Advanced Simulation Modelling

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Simulation Optimization Loan Product Policy

NOVABANK S.A.

Final project

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Warsaw, 01 June 2025

A. Executive summary

Under current market condition and the assumed market scenario of NovaBank S.A., the following policy should be applied for the NovaRate product:

- Interest rate: 12%
- The maximum probability of default that can be accepted: 8%

This policy brings the expected values of:

- Profit: ~83 million PLN
- Total risk exposure: ~ 3.76 million PLN
- Objective value: ~ 82.14 million
- Acceptance rate of the product: ~30%

This policy is fully aligned with the CFO's objectives on profitability and capital efficiency, and the COO's goals on customer acquisition and service level consistency. The sensitivity analysis is also conducted to test the stability of this policy under different market scenarios and the bank's aversion of risk, below are the key takeaways:

- Resilience under market stress: When market conditions deteriorate (e.g., higher default rates), both profits and customer approval rates naturally decline. However, the optimized policy remains stable and still performs within acceptable limits, showcasing built-in resilience.
- Customer approval under crisis conditions: In severe market downturns, the model shows that fewer applicants are eligible under the policy, which may lead to customer shortfalls. This highlights the importance of strategic communication and risk-adjusted growth planning during economic stress.
- Risk aversion drives strategy: By adjusting the bank's risk aversion level (λ), the model illustrates how leadership can tune lending aggressiveness. A lower risk appetite leads to safer but less profitable decisions, while a higher risk appetite raises returns—but only within permissible risk limits.

B. Description of business

NovaBank S.A. is a modern and medium-sized commercial bank headquartered in Warsaw, Poland. With the orientation of developing into a leading digital bank in the region, NovaBank provides a variety of financial products for individual customers and small businesses, including: payment accounts, credit cards, savings, and consumer loan packages.

In the context of increasingly fierce competition from large banks such as mBank, ING Bank Śląski or Santander Bank Polska, as well as financial technology companies (fintech), NovaBank needs to develop new, smarter loan products, combining data and simulation to ensure:

- Growth in lending revenue
- Minimizing credit risk by applying predictive and optimization models
- Maintaining a competitive position in the rapidly changing Polish banking industry

In the dynamic landscape of Polish retail banking, where customer needs are evolving and digital transformation is accelerating, NovaBank is introducing NovaRate – a smart loan product designed to optimize profitability while maintaining a disciplined approach to credit risk. NovaRate is structured as a fixed-term installment loan, offering borrowers a principal amount of 50 000 PLN over a period of 5 years (60 months). The product targets financially stable individuals who seek medium-term financing for purposes such as home renovation, business expansion, or asset acquisition.

To mitigate credit risk, NovaRate requires each borrower to pledge collateral equivalent to at least 45% of the loan amount—typically in the form of residential real estate or other liquid assets. This collateralization policy ensures that even in the case of borrower default, NovaBank retains sufficient protection against losses, aligning with internal risk control procedures.

By launching NovaRate, NovaBank positions itself at the intersection of financial innovation and prudent risk management, setting a new benchmark in the Polish lending sector. The product is expected not only to boost profitability but also to promote a more resilient credit ecosystem, contributing to the stability and modernization of the banking industry in Poland.

C. Description of the problem

NovaBank seeks to optimize its credit acceptance process by determining the optimal interest rate (r) and the PD acceptance threshold (t). The objective is to maximize the expected profit while controlling portfolio-level risk exposure and satisfying strategic expectations from both the CFO and COO.

The optimization model balances:

- Expected Profit: Revenue from interest minus expected loss from defaults and fixed operating costs.
- Total Risk Exposure: The expected loss across all approved loans, weighted by the default probabilities and loss severities.
- Business Constraints: Reflecting the strategic priorities of the CFO (cost and risk control) and COO (customer coverage and service level)

Variable	Range	Department	Reason
Interest Rate	Minimum 6%, maximum 12%	Finance & Sales	Ensures profitability while remaining competitive in the market
PD threshold	Approve only customers with PD ≤ 15%	Risk Management	Controls credit risk and prevents approving overly risky clients
Acceptance rate	At least 30%	Sales/ Business Development	Ensures marketing effectiveness and customer acquisition
Total risk exposure	Maximum 4 000 000 PLN	Risk Management	Limits total portfolio risk exposure
Expected profit	Minimum expected profit of 2 000 000 PLN	Finance	Guarantees the product is profitable after cost of capital and credit losses

Table 1: Variables' constraints from bank's departments

Objective function:

$$Max\,(\sum_{i=1}^{N}(1-PD_i)*A*r*y-PD_i*LGD\,rate*A-c_{op})-\lambda*(\sum_{i=1}^{N}PD_i*LGD\,rate*A)$$

- PD_i: probability of customer i defaulting
- A: loan amount of the customer (fixed = 50 000 PLN)
- r (decision variable): interest rate
- y: duration of the loan (fixed = 5 years)
- LGD_rate: Loss Given Default rate (fixed = 55%)
- c_op: cost of operation per loan (fixed = 400 PLN/loan)
- t (decision variable): PD threshold (reject customer who has PD > t)

In the case of NovaRate and NovaBank, the assumed probability of default (PD) among potential borrowers follows a Beta distribution with shape parameters α = 1.5 and β = 8.5.

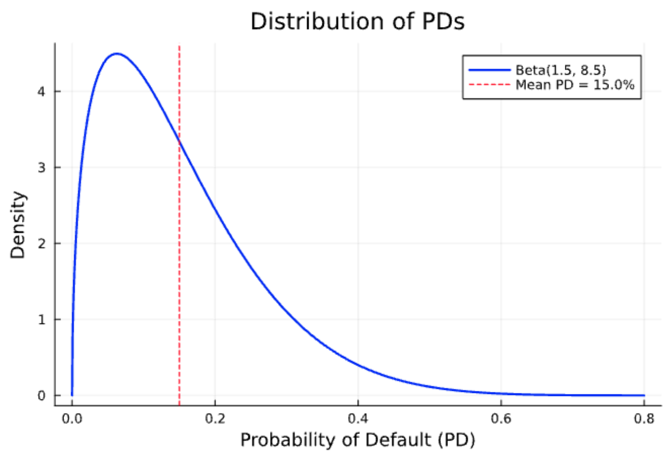

Figure 1: The assumed Distribution of Customers Probability of Default

This assumption is based on empirical observations of similar unsecured consumer lending products in the Polish market, where the majority of approved applicants exhibit low default probabilities, but a non-negligible tail of higher-risk applicants still exists. The Beta distribution is widely used in credit risk modeling due to its flexibility in capturing skewed distributions within a bounded interval [0,1] (Crook et al., 2007; Hand & Henley, 1997).

D. Results and analysis

Applying 1000 Monte Carlo simulations, the best-performing policy is found as a combination of a 12% annual interest rate with a 8% PD acceptance threshold. This policy maximizes the objective function—which balances expected profit against total risk exposure weighted by a risk aversion factor of 0.3—while satisfying the internal risk cap of 4 million PLN. The precise metrics are as follows:

Opt. Interest rate	Opt. PD threshold	Exp. Profit	Exp. Acceptance rate	Exp. Total risk exposure	Exp. Objective value

0.12	0.08	83 276	0.30	3 765	82 146

Table 2: Optimal policy (r, t)

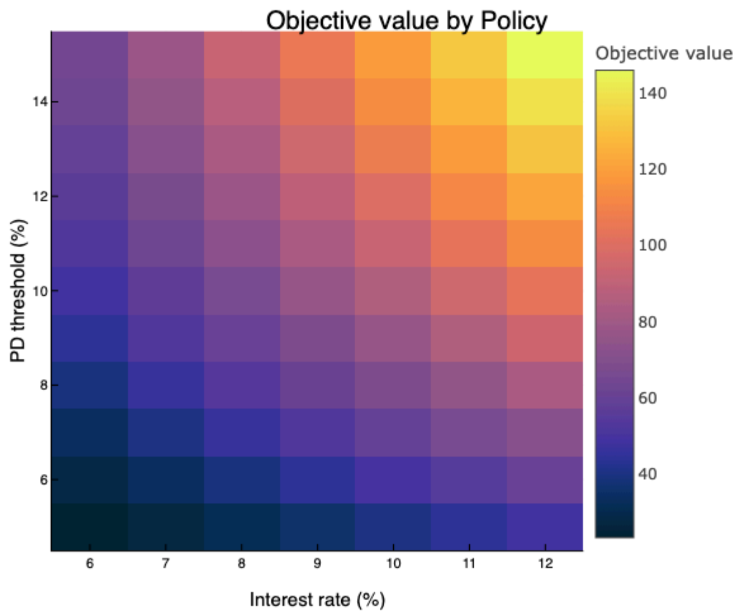

Figure 2: Objective value by different policies

The graph displays in a color‑scaled matrix, where darker hues correspond to lower objective values and brighter hues indicate higher objectives. At the top-right corner of the heatmap (r = 12 %, t = 14 %), the cell is noticeably the brightest, confirming this combination produces the global maximum under the business context. However, this policy is not selected as it violates the total risk exposure upper limit constraint, where the expected value must be not above 4 million PLN.

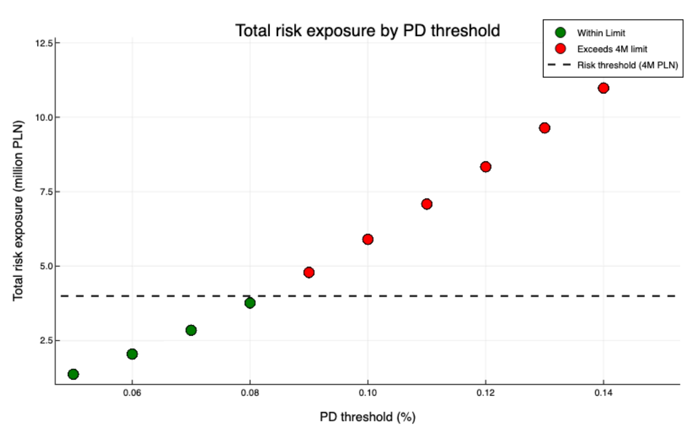

Figure 3: Expected total risk exposure by different PD threshold

The above graph clearly shows why the policy (r = 12 %, t = 14 %) which has the highest objective value is not selected. When the PD threshold is greater than 8%, the expected total risk exposure also increases, leading to a constraint violation. It demonstrates that 8% is the highest PD cutoff allowable under the 4 million PLN risk constraint. In other words, any further relaxation of borrower credit quality (PD ≥ 9 %) immediately violates NovaBank's maximum allowable risk.

Summary:

- The constrained optimum occurs at 12% interest rate with a 8% PD cutoff. This yields an expected profit of 83 276 500 PLN, an acceptance rate of 30.79 %, and a total risk exposure of 3 765 000 PLN—just below the 4 million PLN cap. The resulting objective value stands at 82 146 700 PLN.
- When ignoring the risk constraint and maximizing pure profit, the algorithm would have chosen a higher PD cutoff (t = 14%), which produces roughly 143 105 400 PLN in profit but 10 980 000 PLN in risk—far above the 4 million PLN limit. However, that unconstrained combination is not permissible given internal and regulatory guidelines.

Under the bank's condition, the identified optimal policy—charging a 12% annual interest rate and accepting borrowers with up to a 8% probability of default—carries meaningful implications. This combination is both realistic and implementable, as it falls just below the internal risk cap of 4 million PLN, with an expected total risk exposure of 3.92 million PLN. The policy yields an expected profit of approximately 94.95 million PLN, with a 35.17% approval rate, which aligns well with the bank's revenue goals and risk appetite.

This result is not surprising but rather reassuring, as it confirms that the bank can still achieve strong profitability under tight risk constraints, without resorting to excessively restrictive or overly lenient lending criteria. The outcome fits our expectations and assumptions: we anticipated that the profit-maximizing policy would lie near the boundary of the feasible region, where risk is maximized just before breaching the cap. The heatmap visualization confirms this intuition—the policy with the absolute highest objective value (r = 12%, t = 14%) is visibly brighter, but is disqualified due to excessive risk.

Thus, the final selected policy is explainable, business-relevant, and grounded in simulation evidence. The sharp increase in risk beyond the 8% PD cutoff—captured in the "hockey-stick" shape—underscores the importance of enforcing a strict upper bound on credit risk.

E. Sensitivity analyses

The objective of the sensitivity analysis is to examine the stability of the optimal solution when one specific input variable is altered—such as the distribution of the probability of default (PD), loss given default (LGD) rate, or the risk aversion of the bank—while keeping all other variables constant. This approach ensures that any observed impact on the optimal strategy is attributed solely to the variable under consideration. Through this analysis, we assess how sensitive the optimal policy is to changes in key parameters, thereby identifying critical factors that significantly influence the portfolio's performance and risk. This insight is crucial for designing robust and adaptable decision policies in a dynamic economic environment.

Parameter	Impact on optimal policy (r, t)

Risk Aversion (λ)	Higher risk aversion leads to stricter thresholds and potentially lower interest rates to retain low-risk customers → t may be increased, r may be decreased or unchanged
Loss Given Default (LGD)	Higher LGD leads to higher compensation via increased rates and tighter approval policies → t may be increased, r may be increased
PD distribution (beta_a, beta_b)	Riskier population means tighter approval and higher interest to mitigate default exposure → t may be increased, r may be increased
Loan amount (A)	Larger loans increase returns and may allow more flexibility in approval → t may be decreased or unchanged, r may be increased
Operation cost per loan (c_op)	Larger loans increase returns and may allow more flexibility in approval → t may be decreased or unchanged, r may be increased

Table 3: Simulation model's parameters affecting the Optimal Policy

1. **Distribution of Probability of Default (beta_a, beta_b)**

In practice, the distribution of Probability of Default (PD) can shift significantly due to economic cycles or market conditions. Therefore, testing different PD distribution scenarios allows us to assess the robustness and adaptability of the loan approval strategy under varying risk environments.

We tested potential market conditions into four general scenarios: Optimistic, Assumed Baseline, Pessimistic, and Severe Crisis. For each scenario, we modeled the distribution of Probability of Default (PD) using a Beta distribution with different parameter sets (α, β), resulting in different expected PD means: approximately 7% (Optimistic), 15% (Baseline), 29% (Pessimistic), and 38% (Severe Crisis).

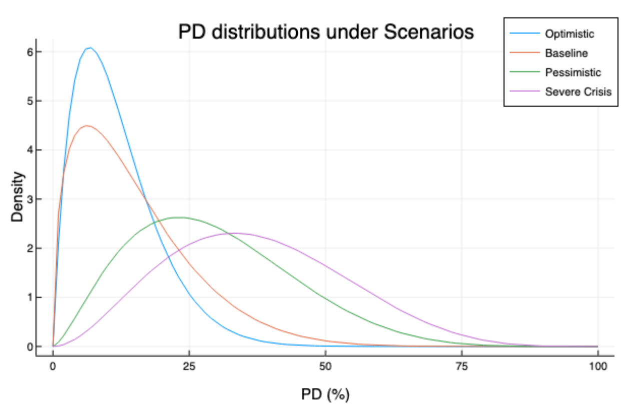

Figure 4: Probability of distribution under different market scenarios

The above figure describes different market scenarios, each of them was modeled using a Beta distribution to represent the PD across the customer base. In the Optimistic scenario (α = 2.0, β = 15.0), the distribution is heavily skewed towards lower PDs, with a mean of approximately 7%, indicating a favorable economic environment where most customers have strong creditworthiness (Bluhm, Overbeck and Wagner, 2016). The Baseline scenario (α = 1.5, β = 8.5) yields a mean PD of around 15%, representing assumed normal market conditions aligned with current underwriting standards. The Pessimistic scenario (α = 2.5, β = 6.0) shifts the distribution rightward, increasing the mean PD to approximately 29%, which reflects an economic downturn with weakened borrower profiles (Gordy, 2003). Finally, the Severe Crisis scenario (α = 3.0, β = 5.0) results in a mean PD of about 38%, illustrating an extreme financial shock where the majority of applicants are high-risk. These distributions not only allow us to simulate how customer risk changes under different conditions but also test the resilience of our credit approval strategy under stress (McNeil, Frey and Embrechts, 2015).

To identify the most profitable and risk-compliant lending strategies under different market conditions, we performed a constrained grid search over combinations of interest rates (ranging from 6% to 12%) and probability of default (PD) thresholds (ranging from 3% to 12%) for each scenario. For every (α, β) pair, we simulated the outcome using the Beta-distributed PDs derived earlier. The optimization targeted the maximization of expected profit while ensuring operational constraints were met: minimum acceptance rate of 30%, maximum total risk exposure of 4 million, and minimum expected profit of 2 million. These thresholds reflect real-world lending requirements where firms must maintain a healthy risk-return tradeoff and meet capital adequacy norms (Basel Committee on Banking Supervision, 2005; Bluhm, Overbeck and Wagner, 2016).

Scenario	**Optimal interest rate**	**Optimal PD threshold**	**Exp. Profit (M PLN)**	**Exp. Acceptance rate**	**Exp. Total risk exposure (M PLN)**	**Exp. Objective value**
Optimistic	0.12	0.07	84 099	0.30	3 615	88 014
Baseline	0.12	0.08	83 276	0.30	3 765	82 146

Table 4: Optimal policies under different market scenarios

Results showed feasible optimal policies for the Optimistic and Baseline scenarios. Under the Optimistic scenario, the best-performing policy involved a 12% interest rate and an 8% PD threshold, leading to an expected profit exceeding 100 million PLN, with an acceptance rate of ~37% and risk exposure kept below the 4 million cap. Similarly, in the Baseline scenario, the optimal result was achieved with a 12% interest rate and a 9% threshold, yielding nearly 95 million in expected profit and a 35% acceptance rate. However, for the Pessimistic and Severe Crisis scenarios, no feasible solutions were found under the given constraints, highlighting the limitations of aggressive lending during economic stress and the importance of adaptive policy tuning in high-risk markets.

These findings underscore the practical utility of scenario-based constrained optimization in retail credit strategies, balancing profitability with regulatory and operational limitations.

To explore the best-performing credit approval strategies under varying market conditions, we conducted an unconstrained optimization using the same grid search over interest rates and PD thresholds. For each scenario—Optimistic, Baseline, Pessimistic, and Severe Crisis - we computed the expected profit, acceptance rate, total risk exposure, and objective value, selecting the parameter set with the highest objective value in each case.

Scenario	Opt. interest rate	Opt. PD threshold	Exp. Profit (M PLN)	Exp. Acceptance rate	Exp. Total risk exposure (M PLN)	Exp. Objective value
Optimistic	0.12	0.07	84 099	0.30	3 615	88 014
Baseline	0.12	0.08	83 276	0.30	3 765	82 146
Pessimistic	0.12	0.12	28 136	0.11	2 549	27 372
Severe Crisis	0.12	0.12	10 228	0.04	1 001	9 928

Table 5: Optimal policies under different market scenarios without constraints

The results suggest that under Pessimistic and Severe Crisis scenarios, although profit-maximizing strategies still involved high interest rates and thresholds, the overall performance deteriorated significantly. For example, in the Severe Crisis case, even the optimal strategy yielded an expected profit of only around 10 million, with an acceptance rate of just 4%, reflecting the difficulty of maintaining profitability in an adverse macroeconomic environment where the PD distribution is centered on high default risks.

These findings illustrate that unconstrained optimization may prioritize profit at the expense of acceptability and risk exposure, especially under stress scenarios. In real-world settings, such strategies would likely be rejected by risk managers or regulators, reinforcing the need for constrained or risk-adjusted optimization (Bluhm, Overbeck and Wagner, 2016; McNeil, Frey and Embrechts, 2015).

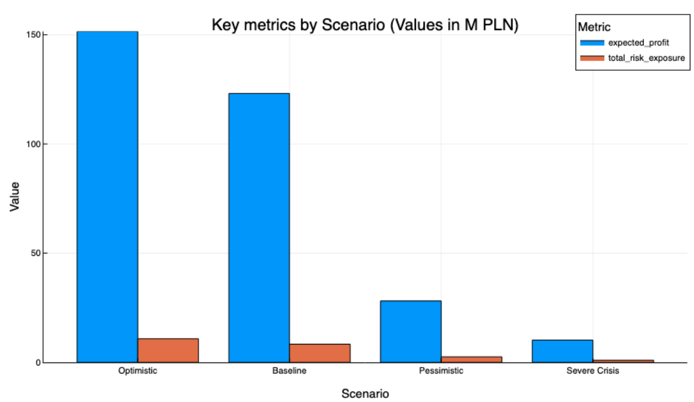

Figure 5: Expected profit and Expected total risk exposure under different market scenarios

The chart illustrates that as market conditions deteriorate, the expected profit of the bank's optimal policy gradually declines. Interestingly, the expected total risk exposure also decreases. This can be explained by the fact that during a market downturn - when more customers are likely to default - the loan approval strategy remains sufficiently robust to reject high-risk applicants. As a result, fewer loans are approved overall, leading to a simultaneous decline in both expected profit and total risk exposure.

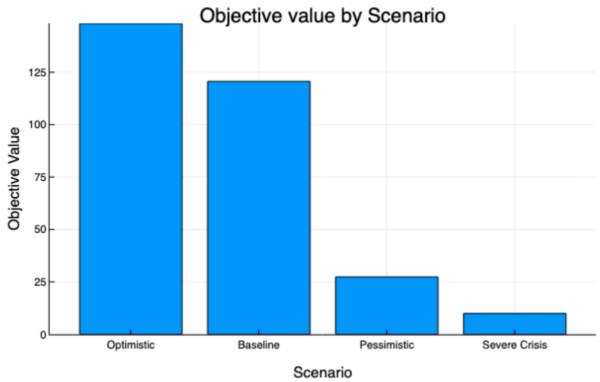

Figure 6: Expected Objective value in different market scenarios

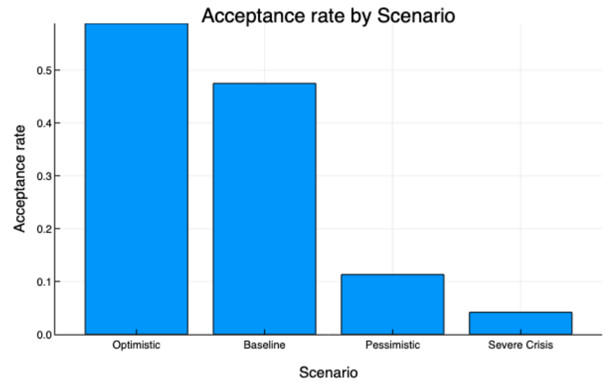

Figure 7: Expected Acceptance rate in different market scenarios

According to the above charts, as market conditions deteriorate—from optimistic, baseline to pessimistic to severe crisis scenarios—both the objective value and the acceptance rate exhibit a consistent downward trend. This reflects the dual effect of increased borrower risk and stricter lending policies. In particular, under the pessimistic and severe crisis scenarios, the acceptance rate falls sharply, to the extent that the model is no longer able to approve enough customers to meet the bank's minimum acceptance rate constraints.

This phenomenon can be explained by the surge in borrower default probabilities during economic downturns. As the market worsens, a higher proportion of applicants are deemed too risky. Since the loan approval policy does not allow accepting customers with high default risk—due to regulatory and internal risk limits—the optimizer is forced to tighten the PD threshold, reducing the eligible customer pool significantly. Consequently, many loan applications are rejected, not because of profitability concerns, but because they would breach the risk cap.

In essence, the model shows that under severe market stress, the bank's lending policy becomes highly conservative, and although this limits losses, it also constrains growth and lending capacity. This trade-off highlights the importance of adaptive policies and possibly re-evaluating risk tolerance or capital buffers during crisis periods.

2. Bank's risk aversion (λ - lambda)

In this analysis, we explore how the optimal loan approval policy evolves as the bank's risk appetite changes, represented by the risk-aversion parameter λ (lambda) in the objective function. By adjusting lambda, we can simulate different strategic mindsets—from aggressive profit-seeking to conservative, risk-averse behavior—and assess how sensitive the policy is to these shifts.

We tested six distinct lambda scenarios:

- Risk-neutral ($\lambda = 0.0$): Focuses purely on maximizing profit with no penalty for risk.
- Low aversion ($\lambda = 0.1$): Mild concern about risk, prioritizing profit but with slight caution.
- Moderate aversion ($\lambda = 0.3$): Balanced approach between profit and risk.
- High aversion ($\lambda = 0.6$): Emphasizes risk control more heavily.
- Extreme aversion ($\lambda = 1.0$): Prioritizes safety, tolerates significantly lower returns.

- Stress testing – crisis (λ = 3.0): Simulates emergency behavior in a crisis environment with extremely low risk tolerance.

This range of scenarios allows us to observe how sensitive the optimal policy (interest rate and PD cutoff) is to changes in the bank's risk preference, and whether small increases in λ result in gradual policy shifts or sharp behavioral changes. It also helps validate the robustness of our recommendations under different internal strategies and market pressures.

The results show that across all tested scenarios—ranging from risk-neutral to extreme risk aversion and crisis-mode stress testing—the optimal policy remains stable: a 12% interest rate and a 8% PD acceptance threshold. Expected profit, acceptance rate, and total risk exposure also stay constant at approximately 94.95 million PLN, 35.17%, and 3.92 million PLN, respectively.

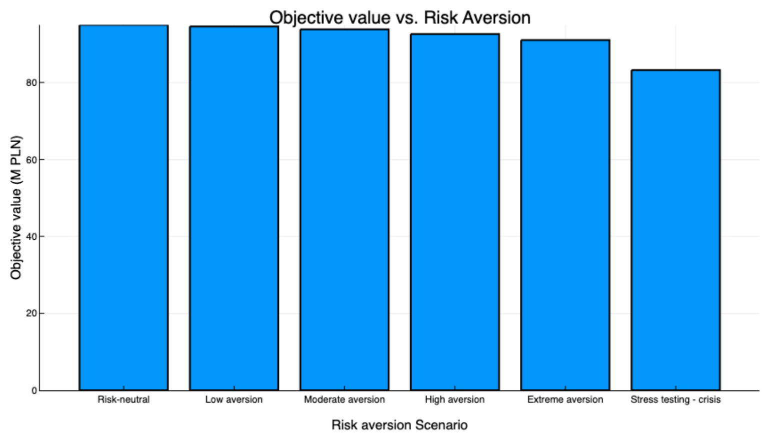

Figure 8: Objective value under different bank's risk aversion scenarios

However, as lambda increases, we observe a progressive decrease in the objective value, reflecting the growing weight placed on risk exposure. While the profit component remains stable, the penalization of risk (through the $\lambda \times$ risk term) reduces the net value of the objective function:

- At $\lambda = 0$ (risk-neutral), the full expected objective value is counted: 83.27 million PLN.
- At $\lambda = 0.3$ (moderate aversion), the objective drops to 82.14 million PLN.
- At $\lambda = 1.0$ (extreme aversion), it falls further to 79.51 million PLN.
- At $\lambda = 3.0$ (stress testing), the objective value drops significantly to 71.97 million PLN.

This indicates that while the optimal decision does not change structurally under varying risk preferences (within the tested range), the perceived value of that decision shifts depending on how heavily the institution penalizes risk. It also suggests that the chosen policy lies at a robust point, where small to moderate shifts in risk appetite do not require a change in strategy. Nevertheless, under more extreme risk-aversion scenarios (such as crisis-mode), the declining objective value signals increasing discomfort with the existing level of exposure—even if it's within the cap.

F. Overall recommendation

The simulation-based optimization and sensitivity analysis conducted for NovaRate offer clear operational insights for NovaBank's credit strategy. By integrating a data-driven framework that dynamically balances expected profit against credit risk exposure, the bank can significantly enhance both the efficiency and resilience of its loan approval process. The identified optimal policy—charging a 12% annual interest rate and accepting applicants with PDs up to 8%—achieves near-maximum profitability (over 83.2 million PLN) while adhering strictly to internal risk caps (≤ 4 million PLN). This confirms the model's ability to generate actionable, compliant decisions under complex constraints.

Sensitivity tests reveal the model's robustness: the optimal policy remains stable across moderate shifts in market conditions, default distributions, and the bank's risk appetite (λ). This allows NovaBank to proactively adjust its approval strategy in response to future shocks or regulatory pressures without requiring major re-engineering of its decision pipeline.

For the NovaRate product, these findings are especially valuable. The model ensures that loan pricing and approval thresholds are grounded in quantifiable risk-return tradeoffs, aligning with both CFO-led profitability targets and COO-led service delivery goals. Moreover, operational teams can use this framework to simulate "what-if" scenarios (e.g., during crises or marketing campaigns), thereby turning NovaRate into an adaptive product rather than a static offering.

In conclusion, we recommend embedding this simulation-optimization architecture into NovaBank's credit risk infrastructure to support ongoing credit product innovation, policy automation, and enterprise-wide risk governance.

G. References

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H. Appendices

The Julia notebook file (.ipynb) used to generate the reported results is attached here: Link to Julia file