Trends in Task Distribution in Japan, 1990–2015: Evidence from the Occupational Information Network of Japan and the Population Census Data

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This article analyzes task trends in Japan from 1990 to 2015, using the Population Census and the Occupational Information Network of Japan (hereinafter, Japanese O-NET) developed in 2020. First, following Acemoglu and Autor (2011), we classified tasks into the five categories: (1) non-routine analytical; (2) non-routine interactive; (3) routine cognitive; (4) routine manual; (5) non-routine manual tasks. Then, we analyzed the changes of each task distribution from 1990 to 2015. The results show a "task polarization" trend. Both high-skilled non-routine analytical and interactive tasks and low-skilled non-routine manual tasks increased but middle-skilled routine manual tasks have decreased. We also show that the trends vary by workers' characteristics such as gender, age, and employment status. For example, women experienced a larger increase in non-routine tasks than men; Polarization trend is apparent especially among female regular workers since 2005.

I. Introduction

Recently, many studies argue that computers have replaced routine tasks carried out by humans, which resulted in labor market polarization in Europe and the United States (e.g., Autor et al. 2003, Spitz-Oener 2006, Goos and Manning 2007, Goos et al. 2009, Ikenaga 2009, Acemoglu and Autor 2011, Autor and Dorn 2013, Ikenaga and Kambayashi 2016). A task is defined as "a unit of work activity that produces output" (Acemoglu and Autor 2011: 1045). In their landmark study, Autor et al. (2003) classified tasks of workers according to whether the task is routine or non-routine and whether intellectual or physical. There are five task categories: (1) non-routine analytical tasks that require problem solving using abstract thinking; (2) non-routine interactive tasks that create value through advanced interpersonal communication; (3) routine cognitive tasks which are clerical tasks that follow explicit rules; (4) routine manual tasks which are physical tasks that follow explicit rules; (5) non-routine manual tasks which are physical tasks that require a flexible response to particular situation without advanced expertise (Ikenaga and Kambayashi 2016).

These studies argue that demand for routine tasks will decrease because they can be replaced by automation, while demand for non-routine tasks will increase because they are complementary to automation.[1] They also show that routine tasks decreased and non-routine tasks increased in line with computerization.

Because jobs with routine tasks provide moderate wages while jobs with non-routine tasks offer higher wages for analytical and interactive tasks and lower wages for manual tasks, the shift from routine to non-routine tasks results in labor market polarization. In these studies, occupational information databases in the United States, such as the DOT (Dictionary of Occupational Titles)[2] and O*NET (Occupational Information Network)[3] are used. These databases measure tasks and skills by 3-digit (or 4-digit) occupations.

In Japan, Ikenaga (2009) and Ikenaga and Kambayashi (2016) used the occupational information website, *Career Matrix*,[4] to analyze the task trends in Japan. They showed that routine tasks decreased while non-routine tasks increased from 1960 to 2005, as in the Western countries. They also pointed out three differences between the United States and Japan. First, while routine cognitive tasks have decreased in the United States since the 1980s, it has increased in Japan (Ikanaga 2009). Second, non-routine manual tasks have risen in Japan, which is contrary to the United States (Ikenaga 2009, Ikenaga and Kambayashi 2016).[5] Finally, progress of task polarization is slower and smaller in Japan than in other countries (Ikenaga and Kambayashi 2016).

This article reveals the trends in task distribution in Japan from 1990 to 2015, using the Japanese O-NET released in 2020 by the Ministry of Health, Labour and Welfare[6] and the Population Census. We explore the following two issues. First, we examine the latest task trends from 1990 to 2015. Second, we disaggregate the overall trends by workers' characteristics, including gender, age, and employment status. Another contribution is to improve the Ikenaga and Kambayashi (2016)'s measurement of tasks by using multiple indicators from Japanese O-NET. We discuss this in detail in the following section.

II. Method

We used two datasets: the Population Census of Japan from 1990 to 2015 and the Japanese O-NET. The formar is conducted every five years. We obtained the aggregated data by 3-digit occupation, gender, 10-year age groups and employment status from e-Stat (https://www.e-stat.go.jp/). The latter is from the Occupational Information Database Quantitative Downloadable Data version 2.01 (https://shigoto.mhlw.go.jp/User/download) with the latest information collected in January and February 2021.[7]

Task scores for each occupation were calculated by matching the occupations of the Population Census with occupations listed in the Japanese O-NET.[8] A very small number of occupations such as unclassifiable occupations and occupations for which there were no similar occupations in the Japanese O-NET were excluded from the analysis.

It should be noted that we assume that the task information obtained from the Japanese O-NET remains constant between the observation periods, from 1990 to 2015. In other words, we do not capture the within-occupational task increase (or decrease). Thus, the scores of task indices change only when the occupational composition changes.[9]

Quantitative information from the Japanese O-NET was used to calculate the five types of tasks for each occupation covered in this study. Table 1 shows the definitions of each category and the indicators used in previous studies and this study for the respective category. Basically, following Acemoglu and Autor (2011), we constructed five task categories. However, we revised Acemoglu and Autor (2011)'s construction of non-routine manual tasks that include "Operating Vehicles, Mechanized Devices, or Equipment" and "manual tasks involving handling objects, tools, and controls," which is related to physical labor dealing with machines and tools. Their operationalization does not include service-related tasks even though the original definition of non-routine manual tasks comprises physical tasks that require flexible response depending on the situation.[10] To reflect the original definition of non-routine manual tasks, instead, we used the following four items: "performing general physical activities," "handling and moving objects," "assisting and caring for others," and "working directly with or for the public."

Our indices also differ from Ikenaga and Kambayashi (2016), which studied the labor market polarization trends in Japan. First, the data sources on tasks are different. We used the Japanese O-NET, while Ikenaga and

Table 1. Definitions and measurements of the five tasks

Five task categories	Definitions	Autor et al. (2003) **DOT**	Ikenaga and Kambayashi (2016) **Career Matrix**	Acemoglu and Autor (2011) **O*NET**	This study **Japanese O-NET**
Non-routine Analytical	Tasks requiring advanced expertise and the ability to solve problems using abstract thinking Examples: Research, surveys, design	General Education Development Index · GED Math	Skills Index · Mathematics	Generalized Work Activities Index · Analyzing data/information · Thinking creatively · Interpreting information for others	Generalized Work Activities Index · Analyzing data/information · Thinking creatively · Interpreting information for others
Non-routine Interactive	Tasks that create and deliver value through advanced interpersonal communication such as negotiation, management and consulting activities Examples: Law, management and administration, consulting, education, arts, performing arts, sales	Temperament Index · Direction, Control, Planning	Skills Index · Negotiation	Generalized Work Activities Index · Establishing and maintaining personal relationships · Guiding, directing and motivating subordinates · Coaching/developing others	Generalized Work Activities Index · Establishing and maintaining personal relationships · Guiding, directing and motivating subordinates · Coaching/developing others
Routine Cognitive	Clerical and information-processing tasks that follow explicit rules Examples: General clerical workers, accountancy clerks, testing and observation	Temperament Index · Set limits, Tolerances, or Standards	Skills Index · Operation and control	Work Context Index · Importance of repeating the same tasks · Importance of being exact or accurate · Structured v. Unstructured work (reverse)	Work Context Index · Importance of repeating the same tasks · Importance of being exact or accurate · Structured v. Unstructured work (reverse)
Routine Manual	Physical tasks that follow explicit rules Examples: Agriculture, manufacturing	Aptitude Index · Finger Dexterity	Skills Index · Repairing	Work Context Index · Pace determined by speed of equipment · Spend time making repetitive motions Generalized Work Activities Index · Controlling machines and processes	Work Context Index · Pace determined by speed of equipment · Spend time making repetitive motions Generalized Work Activities Index · Controlling machines and processes
Non-routine Manual	Physical tasks not requiring a high level of specialized knowledge, but requiring a flexible response to particular situation Examples: Service, hospitality, beauty, security, operation of transport equipment, maintenance and repair	Aptitude Index · Eye-Hand-Foot Coordination	Skills Index · Service orientation	Generalized Work Activities Index · Operating vehicles, mechanized devices, or equipment Work Context Index · Spend time using hands to handle, control or feel objects, tools or controls Abilities Index · Manual dexterity · Spatial orientation	Generalized Work Activities Index · Performing general physical activities · Handling and moving objects by using hands and arms · Assisting and caring for others · Performing for or working directly with the public

Sources: Autor et al. (2003), Ikenaga (2009), Acemoglu and Autor (2011), Ikenaga and Kambayashi (2016).

Kambayashi (2016) used the Career Matrix. Second, we utilized multiple indicators to construct each task index, while they utilized only one indicator. Third, the content of items to construct routine cognitive tasks are quite different. While Ikenaga and Kambayashi (2016) measured routine cognitive tasks by the indicator "skill with equipment and controls (controlling the motion and operation of devices, equipment, or systems)", we measured tasks by the indicators "repetition of the same task (continuous and repetitive mental and physical activity)," "rigor and accuracy (precision and accuracy in performing work)," and "structuring of work (extent to which work priorities and goals are determined with little scope for judgment)." Ikenaga and Kambayashi's (2016) definition of routine cognitive tasks refers to physical labor using machines, while ours refers to not only physical work but also clerical work. Fourth and finally, the contents of indicators to construct non-routine manual tasks are also different. Although Ikenaga and Kambayashi (2016) used the index "skill with interpersonal support services (proactively seeking effective solutions to assist others, such as customers and people in need)," we consider this skill requires relatively a high degree of expertise and therefore deviates from the original definition of non-routine manual tasks.[11]

Following Acemoglu and Autor (2011: 1164), we calculated the five task scores as follows. First, each scale is standardized to have a mean zero and a standard deviation one, using the weight of the number of workers from the Population Census 2005. Second, we added respective constituent scales to create a composite task index. Third, the composite task index is re-standardized to have a mean zero and a standard deviation one, using the weight of the number of workers from the Population Census 2005.

III. Results

1. Characteristics of the Five Tasks

Before moving on to the discussion of task trends, let us examine the types of occupations that had high scores for each task, and correlations among tasks. Table 2 shows the occupations with the top ten highest scores for the five task categories. The occupations with the highest scores of non-routine analytical tasks are researchers and university professors. The occupations with the highest score of non-routine interactive task score is administrative and managerial workers. The occupations with the highest score of routine cognitive task and routine manual tasks is railway drivers. Meanwhile, the occupation with the highest score of the non-routine manual task score is midwives.

Table 3 shows the correlation coefficients among the five task categories. The correlation between non-routine analytical tasks and non-routine interactive tasks is high at 0.87, as these tasks have similar characteristics. The correlation between non-routine interactive tasks and non-routine manual tasks is also relatively high at 0.53. On the other hand, there is a slight negative correlation between non-routine analytical/non-routine interactive tasks and routine manual tasks.

2. Trends in Task Distribution

Figure 1 shows how the scores for each task changed from 1990 to 2015, with 2005 as zero. As described above, changes in task scores correspond to changes in the occupation distribution. For example, an upward trend in scores for non-routine analytical tasks indicates either an increase in the share of occupations that perform more non-routine analytical tasks or a decrease in the share of occupations that perform fewer non-routine analytical tasks.

Non-routine analytical tasks, non-routine interactive tasks, and non-routine manual tasks, which are considered difficult to replace through automation, increased, while routine manual tasks decreased. Furthermore, routine cognitive tasks were on the increase from 1990 to 2005, but have been flat since 2005. In terms of differences from previous studies, non-routine manual tasks trended downward in the United States (Autor et al. 2003), but trended upward in Japan. Meanwhile, routine cognitive tasks have increased from 1990 to 2000, in contrast to Ikenaga and Kambayashi (2016).

Table 2. Top ten occupations with the highest scores for each task

	Non-routine Analytical			Non-routine Interactive			Routine Cognitive	
1	Natural science researchers	3.04	1	Administrative and managerial workers not classified elsewhere	3.12	1	Railway drivers	4.21
2	University professors	3.04	2	Administrative civil servants	3.12	2	Train conductors	3.01
3	Humanities, social science and other researchers	3.04	3	Corporate and organizational management professionals	3.12	3	Prison guards, other public security officers	2.91
4	Dancers, actors, directors, performers	2.34	4	Firefighters	2.87	4	Clinical laboratory technicians	2.89
5	Certified Public Accountants	2.32	5	Midwives	2.71	5	Transportation machinery maintenance and repair workers (excluding automobiles)	2.79
6	Journalists, editors	2.31	6	Transportation machinery maintenance and repair workers (excluding automobiles)	2.65	6	Aircraft pilots	2.42
7	System consultants, System designers	2.26	7	Prison guards, other public security officers	2.51	7	Railway line construction workers	2.30
8	Physio therapists, occupational therapists	2.25	8	Restaurateurs, restaurant managers	2.44	8	Other outdoor service workers	2.16
9	Chemical engineers	2.15	9	Railway line construction workers	2.29	9	Money collectors	2.16
10	Pharmaceutical sales professionals	2.13	10	Police officers, maritime safety officials	2.29	10	Investigators	2.16

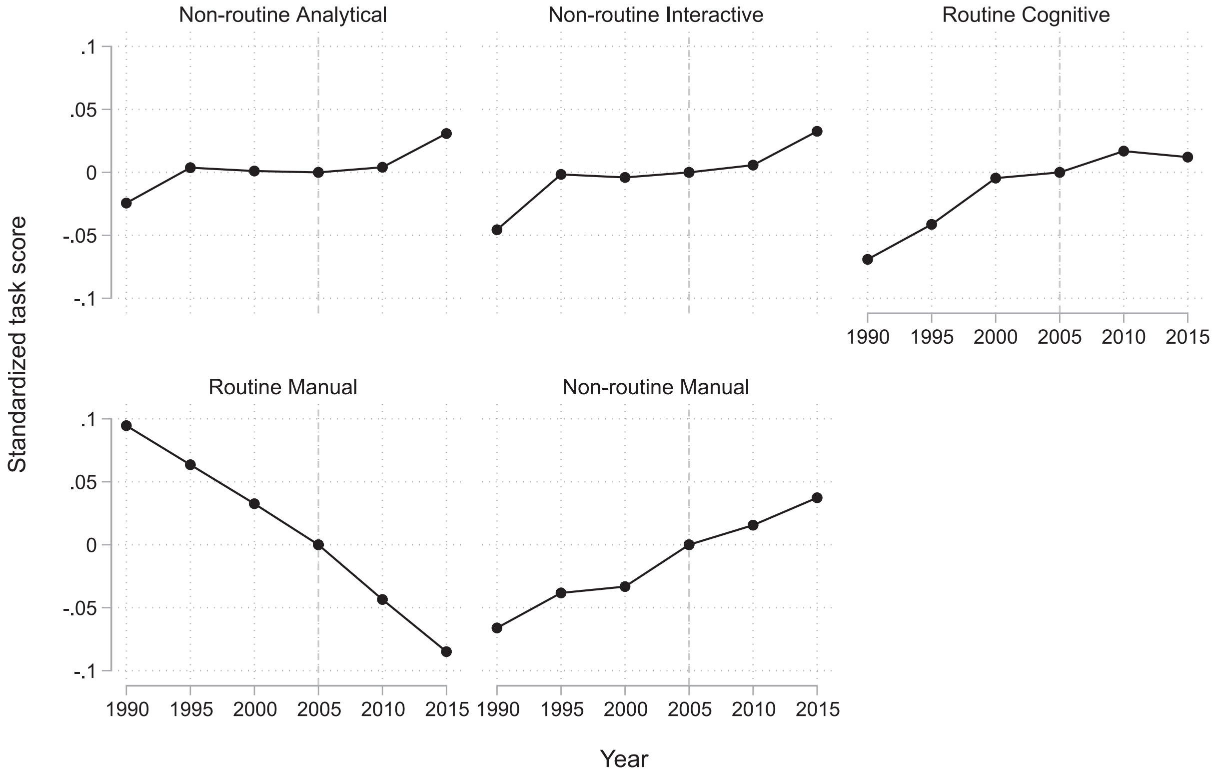
	Routine Manual			Non-routine Manual	
1	Railway drivers	3.93	1	Midwives	3.57
2	Aircraft pilots	3.42	2	Firefighters	3.53
3	Ship's chief engineers, engineers (except fishing boats)	3.22	3	Physio therapists, occupational therapists	3.25
4	Cleaning workers	3.12	4	Childcare workers	2.78
5	Clinical laboratory technicians	2.99	5	Personal trainers (sports)	2.70
6	Pig-iron forging, steelmaking, non-ferrous metal smelting workers	2.39	6	Nurses (including assistant nurses)	2.64
7	Metal cutting and machining workers	2.39	7	Special-needs school education teachers	2.56
8	Construction, well-drilling machinery operators	2.28	8	Home visiting care workers	2.33
9	Crane/winch operators	2.28	9	Other healthcare service professionals	2.31
10	Transportation machinery maintenance and repair workers (excluding automobiles)	2.23	10	Travel and tourist guides	2.30

Note: Authors' calculations using data from the Population Census and the Japanese O-NET. It shows standardized task scores weighted by number of workers in 2005.

Table 3. Correlation coefficients among the five tasks

	Non-routine Analytic	Non-routine Interactive	Routine Cognitive	Routine Manual	Non-routine Manual
Non-routine Analytic	1.00				
Non-routine Interactive	0.87	1.00			
Routine Cognitive	0.12	0.26	1.00		
Routine Manual	-0.17	-0.09	0.31	1.00	
Non-routine Manual	0.28	0.53	0.09	0.35	1.00

Note: Authors' calculations using data from the Population Census and Japanese O-NET. It shows correlation coefficients weighted by the number of workers in 2005.

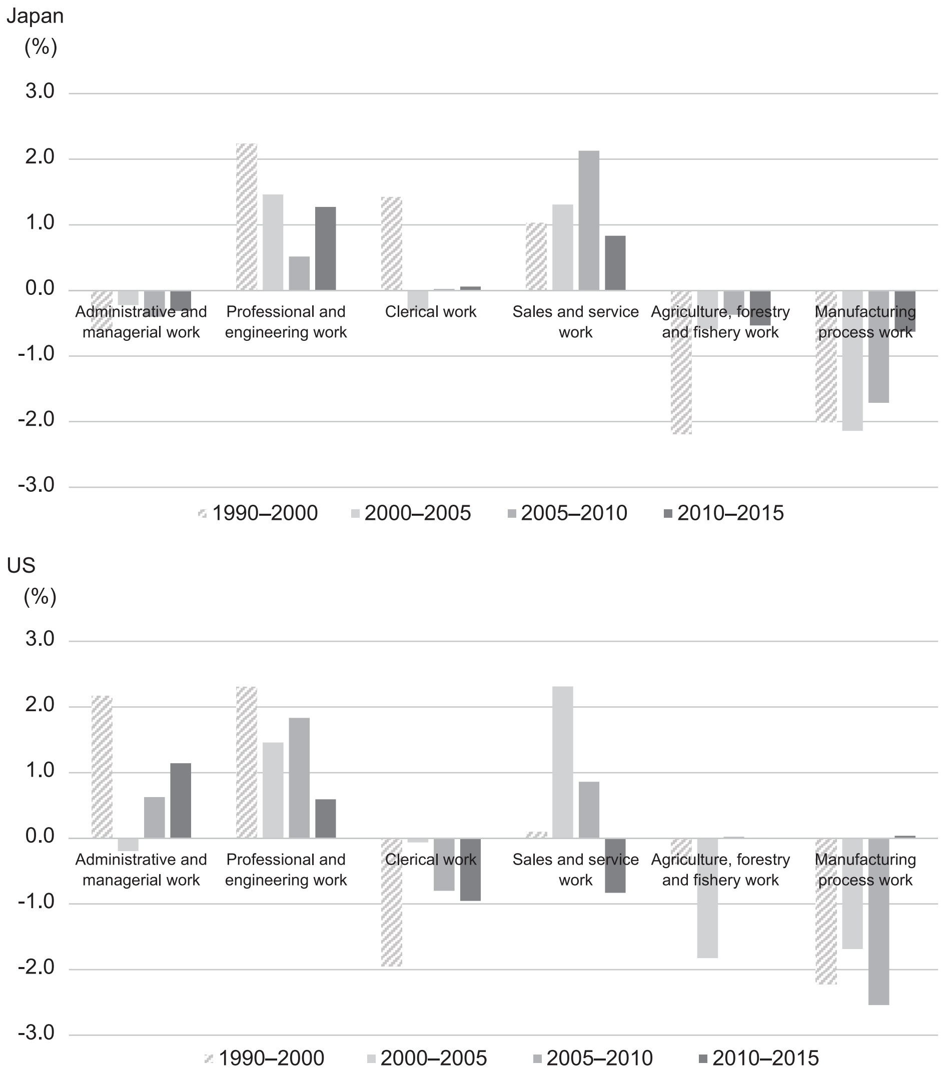


Note: Authors' calculations using data from the Population Census and Japanese O-NET. Old codes are used until 2005 and new codes from 2010 onward. The Standardized task score for each year is calculated with 2005 as zero.

Figure 1. Trends in task scores (1990–2015)

In Acemoglu and Autor (2011), each task corresponds to major occupational categories: non-routine analytical and interactive tasks are strongly correlated with, for example, managers and professional engineers, routine cognitive tasks with clerical and sales clerks, routine cognitive and routine manual tasks with manufacturing process workers, and non-routine manual tasks with service staff. In this context, here we will examine the changes in the share of workers by major occupational categories, comparing Japan with the United States between 1990 and 2015 (Figure 2). The common trend is that the shares of professional and engineering workers and sales and service workers are increasing, while the share of agriculture, forestry, and fishery workers and manufacturing process workers is decreasing. On the other hand, there are some differences. From 1990 to 2015, the share of administrative and managerial workers increased in the US, while it decreased in Japan. Furthermore, in the US, the share of clerical workers declined consistently, while in Japan, the share of clerical workers increased significantly until 2000 with no significant downward trend as in the US.

In addition, Table 4 shows the specific top ten occupations whose share of workers increased or decreased



Source: ILOSTAT Database.

Figure 2. Changes in the share of workers by major occupational category (1990–2015) in Japan and US

between 1990 and 2015. Changes from 1990 to 2005 are shown using the old code, and those from 2005 to 2015 are shown using the new code.

First, let us examine the top ten occupations in terms of the rate of increase/decrease in the share of workers from 1990 to 2005. The share of agricultural workers and manufacturing process workers with high routine manual task scores decreased, while the share of general clerical workers with high routine cognitive task scores increased significantly, and the share of service workers with high non-routine manual task scores increased. Meanwhile, the share of non-routine analytical and interactive task scores rose, despite the decrease in the share of managers with high non-routine analytical and interactive task scores. This is partly because the increase in the share of clerical workers and professional engineers with high non-routine analytical and interactive task scores was greater than the rate of decrease in the share of managers.

Next, focusing on changes between 2005 and 2015, the share of agricultural workers and manufacturing process workers with high routine manual task scores continued to decrease. On the other hand, the share of clerical workers and professional engineers with high non-routine analytical and interactive task scores, and the share of care workers with high non-routine manual task scores increased. It is notable that from 2005 to

Table 4. Task scores for top ten occupations in which share of workers increased or decreased

[1990–2005]

	Top 10 occupations of increase rate in share of workers engaged	Share in 1990	Increase rate in share of workers engaged (%point)	Non-routine Analytical	Non-routine Interactive	Routine Cognitive	Routine Manual	Non-routine Manual
1	General clerical workers	13.6%	1.6%	0.47	0.18	0.17	-0.99	-0.95
2	Service industry workers not otherwise classified	0.2%	1.4%	-0.05	0.22	-0.04	-0.71	1.12
3	Cleaning workers	0.9%	0.7%	-1.40	-0.39	-0.78	0.33	0.58
4	Sales clerks	5.0%	0.6%	-0.65	-0.40	-0.12	-0.24	0.11
5	Sales people (excluding products, insurance, and real estate)	1.4%	0.6%	1.13	1.01	-0.25	-1.22	-0.50
6	Nurses	1.2%	0.5%	1.25	1.72	1.50	1.11	2.80
7	Other food manufacturing workers	0.6%	0.5%	-0.70	-0.64	0.67	1.98	-0.27
8	Housework service providers	0.2%	0.4%	-0.75	-0.72	-0.98	-1.64	1.22
9	Data processing technicians	0.9%	0.4%	1.74	0.79	-0.69	-1.26	-1.22
10	Cooks	2.7%	0.4%	-1.11	-0.36	-0.17	0.62	0.25

	Top 10 occupations of decrease rate in share of workers engaged	Share in 1990	Decrease rate in share of workers engaged (%point)	Non-routine Analytical	Non-routine Interactive	Routine Cognitive	Routine Manual	Non-routine Manual
1	Agricultural and sericulture workers	5.7%	-1.9%	-1.15	-1.93	-2.53	0.44	-0.29
2	Company executives	2.5%	-0.8%	0.65	0.38	-2.18	-0.97	-0.05
3	Sewing machine operators	1.1%	-0.7%	-0.95	-1.61	-1.17	1.10	-1.05
4	Accountancy clerks	4.4%	-0.7%	0.18	0.29	1.77	-0.64	-1.24
5	Corporate and organizational management professionals	1.2%	-0.7%	1.86	3.34	0.56	0.14	1.61
6	Retail managers	1.7%	-0.6%	1.39	1.69	-0.30	0.62	0.68
7	Electro-mechanical apparatus assembly workers	1.4%	-0.5%	-0.42	-0.75	0.37	0.26	-0.67
8	Other metalworkers	1.4%	-0.4%	-0.88	-0.52	1.12	1.03	-0.32
9	Carpenters	1.2%	-0.3%	-0.47	-0.82	-0.01	1.72	0.82
10	Motor vehicle drivers	3.1%	-0.3%	-1.17	-0.96	-0.26	0.25	0.15

[2005–2015]

	Top 10 occupations of increase rate in share of workers engaged	Share in 2005	Increase rate in share of workers engaged (%point)	Non-routine Analytical	Non-routine Interactive	Routine Cognitive	Routine Manual	Non-routine Manual
1	Nursing staff (at medical or welfare facilities, etc.)	1.2%	0.9%	-0.09	0.16	0.26	-0.90	1.39
2	General affairs and human resources workers	1.5%	0.6%	0.68	0.46	-0.26	-1.40	-0.76
3	Building cleaning workers	0.9%	0.5%	-2.84	-2.35	-1.26	-1.06	-0.82
4	Other general clerical workers	5.3%	0.5%	0.71	0.40	0.11	-1.13	-0.73
5	Other social welfare professionals	0.4%	0.4%	1.24	1.45	-0.20	-0.60	1.72
6	Other carrying, cleaning, packaging, and related workers	1.3%	0.4%	-1.97	-1.63	0.31	0.30	-0.67
7	Nurses (including assistant nurses)	1.8%	0.4%	1.28	1.67	1.59	1.07	2.64
8	Automobile assembly workers	0.2%	0.4%	-0.08	-0.05	0.17	0.83	0.29
9	Sales clerks and sales clerical workers	0.9%	0.3%	0.62	0.59	0.44	-0.53	-0.56
10	Software creators	0.1%	0.3%	1.45	0.41	-0.75	-1.46	-1.25

	Top 10 occupations of decrease rate in share of workers engaged	Share in 2005	Decrease rate in share of workers engaged (%point)	Non-routine Analytical	Non-routine Interactive	Routine Cognitive	Routine Manual	Non-routine Manual
1	Agricultural workers	3.8%	-1.0%	-0.98	-1.62	-2.56	0.42	-0.16
2	General clerical workers	5.6%	-0.9%	-1.06	-1.21	-0.08	-0.92	-1.81
3	Other sales clerical workers	3.7%	-0.8%	0.84	0.60	-0.13	-1.05	-0.66
4	Shop assistants	6.4%	-0.6%	-0.50	-0.24	-0.12	-0.25	0.19
5	Retailers, retail managers	1.1%	-0.4%	1.37	1.63	-0.24	0.59	0.71
6	Electro-mechanical apparatus assembly workers	1.2%	-0.4%	-0.14	-0.58	0.72	0.98	-0.65
7	General-purpose, manufacturing, and business-use mechanical apparatus assembly workers	0.9%	-0.4%	-0.28	-0.64	0.66	0.73	-0.32
8	Other cleaning workers	0.6%	-0.4%	-0.23	0.90	0.07	0.76	1.03
9	Accountancy clerks	2.9%	-0.3%	0.29	0.38	1.80	-0.64	-1.07
10	Spinning, weaving, apparel, and fiber product inspection workers	0.9%	-0.3%	-0.51	-1.01	-0.65	1.15	-0.63

Note: Authors' calculations using data from the Population Census and the Japanese O-NET.Gray shading is for non-routine analytical, non-routine interactive and non-routine manual tasks with a positive standardized score.

2015, the share of building cleaning workers and other carrying, cleaning, packaging, and related workers with low non-routine analytical and interactive/manual task scores increased. The growth of these occupations is thought to result from the fact that there are detailed tasks that can only be done by people who are irreplaceable by machines, and that human workers are cheaper than automation in these occupations.

Finally, let us examine the changes in the share of clerical workers with high routine cognitive task scores. After 2005 when the occupational category of "clerical workers" was subdivided, the share of general clerical workers with low non-routine analytical/interactive task scores and that of accountancy clerks with high routine cognitive task scores decreased. On the other hand, the share of general affairs and human resources workers, other general clerical workers, and sales clerks and other clerical sales workers with relatively high non-routine analytical and interactive task scores increased. As shown in Figure 2, there was no increase in the share of clerical workers as a major occupational category after 2005, but in terms of more specific occupational categories, we see that the share of the occupation increased or decreased depending on whether or not analytical and/or interactive tasks are involved.

3. Trends in task distribution by gender

Are there different task trends between men and women? Figure 3 shows trends in the five task scores by gender from 1990 to 2015. Regarding non-routine analytical and interactive tasks, the increase for women is larger than that for men, shrinking the gender gap. Routine cognitive tasks did not change significantly for men, but increased for women until 2000 and then leveled off from 2005 on. Routine manual tasks decreased for both men and women, and non-routine manual tasks did not change significantly for men, but increased significantly for women.

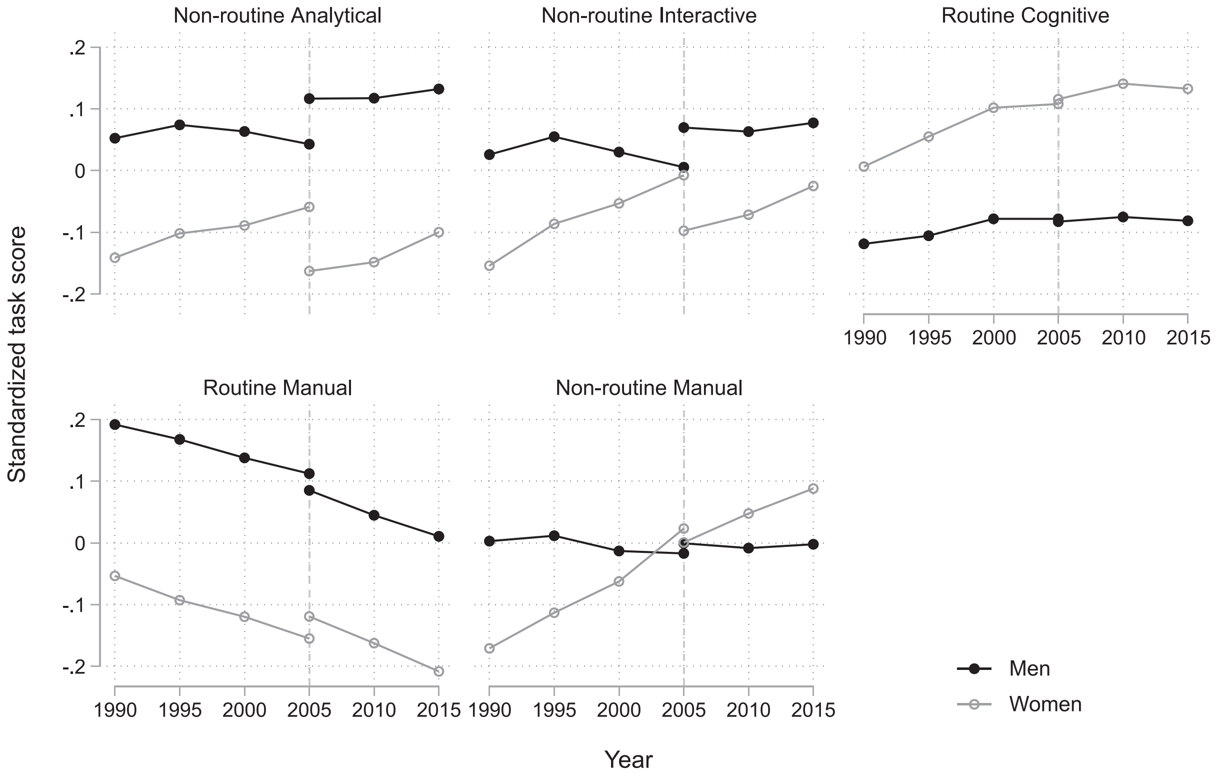
Focusing on non-routine analytical and interactive tasks, there are major differences between men and women in 2005. In particular, clerical work is the area of revision that seems to have greatly impacted the disparity in results between the new and old code. In the new code, clerical jobs that were previously grouped into a small number of categories have been divided into clerical jobs with high non-routine analytical and interactive task scores (general affairs and human resources workers, other general clerical workers, production-related clerical workers, sales clerks and sales clerical workers) and clerical jobs with low non-routine analytical and interactive task scores (general clerical workers, reception and guidance clerical workers). There are more male workers in clerical jobs with high non-routine analytical and interactive task scores, and more female workers in clerical jobs with low non-routine analytical and interactive task scores. Thus, it appears likely that the gender difference in task scores widened with the new code.

Examining the top ten occupations from 2005 to 2015, for men, professional technical positions with high non-routine task scores increased. However, it was offset by a decrease of sales positions, retailers and retail managers, administrative positions and other occupations with high non-routine task scores. Meanwhile, for women, clerical workers, sales clerks, manufacturing process workers and other occupations with low non-routine analytical and interactive task scores decreased, and clerical workers and professional technical staff with high non-routine analytical and interactive task scores increased. This explains the increase of non-routine analytical and interactive tasks for women is larger than that for men.

4. Trends in task distribution by age group

It is clear that task trends differ between men and women. Do task trends also differ depending on age, even among the same gender? Figure 4 shows trends in scores in the five task categories by both gender and age group.

For men aged 25–34, non-routine analytical and interactive tasks decreased from 1995 to 2005, while routine and non-routine manual tasks increased. In terms of specific occupations, from 1990 to 2005, the share of men aged 25 to 34 in white-collar jobs with high non-routine analytical and interactive task scores (sales people, teachers, engineers, and so forth) shrank, while the share of manufacturing process workers and service



Note: Authors' calculations using data from the Population Census and Japanese O-NET.

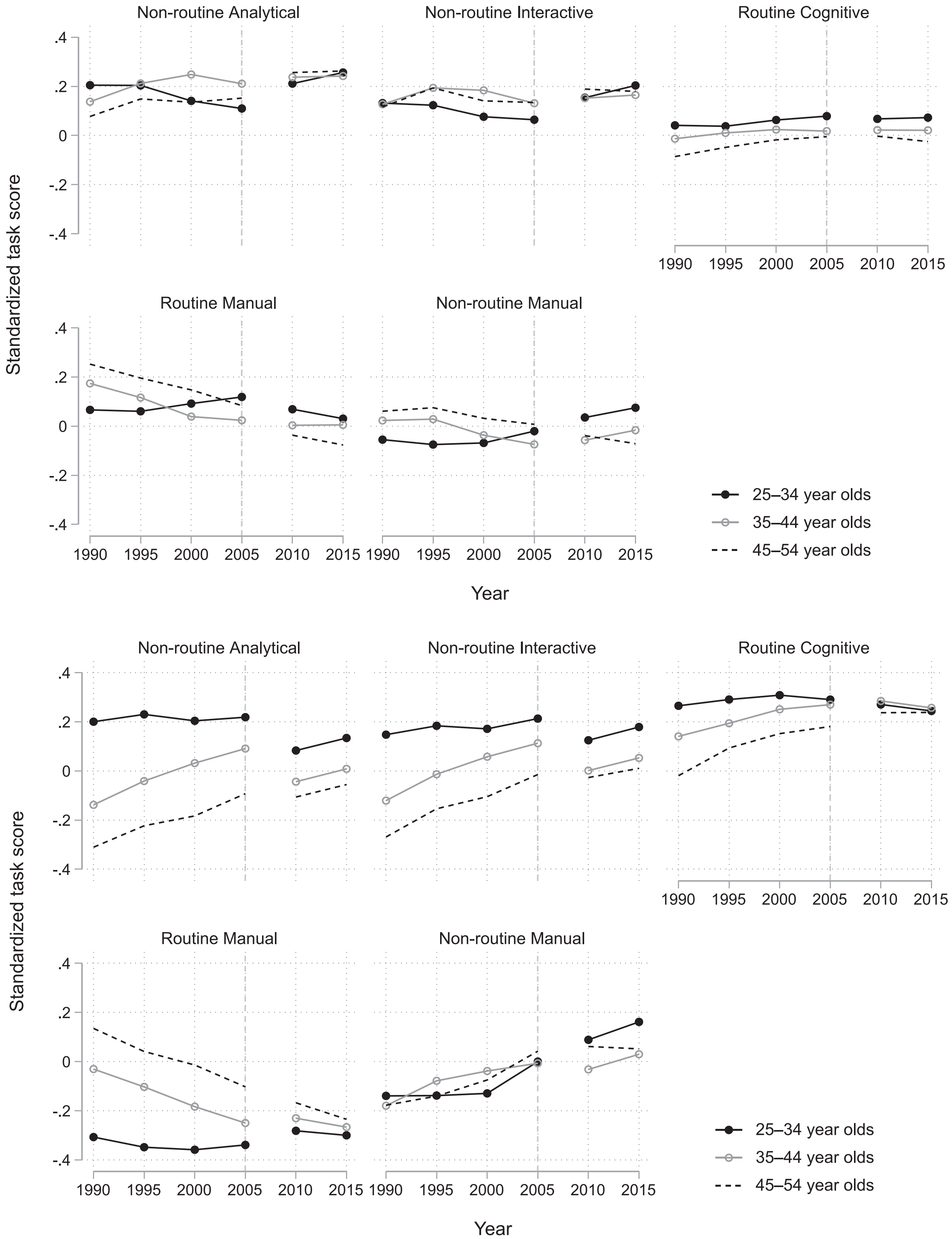
Figure 3. Trends in task scores, by gender (1990–2015)

staff with high routine manual task scores grew. In the meantime, among men aged 35 and over, non-routine analytical and interactive tasks increased while routine manual and non-routine manual task scores decreased from 1990 to 2005. It is interesting to see opposite tendencies among young and middle-aged workers, which will be examined later in the discussion.

For middle-aged and older women, non-routine analytical and interactive/manual tasks and routine cognitive tasks increased from 1990 to 2005, while routine manual tasks decreased. Specifically, the share of manufacturing process laborers and agricultural workers with high routine manual task scores fell, while the share of occupations with high non-routine analytical, interactive and manual task scores, such as general clerical workers, nurses, childcare workers, and housework service providers, rose during the same period. Turning to young women aged 25 to 34, there was no upward trend for non-routine analytical and interactive tasks from 1990 to 2005, but non-routine manual tasks trended upward from 2000 onward.

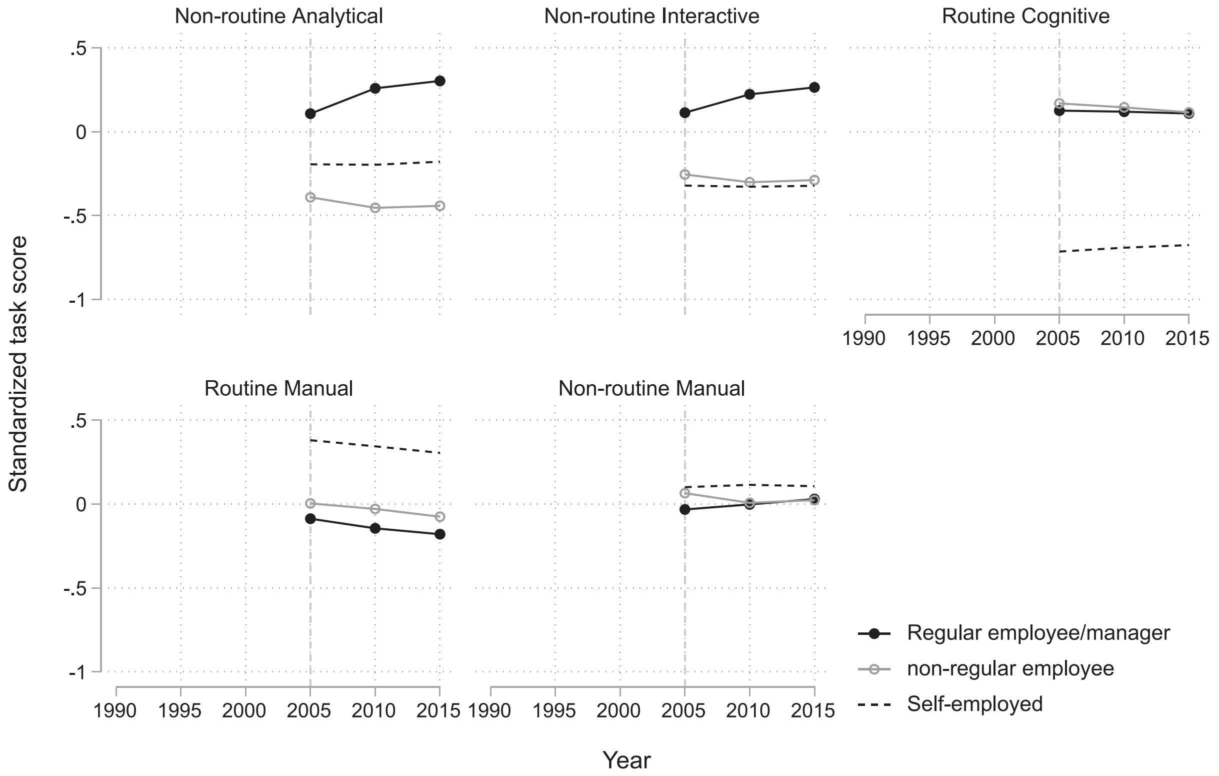
5. Trends in task distribution by employment status

In Japan, non-regular employment has been on the rise since the late 1990s. How do task score trends differ depending on the employment status? Figure 5 shows the change in scores in the five task categories by employment status between 2005 and 2015.[12] While non-routine analytical and interactive task scores rose for regular employment, task scores for non-regular employment fell slightly. As a result, the difference between non-routine analytical and interactive task scores of regular and non-regular employees is widening. Looking at specific occupations, among regular employees and managers, the share of clerical workers and specialized engineers with high non-routine analytical and interactive task scores increased, while the share of occupations with low non-routine analytical and interactive task scores, such as sales clerks and food and drink preparatory workers, declined. On the other hand, in non-regular employment, the share of occupations such as sales



Note: Authors' calculations using data from the Population Census and the Japanese O-NET.

Figure 4. Trends in task scores, by gender and age group (1990–2015)



Note: Authors' calculations using data from the Population Census and Japanese O-NET.

Figure 5. Trends in task scores, by employment status (2005–2015)

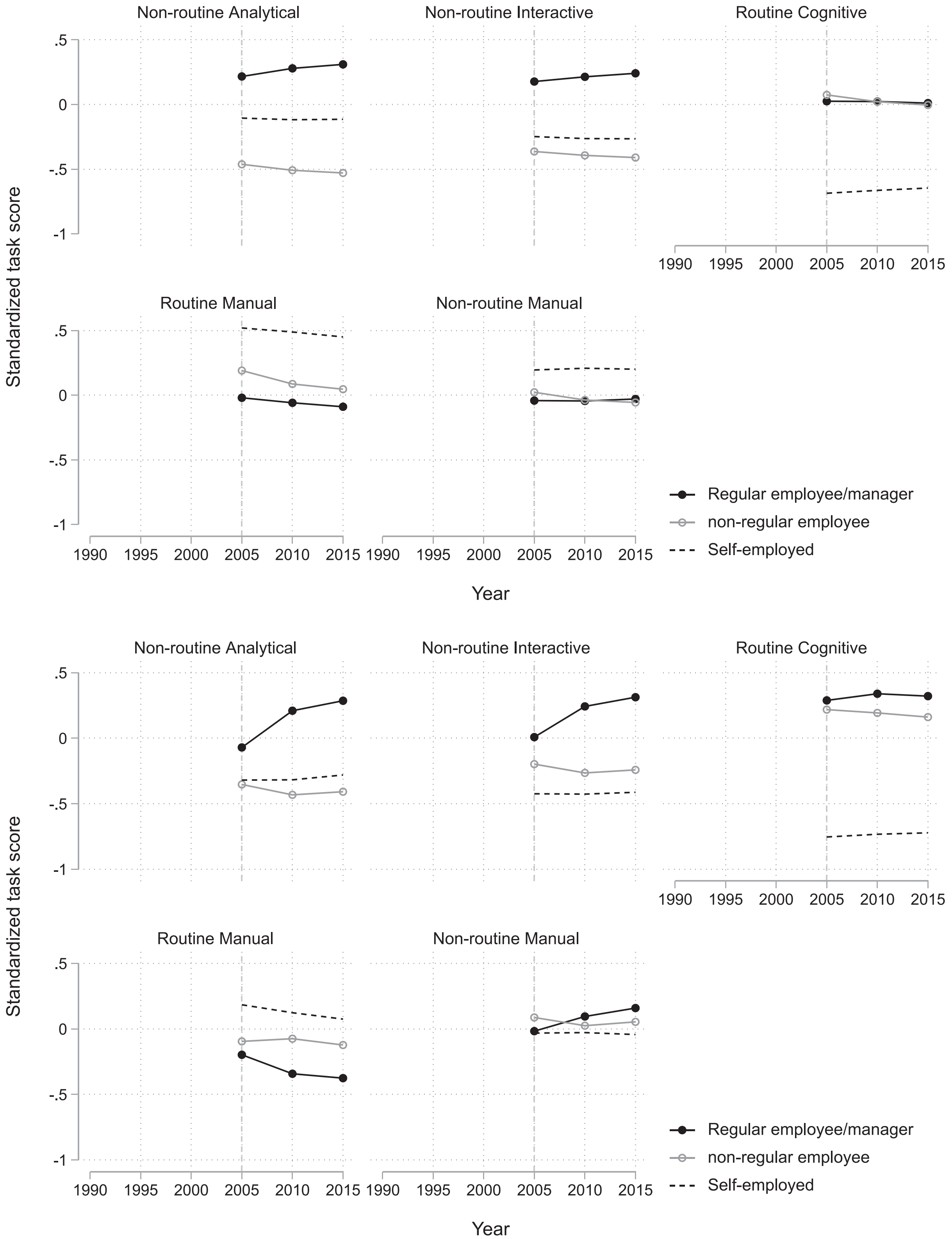
clerks, cooks and food manufacturing showed an increase, while they fell among regular employees and executives. The downward trend of non-routine analytical and interactive task scores in non-regular employment suggests that non-regular employees may have replaced regular employees in occupations that do not require these tasks.

Do task score trends by employment status differ between men and women? Figure 6 shows trends in scores for the five task categories by both gender and employment status. By gender, trends for men did not change significantly between 2005 and 2015, while for women, there was an increase in non-routine analytical, interactive and manual task scores for regular employees and managers. As a result, the difference between non-routine analytical and interactive task scores of regular and those of non-regular employees is widening.

Why is the increase in non-routine analytical, interactive and manual task scores of regular employees and managers only seen among women? Among female regular employees, the share of medical welfare professionals, clerical workers, and nursing care staff with high non-routine analytical and interactive and manual task scores rose, while the share of sales and service staff with low scores in these areas fell. Meanwhile, these changes were not so pronounced among male regular employees. As the occupational distribution of women changed significantly from 2005 to 2015, their ask scores also rapidly changed.

IV. Conclusion

In this study, we used the occupation matching data from the Japanese O-NET and the Population Census to examine task trends in the Japanese labor market from 1990 to 2015. As a result, the following points were clarified. First, non-routine analytical, interactive and manual tasks are increasing, while routine manual tasks are decreasing. Also, routine cognitive tasks, which increased until around 2000, have remained flat since



Note: Authors' calculations using data from the Population Census and Japanese O-NET.

Figure 6. Trends in task scores, by gender and employment status (2005–2015)

2005. Second, task trends differ depending on workers' characteristics such as gender, age, and employment status. On gender, the rate of increase of non-routine analytical, interactive and manual tasks among women is consistently higher than that among men from 1990 to 2015. Examining different age groups by gender, non-routine analytical and interactive tasks for young men decreased and routine manual tasks increased, a contrasting trend for overall and among middle-aged men. By employment status, since 2005 non-routine analytical and interactive tasks increased for regular employees and managers, while the same tasks decreased slightly among non-regular employees. This tendency is particularly pronounced among female regular employees.

This study observed the latest task trends from 1990 to 2015 by using task indicators from the Japanese O-NET. As a result, even with task indicators different from those of Ikenaga and Kambayashi, it became clear that there was growing "task polarization" in Japan from 1990 to 2015, with high-level and low-level non-routine tasks increasing while routine tasks decreased. In addition, this study showed new findings, such as different task distribution by workers' characteristics and changes in the trends in routine cognitive tasks around 2005. We will discuss these findings further below.

First, this study showed that task trends vary by workers' characteristics such as age and gender. The results clearly indicate that the change in task distribution for men was small while the increase in non-routine tasks for women was large, resulting in a greater task polarization among women. In addition, there were changes especially among middle-aged and older women and young men. In the context of an aging population and the growth of the service economy, the demand for agriculture and manufacturing jobs with predominantly manual tasks declined, which is counterbalanced by increased demand for medical and welfare service occupations that require non-routine tasks. Middle-aged and older women may have filled this demand. By contrast, younger men were less likely to be engaged in highly skilled tasks, such as non-routine analytical and interactive tasks, during the recession from the late 1990s through the mid-2000s. This suggests that young men did not have opportunities to obtain jobs with favorable conditions due to curtailing of new hires amid the economic downturn. The fact that task trends differ depending on workers' characteristics means that changes in the industrial structure have a non-uniform effect on workers. To examine changes in task distribution, demographic factors such as aging and increasing female employment and employment practices need to be taken into account instead of focusing only on technological innovations.

Second, this study showed that routine cognitive tasks were on the rise from 1990 to 2000, but have leveled off since 2005. In terms of specific occupations, even within the single major category of "clerical workers," the share of clerical workers that perform many advanced non-routine analytical and interactive tasks has risen, while the share of clerical workers who do not perform many of these tasks has fallen since 2005. DeLaRica and Gortazar (2016) pointed out that Japan has a higher degree of routine tasks than Western countries. Ikenaga and Kambayashi (2016) also pointed out that Japan's transition to IT has been more gradual than that of the United States. However, changing trends in routine cognitive tasks since 2005 suggest the possibility that highly routine occupations that involve few non-routine analytical and interactive tasks will decrease due to progress in the introduction of ICT (information and communications technology) and artificial intelligence in Japan.

Third, this study's use of task indicators differing from that of Acemoglu and Autor (2011) and Ikenaga and Kambayashi (2016) delivered some different results. While non-routine manual tasks decreased in the United States (Autor et al. 2003), we showed the tasks increased in Japan as in Ikenaga and Kambayashi (2016), despite the difference in measurements. However, we think that our measurements are appropriate because it conforms to the original definition of "non-routine manual tasks." Also, routine cognitive tasks increased from 1990 to 2000 in this study, unlike in Ikenaga and Kambayashi (2016), which showed a consistent decrease from 1965 to 2005. This is because the measurement of routine cognigive tasks is different from the one in Ikenaga and Kambayashi (2016). Their measurement for routine cognitive tasks is "skill with equipment and controls", which refers only to physical labor using machines, i.e. does not include clerical work, which is the reason for the consistent downward trend. However, as shown in Figure 2, unlike in the United States, the share of clerical workers correlated with the increase of routine cognitive tasks from to1990 to 2000 in Japan. Thus, the upward trend of routine cognitive tasks from 1990 to 2000 in this article, which uses the same indicators as Acemoglu and Autor (2011), appears to be a reasonable finding.

The results of the analysis in this article suggest that it is important to develop and foster non-routine skills that are less likely to be replaced by ICT and AI than routine tasks. To that end, in addition to establishing a safety net for workers whose jobs are replaced by ICT or AI, public vocational training should be expanded, so that such workers can develop skills irreplaceable by ICT and AI.

We make it clear that the changes in task distribution were not the same between women and men in Japan. Future studies are required to reveal why the trends in task distribution differs according to gender and employment status, using more detailed individual data.

This paper is based on "Nihonban O-NET no suuchi Johou o shiyou shita ouyou kenkyu no kanosei" [Trends in Task Distribution in Japan: Evidence from the Occupational Information Network of Japan and the Population Census Data], JILPT Discussion Paper 21-11 (March 2021, in Japanese, https://www.jil.go.jp/institute/discussion/2021/documents/DP21-11.pdf) with additions and amendments in line with the gist of *Japan Labor Issues*.

Notes

1. For a theoretical framework of the task approach, cf. Autor et al. (2003), Acemoglu and Autor (2011), Acemoglu and Restrepo (2018).
2. DOT was first released by the US Department of Labor in 1939, and was revised in 1949, 1965, 1977, and 1991. When it was first released, it contained qualitative occupational information centered around tasks, but in subsequent revisions, other multifaceted quantitative data have been added, such as the length of training period, worker functions, physical requirements, working environment, GATB (General Aptitude Test Battery) benchmarks, personality, and interests (JILPT 2011).
3. O*NET was constructed to resolve the DOT's problem of the huge budget and time required to collect occupational information (Peterson et. al 2001). O*NET is an occupational information website operated by the US Employment and Training Administration, containing 923 occupations (as of March 2021).
4. Career Matrix was an occupational information website launched in 2006 by the Japan Institute for Labour Policy and Training (JILPT). The project was suspended in March 2011.
5. Autor et al. (2003) state that there is no clear relationship between IT introduction and non-routine manual tasks in terms of replacement or supplementation,.
6. The Japanese O-NET was developed with reference to O*NET in the United States, and information on jobs, tasks, skill requirements and knowledge, generalized work activities and so forth for about 500 occupations is provided online. Skill requirements, knowledge, generalized work activities, etc. for these occupations are quantified.
7. Quantitative information was collected between 2018 and 2021 through an online survey of workers conducted by the JILPT and a supplementary paper-based survey. In addition to the respondents' attributes (employment status, occupation, specific work contents, years of experience, etc.) for each occupation, data was collected on their "Occupational Interest," "Work Values," "Education and Training," "Skills," "Knowledge," "Work Context," and "Generalized Work Activities." As for the method of selecting occupations, details of survey contents and overall trends of respondents, etc., see JILPT (2020, 2021) and Kamakura et al. (2020)
8. As the Occupational coding system in the Population Census was revised in 2010, the occupational categories used in the Population Census from 1990 to 2005 are referred to as the old code, while the occupational categories used in the Population Census from 2010 to 2015 are referred to as the new code. At the same time, data on workers by gender from the 2005 Population Census, were retroactively tabulated with the new categories used in the 2010 census. Therefore, this study used new categories as well as old categories for the 2005 Population Census.
9. In the future, Japanese O-NET will regularly re-examine quantitative information for each occupation, which allows us to grasp changes in tasks within occupations.
10. In Acemoglu and Autor (2011), the non-routine manual task score for manufacturing process workers is as high as the routine manual task score, while the non-routine manual task score for service workers is not high. Autor et al. (2003) also pointed out a drawback of DOT in that the sample of service sector occupations is limited and important job skills are omitted, suggesting that these shortcomings of DOT are likely to reduce the precision of their analysis.
11. Top ten occupations requiring "skill with interpersonal support services" are public health nurses, midwives, judges/prosecutors/attorneys, teachers, physiotherapists and occupational therapists, dentists, and nurses. Also, the correlation between non-routine manual tasks and non-routine analytical and interactive tasks is high at 0.70 and 0.77. Therefore, we think that occupations in "interpersonal support services" require relatively advanced skills.
12. The Population Census has been inquiring about the employment status since 2000, but as the 2000 Population Census uses the old code, data from 2005 onwards was used in this study.

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