

MATH 789 Final Project

Jordan Andrew

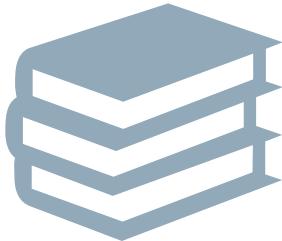
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Overview



Technical Section

Introduction

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Conceptual Background

Methodology

Sensitivity Analysis

Research Questions

Results



Non-Technical Section

Company Background

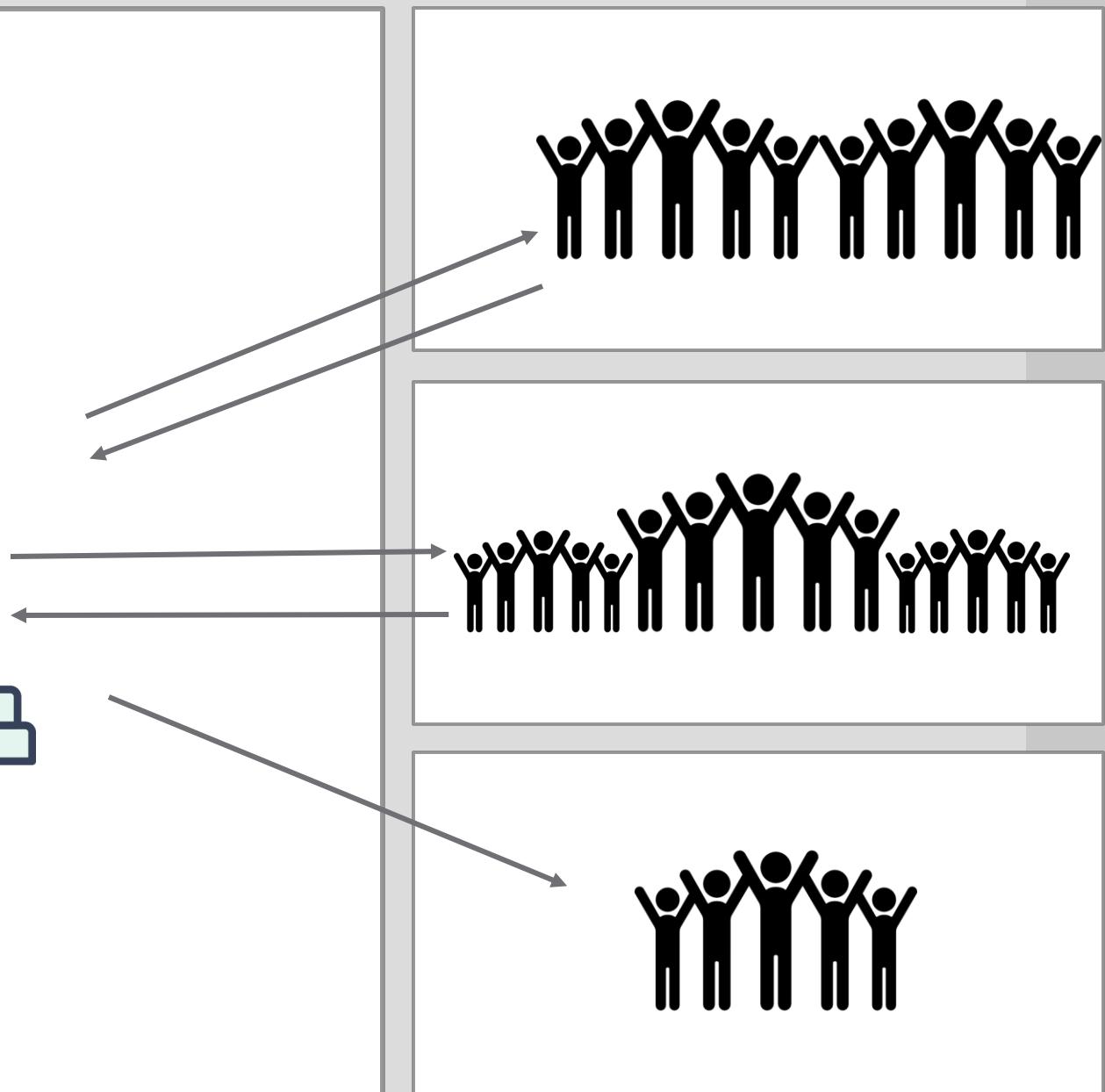
Role Description

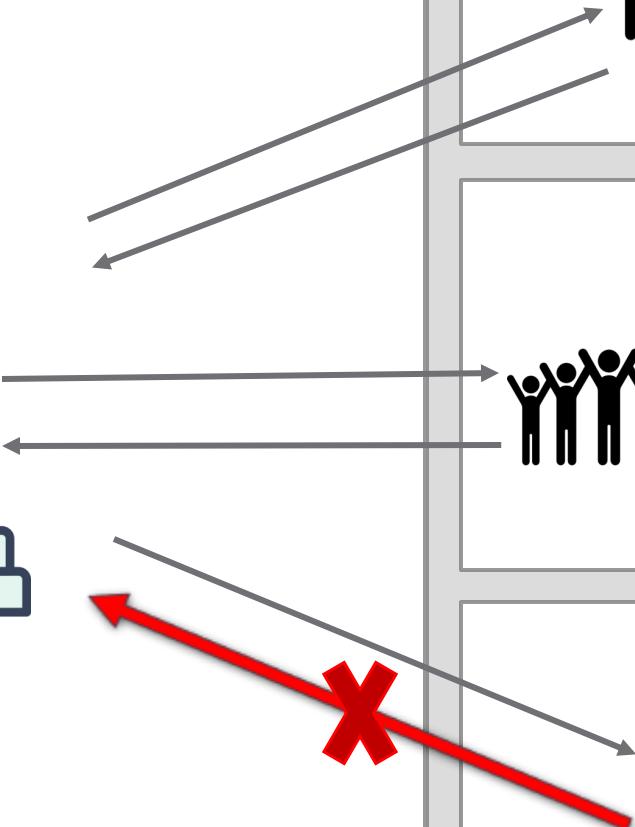
Suggested Preparation

Motivation

Technical Section

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





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

Value at Risk (VaR): 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:

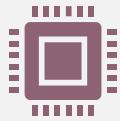
Default Probability: 3% to 22.15%

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)*:** $3\% \rightarrow 22.15\%$
 - Individual client default likelihood
 - Driver of expected portfolio losses
- **Default Correlation (ρ)*:** $5\% \rightarrow 15\%$
 - 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 \longrightarrow tail losses increase less dramatically because of heavier loss distribution

% Change
in
Expected
vs. Max
Loss

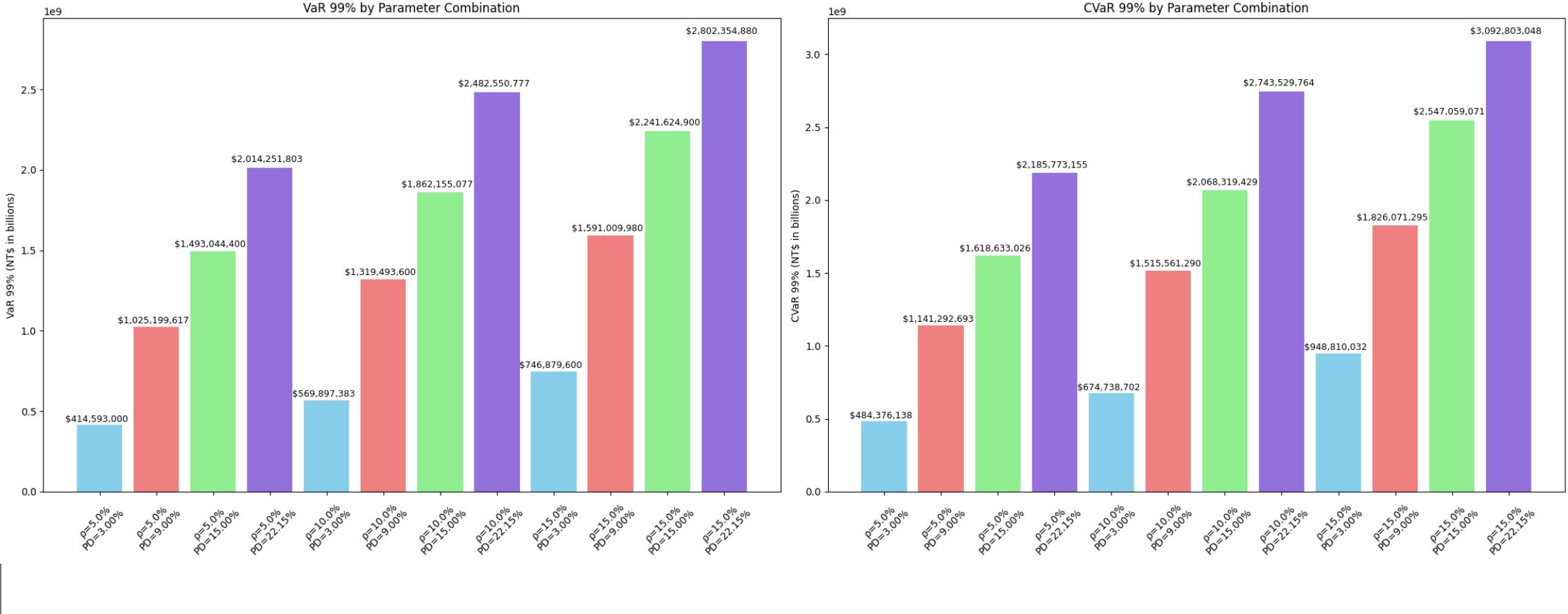
Correlation	PD	Expected Loss → Max Loss (%)
5%	3.00%	473.3%
5%	9.00%	253.6%
5%	15.00%	172.8%
5%	22.15%	150.0%
10%	3.00%	744.0%
10%	9.00%	414.6%
10%	15.00%	257.6%
10%	22.15%	220.1%
15%	3.00%	1025.0%
15%	9.00%	506.7%
15%	15.00%	361.1%
15%	22.15%	287.5%

% Change in Expected vs. Max Loss

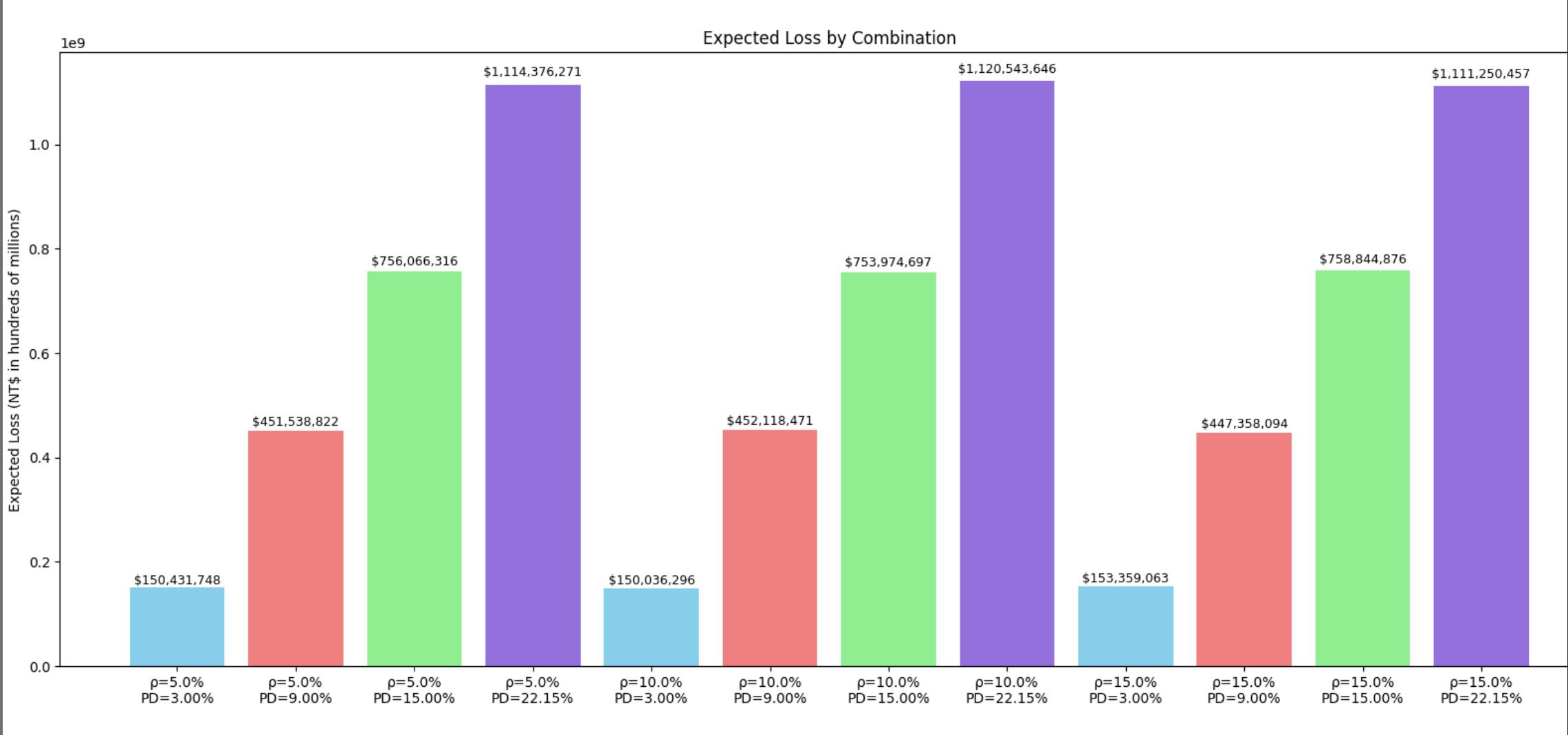
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10%	3.00%	744.0%
10%	9.00%	414.6%
10%	15.00%	257.6%
10%	22.15%	220.1%
15%	3.00%	1025.0%
15%	9.00%	506.7%
15%	15.00%	361.1%
15%	22.15%	287.5%

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

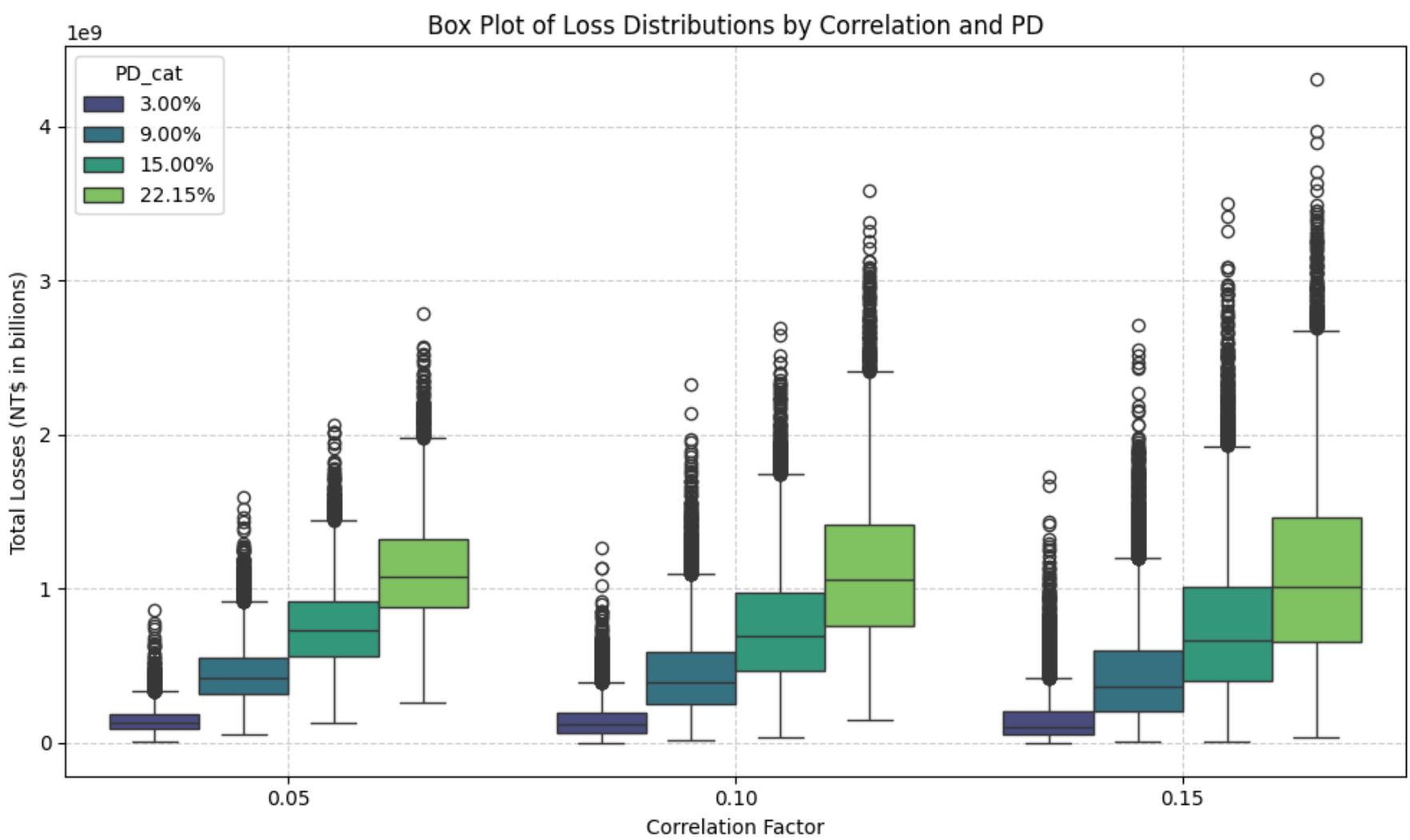


When PD and correlation rise together, our tail risk (VaR + CVaR) increases explosively.



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"

- Among largest U.S. financial institutions
- Unique blend: Traditional banking + Tech-forward mindset



Bank acquisitions

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

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?