CAN MACHINE LEARNING ALGORITHMS CHANGE THE LANDSCAPE OF CREDIT CARD LOAN PORTFOLIOS?

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- *Machine learning gives the capability to move from risk-based to profit-based underwriting in credit card loan portfolios.*
- *The banks can now focus on a 'sweet spot' that exists on the risk gradient which focuses on borrowers with sufficiently large credit limits, sufficiently long loan lives, and sufficient revolvers to accumulate finance charges that the borrowers subsequently pay back. The objective of profit-based underwriting should be to identify and enable operations in this sweet spot.*

Financial institutions now have access to a broader and more varied array of data sources, which enables them to make more informed decisions regarding credit-related matters. The surge in internet usage and the subsequent digital transformation of monetary transactions have given rise to various forms of alternative informational collaterals[1]. This alternative data encompasses a range of sources such as digital footprints, behaviour on social media platforms, cash flow patterns, utility bill payments, geographic locations, and mobile applications. Such alternative data can serve as a crucial precursor and enhance the management of credit risks.

MACHINE LEARNING AND PROFIT-BASED MODELLING OF CREDIT CARD PORTFOLIOS

The research paper titled **Machine Learning-Based Profit Modeling for Credit Card Underwriting - Implications for Credit Risk,** published in the **Journal of Banking and Finance in 2023,** explores a shift **from risk-based to profit-based underwriting** in credit card loan portfolios.

The study applies machine learning (ML) algorithms to a sample of 1,50,000 loans that were initiated in 2012 and tracked through December 2015. Researchers used the USA's Office of the Comptroller of the Currency (OCC) Credit Card Metrics dataset, which has account-level information on over 400 million credit cards from a variety of banks.

Banks typically underwrite credit card loans based on risk scores. Focusing on customers that generate higher profits for a bank, this study examines the implications of changing the underwriting model from risk to a profit-based score.

Highlights of the study:

1. Targeted Underwriting

   Automated underwriting and account management systems have been widely used in the retail credit industry for at least the past two decades. Instead of a traditional interview-based underwriting system, where loan officers gauge a customer's credit worthiness using subjective criteria, banks automate the process by estimating models that predict the probability of a 'bad' customer using both data pulled from external credit bureau data as well as their own internal account management data. However, models that predict account-level profit are relatively uncommon. However, using AI/ML, models can be built to estimate complicated relationships at the account level. **The researchers have identified that advances in AI/ML gives banks the ability to precisely target profitable but risky customers.**

2. Implications of Profit-based Underwriting

   a. **The study finds that profit-based underwriting generally targets wealthy, high-spending, 'revolving' customers[2] , while risk score-based underwriting target low-activity 'transacting' customers.**

   b. Profit-based underwriting would generally lead to a significantly riskier portfolio than risk-based underwriting. However, this also depends on the type of underlying credit card loan portfolio. Nonetheless, given the significantly higher profitability of portfolios using profit-based underwriting, whether this increase is sufficient to counter-balance the corresponding increase in losses is a natural question.

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[1] Zenstar Technologies (2023). The Case for Re-inventing the Credit Decisioning Approach

[2] 'Revolving customers' refers to credit card users who carry a balance on their credit card from month to month, rather than paying off the entire balance in full. These customers are charged interest on the remaining balance. In contrast, 'transacting customers' pay off their entire balance every month and therefore typically do not incur interest charges.

[3] Revolving loans allow customers to borrow money up to a set credit limit, repay it, and borrow again as needed. Credit cards are an example of this type of loan.

c. Profit-based underwriting models focus on customers, who revolve their loans. Therefore, income for the bank is higher. Interest income typically accounts for 40-50% of banks' overall income from credit card business. Now, for portfolios that rely on high-end transactions which revolve their loans, profit-based underwriting leads to a relatively minor increase in risk. However, for portfolios that dip lower into the credit spectrum and are heavily reliant on customers that revolve on their loans[3] , profit-based underwriting significantly increases the riskiness of the portfolio. In fact, the increase in losses is higher than the increase in profits, meaning that even after adjusting for increased profit margins, the portfolios are riskier. **Hence, appropriate risk-based guardrails are important when using profit-based underwriting in acquisitions for portfolios that concentrate on lower credit quality customers.**

d. Looking at the risk spectrum, on one end, low-risk customers bring little in the way of revenue since they are primarily transactors and do not accumulate interest. At the other end, very high-risk customers with relatively small loan lives and credit limits, so they cannot accumulate the amount of interest over a sufficiently long period to generate a significant sum for the bank. A **'sweet spot' exists on the risk gradient that focuses on borrowers with sufficiently large credit limits, sufficiently long loan lives, and sufficient revolvers to accumulate finance charges that the borrowers subsequently pay back. The objective of profit-based underwriting should be to identify and enable operations in this sweet spot.** Interestingly, in risk-based underwriting, issuers may be tempted to continually loosen their credit standards to raise profit, which is less of an issue with profit-based underwriting, which focuses on the sweet spot.

e. Further advances in customer data collection can help enhance profit forecasting in higher-risk segments. For example, data which provide banks with information on borrowers' payment habits from other tradelines, would help further strengthen the profit-based underwriting models.

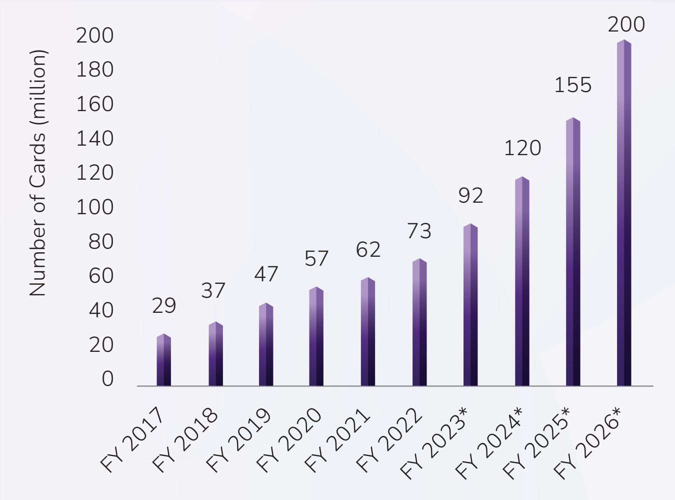
CREDIT CARD BUSINESS IN INDIA

India has traditionally been a debit card market. However, the growth in credit card issuance in the last decade has changed this narrative (Figures 1A and 1B). The volume of transactions via credit cards is expected to surpass debit cards by FY2024–2025[4]. The transaction volume is also anticipated to increase in the forthcoming years, driven by their integration with UPI (Unified Payments Interface) and the entry of new players into the credit card issuance market.

Interest income is the primary source of revenue for credit card issuers. Approximately 40–50% of a card issuer's revenue is derived from interest charges paid by 15–20% of customers, who maintain a revolving balance. The interest rates charged by issuers vary between 18% and 42% depending on the specific credit card product[5]. Another significant revenue stream for card issuers is interchange income. This income is generated from the fees charged for processing each transaction. Interchange fees, which differ based on card type and customer segment, usually range from 1.2–2%. This interchange income accounts for approximately 20–25% of the total revenue earned by the card issuer[5].

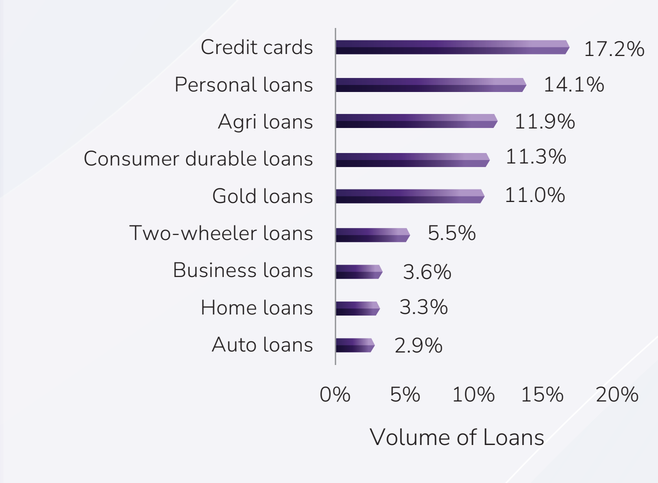
A recent World Bank survey (Figure 2) revealed that despite the remarkable rise in demand for revenue-generating credit cards, only 6% of the richest 60% of India's population own a credit card.

Figure 1A: Credit Card Issuance in India



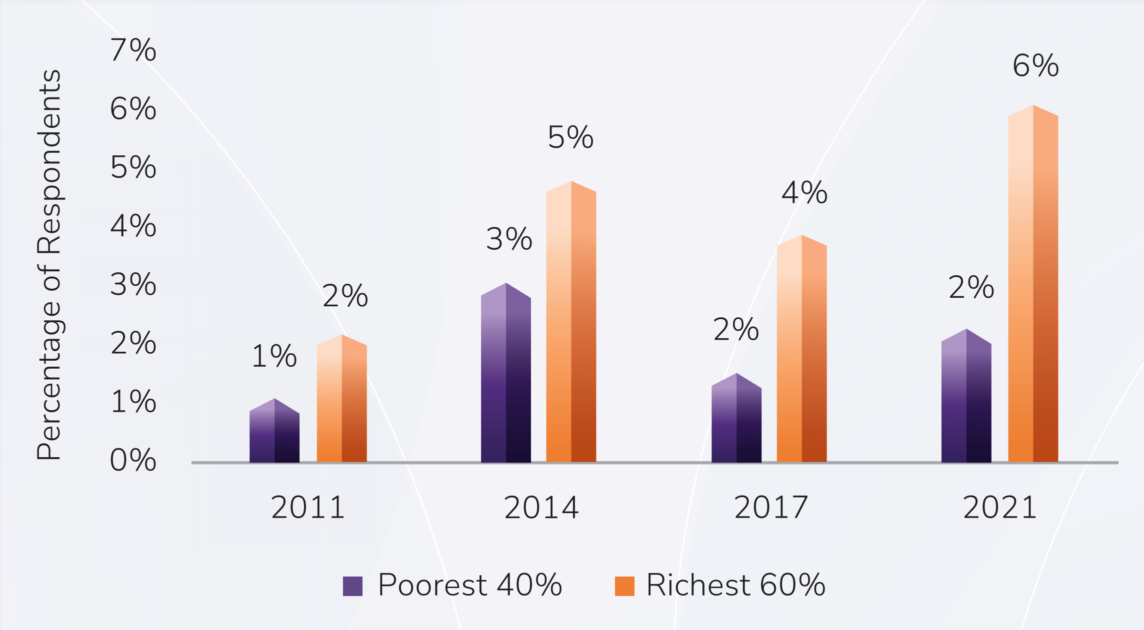
Source: Statista (2023). Credit and Debit Card Market in India

Figure 1B: Top Retail Loan Type in India, by Volume of Active Loans, FY 2022



Source: CIRF High Mark (2022). How India Lends FY2022

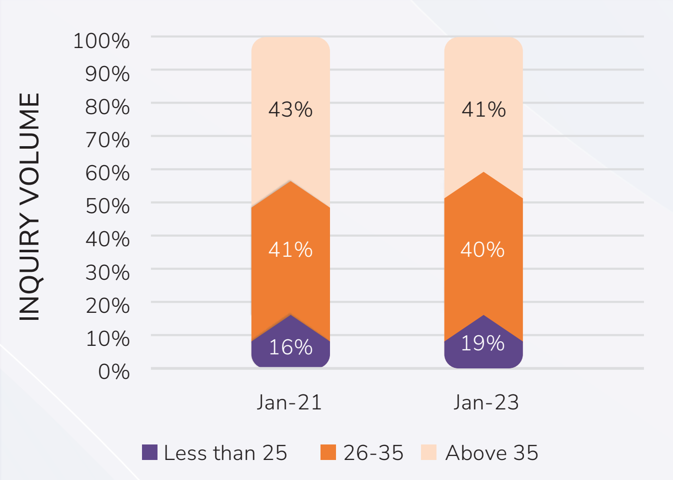
Figure 2: Credit Card Ownership (by income)



Source: The World Bank (2022). Global Findex Database 2021

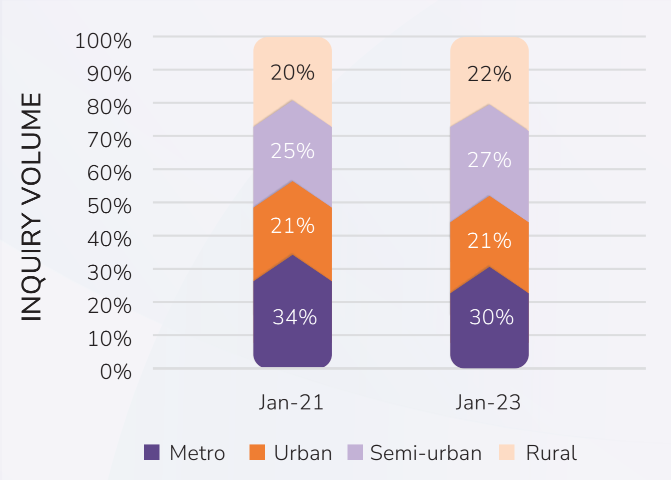
Furthermore, according to the TransUnion CIBIL report, the Indian retail credit market is witnessing a significant demographic shift driven by the increasing demand for credit among young consumers (Figure 3A), particularly those under 25 years of age. Additionally, there is a noticeable year-to-year growth in credit demand from rural and semi-urban areas (Figure 3B).

Figure 3A: Demand for Credit by Consumer Age



Source: TransUnion CIBIL (2023). Credit Market Indicator, October 2023

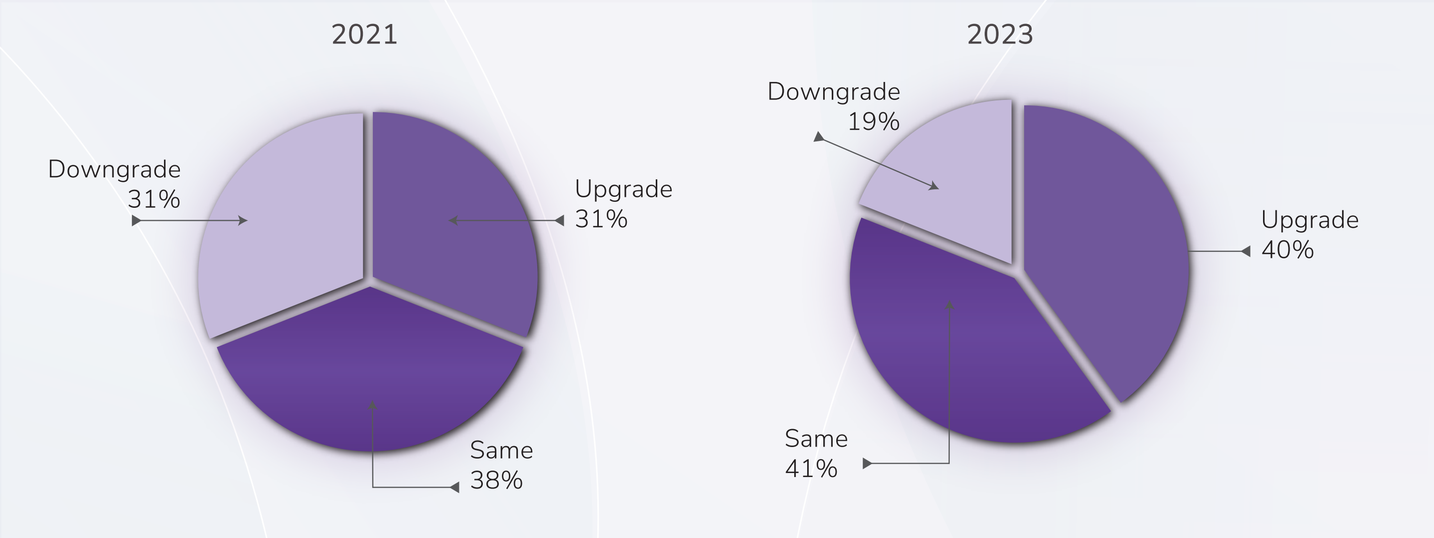
Figure 3B: Demand for Credit by City Tier



Source: TransUnion CIBIL (2023). Credit Market Indicator, October 2023

Indian consumers' credit behaviour has exhibited positive progress, as evidenced by an increased proportion of consumers with higher credit scores (Figure 4).

Figure 4: Near Prime Segment 12 Months Score Migration



Source: TransUnion CIBIL (2023). Credit Market Indicator, October 2023

Advancements in AI and ML have significantly influenced the thriving Indian start-up landscape, particularly in the fintech and technology sectors. This trend is a clear indicator for banks to embrace these developments. By leveraging ML algorithms, banks have a unique opportunity to enhance their credit card business through profit-focused underwriting models, tapping into the innovative momentum of India's technological ecosystem.

REFERENCES

1. CIRF High Mark (2022). How India Lends FY2022
2. Krivorotov, G. (2023). Machine Learning-based Profit Modeling for Credit card Underwriting-Implications for Credit Risk. Journal of Banking & Finance, Vol 149.
3. PwC (2021). The Changing Landscape of India's Credit Industry
4. PwC (2023). The Indian Payments Handbook, 2022-2027
5. Statista (2023). Credit and Debit Card Market in India
6. TransUnion CIBIL (2023). Credit Market Indicator, October 2023
7. World Bank (2022). Global Findex Database 2021
8. Zenstar Technologies (2023). The Case for Re-inventing the Credit Decisioning Approach