

The background of the slide features a stack of several books with various colored covers (red, blue, yellow, and grey) and a portion of a laptop keyboard, all slightly out of focus. The text is overlaid on a dark, textured background.

# MATH 789 Final Project

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# Overview



## Technical Section

Introduction  
Objectives  
Conceptual Background  
Methodology  
Sensitivity Analysis  
Research Questions  
Results



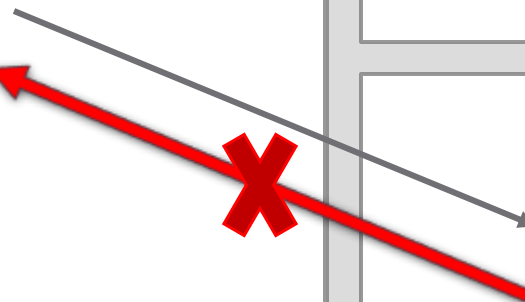
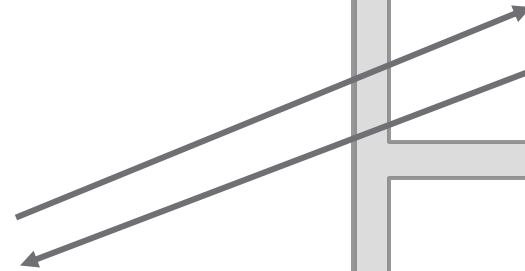
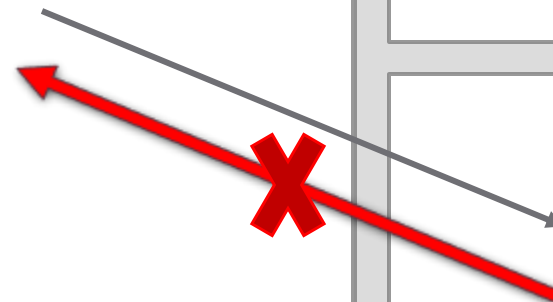
## Non-Technical Section

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:**

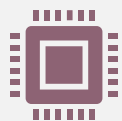
Default Probability: 3% to 22.15%

# 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% → 22.15%**
  - Individual client default likelihood
  - Driver of expected portfolio losses
- **Default Correlation ( $\rho$ )\*: 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?

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	% $\Delta$ VaR 90 $\rightarrow$ 95	% $\Delta$ VaR 95 $\rightarrow$ 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

VaR  
% Change  
by  
Confidence  
Level



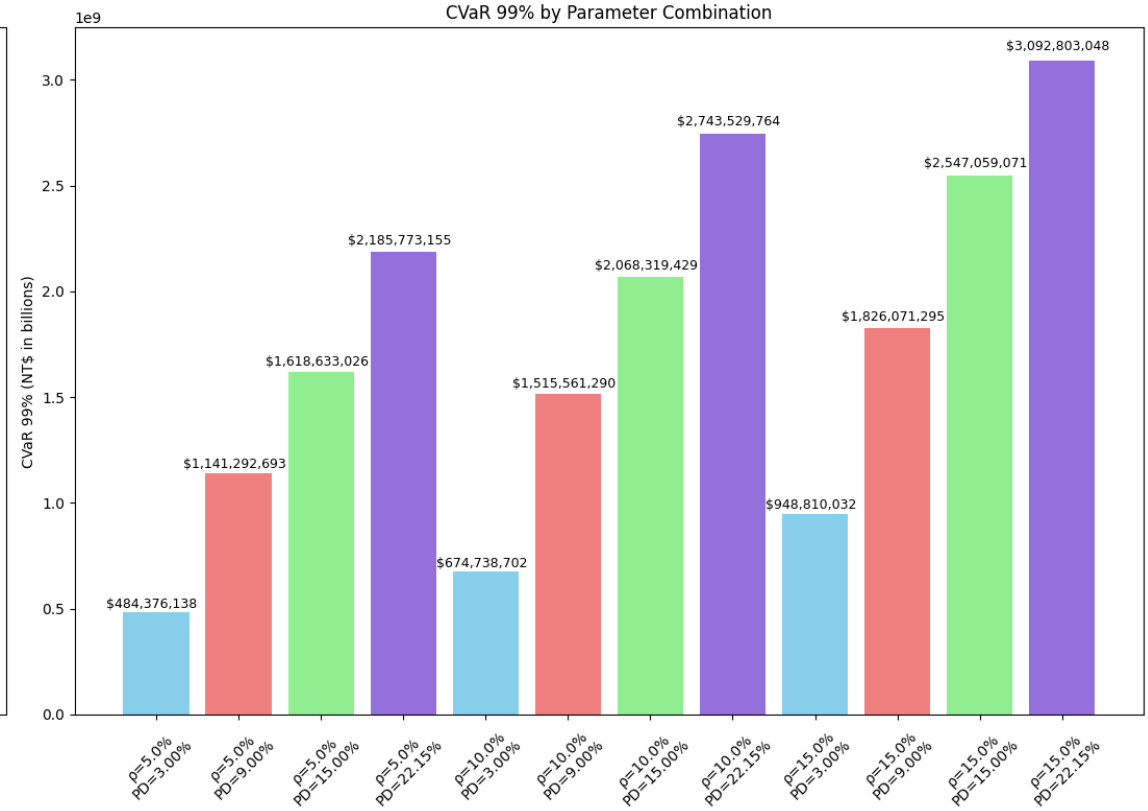
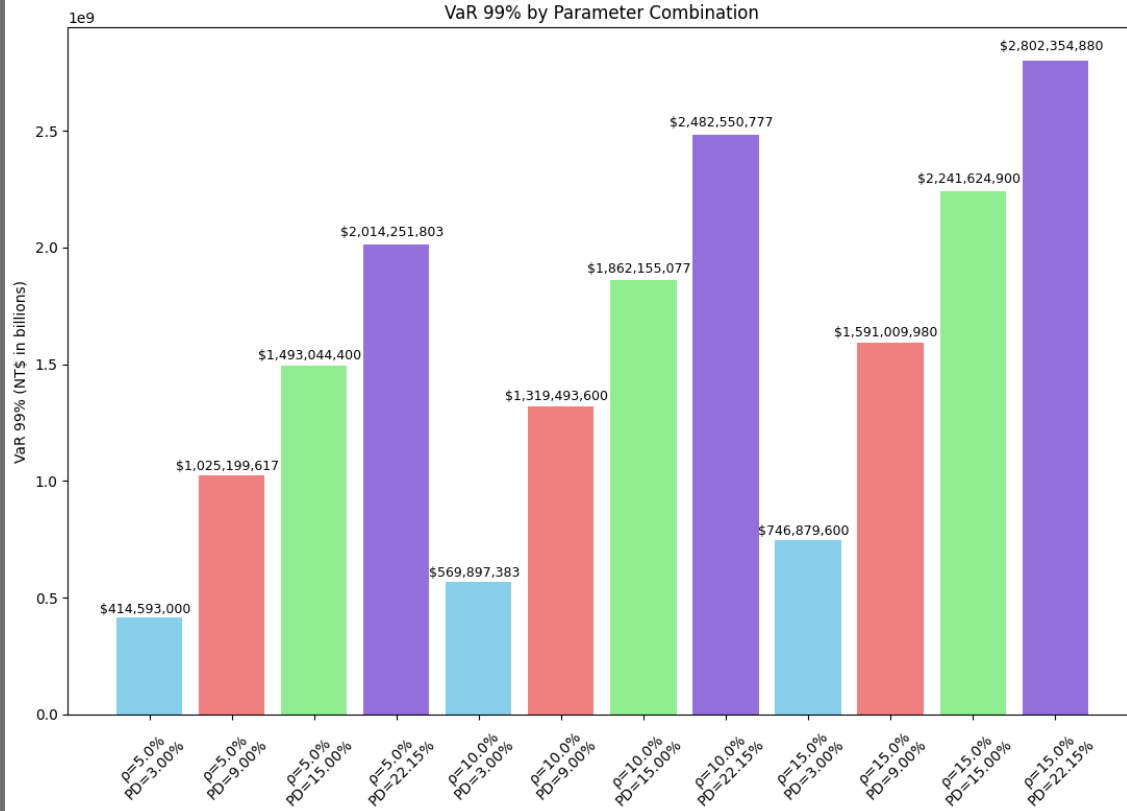
Correlation	PD	Expected Loss → Max Loss (%)
5%	3.00%	473.3%
5%	9.00%	253.6%
5%	15.00%	172.8%
5%	22.15%	150.0%
10%	3.00%	744.0%
10%	9.00%	414.6%
10%	15.00%	257.6%
10%	22.15%	220.1%
15%	3.00%	1025.0%
15%	9.00%	506.7%
15%	15.00%	361.1%
15%	22.15%	287.5%

% 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%
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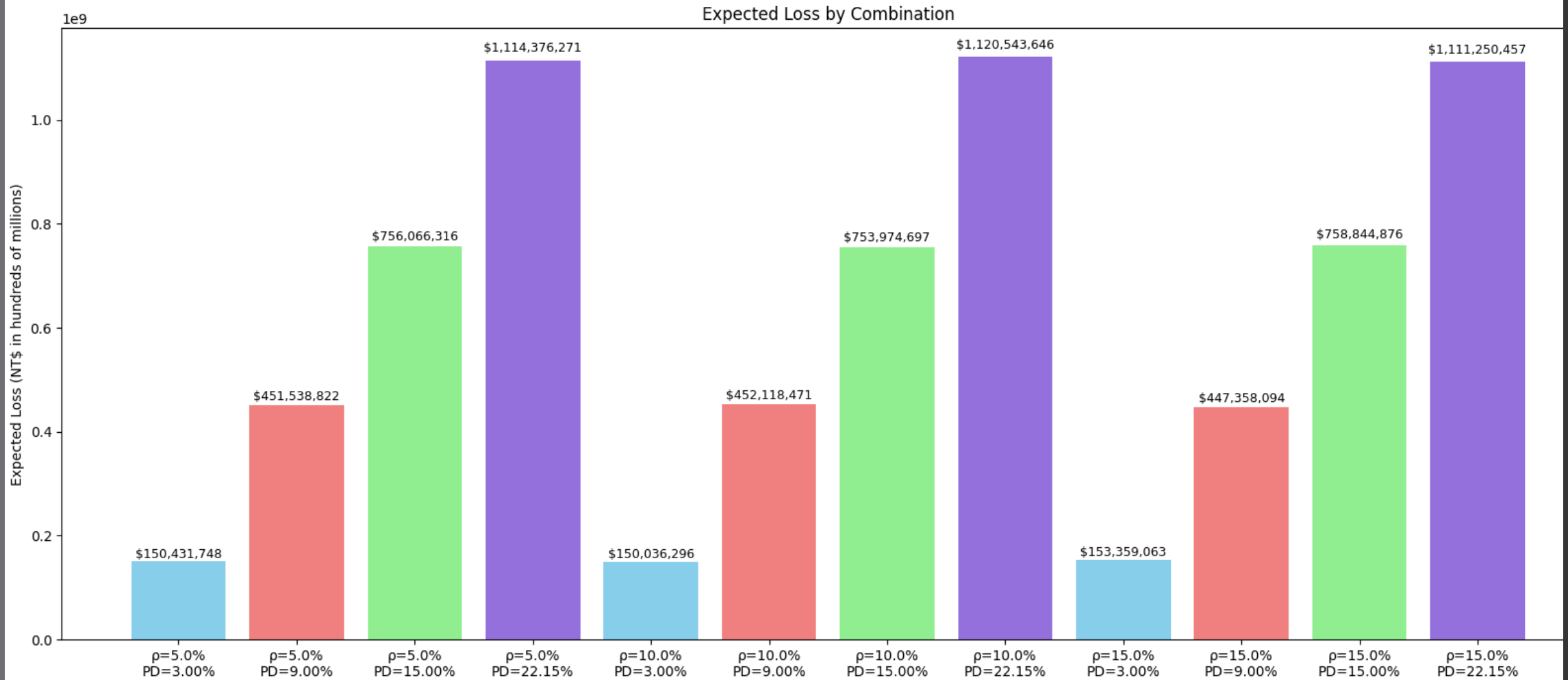
% Change  
in  
Expected  
vs. Max  
Loss

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



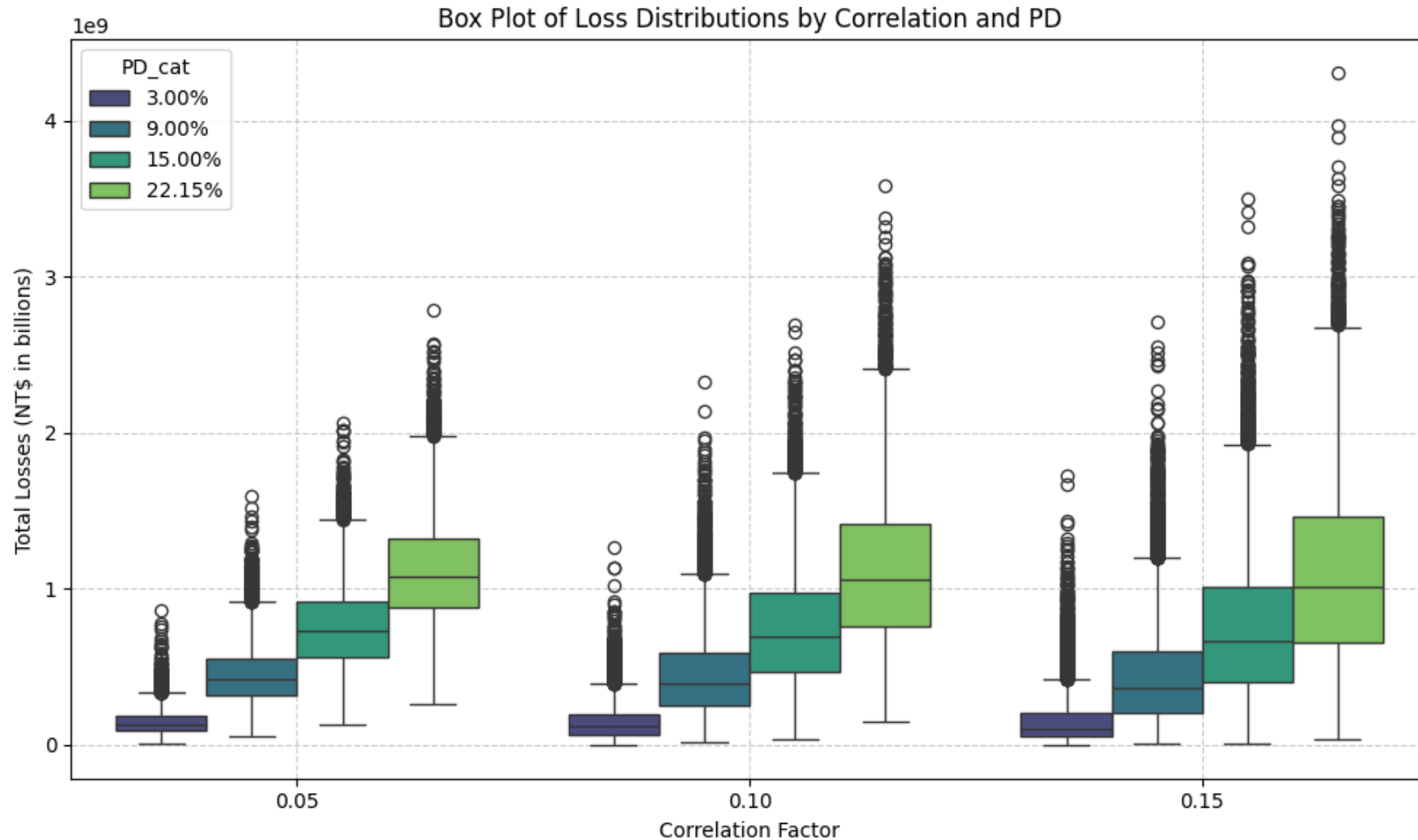
# VaR 99 and CVaR 99

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

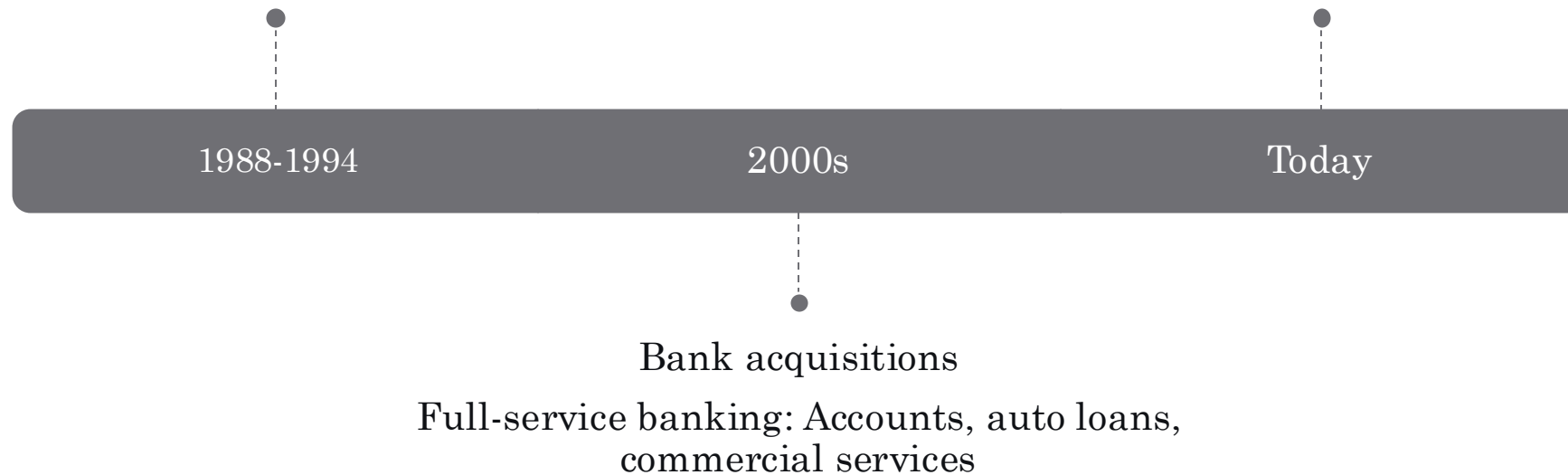
# Company Background

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



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?