Paper Session 1:

Economic Effects of Payments, Data, and AI in Financial Services

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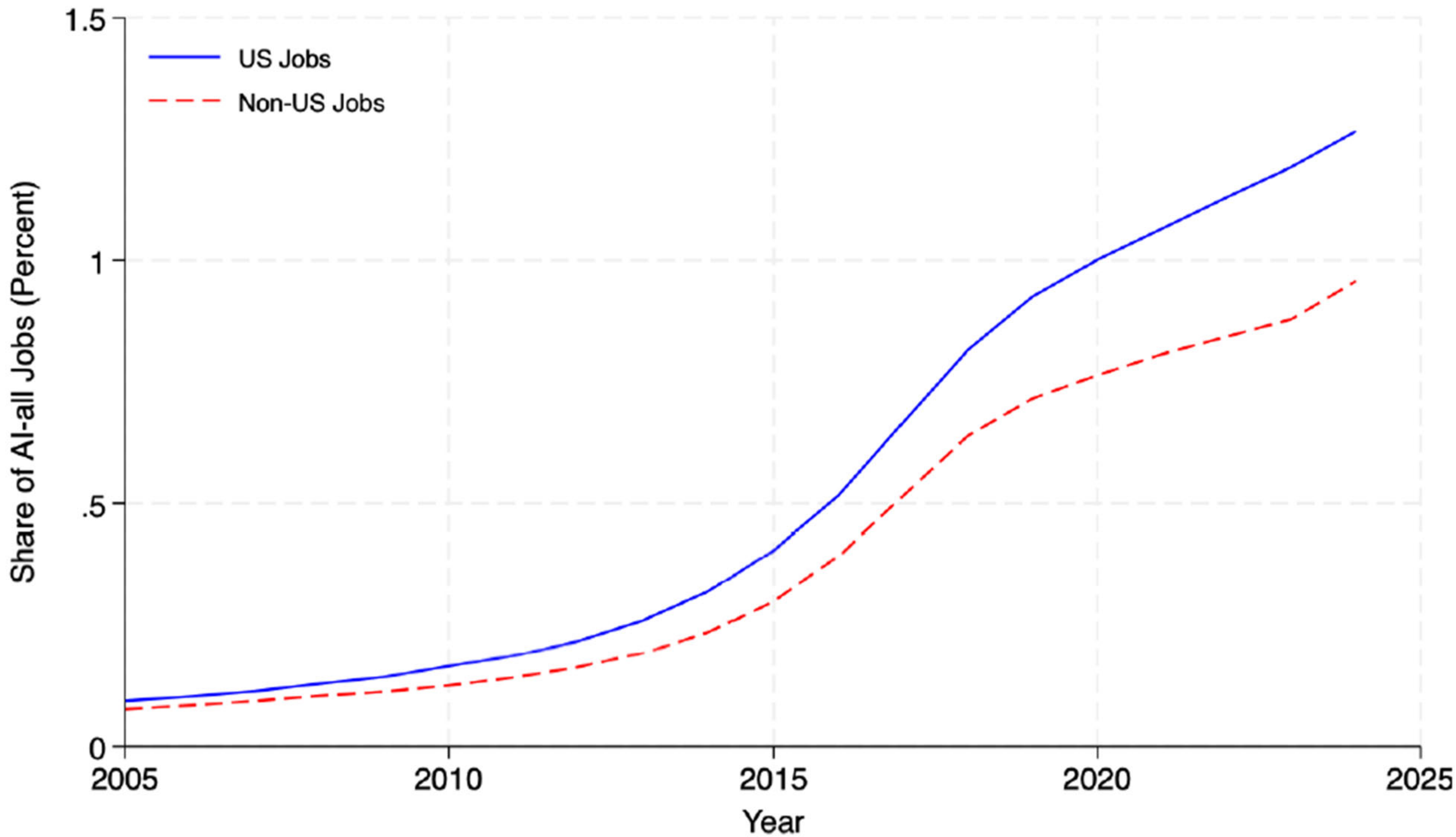
AI Became Important over Past Decade



Babina et at (2025): “Artificial Intelligence and Firms' Systematic Risk”

Which Firms Benefit from AI?

- Anyone can buy *some* key inputs to AI
  - Hire Deep Learning Engineers, rent data storage and compute, use open-source models

- But, firms with large proprietary data have competitive edge in AI
  - Large firms that generate more data have better AI
  - Babina et al (2024) JFE: *"Artificial Intelligence, Firm Growth, and Product Innovation"*

Why? Large Firms Own Customer Data (Not Their Customers!)

- This gives large banks monopoly power over customer data and advantage in AI

- Solution: policies that reallocate data ownership rights away from bank to its customers
  - *Babina et al (2025) JFE: "Customer Data Access and Fintech Entry: Early Evidence from Open Banking"*

Broader Economic Issues: Drivers of Data Monopolies and Policies for Remedy

- Legal property rights (firms own customer data)
  - Policy: open banking (Norway BNPL paper)
- Market fragmentation (inability to pay across apps)
  - Policy: fast payments systems (India UPI paper)
- Incumbent inertia (innovator dilemma)
  - Policy: Fintech law forcing firms to use AI (China paper)

Discussion of:

Buy Now Pay (Less) Later Leveraging Private BNPL Data in Consumer Banking

By **Kasper Roszbach**

(Norges Bank and University of Groningen) et al

Big Picture Questions

- How competitive is this market?
- What does the key regression capture?
  - Information vs. selection vs. learning effects
- Who are BNPL customers?

How Competitive is this Market? Market Structure and Sample

- 1,066,000 loan applicants (2018–2022)
- 31% (393,000) receive offers from Bank
- Only 8,052 (2%) accept loan

- Competitive market, yet tests on market power
- Selection at each stage needs more clarity

Key Regression Framework

- Outcome = β × BNPL Customer + controls

- What does β capture?
  – Selection into BNPL customers?
  – Bank's private information?
  – Learning by doing (aka by borrowing)?

Evidence from Tables

- Table 3 (Cols 4–6): Coefficient drops 50% with controls
- Economic significance falls: 100% → 25% (17/66.7)
  - Suggests **selection** is key
- Table 10: No repayment difference internal vs. external BNPL
  - Challenges 'learning by doing' claim

Information Channel

- Internal BNPL customers:
  – More likely to receive loan offers
  – Offered lower interest rates
- No difference in defaults vs. external BNPL customers

- Strong evidence of **information channel**

Discussion of:

Integrating Fragmented Networks: The Value of Interoperability in Money and Payments

By **Alexander Copestake**
(International Monetary Fund) et al

Authors' Main Argument (Paper's Contribution)

- **Interoperability** across fragmented payment platforms boosted UPI adoption
- Cross-app payments enabled transactions impossible in closed systems

Additional Mechanism: **Lower Costs**

- Consumers pay no fees; merchants face minimal acceptance costs via QR codes
  - Easy QR code deployment → wide merchant coverage

- **Effective transaction cost = 0 → encourages adoption**

- Not clear how much **interoperability** mattered vs. **lower transactions costs** (and other drivers of transaction volume)

Discussion of:

The Transformative Role of Artificial Intelligence and Big Data in Banking

By **Junjie Xia**
(Central University of Finance and Economics and Peking University) et al

Big Picture Questions

- What is the key contribution?
  - Need more thorough literature review
  - Eg, what is marginal contribution to Babina et al JFE 2025 "*Customer Data Access and Fintech Entry: Early Evidence from Open Banking*"?
- Threats to identification

What is the Key Contribution?
Literature Review in Table 1 as Reference Point:
by Chioda, Gertler, Higgins, Medina
«FinTech Lending to Borrowers with No Credit History”

Table 1: Comparison of studies that predict creditworthiness

Citation (1)	Country (2)	Loan Type (3)	% with Credit Bureau Score (4)	Data (5)	Methods (6)	AUC (7)
This paper	Mexico	FinTech credit card	0%	Delivery app transactions data, digital footprints, credit history for those with limited credit history (but no credit scores)	XGBoost	0.796
Agarwal, Alok, Ghosh, and Gupta (2023)	India	FinTech loan	81%	Digital data from mobile phones; call logs; demographics, address, bank statements, salary slips; traditional credit score (CIBIL)	Random forest, XGBoost, logit	0.738 for sample with credit history, 0.674 for sample without credit history
Albanessi and Vamossy (2024)	US	Credit card	100%	Credit bureau files and credit scores	Hybrid deep neural network/gradient boosting	0.906
Berg, Burg, Gombovi, and Puri (2020)	Germany	FinTech loan	94%	Digital footprints (device type, operating system, email service provider, writing style, etc.), credit scores	Logit	0.734
Björkegren and Grissen (2020)	A middle-income South American country	Mobile phone airtime credit	85%	Mobile phone call logs and text data, history of phone bill payment, credit bureau data	Random forest, logit	0.772

Threats to Identification: Key Regression Framework

- Outcome = $\beta \times Post\_2019 \times Small\_firm$ + controls
  - Identification: FinTech initiative in 2019 as exogenous shock
  - Identification relies on differences for small vs large firms after this aggregate shock
  - Potential confounds: **COVID**, Ant Group crackdown
  - SUTVA concerns: aggregate shock, GE effects
- Need to address key threats to identification heads on

Thank you!