CompNet-Japan Workshop
12, May, 2025
Gakushuin University, Tokyo, Japan

AI and Intangible Investments in Korea from The Survey of Business Activities

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Ⅰ. Trend of AI firms

- The proportion of AI-invested firms among total sample firms in the Survey of Business Activity conducted by Statistics Korea has an increasing trend. On average 3.5% in the Korean sample firms during 2017-2023 had invested in AI.

Ⅱ. Proportion of AI firms by firm-specifics

- The proportion of AI firms is relatively bigger in service than in manufacturing
- The proportion of AI firms in ICT sector such as ICT-Producing, ICT-Using sector are bigger than in Non-ICT sector

Table 1 Trend of AI firms (Total Sample Firms)

<firms, %>

	Total (A)	AI firms (B)	Non-AI firms (C)	B/A*100	C/A*100
2017	12,579	173	12,406	1.4	98.6
2018	13,144	350	12,794	2.7	97.3
2019	13,255	407	12,848	3.1	96.9
2020	13,429	469	12,960	3.5	96.5
2021	13,448	504	12,944	3.7	96.3
2022	13,824	577	13,247	4.2	95.8
2023	14,546	865	13,681	5.9	94.1
Avg.				**3.5**	

Source: Statistical Office(2017-2023), Survey of Business Activities

Ⅱ. Ratio of AI firms by firm-specifics

- The proportion of AI firms in detailed industries are in descending order as follows:

  i) insurance,

  ii) computer programming,

  iii) publishing,

  iv) information service,

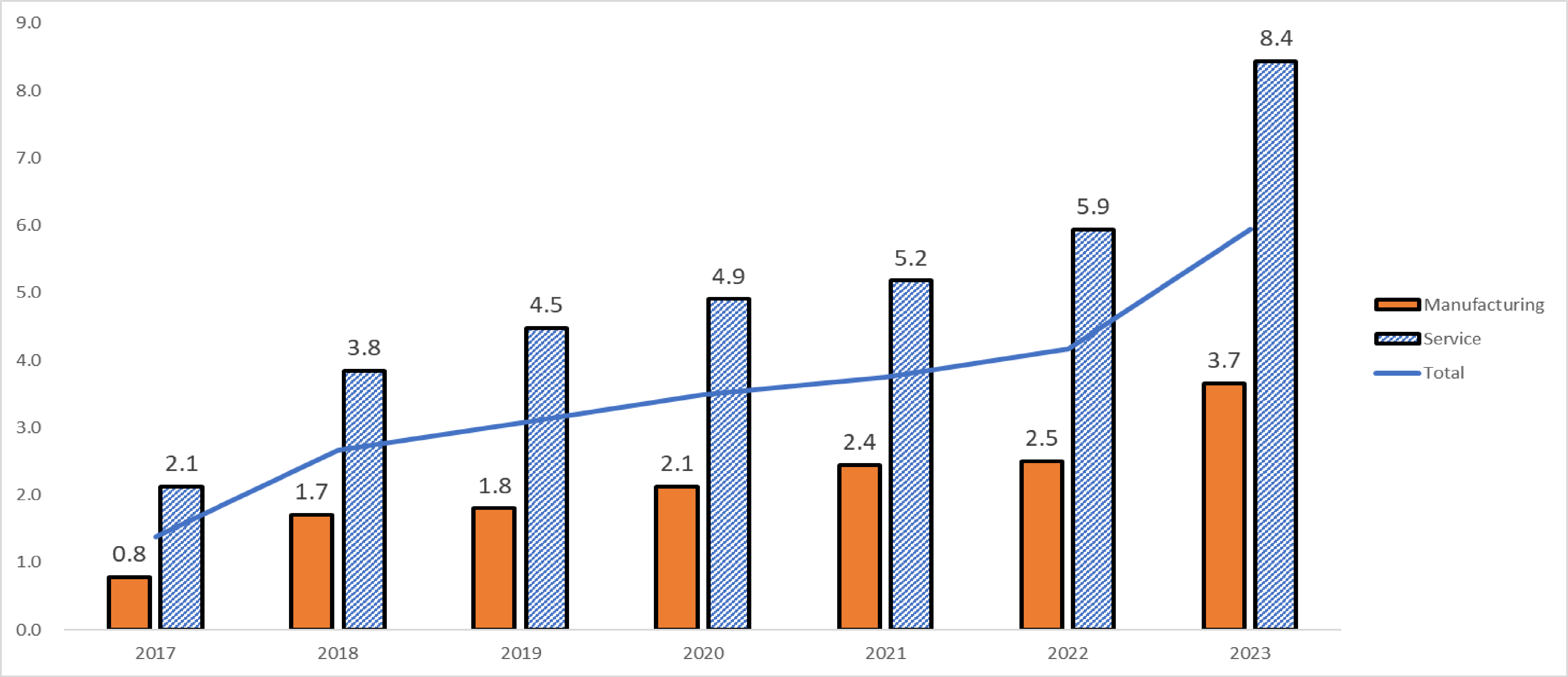
  v) telecommunications,

  vi) financial service etc.

- The proportion of AI firms is bigger in large business than in SMEs

Figure 1 Proportion of AI firms (Manufacturing vs. Service)

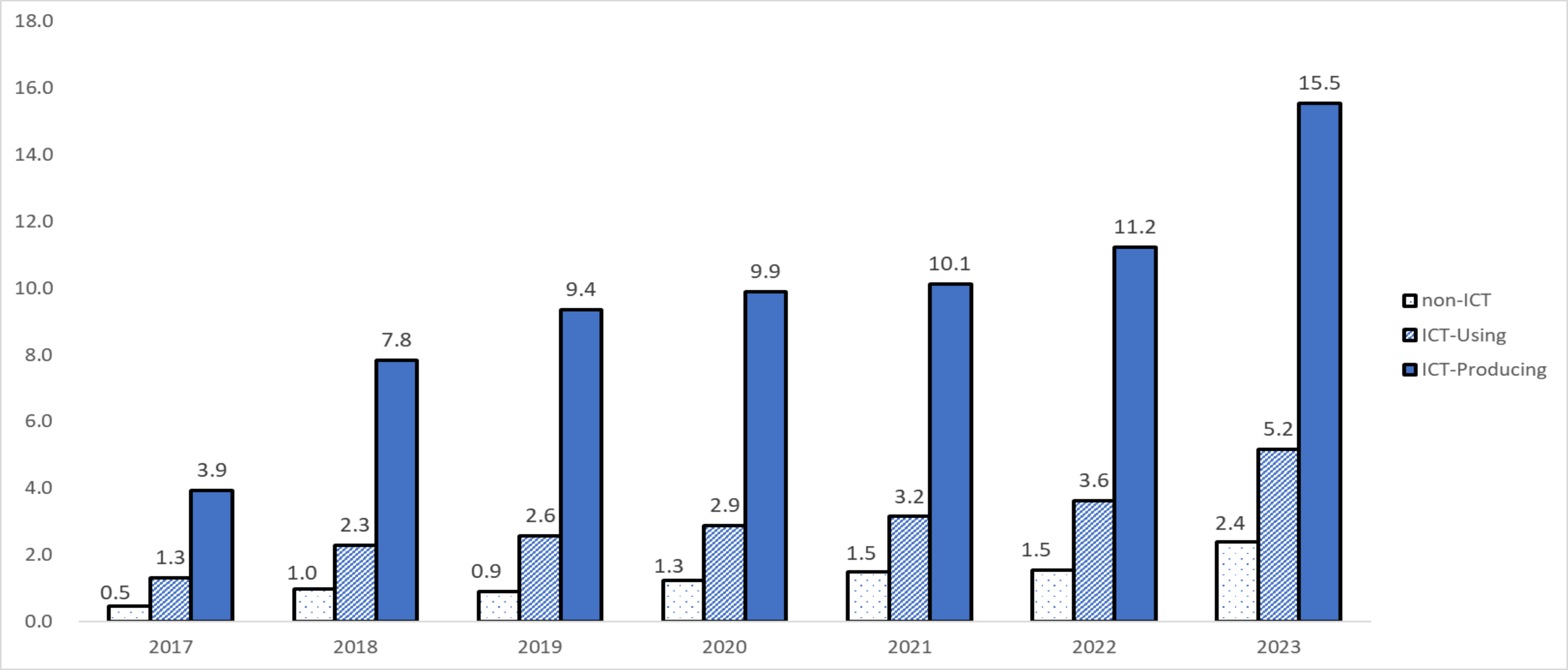
<rate(%)>



Source: Statistical Office(2017-2023), Survey of Business Activities

Figure 2 Proportion of AI firms(ICT sectors)

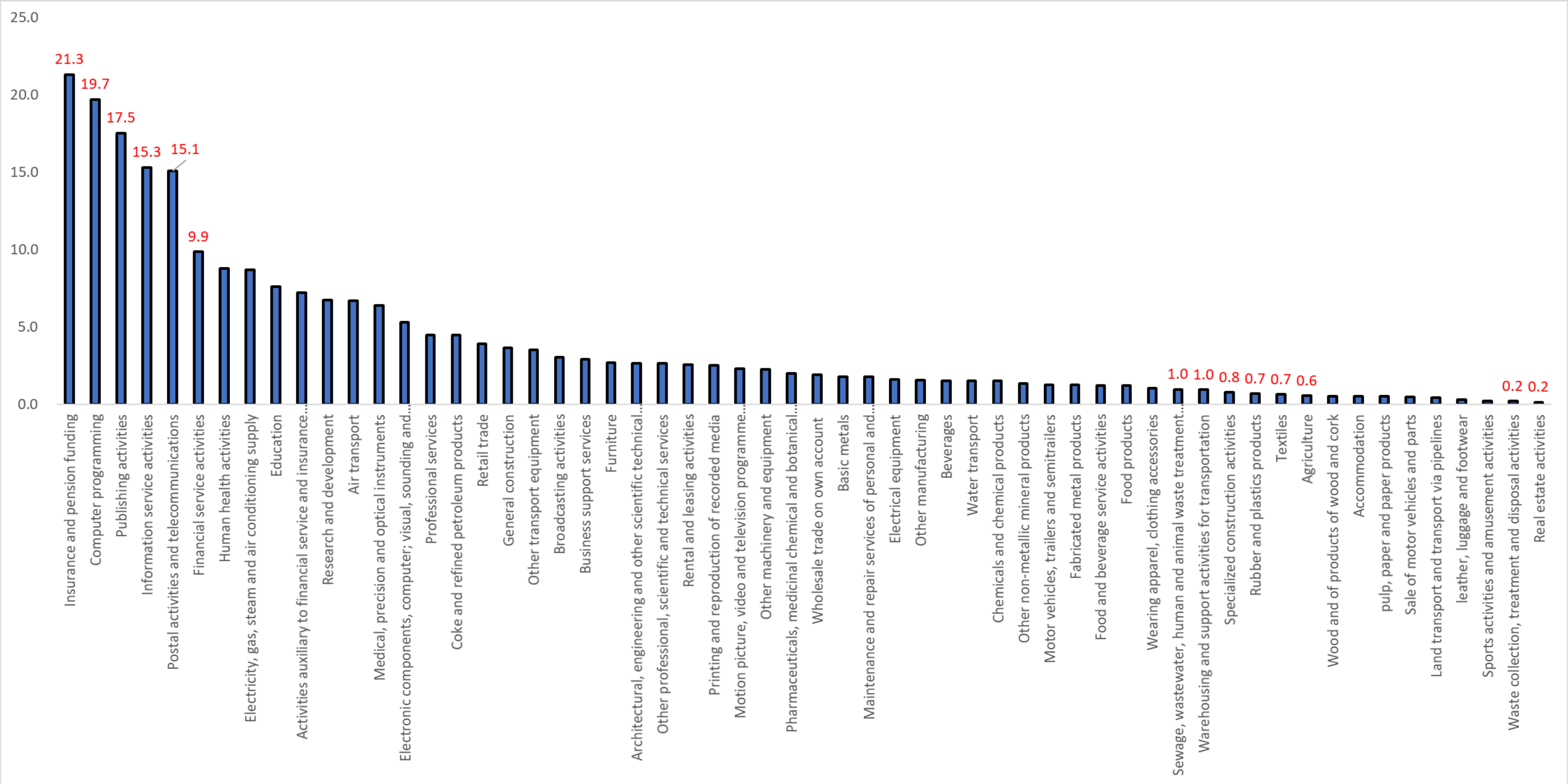
<rate(%)>



Source: Statistical Office(2017-2023), Survey of Business Activities

Figure 3 Proportion of AI firms(2-digit industries)

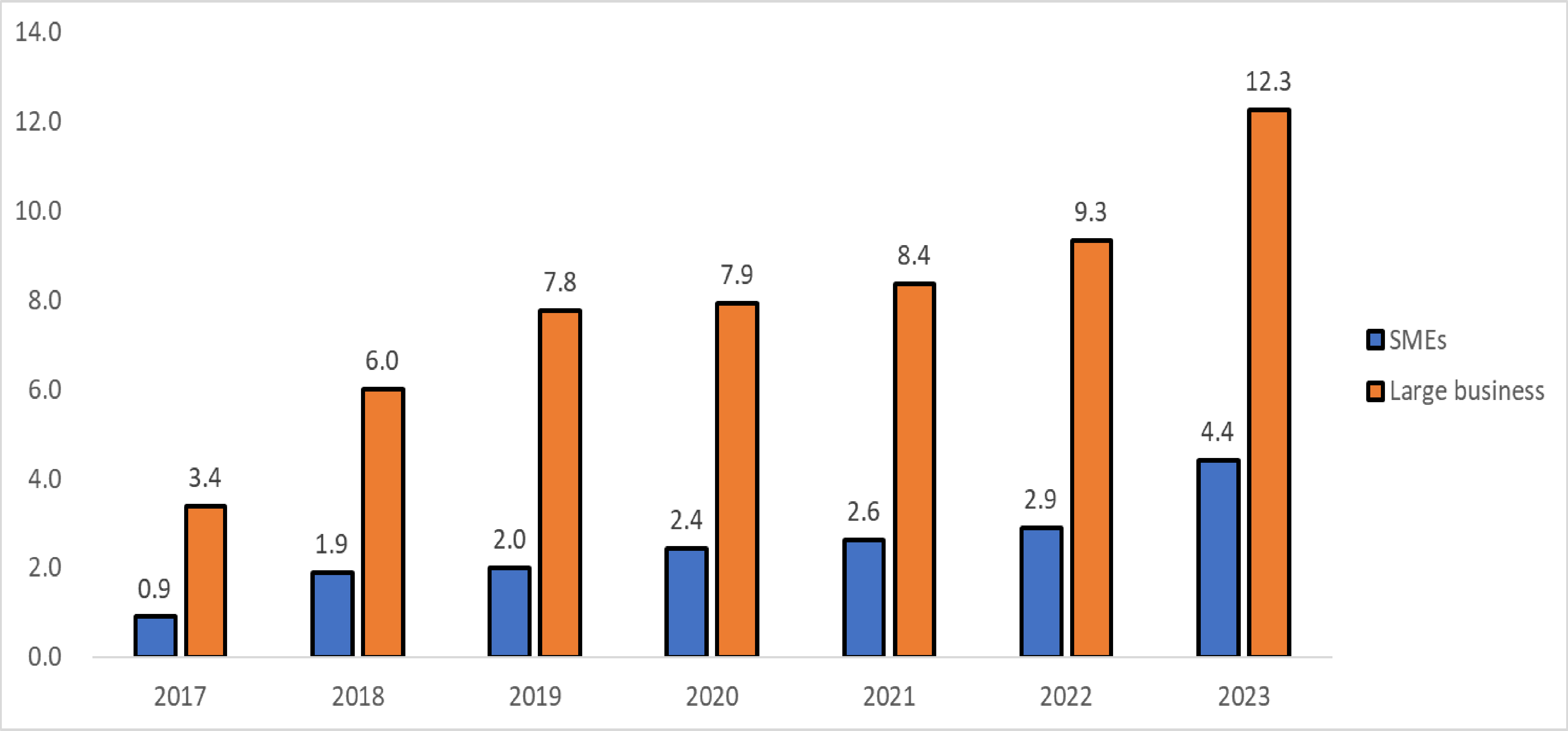
<rate(%)>



Source: Statistical Office(2017-2023), Survey of Business Activities

Figure 4 Proportion of AI firms by firm size

<rate(%)>



Source: Statistical Office(2017-2023), Survey of Business Activities

Ⅲ. Purpose of AI-Adoption: Response by Sample Firms

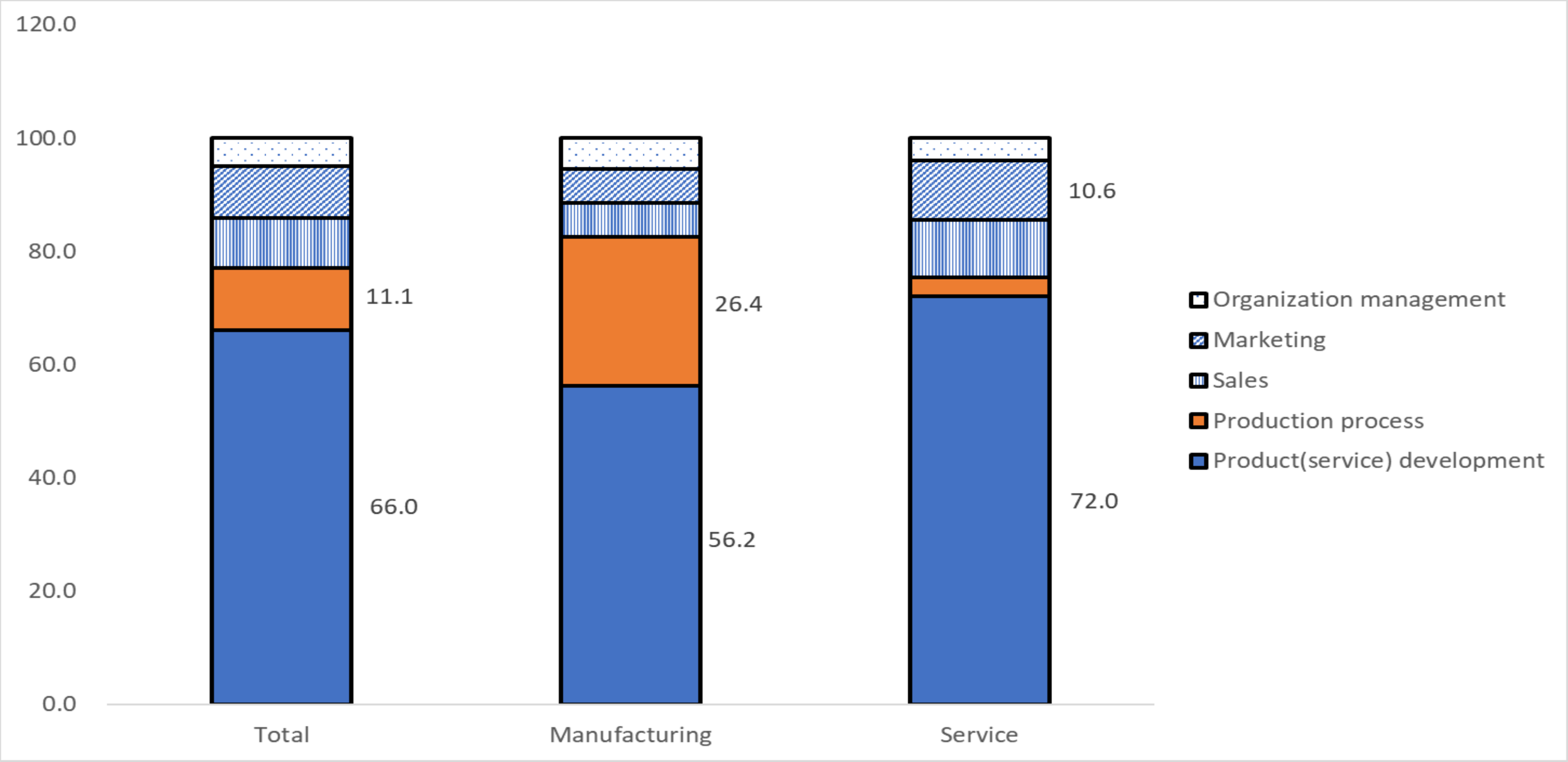
- The main purpose in adoption of AI technology is product(or service) development among other purposes. The other purposes are cited as below;

- (Manufacturing) production process

- (Service) sales or marketing

Figure 5 Purposes of AI adoption (Manufacturing vs. Service)

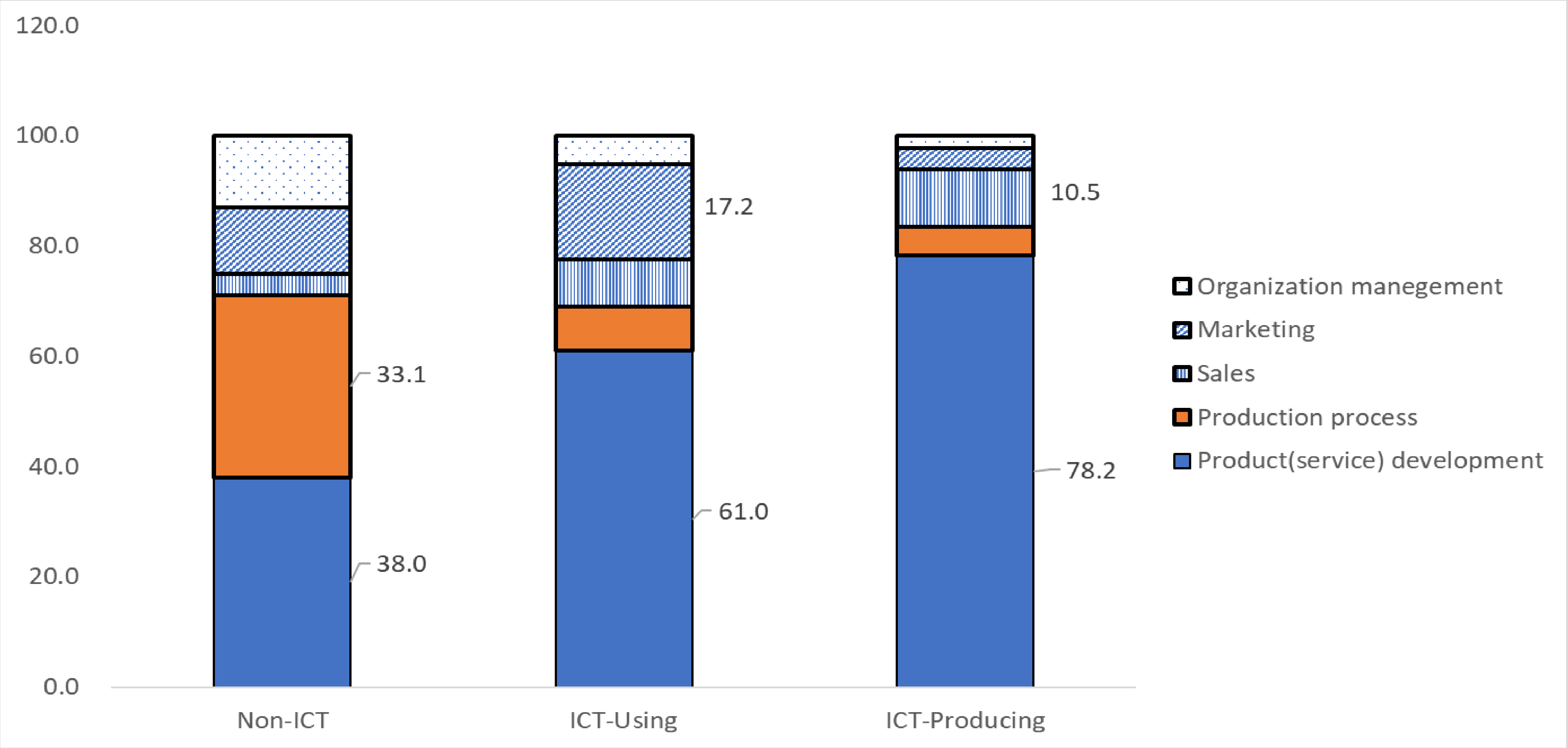
<rate(%)>



Source: Statistical Office(2017-2023), Survey of Business Activities

Figure 6 Purpose of AI adoption (ICT-sectors)

<rate(%)>



Source: Statistical Office(2017-2023), Survey of Business Activities

Ⅳ. AI Intensity

- AI Intensity=$\sum_i^j A_{ij}$ / Maximum value (Table 2)

$$i = complementary\ assets$$

(ex: IoT, Cloud, Big Data, 3D printing, Robotics etc.)

$$j = AI\ adoption\ purposes$$

$$Max.\,value = 30$$

Reference:

1) Czarnitzki, Fernandez, and Rammer (2023), Artificial Intelligence and Firm-level Productivity, *Journal of Economic Behavior and Organization*, Vol. 211, p. 194
2) Lee, Yong Suk, Taekyun Kim, Sukwoong Choi, and Wonjoon Kim (2022), When does AI pay off? AI-adoption intensity, complementary investments, and R&D strategy. *Technovation* 118, pp. 4-5

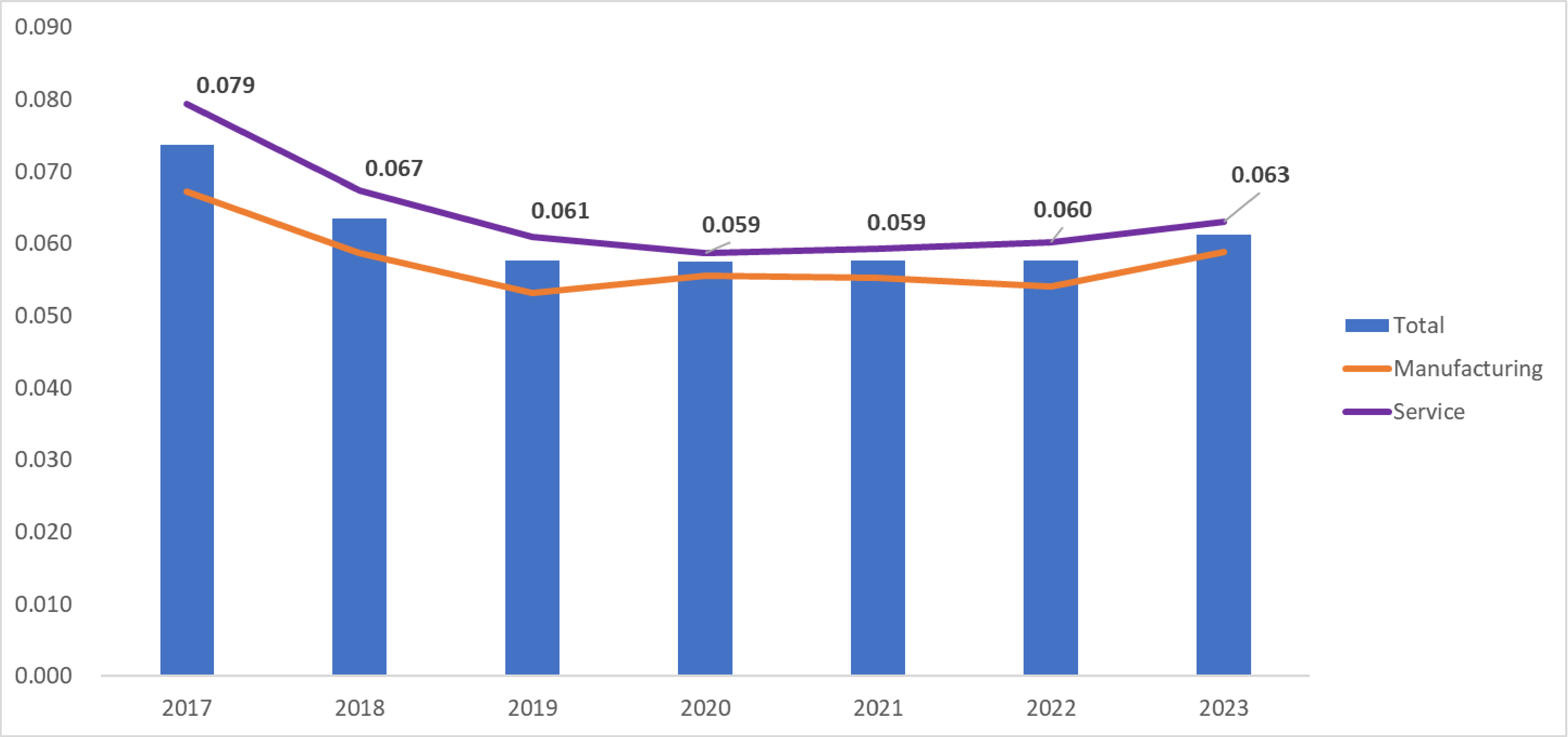
Table 2 Basic format for AI Intensity

	(A) Product(service) development	(B) Production process	(C) Sales	(D) Marketing	(E) Organization management
(1) IoT					
(2) Cloud					
(3) Big Data					
(4) AI					
(5) 3D Printing					
(6) Robotics					

Source: Statistical Office(2017-2023), Survey of Business Activities
Note: The 6 technologies are related with the 4th Industrial Revolution, and complementary technologies

Figure 7 AI Intensity (Manufacturing vs. Service)

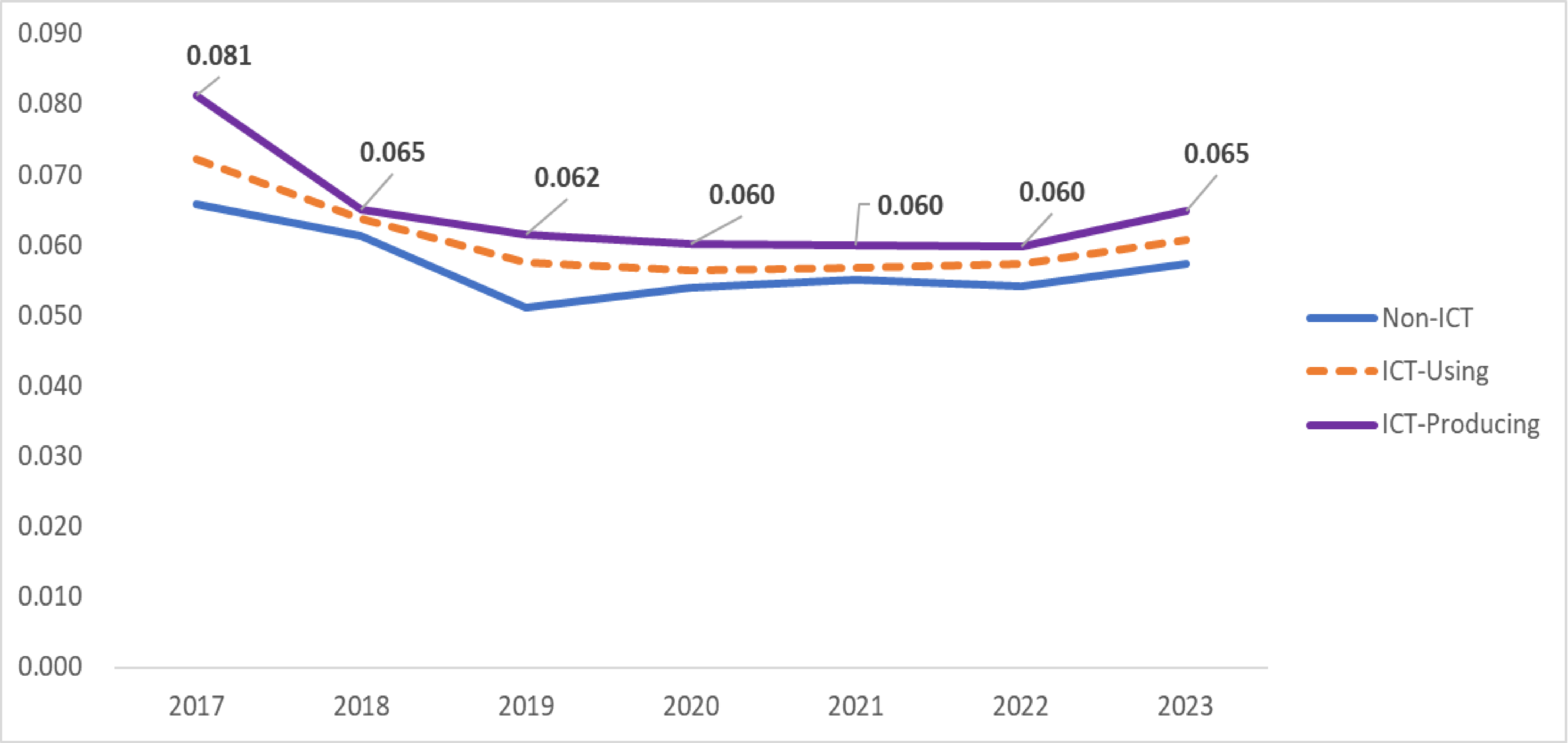
<intensity>



Source: Statistical Office(2017-2023), Survey of Business Activities

Figure 8 AI Intensity (ICT sectors)

<intensity>



Source: Statistical Office(2017-2023), Survey of Business Activities

Ⅴ. AI adoption and Labor productivity

- Labor productivity= Real value-added / employee

- Measurement of value added

  1) Operating profit

  2) Labor cost

  3) Taxes and Dues

  4) Depreciation expenses

  5) Bad debt expenses

Source: Statistical Office(2017-2023), Survey of Business Activities

1. Level of Labor Productivity

Table 3 Labor Productivity of AI firm and Non-AI firm(Total samples) (Mill. KRW, %)

	Labor productivity		
	AI firms (A)	Non-AI firms (B)	A/B
2017	174	125	1.4
2018	214	119	1.8
2019	205	112	1.8
2020	215	114	1.9
2021	278	116	2.4
2022	289	118	2.4
2023	240	109	2.2
Avg.	**231**	**116**	**2.0**

Source: Statistical Office(2017-2023), Survey of Business Activities

Table 4 Labor Productivity of AI firm and Non-AI firm(Manufacturing vs. Service)

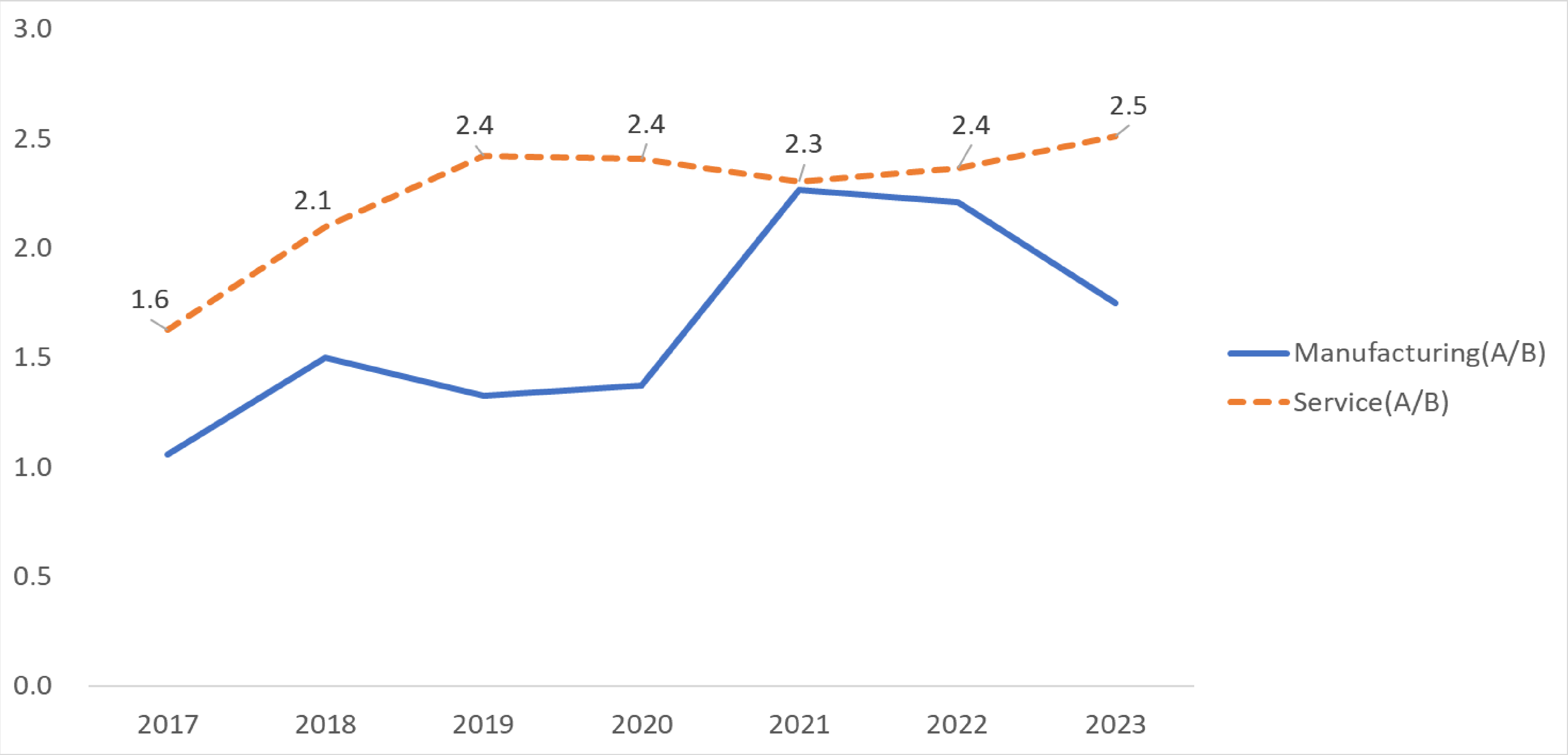
(Mill. KRW, %)

	Manufacturing			Service		
	AI firms (A)	Non-AI firms (B)	A/B	AI firms (A)	Non-AI firms (B)	A/B
2017	163	154	1.1	157	96	1.6
2018	222	148	1.5	192	91	2.1
2019	178	134	1.3	222	92	2.4
2020	185	135	1.4	227	94	2.4
2021	303	134	2.3	238	103	2.3
2022	304	138	2.2	248	105	2.4
2023	225	129	1.7	245	98	2.5
Avg.	**226**	**139**	**1.6**	**218**	**97**	**2.2**

Source: Statistical Office(2017-2023), Survey of Business Activities

Figure 9 Labor Productivity Gap between AI firms and Non-AI firms (Manufacturing and Service)

<productivity gap>



Source: Statistical Office(2017-2023), Survey of Business Activities

Table 5 Labor Productivity between AI firm and Non-AI firm (ICT sectors, 2017-23)

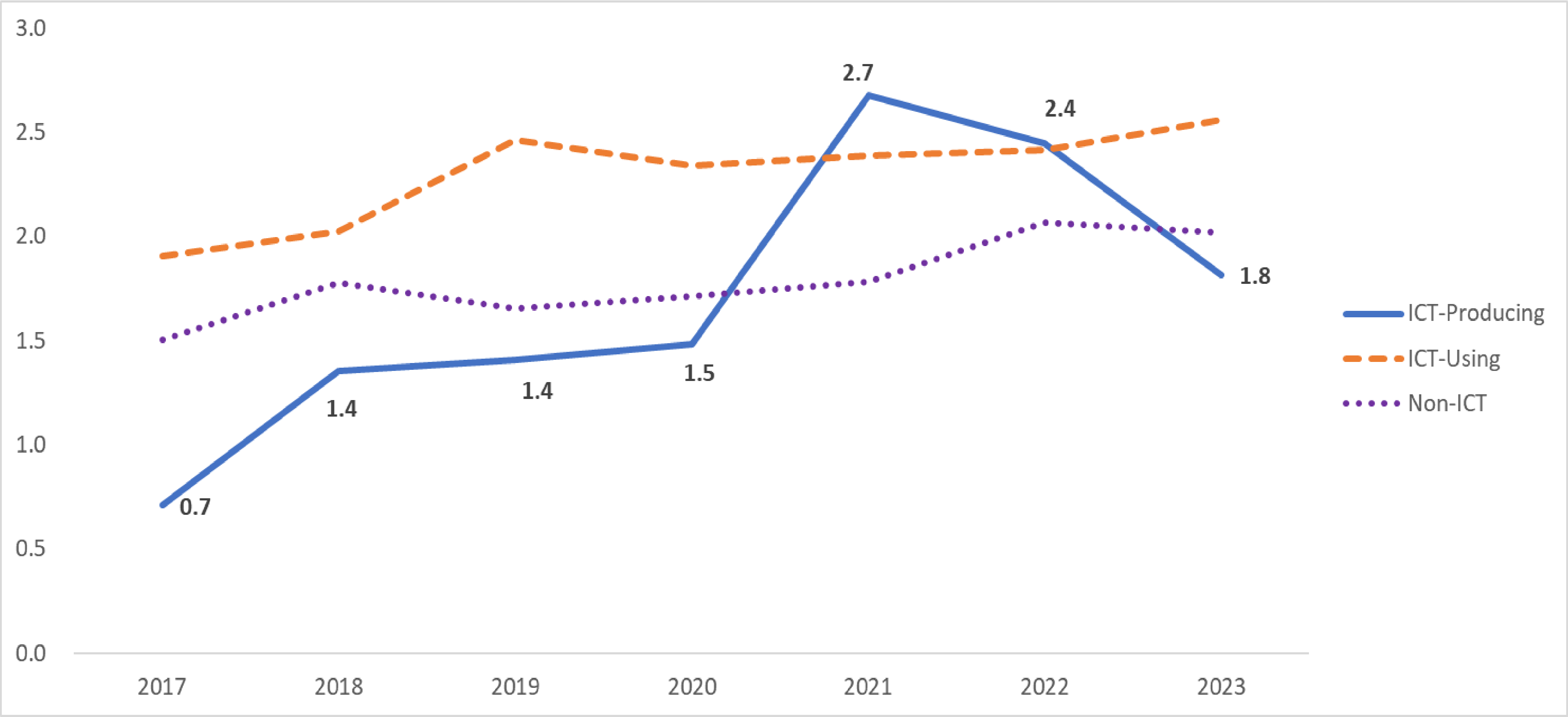
(Mill. KRW, %)

	AI firms (A)	Non-AI firms (B)	A/B
ICT-Producing	**253**	152	1.7
ICT-Using	**231**	100	2.3
Non-ICT	**207**	116	1.8

Source: Statistical Office(2017-2023), Survey of Business Activities

Figure 10 Labor Productivity Gap between AI firms and Non-AI firms (ICT sectors)

<productivity gap>



Source: Statistical Office(2017-2023), Survey of Business Activities

Table 6 Labor Productivity Gap between AI firms and Non-AI firms (detailed industries, Manufacturing)

(Mill. KRW, %)

	AI firm(A)	Non-AI FIRM(B)	A/B
1) Printing and reproduction of recorded media	174	65	2.7
2) Basic metals	276	131	2.1
3) Motor vehicles, trailers and semitrailers	191	119	1.6
4) Electronic components, computer	310	193	1.6
5) Fabricated metal products	119	88	1.4
6) Coke and refined petroleum products	**522**	396	1.3
7) Medical, precision and optical instruments	137	108	1.3
8) Other machinery and equipment	145	118	1.2
9) pulp, paper and paper products	156	131	1.2
10) Rubber and plastics products	121	103	1.2
11) Other manufacturing	92	86	1.1
12) Pharmaceuticals, medicinal chemical and botanical products	132	125	1.1
13) Food products	96	95	1.0
14) Chemicals and chemical products	202	219	0.9
15) Other transport equipment	79	86	0.9
16) Other non-metallic mineral products	126	152	0.8
17) Electrical equipment	96	117	0.8
18) Beverages	139	179	0.8

Source: Statistical Office(2017-2023), Survey of Business Activities

Table 7 Labor Productivity Gap between AI firms and Non-AI firms (detailed industries, Service)

(Mill. KRW, %)

	AI firm(A)	Non-AI FIRM(B)	A/B
1) Land transport and transport via pipelines	198	61	3.3
2) Broadcasting activities	322	141	2.3
3) Computer programming	173	79	2.2
4) Activities auxiliary to financial service and insurance activities	291	134	2.2
5) Postal activities and telecommunications	**357**	204	1.8
6) Architectural, engineering and other scientific technical services	134	77	1.7
7) Air transport	247	165	1.5
8) Business support services	51	39	1.3
9) Wholesale trade on own account	148	127	1.2
10) Retail trade	88	82	1.1
11) Rental and leasing activities	349	328	1.1
12) Accommodation	90	86	1.1
13) Insurance and pension funding	164	158	1.0
14) Publishing activities	93	96	1.0
15) Education	52	56	0.9
16) Financial service activities	420	460	0.9
17) Information service activities	185	217	0.9
18) Water transport	495	592	0.8
19) Professional services	112	139	0.8
20) Other professional, scientific and technical services	89	137	0.6

Source: Statistical Office(2017-2023), Survey of Business Activities

2. Growth of Labor Productivity

Table 8 Growth of Labor Productivity (AI firms, Total samples) (log growth rates(%))

	Real VA	Employees	Productivity
2017	-	-	-
2018	75.9	55.0	20.9
2019	12.9	16.9	-4.0
2020	3.6	-1.0	4.6
2021	51.1	25.3	25.8
2022	12.1	8.1	3.9
2023	-4.4	14.5	-18.9
Avg.	**25.2**	**19.8**	**5.4**

Source: Statistical Office(2017-2023), Survey of Business Activities

Table 9 Growth of Labor Productivity (Non-AI firms, Total samples)

(log growth rates(%))

	Real VA	Employees	Productivity
2017	-	-	-
2018	-8.8	-4.3	-4.5
2019	-6.4	-0.5	-5.9
2020	3.0	1.3	1.8
2021	1.3	-0.1	1.4
2022	1.9	-0.2	2.1
2023	-7.3	0.7	-8.0
Avg.	**-2.7**	**-0.5**	**-2.2**

Source: Statistical Office(2017-2023), Survey of Business Activities

Table 10 Growth of Labor Productivity (Manufacturing, 2017-23)

(log growth rates(%))

	Real VA	Employees	Productivity
AI firms	31.7	26.2	**5.4**
Non-AI firms	-5.7	-2.8	**-2.9**

Source: Statistical Office(2017-2023), Survey of Business Activities

Table 11 Growth of Labor Productivity (Service, 2017-23)

(log growth rates(%))

	Real VA	Employees	Productivity
AI firms	23.1	15.6	**7.5**
Non-AI firms	1.2	0.9	**0.2**

Source: Statistical Office(2017-2023), Survey of Business Activities

Table 12 Growth of Labor Productivity (ICT sectors, 2017-23)

(log growth rates(%))

	Real VA	Employees	Productivity
		ICT-Producing	
AI firm	40.5	29.2	11.4
Non-AI firm	-10.1	-5.8	-4.3
		ICT-Using	
AI firm	21.7	15.9	5.8
Non-AI firm	1.3	0.4	0.9
		Non-ICT	
AI firm	17.9	15.9	2.0
Non-AI firm	-2.3	0.6	-2.8

Source: Statistical Office(2017-2023), Survey of Business Activities

Ⅵ. Determinants of Labor Productivity with AI

- **Model(1)**

$$lnPL_{it} = \alpha + \beta_1 lnPL_{-1} + \beta_2 AI(1)_{it} + \beta_3 f_{it} + \beta_4 D_i + e_{it}$$

- **Model(2)**

$$lnPL_{it} = \alpha + \beta_1 lnPL_{-1} + \beta_2 AI(2)_{it} + \beta_3 f_{it} + \beta_4 D_i + e_{it}$$

Then

- $PL = labor\ productivity$
- $AI(1) = AI\ adoption(binary),\quad AI(2) = AI\ Intensity$
- $f = firm\ fixed\ effect,$
    - **(RATE) rate of intangible to tangible asset**
    - **(COMP) complementary asset points**
    - **(SIZE) firm size**
    - **(ICT) ICT sector (ICT-Producing, ICT-Using, Non-ICT)**
- $D = dummy\ var.(2020\ year = 1)$

Table 13 Determinants of labor productivity

	OLS		Fixed effect		First Difference		Sys-GMM	
	M1	M2	M1	M2	M1	M2	M1	M2
PL_1	0.786*** (0.008)	0.786*** (0.008)	0.006 (0.017)	0.006 (0.017)	0.183*** (0.054)	0.183*** (0.054)	0.300*** (0.070)	0.300*** (0.070)
AI(1)	0.017 (0.015)		0.010 (0.023)		-0.014 (0.030)		-0.018 (0.024)	
AI(2)		0.528 (0.456)		0.318 (0.718)		-0.438 (0.905)		-0.565 (0.741)
Rate	-0.000 (0.000)	-0.000 (0.000)	-0.001** (0.000)	-0.001 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.002 (0.001)	-0.002 (0.001)
COMP	0.006 (0.007)	-0.011 (0.018)	-0.018* (0.011)	-0.029 (0.028)	0.013 (0.014)	0.027 (0.035)	-0.010 (0.014)	0.008 (0.031)
SIZE	0.068*** (0.015)	0.068*** (0.015)	-0.388*** (0.047)	-0.388*** (0.047)	-0.485*** (0.064)	-0.485*** (0.064)	-0.440*** (0.079)	-0.440*** (0.079)
ICT	0.015 (0.016)	0.015 (0.016)	0.010 (0.109)	0.010 (0.109)	-0.245 (0.191)	-0.245 (0.191)	-0.467* (0.251)	-0.467* (0.251)
Dum	-0.074*** (0.018)	-0.074*** (0.018)	-0.073*** (0.015)	-0.073*** (0.015)	-0.062*** (0.018)	-0.062*** (0.018)	-0.076*** (0.020)	-0.076*** (0.020)
Const.	0.972*** (0.041)	0.972*** (0.041)	4.780*** (0.118)	4.780*** (0.118)	-0.001 (0.011)	-0.001 (0.011)	3.816*** (0.399)	3.816*** (0.399)
Adj R^2	0.67	0.67	0.02	0.02	0.00	0.00		
Obs.	4,915	4,915	4,915	4,915	1,762	1,762	4,915	4,915
x^2			1485.10***	1485.10***				
Prob > z							AR(1) -7.54*** AR(2) 1.39	AR(1) -7.54*** AR(2) 1.39

[Estimation Results]

- **AI effect** **to labor productivity growth is not verified definitely**
- **The effect of complementary asset of AI** **to labor productivity growth is not also mixed but can not be confirmed**
- **The effect of the intangible over tangible rate** **is negative but insignificant**
- **Labor productivity growth of** **SMEs** **becomes to be larger than large business**
- **Time dummy of** **COVID-19** **is confirmed**

Ⅶ. Summary and Implications

1. Stylized facts

✓Adoption ratio of AI (2017-23) : 3.5%

✓AI-led sectors:

- Service than manufacturing
- ICT-Producing than other ICT sectors
- Large business than SMEs

✓AI adoption purpose

- Production (service) development

✓Level of aggregated labor productivity (2017-23)

- labor productivity gap (Industry base)
  - Total samples : 2.0 (AI firm(231) /Non-AI firm (113 mill. KRW))
  - Manufacturing : 1.6 (AI firm(226) /Non-AI firm (139 mill. KRW))
  - Service : 2.2 (AI firm(218) /Non-AI firm (97 mill. KRW))

- labor productivity gap (ICT sector)
  - ICT-Producing : 1.7 (AI firm(253) /Non-AI firm (152 mill. KRW))
  - ICT-Using : 2.3 (AI firm(231) /Non-AI firm (100 mill. KRW))
  - Non-ICT : 1.8 (AI firm(207) /Non-AI firm (116 mill. KRW))

- labor productivity gap (detailed industries, Manufacturing)
  1) Printing and reproduction of recorded media(2.7)
  2) Basic metals(2.1)
  3) Motor vehicles, trailers and semitrailers(1.6)
  4) Electronic components, computer(1.6)
  5) Fabricated metal products(1.4)

- labor productivity gap (detailed industries, Service)
  1) Land transport and transport via pipelines(3.3)
  2) Broadcasting activities(2.3)
  3) Computer programming(2.2)
  4) Activities auxiliary to financial service and insurance activities(2.2)
  5) Postal activities and telecommunications(1.8)

✓Growth of labor productivity (2017-23 avg.)

- Total samples : AI firm(5.4%) > Non-AI firm (-2.2%)
- Manufacturing: AI firm(5.4%) > Non-AI firm (-2.9%)
- Service : AI firm(7.5%) > Non-AI firm (0.2%)

✓Growth of labor productivity (2017-23 avg.)

- Total samples : AI firm(11.4%) > Non-AI firm (-4.3%)
- Manufacturing: AI firm(5.8%) > Non-AI firm (0.9%)
- Service : AI firm(2.0%) > Non-AI firm (-2.8%)

2. Determinants of labor productivity

- AI effect to labor productivity growth is not verified definitely
- The effect of complementary asset of AI to labor productivity growth is not also mixed but can not be confirmed
- The effect of the intangible over tangible rate is negative but insignificant
- Labor productivity growth of SMEs becomes to be larger than large business
- Time dummy of COVID-19 is confirmed

3. Implications

- We should put in mind there may be the positive as well as the negative reaction of the AI effect to the achievement of firms including productivity. We have to reconsider productivity paradox, and productivity J-curve.

- Considering the beginning of AI adoption we need to invest positively on digital infrastructure, digital capacities, digital skill in order that AI technology becomes to be matured as General Purpose Technology (GPT)

- Simultaneously, we have to understand that AI is an intangible capital of SW in CHS classification if we take into account the intangible capital as another axis of economic growth.

- We have to consider that the spillover effects of AI have influenced not only the upstream cycle but also the downstream cycle, so it would be a new production factor impacting product innovation and process innovation.

Appendix

- **Binary Probit Model (AI-adopted firm = 1)**

$$\Pr\left(ADOP_{AI,i} = 1\right) = \varphi(\beta_0 + \beta_1 \log L_i + \beta_2 \log INTANASS_i$$
$$+\beta_3 ADOP_{Big,i} + \beta_4 ADOP_{IoT,i} + \beta_5 ADOP_{CLO,i} + \gamma_j)$$

Delta Method for Marginal Effects: $\dfrac{\Delta \Pr\left(ADOP_{AI,i} = 1\right)}{\Delta x_k} = \varphi(X\beta) \cdot \beta_k$

Then

- $ADOP_{AI,i}$ = Binary indicator (AI-adopted firm i = 1, Non-use of AI = 0)
- $\log L_i$ = Log of number of workers of firm i
- $\log INTANASS_i$ = Log of intangible assets of firm i
- $ADOP_{Big,i}, ADOP_{IoT,i}, and\ ADOP_{CLO,i}$ = Binary indicator (Technology-adopted (Bigdata, IoT, and Cloud computing) = 1 , Non-use = 0)
- γ_j = Industry-fixed effect for industry j
- $\varphi(X\beta)$ = Standard normal density function (PDF)

Appendix

Table 1. Empirical Result

Variable	Log likelihood	Delta-method (dy/dx)
Log_Number of Workers	.1349*** (.0139)	.0432*** (.0044)
Log_Intangible Assests	.0347*** (.0066)	.0111*** (.0021)
Big Data (Adopted = 1, Non-use = 0)	.4404*** (.0298)	.1409*** (.0092)
IoT (Adopted = 1, Non-use = 0)	.0322 (.0309)	.0103 (.0099)
Cloud computing (Adopted = 1, Non-use = 0)	-.2104*** (.0293)	-.0673*** (.0093)
Observation	9,390	9,390
Industry-Fixed Effect	O	O
R-squared	.1110	X

Note: ( ) indicates standard errors for each variable
*Significance level: * p < 0.10, ** p < 0.05, *** p < 0.01*

Appendix

1. Industry-specific Analysis

- Firms in the manufacture of electronic components, computer, visual, sounding, and communication equipment sector with more than 100 employees ($L \geq 100$).

- For a more precise estimation, two separate models were employed:
  a) Model including the number of employees (L)
  b) Model excluding it

- This approach allows for accounting for potential size effects while isolating the impact of other factors, particularly important in our industry-specific analysis of firms with more than 100 employees ($L \geq 100$).

Appendix

Table 2. Results of Industry-specific Analysis with *L*

Variable	Log likelihood	Delta-method (dy/dx)
Log_Number of Workers	.1662** (.0701)	.0542** (.0224)
Log_Intangible Assests	.0460 (.0325)	.0150 (.0105)
Big Data (Adopted = 1, Non-use = 0)	.6837*** (.1564)	.2229*** (.0480)
IoT (Adopted = 1, Non-use = 0)	-.4963*** (.1272)	-.1618*** (.0397)
Cloud computing (Adopted = 1, Non-use = 0)	-.0806 (.1448)	-.0263 (.0472)
Observation	468	468
Industry-Fixed Effect	X	X
R-squared	.1144	X

Note: ( ) indicates standard errors for each variable
*Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

Appendix

Table 3. Results of Industry-specific Analysis without *L*

Variable	Log likelihood	Delta-method (dy/dx)
Log_Intangible Assests	.0947*** (.0256)	.0313*** (.0081)
Big Data (Adopted = 1, Non-use = 0)	.7435*** (.1536)	.2454*** (.0468)
IoT (Adopted = 1, Non-use = 0)	-.5074*** (.1267)	-.1675*** (.0399)
Cloud computing (Adopted = 1, Non-use = 0)	-.0435 (.1436)	-.0143 (.0474)
Observation	468	468
Industry-Fixed Effect	X	X
R-squared	.1050	X

Note: ( ) indicates standard errors for each variable
*Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

Appendix 1 Binary Probit Model (AI-adopted firm = 1)

1. Model

- Binary Probit Model (AI-adopted firm = 1)

$$\Pr\left(ADOP_{AI,i} = 1\right) = \varphi(\boldsymbol{\beta X}_i)$$

Marginal Effects: $$\frac{\Delta \Pr\left(ADOP_{AI,i} = 1\right)}{\Delta X_{ih}} = \varphi(\boldsymbol{\beta X}_i) \cdot \beta_h$$

Then

- $ADOP_{AI,i}$ = Binary indicator (AI-adopted firm i = 1, Non-use of AI = 0)
- $\boldsymbol{X}_i$ = Explanatory variables
- $\varphi(X\beta)$ = Standard normal density function (PDF)

Appendix 1

2. Data
- Business Activity Survey from kostats
- Handling Missing Data with Random Forest Imputation

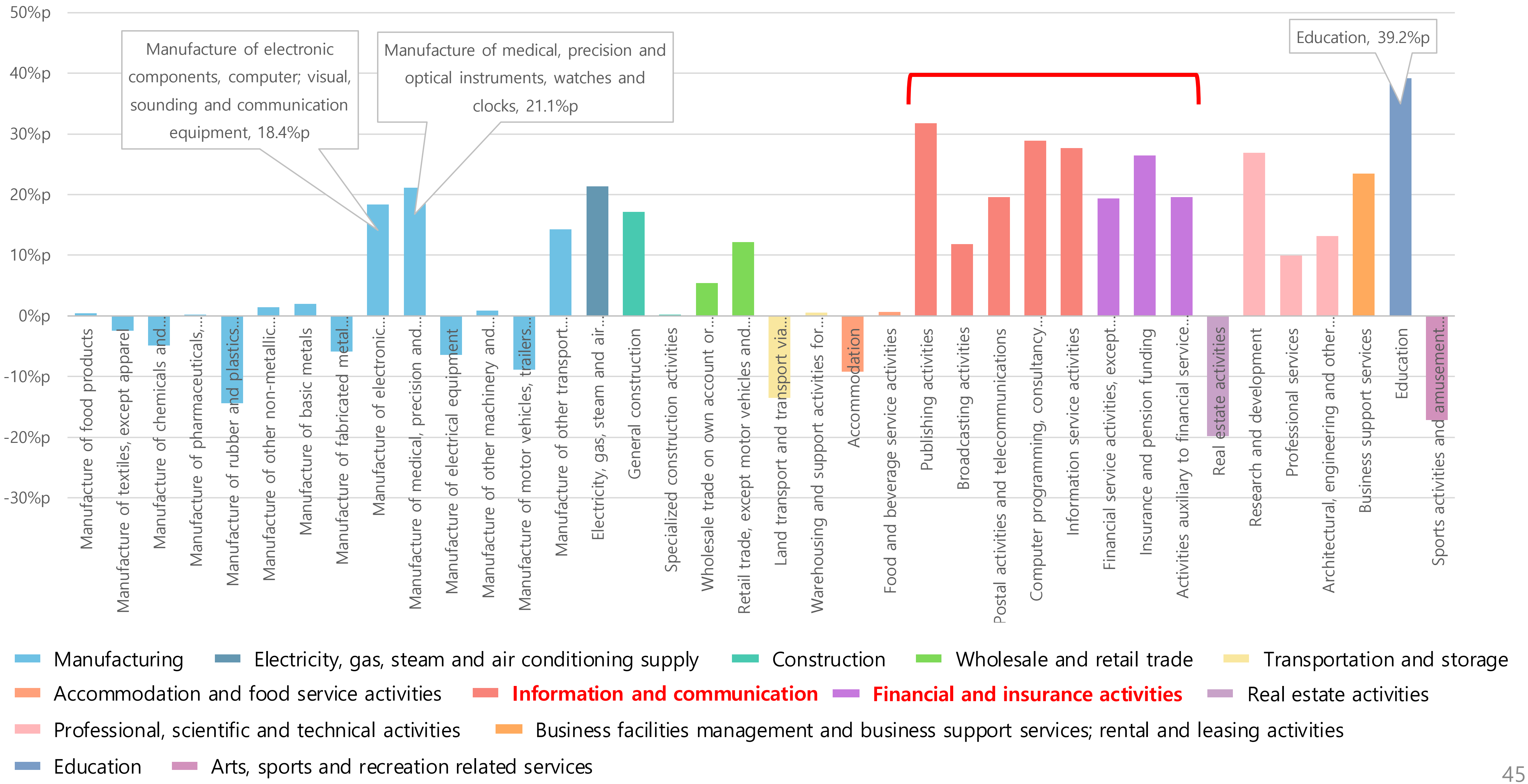
3. Selecting Explanatory variables
- Some important variables (McFadden R-squared 0.1332) [Figure A-1]

- Industry Division
- Financial Status (Intangible Asset, Non-Intangible Asset, Debt, Real-Value Added)
- Adoption of Complementary Assets of AI (IOT, Cloud Computing, Bigdata, 3D Printing, Robotics)

- Stepwise Selection Method (McFadden R-squared 0.1848) [Figure A-2]

- A method to find the most predictive combination of variables through repeated addition and removal of variables
- The Brier Score was used to assess predictive accuracy (Brier Score = $\frac{1}{n}\sum_{t=1}^{n} estimated\ prob_t - real_t$)

Figure A-1 Industry Effects on AI Adoption Probability



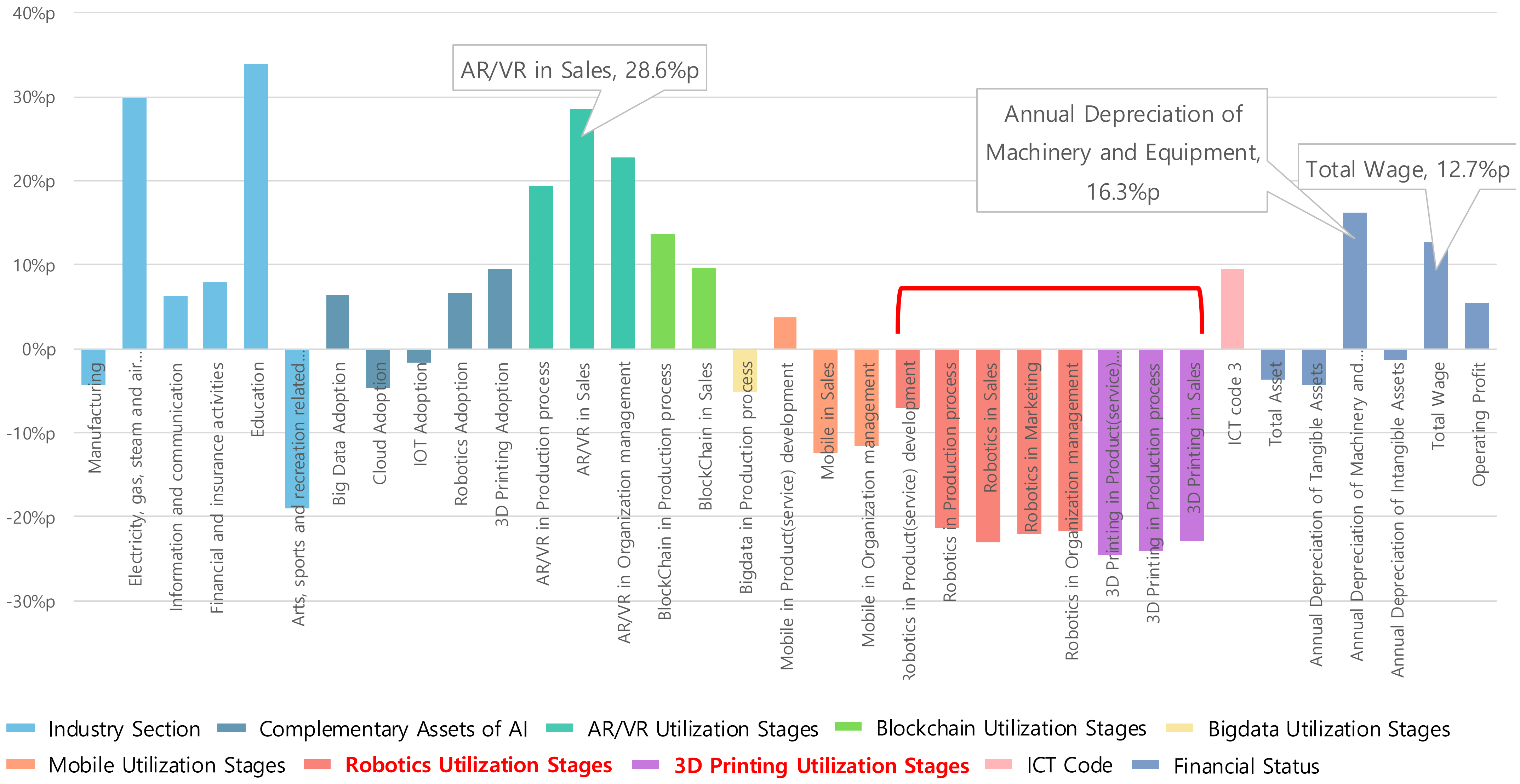
Appendix 1 Implications

- Among all industries, the probability of AI adoption has increased the most in the education division.

- While the probability of AI adoption has declined in most manufacturing industries, it has increased in high-tech divisions such as the manufacture of electronic components, computers, visual, sound, and communication equipment, as well as the manufacture of medical, precision, and optical instruments, watches, and clocks.

- The probability of AI adoption has increased significantly in certain service industries, such as information and communication, as well as financial and insurance sectors.

Figure A-2 Key Factors on AI Adoption Probability



Appendix 1 Implications

- The use of augmented reality (AR) or virtual reality (VR) in the sales stage has greatly boosted the probability of AI adoption

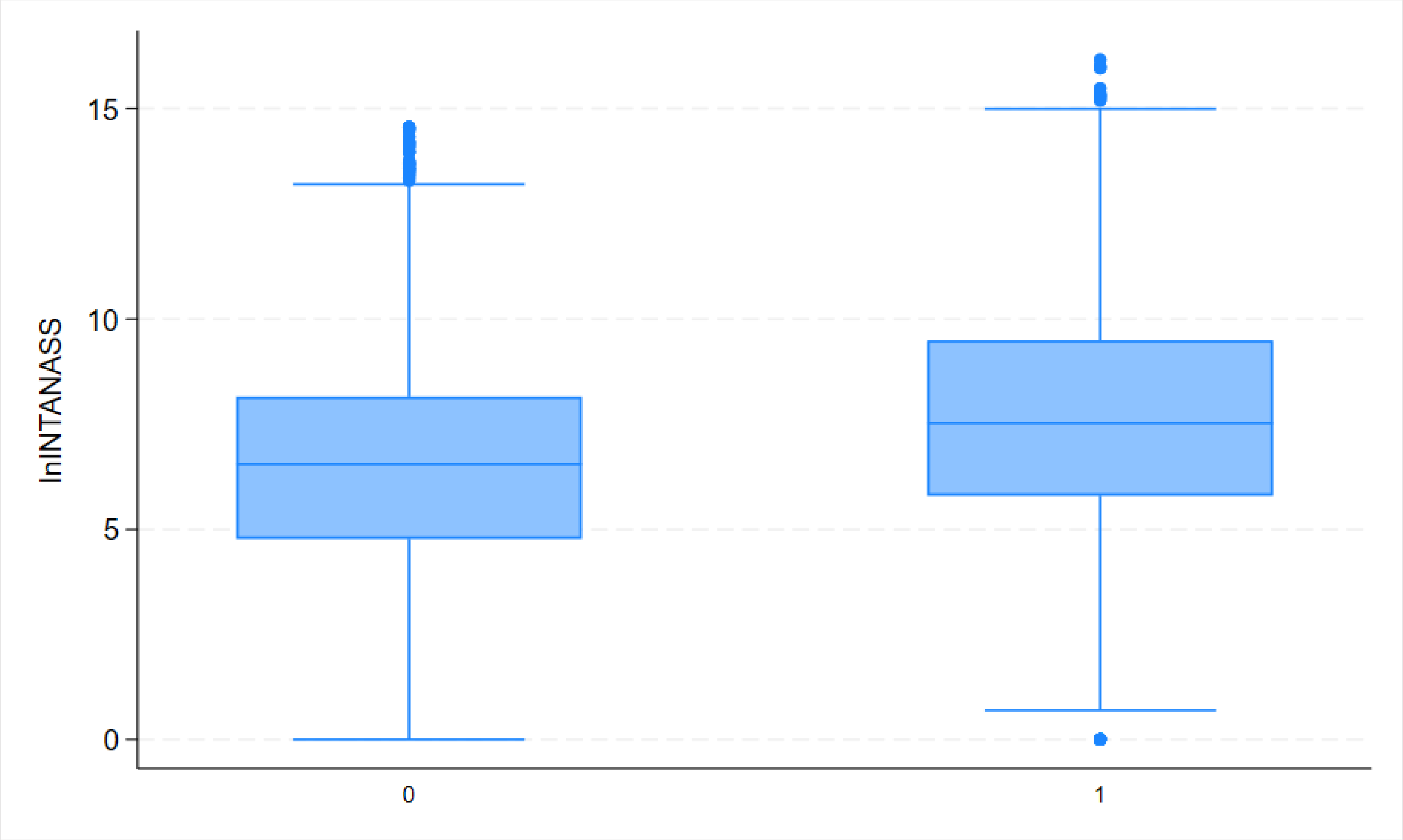
- Robotics and 3D printing utilization had a negative impact on the probability of AI adoption across multiple stages of use.

- Firms with higher annual depreciation of machinery and equipment show a significantly greater probability of adopting AI. An increase of about $350 million in annual depreciation of machinery and equipment raises the probability of AI adoption by 16.3 %p for a firm with average depreciation.

- Firms with higher total wages show a significantly greater probability of adopting AI. An increase of about $240 million in total wages raises the probability of AI adoption by 12.7 %p for a firm with average total wages.

Appendix 2

Figure 1. Intangible Assets by AI Adoption



Appendix 2 Implications

- The standard deviation is higher for AI adopters (3.02 vs. 2.72), indicating more dispersion in intangible asset levels among adopters.

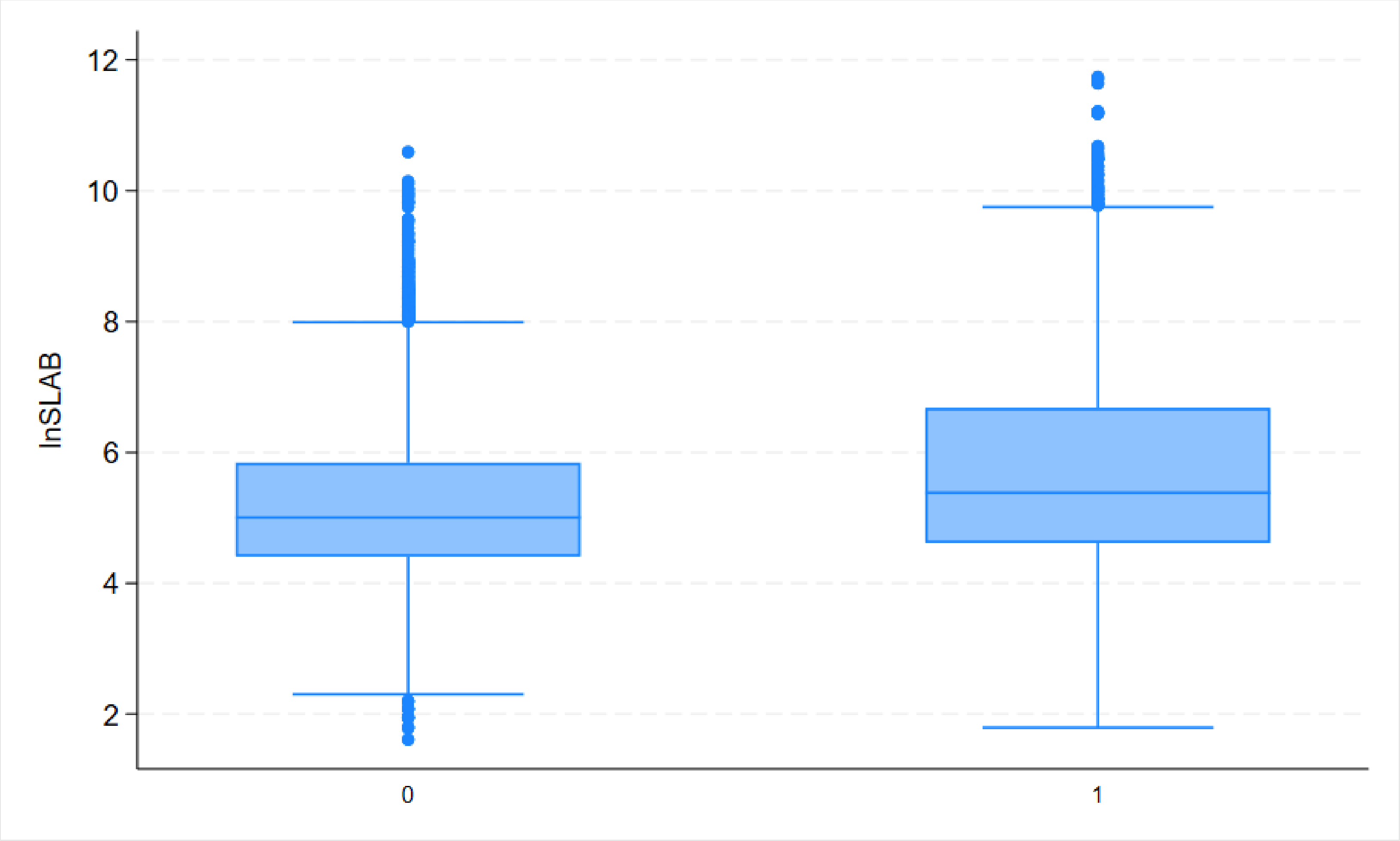
- The maximum value among adopters (16.16) exceeds that of non-adopters (14.56), reinforcing the pattern that the most intangible-capital-rich firms are also the ones adopting AI.

- This evidence supports the hypothesis that intangible assets—such as R&D, software, design, and organizational capital—serve as enabling conditions for AI adoption.

- Firms with greater intangible resources likely have better absorptive capacity, more advanced digital infrastructure, and a more innovative-oriented management structure, all of which facilitate AI implementation.

Appendix 2

Figure 2. Firm Size by AI Adoption



Appendix 2 Implications

- Firms that have adopted AI (ADOP_AI = 1) have a higher average firm size, with a mean lnSLAB of 5.75, compared to 5.21 among non-adopters (ADOP_AI = 0).

- This corresponds to a substantively meaningful gap: using the exponential function, the average number of employees is roughly 316 (exp(5.75)) for adopters versus 184 (exp(5.21)) for non-adopters.

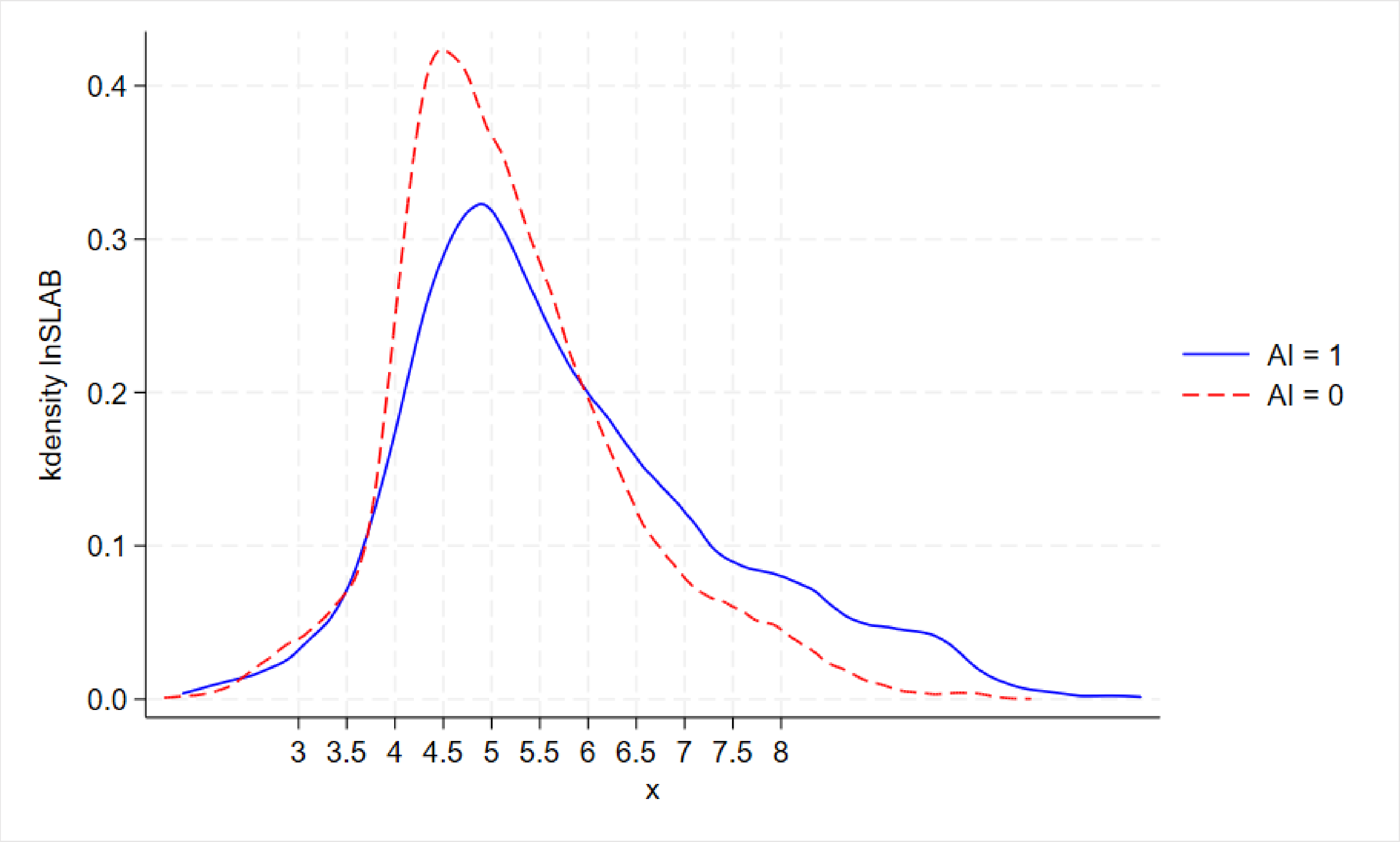
- Furthermore, the standard deviation among adopters is larger (1.61 vs. 1.21), suggesting greater variability in firm size among AI adopters, which may include both large conglomerates and emerging tech-intensive SMEs.

- The minimum and maximum values also indicate that the largest firms (in terms of workforce) are predominantly among AI adopters, with a maximum log of number of employees of 11.73 (≈ 124,000 employees) versus 10.59 (≈ 39,800 employees) for non-adopters.

- These patterns highlight the importance of scale effects in AI adoption: larger firms are not only more capable of adopting AI but are also more likely to do so, likely due to greater financial capacity, infrastructure, and technical workforce.

Appendix 2

Figure 3. Kernel Density of Firm Size by AI Adoption



Appendix 2 Implications

- The density plot shows a noticeable rightward shift in the firm size (= number of employees) distribution for AI-adopted firms, indicating that the probability mass is concentrated among larger firms, not only in mean but across the entire distribution.

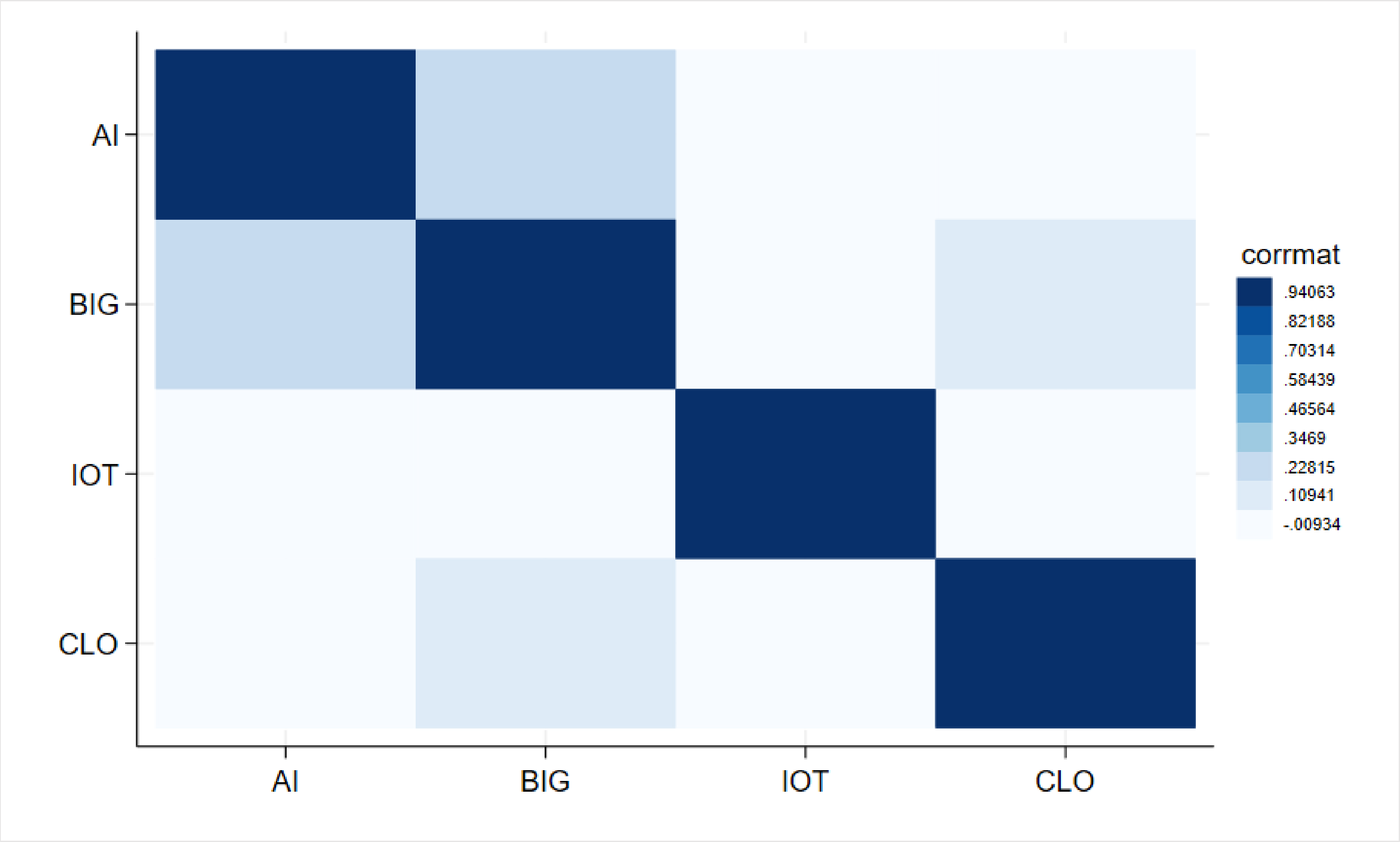
- AI-adopted firms display greater dispersion in firm size, suggesting that while adoption is more common among larger firms, a subset of mid-sized or smaller firms with advanced capabilities also engage in AI transformation.

- The density function for non-use of AI firms are more peaked and left-skewed, highlighting a concentration of smaller firms that may lack the capacity or strategic incentive to invest in AI.

- These distributional differences support the notion that AI diffusion is unevenly distributed across the firm size spectrum, reinforcing the need for differentiated policy interventions targeting Small & Medium-sized Enterprises.

Appendix 2

Figure 4. Heatmap of Technology Co-Adoption



Appendix 2 Implications

- The heatmap shows that Big Data and Cloud tend to co-occur more frequently, suggesting these technologies are often implemented as part of integrated digital strategies rather than in isolation.

- The weak co-adoption signals between AI and IoT may reflect limited technical interoperability or lower organizational readiness for real-time sensor-AI integration in the Korean context.

- The generally low correlation values across technologies point to a fragmented pattern of digital adoption, where firms adopt technologies selectively based on specific needs or resource constraints, rather than through a unified transformation roadmap.

- The heatmap highlights opportunities for cross-technology synergies, indicating that firms adopting one digital technology may benefit from targeted incentives or support to extend adoption into complementary areas like AI.

Appendix 2 Implications

- Firms that adopt AI have significantly larger intangible assets, with an average log of Intangible Assets of 7.55 (≈ 1,905 in natural scale) compared to 6.39 (≈ 598) for non-adopters, indicating 3.8 times more intangible assets on average, highlights the critical role of intangible resources like R&D, software, and organizational capital in supporting AI adoption.

- AI adopters also tend to be significantly larger, with an average log of the number of workers of 5.75 (≈ 316 employees) versus 5.21 (≈ 184 employees) for non-adopters, reinforcing the importance of scale effects in AI adoption.

- The Kolmogorov-Smirnov (K-S) test confirms that the firm size distribution for adopters is statistically larger than that for non-adopters (K-S statistic = 0.154, p = 0.000), suggesting that AI adoption is not just a function of average size but reflects a broader structural difference.

- AI adoption is moderately correlated with Big Data adoption (0.2381), indicating that data infrastructure is a critical enabler of AI. In contrast, the weak correlations with IoT (0.0121) and Cloud (-0.0078) suggest that these technologies may play less central roles in AI adoption, potentially reflecting different integration strategies or technological maturity levels.