The Value of Man in AI + Man:
Field Evidence from Small Business Lending

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Insight 1: Opening the soft-information black box

Classic empirical challenge

- Soft information is usually **unobserved**.
- Proxies: geographic distance (Petersen and Rajan 2002); hierarchical distance (Liberti and Mian 2009); keyword ratios (Campbell et al. 2019); regression residuals (Liu 2022).

This paper

- Observes loan officers' written comments.
- Classifies concrete soft-information categories.

business prospects | family support | lawsuit / cash-flow explanations | referrals

Moves from *"soft information matters"* to *"which soft signals matter under AI assistance?"*

Insight 2: From “AI vs. human” to “AI + human”

AI recommendation
score / terms / denial

→

Human discretion
override / adjust / approve

→

Loan outcome
profit / risk / value

Conditional on AI already being used, what is the **marginal product of human discretion**?

- Differs from Cao et al. (2024): *Man + AI* has AI as final decision-maker.
- Differs from Costello et al. (2020): grants discretion, rather than asking **when discretion pays off**.
- The *AI + Man* framing makes organizational design issue explicit.

Insight 2: AI + Man as organizational design

- Opens the door to **organizational design** in the AI era.
- Allocation of control rights: override, monitor, or defer?
- Value of human discretion depends on **information**, **incentives**, and **behavioral frictions**.

Information
soft signals

Incentives
agency / KPIs

Frictions
aversion / fatigue

Value of discretion

Scope beyond lending: audit, analyst forecasts, hiring, underwriting, fraud detection, etc.

Primary comment 1: the outcome is a constructed counterfactual

The authors do **not observe** outcomes had the firm followed AI recommendations.

$$\text{Deviation\_Profit} = 100 \times \frac{Profit_{Man} - \widehat{Profit}_{AI}}{Invoice\ Amount_{Man}}$$

Key assumptions behind $\widehat{Profit}_{AI}$:

(a) Same default likelihood under AI and human decisions.

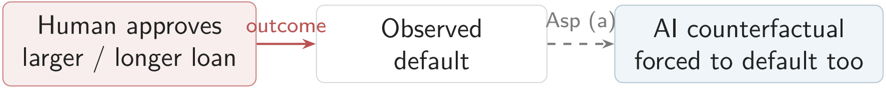
(b) AI invoice amount scales with actual invoice amount.

(c) AI principal repayment scales with actual repayment.

(d) AI-denied cases use prior-month average rate.

Most troubling: same default risk despite loan size / term / rate. This implies AI recommendations carry no additional default-risk information—contradicting the premise of the AI system.

Primary comment 1: why the same-default assumption matters



- The most meaningful value-destroying cases: human expansion **causes default**.
- Assumption (a) assigns the same default to the AI counterfactual.
- This removes the variation separating good vs. bad discretion.
- If construction error correlates with **soft information**, **agency**, or **bias**, H1–H3 may partly reflect measurement error.

Primary comment 1: feasible fixes

1. Use realized outcomes

- Drop counterfactual for subset tests.
- Outcomes: 10-day delay, days late, principal repaid, renewal, recovery time.

3. Use AI's own risk score

- Control for AI predicted PD / risk score.
- Regress $Profit_{Man}$ on AI score, AI terms, proxies.

2. Let PD vary under AI terms

- Estimate $P(Delinq) = f(Amount, Rate, Term, X, FE)$.
- Predict delinquency under AI amount / rate / term.

4. Split the question

- Stage 1: proxies $\rightarrow$ amount / rate / term / override.
- Stage 2: deviations $\rightarrow$ realized delinquency / profit.

Primary Comment 2: Approved-only sample truncation

Observed sample

	Man approve	Man reject
AI approve	**in**	missing
AI reject	**in**	missing

Why it matters

- Sample is conditional on **human approval**.
- Footnote 11: AI–Man agreement in rejections "will not affect inferences."
- True for the **average deviation**; less clear for **H1–H3**.

If officers approve selectively when they perceive a soft-information edge, soft-information coefficients may reflect **selection into approval**, not only value creation.

Approved-only sample: direction of bias

H1: soft information

- Bias likely **positive**.
- Proxies capture favorable soft signals: family support, prospects, referrals, explanations.

H2: agency

- Bias may cut **in authors' favor**.
- Agency frictions push marginal approvals.
- Missing rejections are likely from less lenient officers.
- Negative agency coefficients may be conservative.

H3: behavioral bias

- Bias is **ambiguous**.
- Algorithm aversion can mean over-approving AI rejects.
- Or rejecting AI approves.
- Current sample captures only the first channel.

Approved-only sample: suggested fixes

1. **Quantify the missing cell.**
   Report aggregate counts of AI-approved / Man-rejected applications by month, officer, industry, and AI risk band.

   If $< 5\%$, concern is small; if 20–30%, cross-sectional tests need stronger caveats.

2. **Replicate within AI-approve / Man-approve loans.**
   Compare human term adjustments holding the binary approval decision fixed.

   Excludes AI-reject overrides, where selection and imputed rates are most severe.

3. **Use AI's risk score around the threshold.**
   Exploit the continuous score behind AI approve/reject.

   Marginal approve vs. marginal reject cases provide an RD-style test of whether soft information predicts deviations.