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The Effect of AI on Wages in Japan Using Computable General Equilibrium Model, with Japanese AI Exposure Rate

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The Effect of AI on Wages in Japan Using Computable General Equilibrium Model with Japanese Patent Data†

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Abstract:

We quantitively analyzed AI deployment on wage inequality using Japanese AI exposure rate by Kawashima (2024) with a 32 sector CGE model. By using normalized AI exposure rate, the simulation results are as follows, (i) industry's average wage inequality decreases whether AI is substitute or complement to human labor, (ii) wage inequality in top 5 and bottom 5 industries' average wage increases if AI is complementary in high-income industries and substitutive in low-income industries, (iii) wage inequality decreases most if AI is substitutive in high-income industries and complementary in low-income industries.

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1. INTRODUCTION

As Artificial Intelligence (AI) technology is now rapidly being developed and deployed in society, the effect of AI on human labor is also being analysed in many ways. AI was understood to be good at repetitive work, but it is developing its area in judgement and Agrawal et al. (2018) shows that humans will delegate some decisions to machines even when the decisions would be superior with human input.

Frey and Osborne (2013) lead a recent assessment of AI on labor and 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. They also suggest that replacement of human labor by AI starts from “low-skilled labor,” that is, low-wage workers.

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 and found that AI is directed at “high-skilled tasks” reduces inequality.

Shinozaki et al. (2022) shows the effect of AI on Wages in Japan Using Computable General Equilibrium Model. It implies that (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. This simulation result depends on Webb (2020)’s AI exposure rate calculated by the US patent data and occupational data with applying to Japanese labor data.

In this paper, we use AI exposure rate by Kawashima (2024) in replace of Webb (2020). Kawashima (2024) calculated occupational AI exposure score using Japanese patent data and Japanese O-net occupational classification in the same manner as Webb. We applied the occupational AI exposure scores and into Japanese JIP data containing 108 industries and 7 cagories of occupations. Then the effect of AI exposure on human labor and wages in Japan is estimated using a computable general equilibrium model (CGE model).

More recent assessment of AI's impact on labor varies in studies. Agrawal et al. (2019) predicts that most applications of artificial intelligence have multiple forces that impact jobs, both increasing and decreasing the demand for labor. The net effect is an empirical question and will vary across and industries. Damioli et al. (2021) shows a positive and significant impact of AI patent families on employment, supporting the labour-friendly nature of AI product innovation.

As for specific technology, Noy and Zhang (2023) shows that participants assigned to use ChatGPT were more productive and efficient, and they enjoyed the tasks more. Participants with weaker skills benefited most from ChatGPT. Brynjolsson et al. (2023) provides suggestive evidence that AI model disseminates the best practices of more able workers and helps newer workers move down the experience curve, with averagely 14% of productivity gains including a 34% improvement for novice and low-skilled workers by using a generative AI-based conversational assistant. In addition, they find that AI assistance improves customer sentiment, increases employee retension, and may lead to worker learning.

As for Large Language Models (LLMs), Eloundou et al. (2023) finds that impacts by LLMs are not restricted to industries with higher recent productivity growth. Their analysis suggests that, with access to an LLM, about 15% of all worker tasks in the US could be completed significantly faster at the same level of quality.

Felten et al. (2023) finds that the top occupations exposed to language modeling include telemarketers and a variety of post-secondary teachers and that the top industries exposed to advances in language modeling are legal services and securities, commodities, and investments. They also find a positive correlation between wages and exposure to AI language modeling. This finding coincides with our analysis.

The remainder of this study is organized as follows. Section 2 introduces the dataset we use in our analysis, including how we converted Kawashima (2024)'s results into JIP data. Section 2 also provides the distribution features of Kawashima (2024)'s AI exposure rate which causes different results on simulation compared with Shinozaki et al. (2022). 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 providing basic descrictive statistics and describes the conversion of Japanese occupational AI exposure rate by Kawashima (2024) to CGE database.

2.1. Japan AI exposure rate

Kawashima (2024) established unique dataset consisted of description and patents. As for job description, "JobTag[1]", which is Japanese O*NET, is used. JobTag provides information about 484 jobs in Japan with their tasks and skills. As for patent data, Kawashima (2024) used Patent Office to use patent data, 9,421,030 patents in total.

After constructing database of job description and patents, verb-noun pairs are extracted by two types, that is, "noun + verb or nominal verb[2]" or "noun by nominal verb[3]". Note that Kawashima (2024) developed "MorePhraseExtractor", which can extract "noun + nominal verb" and "noun by nominal verb" pairs in addition to "noun + verb" pairs.

After setting up verb-noun pairs' database of patent and job description, Kawashima (2024) follows Webb (2020) for AI exposure rate calculation, that is, calculating an occupation's final exposure score using the set of aggregated verb-noun pairs extracted from its task descriptions in the following manner. For a given technology, $t \in T$, let f_c^t denote the raw count of occurrences of aggregated verb-noun pair *c* extracted from technology *t* patent, and let C^t denote the full set of aggregated verb-noun pairs for technology. The relative frequency, rf_c^t, of aggregated verb-noun pair *c* in technology *t* patent is as follows.

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

1 https://shigoto.mhlw.go.jp/User/
2 Nominal verb is known as "sa-hen doshi".
3 Noun by nominal verb is known as "sa-hen meshi".

Then we have AI exposure rate by the following equation.

$$Exposure_{i,t} = \sum\nolimits_{k\in K_i}\left[\omega_{k,i} * \sum\nolimits_{c\in S_k} rf_c^t\right] \Big/ \sum\nolimits_{k\in K_i}\left[\omega_{k,i} * |\{c: c \in S_k\}|\right].$$

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. Nomalization

Now we have Japanese AI exposure rate by occupation[4] and these rates will be normalized by following Webb (2020)'s standardization. First, we multiply original AI exposure rate by 1000[5]. Secondly, we set minimum value to be 0 and maximum value to be 100. By the calculation of $y = \{(x - x_{min})/(x_{max} - x_{min})\} * 100$ where x is original series, we have normalized AI exposure rate. Let this series call "AE1". Figure 1 shows the histogram of normalized series, but it looks skewed in low values compared with the standardized result of Webb (2020) as in Figure 2.

Then we first take logarithm of Kawashima (2024)'s AI exposure rate and normalize it. Note that two occupations[6] with zero is set to be zero. Again, by the calculation of $y = \{(x - x_{min})/(x_{max} - x_{min})\} * 100$ where x is logarithm of original series. Let this series call "AE2". Figure 3 shows the histogram of AE2.

The advantage of using AE2 is less dependance by outliers and its distribution is less skewd. Note that Webb (2020)'s original AI exposure score also has skewed distribution as in Figure 5 and standardized to almost uniform distribution as in Figure 3. Then it seems better to reduce the effect of ouliers for computation work and we will use AE2 instead of AE1. We will show the calculation results of AE1 and compare it with the result of AE2 in the sensitivity analysis section.

[4] Data is available; https://www.esri.cao.go.jp/jp/esri/prj/hou/hou089/hou89.pdf.
[5] AI exposure rate is not probability but measure of AI exposure. Webb (2020) also multiplied original series by 1000.
[6] Tour guide and illustrator.

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

Kawashima (2024)'s AI exposure rate has 425 occupations and it is converted into Japanese occupations in line with the Japan Industrial Productivity Database (JIP) code. JIP code has 108 industries and six 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 Kawashima (2024)'s US AI exposure rate cannot have one-to-one correspondence with JIP for all of the occupations.

We tried to match occupations to industries and categories of occupations that are expected to belong to. It implies that an ocuupation can be allocated into multiple industries. Table 1 shows allocation results of occupations to six types of occupations in Automobile industry. Occupational AI exposure rate by industry are calculated by taking simple average of AE1 and AE2 values.

Table 2 shows the aggregate occupational types' AI exposure rate calculation results. Average of aggregate occupational types' results show that average of AE 1 is far less than that of AI exposure rate by Webb (2020) while average of AE 2 is bigger than Webb (2020). This difference comes from basic nature of their distribution. Figure 2 shows frequency of AE 1 and Figure 3 and Figure 4 show that of Webb (2020) and AE 2 respectively.

Figure 2 shows a skewed distribution of AE1 compared with Webb (2020) in Figure 3. Figure 3 looks a uniform distribution. Another feature of AE1 is that most occupations are distributed between 0 to 20. It implies that whole distribution is affected by some outliers in the process of normalization. Then we have AE2 in Figure 4, which is normalized after taking logarithm, it looks more normally distributed than AE1. Disturbance by some outliers is expected to be mitigated by the combination of logarithm and normalization. Then we will use AE2 for simulation work from now.

2.3. Relationship between AI Exposure Rate and Wages

Next, let us discuss the relationship between AI exposure rate and wages. Webb (2020) found high-skilled tasks could be replaced by AI, while software or robots could replace low-skilled tasks. He implies that there can be a positive relationship between AI exposure rate and wages. In Shinozaki et al. (2022), Webb (2020)'s AI exposure rate, which is converted into JIP data, shows positive relationship with average wage by industry.

Figure 6 shows the result of AE 2 and implies that industries with high average wage correspond to high-AI exposure rate. This result is in line with Webb (2020) and AI exposure rate by Kawashima (2024) has the same characteristics. Note that this is a relationship between AI exposure rate and average wage by industry, not a direct correspondence between AI exposure rate by occupation and its wage. Since Japanese O*NET does not provide precise information about wage for each occupation then we do not discuss about a direct correspondence between AI exposure rate by occupation and its wage.

Table 2 shows occupational AI exposure rate of Shinozaki et al. (2022), AE2 and AE1, for reference. AE2 and AE1 share common features with Shinozaki et al. (2022) that 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.

However, difference between high-skilled workers and low-skilled workers is not so high in AE2 compared with Webb (2020). This is from difference of the AI exposure rate's distribution of AE2, which is almost normal distribution, and Webb (2020), which is almost uniform distribution. Webb (2020) provides tail-sided AI exposure rate to occupations more than Kawashima (2024).

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) and the model structure is almost the same as Shinozaki et al. (2022). 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[7]. All markets are assumed to be perfectly

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

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-exposed labor and non-AI-exposed labor. 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 2024. 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. We are going to use four scenarios, which are set by the value of elasticity of substitution of AI and AI-exposed labor. To analyze the effect on income inequality by a Gini coefficient and the ratio between top five industries' average wage and bottom five industries' average wage.

4.1. Simulation Scenario

First, we use the same assumption of initial AI deployment to physical capital as Shinozaki et al. (2022), that is 3 percent[8]. The model is first solved with that amount of 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.

As for four scenarios, we have Case 1, Case 2, Case 3 and Case 4[9], with elasticity of substitution of 0.5, 0.8, 3, 5 and 8 depending on our assumption of AI on employment. Elasticity of substitution more than one implies that AI is substitutive to human labor while elasticity of substitution less than one implies AI is complement to human labor. In Case 3 and Case 4, AI is assumed to have both substitution effect and complement effect. This is because AI is found to have different effects, substitution or comeplement, to human labor by nature

[8] 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.

[9] 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.

of ocuupations' tasks and average wage by the following research. Kanazawa et al. (2021) estimated high-productivity gains for low-skilled taxi drivers[10]. On the other hand, Grenan and Michaely (2020) says that AI deployment is being done in high wage industry. Then we set elasticity of substitution to be 0.8 in five lowest average wage industries and 5 in five highest average wage industries in Case 3. In Case 4, we set parameter in the opposite direction, that is, 0.5 is set for half industries in ascending order of average wage and 8 for half industries in descending order of average wage. Then Case 4 implies that AI is complement in high-wage industries and substitutive in low-wage industry. Note that we discuss the simulation result of Case 3 and Case 4 only in inequality, Gini coefficient and average wage disparity.

4.2. Simulation Results

Simulation results of change in average wage by industry in Case 1[11] and Case 2 are shown in Figure 7 and Figure 8 respectively. Case 1's average wage of high-wage industry decreases in Figure 7, while we see a weak rise in average wage of high-wage industry in Case 2, in Figure 8. In addition, in Case 1, almost all industries show a deline in average wage and in Case 2, almost all industries show a rise in average wage. This result implies high substitution effect for high-wage industries and weak complementary effect for low-wage industries. Then income inequality may be decreased by an increase of AI deployment.

Figure 9 and Figure 10 shows the simulation results of changes of wage and number of employees in Case 1 and Case 2, respectively. In both cases, the change of number of employees has potive relationship with the change of average wage. That is, more workers get jobs in better paid industries.

Now Figure 11 and 12 show the result of change in wages by AI exposure rate in Case 1 and Case 2 respectively. Average wage in high AI exposure rate industry decreases in Figure 11 while average wage in high AI exposure rate industry increases in Figure 12. The opposite

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

[11] For simplicity, we discuss the result of Case 1 and Case 2 from Figure 7 to Figure 12.

results are from substitution effect in Case 1 and complementary effect in Case 2 by deployment of AI. Those results are in line with assumptions on AI of each case.

Figure 13 shows the simulation result of the ratio between the top five industries' average wage and bottom five industries' average wage by deployment of AI. Even though Case 1 and Case 2 has opposite effect of AI on wages, the ratio decreases. It implies that deployment of AI, calculated by Kawashima (2024), reduces income inequality if AI is substitutive or complementary as in Figure 7 and Figure 8. In Case 3, the ratio decreases most since elasticity is set to be complementary for low-wage industry and supplementary for high wage industry. In Case 4, elasticity is set to the opposite to Case 3. That is, elasticity is set to be complementary for high-wage industry and substitutive for low-wage industry. AI deployment amplifies substitution effect on low-wage workers and complementary effect on high-wage workers then AI deployment intensifies wage disparity.

Figure 14 shows the simulation result of Gini coefficient and the result is in line with the wage ratio. Gini coefficient falls in Case 1, Case 2 and Case 3 and increases in Case 4. Then we could check the effect of AI deployment on wage depending on its assumptions being substitutive or complement.

4.3. Sensitivity Analysis

4.3.1 Elasticity

We made sensitivity analyses on different values of E_AI. Table 4 shows that for wage inequality in top 5 and bottom 5 industry's average wage, wage inequality shrinks even with high complementary E_AI value, 0.6 but income inequality shrinks faster with high substitutive value, 7. We see the same result in Gini coeficient. This result is in line with our simulation results in Figure 14. The result of sensivity analyses proves a certain level of robustness in our simulation results in the previous section.

4.3.2 Another AI exposure rate

Another robustness check is about another AI exposure rate, AE 1. Figure 15 and Figure

16 show the simulation results of AE1 on wage ratio and Gini coefficient. We can observe a difference in simulation result of average wage ratio in Case 2. In Figure 13, the average wage ratio decreases with an increase of AI capital while it increases slightly in Figure 15. This is from occupational disparity of AI exposure rate is higher in AE1 than in AE2. But in terms of Gini coefficient, inequality decreases in Case 2 with AE1. Even though we see some differences with Figure 13 and Figure 14, the basic results are almost the same. It implies that robustness of computation work does not depend so much on selection of AE1 and AE2, that is, difference of normalization process of AI exposure rate.

5. CONCLUSION

We adopted occupational AI exposure rate, computed by Kawashima (2024) which used JobTag and Japanese patent data, and quantitatively analyzed the effect of AI deployment to wage inequality by following Shinozaki et al. (2022) with a 32-sector CGE model. AI exposure rate by aggregate occupation types show that AI exposure rate is higher in skilled workers but its occupational difference is less than Webb (2020).

AI-exposed labor and non-AI-exposed labor are divided by using four types of labor force and their AI exposure rate by industry. In the CGE model, 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 for computation. Four scenarios are set as follows; (1) AI and AI-exposed labor are substitute, (2) complement, (3) substitute in high average wage industry and complement in low average wage industry, (4) complement in high average wage industry and substitute in low average wage industry. The effect on indutry average wage inequality is examined by increasing AI capital from 3% of physical capital to 6% of physical capital for those four scenarios.

The simulation results are as follows; (i) industry's average wage inequality decreases whether AI is substitute or complement to human labor, (ii) wage inequality in top 5 and bottom 5 industries' average wage increases if AI is complementary in high-income industries and substitutive in low-income industries, (iii) wage inequality decreases most if AI is substitutive in high-income industries and complementary in low-income industries. Simulation results are consistent with Shinozaki (2024). Furthermore, AI's larger impact on high-wage workers, which can be negative or positive depending on assumptions, is in line with Webb (2020).

Our main results still have some limitations. First, conversion of Kawashima (2024)'s occupational AI exposure rate to Japanese occupation in CGE might not be so precise and accurate. Second, even though this is the nature of CGE model, indicator of wage inequality is calculated not by more detailed occupational wage but by industry aggregate average wage. We usually see a wage difference among workers who belong to the same industry and are engaged in the same job. Wage disparity can be explained by some factors, such as work experience, educational attainment e.t.c., which are assumed to be replaced by AI. In a third, 2010 Input Output data is used in the model. It seems better to use latest IO data for calculation to reflect current economic structure.

For future research, the convergenve of AI and Robotics using time series data of those two Exposure Rates can evaluate the effect especially on wages of low-skilled workers since AI seems to have potentially larger impact on high-skilled workers as we see in this paper.

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Table 1: Conversion of Kawashima (2024)'s AI exposure rate to JIP, Automobile industry

54. Automobile			
Professional and technical workers		AE1	AE2
	Marketing researcher	45.9	82.0
	Industrial designer	20.5	72.1
	CAD operator	15.5	68.6
	Planning and coorddination staff	4.5	53.5
	Entrepreneur	3.6	50.8
	NC machine tool engineer	7.3	59.4
	Mold pattern engineer	9.3	62.4
	Boiler operator	13.2	66.6
	Autonomous driving engineer	4.2	52.7
	Mechanical design engineer	14.6	67.9
	Plant design ensineer	7.4	59.6
	Average	**13.3**	**63.2**
Administrative occupation workers			
	Manager	0.3	21.2
	Sales manager	30.1	76.8
	Quality control manager	86.6	89.8
	Operation/management (IT)	31.5	77.4
	Human resources manager	25.8	74.9
	Accounting manager	23.9	74.0
	General affairs manager	21.1	72.4
	Average	31.3	69.5
Clerical workers			
	General affairs staff	10.9	64.3
	Human resources staff	3.9	51.7
	Production and process management staff	11.9	65.3
	Clerical worker	25.7	74.8
	Legal staff	17.6	70.2
	Accounting staff	6.9	58.7
	Average	**12.8**	**64.2**
Sales workers			
	Web marketing staff	26.8	75.4
	IR staff	20.9	72.3
	PR staff	6.0	56.9
	Sales staff	14.1	67.4
	Average	**16.9**	**68.0**
Service workers			
	Secretary	2.0	43.7
	Receptionist	3.5	50.5
	Average	**2.8**	**47.1**
Craftsman and manufacturing and construction workers			
	Forklift driver	37.3	79.4
	Factory worker	52.1	83.5
	Welder	7.3	59.3
	Average	**32.2**	**74.1**

Table 2: Aggregate AI Exposure Rate by Occupation

Occupations	AI exposure rate (Webb(2020))	AE1	AE2
Professional and technical workers	62.3	15.5	62.4
Administrative occupation workers	67.3	23.0	65.3
Clerical workers	62.5	13.0	64.0
Sales workers	26.4	12.2	56.3
Service workers	29.2	5.3	47.3
Craftsman and manufacturing and construction workers	51.9	21.0	64.7

Table 3: 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 4: Difference Between Benchmark and 100% increase of AI Capital, AE2

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

EOS_AI	0.6	-0.0035	EOS_AI	3	-0.0092
	0.8	-0.0045		5	-0.0102
	0.9	-0.0050		7	-0.0107

Gini Coefficient

EOS_AI	0.6	-0.0001	EOS_AI	3	-0.0011
	0.8	-0.0003		5	-0.0012
	0.9	-0.0004		7	-0.0013

Figure 1 Illustration of process for constructing AI exposure rate [1]

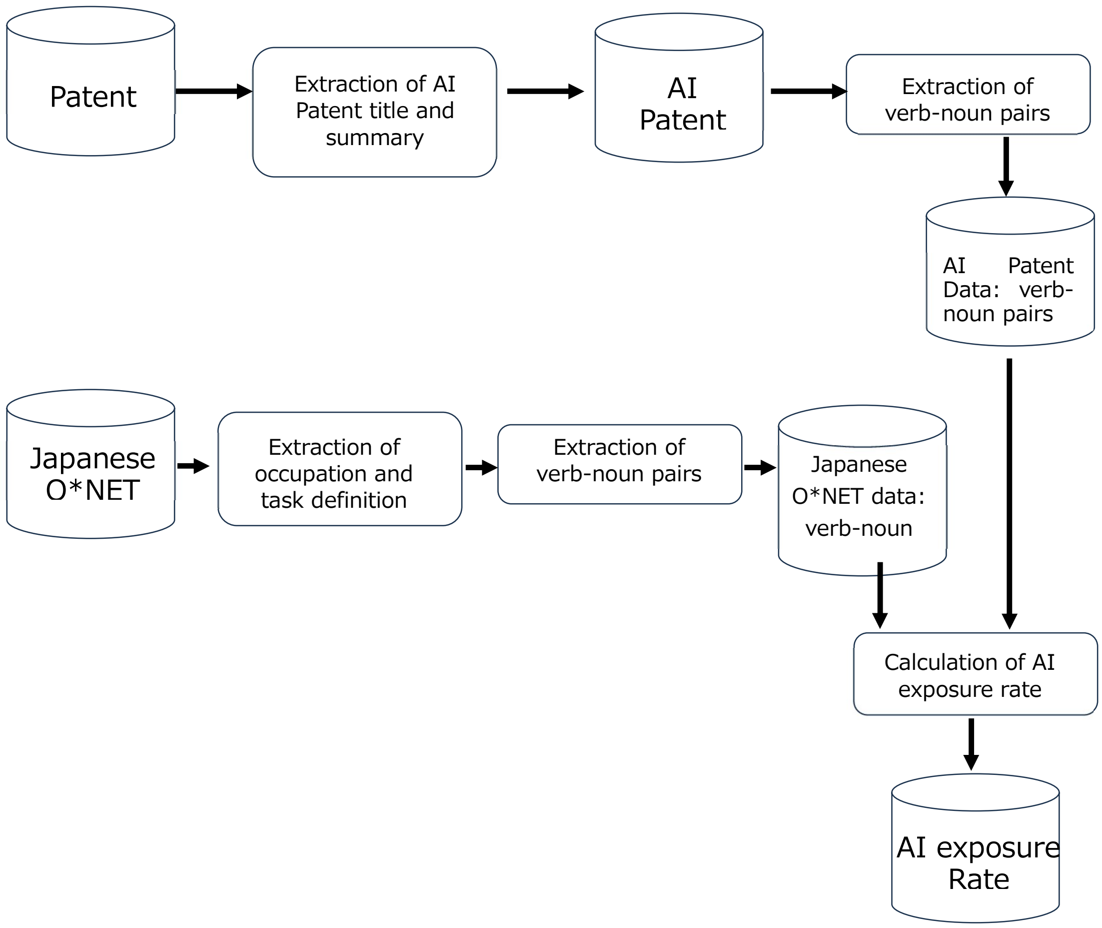
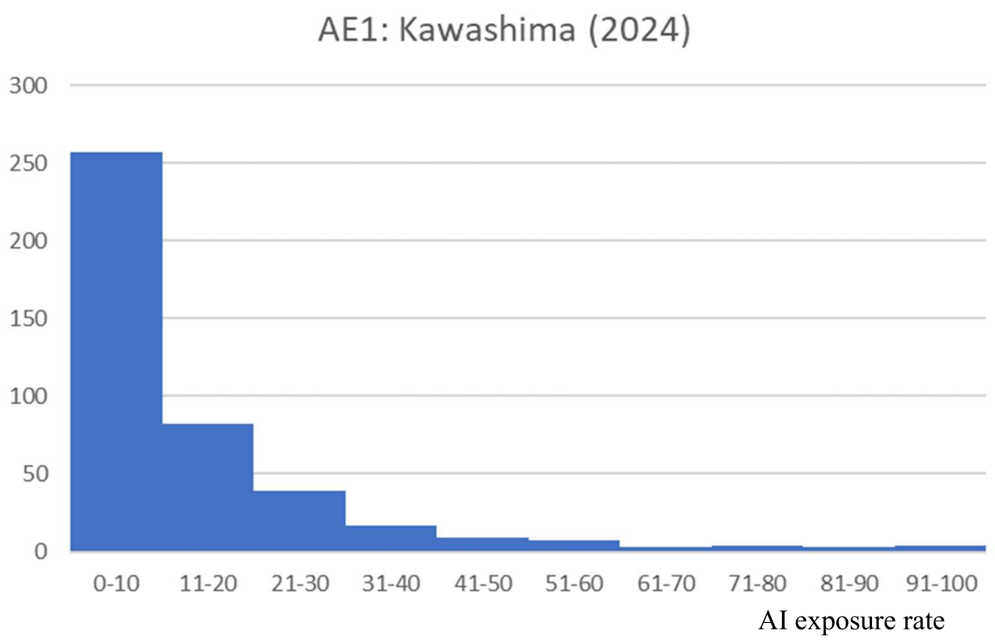


Figure 2: Frequency of Original AI Exposure Rate 1 (AE1)



[1] Figure 1 is edited from Kawashima (2024).

Figure 3: Frequency of AI Exposure Rate, Webb (2020)

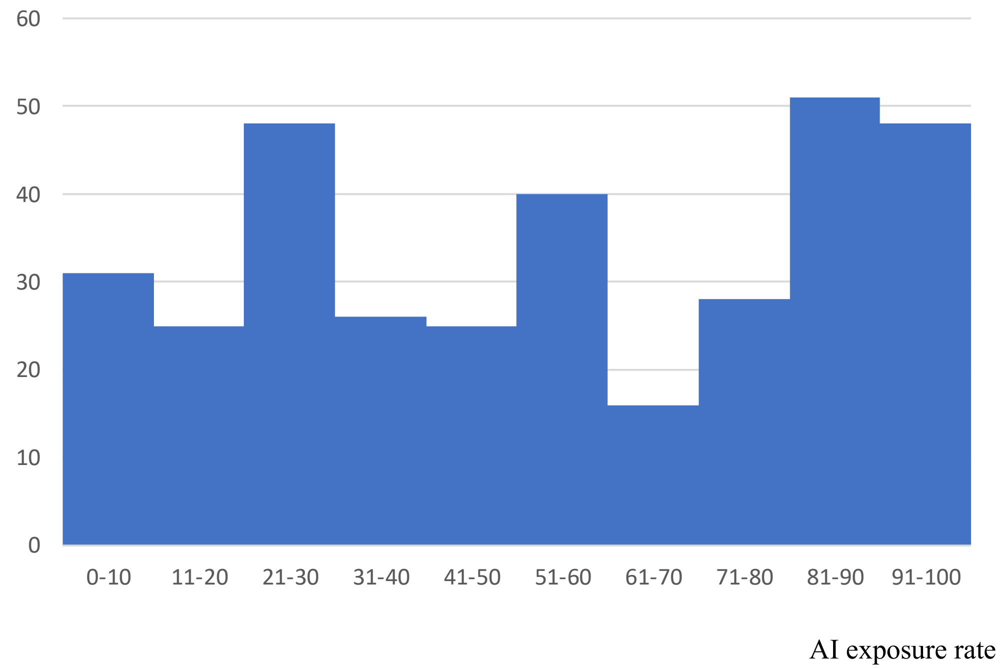


Figure 4: Frequency of Normalized AI Exposure Rate 2 (AE2)

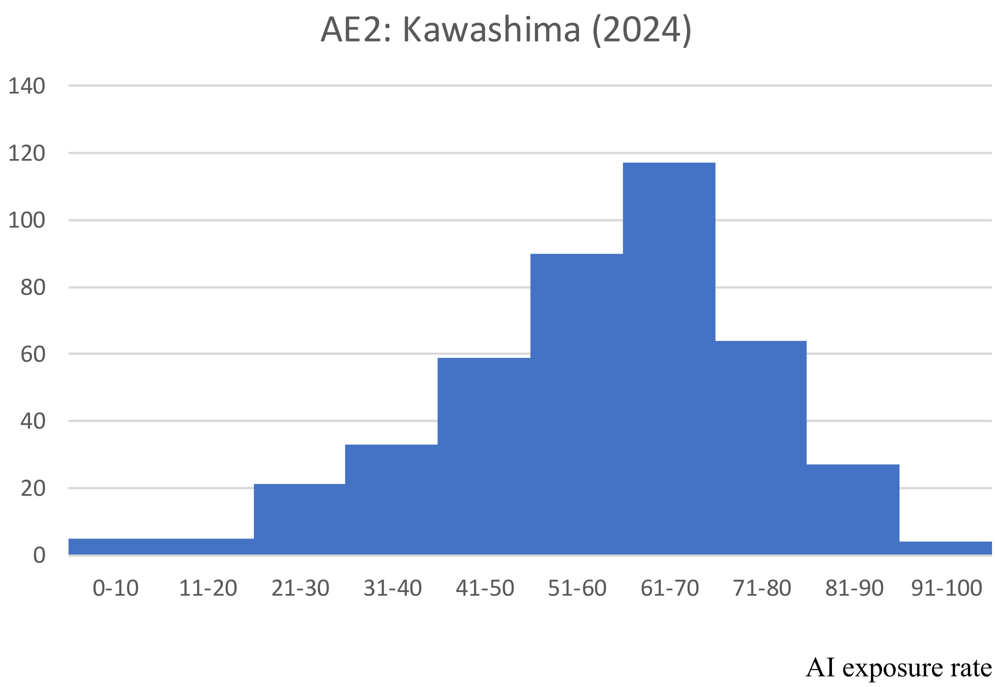


Figure 5: Distribution of Webb (2020)'s original AI exposure scores

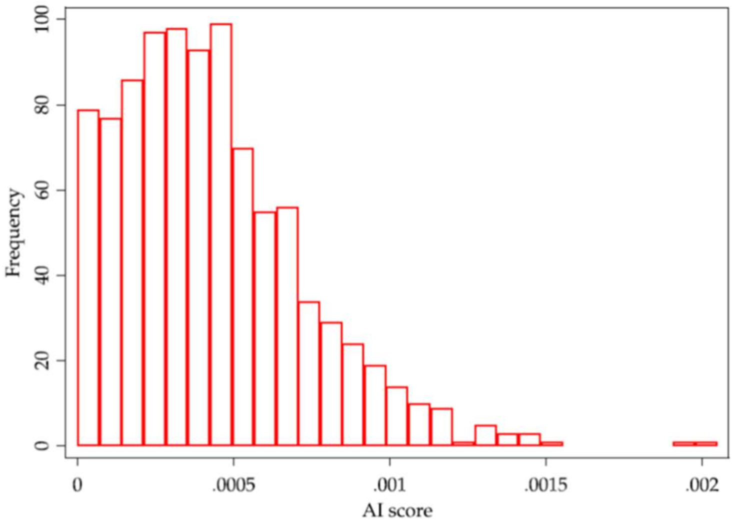


Figure A2: **Distribution of AI exposure scores across occupations.**

Notes: Figure displays the distribution across occupations of artificial intelligence exposure scores.

(note) Figure 5 is from Webb (2020).

Figure 6: Average Wage and AI Exposure Rate by Industry, AE2

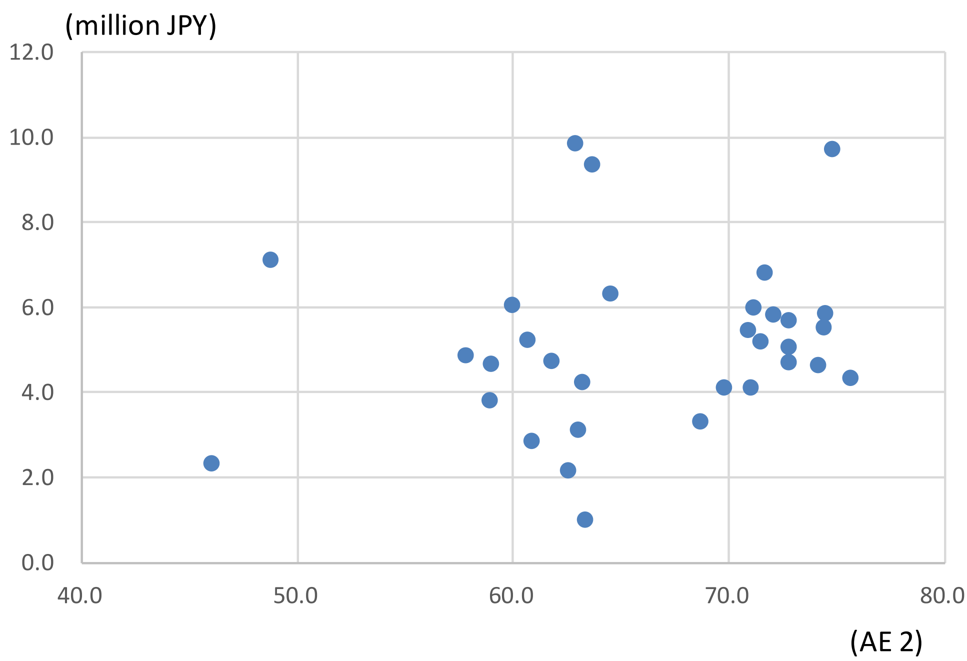


Figure 7: Change in Wages, E_AI = 5, Case 1, AE2

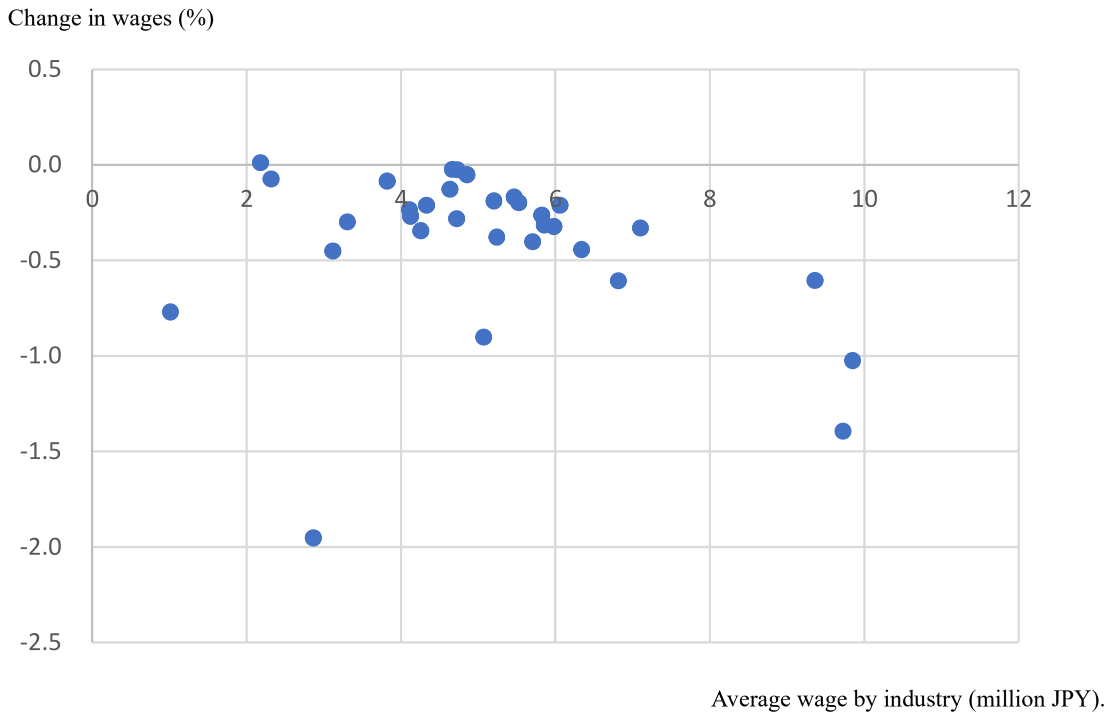


Figure 8: Change in Wages by Industry, E_AI = 0.8, Case 2, AE2

Figure 9: Change in Wages and Number of Employees, E_AI = 5, Case 1, AE2

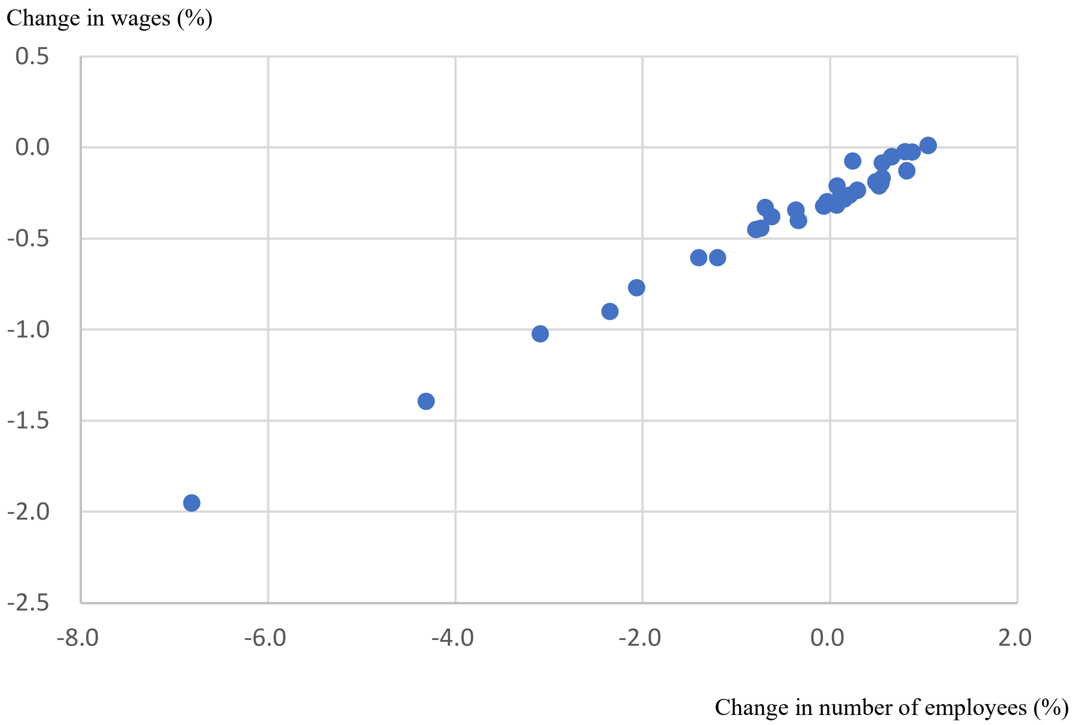


Figure 10: Change in Wages and Number of Employees, E_AI = 0.8, Case 2, AE2

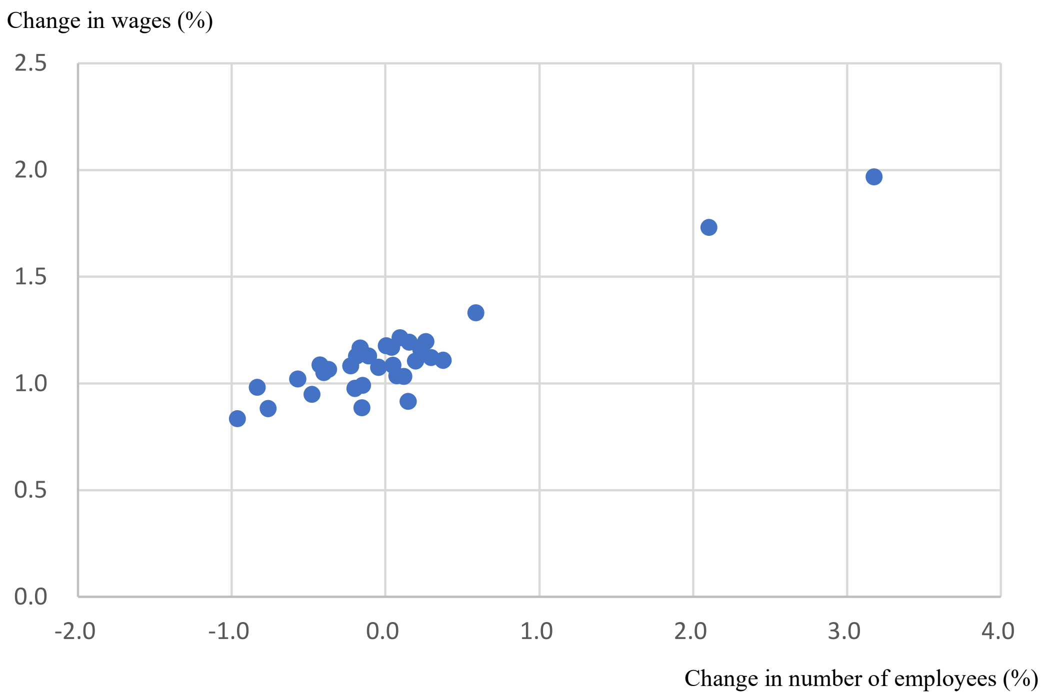


Figure 11: Change in Wages and AI exposure rate, E_AI = 5, Case 1, AE2

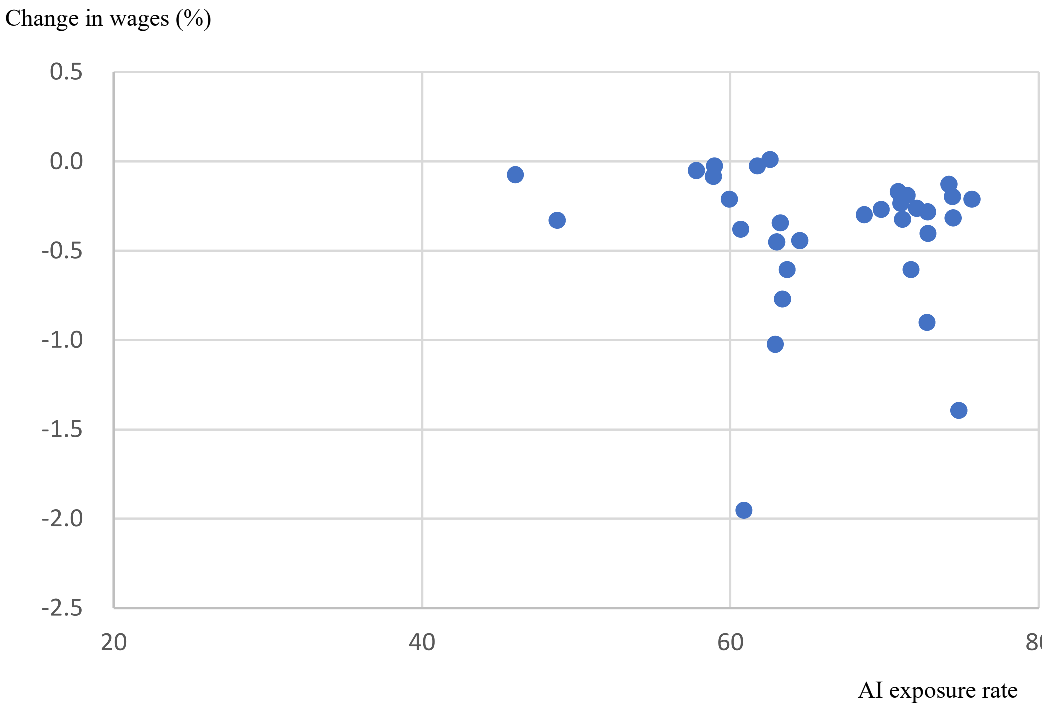


Figure 12: Change in Wages and AI exposure rate, E_AI = 5, Case 2, AE2

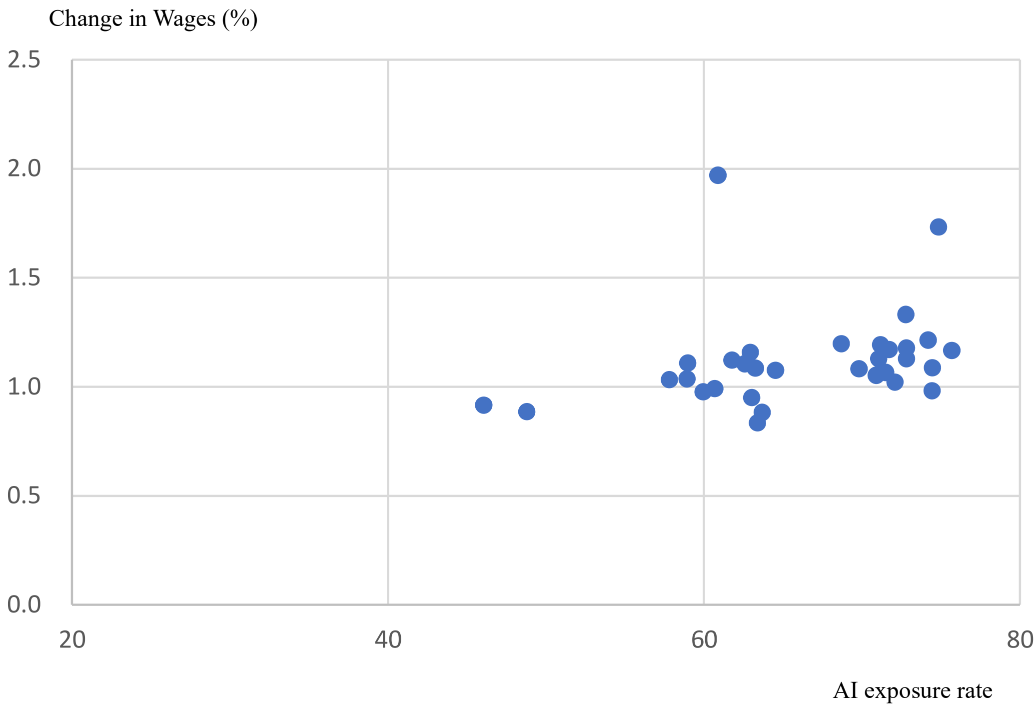


Figure 13: Ratio Between Top 5 and Bottom 5 Industries' Average Wage with an Increase of AI, AE2

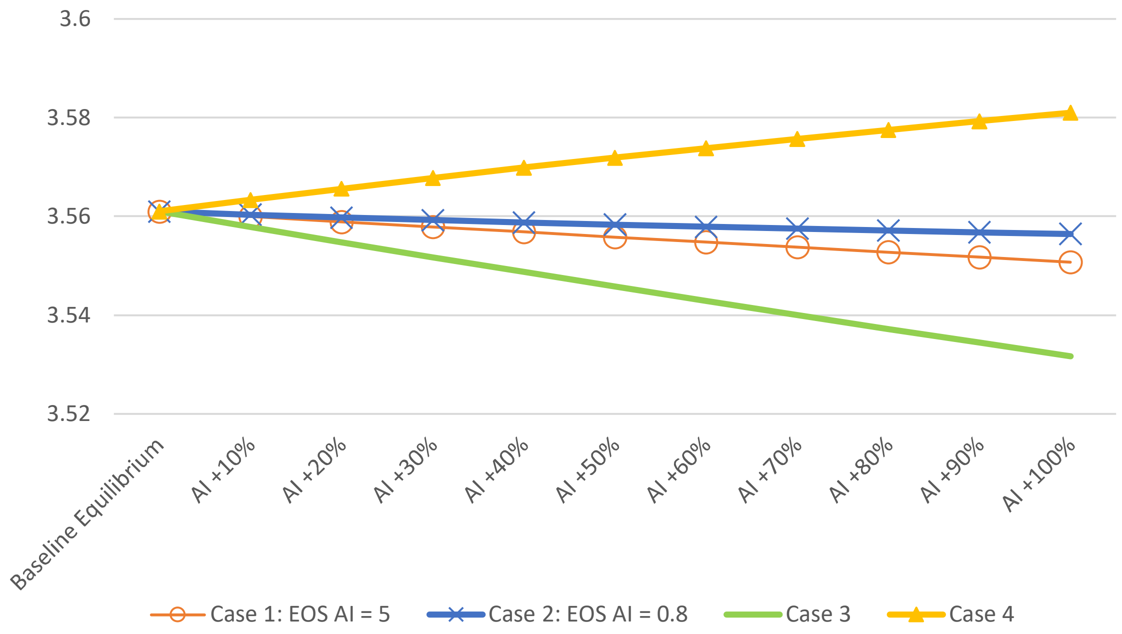


Figure 14: Gini coefficient with an Increase of AI, AE2

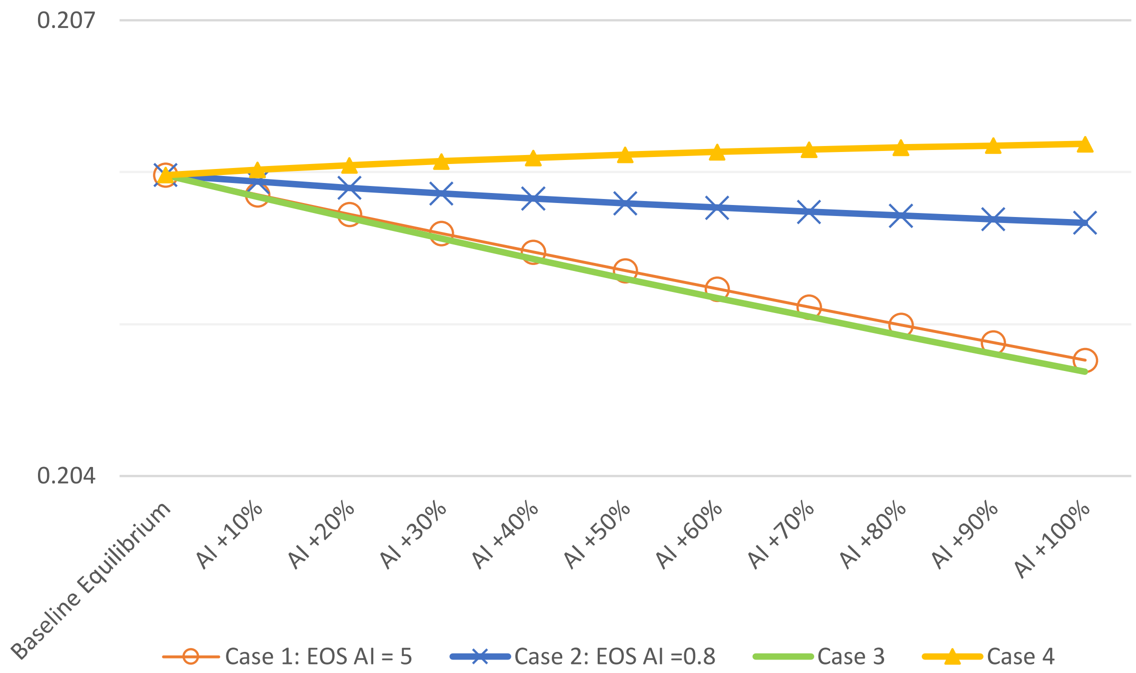


Figure 15: Ratio Between Top 5 and Bottom 5 Industries' Average Wage with an Increase of AI, AE1

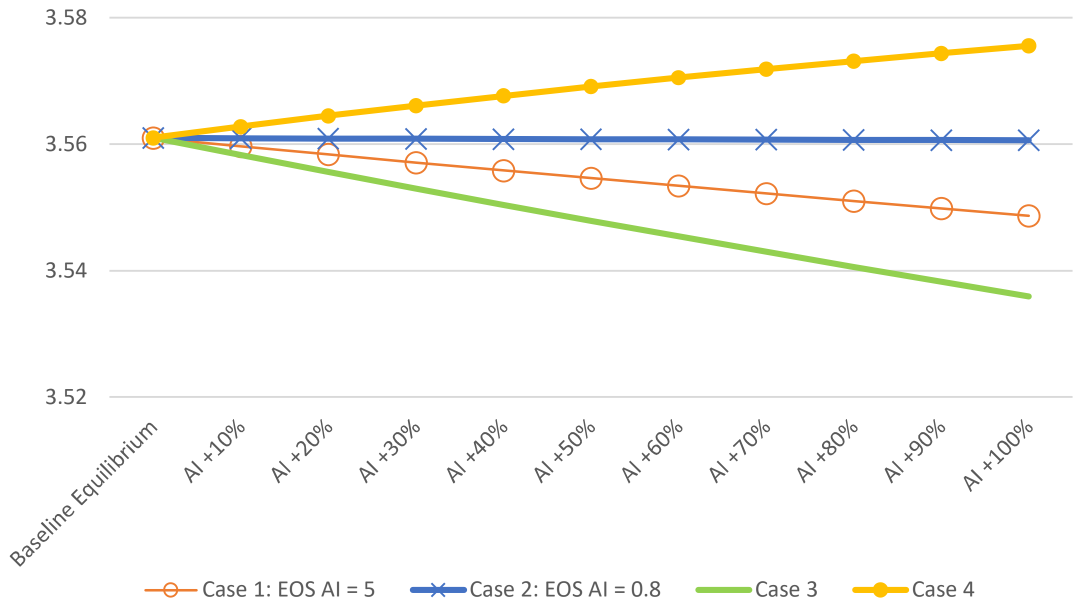
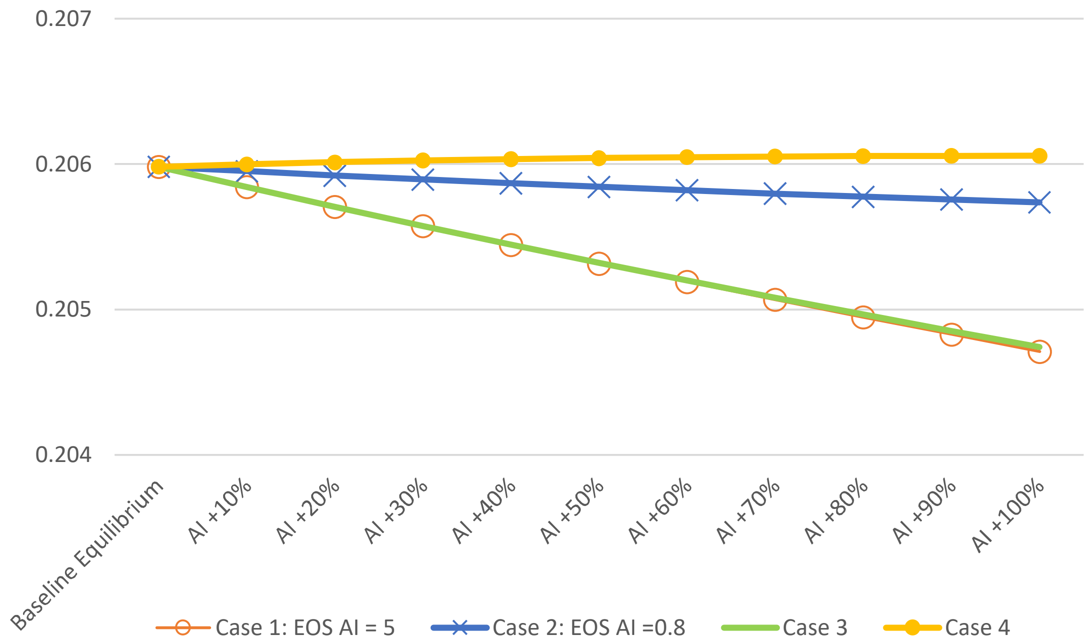
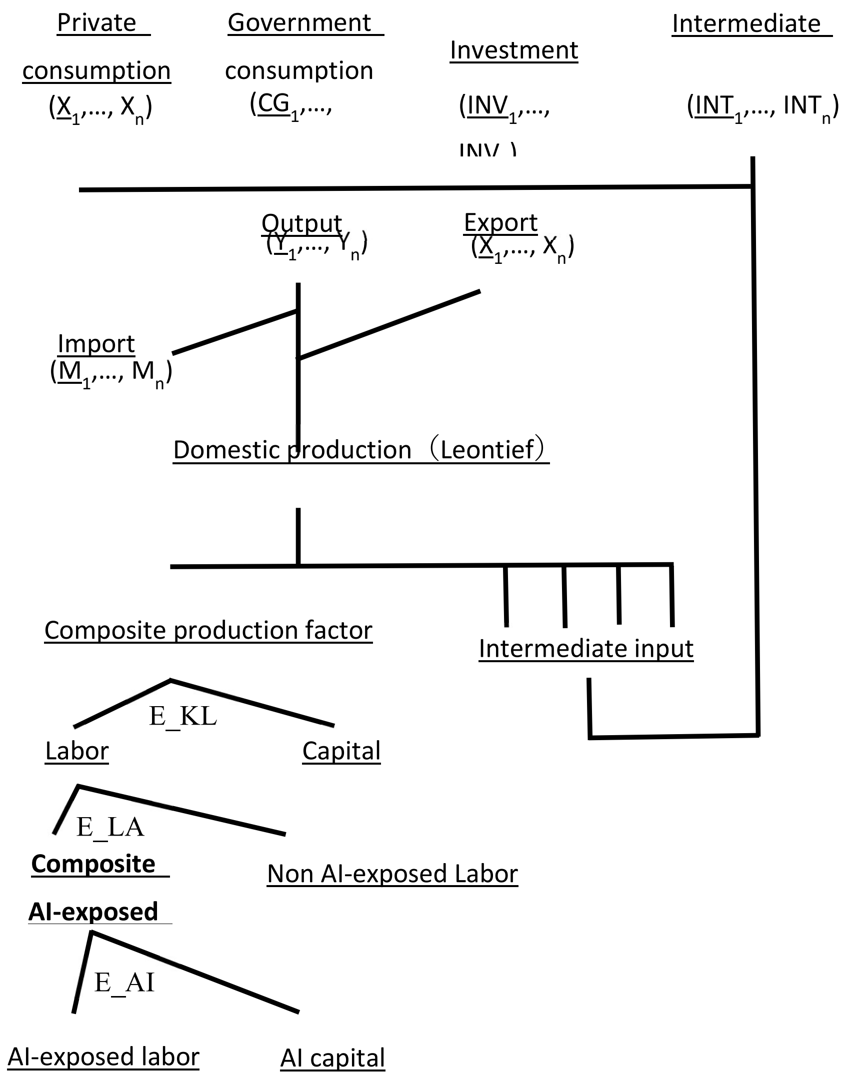


Figure 16: Gini coefficient with an Increase of AI, AE1



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