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Macroeconomic Impact of Artificial Intelligence on Productivity: An estimate from a survey*

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Abstract

Based on a survey of Japanese workers, this study documents the characteristics of workers who use artificial intelligence (AI) in their jobs and estimates the effects of this new general-purpose technology on macroeconomic productivity. The results indicate, first, 8.3% of workers used AI in their jobs in 2024, which is approximately 1.5 times than in 2023. Second, more educated and high-wage workers tend to use AI, suggesting that its diffusion may increase labor market inequality. Third, the use of AI is estimated to have increased labor productivity in the macroeconomy by 0.5–0.6%. Fourth, nearly 30% of workers expect to use AI for their jobs in the future, suggesting that its macroeconomic effects will increase. However, the productivity effect of AI for those who recently started using it is relatively small, suggesting a diminishing productivity impact of AI.

Keywords: artificial intelligence, productivity
JEL Classification: D24, J24, J31, O33, O47

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1. Introduction

The business use of artificial intelligence (AI), including generative AI, is spreading rapidly and expected to substantially increase macroeconomic productivity. Among automation technologies, many studies have quantified the productivity impact of industrial robots (e.g., Graetz and Michaels, 2018; Kromann *et al*., 2020; Cette *et al*., 2021; Dauth *et al*., 2021) because data on their use are available from the International Federation of Robotics. Data on the use of industrial robots in Japan are available from the Japan Robot Association, and studies have been conducted using these data (e.g., Dekle, 2020; Adachi *et al*., 2024). However, the quantitative impact of AI on productivity is not yet well understood, mainly because of the lack of statistical data on the use of AI.

Recently, several studies have reported results from randomized experiments on specific tasks, showing that AI has a substantial positive effect on productivity (e.g., Kanazawa et al., 2022; Brynjolfsson *et al*., 2023; Noy and Zhang, 2023; Peng *et al*., 2023). These studies provide valuable contributions, as they reveal the causal effects of AI on productivity. However, the macroeconomic effects are impossible to infer from these results because the analysis covers narrowly defined tasks, such as taxi driving, customer support, writing tasks, and software programming.

Acemoglu (2024) estimates the medium-term effect of AI on productivity over the next 10 years as the percentage of tasks affected by AI multiplied by task-level cost savings based on existing task-level studies. According to his study, the macroeconomic impact of AI is non-negligible but small, with a cumulative total factor productivity (TFP) increase of less than 0.7% over 10 years. However, he expresses reservations, in that which tasks will be automated and what the cost savings will be are largely uncertain.

Bick *et al*. (2024) apply survey data to show generative AI use by US workers and estimate that generative AI increases labor productivity by 0.125–0.875 percentage points. However, this figure is based on the assumption that the task-level productivity effect is 25%, which is the median of five recent studies. Based on a Danish survey of workers in 11 occupations with high exposure to generative AI (e.g., software developers and marketing professionals), Humlum and Vestergaard (2024) report that 32% are using ChatGPT, a representative generative AI program, and that they estimate that ChatGPT halves their working hours for one-third of their tasks, on average. These findings indicate that ChatGPT increases the aggregate-level labor productivity of these occupations by approximately 5%. However, this cannot be generalized to the entire labor market because the reported figures are for specific occupations with high AI exposure.

Against this background, this study uses a survey of Japanese workers conducted in October 2024 to identify the number and type of workers using AI in their jobs and estimates the impact of this new general-purpose technology on macroeconomic productivity. Although this study employs an extremely simple approach, it can capture the macroeconomic effects of AI because it covers the entire workforce rather than specific occupations. Although the productivity effects are based on the subjective evaluations of workers who use AI, this method has the advantage of avoiding endogeneity concerns, unlike, for example, a production function approach, because the survey asks AI users to make comparisons with situations in which AI is not used. Furthermore, because this study uses two-year panel data, we can compare workers who began using AI in the past year with those who have been using AI longer.

The main findings are summarized as follows. First, approximately 8% of workers currently use AI in their jobs, and this number is rapidly increasing. Second, more educated and high-wage workers tend to use AI, which may increase inequality in the labor market. Third, we estimate that AI use has increased macroeconomic labor productivity by 0.5–0.6%. Fourth, nearly 30% of the respondents expect to use AI in their jobs in the future, suggesting that the macroeconomic effects of AI will likely increase. However, the productivity effects of those who have recently begun using AI are relatively small, suggesting the possibility that AI's impact on productivity will gradually diminish.

The remainder of this paper is organized as follows. Section 2 describes the worker survey and analysis method used in this study. Section 3 reports our results on the macroeconomic impact of AI and the characteristics of workers who use AI for their jobs. Section 4 summarizes the findings and discusses their implications.

2. Outline of the survey

The data were retrieved from the "Survey of Life and Consumption under the Changing Economic Structure" designed by the author and administered by Rakuten Insight, Inc. in October 2024. The survey targeted respondents from a survey conducted in September 2023 (Morikawa, 2024). The 2023 survey was conducted with workers aged 20 years and older from a sample pool of more than 2 million registered individuals. The study sample was selected such that the gender and age composition matched that of the 2022 Employment Status Survey (Ministry of Internal Affairs and Communications), which is an official statistical survey conducted in Japan every five years. Thus, the sample is representative of the entire Japanese workforce. The 2023 survey had 13,150 respondents. Of these, 12,763 still registered at the time of the 2024 survey were sent questionnaires, and 8,633 responded. Data from 8,269 of these respondents, excluding those not working as of the 2024 survey, are used in the analysis. The gender and age composition of the respondents is shown in appendix **Table A1**.

The main survey items used in this study assess the following: (1) the use of AI at work, (2) percentage of tasks performed using AI, and (3) effect of AI use on work efficiency. In addition, the survey includes information on the respondents' gender, age, educational background, industry in which they work (44 categories aggregated into 14 categories), occupation (13 categories such as managerial, professional/technical, clerical, and sales positions), type of employment (10 categories such as full-time regular employment, part-time employment, and self-employment), weekly working hours (12 categories), and wages (18 categories denoting annual earnings from work), which are used in the analysis. [1]

The specific question regarding the use of AI at work is "We would like to ask you about your use of Artificial Intelligence (AI) including generative AI." The three choices are: 1) "I currently use AI at work," 2) "I do not currently use AI at work, but I think I will in the future," and 3) "I do not use AI at work and do not think I will in the future."

Respondents who select the first response are asked about the percentage of their work tasks that used AI and the effect of AI on their work efficiency. The question regarding the percentage of tasks performed using AI is "What percentage of your overall tasks is performed using AI?" Answers are provided as specific numbers (%). [2] The question about the efficiency gains from AI is "How much more efficient do you feel the use of AI in your tasks compared to without using AI?" This question is also answered in the form of a specific number (%). The lower bound of the response is set at 0% (if the respondent believes that AI use has nothing to do with work efficiency), and the upper bound is set at 100% to avoid extreme responses, although in some cases, efficiency may be as much as twice as high with AI than without. However, because only

[1] The weekly working hours are divided into 12 categories: less than 15 hours, 15–19 hours, 20–21 hours, 22–29 hours, 30–34 hours, 35–42 hours, 43–45 hours, 46–48 hours, 49–59 hours, 60–64 hours, 65–74 hours, and 75 hours or more. Workers' annual income is divided into 18 categories: less than JPY 500 thousand, JPY 500 to 990 thousand, JPY 1,000 to 1,490 thousand, ..., JPY 15,000 to 1,749 thousand, JPY 1,750 to 1,999 thousand, and more than JPY 20,000 thousand.

[2] The lower and upper bounds of the response are set at 1% and 100%, respectively.

a small number of AI users (1.7%) responded 100%, the possible downward bias arising from setting the upper bound is limited.

Based on the answers to these questions, the percentage of workers who use AI for their work (*AI_User*), percentage of tasks using AI (*AI_Taskshare*), and efficiency gains (*AI_Efficiency*) are tabulated by gender, age, education, and other worker characteristics. The worker-level productivity effect (*AI_Productivity*) is calculated for AI users as *AI_Taskshare***AI_Efficiency*. For example, if a worker uses AI for 30% of their tasks and the efficiency effect of AI is 20%, the overall productivity of their work is 6% higher than when they do not use AI. Multiplying the mean of this figure by the percentage of AI users indicates the macroeconomic productivity effect.

However, AI users may be more likely than non-users to have longer working hours, such as full-time employees, and may be more highly educated and earn higher wages. Therefore, we perform an aggregation weighted by (1) working hours and (2) annual earnings. When working hours are used as weights, macroeconomic effects are estimated on a labor input basis, and when annual earnings are used as weights, macroeconomic effects are estimated closer to a value-added basis.

When estimating the effects of AI use on productivity, for example, an approach to estimating a production function, selection bias results in a serious problem in which firms and workers with higher productivity tend to use AI more than those with lower productivity. Although the estimated productivity effects in this study depend on workers' subjective evaluations, meaning that measurement errors are inevitable, our approach has the advantage of avoiding such endogeneity bias because the survey asks AI users about efficiency gains in comparison to situations in which AI is not used.

3. Results

3.1. Use of AI and Productivity Effects

Table 1 summarizes the aggregation results of the main survey questions. Of the respondents, 8.3% use AI at work (*AI_User*). In the 2023 survey conducted a year earlier, the corresponding figure was 5.8% (5.3% when limiting the sample to those who also responded to the 2024 survey). Therefore, the number of workers who use AI at work is approximately 1.5 times higher than it was in the previous year (Morikawa, 2024).[3] The percentage of respondents who choose "I do

[3] The three response choices in the 2023 survey are (1) using AI at work, (2) using AI but not at

not currently use AI at work, but I think I will in the future," is 27.8%, suggesting that the use of AI in work will continue to increase.

Table 1. Use of AI and its effect (%)

	Mean	Std. Dev.	N
A. *AI_User*	8.32	-	8,269
B. *AI_Taskshare*	15.1	16.8	688
C. *AI_Efficiency*	25.9	22.9	688

Note: Rows B and C show the figures for the respondents who use AI in their work.

The mean percentage of tasks that use AI (*AI_Taskshare*) among those who use AI for their jobs is 15.1%, although the individual differences are large, with a standard deviation of 16.8%. Therefore, even when AI is used for work, the percentage of tasks that do not use AI is much higher than that of tasks that do.

The subjective effect of AI use on work efficiency (*AI_Efficiency*) also varies widely among individual workers; however, the mean value is 25.9% (standard deviation is 22.9%).[4] As we do not have information on the cost of AI (capital input), these figures should be interpreted as the effects on labor productivity, not TFP. Although their study is limited to the effects of generative AI, Bick *et al.* (2024) assume a 25% productivity effect of generative AI use when conducting their analysis. The figure in our study is not simply comparable with theirs but is almost identical. A positive correlation is observed between *AI_Efficiency* and *AI_Taskshare*, with those who evaluate the efficiency gains of AI reporting a higher percentage of tasks using AI. Quantitatively, a 1 percentage point increase in *AI_Efficiency* is associated with a 0.3 percentage point increase in *AI_Taskshare*.

The mean productivity effect of AI at the worker level (*AI_Productivity*) is 5.6%, meaning that workers who use AI for their jobs are 5.6% more productive than those who do not. The macroeconomic productivity effect, calculated by multiplying this figure by the percentage of AI users, is +0.46% (column (1) of **Table 2**). However, this figure is based on the number of workers and does not consider the differences in working hours and wages. When the productivity effect is calculated using working hours as the weight, it is +0.50% (column (2) of **Table 2**), and when annual earnings are used as the weight, it is +0.58% (column (3) of the table).[5] This difference

work, and (3) not using AI.

[4] The same question was asked in the 2023 survey, and the mean was 21.8% (21.0% for a panel sample). Thus, the figure for 2024 is somewhat higher.

[5] Based on the results by industry, a weighted average using the ratio of the number of workers by industry in the Employment Status Survey of 2022 yields slightly lower productivity effects: unweighted 0.42%, weighted by working hours 0.46%, and weighted by annual earnings 0.50%.

mainly reflects that those with longer working hours and those with higher annual earnings are more likely to use AI (extensive margin), whereas the differences in the intensive margin, proportion of tasks using AI (*AI_Taskshare*), and productivity effect of AI use (*AI_Efficiency*) are relatively small. In terms of the effect on value added at the macro level, annual earnings are appropriate to use as the weight. Therefore, at this point, our preferred estimate is a 0.5–0.6% boost to labor productivity at the macro level compared to the case without AI. [6] **Table 2** presents the results by industry, education, and annual earnings, which are discussed later in this paper.

Table 2. Macroeconomic productivity effects of AI (%)

	(1) Unweighted	(2) Hours weighted	(3) Annual earnings weighted
All industries	0.46	0.50	0.58
Construction	0.30	0.33	0.31
Manufacturing (machinary)	0.66	0.70	0.82
Manufacturing (others)	0.36	0.37	0.49
Utilities	1.41	0.88	0.88
Information and communications	1.54	1.76	1.60
Transportation	0.57	0.69	0.70
Wholesale	0.14	0.16	0.18
Retail	0.55	0.62	0.62
Banking and finance	0.83	0.90	0.94
Services	0.30	0.32	0.40
Education	0.30	0.25	0.38
Healthcare	0.30	0.26	0.41
Public services	0.31	0.30	0.28
Other industries	0.22	0.28	0.31
High school or less	0.21	0.35	0.39
Vocational school	0.28	0.43	0.46
Junior college	0.18	0.26	0.34
University	0.38	0.58	0.58
Graduate school	0.70	0.86	1.02
Less than 5,000 thousand	0.25	0.39	0.37
5,000-9,999 thousand	0.45	0.64	0.63
10 million or higher	0.56	0.72	0.75

Note: Productivity effects in column (1) are calculated as *AI_User*AI_Taskshare*AI_Efficiency*. Figures in columns (2) and (3) are calculated using working hours and annual earnings as weights, respectively.

Therefore, respondents to our survey tend to work in industries with high levels of AI use.

[6] The labor productivity effect estimated here is approximately 0.3% when converted to TFP using the labor share figure (0.535) used by Acemoglu (2024).

The 2024 survey was conducted with respondents who also participated in the 2023 survey, and the 2023 survey also asked about AI use at work. Therefore, those who recently started using AI during the past year can be disaggregated from those who have continued to use AI. **Table 3** summarizes the comparison between these two categories of AI users. Both the percentage of tasks using AI (*AI_Taskshare*) and the effect on work efficiency (*AI_Efficiency*) are significantly lower for those who recently started using AI than for those who have used it continuously. Thus, the effect of AI use on overall work productivity differs significantly (*AI_Productivity*). *AI_Productivity* for continuous and new AI users is 7.9% and 4.4%, respectively. This result suggests that the diffusion of AI started with jobs for which its effect is large and gradually spread to jobs for which its effect is small. [7] If these trends continue, the additional contribution of AI to macroeconomic productivity may diminish gradually as the number of AI users increases.

Table 3. Comparison of new and continuous AI users (%)

	New AI users	Continuous AI users	Diff.	
AI_*Taskshare*	13.73	17.78	-4.05	***
AI_*Efficiency*	23.60	30.16	-6.56	***
AI_*Productivity*	4.37	7.85	-3.48	***
N	451	237		

Note: ***: $p < 0.01$. New AI users are those who started using AI in the past year.

In addition to those who currently use AI in their jobs, 27.8% of the respondents answered that they expect to start using AI in the future. Assuming that the percentage of work that uses AI and the effect on work efficiency associated with AI use are the same as those of current AI users, the additional macroeconomic productivity effect of these potential users would be approximately four times greater, or approximately +2%, compared to the case without AI.[8] However, as noted above, the percentage of tasks that use AI and the effect of AI on work efficiency may become smaller compared to tasks for which AI was used earlier. However, if the ratio of tasks that use AI increases among workers who continuously use AI for their jobs, the overall productivity effect may increase.

[7] Some workers used AI for their jobs at the time of the 2023 survey but not in 2024 (“quitter”). The average effect of AI on work efficiency for these individuals in 2023 is 18.7%, which is lower than the figure for those who continued to use AI in 2024 (22.9%), although the difference is quantitatively small.

[8] The estimated effect on TFP, considering the labor share, is +1.1%, which is larger than the figure reported in Acemoglu (2024).

3.2. Characteristics of Workers Who Use AI for their Jobs

The calculation results, disaggregated by worker characteristics, are reported in appendix **Table A2**. Workers with higher rates of AI use are generally male, in their 20s and 30s, and highly educated, especially those with advanced degrees (see column (1) of the table). [9] By industry, the information and communications, manufacturing (machinery), and finance/insurance industries have high rates of AI use. By occupation, management, sales, and professional/technical occupations have high rates of AI use. By type of employment, company executives and full-time employees have high rates of AI use. High-income workers (annual earnings of 10 million yen or more) have high rates of AI use. [10]

Column (1) of **Table 4** shows the results of a simple probit estimation that explains the use of AI at work according to worker characteristics. Annual earnings are log-transformed using the median of the 18 categories. The lowest category is treated as JPY 250 thousand and the highest category is treated as JPY 22.5 million.[11] The coefficient for female is insignificant, indicating no gender differences in AI use when controlling for industry, occupation, type of employment, and other control variables. Younger workers in their 20s and 30s, those with higher education (college and graduate degrees), and those with higher annual earnings from work have a higher probability of using AI.[12] Column (2) of **Table 4** shows the results of the same estimation using data from the 2023 survey. The relationships between age, education, and annual income and the probability of AI use are the same as those found in the 2024 survey. Morikawa (2017), in an early study that analyzed the relationship between AI adoption and employee education using Japanese firm-level survey data, indicates a complementarity between AI and worker education. Draca *et al*. (2024) demonstrates the complementarity between machine learning/AI and skills (college graduates and STEM occupations) through an analysis using UK data. Our results are consistent with those of

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[9] Among the education categories, "junior high school and elementary school graduates" are merged with "high school graduates" and listed as "high school graduates and below." Graduate school is surveyed separately for master's and doctoral degrees, but they are merged into "graduate school."

[10] In the survey, annual earnings from work are classified into 18 categories ranging from "less than JPY 500 thousand yen" to "more than 20 million yen," but to avoid complications, annual earnings are aggregated into three categories.

[11] The weekly working hours are used as a control variable by log-transforming the median of the 12 categories.

[12] Through a different approach, Eloundou *et al*. (2024) indicate that individuals earning higher incomes have greater exposure to large language models.

previous studies.

Table 4. Worker characteristics and the probability of AI use

	(1) 2024FY			(2) 2023FY		
	dF/dx	Robust SE		dF/dx	Robust SE	
Female	0.009	(0.007)		-0.007	(0.004)	*
20s	0.062	(0.013)	***	0.047	(0.008)	***
30s	0.027	(0.009)	***	0.026	(0.006)	***
50s	-0.013	(0.007)	*	-0.009	(0.005)	*
60s	-0.020	(0.008)	**	-0.010	(0.005)	*
70 or older	-0.024	(0.016)		0.017	(0.014)	
Vocational school	0.008	(0.012)		0.008	(0.007)	
Junior college	0.006	(0.012)		-0.005	(0.007)	
University	0.034	(0.008)	***	0.018	(0.005)	***
Graduate school	0.104	(0.020)	***	0.046	(0.011)	***
ln earnings	0.026	(0.005)	***	0.019	(0.003)	***
ln working hours	yes			yes		
Industry	yes			yes		
Occupation	yes			yes		
Work type	yes			yes		
Observations	8,200			13,140		
Pseudo R^2	0.1102			0.1120		

Notes: Probit estimations with robust standard errors are in parentheses. The figures indicate marginal effects. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$. The reference categories are male, age 40s, and high school education or less.

The percentage of tasks that use AI and the effect of AI on work efficiency (columns (2) and (3) of appendix **Table A2**) have no clear relationship with worker characteristics. In many cases, the percentage of tasks that use AI or the effect of AI on work efficiency is high, even in categories with low rates of AI use. Thus, the differences in the productivity effects of AI based on worker characteristics are limited. However, a weak but systematic relationship exists between education and annual income with the productivity effects of AI. The productivity effect of AI tends to be smaller for those with more education and higher earnings. Therefore, although less-educated and low-wage workers are notably less likely to use AI in their jobs, the productivity effects are somewhat larger when they do.

Recent studies on specific tasks (e.g., Kanazawa et al., 2022; Brynjolfsson et al., 2023; Noy and Zhang, 2023) have shown that AI productivity effects are greater for relatively less-skilled workers in the same task. The above findings are similar to those in these previous studies. However, when ordinary least square estimation is performed using gender, age, education, industry, occupation, employment type, annual earnings, and hours worked per week as explanatory variables, the coefficients for education and annual earnings are statistically insignificant. Furthermore, the coefficients of industry, occupation, and type of work are largely insignificant. Thus, the productivity effect of using AI for work is generally unrelated to observable worker characteristics.

Table 2 shows the macroeconomic productivity effects of AI disaggregated by industry, education, and annual earnings. The industry-level productivity effects (weighted by annual earnings) are large for the information and communications (1.60%) and finance/insurance (0.94%) industries and small for the wholesale and construction industries. The differences among industries are mostly due to differences in the percentage of AI users (extensive margin). For example, the information and communications industry does not have particularly high AI-using tasks or efficiency effects of AI use. By worker characteristics, aggregated productivity effects are greater for highly educated and high-income worker groups.

4. Conclusion

Using data from an original survey of Japanese workers, this study shows the characteristics of workers who use AI in their jobs and estimates the macroeconomic effects of AI on productivity. The main results are as follows. First, 8.3% of workers were using AI at work as of the fall of 2024, reflecting an increase of approximately 50% from the previous year. Second, based on individual characteristics, highly educated and high-wage workers are more likely to use AI. Several experimental studies on specific tasks indicate that the use of AI reduces skill gaps within the same task; however, our results suggest that the diffusion of AI may widen overall labor market inequality. Third, we estimate that macroeconomic productivity impact is 0.5–0.6% when AI is used than when it is not. Fourth, as approximately 28% of the respondents expect to use AI for their jobs in the future, the macroeconomic effects of AI are likely to expand. However, because the productivity gain of AI for those who have recently started using AI is smaller than that for those who have been using AI continuously, the additional productivity gain is likely to diminish over time.

Although economic analysis of the effects of AI has surged, the impact of AI on productivity is not yet well understood. Although this paper only presents a rough estimation, it makes a novel contribution in that it quantifies the effects of AI on macroeconomic productivity. A limitation of this study is that it depends on workers' subjective evaluations; however, this approach has the advantage of avoiding the endogeneity problem in the selective use of AI. Because the subject of this study is a rapidly changing field, the actual use and productivity effects of this new technology should be monitored regularly.

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Appendix Tables

Table A1. Gender and age composition of respondents (%)

Age	2024 survey		2023 survey		2022 Employment Status Survey	
	Male	Female	Male	Female	Male	Female
20-29	5.9	5.2	8.2	8.1	7.7	7.3
30-39	9.8	6.7	9.9	8.3	9.7	8.1
40-49	14.3	10.5	12.7	10.8	12.4	10.5
50-59	15.8	10.8	12.8	10.4	12.2	10.1
60 or older	12.8	8.2	11.3	7.7	12.8	9.2

Note: Percentages from the Employment Status Survey 2022 are figures for workers aged 20 years and older.

Table A2. Aggregated results by worker characteristics (%)

		(1) *AI_User*	(2) *AI_Taskshare*	(3) *AI_Efficiency*
All		8.3	15.1	25.9
Gender	Male	9.8	14.0	26.2
	Female	6.2	17.7	25.1
Age	20s	14.1	20.6	28.5
	30s	11.1	15.3	25.7
	40s	8.2	12.3	23.4
	50s	6.9	12.9	24.8
	60s	5.2	14.3	27.8
	70-	3.6	32.5	40.0
Education	High school or less	4.2	17.5	28.7
	Vocational school	5.2	19.9	27.2
	Junior college	4.5	16.4	23.8
	University	10.5	14.2	25.6
	Graduate school	20.1	14.0	24.8
Industry	Construction	5.1	17.5	27.7
	Manufacturing (machinary)	15.7	13.6	23.7
	Manufacturing (others)	10.9	11.6	24.0
	Utilities	12.7	20.8	30.5
	Information and communications	23.9	15.4	25.6
	Transportation	4.0	24.1	32.1
	Wholesale	6.1	8.0	21.8
	Retail	6.3	22.5	29.3
	Banking and finance	14.1	18.1	25.2
	Services	6.5	14.4	26.3
	Education	7.6	11.5	23.3
	Healthcare	3.5	17.4	30.9
	Public services	5.3	14.1	29.2
	Other industries	5.3	14.6	22.8
Occupation	Managerial	13.7	12.3	26.2
	Professional & engineering	10.6	13.5	23.9
	Clerical	8.0	14.2	26.6
	Sales	5.1	19.0	22.4
	Trade-related	11.0	15.2	25.5
	Service	5.6	19.8	28.0
	Safety	2.8	23.3	15.0
	Agricultural	0.0	-	-
	Production	4.5	16.6	19.3
	Transportation & Machinery Operation	2.8	66.7	56.7
	Construction	3.8	25.0	31.7
	Cleaning, packaging, etc.	1.9	51.3	50.0
	Others	5.9	17.1	28.8
Work type	Executives	11.8	17.7	27.3
	Self-employed	6.9	16.8	31.5
	Family workers	1.3	1.0	10.0
	Standard employee	10.8	13.6	24.6
	Part-time workers	3.2	25.0	27.0
	Temporary workers	3.0	30.8	27.8
	Dispatched workers	4.4	16.0	40.5
	Contract employees	7.4	13.2	24.3
	Entrusted employees	6.0	14.5	35.8
	Others	7.1	20.0	40.0
Annual earnings	Less than 5,000 thousand	5.3	17.8	26.4
	5,000-9,999 thousand	12.1	13.9	26.6
	10 million or higher	21.2	11.7	22.7