Optimizations in VaR Computations

Olivier Croissant
Director, Financial Engineering
Renaissance Software, Inc.

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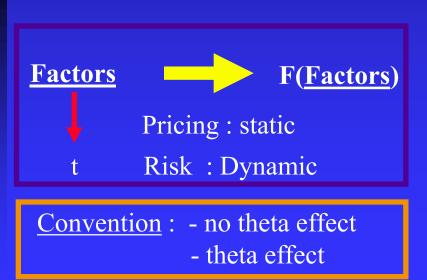
Overview

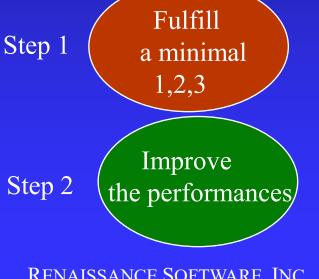
- Risk calculation process
 - ☐ Optimizing a MC VaR computation
 - Optimizing a Historical VaR computation
 - Optimizing a Delta-Gamma VaR computation
- Integration
- Conclusion



Characteristics of Operational Risk Calculations

- 1- Include in the handled risk dimensions, all the variable determinant parameters of the PV
- 2- The arbitragefreeness of the models is assumed, but it will be destroyed most of the time by the handling
- 3- Perform for all necessary computations within the time frame compatible with the targeted risk management.







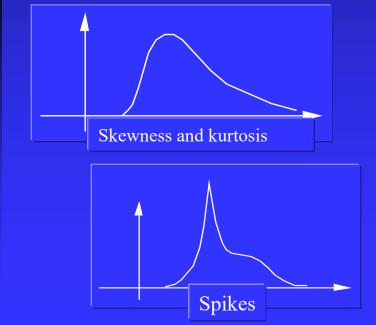
Risk Methodologies

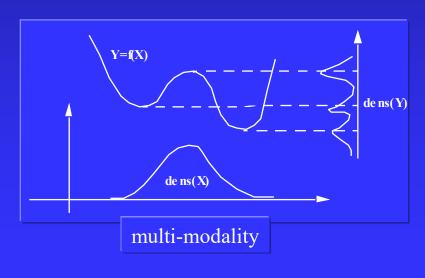
- Probabilistic methods
 - **■** Monte Carlo calculation
 - ☐ Historical simulation -> no covariance matrix
 - ☐ First order sensitivities based risk computations
- Non probabilistic methods
 - **□** Worst case analysis
 - ☐ Preferred (customized) scenarios based analysis
- Improved Methods
 - **■** Randomized quasi Monte-Carlo: improves the convergence
 - Enhanced historical methods: increases the number of points
 - Second order sensitivities based risk computations



Difficulties Associated with Real Portfolios Distributions

- Skewness and kurtosis
 - ☐ Risk of buying and option # Risk of selling an option
- Spikes in the density
 - ☐ High gamma without corresponding delta: infinite density
- Multi Modality
 - **■** Non Local effects (pile of option spreads)







Optimization of VaR Computation

- Monte Carlo VaR
- Historical VaR
- Sensitivities Based VaR





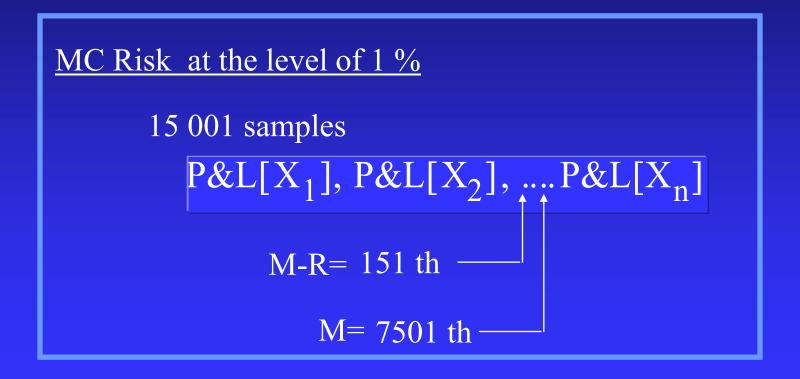






Link Between MC Risk and MC Price

- MC price = Expectation of P&L[X]
- MC risk = Expectation of $(P\&L[X])^n$ -> Distribution







Do you believe in your risk calculation?

- Observe a convergence? When it will happen?
- Expect a convergence. Because of a theoretical result.

Two types of theoretical results:

Probabilistic: Variance[S-I] < epsilon[N]

Absolute: | S - I | < epsilon [N]

I : Real value N=1000 2000 3000 5000 S=45.3 48.3 47.3 52.3





Two Approaches

| S - I | < epsilon [N]

Old Style

New Style

Std Dev [10 000 sample] = 1%

Very often practical good convergence

No more than 12 dimensions

10 000 samples

The same pseudo-generator for all cases

MC Discrepancy = 0.003

Structured RQMC is performed on a class of integrand

25 dimensions among 360

10 000 samples

The structure of the sample set is adapted to the effective dimensionality

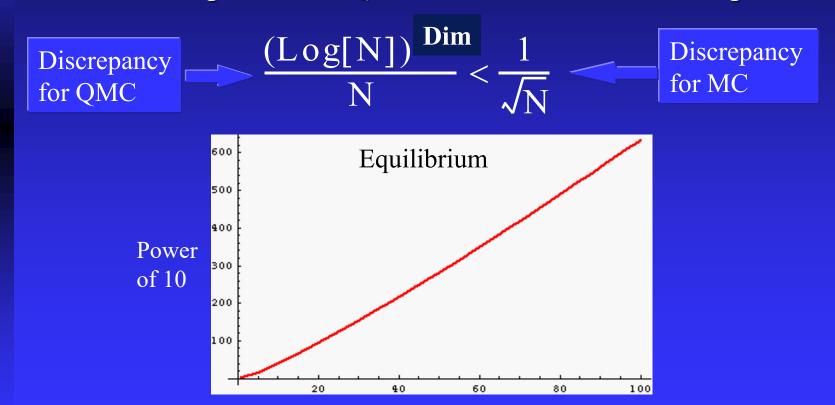






High dimension MC calculation

- □ 20 2000 dimensions MC : only a probabilistic answer
 - ☐ Some dimensions can be overlooked: hidden risk
- Low Discrepancies of Quasi-Monte-Carlo are no help.



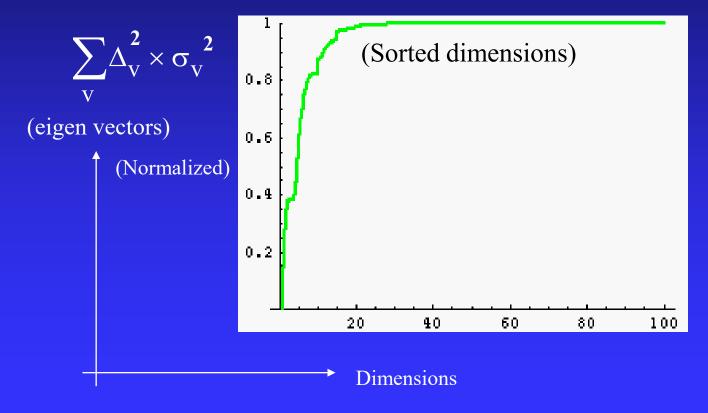
Dimension





Real Dimensionality (effective)

Analysis of a typical portfolio in 121 dimensions, with 5 currencies, 14 maturities, bonds, swaps, caps and floors



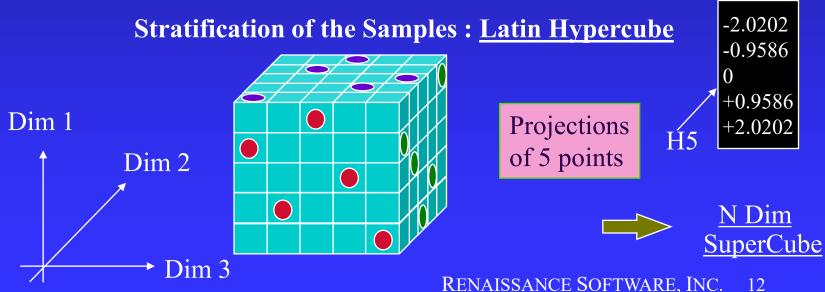




How to exploit the real dimensionality

- Adapt the sample generator
 - Some dimensions are stably more important than the others
 - ☐ Analysis in principal components of the interest rates

First component : General level of rates Second component: Slope of the curve Third component: Torsion of the curve





Historical Simulation

- Use of Historical series of market prices
 - ☐ Factors / Market Prices
- Empirical Distribution
 - Simplicity
 - **■** Leptokurtic distribution
 - **real correlations with non linear behavior**
- Limited Historic Series
 - \Box One year = 250 Points
 - ☐ Synchronicity of sampling, liquidity of the markets, emerging markets
 - **□** Smoothing of the Empirical distribution to get a risk (parameterization)



Increasing the resolution of a historical VaR

- We assume a market prices set of 1000 points
- We want a 10 000 samples
 - ☐ To have a finer "resolution" of our VaR measure
- We want to keep the mean and covariance structure

$$\underline{\text{Dimension} = 1} \quad \mathbf{Data \ set} = (-1, 1, 2)$$



Multipliers =
$$\frac{-3 - \sqrt{21}}{6}$$
 , $\frac{-3 + \sqrt{21}}{6}$

Enhanced Dat set

{-1.52, -1, -0.26, 0.73, 1, 1.26, 1.52, 2, 2.26}



N Dimensions

Engineering the Market Data Set (I)

Keeping E[XY] and E[X]

$$(x_{j})_{1 \leq j \leq N}$$

$$y_{i,j} = \lambda_{i}x_{j} + x_{0}$$
Multipliers

Conditions
$$\sum_{i} \left(\lambda_{i}^{2} + \frac{x_{0}}{\overline{x^{2}}} (2\overline{x} - x_{0}) - 1 \right) = 0$$

$$\sum_{i} \left(\lambda_{i} + \frac{x_{0}}{\overline{x}} - 1 \right) = 0$$

Extension of the resolution associated with the samples
 Cost -> Perturbation of the higher orders

Skewness Kurtosis

$$\begin{array}{ccc} \underline{\text{Third order correlation information}} \\ E[X^2Y] & E[XY^2] & E[XYZ] \end{array}$$

- Extend our analysis to include higher moments
- Control the samples distribution for important subspaces
- Consider linear combinations of market points





Engineering the Market Data Set (II)

It is possible to decompose the factors into domains

Interest rates and volatilities = 20 X (14 + 6) = 400 dimEquity indexes and volatilities = $20 \times (1 + 6) = 140 \text{ dim}$ FX Rates and volatilities $= 19 \times (1 + 3)$ $300 \times 300 \times 300 = 27\ 000\ 000\ Samples$ 300 Samples (Quasi) Random Selection 30 among 300 X 30 among 300 Sampling on X 30 among 300 **Empirical Distribution** 27 000 Samples



The Quadratic VaR

Distribution of a quadratic polynomial in normal variables

$$PV[X_{1}, X_{2},, X_{s}] = PV_{0} + \Theta + \sum_{1 \leq i \leq s} \Delta_{i}X_{i} + \frac{1}{2} \sum_{1 \leq i, j \leq s} \Gamma_{i, j}X_{i}X_{j}$$



Diagonal gammas

Non diagonal gammas

Pseudo gamma matrix

Quadratic VaR[pseudo gamma] ~True VaR

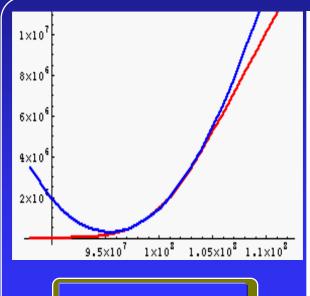




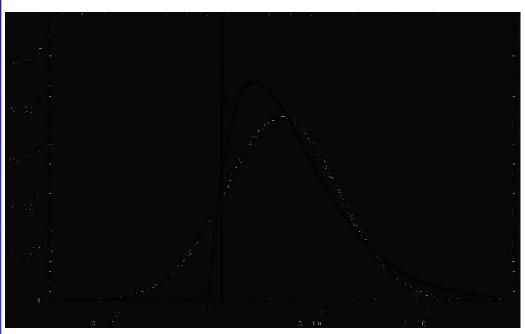
Quadratic Approximation of a Call

- An at the money call
 - □ two weeks
 - □ notional=100m

- □1% risk=1.27 M
- □1% Quad=1.14 M
- 1% Lin = 2.47 M





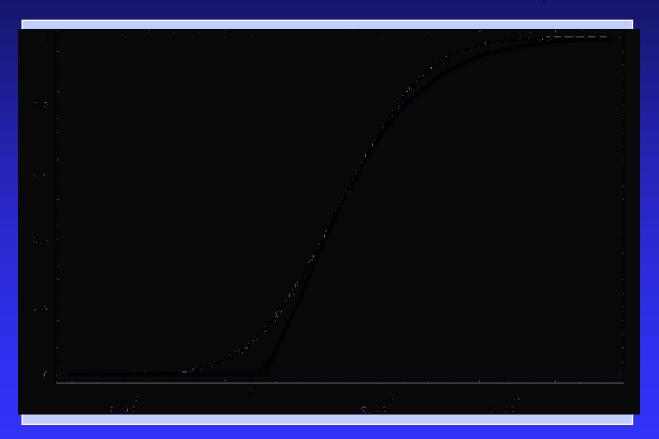






Quadratic Approximation (II)

Risk Curve: Distribution for a call k=1.05, T=1 week







Quadratic Approximation (III)

Compact formula for the Computation of the 4 first cumulants

$$var[Y] = {}^{t}\Delta\Sigma\Delta + \frac{1}{2}Trace[(\Gamma\Sigma)^{2}]$$

$$skew[Y] = 3{}^{t}\Delta\Sigma\Gamma\Sigma\Delta + Trace[(\Gamma\Sigma)^{3}]$$

$$kurtosis[Y] = 12{}^{t}\Delta\Sigma(\Gamma\Sigma)^{2}\Delta + Trace[3(\Gamma\Sigma)^{4}]$$

Var Skewness kurtosis Parameterization

Pearson,
Johnson,

EdgeWorth,

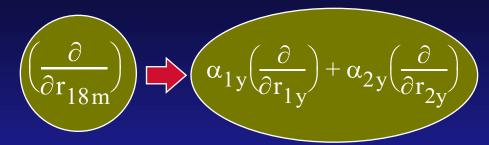
customized...



Risk 1%

Mapping of the Sensitivities

- First order mapping
- Second order mapping



Interpolation

For any deal dependent on the 18 m rate

$$r_{18m} = \frac{r_{1y} + r_{2y}}{2}$$

$$PV \approx PV_0 + \delta \cdot (r_{18m} - r_{0, 18m}) + \frac{1}{2}\gamma \cdot (r_{18m} - r_{0, 18m})^2$$

Therefore by replacing

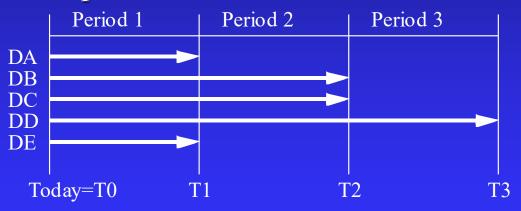
$$|PV \approx PV_0 + \Delta \cdot \begin{pmatrix} dr_1 y \\ dr_2 y \end{pmatrix} + \frac{1}{2} \begin{pmatrix} dr_1 y \\ dr_2 y \end{pmatrix} \Gamma \begin{pmatrix} dr_1 y \\ dr_2 y \end{pmatrix} \qquad \Delta = \delta \begin{pmatrix} \frac{1}{2} \\ \frac{1}{2} \end{pmatrix} \qquad \Gamma = \gamma \begin{pmatrix} \frac{1}{2} \frac{1}{2} \\ \frac{1}{2} \frac{1}{2} \end{pmatrix}$$

Does the cash flow mapping derive from an interpolation?



Handling Liquidity Risk

- DEaR # VaR
- The sensitivity framework is the only one which can simply take into account the liquidity risk (unwinding period)
- Cumulants (variance, skewness, kurtosis,..) cumul over independent period of time.

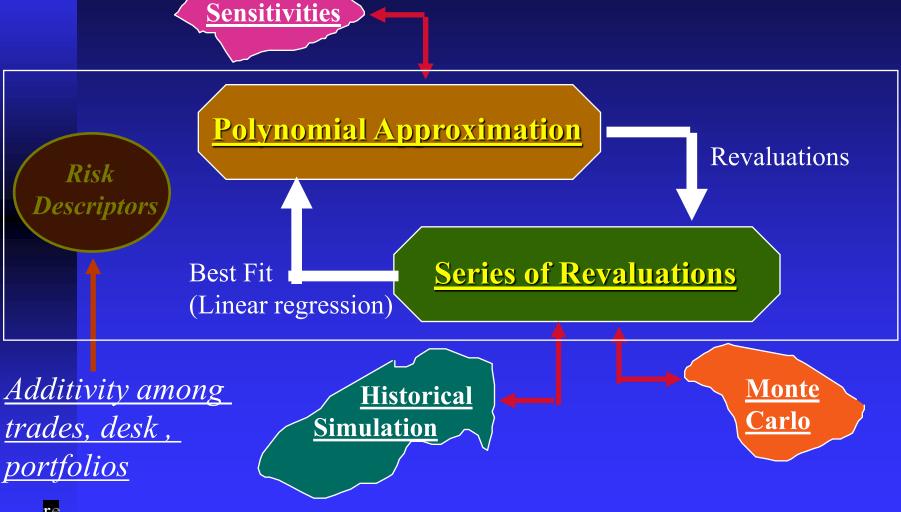


$$PL(3)-PL(0)={PL(3)-PL(2)} + {PL(2)-PL(1)} + {PL(1)-PL(0)}$$

$$Var[PL_3 - PL_0] = Var[PL_3 - PL_2] + Var[PL_2 - PL_1] + Var[PL_1 - PL_0]$$



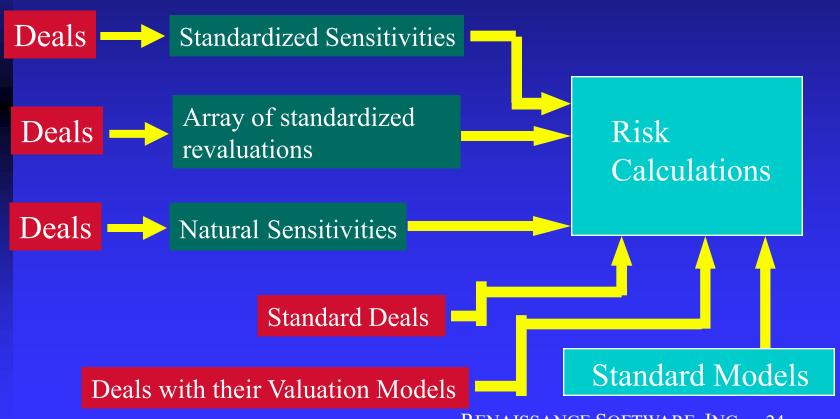
Merging the Three VaR Types





Integrated Handling of Risk Descriptors

The usefulness of risk calculation depends on the complete integration of risks.





Conclusion

- No method is better than the others, each one bring a light on an aspect of the risk.
- Integration is the only way for a worldwide risk management
- Flexible design allows optimization
- Smart use of statistics can beat the combinatorial problem





