MATH 789 Final Project

Jordan Andrew

Ammy Lin

Farnoosh Memari

Tonantzin Real Rojas

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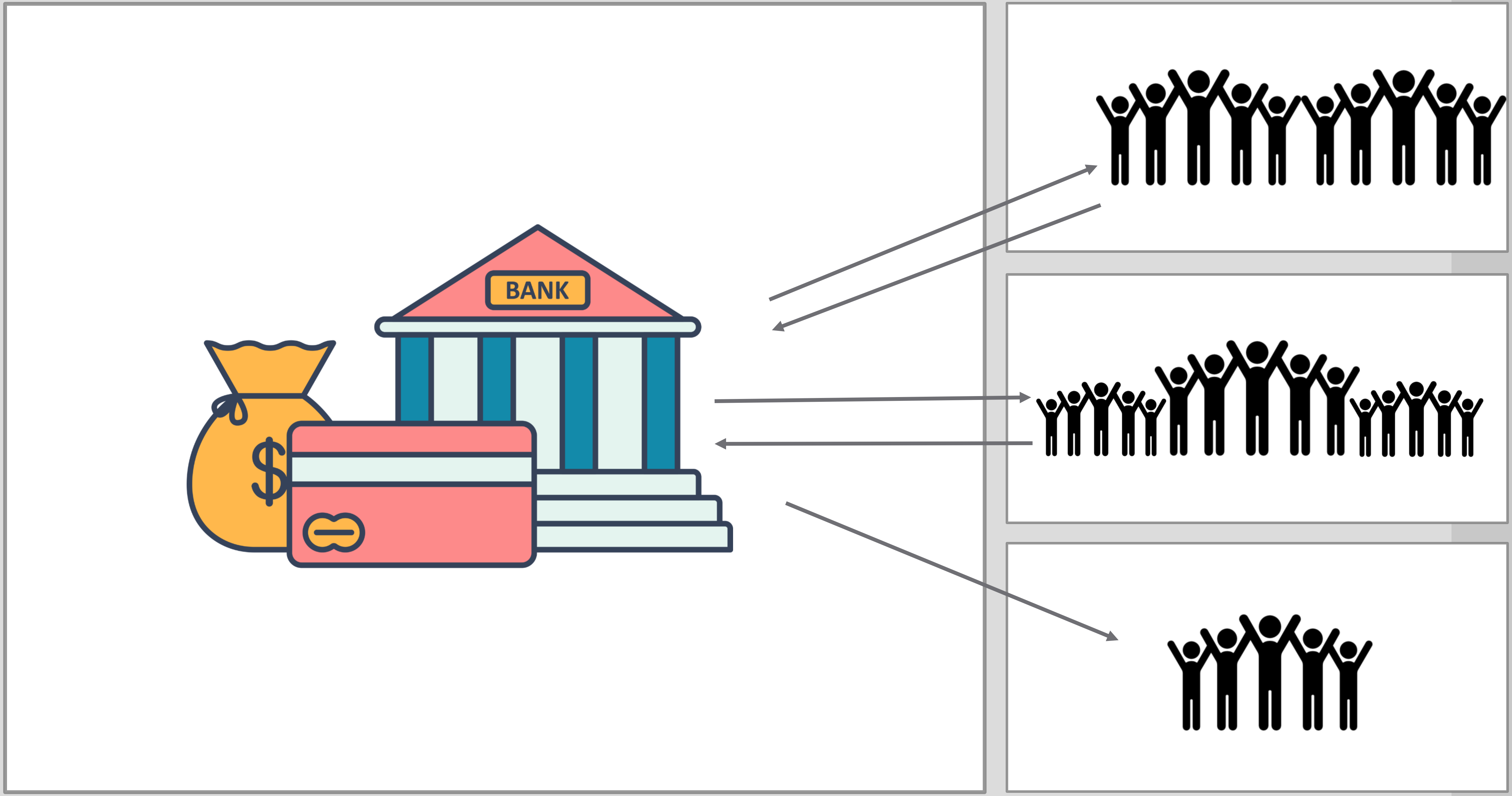
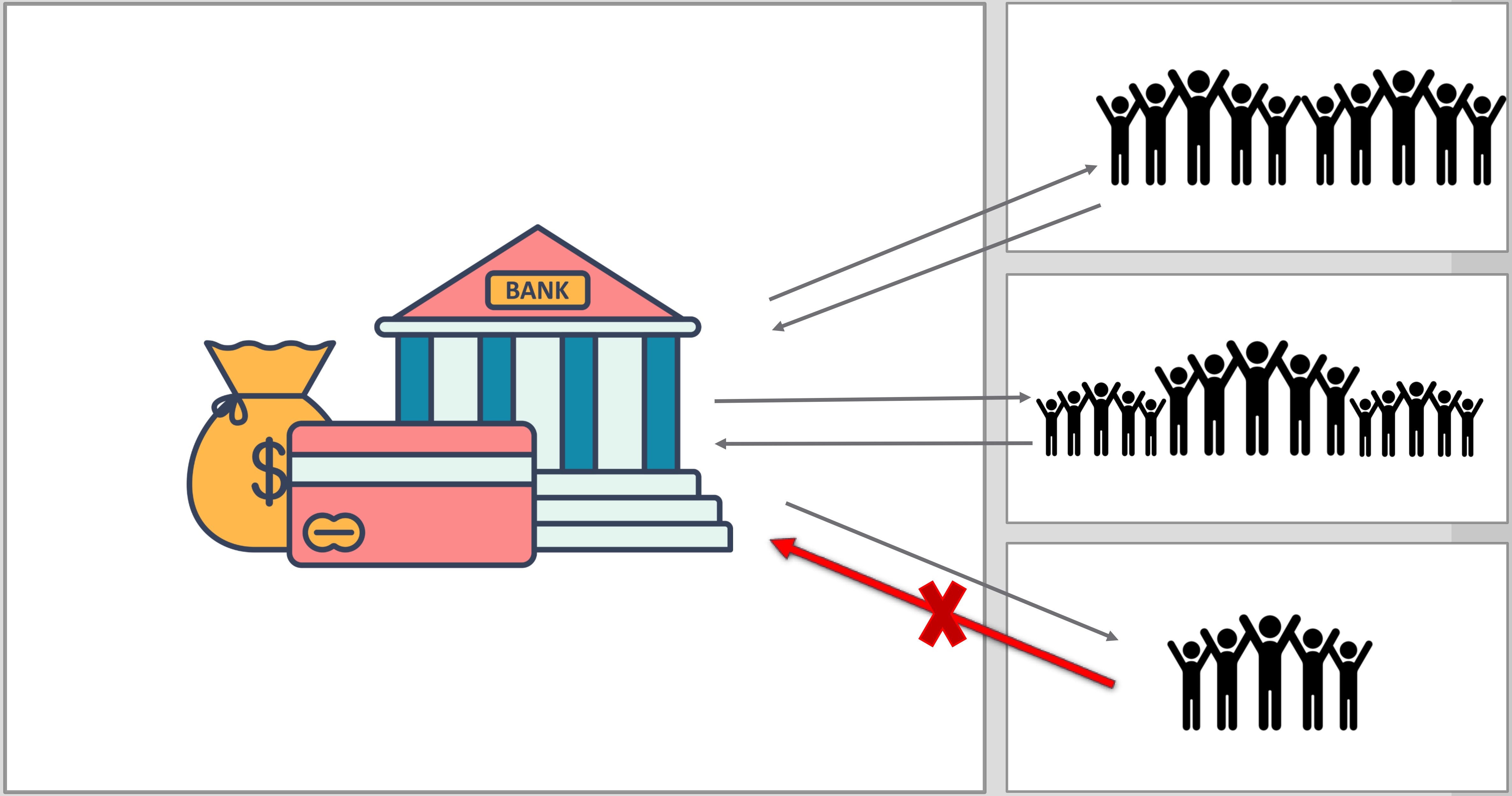
Technical Section

Measuring Credit Card Portfolio Risk: A Vasicek Model Approach with Monte Carlo Simulation for Value at Risk


BANK


BANK

In the worst possible scenario, how much money could the bank lose?

<u>Value at Risk (VaR):</u> the maximum potential loss on a portfolio over a defined period at a specified confidence level

Implications

- Helps the bank:
  - Determine how much to reserve for losses
  - Make informed lending decisions
  - Increase stakeholder confidence
  - Comply with international regulations like Basel III, which mandates effective risk management practices

Objectives

- Using the Vasicek One-Factor Model and Monte Carlo simulations, we will:
  - Estimate portfolio losses
  - Measure extreme loss risk
  - Assess the effects of changes in default probability and default correlation

Conceptual Background

Credit Risk
Risk of borrowers not repaying their debt.

Default Correlation
Borrowers tend to default together during downturns.

Value at Risk (VaR)
Worst expected loss at a given confidence level

Expected Shortfall (CVaR)
Average loss when things go worse than VaR

Conceptual Background

Probability of Default (PD):
Chance a borrower defaults in a set of time

Monte Carlo Simulation:
Randomly simulates economic scenarios to model loss outcomes.

Vasicek Model
A one-factor framework for correlated default risk

$$X_i = \sqrt{\rho} \cdot Z + \sqrt{(1 - \rho)} \cdot \varepsilon_i$$

Dataset

Credit Card Clients (30K)

Taiwan

April – September 2005

Key Insight:
Default Probability: 3% to 22.15%

Methodology

Monte Carlo Simulation

Monte Carlo simulation of a 30K-customer portfolio using the one-factor Vasicek model.

Correlated Defaults

Correlated defaults via shared economic and individual risk factors

Risk Quantification

Loss estimation (10K) of simulated scenarios.

Sensitivity Analysis

Parameter Ranges Tested

- **Probability of Default (PD)*: 3% → 22.15%**
  - Individual client default likelihood
  - Driver of expected portfolio losses
- **Default Correlation (ρ)*: 5% → 15%**
  - Synchronized defaults during economic crises
  - Amplifier of tail/extreme losses
- **Confidence Levels: 90%, 95%, 99%**
  - Statistical certainty in loss estimates

**These values were derived from literature*

Key Research Questions

1. Correlation Sensitivity

How sensitive is VaR to changes in default correlations?

2. PD vs. Tail Risk

What's the impact of higher default rates on tail risk?

3. Confidence Level Scaling

How do risk metrics behave across confidence levels?

VaR % Change by Confidence Level

Correlation	PD	%Δ VaR 90→95	%Δ VaR 95→99
5%	3.00%	18.05%	37.33%
5%	9.00%	14.51%	27.52%
5%	15.00%	11.10%	21.36%
5%	22.15%	10.08%	17.03%
10%	3.00%	26.90%	50.64%
10%	9.00%	17.35%	36.69%
10%	15.00%	15.90%	26.14%
10%	22.15%	12.80%	23.29%
15%	3.00%	32.57%	65.18%
15%	9.00%	24.31%	44.30%
15%	15.00%	19.26%	34.30%
15%	22.15%	15.66%	25.68%

VaR % Change by Confidence Level

Correlation	PD	%Δ VaR 90→95	%Δ VaR 95→99
5%	3.00%	18.05%	37.33%
10%	3.00%	26.90%	50.64%
15%	3.00%	32.57%	65.18%

Magnitude of increase in VaR is larger at higher correlation values → correlation amplifies increases in VaR

VaR % Change by Confidence Level

Correlation	PD	%Δ VaR 90→95	%Δ VaR 95→99
5%	3.00%	18.05%	37.33%
5%	9.00%	14.51%	27.52%
10%	3.00%	26.90%	50.64%
10%	9.00%	17.35%	36.69%
15%	3.00%	32.57%	65.18%
15%	9.00%	24.31%	44.30%

Higher PD reduces % increase in VaR as confidence levels rise ⟹ tail losses increase less dramatically because of heavier loss distribution

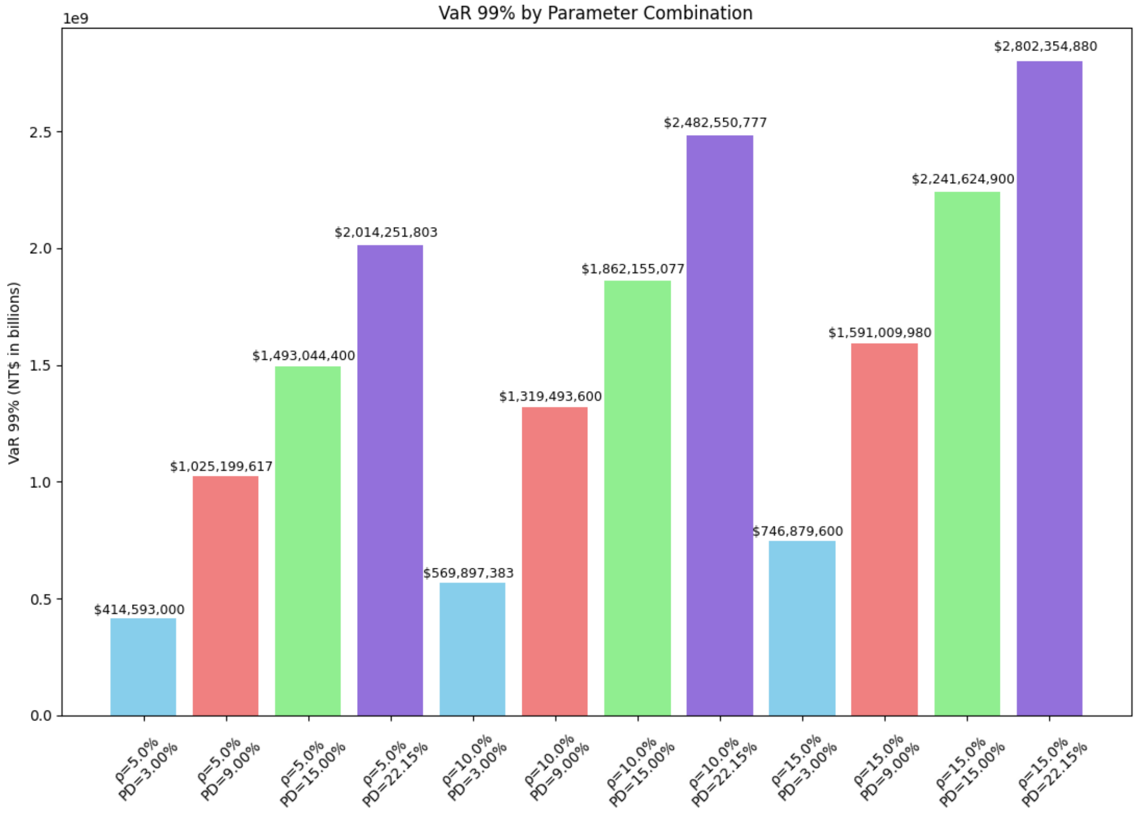
% Change in Expected vs. Max Loss

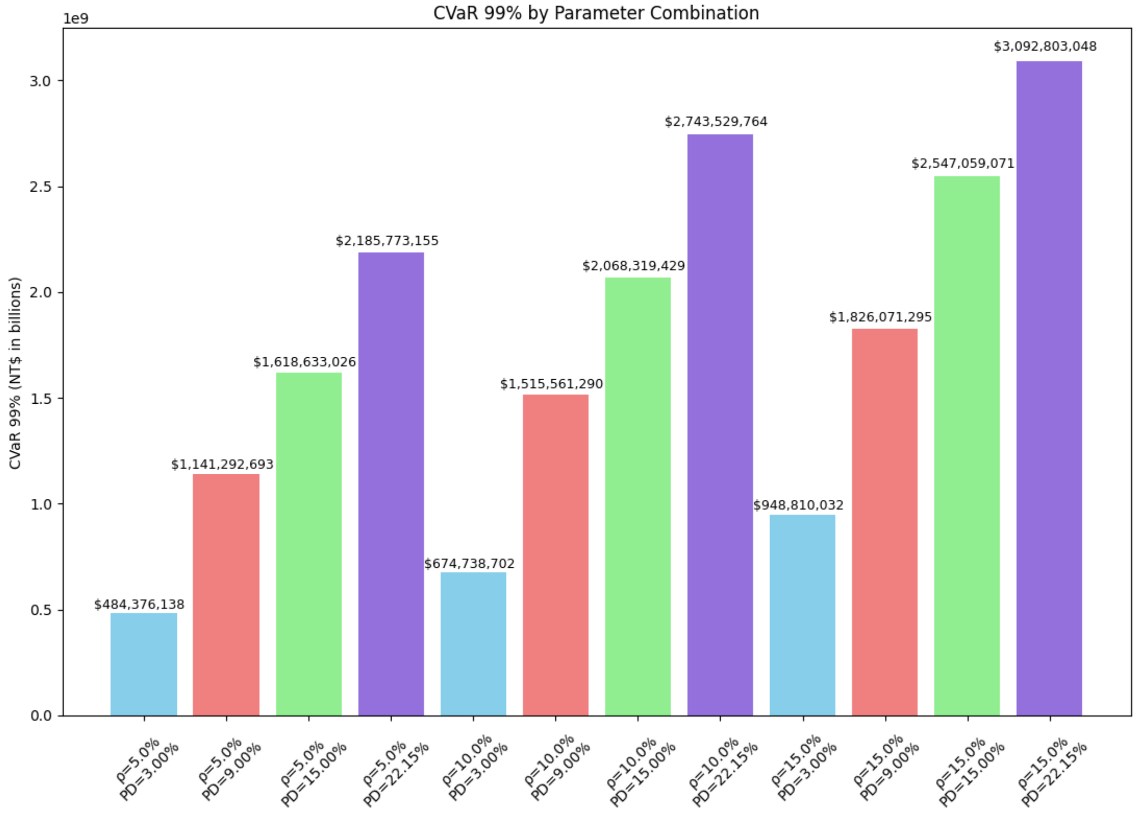
Correlation	PD	Expected Loss → Max Loss (%)
5%	3.00%	473.3%
5%	9.00%	253.6%
5%	15.00%	172.8%
5%	22.15%	150.0%
10%	3.00%	744.0%
10%	9.00%	414.6%
10%	15.00%	257.6%
10%	22.15%	220.1%
15%	3.00%	1025.0%
15%	9.00%	506.7%
15%	15.00%	361.1%
15%	22.15%	287.5%

% Change in Expected vs. Max Loss

Correlation	PD	Expected Loss → Max Loss (%)
5%	3.00%	473.3%
5%	9.00%	253.6%
5%	15.00%	172.8%
5%	22.15%	150.0%
10%	3.00%	744.0%
10%	9.00%	414.6%
10%	15.00%	257.6%
10%	22.15%	220.1%
15%	3.00%	1025.0%
15%	9.00%	506.7%
15%	15.00%	361.1%
15%	22.15%	287.5%

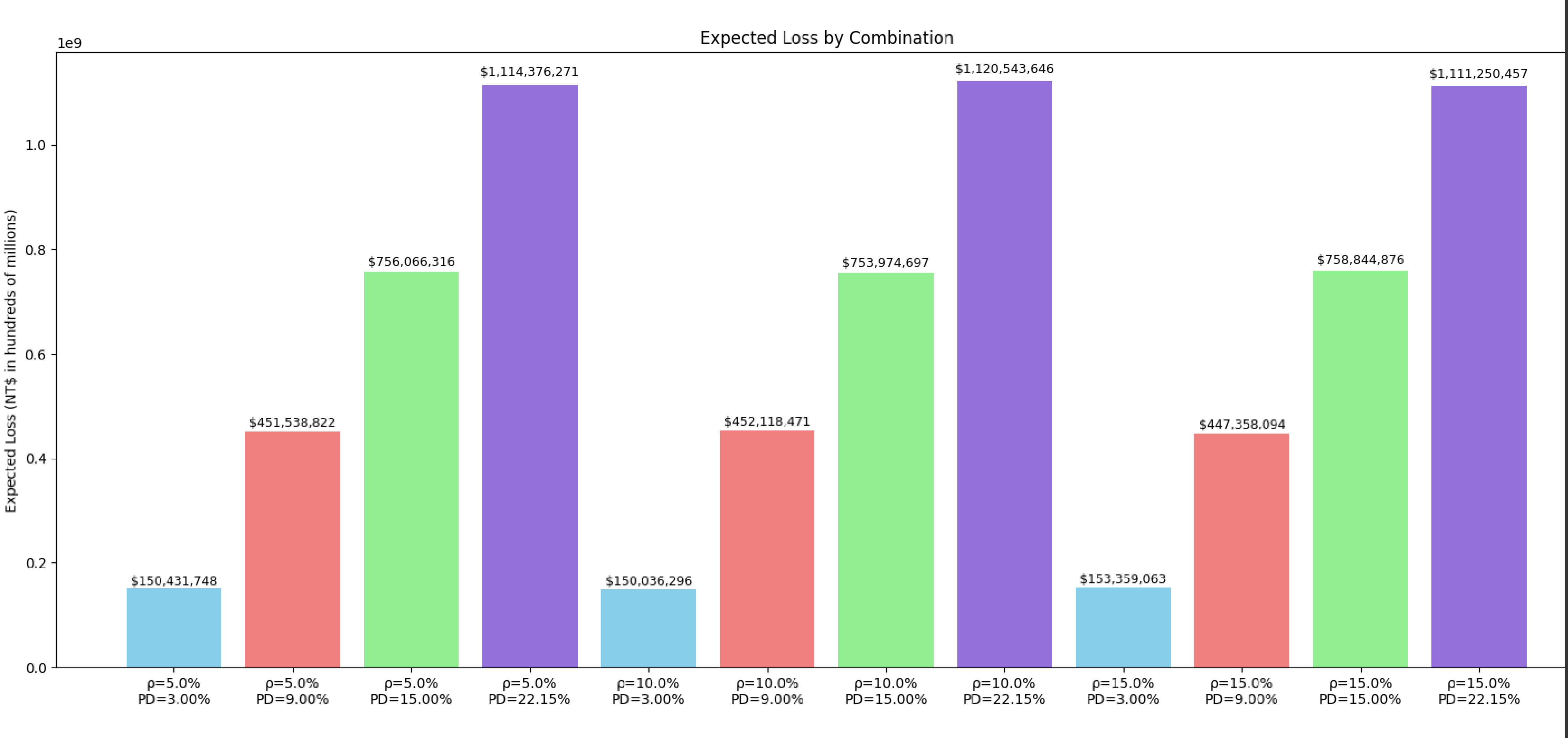
At low PD and high correlation, maximum loss is much larger than expected loss ⟹ high correlation means defaults cluster, so losses are bigger





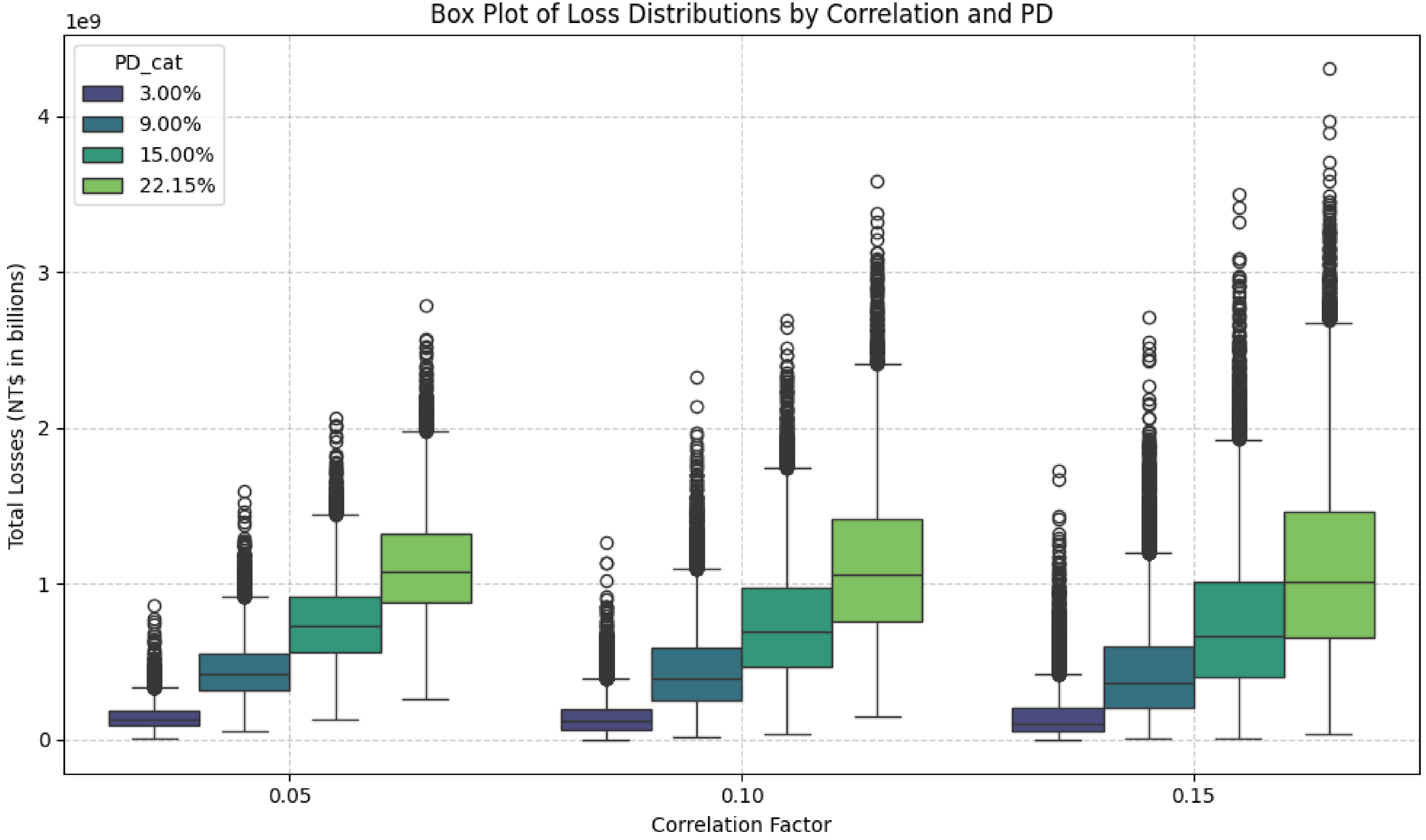
VaR 99 and CVaR 99

When PD and correlation rise together, our tail risk (VaR + CVaR) increases explosively.



Expected Loss

Expected loss is driven almost entirely by PD — correlation barely matters.



Total Loss Distribution

PD sets the baseline loss level, while correlation drives how extreme the worst-case losses get.

Non-Technical Section

Capital One: Evolution and Data Analytics in Credit Risk

Company Background

Data analytics for personalized credit

- Spin-off from Signet Bank (1994)
- Disrupted industry: "No more generic credit cards"

1988-1994

2000s

Bank acquisitions

Full-service banking: Accounts, auto loans, commercial services

Today

Among largest U.S. financial institutions

- Unique blend: Traditional banking + Tech-forward mindset

Pioneered using data to understand customers, not just process transactions

Role Description

- Uses data to support credit-risk decisions
- Transforms large datasets into clear insights
- Builds automated analytics and dashboards
- Works with teams across business, product, and engineering
- Ensures data accuracy, consistency, and governance
- Helps develop and evaluate credit policies
- Communicates findings to leadership and stakeholders

Suggested Preparation

- Strengthen Technical Skills
- Build Credit Risk & Financial Analytics Knowledge
- Grow Data Management & Governance Skills
- Improve Business Intelligence & Communication Skills
- Professional Development & Networking

Motivation for the Role

- Excited by Capital One's focus on advanced analytics and data-driven credit risk solutions
- Strong fit for applying skills in statistical modeling, Python/R, SQL, and cloud-based data management
- Experience running Monte Carlo simulations to quantify portfolio risk (ex: VaR & CVaR)
- Driven to contribute to meaningful, real-world credit risk management strategies

Thank you!
Questions?