AI Adoption and Firm Productivity

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Artificial intelligence (AI)

- Statistics Korea (2018)
  - The technology underpinning programs capable of human-like learning, reasoning, perception, and understanding of natural language, etc.

- OECD (2019)
  - A technology that enables machines to become intelligent, including the ability to learn, deduce, perceive, and understand natural language through computer programs, and to perceive, analyze, determine responses and act appropriately in a human environment. For a given set of human-defined objectives, AI is capable of making predictions, recommendations or decisions influencing real or virtual environments

Advances in the development and diffusion of AI

- More businesses are relying on AI for their business operations
  - Firms are applying AI tools across a host of use cases including managerial tasks, market analysis and future projections and decision making
    - Iansiti and Lakhani 2020; Davenport and Ronanki 2018; European Parliament 2020

- AI is considered to be the next general-purpose technology(GPT)
  - Expected to affect every aspect of a firm's business, remaking its internal organization, influencing its external competition, and altering its consumer relationships
    - Cho et al. 2021; Iansiti and Lakhani 2020; Goldfarb, Taska and Teodoridis 2020; Agrawal, Gans, and Goldfarb 2018; Brynjolfsson and McAfee 2014

- However, there remains limited empirical evidence for the relationship between AI use and firm performance
  - Few reliable and representative datasets on firm AI (Raj and Seamans, 2018)
  - First surveys conducted by consultancy companies typically covered a small number of large firms (Knight, 2020)

The effects of AI adoption on firm performance

- Question: **What is the effect of AI adoption on firm productivity?**

- Challenges for the research
  1. Limited firm-level data in large sample sizes
     - AI usage rates are considerably lower (Cho et al, 2021; Zola et al. 2020; Rammer et al. 2021)
     - Similar to digital tech. AI may have a large firm bias
  2. Endogeneity issues
     - Between new tech and productivity
  3. What/why determines the relationship
     - See other moment changes within firms

This paper

- Provides empirical evidence for the effects of AI adoption on firm prod.
  - Using unique firm and plant-level data from Statistics Korea

- Three key findings about the relationship between AI and firm prod.
  ① Overall, we find limited evidence for a positive relationship
    - Both OLS and IV estimations

  ② The productivity gains appear to be concentrated among multi-plant firms
    - 15% higher compared to single-plant firms

  ③ Evidence that AI adoption helps narrow productivity gap among plants within the same firm
    - The gap is reduced by 25%

- Paper contributes to AI literature with comprehensive empirical analysis employing extensive firm-level data

Related literature

- Studies on AI adoption and firm performance
  - (Job posting) Goldfarb et al (2022), Babina et al. (2022), Alekseeva et al. (2020)
  - (Patent) Alderucci et al. (2020), Damioli et al. (2021), Yang (2022)
  - (Digital Technology – Firm-level) Goldfarb et al 2020; Babina et al 2020; Jin and McElheran 2018; Cardona, Kretschmer and Strobel 2013; Brynjolfsson and McAfee 2014; Bloom, Sadun and Van Reenen 2012; Syverson 2011
  - (Digital Technology – Aggregate-level) Niebel 2018; Fernald 2014; Timmer et al. 2011; O'Mahoney, Van Ark and Timmer 2008

- Modern productivity paradox and heterogeneity across different firms
  - (Productivity paradox) Brynjolfsson et al. (2019)
  - (Heterogeneity in AI adoption) Gibbs & Kraemer (2004), Bommadevara, Del Miglio, & Jansen, (2018) Iansiti & Lakhani (2020) Cho et al. (2022)

- Considering endogeneity issues regarding AI adoption and productivity
  - Yang (2022)

Outline

- Data and basic statistics
- AI adoption and firm productivity
  - Instrumental variables
  - Single plant vs. multi-plant
- AI adoption and the plant productivity gap within firms
- Conclusion

Data and Basic Statistics

Survey of Business Activities (SBA)

- Since 2005, Statistics Korea has conducted the SBA
  - A wide ranging survey of firm activities across all industries.
  - All establishments with 50 or more regular workers and KRW 300 million in capital
- Since 2018, SBA has surveyed respondents on the adoption of nine advanced 4IR technologies
  - AI, big data, mobile, cloud computing, IoT, robots, AR/VR, blockchain
  - Reference year 2017
- Directly asks respondents whether they have adopted any of the technologies, and responses are compiled into a binary variable

SBA questionnaires on 4IR technologies

- Directly asks respondents whether they have adopted any of the technologies, and responses are compiled into a binary variable
  - Issue regarding development vs. adoption

Question 2.	Is your company currently utilizing or developing Fourth Industrial Revolution technologies?	
① Yes ↓ ② No → Go to Q. 3		
(Q. 2-1) What technology is your company currently using or developing? (Verify each applicable item)	(Q. 2-2) Where does your company utilize technology? (Select only one primary utilization step) * Go to (Q. 2-3) if you are developing.	(Q. 2-3) What is the primary development method for self- or consigned technology development (excluding being entrusted by the client)? (Select one)
① IoT	① None ② Product(service) development ③ Marketing strategy ④ Production process ⑤ Organizational management ⑥ Sales Purpose	① None ② Self-development ③ Domestic consignment ④ Overseas consignment
② Cloud	① None ② Product(service) development ③ Marketing strategy ④ Production process ⑤ Organizational management ⑥ Sales Purpose	① None ② Self-development ③ Domestic consignment ④ Overseas consignment
③ Big Data	① None ② Product(service) development ③ Marketing strategy ④ Production process ⑤ Organizational management ⑥ Sales Purpose	① None ② Self-development ③ Domestic consignment ④ Overseas consignment
④ 5G	① None ② Product(service) development ③ Marketing strategy ④ Production process ⑤ Organizational management ⑥ Sales Purpose	① None ② Self-development ③ Domestic consignment ④ Overseas consignment
⑤ A.I.	① None ② Product(service) development ③ Marketing strategy ④ Production process ⑤ Organizational management ⑥ Sales Purpose	① None ② Self-development ③ Domestic consignment ④ Overseas consignment
⑥ Block Chain	① None ② Product(service) development ③ Marketing strategy ④ Production process ⑤ Organizational management ⑥ Sales Purpose	① None ② Self-development ③ Domestic consignment ④ Overseas consignment
⑦ 3D Printing	① None ② Product(service) development ③ Marketing strategy ④ Production process ⑤ Organizational management ⑥ Sales Purpose	① None ② Self-development ③ Domestic consignment ④ Overseas consignment
⑧ Robotics	① None ② Product(service) development ③ Marketing strategy ④ Production process ⑤ Organizational management ⑥ Sales Purpose	① None ② Self-development ③ Domestic consignment ④ Overseas consignment
⑨ VR, AR	① None ② Product(service) development ③ Marketing strategy ④ Production process ⑤ Organizational management ⑥ Sales Purpose	① None ② Self-development ③ Domestic consignment ④ Overseas consignment

Source: Statistics Korea (2020). The Survey of Business Activities.

Direct vs indirect measure of AI Adoption

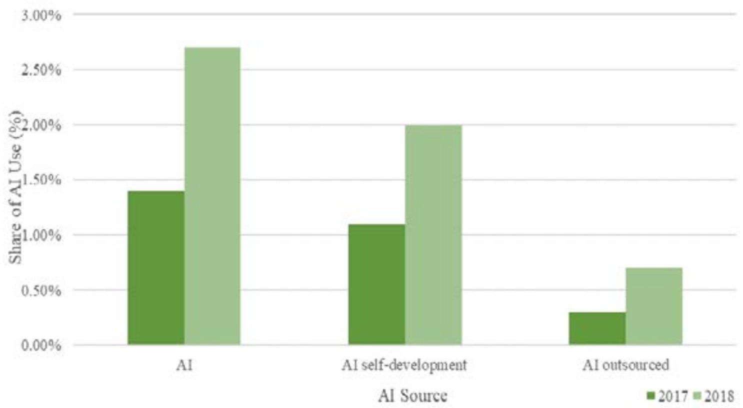
- Previous studies indirectly measured the use of AI via proxy variables such as job postings
  - Patent registration data (Damioli et al., 2021; Alderucci et al., 2020.; Yang, 2022)
  - Job postings (Alekseeva et al., 2020, 2021; Babina et al., 2021)

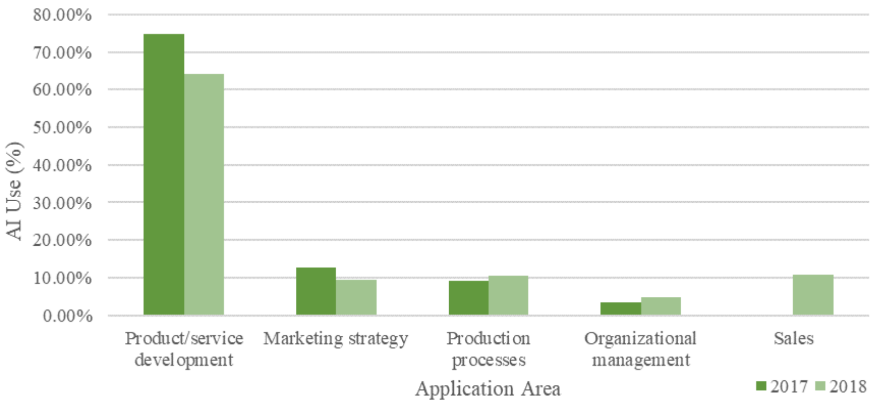
- Difficult to confirm whether firms use AI technologies in production processes
  - Patent data may exclude instances of adoption through outright purchase or licensing of AI technologies or cases in which AI technology inputs were outsourced
  - Skill-related technology requirements in job postings often fail to distinguish whether demand for AI increases or decreases due to development, adoption, or preparation

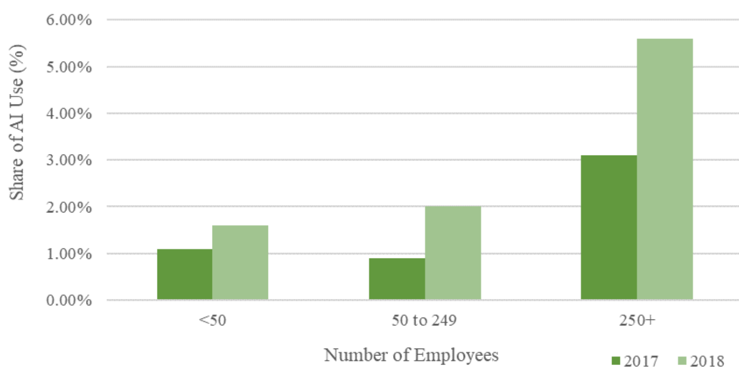
AI adoption by industry, 2017 and 2018 (SBA)

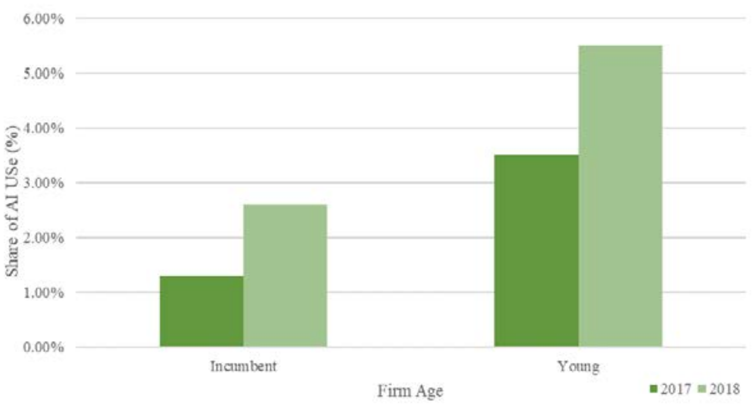
Industry	2017		2018	
	4IR	AI	4IR	AI
All	8.06%	1.38%	11.41%	2.70%
Agriculture, forestry and fisheries	0.00%	0.00%	6.67%	0.00%
Manufacturing	6.68%	0.79%	10.00%	1.74%
Electricity and gas	15.25%	3.39%	16.13%	3.23%
Construction	5.16%	0.37%	8.64%	1.59%
Wholesale and retail	6.71%	0.93%	9.06%	2.25%
Transportation and warehousing	3.08%	0.14%	4.11%	0.40%
Lodging and restaurant	5.88%	0.62%	4.03%	0.58%
Information and communications	25.31%	6.78%	38.15%	12.62%
Real estate	0.92%	6.12%	2.38%	0.00%
Other services	46.34%	0.00%	6.77%	1.39%
Finance and insurance	2.93%	0.85%	21.57%	8.68%

Share of AI adoption, 2017 and 2018 (Cho et al, 2022)









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Mining and Manufacturing Survey (MMS)

- MMS conducted by Statistics Korea
  - Aims to ascertain the industry's overall structure, as well as the nature of distribution and industrial activities
  - All plants with ten or more workers in the mining or manufacturing industry

- The sample is defined as establishments in the manufacturing sector and their production facilities
  - Considers only manufacturing firms among SBA respondents
    - Heterogeneity in AI adoption across industries
    - Little bias due to the broad recognition of development and adoption

Main variables

- Firm characteristics (SBA) + Plant information (MMS)

Description	Variable	Definition
Adopting AI	AI	1 if a firm adopts AI; 0 otherwise
Financial status	lnSales	log (Sales)
	cash_assets	Cash/Total assets
	ROS	Profit/Sales
Productivity	lnLP	Value-added/number of employees
Size	lnLa	Number of employees
Governance	foreign	1 if the share of foreign assets ≥ 0.5; 0 otherwise
	group	1 if a firm is part of a conglomerate; zero otherwise
Age	lnage	log (age)
Technology	lnPatent	log (number of patents)
	BIM	1 if a firm adopts either big data, IoT, or mobile; 0 otherwise
Competition	HHI	Herfindahl–Hirschman index for the industry where a firm exists
Exposure to AI	ai_ratio	The share of firms that adopt AI in the same industry
Multi-plant firm	multi-plants	1 if a firm has two or more plants; 0 otherwise
Industry	industry FE	Dummies by Korea Standard Industry Code at 2-digit level
Year	year FE	Dummies for years

AI adopters vs. non-adopters (main variables)

- In general, firms adopting AI are superior to others in terms of performance
  - Almost all variables have higher values at firms that have adopted AI
    - Sales, employment, patents, technology infrastructure, and the number of plants is particularly notable (Cho et al., 2022)
  - Alderucci et al. (2020)
    - US firms with AI tend to have more employees, better business capabilities, and more than one production facility compared to those without

	AI adopters		Non-adopters	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
AI	1	-	0	-
lnSales	12.320	2.087	10.816	1.204
cash_assets	0.355	0.170	0.329	0.168
ROS	0.007	0.225	-0.001	0.401
lnLa	6.116	1.673	4.942	0.820
foreign	0.160	0.367	0.198	0.398
group	0.176	0.382	0.032	0.175
lnLP	4.691	0.739	4.427	0.632
lnage	3.081	0.741	3.075	0.563
lnPatent	3.908	2.268	2.122	1.452
BIM	0.660	0.475	0.044	0.204
HHI	0.087	0.094	0.061	0.071
ai_ratio	0.028	0.019	0.014	0.014
multi-plants	0.727	0.446	0.537	0.499

AI adoption and firm productivity

AI adoption and firm productivity

- The relationship between AI adoption and firm productivity is ambiguous
  - Analysis limited by sample size
  - Measurement issues (as noted in previous slides)
  - Simple correlation & endogeneity in econometrics

- Modern productivity paradox
  - Productivity paradox (Brynjolfsson, 1993)
    - ICT (a GPT in the 1990s) led to insignificant productivity gains
  - Possible causes
    - Learning and adjustment period, i.e. ICT management or organization
  - AI as an emerging and influential GPT is not exceptional
    - (Jovanovic and Rousseau, 2005; Brynjolfsson et al., 2019)

- Despite a positive relationship, empirical evidence gives little information
  - Regression can’t explain reasons for correlation (or lack thereof)

Model specification

- We estimate the relationship between the adoption of AI and firm prod.

$$Y_{ijt} = \alpha AI_{ijt} + \beta X_{ijt} + \mu_j + \upsilon_t + \varepsilon_{ijt}$$

- Y_{ijt} : firm (i)'s productivity in industry (j) at time (t) as value-added divided by the number of employees
  - Labor productivity is more intuitive as interpreted over the entire production cycle
  - Labor productivity is less sensitive than TFP (Brynjolfsson et al, 2019)
  - Better to compare the results of previous studies (Alderucci et al., 2020; Babina et al., 2021; Damioli et al., 2021)
- X_{ijt} : Firm and industry characteristics
  - Financial status: sales, cashable asset weight, sales return
  - Size: number of employees
  - Governance structure: foreign equity, large business group
  - Business history, R&D capacity, competitive exposure, and multi-plant status

Endogeneity issues

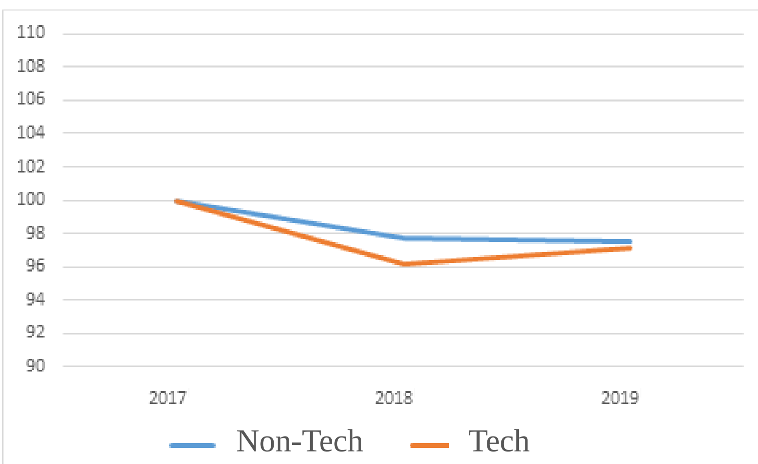
- Firms with certain characteristics may self-select to develop/adopt AI; existence of reverse causality problem cannot be dismissed (from AI to firm characteristics)
  - Frederick et al. (2018): Entrepreneurship related to advanced tech in digital companies
  - Cho et al. (2022): Complementary across advanced technologies
  - Cho et al. (2022): AI adoption is highly correlated with use of big data, mobile, cloud computing

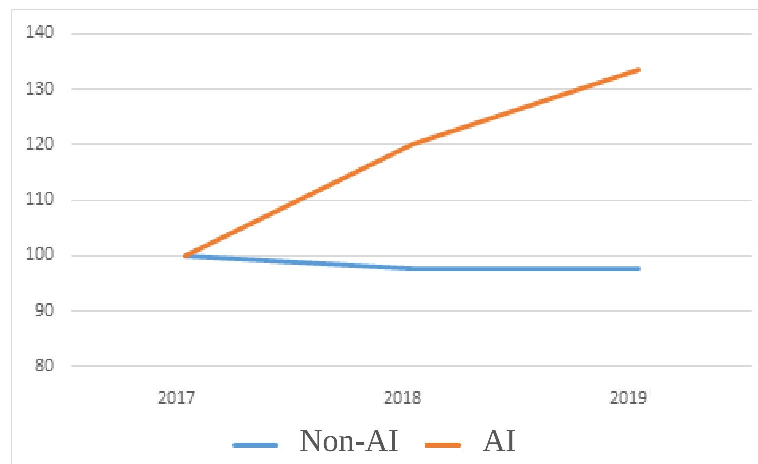
- Yang (2022) employs GMM for dynamic panel data model
  - Productivity may be path-dependent

Instrumental Variables

- We consider instrumental variables
  - (Fim-level) BIM: Either big data, IoT or mobile (following Cho et al., 2022)
  - (Industry-level) Competition and the level of knowledge diffusion: AI utilization rate in the same industries

- Additional validation of IVs (The exclusion restriction)





(Note) Data Source: SBA, Normalized to 100 in the year 2017, Tech: Firms have adopted any of the technologies, IoT, Cloud, Big Data, 5G, AI, Block Chain, 3D printing, Robotics, VR/AR, AI: Firms have adopted AI, Non-: Firms have not adopted

Analysis with instrumental variables

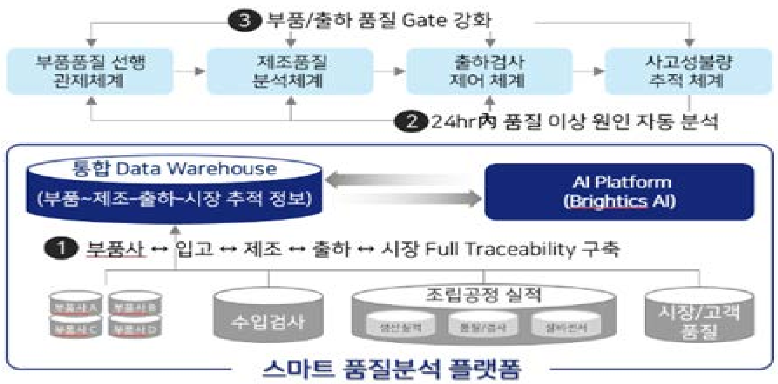
- Both OLS and IV estimations suggest statistically insignificant relationship
  - Magnitude increases with IVs
    - Consistent with findings of Damioli et al. (2021), Babina et al. (2021)

Variables	OLS	IV (1st stage)	IV (2nd stage)
AI	-0.00606		-0.0262
	(0.0315)		(0.114)
ai_firm_ratio1		0.994***	
		(0.234)	
bim		0.156***	
		(0.0130)	
Constant	0.959***	-0.0933***	0.956***
	(0.0621)	(0.0171)	(0.0647)
Controls	Y	Y	Y
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	12,599	12,782	12,599
F-stat		72.59	
R-squared	0.511	0.128	0.511

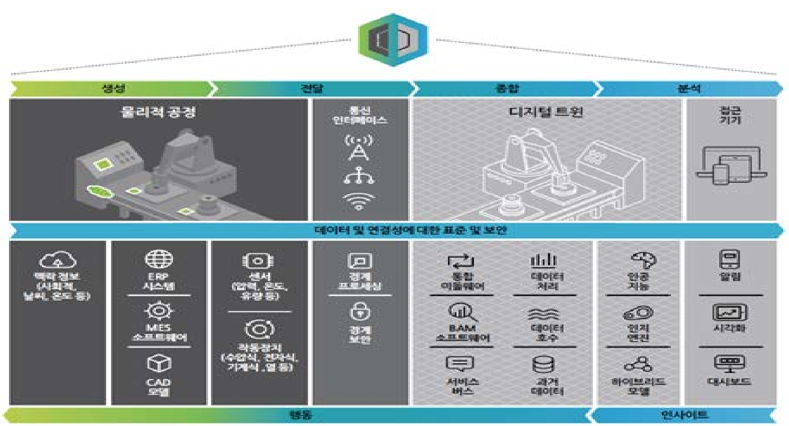
Note 1: IVs are (i) artificial intelligence introduction rate and (ii) whether to adopt technologies (Big, IOT, 5G)
Note 2: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
Note 3: The analytical model is the result of including control variables (Controls), Industry FE, and Year FE.

Adopting AI in Manufacturing: The Case of Multi-plant Firms

- Processing intelligence



- Digital twins



Single-plant vs. Multi-plant firms

- About 15 percent higher productivity with AI at multi-plant firms

	(1)		(2)	
Variables	OLS	IV	OLS	IV
AI	-0.0980	-0.596**	-0.0846*	-0.251
	(0.0759)	(0.299)	(0.0496)	(0.189)
AI*multi	0.126	0.743**	0.0565***	0.151**
	(0.0814)	(0.302)	(0.0198)	(0.0654)
multi	-0.0100	-0.0172*	-0.00551	-0.00908
	(0.00909)	(0.00943)	(0.00609)	(0.00636)
Constant	0.961***	0.961***	0.959***	0.957***
	(0.0621)	(0.0646)	(0.0648)	(0.0669)
Controls	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	12,599	12,599	12,599	12,599
R-squared	0.511	0.508	0.511	0.511

Note 1: (1) Interaction of dummy variable, multi-business dummy variable, and tool variable of 1st stage showed statistically significant + values, and F-stat (AI)=36.55, F-stat (AI*multi)=33.59. (2) Interaction variable between dummy variable and business variable (interaction n).
Note 2: IVs are (i) artificial intelligence adoption rate, (ii) adoption or lack thereof of quaternary technologies (big data, IoT, 5G)

AI adoption and the Plant Productivity Gap within Firms

The Characteristics of Multi-plant Firms and Single-plant firms

- Multi-plant firms are superior to their counterparts
  - Higher levels of sales, employment, productivity, age, patents, and AI-related technologies

	Multi-plant firms		Single-plant firms	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
AI	0.018	0.133	0.008	0.089
lnSales	11.21	1.319	10.40	0.952
cash_assets	0.326	0.162	0.332	0.175
ROS	0.008	0.303	-0.010	0.488
lnLa	5.211	0.948	4.660	0.585
foreign	0.185	0.389	0.211	0.408
group	0.045	0.207	0.021	0.142
lnage	3.172	0.565	2.961	0.546
lnPatent	2.370	1.571	1.858	1.311
HHI	0.059	0.067	0.064	0.075
BIM	0.063	0.243	0.039	0.194
lnLP	4.507	0.643	4.340	0.612

Source : SBA & MMS

Model specification

- We estimate the relationship between the adoption of AI and firm prod. gap

$$Gap_{ijt} = \alpha AI_{ijt} + \beta X_{ijt} + \mu_j + \upsilon_t + \varepsilon_{ijt}$$

- GAP_{ijt} : the productivity gap between plants in firm (i) in industry (j) at year (t)
  - the difference between maximum and minimum labor productivity among the plants

- X_{ijt} : Firm and industry characteristics
  - Financial status: sales, cashable asset weight, sales return
  - Size: number of employees
  - Governance structure: foreign equity, large business group
  - Business history, R&D capacity, competitive exposure, and multi-plant status

AI adoption and the gap in plant productivity

- The estimation result shows a narrowing of the productivity gap between plants due to the adoption of AI

VARIABLES	Dependent: The gap in plant productivity
AI	-0.248***
	(0.0776)
Constant	-2.442***
	(0.182)
Controls	Y
Industry FE	Y
Year FE	Y
Observations	10,239
R-squared	0.426

Note1: The dependent variable is the difference between maximum and minimum of plants′ labor productivity.
Note 2: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
Note 3: We control Controls, Industry fixed-effect and year fixed-effect

- The productivity gap between plants within the company narrows, and firm productivity increases due to the adoption of AI
- Unfortunately, it is difficult to grasp the *direction* of productivity changes in each plant within the firm from the estimation

Conclusion

Conclusion

- Limits to building standardized data and conducting cross-space and cross-time empirical analyses of AI

- This paper helps to fill this gap by investigating the relationship between the adoption of AI and firm productivity using Korean manufacturing data
  - Contributes to the literature by providing empirical evidence using large-scale samples of firms obtained from a national database in South Korea
  - The analysis pulls together firm level data on AI use along with plant-level performance metrics

- The paper examines the extent to which AI gains are on average obtained by all types of firms or whether they are concentrated among the certain entities
  - Peering below the firm level, we also explore possible intra-business mechanisms that may explain efficiency gains from AI
  - We attempt to control for the likely presence of endogeneity bias in the adoption process by conducting an instrumental variable approach

Conclusion

- We find that AI adoption does not lead to efficiency gains for firms overall
  - No statistical evidence between AI adoption and productivity
- Multi-plants appear to reap efficiency gains from AI adoption
  - About 15 percent efficiency gain
- The mechanism: reductions in the productivity gap among plants within the firm
  - About 25 percent of the gap

Some limitations and implications for future research

- No metric for the quality of the technologies, or for the degree to which firms are making these investments and acquisitions
  - Only able to capture the extensive margin of AI adoption

- The adjustment costs some firms may face in implementing AI may take longer to recoup
  - Performance gains may require additional time for smaller firms to achieve

- Limit to a sample of manufacturing firms
  - Service sector may employ and achieve performance gains from AI differently from their counterparts

Thank you