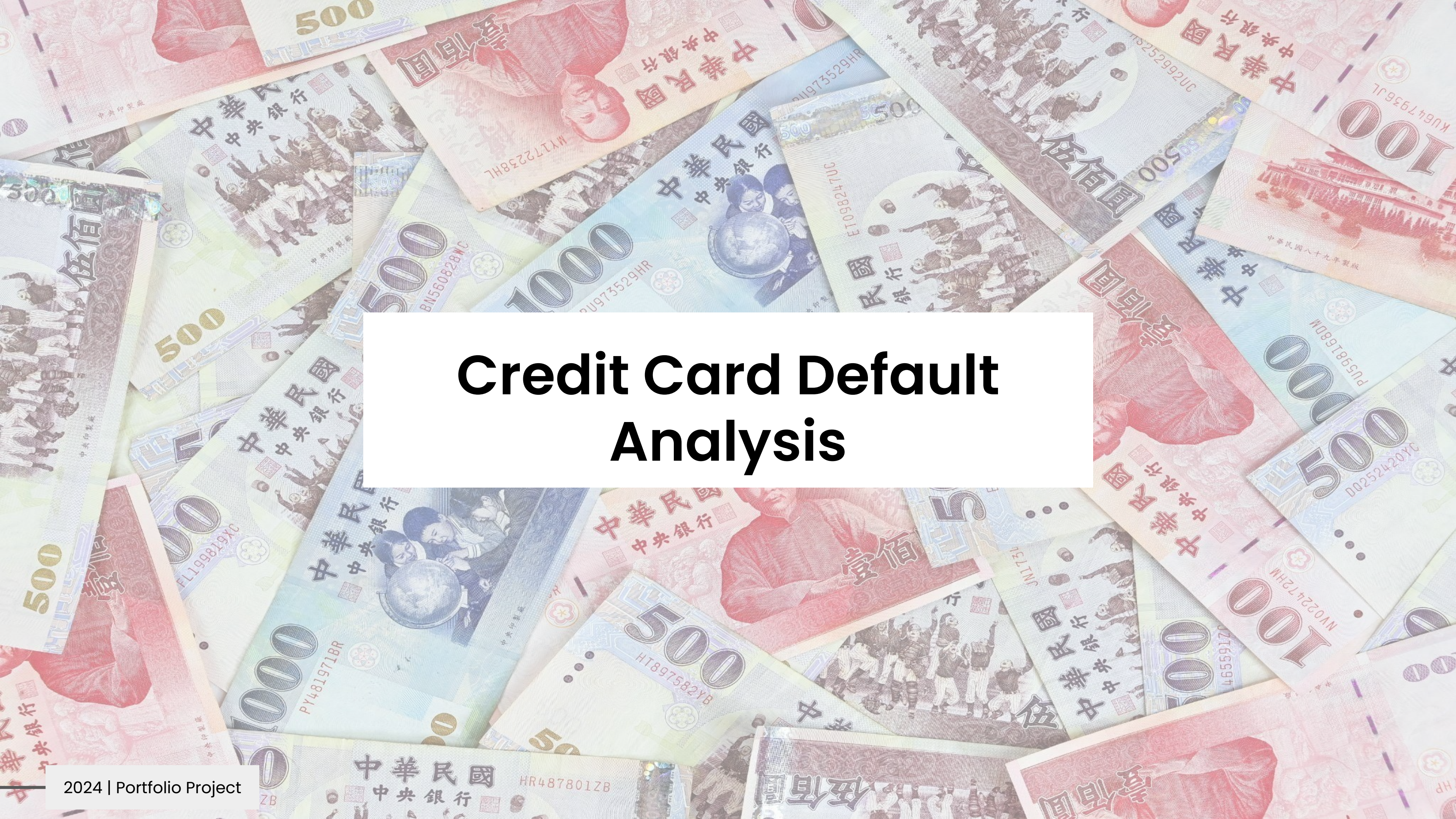

Credit Card Default Analysis

2024 | Portfolio Project

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I am a **Credit Risk Analyst** at private digital bank, responsible for conducting **underwriting** processes to assess borrower creditworthiness and performing **KYC** risk assessments. I work to ensure compliance with regulatory standards while managing risks effectively through data analysis and collaboration with relevant teams.

Outlines:

- ❑ Profile Background
- ❑ **Taiwan's Debt Crisis:** Uncovering the Root Causes
- ❑ **Credit Cardholder Transaction Data:** A Comprehensive Overview
- ❑ **Gender-Based Demographic Insights:** Credit Cardholder Default Risk
- ❑ **Transaction Status Breakdown:** Insights into Credit Cardholder Behavior
- ❑ **Default Progression:** Analyzing Payment Trends Over Time
- ❑ **Payment Performance Trends:** Balancing Outstanding Debt and Repayments

Taiwan's Debt Crisis: Uncovering the Root Causes

In past years, credit card issuers in Taiwan faced a debt crisis, with delinquency expected to peak by the third quarter of 2006 (Chou, 2006). To boost market share, banks over-issued credit and cash cards to unqualified applicants. Many cardholders, regardless of their ability to repay, overused their cards and built up large debts. This crisis hurt consumer confidence in finance and posed a major challenge for both banks and cardholders (Cheng, 2009).

In a strong financial system, crisis management comes after risk prediction. The main goal of risk prediction is to use financial data, like business statements and customer transaction records, to foresee business performance or credit risk and minimize potential losses.

Credit Cardholder Transaction Data: A Comprehensive Overview

This dataset consists of transaction records from Taiwanese individuals in October 2005, acquired from a major bank (a cash and credit card issuer). The dataset includes 30,000 observations, categorized as either default or non-default, which will be processed for analysis.

Dataset was obtained from the [UC Irvine Machine Learning Repository] (donated on 1/25/2016) and consists of 25 variables as follows:

1. Key variable

Variable	Description
ID	Unique number of each clients

2. Payment history variables

Variables	Description
PAY_1	Repayment status in September
PAY_2	Repayment status in August
....	....
PAY_6	Repayment status in April

3. Demographic variables

Variable	Description
SEX	Gender of clients
EDUCATION	Highest level of education
MARRIAGE	Marital status
AGE	Age in years

4. Credit limit variable

Variable	Description
LIMIT_BAL	Amount of given credit

Credit Cardholder Transaction Data: A Comprehensive Overview (2)

5. Amount of bill variables

Variables	Description
BILL_AMT1	Amount of bill statement in September
BILL_AMT2	Amount of bill statement in August
....	....
BILL_AMT6	Amount of bill statement in April

6. Amount of prev payment variables

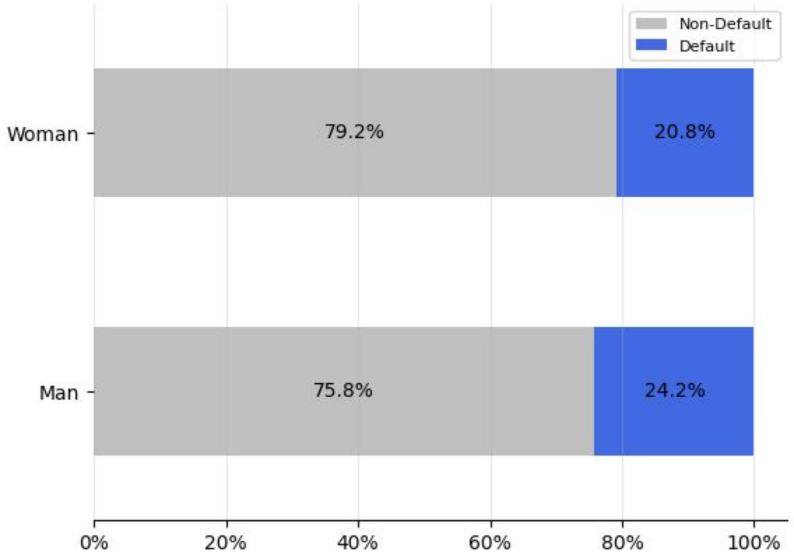
Variables	Description
PAY_AMT1	Amount of prev payment in September
PAY_AMT2	Amount of prev payment in August
....	....
PAY_AMT6	Amount of prev payment in April

7. Dependent variable

Variable	Description
def_status	Whether default or not

Note:
1. ‘SEX’ -> 1 = man, 2 = woman
2. ‘EDUCATION’ -> 1 = grad school, 2 = univ stud, 3 = high school, 4 - 6 = others
3. ‘MARRIAGE’ -> 1 = married, 2 = single, 3 = others
4. ‘PAY_0’ - ‘PAY_6’ -> -2 = prepayment, -1 = pay duly, 0 = grace payment, 1 - 8 = delay 1-8 month
5. ‘BILL_AMT’ -> In period time of month from September - April 2005 (NT$)
6. ‘PAY_AMT’ -> In period time of month from September - April 2005 (NT$)
7. ‘default.payment.next.month’ -> 1 = default, 0 = not default

Gender-Based Demographic Insights: Credit Cardholder Default Risk



A detailed distribution of default status

51% of individuals have attained a **University** education.

49% of individuals are **"married"**.

33% of individuals are between the ages of **31 and 40**.

A detailed distribution of default status

49% of individuals have attained a **University** education.

52% of individuals are **"single"**.

37% of individuals are between the ages of **31 and 40**.

Key insight:
The analysis indicates that male clients exhibit a higher default rate compared to female clients, despite a balanced representation between the two. Among defaulters, the majority possess a university-level education. Single clients show a greater likelihood of default compared to married clients, while the 31-40 age group emerges as the most susceptible to default, likely due to heightened financial obligations, positioning them as the highest credit risk demographic.

Transaction Status Breakdown: Insights into Credit Cardholder Behavior

	April	May	June	July	August	September
Prepayment	4,895	4,546	4,348	4,085	3,782	2,759
Pay Duly	6,740	5,539	5,687	5,938	6,050	5,686
Grace Period	16,286	16,947	16,455	15,764	15,730	14,737
1	0	0	2	4	28	3,688
2	2,766	2,626	3,159	3,819	3,927	2,667
3	184	178	180	240	326	322
4	49	84	69	76	99	76
5	13	17	35	21	25	26
6	19	4	5	23	12	11
7	46	58	58	27	20	9
8	2	1	2	3	1	19

Note:
1 represents a payment delayed by 1 month, and similarly up to 8, respectively.

44% the decline in customers making **prepayments** has been the **most significant**. Over the past six months, it has dropped by nearly half.

<1% customers making **on-time payments** can be considered **stable** during the sample data period.

9.5% the decline in customers making payments within the '**grace period**' over the past six months remains significant, yet this payment status continues to be the **most prevalent**.

When viewed holistically, there has been a noticeable rise in late payments ranging from 1 to 8 months over the course of the past semester. This trend suggests a significant decline in the financial strength and payment capacity of credit card customers, indicating a **weakening ability to meet their obligations on time**.

Key insights:

- The nearly 50% drop in prepayments shows that many customers may be facing financial difficulties. On the other hand, customers who consistently make on-time payments have remained stable, indicating they can handle economic changes. This difference suggests a need to support those at risk of default while maintaining the stability of reliable payers.
- From the standpoint of customers who have defaulted, there has been a notable surge in payments that are overdue by one month. Additionally, it is essential to implement a restructuring plan for customers who have experienced a two-month delinquency, with the potential option of deferring their payments to facilitate better financial management and mitigate further risk.

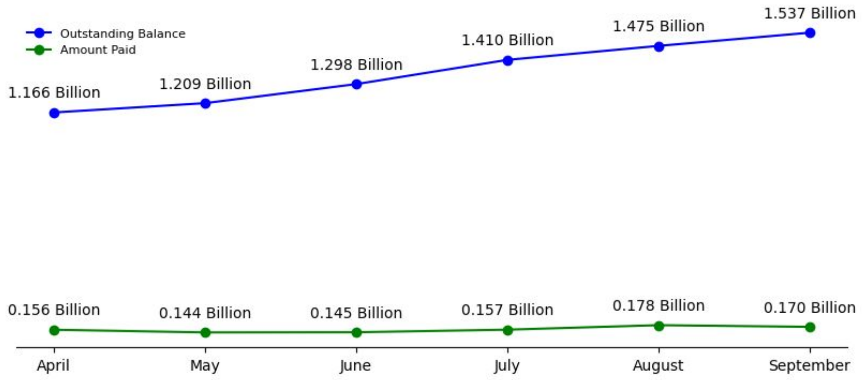
Default Progression: Analyzing Payment Trends Over Time

Month	FPD	DPD 1	DPD 2	DPD 3	DPD 4	DPD 5
April	11.56%	11.56%	1,79%	3.33%	2.63%	2.57%
May	11.82%	1.79%	1.79%	0.93%	0.91%	0.82%
June	12.04%	3.33%	0.93%	3.33%	0.96%	1.36%
July	11.32%	2.63%	0.91%	0.96%	2.63%	0.86%
August	10.69%	2.57%	0.82%	1.36%	0.86%	2.57%
September	11.65%	2.56%	0.86%	1.15%	1.19%	0.82%

Explanation
FPD : *first payment default*, first payment designated as a default
DPD 1 : *day pass due*, second payment classified as a default
DPD 2 : *day pass due*, third payment classified as a default
DPD 3 : *day pass due*, fourth payment classified as a default
DPD 4 : *day pass due*, fifth payment classified as a default
DPD 5 : *day pass due*, sixth payment classified as a default

Key insight:
The consistency of higher default rates in the first billing month across the six-month period indicates a recurring pattern of early payment distress among cardholders. This trend suggests that the majority of defaults tend to occur immediately after the first billing cycle, with little variation from month to month. Additionally, this pattern may highlight that cardholders struggle to meet their payment obligations early on, potentially reflecting underlying financial stress or mismatches between credit issuance and repayment capacity.

Payment Performance Trends: Balancing Outstanding Debt and Repayments



Key insight:
The graph shows a steady increase in the total outstanding balance from 1.166 billion in April to 1.537 billion in September, while the amount paid remains relatively stable, fluctuating between 0.144 billion and 0.178 billion. This growing gap between the rising outstanding balance and the consistent payment amounts suggests that payments are not keeping pace with the increasing debt, which may indicate a potential financial imbalance if this trend continues.

Risk-Based Clustering: A Strategic Approach to Credit Cardholders

The segmentation using the KMeans clustering method resulted in three distinct groups based on their respective risk levels.
The criteria for each group are as follows:

Cluster 1 - *Low Risk*

Default rate : 16.48%

Age range : *31-40 y.o*
Most marriage status : *single*
Most education status: *grad school*
Majority gender: *woman*
Most pay history : *pay duly*

Avg bill amounts : *NT$7,167*
Avg pay amounts : *NT$747*

Cluster 2 - *Medium Risk*

Default rate : 18.86%

Age range : *31-40 y.o*
Most marriage status : *single*
Most education status: *univ student*
Majority gender: *woman*
Most pay history : *grace period*

Avg bill amounts : *NT$ 183,856*
Avg pay amounts : *NT$ 6,806*

Cluster 3 - *High Risk*

Default rate : *26.57%*

Age range : *21-30 y.o*
Most marriage status : *single*
Most education status: *univ student*
Majority gender: *woman*
Most pay history : *grace period*

Avg bill amounts : *NT$ 38,935*
Avg pay amounts : *NT$ 1,710*

Key Insight:
The analysis divides credit cardholders into three risk groups based on their age, education, and payment behavior. Cluster 1 (Low Risk) includes individuals aged 31-40 who are highly educated and manage their finances well, with the lowest default rate of 16.48%. Cluster 2 (Medium Risk) also has individuals aged 31-40, mostly university students, who show a higher default rate (18.86%) and often use the grace period, indicating a need for financial support. Cluster 3 (High Risk) consists of younger individuals aged 21-30, mostly university students, with the highest default rate (26.57%) and low bill amounts, suggesting the need for stricter credit limits and financial education to reduce risk.

To access the full document, you can refer to the following websites:

https://github.com/febrifaresi/CreditCard_Default_Analysis

https://www.linkedin.com/in/febrifaresi/

https://drive.google.com/drive/folders/1_2RNL0xf4wokjwHgTKjG7RiYKWvzNUDT?usp=sharing