ISTANBUL TECHNICAL UNIVERSITY | FACULTY OF SCIENCE AND LETTERS

MATHEMATICAL ENGINEERING DEPARTMENT

MAT 116E: ADVANCED SCIENTIFIC AND ENGINEERING COMPUTING TERM PROJECT

MONTE CARLO SIMULATION FOR CREDIT PORTFOLIO RISK ANALYSIS

A Multi-Model Approach to Financial Stress Testing and Capital Allocation

Models	**Analytical Focus**	**Core Mechanism**
Model 1	Baseline credit risk under independent default assumptions	Independent Bernoulli trials.
Model 2	Impact of macroeconomic conditions on correlated default behavior	Correlation with the economic factor (M) using the Vasicek model.
Model 3	Effect of the time value of money on future credit losses	Present value calculation via continuous discounting ((e^{-rT})).
Model 4	Effect of exposure concentration on portfolio tail risk	Concentration of exposures into a few large obligors, increasing tail losses due to loss of portfolio granularity.
Model 5	Risk reduction through sectoral diversification and multi-factor dependence	Sectoral correlation analysis using Cholesky decomposition.

Prepared By: Enes Şenbülbül

Date: December 2025

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1. Introduction and Project Purpose

This project is developed to analyze financial risks within a credit portfolio using the Monte Carlo Simulation method. In banking, the primary risk is "default" - the possibility that a borrower fails to repay their loan. However, this risk is not static; it changes based on economic conditions, industry trends, and portfolio structure. This software provides a dynamic environment to simulate these uncertainties through thousands of random scenarios to estimate how much money a bank might lose in the "worst-case" situations.

1.1. Objectives of the Models and Financial Context

The project implements five different models, each representing a specific real-world economic scenario:

1. **Independent Model (Bernoulli):** Represents "normal" times where each borrower's default is independent of others. It serves as a baseline for the portfolio's risk.
2. **Systemic Risk Model (Vasicek):** Simulates how economic recessions affect all borrowers simultaneously. It answers the question: "What happens to my loans if the overall economy crashes?"
3. **Time Value Model (Discounted):** Calculates the "Present Value" of potential future losses using continuous discounting (e^{-rT}). This is vital for long-term financial planning.
4. **Concentration Risk Model:** Tests the danger of "putting all eggs in one basket" by assigning a large portion of the portfolio (e.g., 30%) to just a few large clients.
5. **Multi-Factor Sectoral Model:** Uses **Cholesky Decomposition** to model the interaction between different industries (e.g., Construction vs. Tourism). It analyzes how diversification across sectors can reduce overall risk.

1.2. Strategic Importance for Banks

These simulations provide two critical benefits for financial institutions:

- **Capital Adequacy:** It helps determine the **Unexpected Loss (UL)**, which is the amount of "buffer capital" a bank must keep to stay solvent during crises, according to international standards like Basel III.
- **Stress Testing:** It allows the bank to perform "what-if" analyses to see if it can survive extreme but plausible negative events.

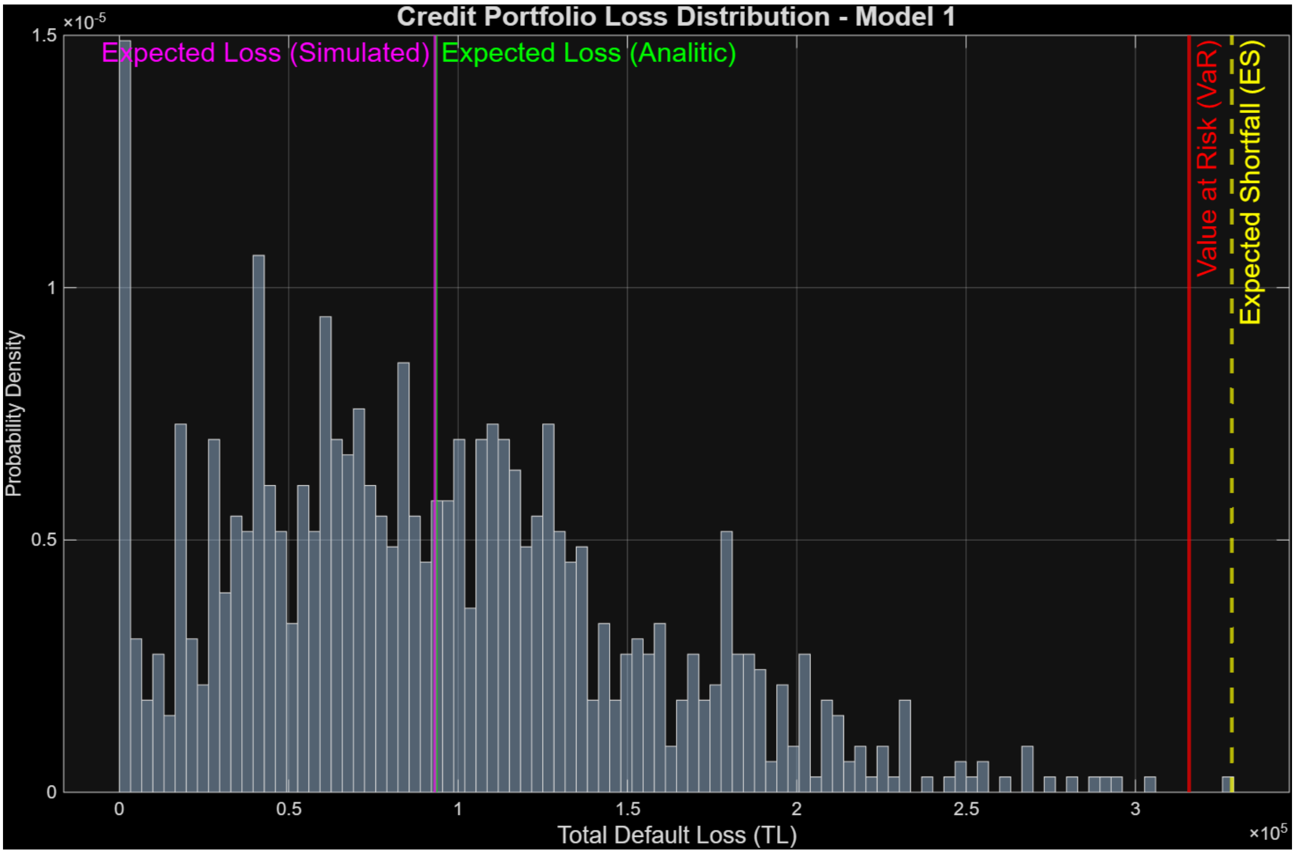
1.3. Comparative Analysis: The Impact of Simulation Size on Accuracy

In Monte Carlo methods, the number of simulations directly affects the precision of the results. As shown in the table below, increasing the sample size significantly reduces the "Simulation Error" and provides a more reliable risk profile:

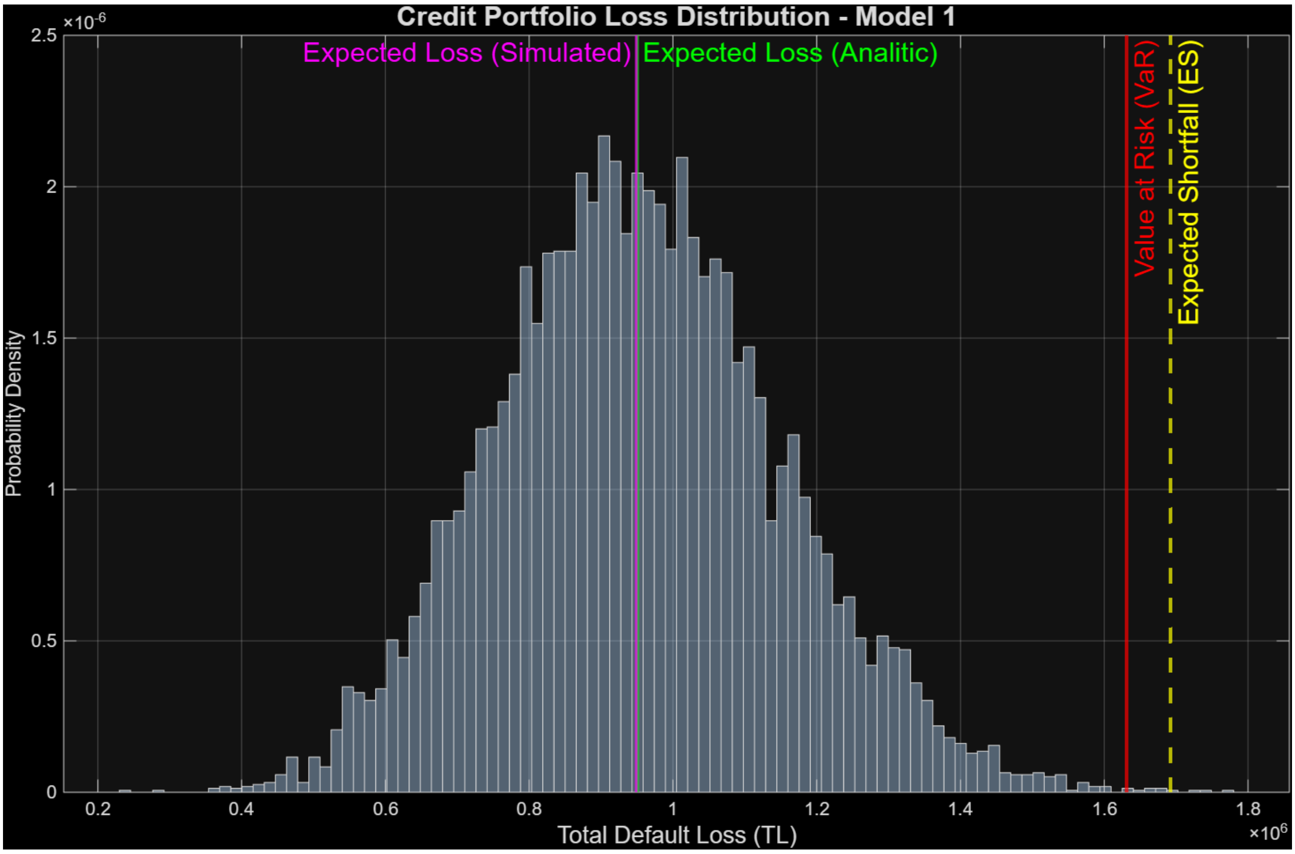
Parameter	Scenario A (Low Sample)	Scenario B (High Sample)
Number of Credits	100	1,000
Number of Simulations	1000	10,000
Simulation Error (%)	**1.07%**	**0.49%**

Table 1: Statistical precision analysis. Apart from the sample sizes shown above, both scenarios utilize the standard parameters from Table 2.2, including the 99.9% confidence level, and the specific limits for Exposure at Default (EAD), Probability of Default (PD), and Loss Given Default (LGD). The reduction in error (from 1.07% to 0.49%) validates that the 10,000-iteration baseline provides the accuracy for systemic risk modeling.

Scenario A Graph:



Scenario B Graph:



Scenario A Output:	Scenario B Output:
Continuing with default parameters. -- -> EAD Limits : 10000 - 100000 TL -> PD Limits : 1.0% - 5.0% -> LGD Limits : 30.0% - 90.0% == RISK ANALYSIS REPORT(SUMMARY) == **Risk_Metric** **Value_TL** _________________________ _________ "Expected Loss (EL)" 93818.36 "Value-at-Risk (VaR)" 315870.33 "Expected Shortfall (ES)" 328464.29 "Capital Reserve (UL)" 222051.97 N_Credits: 100 | N_Simulation: 1000 |Confidence Level: 99.9% Analitic Expected Loss: 92826.39 TL | Simulated Expected Loss: 93818.36 TL Simulation Error: 1.07% ==	Continuing with default parameters. -- -> EAD Limits : 10000 - 100000 TL -> PD Limits : 1.0% - 5.0% -> LGD Limits : 30.0% - 90.0% == RISK ANALYSIS REPORT(SUMMARY) == **Risk_Metric** **Value_TL** _________________________ __________ "Expected Loss (EL)" 952138.06 "Value-at-Risk (VaR)" 1631140.75 "Expected Shortfall (ES)" 1692206.02 "Capital Reserve (UL)" 679002.69 N_Credits: 1000 | N_Simulation: 10000 |Confidence Level: 99.9% Analitic Expected Loss: 947455.46 TL | Simulated Expected Loss: 952138.06 TL Simulation Error: 0.49% ==

Analysis: The data demonstrates that while low-sample simulations in Scenario A (1,000 iterations) provide only a rough estimate, the 10,000 simulations conducted in Scenario B yield a highly accurate result with a simulation error rate of less than 1%. As shown in the comparative logs, the error dropped from 1.07% to 0.49% when the portfolio and simulation sizes were increased. Furthermore, Figures 1 and 2 visualize how the loss distribution becomes significantly smoother and more statistically defined as the simulation count increases, effectively reducing the noise in the tail of the distribution.

2. Core Risk Parameters and Metrics

To calculate the total risk of a portfolio, the model relies on three fundamental financial variables for each loan:

- **EAD (Exposure at Default):** The total outstanding balance of the loan at the time of default.
- **PD (Probability of Default):** The likelihood that a borrower will fail to make their payments. In our simulation, this is used as a mathematical threshold to trigger a default event.
- **LGD (Loss Given Default):** The percentage of the exposure that is actually lost after the bank attempts to recover funds through collateral.

2.1. Simulation Outputs: EL, VaR, and UL

The Monte Carlo simulation processes these parameters over thousands of iterations to generate the following key metrics:

1. **Expected Loss (EL):** The average loss the bank anticipates in a normal year. Analytically, it is calculated as $EL = EAD \times PD \times LGD$.
2. **Value-at-Risk (VaR):** The maximum potential loss at a specific confidence level (e.g., 99.9%). It represents a "worst-case" scenario.
3. **Expected Shortfall (ES):** Also known as Conditional VaR, it measures the average loss in the extreme cases where the loss exceeds the VaR threshold.
4. **Unexpected Loss (UL - Capital Reserve):** Calculated as $VaR - EL$, this represents the amount of capital the bank must hold as a reserve to stay solvent during extreme events.

2.2. Baseline Scenario and Parameter Set

To ensure consistency across model comparisons, a standardized set of parameters was applied to all simulations unless otherwise specified. These values represent a typical mid-sized credit portfolio under Basel III stress-testing conditions.

Parameters	Description	Value / Range
Global Seed (rng)	Reproducibility of pseudo-random sequences	93
N_credits	Total Number of Credits in Portfolio	1,000
N_simulations	Total Monte Carlo Iterations	10,000
Confidence Level	VaR Confidence Level (Basel III Standard)	99.9%
EAD Limits	Exposure at Default Range (TL)	10,000 - 100,000
PD Limits	Probability of Default Range	1.0% - 5.0%
LGD Limits	Loss Given Default Range	30% - 90%
ρ (rho)	Asset Correlation (Systemic Risk)	0.15
r	Annual Risk-Free Rate (Model 3)	8.0%
T	Time Horizon (Model 3)	1 Year
Conc. Weight	Concentration Weight (Model 4)	30% for Top 10 Credits

3. Model Comparison: Independence vs. Systemic Risk

This section analyzes the difference between a portfolio where defaults are completely independent and one where an economic crisis affects everyone simultaneously.

3.1. Independent Model (Model 1)

In this model, the default of one borrower does not affect another. Using **Bernoulli trials**, the simulation shows that losses tend to cluster around the average (EL), and extreme "catastrophic" losses are very rare.

3.2. Systemic Risk and the Vasicek Model (Model 2)

In reality, economic downturns cause many borrowers to default at once. We use the Vasicek Model, which introduces an Asset Correlation (ρ) factor. The health of each loan depends on a shared "Economic Factor" (M) and a unique "Idiosyncratic Factor" (Z):

$$Asset\_Value = \sqrt{\rho}M + \sqrt{1-\rho}Z$$

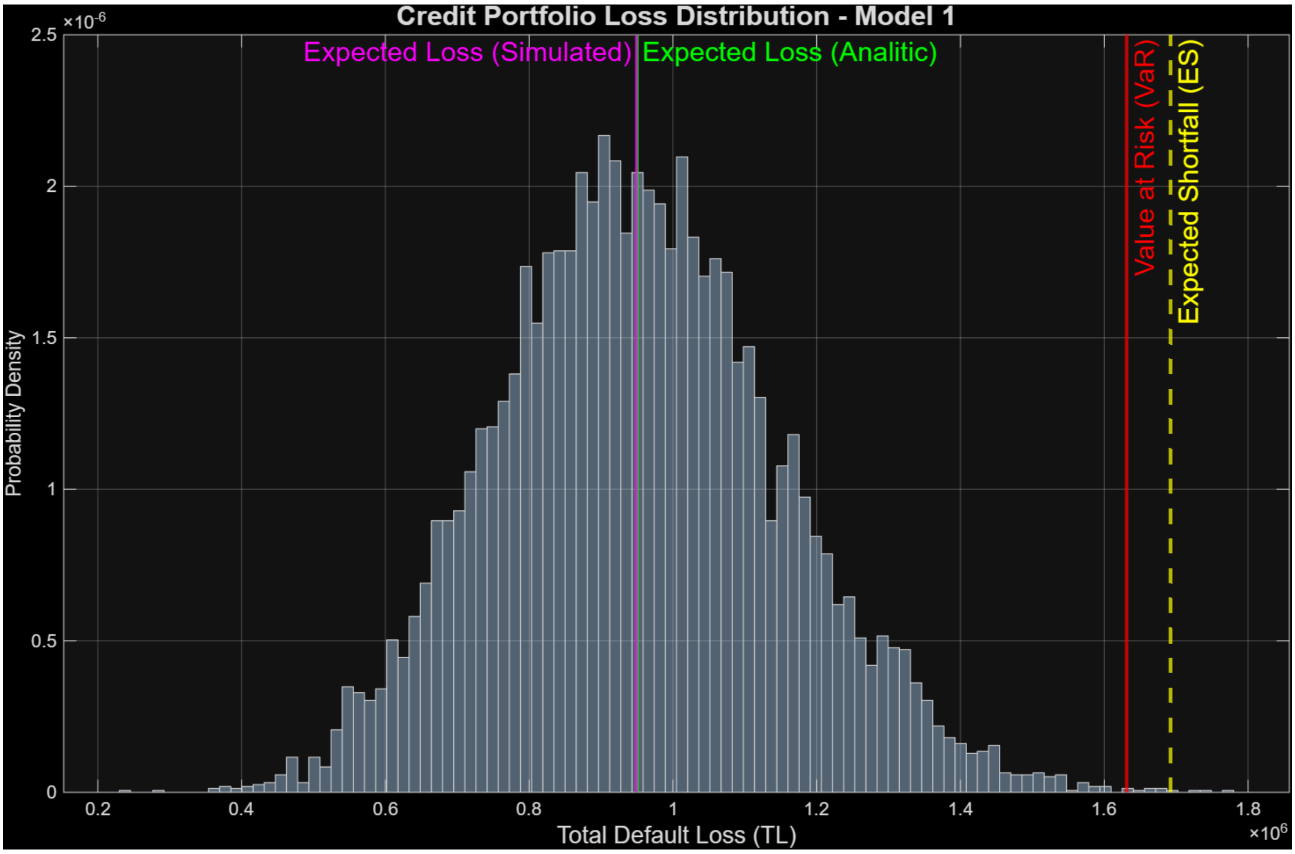
For this project, a baseline value of 0.15 was selected. This value is standardized to represent a typical credit portfolio under Basel III stress-testing conditions, ensuring the simulation reflects realistic regulatory capital requirements.

Comparative Results Table:

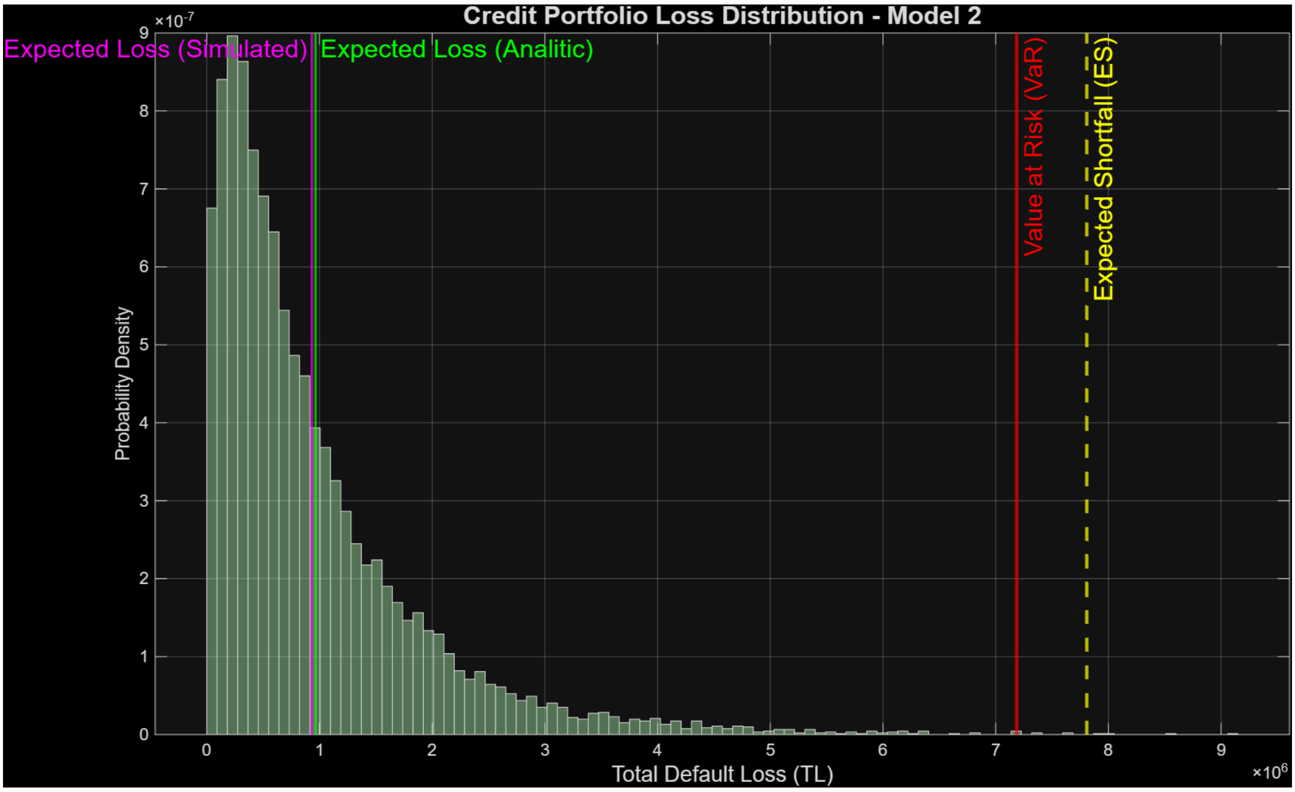
Risk Metric	**Independent Model (Model 1)**	**Systemic Risk (Model 2)**	**Growth Factor**
Expected Loss (EL)	952,138 TL	951,267 TL	~1.0x
Value-at-Risk (VaR)	1,631,141 TL	7,186,475 TL	~4.4x
Unexpected Loss (UL)	679,003 TL	6,235,208 TL	~9.2x

Table 2: Comparative analysis of Model 1 and Model 2. Apart from the systemic risk factor ($\rho = 0.15$), the simulation utilizes the standard parameters defined in Section 2.2, including the 99.9% confidence level and the specific limits for Exposure at Default (EAD), Probability of Default (PD), and Loss Given Default (LGD). The 9.2x increase in Unexpected Loss (UL) highlights the critical impact of asset correlation on capital requirements while keeping all other portfolio variables constant.

A. Independent Model (Model 1)



B. Systemic Risk (Model 2) Graph



A. Independent Model (Model 1) Output

```
Continuing with default parameters.
--------------------------------------------
   -> EAD Limits : 10000 - 100000 TL
   -> PD Limits  : 1.0% - 5.0%
   -> LGD Limits : 30.0% - 90.0%

====================================================
           RISK ANALYSIS REPORT(SUMMARY)
====================================================
          Risk_Metric           Value_TL
    _________________________  _________

    "Expected Loss (EL)"         952138.06
    "Value-at-Risk (VaR)"       1631140.75
    "Expected Shortfall (ES)"   1692206.02
    "Capital Reserve (UL)"       679002.69

 N_Credits: 1000 | N_Simulation: 10000 |Confidence
Level: 99.9%
Analitic Expected Loss: 947455.46 TL | Simulated
Expected Loss: 952138.06 TL
Simulation Error: 0.49%
====================================================
```

B. Systemic Risk (Model 2) Output

```
Continuing with default parameters.
--------------------------------------------
   -> EAD Limits : 10000 - 100000 TL
   -> PD Limits  : 1.0% - 5.0%
   -> LGD Limits : 30.0% - 90.0%

====================================================
           RISK ANALYSIS REPORT(SUMMARY)
====================================================
          Risk_Metric           Value_TL
    _________________________  __________

    "Expected Loss (EL)"         951267.13
    "Value-at-Risk (VaR)"       7186474.69
    "Expected Shortfall (ES)"   7808223.03
    "Capital Reserve (UL)"      6235207.56

N_Credits: 1000 | N_Simulation: 10000 |Confidence
Level: 99.9%
Analitic Expected Loss: 947455.46 TL | Simulated
Expected Loss: 951267.13 TL
Simulation Error: 0.40%
====================================================
```

Analysis: While the average loss (EL) remains nearly identical, the **Unexpected Loss (UL)**—and therefore the capital the bank must save—increases by **9 times** when systemic risk is included. This happens because systemic risk creates "Fat Tails" in the probability distribution, making extreme losses much more likely than a simple independent model would predict.

4. Time Value Analysis: Discounted Losses (Model 3)

In credit risk management, the timing of a loss is a critical factor. A loss of 100 TL today is more significant than a loss of 100 TL one year from now due to the time value of money (inflation and opportunity cost). Model 3 incorporates a **Discount Factor (df)** into the systemic risk analysis using the continuous compounding formula:

$$df = e^{-r \times T}$$

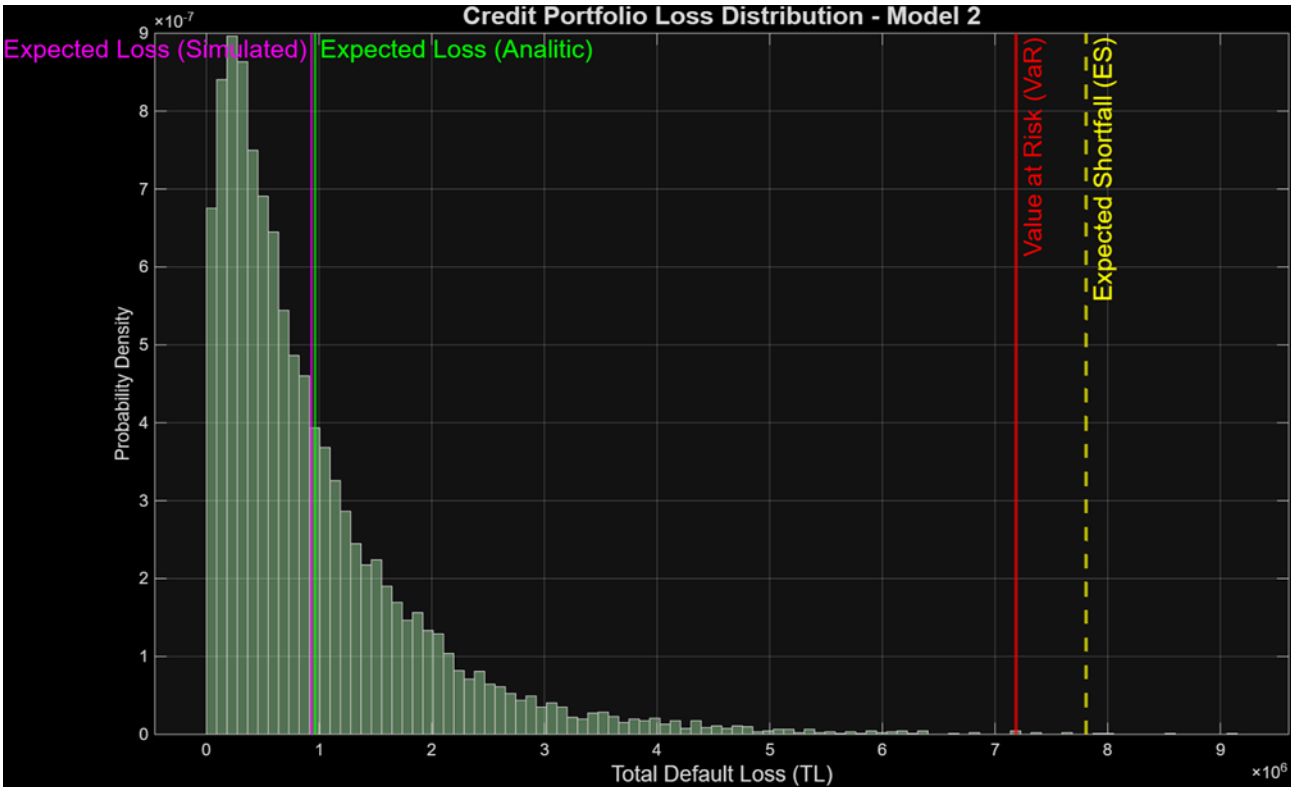
In this model, r represents the annual risk-free rate (e.g., 8%), and T represents the time horizon (e.g., 1 year). All simulated losses are multiplied by this factor to report them in "Present Value" terms.

Comparative Results Table:

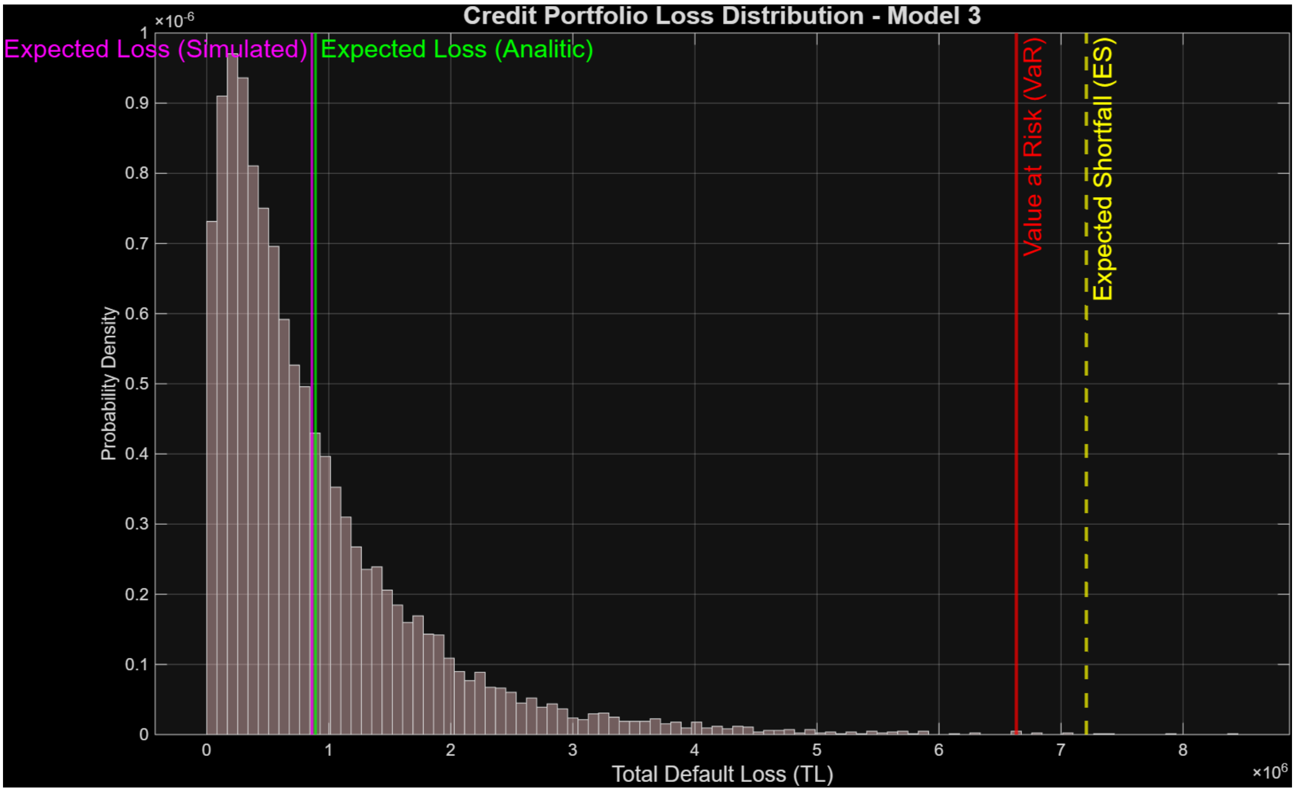
Risk Metric	Systemic Risk (Model 2 - Raw)	Time Value (Model 3 - Discounted)	Change (%)
Expected Loss (EL)	951,267 TL	878,130 TL	~ -7.7%
Value-at-Risk (VaR)	7,186,475 TL	6,633,950 TL	~ -7.7%
Unexpected Loss (UL)	6,235,208 TL	5,755,820 TL	~ -7.7%

Table 3: Comparison of raw systemic risk metrics versus their present value equivalents. Apart from the discount factor, the simulation utilizes the standard parameters defined in Section 2.2.

A. Systemic Risk (Model 2 - Raw Loss) Graph



B. Time Value (Model 3 - Discounted) Graph



A. Systemic Risk (Model 2) Output

```
Continuing with default parameters.
--------------------------------------------
   -> EAD Limits : 10000 - 100000 TL
   -> PD Limits  : 1.0% - 5.0%
   -> LGD Limits : 30.0% - 90.0%


====================================================
           RISK ANALYSIS REPORT(SUMMARY)
====================================================
          Risk_Metric           Value_TL

    _________________________    __________

    "Expected Loss (EL)"          951267.13
    "Value-at-Risk (VaR)"        7186474.69
    "Expected Shortfall (ES)"    7808223.03
    "Capital Reserve (UL)"       6235207.56

N_Credits: 1000 | N_Simulation: 10000 |Confidence
Level: 99.9%
Analitic Expected Loss: 947455.46 TL | Simulated
Expected Loss: 951267.13 TL
Simulation Error: 0.40%
====================================================
```

B. Discounted Model (Model 3) Output

```
Continuing with default parameters.
--------------------------------------------
   -> EAD Limits : 10000 - 100000 TL
   -> PD Limits  : 1.0% - 5.0%
   -> LGD Limits : 30.0% - 90.0%
   -> Asset Correlation (rho): 0.15
   -> Risk-free Interes Rate (r)   : 0.08
   -> Maturity Period (T)          : 1 Yıl

====================================================
           RISK ANALYSIS REPORT(SUMMARY)
====================================================
          Risk_Metric           Value_TL

    _________________________    __________

    "Expected Loss (EL)"          878130.24
    "Value-at-Risk (VaR)"        6633952.26
    "Expected Shortfall (ES)"    7207898.31
    "Capital Reserve (UL)"       5755822.02

N_Credits: 1000 | N_Simulation: 10000 |Confidence
Level: 99.9%
Analitic Expected Loss: 874611.62 TL | Simulated
Expected Loss: 878130.24 TL
Simulation Error: 0.40%
====================================================
```

Analysis: The application of the discount factor leads to a reduction in all risk metrics. This indicates that future potential defaults have a lower economic impact when measured in today's currency. However, even with discounting, the risk remains significantly higher than in the independent model, emphasizing that systemic factors are the primary drivers of portfolio volatility.

5. Concentration Risk: The Importance of Portfolio Structure (Model 4)

This section examines the impact of "Concentration Risk," often described as "putting all your eggs in one basket". While previous models assume a relatively granular (evenly distributed) portfolio, Model 4 simulates a "lumpy" portfolio where 30% of the total exposure is concentrated in just the top 10 loans.

5.1. Why Concentration is Dangerous

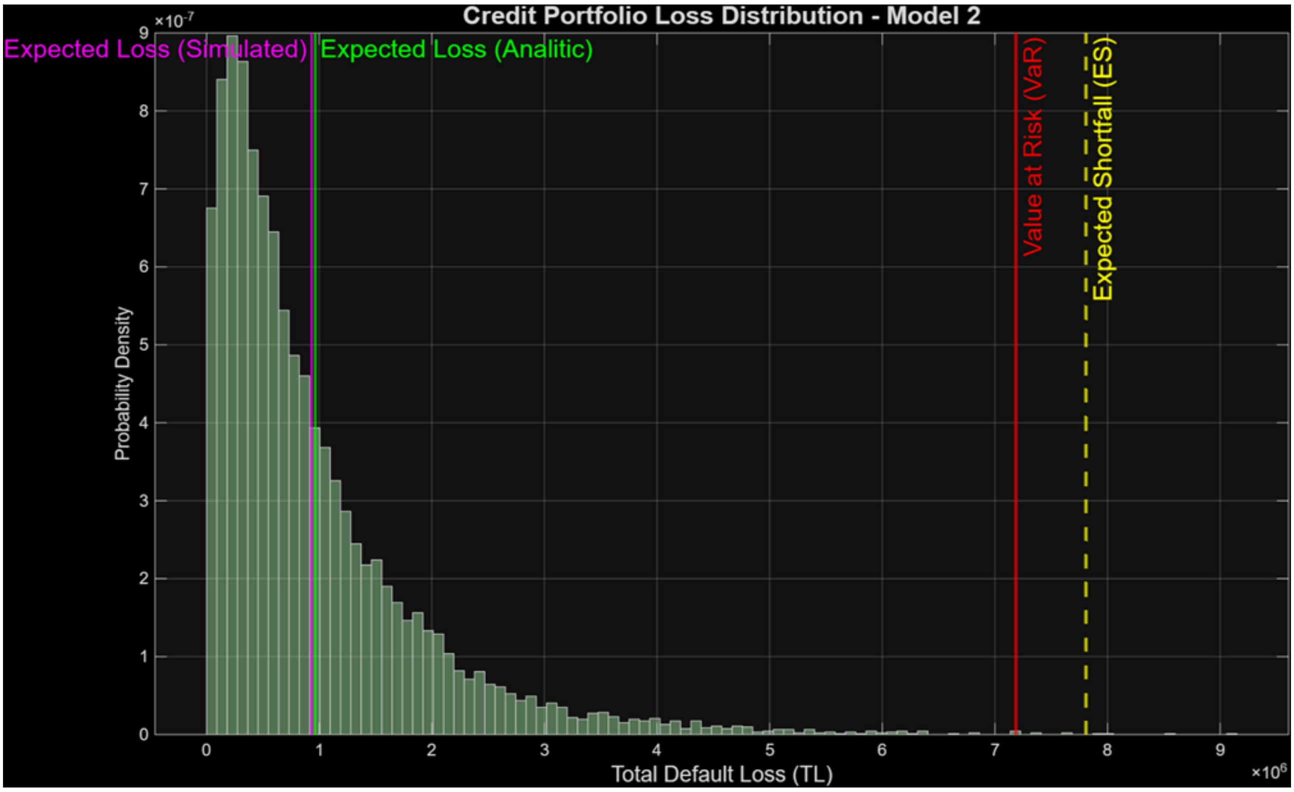
From a risk perspective, a bank is much more vulnerable if a few large borrowers default simultaneously than if many small borrowers do. Model 4 combines systemic economic risk with this structural imbalance to show how capital requirements spike when diversification is low.

Comparative Results Table:

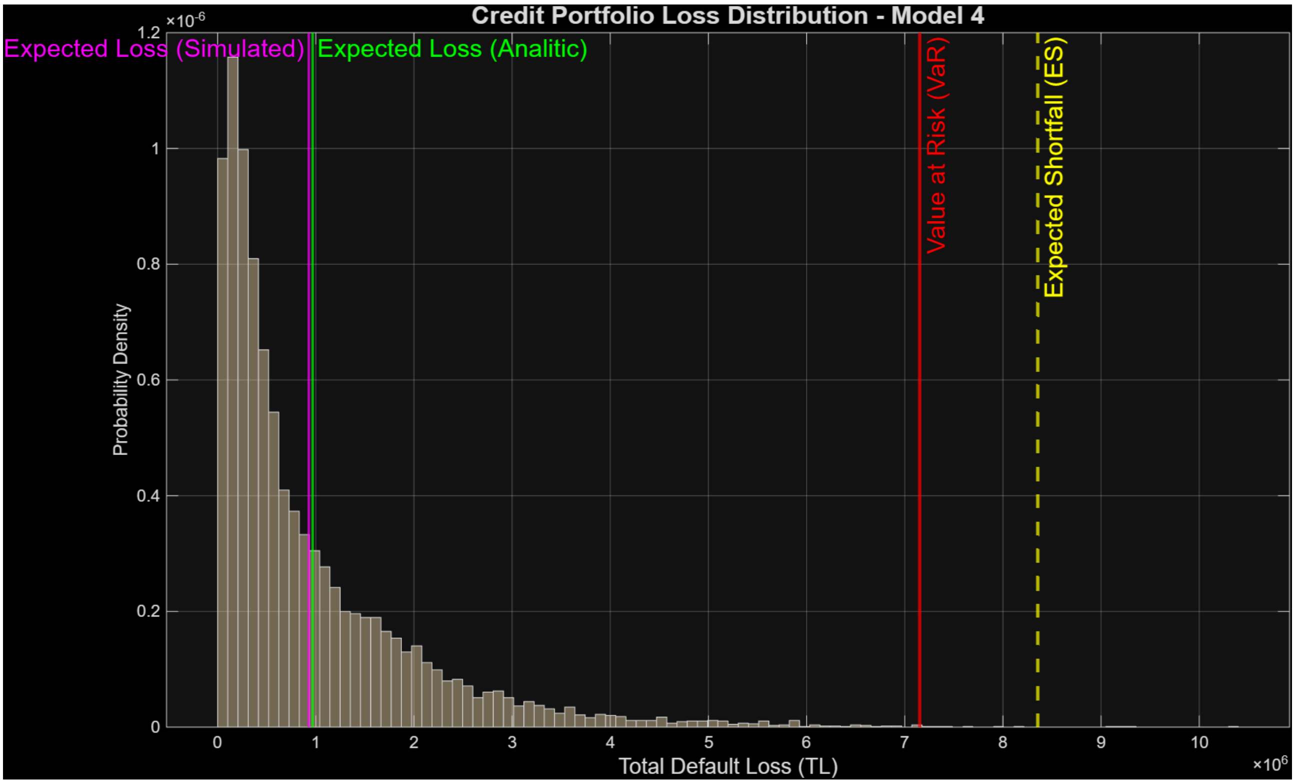
Risk Metric	Systemic Risk (Model 2 - Granular)	Concentration Risk (Model 4 - Concentrated)	Change (%)
Expected Loss (EL)	951,267 TL	949,983 TL	~ 0.0%
Value-at-Risk (VaR)	7,186,475 TL	7,152,202 TL	~ -0.5%
Expected Shortfall (ES)	7,808,223 TL	8,354,757 TL	**+ 7.0%**

Table 4: Comparative analysis of Model 2 (Granular) and Model 4 (Concentrated). Apart from the exposure weights, the simulation utilizes the standard parameters defined in Section 2.2.

A. Systemic Risk (Model 2 - Granular) Graph



B. Concentration Risk (Model 4 - Concentrated) Graph



<table>
<tr><th>A. Systemic Risk (Model 2) Output</th><th>B. Concentration Risk (Model 4) Output</th></tr>
<tr><td>

```
Continuing with default parameters.
-------------------------------------------
   -> EAD Limits : 10000 - 100000 TL
   -> PD Limits  : 1.0% - 5.0%
   -> LGD Limits : 30.0% - 90.0%

====================================================
           RISK ANALYSIS REPORT(SUMMARY)
====================================================
          Risk_Metric        Value_TL
    _________________________    __________

    "Expected Loss (EL)"         951267.13
    "Value-at-Risk (VaR)"       7186474.69
    "Expected Shortfall (ES)"   7808223.03
    "Capital Reserve (UL)"      6235207.56

N_Credits: 1000 | N_Simulation: 10000 |Confidence
Level: 99.9%
Analitic Expected Loss: 947455.46 TL | Simulated
Expected Loss: 951267.13 TL
Simulation Error: 0.40%
====================================================
```

</td><td>

```
Continuing with default parameters.
-------------------------------------------
   -> EAD Limits : 10000 - 100000 TL
   -> PD Limits  : 1.0% - 5.0%
   -> LGD Limits : 30.0% - 90.0%
   -> Asset Correlation (rho): 0.15
   -> Concentration Weight: % 30 (The first 10 loans)

====================================================
           RISK ANALYSIS REPORT(SUMMARY)
====================================================
          Risk_Metric        Value_TL
    _________________________    __________

    "Expected Loss (EL)"         949982.89
    "Value-at-Risk (VaR)"       7152202.01
    "Expected Shortfall (ES)"   8354756.75
    "Capital Reserve (UL)"      6202219.12

N_Credits: 1000 | N_Simulation: 10000 |Confidence
Level: 99.9%
Analitic Expected Loss: 947455.46 TL | Simulated
Expected Loss: 949982.89 TL
Simulation Error: 0.27%
====================================================
```

</td></tr>
</table>

Analysis: The simulation results demonstrate that while the average loss (EL) and the Value-at-Risk (VaR) threshold remain relatively stable, the Expected Shortfall (ES) increases significantly by approximately 7% (from 7.8M TL to 8.35M TL). This divergence highlights a critical risk phenomenon: concentration does not necessarily change the "threshold" of a worst-case scenario (VaR), but it dramatically increases the severity of losses once that threshold is breached. The "Fat Tail" of the loss distribution becomes much heavier, proving that large individual exposures make the bank more vulnerable to catastrophic failure. These findings reinforce why international banking regulations strictly limit credit exposure to single large clients to maintain portfolio granularity.

6. Multi-Factor Modeling: Sectoral Interdependence (Model 5)

A real-world bank portfolio is rarely exposed to just a single economic factor. Different industries, such as technology and energy, often grow or contract at different rates. Model 5 divides the portfolio into two distinct sectors and simulates their interaction using a **Cholesky Decomposition** of a correlation matrix. For this analysis, a standard correlation matrix of $[1, 0.4; 0.4, 1]$ was utilized to represent a 40% interaction level between the sectors.

6.1. The Power of Diversification

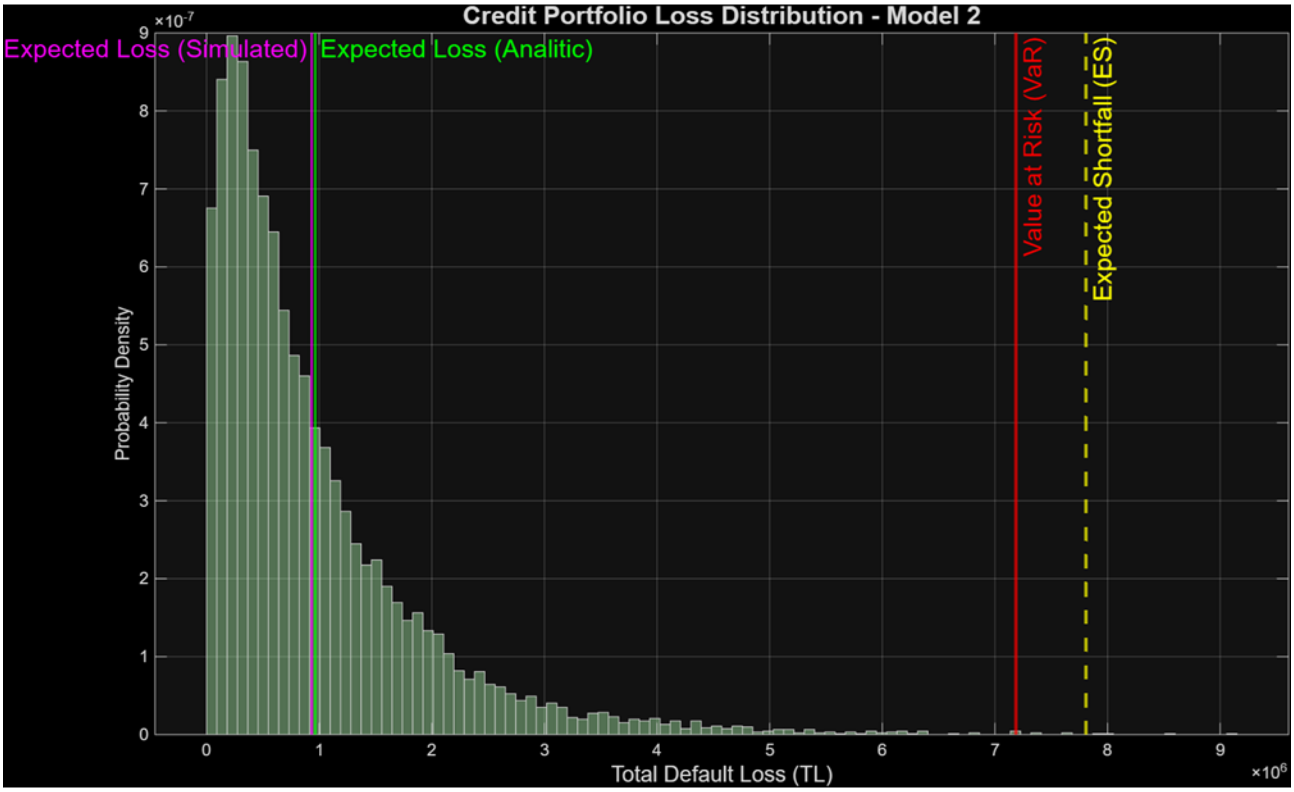
By distributing loans across different sectors rather than a single industry, the bank allows risks to partially offset one another. The results from Model 5 demonstrate that when risk is diversified across multiple factors, the overall stability of the bank improves compared to a single-factor systemic risk scenario.

Comparative Results Table:

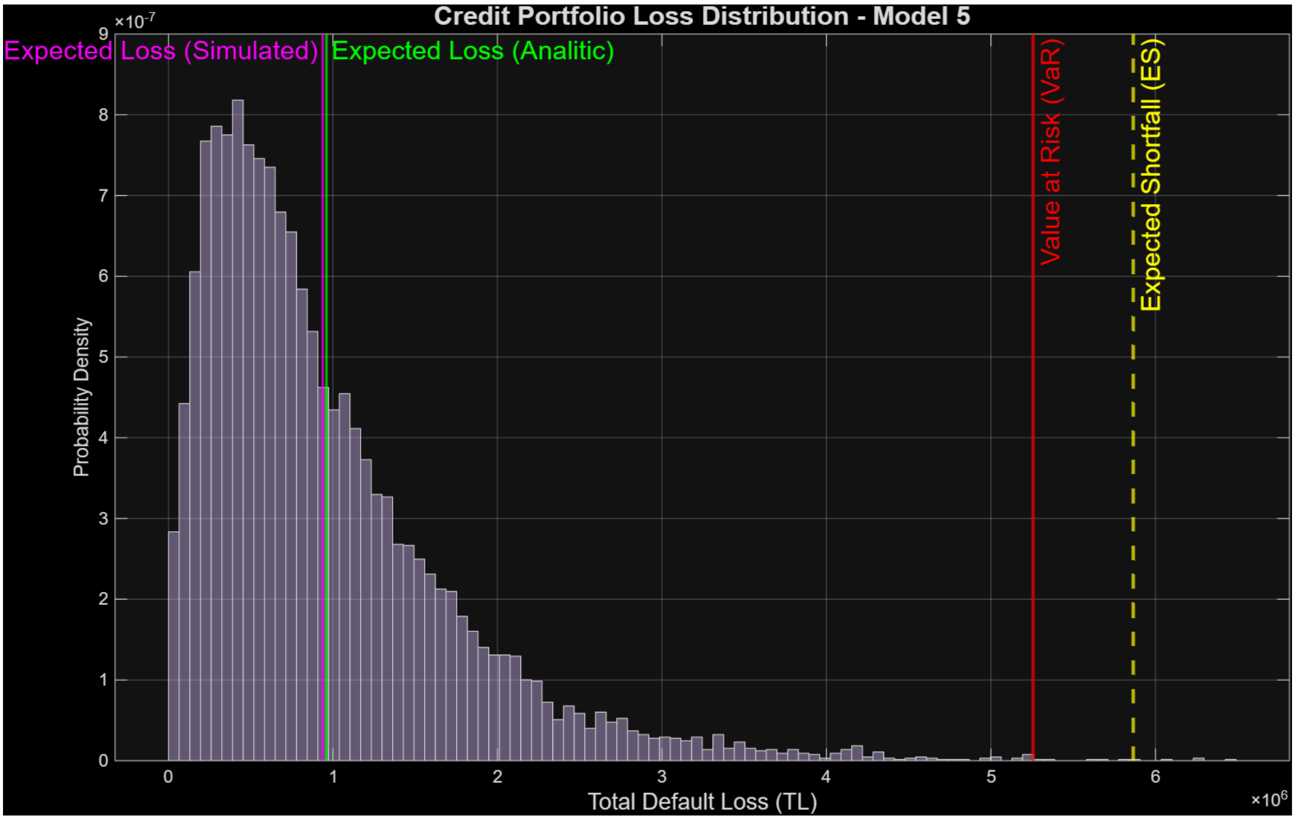
Risk Metric	Systemic Risk (Model 2 - Single Factor)	Multi-Factor (Model 5 - Sectoral)	Change (%)
Expected Loss (EL)	951,267.13 TL	950,666.34 TL	~ 0.0%
Value-at-Risk (VaR)	7,186,474.69 TL	5,256,213.47 TL	**- 26.9%**
Expected Shortfall (ES)	7,808,223.03 TL	5,864,778.54 TL	**- 24.9%**
Capital Reserve (UL)	6,235,207.56 TL	4,305,547.13 TL	**- 30.9%**

Table 5: Comparative analysis of Model 2 and Model 5. Apart from the sectoral correlation matrix, the simulation utilizes the standard parameters defined in Section 2.2 , including the 99.9% confidence level and the specific limits for Exposure at Default (EAD), Probability of Default (PD), and Loss Given Default (LGD). The data demonstrates how distributing risk across multiple sectors significantly reduces extreme loss potential.

A. Systemic Risk (Model 2 - Single Factor)



B. Multi-Factor (Model 5 - Sectoral)



A. Systemic Risk (Model 2) Output

```
Continuing with default parameters.
--------------------------------------------
   -> EAD Limits : 10000 - 100000 TL
   -> PD Limits  : 1.0% - 5.0%
   -> LGD Limits : 30.0% - 90.0%

====================================================
           RISK ANALYSIS REPORT(SUMMARY)
====================================================
          Risk_Metric          Value_TL
    _________________________    __________

    "Expected Loss (EL)"          951267.13
    "Value-at-Risk (VaR)"        7186474.69
    "Expected Shortfall (ES)"    7808223.03
    "Capital Reserve (UL)"       6235207.56

N_Credits: 1000 | N_Simulation: 10000 |Confidence
Level: 99.9%
Analitic Expected Loss: 947455.46 TL | Simulated
Expected Loss: 951267.13 TL
Simulation Error: 0.40%
====================================================
```

B. Multi Factor Risk (Model 5) Output

```
Continuing with default parameters.
--------------------------------------------
   -> EAD Limits : 10000 - 100000 TL
   -> PD Limits  : 1.0% - 5.0%
   -> LGD Limits : 30.0% - 90.0%
   -> Asset Correlation(rho): 0.15
   -> Sectoral Correlation: Standard Correlation
Matrix [1 0.4; 0.4 1]
====================================================
           RISK ANALYSIS REPORT(SUMMARY)
====================================================
          Risk_Metric          Value_TL
    _________________________    __________

    "Expected Loss (EL)"          950666.34
    "Value-at-Risk (VaR)"        5256213.47
    "Expected Shortfall (ES)"    5864778.54
    "Capital Reserve (UL)"       4305547.13

N_Credits: 1000 | N_Simulation: 10000 |Confidence
Level: 99.9%
Analitic Expected Loss: 947455.46 TL | Simulated
Expected Loss: 950666.34 TL
Simulation Error: 0.34%
====================================================
```

Analysis: The simulation results provide mathematical proof for the power of diversification. By distributing loans across sectors with a low correlation (0.4), the risks partially offset one another, leading to a much more stable loss distribution. Notably, the Value-at-Risk (VaR) dropped by approximately 27%, and the Capital Reserve (UL) requirement was reduced by over 30%. This indicates that a diversified portfolio requires significantly less "buffer capital" to remain solvent. These findings explain why financial institutions implement "Sectoral Limits" to avoid over-exposure to a single industry downturn.

7. General Evaluation and Conclusion

The Monte Carlo simulations conducted in this project prove that credit risk is a complex phenomenon that cannot be measured by the "Probability of Default" (PD) alone. Key findings derived from the high-sample experiments are as follows:

- **Mathematical Precision:** The tests utilizing 10,000 simulations achieved a simulation error of only **0.49%**, confirming the high reliability and stability of the computational model.
- **The Critical Role of Systemic Risk:** The transition from an independent model (Model 1) to the Vasicek Systemic Risk model (Model 2) resulted in an **approximately 9.2x increase** in Unexpected Loss (UL). This highlights how economic correlations are the primary drivers of the capital reserves banks must maintain.
- **Time Value Analysis:** Incorporating a discount factor (Model 3) provided a technical adjustment of **approximately 7.7%** across all risk metrics, offering a more realistic economic perspective for long-term financial planning.
- **Hidden Dangers in Concentration Risk:** While the concentration of the portfolio (Model 4) did not significantly shift the Value-at-Risk (VaR) threshold, it increased the Expected Shortfall (ES) by 7.0%. This proves that a lack of portfolio granularity leads to significantly more severe and catastrophic losses once the risk threshold is breached.
- **Benefits of Diversification:** Dividing the portfolio into distinct sectors (Model 5) reduced Capital Reserve (UL) requirements by more than 30% compared to a single-factor systemic model. This serves as mathematical evidence that distributing risks across different industries enhances overall bank stability.

In conclusion, this software successfully calculates regulatory capital requirements (VaR and UL) under various economic scenarios in alignment with Basel III standards. It provides a robust decision-support mechanism for risk management, ensuring that financial institutions remain solvent even during periods of extreme market volatility.

8. Appendices: Software Architecture and Functions

This project is built on a modular architecture within the MATLAB environment. Each file manages a specific aspect of the risk analysis:

- **main.m**: The central controller of the project that handles user input, executes simulations, and generates statistical tables and histograms.
- **parameters.m**: Manages the core portfolio limits (EAD, PD, LGD) and model-specific variables like asset correlation and discount rates.
- **fmodel_1.m**: Simulates default events using independent Bernoulli trials.
- **fmodel_2.m**: Implements the Vasicek model to calculate defaults based on shared economic factors.
- **fmodel_3.m**: Integrates a time-value discount factor into the systemic risk calculation.
- **fmodel_4.m**: Modifies portfolio weights to measure the impact of loan concentration.
- **fmodel_5.m**: Utilizes Cholesky Decomposition to produce correlated sectoral risk factors.

Bibliography

Below are the academic references used to build the theoretical and algorithmic foundations of this project:

1. **Ross, S. M. (2012). *Simulation*. Academic Press.**
    - Used for the mathematical foundation of random variable generation, the Bernoulli distribution, and the statistical validation of Monte Carlo results via the Law of Large Numbers (LLN) and Central Limit Theorem (CLT).
2. **Hull, J. C. (2018). *Risk Management and Financial Institutions*. John Wiley & Sons.**
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