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

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May 2026

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Research Objective

- To investigate the value of humans in an “AI + Man” loan setting
  - Utilizing proprietary loan-level data from a Fin-Tech company where human loan officers make loan decisions based on AI’s recommendations
  - Exploring the conditions under which the incremental value of loan officers is higher or lower

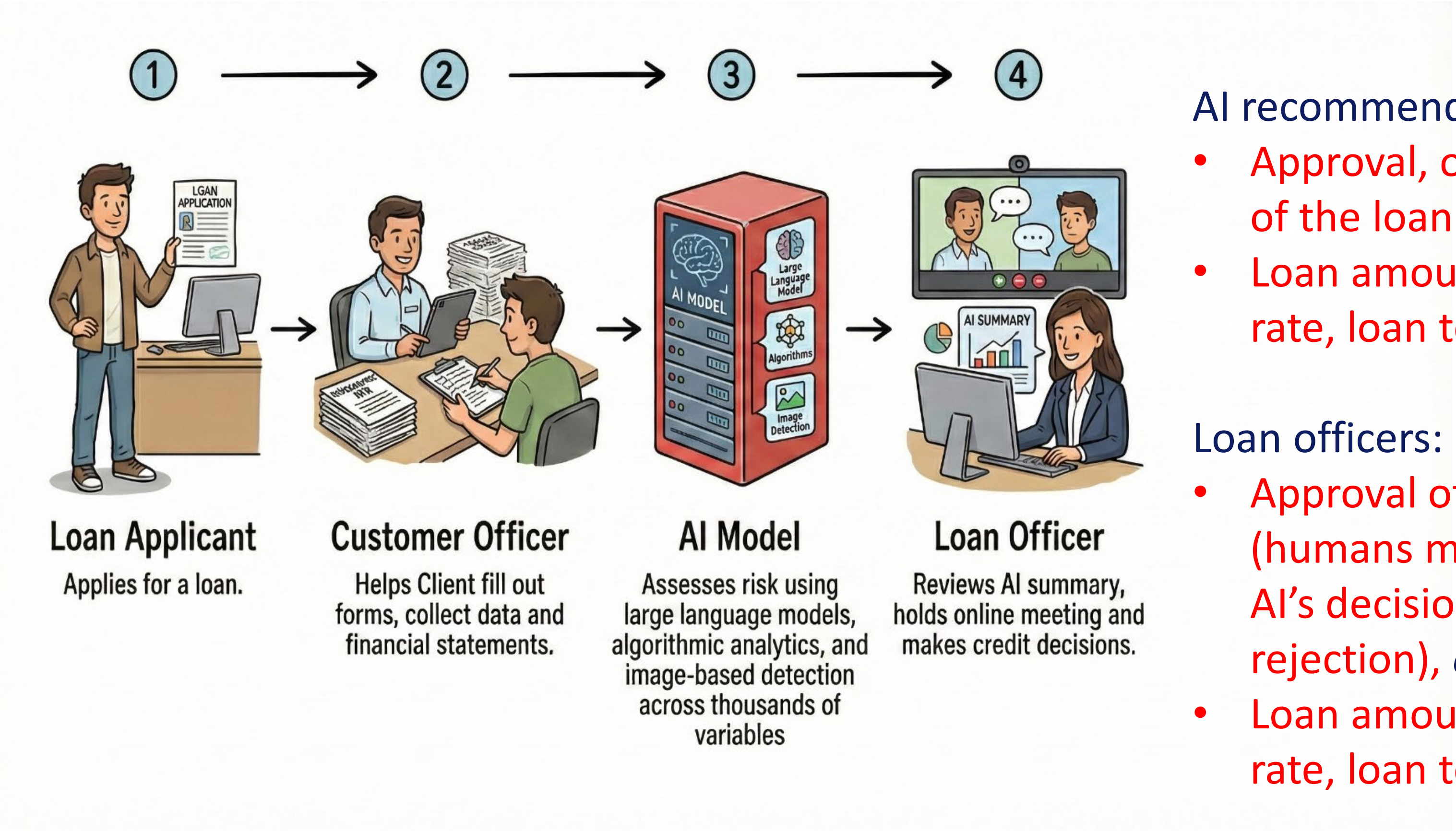
Motivations

- Substantial investments in AI in recent years
- The increasing adoption of AI assistance in workplace
- The rapid expansion of FinTech platforms
- Understanding the variation of humans' value-addition in AI-assisted lending decisions can (i) help us understand how humans build upon AI to add value and (ii) inform FinTech companies and banks in business strategies in an era of accelerating technological integration.

Institutional background

- Focal company: a lending company in Zhejiang, China
  - Providing loans to small businesses (typically several hundred thousand CNY).
- Three different decision models:
  - Expert Decision Phase (2016–2020): human decision only
  - AI Decision Phase (2021–mid 2023): AI decision only (reflecting the surge of Fintech)
  - **AI + Man Decision Phase** **(from mid 2023)**: loan officers make decisions based on AI recommendations
    - To purse growth and expand the market to more clients where soft information may be more important
    - To respond to interest cap imposed by the government
- We focus on loans approved in 2024 to evaluate the value of human decisions over AI recommendations.

Institutional background: Loan application workflow



AI recommendation:

- Approval, or rejection of the loan
- Loan amount, interest rate, loan term

Loan officers:

- Approval of the loan (humans may override AI's decision of loan rejection), *or rejection*
- Loan amount, interest rate, loan term

Hypothesis Development (1)

- The potential benefits of human intervention – soft information
  - AI has limited ability to acquire and interpret soft information (Campbell et al. 2019; Liberti and Petersen 2019).
    - Soft information: qualitative, non-standardized, or relationship-based information
    - Humans' contextual knowledge can help with loan decisions.
- **H1:** Ceteris paribus, human intervention is more likely to improve the value of loans when soft information is used.
- Tension
  - AI models might be able to incorporate some factors that are correlated with soft information or harden soft information (Liberti and Petersen 2009; Sutherland 2020).
  - The increasing amount of information used by AI models (20,000 variables used by the focal company's AI model) reduces the marginal value of soft information collected by loan officers.

Hypothesis Development (2)

- The potential costs of human intervention – agency issues
  - Loan officers may face misaligned incentives (e.g., Liberti and Petersen 2019).
    - Personal connections
    - The pressure to meet KPI targets
- **H2:** Ceteris paribus, human intervention is less likely to increase the value of loans when loan officers face more severe agency issues.

Hypothesis Development (3)

- The potential costs of human intervention – behavioral bias
  - Algorithm aversion
    - Avoiding or reducing the reliance on AI assistance even when doing so reduces task performance (e.g., Dietvorst et al. 2015; Commerford et al. 2022; Commerford et al. 2024; Bockstedt and Buckman 2025)
    - "with more than ten years of experience, we have better judgement than the model."
  - Mental fatigue
    - Mental fatigue can reduce the quality of professional judgment, particularly under time pressure or with high workloads (e.g., Baumeister et al. 1998; Hirshleifer et al. 2019).
- **H3:** Ceteris paribus, human intervention is less likely to increase the value of loans when loan officers are more likely to be subject to behavioral bias.

Sample selection (Table 1)

	Obs.
All loans approved in 2024	28,198
Less:	
Loans that have invoices not matured at the time of data collection	(6,791)
Loans with missing values on loan outcomes or other variables	(2,706)
Loans approved by loan officers who approved fewer than 100 loans in 2024	(52)
Singleton observations	(159)
Final sample	18,490

Loan profit calculation

$$Profit = \sum_m [PV(Payment_m) + PV(Recovery|Default)] - Initial\ Investment,$$

- $Profit_{\_Man}$: profit based on loans' actual cash flows (Jensan et al. 2025)
- $Profit_{\_AI}$: hypothetical profit based on AI recommendations
  - Interest rate = recommended interest rate for AI approved loans and the average interest rate of loans approved in the previous month for AI rejected loans
  - Adjust loan dispensed amount, interest payment, and repaid principal by the loan amount ratio (i.e., AI's recommendation of loan amount/actual loan amount)
- $Profit_{\_Man}$ and $Profit_{\_AI}$ are aggregated across invoices to obtain the loan-level profit.
- The value of loan officer: $Deviation\_Profit\ (\%) = 100 \times \frac{Profit_{-Man} - Profit_{-AI}}{Loan\ Amount_{-Man}}$

Loan profit calculation $Profit\_{AI}$ key assumptions:

- Borrowed amount increases with approved loan amount (i.e., credit limit)
- Default risk is similar under AI recommendation and human decisions
  - Principal and interest collection schedule is set independently by loan collection department
  - The results are robust to using the sample of loans with low default risk
- For loans recommended rejection by AI, we assume that the firm lends the money out using the average interest rate in the previous month

- The results are robust to using alternative assumptions.

Research design

$$Deviation\_Profit(\%)_l = \alpha + \beta_1 Soft\_Information_l + \beta_2 Agency\_Issue_l + \beta_3 Behavioral\_Bias_l + \varepsilon_l$$

- A positive coefficient indicates that the factor enhances the value created by human loan officers beyond AI recommendations.
  - A negative coefficient indicates that the factor reduces the value created by human loan officers beyond AI recommendations.
- Loan-level characteristics and borrower characteristics are (implicitly) controlled for with the calculation of *Deviation_Profit*.
- We control for month, industry, and loan officer fixed effects.
- Standard errors are clustered at the loan officer level.

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Descriptive statistics loan parameters (Table 2, Panel A)

	AI recommendations		Loan officers' decisions		Difference in mean	
	Mean (1)	Std. (2)	Mean (3)	Std. (4)	(3) − (1)	*t*-statistics
Loan Amount (CNY)	126,947	97,540	161,846	50,632	34,899***	46.21
Interest Rate (%)	18.15	1.60	14.51	2.54	-3.64***	-170.00
Hypothetical AI Rate (%)	16.39	1.85			-1.87***	-91.74
Loan Term (month)	16.58	6.28	24.62	11.37	8.04***	83.99

The average value of human intervention

Table 3, Panel A (loan profit)

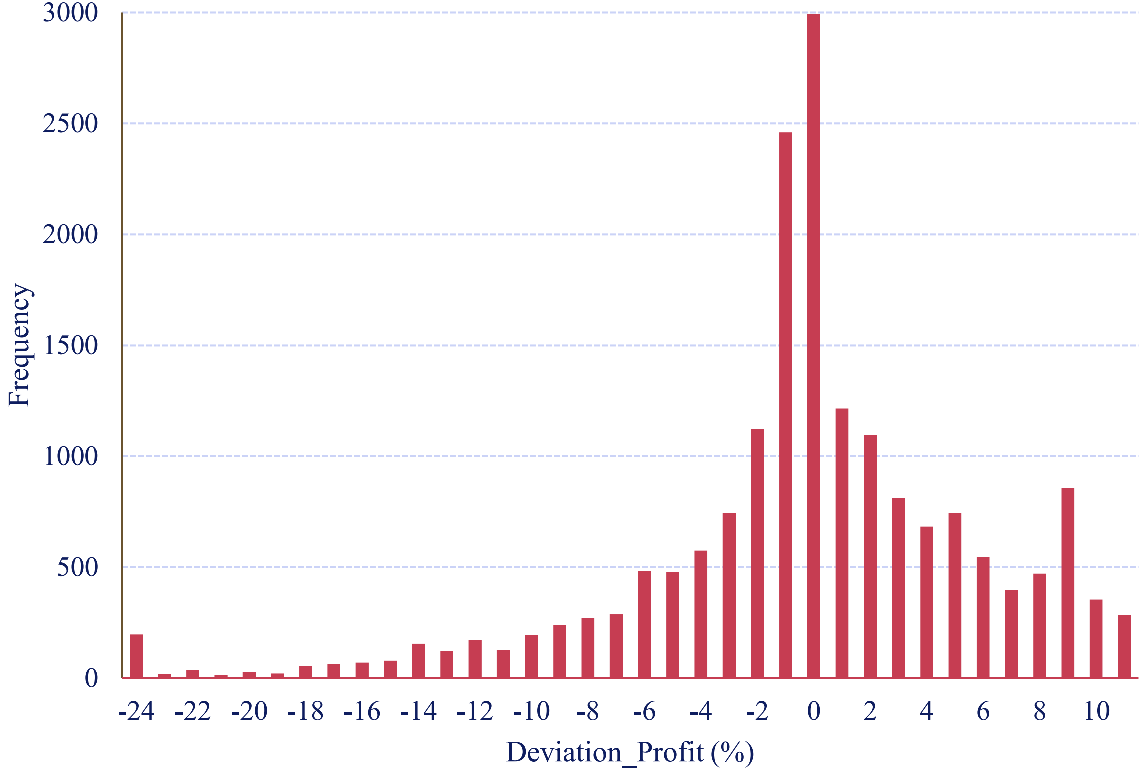
Profit (CNY)	AI recommendations (1)	Loan officers' decisions (2)	Difference in Mean (2) – (1)	*t*-statistic
Mean	12,109.10	13,153.45	1,044.36***	13.38
Std.	12,083.90	8,297.73		

Table 3, Panel B (deviation in profit)

Variable	Mean	Std.	Q1	Median	Q3
Deviation_Profit (%)	0.209	6.164	-1.813	0.177	3.644

- The mean of *Deviation_Profit* (%) is positive (0.209).
- *Deviation_Profit* (%) is positive for 57% of the loans.
- On average, human intervention creates value.

Distribution of the deviation in profit



- The standard deviation of *Deviation_Profit* (%) is large: 6.164.
- It's important to investigate what causes the variation in the deviation in profit between human decisions and AI recommendations.

Tests of H1: Proxies for soft information:

- Comments made by loan officers when making decisions, which mainly contain soft information
- *Comment_Long*: the length of comments made by loan officers ≥ Q3
- *Business_Prospect*: the discussion of borrowers' business prospects
  - "The borrower demonstrates strong operational capability, exhibits favorable growth prospects, with the business currently in an expansion phase."
- *Family_Support*: the support for borrowers from family members
  - "The client operates a food processing business. … The client's son is willing to co-pay interests, indicating a strong intent to pay the loan."
- *Credit_Anomalies*: the impact of the lawsuit faced by the borrowers and cash flow anomalies on borrowers' creditworthiness
  - "The increase in liabilities in the last two years is primarily attributable to the renovation of the homestead, which has now been completed."
- *Referral*: the referral from existing clients or loan officers' acquaintances

Tests of H1 (Soft information, Table 4)

Dependent variable =	*Deviation_Profit (%)*				
	(1)	(2)	(3)	(4)	(5)
Comment_Long	0.366***				
	(2.65)				
Business_Prospect		0.215**			
		(2.05)			
Family_Support			0.460***		
			(2.92)		
Credit_Anomalies				0.440***	
				(2.95)	
Referral					0.219***
					(2.70)
Month FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Loan Officer FE	Yes	Yes	Yes	Yes	Yes
Obs.	18,490	18,490	18,490	18,490	18,490
Adj. R^2	0.011	0.011	0.011	0.011	0.011

- Human loan officers can create value in an AI + Man setting through the use of soft information.
- The impact ranges from 3.5% to 7.5% of the standard deviation of *Deviation_Profit* (%).

Test of H2: Proxies for agency issues

- *Hometown_Tie*: the hometown tie between loan officers and the borrowers
  - Prior research finds that hometown ties affect a wide range of decisions, such as politicians' career progression (Fisman et al. 2020), the quality of government monitoring (Chu et al. 2021), and audit quality (Deng, Zhang, and Liu 2023).

- *Remote_Area:* customer officers located in remote areas
  - The company requires loan officers to evaluate the quality of customers officers, which is more difficult for customer officers located in remote areas.

- *Peer_Pressure*: the peer pressure in achieving KPIs on the loan officers who lag behind peers in loan approvals
  - The focal company installed a large screen in the meeting room for loan officers to display real-time approval progress, allowing loan officers to observe their colleagues' workloads in real time.

Tests of H2 (Agency issues, Table 5)

Dependent variable =	*Deviation_Profit (%)*		
	(1)	(2)	(3)
Hometown_Tie	-0.998***		
	(-4.44)		
Remote_Area		-0.596***	
		(-4.70)	
Peer_Pressure			-0.700***
			(-5.98)
Month FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Loan Officer FE	Yes	Yes	Yes
Obs.	18,490	18,490	18,490
Adj. R^2	0.012	0.014	0.014

- Loan officers faced with agency issues create less value, or destroy value, by deviating from AI's recommendations.
- The impact ranges from 9.7% to 16.2% of the standard deviation of *Deviation_Profit (%)*.

Test of H3: Proxies for behavioral bias

- Algorithm aversion:
  - *Multi_Loan*: loans applied by borrowers who have loans from other financial institutions (AI have comparative advantages in such cases)
  - *Infor_Request*: loan officers requesting hard information already processed by AI

- Mental fatigue:
  - *Peak_Hour:* the hours when loan officers approve the highest number of loans (10-11am and 4-5pm)
  - *Around_Holiday*: working hours around national holidays

Tests of H3 (Behavioral bias, Table 6)

Dependent variable =	*Deviation_Profit (%)*			
	(1)	(2)	(3)	(4)
Multi_Loan	-1.465***			
	(-12.07)			
Infor_Request		-0.481***		
		(-3.52)		
Peak_Hour			-0.233***	
			(-2.68)	
Around_Holiday				-0.385***
				(-2.60)
Month FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Loan Officer FE	Yes	Yes	Yes	Yes
Obs.	18,490	18,490	18,490	18,490
Adj. R^2	0.024	0.011	0.011	0.011

- Loan officers' contribution over AI's recommendation is lower when experiencing algorithm aversion and mental fatigue.
- The impact ranges from 3.8% to 23.8% of the standard deviation of *Deviation_Profit (%)*.

Performance evaluation criteria for loan officers (Table 7)

- On July 1, 2024, the focal company started to implement a policy on the evaluation of loan officers, considering both the quantity (the number of approved loans) and *quality (the default rate)* of loan decisions.

Dependent variable =	*Deviation_Profit (%)*				
Soft information proxy =	*Comment_Long*	*Business_Prospect*	*Family_Support*	*Credit_Anomalies*	*Referral*
Loans approved in January-June of 2024					
Soft information proxy (1)	0.263	0.022	0.204	0.404**	0.267***
	(1.55)	(0.16)	(0.87)	(2.25)	(3.06)
Loans approved in July-December of 2024					
Soft information proxy (2)	0.479***	0.466***	0.787***	0.483***	0.154
	(2.97)	(2.84)	(4.18)	(3.01)	(1.16)
Difference in coefficient: (2) – (1)	0.216	0.444*	0.583**	0.079	-0.113
(p-value)	(0.184)	(0.062)	(0.020)	(0.438)	(0.300)

- Soft information is more important when loan officers pay closer attention to loan quality.

Additional analyses: first and second half of 2024 (Table 7)

Dependent variable =	*Deviation_Profit (%)*		
Agency issue proxy =	*Hometown_Tie*	*Remote_Area*	*Peer_Pressure*
Loans approved in January-June of 2024			
Agency issue proxy (1)	-1.569***	-0.884***	-0.597***
	(-6.46)	(-5.00)	(-4.63)
Loans approved in July-December of 2024			
Agency issue proxy (2)	-0.306	-0.203	-0.937***
	(-0.87)	(-1.52)	(-4.25)
Difference in coefficient: (2) – (1)	1.263***	0.681***	-0.340**
(p-value)	(0.01)	(0.002)	(0.038)

- Paying closer attention to loan quality can mitigate agency issues to some extent.
  - It exacerbates the impact of peer pressure.

Additional analyses: first and second half of 2024 (Table 7)

Dependent variable =	*Deviation_Profit (%)*			
Cognitive constraint proxy =	*Multi_Loan*	*Infor_Request*	*Peak_Hour*	*Around_Holiday*
Loans approved in January-June of 2024				
Cognitive constraint proxy (1)	-1.324***	-0.353***	-0.001	-0.221
	(-8.53)	(-2.82)	(-0.01)	(-0.96)
Loans approved in July-December of 2024				
Cognitive constraint proxy (2)	-1.718***	-0.737***	-0.603***	-0.846***
	(-12.04)	(-2.91)	(-4.58)	(-2.61)
Difference in coefficient: (2) – (1)	-0.394**	-0.383*	-0.602***	-0.625
(p-value)	(0.02)	(0.076)	(0.004)	(0.108)

- Paying closer attention to loan quality can exacerbate algorithm aversion and mental fatigue.

Including all proxies at the same time (Table 8)

- The inferences remain the same.

Dependent variable =		Deviation_Profit (%)			
		(1)	(2)	(3)	(4)
Soft information	*Comment_Long*	0.246*			0.294**
		(1.88)			(2.22)
	Business_Prospect	0.178*			0.178
		(1.66)			(1.56)
	Family_Support	0.405**			0.358**
		(2.49)			(2.14)
	Credit_Anomalies	0.372***			0.338**
		(2.63)			(2.06)
	Referral	0.215***			0.158*
		(2.61)			(1.75)
Agency issues	*Hometown_Tie*		-1.062***		-1.167***
			(-4.52)		(-4.83)
	Remote_Area		-0.635***		-0.564***
			(-4.83)		(-4.39)
	Peer_Pressure		-0.694***		-0.644***
			(-5.87)		(-5.82)
Behavioral bias	*Multi_Loan*			-1.453***	-1.443***
				(-12.16)	(-12.27)
	Infor_Request			-0.424***	-0.196
				(-3.12)	(-1.30)
	Peak_Hour			-0.255***	-0.243***
				(-2.74)	(-2.62)
	Around_Holiday			-0.367**	-0.341**
				(-2.37)	(-2.20)

Sensitivity tests based on alternative research design

- Important assumptions when calculating loan profit under AI recommendations:
- Interest rate = opportunity cost for the AI rejected loans
  - For the loans denied by AI, we use the interest rate recommended by AI (assuming that it is this interest rate that the company will charge).
- The same default risk as actual default risk
  - The assumption is more likely to be valid when the default risk is low.

  → Restricting the sample to loans not in default
- Proportional invoice amount
  - Assuming borrowers borrow the same amount regardless of the credit limit.

  → Using the lower of the actual invoice amount and the credit limit approved by AI

Sensitivity tests based on alternative research design (Table 9)

- The inferences remain the same.
- The results are weaker in column (3).

Dependent variable =	*Deviation_Profit (%)*		
	(1) Alternative interest rate for *Profit_AI*	(2) Sample of loans not in default	(3) Alternative invoice amount for *Profit_AI*
Comment_Long	0.503***	0.189*	0.167
	(3.01)	(1.78)	(1.26)
Business_Prospect	0.317**	0.182	0.097
	(2.38)	(1.31)	(1.18)
Family_Support	0.338*	0.327*	0.133
	(1.82)	(1.80)	(1.25)
Credit_Anomalies	0.487***	0.334*	0.184**
	(2.90)	(1.93)	(1.98)
Referral	0.116	0.091	0.144*
	(0.86)	(0.89)	(1.82)
Hometown_Tie	-1.233***	-1.085***	-0.890***
	(-4.39)	(-4.37)	(-6.24)
Remote_Area	-0.713***	-0.640***	-0.411***
	(-3.72)	(-4.91)	(-4.65)
Peer_Pressure	-0.750***	-0.684***	-0.408***
	(-5.41)	(-6.76)	(-5.44)
Multi_Loan	-1.502***	-1.459***	-0.570***
	(-8.94)	(-11.00)	(-9.73)
Infor_Request	-0.167	-0.209	-0.123
	(-0.90)	(-1.18)	(-1.30)
Peak_Hour	-0.266**	-0.224**	-0.099
	(-2.50)	(-2.29)	(-1.59)
Around_Holiday	-0.300	-0.330*	-0.021
	(-1.34)	(-1.76)	(-0.18)

Analyses of the Actual Profit (Table 10)

- Objective: To reduce the impact of the measurement error in *Profit_AI*
- The inferences remain the same.

Dependent variable =		Ln(Profit_Man)
Ln(Profit_AI)		0.663***
		(64.67)
Soft information	Comment_Long	0.126***
		(5.36)
	Business_Prospect	0.041*
		(1.79)
	Family_Support	0.029
		(1.41)
	Credit_Anomalies	0.079***
		(3.45)
	Referral	0.067***
		(4.07)
Agency issues	Hometown_Tie	-0.000
		(-0.00)
	Remote_Area	-0.138***
		(-7.14)
	Peer_Pressure	-0.092***
		(-5.40)
Behavior bias	Multi_Loan	-0.141***
		(-13.09)
	Infor_Request	-0.005
		(-0.26)
	Peak_Hour	-0.015
		(-1.20)
	Around_Holiday	-0.005
		(-0.15)

Summary of results

- The value created by human loan officers has a large variation.
- The value created by human loan officers
  - Increases with the use of soft information
  - Decreases with the extent of agency issues faced by loan officers
  - Decreases with behavioral bias (algorithm aversion, mental fatigue)
- The performance evaluation policy emphasizing loan quality enhances the value of soft information, mitigates agency issues, but exacerbates behavior bias.

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Contributions

- The results of the paper shed light on the conditions under which the contribution of humans is higher (or lower).
- The literature on AI
  - The value of humans in AI-assisted decision-making settings
  - → important for companies providing AI assistance to workers
- The literature on FinTech an banks
  - Providing insights into the design of human-machine collaboration and the performance evaluation policies for workers
- The literature on soft information in lending
  - Identifying the specific soft information used by loan officers (not just its existence)

Thank you!

Related research – Growing literature on AI

- Productivity gains from AI adoption (e.g., Babina et al. 2024)
- AI reshaping the labor market (e.g., Acemoglu et al. 2022; Abis and Veldkamp 2024)
- Performance of AI in security analyses
  - Grennan and Michaely (2021), Coleman, Merkley, and Pacelli (2022) , Bertomeu et al. (2025) …
  - Cao et al. (2024) compare AI vs. Man + AI (self-constructed machine learning model with human analysts' forecasts as an additional input)
    - They find that human input adds more value for firms with lower liquidity, more intangible assets, higher earnings volatility and distress risk .
    - Our set up is closer to the real-world practices of companies providing AI assistance to employees.
    - We speak to humans' advantages/disadvantages due to soft information, agency costs, behavioral bias in the loan setting.

Related research – AI in the lending setting

- Liu (2022) and Jansen et al. (2025) compare the performance of AI vs. Man.
  - Liu (2022) uses a small lender setting and finds that AI outperforms man, primarily due to man's constraints in processing hard information.
  - Jansen et al. (2025) use the car loan setting and find that machine underwriters outperform human ones due to agency conflicts faced by humans and humans' poorer ability in processing hard information in complex cases.
- How are we different: different research question
  - We examine the incremental value of man in an AI + Man decision setting.
  - We focus on how the incremental value of humans varies with soft information, agency costs, and behavioral bias.

Related research – AI in the lending setting (cont'd)

- Costello et al. (2020) examine AI + Man in a trade credit extension setting:
  - They allow half of the trade credit lenders additional discretion in deviating from the machine's recommendations.
  - They find that on average, allowing humans more discretion is associated with a greater reduction in credit risk, especially for private clients without social media accounts.
- How are we different?
  - We examine the loan setting.
    - Unlike loans, trade credit extension is tied to the exchange of underlying goods or services.
    - Trade credit has a short duration and does not carry explicit interest rate.
  - We focus on how human loan officers add or destroy value.
  - We can observe the soft information used by, agency issues faced by, and behavioral bias of loan officers.

Determinants of deviation in profit (Table 3)

Dependent variable =	*Deviation_Profit (%)*				
	(1)	(2)	(3)	(4)	(5)
Deviation_Amount	1.112***				1.132***
	(63.13)				(62.82)
Deviation_Rate (%)		0.393***			0.477***
		(20.14)			(29.08)
Deviation_Term			0.028***		0.020***
			(5.82)		(5.28)
Override				1.750***	-0.010
				(14.60)	(-0.11)
Month FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Loan Officer FE	Yes	Yes	Yes	Yes	Yes
Obs.	18,490	18,490	18,490	18,490	18,490
Adj. R^2	0.374	0.039	0.014	0.027	0.418

- The deviation in profit is mainly driven by the difference in loan amount, interest rate, and term.