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APPENDIX

Implications of Artificial Intelligence and Robots for Employment and Labor Productivity: Firm-Level Evidence from the Republic of Korea

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TABLES AND FIGURES

Table 1: Summary Statistics

	Robots	AI	Both	None	All
Permanent employment	5.83	5.83	6.82	4.84	4.87
	(1.56)	(1.60)	(1.88)	(1.05)	(1.08)
Temporary employment	3.54	3.42	4.51	2.63	2.67
	(2.06)	(2.02)	(2.12)	(1.81)	(1.82)
Total employment	5.86	5.89	6.87	4.92	4.95
	(1.58)	(1.61)	(1.89)	(1.07)	(1.10)
Sales	7.28	7.13	8.60	5.95	5.98
	(2.08)	(2.28)	(2.47)	(1.45)	(1.49)
Labor productivity	-0.05	-0.03	0.23	-0.26	-0.25
	(0.78)	(0.92)	(0.88)	(0.80)	(0.80)
Labor share	0.72	0.73	0.66	0.77	0.77
	(0.60)	(0.63)	(0.54)	(0.59)	(0.59)
Parent company	0.30	0.32	0.34	0.26	0.26
	(0.46)	(0.47)	(0.48)	(0.44)	(0.44)
Stock listing	0.30	0.35	0.44	0.14	0.14
	(0.46)	(0.48)	(0.50)	(0.34)	(0.35)
Capital intensity	0.12	-0.49	0.12	-0.51	-0.50
	(1.25)	(1.66)	(1.48)	(2.01)	(1.99)
R&D intensity	-4.21	-4.01	-4.42	-4.43	-4.41
	(1.55)	(1.79)	(1.93)	(1.51)	(1.52)
Share of manufacturing workers	-0.67	-1.04	-1.00	-0.73	-0.73
	(0.89)	(1.18)	(1.17)	(0.89)	(0.90)
Exporter	0.87	0.73	0.87	0.80	0.80
	(0.33)	(0.44)	(0.34)	(0.40)	(0.40)
Importer	0.90	0.75	0.87	0.82	0.82
	(0.30)	(0.43)	(0.34)	(0.38)	(0.38)
Foreign-owned	0.14	0.09	0.16	0.10	0.10
	(0.35)	(0.28)	(0.37)	(0.30)	(0.30)
Observations	945	1,806	297	72,221	74,675

AI = artificial intelligence; R&D = research and development.

Notes: Permanent employment refers to individuals who have an employment contract with their employer for at least 1 year or who are employed as permanent staff without a fixed term. Temporary employment includes workers with contracts of less than 1 year and encompasses categories such as daily, part-time, and freelance workers. The classification of whether an employee is a manufacturing worker is applied only to permanent workers; thus, the share of manufacturing workers is calculated as the ratio of manufacturing workers to total permanent workers. Labor productivity is defined as value added per worker. Parent company refers to the case when there is a parent company that owns more than 50% of the total issued shares of the firm. If the parent company is from a foreign country, it is defined as foreign-owned. Labor share is defined as the ratio of deflated labor costs to deflated value added. Capital intensity measures the sum of tangible and intangible assets divided by the total number of workers. R&D intensity is defined by deflated R&D expenses that include all associated costs, such as labor, raw materials, depreciation of tangible assets, utilities, and supplies, divided by deflated sales. Export and import dummies indicate whether the firm engages in export or import activities. Sales, labor productivity, capital intensity, R&D intensity, and the share of manufacturing workers are transformed using logarithms. Values in parentheses are standard deviations. “Robots” indicates firms that adopt robots, “AI” signifies firms that use AI, “Both” refers to firms that utilize both technologies, “None” indicates firms that do not adopt any such technologies, and “All” encompasses all firms.

Source: Authors’ calculations.

Table 2.1: Characteristics of Firms That Adopt Robots: Ordinary Least Squares Estimation

OLS	Robot Adoption (0/1 indicator)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sales	0.004***	0.007***	0.004***	0.007***	0.005***	0.007***	0.005***	0.007***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Labor productivity					-0.003**	-0.005	-0.002**	-0.005
					(0.001)	(0.003)	(0.001)	(0.005)
Capital intensity	0.001	-0.005***		-0.005**	0.001***	-0.004***		-0.004***
	(0.000)	(0.001)		(0.001)	(0.001)	(0.001)		(0.001)
R&D intensity	0.019***	0.021		0.021***	0.018***	0.021***		0.020***
	(0.004)	(0.006)		(0.007)	(0.004)	(0.006)		(0.007)
Share of manufacturing employment		-0.010**		-0.010**		-0.010**		-0.010**
		(0.004)		(0.004)		(0.004)		(0.005)
Average wage		0.003		0.002		0.008		0.008
		(0.004)		(0.004)		(0.006)		(0.007)
Exporter			0.000	0.000			0.001	0.000
			(0.001)	(0.001)			(0.001)	(0.001)
Importer			0.001**	0.002			0.001	0.002
			(0.001)	(0.001)			(0.001)	(0.001)
Foreign-owned			-0.000	0.005			-0.000	0.005
			(0.001)	(0.004)			(0.002)	(0.004)
Observations	35,826	14,237	65,852	13,249	35,826	14,237	35,626	14,237
R-squared	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.02

OLS = Ordinary Least Squares; R&D = research and development.

Notes: The dependent variable is an indicator for robot use by the firm during the sample period, 2017–2022. The independent variables are measured in the base year, 2016, which is 1 year prior to commencement of the survey on artificial intelligence and robot adoption. Definitions of the variables are detailed in the note to Table 1. Sales, labor productivity, capital intensity, R&D intensity, and share of manufacturing workers are transformed using logarithms to normalize the data. We report the results of the OLS estimation. Column (1) represents the baseline specification. Column (2) incorporates all factor intensity variables, while column (3) adds all globalization variables. Column (4) includes both factor intensity and globalization variables. Columns (5) through (8) replicate columns (1) through (4) but also include labor productivity as a regressor. All estimations include an intercept and industry dummies, although their coefficients are not reported. Robust standard errors are indicated in parentheses, and asterisks $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Source: Authors' calculations.

Table 2.2: Characteristics of Firms That Adopt Artificial Intelligence: Ordinary Least Squares Estimation

OLS	AI Adoption (0/1 indicator)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sales	0.013***	0.013***	0.010***	0.015***	0.014***	0.015***	0.013***	0.015***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Labor productivity					- 0.005***	- 0.017***	- 0.007***	- 0.018***
					(0.002)	(0.005)	(0.002)	(0.006)
Capital intensity	-0.001	-0.001		- 0.004***	-0.000	-0.001		-0.001
	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)		(0.002)
R&D intensity	0.221***	0.150***		0.163***	0.220***	0.146***		0.159***
	(0.031)	(0.036)		(0.040)	(0.031)	(0.036)		(0.040)
Share of manufacturing employment		- 0.015***		- 0.015***		- 0.016***		- 0.016***
		(0.004)		(0.005)		(0.004)		(0.005)
Average wage		-0.007		-0.005		0.012		0.014**
		(0.005)		(0.006)		(0.008)		(0.009)
Exporter			-0.003	-0.004			-0.002	-0.004
			(0.002)	(0.003)			(0.002)	(0.003)
Importer			-0.004**	0.001			-0.005	0.000
			(0.002)	(0.003)			(0.002)	(0.003)
Foreign-owned			- 0.009***	-0.008**			- 0.010***	-0.007*
			(0.001)	(0.004)			(0.002)	(0.004)
Observations	35,163	14,178	64,880	13,195	35,163	14,178	34,976	13,195
R-squared	0.03	0.03	0.02	0.04	0.02	0.04	0.02	0.04

AI = artificial intelligence; OLS = Ordinary Least Squares; R&D = research and development.

Notes: The dependent variable is an indicator for AI use by the firm during the sample period, 2017–2022. The independent variables are measured in the base year, 2016, which is 1 year prior to the commencement of the survey on AI and robot adoption. Definitions of the variables are detailed in the note to Table 1. Sales, labor productivity, capital intensity, R&D intensity, and share of manufacturing workers are transformed using logarithms to normalize the data. We report the results of the OLS estimation. Column (1) represents the baseline specification. Column (2) incorporates all factor intensity variables, while column (3) adds all globalization variables. Column (4) includes both factor intensity and globalization variables. Columns (5) through (8) replicate columns (1) through (4) but also include labor productivity as a regressor. All estimations include an intercept and industry dummies, although their coefficients are not reported. Robust standard errors are indicated in parentheses, and asterisks $*$, $**$, $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Source: Authors' calculations.

Table 2.3: Characteristics of Firms That Adopt Both Technologies: Ordinary Least Squares Estimation

OLS	Adoption of Both (0/1 indicator)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sales	0.003***	0.006***	0.003***	0.006***	0.004***	0.006***	0.004***	0.007***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Labor productivity					- 0.003***	-0.008*	-0.002*	-0.008*
					(0.001)	(0.004)	(0.001)	(0.004)
Capital intensity	0.001**	- 0.002***		- 0.002***	0.002***	-0.001		-0.001
	(0.000)	(0.001)		(0.001)	(0.000)	(0.001)		(0.001)
R&D intensity	0.010***	0.012***		0.014***	0.009***	0.011***		0.012***
	(0.002)	(0.004)		(0.004)	(0.002)	(0.004)		(0.004)
Share of manufacturing employment		-0.005**		-0.006**		-0.006**		-0.006**
		(0.003)		(0.003)		(0.003)		(0.003)
Average wage		-0.001		0.001		0.009*		0.010*
		(0.002)		(0.003)		(0.006)		(0.006)
Exporter			-0.000	-0.001			-0.000	-0.001
			(0.000)	(0.001)			(0.000)	(0.001)
Importer			-0.000	-0.001			0.001	-0.001
			(0.000)	(0.001)			(0.000)	(0.001)
Foreign-owned			-0.001	0.000			-0.002	0.001
			(0.001)	(0.002)			(0.001)	(0.002)
Observations	36,658	14,683	67,415	13,671	36,658	14,683	36,417	13,671
R-squared	0.01	0.02	0.01	0.03	0.01	0.02	0.01	0.03

AI = artificial intelligence; OLS = Ordinary Least Squares; R&D = research and development.

Notes: The dependent variable is an indicator for robot and AI use by the firm during the sample period, 2017–2022. The independent variables are measured in the base year, 2016, which is 1 year prior to the commencement of the survey on AI and robot adoption. Definitions of the variables are detailed in the note to Table 1. Sales, labor productivity, capital intensity, R&D intensity, and share of manufacturing workers are transformed using logarithms to normalize the data. We report the results of the OLS estimation. Column (1) represents the baseline specification. Column (2) incorporates all factor intensity variables, while column (3) adds all globalization variables. Column (4) includes both factor intensity and globalization variables. Columns (5) through (8) replicate columns (1) through (4) but also include labor productivity as a regressor. All estimations include an intercept and industry dummies, although their coefficients are not reported. Robust standard errors are indicated in parentheses, and asterisks *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Source: Authors' calculations.

Table 3.1: Characteristics of Firms That Adopt Robots: Probit Estimation

Probit	Robot Adoption (0/1 indicator)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sales	0.24***	0.26***	0.21***	0.25***	0.25***	0.26***	0.26***	0.26***
	(0.02)	(0.03)	(0.01)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)
Labor productivity					-0.11	0.02	-0.15**	0.00
					(0.08)	(0.15)	(0.07)	(0.15)
Capital intensity	-0.05	-0.38***		-0.38***	0.03	-0.38***		-0.38***
	(0.04)	(0.07)		(0.07)	(0.04)	(0.08)		(0.08)
R&D intensity	1.07***	0.81***		0.78***	1.03***	0.82***		0.78***
	(0.20)	(0.27)		(0.29)	(0.20)	(0.27)		(0.29)
Share of manufacturing employment		-0.45**		-0.46**		-0.45**		-0.46**
		(0.20)		(0.20)		(0.20)		(0.21)
Average wage		0.23*		0.26		0.21		0.25
		(0.13)		(0.16)		(0.19)		(0.21)
Exporter			-0.02	0.07			0.03	0.07
			(0.07)	(0.14)			(0.10)	(0.14)
Importer			0.19**	0.49**			0.17	0.49***
			(0.08)	(0.19)			(0.12)	(0.19)
Foreign-owned			0.02	0.13			0.02	0.13
			(0.06)	(0.10)			(0.09)	(0.10)
Observations	35,826	14,237	65,852	13,249	35,826	14,237	35,626	13,249
Pseudo R-squared	0.13	0.13	0.09	0.14	0.13	0.13	0.14	0.14

R&D = research and development.

Notes: The dependent variable is an indicator for robot use by the firm during the sample period, 2017–2022. The independent variables are measured in the base year, 2016, which is 1 year prior to the commencement of the survey on artificial intelligence and robot adoption. Definitions of the variables are detailed in the note to Table 1. Sales, labor productivity, capital intensity, R&D intensity, and share of manufacturing workers are transformed using logarithms to normalize the data. We report the results of the probit estimation. Column (1) represents the baseline specification. Column (2) incorporates all factor intensity variables, while column (3) adds all globalization variables. Column (4) includes both factor intensity and globalization variables. Columns (5) through (8) replicate columns (1) through (4) but also include labor productivity as a regressor. All estimations include an intercept and industry dummies, although their coefficients are not reported. Robust standard errors are indicated in parentheses, and asterisks $*$, $**$, $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Source: Authors' calculations.

Table 3.2: Characteristics of Firms That Adopt Artificial Intelligence: Probit Estimation

Probit	AI Adoption (0/1 indicator)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sales	0.26***	0.30***	0.21***	0.31***	0.27***	0.31***	0.26***	0.32***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Labor productivity					-0.11***	-0.30**	-0.16***	-0.29**
					(0.04)	(0.12)	(0.04)	(0.12)
Capital intensity	-0.07***	-0.13***		-0.15**	-0.05**	-0.08**		-0.10**
	(0.02)	(0.04)		(0.04)	(0.02)	(0.04)		(0.04)
R&D intensity	2.64***	2.23***		2.28***	2.63***	2.18***		2.24***
	(0.26)	(0.33)		(0.36)	(0.26)	(0.33)		(0.36)
Share of manufacturing employment		-0.63***		-0.60***		-0.65***		-0.62***
		(0.17)		(0.17)		(0.17)		(0.17)
Average wage		-0.20		-0.16		0.15		0.17
		(0.15)		(0.16)		(0.21)		(0.22)
Exporter			-0.09*	-0.15			-0.08	-0.15
			(0.05)	(0.11)			(0.07)	(0.11)
Importer			-0.08	0.18			0.04	0.17
			(0.05)	(0.14)			(0.07)	(0.13)
Foreign-owned			-0.25***	-0.11			-0.23***	-0.09
			(0.05)	(0.11)			(0.07)	(0.11)
Observations	35,163	14,178	64,880	13,195	35,163	14,178	34,976	13,195
Pseudo R-squared	0.13	0.18	0.09	0.18	0.14	0.18	0.11	0.19

AI = artificial intelligence; R&D = research and development.

Notes: The dependent variable is an indicator for AI use by the firm during the sample period, 2017–2022. The independent variables are measured in the base year, 2016, which is one year prior to the commencement of the survey on AI and robot adoption. Definitions of the variables are detailed in the note to Table 1. Sales, labor productivity, capital intensity, R&D intensity, and share of manufacturing workers are transformed using logarithms to normalize the data. We report the results of the probit estimation. Column (1) represents the baseline specification. Column (2) incorporates all factor intensity variables, while column (3) adds all globalization variables. Column (4) includes both factor intensity and globalization variables. Columns (5) through (8) replicate columns (1) through (4) but also include labor productivity as a regressor. All estimations include an intercept and industry dummies, although their coefficients are not reported. Robust standard errors are indicated in parentheses, and asterisks $*$, $**$, $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Source: Authors' calculations.

Table 3.3: Characteristics of Firms That Adopt Both Technologies: Probit Estimation

Probit	Adoption of Both (0/1 indicator)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sales	0.35***	0.55***	0.31***	0.56***	0.37***	0.55***	0.39***	0.56***
	(0.03)	(0.07)	(0.02)	(0.08)	(0.03)	(0.02)	(0.01)	(0.02)
Labor productivity					-0.28**	-0.09	-0.22**	-0.09
					(0.11)	(0.23)	(0.09)	(0.23)
Capital intensity	0.01	-0.60***		-0.58***	0.08	-0.57***		-0.54***
	(0.06)	(0.14)		(0.14)	(0.07)	(0.16)		(0.16)
R&D intensity	0.25	-4.27		-4.14	-0.25	-4.51		-4.39
	(1.05)	(5.26)		(5.34)	(1.32)	(5.15)		(5.24)
Share of manufacturing employment		-0.86**		-0.88*		-0.86*		-0.88*
		(0.44)		(0.45)		(0.44)		(0.46)
Average wage		0.26		0.30		0.35		0.40
		(0.20)		(0.27)		(0.31)		(0.36)
Exporter			-0.11	-0.34			-0.22	-0.34
			(0.11)	(0.25)			(0.14)	(0.24)
Importer			0.05	0.53*			0.36*	0.52*
			(0.13)	(0.29)			(0.19)	(0.28)
Foreign owned			-0.03	0.11			-0.12	0.12
			(0.09)	(0.16)			(0.13)	(0.17)
Observations	36,658	14,683	67,415	13,671	36,658	14,683	36,417	13,671
Pseudo R-squared	0.27	0.41	0.21	0.41	0.27	0.41	0.28	0.42

Notes: The dependent variable is an indicator for robot and AI use by the firm during the sample period, 2017–2022. The independent variables are measured in the base year, 2016, which is 1 year prior to the commencement of the survey on AI and robot adoption. Definitions of the variables are detailed in the note to Table 1. Sales, labor productivity, capital intensity, R&D intensity, and share of manufacturing workers are transformed using logarithms to normalize the data. We report the results of the probit estimation. Column (1) represents the baseline specification. Column (2) incorporates all factor intensity variables, while column (3) adds all globalization variables. Column (4) includes both factor intensity and globalization variables. Columns (5) through (8) replicate columns (1) through (4) but also include labor productivity as a regressor. All estimations include an intercept and industry dummies, although their coefficients are not reported. Robust standard errors are indicated in parentheses, and asterisks *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Source: Authors' calculations.

Table 4.1: Impact of Robot Adoption on Permanent Employment: Difference-in-Differences Analyses

Dependent Variable: Permanent Employment

	ATT	Treatment Year	Control Year	Measurement Year	Observations	Parallel Trend Assumption Test
T						
	0.06	2017	2016	2017	22,588	0.000
	(0.06)					
	-0.01	2018	2017	2018	23,162	0.000
	(0.04)					
	-0.01	2019	2018	2019	24,555	0.000
	(0.10)					
	-0.01	2020	2019	2020	24,607	0.000
	(0.09)					
	0.03	2021	2020	2021	24,776	0.000
	(0.04)					
T+1						
	0.13	2017	2016	2018	23,886	0.000
	(0.08)					
	0.01	2018	2017	2019	23,249	0.000
	(0.07)					
	0.03	2019	2018	2020	24,524	0.000
	(0.06)					
	-0.08	2020	2019	2021	24,673	0.000
	(0.06)					
T+2						
	0.12	2017	2016	2019	23,972	0.000
	(0.10)					
	-0.01	2018	2017	2020	23,219	0.000
	(0.08)					
	0.07	2019	2018	2021	24,587	0.000
	(0.08)					
T+3						
	0.12	2017	2016	2020	23,941	0.000
	(0.13)					
	0.06	2018	2017	2021	23,283	0.000
	(0.11)					
T+4						
	0.10	2017	2016	2021	24,166	0.000
	(0.17)					

ATT = average treatment effect on the treated.

Notes: The dependent variable is the logarithm of permanent employment. The “treatment year” corresponds to the year in which the firm adopts robots, while “period 1” serves as the control year and “period 2” as the measurement year. Consequently, T, T+1, T+2, T+3, and T+4 represent the years in which the effects are observed: the same year as the adoption, 1 year after, 2 years after, 3 years after, and 4 years after, respectively. All estimations include an intercept and industry dummies, although their coefficients are not reported. The last column tests the null hypothesis that trend coefficients are identical between groups, thus assessing the parallel trend assumption prior to treatment. Robust standard errors are shown in parentheses. Significance levels are denoted with asterisks: $*$ for 10%, $**$ for 5%, and $***$ for 1%.

Source: Authors’ calculations.

Table 4.2: Impact of Robot Adoption on Temporary Employment: Difference-in-Differences Analyses

Dependent Variable: Temporary Employment

	ATT	Treatment Year	Control Year	Measurement Year	Observations	Parallel Trend Assumption Test
T						
	-0.24	2017	2016	2017	6,060	0.089
	(0.53)					
	0.08	2018	2017	2018	6,122	0.003
	(0.23)					
	0.24	2019	2018	2019	6,460	0.218
	(0.55)					
	-0.67	2020	2019	2020	6,567	0.194
	(0.72)					
	0.34	2021	2020	2021	7,050	0.047
	(0.54)					
T+1						
	-0.57	2017	2016	2018	6,549	0.089
	(1.06)					
	0.40	2018	2017	2019	5,971	0.003
	(0.57)					
	0.47	2019	2018	2020	6,739	0.218
	(0.87)					
	0.25	2020	2019	2021	6,733	0.194
	(0.62)					
T+2						
	-1.68	2017	2016	2019	6,391	0.089
	(1.91)					
	-0.01	2018	2017	2020	6,243	0.003
	(0.98)					
	0.51	2019	2018	2021	6,902	0.218
	(0.87)					
T+3						
	-0.51	2017	2016	2020	6,667	0.089
	(0.52)					
	0.31	2018	2017	2021	6,409	0.003
	(0.83)					
T+4						
	-0.83***	2017	2016	2021	6,830	0.089
	(0.11)					

ATT = average treatment effect on the treated.

Notes: The dependent variable is the logarithm of temporary employment. The “treatment year” corresponds to the year in which the firm adopts robots, while “period 1” serves as the control year and “period 2” as the measurement year. Consequently, T, T+1, T+2, T+3, and T+4 represent the years in which the effects are observed: the same year as the adoption, 1 year after, 2 years after, 3 years after, and 4 years after, respectively. All estimations include an intercept and industry dummies, although their coefficients are not reported. The last column tests the null hypothesis that trend coefficients are identical between groups, thus assessing the parallel trend assumption prior to treatment. Robust standard errors are shown in parentheses. Significance levels are denoted with asterisks: $*$ for 10%, $**$ for 5%, and $***$ for 1%.

Source: Authors’ calculations.

Table 4.3: Impact of Robot Adoption on Labor Productivity: Difference-in-Differences Analyses

Dependent Variable: Labor Productivity

	ATT	Treatment Year	Control Year	Measurement Year	Observations	Parallel Trend Assumption Test
T						
	0.11	2017	2016	2017	15,640	0.335
	(0.17)					
	-0.04	2018	2017	2018	22,553	0.003
	(0.06)					
	-0.13	2019	2018	2019	24,555	0.000
	(0.10)					
	-0.06	2020	2019	2020	24,606	0.000
	(0.13)					
	-0.07	2021	2020	2021	24,775	0.000
	(0.08)					
T+1						
	0.44	2017	2016	2018	17,548	0.335
	(0.40)					
	-0.15	2018	2017	2019	22,640	0.003
	(0.11)					
	-0.06	2019	2018	2020	24,523	0.000
	(0.13)					
	-0.11	2020	2019	2021	24,673	0.000
	(0.13)					
T+2						
	0.34**	2017	2016	2019	17,634	0.335
	(0.18)					
	-0.12	2018	2017	2020	22,609	0.003
	(0.12)					
	-0.03	2019	2018	2021	24,587	0.000
	(0.11)					
T+3						
	0.19	2017	2016	2020	17,602	0.335
	(0.36)					
	-0.19	2018	2017	2021	22,674	0.003
	(0.17)					
T+4						
	0.33	2017	2016	2021	17,668	0.335
	(0.24)					

ATT = average treatment effect on the treated.

Notes: The dependent variable is the logarithm of labor productivity. The “treatment year” corresponds to the year in which the firm adopts robots, while “period 1” serves as the control year and “period 2” as the measurement year. Consequently, T, T+1, T+2, T+3, and T+4 represent the years in which the effects are observed: the same year as the adoption, 1 year after, 2 years after, 3 years after, and 4 years after, respectively. All estimations include an intercept and industry dummies, although their coefficients are not reported. The last column tests the null hypothesis that trend coefficients are identical between groups, thus assessing the parallel trend assumption prior to treatment. Robust standard errors are shown in parentheses. Significance levels are denoted with asterisks: $*$ for 10%, $**$ for 5%, and $***$ for 1%.

Source: Authors’ calculations.

Table 5.1: Impact of Artificial Intelligence Adoption on Permanent Employment: Difference-in-Differences Analyses

Dependent Variable: Permanent Employment

	ATT	Treatment Year	Control Year	Measurement Year	Observations	Parallel Trend Assumption Test
T						
	0.06	2017	2016	2017	22,129	0.000
	(0.04)					
	0.00	2018	2017	2018	22,664	0.000
	(0.02)					
	0.05	2019	2018	2019	23,960	0.000
	(0.03)					
	0.07	2020	2019	2020	24,020	0.000
	(0.06)					
	0.07	2021	2020	2021	24,212	0.000
	(0.05)					
T+1						
	0.07	2017	2016	2018	23,347	0.000
	(0.06)					
	0.01	2018	2017	2019	22,748	0.000
	(0.05)					
	0.07	2019	2018	2020	23,913	0.000
	(0.07)					
	0.08	2020	2019	2021	24,075	0.000
	(0.06)					
T+2						
	0.13	2017	2016	2019	23,430	0.000
	(0.10)					
	-0.02	2018	2017	2020	22,699	0.000
	(0.06)					
	0.08	2019	2018	2021	23,968	0.000
	(0.08)					
T+3						
	0.02	2017	2016	2020	23,384	0.000
	(0.17)					
	0.03	2018	2017	2021	22,755	0.000
	(0.07)					
T+4						
	0.02	2017	2016	2021	23,638	0.000
	(0.18)					

ATT = average treatment effect on the treated.

Notes: The dependent variable is the logarithm of permanent employment. The “treatment year” corresponds to the year in which the firm adopts robots, while “period 1” serves as the control year and “period 2” as the measurement year. Consequently, T, T+1, T+2, T+3, and T+4 represent the years in which the effects are observed: the same year as the adoption, 1 year after, 2 years after, 3 years after, and 4 years after, respectively. All estimations include an intercept and industry dummies, although their coefficients are not reported. The last column tests the null hypothesis that trend coefficients are identical between groups, thus assessing the parallel trend assumption prior to treatment. Robust standard errors are shown in parentheses. Significance levels are denoted with asterisks: $*$ for 10%, $**$ for 5%, and $***$ for 1%.

Source: Authors’ calculations.

Table 5.2: Impact of Artificial Intelligence Adoption on Temporary Employment: Difference-in-Differences Analyses

Dependent Variable: Temporary Employment

	ATT	Treatment Year	Control Year	Measurement Year	Observations	Parallel Trend Assumption Test
T						
	-0.17	2017	2016	2017	5,848	0.045
	(0.48)					
	0.52	2018	2017	2018	5,848	0.032
	(0.38)					
	0.16	2019	2018	2019	6,149	0.000
	(0.30)					
	0.33	2020	2019	2020	6,258	0.161
	(0.63)					
	0.18	2021	2020	2021	6,720	0.007
	(0.31)					
T+1						
	-0.51	2017	2016	2018	6,280	0.045
	(0.67)					
	0.57	2018	2017	2019	5,716	0.032
	(0.45)					
	0.09	2019	2018	2020	6,406	0.000
	(0.28)					
	0.33	2020	2019	2021	6,399	0.161
	(0.55)					
T+2						
	-0.17	2017	2016	2019	6,147	0.045
	(0.76)					
	0.50	2018	2017	2020	5,966	0.032
	(0.65)					
	-0.21	2019	2018	2021	6,534	0.000
	(0.42)					
T+3						
	-0.01	2017	2016	2020	6,396	0.045
	(0.78)					
	0.38	2018	2017	2021	6,098	0.032
	(0.80)					
T+4						
	0.61	2017	2016	2021	6,520	0.045
	(0.98)					

ATT = average treatment effect on the treated.

Notes: The dependent variable is the logarithm of temporary employment. The “treatment year” corresponds to the year in which the firm adopts robots, while “period 1” serves as the control year and “period 2” as the measurement year. Consequently, T, T+1, T+2, T+3, and T+4 represent the years in which the effects are observed: the same year as the adoption, 1 year after, 2 years after, 3 years after, and 4 years after, respectively. All estimations include an intercept and industry dummies, although their coefficients are not reported. The last column tests the null hypothesis that trend coefficients are identical between groups, thus assessing the parallel trend assumption prior to treatment. Robust standard errors are shown in parentheses. Significance levels are denoted with asterisks: $*$ for 10%, $**$ for 5%, and $***$ for 1%.

Source: Authors’ calculations.

Table 5.3: Impact of Artificial Intelligence Adoption on Labor Productivity: Difference-in-Differences Analyses

Dependent Variable: Labor Productivity

	ATT	Treatment Year	Control Year	Measurement Year	Observations	Parallel Trend Assumption Test
T						
	-0.01	2017	2016	2017	15,296	0.012
	(0.16)					
	-0.02	2018	2017	2018	22,069	0.000
	(0.05)					
	0.02	2019	2018	2019	23,960	0.000
	(0.06)					
	0.02	2020	2019	2020	24,020	0.000
	(0.10)					
	-0.01	2021	2020	2021	24,212	0.000
	(0.06)					
T+1						
	0.14	2017	2016	2018	17,110	0.012
	(0.21)					
	-0.05	2018	2017	2019	22,153	0.000
	(0.07)					
	0.01	2019	2018	2020	23,913	0.000
	(0.11)					
	0.01	2020	2019	2021	24,075	0.000
	(0.10)					
T+2						
	0.07	2017	2016	2019	17,193	0.012
	(0.27)					
	0.01	2018	2017	2020	22,104	0.000
	(0.08)					
	0.13	2019	2018	2021	23,968	0.000
	(0.12)					
T+3						
	0.13	2017	2016	2020	17,147	0.012
	(0.29)					
	0.00	2018	2017	2021	22,160	0.000
	(0.10)					
T+4						
	0.15	2017	2016	2021	17,203	0.012
	(0.35)					

ATT = average treatment effect on the treated.

Notes: The dependent variable is the logarithm of labor productivity. The “treatment year” corresponds to the year in which the firm adopts robots, while “period 1” serves as the control year and “period 2” as the measurement year. Consequently, T, T+1, T+2, T+3, and T+4 represent the years in which the effects are observed: the same year as the adoption, 1 year after, 2 years after, 3 years after, and 4 years after, respectively. All estimations include an intercept and industry dummies, although their coefficients are not reported. The last column tests the null hypothesis that trend coefficients are identical between groups, thus assessing the parallel trend assumption prior to treatment. Robust standard errors are shown in parentheses. Significance levels are denoted with asterisks: $*$ for 10%, $**$ for 5%, and $***$ for 1%.

Source: Authors’ calculations.

Table 6.1: Impact of Robot and Artificial Intelligence Adoption on Permanent Employment: Difference-in-Differences Analyses

Dependent Variable: Permanent Employment

	ATT	Treatment Year	Control Year	Measurement Year	Observations	Parallel Trend Assumption Test
T						
	0.103	2017	2016	2017	23,236	0.000
	(0.088)					
	-0.036	2018	2017	2018	23,808	0.000
	(0.066)					
	0.081	2019	2018	2019	25,220	0.000
	(0.061)					
	-0.033	2020	2019	2020	25,285	0.000
	(0.088)					
	0.076	2021	2020	2021	25,373	0.000
	(0.072)					
T+1						
	0.156	2017	2016	2018	24,550	0.000
	(0.125)					
	-0.019	2018	2017	2019	23,904	0.000
	(0.106)					
	-0.028	2019	2018	2020	25,190	0.000
	(0.106)					
	-0.020	2020	2019	2021	25,348	0.000
	(0.114)					
T+2						
	0.200	2017	2016	2019	24,645	0.000
	(0.192)					
	-0.075	2018	2017	2020	23,874	0.000
	(0.102)					
	0.021	2019	2018	2021	25,252	0.000
	(0.169)					
T+3						
	0.156	2017	2016	2020	24,615	0.000
	(0.227)					
	0.078	2018	2017	2021	23,936	0.000
	(0.182)					
T+4						
	0.149	2017	2016	2021	23,638	0.000
	(0.401)					

ATT = average treatment effect on the treated.

Notes: The dependent variable is the logarithm of permanent employment. The “treatment year” corresponds to the year in which the firm adopts robots, while “period 1” serves as the control year and “period 2” as the measurement year. Consequently, T, T+1, T+2, T+3, and T+4 represent the years in which the effects are observed: the same year as the adoption, 1 year after, 2 years after, 3 years after, and 4 years after, respectively. All estimations include an intercept and industry dummies, although their coefficients are not reported. The last column tests the null hypothesis that trend coefficients are identical between groups, thus assessing the parallel trend assumption prior to treatment. Robust standard errors are shown in parentheses. Significance levels are denoted with asterisks: $*$ for 10%, $**$ for 5%, and $***$ for 1%.

Source: Authors’ calculations.

Table 6.2: Impact of and Artificial Intelligence Adoption on Temporary Employment: Difference-in-Differences Analyses

Dependent Variable: Temporary Employment

	ATT	Treatment Year	Control Year	Measurement Year	Observations	Parallel Trend Assumption Test
T						
	-0.386	2017	2016	2017	6,225	0.430
	(0.719)					
	0.138	2018	2017	2018	6,277	0.000
	(0.375)					
	0.667	2019	2018	2019	6,608	0.000
	(0.798)					
	0.001	2020	2019	2020	6,734	0.907
	(0.692)					
	0.288	2021	2020	2021	7,236	0.013
	(0.533)					
T+1						
	-0.925	2017	2016	2018	6,718	0.430
	(1.347)					
	0.488	2018	2017	2019	6,114	0.000
	(0.711)					
	0.311	2019	2018	2020	6,908	0.000
	(0.943)					
	0.156	2020	2019	2021	6,910	0.907
	(0.176)					
T+2						
	-1.680	2017	2016	2019	6,553	0.430
	(1.915)					
	0.453	2018	2017	2020	6,413	0.000
	(0.817)					
	0.628	2019	2018	2021	7,080	0.000
	(0.835)					
T+3						
	-0.682	2017	2016	2020	6,851	0.430
	(0.634)					
	-0.022	2018	2017	2021	6,583	0.000
	(0.539)					
T+4						
	-0.859***	2017	2016	2021	7,023	0.430
	(0.099)					

ATT = average treatment effect on the treated.

Notes: The dependent variable is the logarithm of temporary employment. The “treatment year” corresponds to the year in which the firm adopts robots, while “period 1” serves as the control year and “period 2” as the measurement year. Consequently, T, T+1, T+2, T+3, and T+4 represent the years in which the effects are observed: the same year as the adoption, 1 year after, 2 years after, 3 years after, and 4 years after, respectively. All estimations include an intercept and industry dummies, although their coefficients are not reported. The last column tests the null hypothesis that trend coefficients are identical between groups, thus assessing the parallel trend assumption prior to treatment. Robust standard errors are shown in parentheses. Significance levels are denoted with asterisks: $*$ for 10%, $**$ for 5%, and $***$ for 1%.

Source: Authors’ calculations.

Table 6.3: Impact of Robot and Artificial Intelligence Adoption on Labor Productivity: Difference-in-Differences Analyses

Dependent Variable: Labor Productivity

	ATT	Treatment Year	Control Year	Measurement Year	Observations	Parallel Trend Assumption Test
T						
	0.216***	2017	2016	2017	16,102	0.527
	(0.071)					
	-0.017	2018	2017	2018	23,193	0.000
	(0.107)					
	-0.188	2019	2018	2019	25,220	0.000
	(0.117)					
	0.028	2020	2019	2020	25,284	0.000
	(0.103)					
	-0.057	2021	2020	2021	25,372	0.000
	(0.135)					
T+1						
	0.677***	2017	2016	2018	18,031	0.527
	(0.155)					
	-0.112	2018	2017	2019	23,289	0.000
	(0.138)					
	-0.303	2019	2018	2020	25,189	0.000
	(0.232)					
	-0.030	2020	2019	2021	25,348	0.000
	(0.144)					
T+2						
	0.388	2017	2016	2019	18,126	0.527
	(0.241)					
	-0.196	2018	2017	2020	23,258	0.000
	(0.177)					
	-0.244	2019	2018	2021	25,252	0.000
	(0.166)					
T+3						
	0.199	2017	2016	2020	18,095	0.527
	(0.535)					
	-0.172	2018	2017	2021	23,321	0.000
	(0.269)					
T+4						
	0.388	2017	2016	2021	18,159	0.527
	(0.333)					

ATT = average treatment effect on the treated.

Notes: The dependent variable is the logarithm of labor productivity. The “treatment year” corresponds to the year in which the firm adopts robots, while “period 1” serves as the control year and “period 2” as the measurement year. Consequently, T, T+1, T+2, T+3, and T+4 represent the years in which the effects are observed: the same year as the adoption, 1 year after, 2 years after, 3 years after, and 4 years after, respectively. All estimations include an intercept and industry dummies, although their coefficients are not reported. The last column tests the null hypothesis that trend coefficients are identical between groups, thus assessing the parallel trend assumption prior to treatment. Robust standard errors are shown in parentheses. Significance levels are denoted with asterisks: $*$ for 10%, $**$ for 5%, and $***$ for 1%.

Source: Authors’ calculations.

Table 7.1: Impact of Robot Adoption on Permanent Employment: Propensity Score Matching

Dependent Variable: Permanent Employment					
Robot	(1)	(2)	(3)	(4)	(5)
	Initial Year	Initial Year	Initial Year	Initial Year	Initial Year
	2017	2018	2019	2020	2021
T	-0.04	0.01	0.04	-0.07	0.03
	(0.04)	(0.04)	(0.03)	(0.07)	(0.03)
Observations	5,064	9,889	11,399	11,371	11,721
SMD before	0.425	0.532	0.515	0.477	0.345
SMD after	0.042	0.107	0.147	0.119	0.109
T+1	-0.11	0.12*	-0.02	-0.05	
	(0.07)	(0.07)	(0.05)	(0.05)	
Observations	4857	9479	10577	10826	
SMD before	0.419	0.526	0.501	0.469	
SMD after	0.210	0.176	0.106	0.126	
T+2	0.09	0.15	0.00		
	(0.21)	(0.11)	(0.13)		
Observations	4653	8843	10106		
SMD before	0.419	0.517	0.495		
SMD after	0.336	0.160	0.110		
T+3	1.37*	0.13			
	(0.83)	(0.09)			
Observations	4349	8470			
SMD before	0.416	0.513			
SMD after	0.111	0.084			
T+4	0.13				
	(0.34)				
Observations	4178				
SMD before	0.415				
SMD after	0.164				

SMD = Standardized Mean Difference.

Notes: We report the impact of robot adoption on permanent employment for the year 2017 under Initial Year 2017, marking the year a firm first employed robots. A counterfactual group was constructed using a logit regression model to estimate the likelihood of adopting robots in 2016. This model incorporated key regressors, including total employment (both permanent and temporary workers), labor productivity, a parent company dummy, and industry dummies. We then analyzed changes in employment for these matched pairs by comparing employment differences from 2016 to 2017 (T). For subsequent analyses, such as the impact in 2018 (T+1), we retained the same matched groups and calculated the treatment effect based on differences in employment from 2016 to 2018, and so forth. To ensure the analysis accounted for variances in the impact of robot adoption from one year to the next, we repeated the procedure for firms adopting robots in 2018 under Initial Year 2018, and similarly for subsequent years. To assess the balance of covariates after propensity score matching, we report the average SMD both before and after matching. Significance levels are indicated by asterisks: * for 10%, ** for 5%, and *** for 1%.

Source: Authors' calculations.

Table 7.2: Impact of Robot Adoption on Temporary Employment: Propensity Score Matching

Dependent Variable: Temporary Employment				
Robot	(1)	(2)	(3)	(4)
	Initial Year	Initial Year	Initial Year	Initial Year
	2018	2019	2020	2021
T	0.01	0.10**	1.45	0.08
	(0.15)	(0.05)	(1.28)	(0.39)
Observations	1,952	1,764	1,793	2,064
SMD before	0.785	0.700	0.430	0.610
SMD after	0.211	0.046	0.688	0.150
T+1	-0.47	-0.38	-0.05	
	(0.53)	(0.31)	(0.29)	
Observations	1,472	1,436	1,667	
SMD before	0.931	0.763	1.042	
SMD after	0.261	0.191	0.541	
T+2	0.28	0.20		
	(0.49)	(0.37)		
Observations	1,233	1,432		
SMD before	1.058	0.667		
SMD after	0.159	0.243		
T+3	-0.083			
	(0.96)			
Observations	1,217			
SMD before	0.695			
SMD after	0.394			

SMD = Standardized Mean Difference.

Notes: We report the impact of robot adoption on temporary employment for the year 2018 under Initial Year 2018, marking the year a firm first employed robots. We do not report the results for Initial Year 2017 since the matching was not satisfactory for the firms that first employed robots in 2017. A counterfactual group was constructed using a logit regression model to estimate the likelihood of adopting robots in 2017. This model incorporated key regressors, including total employment (both permanent and temporary workers), labor productivity, a parent company dummy, and industry dummies. We then analyzed changes in employment for these matched pairs by comparing employment differences from 2017 to 2018 (T). For subsequent analyses, such as the impact in 2019 (T+1), we retained the same matched groups and calculated the treatment effect based on differences in employment from 2017 to 2019, and so forth. To ensure the analysis accounted for variances in the impact of robot adoption from one year to the next, we repeated the procedure for firms adopting robots in 2019 under Initial Year 2019, and similarly for subsequent years. To assess the balance of covariates after propensity score matching, we report the average SMD both before and after matching. Significance levels are indicated by asterisks: * for 10%, ** for 5%, and *** for 1%.

Source: Authors' calculations.

Table 7.3: Impact of Robot Adoption on Labor Productivity: Propensity Score Matching

Dependent Variable: Labor Productivity					
Robot	(1)	(2)	(3)	(4)	(5)
	Initial Year 2017	Initial Year 2018	Initial Year 2019	Initial Year 2020	Initial Year 2021
T	0.04	-0.12	-0.02	-0.06	-0.12*
	(0.12)	(0.09)	(0.09)	(0.13)	(0.07)
Observations	4,471	9,737	11,267	11,181	11,565
SMD before	0.465	0.569	0.512	0.473	0.034
SMD after	0.493	0.088	0.131	0.165	0.036
T+1	0.46**	-0.25**	-0.04	0.14	
	(0.22)	(0.11)	(0.12)	(0.09)	
Observations	4,780	9,331	10,380	10,653	
SMD before	0.418	0.562	0.498	0.464	
SMD after	0.047	0.201	0.119	0.091	
T+2	-0.05	0.00	-0.09		
	(0.08)	(0.15)	(0.13)		
Observations	4,591	8,665	9,929		
SMD before	0.580	0.514	0.475		
SMD after	0.331	0.161	0.177		
T+3	-0.12	0.09			
	(0.29)	(0.11)			
Observations	4,267	8,324			
SMD before	0.576	0.481			
SMD after	0.252	0.155			
T+4	-0.37				
	(0.67)				
Observations	4,101				
SMD before	0.417				
SMD after	0.423				

SMD = Standardized Mean Difference.

Notes: We report the impact of robot adoption on labor productivity for the year 2017 under Initial Year 2017, marking the year a firm first employed robots. A counterfactual group was constructed using a logit regression model to estimate the likelihood of adopting robots in 2016. This model incorporated key regressors, including total employment (both permanent and temporary workers), labor productivity, a parent company dummy, and industry dummies. We then analyzed changes in employment for these matched pairs by comparing employment differences from 2016 to 2017 (T). For subsequent analyses, such as the impact in 2018 (T+1), we retained the same matched groups and calculated the treatment effect based on differences in employment from 2016 to 2018, and so forth. To ensure the analysis accounted for variances in the impact of robot adoption from one year to the next, we repeated the procedure for firms adopting robots in 2018 under Initial Year 2018, and similarly for subsequent years. To assess the balance of covariates after propensity score matching, we report the average SMD both before and after matching. Significance levels are indicated by asterisks: * for 10%, ** for 5%, and *** for 1%.

Source: Authors' calculations.

Table 7.4: Impact of Robot Adoption on Labor Share: Propensity Score Matching

Dependent Variable: Labor Share				
Robot	(1) Initial Year 2018	(2) Initial Year 2019	(3) Initial Year 2020	(4) Initial Year 2021
T	-0.12	0.00	0.01	0.18*
	(0.15)	(0.06)	(0.40)	(0.11)
Observations	9,889	11,399	11,369	11,721
SMD before	0.532	0.515	0.477	0.345
SMD after	0.107	0.147	0.208	0.109
T+1	-0.28	-0.01	-0.13	
	(0.42)	(0.17)	(0.12)	
Observations	9,479	10,574	10,826	
SMD before	0.526	0.501	0.469	
SMD after	0.176	0.071	0.126	
T+2	0.08	-0.79		
	(0.06)	(0.59)		
Observations	8,842	10,106		
SMD before	0.517	0.495		
SMD after	0.203	0.110		
T+3	0.09			
	(0.14)			
Observations	8,470			
SMD before	0.513			
SMD after	0.084			

SMD = Standardized Mean Difference.

Notes: We report the impact of robot adoption on labor share for the year 2018 under Initial Year 2018, marking the year a firm first employed robots. We do not report the results for Initial Year 2017 since the matching was not satisfactory for the firms that first employed robots in 2017. A counterfactual group was constructed using a logit regression model to estimate the likelihood of adopting robots in 2017. This model incorporated key regressors, including total employment (both permanent and temporary workers), labor productivity, a parent company dummy, and industry dummies. We then analyzed changes in employment for these matched pairs by comparing employment differences from 2017 to 2018 (T). For subsequent analyses, such as the impact in 2019 (T+1), we retained the same matched groups and calculated the treatment effect based on differences in employment from 2017 to 2019, and so forth. To ensure the analysis accounted for variances in the impact of robot adoption from one year to the next, we repeated the procedure for firms adopting robots in 2019 under Initial Year 2019, and similarly for subsequent years. To assess the balance of covariates after propensity score matching, we report the average SMD both before and after matching. Significance levels are indicated by asterisks: * for 10%, ** for 5%, and *** for 1%.

Source: Authors' calculations.

Table 8.1: Impact of Artificial Intelligence Adoption on Permanent Employment: Propensity Score Matching

Dependent Variable: Permanent Employment					
AI	(1)	(2)	(3)	(4)	(5)
	Initial Year 2017	Initial Year 2018	Initial Year 2019	Initial Year 2020	Initial Year 2021
T	-0.06	0.02	0.02	0.16*	0.05
	(0.06)	(0.03)	(0.04)	(0.1)	(0.04)
Observations	5,020	9,723	11,383	11,088	11,464
SMD before	0.469	0.462	0.431	0.375	0.193
SMD after	0.161	0.120	0.080	0.009	0.048
T+1	-0.04	-0.01	0.09	0.10*	
	(0.08)	(0.06)	(0.07)	(0.06)	
Observations	4,806	9,313	10,535	10,547	
SMD before	0.456	0.455	0.418	0.365	
SMD after	0.123	0.088	0.102	0.065	
T+2	0.05	-0.11	0.14*		
	(0.1)	(0.07)	(0.07)		
Observations	4,604	8,672	10,050		
SMD before	0.449	0.447	0.410		
SMD after	0.177	0.090	0.078		
T+3	0.12	0.03			
	(0.17)	(0.05)			
Observations	4,295	8,302			
SMD before	0.439	0.442			
SMD after	0.152	0.130			
T+4	0.12				
	(0.16)				
Observations	4,124				
SMD before	0.431				
SMD after	0.114				

AI = artificial intelligence; SMD = Standardized Mean Difference.

Notes: We report the impact of AI adoption on permanent employment for the year 2017 under Initial Year 2017, marking the year a firm first employed robots. A counterfactual group was constructed using a logit regression model to estimate the likelihood of adopting robots in 2016. This model incorporated key regressors, including total employment (both permanent and temporary workers), labor productivity, a parent company dummy, and industry dummies. We then analyzed changes in employment for these matched pairs by comparing employment differences from 2016 to 2017 (T). For subsequent analyses, such as the impact in 2018 (T+1), we retained the same matched groups and calculated the treatment effect based on differences in employment from 2016 to 2018, and so forth. To ensure the analysis accounted for variances in the impact of robot adoption from one year to the next, we repeated the procedure for firms adopting robots in 2018 under Initial Year 2018, and similarly for subsequent years. To assess the balance of covariates after propensity score matching, we report the average SMD both before and after matching. Significance levels are indicated by asterisks: * for 10%, ** for 5%, and *** for 1%.

Source: Authors' calculations.

Table 8.2: Impact of Artificial Intelligence Adoption on Temporary Employment: Propensity Score Matching

Dependent Variable: Temporary Employment					
AI	(1)	(2)	(3)	(4)	(5)
	Initial Year 2017	Initial Year 2018	Initial Year 2019	Initial Year 2020	Initial Year 2021
T	-0.11	0.61***	0.09	0.48	0.36
	(0.43)	(0.22)	(0.20)	(0.37)	(0.38)
Observations	1,909	1,878	1,894	1,685	1,949
SMD before	0.500	0.529	0.544	0.436	0.277
SMD after	0.177	0.132	0.275	0.155	0.094
T+1	-0.47	0.60*	-0.34	0.43*	
	(0.49)	(0.35)	(0.42)	(0.24)	
Observations	1,691	1,409	1,496	1,562	
SMD before	0.517	0.480	0.547	0.366	
SMD after	0.343	0.192	0.219	0.101	
T+2	-0.13	0.71	-1.26***		
	(0.63)	(0.47)	(0.42)		
Observations	1,376	1,172	1,492		
SMD before	0.663	0.620	0.424		
SMD after	0.115	0.196	0.064		
T+3	1.61*	0.47			
	(0.96)	(0.48)			
Observations	1,244	1,153			
SMD before	0.722	0.515			
SMD after	0.276	0.229			
T+4	0.03				
	(0.54)				
Observations	1,199				
SMD before	0.798				
SMD after	0.066				

AI = artificial intelligence; SMD = Standardized Mean Difference.

Notes: We report the impact of AI adoption on temporary employment for the year 2017 under Initial Year 2017, marking the year a firm first employed robots. A counterfactual group was constructed using a logit regression model to estimate the likelihood of adopting robots in 2016. This model incorporated key regressors, including total employment (both permanent and temporary workers), labor productivity, a parent company dummy, and industry dummies. We then analyzed changes in employment for these matched pairs by comparing employment differences from 2016 to 2017 (T). For subsequent analyses, such as the impact in 2018 (T+1), we retained the same matched groups and calculated the treatment effect based on differences in employment from 2016 to 2018, and so forth. To ensure the analysis accounted for variances in the impact of robot adoption from one year to the next, we repeated the procedure for firms adopting robots in 2018 under Initial Year 2018, and similarly for subsequent years. To assess the balance of covariates after propensity score matching, we report the average SMD both before and after matching. Significance levels are indicated by asterisks: * for 10%, ** for 5%, and *** for 1%.

Source: Authors' calculations.

Table 8.3: Impact of Artificial Intelligence Adoption on Labor Productivity: Propensity Score Matching

Dependent Variable: Labor Productivity					
AI	(1)	(2)	(3)	(4)	(5)
	Initial Year 2017	Initial Year 2018	Initial Year 2019	Initial Year 2020	Initial Year 2021
T	-0.01	-0.01	0.06	-0.11	0.04
	(0.10)	(0.06)	(0.06)	(0.13)	(0.06)
Observations	4,458	9,578	11,253	10,907	11,311
SMD before	0.620	0.459	0.428	0.373	0.201
SMD after	0.253	0.137	0.102	0.094	0.087
T+1	0.24	-0.05	0.04	0.13	
	(0.23)	(0.07)	(0.14)	(0.11)	
Observations	4,734	9,171	10,343	10,379	
SMD before	0.450	0.454	0.416	0.363	
SMD after	0.081	0.103	0.198	0.069	
T+2	0.31**	-0.05	0.22*		
	(0.16)	(0.08)	(0.13)		
Observations	4,545	8,502	9,871		
SMD before	0.502	0.447	0.409		
SMD after	0.297	0.140	0.095		
T+3	0.08	0.24**			
	(0.18)	(0.10)			
Observations	4,213	8,156			
SMD before	0.492	0.434			
SMD after	0.227	0.088			
T+4	0.14				
	(0.31)				
Observations	4,050				
SMD before	0.429				
SMD after	0.061				

AI = artificial intelligence; SMD = Standardized Mean Difference.

Notes: We report the impact of AI adoption on labor productivity for the year 2017 under Initial Year 2017, marking the year a firm first employed robots. A counterfactual group was constructed using a logit regression model to estimate the likelihood of adopting robots in 2016. This model incorporated key regressors, including total employment (both permanent and temporary workers), labor productivity, a parent company dummy, and industry dummies. We then analyzed changes in employment for these matched pairs by comparing employment differences from 2016 to 2017 (T). For subsequent analyses, such as the impact in 2018 (T+1), we retained the same matched groups and calculated the treatment effect based on differences in employment from 2016 to 2018, and so forth. To ensure the analysis accounted for variances in the impact of robot adoption from one year to the next, we repeated the procedure for firms adopting robots in 2018 under Initial Year 2018, and similarly for subsequent years. To assess the balance of covariates after propensity score matching, we report the average SMD both before and after matching. Significance levels are indicated by asterisks: * for 10%, ** for 5%, and *** for 1%.

Source: Authors' calculations.

Table 8.4: Impact of Artificial Intelligence Adoption on Labor Share: Propensity Score Matching

Dependent Variable: Labor Share					
AI	(1) Initial Year 2017	(2) Initial Year 2018	(3) Initial Year 2019	(4) Initial Year 2020	(5) Initial Year 2021
T	0.06	0.04	-0.06	0.16	-0.92
	(0.14)	(0.03)	(0.04)	(0.38)	(0.65)
Observations	4,677	9,723	11,383	11,086	11,464
SMD before	0.431	0.442	0.410	0.365	0.193
SMD after	0.114	0.130	0.078	0.065	0.050
T+1	-0.32*	0.01	0.02	-0.03	
	(0.18)	(0.03)	(0.32)	(0.06)	
Observations	4,806	9,313	10,532	10,547	
SMD before	0.439	0.447	0.418	0.375	
SMD after	0.095	0.052	0.118	0.019	
T+2	-0.43	-0.02	-0.46*		
	(0.26)	(0.22)	(0.25)		
Observations	4,604	8,671	10,050		
SMD before	0.449	0.455	0.431		
SMD after	0.177	0.088	0.080		
T+3	-0.40	-0.02			
	(0.55)	(0.07)			
Observations	4,294	8,302			
SMD before	0.456	0.462			
SMD after	0.123	0.120			
T+4	0.16				
	(0.66)				
Observations	4,124				
SMD before	0.540				
SMD after	0.270				

AI = artificial intelligence; SMD = Standardized Mean Difference.

Notes: We report the impact of AI adoption on labor share for the year 2017 under Initial Year 2017, marking the year a firm first employed robots. A counterfactual group was constructed using a logit regression model to estimate the likelihood of adopting robots in 2016. This model incorporated key regressors, including total employment (both permanent and temporary workers), labor productivity, a parent company dummy, and industry dummies. We then analyzed changes in employment for these matched pairs by comparing employment differences from 2016 to 2017 (T). For subsequent analyses, such as the impact in 2018 (T+1), we retained the same matched groups and calculated the treatment effect based on differences in employment from 2016 to 2018, and so forth. To ensure the analysis accounted for variances in the impact of robot adoption from one year to the next, we repeated the procedure for firms adopting robots in 2018 under Initial Year 2018, and similarly for subsequent years. To assess the balance of covariates after propensity score matching, we report the average SMD both before and after matching. Significance levels are indicated by asterisks: * for 10%, ** for 5%, and *** for 1%.

Source: Authors' calculations.

Table 9.1: Impact of Adopting Both on Permanent Employment: Propensity Score Matching

Dependent Variable: Permanent Employment					
Both	(1)	(2)	(3)	(4)	(5)
	Initial Year 2017	Initial Year 2018	Initial Year 2019	Initial Year 2020	Initial Year 2021
T	0.09	-0.04	-0.14	-0.15**	0.18**
	(0.05)	(0.07)	(0.24)	(0.06)	(0.08)
Observations	5,264	9,666	10,185	11,703	11,931
SMD before	0.489	0.872	0.876	0.548	0.448
SMD after	0.290	0.094	0.178	0.122	0.073
T+1	0.02	-0.00	-0.13**	-0.13	
	(0.19)	(0.11)	(0.06)	(0.08)	
Observations	5,053	9,280	9,478	11,150	
SMD before	0.482	0.868	0.867	0.539	
SMD after	0.471	0.130	0.154	0.212	
T+2	0.07	0.00	0.07		
	(0.16)	(0.13)	(0.08)		
Observations	4,845	8,683	9,072		
SMD before	0.482	0.862	0.863		
SMD after	0.437	0.200	0.086		
T+3	0.25	0.04			
	(0.28)	(0.11)			
Observations	4,531	8,323			
SMD before	0.477	0.859			
SMD after	0.343	0.279			
T+4	0.19				
	(0.40)				
Observations	4,356				
SMD before	0.475				
SMD after	0.059				

SMD = Standardized Mean Difference.

Notes: We report the impact of adopting both robots and artificial intelligence on permanent employment for the year 2017 under Initial Year 2017, marking the year a firm first employed robots. A counterfactual group was constructed using a logit regression model to estimate the likelihood of adopting robots in 2016. This model incorporated key regressors, including total employment (both permanent and temporary workers), labor productivity, a parent company dummy, and industry dummies. We then analyzed changes in employment for these matched pairs by comparing employment differences from 2016 to 2017 (T). For subsequent analyses, such as the impact in 2018 (T+1), we retained the same matched groups and calculated the treatment effect based on differences in employment from 2016 to 2018, and so forth. To ensure the analysis accounted for variances in the impact of robot adoption from one year to the next, we repeated the procedure for firms adopting robots in 2018 under Initial Year 2018, and similarly for subsequent years. To assess the balance of covariates after propensity score matching, we report the average SMD both before and after matching. Significance levels are indicated by asterisks: * for 10%, ** for 5%, and *** for 1%.

Source: Authors' calculations.

Table 9.2: Impact of Adopting Both on Temporary Employment: Propensity Score Matching

Dependent Variable: Temporary Employment			
Both	(1)	(2)	(3)
	Initial Year	Initial Year	Initial Year
	2018	2019	2021
T	-0.07	1.05**	0.57*
	(0.30)	(0.50)	(0.30)
Observations	1,624	2,007	2,132
SMD before	1.268	1.307	0.712
SMD after	0.461	0.303	0.103
T+1	0.08	0.16	
	(0.49)	(0.35)	
Observations	1,239	1,618	
SMD before	1.260	1.128	
SMD after	0.253	0.388	
T+2	0.39	0.89	
	(0.36)	(0.64)	
Observations	1,078	1,624	
SMD before	1.203	1.134	
SMD after	0.296	0.165	
T+3	-0.22		
	(0.53)		
Observations	1,062		
SMD before	1.179		
SMD after	0.112		

SMD = Standardized Mean Difference.

Notes: We report the impact of adopting both robots and artificial intelligence on temporary employment for the year 2017 under Initial Year 2017, marking the year a firm first employed robots. A counterfactual group was constructed using a logit regression model to estimate the likelihood of adopting robots in 2016. This model incorporated key regressors, including total employment (both permanent and temporary workers), labor productivity, a parent company dummy, and industry dummies. We then analyzed changes in employment for these matched pairs by comparing employment differences from 2016 to 2017 (T). For subsequent analyses, such as the impact in 2018 (T+1), we retained the same matched groups and calculated the treatment effect based on differences in employment from 2016 to 2018, and so forth. To ensure the analysis accounted for variances in the impact of robot adoption from one year to the next, we repeated the procedure for firms adopting robots in 2018 under Initial Year 2018, and similarly for subsequent years. To assess the balance of covariates after propensity score matching, we report the average SMD both before and after matching. Significance levels are indicated by asterisks: * for 10%, ** for 5%, and *** for 1%.

Source: Authors' calculations.

Table 9.3: Impact of Adopting Both on Labor Productivity: Propensity Score Matching

Dependent Variable: Labor Productivity				
Both	(1)	(2)	(3)	(4)
	Initial Year 2018	Initial Year 2019	Initial Year 2020	Initial Year 2021
T	-0.12	0.06	0.06	-0.11
	(0.10)	(0.08)	(0.17)	(0.16)
Observations	9,253	11,524	11,510	11,872
SMD before	0.871	0.874	0.547	0.444
SMD after	0.117	0.246	0.019	0.092
T+1	-0.12	0.14	-0.15	
	(0.08)	(0.10)	(0.12)	
Observations	8,905	10,678	10,972	
SMD before	0.867	0.866	0.538	
SMD after	0.300	0.185	0.310	
T+2	-0.06	-0.25*		
	(0.14)	(0.14)		
Observations	8,327	10,243		
SMD before	0.861	0.888		
SMD after	0.300	0.082		
T+3	-0.03			
	(0.14)			
Observations	8,009			
SMD before	0.786			
SMD after	0.250			

SMD = Standardized Mean Difference.

Notes: We report the impact of adopting both robots and artificial intelligence on labor productivity for the year 2017 under Initial Year 2017, marking the year a firm first employed robots. A counterfactual group was constructed using a logit regression model to estimate the likelihood of adopting robots in 2016. This model incorporated key regressors, including total employment (both permanent and temporary workers), labor productivity, a parent company dummy, and industry dummies. We then analyzed changes in employment for these matched pairs by comparing employment differences from 2016 to 2017 (T). For subsequent analyses, such as the impact in 2018 (T+1), we retained the same matched groups and calculated the treatment effect based on differences in employment from 2016 to 2018, and so forth. To ensure the analysis accounted for variances in the impact of robot adoption from one year to the next, we repeated the procedure for firms adopting robots in 2018 under Initial Year 2018, and similarly for subsequent years. To assess the balance of covariates after propensity score matching, we report the average SMD both before and after matching. Significance levels are indicated by asterisks: * for 10%, ** for 5%, and *** for 1%.

Source: Authors' calculations.

Table 9.4: Impact of Adopting Both on Labor Share: Propensity Score Matching

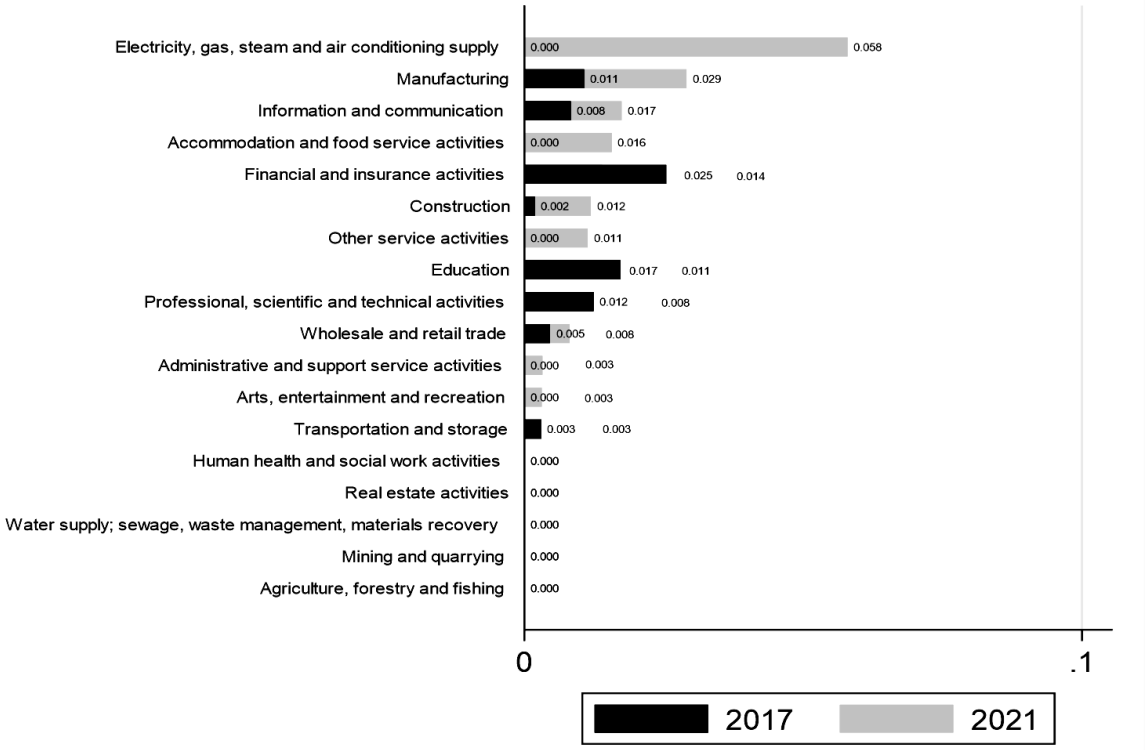
Dependent Variable: Labor Share					
Both	(1)	(2)	(3)	(4)	(5)
	Initial Year 2017	Initial Year 2018	Initial Year 2019	Initial Year 2020	Initial Year 2021
T	-0.03	0.05	0.01	0.05	0.44*
	(0.55)	(0.05)	(0.02)	(0.04)	(0.24)
Observations	4,937	9,370	11,638	11,700	12,031
SMD before	0.523	0.872	0.876	0.548	0.448
SMD after	0.409	0.094	0.178	0.080	0.073
T+1	-0.47***	0.08*	0.20	0.05	
	(0.17)	(0.05)	(1.72)	(0.05)	
Observations	5,096	9,016	10,859	11,150	
SMD before	0.482	0.868	0.867	0.539	
SMD after	0.471	0.130	0.141	0.212	
T+2	-1.25	0.10	-1.52		
	(0.97)	(0.08)	(1.51)		
Observations	4,887	8,474	10,402		
SMD before	0.482	0.862	0.863		
SMD after	0.437	0.200	0.086		
T+3	-7.02***	-0.07			
	(2.45)	(0.12)			
Observations	4,568	8,130			
SMD before	0.477	0.859			
SMD after	0.267	0.279			
T+4	4.53				
	(3.88)				
Observations	4,391				
SMD before	0.475				
SMD after	0.059				

SMD = Standardized Mean Difference.

Notes: We report the impact of adopting both robots and artificial intelligence on labor share for the year 2017 under Initial Year 2017, marking the year a firm first employed robots. A counterfactual group was constructed using a logit regression model to estimate the likelihood of adopting robots in 2016. This model incorporated key regressors, including total employment (both permanent and temporary workers), labor productivity, a parent company dummy, and industry dummies. We then analyzed changes in employment for these matched pairs by comparing employment differences from 2016 to 2017 (T). For subsequent analyses, such as the impact in 2018 (T+1), we retained the same matched groups and calculated the treatment effect based on differences in employment from 2016 to 2018, and so forth. To ensure the analysis accounted for variances in the impact of robot adoption from one year to the next, we repeated the procedure for firms adopting robots in 2018 under Initial Year 2018, and similarly for subsequent years. To assess the balance of covariates after propensity score matching, we report the average SMD both before and after matching. Significance levels are indicated by asterisks: * for 10%, ** for 5%, and *** for 1%.

Source: Authors' calculations.

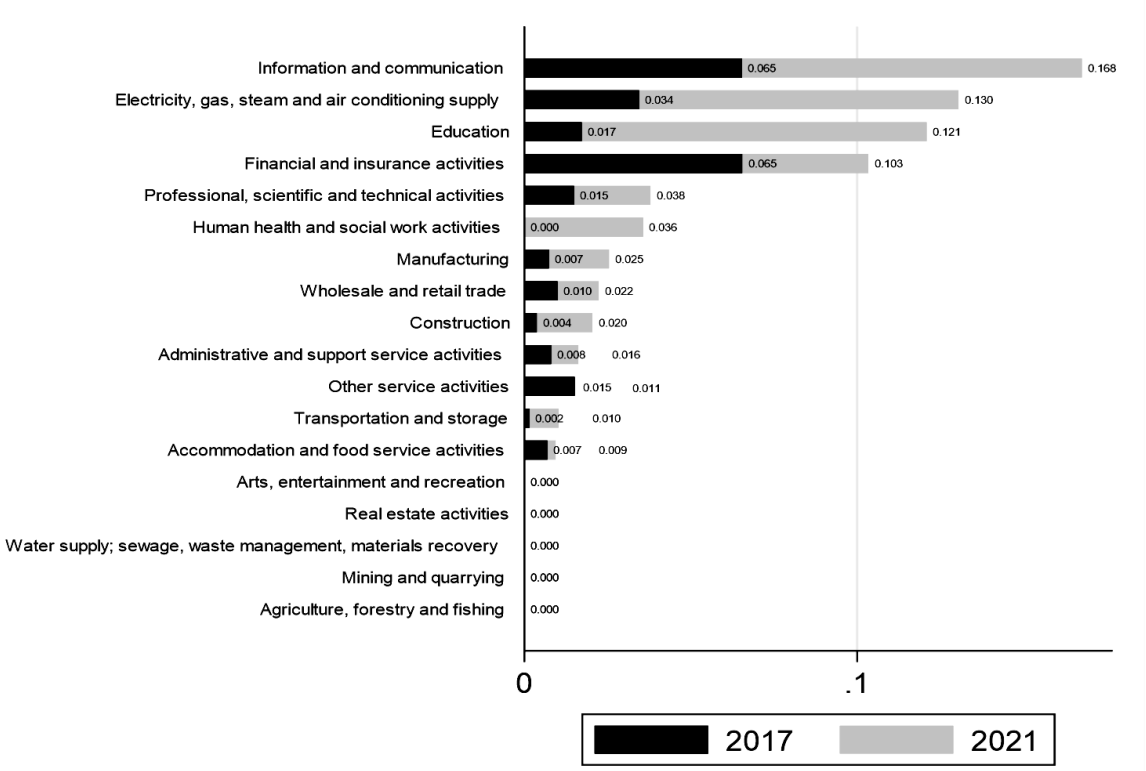
Figure 1.1: Share of Firms Adopting Robots



Notes: The Korean industry classification follows the 1-digit level of the Korean Standard Industrial Classification. Industries without firms adopting robots are excluded. The share is calculated as the number of robot-adopting firms divided by the total number of firms within each industry.

Source: Authors' calculations

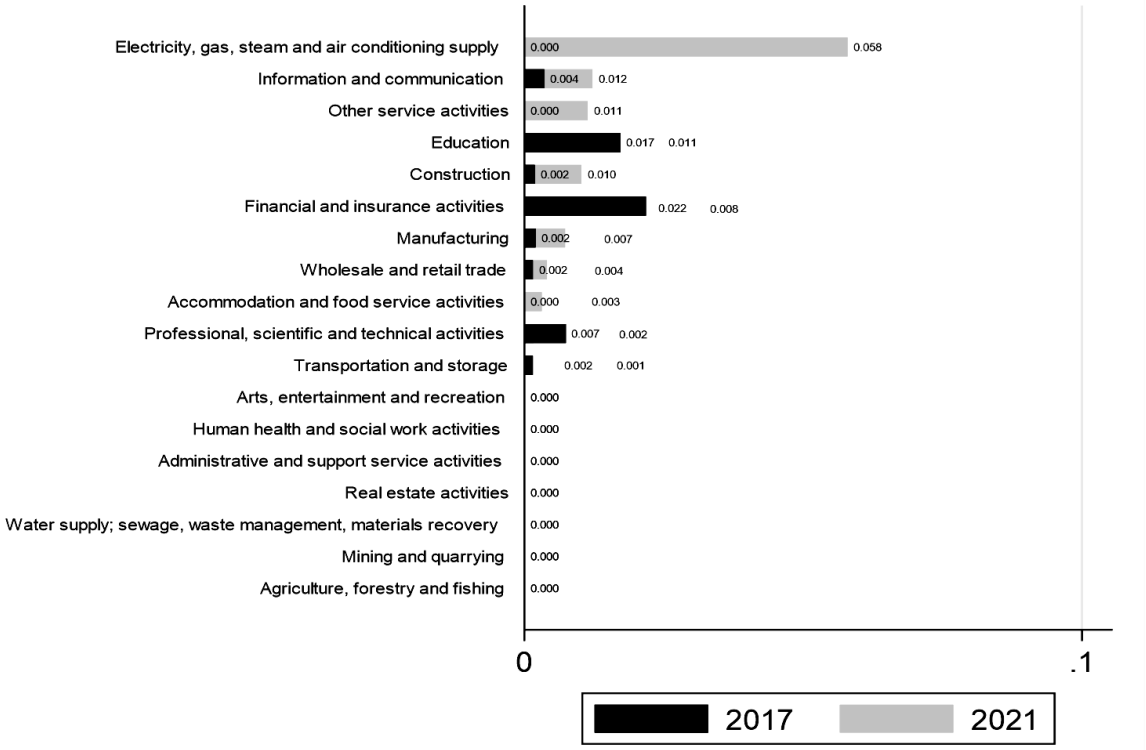
Figure 1.2: Share of Firms Adopting Artificial Intelligence



Notes: The Korean industry classification follows the 1-digit level of the Korean Standard Industrial Classification. Industries without firms adopting artificial intelligence are excluded. The share is calculated as the number of artificial intelligence-adopting firms divided by the total number of firms within each industry.

Source: Authors' calculations

Figure 1.3: Share of Firms Adopting Both Robots and Artificial Intelligence

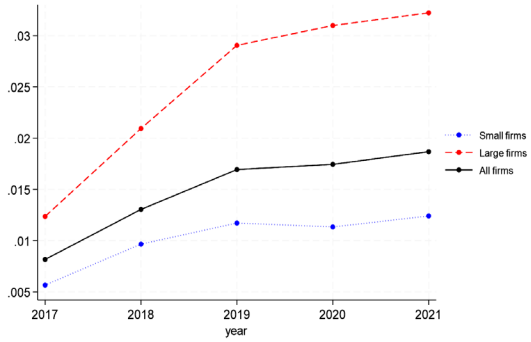


Notes: The Korean industry classification follows the 1-digit level of the Korean Standard Industrial Classification. Industries without firms adopting both robots and artificial intelligence are excluded. The share is calculated as the number of firms adopting both robots and artificial intelligence divided by the total number of firms within each industry.

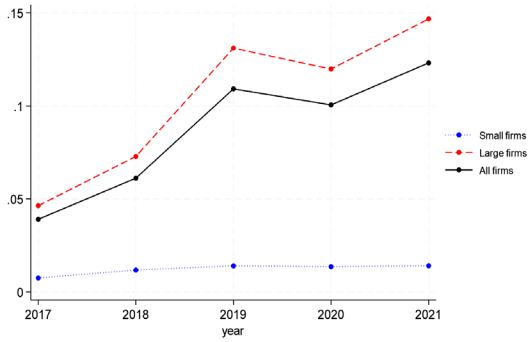
Source: Authors' calculations

Figure 2.1: Evolution of Robot Adoption

(a) Firm Shares



(b) Employment Shares

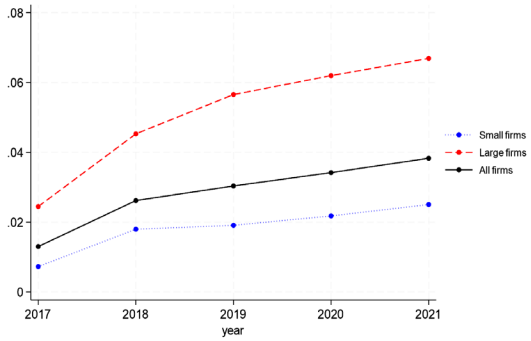


Notes: Panel (a) illustrates the shares of robot-adopting firms, categorized into small firms (dotted line), large firms (dashed line), and all firms (solid line). Small firms are defined as those with fewer than 200 employees, while large firms include those with 200 or more employees. Panel (b) presents the employment shares corresponding to these firms.

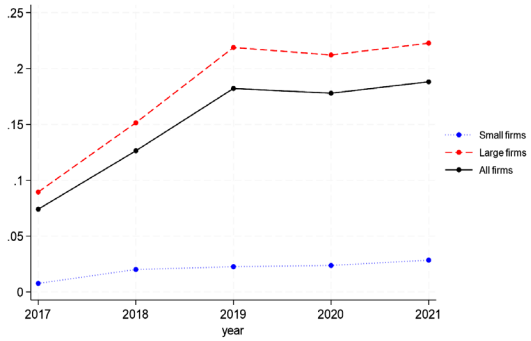
Source: Authors' calculations.

Figure 2.2: Evolution of Artificial Intelligence Adoption

(a) Firm Shares



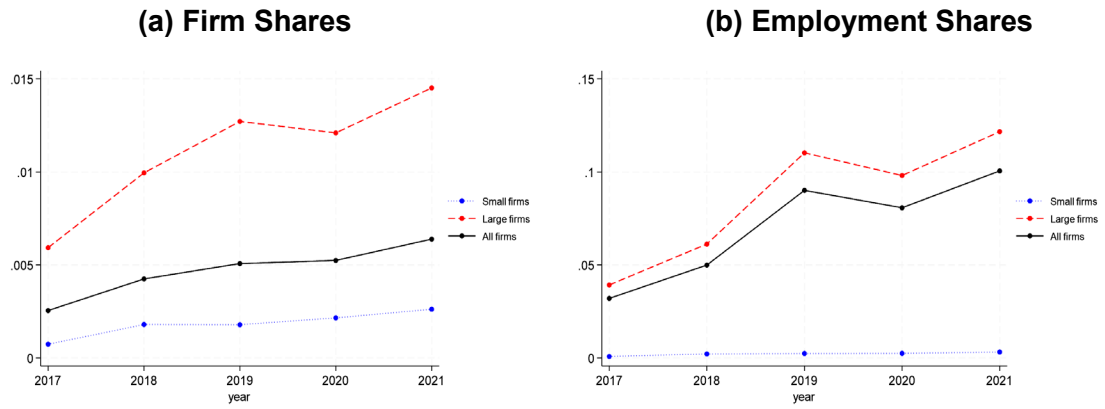
(b) Employment Shares



Notes: Panel (a) illustrates the shares of artificial intelligence-adopting firms, categorized into small firms (dotted line), large firms (dashed line), and all firms (solid line). Small firms are defined as those with fewer than 200 employees, while large firms include those with 200 or more employees. Panel (b) presents the employment shares corresponding to these firms.

Source: Authors' calculations.

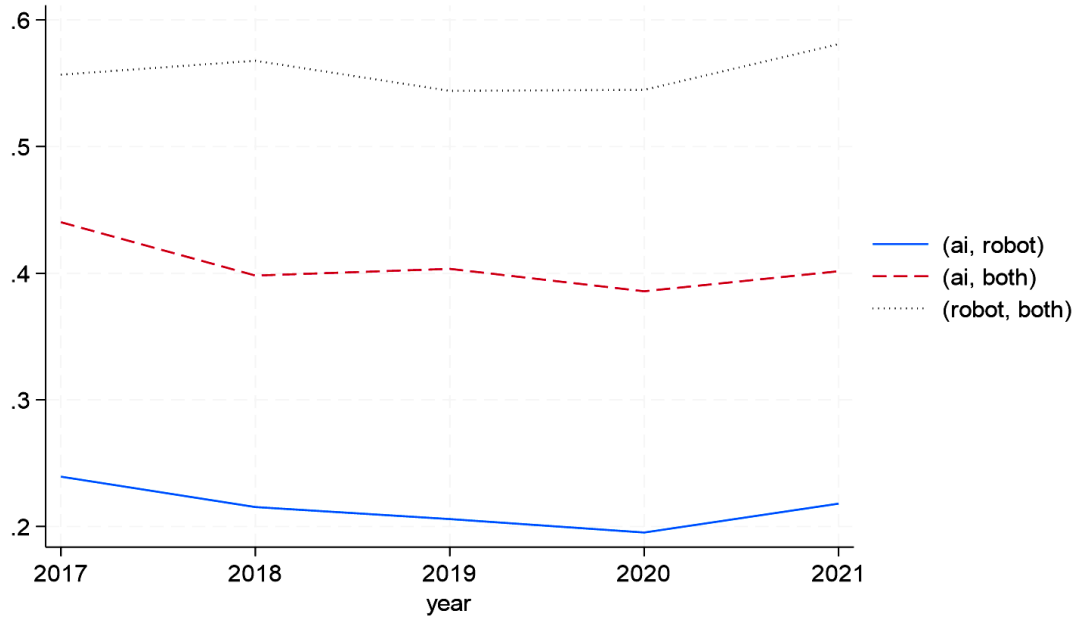
Figure 2.3: Evolution of Both Robot and Artificial Intelligence Adoption



Notes: Panel (a) illustrates the shares of firms adopting both robots and artificial intelligence, categorized by small firms (dotted line), large firms (dashed line), and all firms (solid line). Small firms are defined as those with fewer than 200 employees, while large firms include those with 200 or more employees. Panel (b) presents the employment shares corresponding to these firms.

Source: Authors' calculations.

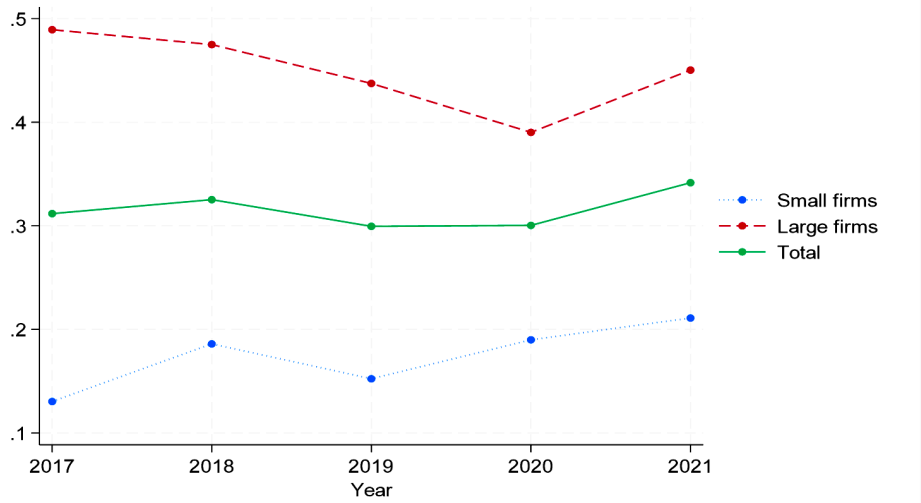
Figure 3: Evolution of Correlation Coefficients Among Robot-Adopting, Artificial Intelligence-Adopting, and Both-Adopting Firms



Notes: The solid line represents the correlation coefficient between robot and artificial intelligence adoption across firms. The dashed line indicates the correlation between firms adopting both robots and artificial intelligence and those adopting only robots, while the dotted line represents the correlation between firms adopting both technologies and those adopting only artificial intelligence.

Source: Authors' calculations.

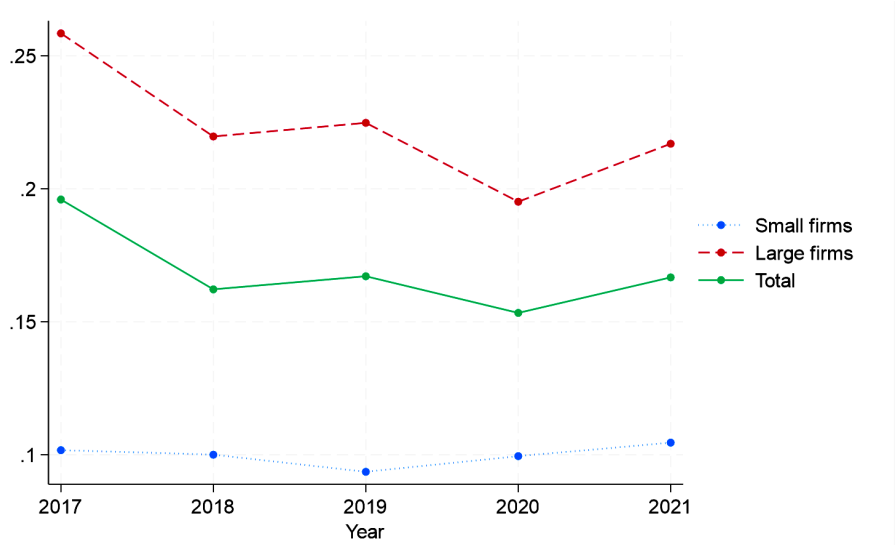
Figure 4.1: Proportion of Firms That Adopt Robots



Notes: The shares of firms that adopted artificial intelligence among those that had previously adopted robots are presented, with a breakdown for small firms (dotted line), large firms (dashed line), and all firms (solid line).

Source: Authors' calculations.

Figure 4.2: Proportion of Firms That Adopt Artificial Intelligence

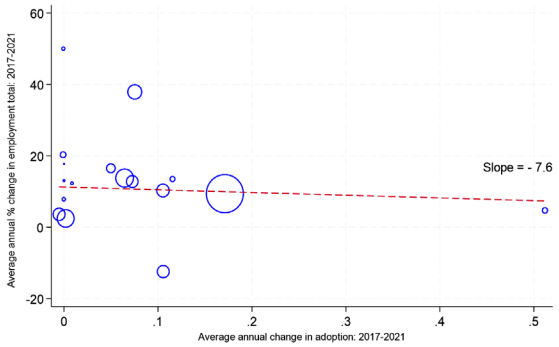


Notes: The shares of firms that adopted robots among those that had previously adopted artificial intelligence are presented, with a breakdown for small firms (dotted line), large firms (dashed line), and all firms (solid line).

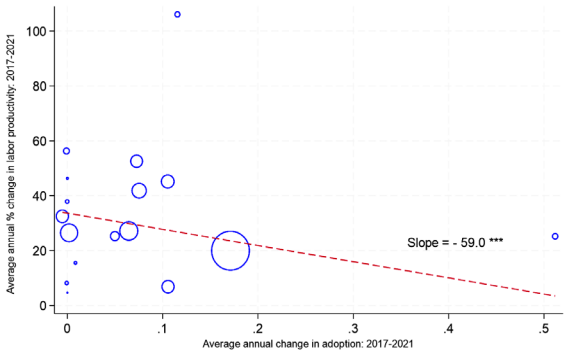
Source: Authors' calculations.

Figure 5.1: Changes in Employment and Labor Productivity Associated with Robot Adoption

(a) Employment



(b) Labor Productivity

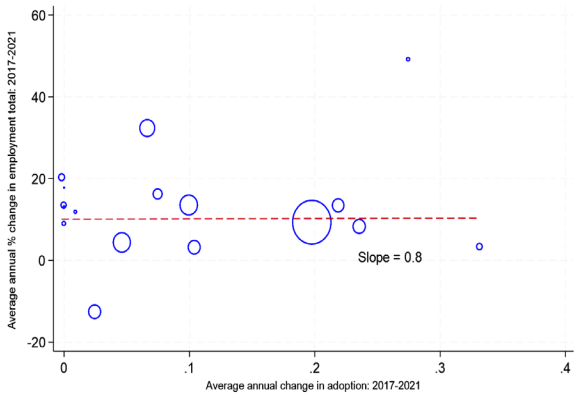


Notes: This figure presents changes in employment and labor productivity in relation to robot adoption at the industry level. In panel (a), the horizontal axis represents the change in the share of employment among firms that adopted robots within each industry from 2017 to 2021, while the vertical axis shows the change in total employment for the same industry. In panel (b), the vertical axis indicates the change in labor productivity at the industry level. The size of each circle represents the employment size of the corresponding industry. The fitted lines are derived from weighted Ordinary Least Squares regressions, with the initial level of employment serving as the weight. *** denotes significance of the fitted line at the 1% level.

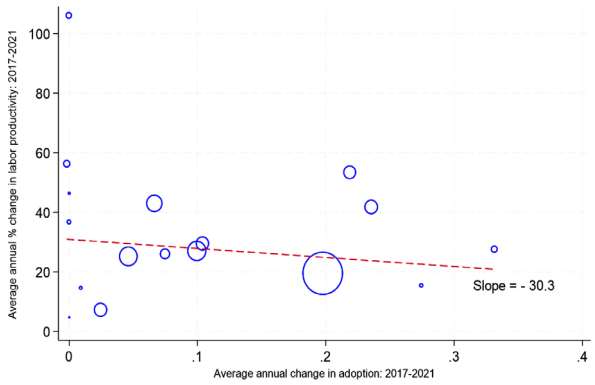
Source: Authors' calculations.

Figure 5.2: Changes in Employment and Labor Productivity Associated with Artificial Intelligence Adoption

(a) Employment



(b) Labor Productivity

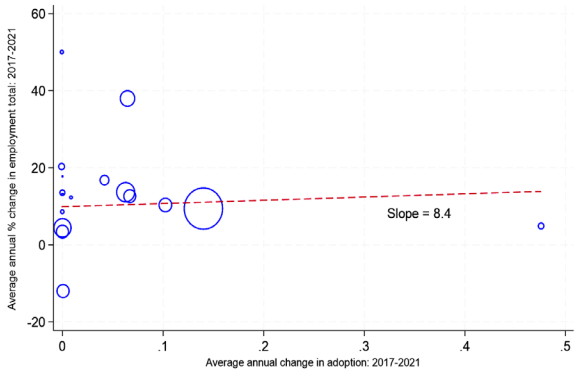


Notes: This figure presents changes in employment and labor productivity in relation to artificial intelligence adoption at the industry level. In panel (a), the horizontal axis represents the change in the share of employment among firms that adopted artificial intelligence within each industry from 2017 to 2021, while the vertical axis shows the change in total employment for the same industry. In panel (b), the vertical axis indicates the change in labor productivity at the industry level. The size of each circle represents the employment size of the corresponding industry. The fitted lines are derived from weighted Ordinary Least Squares regressions, with the initial level of employment serving as the weight.

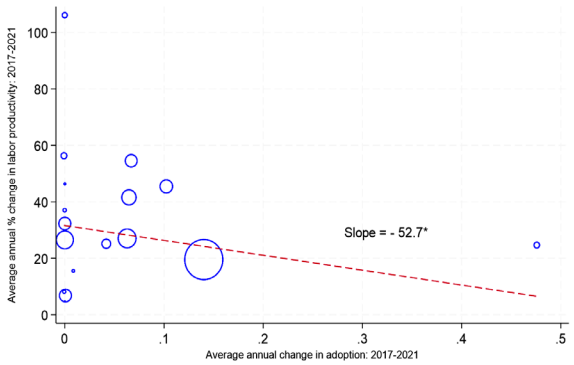
Source: Authors' calculations.

Figure 5.3: Changes in Employment and Labor Productivity Associated with Both Robot and Artificial Intelligence Adoption

(a) Employment



(b) Labor Productivity



Notes: This figure presents changes in employment and labor productivity in relation to both robot and artificial intelligence adoption at the industry level. In panel (a), the horizontal axis represents the change in the share of employment among firms that adopted both robots and artificial intelligence within each industry from 2017 to 2021, while the vertical axis shows the change in total employment for the same industry. In panel (b), the vertical axis indicates the change in labor productivity at the industry level. The size of each circle represents the employment size of the corresponding industry. The fitted lines are derived from weighted Ordinary Least Squares regressions, with the initial level of employment serving as the weight. * denotes significance of the fitted line at the 10% level.

Source: Authors' calculations.