Retail Lending

Introduction to Loan Types

Loan Types

	Term Loans	Lines of Credit (LOC)
Secured	Mortgage, Auto Loan	HELOC (Home Equity Line of Credit), Margin Loan
Unsecured	Personal Loan, Student Loan	Credit Card, Personal Line of Credit

Term Loans vs. Lines of Credit

Term Loans

- Fixed loan amount disbursed upfront
- Fixed repayment schedule with a maturity date (specified loan end date)
- Interest calculated on the outstanding loan amount
- Once repaid, a new loan application is required
- Examples: Mortgages, Personal Loans

Lines of Credit

- Revolving credit with a maximum limit
- May or may not have maturity date
- Interest charged only on the amount utilized (borrowed)
- Borrow, repay, and re-borrow as needed without reapplying
- Examples: Credit cards, HELOCs, Margin Loans

Secured vs. Unsecured Loans/LOCs

Secured Loans/LOCs

- Backed by collateral
- Lender can seize and sell collateral if the borrower defaults
- Lower interest rates due to reduced lender risk
- Examples:
  - Mortgages and HELOC (secured by real estate)
  - Auto loans (secured by vehicle)
  - Margin loans (secured by brokerage account)

Unsecured Loans/LOCs

- No collateral
- Default may result in negative credit reporting and potential legal actions
- Higher interest rates to compensate for increased lender risk
- Examples:
  - Credit Cards
  - Personal Loans

Mortgages

- Term
  - 15 years
  - 30 years
- Rate Type
  - Fixed-rate: Same interest rate (“note rate”) for the entire term
  - Adjustable-rate: Interest rate changes periodically
  - Hybrid: Initial fixed interest rate (“teaser rate”), followed by adjustable rates

More about mortgages

- Amortization Type
  - Fully-amortizing: Each payment reduces the principal balance
  - Interest-only: Small initial payments (IO period), then loan amount amortizes (big payments)
- Conforming Type
  - Conforming: Mortgage can be sold to Fannie Mae and Freddie Mac
  - Non-conforming (jumbo): Mortgage cannot be sold to Fannie Mae and Freddie Mac

Other Loan Products

- **Credit Cards**: Unsecured, line of credit, variable rate, **no maturity date**
- **Auto Loans**: Secured, term loan, fixed rate
- **Personal Loans**: Unsecured, term loan, fixed rate
- **Home Equity Products**:
  - Home equity loans: Secured, term loan, fixed rate
  - HELOCs: Secured, line of credit, variable rate, draw period followed by amortizing period
- **Student Loans**: Unsecured, term loan, fixed rate

Credit Scoring Systems

History of Credit Scores

- **Pre-1950s**: Credit decisions were highly subjective.
  - Based on personal relationships, lender judgment, and the "3 Cs" (Character, Capacity, Capital).
  - Prone to inconsistency and discriminatory practices.
- **1956**: Fair Isaac Corporation began developing *custom* credit scoring models for individual lenders using their internal data. These early systems aimed to provide objective risk assessment but faced initial resistance.
- **1970s**: Regulatory changes pushed for fairer lending.
  - **Fair Credit Reporting Act (FCRA, 1970)**: Gave consumers rights regarding their credit information.
  - **Equal Credit Opportunity Act (ECOA, 1974)**: Prohibited credit discrimination.
  - These acts encouraged lenders to adopt more objective methods like credit scoring to ensure compliance and reduce bias.

Modern History of Credit Scores

- **1989**: FICO launched the first *general-purpose* FICO Score, calculated using data from credit bureaus. This made standardized scores widely available to lenders.
- **1995**: Fannie Mae and Freddie Mac began requiring FICO Scores for mortgage purchases, cementing their importance in the largest consumer lending market.
- **2006**: The three major credit bureaus (Equifax, Experian, TransUnion) jointly launched VantageScore as a competitor to FICO.
- **Today**: Credit scores are integral to the financial system, influencing:
  - Loan approvals and interest rates (mortgages, auto loans, credit cards, etc.)
  - Insurance premiums
  - Rental application decisions
  - Sometimes, employment screenings (where permissible)

Credit Scoring Companies vs. Credit Bureaus

Credit Scoring Companies

- Develop algorithms to calculate credit scores
- Do not collect or own consumer data
- License scoring models to credit bureaus
- Revenue from algorithm licensing and analytics services
- Examples:
  - Fair Isaac Corporation (FICO)
  - VantageScore (joint venture but independently operated)

Credit Bureaus

- Collect and maintain consumer credit data
- Provide credit reports and scores to authorized users
- Apply scoring algorithms (e.g., FICO) to generate scores
- Revenue from selling credit reports and scores
- Equifax, Experian, TransUnion

Corporate Relationships

- **Fair Isaac Corporation (FICO)**:
  - Independent company that developed the FICO scoring model
  - Licenses algorithms to all three major credit bureaus
  - Dominant in credit scoring since the 1980s
- **VantageScore**:
  - Joint venture by Equifax, Experian, and TransUnion (2006)
  - Competes with FICO's scoring models
  - Reduces dependency on FICO's proprietary algorithms
- **Equifax, Experian, and TransUnion**:
  - Compete in data services but collaborate on VantageScore
  - Pay licensing fees to FICO for score calculations
  - Use slightly different implementations of FICO algorithms

Points to Double Odds (PDO)

- **Definition**: PDO is the number of credit score points required to double the odds of being a “good” borrower (or halve the odds of default)
- **Example**:
  - Suppose that Score 680 has 10:1 odds of being “good”
  - If PDO = 40:
    - Add 40 points → Score 720 → 20:1 odds (doubled)
    - Add another 40 points → Score 760 → 40:1 odds (doubled again)
    - Add another 40 points → Score 800 → 80:1 odds (doubled again)

PDO: Mathematical Details - Part 1

- **Mathematical relationship**: Let p be the probability of default and define the odds as $\frac{p}{1-p}$; then:

$$\text{Score} = A - B \cdot \ln\left(\frac{p}{1-p}\right)$$

  - Here, B is defined as $\text{PDO}/\ln(2)$.
  - The scaling factor $(1/\ln(2))$ ensures that an increase of PDO points in the score exactly doubles the odds of being a “good” borrower.
  - A is a scaling constant (reference score) to position the score in the desired range.
- **Ambiguity in odds definition**: The “odds of being a good borrower” $\frac{1-p}{p}$ is the inverse of the “odds of default” $\frac{p}{1-p}$. In the formula above, as the score increases by PDO points, the odds of default are halved, which is equivalent to saying the odds of being a good borrower are doubled.

PDO: Mathematical Details - Part 2

- For PDO = 40:
  1. Calculate $B = 40/\ln(2) \approx 40/0.693 \approx 57.7$.
  2. If a 650 score corresponds to a 5% default probability ($p = 0.05$):
     - Compute the odds: $\frac{0.05}{1-0.05} = \frac{0.05}{0.95} \approx 0.0526$ and $\ln(0.0526) \approx -2.944$.
     - Then, $650 = A - 57.7 \cdot (-2.944) = A + 169.7$.
     - Solve for $A \approx 650 - 169.7 \approx 480.3$.
  3. Final formula:

$$\text{Score} = 480.3 - 57.7 \cdot \ln\left(\frac{p}{1-p}\right)$$

Industry Standards

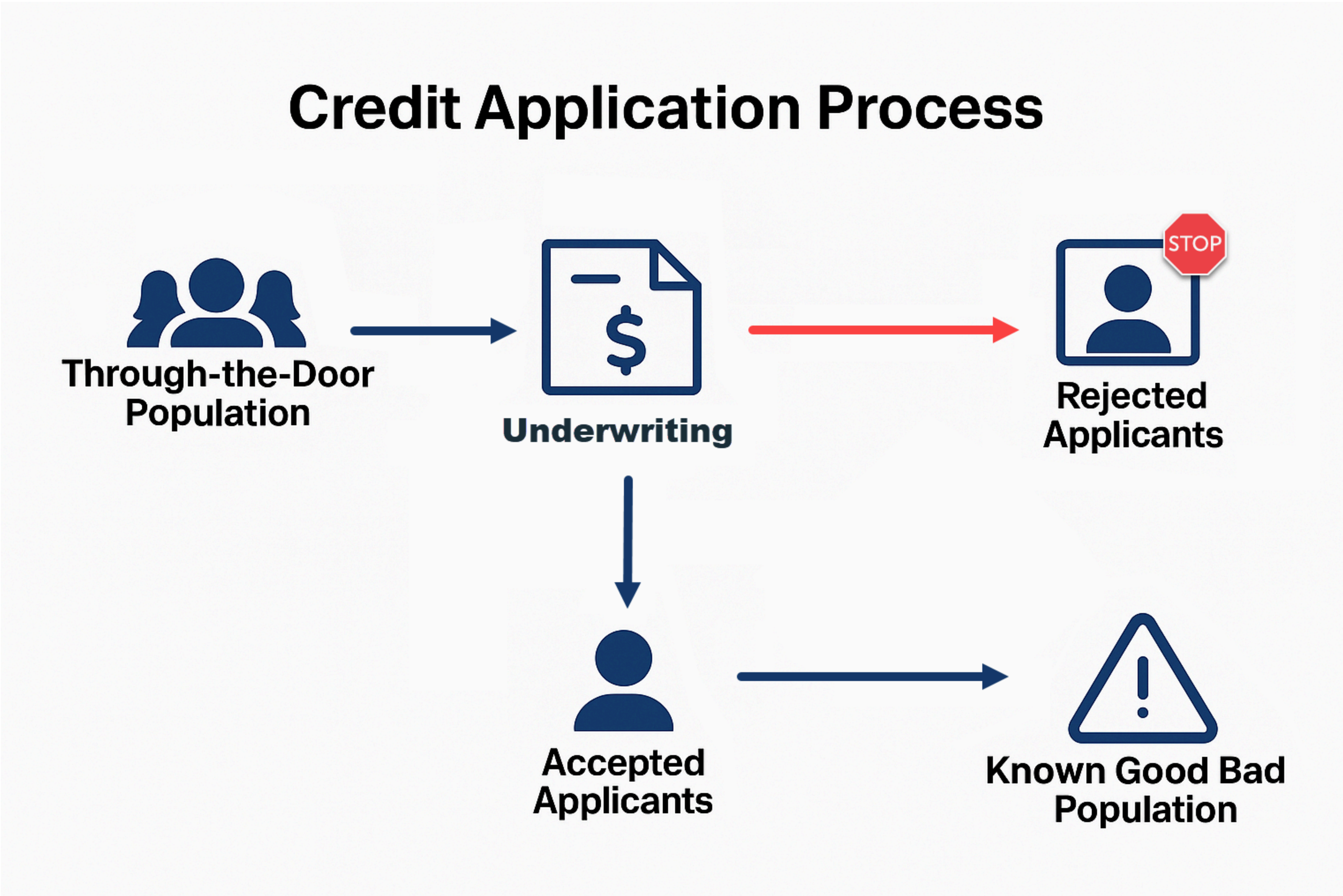
- A is typically set to align scores with the standard score range (300-850)
- A could range from 600–650 depending on the scoring model
- **FICO** and **VantageScore** do not disclose exact PDO values
- **Typical PDO values**: Range from 20 to 40 points
- Credit scoring systems may change PDO when they publish new versions of their models (e.g., FICO 8, FICO 9)
- A low PDO (like 20) indicates a more sensitive scoring model, while a high PDO (like 40) indicates a less sensitive model

Credit Scores as Risk Rankings

- **Ordinal Measure**: A 720 score indicates lower risk than 680 but does **not** directly equate to a fixed default probability. Credit scores are best understood as ranking borrowers rather than quantifying exact default rates.
- Credit scores **do not** directly represent default probabilities.
  - Example: A 680 score does not mean a 6.8% chance of default.
  - Default rates vary with economic conditions.
  - During recessions, default rates for a 720 score may rise, but should have lower default rates than a 680 score

Underwriting and Selection Bias

Credit Application Process



Through-the-Door (TTD) Population

- **Definition**: The set of all consumers who apply for credit.
- **Characteristics**:
  - Represents the full spectrum of credit risk in the applicant pool.
  - Contains both high-quality and high-risk applicants.
- **Importance in modeling**:
  - The TTD population contains the complete risk profile.
  - Models should ideally predict risk across the entire TTD population.
  - TTD data serves as the starting point for underwriting decisions.
- **Challenges**:
  - Complete TTD data rarely available for model development.
  - Selection bias introduced during the underwriting process.
  - Difficult to know true risk for rejected applicants.

Underwriting Process - Part 1

Underwriting segments the TTD population into accepted and rejected populations:

1. **Application receipt**: Gather applicant information and credit reports.
    - Personal identification.
    - Income and employment verification.
    - Credit bureau data retrieval.
    - Fraud detection checks (e.g., identity theft screening).
2. **Initial screening**: Apply basic eligibility requirements.
    - Minimum age requirements.
    - Identity verification.
    - Geographic restrictions.
    - Compliance with anti-money laundering (AML) and know-your-customer (KYC) regulations.

Underwriting Process - Part 2

3. **Credit evaluation**: Apply credit risk assessment.
    - Credit score thresholds.
    - Debt-to-income ratio analysis.
    - Payment history review.
    - Employment stability assessment.
    - Collateral valuation (for secured loans).
    - Behavioral data analysis (e.g., transaction patterns, if available).

Underwriting Process - Part 3

4. **Decision**: Approve, conditionally approve, or reject.
    - Approve: Meets all lending criteria.
    - Conditional: Requires additional documentation or guarantor or manual review.
    - Reject: Fails to meet minimum lending standards.
5. **Pricing and terms**: For approved applicants.
    - Interest rate determination.
    - Loan amount calculation.
    - Term length assignment.
    - Risk-based pricing adjustments (e.g., higher rates for higher-risk applicants).

Known Good Bad (KGB) Population

- **Definition**: The subset of applicants who were approved for credit.
- **Key characteristics**:
  - Only represents a portion of the TTD population.
  - Typically includes high-quality applicants.
  - Has complete performance data (repayment history).
  - Contains both “good” (non-default) and “bad” (default) loans.
  - Truncated feature distribution compared to the full TTD population.

More about KGB Population

- **Terminology**:
  - “Good”: Accounts that perform as expected (make payments on time).
  - “Bad”: Accounts that default or become seriously delinquent.
  - “Known”: Performance outcome (default indicator) is observed.
- **Modeling implication**:
  - Models developed only on KGB data suffer from selection bias.
  - Risk assessments based only on KGB data tend to underestimate true risk.

Selection Bias Problem

When models are trained only on the KGB population, they encounter a fundamental selection bias:

- **Truncated sample**: Rejected applicants (typically higher risk) are missing from the training data.
- **Risk underestimation**: Models cannot learn patterns from the high-risk rejected population.
- **Extrapolation error**: When applied to the full TTD population, models make poor predictions for segments they never observed.
- **Mathematical perspective**: The model learns $P(\text{default}|\text{approved})$ instead of the desired $P(\text{default}|\text{applied})$.
- **Visual illustration**: In the figure (next slide), KGB data only includes the green portion, missing the critical red portion:

Selection Bias Visualization

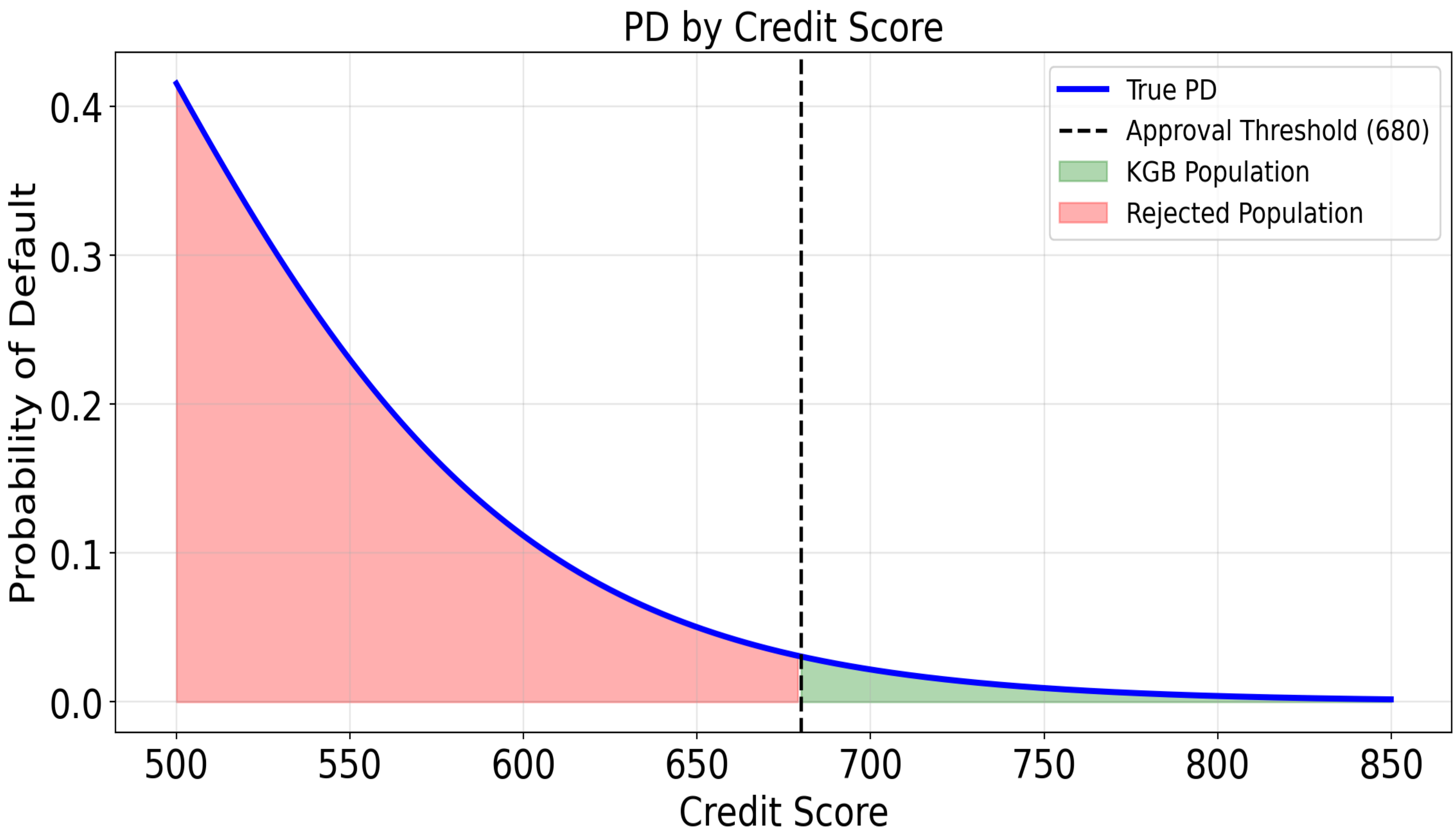


Figure 1: Selection Bias Visualization

Selection Bias and Reject Inference

Simulating the Selection Bias Problem

Let's create a simulation to demonstrate how selection bias affects model performance:

- Simulate 300,000 credit applicants (TTD population).
- Default rates decrease exponentially as credit scores increase.
- Reject all applicants with scores below 680.
- Train a model on KGB population and examine its predictions.

Simulation Results

Table 1: Summary Statistics

Metric	Value
TTD population size	300,000
KGB population size	114,722
Rejection rate	61.8%
Overall default rate in TTD	11.7%
Default rate in KGB	1.2%

Training the KGB Model

- Train an AutoGluon model using only the KGB population
- Set the best model to CatBoost
- Evaluate the model's performance on the entire TTD population

Underestimating Risk for Rejected Applicants

Table 2: True vs. Predicted PD

approved	num_loans	predicted_default_prob	true_default_prob
False	37035	0.029444	0.181625
True	22965	0.012437	0.012837

Average PDs by Credit Score

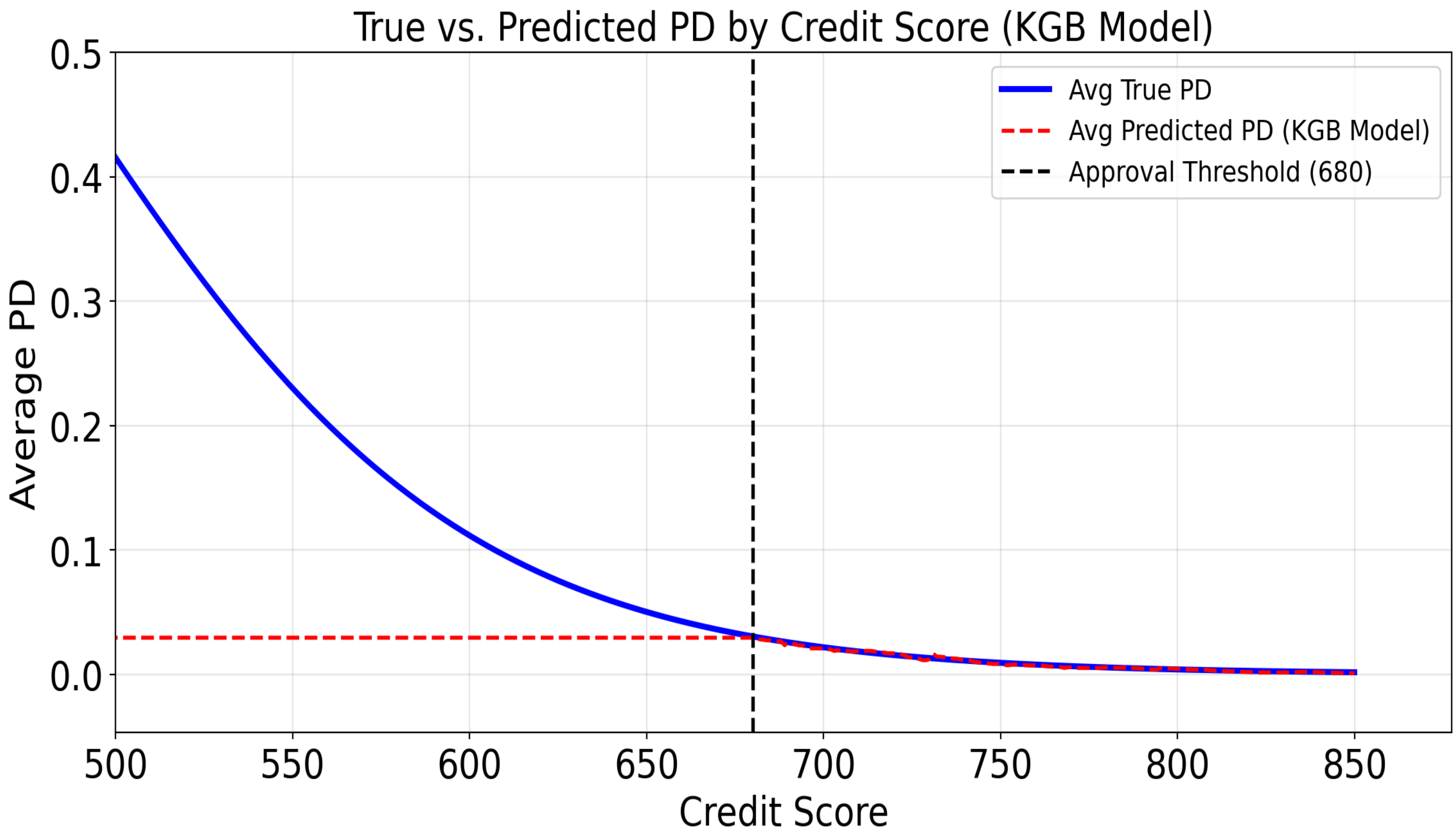


Figure 2: Average True PD vs. Predicted PD (KGB Model)

Reducing Bias: Naive Augmentation

- Augmentation is the process of including rejected applicants in the training data
- Naive Augmentation: Assume all rejected applicants would default
- Using the “all-bad assumption” for rejected applicants is a huge oversimplification
- The approach is not data-driven and not commonly used.

Naive Augmentation: Results

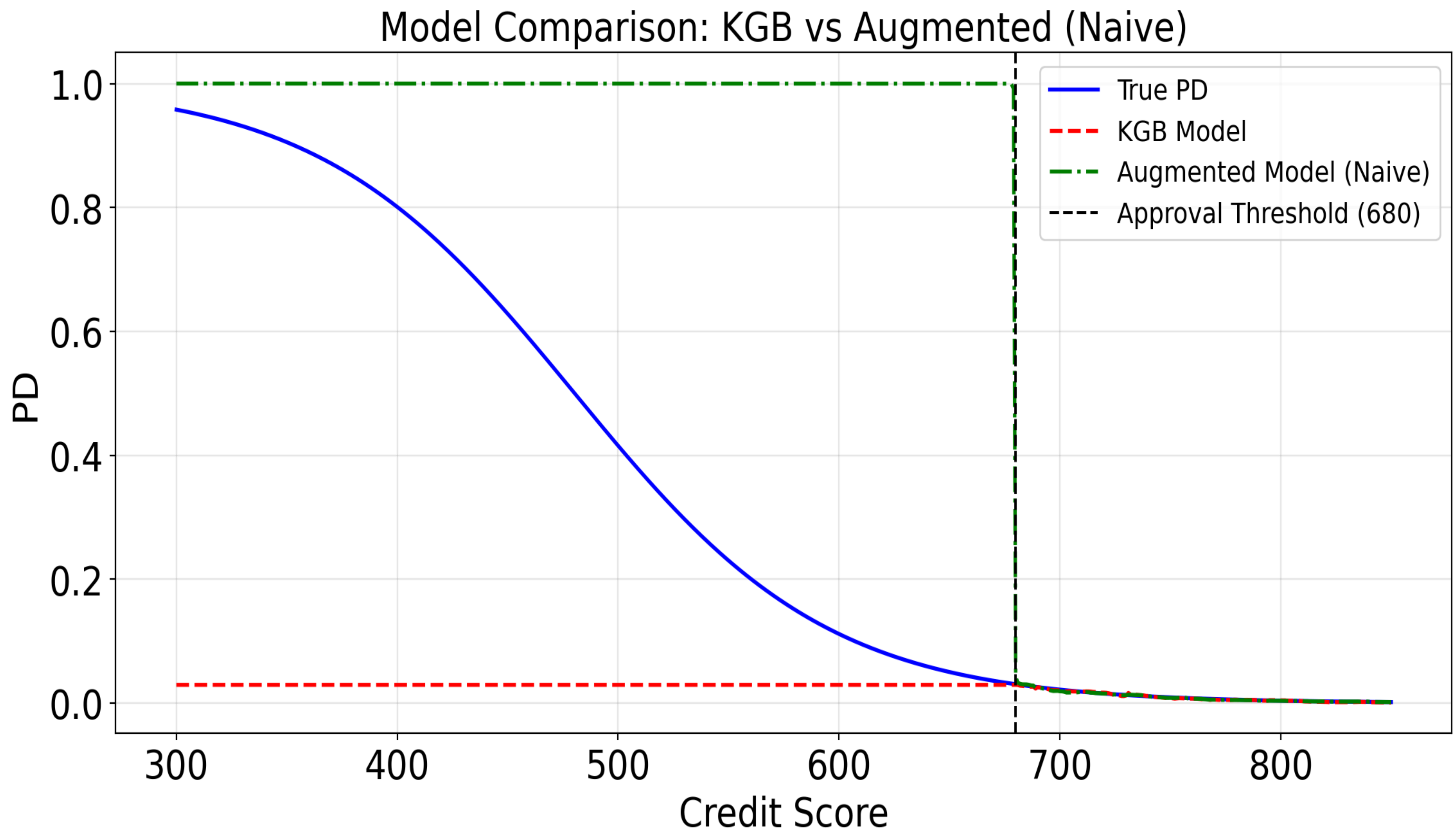


Figure 3: Model Comparison: KGB vs Augmented (Naive)

Impact of Naive Augmentation

Table 3: Mean Absolute Error (MAE) Comparison

Model	Score Range	MAE
Augmented (Naive)	Rejected (< 680)	53.4%
Augmented (Naive)	Approved (>= 680)	0.1%
KGB	Rejected (< 680)	43.7%
KGB	Approved (>= 680)	0.1%

Reducing Bias: Bureau Augmentation

- Bureau Proxy Augmentation: Send the list of rejected applicants to a credit bureau and append the default indicator from each rejected applicant **who were granted credit in the past**
- Include the rejected applicants who were granted credit in the past in the training data
- The major drawback is that only a subset of rejected applicants would be included in the training data

Bureau Proxy Metrics

Table 4: Bureau Proxy Statistics

Metric	Value
TTD Applicants	240,000
KGB Applicants	91,757
Rejected Applicants	148,243
Rejected Applicants with proxies	8,534 of 148,243 (5.8%)
Rejected Applicants without proxies (excluded)	139,709
KGB + Bureau Proxy Applicants	100,291

Bureau Augmentation: Results

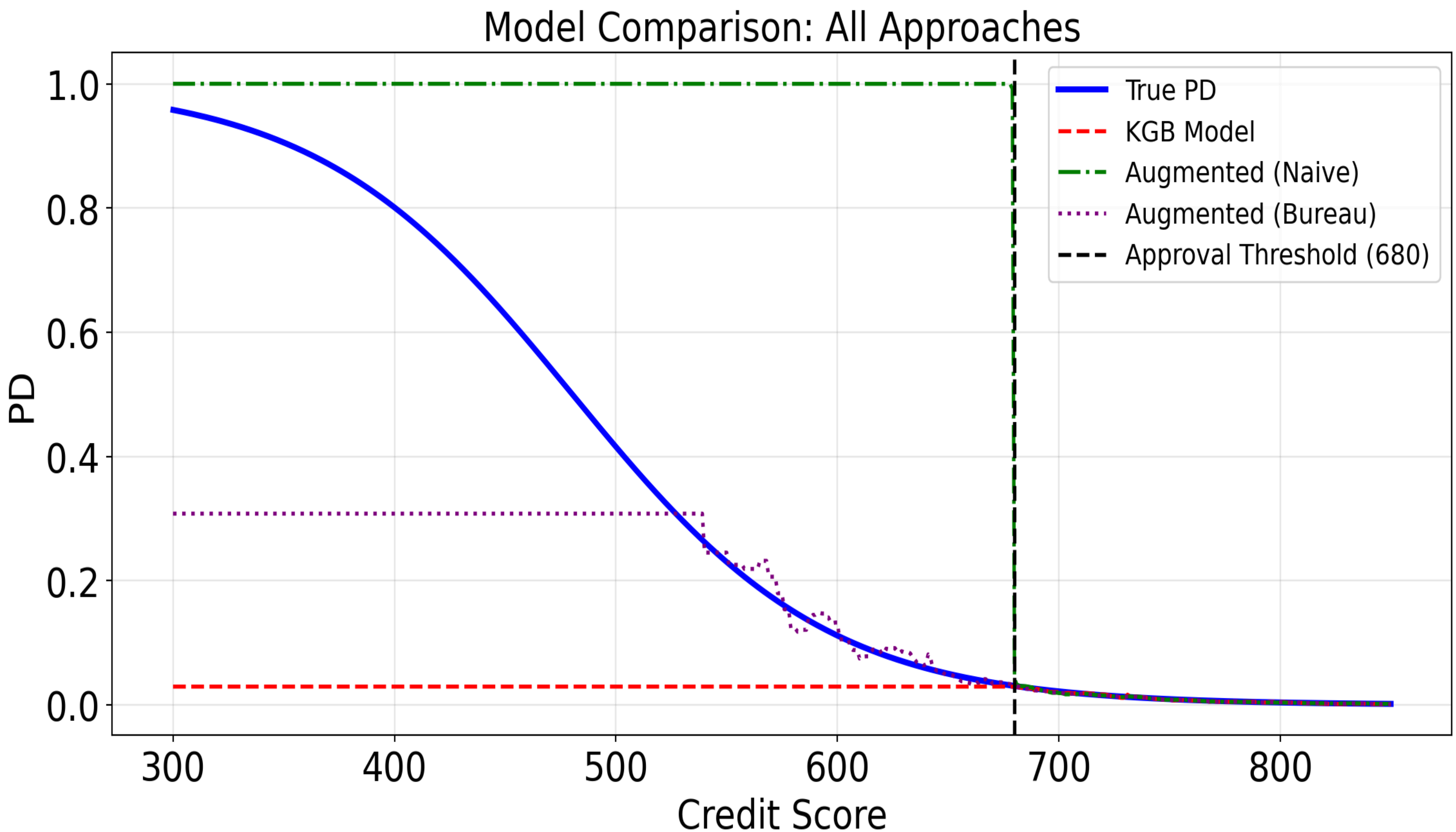


Figure 4: Model Comparison: All Approaches

Impact of Bureau Augmentation

Table 5: Bureau Proxy Error Metrics

Model	Score Range	MAE
Augmented (Naive)	Rejected (< 680)	53.4%
Augmented (Naive)	Approved (>= 680)	0.1%
KGB	Rejected (< 680)	43.7%
KGB	Approved (>= 680)	0.1%
Augmented (Bureau)	Rejected (< 680)	23.8%
Augmented (Bureau)	Approved (>= 680)	0.1%

Key Takeaways

- **Selection Bias**:
  - KGB population is a non-random sample (bias sample) of the TTD population.
  - Models trained only on KGB data may underestimate risk for rejected applicants.
  - Tree-based models (like **CatBoost**) can amplify selection bias through poor extrapolation.
- **Reject Inference Techniques**:
  - Augmentation incorporates rejected applicants into the training data.
  - **Naive Augmentation**: Simple but substantially overestimates risk. Do not use.
  - **Bureau Augmentation**: More accurate but may exclude most rejected applicants.