“The Effect of AI on Wages in Japan Using Computable General Equilibrium Model”

2022年9月9日

Motivation

- Frey and Osbourne (2013) : 47% of US employment at risk.

- Arntz, Gregory and Zierahn (2016): 9% of OECD country employment are automatable

→The effect of AI deployment on future employment is predicted. No consensus on the effect.

- Impact of AI deployment on wages and income inequality is unclear.

Acemoglu et al (2021):

A regression analysis about AI-related vacancies over 2010-2018.

No detectable aggregate labor market consequences.

AI is currently substituting for humans in a subset of tasks but it is not yet having detectable aggregate labor market consequences.

Preceding Paper 2

Watanabe et al (2021):

Micro level analysis about the role of AI on worker's productivity in the same occupation.

AI is complementary to human labor and will raise productivity.

AI improves driver's productivity by 5% on average and **its gain is concentrated on low-skilled drivers** while almost zero on high-skilled drivers.

Grenan and Michaely (2020):

Analysts with portfolios that are more exposed to AI are more likely to reallocate efforts to soft skills, shift coverage towards low AI stocks, and **even leave the profession.**

Analyst departures disproportionately occur among highly accurate analysts, leaving for non-research jobs.

Reallocating efforts toward tasks that rely on social skills improve consensus forecasts. However, **increased exposure to AI reduces the novelty in analysts' research which reduces compensation.**

Webb (2020):

Develop a method to predict the impacts of any technology of occupations by using the overlap between the text of job task descriptions and the text of patents to construct a measure of the exposure of tasks to automation.

AI is directed at high-skilled tasks.

AI will reduce 90:10 wage inequality but not affect 1%.

Webb(2020)'s AI exposure rate

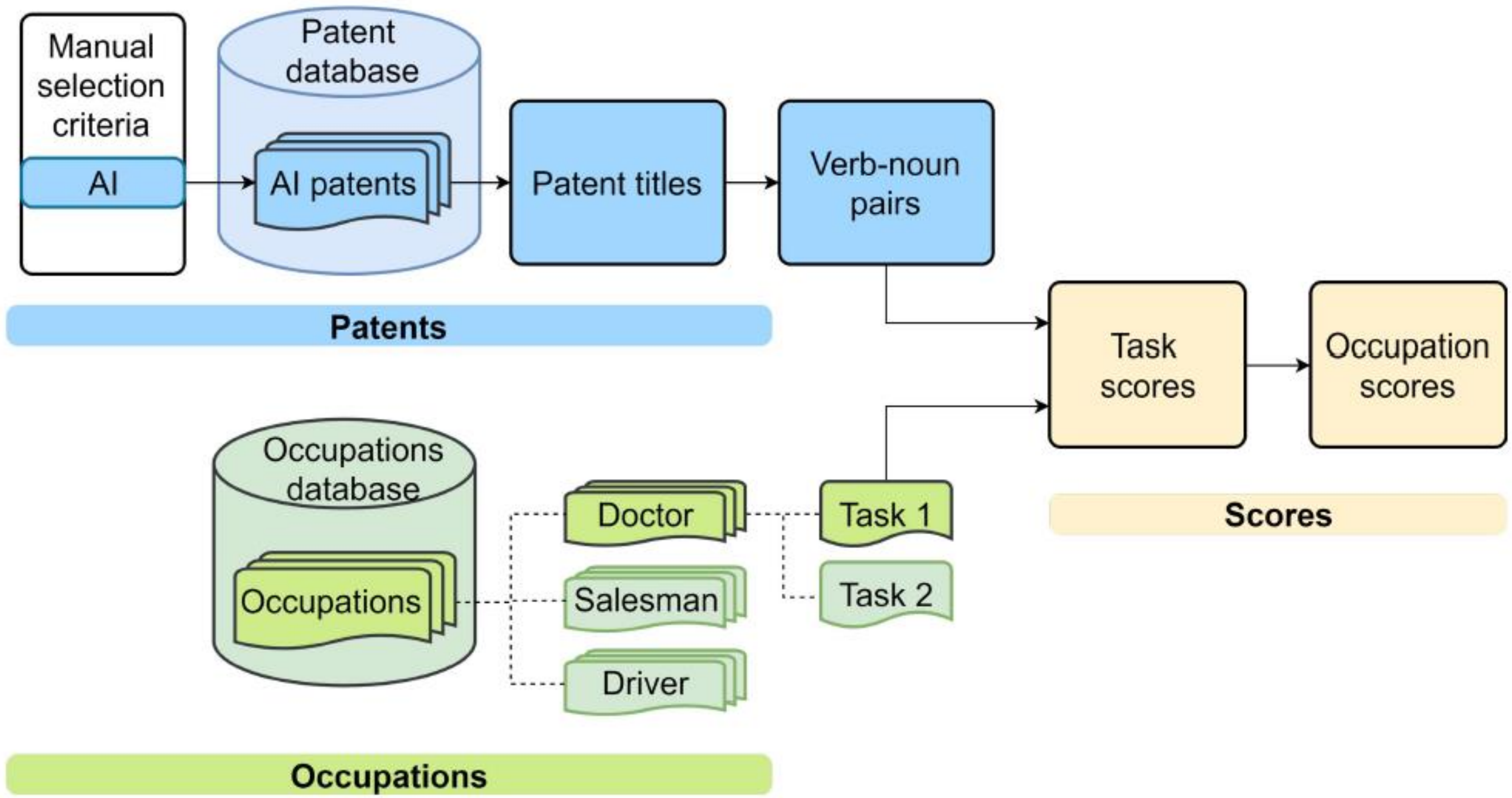


Figure 2: Illustration of process for constructing technology exposure measures

Webb(2020)'s AI exposure rate

Table 1: **Tasks and exposure scores for precision agriculture technicians.**

Task	**Weight in occupation**	**Extracted pairs**	**AI exposure score x100**
Use geospatial technology to develop soil sampling grids or identify sampling sites for testing characteristics such as nitrogen, phosphorus, or potassium content, ph, or micronutrients.	0.050	(develop, grid)	0.050
		(identify, site)	0.234
		(test, characteristic)	0.084
Document and maintain records of precision agriculture information.	0.049	(maintain, record)	0.000
Analyze geospatial data to determine agricultural implications of factors such as soil quality, terrain, field productivity, fertilizers, or weather conditions.	0.048	(analyze, datum)	0.469
		(determine, implication)	0.837
Apply precision agriculture information to specifically reduce the negative environmental impacts of farming practices.	0.048	(apply, information)	0.000
		(reduce, impact)	0.151
Install, calibrate, or maintain sensors, mechanical controls, GPS-based vehicle guidance systems, or computer settings.	0.045	(maintain, sensor)	0.000
Identify areas in need of pesticide treatment by analyzing geospatial data to determine insect movement and damage patterns.	0.038	(identify, area)	0.234
		(analyze, datum)	0.469
		(determine, movement)	0.502

Notes: Table displays six of the twenty-two tasks recorded for precision agriculture technicians in the O*NET database. For each task, the weight is an average of the frequency, importance, and relevance of that task to the occupation, as specified in O*NET, with weights scaled to sum to one. The verb-noun pairs in the third column are extracted from the task text by a dependency parsing algorithm. The AI exposure score for an extracted pair is equal to the relative frequency of similar pairs in the titles of AI patents. The score multiplied by 100 is thus a percentage; for example, pairs similar to "determine implications" represent 0.84% of pairs extracted from AI patents.

Webb(2020)'s AI exposure rate

Rf (=Relative Frequency), of aggregated verb-noun pair c in technology t patent title is

$$rf_c^t = \frac{f_c^t}{\sum_{c \in C^t} f_c^t}.$$

For each occupation i, Webb (2020) then take a weighted average of these task-level scores to produce an overall technology t exposure score for the occupation,

$$Exposure_{i,t} = \frac{\sum_{k \in K_i} \left[w_{k,i} \cdot \sum_{c \in S_k} rf_c^t \right]}{\sum_{k \in K_i} \left[w_{k,i} \cdot |\{c : c \in S_k\}| \right]}.$$

K_i : the set of tasks in occupation i.

S_k : the set of verb-noun pairs extracted from task $k \in Ki$.

Webb(2020)'s AI exposure rate

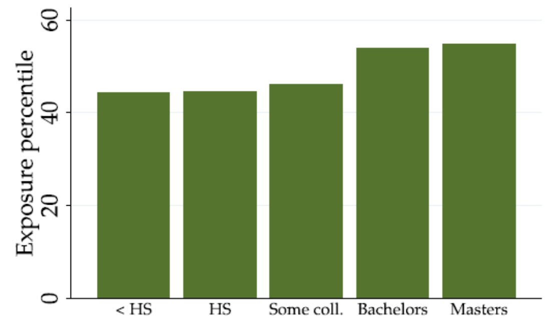
Table 10: **Top extracted verbs and characteristic nouns for AI.**

Verb	Example nouns	Verb	Example nouns
recognize	pattern, image, speech, face, voice, automobile, emotion, gesture, disease	**determine**	state, similarity, relevance, importance, characteristic, strategy, risk
predict	quality, performance, fault, behavior, traffic, prognosis	**control**	process, emission, traffic, engine, robot, turbine, plant
detect	signal, abnormality, defect, object, fraud, event, spammer, human, cancer	**generate**	image, rating, lexicon, warning, description, recommendation
identify	object, type, damage, illegality, classification, relationship, importance	**classify**	data, object, image, pattern, signal, text, electrogram, speech, motion

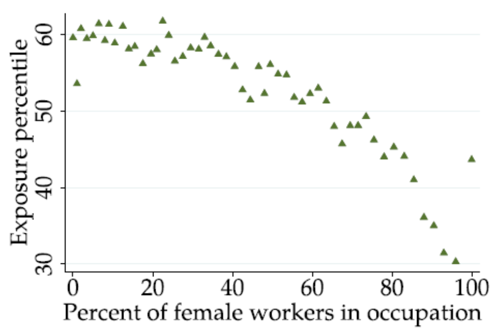
Notes: This table lists the top eight verbs by pair frequency extracted from the title text of patents corresponding to AI, together with characteristic direct objects for each verb chosen manually to illustrate a range of applications. Patents corresponding to each technology are selected using a keyword search. A dependency parsing algorithm is used to extract verbs and their direct objects from patent titles.

Webb(2020)'s AI exposure rate

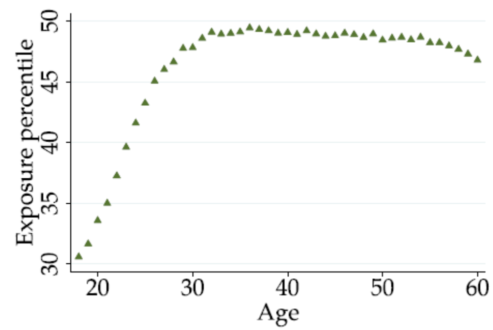
(a) Smoothed scores by occupational wage percentile



(b) Exposure by level of education



(c) Exposure by percent of female workers in occupation



(d) Exposure by age.

Figure 7: **Exposure to AI by demographic group**

Notes: Plot (a) shows the average of standardized occupation-level exposure scores for AI by occupational wage percentile rank using a locally weighted smoothing regression (bandwidth 0.8 with 100 observations), following Acemoglu and Autor (2011). Wage percentiles are measured as the employment-weighted percentile rank of an occupation's mean hourly wage in the May 2016 Occupational Employment Statistics. Plot (b) is a bar graph showing the exposure score percentile for AI averaged across all industry-occupation observations, weighted by 2010 total employment in given educational category. Plot (c) is a binscatter. The x-axis is the percent of workers in an industry-occupation observation reported female in the 2010 census. Plot (d) is a binscatter. The x-axis is the average age of workers in an industry-occupation observation in the 2010 census.

Webb(2020)'s AI exposure rate

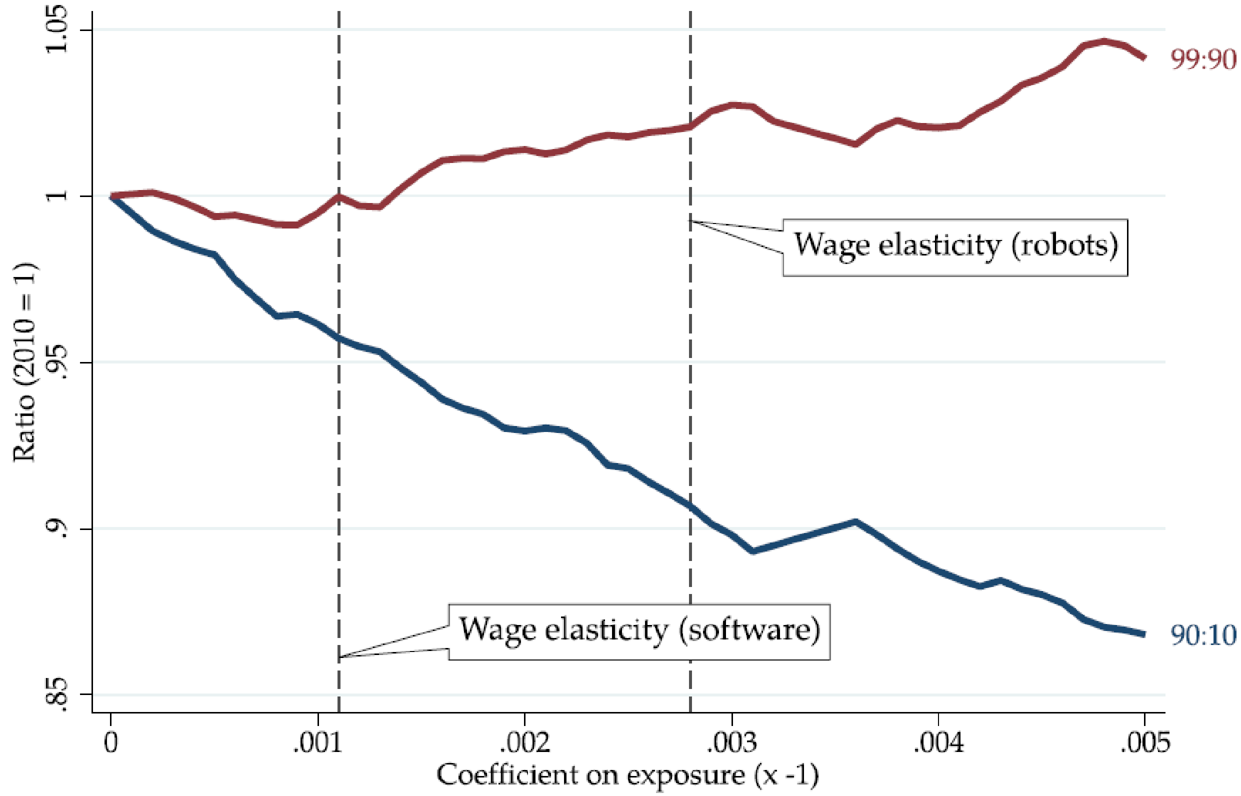


Figure 8: **Potential impacts of artificial intelligence on inequality.**

Notes: Ratios calculated from the percentiles of wage $* e^{\beta * \text{exposure}}$ for various values of β, the coefficient on exposure in a regression with change in log wages as the dependent variable. The sign of the coefficient has been flipped.

JIP（2013）’s Occupational enrollment ratio

JIPcode		year	tech	manage	office	sales	service	prod
0	合計	2010	0.144	0.024	0.182	0.136	0.112	0.252
1	米麦生産業	2010	0.001	0.002	0.006	0.004	0.000	0.012
2	その他の耕種農業	2010	0.001	0.002	0.006	0.004	0.000	0.012
3	畜産・養蚕業	2010	0.001	0.002	0.006	0.004	0.000	0.012
4	農業サービス	2010	0.091	0.014	0.102	0.010	0.094	0.158
5	林業	2010	0.017	0.027	0.175	0.011	0.001	0.051
6	漁業	2010	0.001	0.013	0.022	0.006	0.005	0.036
7	鉱業	2010	0.035	0.064	0.236	0.038	0.002	0.495
8	畜産食料品	2010	0.016	0.017	0.124	0.050	0.002	0.781
9	水産食料品	2010	0.006	0.032	0.096	0.052	0.001	0.804
10	精穀・製粉	2010	0.029	0.042	0.179	0.095	0.003	0.624
11	その他の食料品	2010	0.015	0.022	0.109	0.048	0.002	0.797
12	飼料・有機質肥料	2010	0.016	0.047	0.178	0.076	0.000	0.626
13	飲料	2010	0.024	0.040	0.203	0.099	0.005	0.611
14	たばこ	2010	0.107	0.026	0.333	0.026	0.000	0.493
15	繊維製品	2010	0.020	0.036	0.118	0.052	0.001	0.770
16	製材・木製品	2010	0.009	0.048	0.137	0.043	0.001	0.730
17	家具・装備品	2010	0.028	0.028	0.144	0.050	0.001	0.745
18	パルプ・紙・板紙・加工紙	2010	0.030	0.020	0.157	0.030	0.001	0.735
19	紙加工品	2010	0.017	0.039	0.146	0.064	0.001	0.715
20	印刷・製版・製本	2010	0.034	0.037	0.171	0.137	0.001	0.615
21	皮革・皮革製品・毛皮	2010	0.010	0.032	0.115	0.072	0.000	0.767
22	ゴム製品	2010	0.058	0.021	0.148	0.035	0.001	0.727
23	化学肥料	2010	0.054	0.042	0.174	0.090	0.000	0.618
24	無機化学基礎製品	2010	0.122	0.028	0.219	0.052	0.001	0.566
25	有機化学基礎製品	2010	0.122	0.028	0.219	0.052	0.001	0.566

108 industries.

Webb's AI Exposure Rate Conversion 1

Table 1: Conversion of Webb (2020)'s AI exposed rate to JIP by industry and occupation

Group-to-group

	Classification	Occupation classification by JIP	Occupations in O*NET	Number of workers in U.S.	Webb's AI exposure rate	AI exposure rate
15	Textile	Professional and technical workers				
			Professiona and technical workers (manufacturing): Average			86
		Administrative occupation workers				
			Administrative occupation workers: Average			60
		Clerical workers				
			Clerical workers: Average			60
		Sales workers				
			Sales Workers: Average			36
		Service workers				
			Service Workers: Average			29
		Craftsman and manufacturing and construction workers				
			Tailors, dressmakers, and sewers	72,514	57	
			Winding and twisting textile and apparel operatives	12,792	92	
			Knitters, loopers, and toppers textile operatives	9,323	100	
			Textile cutting and dyeing machine operators	11,137	98	
			Textile sewing machine operators	205,365	47	
			Clothing pressing machine operators	45,425	21	
			Miscellanious textile machine operators	24,388	84	<u>52</u>
69	Finance	Professional and technical workers				
			Professiona and technical workers (non-manufacturing): Average			64
		Administrative occupation workers				
			Financial managers		67	67
		Clerical workers				
			Clerical workers: Average			60
		Sales workers				
			Financial service sales occupations		64	64
		Service workers				
			Bank tellers		24	24
		Craftsman and manufacturing and construction workers				
			Crafts man and manufacturing and construction workers: Average			29

Group-to-one

One-to-one

One-to-one

69	Finance	Professional and technical workers				
			Professiona and technical workers (non-manufacturing): Average			64
		Administrative occupation workers				
			Financial managers		67	67
		Clerical workers				
			Clerical workers: Average			60
		Sales workers				
			Financial service sales occupations		64	64
		Service workers				
			Bank tellers		24	24
		Craftsman and manufacturing and construction workers				
			Crafts man and manufacturing and construction workers: Average			29

Webb's AI Exposure Rate Conversion 3: group-to-one

15	Textile

Craftsman and manufacturing and construction workers

Tailors, dressmakers, and sewers	72,514	57	
Winding and twisting textile and apparel operatives	12,792	92	
Knitters, loopers, and toppers textile operatives	9,323	100	
Textile cutting and dyeing machine operators	11,137	98	
Textile sewing machine operators	205,365	47	
Clothing pressing machine operators	45,425	21	
Miscellanious textile machine operators	24,388	84	52

Webb’s AI Exposure Rate Conversion 4: group-to-group

Table 2: Composition of Professional and Technical Workers (Manufacturing): Average

Occupations in O*NET	Number of workers in U.S.	Webb's AI exposure rate	AI exposure rate
Production supervisors or foremen	1,101,858	96	
Metallurgical and materials engineers	44,872	100	
Civil engineers	362,290	85	
Electrical engineers	360,764	87	
Industrial engineers	218,636	84	
Mechanical engineers	267,666	75	
Engineers and other professionals, n.e.c.	557,823	90	
Operations and systems researchers and analysts	273,519	83	
Designers	785,607	77	
Engineering and science technicians	496,318	91	
Drafters	188,068	81	
Surveryors, cartographers, mapping scientists/techs	116,280	84	
Biological technicians	56,885	84	
Chemical technicians	79,569	23	86

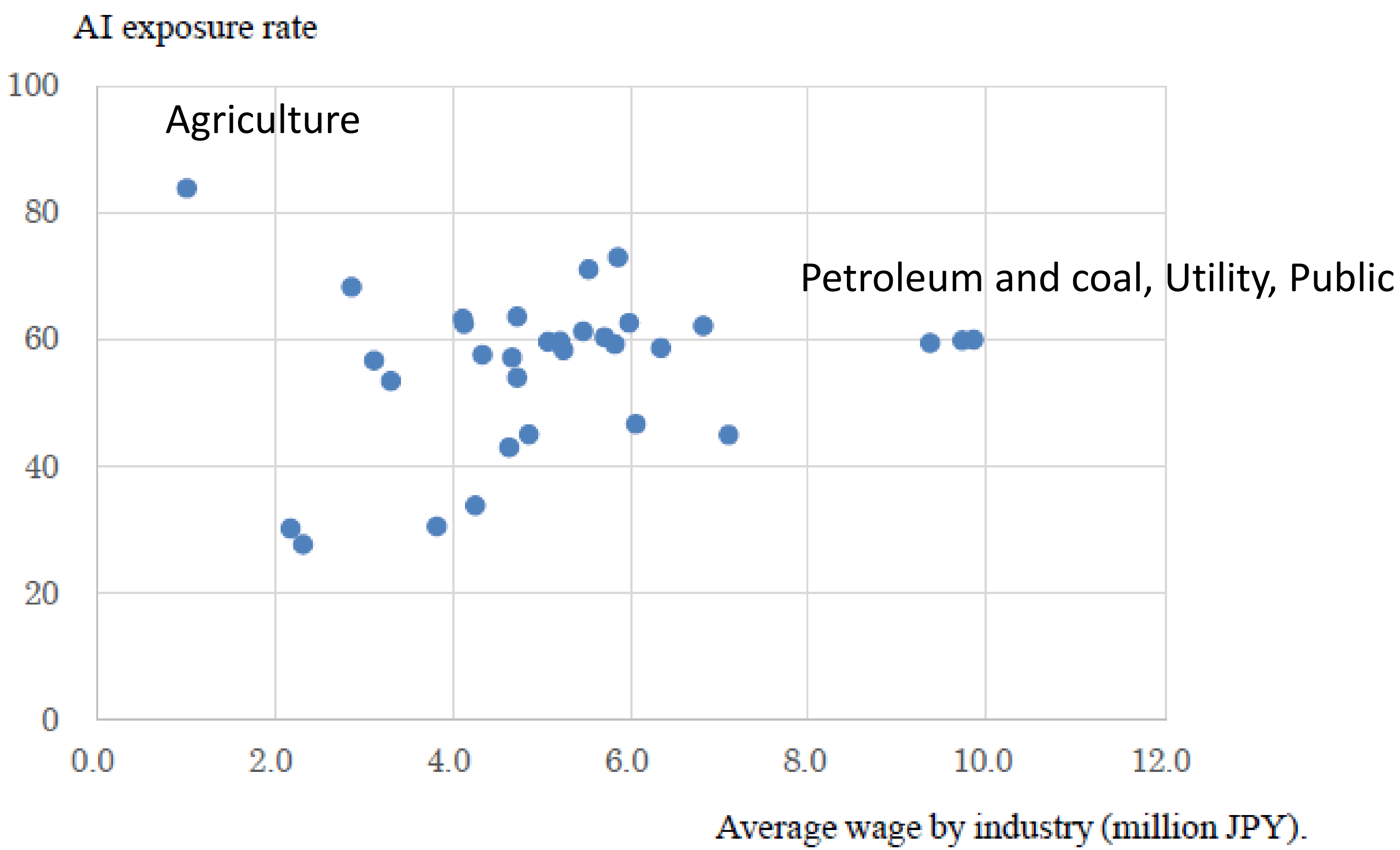
Webb's AI Exposure Rate Conversion 5: Total by occupation

Table 3: Aggregate AI Exposure Rate by Occupation

Occupations	AI exposure rate
Professional and technical workers	62.3
Administrative occupation workers	67.3
Clerical workers	62.5
Sales workers	26.4
Service workers	29.2
Craftsman and manufacturing and construction workers	51.9

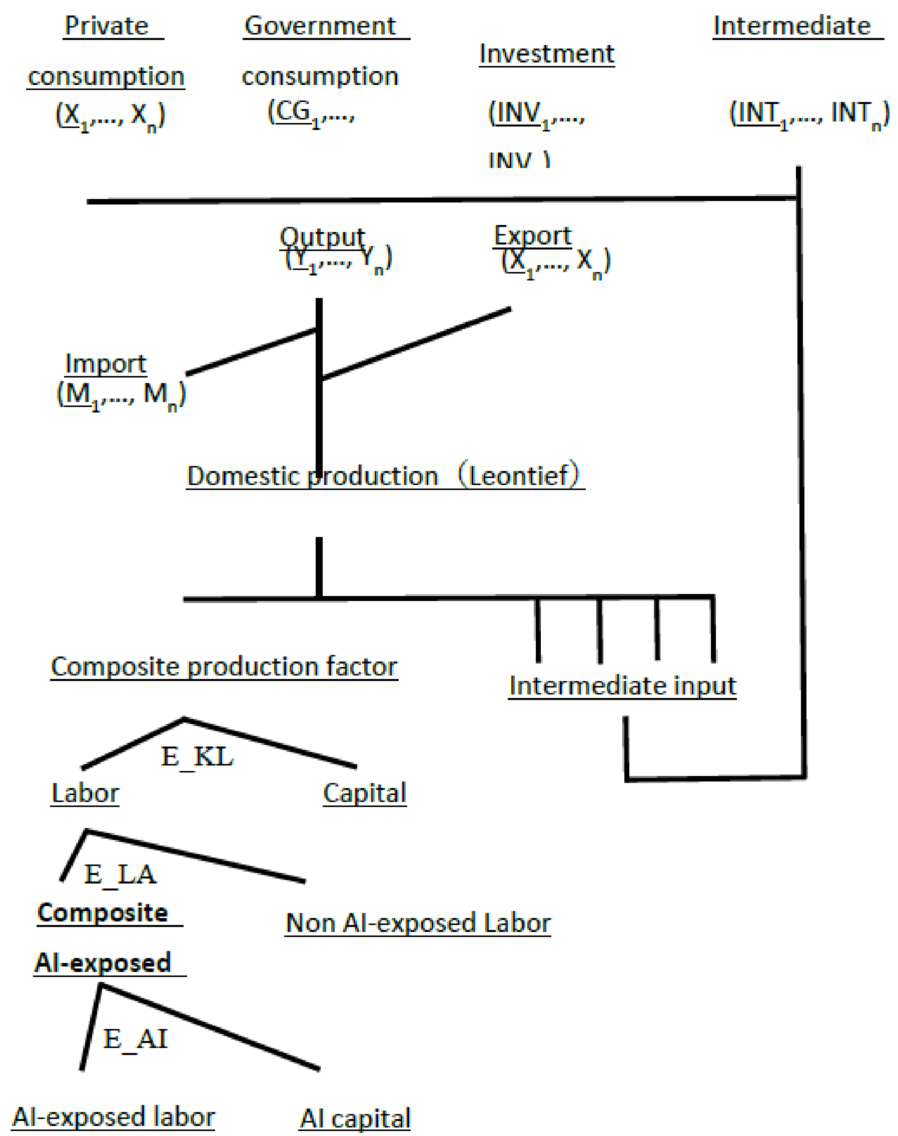
Webb's AI Exposure Rate Conversion 5: Result

Figure 1: Average Wage by Industry and AI Exposure Rate



CGE Model

Appendix 1: CGE Model Structure



Simulation Scenario

Case 1: Elasticity of substitution between AI and AI-exposed labor = 5

Case 2: Elasticity of substitution between AI and AI-exposed labor = 0.8

Case 3: Top 5 industries, elasticity of substitution between AI and AI-exposed labor = 5

Bottom 5 industries, elasticity of substitution between AI and AI-exposed labor = 0.8

Medium-income industries, elasticity of substitution between AI and AI-exposed labor = 3

Simulation premise

- AI capital endowment
  3% of physical capital, but 1 % for real estate ,and petroleum and coal products industry.

- AI capital increased by 10 percentage point to 6% of physical capital.

- Outflow of wage of AI capital: No outflow.

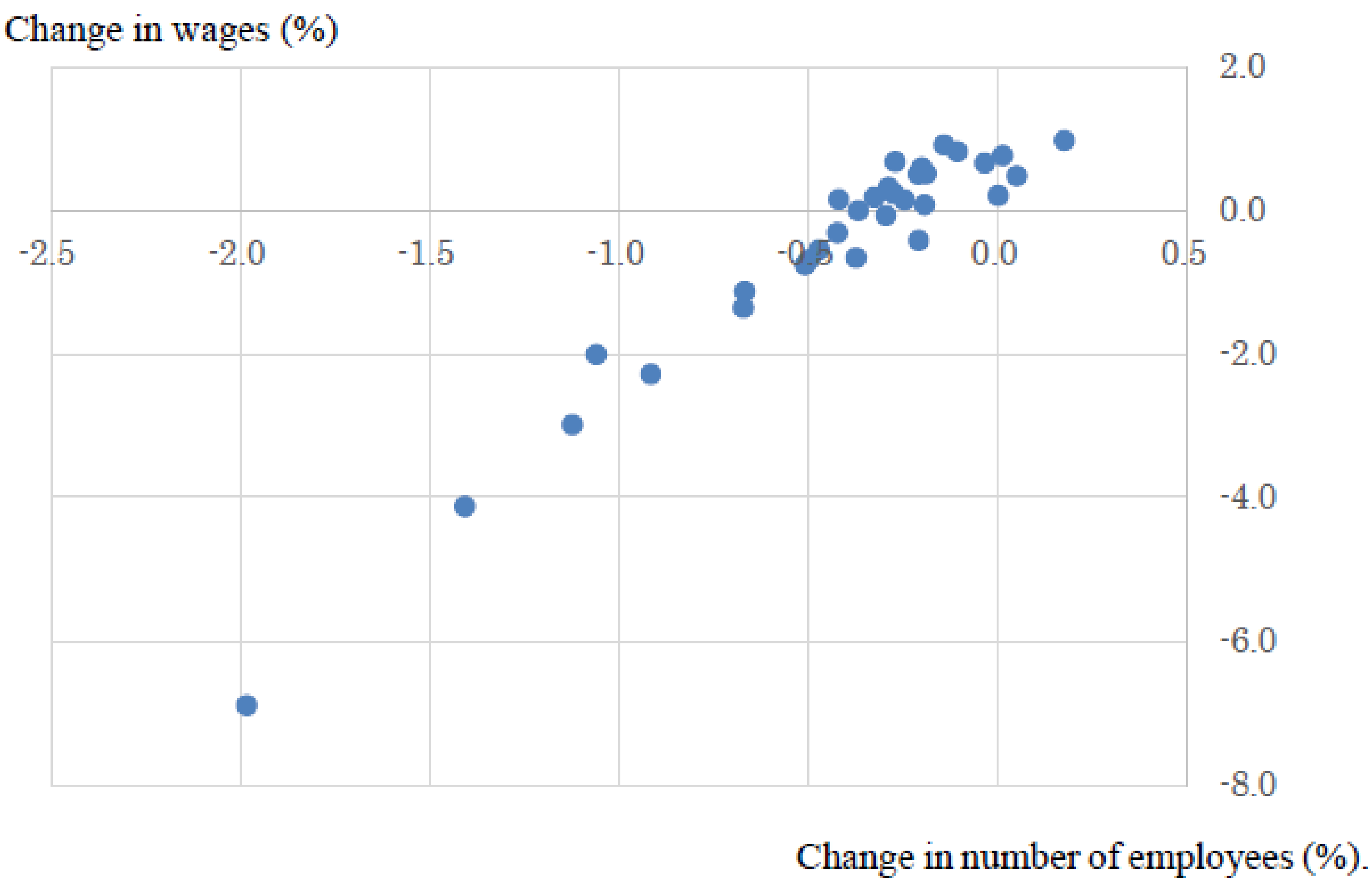
- CGE model follows Saito et al (2017).

Simulation Result: Case1, Change in wages and average wage by industry

Figure 2: Change in Wages, E_AI = 5, Case 1

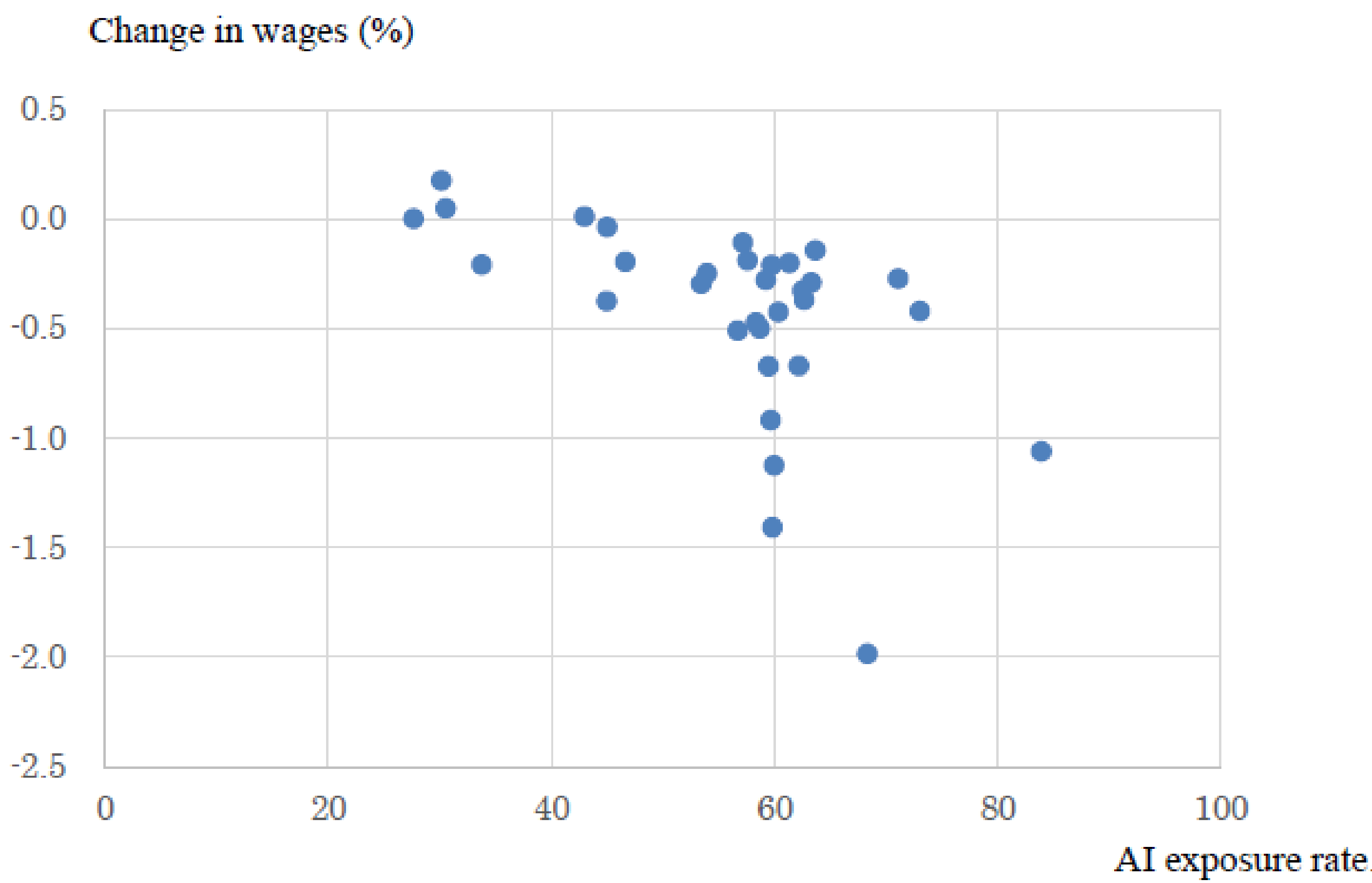
Simulation Result: Case1, Change in wages and change in number of employees

Figure 4: Change in Wages and Number of Employees, E_AI = 5, Case 1



Simulation Result: Case1, Change in wages and AI exposure rate

Figure 6: Change in Wages and AI exposure rate, E_AI = 5, Case 1

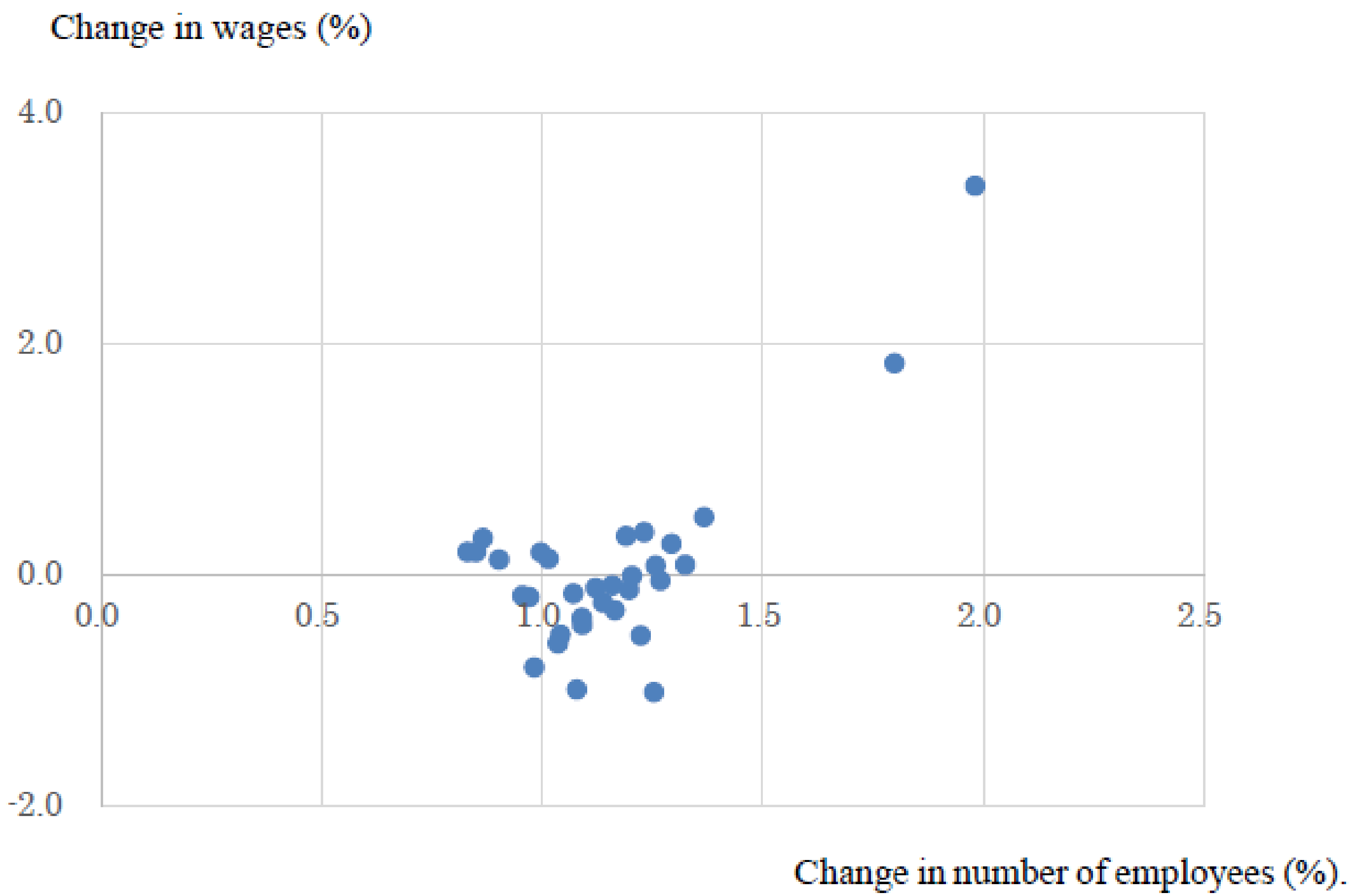


Simulation Result: Case2, Change in wages and average wage by industry

Figure 3: Change in Wages and Average Wage by Industry, E_AI = 0.8, Case 2

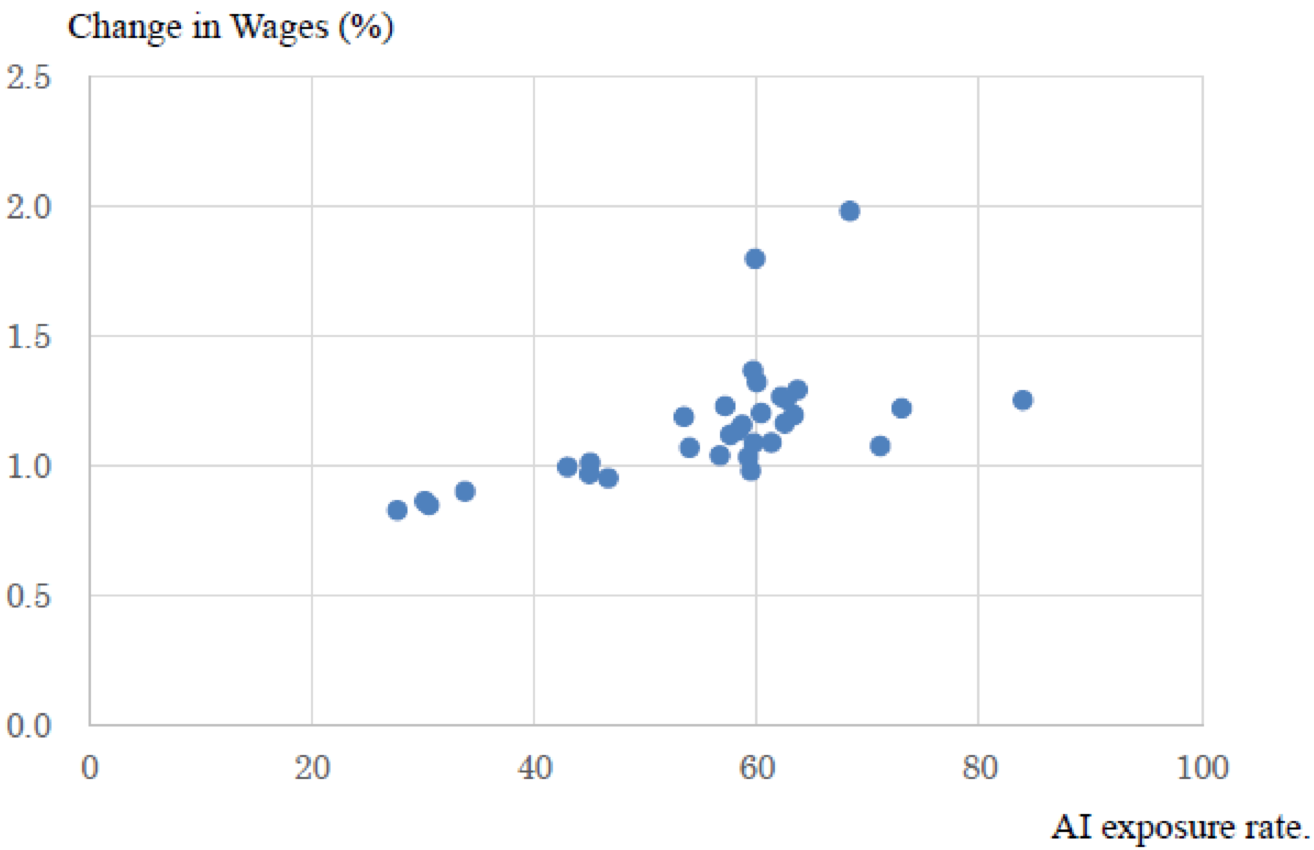
Simulation Result: Case2, Change in wages and change in number of employees

Figure 5: Change in Wages and Number of Employees, E_AI = 0.8, Case 2



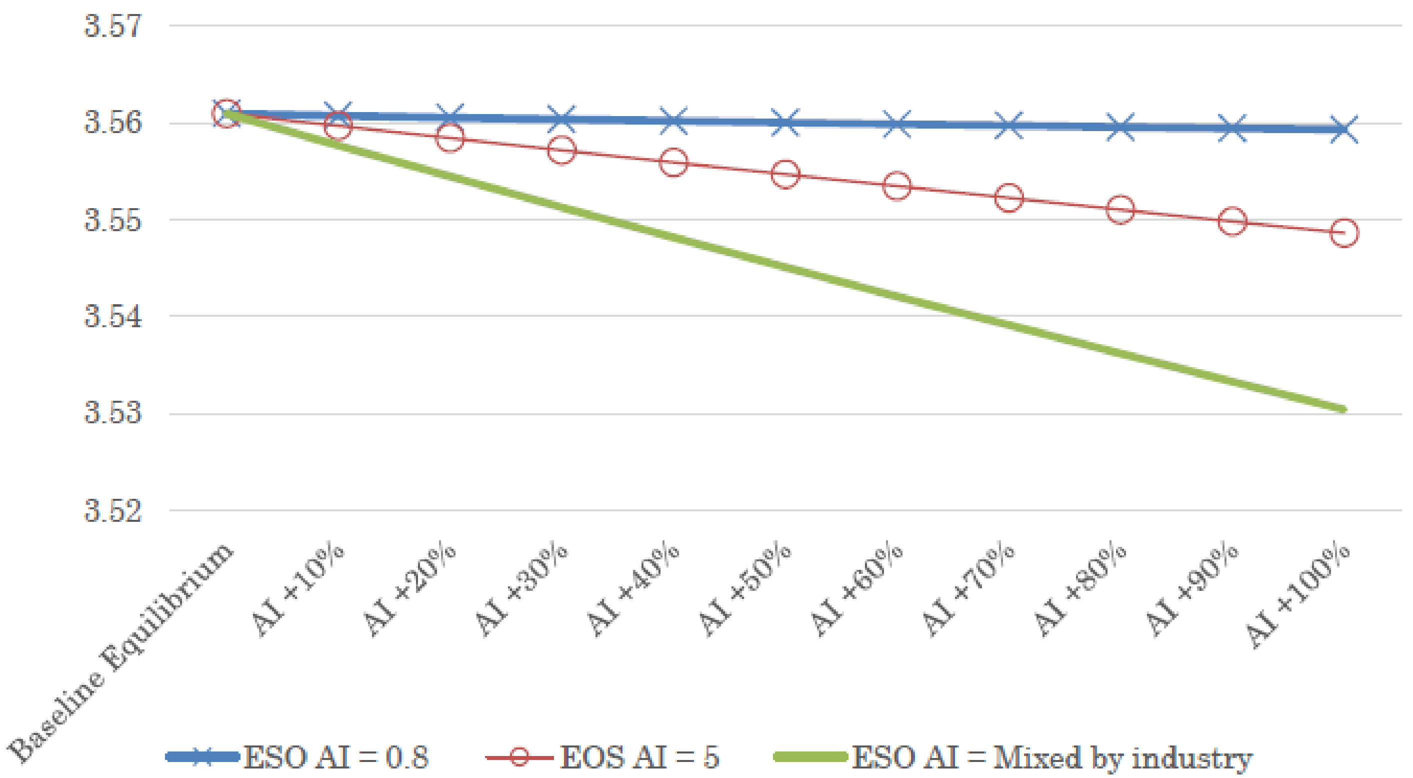
Simulation Result: Case 2, Change in wages and AI exposure rate

Figure 7: Change in Wages and AI exposure rate, E_AI = 5, Case 2



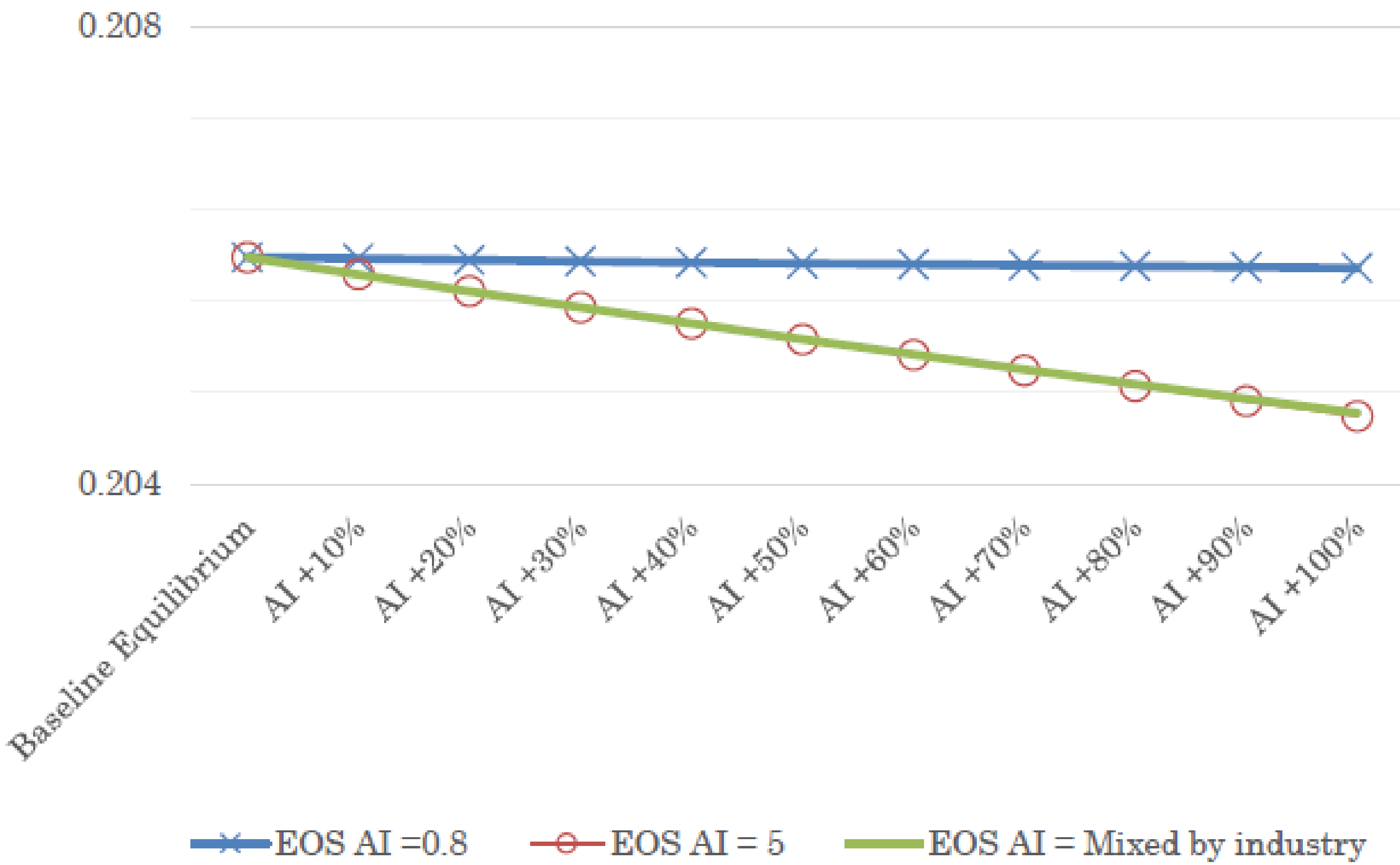
Simulation Result: Inequality in wage, ratio of top 5 and bottom 5

Figure 8: Ratio Between Top 5 Industry Average Wage and Bottom 5 Industry Average Wage with an Increase of AI



Simulation Result: Inequality in wage, Gini coefficient

Figure 9: Gini Coefficient with an Increase of AI



Sensitivity Analysis

Table 5: Difference Between Baseline and 100% increase of AI Capital

Wage inequality in top 5 and bottom 5 industry's average wage

EOS_AI	0.6	0.0006	EOS_AI	3	-0.0105
	0.8	-0.0021		5	-0.0123
	0.9	-0.0016		7	-0.0132

Gini Coefficient

EOS_AI	0.6	0.00020	EOS_AI	3	-0.00116
	0.8	-0.00015		5	-0.00138
	0.9	-0.00009		7	-0.00149

Conclusion 1

(Main findings)

1. Wage inequality decreases with an increase of AI capital if substitution of AI and AI exposed labor is not so complementary.

2. Wage inequality in top 5 and bottom 5 industry's average wage decreases most in Case 3.

3. Wage inequality in the Gini coefficient decreases most in Case 1.

Conclusion 2

(Limitation)

1. Accuracy of conversion from Webb's AI exposure rate to JIP.
2. Analysis made by average wage by industry.
3. AI deployment can be done disproportionately by industry.

(Future research)

1. Comparison of simulation result by Webb's IT and robot exposure rate.
2. AI exposure rate other than Webb (2020).