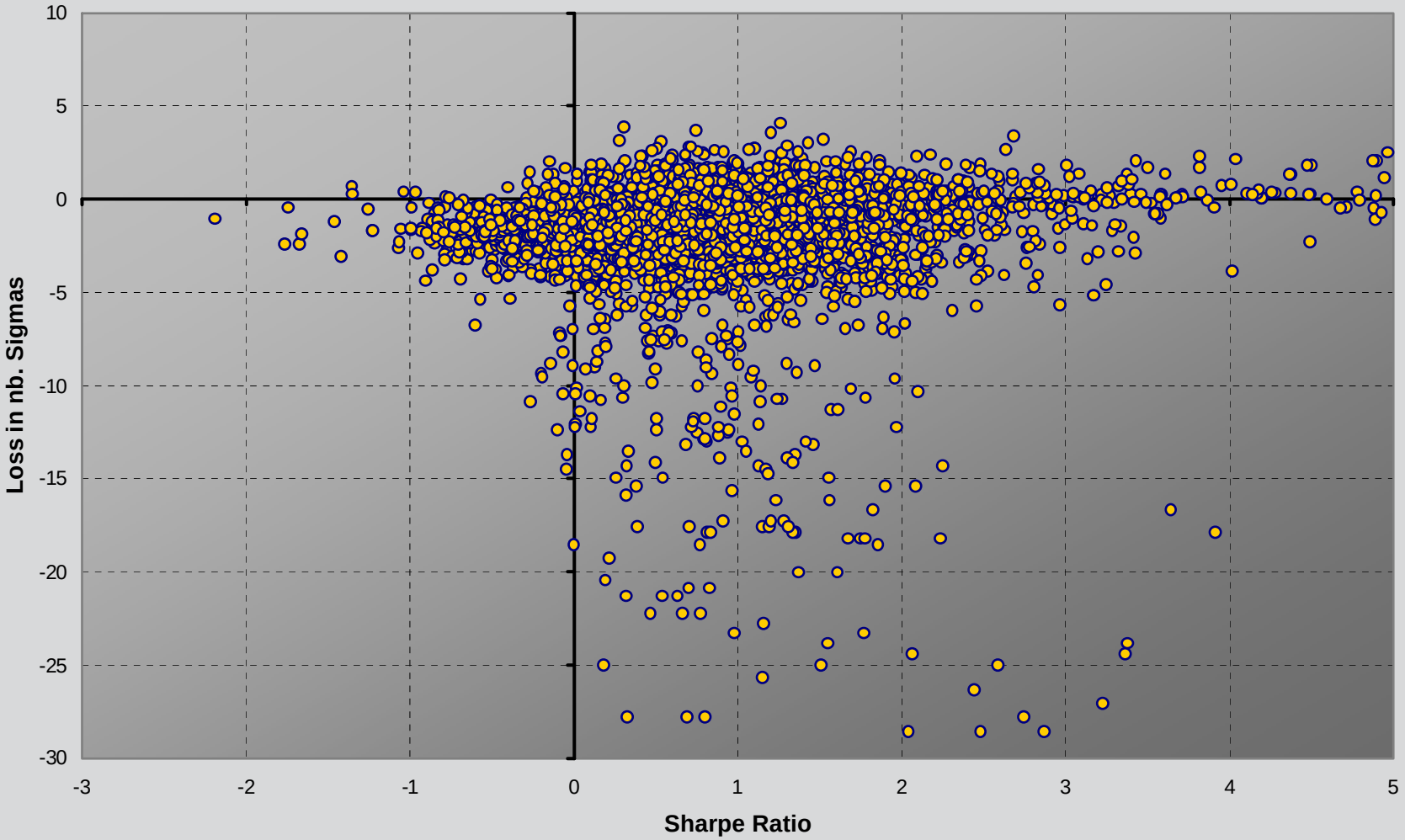
**Loss in Sep-Oct 08 > 2 x Max Draw Down Prior to Crisis**




**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.**

# Sharpe Ratio Before Crisis vs. Ex-Post Hidden Risk




**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

| Source of Hidden Risk | Example | Effect on Sharpe Ratio |
|---|---|---|
| **Return Smoothing**<br>**Fraud** | Illiquid Securities | +++ High Sharpe Ratio |
| **Time Bomb**<br>**Short Gamma** | Event Driven<br>Sub-Prime | +++ High Sharpe Ratio |
| **Time Bomb**<br>**Surf the Trend** | Event Driven<br>Relative Value... | +++ High Sharpe Ratio |

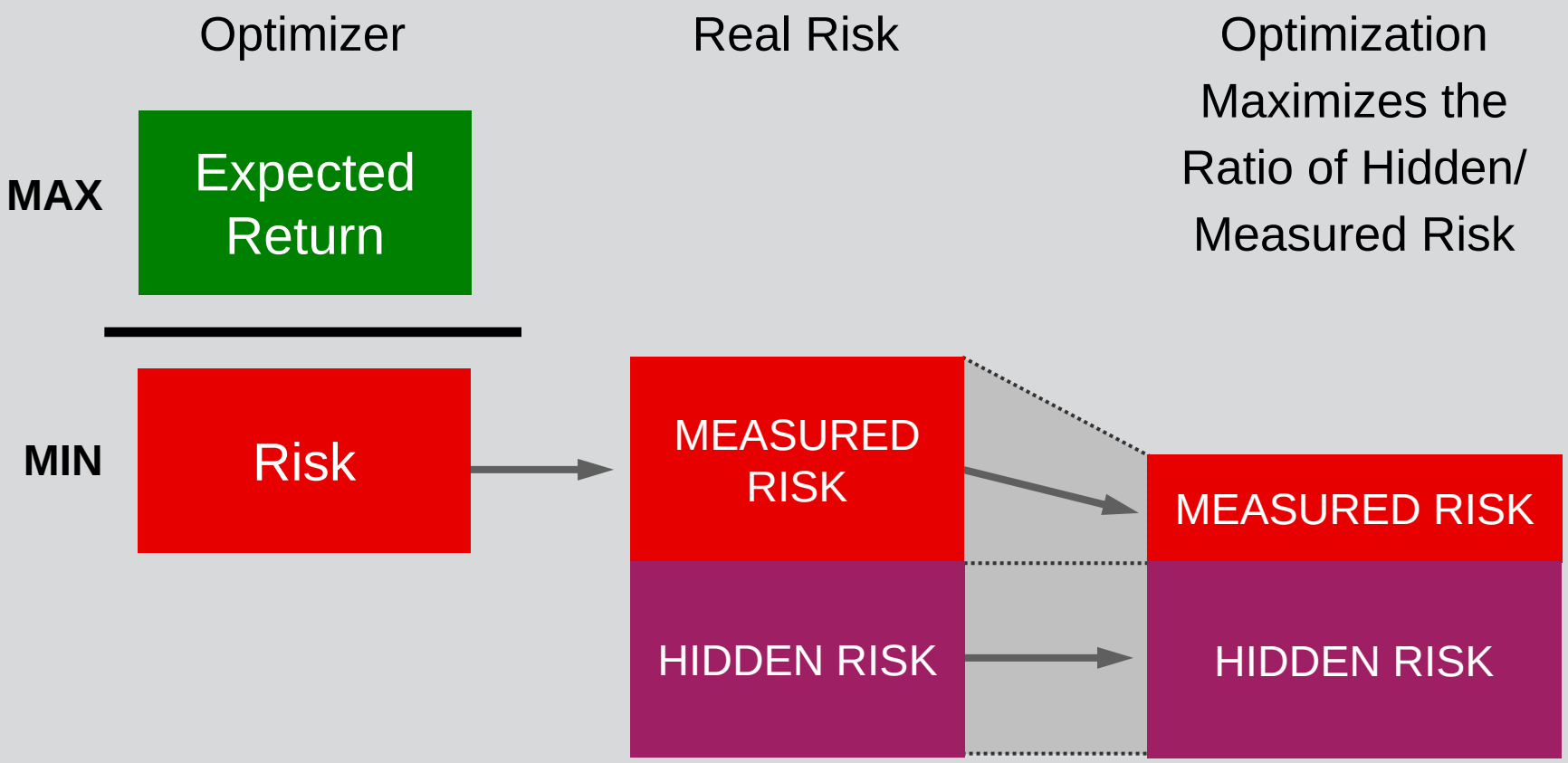
**Practically all sources of hidden risks have the effect of boosting the Sharpe ratio.**

**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).**

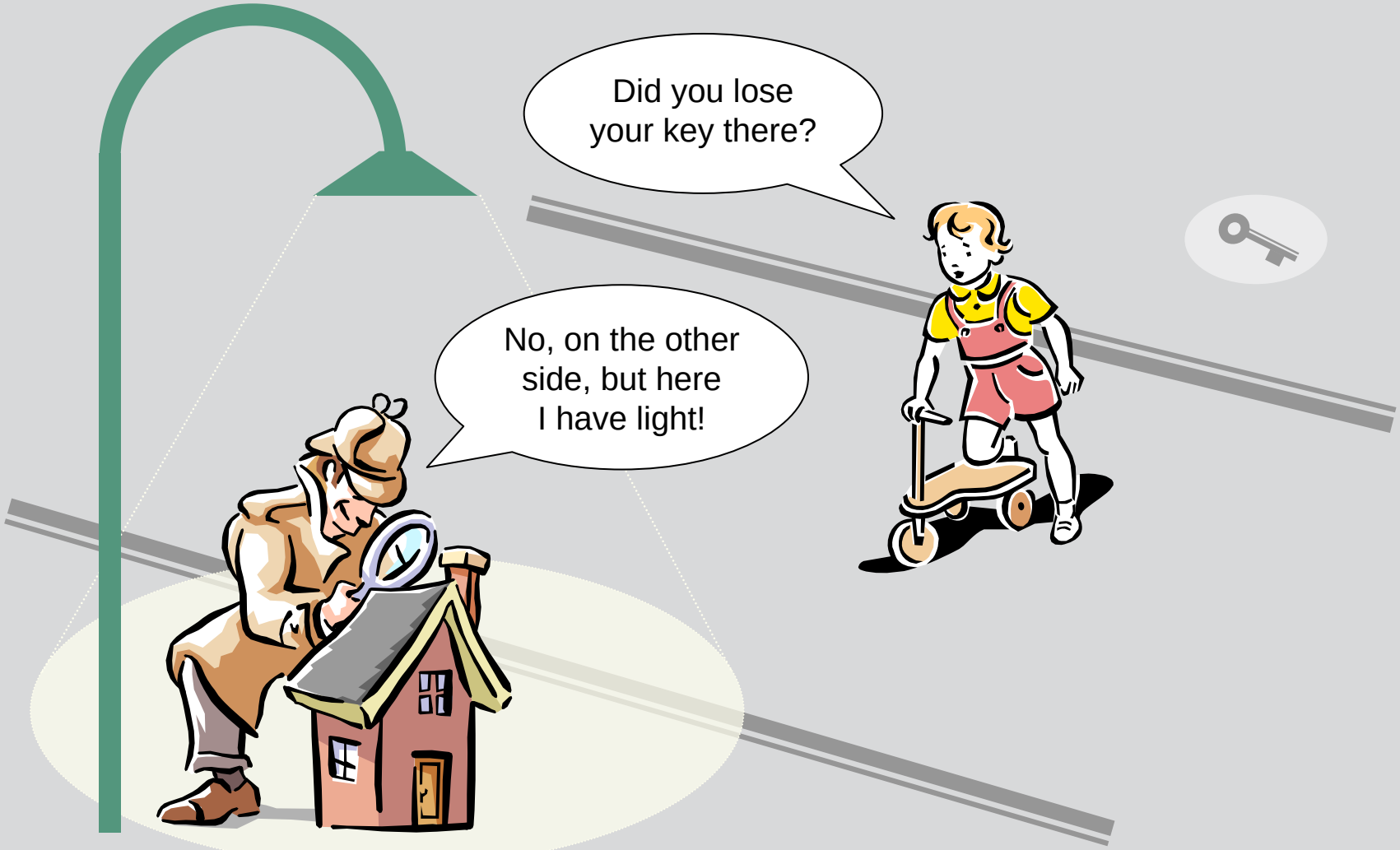
# Optimizers Failed, However Advanced...



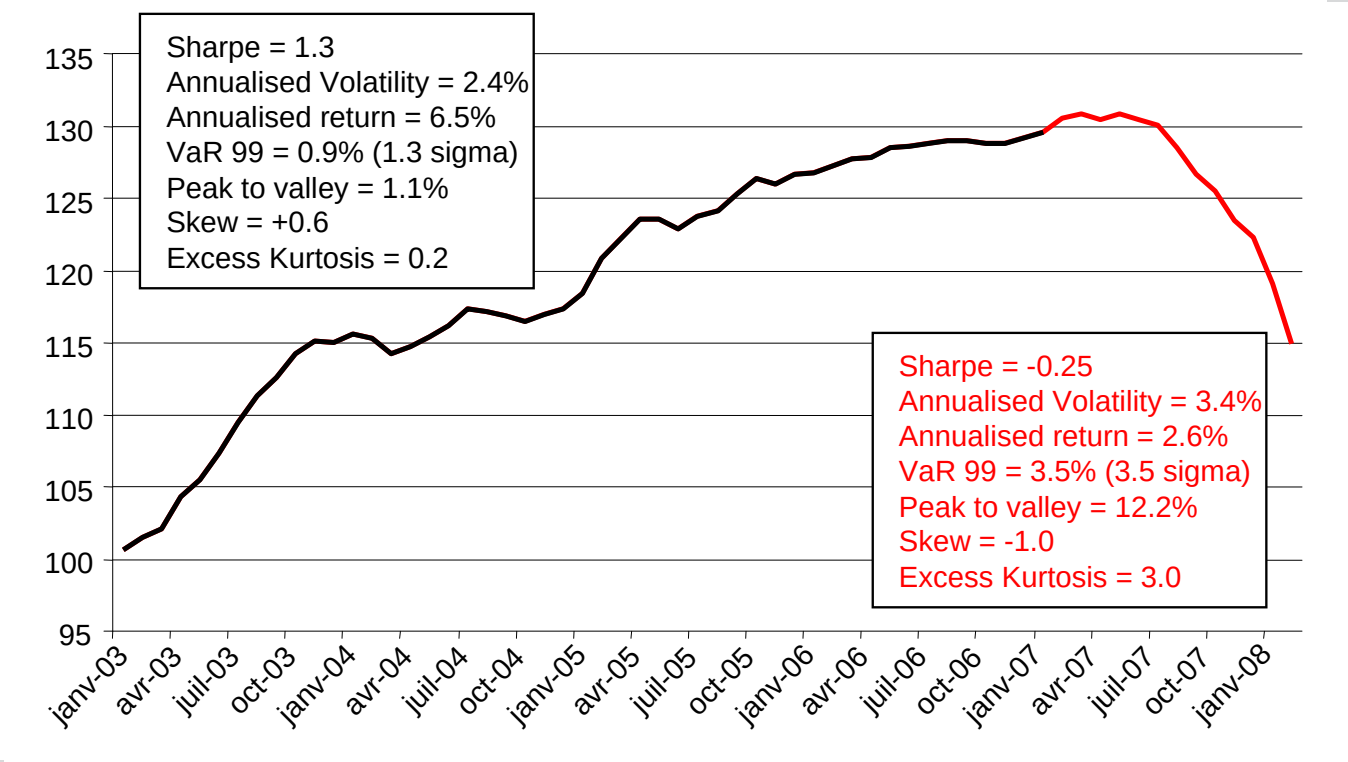

**Optimizers, however sophisticated, simply maximize expected return while minimizing *measured* risk. Therefore, by design, optimizers maximize the proportion of unmeasurable risk – i.e. hidden risk – leading automatically to portfolios which eventually deliver very nasty surprises….**

# Factor Analysis

# What Are You Looking For?



# Pure Performance Analysis

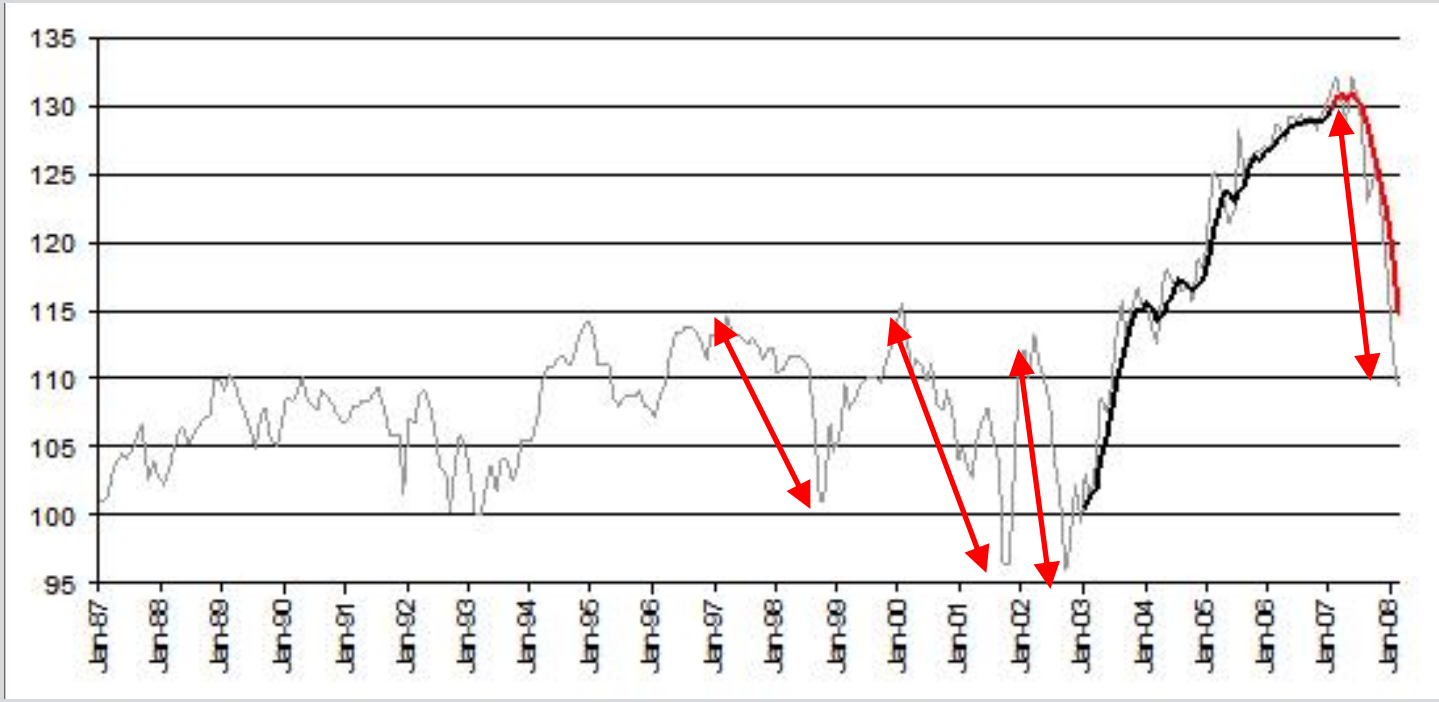



## Credit driven fund:

- Long AAA bonds, Short T-bonds, duration 10Y

**Could such a loss be anticipated by looking only at the past fund performances?**

# Factor Analysis




## > 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.**

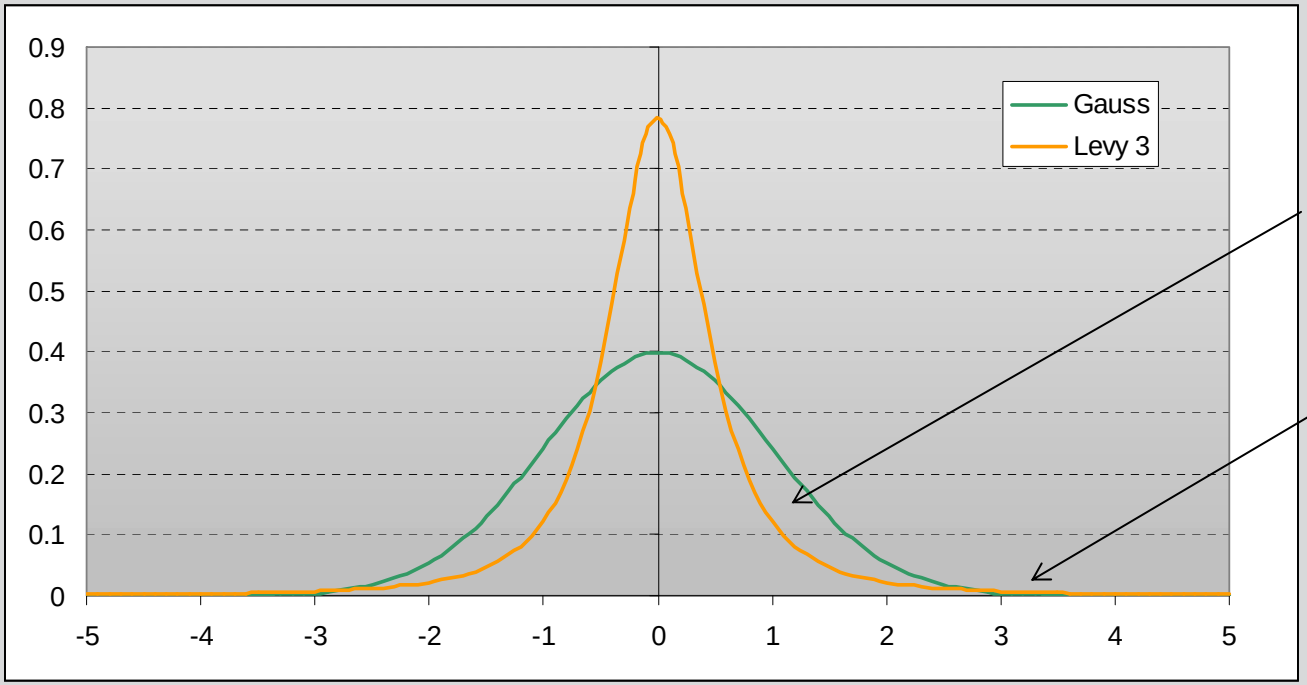
**This leads us to the way extreme risk can be anticipated through the concept of STRESS VAR. One can see that the loss experienced in 2007 had several similar precedents. The loss of the fund is in line with its Stress VaR, which itself is derived from "extrapolated" losses of the fund, prior to its actual track record.**

# Models That Don’t Work

# The Delusion of Fat Tails

## > Principle of “Fat Tail” Models

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



# 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

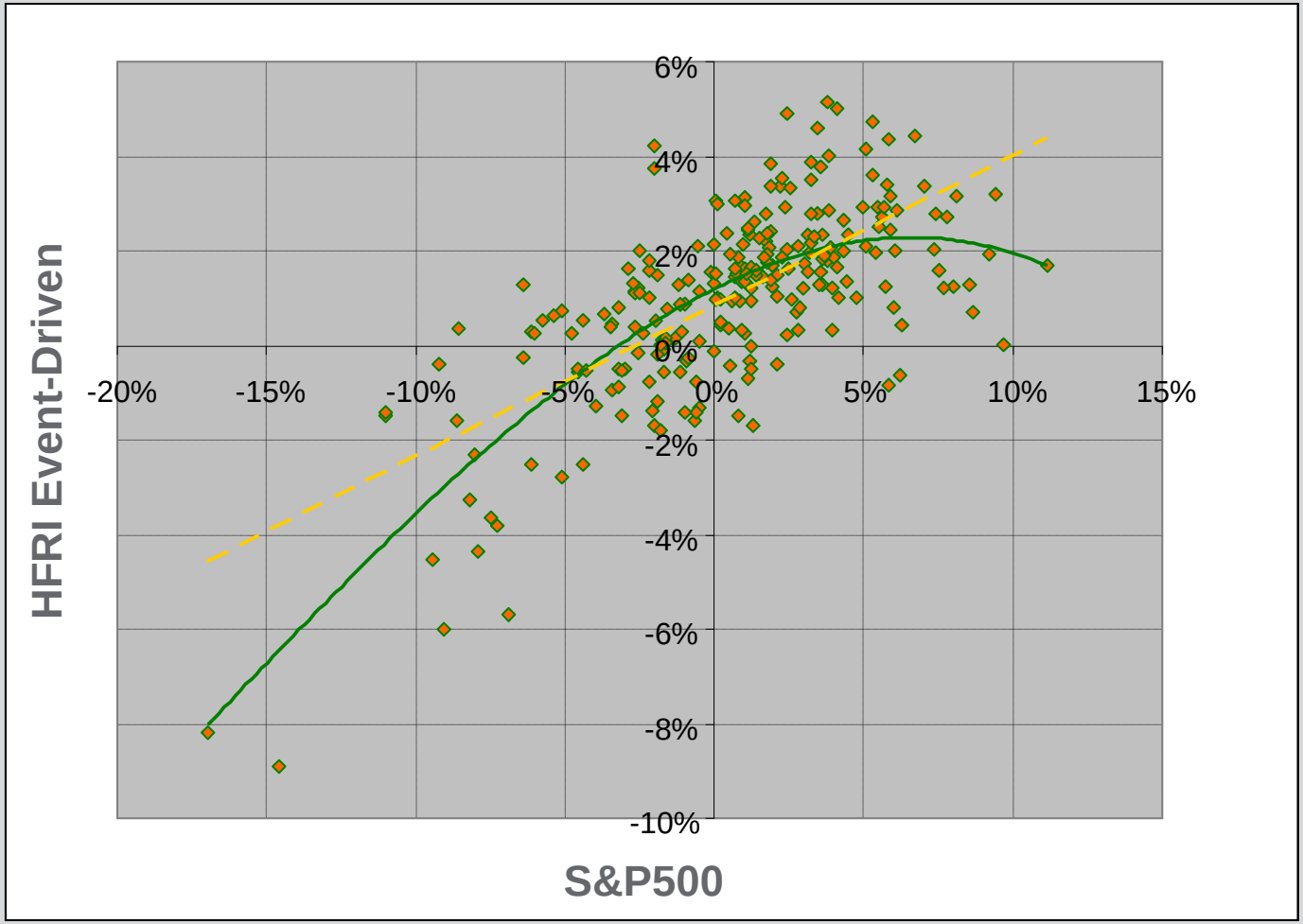
> Flaws

- **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

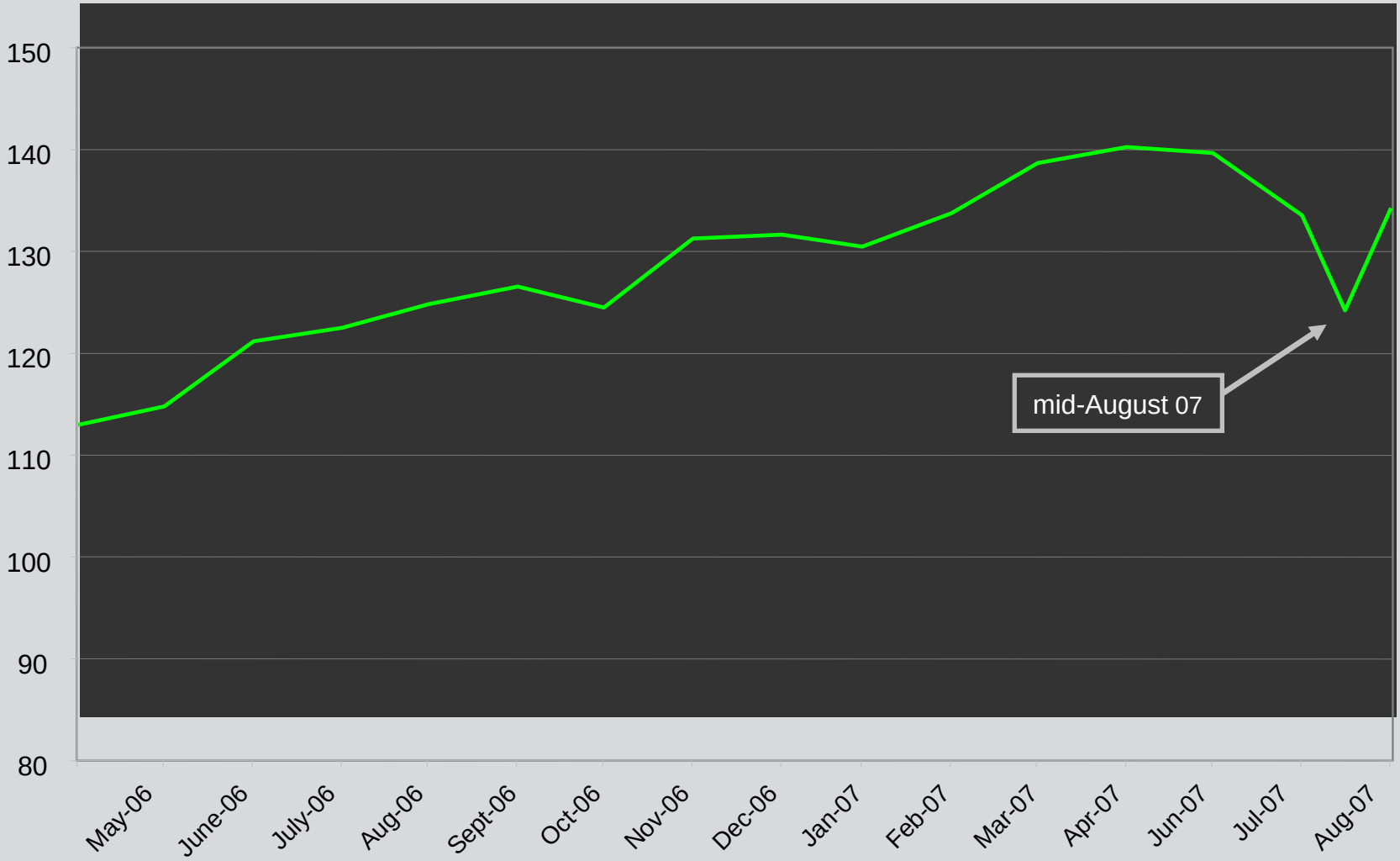
- Positions change with market
- Mimic **OPTION REPLICATION**

> **3** Nonlinear Relation Between Assets

- 3.1 **BONDS vs. STOCKS**
  (credit spreads increase when the stock declines)
- 3.2 Options…

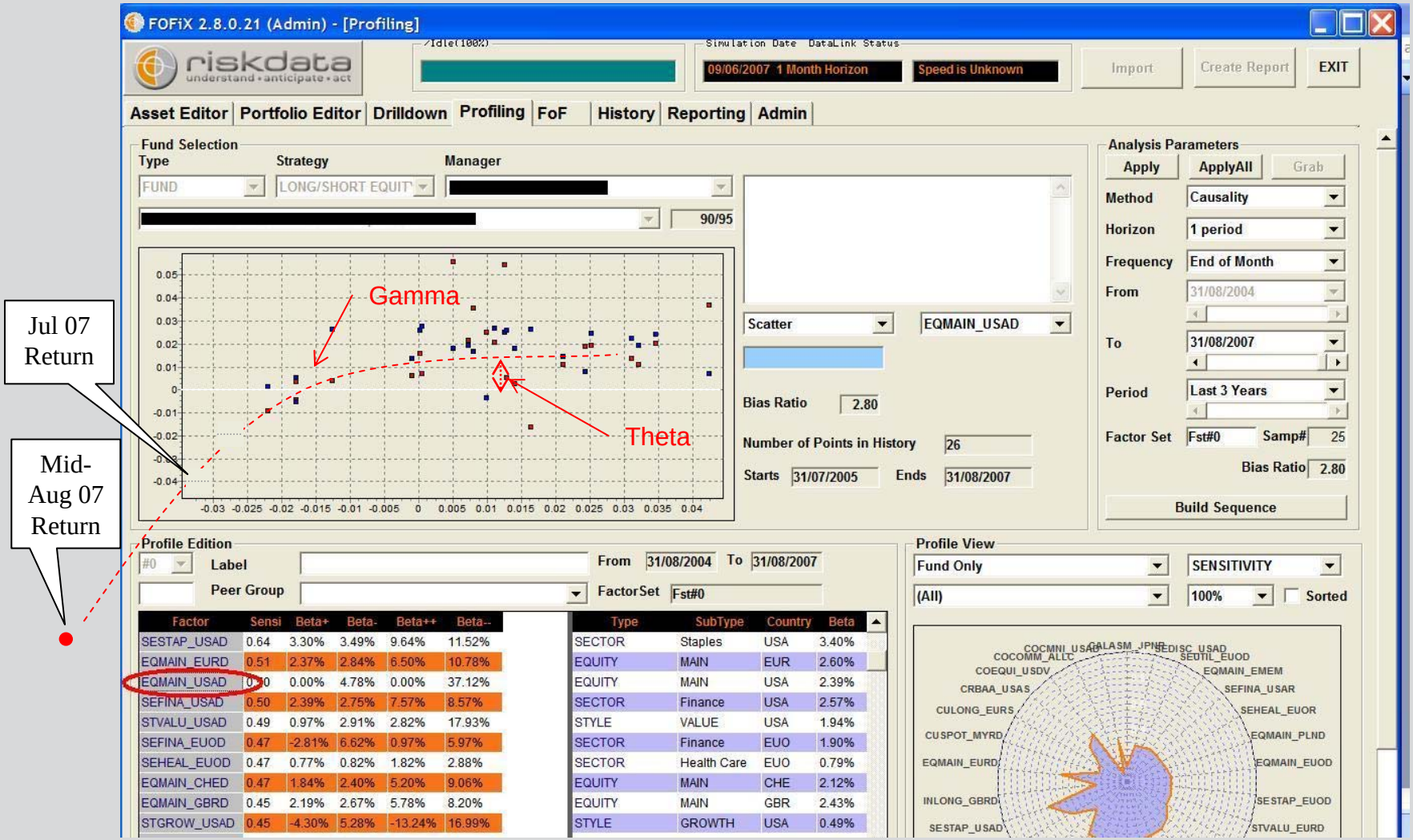
**Options are commonly considered as being responsible for nonlinearities. However, this is only the least cause of nonlinearities. Rather, the first cause of *correlations*-in-flux is the impact of liquidity gaps.**

# L/S Equity: Major Source of Hidden Risk = Nonlinearity




**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: $\text{Fund} = \beta_i \text{Fact}_i + \alpha_i \qquad i = 1 \ldots n$
- Nonlinear + lags:

$$\text{Fund} = \varphi_i(\text{Fact}_i) + \psi_i(\text{Fact}_i(t\text{-}1)) + \rho_i \text{Fund}(t\text{-}1) + \alpha_i \qquad i = 1 \ldots n$$

- Score each model by relevance in ***extreme*** scenarios

# Poly-Models

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

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

## > **Nonlinear** Modelling

- Hermitte Polynomials $H_k$: $\qquad \varphi_i(\text{Fact}_i) = \sum \beta_i^k H_k(\text{Fact}_i) + \alpha_i$
- Nonlinear Multi-factor model by inverting Cov($H_k$(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.

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

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

  p-value = Percentile of E(Fund) 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

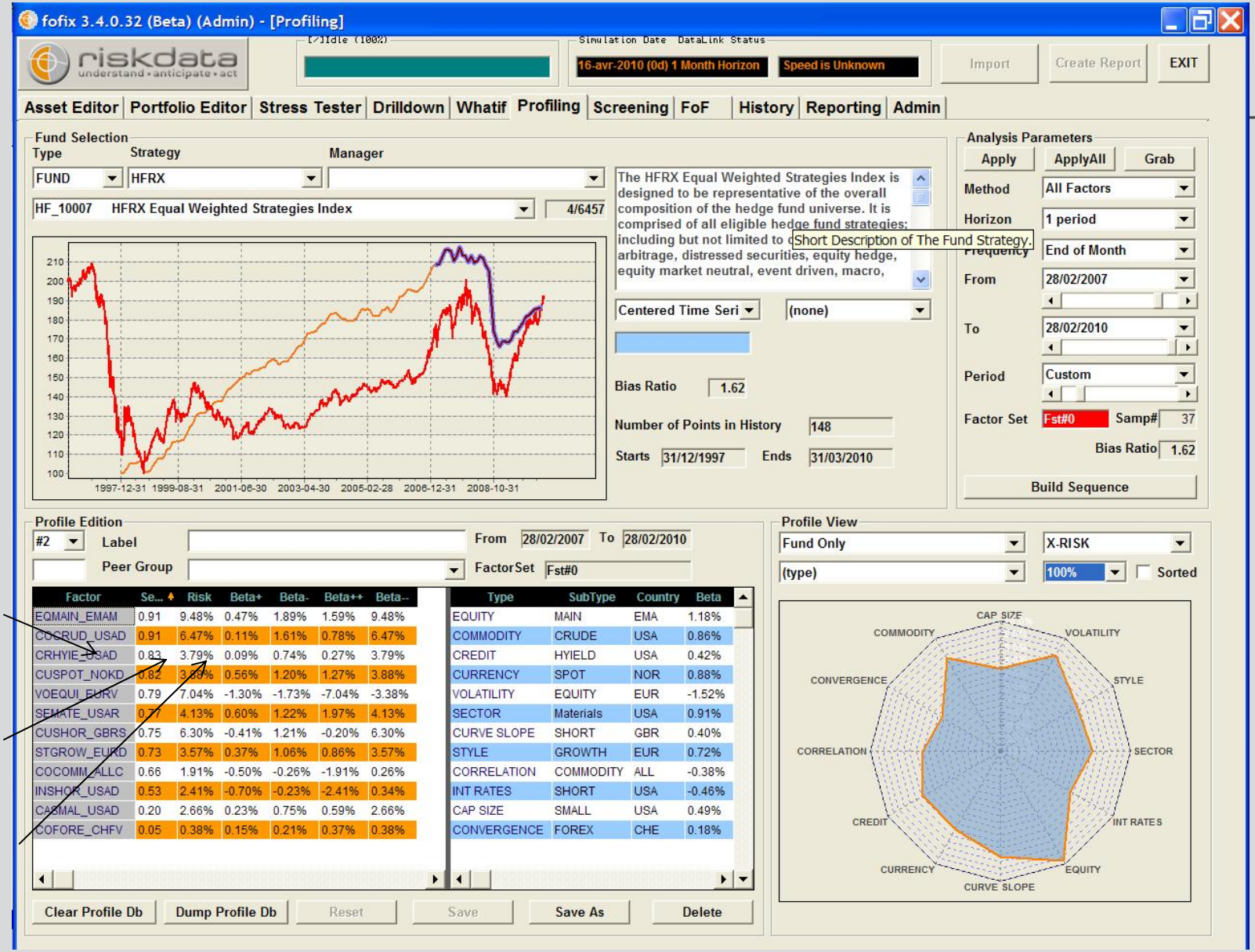
- Select only factors with a strong statistical relationship to the fund
- Focus on **EXTREME MOVES**

> **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.**




List of Market Factors

Relevance of Factors

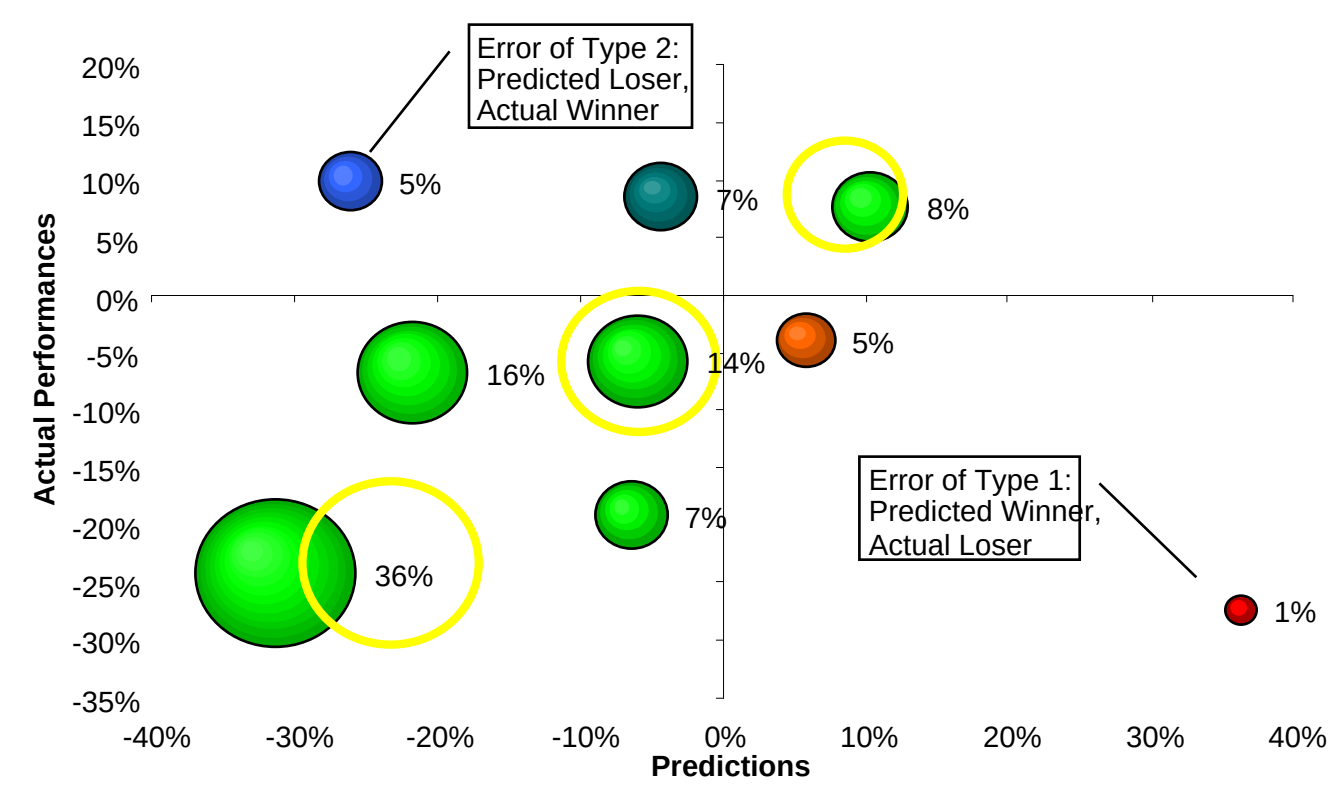
Stress Test of each factor

**FOFiX® interface shows the implementation of the 3-steps StressVaR process.**

# 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?



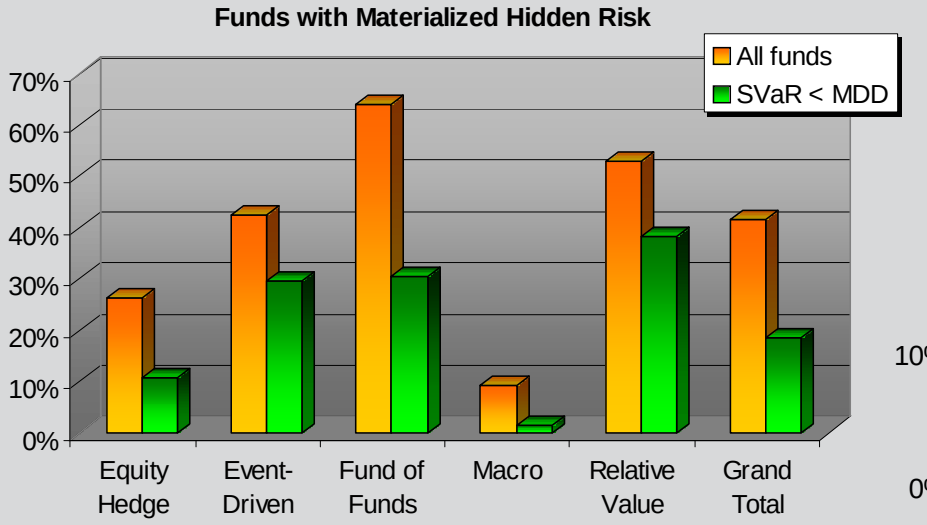

**Actual vs. predicted performances of hedge funds during the 2008 crisis**

**This graph compares the actual performance of hedge funds during Sep-Oct 08 with the pattern of what could have been predicted by FOFiX'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.**

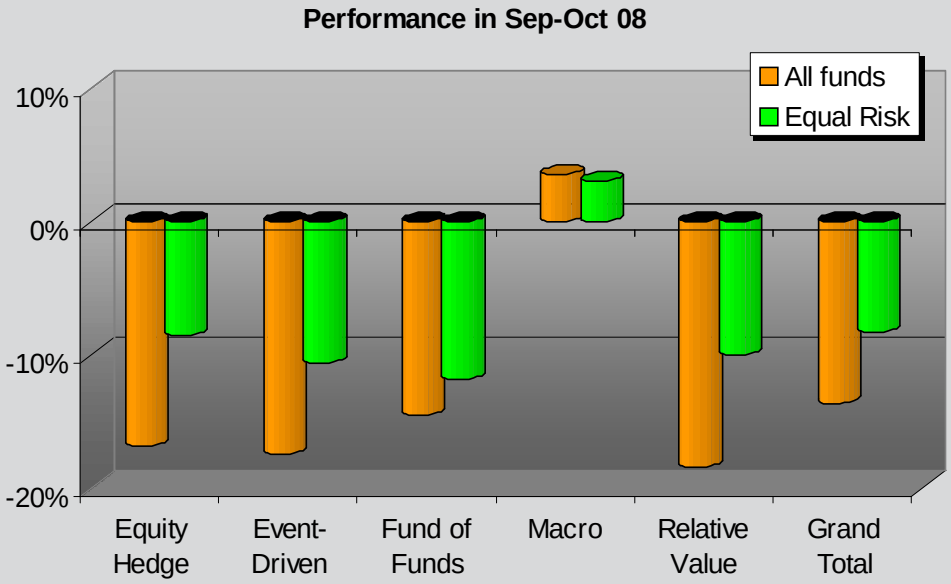
**In the following slides we will see the techniques put in place to generate such a result.**

# Fund Selection by StressVaR




- **Eliminate if StressVaR > Max Draw Down**
- **Allocation ~ 1 / StressVaR**

**⇒ Losses mitigated by 40%!**



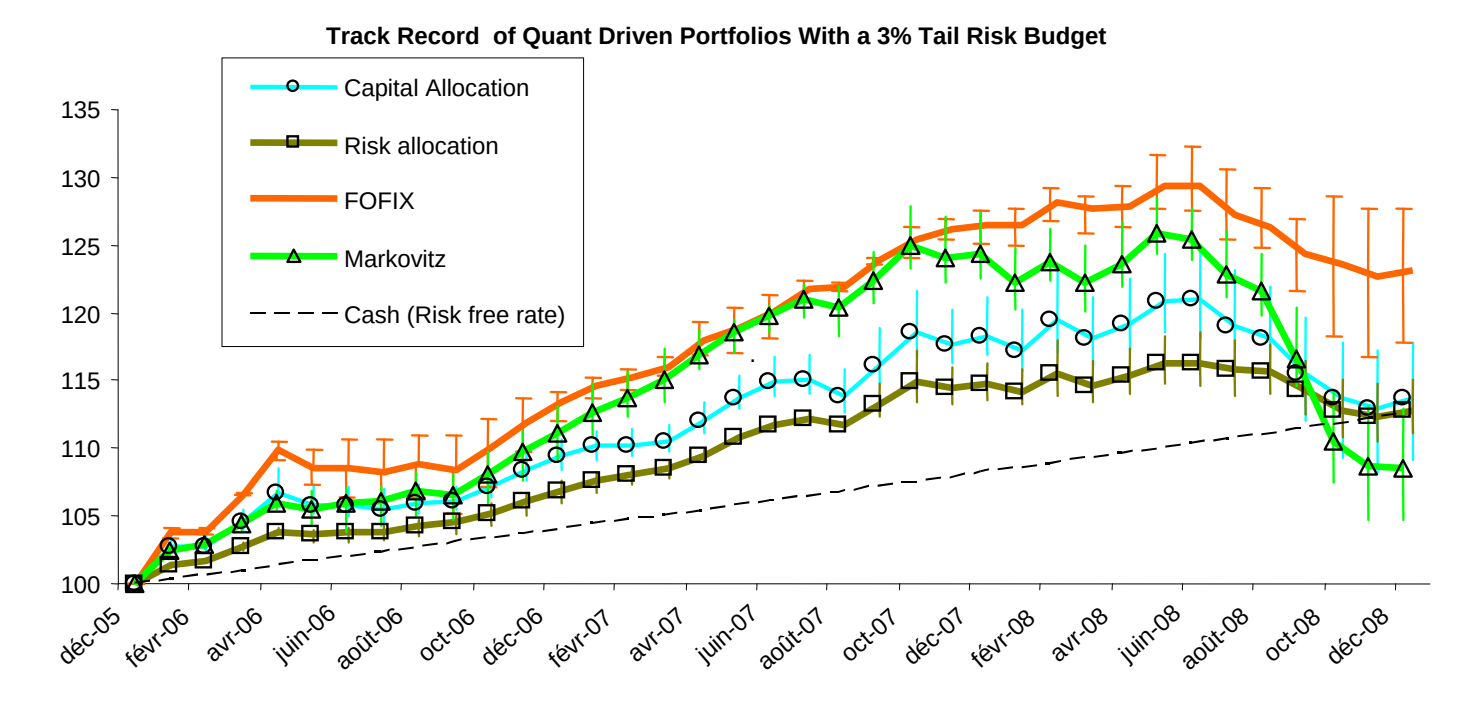

**Materialized Hidden Risk if**

**Loss > 2 x Past Max Draw Down**

**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.**

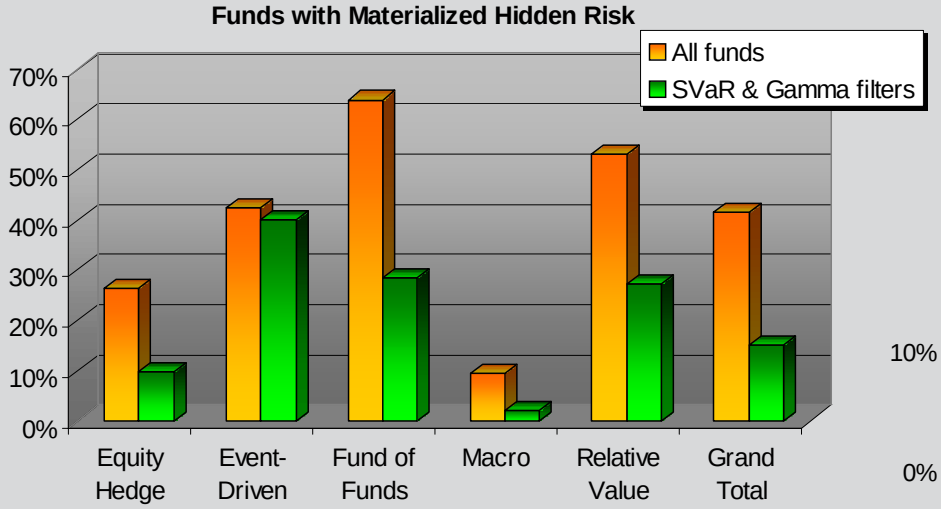
# Manage with Constant Extreme Risk Budgets Rather Than Static Allocation or Constant Volatility



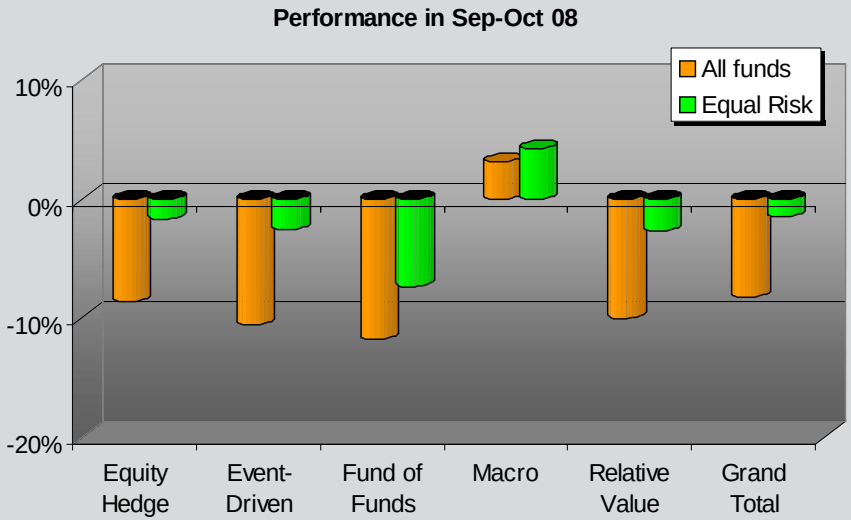

| | | |
|---|---|---|
| Capital Allocation | Medium Performance | Medium Risk Control |
| Risk Allocation | Weak Performance | Risk Control OK |
| Markowitz | Performance OK | Bad Risk Control |
| FOFiX | Performance OK | Good Risk Control |

# Ex-Ante Fund Selection by Convexity

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




**Average loss almost cancelled (< 1.5%)**




**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!