# A comparison of Value–at–Risk methods for measurement of the financial risk

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E Leader Conference Prague, june 2007

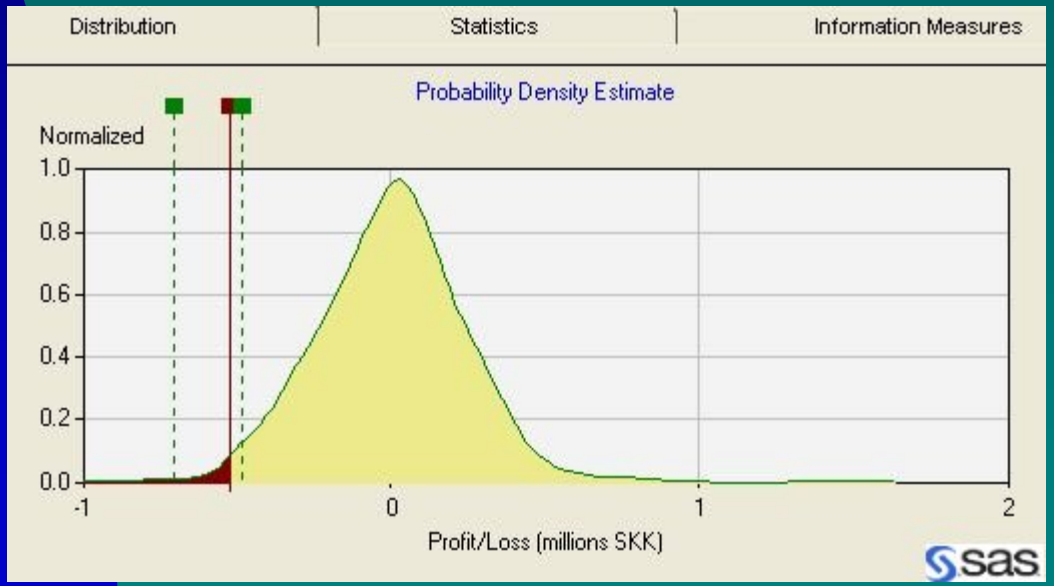
The methodologie Value at Risk provides a way of quantifying and managing the financial risks of a financial portfolios

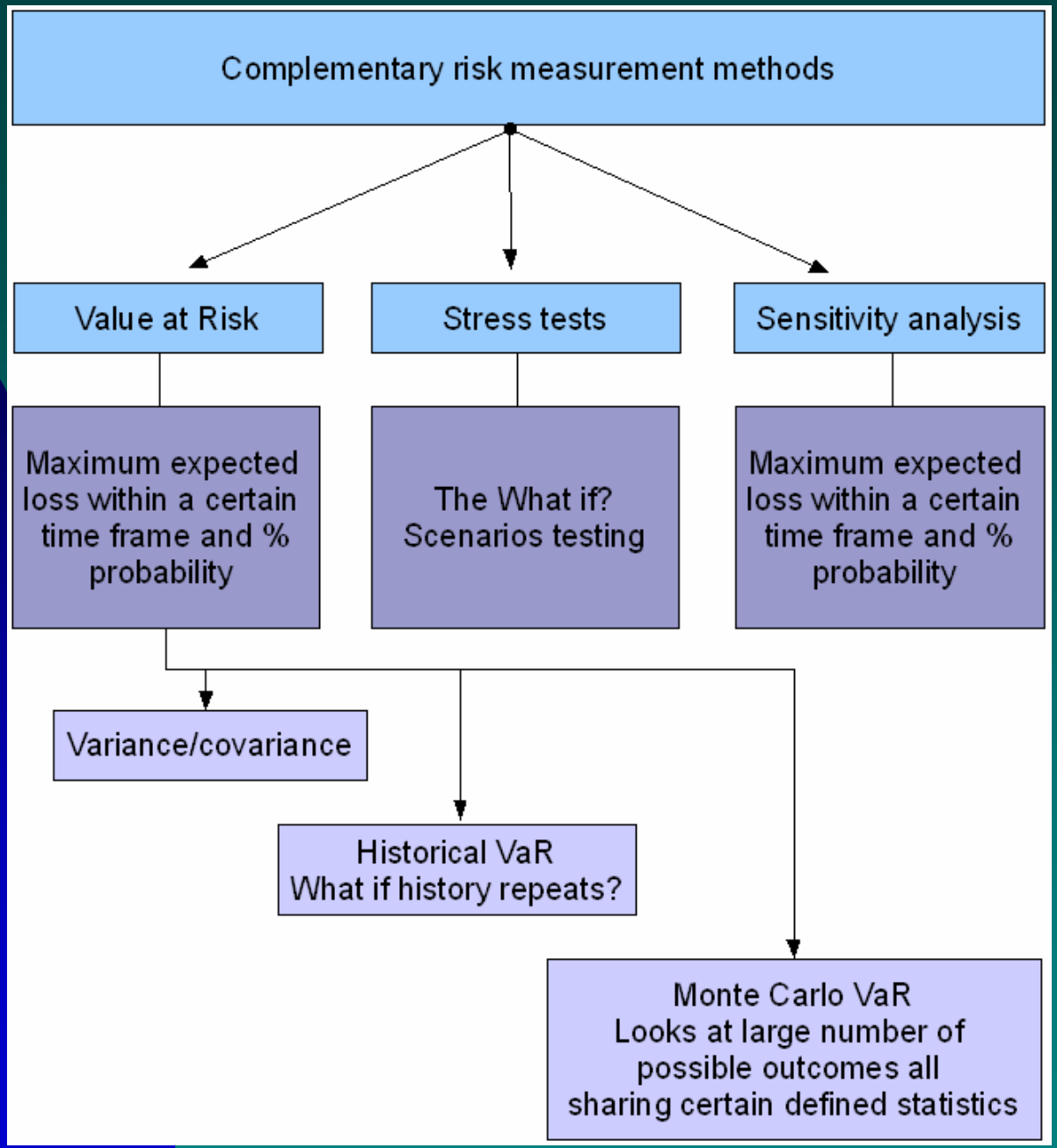
# The reasons for development of the methods for measuring of the risks

- Response to various financial disasters
- Complicated economic terms
- Central Banks wanted a methodology to set minimum capital requirements in banks
- BASEL II – necessity to control, to measure, to manage and to regulate financial risks

# Value at Risk (VaR)

VaR measures the worst expected loss over a given time horizon with a certain confidence – or probability – level.

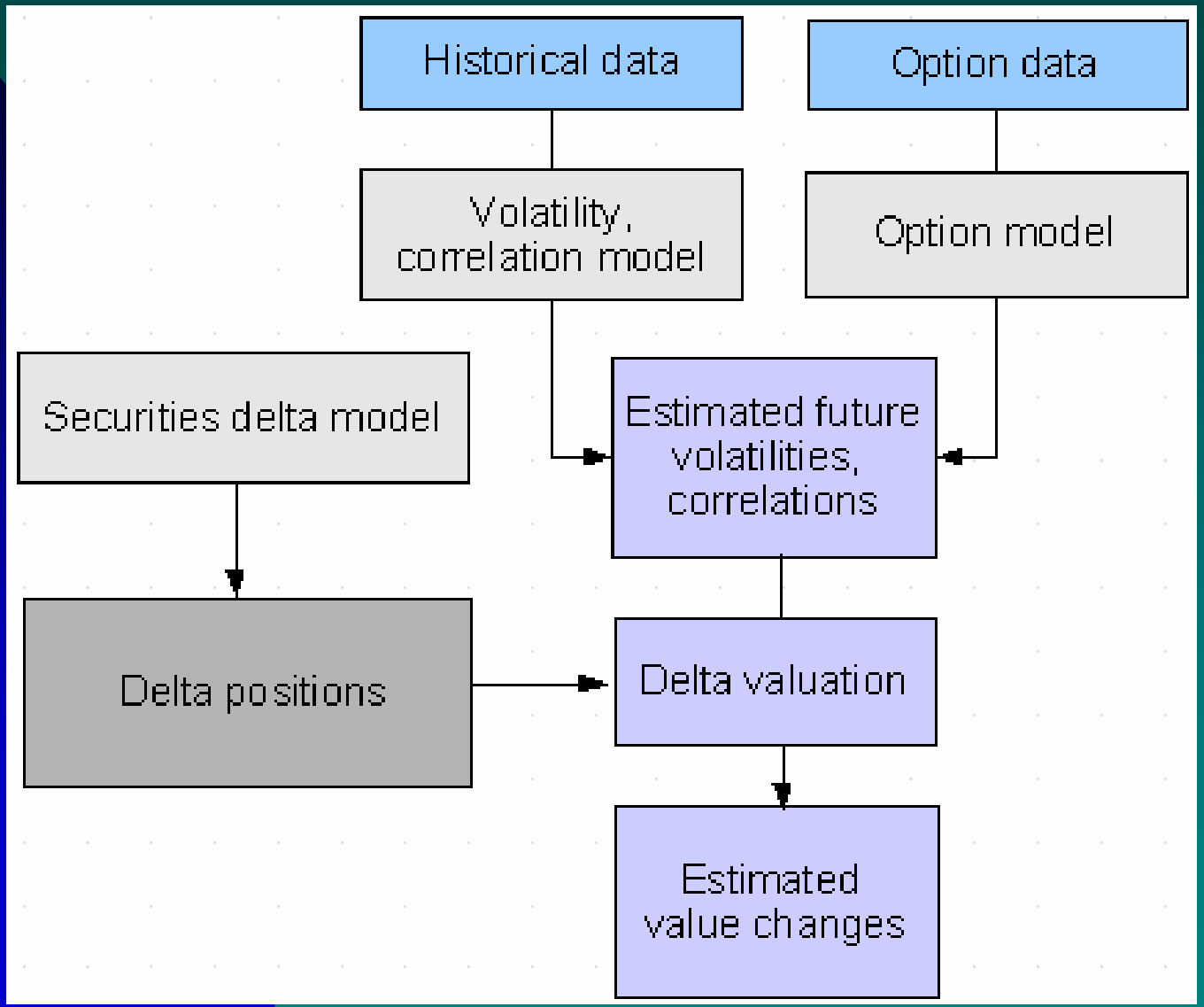



Complementary risk measurement methods
Value at Risk
Stress tests
Sensitivity analysis
Maximum expected loss within a certain time frame and % probability
The What if? Scenarios testing
Maximum expected loss within a certain time frame and % probability
Variance/covariance
Historical VaR
What if history repeats?
Monte Carlo VaR
Looks at large number of possible outcomes all sharing certain defined statistics

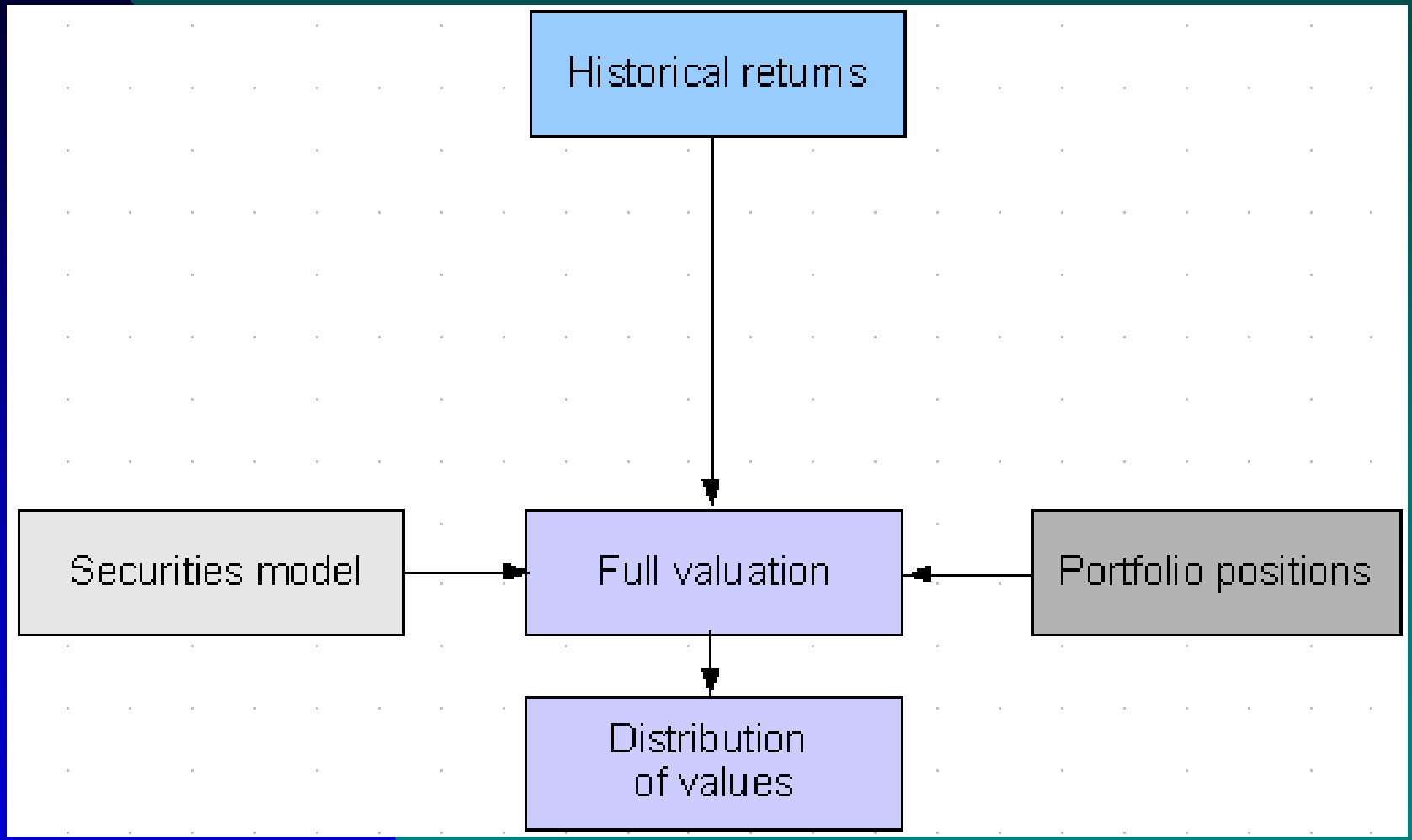
# General technique for computing VaR

- *Parametric*
  - Delta-Normal method
- *Nonparametric*
  - Historical simulation
- *Stochastic simulation*
  - Monte Carlo Simulation

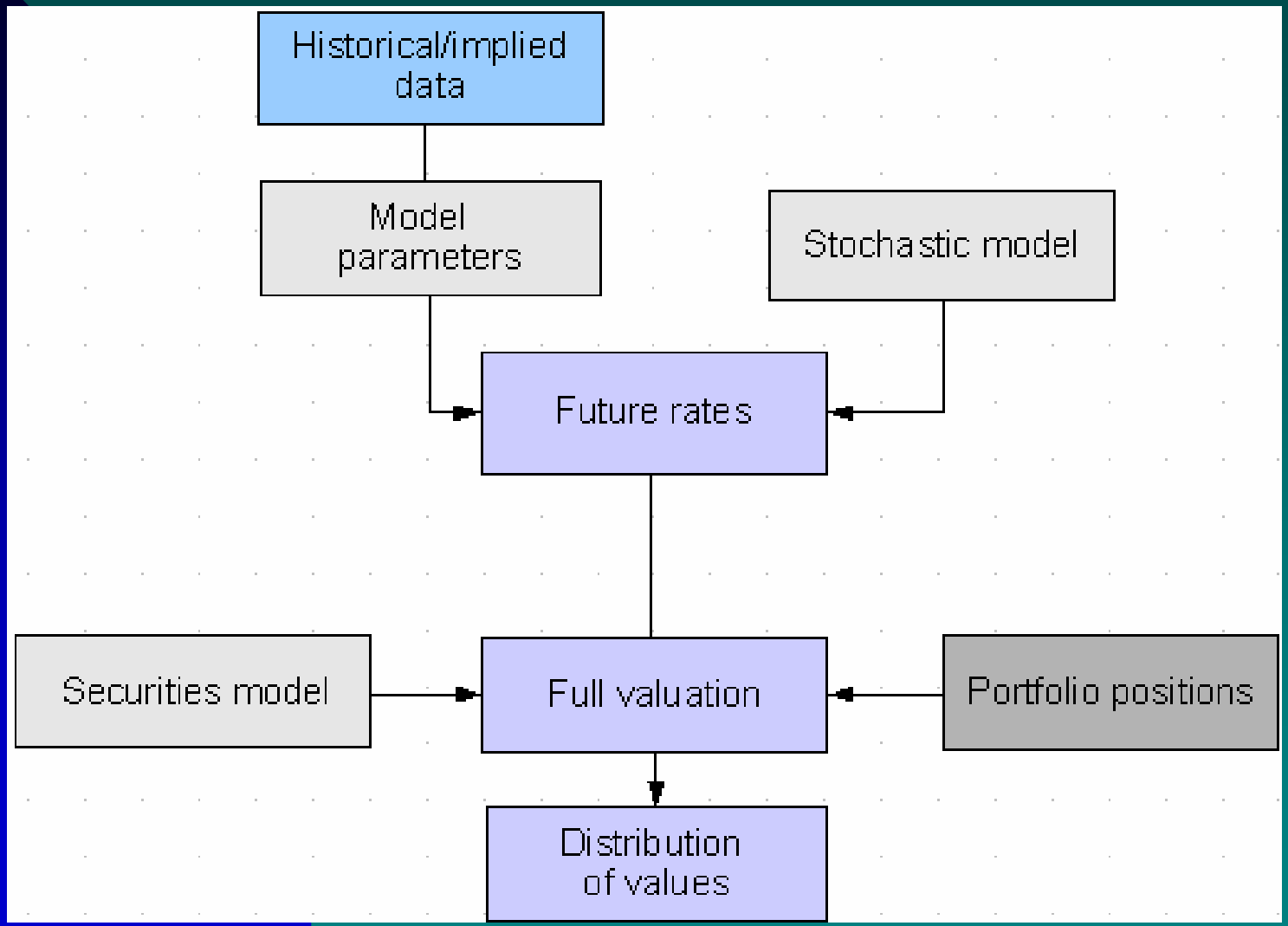
# Delta-Normal Method



# Historical simulation



# Monte Carlo simulation method



# Monte Carlo simulation consists of three major steps

- Scenario generation using the volatility and correlation estimates for the underlying assets in our portfolio produces a large number of future price scenarios in accordance with the lognormal models.
- Computing a portfolio value.
- Reporting the results of the simulation, either as a portfolio distribution or as a particular risk measure.

# Problems

- How to generate random scenario.
- How to model a fat tails in the distribution of returns on most financial assets.
- How to describe dependence structure of the risk factors

# Generation of the random scenario

1. *Pseudo random number generator* (high discrepancy sequences)
2. *Quasi random number generator* (low discrepancy sequences)

   A quasi-random number generator produces numbers which have not random component.

   e.g. the Sobol's sequence

   the Faure's sequence

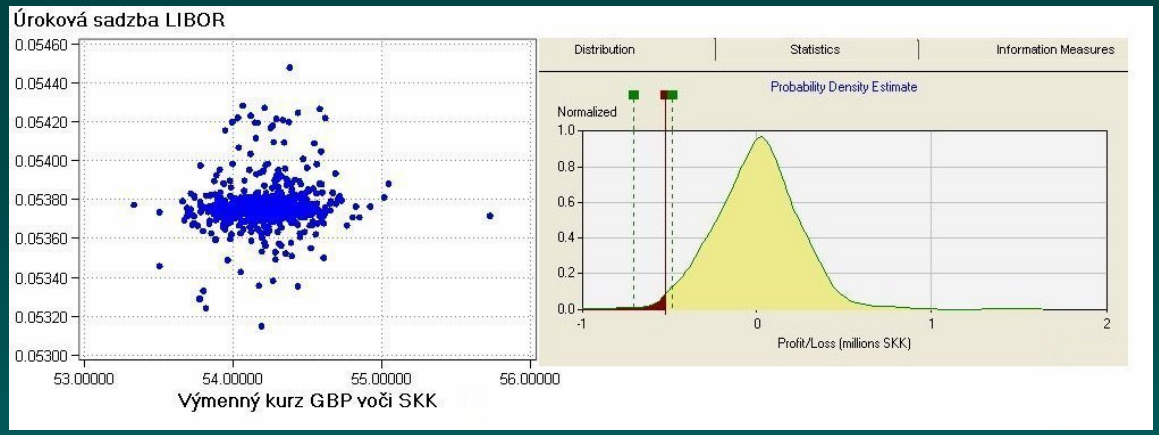
# Dependence structure of the risks factors

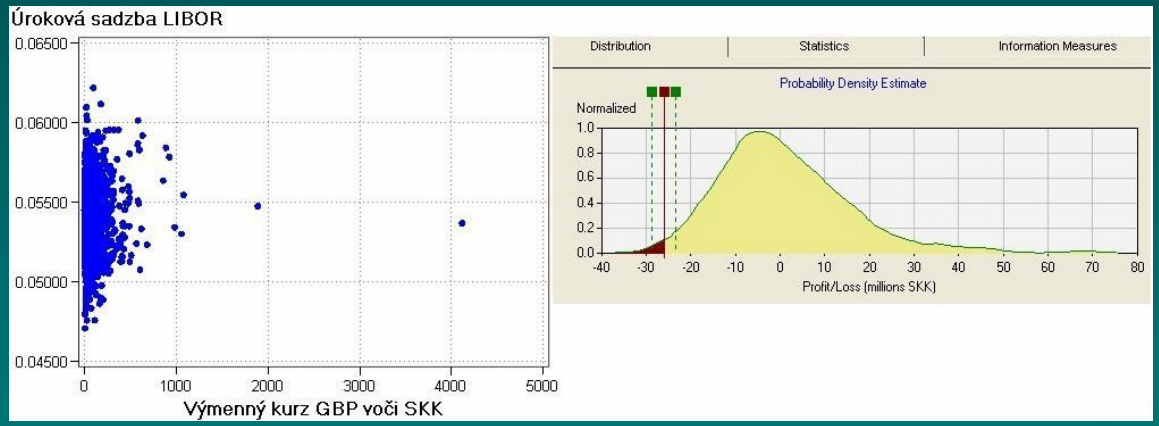
- is described by covariances and multinormal distribution, *in clasical approach*
- is described by copula function and by conveniently distributions, *in modern approach*
  (Copulas are functions that “couple” joint distributions to their marginal distributions)

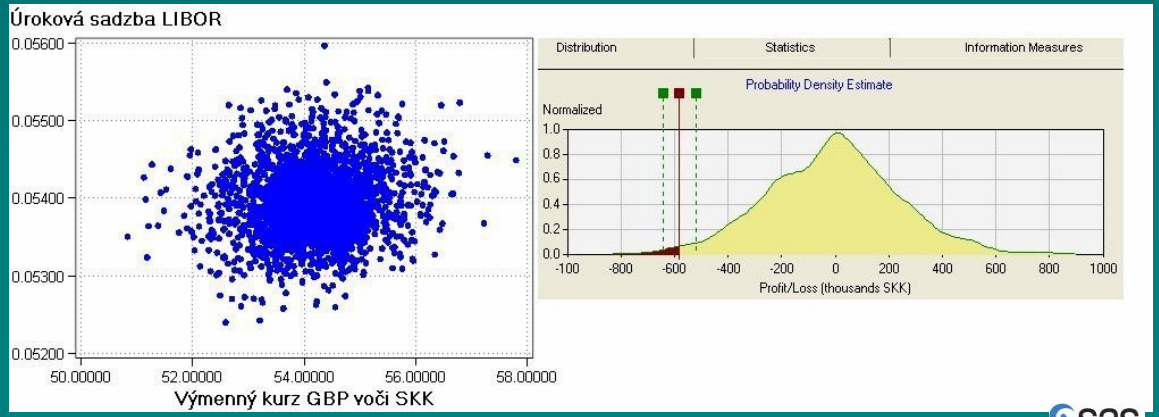
Historical simulation

Monte Carlo simulation

Monte Carlo with dynamic risk factor modeling



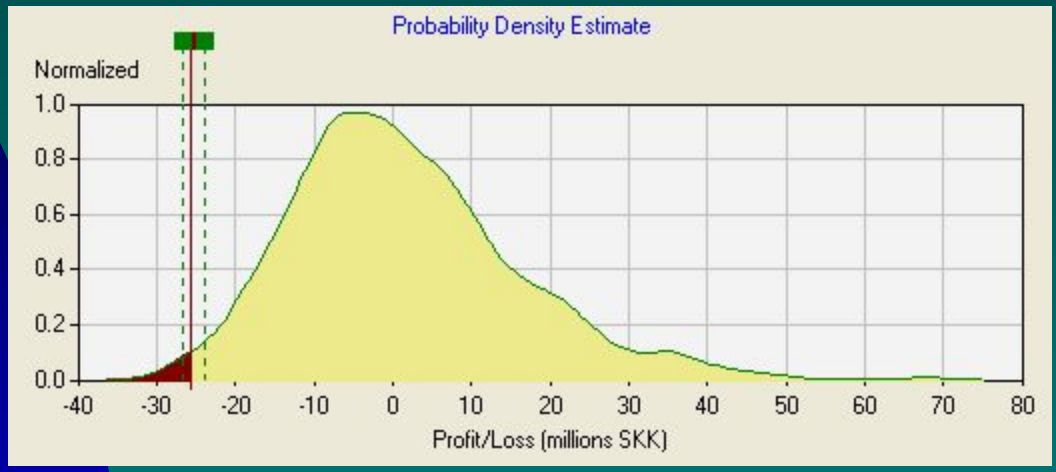



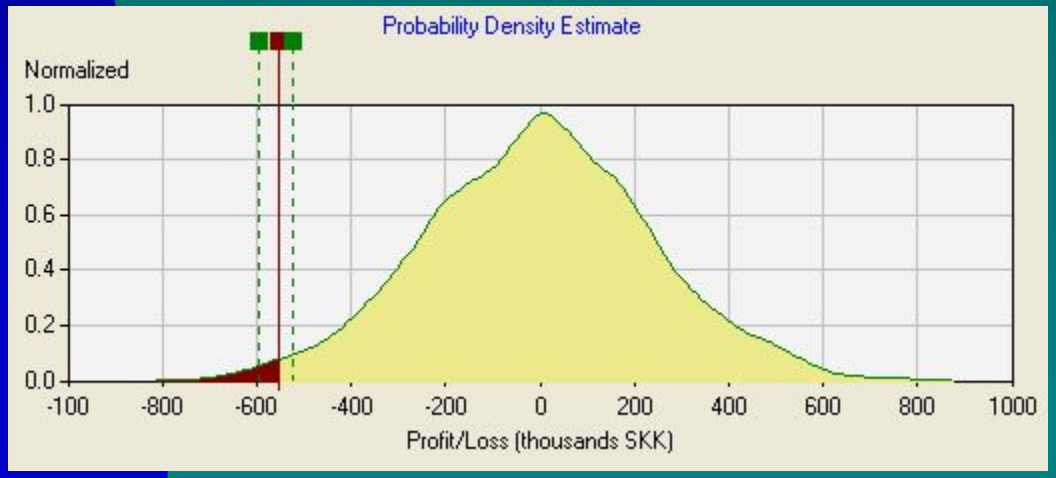
# Comparison of VaR methods

| Mark to Market Value (SKK) | VaR | Delta-normal method | Historical Simulation | Monte Carlo RiskMetrics | Monte Carlo (dynamic modelling) pseudo random number | Monte Carlo (dynamic modelling) Faure's quasi random number |
|---|---|---|---|---|---|---|
| 53993907.96 | 1% | 59.21 | 0.97 | 48.02 | 1.08 | 1.08 |
| | 5% | 41.86 | 0.73 | 36.01 | 0.74 | 0.77 |
| | 10% | 32.62 | 0.56 | 28.73 | 0.59 | 0.57 |

# Comparison of the MC method and the MC method with dynamic risk factor modeling

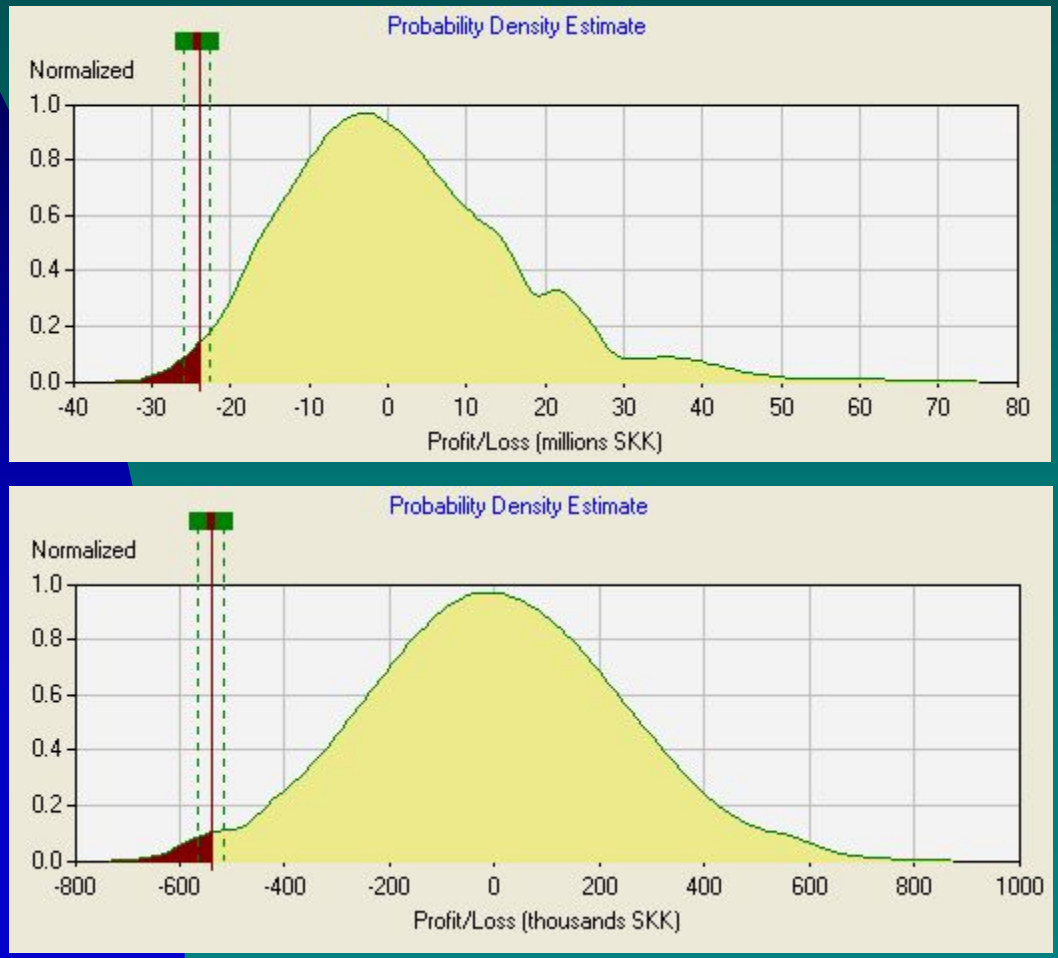
(pseudo random generator)



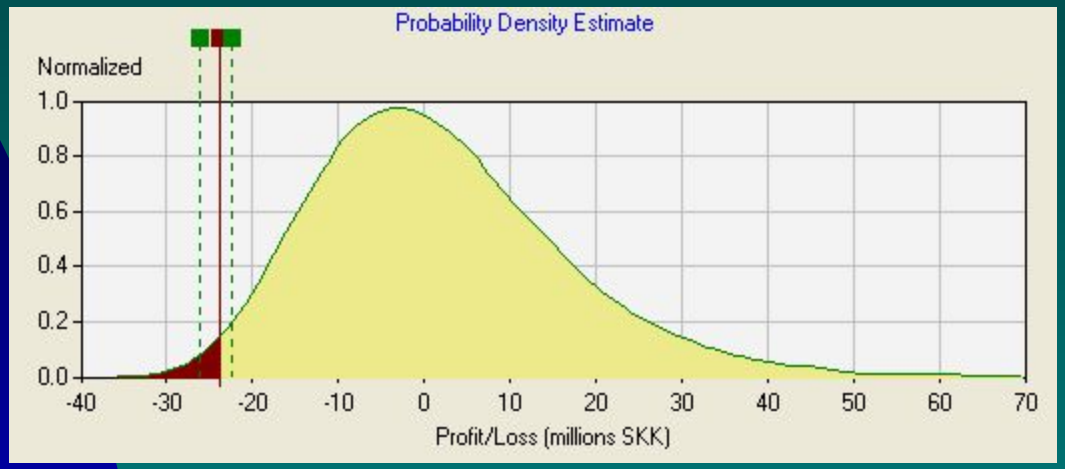
# Comparison of the MC method and the MC method with dynamic risk factor modeling

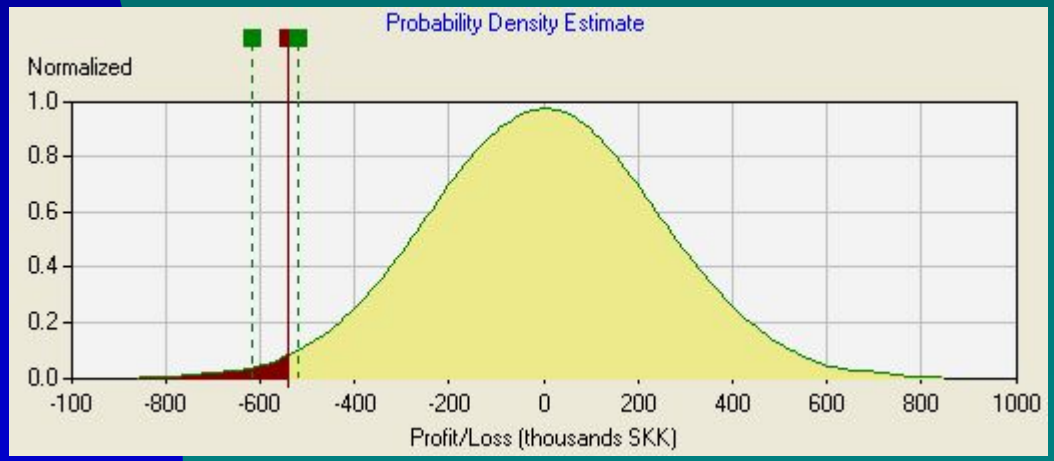
## (Faure's quasi random generator)



# Comparison of the MC method and the MC method with dynamic risk factor modeling

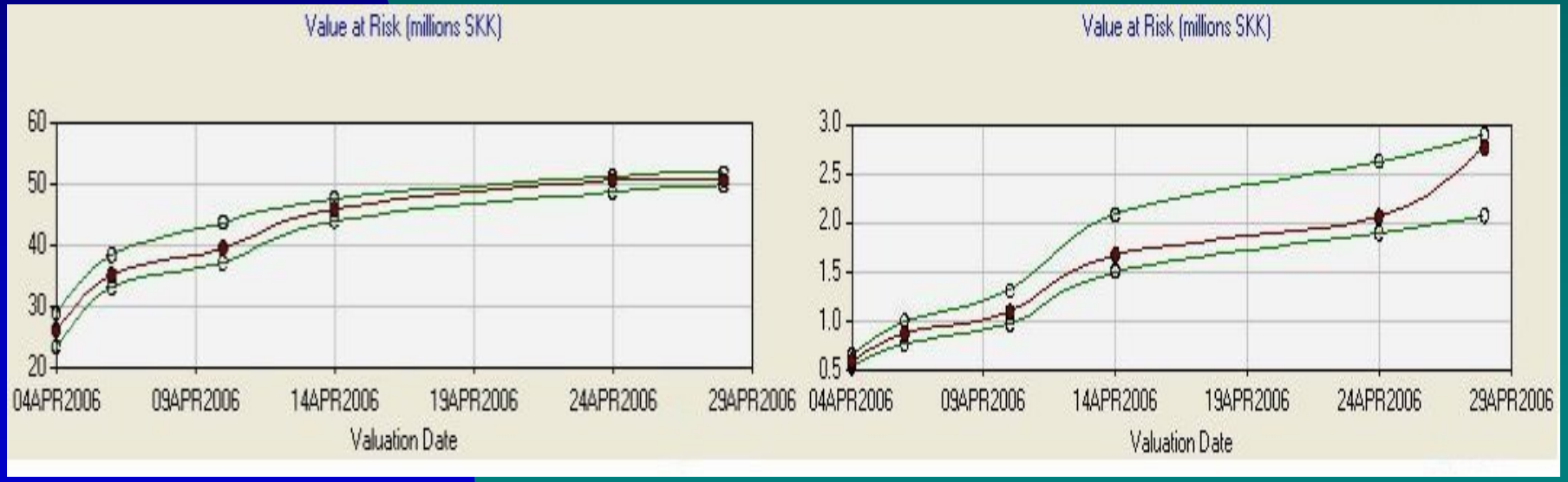
## (Sobol's quasi random generator)



# Comparison of 99% VaR during one month

***Monte Carlo simulation and Monte Carlo simulation with dynamic risk factor modeling***



In this paper was used
system SAS® RISK Dimensions®

# Thank you for your attention