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

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The Effect of AI on Wages in Japan Using Computable General Equilibrium Model[†]

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Abstract:

We quantitatively analyzed the effect of AI deployment to wage inequality with a 32-sector CGE model. In our model, labor force was divided into AI-exposed labor and non-AI-exposed labor using Webb (2020)'s AI exposure rate. We examined the effect on wage inequality by increasing AI capital from 3% of physical capital to 6% of physical capital. The results are as follows, (i) wage inequality decreases with an increase of AI capital if AI is not so complmentary to human labor, (ii) wage inequality in top 5 and bottom 5 industry's average wage decreases most if AI is substitutive in high-income industries and AI is complementary to low-income industries, and (iii) wage inequality in Gini coefficient decreases most if AI is substitutive to human labor.

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1. INTRODUCTION

Artificial Intelligence (AI) technology is now rapidly being developed and deployed in society. Some of the tasks of human labor are considered to be replaced by AI. The effect of AI on human labor differs depending on the role of AI in that occupation, replacement of some tasks, or replace of occupation as a whole. Occupation-based analysis using machine learning by Frey and Osbourne (2013) predicts 47 percent of occupations can be replaced by AI, while task-based analysis in the same manner as Arntz, Gregory, and Zierahn (2016) predicts only 7 percent of jobs will be replaced by AI.

In this paper, we analyzed the effect of AI exposure on human labor and wages using a computable general equilibrium model (CGE model) and AI exposure rate by occupation calculated by Webb (2020). AI exposure rate, which is a measure of the "exposure" of occupations in AI technology, calculation follows occ1990dd classifications [1]. We convert that occupation classification into Japanese JIP data containing 108 industries and 7 categories of occupations. For each industry by category, AI exposure rate is assigned and number of AI-exposed human labor is calculated. In our CGE model, AI is considered to be substitute or complement to AI-exposed human labor and the composite of AI and AI-exposed human labor is used as a production factor in the model in the same war as non-AI-exposed human labor and capital.

What occupation will be exposed to AI most? Webb (2020) points out "in contrast to software and robots, AI is directed at high-skilled tasks." That is, Webb's AI exposure rate has a positive relationship with wage. It implies that if AI is a substitute of AI-exposed human labor, average wage in those industries that use AI-exposed human labor intensively decreases as an increase of AI input and that of those industries that do not use AI-exposed human labor increases or at least not decrease so much compared with high AI exposed industries. Under this assumption, wage inequality is expected to decrease mainly because a decrease in wages in high-AI-exposed occupations, which are usually high wage. However, if AI is

[1] The occ1990dd occupation classification is U.S. Census occupation codes of occupations for the 1980, 1990, and 2000 Census.

complementary to AI-exposed human labor, the average wage of "all" industries increases and we miss the quantitative impact of AI to income inequality. Note that the mechanism of AI deployment to mitigate or aggravate income inequality by industry is unique from a view of previous studies.[2] Still we have no consensus about the role of AI deployment yet.

To assess the impact of AI deployment in the CGE model, we set three scenarios of relationships between AI and AI-exposed human labor; Case 1 is substitutive, Case 2 is complementary, Case 3 is complementary to bottom 5 industries and substitutive to top 5 industries. We set up the Case 3 by following implication of previous studies in the below which mention negative impact on high-income occupations and positive effect on low-income occupations.

Our simulation results show that as for the ratio between top 5 industries' average wage and bottom 5 industries' average wage, Case 1 lowers income inequality more than Case 2 and Case 3 tops to improve income inequality. As for the Gini coefficient, Case 1 tops to improve income inequality and Case 3 shows almost the same effect as Case 1 while Case 2 merely works to improve income inequality. Poor results of Case 2, to improve income inequality, can be explained by a high AI capital accumulation for middle-AI-exposed ratio industries, which tend to have more physical capital. Average wage of those industries rises and consequently income inequality was not fixed well.

We begin by reviewing recent development of assessment of AI on labor. Frey and Osborne (2013) built a model and calculated the probability of job automation for 702 occupations and then classified occupations based on these probabilities to estimate the expected impact of automation on the US labor market by using 70 original hand-labelled occupations as training data. Their estimates suggest that 47 percent of jobs in the US were at a "high-risk" (of more than 70 percent) of being replaced by computerization within the next one or two decades. One other feature of their calculation is that replacement of human labor by AI starts from

[2] Higuchi (1991) reports "wages by industry are affected by current profit, product price, production level and globalization." By Ota (2010), wage premium by industry can also be affected by deregulation. Ota (2010) also points out that wage premium by industry has not changed so much up to 2006, after a shrink in the first half of 1990s in Japan.

"low skilled labor," that is, low-wage workers.

Based on the approach by Frey and Osborne (2013), Arntz, Gregory, and Zierahn (2016) estimated the risk of automation and digitalization for jobs while taking the heterogeneity of workers' "tasks" within occupations into account. They found that, when examined at the task level, an average of 9 percent of jobs across the 21 OECD countries are automatable. Even though automatability and digitalization are unlikely to destroy large number of jobs in the paper, low qualified workers will likely bear the brunt of the adjustment costs as automatability of their jobs is higher compared with highly qualified workers.

Acemoglu et al. (2021) made a regression analysis about AI-related vacancies over 2010-2018 and found no discernible impact of AI exposure on employment or wages at the occupation or industry level, implying that AI is currently substituting for humans in a subset of tasks but it is not yet having detectable aggregate labor market consequences [3].

Watanabe et al. (2021) made micro-level analysis about the role of AI on worker's productivity in the same occupation, suggesting AI is complementary to human labor and will raise productivity. They found that AI improves drivers' productivity by 5% on average and its gain is concentrated on low-skilled drivers while almost zero gains on high-skilled drivers.

Webb (2020) developed a new method to predict the impacts of technology 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. Webb found that, in contrast to software and robots, AI is directed at high-skilled tasks. Under the assumption that historical patterns of long-run substitution will continue, Webb estimated that AI will reduce 90:10 inequality, but will not affect the top 1%.

The remainder of this study is organized as follows. Section 2 introduces the dataset we use in our analysis, including how we converted Webb's AI exposure rate for US occupation into Ja. In addition, it provides descriptive statistics and describes the relationships among

[3] Contrary to Acemoglu et al. (2021), Grenan and Michaely (2020) reports "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."

variables. Section 3 presents a CGE model whose factors are AI-exposed human labor, non-AI-exposed human labor, physical capital, and AI. Section 4 presents our model simulation results. Finally, Section 5 concludes and presents remarks on possible future extensions.

2. DATA

This section introduces the data we use in our CGE analysis, describes the conversion of US occupational AI exposure by Webb (2020) to that of Japan, and provides basic descriptive statistics.

2.1.US AI exposure rate

Here the way of AI exposure rate calculation method by Webb (2020) is briefly explained. Webb (2020) used Google Patents Public Data and O*NET database of occupations and tasks for job descriptions. On the patent side, Webb chose the set of patents corresponding to a particular technology. For each pair, Webb (2020) calculated how often that pair, or ones similar to it, occurs in the list of all pairs. For occupation, verb-noun pairs are collected and the relative frequency of similar pairs in patent titles are assigned. To get a single overall score of occupations, an average of all the verb-noun pairs mentioned in the task descriptions of the occupation, weighted by the "importance" of the task to the occupation.

Relative frequency is calculated as $rf_c^t = \frac{rf_c^t}{\sum_{c \in C^t} f_c^t}$, where technology t, verb-noun pair c. By this relative frequency, AI exposure is calculated as follows.

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

In the above equation, $K_i$is the set of tasks in the occupation i,$S_k$is the set of the verb-noun pairs extracted from task $k \in K_i$.$\omega_{k,i}$, the weight of task k in occupation i, is an average of the frequency, importance, and relevance of task k to occupation i, as specified in the O*NET database, with weights scaled to sum to one.

2.2. Conversion Webb's US AI exposure rate to Japanese occupation classification

Webb's US AI exposure rate has 341 occupations and it is converted into Japanese occupations in line with the Japan Industrial Productivity Database (JIP) code. JIP code has 108 industries and seven categories of occupations, technicians, managers, office workers, sales workers, service personnel, and production workers for each industry. That is, we have 756 categories of occupations in JIP and it implies that Webb's US AI exposure rate cannot have one-to-one correspondence with JIP for all of the occupations.

We tried to match occupations by US AI exposure rate with occupations by industry of JIP in three ways: (i) one-to-one conversion, (ii) group-to-one conversion, (iii) group-to-group conversion, which are prioritized in this order.

As an example of (i) one-to-one conversion, we can use "Financial managers" in O*NET assigned to financial industry's "administrative occupation worker" in JIP. As an example of (ii) group-to-one conversion, we use a group of occupations such as "Tailors, dressmakers, and seamstresses," "Winding and twisting textile and apparel operatives," etc. corresponds to textile industry's craftsman and manufacturing and construction workers." Webb's AI exposure rate is weighted sum by the number of each occupation in the US. As for (iii) group to group conversion, I assigned the group of workers in O*NET to professions in several industries in JIP since I could not find out one-to-one or group-to-one correspondence in some professions between O*NET and JIP. For example, "professional and technical workers: manufacturing average," which is a weighted sum of occupations in Table 2, are assigned to "professional and technical workers" of textile industry, and pulp paper and wood products in JIP.

JIP, for all occupations, assigns the proportion of workers, $Occ_{i,j}$ industry i and occupation$j$, is summed to be one, $\sum_j Occ_{i,j} = 1$. Let the AI exposure rate for industry i and occupation$j$be $AI\_rate_{i,j}$. AI exposure rate for industry $i$can be calculated as $AI\_rate = \sum_j AI\_rate_{i,j} * Occ_{i,j}$.

2.3. Relationship between AI Exposure Rate and Wages

Before we discuss the model, let us discuss the relationship between AI exposure rate and wages. In previous studies, Frey and Osbourne (2013) discussed that negative relationship between wages and educational attainment with an occupation's probability of computerization. Arnz, Gregory and Zierahan (2016) also pointed out that automatibility of low-qualified workers is highly likely to be higher than that of high qualified workers and they might bear the adjustment cost of automatibility. Contrary to preceding papers, Webb (2020) found high-skilled tasks could be replaced by AI, while software or robots could replace low-skilled tasks.

Figure 1 shows the result of conversion to JIP. High-wage industry corresponds to high-AI exposure rate. This result is in line with Webb (2020). Note that we cannot see the relationship between the wage of executives and their AI exposure rate directly since this is industry-level aggregation.

Table 3 shows occupational average wage and AI exposure rate. High-skilled occupations, such as professional and technical workers, administrative workers and clerical workers, are highly exposed to AI, while low-skilled occupations, such as sales workers, service workers and craftsman and manufacturing and construction workers, are not. The reason of low-AI-exposure rate for low-skilled occupation is that tasks of those occupations are composed of more physical tasks than high skilled occupations and AI cannot be substitutable to those tasks.

3. THE MODEL

In this section we explain the model for simulations. The structure of the model is based on Saito, Kato and Takeda (2017). In our model, AI capital and a composite AI-exposed labor are added. Our model is a small open economy for Japan with 32 sectors[4]. All markets are considered to be perfectly competitive and all agents act as price takers.

As for production, firms are assumed to have production function with constant returns to scale. Appendix 1 shows the model structure including production function, which is a multi-stage CES function. Note that E_KL, E_LA, E_AI in Appendix 1 are elasticity of substitution of each stage. Firms use intermediate inputs, capital stock, and two types of labor force, AI-

[4] Originally, JIP data and corresponding IO table of Japan have 108 sectors.

exposed labor and non-AI-exposed labor, explained in the previous section. Note that mining sector uses specific factor, that is natural resource, and mining sector's production function tree is different in this point.

AI and AI-exposed labor are first aggregated into a labor composite, then composite of AI-exposed labor and non-AI-exposed labor are aggregated into labor composite. Finally, labor composite and capital are aggregated into a primary factor composite. The output is determined using a fixed coefficient aggregation of the primary factor composite and other intermediate inputs, that is Leontief production function.

The value of the elasticity of substitution is provided in Table 4. Therefore, our model is a standard CGE model, while labor is divided into two types, AI-exposed labor and non-AI-exposed labor, and AI is introduced in the production function. The products are allocated to foreign and domestic markets through a constant elasticity of transformation (CET) function.

As for the demand side, we assume a representative household to maximize its utility with CES utility function. The household earns its income by providing production factors to firms and uses its income for consumption and saving. Saving rate is assumed to be constant. Savings are used for investment and accumulated to capital stock.

As for trade, Japan is assumed to be a small country and the Armington assumption is used. Under the Armington assumption, domestically produced goods and imported goods are imperfect substitutes. Domestic and imported goods are aggregated through a CES function. In this model, the current account is equal to trade balance minus remittance by AI capital holders. We see the effect of remittance mainly on consumption by with and without remittance. Exchange rate, the price of foreign currency, is determined such that the current account is equal to the benchmark value.

Note that our CGE model comes from the dataset of 2010 Input-Output Table of Japan, in which AI is not so much included as 2022. In that sense, this study has limits in functions and parameters of which AI has different values from physical capital or traditional software investment.

4. SIMULATIONS AND THEIR RESULTS

In this section, we simulated the effect of AI deployment to average wage by industry using the CGE model explained in the last section. Three scenarios are set by the value of elasticity of substitution of AI and AI-exposed labor. The effect on income inequality is measured by a Gini coefficient and the ratio between top five industries' average wage and bottom five industries' average wage.

4.1. Simulation Scenario

We assume initial AI deployment is 3 percent to physical capital [5] and the model is solved with that AI capital then AI capital is increased by 10 percent point up to be doubled and become 6 percent of physical capital and the rise of AI capital effect on wage and wage gap by industry is calculated. Let us call this benchmark equilibrium. Note that each scenario, explained below, has its own benchmark equilibrium.

Next, we set elasticity of substitution between AI and AI-exposed labor from 5, AI-exposed labor being strongly substitute to AI, to 0.8, AI-exposed labor being complement to AI and analyzed the effect on wage and wage gap by industry. Let the former be Case 1 and the latter be Case 2. In the Case 1 assumption, AI's complementarity of human labor is from Kanazawa et al. (2021), "AI improves drivers' productivity by shortening the time to search for customers by 5% on average." Case 2 assumption, AI's substitute of human labor, is from Frey and Osbourne (2013), "According to our estimates, around 47 percent of total US employment is in the high-risk category."

Finally, we analyzed the mixture of AI's complementary effect and substitute effect at the same time by letting the AI and AI-exposed labor's elasticity of substitution of low-income industry, whose wages are lower than average, be 0.8 and that of high-income industry, whose wages are higher than average, be 5. For middle-income industries, we set elasticity of

[5] In the model, the share of AI to physical capital of real estate and petroleum and coal products are set to be 0.01 since its level of physical capital is large.

substitution to be 3. This Case is called Case 3 [6]. We set this scenario because preceding papers indicate that AI has different effects on wages by the nature of tasks, and same for occupations. Kanazawa et al. (2021) estimated high-productivity gains for low-skilled taxi drivers [7]. On the other hand, there are some researches which say AI deployment is being done in high wage industry such as Grenan and Michaely (2020). We discuss the simulation result of Case 3 only in inequality.

4.2. Simulation Results

First, we see the results of Cases 1 and 2. Simulation results of wage change and average wage by industry are shown in Figures 2 and 3. In Case 1, average wage of high-wage industry decreases, while the average wage of high-wage industry increases in Case 2. In particular, there is a large difference in impact on wages in middle-income industries, that is negative impact in Case 1 and positive impact in Case 2. The results reflect the relatively high AI exposure rate of middle-income industries in Figure 1. The impact on wages in middle-income industries affects income inequality by the Gini coefficient. Note that we observe a productivity gain, in terms of per capita GDP, by 0.9 percent with an increase of AI capital by 3 percentage points. As is the case of physical capital, capital accumulation leads a productivity gain in our model.

The changes of wage and number of employees are shown in Figures 4 and 5. In both Case 1 and Case 2, the number of employees decreases as average wage decreases. In the CGE model, since there is no unemployment, all workers are employed and the number of employees increases even though the average wage of some sectors decreases.

We compare the change of wages and AI exposure rate in Figures 6 and 7. Average wage in high AI exposure rate industry decreases in Figure 6 while average wage in high AI exposure rate increases in Figure 7. The wage increase in middle AI exposure rate industry is large in

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[6] All elasticity of substitution values is shown in Table 4.

[7] In our model, taxi driver is classified into transport sector, TRS in Appendix 3. However, taxi driver's income is not high enough.

Figure 7.

Figure 8 shows the ratio between the top five industries' average wage and bottom five industries' average wage. It is intuitive that Case 1, the high substitution case, lowers income inequality by AI capital accumulation since high-income industries' AI exposure rates are higher and its average wage decreases more as in Figure 2. On the other hand, Case 2, the complementary case, does not change the ratio since average wage in both low-income industries and high-income industries increased as in Figure 3. In Case 3, average wage decreases for top 5 industries, whose AI-exposed rate is high, while average wage increases for bottom 5 industries. Then the ratio decreases most and income inequality is corrected.

The Gini coefficient in Figure 9 also shows Case 1 has lowered income inequality much while Case 2 does not affect income inequality so much. The result of Case 2 can be explained by AI capital accumulation for middle AI-exposed ratio industries, which tend to have more physical capital as in Figure 10, and that high AI capital raised wages of those middle-income industry. Consequently, all industry wages increased in Case 2 and income inequality does not change so much. In Case 3, since E_AI is set 3 for middle-income industries and average wage for those industries decrease, the simulation result of Gini coefficient is almost the same as Case 1.

4.3. Sensitivity Analyses

Since our simulation depends much on the value of E_AI, elasticity of substitution between AI and AI-exposed labor, then we did sensitivity analyses on different values of E_AI.

Table 5 shows that for wage inequality in top 5 and bottom 5 industry's average wage, wage inequality widens with high complementary E_AI value, 0.6 while income inequality shrinks with high substitutive value, 7. This result is in line with our main results.

The result of Gini Coefficient is in the same direction. Inequality widens with high complementary E_AI value, 0.6 while income inequality shrinks with high substitutive value, 7.

From those two values, the simulation results', whose assumption of E_AI has changed, quantative impact is in line with our main simulation results. It follows that the analyses in the previous sections have a certain level of robustness.

5. CONCLUSION

We quantitatively analyzed the effect of AI deployment to wage inequality. AI capital was introduced into a CGE model with a 32-sector CGE model. Labor force was divided into AI-exposed labor and non-AI-exposed labor. AI capital was combined with AI-exposed labor, then the composite of AI capital and AI-exposed labor is combined with non-AI combined labor. Three scenarios are thus set: AI and AI-exposed labor are substitute (Case 1), complement (Case 2) and substitute in high average wage industry and complement in low average wage industry (Case 3).

We examined the effect on wage inequality by increasing AI capital from 3% of physical capital to 6% of physical capital. The results are as follows, (i) wage inequality decreases with an increase of AI capital if substitution of AI and human labor is not so complmentary, (ii) wage inequality in top 5 and bottom 5 industry's average wage decreases most in Case 3, and (iii) wage inequality in the Gini coefficient decreases most in Case 1.

A decrease in wage inequality by substitutive elasticity of AI is from average wage reduction in relatively higher wage industries because their AI exposure rate is high. This result is in line with Webb (2020). Wage inequality decreased some under complementary elasticity of AI. Our simulation results suggest that AI capital accumulation reduce income inequality in some extent. However, as in Table 5, if we set super high complementary subsutitution value for E_AI, then wage inequality rises.

Our main results have some limitations. First, conversion of Webb's AI exposure rate to Japanese occupation might not be so precise and accurate. Second, indicator of wage inequality is calculated by industry aggregate average wage. There could be a wage difference in the same occupation and in the same industry. In a third, we expect AI deployment to start uniformly and proportionate to industry physical capital. There can be some other assumption to set AI capital deployment depending on industry level affinity to AI.

For future research, using exposure rate of robotics and IT that Webb (2020) calculated can be used to compare the results of this paper. Webb (2020) estimated that the particular occupation exposed to robots or software have resulted in declines in employment and wages even though the occupations that are exposed to robots and software are different from those of AI. In addition, income outflow by AI capital developers and holders, who are sometimes foreign companies, can also be discussed.

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

	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	**52**
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

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

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

Table 4: Values of Elasticity of substitution

Symbol	Sectors		Value
E_KL			
	AGR		0.2431
	MIN		0.2000
	FOO		1.1200
	TEX,PPW,CHM,PAC,CSC,IAS,NFM, MET, GMA, ELE, ICE, ELC, TRN, PRE, OTH, CNS, EGW, WAW, COM, FAI, RES, TRS, CAB, PUB, EDR, MED, OPS, BSE, PSE		1.2600
	ONS		1.4000
	COM, TRS		1.6800
E_LA			2
E_AI			
	Scenario		
	Case 1	for all industries	5.0
	Case 2	for all industries	0.8
	Case 3		
		Top 5 industry	
	CHM, PAC, EGW, WAW, PUB		5.0
		Bottom 5 industry	
	AGR, RES, MED, OPS, PSE		0.8
		Middle income industry	
	MIN,FOO,TEX,PPW,CSC,IAS,NFM,MET,GMA,ELE,ICE,ELC,TRN,PRE,OTH,CNS, COM,FAI,TRS,CAB,EDR,BSE		3.0

Note: Values of E_KL and E_LA is from Saito et al. (2017). Abbreviation of industries is in Appendix 2.

Table 5: Difference Between Benchmark 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

Figure 1: Average Wage by Industry and AI Exposure Rate

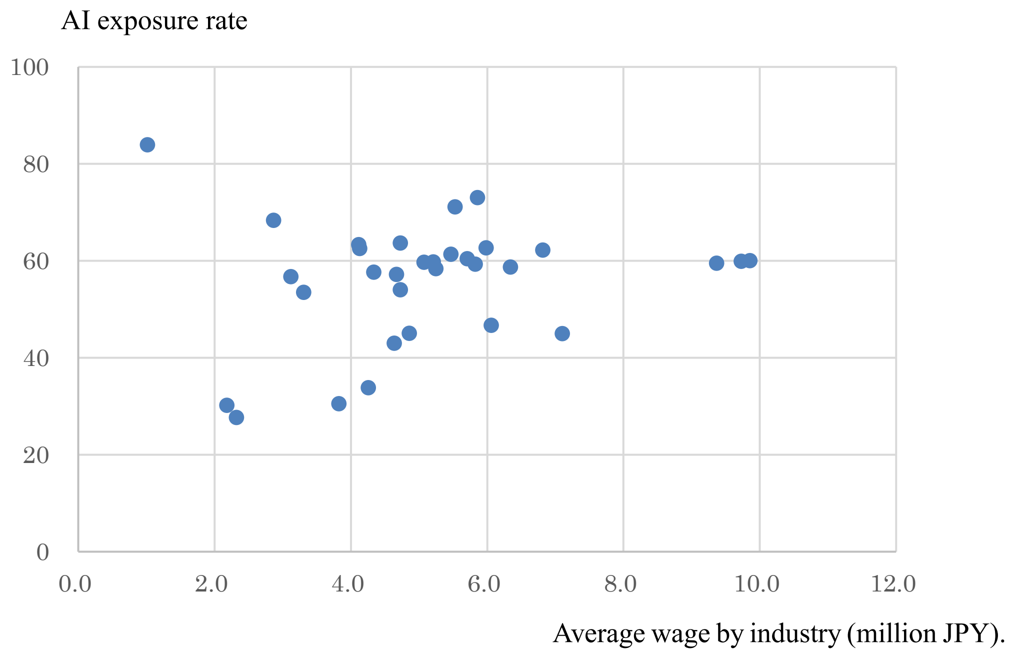


Figure 2: Change in Wages, E_AI = 5, Case 1

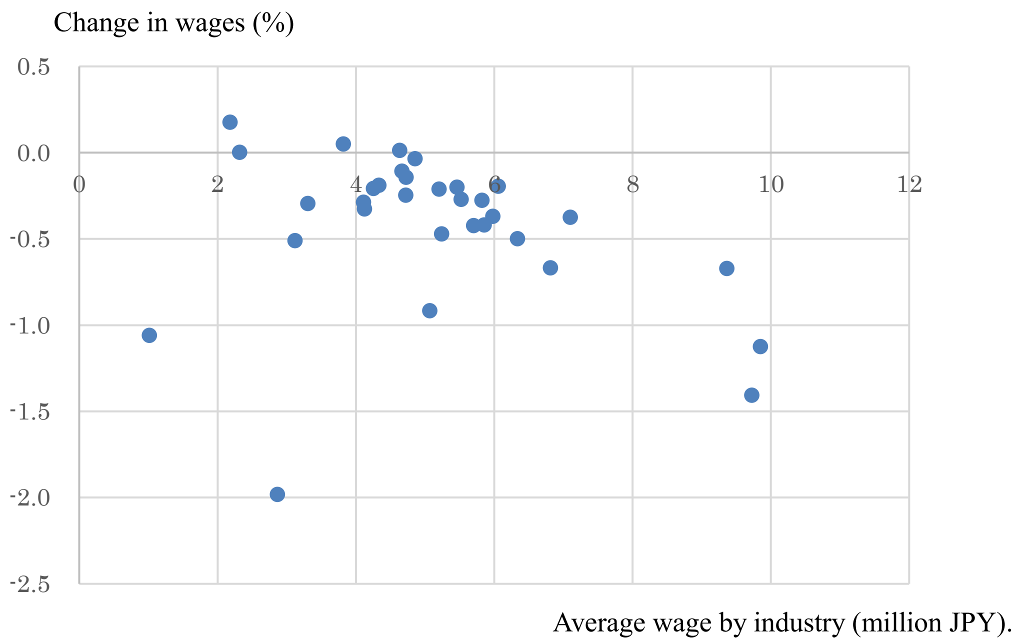
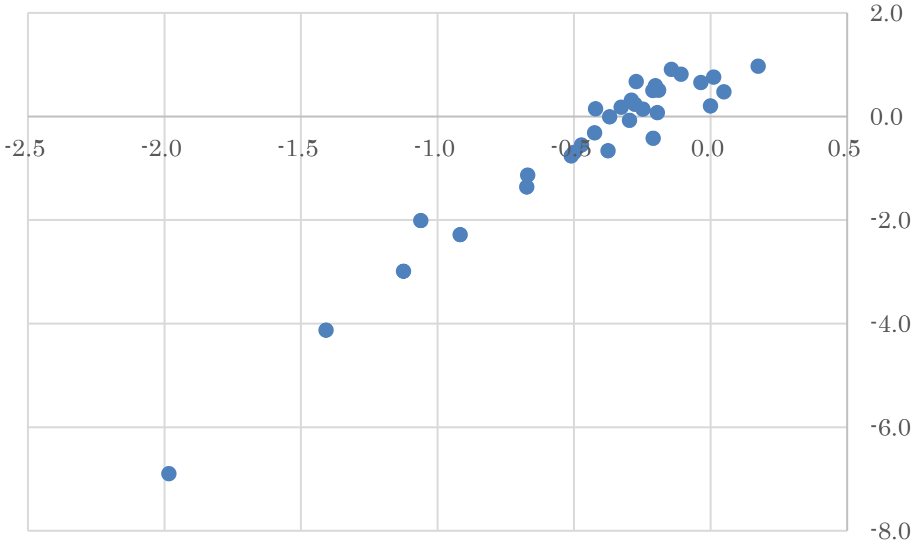


Figure 3: Change in Wages and Average Wage by Industry, E_AI = 0.8, Case 2

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

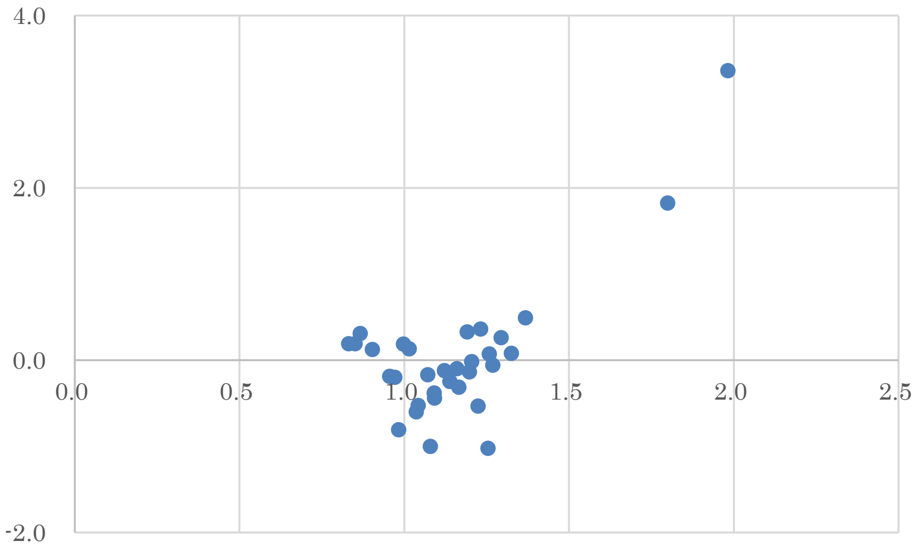
Change in wages (%)



Change in number of employees (%).

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

Change in wages (%)



Change in number of employees (%).

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

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

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

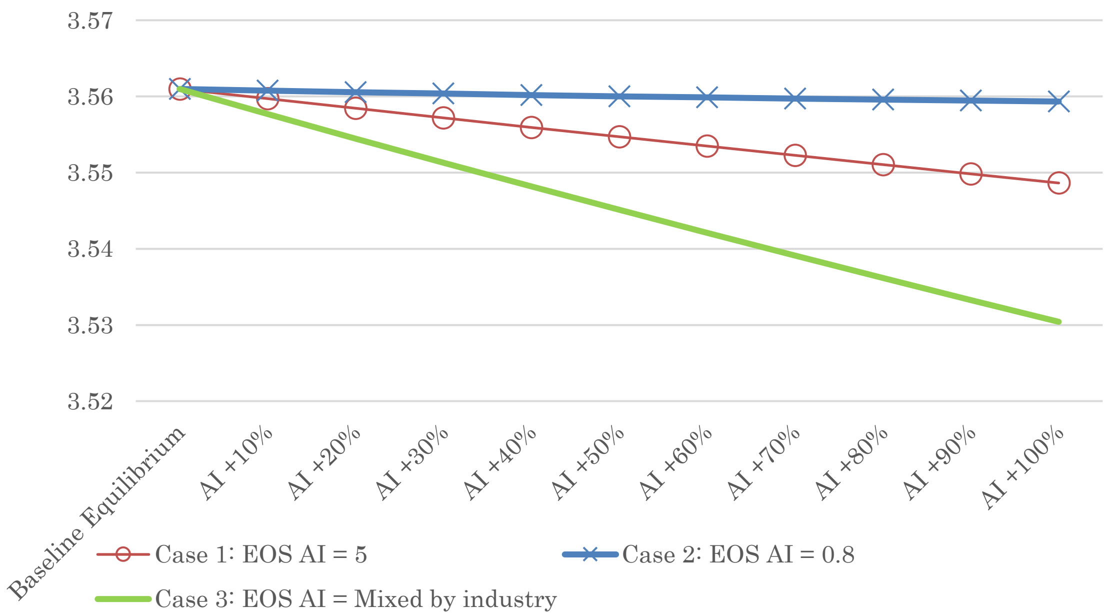


Figure 9: Gini Coefficient with an Increase of AI

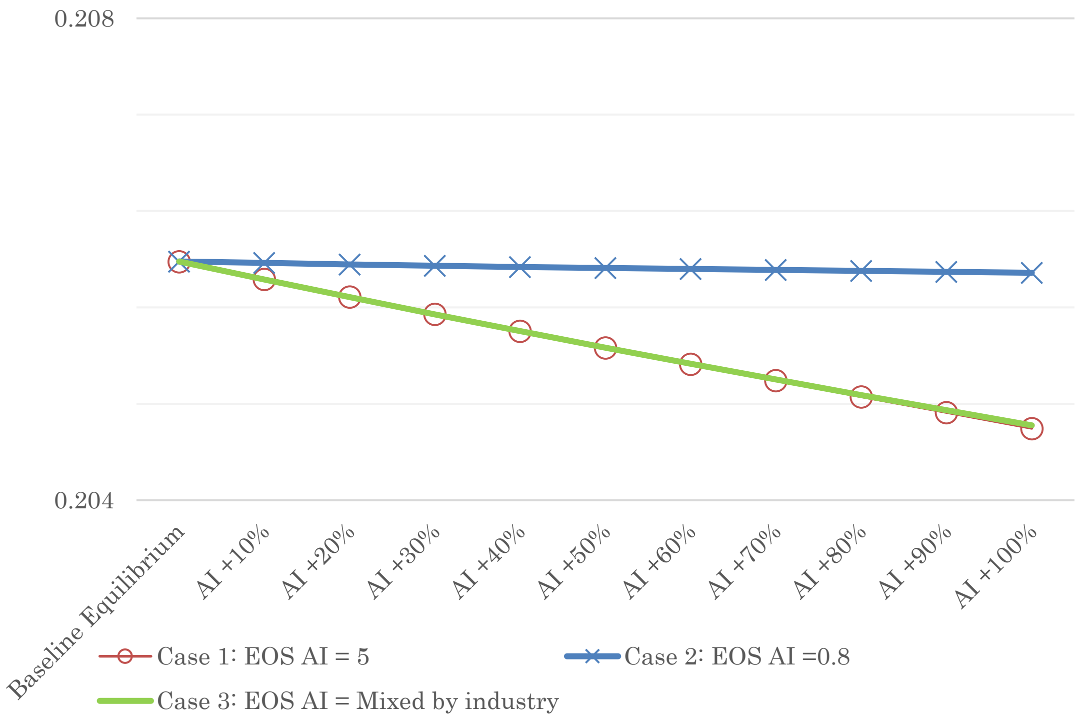
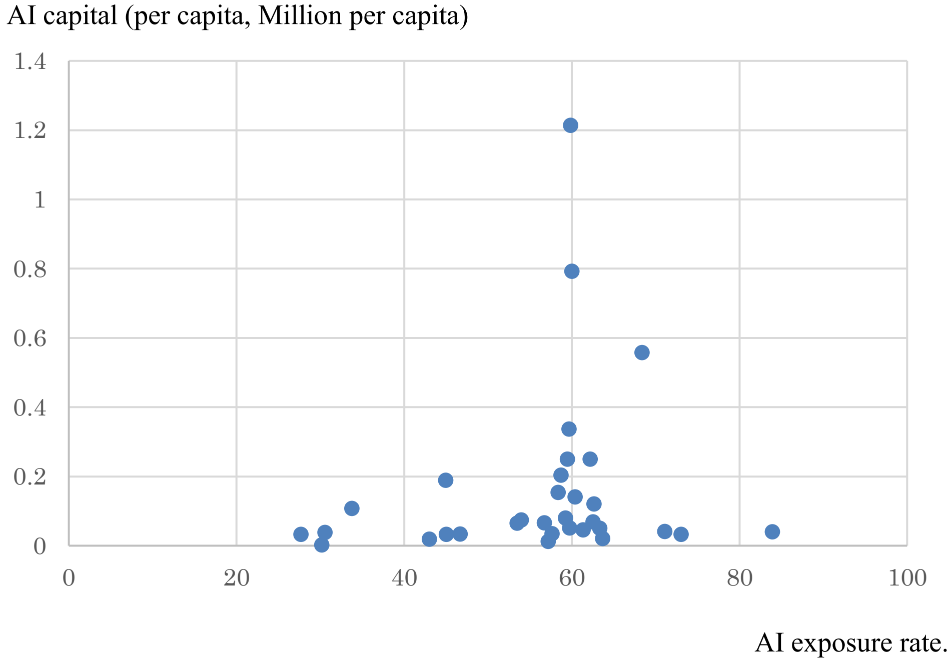
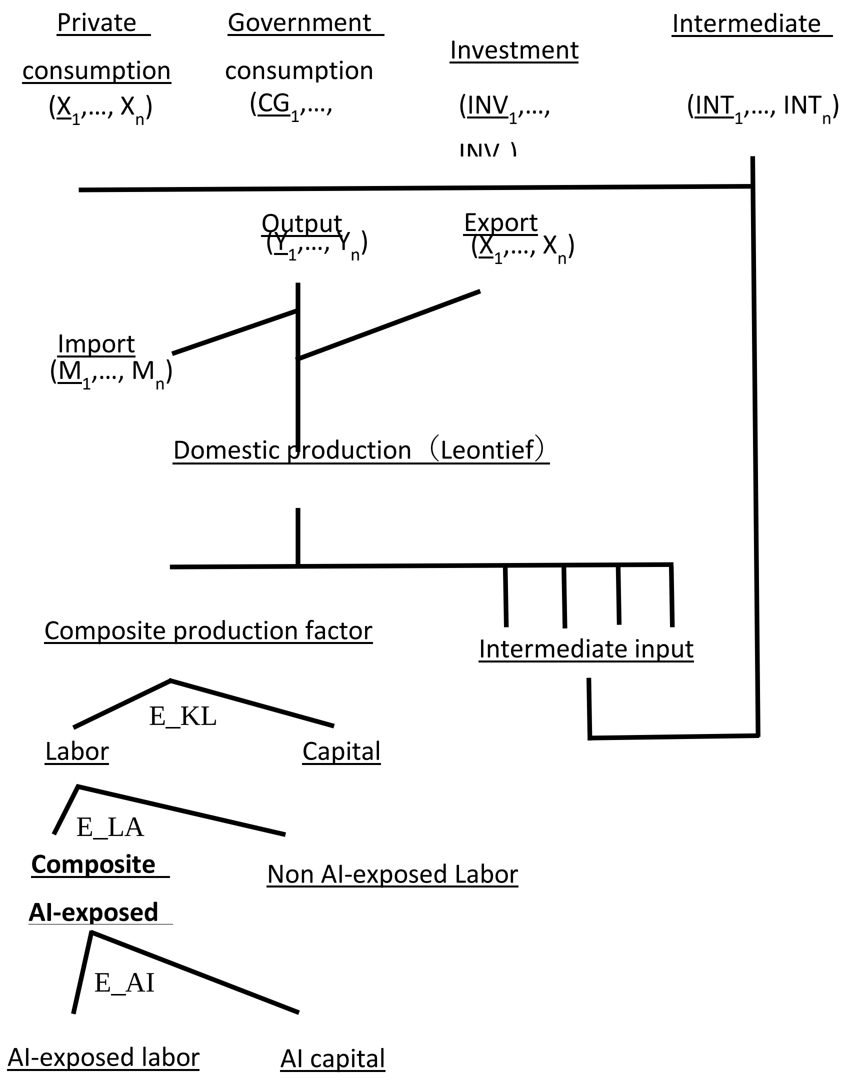


Figure 10: AI Capital and AI Exposure Rate



Appendix 1: CGE Model Structure



Appendix 2: Classification of 32 Industries

Symbol	Explanation	Symbol	Explanation
AGR	Agriculture, forestry and fishery	PRE	Precision instruments
MIN	Mining	OTH	Other manufacturing products
FOO	Food products	CNS	Construction
TEX	Textile products	EGW	Electricity, gas and heat supply
PPW	Pulp, paper and wooden products	WAW	Water supply and waste
CHM	Chemical products	COM	Commerce
PAC	Petroleum and coal products	FAI	Financial and insurance
CSC	Ceramic, stone and cray products	RES	Real estate
IAS	Iron and Steel	TRS	Transport
NFM	Non-ferrous metal	CAB	Communication and broadcasting
MET	Metal Products	PUB	Public administration
GMA	General Machinery	EDR	Education and research
ELE	Electrical Macinery	MED	Medical service, health and social security, and nursing care
ICE	Information and communication equipment	OPS	Other public services
ELC	Electrical equipment	BSE	Business services
TRN	Transportation equipment	PSE	Personnel services