

End-to-End Credit Risk Analysis and Policy Scenario Evaluation

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1. EXECUTIVE SUMMARY

This report presents an end-to-end credit risk analysis based on a large-scale consumer lending dataset. The objective is to understand portfolio-level risk, identify high-risk customer segments, and evaluate how changes in credit policy thresholds impact approval volumes and default risk. The analysis combines SQL-based data preparation, analytical modelling in Power BI using DAX, and interactive scenario analysis.

Overall, the portfolio shows a relatively low default rate at an aggregate level. However, risk is not evenly distributed. Defaults are concentrated within specific customer segments, particularly younger customers in lower income bands and customers with a history of previous credit refusals. Scenario analysis further demonstrates clear trade-offs between approval volume and risk when adjusting credit-to-income (CTI) thresholds.

The findings highlight strong opportunities for targeted, risk-based policy optimisation rather than uniform credit tightening.

2. DATA OVERVIEW AND PREPARATION

This analysis is based on the *Bank Loan Case Study Dataset* (Kaggle), which provides multiple relational tables representing customer applications, historical loan activity, and credit outcomes. These raw tables were integrated in PostgreSQL using SQL joins and aggregations to construct a unified, customer-level analytical base table.

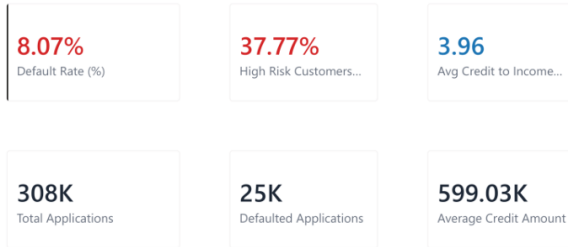
The final analytical table contains customer demographics (age, income), credit characteristics (loan amount, interest rate, credit-to-income ratio), behavioural indicators (previous application counts, refused application counts, and average previous credit exposure), and the default outcome variable.

Key preprocessing steps included handling missing and invalid records, creating categorical age and income bands, engineering behavioural and affordability features, and validating aggregates against raw source tables to ensure consistency across SQL, Python, and Power BI layers.

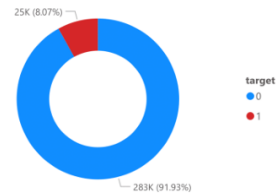
3. EXECUTIVE RISK OVERVIEW (PORTFOLIO LEVEL)

Executive Risk Overview

Portfolio-level credit risk summary



Default vs Non-default Applications



Only 8.1% of applications default, however over one-third of customers fall into high-risk segments, highlighting a strong opportunity for targeted risk-based policy optimisation.

Key Metrics

At a portfolio level, the following metrics summarise overall performance:

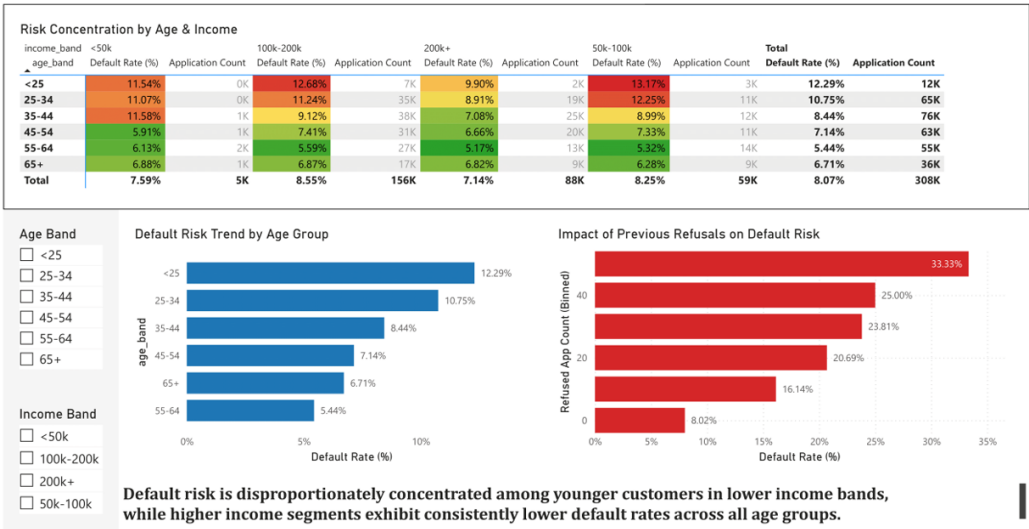
- **Default Rate:** Approximately 8% of applications result in default
- **High-Risk Customers:** Over one-third of customers fall into high-risk segments
- **Total Applications:** The portfolio contains several hundred thousand applications
- **Average Credit-to-Income Ratio:** Indicates moderate leverage across the portfolio

Insight

High-risk segments are defined based on a combination of elevated default rates and unfavourable affordability and behavioural indicators. In this analysis, customers are classified as higher risk when they belong to segments exhibiting persistently above average default rates, high credit-to-income ratios, and/or a history of previous credit refusals.

4. CUSTOMER RISK SEGMENTATION ANALYSIS

Customer Risk Segments



4.1 Risk Concentration by Age and Income

A two -dimensional risk matrix was used to analyse default rates across age bands and income bands. This matrix reveals that:

- Younger customers consistently exhibit higher default rates than older cohorts
- Lower income bands show elevated risk across nearly all age groups
- Higher income segments demonstrate relatively stable and lower default rates, regardless of age

Insight

Default risk is disproportionately concentrated among younger customers in lower income bands. This suggests that demographic and affordability factors jointly influence credit risk, and should be considered together rather than independently.

4.2 Default Risk Trends by Age Group

A ranked comparison of default rates by age group highlights a clear downward trend:

- Customers under 35 show the highest default rates
- Risk steadily declines with age
- Customers aged 55 and above consistently demonstrate the lowest default risk

Insight

Age acts as a strong proxy for financial stability and repayment behaviour. Younger customers may face income volatility, limited credit history, or higher financial pressure, increasing default likelihood.

4.3 Impact of Previous Credit Refusals

Behavioural analysis shows a strong relationship between historical refusals and future default risk:

- Customers with no prior refusals exhibit the lowest default rates
- Default rates increase sharply as the number of previous refusals rises
- At high refusal counts, default risk increases disproportionately

Insight

Refused application counts were grouped into discrete behavioural bands to improve interpretability. These bands represent customers with no prior refusals, low refusal frequency, and repeated historical refusals. The analysis shows a non-linear relationship, where default risk increases modestly at low refusal levels but rises sharply once customers exceed higher refusal thresholds.

5. POLICY AND SCENARIO ANALYSIS

Policy & Scenario Analysis

Trade-offs between approval volume and default risk under different CTI thresholds

CTI Threshold

1



5.26%

Approval Rate (%)

6.44%

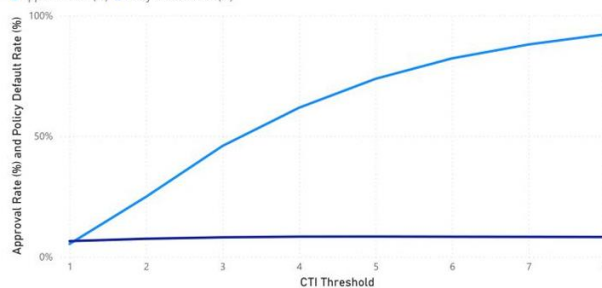
Policy Default Rate (%)

16.174K

Approved Applications (CTI Policy)

Approval Rate (%) and Policy Default Rate (%) by CTI Threshold

● Approval Rate (%) ● Policy Default Rate (%)



Relaxing the CTI threshold materially increases approval volumes, but at the cost of a rising default rate. An optimal policy point balances marginal approval gains against disproportionate increases in risk.

The credit-to-income (CTI) ratio is defined as the ratio of the approved credit amount to a customer's annual income. It is used as a proxy for affordability risk, where higher CTI values indicate greater financial leverage and an increased likelihood of repayment stress.

5.1 CTI Threshold Trade-Offs

A what-if scenario analysis was conducted by varying the credit-to-income (CTI) threshold and observing its impact on:

- Approval rate
- Number of approved applications
- Policy-level default rate

The analysis shows that:

- Relaxing CTI thresholds materially increases approval volumes
- Default risk rises as approval criteria are loosened
- Beyond mid-range CTI values, approval gains begin to plateau while default risk continues to rise

Insight

There exists a clear inflection point where incremental approval gains are outweighed by disproportionate increases in default risk. This demonstrates that aggressive policy

relaxation delivers diminishing returns.

6. KEY INSIGHTS SUMMARY

1. Portfolio-level default rates understate underlying risk concentration
2. Younger, lower-income customers represent the highest-risk segments
3. Previous credit refusals are a strong predictor of future default
4. Credit policy adjustments involve clear and measurable risk-volume trade-offs
5. A single uniform policy is suboptimal across heterogeneous customer segments

7. Recommendations

7.1 Segment-Based Credit Policy

Rather than applying uniform CTI thresholds, introduce differentiated policies by age and income segments. Lower-risk segments can sustain slightly relaxed thresholds, while high risk segments require tighter controls.

7.2 Behavioural Risk Weighting

Incorporate previous refusal counts directly into credit decisioning, with non-linear penalties applied beyond defined thresholds.

7.3 Controlled Policy Optimisation

Use scenario analysis outputs to identify CTI ranges where approval gains remain efficient. Avoid threshold levels where default risk accelerates without proportional business benefit.

7.4 Ongoing Monitoring

Establish dashboards to continuously monitor segment-level default rates and policy performance, enabling early detection of risk drift.

8. Limitations and Next Steps

This analysis is based on historical application data and does not account for macroeconomic changes or external credit bureau updates. Future work could include:

- Time -based cohort analysis
- Predictive modelling using machine learning
- Stress testing under adverse economic scenarios

9. PROJECT RESOURCES & CONTACT

GitHub Repository

https://github.com/su7ri/home_credit

Portfolio Website

<https://azed.uk>

Power BI Dashboard (PBIX)

The Power BI dashboard file (PBIX) is included in the GitHub repository for local exploration

and review.

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10. Data Source

This project uses the Bank Loan Case Study Dataset from Kaggle:

<https://www.kaggle.com/datasets/shreshthvashisht/bank-loan-case-study-dataset>

The dataset consists of multiple relational tables capturing loan applications, customer attributes, and historical credit behaviour. These tables were integrated and transformed in SQL to produce an analysis-ready customer-level dataset used for segmentation, risk modelling, and policy scenario analysis.

11. Conclusion

This project demonstrates how integrated data analytics, segmentation analysis, and scenario modelling can support evidence-based credit policy decisions. By moving beyond aggregate metrics and focusing on segment-level behaviour and policy trade-offs, organisations can achieve a more balanced approach to growth and risk management.

Appendix A: SQL Data Preparation and Feature Engineering

This appendix documents the SQL pipeline used to transform the raw, multi-table *Bank Loan Case Study* data into a clean, analysis-ready customer-level dataset.

A.1 Data Integration (Joins)

Multiple relational tables (applications, previous loans, and historical credit records) were combined using SQL joins to create a unified customer-level view. Left joins were used to retain the full population of loan applications while enriching records with available historical and behavioural information.

A.2 Data Cleaning and Validation

Duplicate records were removed, missing or invalid financial values were handled, and numeric ranges (e.g., income, loan amount) were validated. Aggregated fields were reconciled against source tables to ensure data integrity.

A.3 Feature Engineering

SQL was used to create analytical features, including age and income bands, credit-to-income ratio (CTI), previous application and refusal counts, and aggregated historical credit exposure (e.g., average previous credit).

A.4 Aggregations and KPI Foundations

SQL aggregations produced application counts, default counts, default rates, and behavioural metrics by segment, which were validated prior to being consumed by Power BI.

A.5 Analytical Views

Reusable SQL views encapsulated the join logic and feature engineering, providing a stable schema for downstream Python and Power BI analysis.

A.6 Rationale for SQL -First Approach

Performing data preparation in SQL provided several advantages:

- Clear separation between data engineering and analytical layers
- Improved performance for large datasets
- Transparent, auditable transformation logic
- Easier collaboration and version control

This SQL -first approach enabled a clean transition to Python for exploratory analysis and to Power BI for interactive reporting.