An Hybrid Optimization Method For Risk Measure Reduction Of A Credit Portfolio Under Constraints

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Outlines

- Problem definition:
  - Credit derivative product description
  - Loss modeling + performance indicators
  - Optimization problems
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- Optimization algorithm:
  - Semi-deterministic algorithm
  - Genetic algorithm
  - Hybridation
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- Problem resolution:
  - Results
  - Financial analysis
Part I: Problem Definition

Outlines

- Historical context
- Considered derivative credit product
- Objective of the work
- $CDO^2$ model: Data
- $CDO^2$ model: Loss evaluation
- Merton's model
- KMV's model
- Default times model
- Density function $\beta_L$
- Performance Indicators
- Risk measures
- Optimization problems

Part II: Hybrid optimization method

Part III: Application to portfolio optimization

Conclusion and perspectives
Historical context

- **Object**: derivative credit products:
  - Development of those products (In 2004: 2300 $\bar{M}$)
Historical context

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- **Main problems:**
  1-Risk management:
  - Risk of a trading partner not fulfilling his obligations on the due date → Loss.
  - Example: Bankruptcy (Enron/Worldcom in 2001/2002)
  - Variation of rating (Telecom. in 2000)

→ Loss evaluation method (Merton 1974...), Risk measure (Rockafellar, Artzner 1998...)
Historical context

- **Object:** derivative credit products:
  - Development of those products (In 2004: $2300 \text{M} \ $)

- **Main problems:**
  1. Risk management:
     - Risk of a trading partner not fulfilling his obligations on the due date $\rightarrow$ Loss.
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  2. Profitability improvement

  Variation of rating (Telecom. in 2000)

  $\rightarrow$ Loss evaluation method (Merton 1974...), Risk measure (Rockafellar, Artzner 1998...)

  2. Profitability improvement
Considered derivative credit product

Collateralized Debt Obligations (CDO)

-Objective: buy securitization in order to protect from eventual defaults.
Considered derivative credit product

\( \text{CDO}^2 / \text{Master CDO} \)

- **Objective**: Resilient to low losses.
- **Main default**: When Losses: Fast and highly severe.

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Objective of the work

Find the nominal coefficients, using an optimization algorithm, that improve desired portfolio characteristics:

- Reduction of Risk measure.
- Augmentation of the income.
- Augmentation of the profitability.
$CDO^2$ model: Data

For each facility $i$, market gives:

- A nominal ($N_i$).
- A maturity ($T_i$) date.
- A spread ($Sp_i$).
- A loss given default ($LGD_i$).
- geographical/zone/stability Coefficients.
**CDO^2 model: Data**

For each facility $i$, market gives:
- A nominal ($N_i$).
- A maturity ($T_i$) date.
- A spread ($Sp_i$).
- A loss given default ($LGD_i$).
- geographical/zone/stability Coefficients.

We can directly compute:
- **Income:** $IC = \sum_{i=1}^{N} Sp_i \times N_i$
- $PN = \sum_{i=1}^{N} N_i$
In order to compute more complex indicator. We consider:

$L$ the CLO$^2$’s amount of losses: Random variable.
In order to compute more complex indicator. We consider:

\[ L \] the CLO^2’s amount of losses: Random variable.

→ We need to determine is Loss density function \( \beta_L \):

Merton’s Model

\[ \Downarrow \]

Kealhofer, McQuown and Vasicek’s Model (Factor Model)

\[ \Downarrow \]

Default Time’s Model
1974: Model of the firm:

The liabilities are divided:

- Debt $D$
- Equities $E$
- Assets $A$

Linked by: $A = D + E$
Merton’s model

\[
\begin{align*}
A &= s \phi(d_1) - x e^{-rt} \phi(d_2) \\
E &= x e^{-rt} \phi(-d_2) - s \phi(-d_1)
\end{align*}
\]

where:
- \( A \) originally corresponds to call price and \( E \) to put price.
- \( \phi \) is the normal probability density function.
- \( d_1 = \frac{\log(s/x)+(r+\sigma^2/2)t}{\sigma \sqrt{t}} \) and \( d_2 = d_1 - \sigma \sqrt{t} \).
- \( s \) the price of the underlying stock.
- \( x \) is the strike price.
- \( r \) is the continuously compounded risk free interest rate.
- \( t \) is the time in years until the expiration of the option.

If at debt maturity:
- \( E \geq D \) no default.
- \( E < D \) default.

TIME CONSUMING
KMV’s model

It’s factor model based on Merton’s model: \( A = D + E \).

Introducing random variables normally distributed and independent of each other:

- 14 global factors \((F^k)_{1 \leq k \leq 14}\) that model the global economic trends.
- Local factors: Facility activity sectors \(C\) (61 sectors) and Facility geographical areas \(I\) (45 areas).

The rate of return of firm, \( r^i_t = \frac{A^i_t - A^i_{t-1}}{\Delta t} \), is given by:

\[
r^i_t = R^i_t \left[ \sum_{k=1}^{14} \alpha^i_k F^k_t + \beta^C_i C^i_t + \beta^I_i I^i_t \right] + \sqrt{1 - R^2_t \varepsilon^i_t}
\]

where \( \varepsilon^i_t \) is the specific rate of return of firm \( i \).
KMV’s model

Monte-Carlo Algorithm:

- Simulate realizations of the latent variables \( \left( F^k_t \right)_{1 \leq k \leq 14} \), \( \left( I^i_t \right)_{1 \leq i \leq 61} \), \( \left( C^i_t \right)_{1 \leq i \leq 45} \), \( \left( \varepsilon^i_t \right)_{1 \leq i \leq N} \) until horizon \( H \).

- Deduce the rates of return of the portfolio’s assets.

- For each facility and for each scenario, compare the asset value (A) with the default point (D).

- For each scenario: evaluate the total loss at given horizon:

  \[
  \sum_{i \text{ default}} LGD_i \times N_i
  \]
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Conclusion and perspectives

KMV’s model
Inconveniences:

- The grid country/industry used to classify firms is not always satisfying.
- Time of computation.
- The determination of default events is achieved by comparing asset values and default points at horizon. A default should occur as soon as the asset value trajectory meets the default point trajectory.
Default times model

We introduce default times \( \tau = (\tau_1, \ldots, \tau_i, \ldots, \tau_n) \).

The default times are computed from Gaussian vector:
\[ A = (A_1, \ldots, A_i, \ldots, A_n) \]
with zero mean and unit variances and covariance matrix \( \Sigma \) given by KMV model:

Considering that \( A_i \) is given by KMV formulation, of the form:
\[
A_i = \rho_i \cdot Y + \sqrt{1 - \rho_i^2} \cdot \epsilon_i
\]
where for \( i = 1, \ldots, n \), \( Y, \epsilon_i, i = 1, \ldots, n \) is a standard gaussian random variable.
Default times model

We define the joint default probability function given by (Copula theory):

\[
F(t_1, \cdots, t_n) = \mathbb{IP}(\tau_1 < t_1, \cdots, \tau_n < t_n)
\]

\[
= \int_{-\infty}^{+\infty} \left( \prod_{i=1}^{n} \Phi \left( \frac{\Phi^{-1}(F_i(t_i)) - \rho_i Y}{\sqrt{1 - \rho_i^2}} \right) \right) \frac{e^{-\frac{t^2}{2}}}{\sqrt{2\pi}} dt
\]

with \( F_i(t) = \mathbb{IP}(\tau_i \leq t) \) the default time’s marginal repartition function.

Default times are given by:

\[
\tau_i = F^{-1} (\Theta(A_i))
\]

where \( \Theta(.) \) denotes the standard normal gaussian density function.
Default times model

Monte-Carlo approach to compute $\beta_L$:
- Simulate KMV coefficients.
- Compute default times.
- Compute loss amount: $\sum_{i=1}^{n} default LGD_i \times N_i$.

Case 1:

```
  SUPER SENIOR  SUPER SENIOR  SUPER SENIOR
  AA            AA            AA
  EQUITY        EQUITY        EQUITY
  CDO1          CDO2          CDO3

  SENIOR
  TRANCHE A
  TRANCHE B
  TRANCHE C
  EQUITY
  MASTER CDO
```

Case 2:

```
  SUPER SENIOR  SUPER SENIOR  SUPER SENIOR
  AA            AA            AA
  EQUITY        EQUITY        EQUITY
  CDO1          CDO2          CDO3

  SENIOR
  TRANCHE A
  TRANCHE B
  TRANCHE C
  EQUITY
  MASTER CDO
```
Density function $\beta_L$
Performance Indicators

- **Expected Loss (EL):**
The expected value, over some specified horizon, of portfolio losses due to default. Given by:

\[
EL(\beta_L) = \int_0^{\text{portfolio's nominal}} \frac{\beta_L(x)}{\text{portfolio's nominal}} \, dx
\]

- **Risk Adjusted Return On Capital (RAROC):**
Profitability. RAROC is given by:

\[
RAROC = \frac{(\sum_{\text{portfolio}} (Sp_i \times x_i) - EL(\beta_L))}{EC}
\]
Risk measures

We consider:
- $\Omega$ a finite set of states of nature.
- A random variable by $X$.
- The probability space $L^\infty(\Omega, \mathcal{F}, \mathbb{P})$ (view as set of all risks: changes in values between two dates).

Any mapping $\rho : L^\infty(\Omega, \mathcal{F}, \mathbb{P}) \rightarrow \mathbb{R}$ is called risk measure.

Important in finance:
A mapping $\rho : L^\infty(\Omega, \mathcal{F}, \mathbb{P}) \rightarrow \mathbb{R}$ satisfying the Sub-additivity propriety: $\rho(X_1 + X_2) \leq \rho(X_1) + \rho(X_2)$ (more generally coherent).
Risk measures

**VaR:** The smallest nominal loss of the worst \( \alpha \) % of losses:

\[
VaR_\alpha (L) = \inf \left\{ L' \mid \int_0^{L'} \beta_L (x) dx < (1 - \alpha) \right\}
\]

**C-VaR (Expected Shortfall):** The average of the worst \( \alpha \) % of losses. In the case of the discrete distribution \( \beta_L \), the \( ES_\alpha \) is given by:

\[
ES_\alpha (L) = -\frac{1}{\alpha} \sum_{p=0}^{\alpha} \inf \left\{ x \mid P[L \leq x] \geq p \right\} dp
\]

CVaR is often preferred: In some case it's coherent and convex risk measure.
Optimize **Facilities’ nominal** of BNP-Paribas Portfolio-Management (PM) portfolio in order to:

- **Reduce risk measure keeping the income higher than the initial value**: \( \alpha = 0.1 - \text{VaR} \).
  Both measures have led to the same kind of results.
- **Maximize Income keeping risk measure lower than the initial value**.
- **Maximize profitability keeping the income higher than the initial value**: We use the RAROC as profitability measure to be maximized.
Part II: Hybrid optimization method
Global Optimization and Dynamical system

We consider a function $J : \Omega_{ad} \to \mathbb{R}$ to be minimized. We assume:
- $J \in C^1(\Omega_{ad}, \mathbb{R})$
- $\Omega_{ad} \subset \mathbb{R}^N$ compact

The minimum of $J$ in $\Omega_{ad}$ is denoted by $J_m$. In practice, when $J_m$ is unknown, we set $J_m$ to a lower value and look for the best solution for a given complexity and computational effort.
Global Optimization and Dynamical system

Most deterministic minimization algorithms can be seen as discretizations of Dynamical Systems.

A numerical global optimization of $J$ with one of those algorithms is possible if the following BVP has a solution:

$$\begin{cases}
\text{First or second order dynamical system} \\
\text{Initial conditions} \\
|J(x(Z)) - J_m| < \epsilon
\end{cases}$$

where: $Z \in \mathbb{R}$ a given time and $\epsilon$ the approximation precision.

This BVP is over-determined.

Idea: Remove over determination.
Recursive semi-deterministic methods

Remove the over determination:

\[
\begin{align*}
\text{First or second order dynamical system} \\
\text{Initial conditions} \\
| J(x(Z)) - J_m | < \epsilon
\end{align*}
\]

One of the initial condition is considered as a variable \( v \)

Then apply BVP techniques: Example: SHOOTING METHOD.
Genetic algorithm

General overview:

We want to minimize: \( J(x) = x_1^2 + x_2^2 \)

- Initial Population
- Selection
- Cross-Over
- Intermediate Population
- Reproduction
- Final Population
- We iterate the process
Genetic algorithm

One matrical representation:

Initial population: \( X^0 = \{ x^0_l \in \Omega_{ad}, l = 1, \ldots, N_p \} \)

\( i^{th} \) Population:

\[
X^i = \begin{bmatrix}
  x^i_1(1) & \cdots & x^i_1(N) \\
  \vdots & \ddots & \vdots \\
  x^i_{N_p}(1) & \cdots & x^i_{N_p}(N)
\end{bmatrix}
\]
Genetic algorithm

- **Selection:**

\[ X^{i+1/3} = S^i X^i \]

- **Crossover:**

\[ X^{i+2/3} = C^i X^{i+1/3} \]

- **Mutation:**

\[ X^{i+1} = X^{i+2/3} + \mathcal{E}^i \]
Genetic algorithm

The new population can be written as:

\[ X^{i+1} = C^i S^i X^i + \mathcal{E}^i \quad (1) \]

Thus genetics algorithms can be associated to:

\[ \dot{X}(t) = \Lambda_2(t, X(t), P) X(t) \Lambda_3(t, X(t), P) - X(t) \]

Where

- \( P \) are a set of fixed parameters
- \( X \) of the form: \( X = \{x_i/ \ i = 1, ..., N_p \ x_i \in \Omega_{ad}\} \)
Genetic algorithm

\[
\begin{aligned}
\dot{X}(t) &= \Lambda_2(t, X(t), p)X(t)\Lambda_3(t, X(t), p) - X(t) \\
X(0) &= X^0 \\
\hat{J}(X(Z)) &\approx J_m
\end{aligned}
\]

Where:
- \(\hat{J}(X) = \min(J(x_i)/x_i \in X)\)
- \(P\) are a set of fixed parameters
- \(X\) of the form: \(X = \{x_i / i = 1, ..., N_p \ x_i \in \Omega_{ad}\}\)

Inconveniences of GA:
- Slow convergence/ computational complexity
- Lack of precision

Idea: Combine our SD method with GA: \(X^0\) Considered as a new variable.
Hybrid algorithm

- **Input:** $X^0, N, \epsilon$

  For $i$ going from $O$ to $N$
  - $o^i = GA(X^i, I, \epsilon)$
  - If $\min\{J(o^k), k = 1, ..., i\} < J_m + \epsilon$ EndFor
  - We construct $X^{i+1}$: $\forall x^i \in X^i$ $x^{i+1} = x^i - J(o_i) \frac{o^i - v^i}{J(o^i) - J(v^i)}$

EndFor

- **Output:** $A_1(X^0, N, \epsilon) = \arg\min\{J(o^k), k = 1, ..., i\}$

We can build recursively algorithm $A_2, A_3, ...$ replacing GA by $A_1, A_2, ...$

GA is taken with small population/generation values.

Have been tested and compared with classical GA on various optimization problem:
- Microfluidic device
- Optical fiber synthesis
- Academic test cases
Part III: Application to portfolio optimization
Considered Portfolio

PM portfolio:
- CLO$^2$ structure
- Compound by 500 facilities dispatched into 40 ICLOs’tranches and 54 Single-Names (‘SN’).
- Portfolio nominal: 2.0e9 Euros (E)
- ICDO nominal: 7.5e8 E.
- SN nominal: 1.25 E.
- Income: 2.1e7 E.
- VaR: 1.9e8 E.
- RAROC: 90 %
Parameterization

Parameters: nominal of each ICDO’s tranches and SN included in the entire PM universe (1500 facilities)

For versatility and respecting the BNP investment guideline, we consider constraints on facility:

- **Avoid too much concentration in one facility**: maximum nominal 1.e8 E.
- **Minimum facility investment**: if nominal <5e6 E → nominal set to 0.
- **Facility quality**: Depending on quality coefficients: The nominal can be raised, decreased or unmodified.

Thus the Parameter number: 65.
Cost function

Optimization problem is of the form:

$$\min_{x \in \Omega} \sum_{n=1}^{n \text{char}} \xi_i J_n(x)$$

$$l c_1 \leq C_1(x) \leq u c_1$$

$$\vdots$$

$$l c_{n \text{cons}} \leq C_{n \text{cons}}(x) \leq u c_{n \text{cons}}$$

We rewrite using wall functions:

$$\tilde{J}(x) = J(x) + \vartheta \sum_{j=1}^{n \text{cons}} (\max(u c_j - C_j(x), 0) + \max(C_j(x) - l c_j, 0))$$
Computational time reduction

Sensitivity analysis is difficult:
- At least 1e6 Monte-Carlo iterations to capt variations → 20 minutes (real time).

Thus we use HSGA + computational reduction techniques:
- Default times are computed once (Need lot of memory 1e5=512 Mb)
- When constraint is not satisfied: intend to project portfolio on admissible space border using proportional coefficient.

## Var min/ IC constraint

<table>
<thead>
<tr>
<th></th>
<th>Nominal</th>
<th>Nom. ICLO</th>
<th>Nom. SN</th>
<th>IC</th>
<th>VaR_{0.1%}</th>
<th>RAROC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial</td>
<td>2.0e9</td>
<td>7.5e8</td>
<td>1.25e9</td>
<td>2.1e7</td>
<td>1.9e8</td>
<td>90%</td>
</tr>
<tr>
<td>Sen.</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>3%</td>
<td>7%</td>
<td>2%</td>
</tr>
<tr>
<td>$P_1$</td>
<td>2e9</td>
<td>5.5e8</td>
<td>1.45e9</td>
<td>2.1e7</td>
<td>1.3e8</td>
<td>87%</td>
</tr>
<tr>
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<td>0%</td>
<td>-26%</td>
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<td>-</td>
<td>-</td>
<td>1%</td>
<td>1%</td>
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</tr>
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</table>

### Table Notes:
- **Nominal** shows the initial values for different metrics.
- **Nom. ICLO** and **Nom. SN** represent variations or parameters in the context of portfolio optimization.
- **IC**, **VaR_{0.1%}**, and **RAROC** are performance indicators.
- **Sen.** indicates sensitivity analysis results.

### Parameters and Constraints:
- **Var min/ IC constraint**
- **IC max/ VaR constraint**
- **RAROC max/ IC constraint**
- **VaR min, IC max, RAROC max**
Var min/ IC constraint

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Conclusion and perspectives
IC max/ VaR constraint

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<td>90%</td>
</tr>
<tr>
<td>Sen.</td>
<td>-</td>
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<td>-</td>
<td>3%</td>
<td>7%</td>
<td>2%</td>
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<td>$P_2$</td>
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Part I: Problem Definition

Part II: Hybrid optimization method

Part III: Application to portfolio optimization

• Considered Portfolio
• Parameterization
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Conclusion and perspectives
### RAROC max/ IC constraint

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</tr>
<tr>
<td>Sen.</td>
<td>-</td>
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<td>7%</td>
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<td>$P_3$</td>
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<td>9.8e3</td>
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RAROC max/ IC constraint

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## VaR min, IC max, RAROC max

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<tr>
<td>Sen.</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>3%</td>
<td>7%</td>
<td>2%</td>
</tr>
<tr>
<td>P₄</td>
<td>2.7e9</td>
<td>73e8</td>
<td>2.0e9</td>
<td>2.5e7</td>
<td>1.4e8</td>
<td>96%</td>
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<td>-16%</td>
<td>57%</td>
<td>17%</td>
<td>-26%</td>
<td>7%</td>
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<td>Sen.</td>
<td>-</td>
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Outlines

Part I: Problem Definition

Part II: Hybrid optimization method

Part III: Application to portfolio optimization

Considered Portfolio Parameterization

Cost function

Computational time reduction

Var min/ IC constraint

IC max/ VaR constraint

RAROC max/ IC constraint

VaR min, IC max, RAROC max

Conclusion and perspectives

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VaR min, IC max, RAROC max
Conclusion and perspectives
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- Perspectives: Try with More complete models, extension to other kind of facilities (hedge)...
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!!! Thank You !!!