

Ways of Estimating Extreme Percentiles for Capital Purposes

Enterprise Risk Management Symposium, Chicago
Session CS E5: Tuesday 3May 2005, 13:00 – 14:30

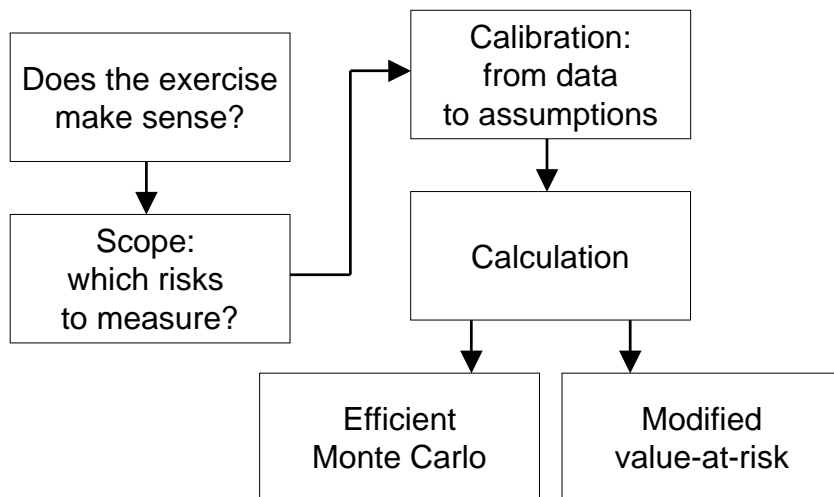
Andrew Smith
AndrewDSmith8@Deloitte.co.uk

This is the framework we're
discussing

Assessing Capital based on:

- Projected Assets > Liabilities
- In one year
- With very high (eg 99.9%) probability
- Applies to life and property-casualty

Decision Path



Value at Risk (VaR)

Value at Risk – Market Level Assumptions

Driver	standard deviation	correlations												
Equity	20%	100%												
Property	15%	50%	100%											
Yield Curve	0.80%	0%	-30%	100%										
Credit Spread	0.30%	-50%	-40%	10%	100%									
Property loss ratio	10.00%	0%	30%	-10%	25%	100%								
Liability loss ratio	15.00%	20%	10%	-15%	25%	50%	100%							
Inflation	1.00%	-50%	-40%	40%	20%	0%	0%	100%						
Mortality	35%	0%	0%	0%	0%	0%	0%	0%	100%					
Lapses	35%	-30%	-30%	30%	0%	-30%	-30%	20%	0%	100%				
Operational	100%	30%	30%	-30%	-20%	-30%	-30%	20%	0%	40%	100%			
Liquidity	100%	25%	25%	-25%	-50%	-20%	-20%	10%	10%	25%	10%	100%		
Group	100%	20%	20%	-20%	-20%	-20%	-20%	20%	20%	20%	20%	20%	100%	

- Bank VaR typically 200 x 200 correlation matrix

Fixing the Correlation Matrix

correlations

100%														
50%	100%													
0%	-30%	100%												
-50%	-40%	10%	100%											
0%	30%	-10%	25%	100%										
20%	10%	-15%	25%	50%	100%									
-50%	-40%	40%	20%	0%	0%	100%								
0%	0%	0%	0%	0%	0%	0%	100%							
-30%	-30%	30%	0%	-30%	-30%	20%	0%	100%						
30%	30%	-30%	-20%	-30%	-30%	20%	0%	40%	100%					
25%	25%	-25%	-50%	-20%	-20%	10%	10%	25%	10%	100%				
20%	20%	-20%	-20%	-20%	-20%	20%	20%	20%	20%	20%	100%			

Not sufficient to have correlations between $\pm 100\%$.
Only positive definite matrices can be valid correlation matrices

best fit positive definite correlations

100%														
51%	100%													
-4%	-31%	100%												
-49%	-40%	9%	100%											
-1%	29%	-9%	25%	100%										
18%	9%	-13%	25%	50%	100%									
-44%	-37%	35%	20%	-1%	-2%	100%								
1%	0%	-1%	0%	0%	0%	1%	100%							
-26%	-28%	26%	0%	-30%	-31%	23%	0%	100%						
25%	27%	-25%	-20%	-28%	-27%	15%	-1%	35%	100%					
22%	23%	-22%	-50%	-19%	-18%	7%	10%	22%	12%	100%				
17%	19%	-17%	-20%	-19%	-19%	17%	20%	18%	22%	21%	100%			

The larger the matrix, the more likely it is that positive definiteness is a problem.

Calculating Value at Risk

Test	Stress	Free Assets	Beta Capital required	
Base Case		200		
Equity	-40%	170	75	39
Property	-25%	183	68	26
Yield Curve	1%	185	-1500	31
Credit Spread	1%	185	-1500	12
Property loss ratio	20%	175	-125	32
Liability loss ratio	20%	170	-150	58
Inflation	1%	180	-2000	52
Mortality	40%	190	-25	23
Lapses	40%	195	-12.5	11
Operational	-1	190	10	26
Liquidity	-1	195	5	13
Group	-1	195	5	13
Total				334
Diversification credit				184
Net required				150

Room for Improvement?

- VaR runs instantly and parameters / assumptions are transparent
- Non-zero mean
 - easy to fix
 - take credit for one year's equity risk premium or one year's profit margin in premiums
- Path dependency, overlapping cohorts
 - Add more variables, which can result in huge matrices to estimate
- Company depends linearly on drivers
 - mitigate by careful choice of stress tests
 - worst for GI because of reinsurance
 - may need mini DFA model to calibrate a VaR model
- Multivariate Normality
 - Strong assumption – was often supposed lethal
 - Before we understood large deviation theory

Large Deviation Theory

Large Deviation Expansions

- In many important examples, we can estimate the moment generating function of net assets
- Large deviation expansions are an efficient way to generate approximate percentiles given moment generating functions
- Exact formulas do exist but they involve numerical integration of complex numbers

LD Expansion: The Formula

To estimate $\text{Prob}\{X \leq c\}$
 Where $\mathbf{E}\exp(\rho X) = \exp[\kappa(\rho)]$
 Find ρ where $\kappa'(\rho) = c$

$$\eta_0 = p \times \sqrt{\frac{2\kappa'(\rho)}{p} - \frac{2\kappa(\rho)}{p^2}}$$

$$\eta_1 = \frac{1}{\eta_0} \ln \left[\frac{p \sqrt{\kappa''(\rho)}}{\eta_0} \right]$$

$\eta_2 = \dots$

$\text{Prob} \Phi(\eta_0 + \eta_1 + \eta_2 + \dots)$

Φ = cumulative normal function

Try $X \sim \text{normal}(\mu, \sigma^2)$

$$\kappa(\rho) = \mu\rho + \frac{1}{2} \sigma^2 \rho^2$$

$$\kappa'(\rho) = \mu + \sigma^2 \rho$$

$$\rho = \sigma^{-2}(c - \mu)$$

$$\eta_0 = \sigma^{-1}(c - \mu)$$

$$\eta_1 = 0$$

LD expansion exact

Try $X \sim \text{exponential}(\text{mean } 1)$

$$\mathbf{E}\exp(\rho X) = (1 - \rho)^{-1}$$

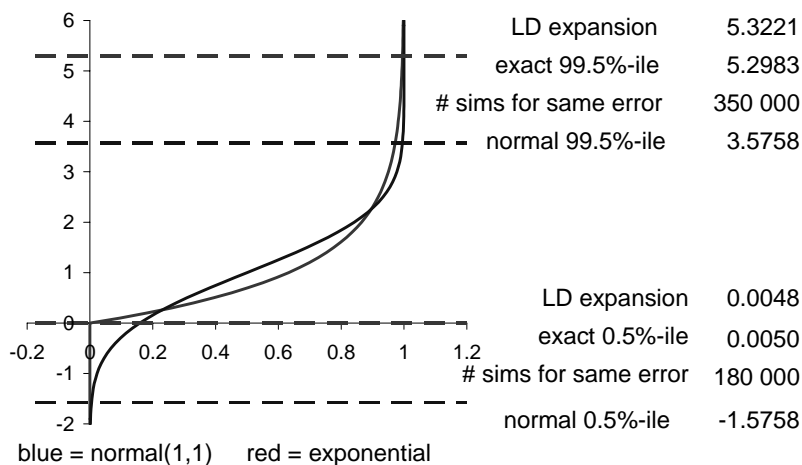
$$\kappa(\rho) = -\ln(1 - \rho)$$

$$\kappa'(\rho) = (1 - \rho)^{-1}$$

$$\rho = 1 - c^{-1}$$

$$\kappa''(\rho) = (1 - \rho)^{-2}$$

Comparison $\eta_0 + \eta_1$ with Monte Carlo



LD Expansion Needs Analytical MGF

Easy

- Normal
- Gamma
- Inverse Gaussian
- Reciprocal Inverse Gaussian
- Generalised hyperbolic
- Poisson / Neg Binomial compounds of the above
- Mixtures of the above

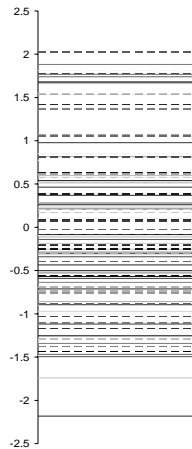
Tricky

- Pareto
- Lognormal
- Weibull
- Copula approaches

Key question: Is there sufficient data to demonstrate we have a tricky problem?

Efficient Simulations:
Importance Sampling

Importance Sampling – How it Works

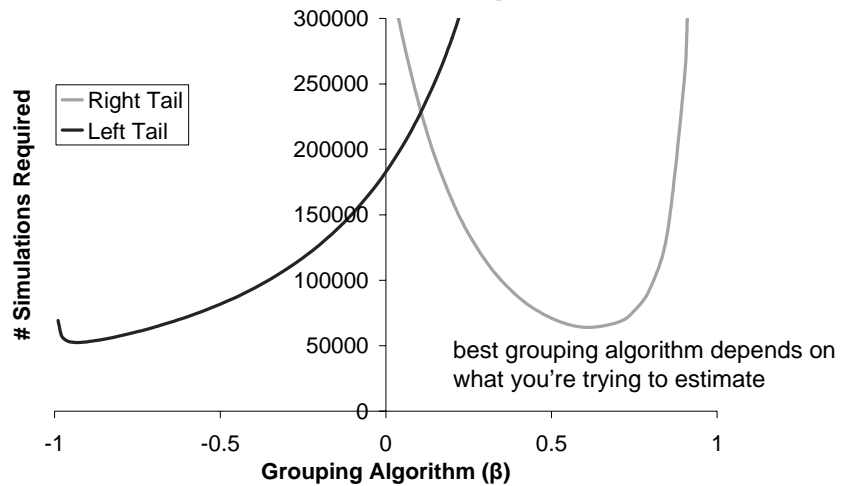


- Generate 1 000 000 simulations
- Group into 1 000 model points
- Outliers: treat individually
- Near the centre: groups of 5000 observations or more for each model point
- Result: 1 000 model points with as much information as 20 000 independent simulations

Importance Sampling: Another View

- We wish to simulate from an $\exp(1)$ distribution
 - density $f(x) = \exp(-x)$
- Instead simulate for an $\exp(1-\beta)$ distribution
 - density $g(x) = (1-\beta)\exp[-(1-\beta)x]$
 - weight $w(X) = (1-\beta)^{-1}\exp(-\beta X)$
- Use weighted average to calculate statistics
 - equivalent to grouping (yes it *does* work!)
- Product rule for multiple drivers

Effectiveness compared to LD



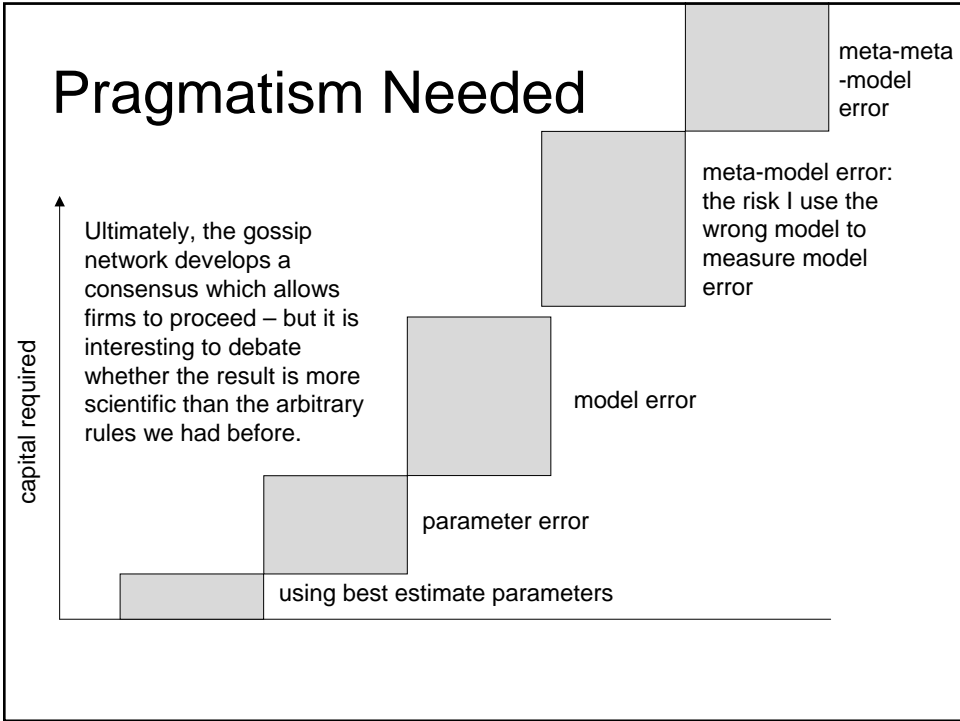
Testing Extreme Value Calibrations

Extreme Value Theory

- | | |
|--|--|
| <h3>Central Limit</h3> <ul style="list-style-type: none">• If $X_1, X_2, X_3 \dots X_n$ are i.i.d.• Finite mean and variance• Then the average A_n is asymptotically normal• Useful theorem because many distributions are covered• Often need higher terms (eg LD expansion). | <h3>Extreme Value</h3> <ul style="list-style-type: none">• If X has an exponential / Pareto tail• Then $(X-k X>k)$ has an asymptotic exponential / Pareto distribution• Many distributions have no limit at all• Higher terms in the expansion poorly understood |
|--|--|

Estimating Extreme Percentiles

- Suppose “true” distribution is lognormal with parameters $\mu=0, \sigma^2=1$.
- Simulate for 20 years
- Fit extreme value distribution to worst 10 observations
- Don’t need to calculate to see this isn’t going to work
- Instability and bias in estimate of 99.5%-ile
- The extreme event: if you have one in the data set its over-represented, otherwise its under-represented.
- Conclusion is invariably a judgment call – was 11/09/2001 a 1-in-10 or 1-in-500 event? What’s the worst loss I ever had / worst I can imagine – call that 1-in-75.
- Problems even worse when trying to estimate correlations / tail correlations / copulas
- Reason to choose a simple model with transparent inputs



Scope – Which Risks to Measure?

Apocalyptic Events



Economic Capital: Who to Trust?



Conclusions

- Existing familiarity of value-at-risk gives it a head start over other approaches.
- Data and scope, but not maths, are the limiting factors for accurate capital calculations.
- If you prefer Monte Carlo, use importance sampling to cut burden by a factor of 5.
- Analytic large deviation theory is as good as 200,000 simulations – but much faster.

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