

UW

Factor Model Based Risk Management for Hedge Funds and Fund of Hedge Funds with Limited Transparency

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Outline

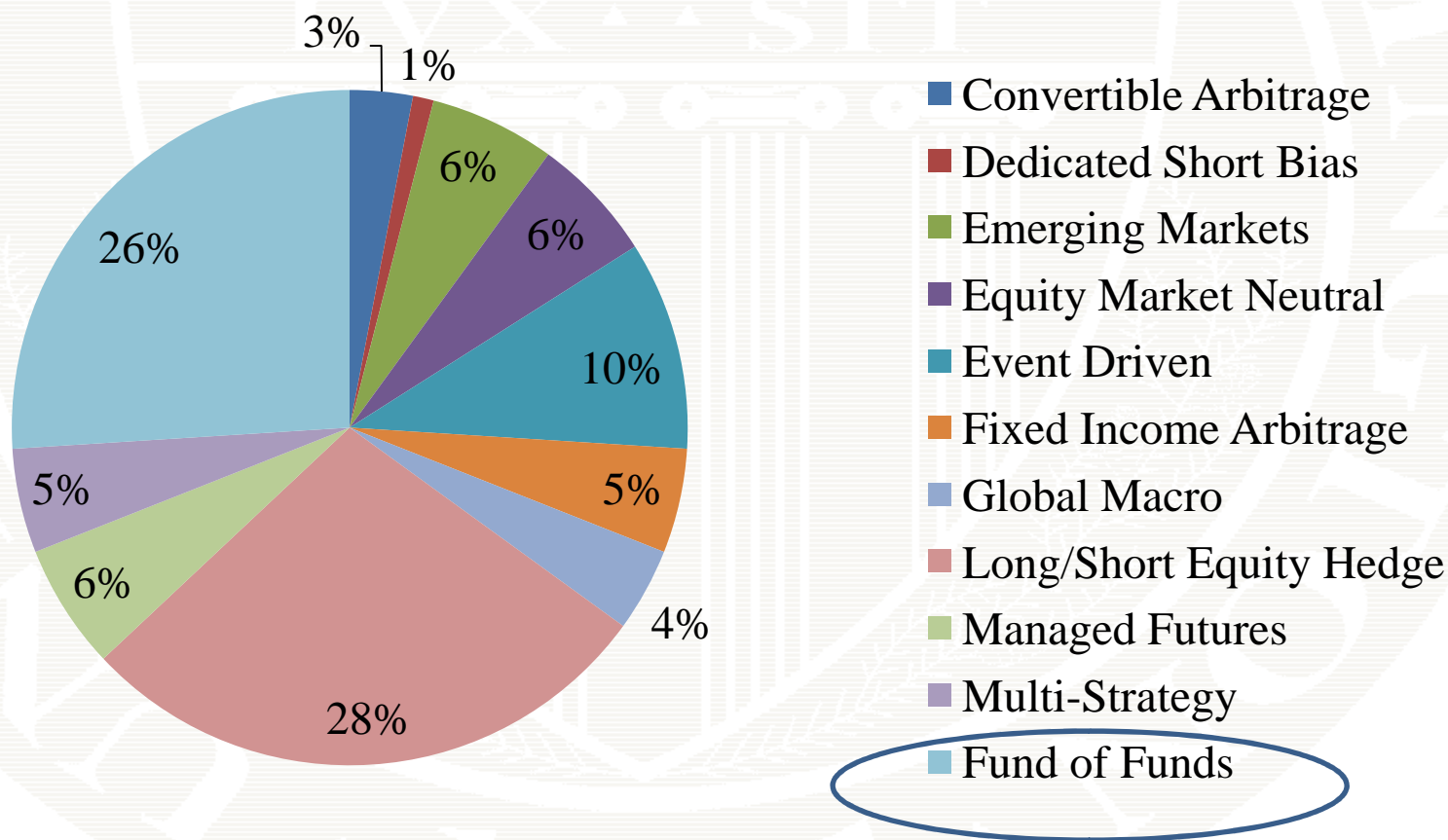
- Fund of hedge funds environment
- Characteristics of hedge fund data
- Linear factor model for hedge fund returns
- Risk Measures
- Factor model Monte Carlo methodology
- Risk decompositions
- Example

Fund of Hedge Funds Environment

- FoHFs are hedge funds that invest in other hedge funds
 - 20 to 30 portfolios of hedge funds
 - Typical portfolio size is 30 funds
- Hedge fund universe is large: 5000 live funds
 - Segmented into 10-15 distinct strategy types
- Hedge funds voluntarily report monthly performance to commercial databases
 - Altvest, CISDM, HedgeFund.net, Lipper TASS, CS/Tremont, HFR
- Limited transparency is typical but that is changing

Hedge Fund Universe

Live funds



Risk Measurement and Management

- Quantify exposures to risk drivers
 - Equity, rates, credit, volatility, currency, commodity, strategy, etc.
- Quantify fund and portfolio risk
 - Return standard deviation, value-at-risk (VaR), expected tail loss (ETL)
- Perform risk decomposition
 - Contribution of risk factors, contribution of constituent funds to portfolio risk
- Stress testing and scenario analysis

Challenges of Hedge Fund Return Data

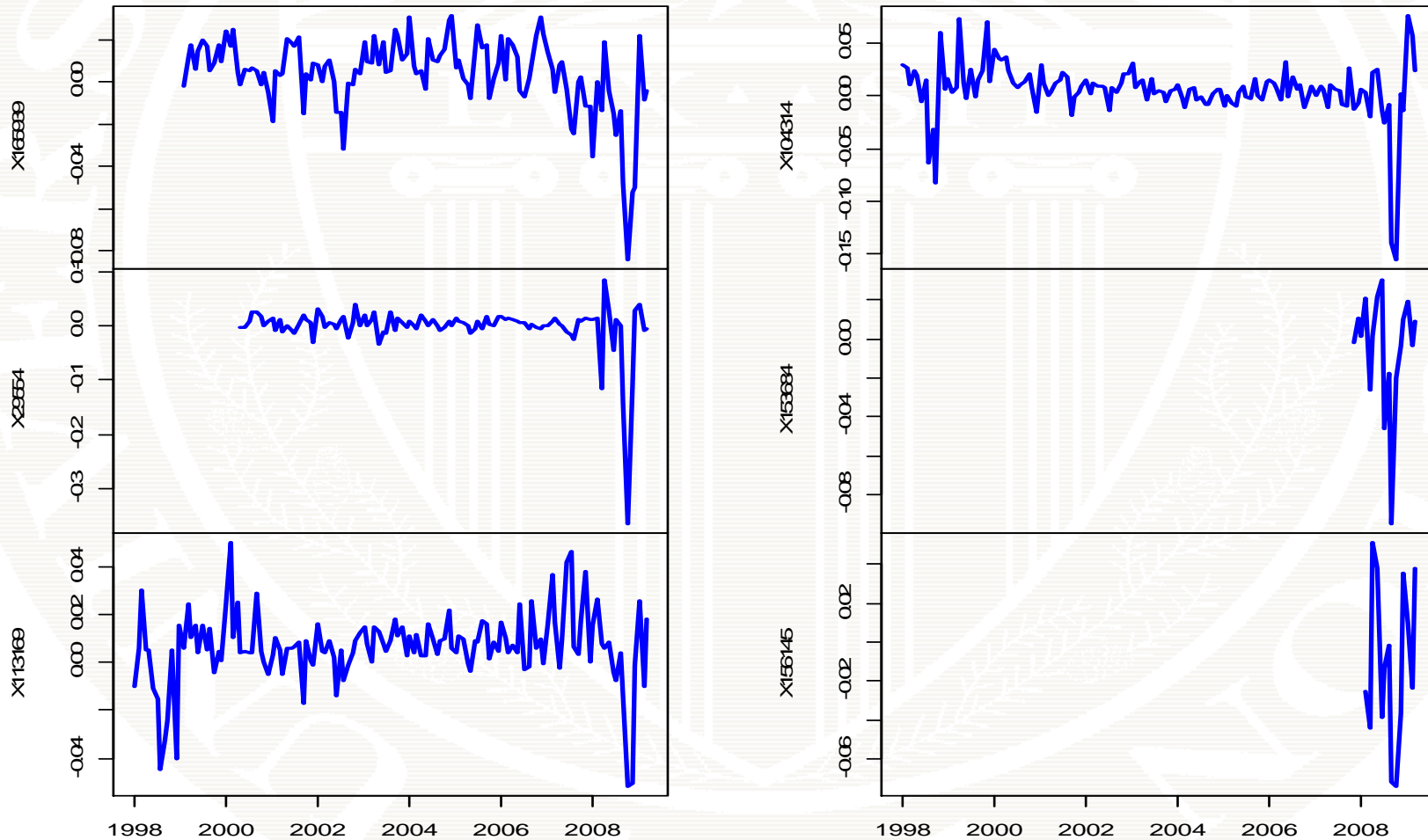
- Reporting biases
 - Survivorship, backfill
- Non-normal behavior
 - Asymmetry (skewness) and fat tails (excess kurtosis)
- Serial correlation
 - Performance smoothing, illiquid positions
- Small sample sizes
- Unequal histories

Hedge Fund Data: Characteristics

	fund1	fund2	fund3	fund4	fund5
Observations	122.0000	107.0000	135.0000	135.0000	135.0000
NAs	13.0000	28.0000	0.0000	0.0000	0.0000
Minimum	-0.0842	-0.3649	-0.0519	-0.1556	-0.2900
Quartile 1	-0.0016	-0.0051	0.0020	-0.0017	-0.0021
Median	0.0058	0.0046	0.0060	0.0073	0.0049
Arithmetic Mean	0.0038	-0.0017	0.0063	0.0059	0.0021
Geometric Mean	0.0037	-0.0029	0.0062	0.0055	0.0014
Quartile 3	0.0158	0.0129	0.0127	0.0157	0.0127
Maximum	0.0311	0.0861	0.0502	0.0762	0.0877
Variance	0.0003	0.0020	0.0002	0.0008	0.0013
Stdev	0.0176	0.0443	0.0152	0.0275	0.0357
Skewness	-1.7753	-5.6202	-0.8810	-2.4839	-4.9948
Kurtosis	5.2887	40.9681	3.7960	13.8201	35.8623
Rho1	0.6060	0.3820	0.3590	0.4400	0.383

Sample: January 1998 – March 2009

Hedge Fund Data: Unequal Histories



Fund Level Linear Factor Model

$$\begin{aligned}R_{it} &= \alpha_i + \beta_{i1}F_{1t} + \cdots + \beta_{ik}F_{kt} + \varepsilon_{it}, \\ &= \alpha_i + \boldsymbol{\beta}'_i \mathbf{F}_t + \varepsilon_{it}\end{aligned}$$

$$i = 1, \dots, n; \quad t = t_i, \dots, T$$

$$\mathbf{F}_t \sim (\boldsymbol{\mu}_F, \boldsymbol{\Sigma}_F)$$

$$\varepsilon_{it} \sim (0, \sigma_{\varepsilon,i}^2)$$

$$\text{cov}(F_{jt}, \varepsilon_{is}) = 0 \text{ for all } j, i, s \text{ and } t$$

$$\text{cov}(\varepsilon_{it}, \varepsilon_{js}) = 0 \text{ for } i \neq j, s \text{ and } t$$

Performance Attribution

$$E[R_{it}] = \alpha_i + \beta_{i1} E[F_{1t}] + \cdots + \beta_{ik} E[F_{kt}]$$

Expected return due to systematic “beta” exposure

$$\beta_{i1} E[F_{1t}] + \cdots + \beta_{ik} E[F_{kt}]$$

Expected return due to manager specific “alpha”

$$\alpha_i = E[R_{it}] - (\beta_{i1} E[F_{1t}] + \cdots + \beta_{ik} E[F_{kt}])$$

Factor Model Covariance

$$\mathbf{R}_t = \boldsymbol{\alpha} + \mathbf{B} \mathbf{F}_t + \boldsymbol{\varepsilon}_t$$

$n \times 1$ $n \times 1$ $n \times k$ $k \times 1$ $n \times 1$

$$\text{var}(\mathbf{R}_t) = \boldsymbol{\Sigma}_{FM} = \mathbf{B} \boldsymbol{\Sigma}_F \mathbf{B}' + \mathbf{D}_\varepsilon$$

$$\mathbf{D}_\varepsilon = \text{diag}(\sigma_{\varepsilon,1}^2, \dots, \sigma_{\varepsilon,n}^2)$$

Note: $\text{cov}(R_{it}, R_{jt}) = \boldsymbol{\beta}'_i \text{var}(\mathbf{F}_t) \boldsymbol{\beta}_j = \boldsymbol{\beta}'_i \boldsymbol{\Sigma}_F \boldsymbol{\beta}_j$

Portfolio Linear Factor Model

$\mathbf{w} = (w_1, \dots, w_n)'$ = portfolio weights

$$\sum_{i=1}^n w_i = 1, \quad w_i \geq 0 \text{ for } i = 1, \dots, n$$

$$R_{p,t} = \mathbf{w}'\mathbf{R}_t = \mathbf{w}'\boldsymbol{\alpha} + \mathbf{w}'\mathbf{B}\mathbf{F}_t + \mathbf{w}'\boldsymbol{\varepsilon}_t$$

$$= \sum_{i=1}^n w_i R_{it} = \sum_{i=1}^n w_i \alpha_i + \sum_{i=1}^n w_i \boldsymbol{\beta}'_i \mathbf{F}_t + \sum_{i=1}^n w_i \varepsilon_{it}$$

$$= \alpha_p + \boldsymbol{\beta}'_p \mathbf{F}_t + \varepsilon_{p,t}$$

Factor Structure

- Traditional Market Factors
 - Tradable indices that measure broad asset class performance of equity, rates, credit, commodities and currency. Factor is excess return on index.
 - Tradable market factors that measure intra-asset class biases
 - Geography, Sector, Style, Capitalization, Credit Quality, Capital Structure, Yield Curve Shape
- Hedge Fund Specific (“Exotic”) Factors
 - Tradable factors that capture performance of passive investment strategies utilized by hedge funds

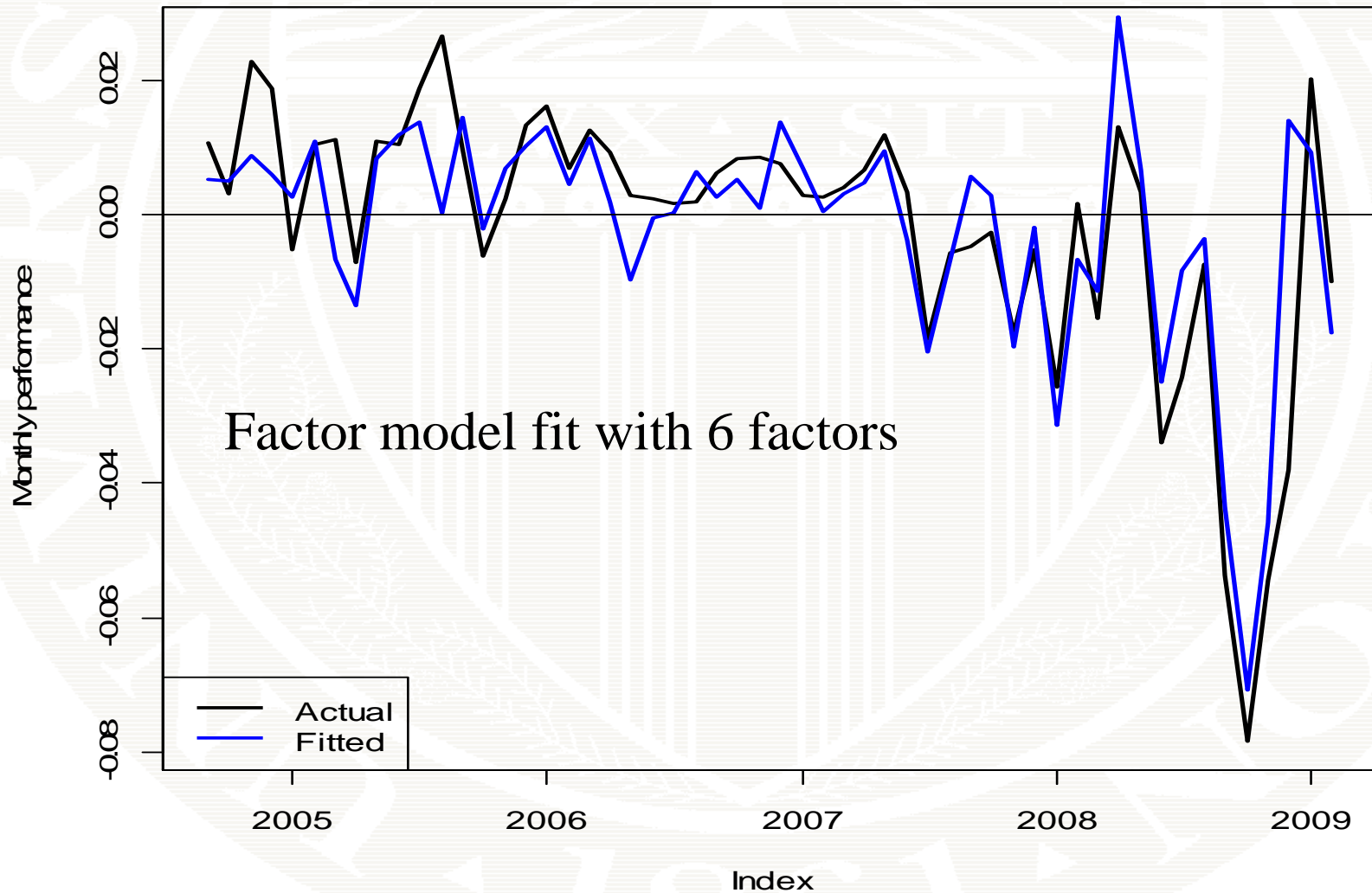
Practical Considerations

- Many potential risk factors (> 50)
- High collinearity among some factors
- Risk factors vary across discipline/strategy
- Nonlinear effects
- Dynamic (lagged) effects
- Factor sensitivities change over time
- Common histories for factors; unequal histories for fund performance

Estimation Methodology

- Choice of Factor Set
 - Statistical variable selection/Data mining techniques
 - Qualitative/subjective selection of factors
 - Hybrid approach
- Estimation technique
 - OLS on full sample
 - Rolling regression
 - Regression on exponentially weighted data
 - Kalman filter
- Use proxy models for funds with short history

Factor Model Fit: Example Fund



Risk Measures

Return Standard Deviation (SD , *aka active risk*)

$$\sigma = SD(R_t) = \left(\boldsymbol{\beta}' \boldsymbol{\Sigma}_F \boldsymbol{\beta} + \sigma_\varepsilon^2 \right)^{1/2}$$

Value-at-Risk (VaR)

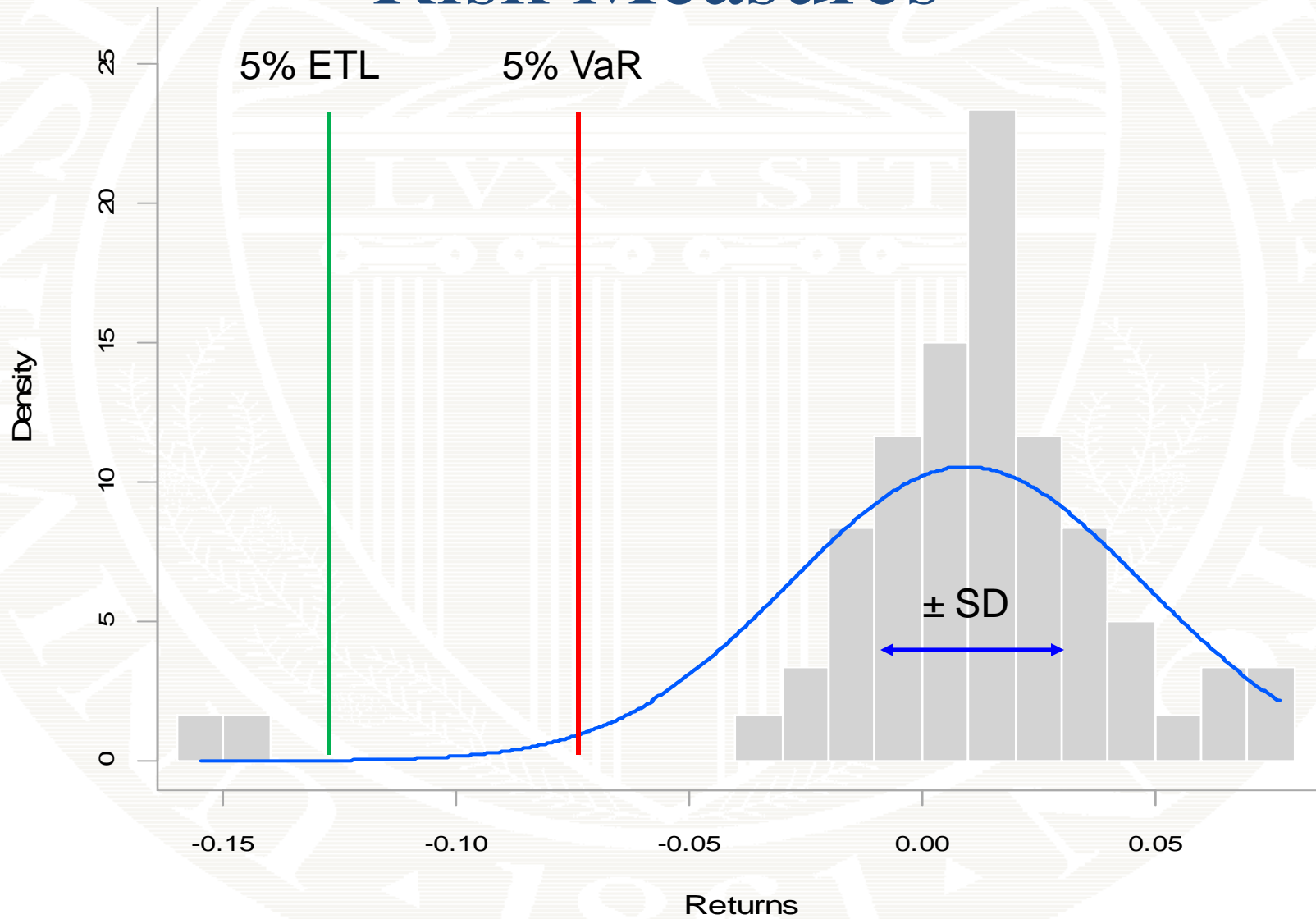
$$VaR_\alpha = q_\alpha = F^{-1}(\alpha), \quad 0.01 \leq \alpha \leq 0.10$$

$F = CDF$ of return R_t

Expected Tail Loss (ETL)

$$ETL_\alpha = E[R_t \mid R_t \leq VaR_\alpha]$$

Risk Measures



Tail Risk Measures: Non-Normal Distributions

- Hedge fund returns are typically non-normal
- Many possible univariate non-normal distributions
 - Student's- t , skewed- t , generalized hyperbolic, Gram-Charlier, α -stable, generalized Pareto, etc.
- Need multivariate non-normal distributions for portfolio analysis.
- Small samples and unequal histories make multivariate modeling difficult

Factor Model Monte Carlo (FMMC)

- Use fitted factor model to simulate pseudo hedge fund return data preserving empirical characteristics of risk factors and residuals
 - Use *full data* for factors and *unequal history* for funds to deal with missing data
- Estimate tail risk and related measures non-parametrically from simulated return data

FMMC: Unequal Histories

Risk factors

Fund performance

$$F_{1,T}, \dots, F_{k,T}$$

$$R_{1,T}$$

$$R_{n,T}$$

⋮

⋮

⋮

$$F_{1,T-T_i}, \dots, F_{k,T-T_i}$$

$$R_{1,T-T_1}$$

⋮

⋮

$$R_{n,T-T_n}$$

$$F_{1,1}, \dots, F_{k,1}$$



Observe full history



Observe partial histories

Simulation Algorithm

- Simulate B values of the risk factors by re-sampling from *full sample* empirical distribution:

$$\{ \mathbf{F}_1^*, \dots, \mathbf{F}_B^* \}$$

- Simulate B values of the factor model residuals from fitted non-normal distribution:

$$\{ \hat{\varepsilon}_{i1}^*, \dots, \hat{\varepsilon}_{iB}^* \}, \quad i = 1, \dots, n$$

- Create factor model returns from factor models fit over *truncated samples*, simulated factor variables drawn from *full sample* and simulated residuals:

$$R_{it}^* = \hat{\alpha}_i + \hat{\boldsymbol{\beta}}_i' \mathbf{F}_t^* + \hat{\varepsilon}_{it}^*, \quad t = 1, \dots, B; i = 1, \dots, n$$

What to do with $\{R_{it}^*\}_{t=1}^B$, $\{\mathbf{F}_{it}^*\}_{t=1}^B$, $\{\hat{\boldsymbol{\epsilon}}_{it}^*\}_{t=1}^B$, ?

- Backfill missing fund performance
- Compute fund and portfolio performance measures (e.g., Sharpe ratios)
- Compute *non-parametric* estimates of fund and portfolio tail risk measures
- Compute *non-parametric* estimates of fund and factor contributions to portfolio tail risk measures

Factor Risk Budgeting

Given linear factor model for fund or portfolio returns,

$$R_t = \alpha + \beta' \mathbf{F}_t + \varepsilon_t = \alpha + \beta' \mathbf{F}_t + \sigma_\varepsilon \times z_t = \alpha + \tilde{\beta}' \tilde{\mathbf{F}}_t$$

$$\tilde{\beta}' = (\beta', \sigma_\varepsilon), \quad \tilde{\mathbf{F}}_t = (\mathbf{F}_t', z_t)', \quad z_t \sim (0, 1)$$

SD, *VaR* and *ETL* are linearly homogenous functions of factor sensitivities $\tilde{\beta}$. Euler's theorem gives additive decomposition

$$RM(\tilde{\beta}) = \sum_{j=1}^{k+1} \tilde{\beta}_j \frac{\partial RM(\tilde{\beta})}{\partial \tilde{\beta}_j}, \quad RM = SD, VaR_\alpha, ETL_\alpha$$

Factor Contributions to Risk

Marginal Contribution to
Risk of factor j :

$$\frac{\partial RM(\tilde{\beta})}{\partial \tilde{\beta}_j}$$

Contribution to Risk
of factor j :

$$\tilde{\beta}_j \frac{\partial RM(\tilde{\beta})}{\partial \tilde{\beta}_j}$$

Percent Contribution to Risk
of factor j :

$$\tilde{\beta}_j \frac{\partial RM(\tilde{\beta})}{\partial \tilde{\beta}_j} / RM(\tilde{\beta})$$

Factor Tail Risk Contributions

For $RM = VaR$, ETL it can be shown that

$$\frac{\partial VaR_{\alpha}(\tilde{\beta})}{\partial \tilde{\beta}_j} = E[\tilde{F}_{jt} \mid R_t = VaR_{\alpha}], j = 1, \dots, k + 1$$

$$\frac{\partial ETL_{\alpha}(\tilde{\beta})}{\partial \tilde{\beta}_j} = E[\tilde{F}_{jt} \mid R_t \leq VaR_{\alpha}], j = 1, \dots, k + 1$$

Notes:

1. Intuitive interpretations as stress loss scenarios
2. Analytic results are available under normality

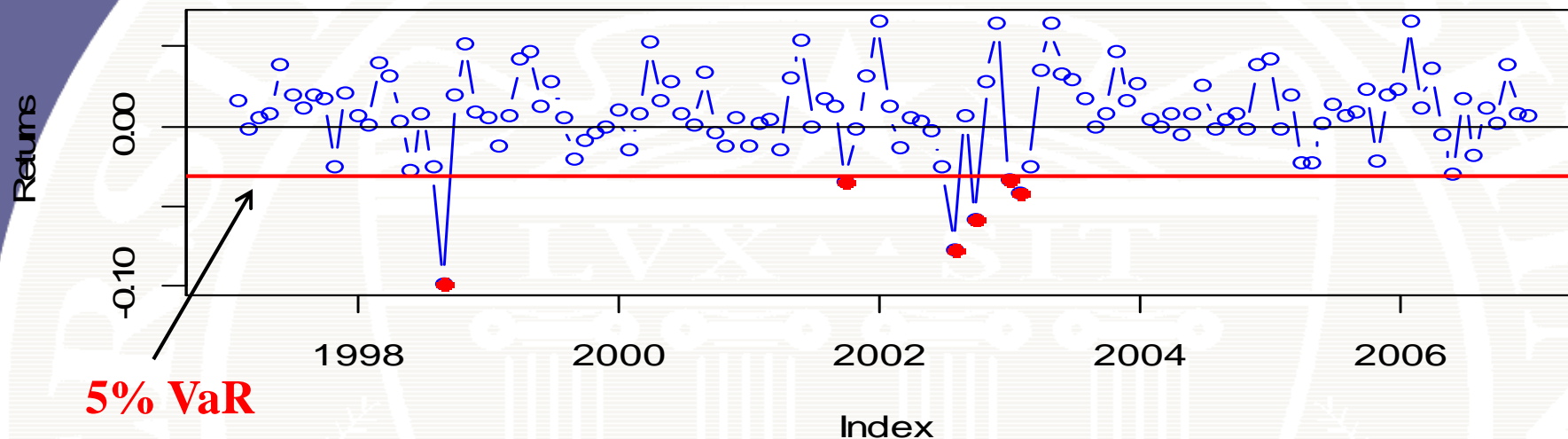
Semi-Parametric Estimation

Factor Model Monte Carlo semi-parametric estimates

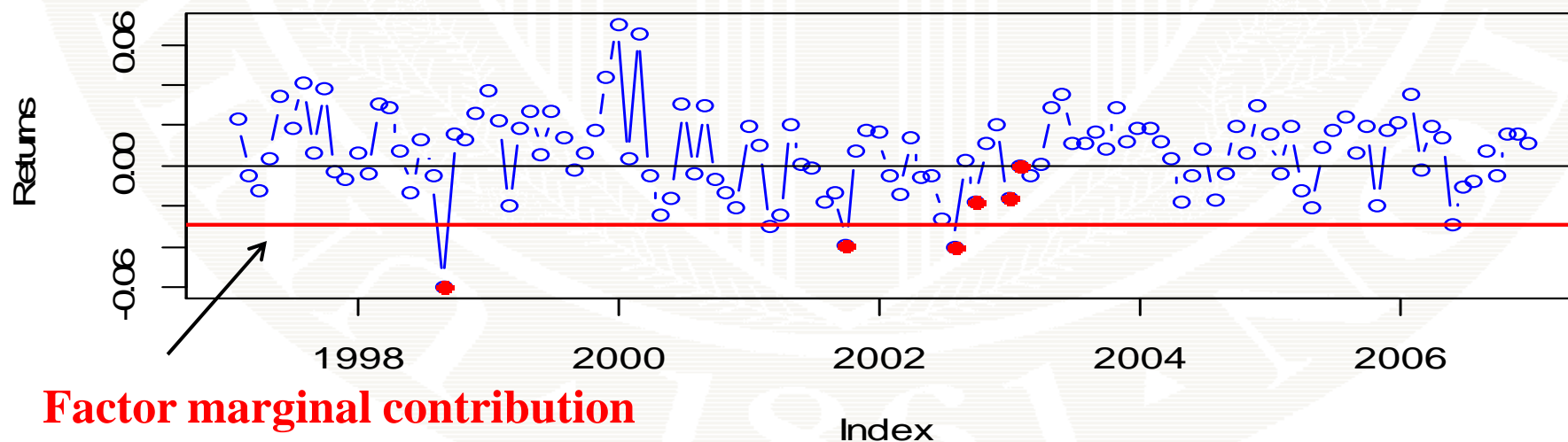
$$\hat{E}[\tilde{F}_{jt} \mid R_t = VaR_\alpha] = \frac{1}{m} \sum_{t=1}^B \tilde{F}_{jt}^* \cdot 1\{VaR_\alpha - \varepsilon \leq R_t^* \leq VaR_\alpha + \varepsilon\}$$

$$\hat{E}[\tilde{F}_{jt} \mid R_t \leq VaR_\alpha] = \frac{1}{[B\alpha]} \sum_{t=1}^B \tilde{F}_{jt}^* \cdot 1\{R_t^* \leq VaR_\alpha\}$$

Hedge fund returns and 5% VaR Violations



Risk factor returns when fund return \leq 5% VaR



Factor marginal contribution to 5% ETL

Portfolio Risk Budgeting

Given portfolio returns,

$$R_{p,t} = \mathbf{w}'\mathbf{R}_t = \sum_{i=1}^n w_i R_{it}$$

SD, *VaR* and *ETL* are linearly homogenous functions of portfolio weights \mathbf{w} . Euler's theorem gives additive decomposition

$$RM(\mathbf{w}) = \sum_{i=1}^n w_i \frac{\partial RM(\mathbf{w})}{\partial w_i}, \quad RM = SD, VaR_{\alpha}, ETL_{\alpha}$$

Fund Contributions to Portfolio Risk

Marginal Contribution to Risk of fund i : $\frac{\partial RM(\mathbf{w})}{\partial w_i}$

Contribution to Risk of fund i : $w_i \frac{\partial RM(\mathbf{w})}{\partial w_i}$

Percent Contribution to Risk of fund i : $w_i \frac{\partial RM(\mathbf{w})}{\partial w_i} / RM(\mathbf{w})$

Portfolio Tail Risk Contributions

For $RM = VaR$, ETL it can be shown that

$$\frac{\partial VaR_{\alpha}(\mathbf{w})}{\partial w_i} = E[R_{it} \mid R_{p,t} = VaR_{\alpha}(\mathbf{w})], \quad i = 1, \dots, n$$

$$\frac{\partial ETL_{\alpha}(\mathbf{w})}{\partial w_i} = E[R_{it} \mid R_{p,t} \leq VaR_{\alpha}(\mathbf{w})], \quad i = 1, \dots, n$$

Note: Analytic results are available under normality

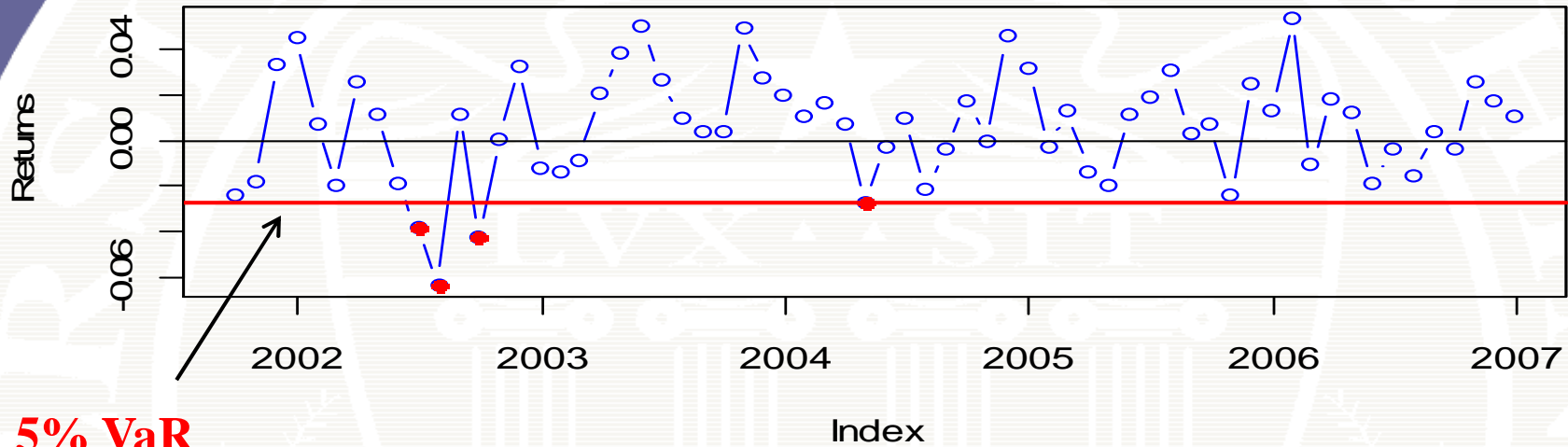
Semi-Parametric Estimation

Factor Model Monte Carlo semi-parametric estimates

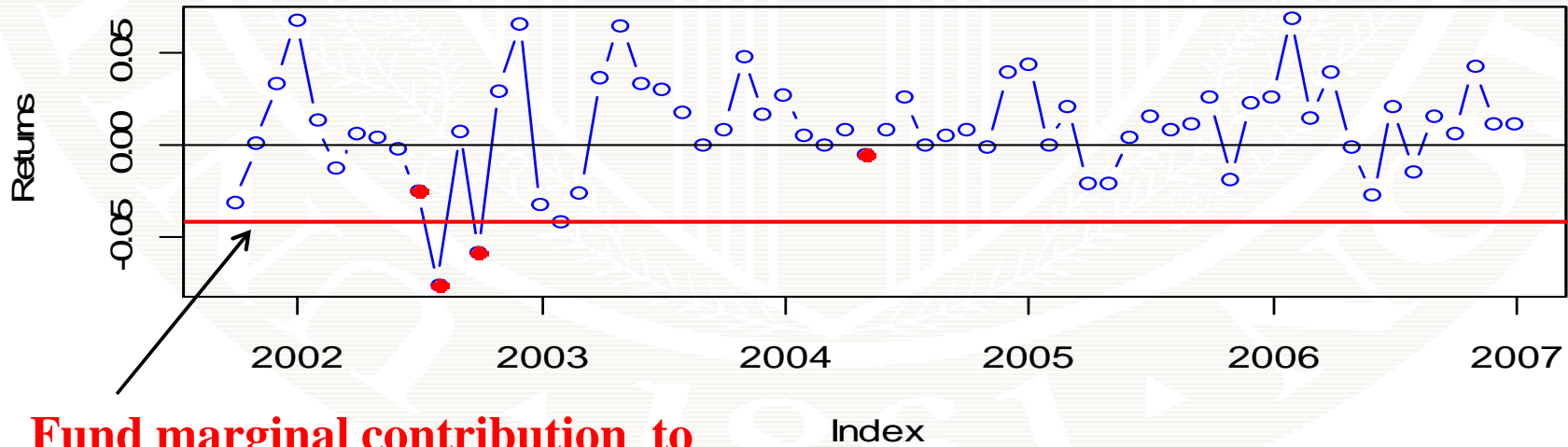
$$\hat{E}[R_{it} | R_{p,t} = VaR_{\alpha}(\mathbf{w})] = \frac{1}{m} \sum_{t=1}^B R_{it}^* \cdot 1\{VaR_{\alpha}(\mathbf{w}) - \varepsilon \leq R_{p,t}^* \leq VaR_{\alpha}(\mathbf{w}) + \varepsilon\}$$

$$\hat{E}[R_{it} | R_t \leq VaR_{\alpha}(\mathbf{w})] = \frac{1}{[B\alpha]} \sum_{t=1}^B R_{it}^* \cdot 1\{R_{p,t}^* \leq VaR_{\alpha}(\mathbf{w})\}$$

FoHF Portfolio Returns and 5% VaR Violations



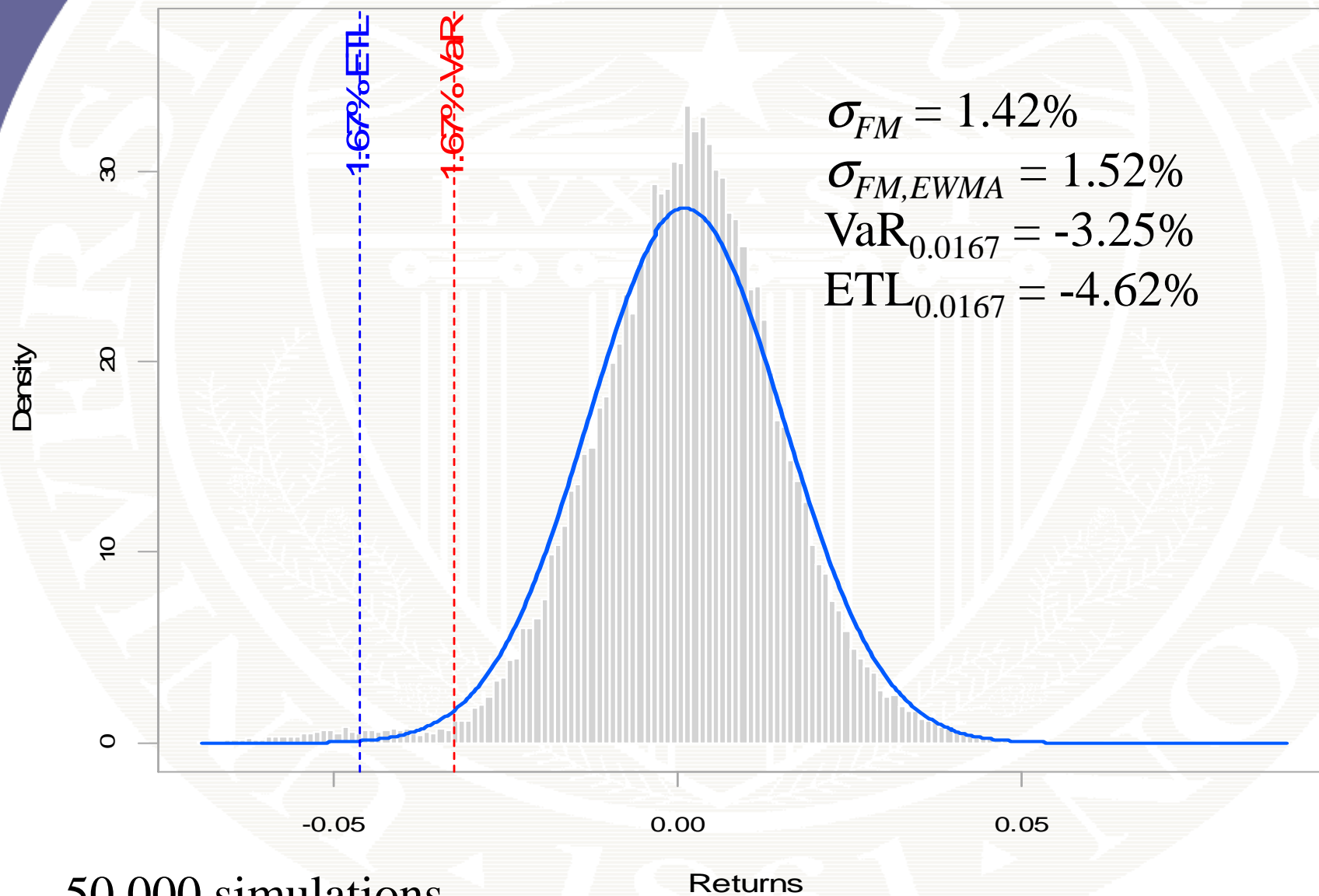
Constituant fund returns when FoHF returns \leq 5% VaR



Example FoHF Portfolio Analysis

- Equally weighted portfolio of 12 large hedge funds
- Strategy disciplines: 3 long-short equity (LS-E), 3 event driven multi-strat (EV-MS), 3 direction trading (DT), 3 relative value (RV)
- Factor universe: 52 potential risk factors
- R^2 of factor model for portfolio $\approx 75\%$, average R^2 of factor models for individual hedge funds $\approx 45\%$

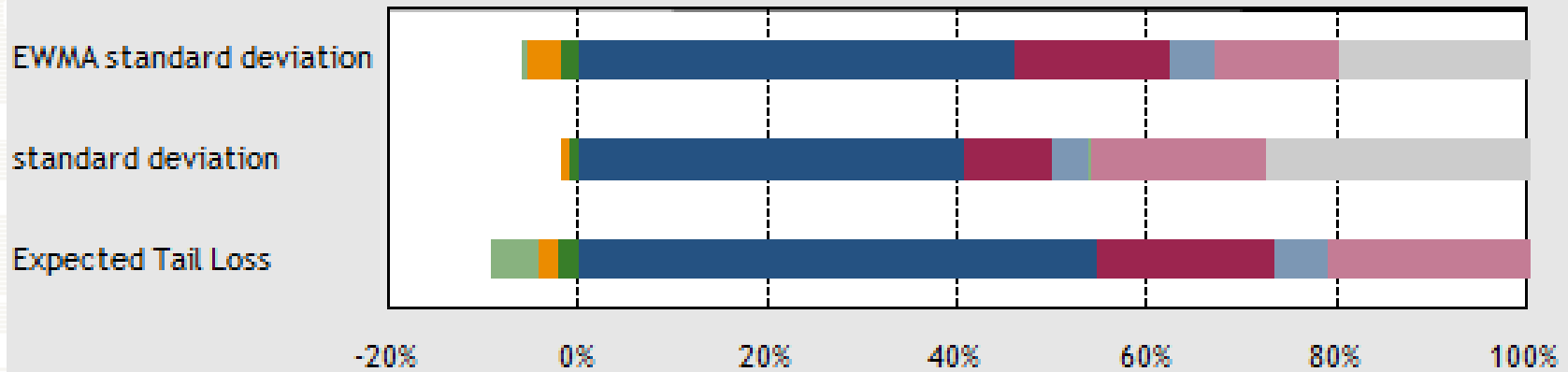
FMMC FoHF Returns



50,000 simulations

Factor Risk Contributions

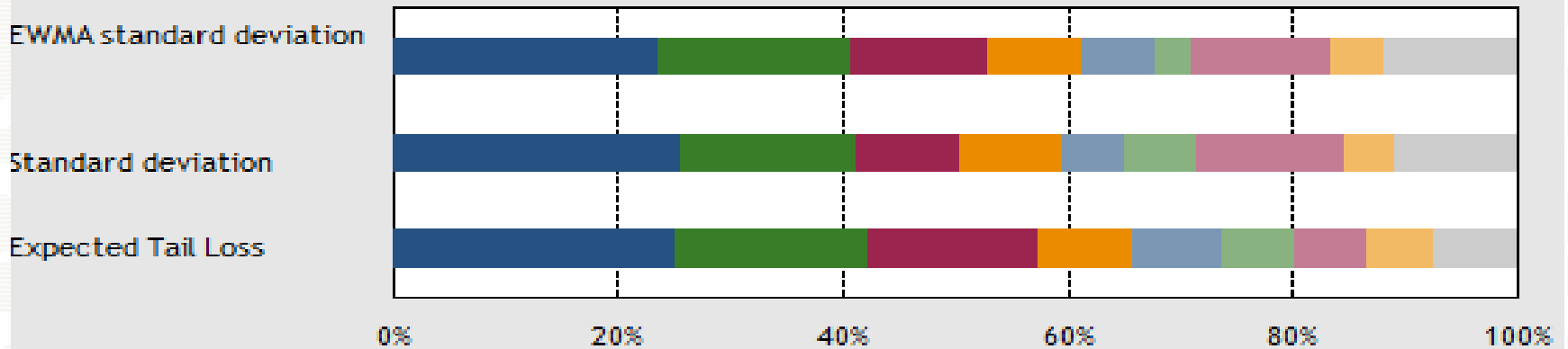
Factor Group % Contribution to Risk



Factor Group	EWMA Std Dev	Std Dev	Expected Tail Loss
Equity	46.3%	40.7%	54.8%
Rates	-1.8%	-0.8%	-2.0%
Credit	16.3%	9.4%	18.6%
Currency	-3.4%	-1.0%	-2.0%
Commodity	4.8%	3.8%	5.6%
Strategy - Observable	-0.5%	0.3%	-5.1%
Strategy - PCA	12.8%	18.3%	22.7%
Specific	25.5%	29.3%	7.3%

Hedge Fund Risk Contributions

Top 8 Programs by % Expected Tail Loss



Hedge Fund	Capital Allocation	EWMA SD Contribution	SD Contribution	ETL Contribution
Fund 3: LS-E	8.3%	23.5%	25.4%	24.9%
Fund 1: LS-E	8.3%	17.1%	15.7%	17.1%
Fund 4: EV-MS	8.3%	12.1%	9.0%	15.1%
Fund 9: DT-M	8.3%	8.5%	9.2%	8.4%
Fund 5: EV-MS	8.3%	6.3%	5.5%	8.1%
Fund 7: DT-M	8.3%	3.3%	6.4%	6.5%
Fund 6: EV-MS	8.3%	12.4%	13.3%	6.3%
Fund 12: RV-MS	8.3%	4.5%	4.4%	6.0%
Other	33.3%	12.1%	11.1%	7.6%

Hedge Fund Risk Contribution

Top 5 Programs by Lowest Marginal EWMA Standard Deviation

Program	Capital Allocation	Marginal Short Risk
Fund 11: RV-R	8.3%	0.5%
Fund 2: LS-E	8.3%	0.8%
Fund 7: DT-M	8.3%	1.0%
Fund 8: DT-F	8.3%	1.1%
Fund 10: RV-MS	8.3%	1.2%

Top 5 Programs by Lowest Marginal Standard Deviation

Program	Capital Allocation	Marginal Long Risk
Fund 2: LS-E	8.3%	0.5%
Fund 11: RV-R	8.3%	0.6%
Fund 10: RV-MS	8.3%	0.8%
Fund 8: DT-F	8.3%	1.2%
Fund 12: RV-MS	8.3%	1.2%

Top 5 Programs by Lowest Marginal Expected Tail Loss

Program	Capital Allocation	Marginal ETL
Fund 8: DT-F	8.3%	-0.8%
Fund 2: LS-E	8.3%	1.5%
Fund 11: RV-R	8.3%	1.5%
Fund 10: RV-MS	8.3%	2.0%
Fund 12: RV-MS	8.3%	3.3%

Summary and Conclusions

- Factor models for asset returns are widely used in academic research and industry practice and are well suited to modeling hedge fund returns
- Tail risk measurement and management of hedge fund portfolios poses unique challenges that can be overcome using Factor Model Monte Carlo methods