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An Asset-Liability Management Stochastic Program of a Leasing Company

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Outline

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We present real and practical application of stochastic programming.

The work

- aims to find the optimal solution,
- of a real-world problem,
- while allowing its flexible modifications,
- with input parameters obtained from real data.

Business Model of a Leasing Company

- It lends money to clients.
- It borrows money from a bank.
- Current practise is that the leasing company (LC) closes mirror deal with a bank as it has with a client (the same amount, the same length)
	- This means that the LC closes its position.
	- Income is generated by different rates on each loan.
- The main idea of the problem is to suggest a better strategy for borrowing from the bank, so that we control the amount of IR risk the company faces.

Stochastic Programming Formulation

- Mathematical notation for related quantities is introduced.
- The dynamics of cash–flows is specified by a set of equations.
- These depend on random quantities (demand, interest rate) as well as on decision variables.
- The objective of the model is to maximise the value of a portfolio of loans at the time horizon *n*.
- Symbol $V_n(\bar{\omega}_n^s)$ denotes the value of a strategy at the investment horizon *n* for scenario $\bar{\omega}_n^s$, while $V_n^0(\bar{\omega}_n^s)$ denotes the value of the benchmark strategy.
- We assumed decision times to be equidistant, with one year gap. Time horizon was chosen to be $n = 6$ years.
- Borrowing was only possible with maximum time to maturity $m = 5$ years.
- The adopted structure of the tree was $8 4 2 2 2 2$ nodes from every scenario in the corresponding stage.
- Scenarios of interest rate were generated from the Hull White model as quantiles of the interest rate distribution.
- Values of charged rates by bank/LC were determined from data of a company CS Autoleasing.

Figure: Scenario values of a one year interest rate in the Czech market in the tree structure used in the optimisation problem.

$$
\max_{x_{,j}(\tilde{\omega}_{j}^{s})} \frac{1}{|S_{n}|} \sum_{s \in S_{n}} V_{n}(\tilde{\omega}_{n}^{s})
$$
\ns.t. $R_{k}(\tilde{\omega}_{k-1}^{s}) = \sum_{i=|k-m|^{+}}^{k-1} \sum_{j=k-i}^{m} \frac{d_{i,j}(a_{i}(\tilde{\omega}_{k-1}^{s}))}{\tilde{r}_{i,j}^{s}}, \qquad 1 \leq k \leq n, s \in S_{k-1},$ \n
$$
Q_{k}(\tilde{\omega}_{k-1}^{s}) = \sum_{i=|k-m|^{+}}^{k-1} \sum_{j=k-i}^{m} \frac{x_{i,j}(a_{i}(\tilde{\omega}_{k-1}^{s}))}{\tilde{s}_{i,j}^{s}}, \qquad 1 \leq k \leq n, s \in S_{k-1},
$$
\n
$$
D_{k}(\tilde{\omega}_{k}^{s}) = \sum_{j=1}^{m} d_{k,j}(\tilde{\omega}_{k}^{s}), \quad X_{k}(\tilde{\omega}_{k}^{s}) = \sum_{j=1}^{m} x_{k,j}(\tilde{\omega}_{k}^{s}), \quad 0 \leq k < n, s \in S_{k},
$$
\n
$$
B_{0} = X_{0}(\omega_{0}^{s}) - Q_{0}(\omega_{0}^{s}), \quad s \in S_{0},
$$
\n
$$
B_{k}(\tilde{\omega}_{k}^{s}) = \frac{B_{k-1}(a_{k-1}(\tilde{\omega}_{k}^{s}))}{p_{k-1,1}(a_{k-1}(\tilde{\omega}_{k}^{s}))} - E_{k-1} + X_{k}(\tilde{\omega}_{k}^{s}) - Q_{k}(a_{k-1}(\tilde{\omega}_{k}^{s}))
$$
\n
$$
+ R_{k}(a_{k-1}(\tilde{\omega}_{k}^{s})) - D_{k}(\tilde{\omega}_{k}^{s}), \quad 1 \leq k < n, s \in S_{k},
$$
\n
$$
B_{n}(\tilde{\omega}_{n-1}^{s}) = \frac{B_{n-1}(a_{n-1}^{s})}{p_{n-1,1}(a_{n-1}^{s})} - E_{n-1} + R_{n}(\tilde{\omega}_{n-1}^{s}) - Q_{n}(\tilde{\omega}_{n-1}^{s}), \quad s \in S_{n-1},
$$

To control for the risk faced by opening the company's interest rate position, the following approaches were considered:

- Chance constraint forces the solution to beat the benchmark with a probability $1 - \alpha, \alpha \in (0, 1)$.
- VaR constraint restricts the 1 α quantile of the portfolio value to be greater than or equal to a given limit $-u_{\alpha}$.
- CVaR constraint sets the average of $1 \alpha \cdot 100\%$ of the worst values to be greater than or equal to a given limit $-V_{\alpha}$.
- SSD constraint forces the optimal strategy to dominate the benchmark strategy by a second order stochastic dominance.

Results

- **•** First, the model with no risk constraint was solved.
- The problem had 7008 variables and 4563 equations.
- The optimal strategy performed better than the benchmark in around 81% of cases.
- At 0.95 level, the VaR of the benchmark was −262.32 mil. CZK, while of the optimal strategy it was −269.1 mil. CZK.
- CVaR the benchmark: −254.88 mil. CZK, the optimal solution: −256.71 mil. CZK.
- The optimal portfolio dominated the benchmark portfolio by SSD.

Returns of Benchmark and Optimal Strategy, No Constraint

Figure: Comparison of portfolio values of the benchmark and the no–risk constraint optimal strategy.

Comparison of Benchmark and Optimal Strategy Returns for Scenarios

Figure: Differences: the optimal portfolio value - the benchmark portfolio value against the one year interest rate in the final stage.

CVaR Constraint

We set limit on the 0.95 conditional Value–at–Risk of the optimal strategy:

 $\text{CVaR}_{\alpha}(-V_{t_n}) \leq V_{\alpha}, \qquad \alpha = 0.95.$

• This could be expressed as

$$
z^{s} \geq -V_{n}(\tilde{\omega}_{n}^{s})-a, \quad z^{s} \geq 0, \quad s \in S_{n},
$$

$$
a+\frac{1}{1-\alpha}\frac{1}{|S_{n}|}\sum_{s \in S_{n}}z^{s} \leq V_{\alpha}, \quad a \in \mathbb{R}.
$$

• The highest reasonable CVaR limit v_α is equal to -256 mil. CZK. The lowest feasible limit was found to be −277.25 mil. CZK.

Conditional Value−at−Risk Sensitivity Analysis

Figure: Dependence of the optimal expected value on the value of the limit v_α in the conditional Value–at–Risk constraint.

Returns of Benchmark and Optimal Strategy, CVaR Constraint

Value of a Portfolio [mil. CZK]

 $\text{K} \text{G} \text{G} \text{D} \text{S} \text{F} \text{F} \text{F}$

Comparison of Optimal Strategies

- Multiple risk constraints were analysed, but we wish to know what are their suggestions for "today's" decision
- Risk limits were chosen in a way that the corresponding risk measure ranks "just better" the optimal portfolio.

Table: Table with the mean value of portfolios in the final stage and the here and now decisions of how to borrow money.

- One can ask what happens when things do not go as we expected (=modelled in our scenario tree).
- Opening the interest rate position can have fatal consequences in case of interest rate increase/decrease.
- Assume that we fix our here and now decision, borrow according to it, but then, a crisis comes.
- We create crisis scenarios by a rapid increase in interest rate.
- Thereafter, we readjust our strategy and learn the new expected value of the portfolio.

Crisis Scenario, Year 1 Short Rate 1.7%

Figure: Scenario tree for stress test with the value of the short rate 1.7%

Figure: The expected value of the optimal solution for different level of stress test and various strategies. Dashed lines show optimal values of the programs after relaxing the (infeasible) risk constraints.

- Stochastic program within an asset–liability model was developed.
- A lot of attention has been paid to creating realistic inputs (e.g. improved calibration procedure of the Hull – White model, market data about leasing loans and rates).
- Four different risk constraints were introduced to offer a possibility to manage interest rate risk.
- Stress test was proposed to asses the effect of unconsidered scenarios on the optimal solutions.
- We found the benchmark strategy to be largely inferior to all optimal strategies in most aspects.

Thank you for your attention.