CREDIT SCORE CUTOFFS AND PROFIT MAXIMIZATION

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CONTENT

HOW DO BANKS DECIDE THE CREDIT LIMIT

Credit History

- Balance of t-1 b_{t-1}
- Credit Score of t-1 s_{t-1}
  - Utilisation ratio
  - Next minimum payment
  - Months on book
  - Payment method...

Bucketing model & Optimization model

Set Credit Limit

l_t

Affect

Future Behavior

- Expected default rate pd_t
- Expected balance b_t

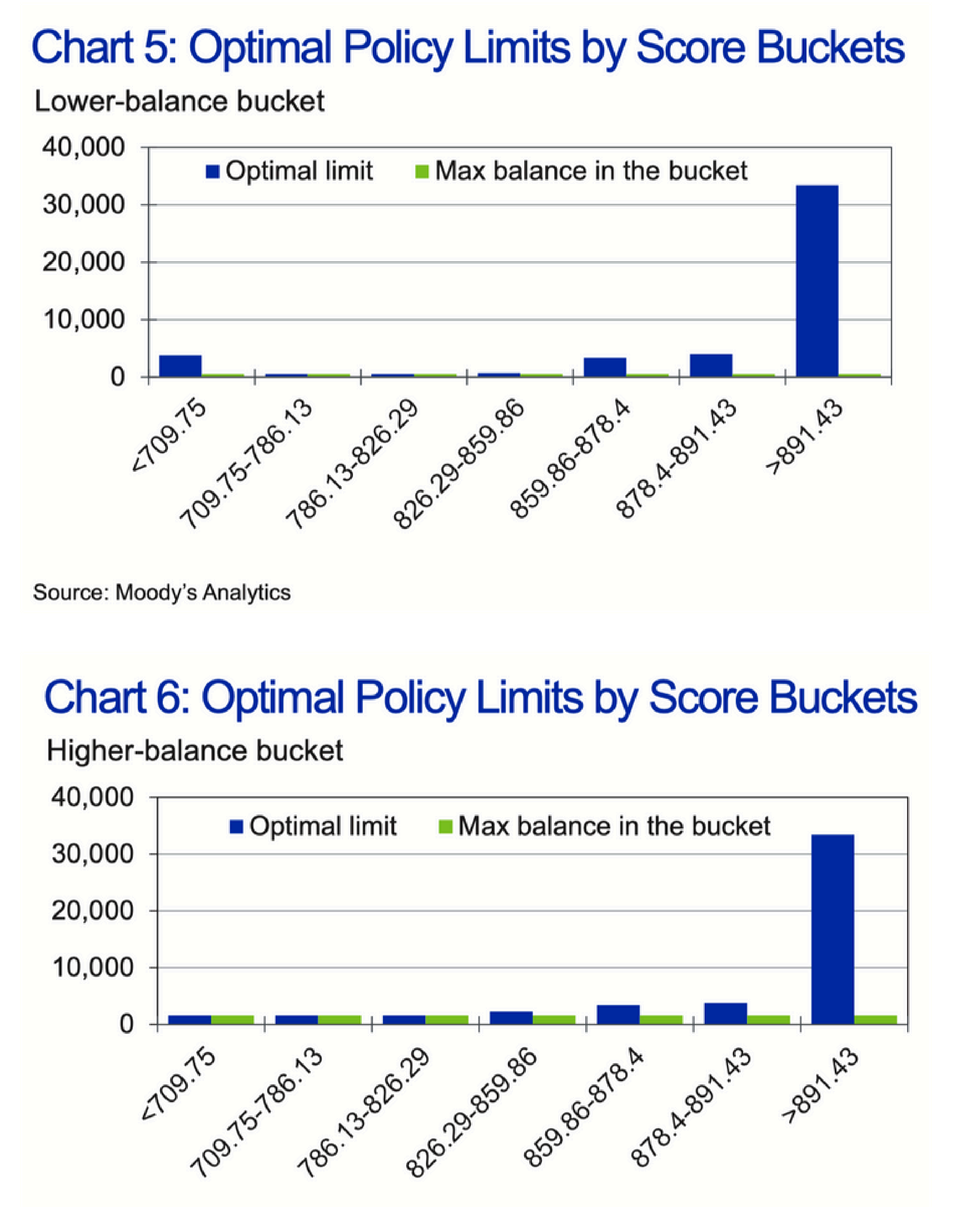
Result

Profit

$$P = -pd_t \times b_t + (1 - pd_t) \times b_t \times r_t$$

Source: Moody's, Determining the Optimal Dynamic Credit Card Limit

MOTIVATION FOR RDD



Source: Moody's, Determining the Optimal Dynamic Credit Card Limit

Algorithm approach

- Logistic regression to generate credit score
- Bucketing algorithm to generate buckets and threshold
- Dynamic programming to generate credit limit for each bucket

RDD as Validation

- Is the bucket really accurate?
  - Data source problem
  - Algorithm bias
- **Use RDD to validate/optimize the threshold**
  - Treatment's effect on default risks & balance
  - Treatment's effect on total profit

RD DESIGN STRUCTURE

This design aims not only to estimate the impact of credit limit assignments on firm profit, through its components: default rate and customer spending, but also to assess whether the current credit score cutoffs are optimally placed.

Running Variable	Cutoff	Treatment	Response Variables (at period t)
Credit Score (at period t-1)	710, 786, 830, 860, 880, 890 Derived from bucketing algorithm based on data at period t-1	Credit Limit A, B, C, D, E, F Derived from DP Model Increasing with credit score bucket	Default Indicator: $D_i = \begin{cases} 1 & \text{if default} \\ 0 & \text{otherwise} \end{cases}$ Spending (Balance): b_i Profit Equation: $Profit_i = (1 - D_i) \times b_i \times r - D_i \times b_i$ where r is the profit margin

LOCAL REGRESSION

Default Indicator Estimation

$$\Pr(D = 1 \mid X) = \frac{1}{1 + \exp(-\eta)}$$

$$\text{where } \eta = \alpha_\ell + \tau T + \beta_\ell(X - c) + (\beta_r - \beta_\ell)T(X - c)$$
$$\text{for } c - h \leq X \leq c + h$$

Spending & Profit Estimation

$$Y = \alpha_\ell + \tau T + \beta_\ell(X - c) + (\beta_r - \beta_\ell)T(X - c) + \varepsilon,$$
$$\text{for } c - h \leq X \leq c + h$$

where X is credit score, T is treatment

c is the cutoff point, and $\tau = \alpha_r - \alpha_l$

BANDWIDTH SELECTION

A bandwidth that is too small leads to high variance and noisy estimates, while a bandwidth that is too large introduces bias by over-smoothing the data. Leave-One-Out Cross-Validation is used to optimize bandwidth selection, minimizing prediction error and providing robust model generalization.

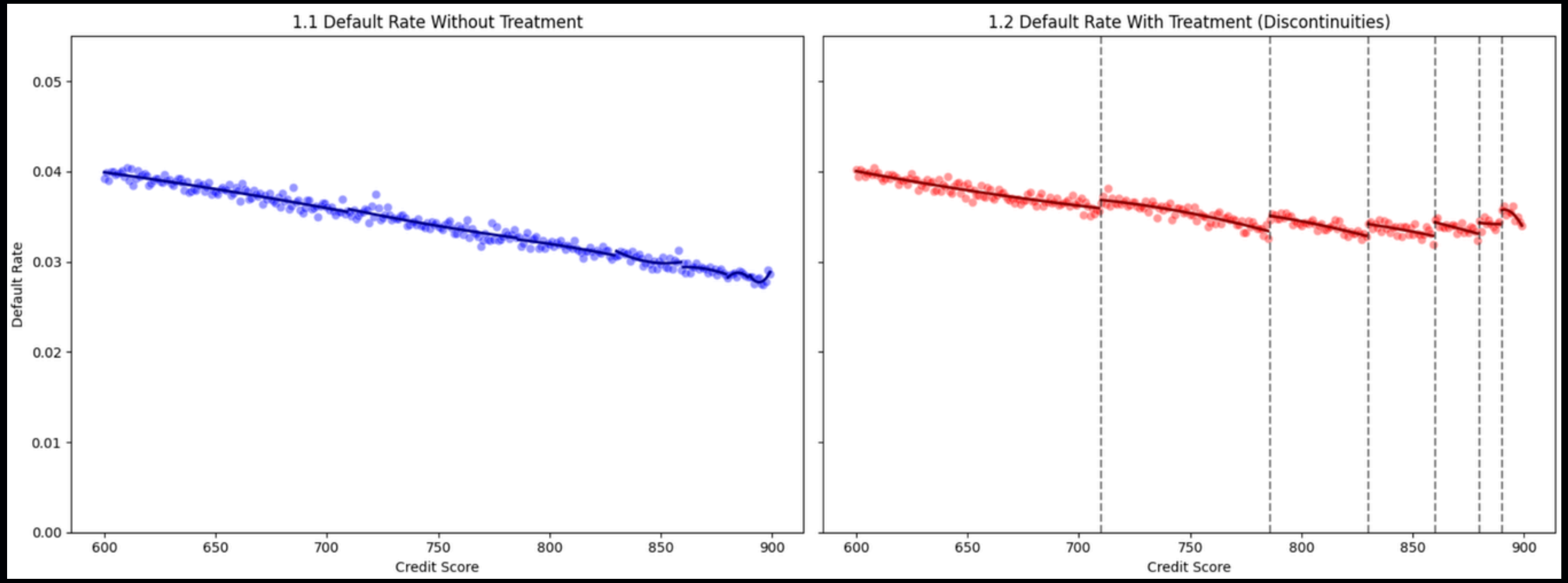
Window	Leave-One-Out	Cross Validation	Optimal Threshold
Only observations with values of X between the median value of X to the left and right of the cutoff could be used to perform the cross-validation.	Leave observation i out for $X_i < c$, estimate regression on $(X_i - h \leq X < X_i)$ for $X_i > c$, estimate regression on $(X_i < X \leq X_i + h)$	$\mathrm{CV}_Y(h) = \frac{1}{N}\sum_{i=1}^{N}(Y_i - \hat{Y}(X_i))^2$	$h_{\mathrm{CV}}^{\mathrm{opt}} = \arg\min_h \mathrm{CV}_Y(h)$

TREATMENT EXPECTATION

"Calculated Risk-Reward Tradeoff": Default vs Spending

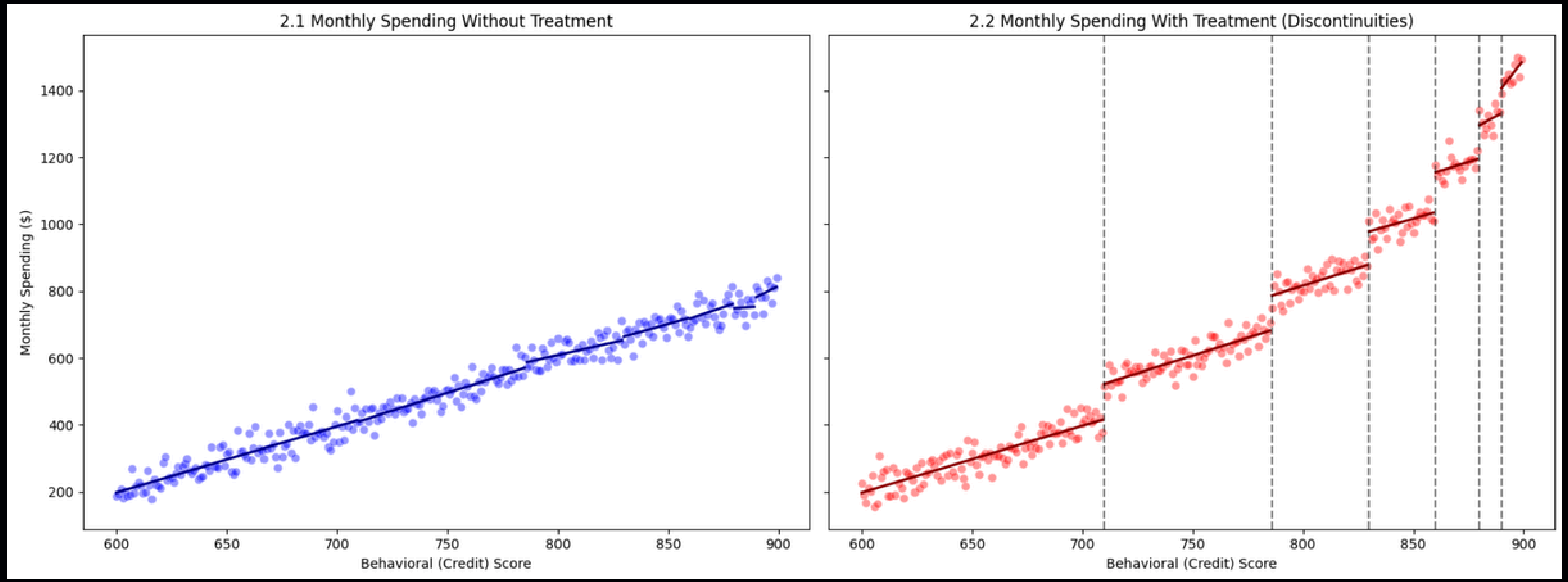
Default Rate

- **Untreated** default rate is expected to be monotonically downard
- **Treatment** of higher credit cap bumps up default rate



Spending

- **Untreated** spending aligns with higher user credibility
- **Treatment** of higher credit cap encourages user spending



*The results presented are based on simulated data for illustrative purposes only.

PROFIT IMPLICATION

“Locating the perfect cutoff”: Fine-tuning treatment cutoff

$$Profit = Spending \times [(1 - P_{default}) * r - P_{default}]$$

Pre-cutoff Lift Off

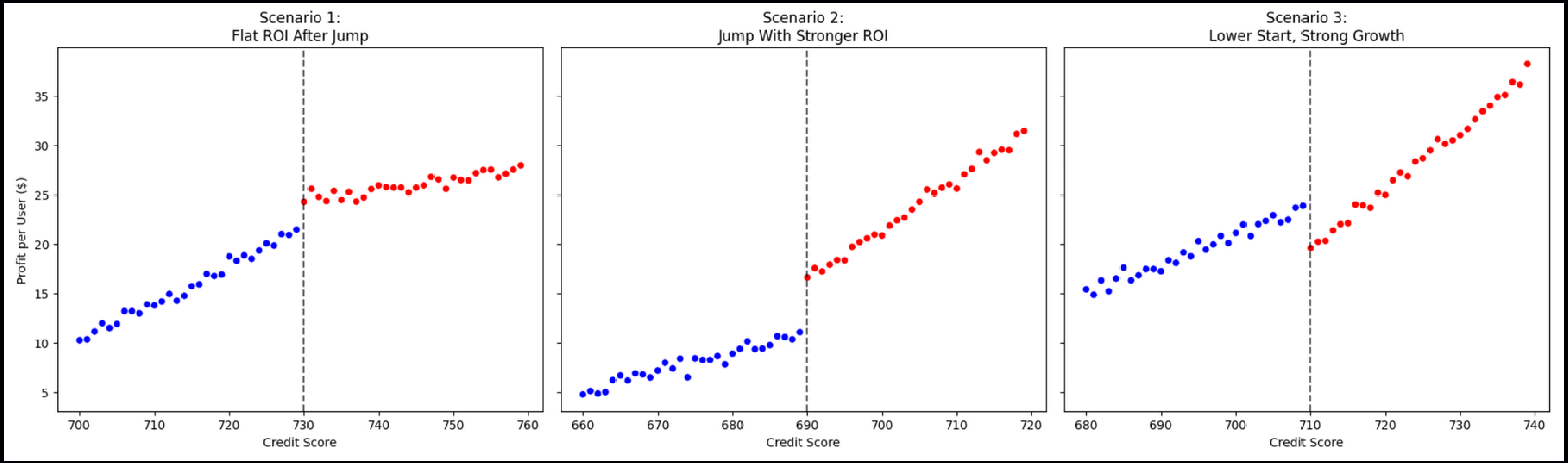
- Treatment effectively raises profit
- Apply partial lift to LHS to raise prior profit

Cutoff Early Adoption

- Treatment effectively raises profit
- Move Cutoff backwards towards intersection

Cutoff Delay

- Treatment effect shows a slow start at cutoff but strong growth at later stage
- Delay cutoff to further capture unrealized profit



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VALIDITY CHECK

Under what conditions would
the RD analysis be “valid”

No manipulation

Users cannot precisely control their credit score;

***McCrary density test.**

Continuity

Default rate and spending change gradually with credit score;

Any jump at the threshold suggests treatment effect, not natural variation.

"As Good as Random"

Borrowers near the cutoff are similar in characteristics.

BASELINE COVARIATES

Behavioral

Current balance
Credit utilization ratio
Payment method
Months on book
History of missed or late payments
Previous monthly spending

Demographic

Age
Income
Employment status
Location

APPENDIX

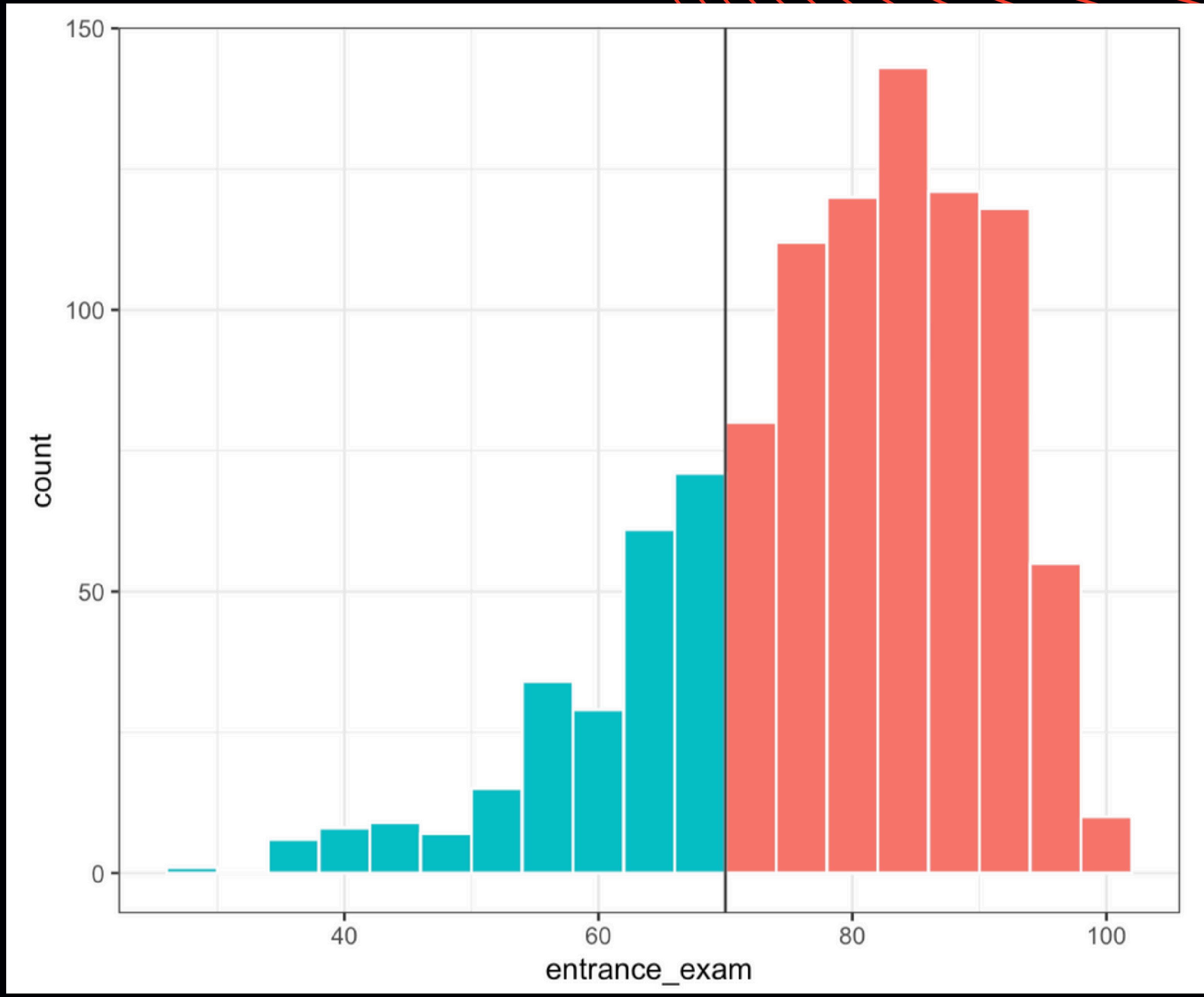
1. How do banks decide credit limits
2. Motivation for RDD
3. RD design structure
4. Local regression
5. Bandwith selection
6. Treatment expectation
7. Profit implication
8. Validity check
9. Baseline covariates
10. *No manipulation
11. *McCrary density test
12. *Continuity

NO MANIPULATION

- **Credit scores are complex and algorithmic:** They depend on multiple weighted factors (e.g., payment history, credit utilization, length of credit history), which are not fully transparent - the model is a black box.
- **Data is reported by lenders with delays:** Reporting cycles are typically monthly, meaning recent actions may not reflect immediately.

MCCRARY DENSITY TEST

- **Checks for manipulation** - if distribution of credit scores is continuous at the cutoff.
- It estimates the frequency (density) of observations just below and just above the cutoff.
- No jump = Valid RD



CONTINUITY

- **Default Rate and Credit Score**
  - Source: Federal Reserve Bank of Kansas City (2015) – Consumer Credit Risk and Pricing
  - Finding: Default rates decline steadily as FICO scores increase; no sharp jumps, supporting a smooth relationship.
  - Quote: “Higher FICO scores are associated with significantly lower default probabilities in a smooth and monotonic fashion.”
- **Spending and Credit Score**
  - Source: Chen, Konana, and Menon (2014) – The Impact of Credit Scores on Consumer Spending Behavior
  - Finding: As credit scores improve, consumers show gradual increases in discretionary spending and credit usage.
  - Quote: “We find a continuous relationship between consumers’ credit scores and their monthly credit card spending.”