IDENTIFYING LOAN DEFAULT RISK EXPLORATORY DATA ANALYSIS

AGENDA

Problem Statement & Business Objectives

Data Overview & Methodology

Key Drivers of Default Risk (Univariate Analysis)

Segmentation Patterns (Bivariate Analysis)

Strategic Recommendations

PROBLEM STATEMENT & BUSINESS CONTEXT

Financial institutions face a crucial challenge in **balancing loan approval decisions** to mitigate financial loss. The decision to approve or reject a loan application carries **inherent risks**, which can impact the company's profitability and stability.

Key Risks:

•**Rejecting good applicants** → Lost business opportunities
•**Approving high-risk applicants** → Increased loan defaults

Objective:

•Use **Exploratory Data Analysis (EDA)** to detect **patterns in repayment behavior**.
•Identify key **risk indicators** to optimize loan decisions.
•Ensure **profitable and data-driven lending** while reducing defaults.

DATA OVERVIEW

Datasets Used:

- application_data.csv - Primary data with applicant profiles
- previous_application.csv - Historical loan decisions

Data Cleaning Steps:

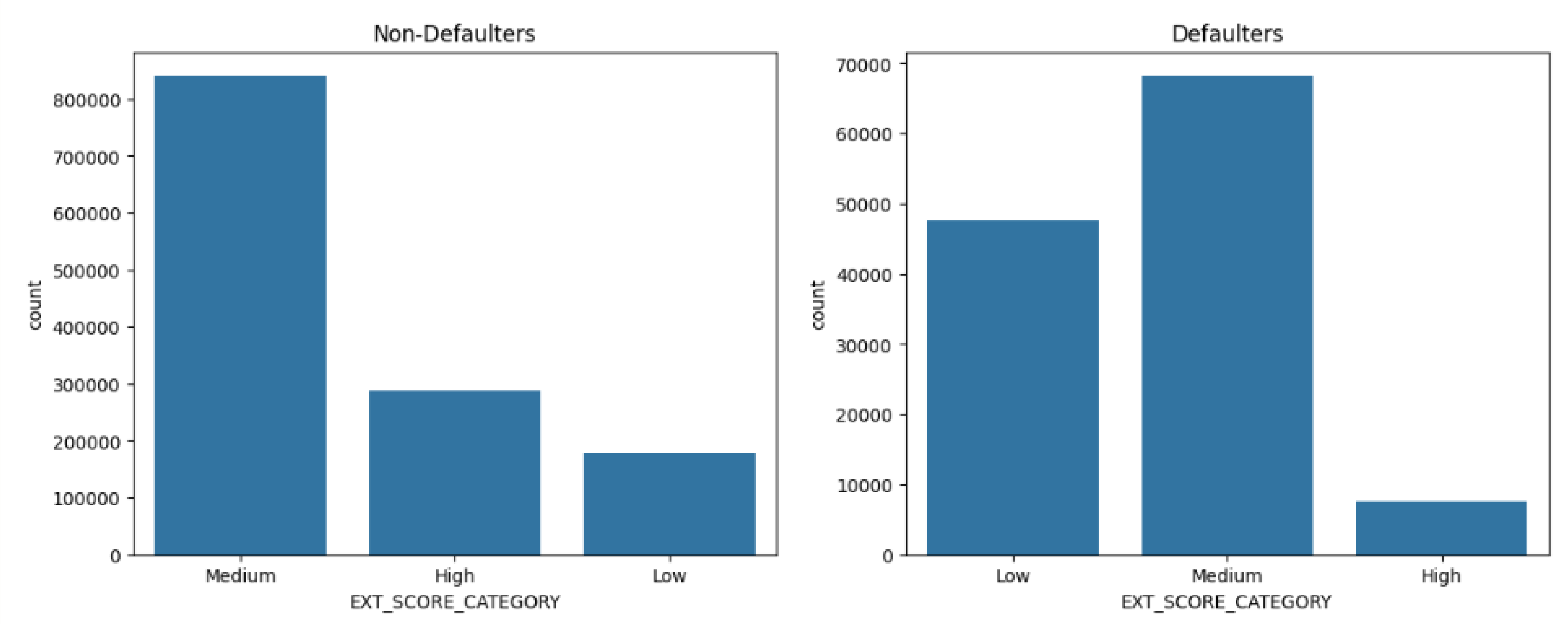
- Missing value treatment
- Removing unnecessary columns
- Fixing readability of columns
- Managing outliers
- Data Imbalance check

METHODOLOGY

- Approach:
  - Univariate analysis (distribution of key variables).
  - Bivariate analysis (correlation with TARGET).
  - Segmentation by risk factors (e.g., income type, credit score).

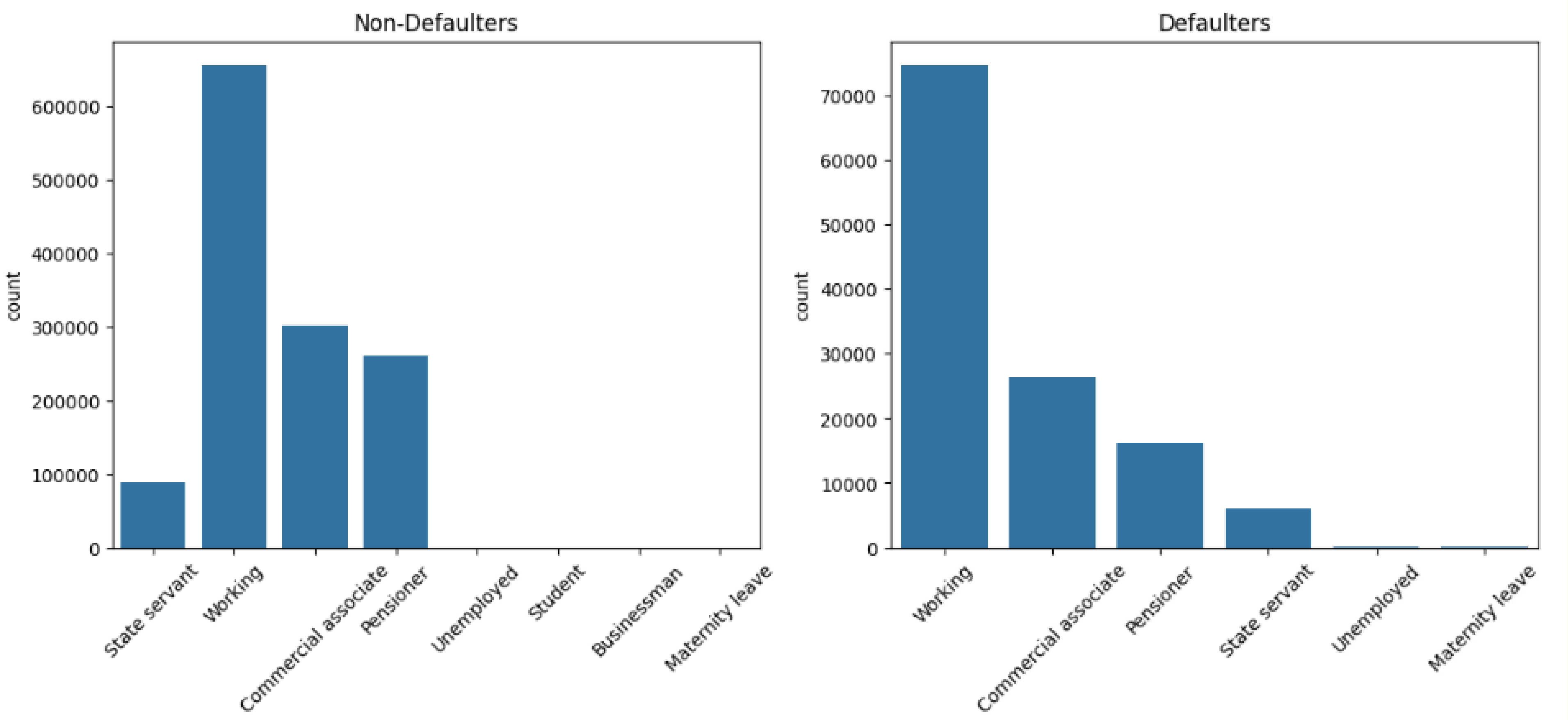
- Tools: Python (Pandas, Matplotlib/Seaborn)

KEY DRIVER 1 – EXTERNAL SCORES



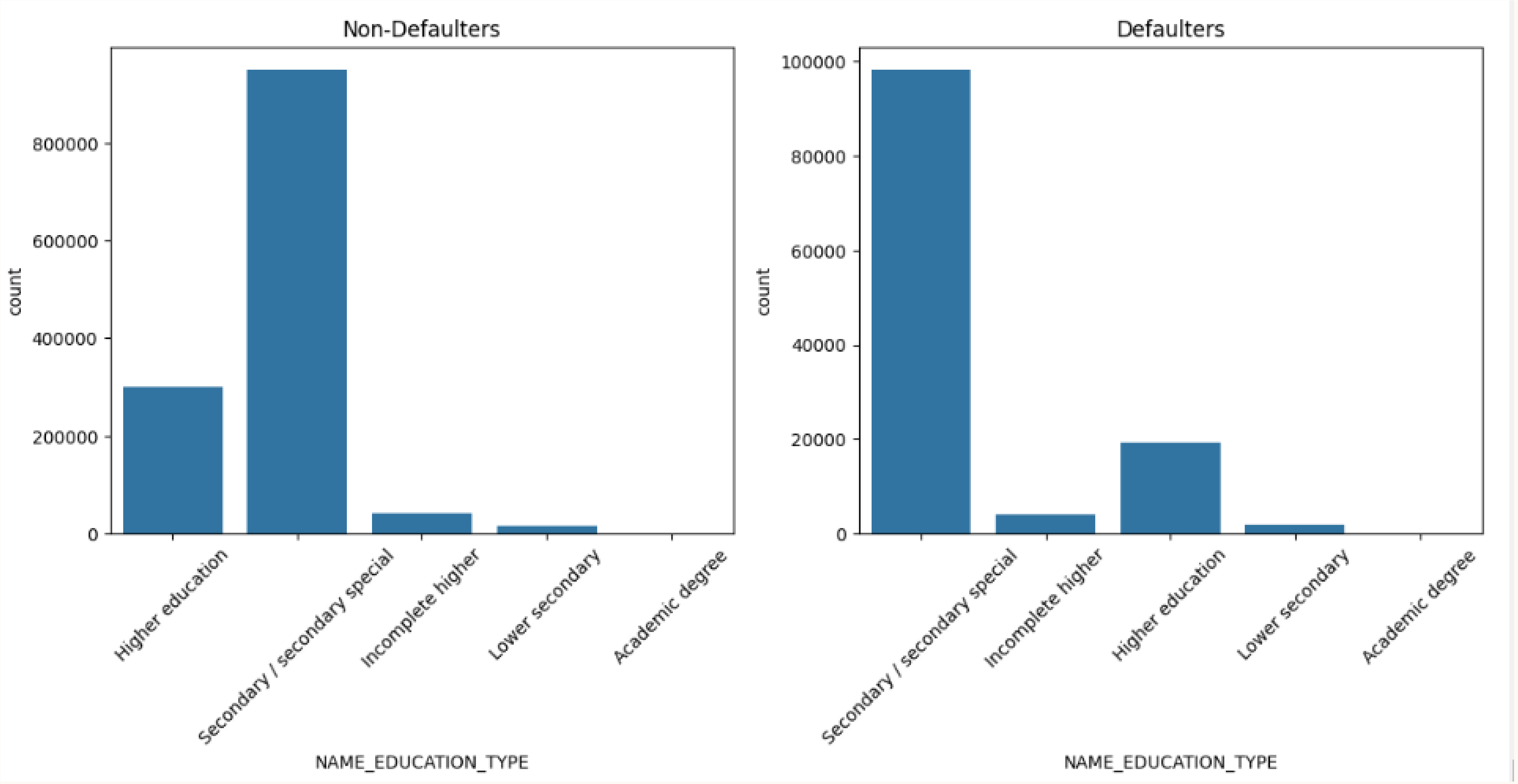
Insight: Low scores indicate higher default risk.

KEY DRIVER 2 – INCOME TYPE



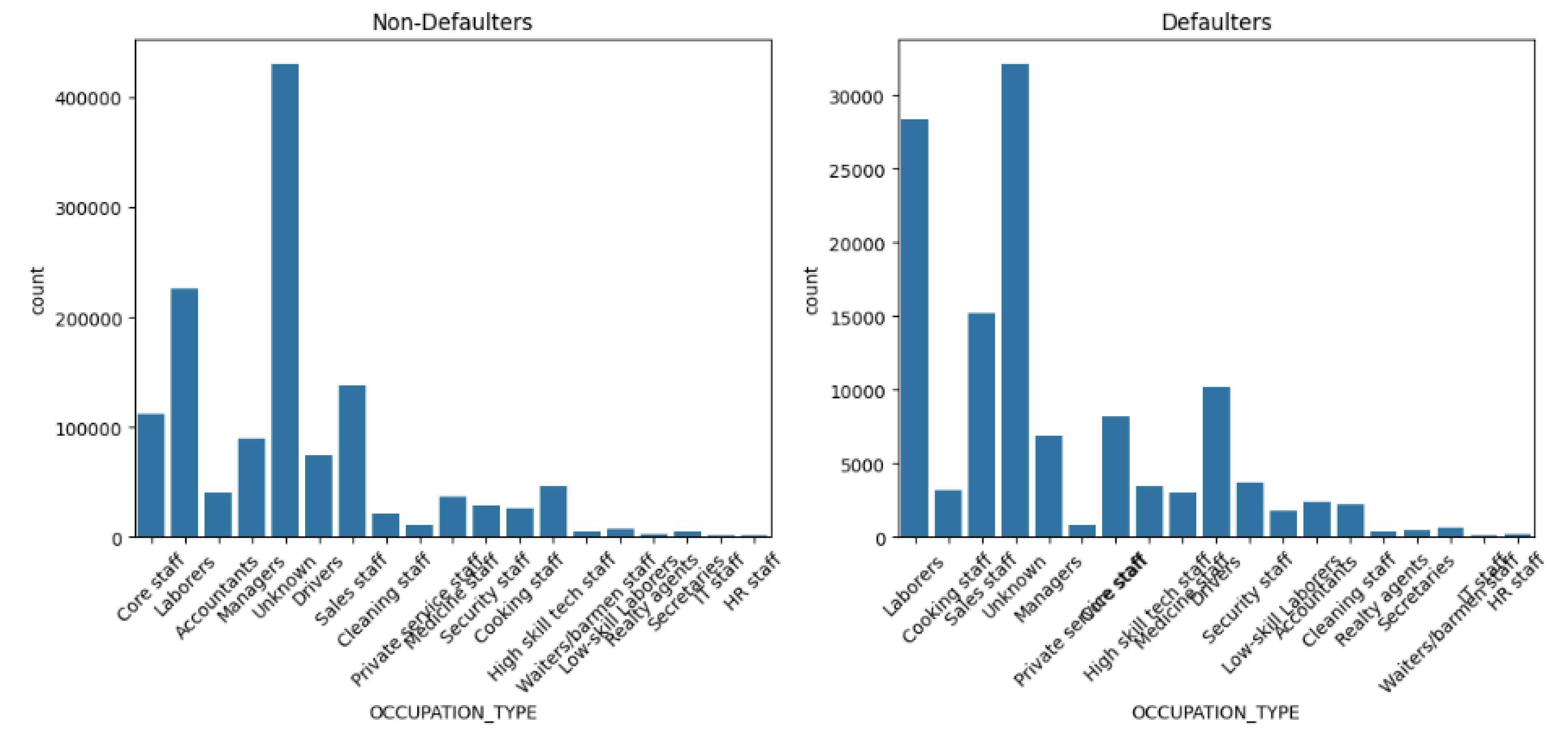
Insight: Income type affects stability; higher proportion of 'Working' among defaulters suggests instability.

KEY DRIVER 3 – EDUCATION TYPE



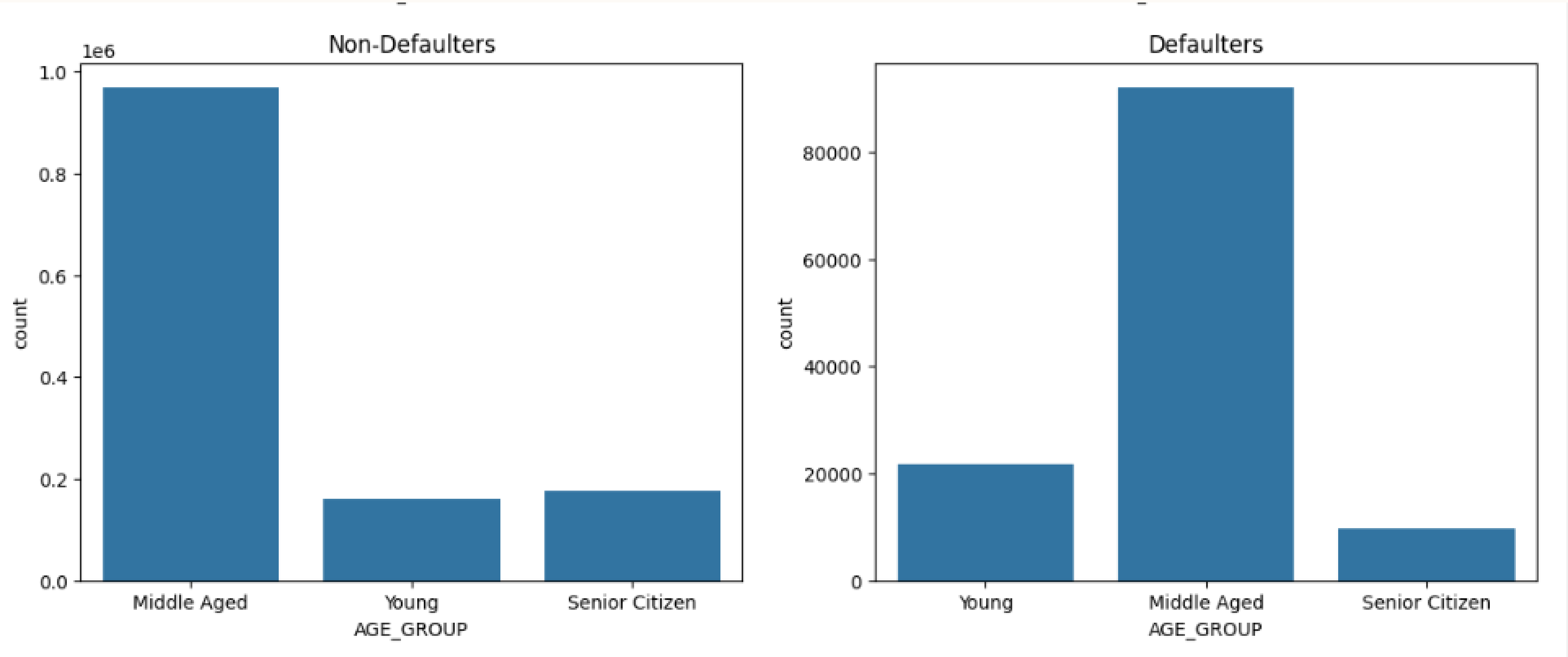
Insight: Lower education levels correlate with higher default risk.

KEY DRIVER 4 – OCCUPATION TYPE



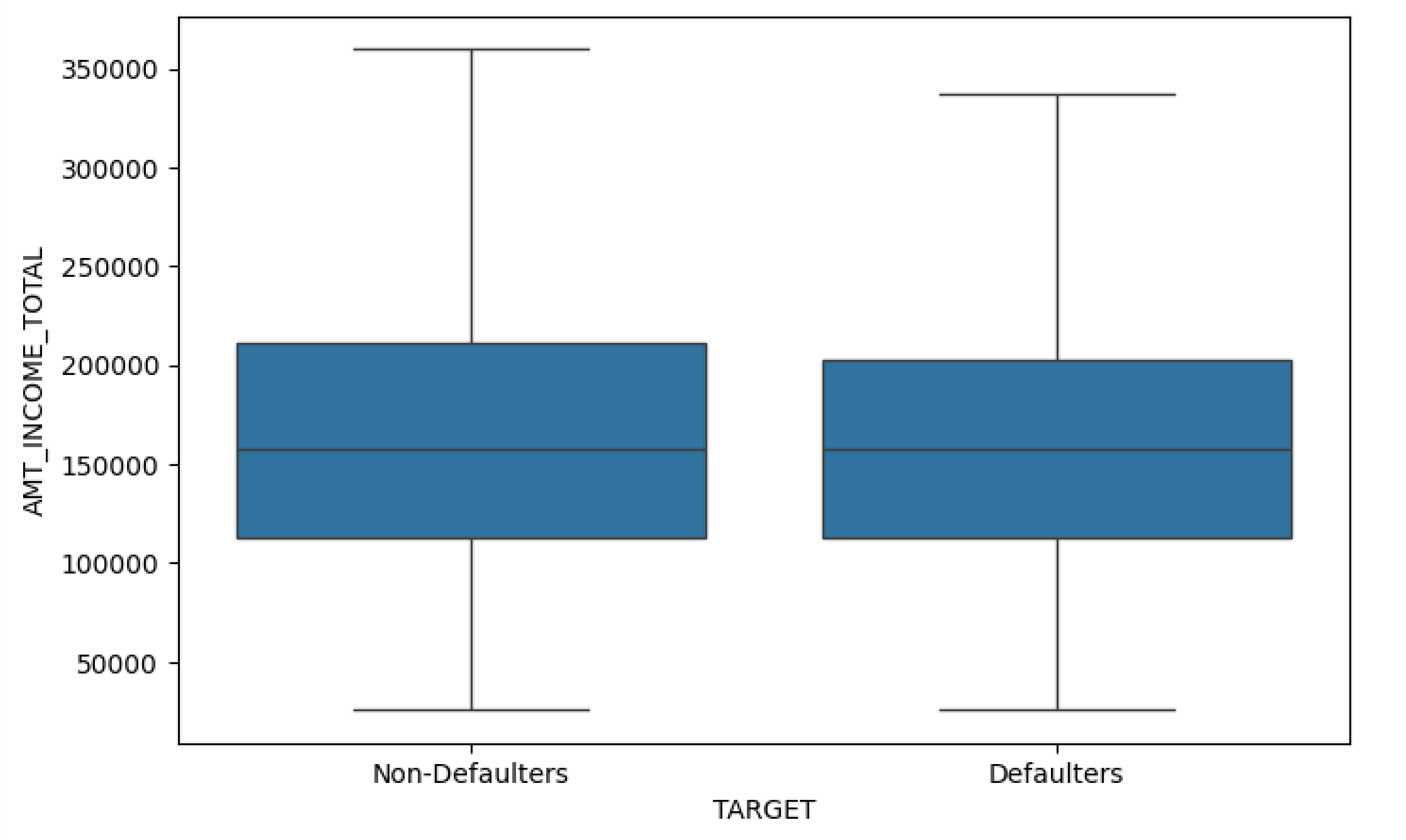
Insight: Lower-skilled occupations (laborers, drivers) show higher default rates.

KEY DRIVER 5 – AGE GROUP



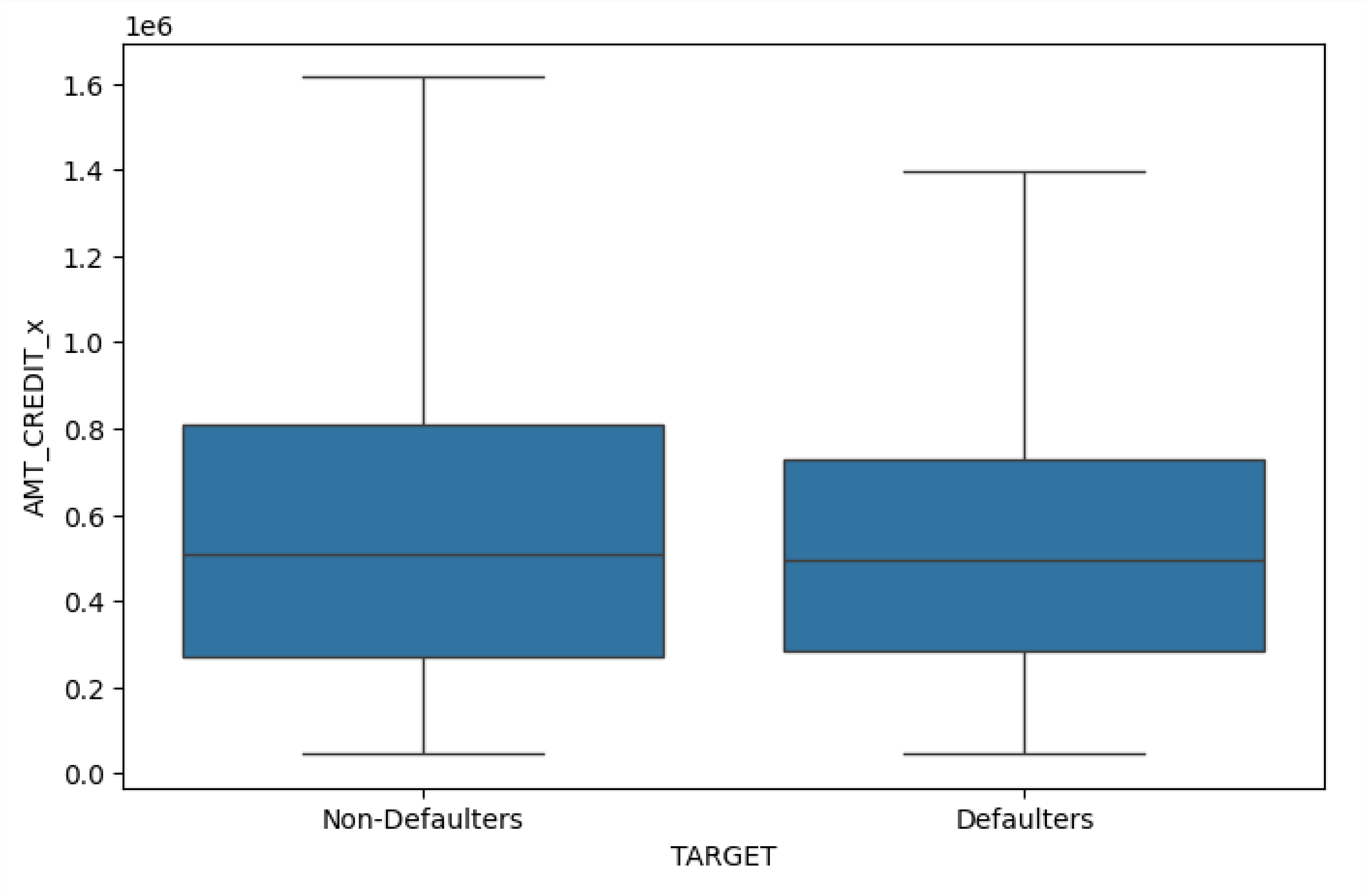
Insight: Younger borrowers have higher default risk due to financial instability, lower savings, and limited credit history.

KEY DRIVER 6 – TOTAL INCOME



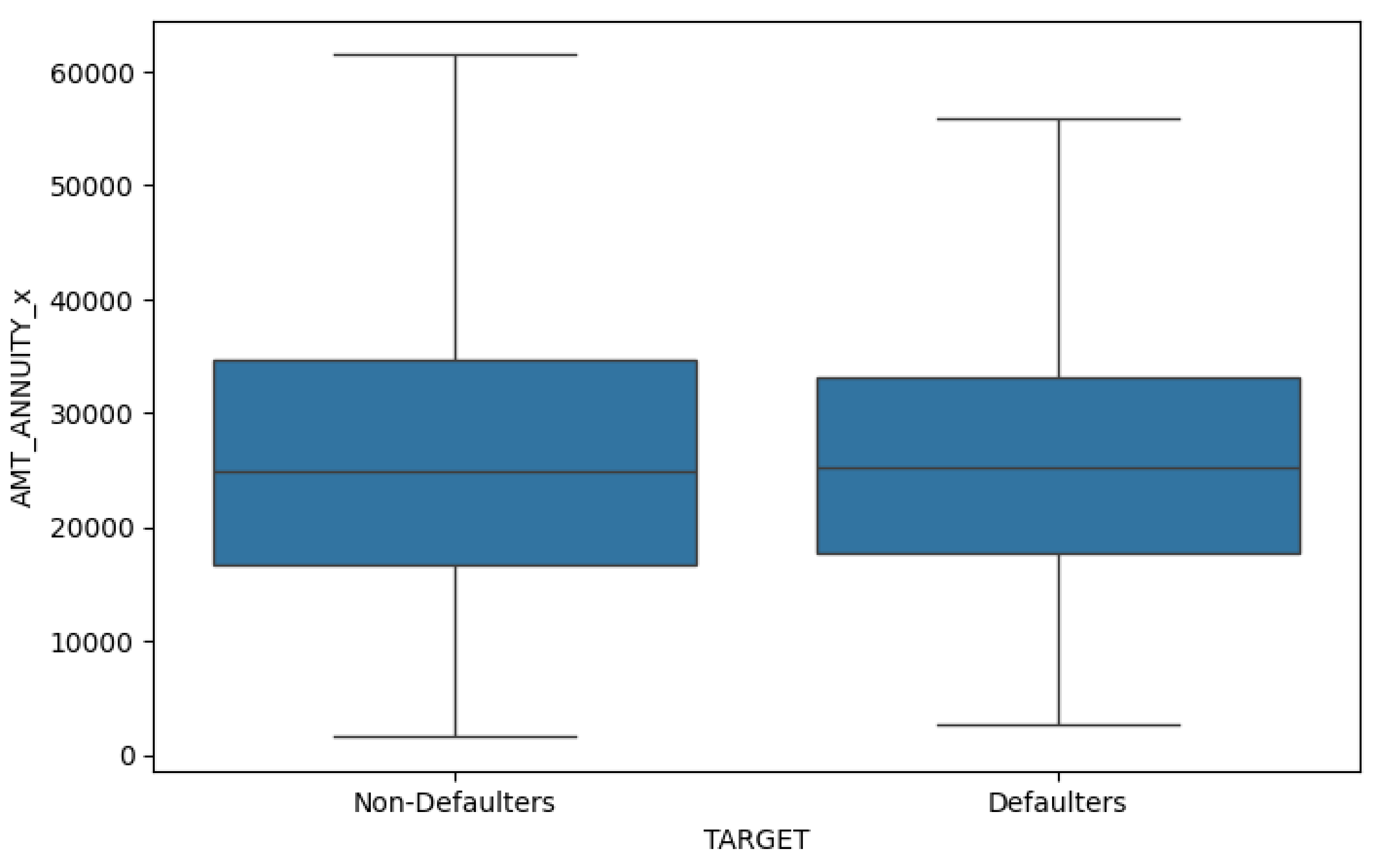
Insight: Higher-income individuals are underrepresented among defaulters.

KEY DRIVER 7 – CREDIT AMOUNT



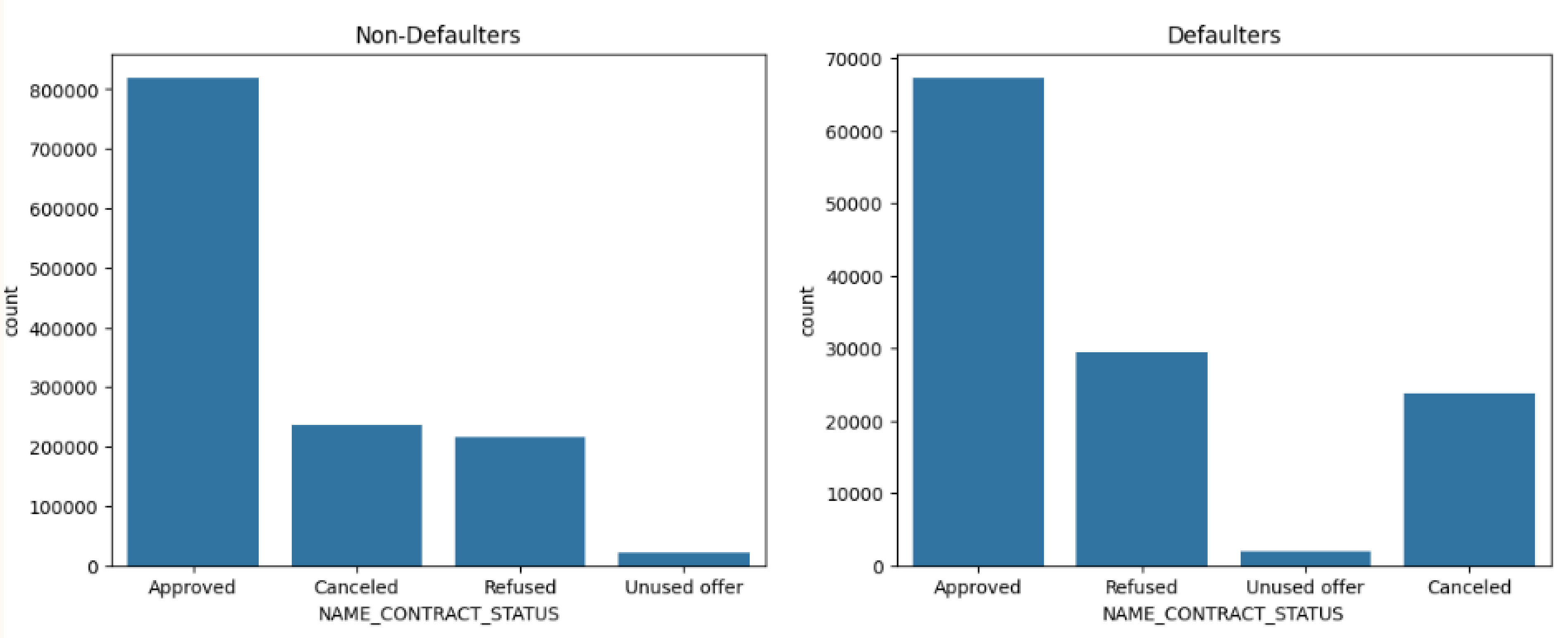
Insight: Lower median and 75th percentile credit amounts among defaulters suggest lenders are cautious.

KEY DRIVER 8 – LOAN ANNUITY



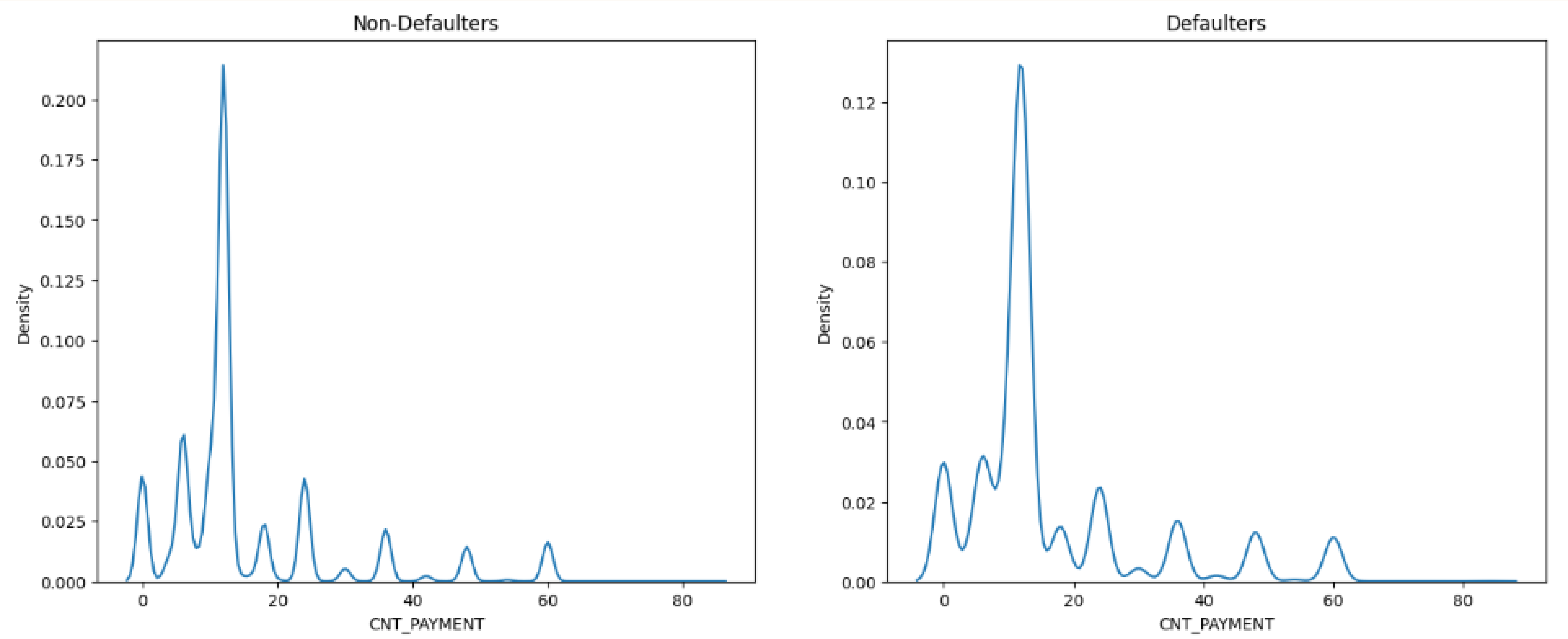
Insight: Higher annuity burden may contribute to default risk.

KEY DRIVER 9 – CONTRACT STATUS OF PREVIOUS APPLICATION



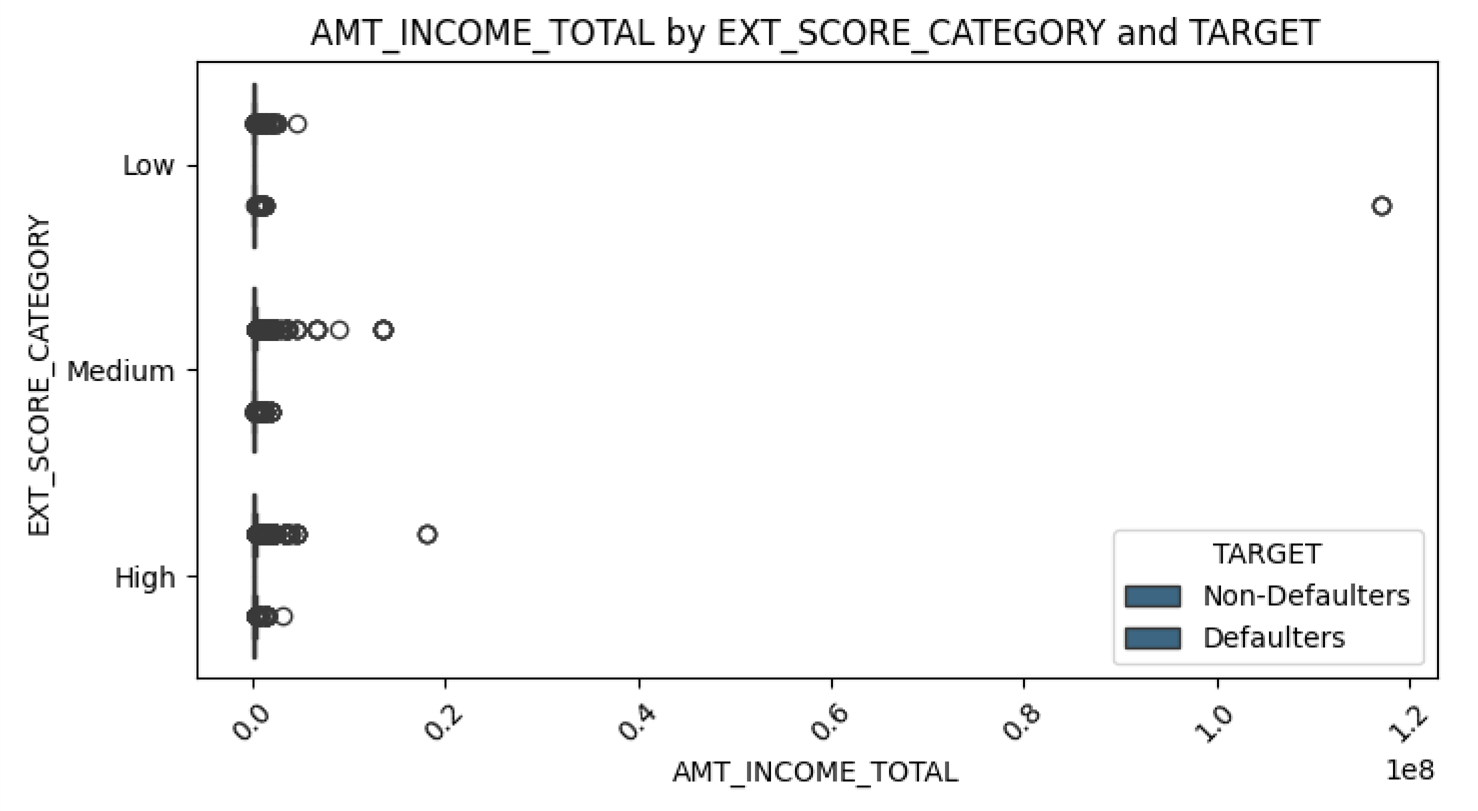
Insight: More refusals in previous applications indicate higher future default risk.

KEY DRIVER 10 – TERM OF CREDIT AT PREVIOUS APPLICATION



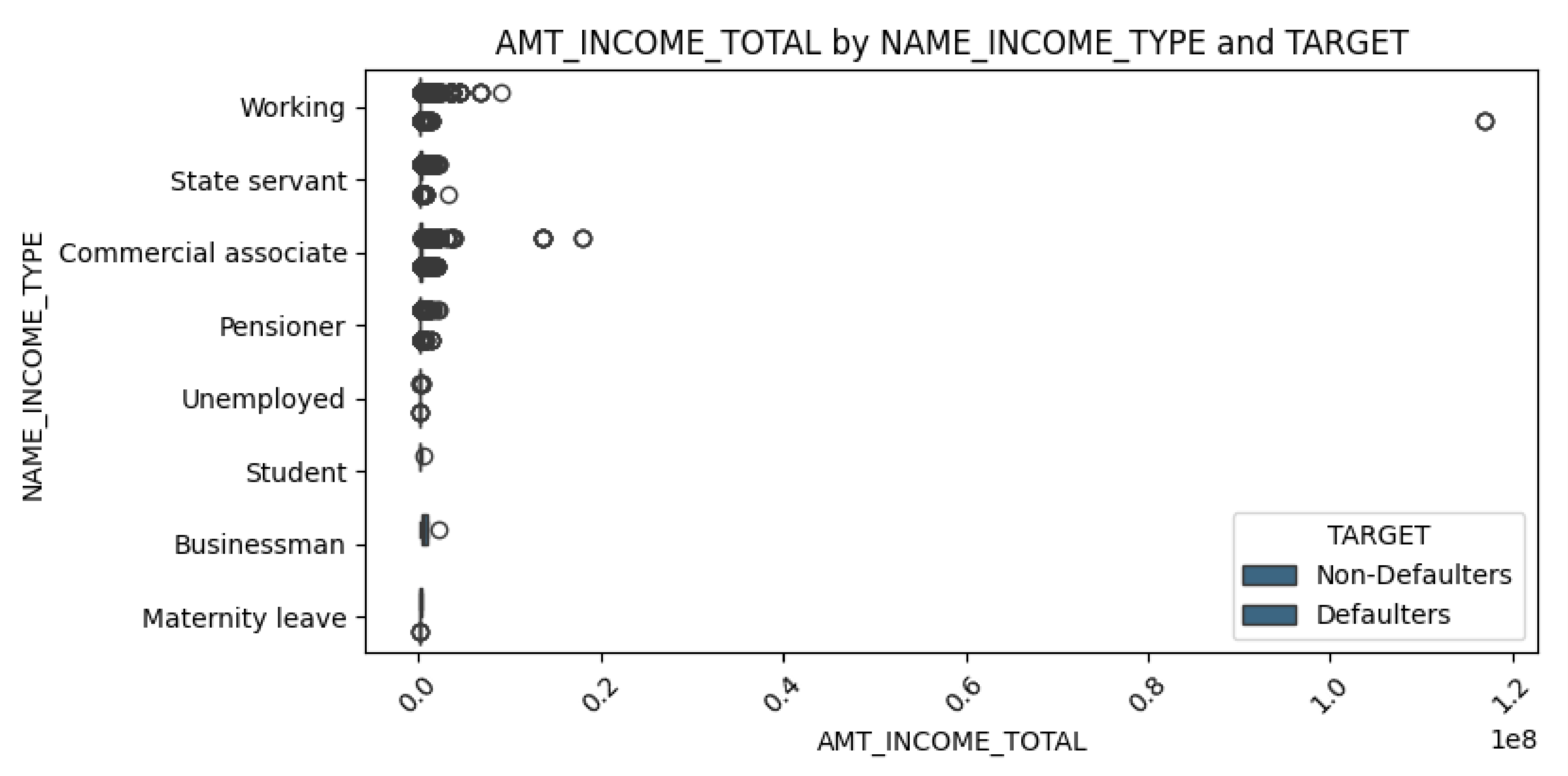
Insight: Defaulters tend to have shorter repayment terms more often, which may indicate financial strain or that lenders impose stricter conditions on high-risk borrowers.

PATTERN: INCOME TOTAL BY EXTERNAL SCORE



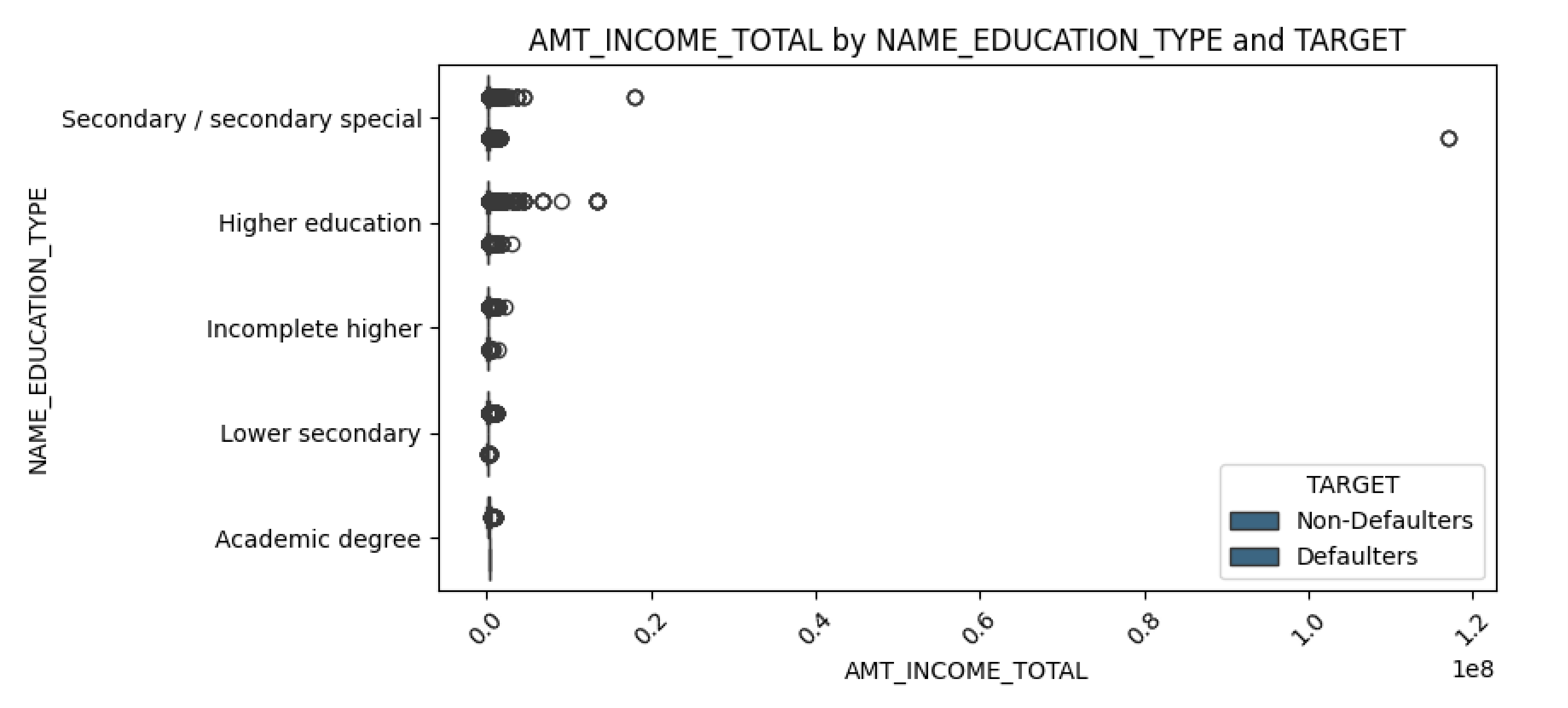
Insight: Higher-income individuals are underrepresented among defaulters, particularly in lower external score segments, underscoring the importance of external credit scoring.

PATTERN: INCOME TOTAL BY INCOME TYPE



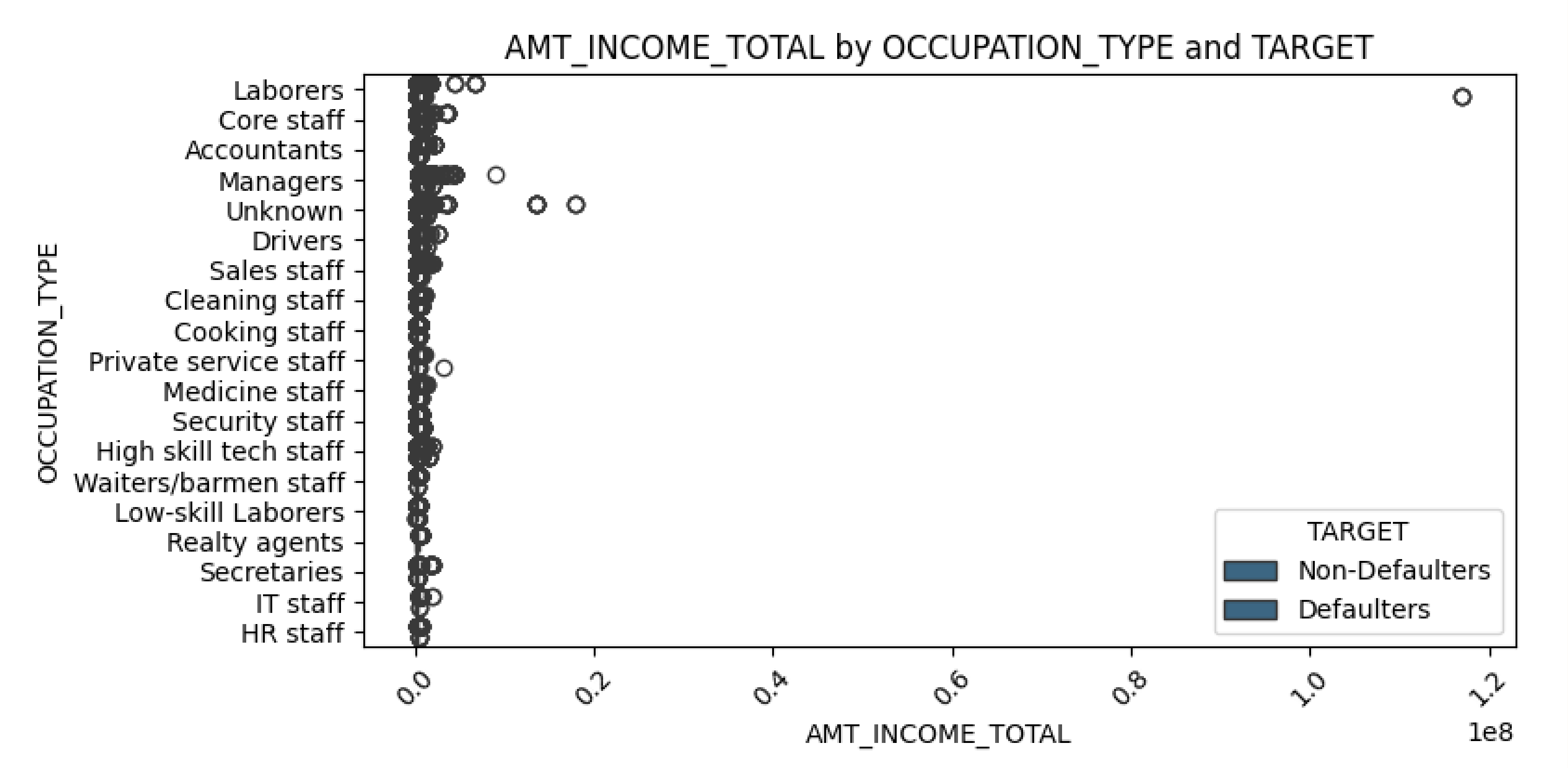
Insight: Income type indicates stability; a higher share of “Working” (often less stable) among defaulters signals increased default risk.

PATTERN: INCOME TOTAL BY EDUCATION TYPE



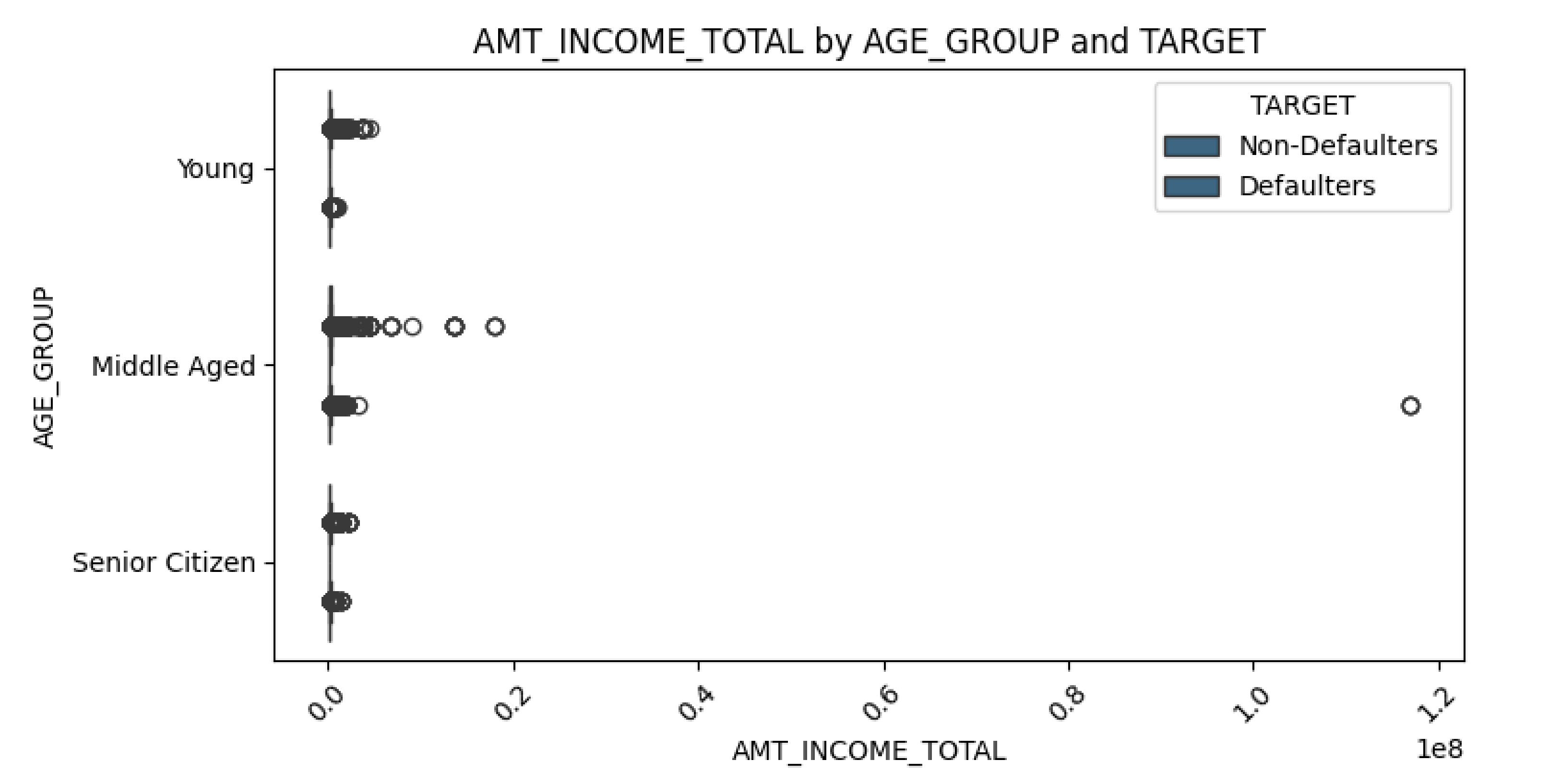
Insight: Lower educational attainment correlates with reduced financial stability and higher default risk.

PATTERN: INCOME TOTAL BY OCCUPATION TYPE



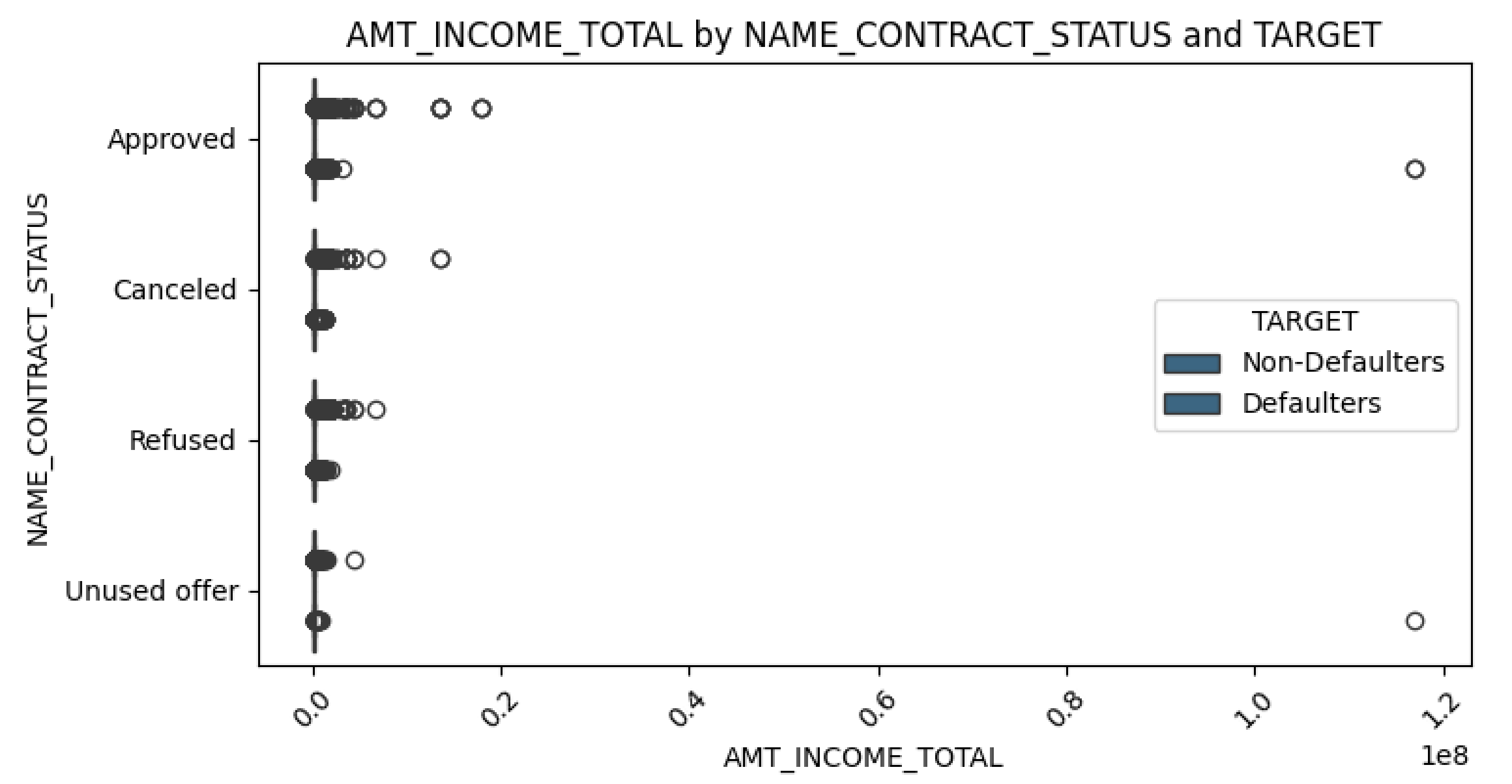
Insight: Occupation reflects job stability; lower-income, less stable occupations are more likely to default.

PATTERN: INCOME TOTAL BY AGE GROUP



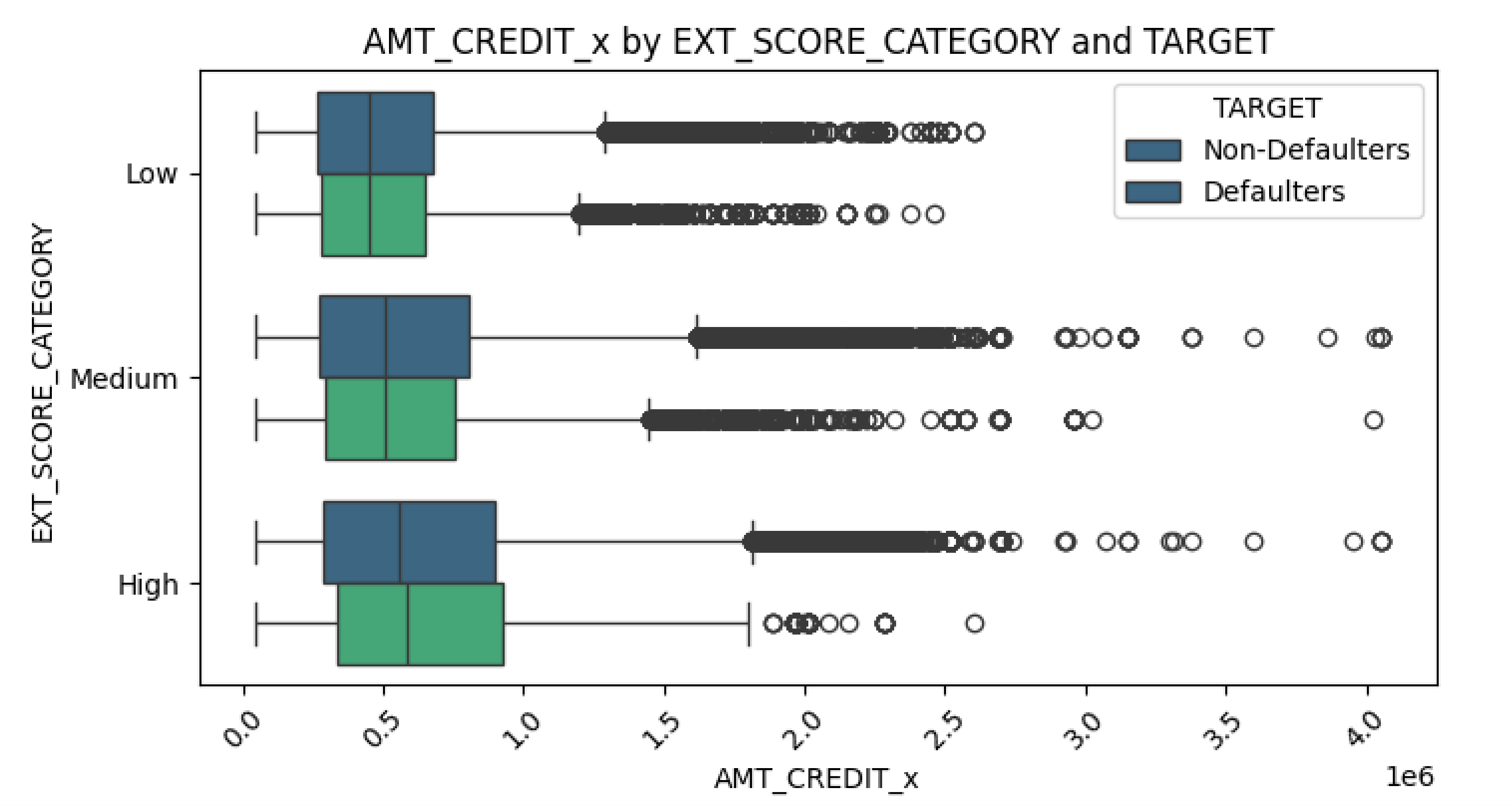
Insight: Younger borrowers may have lower maximum income potential, increasing default risk.

PATTERN: INCOME TOTAL BY PREVIOUS LOAN APPLICATION STATUS



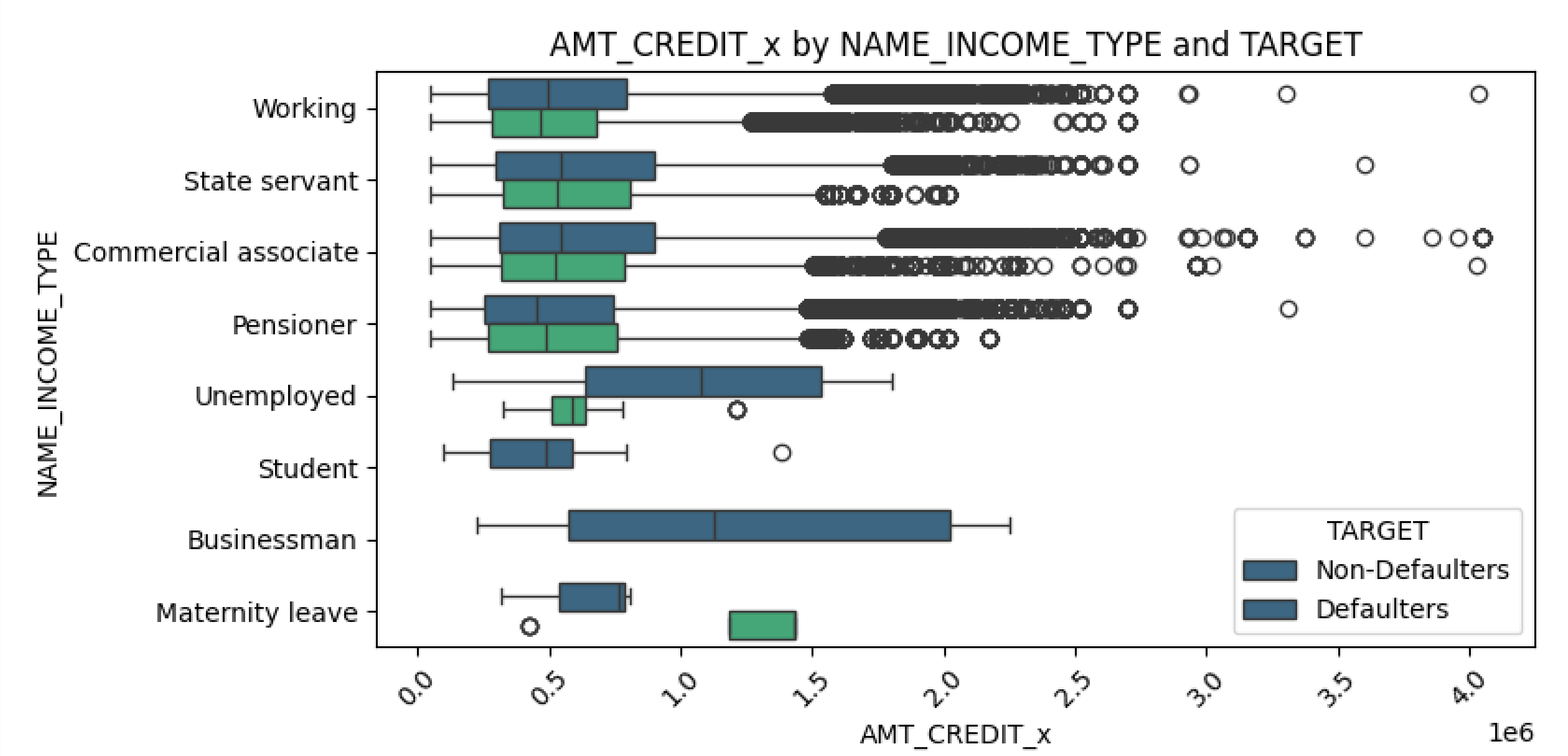
Insight: A history of refusals is a strong predictor of future default risk.

PATTERN: CREDIT AMOUNT BY EXTERNAL SCORE



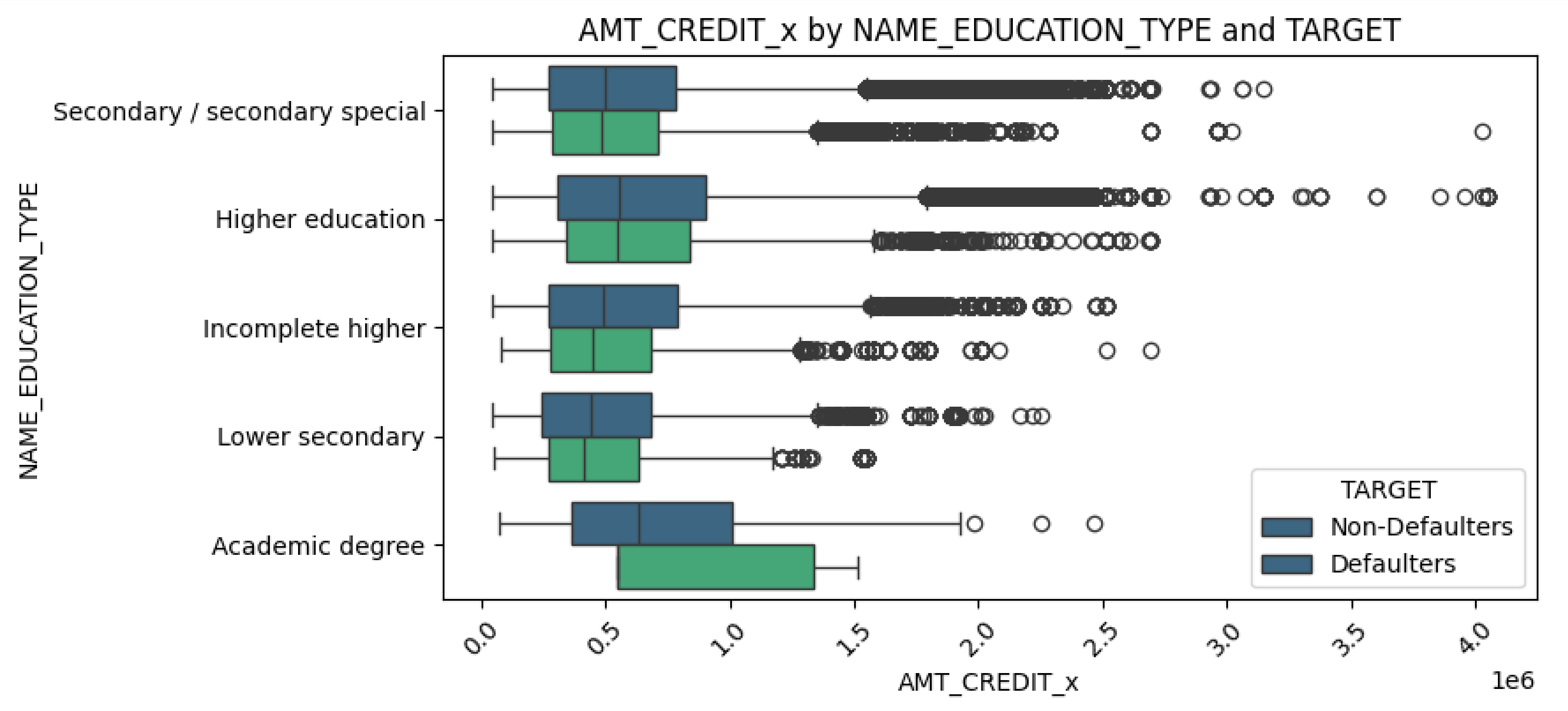
Insight: Lower approved credit amounts for defaulters suggest risk-adjusted lending based on external scores.

PATTERN: CREDIT AMOUNT BY INCOME TYPE



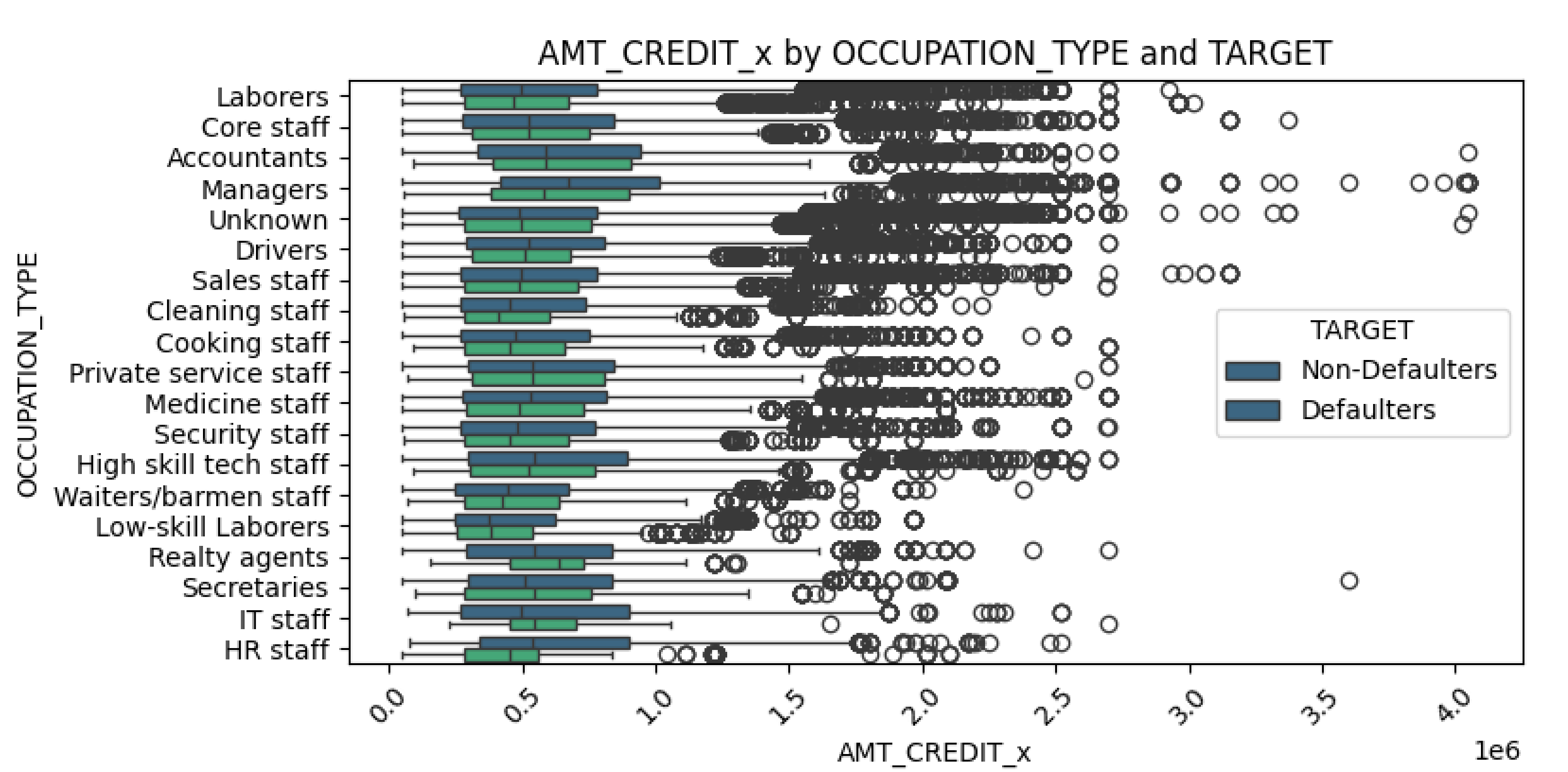
Insight: Lenders limit credit for riskier income types, indicating higher default risk.

PATTERN: CREDIT AMOUNT BY EDUCATION TYPE



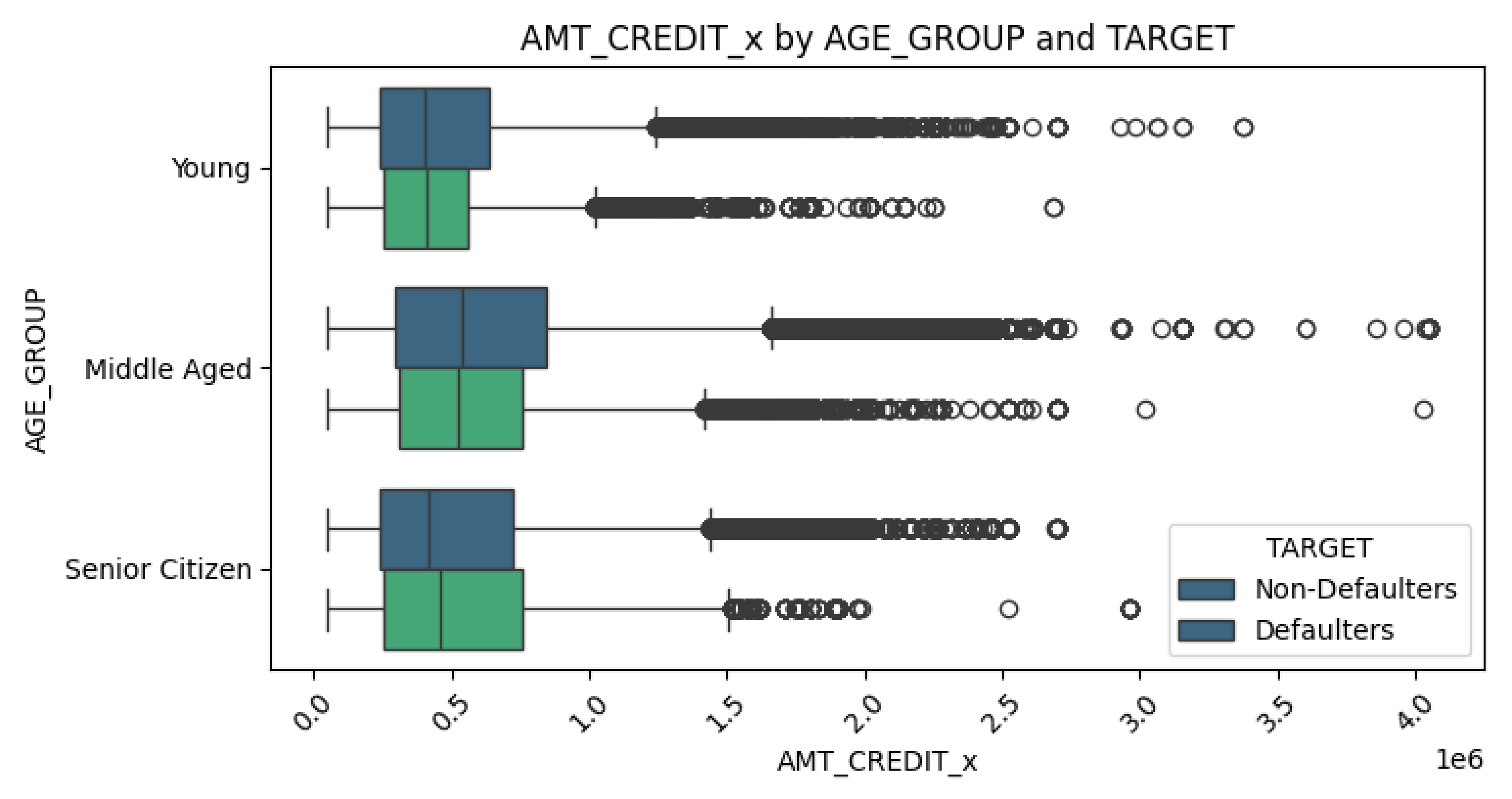
Insight: A more uniform credit amount for defaulters may reflect conservative lending to riskier (lower-educated) borrowers.

PATTERN: CREDIT AMOUNT BY OCCUPATION TYPE



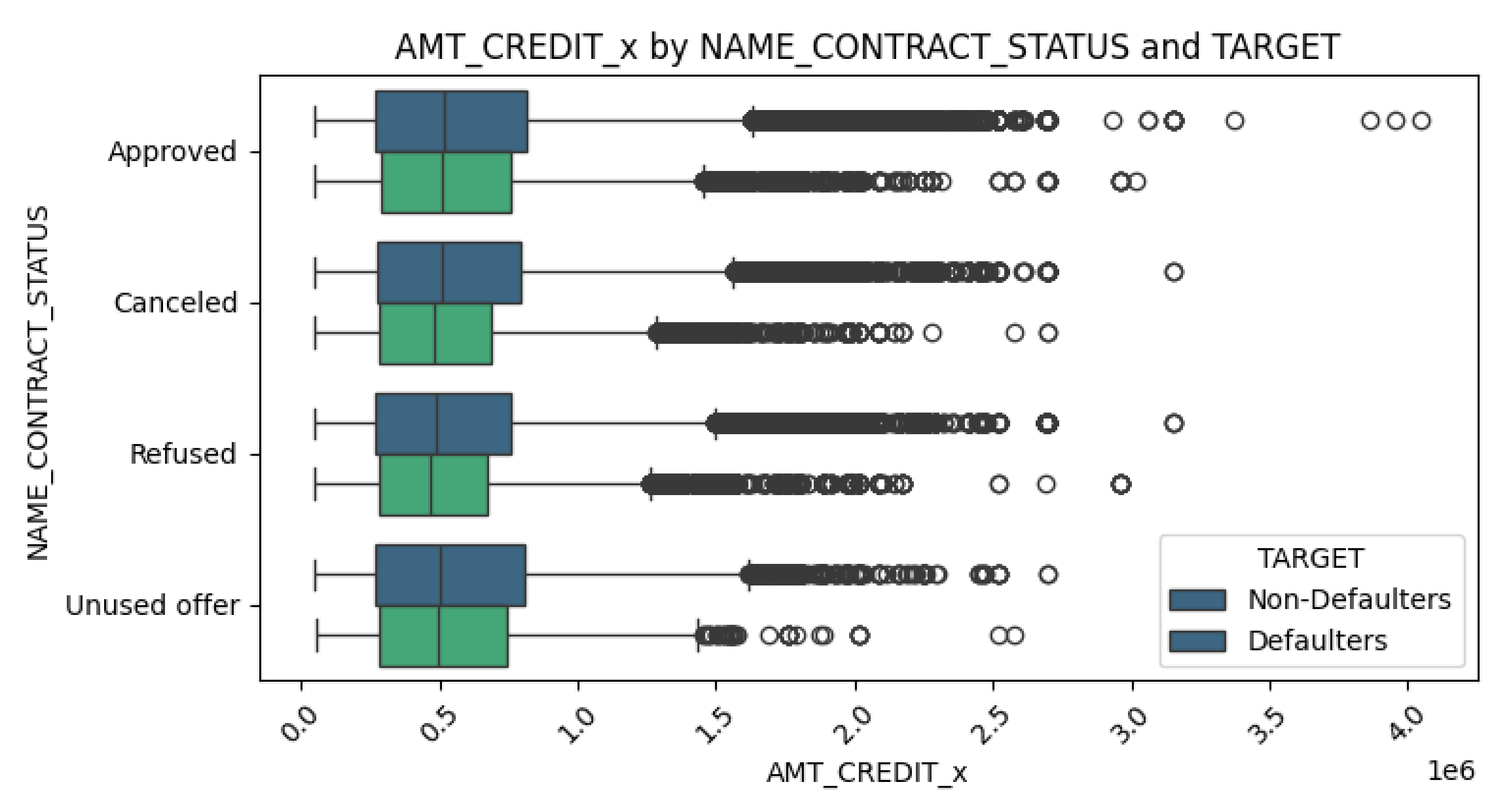
Insight: Occupation influences lending decisions; credit limits in lower-skilled occupations signal higher risk.

PATTERN: CREDIT AMOUNT BY AGE GROUP



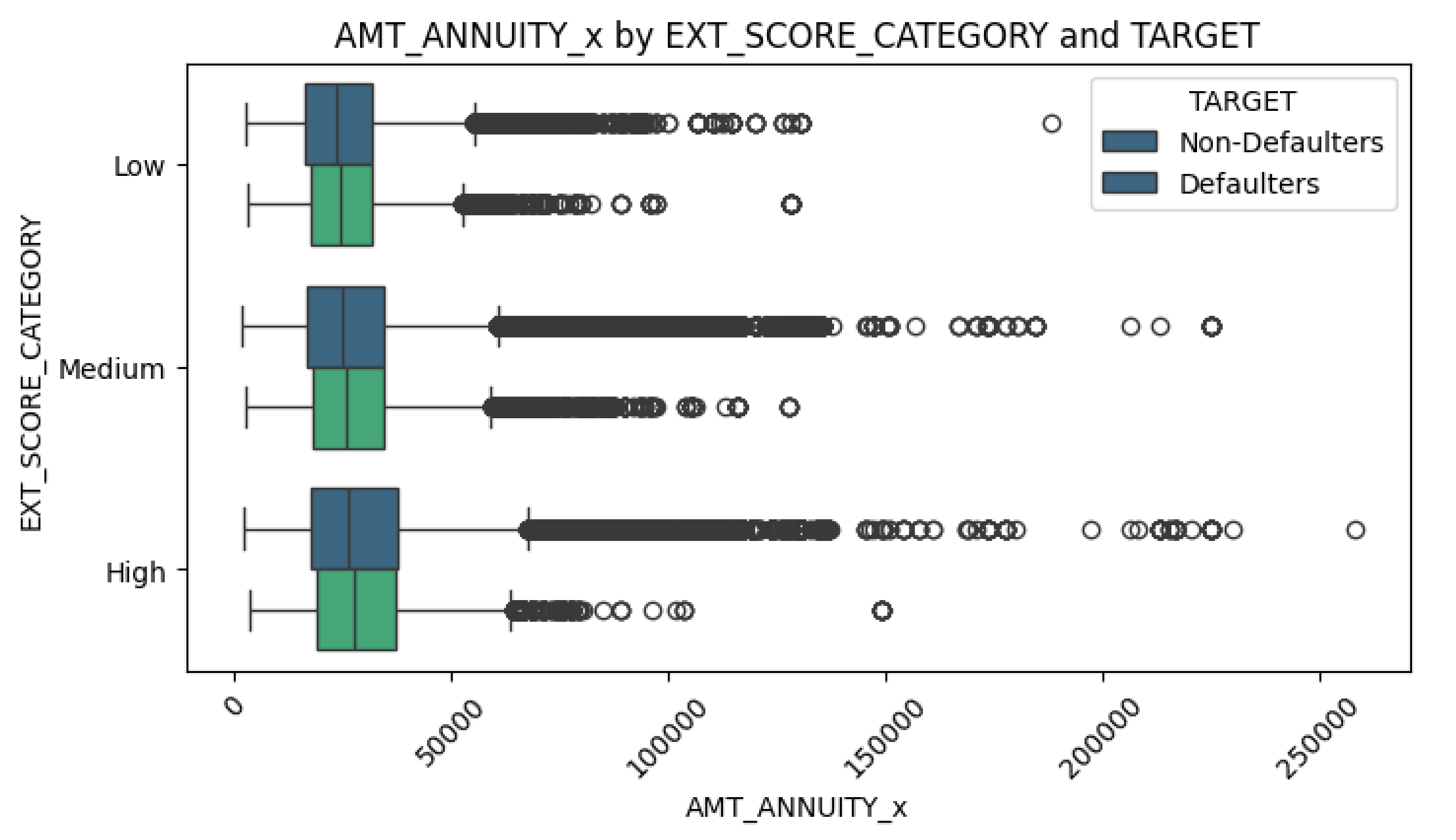
Insight: Age affects borrowing; lower credit for older defaulters may indicate cautious lending for perceived higher risk.

PATTERN: CREDIT AMOUNT BY PREVIOUS LOAN APPLICATION STATUS



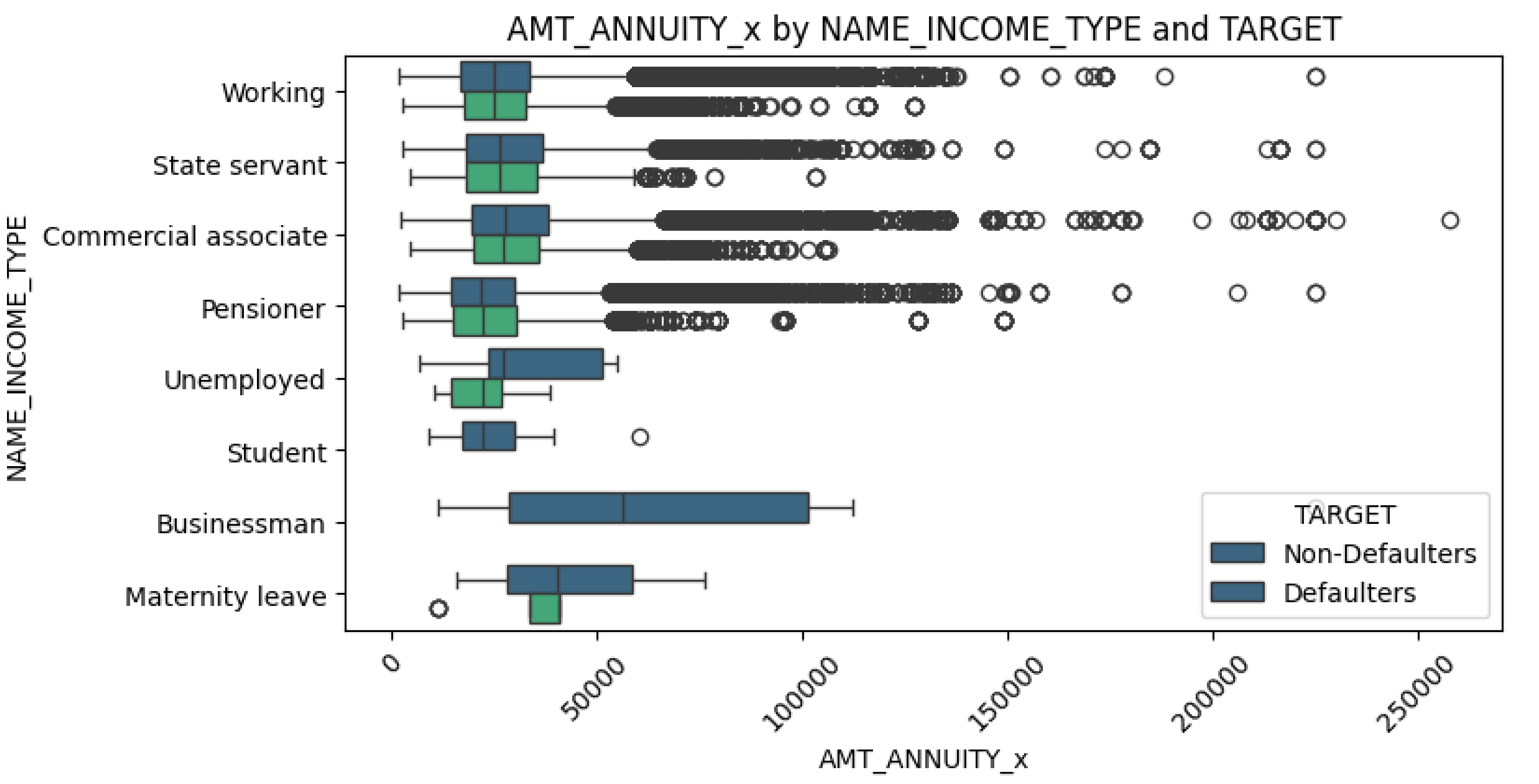
Insight: Historical lending outcomes correlate with current credit limits—more adverse histories result in lower approvals.

PATTERN: LOAN ANNUITY BY EXTERNAL SCORE



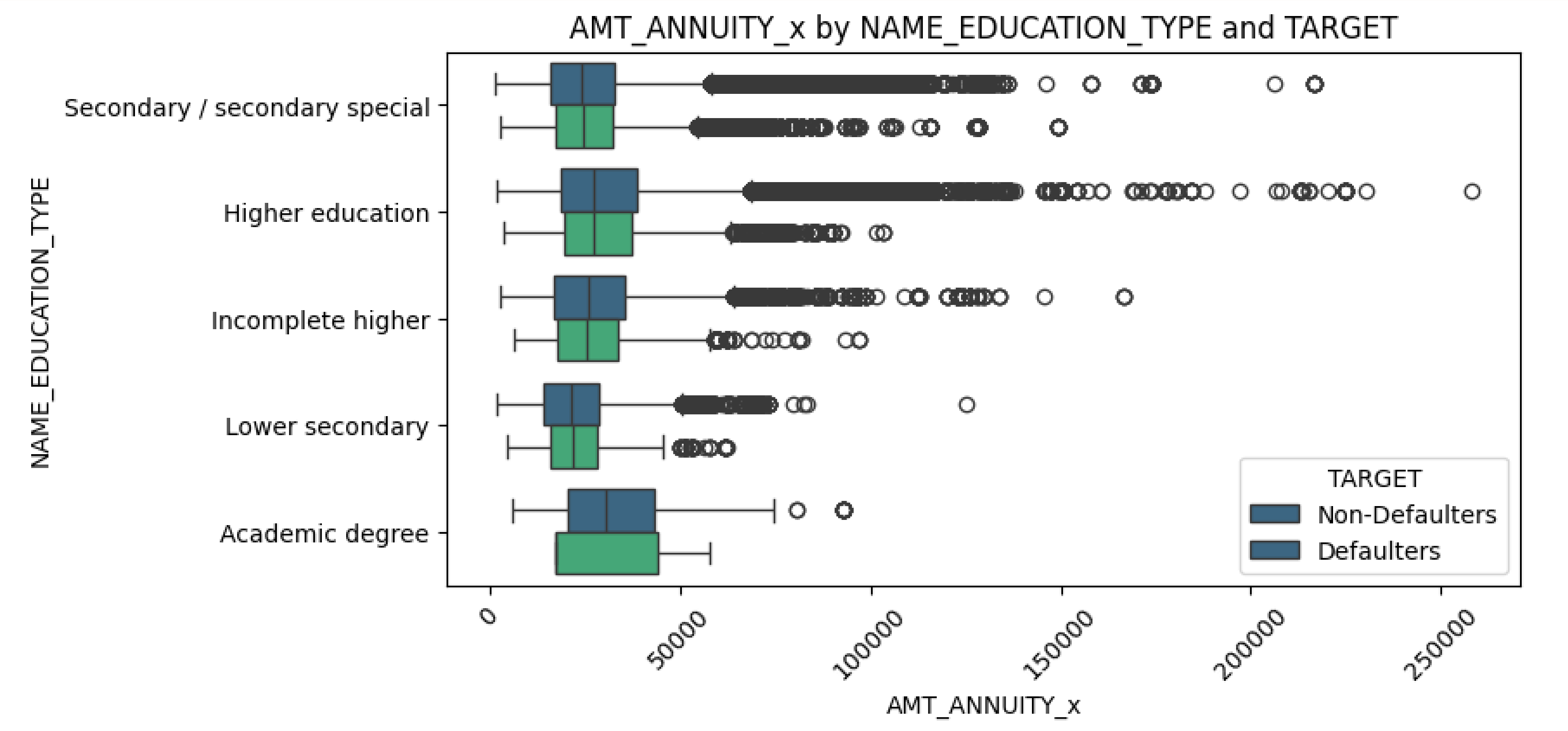
Insight: A higher regular payment burden, even if slight, can stress repayment ability when coupled with lower external scores.

PATTERN: LOAN ANNUITY BY INCOME TYPE



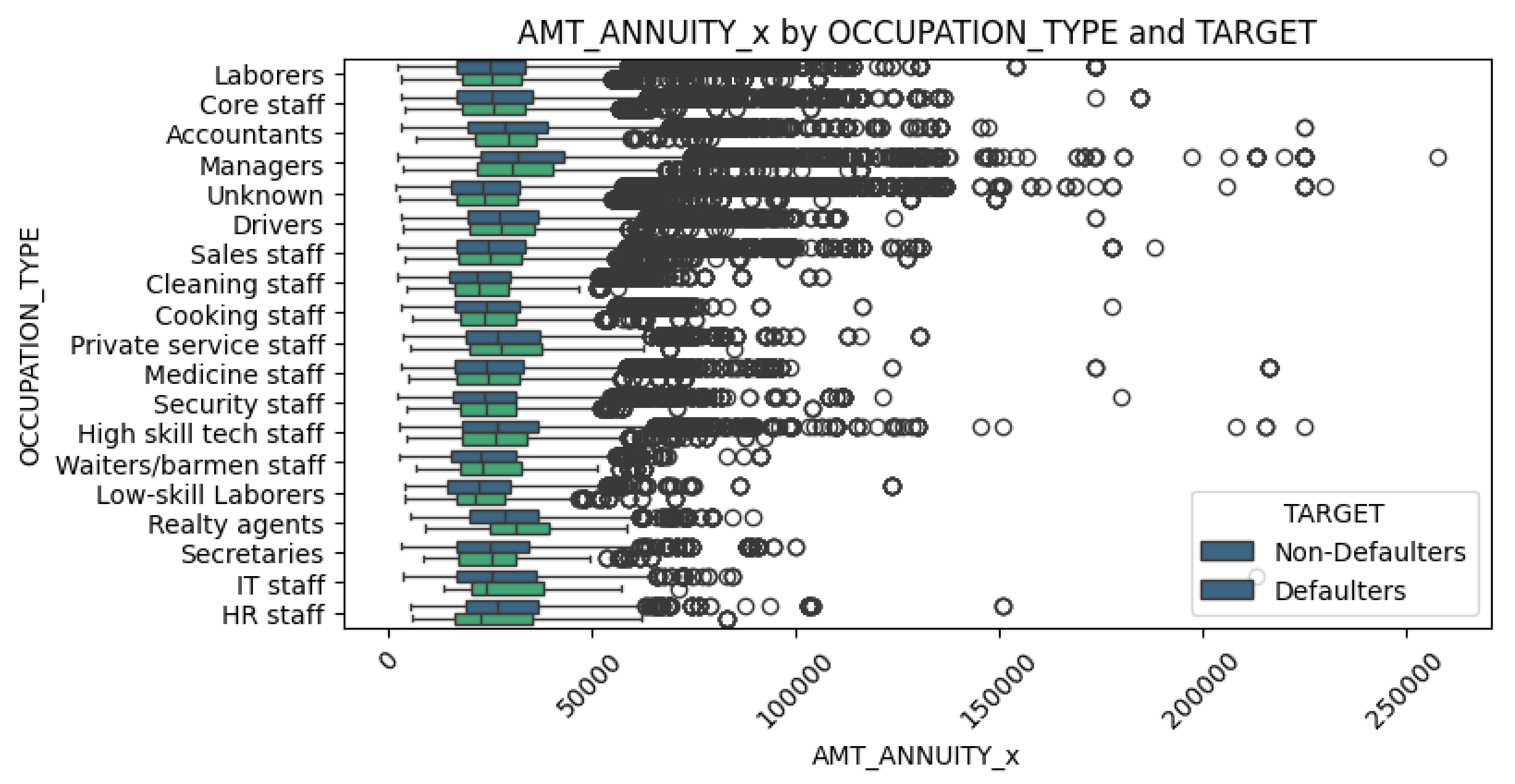
Insight: Payment burdens relative to income type help reveal affordability issues among riskier income groups.

PATTERN: LOAN ANNUITY BY EDUCATION TYPE



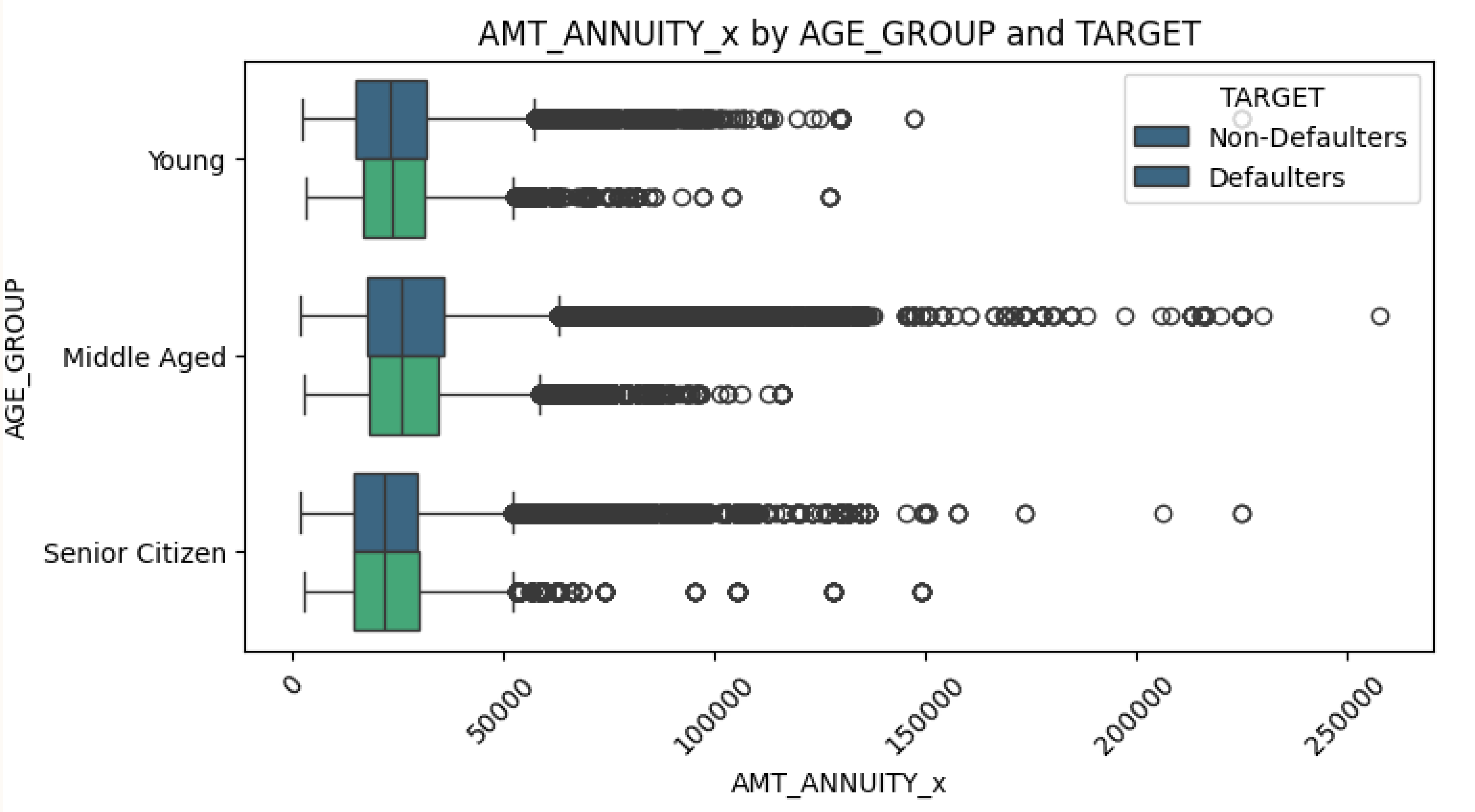
Insight: Latest annuity amounts imply that differences in default risk may lie in borrowers' capacity to pay rather than in the payment amount itself.

PATTERN: LOAN ANNUITY BY OCCUPATION TYPE



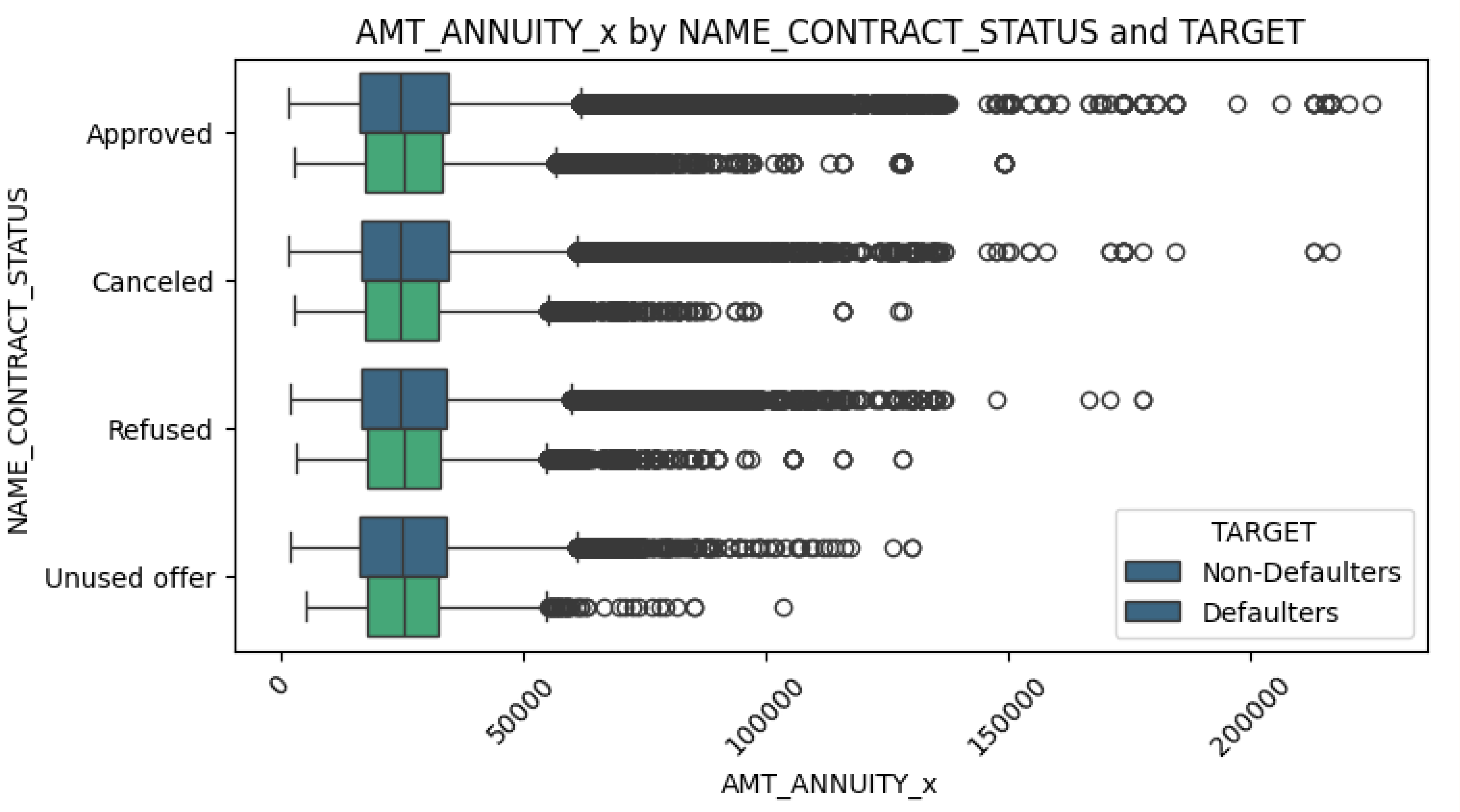
Insight: While the annuity is standard, the underlying income differences by occupation may still drive risk, even if the payment amount is fixed.

PATTERN: LOAN ANNUITY BY AGE GROUP



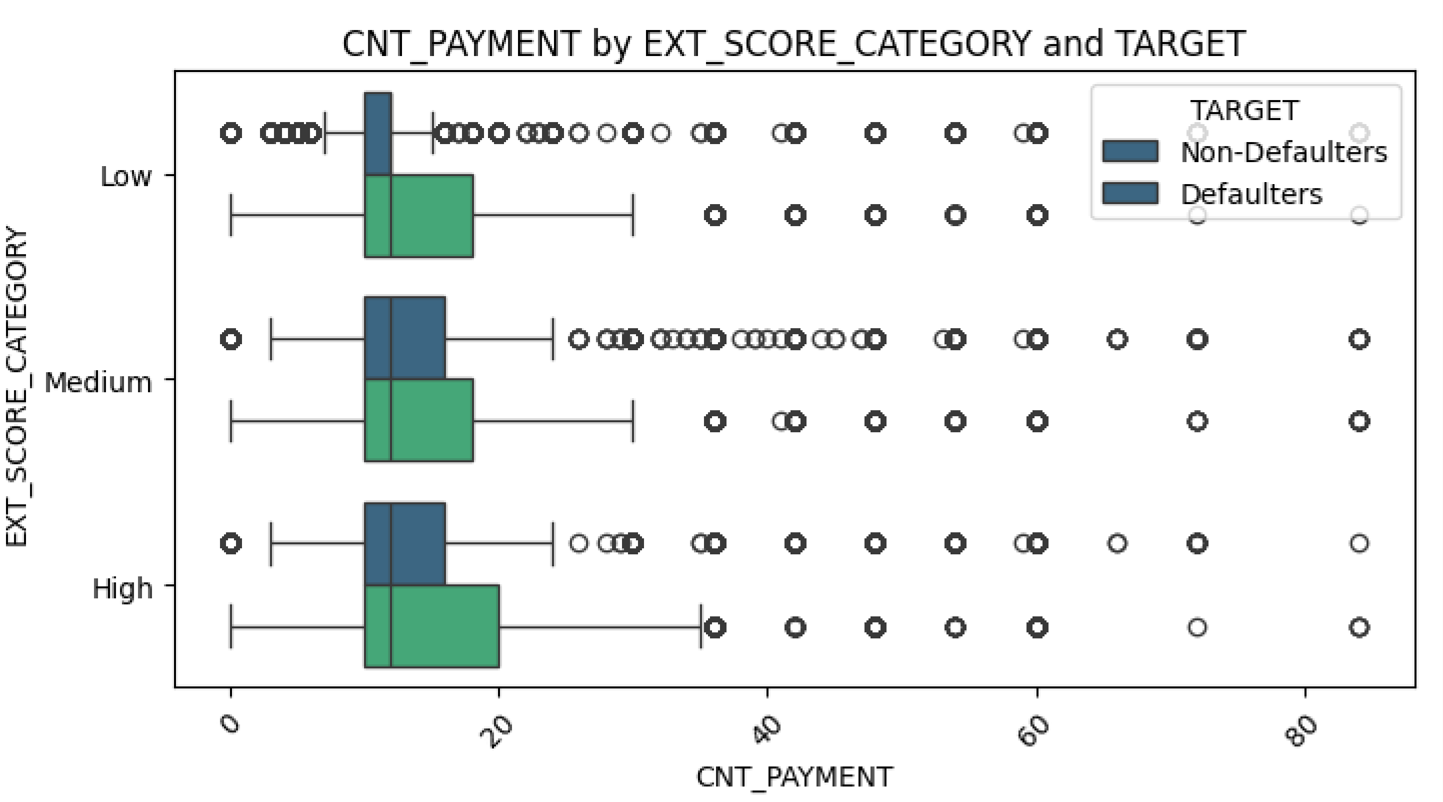
Insight: Younger borrowers may face more variable payment burdens, contributing to higher default risk due to inexperience.

PATTERN: LOAN ANNUITY BY PREVIOUS LOAN APPLICATION STATUS



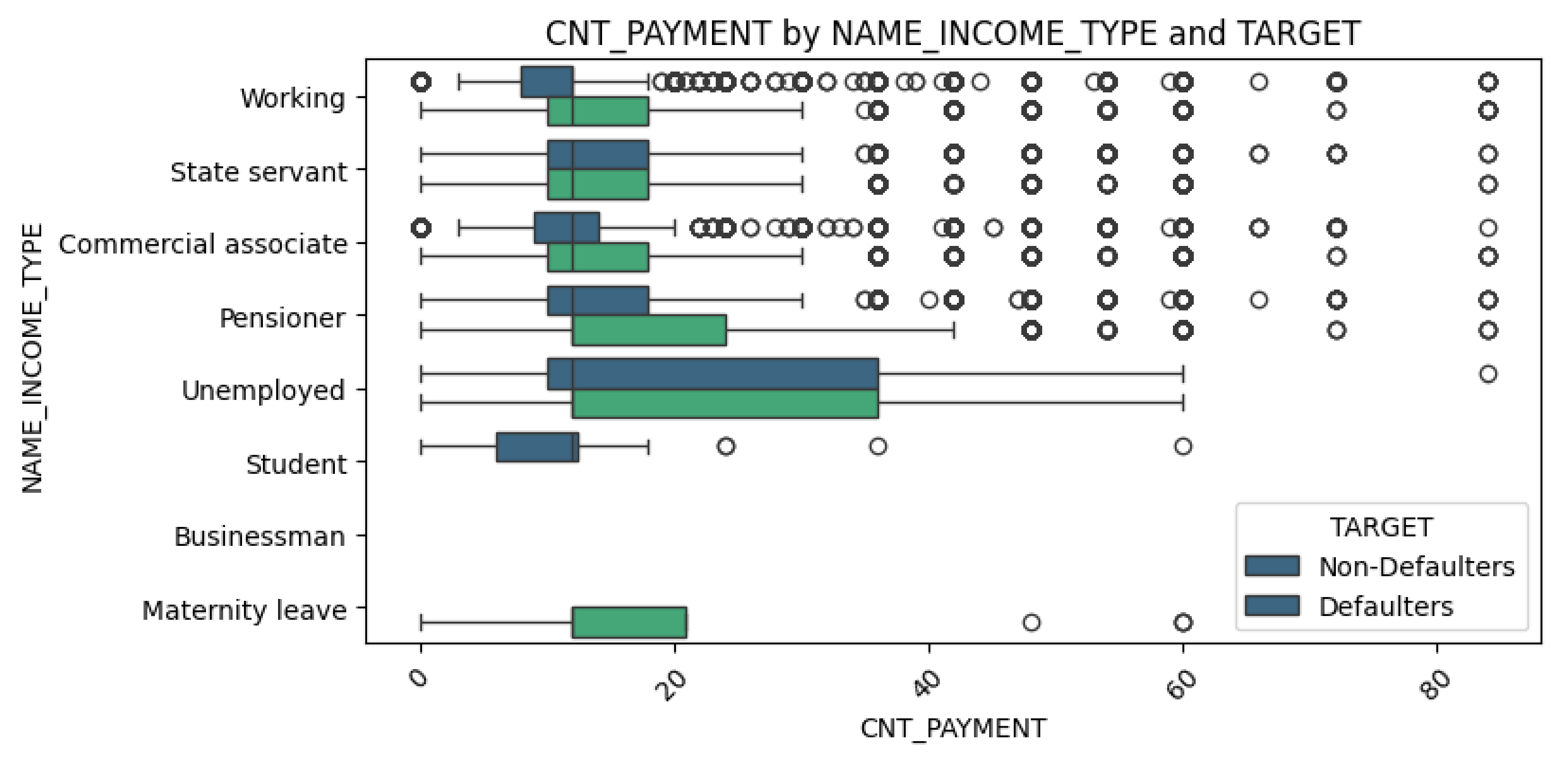
Insight: Despite uniform payment amounts, historical loan outcomes remain a critical risk signal when paired with latest annuity obligations.

PATTERN: TERM OF PREVIOUS CREDIT BY EXTERNAL SCORE



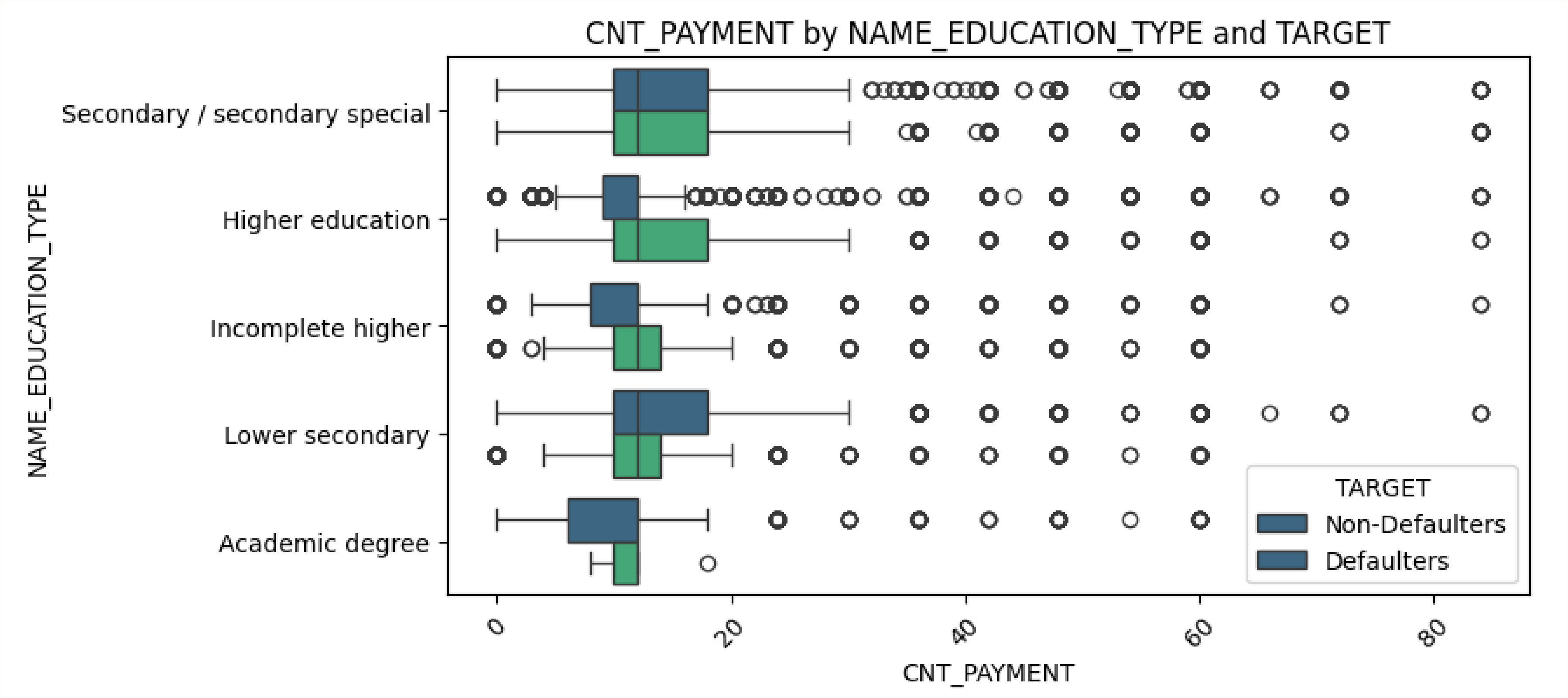
Insight: Although most borrowers complete 12 payments, a higher upper range among defaulters may indicate irregular or shortened repayment periods, hinting at financial distress.

PATTERN: TERM OF PREVIOUS CREDIT BY INCOME TYPE



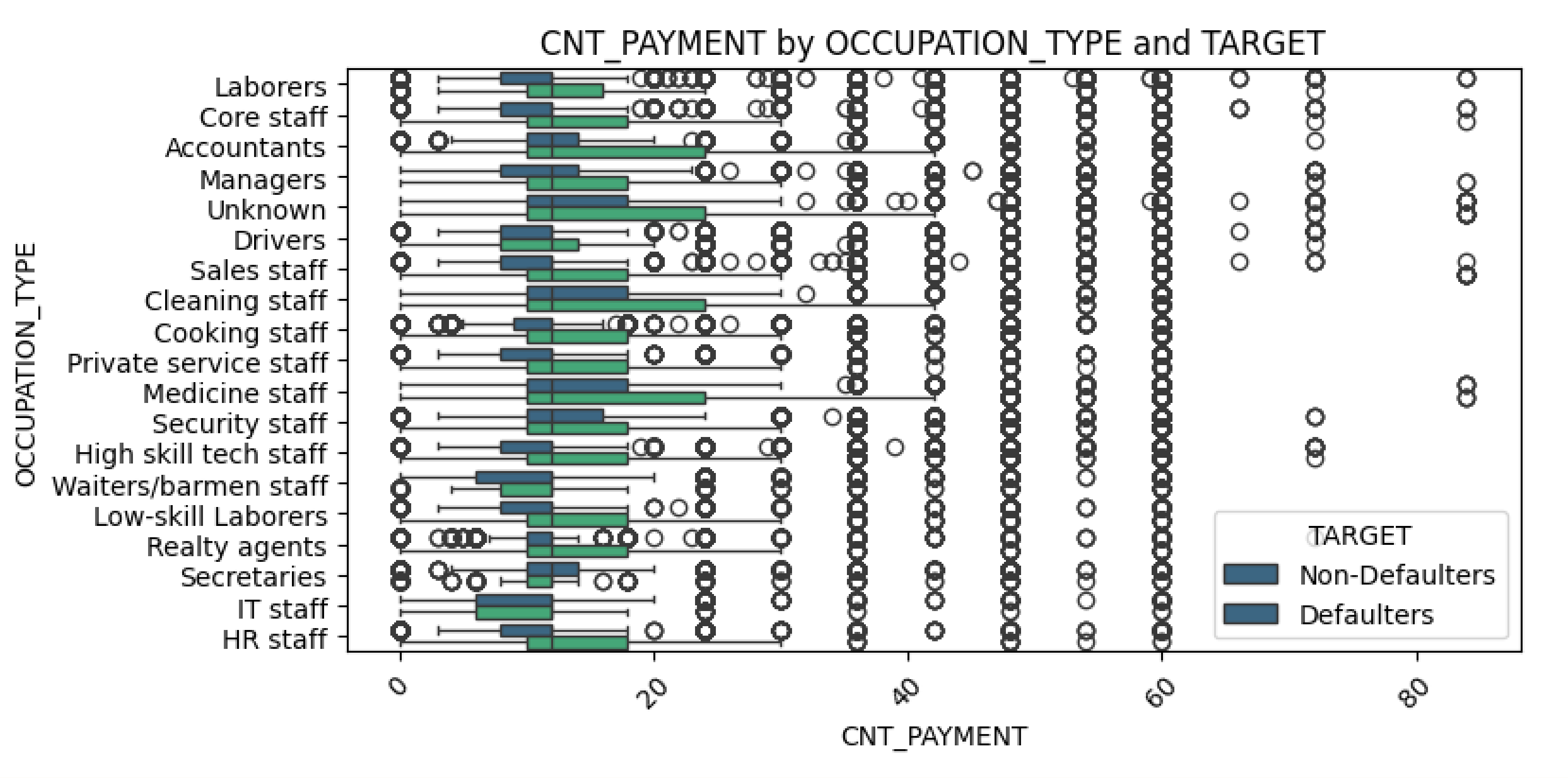
Insight: Standardized credit terms mask subtle differences in repayment behavior that, when combined with income type, may signal risk.

PATTERN: TERM OF PREVIOUS CREDIT BY EDUCATION TYPE



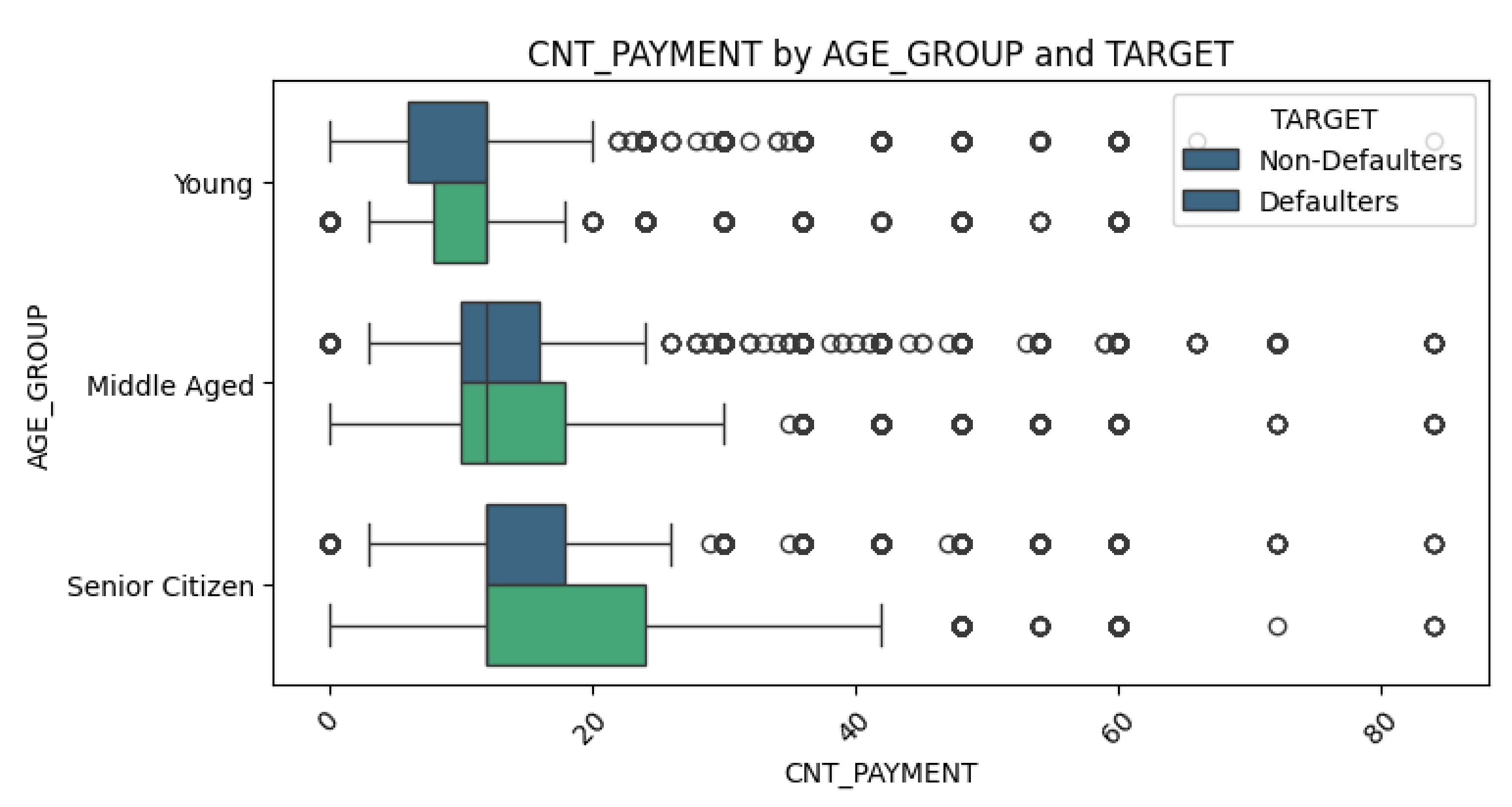
Insight: The consistent payment term across education groups suggests that factors other than term length (e.g., income stability) drive default risk.

PATTERN: TERM OF PREVIOUS CREDIT BY OCCUPATION TYPE



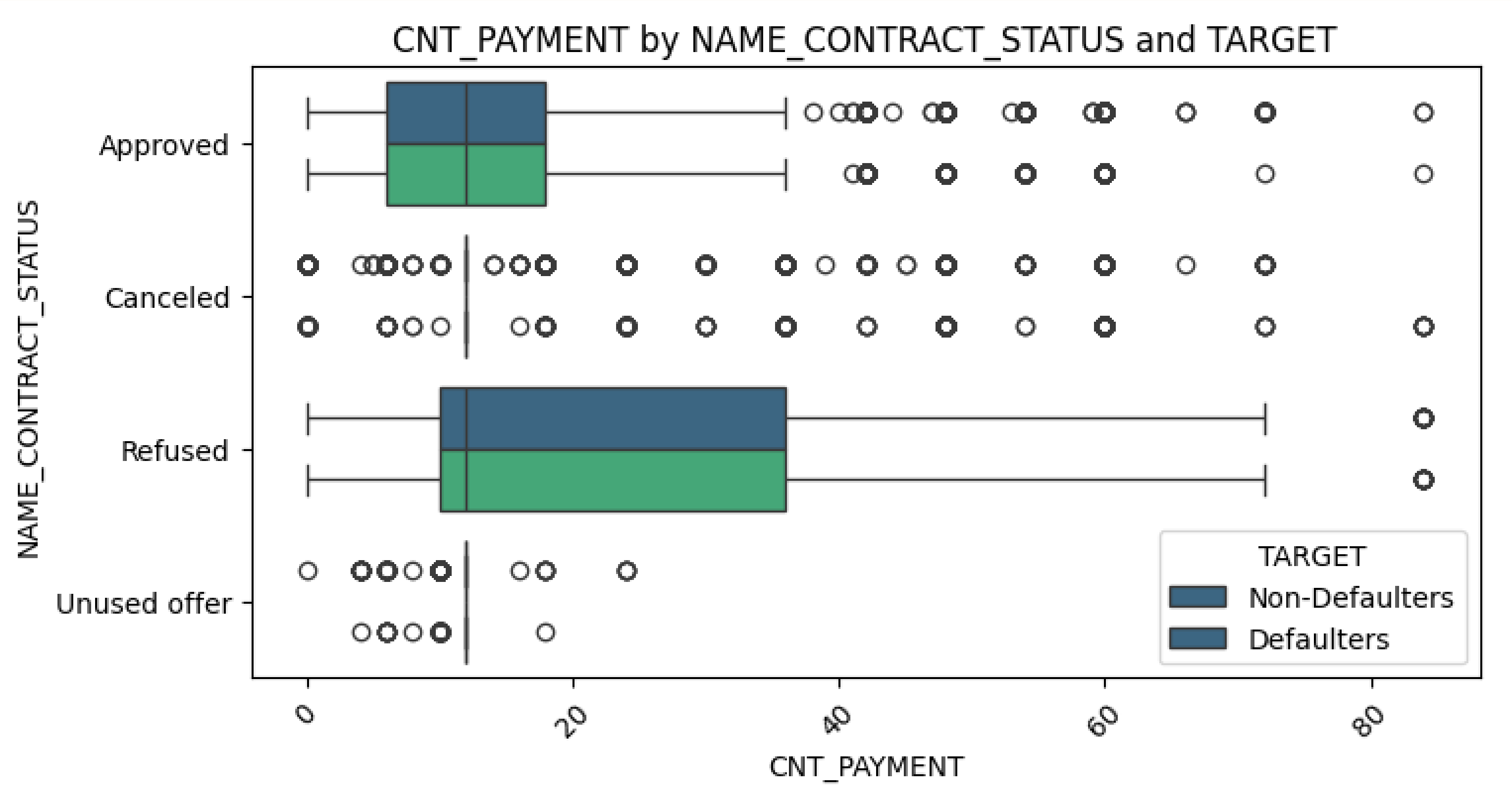
Insight: Increased variability in repayment terms for certain occupations may reflect financial strain among riskier occupational groups.

PATTERN: TERM OF PREVIOUS CREDIT BY AGE GROUP



Insight: Age-related differences in payment counts may reflect tailored lending terms; longer repayment terms for older defaulters might indicate past repayment difficulties.

PATTERN: TERM OF PREVIOUS CREDIT BY PREVIOUS LOAN APPLICATION STATUS



Insight: A notably longer term for defaulters with refused contracts suggests that historical adverse credit behavior is linked to irregular or extended repayment schedules.

STRATEGIC RECOMMENDATIONS

- **Risk-Based Pricing:** Implement dynamic interest rates tied to external credit scores and income stability.
- **Segmented Loan Products:** Design shorter-term loans for young applicants and those in high-risk occupations.
- **Proactive Monitoring:** Track annuity-to-income ratios in real-time to identify early signs of repayment stress.
- **Portfolio Diversification:** Balance high-risk loans (e.g., to younger borrowers) with low-risk segments (e.g., pensioners) to mitigate overall exposure.

THANK YOU

Ekessh Thorali Kuppusamy Sarathi
ekesshtks@gmail.com