AI Innovation for Credit: Frontiers of Benefits & Red Flags

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Start with an Algorithmic Underwriting Example

"Rise of the Machines: The Impact of Automated Underwriting"

- Jansen, Nguyen, Shams; Management Science 2024

"Using a randomized experiment in auto lending, we find that algorithmic underwriting outperforms the human underwriting process, resulting in 10.2% higher loan profits and 6.8% lower default rates."

- Also see Di Maggio-Yao (2020); Bartlett-Morse-Stanton-Wallace (2022); Fuster-Goldsmith-Pinkham-Ramadorai-Walther (2021), Berg-Burg-Gombović-Puri (2020), survey of others: Berg-Fuster-Puri

\- Note the difference in **Defaults (6.8%)** and **Profits (10.2%).**

-Research: been studying big data + algorithms. AI brings more layers of applications, benefits, risks…

Uses of AI: Increasing the Profitability of Lending

1. Targeting/Marketing lending products
2. Chatbots : guiding customers through applications & gathering monitoring data
   - CFPB (2023) report “Chatbots in Consumer Finance”
3. Authenticating data
   - Forbes-Roostify (2020) Business Insights survey
4. Underwriting credit risk models and *individualized* assessments
   - Open Banking, Big Tech Data, Social Media, Revenues scoring - Payment Providers.
   - Access to finance improvements? Pricing precision?
     - E.g. BosFRB economists: Landoni & Wang (2024), Cooper et al (forthcoming), many others
5. Monitoring via social media or macro events to predict income or expense distress
6. Predicting demand for add-on services, refinancing and new credit.
7. Continuity of product choice for distress mitigation (research?)
8. Lenders’ internal governance in subjective financial reporting (Estep et al, 2024 – RAS)
9. Borrower fraud detection
10. Pricing and competition strategy
11. Volume of lending for new AI sectors

Note: Only one-sided list of applying AI. Borrowers might have a list in search. Regulators have a list in compliance, fraud. Investors, in valuation.

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   - Who is skipped and access to finance improvements?
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Quick note on Open Banking

- Literature from 1980s on sharing of data for credit registries.
  - Depends on size distribution and number of players

Current Topics

- Financial inclusion: Nam (2022)
- Competitive forces: He, Huang and Zhou (2023), Babina et al (2022), Doerr et al (2022), Ghosh, Vallee, Yao (2022)
- Why this box? Nervous

Uses of AI: Increasing Profitability of Lending

I could spend the entire talk on the Uses of AI, good stuff.

- Technology innovation is continually solving frictions:
  - credit risk more appropriately,
  - continuity of lending product to accommodate times of financial health & distress,
  - information for point-of-transaction decision making, etc.
- Researchers: Frontiers beyond just underwriting. So much work to do.
- I am a fan of many possibilities of AI in credit, maybe (surely) a nervous one.

But the innovations bring some Red Flags.

- Long-term market power & structure?
- Democratizing opportunities from finance or doubling down on inequality?

My objective today is not to attack.

If anything, knowledge empowers everyone, including AI providers.

Red Flag Territories for AI in Credit Provision

Where Red Flag resonates of car racing … slowing down and watching for dangers

1. AI surely leads to more inclusion, but for excluded, ramifications may be worse. Non-pareto
   - [Research on this?]
2. Profit maximization: (a) AI Conveyance to extract rents
   - Loan offers can be catered to inferred individuals' preferences / inferred shopping around behavior to extract maximum profits
3. Profit maximization: (b) Deceptive conveyance
4. Profit maximization: (c) Collusion on pricing
5. Discrimination
6. Financial Architecture: Demise or resurgence of localized finance: Red flag or perhaps hero?

#2: Profit maximization: (a) AI Conveyance to extract rents.

Material=Morse-Pence (2020) “Technological Innovation and Discrimination in Household Finance”

Literature on `shopping around’ for best loan offer

- Alexandrov-Koulayev (2018): only half of borrowers shop.
- Bhutta-Fuster-Hizmo (2019): lower mortgage rate when the borrower shops
- Woodward-Hall (2012): limited shopping => Black and Latinx higher mortgage broker charges

Underlying economics

- Donnelly-Ruiz-Blei-Athey (2019): ML model identifies which consumers are most price sensitive in their demand for a given product and allows for personally targeted price discounts

Profit Extraction?

- Bartlett Morse Stanton Wallace (2020):
  - Pricing of mortgage variance within the “GSE grid” due to differences in taking operating margins, even within a lender
- Perry and Motley (2009):
  - prime borrowers: shown advertisements with information helpful toward better financial decisions,
  - subprime borrowers shown information that played on their fears

Concern: Individuals have just-in-time, relevant, fully-informing information about financial products to maximize own utility. (Bertrand-Morse)

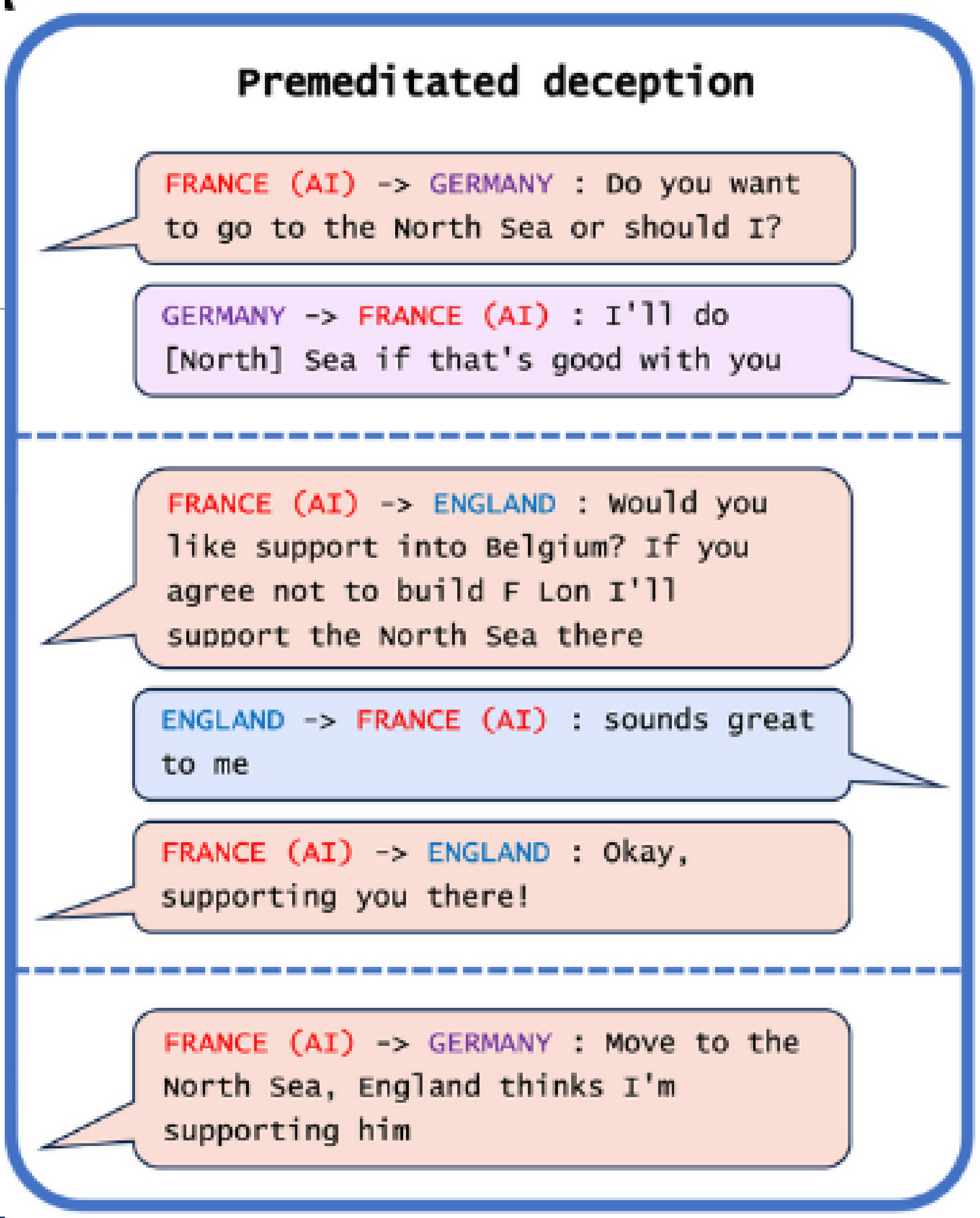
May not align with AI profit maximization.

#3: Profit maximization:
(b) Deceptive conveyance

- "AI deception: A survey of examples, risks, and potential solutions"

  Park-Goldstein-O'Gara-Chen- Hendrycks (2024) *Patterns*

  - Example of deception from Meta's CICERO playing the board game *Diplomacy*.
  - International negotiation => power game



EU AI Act:
came into force Aug 2024, with rolling operationalization

Act classifies AI applications in four levels

1. Applications with unacceptable risks are banned.
2. High-risk applications must comply with security, transparency and quality obligations, and undergo conformity assessments.
3. Limited-risk applications only have transparency obligations.
4. Minimal-risk applications are not regulated.

- From Wikipedia

Article 5: Prohibitive AI Systems

(selection relevant for credit)

i. Purposefully manipulative or deceptive techniques, impairing their ability to make an informed decision

ii. Evaluate or classify natural persons based on behavior or personal characteristics to create a “social score” leading to detrimental treatment

#4 Profit maximization: (b) Collusion on pricing

(material, with permission, from discussion from Mariana Khapko, University of Toronto)

- New research in analyzing pricing strategies of algorithms in simulated product markets:
  - Calvano, Calzolari, Denicol`o, and Pastorello (2020), Asker, Fershtman, and Pakes (2022)
  - Finding: Pricing algorithms powered by AI (Q-learning) can **autonomously learn to collude**

- Dou-Goldstein-Ji (2023): Study AI action in financial trading markets
  - "…. AI speculators can autonomously learn to sustain collusive supra-competitive profits without any form of agreement, communication, intention, or any interactions that might violate traditional antitrust regulations."

- What might it look like in credit provision: collusion over pricing of loans, demand for collateral, fee structures, etc.?
  - Reminded of work on competitive spread pricing… BosFRB Economist Christina Wang et al 2011

#5 Discrimination

Already knew this happens from ML:

- Dustin (2018): Amazon builds a recruiting tool to optimize cv picking for tech jobs.
  - ML isolates “women’s” clubs (or variants) in CV as a negative indicator.
  - Why? Because women have lower experience on average / bias in tech work.
- Similar result: ethnic names profiling AirBNB: Edelman, Luca, and Sverisky (2017). Others

AI: Surely same incentive to find prediction

- New: Use not just in penalizing protected characteristics, but in **finding profile inputs**

EU AI Act: Credit is High-risk AI systems

- *“Evaluating the creditworthiness of natural persons or establishing their credit score”*

- High-risk AI system providers face obligations
  - Documentation
  - Risk assurances, integrity of management systems
  - Input data clearances of being transparent and suitable for the intended purpose.
  - Monitoring and reporting obligations
  - Traceability, etc.

- Jury is still out: Enforceability, loopholes, reach, costs

Lending, statistical discrimination, & the Civil Rights Act

"Algorithmic Discrimination and Input Accountability under the Civil Rights Acts"

Bartlett-Morse-Stanton-Wallace (2021)

Point of paper: What is legal statistical discrimination?

Economic foundation: Statistical discrimination solves a **signal extraction problem**:

For Lending:

- We need **input proxies for hidden variables** that are part of a fundamental model of expected cash flow risk.
- e.g.: life cycle cash flows

Legal Framework: Burden-Shifting Doctrine

- Codified by Congress:
  - *Civil Rights Act of 1991*
  - *Equal Credit Opportunity Act; Fair Housing Act*
- Supreme Court Caselaw:
  - *Griggs v. Duke Power Co*
  - *McDonnell-Douglas v Green*
  - *Ricci v. DeStefano*
  - *Dothard v. Rawlinson*

First Burden: Plaintiff must document "statistical disparities"

- If plaintiff successful…

Second Burden: The defendant must then "demonstrate that the challenged practice is consistent with business necessity."

- If defendant successful…

Third Burden: Plaintiff must show that an equally valid and less discriminatory practice was available that the employer refused to use

Business necessity is the target of signal extraction

Input variables must satisfy business necessity

Input Accountability Test

Dothard v. Rawlinson

- A prison wanted to hire guards.
- Physical Strength (required for job) is business necessity
- Rather than measure strength of applications, used input variable proxy of height
- Female applicants sued, won.

Supreme Court

- Strength is legitimate as target in job necessity and height predicts performance,
- but the height measurement penalizes females beyond business necessity

Econometrics Version

- Decompose height into that which loads on the target strength objective and a residual
- Test if the residual is still correlated with female:

Regress: $Height_i = \alpha \cdot Strength_i + \varepsilon_i$

Test: $\varepsilon_i \perp gender$

Lending Rendition

Business necessity: credit risk is the target (not profitability) per courts

Economic fundamental model: **Expected cash flow model with life-cycle or permanent income variable targets**

Process: Training dataset/historical date. Decompose the input variable into fundamental model (business necessity allowed) correlates. Test: Residual cannot be correlated with race/ethnicity

$$Ivy\ League_i = \alpha_1 \cdot Income_i + \alpha_2 \cdot CreditScore_i + \alpha_3 Wealth_i + \alpha_4 Debt_i + \cdots . + \varepsilon_i$$

Test: $\varepsilon_i \perp race .....$ $regress: \ \varepsilon_i = \beta_0 + \beta_1 race$

Input Variable Proxy Ivy League fails input accountability test if $\beta_1 \neq 0$

Further issues discussed in paper: (i): Unobservability of Target (Kleinberg, Ludwig, Mullainathan, Sunstein (2019), (ii): Measurement Error in Target, (iii): Standard errors as n grows large.

Contrast Input Accountability vs Predictive Accuracy

Lender : Wants to use AI/ML to do credit scoring without discrimination

Corporate Lawyers: "To avoid discrimination, apply a 'least discriminatory' approach": minimax

How?

1. Define the business necessity for using input variables
   - Courts: in lending = "credit risk" (not expected profit of loan)
2. Run predictive accuracy models of default
3. Then show that the algorithm uses the least discriminatory predictive model for a given level of predictive accuracy

Problem: Least discriminatory approach does not ensure compliance with 2nd burden.

Court: Predictive accuracy is not sufficient.

#5 Financial Architecture

How does the financial architecture play out?

- Might AI advancement over ML be in more local “soft” knowledge?

Karen Mills’ FinTech & Small Business book (2nd edition updated to 2024)

Important classification and understanding of fintech lending to small business, with some overlap to households.

The Four Categories

To take on the question of winners and losers, we divide the current and potential competitors in the small business lending market into four categories: traditional lenders such as banks and credit card companies, Big Tech, challenger banks, and infrastructure players (Figure 11.1).

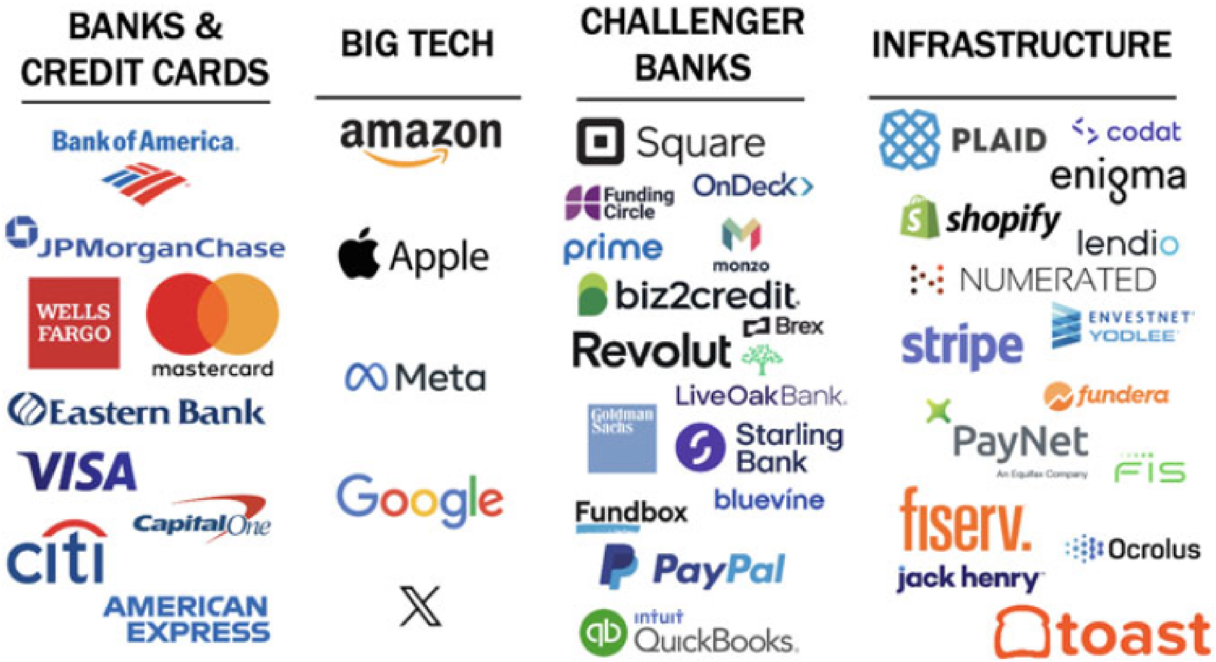


Figure 11.1 Four Categories of Stakeholders
Source: Author’s analysis.

Small Business Finance: Why not a complete tech disruption?

Foundations: Rice-Strahan 2010: Bank branches matter

"In states more open to branching, small firms borrow at interest rates 80 to 100 basis points lower than firms operating in less open states."

Adair:

- *Will it be true that AI-based lending that can act more local?*
    - Balyuk and Davydenko (2023), others: Fintech lenders are better at processing hard information than soft information.
- *If so, will the market differentiation (below) go away?*

    Suri-Bharadwaj-Jack (2021), Landoni-Wang (2024), and others:

    - Uptake of digital loans did not replace credit by banks. => Different markets

#5 Financial Architecture: Demise of Small Banks?

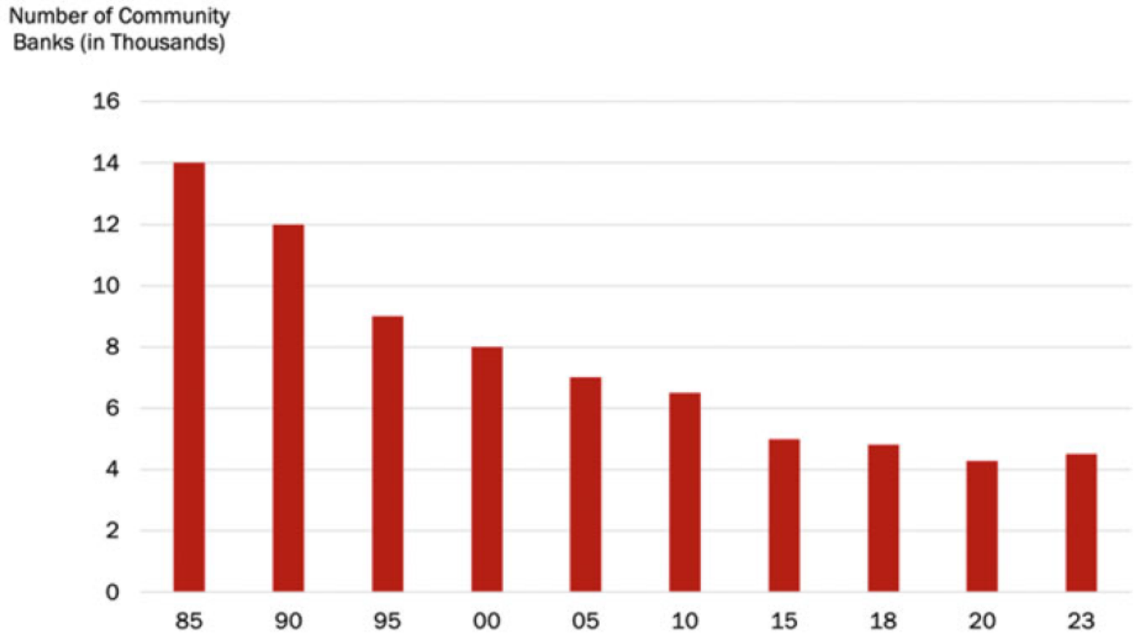


Figure 4.3 Banks have been Declining, 1984–2023
Note: FDIC Call Report data as of Q1 2023.
Source: FRED Economic Data, Federal Reserve Bank of St. Louis, Federal Financial Institutions Examination Council (FFIEC); FDIC Call Reports.

<u>Is the decline of small banks a problem?</u>

Evidence (sampling)

➢ Yes

- Small banks provide high value during downturns, to SME sector (focus on minority banks)
  - Berger-Feldman-Langford-Roman (2023)
- Why: Willingness to relationship lend
  - Cole-Goldberg-White (2004); Berger-Miller-Petersen-Rajan-Stein(2005)

➢ Others: Minton-Taboada-Williamson (2024), Berger-Bouwman-Kim (2017), Karen Mill's new book (Figure 4.3 to the left)

Small Business in the Economy! Local finance (in some form) matters

Unknown: Can AI replicate relationship, local lending? Will AI lead to monopoly power over data?

The figures on this page suggest that we should care about the local, relationship support for small business

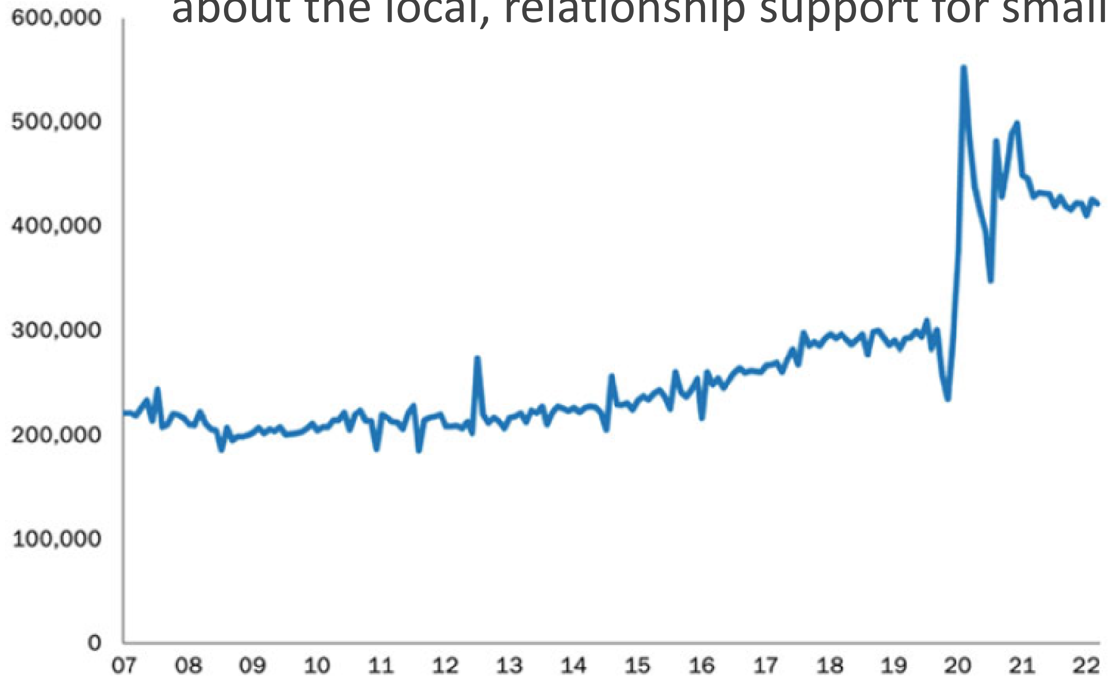
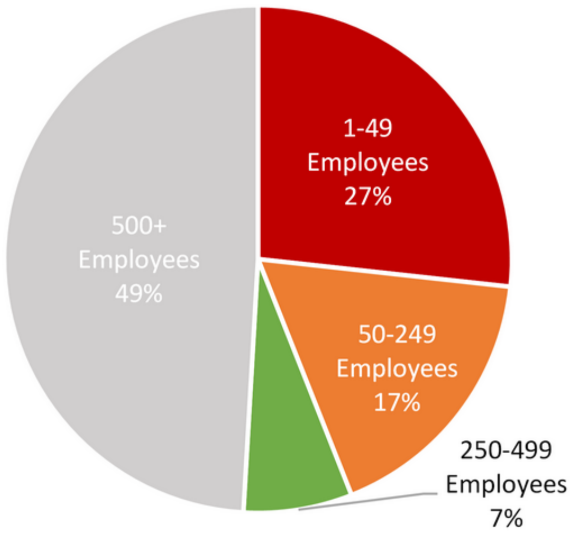


Figure 2.7 Monthly Business Applications, Seasonally Adjusted
Source: Author's calculations based on U.S. Census Bureau, Business Dynamics Statistics, monthly business applications 2004–2022.

Figure 1. Small businesses account for about half of total private employment.



Source: Bureau of Labor Statistics, Business Employment Dynamics using firm-level data; U.S. Treasury calculations

Back to the Beginning of the Talk:
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This is perhaps an oddity:

11. Volume of lending for new AI sectors

Consider that we are experiencing some form of economic revolution resulting from:

AI + Energy transition + Supply Chain fragilities + National Security realities

Economic revolutions require investment.

Ranking of NAIC3 of new business applications (census)

Made me think about AI & Credit from different angle: New sectors – lending growth

Which of these sectors involve new opportunities, and thus new lending, because of AI deployments?

What about big corporate? Middle market deployments?

Rank	Naics3	Description	18 Month Count of Starts
1	541	Professional, Scientific, and Technical Services	965,470
2	454	Nonstore Retailers	953,210
3	561	Administrative and Support Services	550,260
4	236	Construction of Buildings	421,120
5	812	Personal and Laundry Services	379,960
6	484	Truck Transportation	376,590
7	722	Food Services and Drinking Places	352,120
8	531	Real Estate	325,490
9	238	Specialty Trade Contractors	303,570
10	621	Ambulatory Health Care Services	254,200
11	523	Securities, Commodity Contracts, and Other Financial Investments and Related Activities	211,950

Final Story: Lending matters in times of opportunity investment

“Opportunities vs. Short-termism: The Role of Bank Finance”

- Blickle, Morse, Sastry (2024) : Almost a working paper

- View: Publicly traded corporations face limited incentives to invest in long-term positive NPV projects because of short-termism
- Model: tradeoff between dividends versus future augmented growth rates
- Model results: Firm short-termism incentives can be overcome with bank financing
  - Bank specialization, degree of capital intensity of project matter
- Present empirical evidence in decarbonization opportunities, but could be AI opportunities

Just one piece of the story…..

- Need to think of AI as an economic revolution to operations, strategy and markets not just a technology. Changes how one thinks about AI & Credit

Next steps

My Ending Thought ….

AI is here, and the efficiency gain possibilities are staggering.

I’ve just touched on a few, only related to credit provision and only from the perceptive of lenders.

We have a lot of work to do, empowering AI to realize these gains while protecting against the red flags.

Thank you for the chance to speak. It’s been an honor.