The Transformative Role of Artificial Intelligence and Big Data in Banking

Binkai Chen
CUFE

Dongmei Guo
CUFE

Junjie Xia
CUFE & Peking U

Zirun Zhang
CUFE

The 24th Annual Bank Research Conference

September 25, 2025

Agenda

- **Motivation**
- **Preview and literature contribution**
- **Data and background**
- **Empirical strategy**
- **Findings and implications**
- **Conclusion**

Motivation

- **Existing literature has explored the impact of FinTech on fund management, market microstructure, distributional effects, corporate culture, small business financing, and banking competition**
  - e.g., Easley et al., 2021; Li et al., 2021; Fuster et al., 2022; DeMiguel et al., 2023; Babina et al., 2024; Hau et al., 2024, Guo et al., 2025

- **Limited empirical evidence on how these technologies reshape banking operations and credit decision-making processes**

What do we do?

- **Empirical study:**

  - Leverage a large loan-level dataset from a leading commercial bank in China

  - Examine how AI and big data impacts the banking operation, particular in credit rating and loan performance

  - Explore the synergy between AI and big data

- **Empirical strategy**:

  - Using a policy mandate to adopt AI and big data as an exogenous shock to the bank

  - Three-Year Development Plan (2019–2021) for FinTech

  - Difference-in-differences approach

What do we find?

- **The adopting of AI and big data enhances *credit rating accuracy* and reduces *loan default rates*, particularly for SMEs**

  - Unclassified credit rating rate drop by 2.4 percentage points (a 40.1% decline)

  - Loan default rate drops by 2.7 percentage points (a 29.6% decline)

- **Highlight the channel of *information advantages* by conducting the heterogenous analysis – the effects are more profound for**

  - Firms lacking formal financial statement information or public data

  - Loans with shorter maturities and no collateral

  - Regions with lower economic development and higher linguistic diversity

  - First-time borrowers and long-distance borrowers

What do we find?

- **Big data unlocks the full potential of AI models**

- **Analyzing the bank's two-stage adoption:**

  - The initial machine learning upgrade (without big data) reduced unclassified credit ratings by 1.6 percentage points

  - Once big data integrated, the reduction reached 3.6 percentage points

  - More than doubled the improvement.

- **Big data turns AI from a static tool into a truly *adaptive and dynamic* analytic instrument**

Literature and contributions (I)

- **Impact of Machine Learning (ML) in Finance:**
  - Fund performance (Easley et al., 2021)
  - Corporate culture (Li et al., 2021)
  - Market microstructure (Fuster et al., 2022)
  - Distributional effects (DeMiguel et al., 2023)
  - Decision-making process (Begenau et al., 2018)

- **Our paper – banking operations**
  - How these technologies affect banking operations – credit ratings and loan default rates
  - Address information asymmetries and scarcity, and improve risk management

Literature and contributions (II)

- **FinTech and SMEs**: (ML, LLM, AI)
  - Financial constraints (Petersen and Rajan, 1994, etc.)
  - Regions with less competitive banking sectors (Frost et al., 2020)
  - Substituting traditional bank lending (Gopal and Schnabl, 2022)
  - Enhances customer acquisition (Agarwal et al., 2019, 2022)
  - Boosts vendor sales growth (Hau et al., 2024)
  - Banking competition (Guo et al., 2025)

- **Our paper – bank loans to SMEs**
  - Enabling more accurate assessments of SME creditworthiness
  - Lower default rates
  - Improves SMEs' access to bank credit with lower cost

Literature and contributions (III)

- **Information advantages of FinTech**

  - Big-Tech company (Alibaba platform) expand credit to vendors (Hau et al., 2024)

  - Mitigates asymmetric information challenges (Livshits et al., 2016)

  - Affect lender competition and lending (Vives and Ye, 2025)

- **Our paper – addressing incomplete information and information asymmetries**

  - Firms with incomplete financial records or limited public information

  - Unsecured loans (without collaterals)

  - Regions with lower economic development and higher linguistic diversity

Literature and contributions (IV)

- **Big data in Economics and Finance**

  - Organizational productivity and efficiency (Brynjolfsson and McElheran, 2016)

  - Enhancing decision-making processes and create competitive advantages for large firms (Begenau et al., 2018)

  - Data accumulation and AI-driven innovation (Cong et al., 2025)

- **Our paper – The synergy of big data and AI models**

  - Unlocks the full potential of AI

  - Combining with structured and unstructured data (scanned financial documents, business contracts, textual transaction records, transactional VAT data, etc.)

  - Produce a more profound effect on banking operations

Institutional background

- **The Bank**

  - Historically, human decision-making through conventional methods, such as shadow ratings and hierarchical analysis

  - Heavily rely on human judgment and the quality of data inputs

  - High "unclassified" or "missing" credit ratings, especially for SMEs

- **FinTech adoption policy**

  - Three-Year Development Plan (2019–2021) for FinTech (PBOC)

  - Promoting the adoption of advanced financial technologies in the banking industry

  - Enabling financial institutions to improve efficiency, reduce costs, and enhance the accuracy of decision-making processes

Institutional background

- **The Bank's adoption on FinTech**

  - In **July 2019**, implementing machine learning techniques, logistic regression models

  - In **October 2020**, incorporating sophisticated techniques and big data

- ***Big data:*** large-scale data and unstructured data

  - External data sources: e.g., National Business Registration System and National Intellectual Property Administration database

  - Unstructured data: e.g., scanned documents, firm-to-firm transaction receipts, and various image-based records

- To **optimize** the utilization of big data, the bank also implement

  - *Machine learning models:* artificial neural networks (ANN) and federated learning models (FLM)

  - *Recognition technologies:* Optical Character Recognition (OCR) and Natural Language Processing (NLP)

Data

- **Source**

  - Loan-level data from a major commercial bank in China

- **Sample**

  - January, 2015 – December, 2023

  - Approximately **4.53** million loans for **475,325** firms

Year	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**Total**
Firms	95291	79448	75266	80416	74611	73353	120429	166237	254644	**475,325**
Loans	417163	333368	321521	352866	305670	281315	523831	776723	1217431	**4,529,888**

Data representative (I)

- **Reginal distribution**

District	*Loans*	*Percent*	*District*	*Loans*	*Percent*
Beijing	169172	3.73%	*Inner Mongolia*	30480	0.67%
Tianjin	67703	1.49%	*Guangxi*	91487	2.02%
Hebei	197199	4.35%	*Chongqing*	91858	2.03%
Shanghai	198793	4.39%	*Sichuan*	217270	4.80%
Jiangsu	415190	9.17%	*Guizhou*	30409	0.67%
Zhejiang	669140	14.77%	*Yunnan*	46548	1.03%
Fujian	240904	5.32%	*Shaanxi*	114423	2.53%
Shandong	283282	6.25%	*Gansu*	37948	0.84%
Guangdong	635024	14.02%	*Qinghai*	5970	0.13%
Hainan	16370	0.36%	*Ningxia*	17439	0.38%
Shanxi	74172	1.64%	*Xinjiang*	39213	0.87%
Anhui	134114	2.96%	*Liaoning*	90109	1.99%
Jiangxi	81157	1.79%	*Jilin*	67890	1.50%
Henan	144924	3.20%	*Heilongjiang*	32638	0.72%
Hubei	131419	2.90%	*Xizang*	1317	0.03%
Hunan	156366	3.45%			

Data representative (II)

- **Industrial distribution**

Industry	*Loan*	*Percent*
Agriculture, forestry, animal husbandry, fishery	39322	0.87%
Mining	15665	0.35%
Manufacturing	1832876	40.46%
Electricity, heat, gas and water production and supply	47701	1.05%
Construction Industry	450478	9.94%
Wholesale and retail industry	1435430	31.69%
Transportation, warehousing and postal services	158771	3.50%
Accommodation and Catering Industry	30876	0.68%
Information transmission, software and information technology	100130	2.21%
Real Estate Industry	35904	0.79%
Leasing and business services industry	158431	3.50%
Scientific Research and Technical Services	89510	1.98%
Water, Environment and Utilities Management Industry	44500	0.98%
Resident services, repairs and other services	27007	0.60%
Education	5843	0.13%
Health and social work	9869	0.22%
Culture, sports and entertainment industry	12398	0.27%
Other	35177	0.78%

Facts on credit rating

- **Unclassified credit ratings**

  - Before the adoption of AI and big data, the bank had a substantially high degree of unclassified credit ratings.

	Before			*After*		
	Overall	Large	SMEs	Overall	Large	SMEs
Number of Firms	170386	7395	162991	374088	4360	369728
Number of Loans	1574635	176504	1398131	2955293	53094	2902199
Unclassified credit rating loans	105221	10978	94243	58863	6879	51984
Rate of unclassified credit rating	6.682%	0.697%	5.985%	1.992%	0.233%	1.759%

- **After the adoption, the rate of unclassified credit rating decline dramatically**

  - Particularly for **SMEs**

SMEs *vs* large firms

- In the pre-adoption period, SMEs had ***higher*** unclassified credit rating rate, ***higher*** loan default rate and ***higher*** interest payment, compared to large firms

Variables	*Unclassified Credit Rating*	*Loan Default Rate*	*Interest Payment*
	(1)	(2)	(3)
SME	0.046***	0.025***	0.582***
	(16.40)	(4.50)	(15.36)
Constant	0.019***	0.068***	4.687***
	(7.48)	(12.62)	(119.72)
Firm F.E.	NO	NO	NO
Industry F.E.	YES	YES	YES
Region F.E.	YES	YES	YES
Quarter F.E.	YES	YES	YES
Observations	1,563,285	1,550,496	1,562,563
R^2	0.071	0.071	0.396

Empirical strategy

- **Difference-in-differences (DID)** setting

  - SMEs as the treatment group

  - Large firms as the control group

  - July 2019 (the mandate to adopt FinTech) as an exogeneous shock

$$Y_{i,t} = \boldsymbol{\beta} SME_f \times Post_t + \varphi_f + \gamma_j + \theta_t + \delta_r + \varepsilon_{i,t},$$

  - Include firm, industry, region, and time fixed-effects

  - Robustness checks: parallel-trend; placebo (non-existent time, Monte Carlo permutation); regional-level variations

Baseline results – credit rating

- Unclassified credit rating rate among SMEs decreases by 2.4 percentage points, constituting an approximately 40.1% decline (=2.4%/5.985%)

Variables	*Dependent Variable: Unclassified Credit Rating*		
	(1)	(2)	(3)
SME × *Post*	-0.117***	-0.025***	$\boxed{-0.024^{***}}$
	(-3.85)	(-6.76)	$\boxed{(-5.63)}$
Post	0.067**	0.015***	
	(2.22)	(3.71)	
SME	0.005		
	(0.18)		
Constant	0.062**	0.036***	0.045***
	(2.13)	(49.66)	(16.46)
Firm F.E.	NO	YES	YES
Industry F.E.	NO	YES	YES
Region F.E.	NO	YES	YES
Year F.E.	NO	YES	NO
Quarter F.E.	NO	NO	YES
Observations	4,529,928	4,378,877	4,378,877
R^2	0.018	0.703	0.706

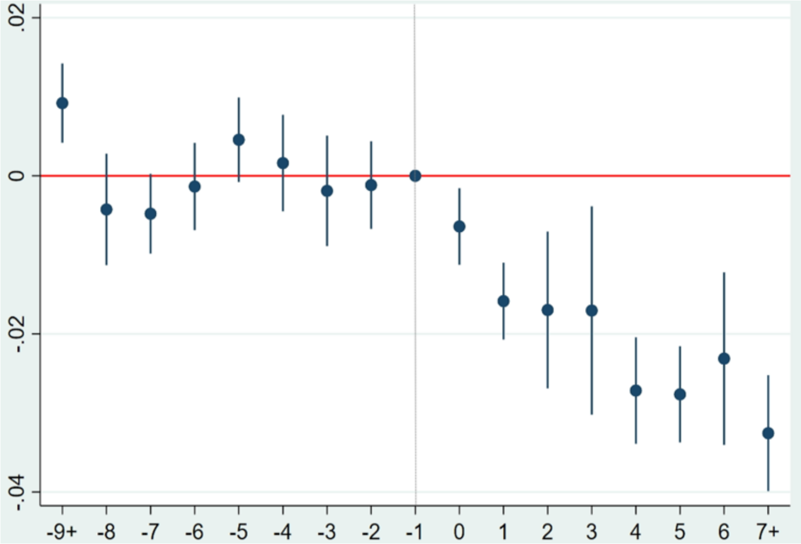
Baseline results – default rate

- Loan default rate among SMEs decreases by 2.7 percentage points, constituting an approximately 29.6% decline (=2.7%/9.12%)

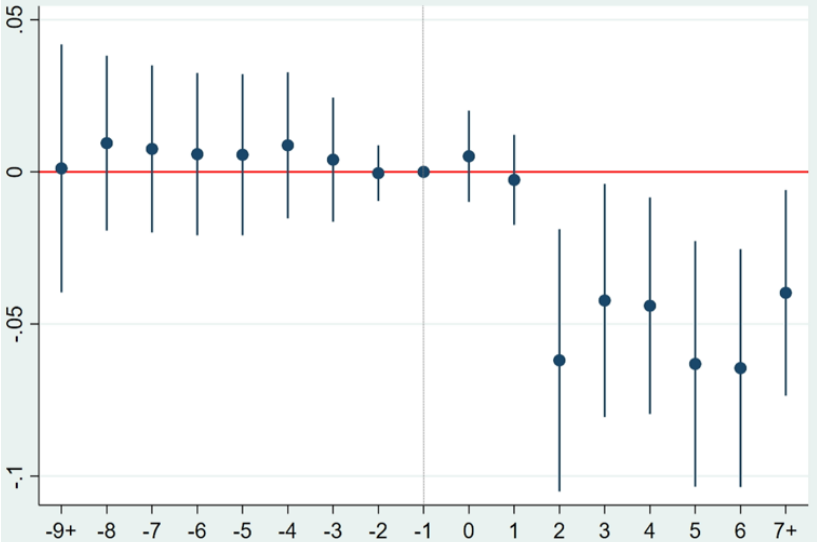
Variables	*Dependent Variable: Loan Default Rate*		
	(1)	(2)	(3)
SME × *Post*	-0.062***	-0.027**	-0.027**
	(-5.19)	(-2.01)	(-2.12)
Post	-0.015	0.023*	
	(-1.29)	(1.76)	
SME	0.029*		
	(1.76)		
Constant	0.065***	0.044***	0.059***
	(3.99)	(62.70)	(7.19)
Firm F.E.	NO	YES	YES
Industry F.E.	NO	YES	YES
Region F.E.	NO	YES	YES
Year F.E.	NO	YES	NO
Quarter F.E.	NO	NO	YES
Observations	4,507,689	4,358,049	4,358,049
R^2	0.031	0.707	0.708

Robustness – parallel-trend

- **No significant pre-trend** in the outcomes prior to the adoption
- **Substantial shift** in both the magnitude and statistical significance following the adoption



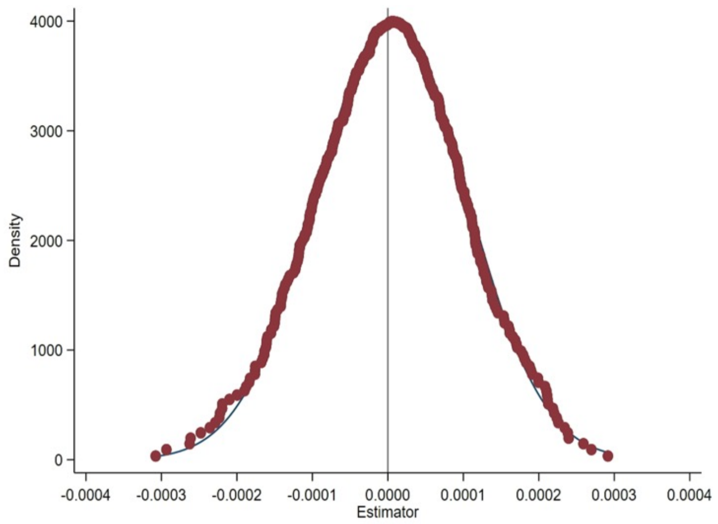
Unclassified credit rating



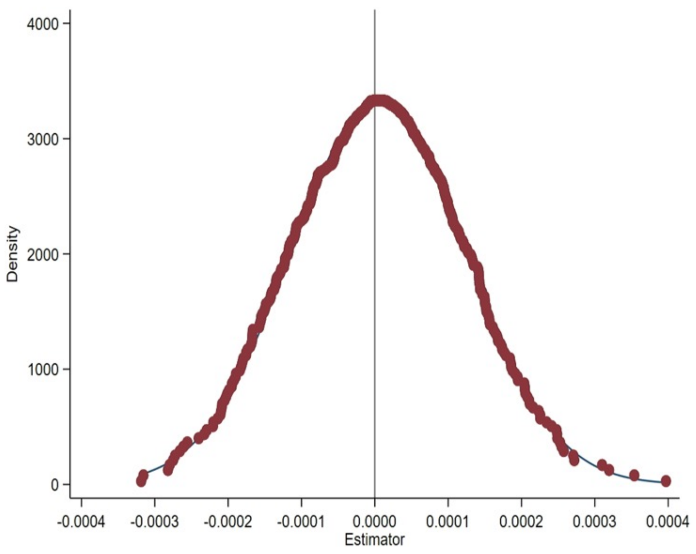
Default rate

Robustness – placebo test I

- Monte Carlo permutation method
- The distributions are **centered around zero**, indicating no systematic bias
- Baseline coefficient **significantly smaller than** the values observed in the placebo (-0.024 for unclassified rating; -0.027 for default rate)



Unclassified credit rating



Default rate

Robustness – placebo test II

- Non-existent time periods
- The coefficient is **statistically insignificant**

Variables	*Unclassified Credit Rating*		*Loan Default Rate*	
	(1)	(2)	(3)	(4)
	2018Q1	2018Q2	2018Q1	2018Q2
SME × *Post*	-0.001	-0.001	-0.001	0.000
	(-0.70)	(-0.48)	(-0.11)	(0.03)
Constant	0.069***	0.069***	0.062***	0.059***
	(116.19)	(122.53)	(23.75)	(21.28)
Firm F.E.	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES
Region F.E.	YES	YES	YES	YES
Quarter F.E.	YES	YES	YES	YES
Observations	635,898	628,293	629,878	622,978
R^2	0.932	0.918	0.853	0.854

Robustness – competing stories

- **Concern:** Other contemporaneous policies aimed at supporting SMEs
  - e.g., government support programs or tax incentives
- **Solution:** Regional variations
  - Compare regions with higher than top 5%/10% pre-adoption unclassified credit rating rates (treatment group) to other regions (control group)

Variables	>= top 5% Region		>= top 10% Region	
	Credit Rating	Default Rates	Credit Rating	Default Rates
	(1)	(2)	(3)	(3)
Region × *Post*	-0.069***	-0.005***	-0.035***	-0.007***
	(-56.63)	(-4.74)	(-24.05)	(-5.74)
Constant	0.067***	0.044***	0.046***	0.044***
	(120.15)	(100.09)	(106.73)	(118.48)
Region F.E.	YES	YES	YES	YES
Time F.E.	YES	YES	YES	YES
Observations	4,529,928	4,507,689	4,529,928	4,507,689
R^2	0.044	0.060	0.041	0.060

Robustness – more controls

- Include an indicator = 1 if missing firm-level financial statement
- Include city-level controls – GDP and fiscal revenue

Variables	*Unclassified credit rating*	*Loan default rate*	*Unclassified credit rating*	*Loan default rate*
	(1)	(2)	(3)	(4)
SME × *Post*	-0.024***	-0.027**	-0.026***	-0.026**
	(-5.87)	(-2.16)	(-5.33)	(-1.99)
Financial Infor	0.006***	0.015***		
	(4.56)	(7.16)		
GDP			0.002	-0.003
			(0.49)	(-0.53)
Fiscal Revenue			0.000	-0.009**
			(0.03)	(-2.34)
Constant	0.040***	0.046***	0.029*	0.217***
	(14.70)	(4.96)	(1.65)	(10.83)
Firm F.E.	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES
Region F.E.	YES	YES	YES	YES
Quarter F.E.	YES	YES	YES	YES
Observations	4,378,877	4,358,049	4,009,378	3,992,325
R^2	0.706	0.708	0.689	0.711

Robustness – more fixed-effects

- Include time-varying city-specific and region-specific fixed-effects
- e.g., local economic cycles, policy interventions or development programs

Variables	*Unclassified Credit Rating*			*Default Rate*		
	(1)	(2)	(3)	(5)	(4)	(6)
SME × *Post*	-0.024***	-0.029***	-0.027***	-0.028**	-0.026***	-0.027***
	(-7.50)	(-8.28)	(-8.23)	(-2.23)	(-3.73)	(-3.74)
Constant	0.045***	0.048**	0.047**	0.060***	0.058***	0.059***
	(21.79)	(21.44)	(22.16)	(7.46)	(13.19)	(12.89)
Firm F.E.	YES	YES	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES	YES	YES
Region F.E.	YES	YES	YES	YES	YES	YES
Time F.E.	YES	YES	YES	YES	YES	YES
Industry × Time	YES		YES	YES		YES
Region × Time		YES	YES		YES	YES
Observations	4,378,872	4,378,870	4,378,865	4,358,044	4,358,042	4,358,037
R^2	0.707	0.714	0.715	0.709	0.714	0.714

Robustness – Small verse medium

- Smaller firms benefit more than medium-sized firms from the adoption
- Information frictions drive the technology's impact

Variables	*Unclassified Credit Rating*	*Default Rate*
	(1)	(2)
Small × *Post*	-0.023***	-0.034***
	(-10.81)	(-9.42)
Constant	0.044***	0.062***
	(33.61)	(27.52)
Firm F.E.	YES	YES
Industry F.E.	YES	YES
Region F.E.	YES	YES
Quarter F.E.	YES	YES
Observations	4,172,952	4,155,047
R^2	0.703	0.708

Heterogeneous analysis – firm-level (I)

- **Information scarcity**

Variables	*Missing Information*		*Non-SOE*	
	Credit Rating	Default Rates	Credit Rating	Default Rates
	(1)	(2)	(3)	(4)
Dummy × SME × Post	-0.028***	-0.056***	-0.021**	-0.077***
	(-6.56)	(-5.52)	(-2.50)	(-6.22)
SME × Post	-0.006**	0.010***	-0.007	0.008
	(-2.31)	(3.56)	(-0.87)	(1.58)
Dummy × Post	0.019***	0.054***	0.006	0.081***
	(4.71)	(5.35)	(0.96)	(6.87)
Dummy × SME	0.010	-0.018**		
	(1.63)	(-2.14)		
Dummy	-0.002	0.031***		
	(-0.32)	(3.75)		
Constant	0.032***	0.026***	0.043***	0.034***
	(18.01)	(12.85)	(11.08)	(15.72)
Firm F.E.	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES
Region F.E.	YES	YES	YES	YES
Quarter F.E.	YES	YES	YES	YES
Observations	4,378,877	4,358,049	4,378,877	4,358,049
R^2	0.706	0.709	0.706	0.708

Heterogeneous analysis – firm-level (II)

- **Missing history**

Variables	*First-time borrower*		*Cross-region borrower*	
	Credit Rating	Default Rates	Credit Rating	Default Rates
	(1)	(2)	(3)	(4)
Dummy × SME × Post	-0.001	-0.006***	-0.015*	-0.013
	(-0.31)	(-2.63)	(-1.69)	(-0.73)
SME × Post	-0.024***	-0.027**	-0.023***	-0.026**
	(-5.78)	(-1.98)	(-5.14)	(-1.99)
Dummy × Post	0.003	-0.006***	-0.002	0.005
	(0.85)	(-2.62)	(-0.21)	(0.32)
Dummy × SME			-0.001	0.018*
			(-0.22)	(1.85)
Dummy			0.017***	-0.015
			(-2.16)	(-1.62)
Constant	0.044***	0.062***	0.044***	0.059***
	(16.61)	(7.15)	(15.36)	(6.93)
Firm F.E.	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES
Region F.E.	YES	YES	YES	YES
Quarter F.E.	YES	YES	YES	YES
Observations	4,378,877	4,358,049	4,378,877	4,358,049
R^2	0.706	0.708	0.706	0.708

Heterogeneous analysis – loan-level

- **Uncollateralized and short-term loans**

Variables	*Unsecured loans = 1*		*Short-term loans = 1*	
	Credit Rating	Default Rates	Credit Rating	Default Rates
	(1)	(2)	(3)	(4)
Dummy × SME × Post	-0.041***	0.033**	-0.011	-0.040***
	(-8.48)	(1.98)	(-1.35)	(-2.73)
SME × Post	-0.011***	-0.045***	-0.012	0.007
	(-9.45)	(-4.07)	(-1.63)	(1.05)
Dummy × Post	-0.006	-0.012	-0.001	0.033**
	(-1.32)	(-0.69)	(-0.10)	(2.29)
Dummy × SME	0.042***	-0.017***	0.024**	-0.003
	(20.22)	(-2.88)	(2.50)	(-0.69)
Dummy	0.005***	-0.008	-0.021**	-0.010**
	(3.10)	(-1.40)	(-2.16)	(-2.30)
Constant	0.030***	0.076***	0.042***	0.054***
	(38.19)	(10.74)	(8.82)	(12.54)
Firm F.E.	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES
Region F.E.	YES	YES	YES	YES
Quarter F.E.	YES	YES	YES	YES
Observations	4,378,877	4,358,049	4,378,877	4,358,049
R^2	0.708	0.709	0.706	0.708

Heterogeneous analysis – region-level

- **Underdeveloped and complex regions**

Variables	*Less developed districts = 1*		*Dialects districts = 1*	
	Credit Rating	Default Rates	Credit Rating	Default Rates
	(1)	(2)	(3)	(4)
Dummy × SME × Post	-0.017**	-0.044***	-0.034***	-0.026
	(-3.27)	(-2.91)	(-6.44)	(-1.39)
SME × Post	-0.017***	-0.011	-0.012***	-0.019
	(-3.53)	(-1.06)	(-2.64)	(-1.26)
Dummy × Post	0.011**	0.060***	0.014***	0.030
	(2.18)	(3.98)	(2.93)	(1.64)
Dummy × SME	0.007	0.009	0.024***	0.015
	(0.76)	(0.80)	(3.65)	(1.42)
Dummy			-0.008	-0.022**
			(-1.26)	(-2.14)
Constant	0.040***	0.038***	0.037***	0.054***
	(6.77)	(3.73)	(11.76)	(5.54)
Firm F.E.	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES
Region F.E.	YES	YES	YES	YES
Quarter F.E.	YES	YES	YES	YES
Observations	4,378,877	4,358,049	4,109,026	4,089,293
R^2	0.706	0.708	0.710	0.712

Extension – accessibility and borrowing cost

- Extend more credit at lower interest rates to SMEs (financial inclusion)

Variables	*Loan Amount*		*Interest Payment*	
	(1)	(2)	(3)	(4)
SME × *Post*	0.049***	0.048***	-0.335***	-0.323***
	(2.82)	(2.79)	(-6.17)	(-7.33)
Post	-0.053***		0.367***	
	(-3.04)		(10.11)	
Constant	14.851***	14.818***	4.366***	4.596***
	(4,577.50)	(1,365.97)	(369.58)	(162.94)
Firm F.E.	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES
Region F.E.	YES	YES	YES	YES
Year F.E.	YES	NO	YES	NO
Quarter F.E.	NO	YES	NO	YES
Observations	1,591,857	1,591,857	4,378,094	4,378,094
R^2	0.780	0.781	0.867	0.890

The synergy between big data and AI models

- **Two significant phases**

  - In **July 2019**, implementing machine learning techniques

  - In **October 2020**, incorporating big data with Advanced AI models and recognition technologies

$$Y_{i,t} = \boldsymbol{\beta_1} SME_f \times Post1_t + \boldsymbol{\beta_2} SME_f \times Post2_t + \varphi_f + \gamma_j + \theta_t + \delta_r + \varepsilon_{i,t},$$

- $\boldsymbol{\beta_1}$ represents the first adoption

- $\boldsymbol{\beta_2}$ represents the second adoption

The synergy between big data and AI models

- Integrating big data produces a more significant impact

Variables	*Unclassified Credit Rating*	*Loan Default Rate*	*Loan Amount*	*Interest Rate*
	(1)	(2)	(3)	(4)
SME × Post1	-0.016***	-0.015	0.014	-0.336***
	(-5.22)	(-1.11)	(0.72)	(-5.35)
SME × Post2	-0.020***	-0.028**	0.058**	-0.031
	(-6.30)	(-2.04)	(2.43)	(0.55)
Constant	0.051***	0.067***	14.809***	4.587***
	(29.86)	(11.70)	(1,186.42)	(305.11)
Firm F.E.	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES
Region F.E.	YES	YES	YES	YES
Quarter F.E.	YES	YES	YES	YES
Observations	4,378,877	4,358,049	1,591,857	4,378,094
R^2	0.706	0.708	0.781	0.890

The synergy between big data and AI models

- Restricting the sample with firm-level financial information
- Improve risk assess and prevent fraud through dynamic monitoring

Variables	*Unclassified Credit Rating*	*Default Rate*	*Loan Amount*	*Interest Rate*
	(1)	(2)	(3)	(4)
SME × Post1	-0.005***	-0.018**	0.030	-0.177***
	(-2.88)	(-2.27)	(1.57)	(-13.42)
SME × Post2	-0.012***	-0.020*	-0.013	-0.062**
	(-4.13)	(-1.78)	(-0.51)	(-2.42)
Constant	0.026***	0.081***	15.687***	4.985***
	(43.05)	(32.68)	(2,795.70)	(1,004.11)
Controls	YES	YES	YES	YES
Firm F.E.	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES
Region F.E.	YES	YES	YES	YES
Quarter F.E.	YES	YES	YES	YES
Observations	1,812,496	1,799,970	670,571	1,811,740
R^2	0.624	0.719	0.769	0.812

Conclusion

- **Provides compelling evidence of the transformative impact of AI and big data on the banking industry**

  - Significantly reduces the prevalence of "unclassified" credit ratings

  - Loan default rate also declines

  - Increase credit accessibility with lower borrowing cost

  - Integrating big data with AI models and recognition technologies has a more profound impact than traditional FinTech models

- **Highlight the information advantages channel**
- **Underscore the importance of big data**

Thank You !