# **Artificial intelligence and relationship lending**

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Discussion by

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Banco de España

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#### Data:

- AnaCredit: Quarterly loan volumes & interest rates (bank-firm level)
- RBLS Survey: Direct measure of AI adoption for credit scoring
- Credit Registry: Relationship duration since 2008
- Cerved: Firm balance sheets (2018-2020)

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## **Key Variables:**

- **Relationship Duration**: Log(quarters) of bank-firm relationship
- Al Indicator: Bank uses AI/ML for credit evaluation (bank-level)
- Crisis Period: D(2020) dummy

**Identification:** Khwaja & Mian (2008) approach

- Firm-time FE: and Bank-time FE: control for firm demand and bank supply factors
- Comparison: Same firm's different relationships, or same bank's different relationships

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- Traditional banks: Longer relationships → Rent extraction (↓ credit, ↑ rates)
- Al banks: **Mitigate extraction** (↑ credit, ↓ rates for given duration)
- ⇒ AI banks offer better terms than traditional banks

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**Real Effects:** Firms more exposed to AI banks with longer main lender relationships see dampened increases in investment and employment during crisis

# My Take on the Paper

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- AI banks: Credit becomes acyclical (responds to firm fundamentals, not macro)
- As AI spreads → Aggregate credit may become less cyclical

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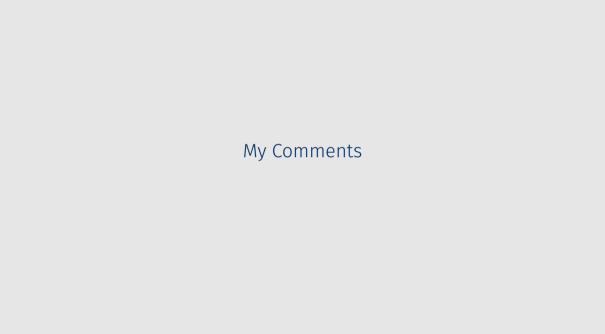
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## Less amplification of shocks vs. loss of insurance for certain firms



# My comments

- 1. Quick Win: Industry × Location × Size × Time FE
- 2. The Mechanism: What Drives the Results?
- 3. Size vs Al Confound
- 4. Guaranteed Loans and Identification
- 5. Minor Comments

# Quick Win: Industry × Location × Size × Time FE

**Current Limitation:** Firm-time FE requires firms with ≥ 2 banks

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## **Current Limitation:** Firm-time FE requires firms with ≥ 2 banks

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- These are likely most relationship-dependent
- May underestimate relationship effects

## **Solution:** Industry $\times$ Location $\times$ Size $\times$ Time FE (Degryse et al., 2019)

- Use full sample (all firms, including single-bank)
- Controls for granular demand shocks

Especially valuable given selection concerns

## What We Know (Stylized Facts):

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These are **not mutually exclusive**, but have different implications

# Candidate Mechanisms: How Does AI Change Relationship Lending?

# **Mechanism 1: State-Invariant Lending**

#### **AI Bank:**

- Credit = Algorithm only
- No crisis adjustment
- Consistent rules across states

#### **Prediction:**

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- No heterogeneity by sector, size, or shock exposure

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### **Mechanism 2: Information Substitution**

#### **AI Bank:**

- Uses: Real-time hard data
- Crisis → Different data still available
- Distinguish temporary vs. permanent shocks

#### **Prediction:**

- AI effects should vary by data availability
- Heterogeneity by:
  - Nature of COVID shock to sector
  - Firm size (data richness)

# Testing the Mechanism: Heterogeneity Analysis

Key Insight: Mechanism 2 predicts heterogeneous effects while Mechanism 1 doesn't

#### **Suggested Tests:**

## 1. Heterogeneity by Sector COVID Impact

- Classify sectors by COVID shock severity
  - High impact: Hospitality, travel, retail (physical)
  - Low impact: Tech, finance, digital services

#### Prediction (if Mechanism 2):

- Smaller  $|\beta_4|$  in digital sectors (real-time data available, conditions maintained)
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## 2. Heterogeneity by Firm Digital Footprint

- Proxies: Firm size, sector digitalization, transaction volume
- Prediction (if Mechanism 2):
  - · AI effects stronger for firms with richer data
  - Weaker insurance loss for digitally active firms

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Table 1: Adoption of AI for credit scoring and bank characteristics

	(1)	(2)
Variables	AI	AI pre Covid
Capital ratio	0.1053	0.2237
	(2.948)	(3.000)
Liquidity ratio	1.9925	1.9506
	(2.177)	(2.335)
ROA	0.5066	0.0899
	(0.475)	(0.541)
Interbank funding ratio	-1.3867	-1.5532
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Size	0.7748***	0.8042***
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Moving from median to p75 of size  $\rightarrow$  +35% in Al-bank

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# Why Bank-Size matters independently: (Berger and Black, 2011)

- Large banks
  - Hard info, less relationship-based
  - May have low rent extraction or crisis insurance
- Small banks: Relationship-oriented
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What the paper does: Bank-time FE control for  $Size_{it}$ , but not  $Size_{it} \times Duration_{ij} \times Crisis$ 

# Size vs. AI - II: Suggested Tests

# Suggestions to Disentangle:

- Horse race regression:
  - Add:  $log(Duration)_{ij} \times Large_i \times D(2020)$
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**Caveat:** Cannot fully separate without exogenous AI adoption variation

# Guaranteed Loans and Identification — I

Problem: COVID period had unprecedented government guaranteed credit

**Why This Matters for Identification:** 

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## Why This Matters for Identification:

- Guaranteed loans = large fraction of COVID lending
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#### **Implication for Results:**

- $\beta_3 > 0$  may conflate relationship insurance + guarantee effects
- $\beta_4 < 0$  unclear: AI effect or differential guarantee allocation?
  - If non-AI banks target guarantees to relationship firms...
  - ...but AI banks distribute uniformly
  - $\rightarrow \beta_4$  captures allocation differences, not AI

# Guaranteed Loans and Identification — II: What the paper does

- AI dummy (bank-level) uncorrelated with guarantee share
- ightarrow AI banks don't use guarantees more/less than non-AI banks  $\checkmark$

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#### **But This Doesn't Resolve the Issue:**

- Bank-level correlation ≠ Bank-Firm level correlation
- Doesn't test: Do AI banks allocate guarantees differently across borrowers?
- Key issue: Guarantee rate for relationship vs. non-relationship firms, by bank type

## **Suggestions:**

- Show guarantee use by relationship duration for AI vs. non-AI banks
  - Is it uniform across bank types?
- Loan-level analysis:
  - Control for guarantee status explicitly in regression
  - Or: Subsample analysis (guaranteed vs. non-guaranteed loans)
- Test: Do results persist in non-guaranteed loan subsample?

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## **Important for External Validity:**

- Alternative crisis shocks (e.g. tariffs, energy crisis)
- Do effects change as banks gain experience with AI  $\rightarrow$  longer panel (2021-2023)

