Long-term Trends in the Polarization of the Japanese Labor Market:

The Increase of Non-routine Task Input and Its Valuation in the Labor Market

January 2010

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Abstract

In this paper, quantifying the various skills required in each occupation, we examine the long-term trend in labor market polarization in Japan in terms of tasks. Specifically, following Autor, Levy and Murnane (2003), we divide tasks according to whether they involve routine or nonroutine work and whether they involve intellectual or physical work into the five categories of nonroutine analytic, nonroutine interactive, routine cognitive, routine manual, and nonroutine manual tasks and statistically examine the trends in inputs of these tasks in the period from 1960 to 2005. We find that the input share of nonroutine tasks (interactive, manual, and analytic) has increased almost consistently, while the input share of routine tasks (cognitive and manual) has decreased almost consistently. With regard to nonroutine tasks, an increase in the input share of both high-skill and low-skill tasks can be observed. Further, we estimate the valuation of the five tasks in the labor market from 1970 to 2000 by regressing the average wage for each occupation on the five tasks. We find the average wage in an occupation is positively correlated with routine cognitive task input and negatively correlated with routine manual task input. Considering the labor market valuation of tasks in relation to trends input shares of tasks over time, we conjecture, with regard to trends in the supply of and demand for tasks, that for nonroutine analytic and routine manual task input, the increasing change in demand seems to dominate, while for nonroutine interactive and nonroutine manual task input as well as for routine cognitive task input, the decreasing changes in supply appears to dominate.

1. Introduction

In the past two decades or so, many advanced economies have experienced a growing income divide and increasing wage inequality. Especially in the United States, a rapid rise in wage inequality was observed in the 1980s, sparking a lively debate in a variety of disciplines ranging from political science to sociology and economics. In the 1990s, the trends observed in the United States not only continued, but took on new facets, spurring even further debate. Specifically, what gained the attention of researchers is the polarization of the labor market, characterized by two major trends. First, whereas the wages of top earners relative to those in the middle continued to rise, wage differentials between those in the middle and those at the bottom started to decrease. And second, at the same time, employment in both high wage and low wage jobs (the latter mainly in the service sector) increased, while the percentage share of those earning wages in the middle decreased.

There is large body of literature, much of it on the United States, exploring the causes of the increase in wage inequality during the 1980s. Following Katz and Autor (1999), studies focusing on these trends can be broadly classified into three categories. The first of these, of which Lee (1999) is a representative example, points to institutional factors as causes for the increase in wage inequality. Specifically, studies in this vein highlight the decline in the real minimum wage and in unionization rates. The second strand of studies, including Wood (1994, 1995, 1996), Sachs and Shatz (1994), and Feenstra and Hanson (1999, 2001), focuses on changes in competition internationally and in domestic product markets. These studies argue that greater international competition, for example through reductions in barriers to trade, and other aspects of globalization such as the rise in outsourcing, have led to an increase in the demand for skilled workers and a decrease in the demand for low-skill workers and that, as a result, wage differentials between the two groups have grown. Finally, the third group of studies, following Berman, Bound and Griliches (1994), focuses on the role of so-called skill-biased technological change (SBTC). Studies along these lines, such as Autor, Katz and Krueger (1998) and Berman, Bound and Machin (1998), see technological change, and in particular the introduction of information and communication technology (ICT) as the main reason for the growing wage inequality. ICT, they argue, is relatively more complementary with skilled occupations, and technological change such as the spread of the computer as a consequence has raised the relative marginal productivity of skilled workers.

Although the different strands offer alternative explanations, a consensus appears to have been formed regarding the important role played by workers' "skills" in explaining the rise in wage inequality. What is more, the concept of "skills" has been a key element in subsequent analyses and it appears that initially, it was thought that developments from the 1990s onward could be explained simply by applying the approaches used for explaining trends during the 1980s. However, on closer inspection, the concept of "skills" proves to be rather ambiguous, and when approaches developed to explain trends in the 1980s were used to address subsequent developments, various problems emerged. In theory, the concept of "skills" refers to the abilities that a worker possesses, but in practice the skills of a particular worker were, for simplicity, normally proxied by his or her educational attainment or the occupational category to which he or she belonged. Workers were then simply being divided into (blue collar) production workers and (white collar) nonproduction workers, high school graduates were assumed to be blue collar workers, college graduates white collar workers, and the former were assume to be low skill, while the latter were skilled.

However, with rising education levels and changes in industrial structures, the types of work performed by workers with the same educational attainment or belonging to the same job category have become increasingly diverse and, as a result, cases in which the skills of workers in the same educational or job category differ have also increased. For that reason, it has become increasingly difficult to assign a particular level of "skill" using external worker characteristics such as educational attainment or broad job category; instead, it is necessary to develop a concept of "skill" that focuses on the content of the work that a particular worker is engaged in. For instance, in order to determine whether a specific worker is skilled, the criterion is not simply whether he or she is a college graduate and/or white collar worker, but whether he or she performs tasks that require specialized expertise and abilities. Similarly, workers are classified as low-skill not on the basis of whether the tasks they perform are mechanical and repetitive or difficult to mechanize, but on the basis that they do not require any specialized expertise or abilities.

Looking at economy-wide trends in labor input from such a task-based perspective, we find that in parallel with the continuous rise in wage inequality, a conspicuous development not only in the United States, but also in European countries and Japan, is a polarization in task input, that is, an increase in labor input of both high skill and low skill tasks coupled with a simultaneous decline in the input of "middle skill" routine tasks. Although there is of course no reason to assume that the economy-wide distribution of workers' skills, understood in the original sense of the concept, and the distribution of tasks at any one time perfectly match, it has been noted that the observed polarization in task input essentially describes the same thing as the polarization in skills and as such provides clear evidence of changes in the labor market since the 1990s.

In a seminal paper, Autor, Levy and Murnane (2003; referred to as ALM hereafter) constructed and tested a simple theoretical model to explain these phenomena. Rejecting the dichotomy between "skilled" and "unskilled" workers that informed the mainstream of studies conducted during the 1990s, ALM instead distinguished the content of tasks in terms of whether they were routine or nonroutine, and whether they were intellectual or physical. Furthermore, keeping in mind the role of computer technology highlighted by the SBTC hypothesis, they examined changes in the composition of task input in the economy overall and showed a polarization in task input. Specifically, ALM divided tasks into the following five types:

- Nonroutine analytic tasks;
- Nonroutine interactive tasks;
- Routine cognitive tasks;
- Routine manual tasks; and
- Nonroutine manual tasks.

Nonroutine analytic tasks are defined as tasks that require highly specialized knowledge and the ability to solve problems using abstract thinking. On the other hand, nonroutine interactive tasks are tasks that create and provide value through complex interpersonal communication such as negotiation, management, and consulting activities. The difference between the two categories is that whereas nonroutine analytic tasks can be performed relatively independently, in the case of nonroutine interactive tasks, a major part of such tasks consists of interaction with other workers or those that the tasks are provided for (such as clients). Next, routine cognitive tasks are clerical and information-processing tasks that can be accomplished following explicit rules. Routine manual tasks also can be accomplished following explicit rules, but are performed through physical work (production involving routine repetitive manual work or work involving the operation of machines). In contrast, nonroutine manual tasks do not require a particularly high level of specialized knowledge, but involve physical work consisting not of routine activities but of activities that require a flexible response to particular situations. One of the main findings obtained by ALM is that, on the one hand, computer technology has substituted for, and led to a decrease in, routine manual and routine cognitive tasks, while on the other it has complemented, and increased the labor demand for, nonroutine analytic and nonroutine interactive tasks. ALM's approach has subsequently been applied to countries other than the United States, with Goos and Manning (2007) and Spitz-Oener (2006), for example, respectively reporting similar trends to those observed in the United States for Britain and West Germany.

The first study to apply ALM's approach to Japan is Ikenaga (2009a). The study grouped the detailed occupational classifications of the *Population Census* into the five task categories distinguished by ALM, that is, into nonroutine analytic, nonroutine interactive, routine cognitive, routine manual, and nonroutine manual tasks. The results suggested that in Japan, too, labor input of knowledge-intensive nonroutine analytic tasks and relatively low-skill nonroutine manual tasks (home help, nursing, protective and guarding services, etc.) has increased from the 1990s onward, while labor input of routine manual tasks has decreased. Moreover, the study indicated that ICT capital complements workers performing nonroutine analytic tasks, but substitutes for workers performing routine tasks (both cognitive and manual), and that overall, the trends and patterns were similar to those in the United States and Europe.

However, the methodology adopted in Ikenaga (2009a) is relatively rough, with entire occupational categories being assigned to the specific task to which they are thought to most closely correspond among the five tasks distinguished by ALM. For example, if nonroutine interactive tasks were thought to be the most important tasks within the duties of a particular occupational category (say, "physician"), then all those employed in that particular occupation (in this case, physicians) were regarded as completely specialized in nonroutine interactive tasks. Therefore, the trends in the composition of task input in the economy are identical to the trends in the occupational composition of the labor force. In practice, however every job normally consists of a mixture of the five tasks, and therefore assuming that those employed in a particular occupational category are completely specialized in one task is rather unreasonable.

Against this background, the aim of the present study is to expand on Ikenaga (2009a) and capture the composition of the task input in the economy overall taking into account that each occupational category comprises a combination of the five tasks. In addition, this study extends the sample period to the 45-year span from 1960 to 2005 and examines the polarization in task input from a more long-term perspective. Specifically, using the *Career Matrix*, a database on the content of occupations prepared by the Japan Institute for Labour Policy and Training, we calculate the intensity of each of the five tasks in each occupational category and by aggregating these intensities using employment data from the *Population Census* as weights obtain percentage shares for each of the five tasks across all occupations. Finally, we estimate how the five tasks are valued in the labor market and by linking this with changes in task input shares make conjectures concerning trends in the demand for and supply of each task.

The main findings of this study can be summarized as follows. First, since 1960, the labor input shares of nonroutine tasks (interactive, manual, and analytic) show an almost consistent monotonic increase and the shares of routine tasks (cognitive and manual) an almost consistent monotonic decrease. In Ikenaga (2009a), which is based on the one occupation-one task correspondence, nonroutine analytic task input showed the highest increase and routine cognitive task input also showed an increase. The present study, which considers the composition of the five tasks within each occupation, in contrast, finds that the share of nonroutine *interactive* task input has overtaken that of nonroutine *analytic* task input, while the input of nonroutine analytic tasks has decreased rather than increased.

Second, the finding of a consistent monotonic decrease in routine task input and increase in nonroutine task input observed in Japan from the 1960s onward differs from the pattern observed for the United States. Especially the long-term trends concerning the input share of manual tasks requiring physical work differ notably for the two countries. Part of this difference arises from differences in industrial and occupational structures in the two countries at the starting point of our comparison, but it also owes to differences in the valuation of skills in Japan and the United States.

Third, using the hedonic wage approach to estimate, for the period from 1970 to 2000, how the five tasks are valued in the labor market, the results show that the average wage for each job category is positively correlated with the score for routine cognitive tasks and negatively correlated with the score for routine manual tasks. If we interpret the estimated coefficients as the price valuation of tasks in the labor market and consider them along with the trend over time in task input shares on a quantity basis, we find that for nonroutine analytic and routine manual task input, changes in demand slightly dominate in terms of explaining changes in task input shares, while for nonroutine interactive and manual tasks as well as routine cognitive tasks, changes in supply dominate.

The remainder of the paper is organized as follows. Section 2 presents the analytical framework and explains the data used in the analysis. In Section 3, using the *Career Matrix* and the *Population Census*, we examine the quantitative trends in the five tasks in the economy overall. Next, in Section 4, we try to discover the reasons for the divergence between our results for these trends in Japan and trends reported for the United States.. In Section 5, we then regress the average wage for each occupational category on the composition of task input of that occupation to obtain the monetary valuation of the five tasks in the labor market and, moreover, examine the relationship between developments in task input shares and the valuation of input of the five different tasks in the labor market. Section 6 offers concluding remarks and discusses issues for future research.

2. Framework and data for measuring the composition of task input

2.1 Measurement framework

We begin by describing how we calculate the share of each of the five tasks based on available statistics on the number of employees by occupation such as the *Population Census*. The number of persons employed in occupation i (i=1,…, I) is represented by X_i. Moreover, the share of task j (j=1,…, J) in the economy overall is represented by Y_j (however, following ALM, the number of tasks throughout this study is set to five, i.e., $J = 5$). Thus, we have

$$X = \begin{pmatrix} X_1 \\ \vdots \\ X_I \end{pmatrix}, \quad Y = \begin{pmatrix} Y_1 \\ \vdots \\ Y_J \end{pmatrix} \qquad \text{(a)}$$

The challenge is how to convert vector X into vector Y. Here, we combine two criteria, the importance of skill s in occupation i, C_{si}, which we call *skill score*, and the importance of each task j for skill s, D_{js}, which we call the *task score*. That is, considering the two matrices

$$C = \begin{pmatrix} C_{11} & \cdots & C_{1I} \\ \vdots & \ddots & \vdots \\ C_{s1} & \cdots & C_{sI} \end{pmatrix} \qquad D = \begin{pmatrix} D_{11} & \cdots & D_{1s} \\ \vdots & \ddots & \vdots \\ D_{J1} & \cdots & D_{Js} \end{pmatrix} \qquad \text{(b)}$$

we calculate the extent to which task j is important in occupation i as DC, the *task intensity*. Doing so, we can then define the task share, Y, as

$$Y \equiv \frac{DCX}{\sum_{j=1}^{5} DCX} \qquad \text{(c)}$$

2.2 Data

For the number of employed persons by occupation, that is, with regard to matrix X, we use the detailed classification of six issues of the *Population Census* spanning the 45-year period that we focus on. Of course, there have been considerable changes to the job classifications within this period. In this study, we therefore focus on 237 occupational categories for which we can construct consistent time series by merging or dividing categories for the entire 45-year period.[3]

For the skill score, which shows the extent to which various skills are important in each occupation, we use the *Career Matrix* by the Japan Institute for Labour Policy and Training. For each of 503 occupational categories, the *Career Matrix* provides a list of 35 skills and their importance for the execution of that particular job on a five-step scale (see Appendix Table 1 for details).[4] For example, for physicians, "reading comprehension" is assigned a value of 5 (=very important), and following the conventions in this paper, this is represented by $C_{si} = 5$.

For the task score, which measures the importance of each of the five tasks for the 35 skills, we enlisted the help of three other researchers in the field of labor economics. Each of us assigned points to the different skills, with 2 points given if a skill was considered to be "absolutely essential," 1 point if "it is better to have this skill," and 0 points if "it is not that important," and then calculated the average point score for each skill in the performance of each of the five tasks. For example, the average score for "reading comprehension" was 2.0 points for those engaged in nonroutine analytic tasks, 1.8 points for those engaged in nonroutine interactive tasks, 1.6 points for those engaged in routine cognitive tasks, 1.4 points for those engaged in routine manual tasks, and also 1.4 points for those engaged in nonroutine manual tasks. We then normalized the average point score so that for each skill the total becomes 1, meaning that of the 1 skill score point for "reading comprehension," 0.24 points were allocated to nonroutine analytic tasks, 0.22 points to nonroutine interactive tasks, 0.20 points to routine cognitive tasks, 0.17 points to routine manual tasks, and 0.17 points to nonroutine manual tasks.

Next, we multiply the skill score, i.e. the score of each of the 35 skills in each occupation with the task score, i.e., the normalized average score and set the total amount as the number of points for the five tasks for that occupation. We call these products the "task intensities" and use them in the hedonic wage approach in Section 5. To continue with the example above: since "reading comprehension" was assigned a skill score of 5 for physicians, the number of points for "reading comprehension" for each physician in the labor force is 1.2 points for nonroutine analytic tasks, 1.1 for nonroutine interactive tasks, 1.0 for routine cognitive tasks, 0.85 for routine manual tasks,

[3] For example, in 1960, scientific researchers were not distinguished into natural science researchers and cultural and social science researchers. We therefore calculate the share of each in 1970 and apply this to the data for 1960. We proceed in a similar fashion for a number of other occupations.

[4] The five-step skill valuation of the *Career Matrix* is based on the judgment of those actually engaged in a particular occupation.

and 0.85 for nonroutine manual tasks. Adding up the points for each of the 35 skills, the number of points for the five tasks for a "physician" is 28.67 for nonroutine analytic tasks, 34.33 for nonroutine interactive tasks, 18.87 for routine cognitive tasks, 21.31 for routine manual tasks, and 18.43 for nonroutine manual tasks (task intensity). Finally, summing up the points for the five tasks for each occupation weighted by the employment share of detailed classification of the *Population Census* in each year, we obtain the total number of points for the five tasks for the labor force as a whole, and by calculating the share of each of the five tasks, we obtain matrix *Y*.

There are two issues that should be noted with regard to this calculation method. The first is that there are some differences in the occupation classification method in the *Career Matrix* under the jurisdiction of the Ministry of Health, Labour and Welfare and that in the *Population Census* under the jurisdiction of the Ministry of Internal Affairs and Communications. Each occupation in the *Career Matrix* is very specific and follows the former Classification of Occupations for Employment Services (ESCO). We cross-checked the ESCO and the *Population Census* classifications and applied each occupation in the *Career Matrix* to the 237 detailed job categories of the *Population Census* as mentioned above.[5]

The second issue concerns the data for the comparison over time. For the calculation of the percentage share of each of the five tasks, data on the occupational composition of the labor force (*X*) are available in five-year intervals from the *Population Census*; however, the *Career Matrix*, from which information for the skill score is taken, is only a very recent publication, while the assessment of the importance of different skills in each tasks for the calculation of the task score was only conducted once and only recently.[6] Therefore, the changes over time in the percentage shares of the five tasks entirely depend on changes in the occupational composition of the labor force, and we would therefore like to alert the reader that our results should be interpreted with caution.

3. The trend in the five tasks over time

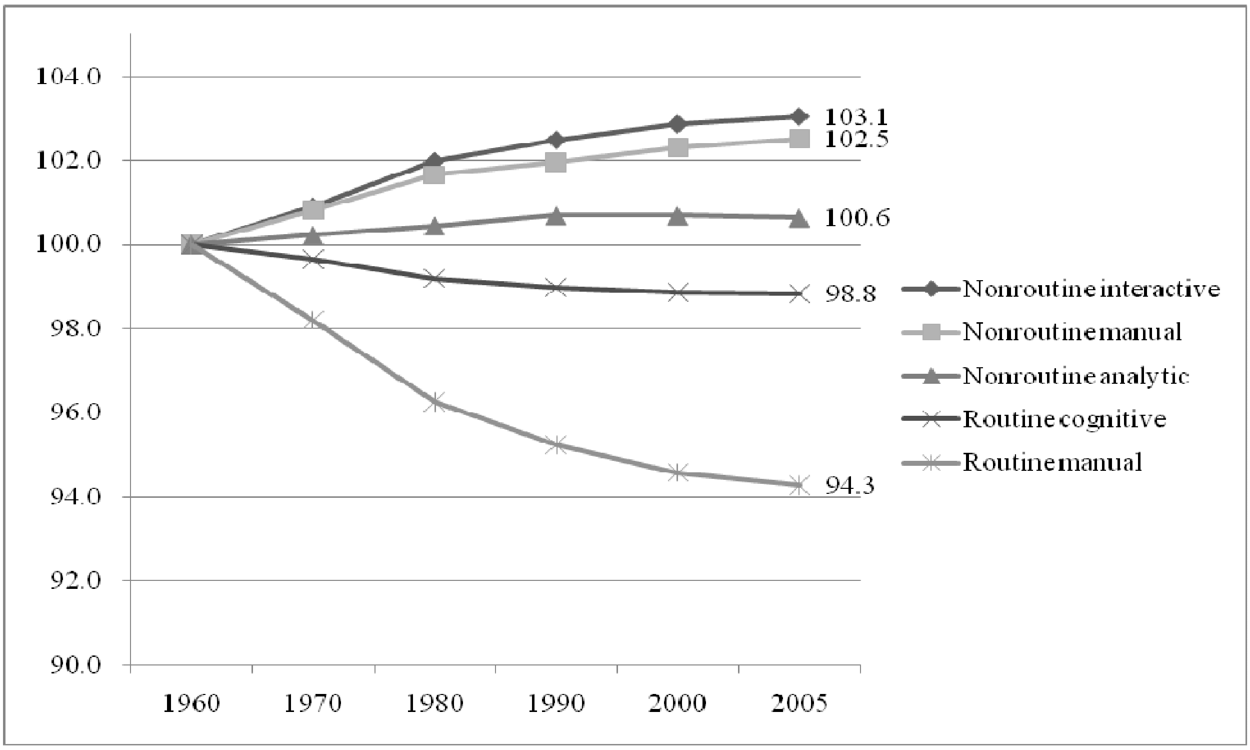
[5] When several occupations in the *Career Matrix* correspond to one detailed category in the *Population Census*, we used the average of these. When there were no corresponding occupations in the *Career Matrix*, we used the score for other occupations in the *Career Matrix* that we think are close in terms of their content.

[6] The *Career Matrix* has been developed since 2003 and was made publicly available in September 2006. On this occasion, the skill evaluation was based on survey results for the first three years. However, in the fourth year, a large-scale survey was conducted, and a revised version of the *Career Matrix* incorporating the results was released in September 2008. This study uses the values from the September 2008 version. However, this revision does not consist of a re-evaluation of skills; instead additional respondents were surveyed and there are a few changes in the numerical results for various occupations; consequently, they do not allow an analysis of changes in the valuation of skills over time.

3.1 Steady long-term polarization

The trends in the shares of each of the five tasks for the period from 1960 to 2005, calculated following the methodology described above and with values for 1960 set to 100, are depicted in Figure 1.

Figure 1: Trends in task input in Japan, 1960 to 2005



Source: Authors' calculation based on data from the *Population Census* and the Japan Institute for Labour and Policy Training's *Career Matrix*. Employment shares normalized with 1960 set to 100 for each task.

The figures illustrates that whereas the share of nonroutine task input shows an almost steady increase during this period, the share of routine task input shows an almost steady decrease. The figure confirms the pattern of labor market polarization repeatedly pointed out in previous studies with an increase in the input shares of nonroutine interactive and analytic tasks, which require highly specialized skills, as well as nonroutine manual tasks, which are relatively low skill but are nonroutine, and a decrease in the input share of intermediate routine tasks. Yet, it should be noted that in contrast with the result obtained in Ikenaga (2009a), where one occupation was classified into one type of task, here the share of nonroutine interactive task input increases, overtaking the share of nonroutine analytic task input, while the share of routine cognitive task input decreases.

Thus, although the overall pattern is more or less in line with preceding studies, there are also a number of conspicuous differences. First, despite the considerable change in the occupational composition of the labor force during the half century, the size of the change in task shares brought to light using the methodology developed here is fairly small. According to the *Population Census*, the shares of agriculture, forestry, and fishery workers and of professional and technical workers were 32.6 percent and 4.9 percent respectively in 1960, but this had changed greatly by 2005, with the former accounting for 4.9 percent and the latter for 14.1 percent.[7] In other words, the share of the former fell by more than five-sixths, while that of the latter rose almost threefold. In contrast, in terms of the index values shown in Figure 1, the share of nonroutine interactive tasks, which expanded the most during the observation period, does not rise above 103.1, while for routine manual tasks, the share of which contracted the most, fell only to 94.3.

Second, the monotonic increase or decrease over the past half century differs from the pattern observed for the United States by ALM, which is shown in Figure 2.

Figure 2: Trends in task input in the United States, 1960 to 1998

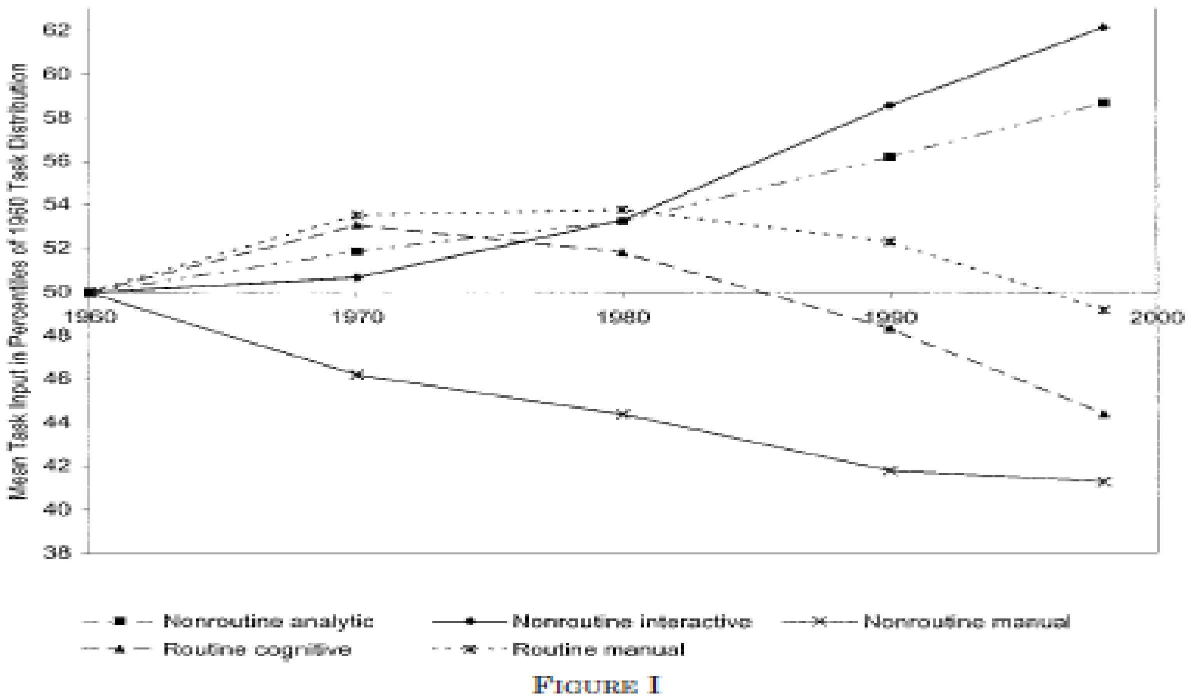


FIGURE I
Trends in Routine and Nonroutine Task Input, 1960 to 1998

Source: Autor, Levy and Murnane (2003: 1296). © MIT Press.

According to ALM, in the United States, nonroutine analytic task input and nonroutine

[7] Authors' calculation based on data from the *Population Census.*

interactive task input registered a consistent and remarkable increase, with the increase in fact accelerating after 1980. However, a conspicuous difference with the pattern we observed for Japan is that in the United States, routine cognitive task input and routine manual task input increased from 1960 to 1970. Only from 1970 onward does routine cognitive task input start to decrease, but does so rapidly, while routine manual task input stagnates until about 1980, but then also decreases greatly. As a result, the trends for the two tasks display a clear hump shape and can be said to reflect the historic change in the labor market brought about by technological progress from the 1980s onward. In addition, the figure shows that nonroutine manual task input decreased most rapidly during the 1960s, but the decline then decelerated somewhat, which is in line with Autor and Dorn's (2009) finding that employment in service occupations stagnated until around 1980 and then started to increase. In sum, ALM show that in the United States, a rapid polarization from the 1980s onward can be observed. In contrast, the polarization we find in Japan is not a relatively recent phenomenon, but spans a much longer period and progressed more gradually and steadily.

3.2 Why is the change in task input shares so small?

What explains the observed trends in task shares in Japan over time? Let us begin by examining why the change in the task composition overall is relatively small. One possible explanation is that this is simply a measurement issue caused by the fact that the difference in numerical point values for the skill score is small. As mentioned earlier, to obtain the data shown in Figure 1, the importance of each skill in performing each of the five tasks was assessed in terms of 0, 1, or 2 points for the construction of the task score (matrix D). Another possibility is that the variation in task intensity across occupations does not come out clearly, because in the *Career Matrix* used for calculating the skill score (matrix C), the intermediate value of 3 on the five-step evaluation scale is very frequent.

Accordingly, taking our measurement with 0, 1, and 2 points for constructing matrix D and the five steps for the skill score as the baseline, we attached a nonlinear bias to the point difference we obtained and carried out the same calculations as above.[8] However, although the size of the changes we obtain are slightly larger and we find that the increase in the nonroutine manual input share exceeds the increase in the nonroutine interactive input share, we essentially do not observe

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[8] That is, we used 0, 1, and 10 points instead of 0,1, and 2 in constructing matrix D and 2 (=2^1), 4 (=2^2), 8 (=2^3), 16 (=2^4), 32 (=2^5) instead of the five-step evaluation.

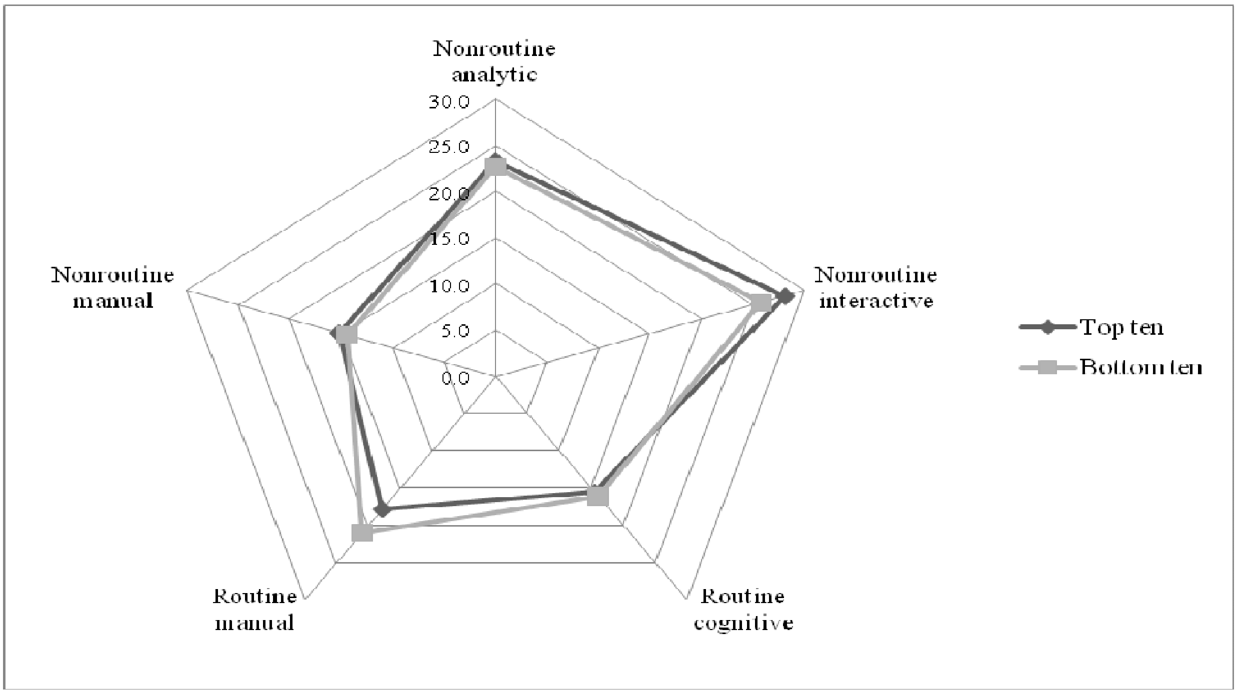
any remarkable differences from the baseline results. Therefore, the fact that the change in task input shares is small does not appear to be caused by our measurement method.

3.3 Changes in task input shares in increasing and decreasing occupations

Another possibility why the change in task input shares is so small may be that changes in increasing and decreasing occupations offset each other. In order to examine whether this is the case, we limit our analysis to the ten occupations whose employment share increased the most in the period from 1960 to 2005 (the "top ten") and the ten occupations whose employment share decreased the most (the "bottom ten") using the intermediate occupation classification and look at the change over time in the share of the five tasks. (A specific list of the occupations included is provided in Appendix Table 2.) Incidentally, with regard to the total employment share of these occupations, the share of the top ten rose from 4.4 percent in 1960 to 20.8 percent in 2005, while that of the bottom ten fell from 41.0 percent to 6.8 percent.

Figure 3 provides a comparison of the shares of the five tasks in the top ten and bottom ten occupations for the year 2005.

Figure 3: Difference in task composition in 2005 between the top ten and bottom ten occupations

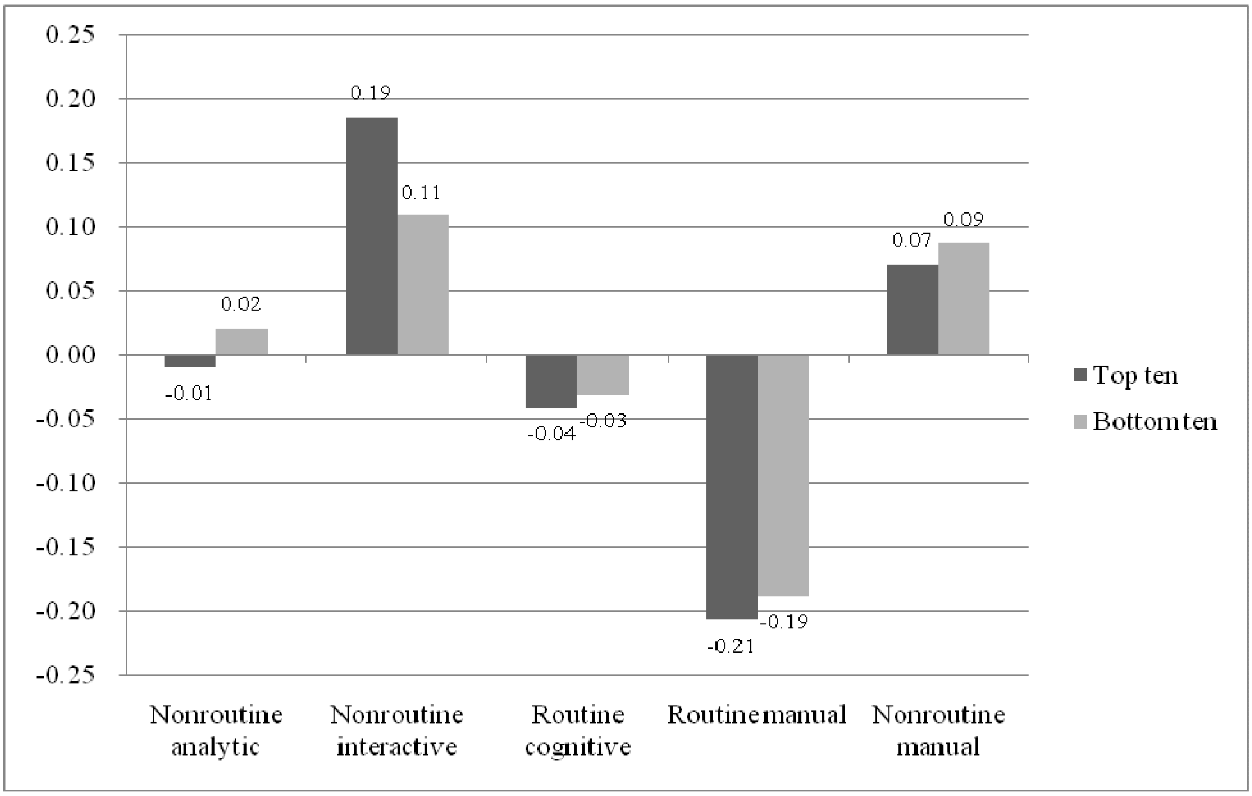


Source: See Figure 1.

Although the top ten occupations are slightly more nonroutine interactive task intensive, while the bottom ten occupations are slightly more routine manual task intensive, the differences are not particularly large. (The difference between the two groups is 2.3 percentage points for nonroutine interactive tasks and 3.2 percentage points for routine manual tasks).

Next, Figure 4 compares the cumulative increase or decrease of the shares of the five tasks from 1960 to 2005. Both the top ten and the bottom ten occupations show largely similar changes, with increases in nonroutine interactive and nonroutine manual task input and decreases in routine cognitive and routine manual task input. There is also generally no great difference with regard to the magnitude of these changes.

Figure 4: Cumulative change in task shares for the top and bottom ten occupations between 1960 and 2005



Source: See Figure 1.

Finally, we conducted a similar exercise as in Figures 3 and 4 but instead of looking at the top ten and bottom ten occupations over the entire 45-year span, we compared the changes in the shares of the five tasks for the ten occupations that showed the greatest increase and decrease over ten-year intervals. However, although the specific occupations that were included in the comparison changed, the changes in the shares of the five tasks in the top and bottom ten were generally the same. Therefore, because task input shares in increasing and decreasing occupations changed in the same direction, we conjecture that changes in the occupational composition offset each other and that for this reason the change in the input shares of the five tasks overall was small compared with the large change in the employment composition by occupation.

4. Why do task input trends in Japan and the United States differ?

As seen in the preceding section, the long-term trends in the input composition of the five tasks in Japan differ from those found for the United States by ALM and shown in Figure 2. Whereas a notable trend toward polarization can be seen in the United Sates only from the 1980s onward, in Japan it has proceeded steadily over a period of half a century. There are a variety of possible reasons for this difference between Japan and the United States. One possibility is that the occupational composition (matrix X) at our starting point in 1960 differed fundamentally, another that subsequent trends therein (i.e., the change over time in matrix X) differed substantially, and yet another that the skills that are considered to be necessary for a particular occupation (matrix C) differ. In this section, we examine these possible explanations in turn.

4.1 Differences in the occupational composition and subsequent trends in Japan and the United States

Figures 5(a) and (b) show the occupational composition in Japan and the United States in various years based on data from the LABORSTA database of the International Labour Organization, which allow an international comparison.[9] Data for the 1960s were unfortunately unavailable, so that we use data for the period 1970-2002.

9 Specifically, we use the ISCO-1968 (International Standard Classification of Occupations), which makes an international comparison possible. LABORSTA is available online at: <http://laborsta.ilo.org/>.

Figure 5(a)： Changes in occupational composition (Japan)

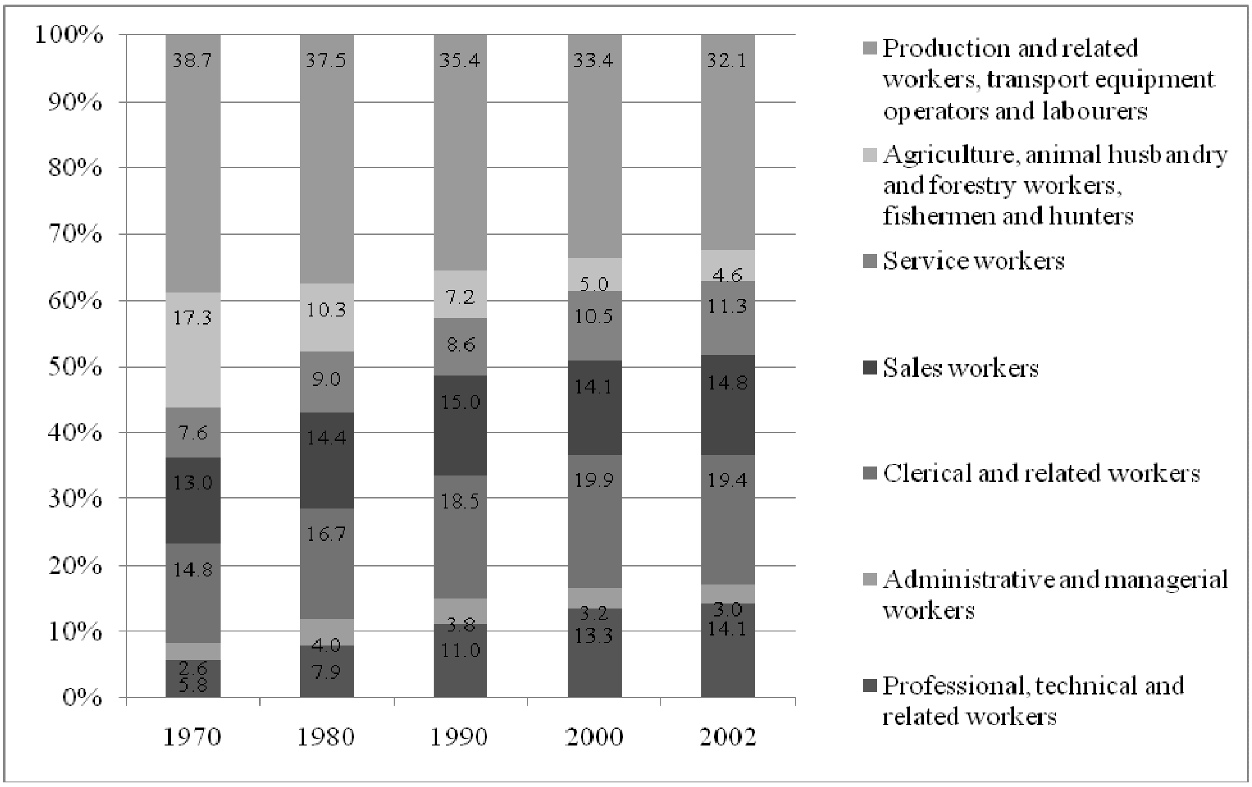
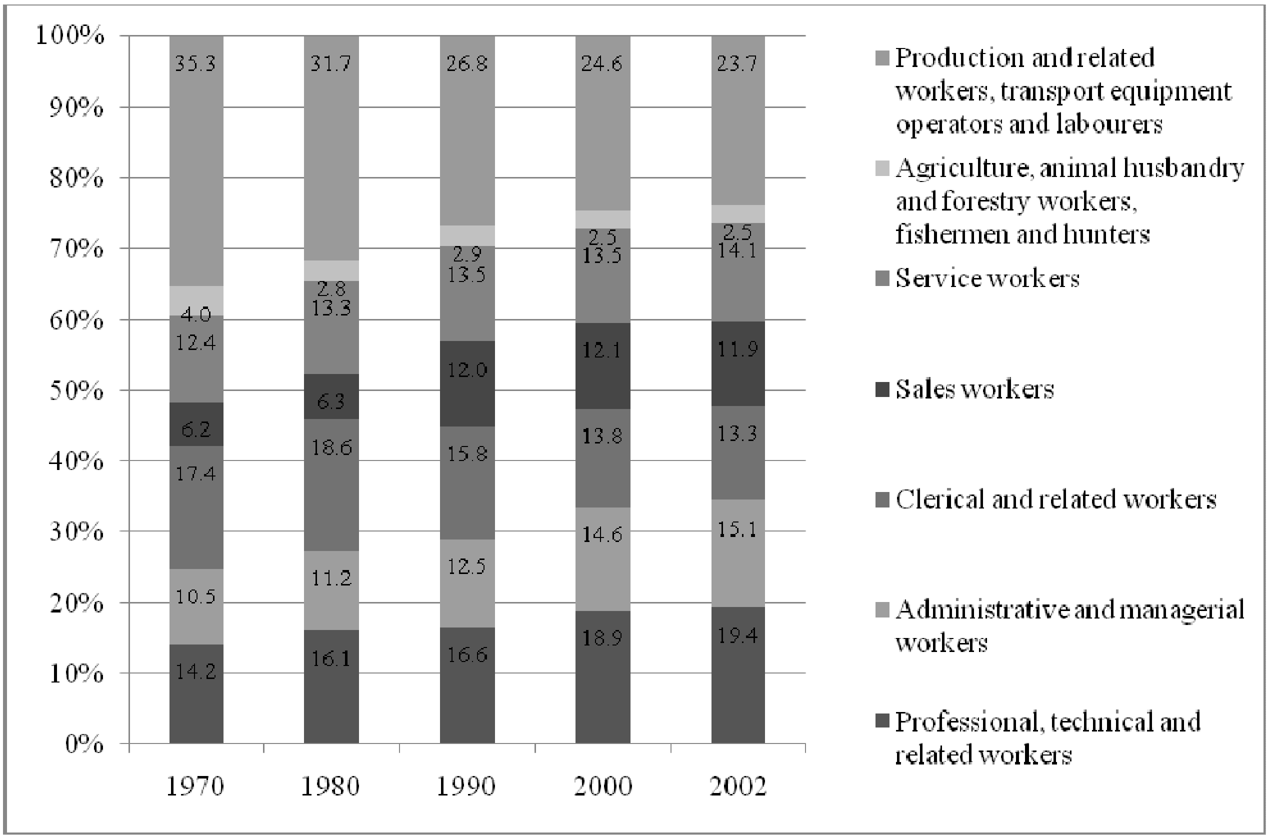


Figure 5(b)： Changes in occupational composition (United States)



Source: LABORSTA, International Labour Organization.

Comparing Figures 1 and 2 in Section 3, the first difference between Japan and the United States is that whereas in Japan routine manual task input has registered a large and consistent decline from the 1960s onward, in the United States it actually increased until 1970, then stagnated, and only from 1980 started to decline. Let us turn to Figures 5(a) and (b) and have a closer look at occupations that consist largely of routine manual task input, that is, “production and related workers, transport equipment operators and labourers” and “agriculture, animal husbandry and forestry workers, fishermen and hunters.” In 1970, the share of these occupations together was considerably higher in Japan than in the United States (56.0 versus 39.3 percent). Looking at employment shares by sector in 1960 for reference, we find that whereas in Japan the share of employment in the primary sector was more than 30 percent, in the United States it had already fallen below 10 percent.[10] Next, returning to Figures 5(a) and (b), we find that in the period from 1970 to 1980, the share of “production and related workers, transport equipment operators and labourers” in Japan changed little, [11] while that of “agriculture, animal husbandry and forestry workers, fishermen and hunters” fell dramatically. On the other hand, in the United States, the shares of both categories declined only by a relatively small margin. Finally, in the period from 1980 onward, the share of both categories declined both in Japan and the United States, but this decline was more pronounced in Japan reflecting the fall in “agriculture, animal husbandry and forestry workers, fishermen and hunters.”

The second difference between Japan and the United States is that whereas in Japan the share of nonroutine manual task input continuously increased from 1960 onward, in the United States, it registered a large decrease in the 1960s and continued to fall at a slightly gentler pace in subsequent decades. Again, let us look at occupations that largely consist of nonroutine manual task input, that is, “service workers.” The share of “service workers” in Japan in 1970 was 7.6 percent, which is considerably lower than the 12.4 percent in the United States. It then increased very slowly in Japan until 1990, when it started to grow more quickly. In the United States, the share more or less stagnated between 1980 and 2000, but then increased somewhat.

The third difference between Japan and the United States is that although routine cognitive task input also decreased in Japan, that decrease was much smaller than in the United States. Looking at the employment shares of “clerical and related workers,” whose work can be thought to largely consist of routine cognitive task input, we find that in 1970, their share in Japan at 14.8 percent

[10] *Rodo Keizai no Bunseki, Showa 56-nen [1981 White Paper on the Labour Economy]*, Ministry of Health, Labour and Welfare.

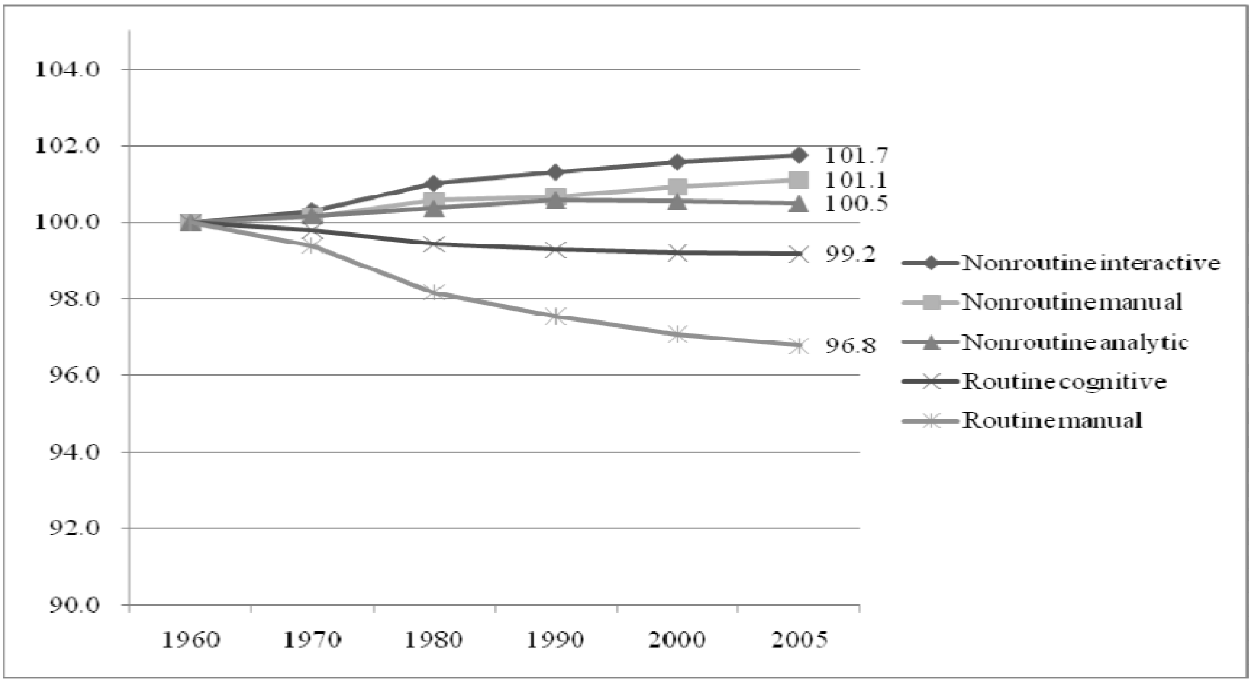
[11] Although not directly comparable to “production and related workers, transport equipment operators and labourers,” the share of “production process and related workers” in the *Population Census* increased between 1960 and 1970, and then from 1970 onward slowly decreased.

was somewhat smaller than in the United States, where it was 17.4 percent. The shares then follow different trends, with that in Japan registering an increase until around 2000, while that in the United States peaked in 1980 and then decreased.

Summing up these observations, it appears that the difference in the trends in the task input composition between Japan and the United States is largely the result of differences in the occupational composition in 1960. That is to say, reflecting the large employment share of “agriculture, animal husbandry and forestry workers, fishermen and hunters,” the share of routine manual task input was extremely high in Japan in 1960, and the large decline in employment in these occupations through the change in industrial structure is likely to be responsibility for the consistent decline in routine manual task input. Moreover, in the United States, the employment share of “service workers” was already relatively large in 1960 and, in this situation, low skill task input may have peaked already then. In contrast, the employment share of “service workers,” and hence the input share of nonroutine manual tasks, were still low in Japan at that time, so that the input share of such tasks increased along with the trend to a service economy. On the other hand, in the case of routine cognitive task input, rather than structural differences in 1960, the divergence in subsequent trends in task input – the consistent gentle decrease in the United States and the consistent increase until around 2000 in Japan – seems to play a larger role.

One of the issues we are interested in in this study is the link between trends in task input and the valuation of these tasks in the labor market, which we examine in Section 5. However, if the labor market polarization observed in Japan were simply due to changes in the employment share of “agriculture, animal husbandry and forestry workers, fishermen and hunters,” it would be rather inappropriate to link the labor market polarization in terms of task input with wage trends. The reason is that those engaged in agriculture, forestry and fisheries in postwar Japan are mainly self-employed and family workers and their employment status thus differs from employed wage earners. Therefore, we also examine the trends in task input excluding agriculture, forestry, and fisheries workers, shown in Figure 6. Comparing this with Figure 1, we find that, overall, the changes are now smaller. Moreover, as expected, the size of the decrease in routine manual task input during the period from 1960 to 1980 becomes notably smaller than when agriculture, forestry and fisheries workers are included. However, the overall trend with a consistent monotonic decline in the share of routine manual task input remains unchanged. Therefore, it seems safe to say that the number of employed persons in agriculture, forestry and fisheries at the starting point of the comparison does not seem to have such a serious effect on the observation results in the preceding sections.

Figure 6: Trends in task input in Japan, 1960 to 2005 (excluding agriculture, forestry and fisheries workers)



Source: See Figure 1.

4.2 Differences in skill valuation between Japan and the United States

One possible explanation for the differences between Japan and the United States is that the skills that are considered to be required for a particular occupation are different. If, for example, in a particular professional occupation whose share increased both in Japan and the United States less importance was attached to routine manual tasks in the skill valuation in the United States, then this would also result in a smaller amount of routine manual skill input in the United States than in Japan. ALM, for the valuation of skills necessary for an occupation, or what we call the skill score in this study, use the 4th edition (1977) and the revised 4th edition (1991) of the Dictionary of Occupational Titles (DOT).[12] In this study, we use *O*Net* (Occupational Information Network, developed by the North Carolina Employment Security Commission under the sponsorship of the Employment and Training Administration of the U.S. Department of Labor[13]), which is a revision of the DOT, to recalculate task shares and see whether using the U.S. valuations instead of those from Japan's *Matrix* plays a role in the differences.

[12] In the DOT, based on the guidelines of the Handbook for Analyzing Jobs (U.S. Ministry of Labour, 1972), more than 12,000 occupations are assessed on the basis of 44 objective and subjective criteria (e.g., training frequency, physical demands, attributes required of workers, character, interests, etc.).

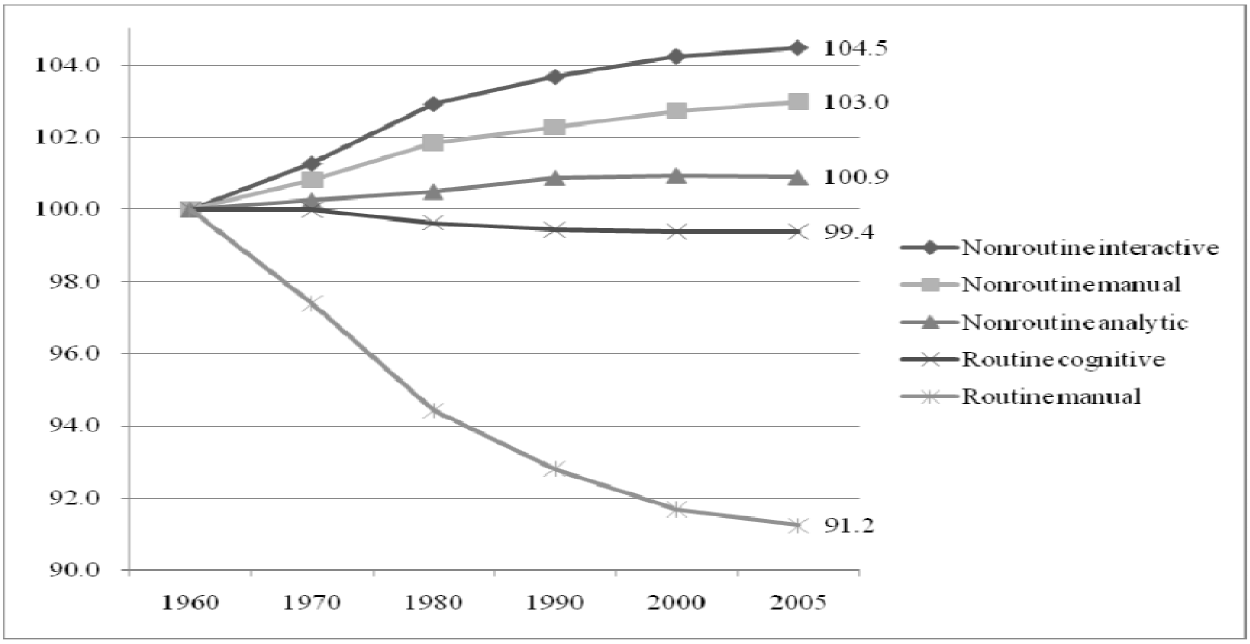
[13] Available online: <http://online.onetcenter.org/>.

The 35 skill categories of the *Career Matrix* correspond to the skills in *O*Net* and skill valuations in both are based on responses from those employed in a particular occupation (see Appendix Table 1).[14] Here, we match each occupation listed in the *Career Matrix* to the corresponding occupation in *O*Net*[15] and, using the valuation of necessary skills for that occupation in *O*Net*, repeat the calculation process of the preceding section and compare the results. That is, for matrix C, we calculate the task score using not Japan's *Career Matrix* but the United States' *O*Net*.

4.2.1 Trends over time in task input

Figure 7, which corresponds exactly to Figure 1, shows the trends in task input shares based on all occupations using *O*Net* instead of the *Career Matrix*, again setting shares in 1960 to 100.

Figure 7: Trends in task input in Japan, 1960 to 2005 (based on *O*Net* scores)



Source: Authors' calculation based on data from the *Population Census*, the *Career Matrix*, and *O*NET*.

As in Figure 1, we find once again that the growth in the nonroutine task input share follows a straight line from 1960 onward, i.e., the labor input shares of nonroutine tasks (interactive,

[14] However, in contrast with the five-step valuation of the *Career Matrix* (September 2008 revision), *O*Net* (January 2009 revision) uses a 100-point scale, so that differences in points are clearer.

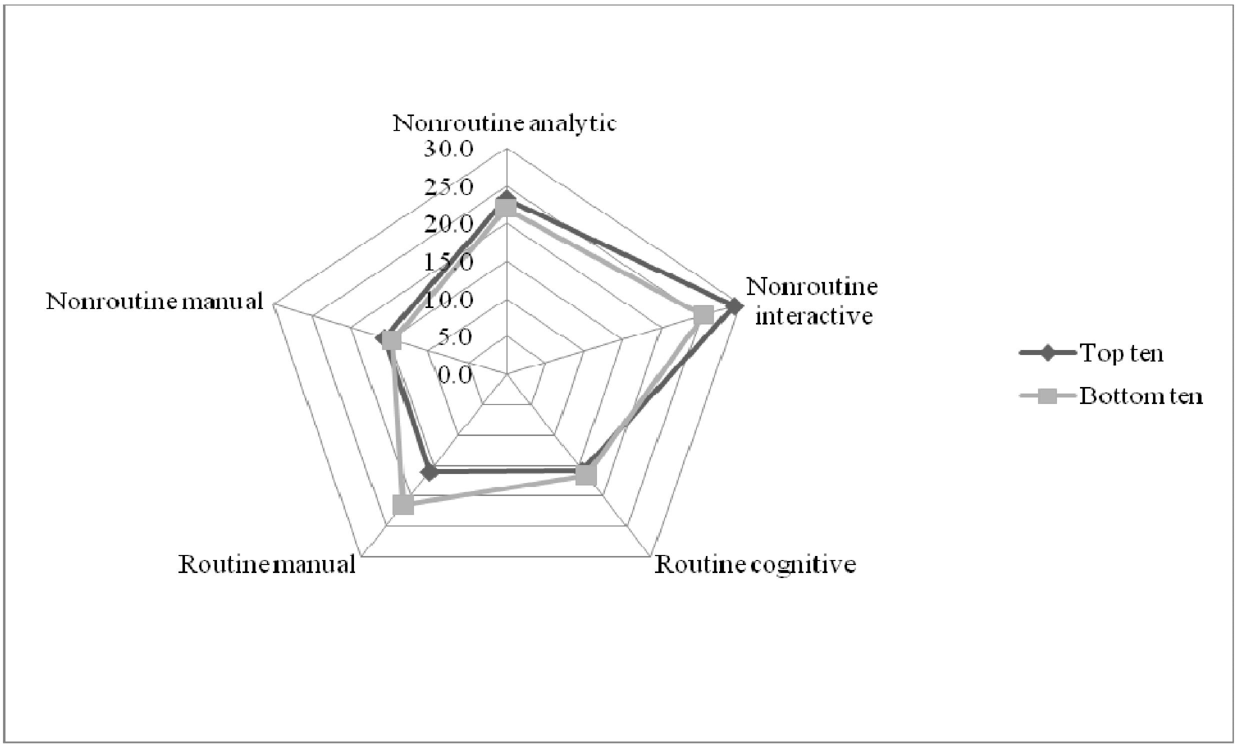
[15] In the case that an occupation in the *Career Matrix* corresponds to several occupations in *O*Net*, we used their simple average, and in the case that there is no corresponding occupation, we used the score of another occupation from *O*Net* that we thought that was close in content.

manual, and analytic) show an almost consistent monotonic increase, while the shares of routine tasks (cognitive and manual) show an almost consistent monotonic decrease. Therefore, the overall trends seen in Figure 1 remain unchanged even when we use American standards for the valuation of necessary skills.

4.2.2 Changes in task input shares in increasing and decreasing occupations

Examining the magnitudes of the changes in Figures 7, we find that with the exception of those for routine cognitive tasks, they are larger than those in Figure 1. Consequently, as in the preceding section, we again look at the task composition in the ten occupations whose employment share increased the most between 1960 and 2005 (the "top ten") and the task composition in the ten occupations whose employment share decreased the most (the "bottom ten"). The results are shown in Figure 8, which directly corresponds to Figure 3.

Figure 8: Difference in task composition in 2005 between the top ten and bottom ten occupations (based on *O*Net* scores)

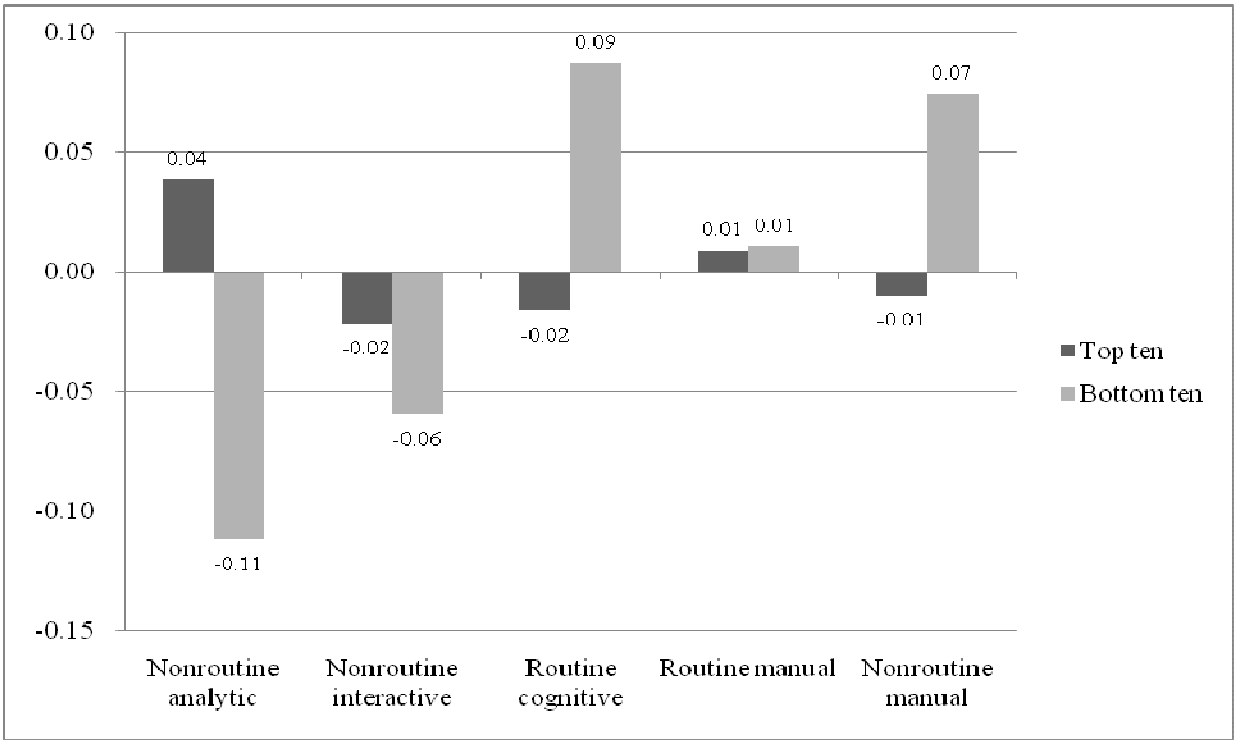


Source: See Figure 7.

Again, we find that the top ten occupations are relatively nonroutine interactive task intensive and the bottom ten occupations relatively routine manual task intensive, and the difference between the top ten and bottom ten occupations is somewhat larger than in Figure 3 (the difference between top ten and bottom ten occupations with regard to nonroutine interactive task input is 3.9 percent instead of 2.3 percent, and that with regard to routine manual task input is 5.5 percent instead of 3.2 percent).

Next, similar to Figure 4, Figure 9 compares the cumulative increase or decrease of the shares of the five tasks.

Figure 9: Cumulative change in task shares for the top and bottom ten occupations between 1960 and 2005 (based on *O*Net* scores)



Source: See Figure 7.

We find that in contrast with Figure 4, where the task input share changed in opposite directions for the top ten and bottom ten occupations only in the case of nonroutine analytic tasks (and the values were small), in Figure 9, changes in opposite directions can be seen for nonroutine analytic, routine cognitive, and nonroutine manual tasks. Moreover, although the changes for nonroutine interactive and routine manual tasks in Figure 9 are in the same direction for the top ten and bottom ten occupations, these directions are the opposite of those in Figure 4, with the change for nonroutine interactive tasks now negative (as opposed to positive in Figure 4) and that for routine manual tasks now marginally positive (as opposed to substantially negative in Figure 4). Therefore, the reason that the change over time in task input became larger when using the *O*Net* data is that the change of the shares of the five tasks differed in increasing and decreasing occupations.

The above considerations indicate that differences in skill valuation between the *Career Matrix* and *O*Net*, that is, differences in the valuation of skills in Japan and the United States with regard to the same occupation, magnify differences in the changes over time in task input shares in Japan and the United States in occupations overall. These differences between Japan and the United States with regard to the valuation of skills can be seen especially in occupations that have increased or decreased over the past half century.

4.2.3 Changes in task input shares in the top ten and bottom ten occupations: Specific examples

Here we further consider the reasons why the change in task input shares in the top ten and bottom ten occupations differs when using the *Career Matrix* and *O*Net*. As seen in Figure 4, in the measurement results using the *Career Matrix,* input in nonroutine interactive tasks and nonroutine manual tasks increased and that in routine manual tasks decreased. If we look at a breakdown of the top ten occupations, we find that in “social and welfare occupations” and “sales relate occupations,” which both gained in weight, the input shares of nonroutine interactive and nonroutine manual tasks are relatively high while the input share of routine manual tasks is relatively low (see Appendix Table 3). In the measurement results using *O*Net*, there was a notable increase in nonroutine analytic task input in the top ten occupations, reflecting the fact that in “social and welfare occupations,” whose weight in increasing occupations rose, the share of nonroutine analytic tasks is high.

Consequently, let us compare in greater detail the skill valuations in the *Career Matrix* and *O*Net* for “social and welfare occupations,” whose share even among the top ten occupations registered a remarkably high rate of increase rate and which play a large role in trends overall. To start with, if we compare the 35 skill scores for this occupation, normalized by setting the maximum points as 1, the differences in the scores between the skills are greater in *O*Net*. In the *Career Matrix,* skills concerning relations with others (social perceptiveness, coordination, persuasion, negotiation, instruction, etc.) are assigned particularly high scores. Meanwhile, in *O*Net*, equipment operations-related work (operation monitoring、installation, maintenance, and repairing of equipment and systems, etc.) receives particularly low scores (see Appendix Figure 1(a)). As a result, in the task composition, the share of routine manual work becomes notably lower based on the *O*Net* valuation than on the *Career Matrix* valuation (see Appendix Figure

1(b)).

Among the bottom ten occupations, a good category for comparison is “clothing and textile products workers,” whose share among the bottom ten occupations has increased and which shape the patterns for decreasing occupations. Looking at the valuation of the 35 skills in this occupation, the scores in *O*Net* overall are lower, and the differences in scores between skills are larger (see Appendix Figure 2(a)). Especially science, persuasion, negotiation, technology design, and equipment operations-related work are assigned low scores. Consequently, looking at the composition of the input of the five tasks, the share of nonroutine analytic task input is lower, and the that of routine cognitive task input higher based on the *O*Net* valuation than on the *Career Matrix* valuation (see Appendix Figure 2(b)).

To sum up, when looking at occupations overall, even when using not the scores of the *Career Matrix* but those of *O*Net*, we find a consistent increase in the share of nonroutine task input from 1960 onward, and differences in skill scores between Japan and the United States did not reverse overall trends. However, when we focus on specific occupations that experienced a notable increase or decrease during the past half century and examine differences in valuations between Japan and the United States, some differences do emerge. That is, in social and welfare occupations which have shaped the trend in increasing occupations, the skill score in the *Career Matrix* puts greater value on the ability to communicate with others. Moreover, in clothing and textile products occupations, which have shaped the trend in decreasing occupations, *O*Net* places relatively greater value on routine cognitive tasks, and the increase in the weight of clothing and textile products workers in decreasing occupations has brought about an increase in routine cognitive task input in decreasing occupations, which is in contrast with the result based on the *Career Matrix.*

5. The valuation of the five tasks in the labor market

5.1 The hedonic wage approach

The trends in the shares of the five tasks described in the preceding sections suggest that the polarization in Japan’s labor market has proceeded relatively gradually and over a longer period when compared with patterns in the United States. The purpose of this section is to examine whether the trends in task input shares are also reflected in wage patterns. To do so, we regress the average wage paid in different occupations, taken from the *Basic Survey on Wage Structure*, on task intensities (the products of matrixes C and D in Section 2) and look at how the price valuation of the five tasks in the labor market has changed over time.

The approach we employ here resembles the estimation of the hedonic wage function which considers the relationship between the wage by occupation and a vector of attributes. Since the seminal contribution of Rosen (1974), hedonic wage models have provided many useful insights in the debate on wage determination, but in practice, as is well known, it is very hard to find appropriate data to identify offer and bid price functions for individual factors. For this reason, consistent empirical estimation of hedonic wage functions is generally difficult and most studies refrain from identifying the causal relationship between demand-side and supply-side factors and simply examine the statistical correlation between wages and the pricing of various factors (see, e.g., Dikerson and Green, 2004). Unfortunately, in this study, too, we cannot escape the same data limitations and therefore do not identify offer and bid price functions for each of the five tasks, but only consider how the valuation of the five tasks in equilibrium moved over time. That being said, although we cannot distinguish between demand and supply factors, we attempt to make conjectures regarding trends in the supply of and demand for input of each of the five tasks by simultaneously considering the changes in task input shares highlighted in the preceding sections and changes in the price valuation of the five task inputs.

For the estimation, we employ an ordinary least squares (OLS) regression of the average wage level by occupation on the task intensities. That is to say, denoting the average wage at time t for occupation i (and sex g) by W_{igt}, the task intensity vector for the occupation in question by Z_i, and the error terms by u_{igt}, we estimate the following model:[16]

$$\ln W_{igt} = \alpha + Z_i \beta + \delta_t + \gamma_g + u_{igt} \quad (d)$$

The sole coefficient of interest is β.

The dependent variable is the logarithm of scheduled hourly earnings by sex and occupation from the *Basic Survey on Wage Structure*. Using the data for 1970, 1980, 1990, 2000, and 2005, we conduct regressions for each of these years and examine the change over time in the estimated β. Independent variable are the task intensities used in Section3. The task intensities are the same for each observation period and the composition of task inputs for a particular occupation is the same for men and women and does not change. For this reason, as the source of identification we

[16] For summary statistics of the variables, refer to Appendix Table 4.

exploit the variation between occupations and consider occupations as a cluster and changes within occupations are controlled for by the female dummy γ_g and year dummies δ_t.

We begin by looking at the results for the pooled estimation showing the average pattern for the entire period from 1970 to 2005 (Table 1(a)). They suggest that, with the exception of routine manual task input, there is a statistically significant positive correlation between the task input intensity in each occupation and the average wage in that occupation. For example, specification 1-1 suggests that a one-point higher nonroutine analytic task input is associated with a 3.2 percent higher average wage. While it is not particularly surprising that a higher task input is associated with a higher average wage, it is noteworthy that the effect differs across the four tasks for which a significant correlation was found. For example, as shown in specification 1-5, a one-point higher nonroutine manual task input is associated with a 7.9 percent higher average wage.

Table 1(a): Estimates of hedonic wage equations: five task scores (1)

	(1-1)	(1-2)	(1-3)	(1-4)	(1-5)	(1-6)
Sample period	1970-2000					
Dependent variable	Log of mean hourly scheduled wage in nominal terms					
Method	OLS					
Nonroutine analytic	0.032 (0.010)***					0.045 (0.033)
Nonroutine interactive		0.040 (0.011)***				-0.071 (0.053)
Routine cognitive			0.033 (0.014)**			0.330 (0.076)***
Routine manual				-0.005 (0.007)		-0.188 (0.036)***
Nonroutine manual					0.079 (0.021)***	0.025 (0.077)
Constant	4.89 (0.236)***	4.546 (0.286)***	5.091 (0.240)***	5.791 (0.163)***	4.427 (0.332)***	4.557 (0.253)***
Year dummies	YES					
Female	YES					
Other control variables	NO					
Observations	727					
No. of clusters	184					
R-squared	0.87	0.88	0.87	0.86	0.88	0.90

Note: Robust standard errors for clustering occupations in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Next, in specification 1-6, we include all five tasks as independent variables and find that the estimated coefficients as well as the standard errors change considerably. This is likely because of the strong correlation between task inputs. Calculating simple correlations, we find that these are quite high at around 90 percent for nonroutine analytic and nonroutine interactive tasks, for nonroutine interactive and nonroutine manual tasks, and for routine cognitive and routine manual tasks (Appendix Table 5). We suspect that the reason for this is that in this study the association between task input shares and skill valuations is based on our "mini-survey" including ourselves and the three other researchers, and most of us regarded some skills as at least to some extent important for all the different tasks, although we may have assigned a different degree of importance to them.[17] Therefore, various robustness checks regarding the results for specification 1-6 seem necessary.

We begin by considering average worker attributes in each occupation as possible explanatory variables. From a theoretical perspective, because the only fundamental factor of production in equation (d) should be the input of the five tasks, there is no reason why the average wage should be directly related with worker attributes such as age (as long as we control for task intensities). However, if we assume that for some reason a certain amount of basic human capital is necessary to fulfill a particular task, it is likely that the average wage is influenced by average worker attributes that are independent from the five tasks. If we find that there is a strong correlation between the input of a particular task and the human capital of workers belonging to a particular occupation, it is necessary to interpret the estimated coefficients in specification 1-6 with care. Based on this reasoning, we added the average age and average years of employment in each occupation (taken from the *Basic Survey on Wage Structure*) and the share of college graduates in each occupation (taken from the large-scale *Population Census* carried out every 10 years) as variables representing workers' human capital into equation (d). The results are shown in Table 1(b) as specification 1-7, which includes average age, average age squared, average tenure, average tenure squared, and the ratio of college graduates as additional variables.

[17] In contrast, ALM, for the United States, and Dikerson and Green (2004), for the Britain, used factor analysis to derive task shares, extracting factors from valuations of professional duties (corresponding to the skill score, matrix C, above).

Table 1(b): Estimates of hedonic wage equations: five task scores (2)

	(1-6)	(1-7)	(1-8)	(1-9)
Sample period	1970-2000			
Dependent variable	Log of mean hourly scheduled wage in nominal terms			
Method	OLS	OLS	RE	RE
Nonroutine analytic	0.045	0.028	0.054	0.044
	(0.033)	(0.025)	(0.028)*	(0.023)*
Nonroutine interactive	-0.071	-0.077	-0.074	-0.080
	(0.053)	(0.033)**	(0.043)*	(0.036)**
Routine cognitive	0.330	0.298	0.321	0.336
	(0.076)***	(0.074)***	(0.058)***	(0.051)***
Routine manual	-0.188	-0.169	-0.186	-0.191
	(0.036)***	(0.032)***	(0.027)***	(0.024)***
Nonroutine manual	0.025	0.044	0.036	0.036
	(0.077)	(0.056)	(0.068)	(0.057)
Constant	4.557	3.848	4.356	3.797
	(0.253)***	(0.422)***	(0.208)***	(0.226)***
Year dummies	YES	YES	YES	YES
Female dummy	YES	YES	YES	YES
Other control variables	NO	YES	NO	YES
Observations	727	665	727	665
No. of Clusters	184	169	184	285
R-squared	0.90	0.94	0.90	0.93

Note: For OLS estimates, robust standard errors for clustering occupations in parentheses. Other control variables include average age, average age squared, average tenure, average tenure squared, and ratio of college graduates. *** p<0.01, ** p<0.05, * p<0.1.

Comparing the results for specifications 1-6 and 1-7, we find that although the estimated coefficients change somewhat, they do so by only 1-3 percent, suggesting that in terms of this test, the estimation results for specification 1-6 appear to be robust.

Next, given that the unit of observation in Table 1(a) is occupations, we attempt to conduct a panel data analysis on occupations. Because the shares of the five tasks in each occupation in a particular period are fixed and do not change, we cannot conduct a fixed effects estimation and therefore conduct a random effects estimation (specification 1-8 in Table 1(b)). The results when the same control variables as in specification 1-7 are included are shown as specification 1-9. Maybe because we were able to achieve an increase in efficiency by assuming random effects, the standard errors become smaller than in the OLS estimation and with the exception of those for nonroutine manual task input, the estimated coefficients are all at least weakly significant. However, there were essentially no changes in the signs and relative sizes of the coefficients. That is to say, while there is a positive correlation between nonroutine *analytic* task input and average wages, input of tasks which are also nonroutine but require interpersonal communication, i.e., nonroutine *interactive* task input, is associated with lower wages. On the other hand, there is no significant correlation between the amount of physical work involved (i.e., nonroutine manual task input) and wages. As for routine tasks, office work (routine cognitive task input) is associated with higher wages, while physical work (routine manual task input) is associated with lower wages. Overall, the impact of routine task input on wages is greater than that of nonroutine task input.

Finally, we examine the possible estimation bias stemming from the smaller coverage of occupations in the *Basic Survey on Wage Structure*. The data used for the calculation of the task shares in Section 2 cover all occupations, and these are summed up in 237 occupations for the 45-year period. On the other hand, as the number of clusters in Table 1(a) shows, the wage data used for the investigation in this estimation cover only roughly 180, or 80 percent, of the occupations. While it is unclear how the occupations recorded in the *Basic Survey on Wage Structure* are determined, if the approach for doing so means that occupations that have some particular task characteristic are picked preferentially, then the estimated coefficients in specification 1-6 do need to be interpreted with care. In practice, when we aggregate task intensities only for occupations in the *Basic Survey on Wage Structure* and examine the trends over time, we find that although the overall pattern with an increase in nonroutine task input and a decrease in routine task input is the same as when task scores are aggregated for all occupations, the results differ in that the increases in the shares of nonroutine interactive task input and nonroutine analytic task input become more pronounced, the share of routine cognitive task input increases somewhat from 1990 onward, and the contraction in the share of routine manual task input becomes less pronounced (see Appendix Figure 3).

Yet, removing this selection bias is difficult because we have little information other than that on the five task inputs. What we do therefore is to calculate the difference of each variable from its population average, setting the average for all occupations as the benchmark, and conduct the same estimation as in specification 1-6. In other words, we attempt to reduce the selection bias by using the difference of the wage for each occupation from the average for all occupations as the dependent variable and the differences of task input shares in each occupation from the average for all occupations as independent variables. The results are presented in Table 1(c), with specification 1-11 showing the result when the control variables are included and specifications 1-12 and 1-13 showing the results for the random effects estimation. They indicate that, even though the dependent variable is not expressed in logarithmic form since it is calculated as the difference from the average, the estimation results are largely unchanged from specification 1-6. Taken together, the results suggest that routine task input has a significant effect on average wages, but this is not the case for nonroutine task input. Overall, it can be surmised that the patterns reported for specification 1-6 are more or less robust.

Table 1(c): Estimates of hedonic wage equations: five task scores (3)

		(1-10)	(1-11)	(1-12)	(1-13)
Sample		1970-2000			
Dependent variable		Mean hourly scheduled wage difference from overall average in nominal terms			
Method		OLS	OLS	RE	RE
Difference from overall average	Nonroutine analytic	52.9	20.7	81.3	45.3
		(60.9)	(44.0)	(55.8)*	(52.5)
	Nonroutine interactive	-73.7	-81.7	-101.8	-106.9
		(85.1)	(54.0)	(87.0)	(82.0)
	Routine cognitive	634.9	522.0	702.4	591.0
		(266.1)**	(308.3)*	(117.1)***	(118.0)***
	Routine manual	-336.1	-265.2	-376.1	-308.0
		(111.3)***	(122.9)**	(54.9)***	(56.7)***
	Nonroutine manual	-63.1	-23.1	-56.7	-14.4
		(146.2)	(145.3)	(137.7)	(130.7)
Constant		-3.4	11.3	40.9	40.6
		(31.5)	(39.9)	(43.2)	(44.3)
Year dummies		YES	YES	YES	YES
Female dummy		YES	YES	YES	YES
Other control variables		NO	YES	NO	YES
Observations		727	665	727	665
No. of Clusters		184	169	184	169
R-squared		0.34	0.51	0.33	0.49

Note: For OLS estimates, robust standard errors for clustering occupations in parentheses. Other control variables include average age, average age squared, average tenure, average tenure squared and ratio of college graduates. *** p<0.01, ** p<0.05, * p<0.1.

5.2 The relationship between changes in task shares and task premiums from 1970 to 2005

Having confirmed that the estimation results in specification 1-6 are more or less stable, we now turn to examining what they mean. Essentially, the estimated coefficients can be interpreted as the price valuation of each task in the labor market. Given the way that the task intensities are constructed, a comparison of the values of the estimated coefficients for the different tasks would not be very meaningful. However, if we take into account that the estimation results for specification 1-6 are relatively stable, splitting the sample into observation years and then examining trends in the estimated coefficient for each occupation along with the trends in the task shares obtained in Section 3, we can make rough conjectures concerning developments in the supply of and demand for the input of different tasks shaping these trends. Table 2 shows the results of the same estimation as specification 1-6 when we divide the sample into subsamples for 1970, 1980, 1990, 2000, and 2005. As in the preceding subsection, we conduct various alternative estimations, including average human capital variables, adopting a random effects model, and using the differences from the averages as our variables. However, since these alternative estimations lead to essentially the same conclusions, we discuss here only the results of the simple OLS estimation. Moreover, in order to facilitate the interpretation of coefficients, we converted wage levels into real terms using the nationwide consumer price index (general, excluding imputed rent).

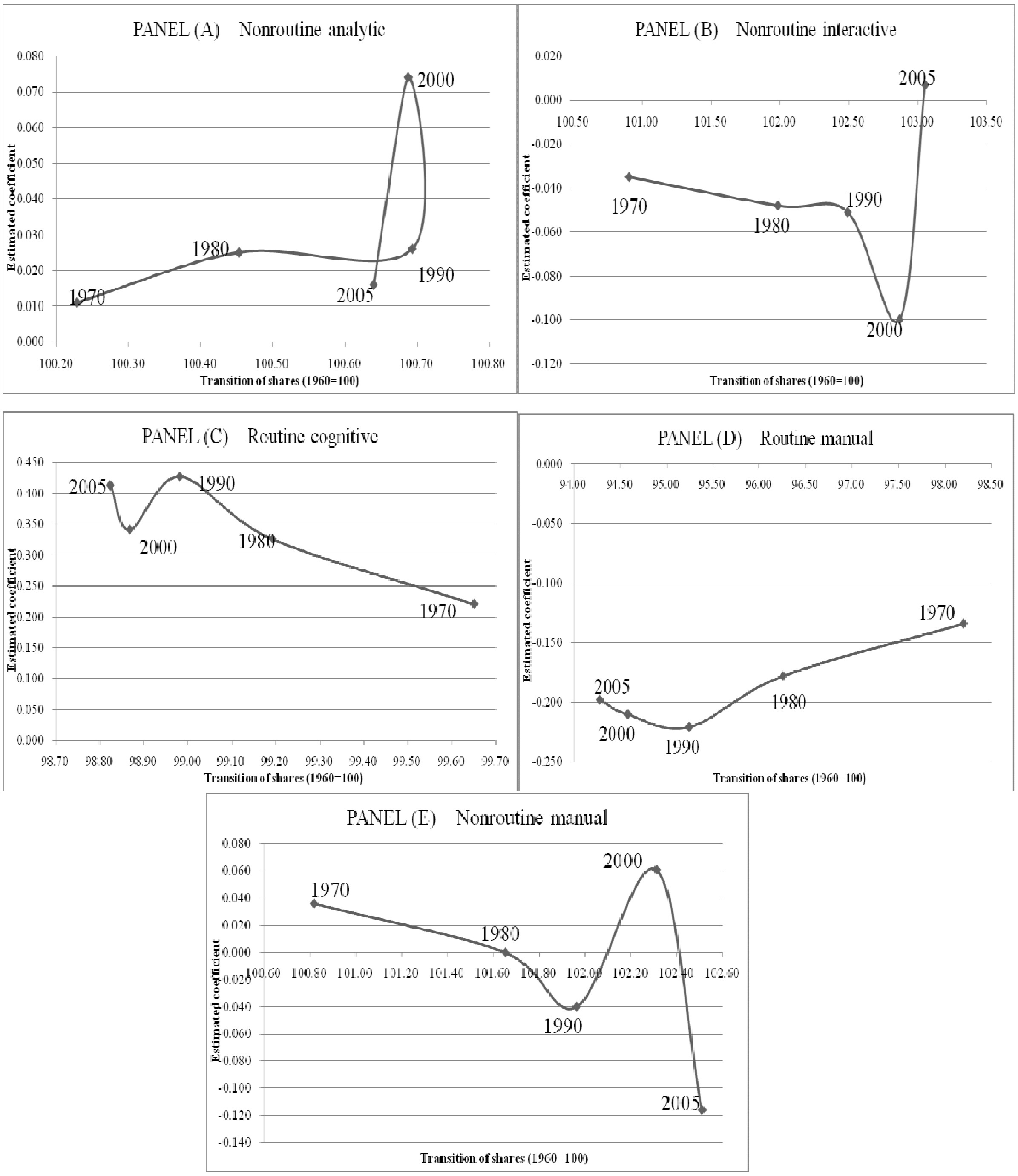
Table 2: Estimates of hedonic wage equations: year by year

	(2-1)	(2-2)	(2-3)	(2-4)	(2-5)
Sample	1970	1980	1990	2000	2005
Dependent variable	Log of hourly scheduled wage in real terms				
Method	OLS	OLS	OLS	OLS	OLS
Nonroutine analytic	0.011	0.025	0.026	0.074	0.016
	(0.028)	(0.035)	(0.040)	(0.048)	(0.053)
Nonroutine interactive	-0.035	-0.048	-0.051	-0.100	0.007
	(0.050)	(0.050)	(0.061)	(0.072)	(0.084)
Routine cognitive	0.221	0.326	0.427	0.341	0.413
	(0.067)***	(0.070)***	(0.128)***	(0.078)***	(0.072)***
Routine manual	-0.134	-0.178	-0.221	-0.210	-0.198
	(0.033)***	(0.033)***	(0.055)***	(0.044)***	(0.039)***
Nonroutine manual	0.036	0.000	-0.040	0.061	-0.116
	(0.072)	(0.073)	(0.094)	(0.098)	(0.114)
Constant	6.034	6.099	6.150	6.121	5.805
	(0.252)***	(0.263)***	(0.331)***	(0.305)***	(0.302)***
Year dummies	NO	NO	NO	NO	NO
Female dummy	YES	YES	YES	YES	YES
Other control variables	NO	NO	NO	NO	NO
Observations	167	157	158	245	257
No. of Clusters	156	137	137	132	131
R-squared	0.54	0.56	0.54	0.51	0.53

Note: For OLS estimates, robust standard errors for clustering occupations in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

As can be seen in the table, the changes in the estimated coefficients for each year from specification 1-6 are not that large and the coefficients show stable trends. That being said, there are not a few movements in the individual estimated coefficients. Especially with regard to routine cognitive tasks and routine manual tasks, the estimated coefficients fluctuate. If we interpret equation (d) as the valuation of each task in the labor market, it can be hypothesized that the estimated coefficients in 2-1 to 2-5 stand in some kind of relationship with the movement over time in the input share of each task. In Figure 10, we therefore plot the movement over time in the share of each of the five tasks obtained in Section 2 and the estimated coefficients, that is, the valuation of each task in the labor market.

Figure 10: Relationship between changes in task shares and task premiums



Note: Authors' calculations based on data from Figure 1 and Table 2 in this article.

All the plots show the labor market equilibrium point for each task input. Although we of course cannot identify bid and offer price functions or decompose changes in the equilibrium point into demand-side and supply-side factors, if we assume that the bid price function is downward sloping and the offer price function is upward sloping, we can derive a number of conjectures from the trajectory of the equilibrium point.

Starting with routine task input, the input shares of both cognitive tasks (primarily office work) and manual tasks have decreased, but the price trends for the two show a stark contrast. That is to say, in the case of cognitive task input, with the exception of 2000, the price has been on a continuous upward trend, while the price for manual task input shows a long-term declining trend. This suggests that, on balance, manual task input appears to have faced a strong decline in demand, while cognitive task input appears to have experienced a strong decline in supply. On the other hand, the input of all nonroutine tasks increased, but for interactive and manual task input, the price shows a declining trend, while for analytic task input, the price shows an increasing trend. This suggests that for the trend in interactive and manual task input, the increase in supply may have been relatively important, while conversely for analytic tasks, the increase in demand may have been relatively important.

6. Conclusion

In this study, using a score for the skills required for each occupation, we examined the trends in the input shares of five types of tasks, that is, nonroutine analytic, nonroutine interactive, routine cognitive, routine manual, and nonroutine manual tasks and their valuation in the labor market during the period 1960-2005. The findings can be summarized as follows. First, since 1960, there has been a long-term increase in nonroutine task input, both low skill and high skill, as manifested in, for example, the fact that the share of nonroutine task input (interactive, manual, and analytic) has shown an almost steady and monotonic rise, while in contrast the input share of routine tasks (cognitive and manual) has undergone an almost steady and monotonic decrease. However, the extent of the change in input shares of the five tasks is moderate. This is likely because, as the examination of the change in task input shares in the top and bottom ten occupations on the basis of the detailed occupational classification of the *Population Census* revealed, the change in task input of the five tasks for the top and bottom ten occupations (that is, the increase in nonroutine interactive and nonroutine manual task input and the decrease in routine cognitive and routine manual task input) is almost the same, thus offset changes in the occupational composition.

Second, long-term trends towards a polarization of the labor market in Japan differ from those in the United States which has experienced a polarization only since the 1990s. While part of the reason is differences in industry and occupational structures in the two countries at our starting point in 1960, differences in the valuation of skills also play a role. Using skill scores from *O*Net* to re-estimate trends in Japan, we find that the trends for all occupations do not change and that the input share of nonroutine tasks increased consistently from 1960 onward. However, the magnitude of the changes are greater when using *O*Net* than when using the *Career Matrix*, except in the case of routine cognitive tasks.

Third, using the hedonic wage approach to estimate the valuation of the five tasks in the labor market for the period 1970-2000, we find a positive correlation between routine cognitive task input with the average wage in an occupation, while for routine manual task input we find a negative correlation. Interpreting the estimated coefficients as the price valuation in the labor market of a particular task input and considering this in relation to the task input share over time, we found that, on balance, for nonroutine analytic and routine manual task input, the change in demand seems to dominate, while for nonroutine interactive and nonroutine manual task input as well as for routine cognitive task input, the changes in supply appears to dominate.

Regarding the increase in nonroutine task input, ALM and others, have sought to provide a theoretical explanation for this trend by relating it to the introduction of computer technology by developing the concept of skill-biased technological change from the 1980s onward. In line with these studies, Ikenaga (2009a), using data from the 1980s onward, also found that ICT capital appears to be complementary to nonroutine analytic task input and substitutive to routine task input. However, the present study suggests that, in Japan, the increase in nonroutine task input and the decrease in routine task input has been underway since 1960, i.e., before the adoption of computer technology achieved critical mass. We would like to highlight that input especially of tasks requiring a flexible and personal response such as nonroutine interactive tasks and nonroutine manuals tasks has registered a continuous increase over the past half century. Of course, from the 1980s onward, it is likely that the introduction of ICT capital has accelerated the increase in nonroutine task input and the decrease in routine task input, but with regard to developments before then, there must be important factors other than the introduction of ICT capital that explain the observed trends.

In this context, the analysis in Ikenaga (2009b) may provide some clues. Although this study focuses on the period from 1990 onward, it showed that with regard to the increase in nonroutine manual task input, structural changes in demand, such as demographic changes (e.g., population aging and the decrease in household sizes), and the increase in the number of highly skilled workers are important. The present study, having estimated the wage premiums for particular tasks, suggests that the wage premium for nonroutine task input is not necessarily large and that the reason for this seems to be the expansion in supply. Against this background, an important issue for future research is to further analyze from both the demand and the supply side how the increase in nonroutine task input and the decrease in routine task input in Japan affects wage differentials.

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Appendix Table 1: Classification of occupational skills in the *Career Matrix* and correspondence with *O*NET*

Skill	Skill description	*O*Net*
1. Reading comprehension	Understanding written sentences and paragraphs in work related documents.	Reading comprehension
2. Active listening	Giving full attention to what other people are saying, taking time to understand the points being made, asking questions as appropriate, and not interrupting at inappropriate times.	Active Listening
3. Writing	Communicating effectively in writing as appropriate for the needs of the audience.	Writing
4.Speaking	Talking to others to convey information effectively.	Speaking
5. Mathematics	Using mathematics to solve problems.	Mathematics
6. Science	Using scientific rules and methods to solve problems.	Science
7. Logic and analysis (Critical thinking)	Using logic and reasoning to identify the strengths and weaknesses of alternative solutions, conclusions or approaches to problems.	Critical thinking
8. Active Learning	Understanding the implications of new information for both current and future problem-solving and decision-making.	Active learning
9. Learning strategies	Selecting and using training/instructional methods and procedures appropriate for the situation when learning or teaching new things.	Learning strategies
10. Monitoring (Observation, evaluation)	Monitoring/Assessing performance of yourself, other individuals, or organizations to make improvements or take corrective action.	Monitoring
11. Complex problem solving	Identifying complex problems and reviewing related information to develop and evaluate options and implement solutions.	Complex problem solving
12. Social perceptiveness	Being aware of others' reactions and understanding why they react as they do.	Social perceptiveness
13. Coordination	Adjusting actions in relation to others' actions.	Coordination
14.Persuasion	Persuading others to change their minds or behavior.	Persuasion
15. Negotiation	Bringing others together and trying to reconcile differences.	Negotiation
16. Instructing	Teaching others how to do something.	Instructing
17. Service orientation	Actively looking for ways to help people.	Service orientation
18. Operations analysis	Analyzing needs and product requirements to create a design.	Operations analysis
19. Technology design	Generating or adapting equipment and technology to serve user needs.	Technology design
20. Equipment selection	Determining the kind of tools and equipment needed to do a job.	Equipment
21. Installation	Installing equipment, machines, wiring, or programs to meet specifications.	Installation
22.Programming	Writing computer programs for various purposes.	Programming
23. Operation monitoring	Watching gauges, dials, or other indicators to make sure a machine is working properly.	Operation monitoring
24. Operation and control	Controlling operations of equipment or systems.	Operation and control
25. Equipment maintenance	Performing routine maintenance on equipment and determining when and what kind of maintenance is needed.	Equipment maintenance
26.Troubleshooting	Determining causes of operating errors and deciding what to do about it.	Troubleshooting
27. Repairing	Repairing machines or systems using the needed tools.	Repairing

(continued)

Skill	**Skill description**	***O*Net***
28. Quality control analysis	Conducting tests and inspections of products, services, or processes to evaluate quality or performance.	Quality control analysis
29. Judgment and decision making	Considering the relative costs and benefits of potential actions to choose the most appropriate one.	Judgment and decision making
30. Systems analysis	Determining how a system should work and how changes in conditions, operations, and the environment will affect outcomes.	Systems analysis
31. Systems evaluation	Identifying measures or indicators of system performance and the actions needed to improve or correct performance, relative to the goals of the system	Systems evaluation
32. Time management	Managing one's own time and the time of others.	Time management
33. Management of financial resources	Determining how money will be spent to get the work done, and accounting for these expenditures.	Management of financial resources
34. Management of material resources	Obtaining and seeing to the appropriate use of equipment, facilities, and materials needed to do certain work.	Management of material resources
35. Management of personnel resources	Motivating, developing, and directing people as they work, identifying the best people for the job.	Management of personnel resources

Sources: *Career Matrix*, Japan Institute for Labour Policy and Training; *O*Net*, North Carolina Employment Security Commission.

Appendix Table 2: Top and bottom ten occupations by growth in employment share between 1960 and 2005

	Rank	Occupation	Annual growth rate (%)
Top ten	1	Other service workers	4.7
	2	Social and welfare workers	4.5
	3	Other professional and technical workers	3.7
	4	Sales related workers	3.7
	5	Engineers and technicians	3.7
	6	Registered accountants and licensed tax accountants	3.2
	7	Fine artists, photographers and designers	3.1
	8	Public health and medical workers	2.8
	9	Scientific researchers	2.6
	10	Musicians and stage artists	2.5
Bottom ten	1	Mining workers	-5.9
	2	Forestry workers	-5.2
	3	Textile workers	-5.0
	4	Agricultural workers	-4.2
	5	Wood, bamboo, grass and vine products workers	-3.1
	6	Fisheries workers	-3.0
	7	Leather and leather products workers	-3.0
	8	Clothing and textile products workers	-2.2
	9	Metal material workers	-2.0
	10	Workers operating marine and air transport equipment	-2.0

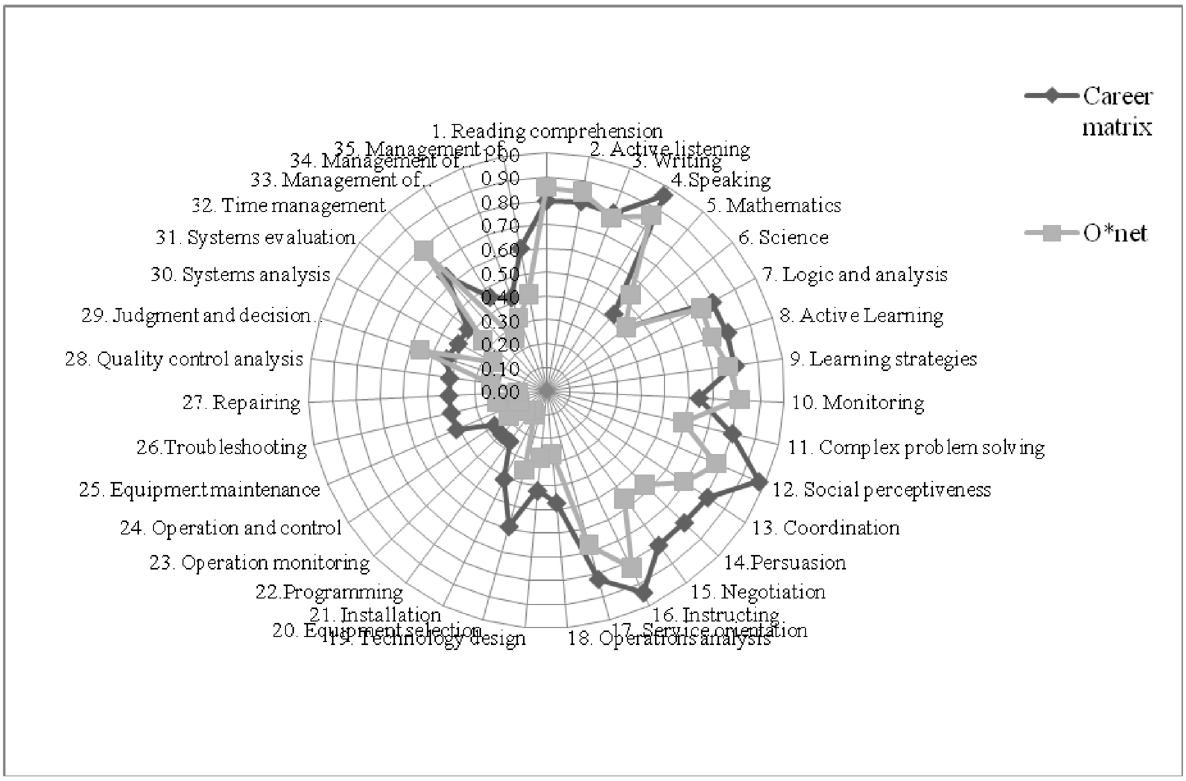
Source: Authors' calculation based on data from the *Population Census.*

Appendix Table 3: Changes in shares of top ten and bottom ten occupations

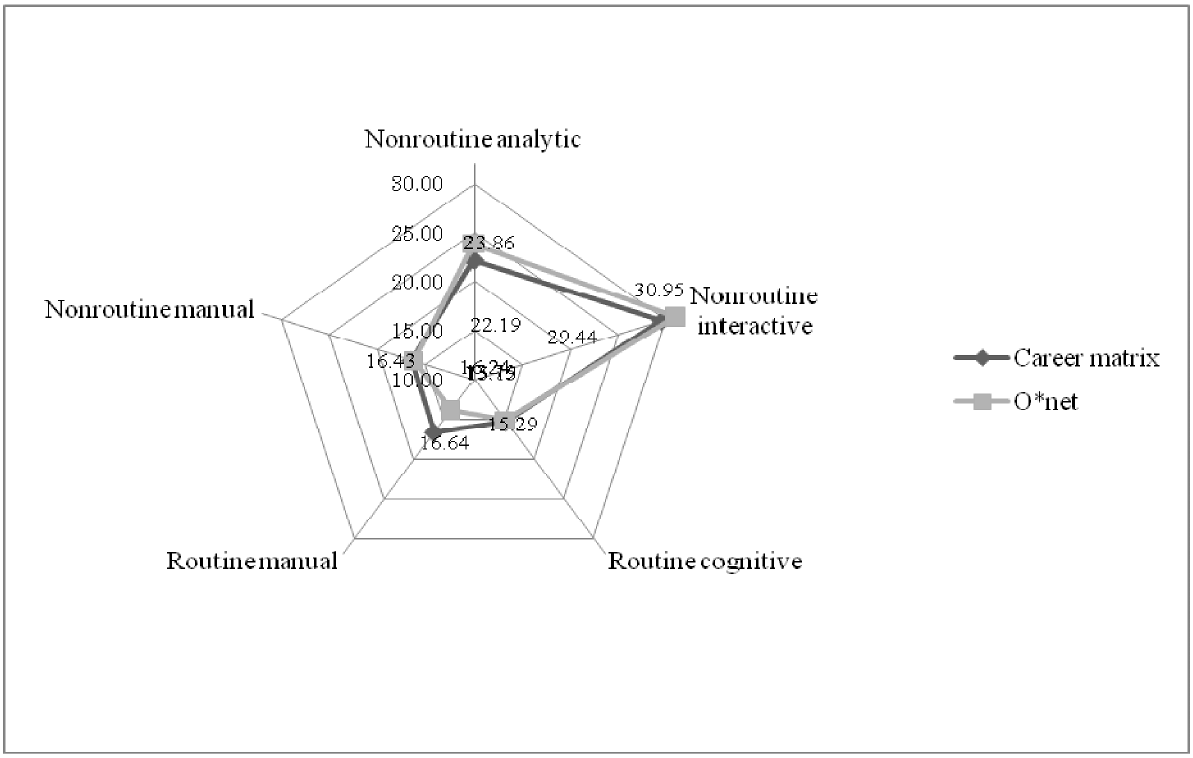
Occupations	1960	2005	1960-2005	*Career Matrix*					*O*Net*				
Total	Share in top ten or bottom ten occupations	Share in top ten or bottom ten occupations	Difference between 1960 and 2005	Non-routine analytic	Non-routine interactive	Routine cogni-tive	Routine manual	Non-routine manual	Non-routine analytic	Non-routine interactive	Routine cogni-tive	Routine manual	Non-routine manual
Top ten occupations	100.0	100.0		The total of top or bottom ten occupation as 1					The total of top or bottom ten occupation as 1				
Other service workers	6.7	11.3	4.6	0.95	1.00	1.02	1.02	1.04	0.93	0.95	1.03	1.12	1.05
Social and welfare workers	3.5	5.2	1.7	0.95	1.05	0.98	0.93	1.09	1.03	1.06	0.96	0.87	1.03
Other professional and technical workers	5.3	5.8	0.5	1.00	1.02	0.99	0.97	1.02	1.00	1.01	0.98	0.99	1.01
Sales related workers	31.5	34.1	2.6	1.01	1.03	0.98	0.93	1.02	1.00	1.05	0.97	0.90	1.04
Engineers and technicians	16.2	17.1	0.9	1.03	0.95	1.01	1.09	0.94	1.06	0.93	1.01	1.13	0.90
Registered accountants and licensed tax accountants	0.7	0.6	-0.1	1.03	1.08	0.97	0.85	1.02	1.08	0.97	1.01	0.99	0.94
Fine artists, photographers and designers	2.6	2.1	-0.5	0.99	0.95	1.02	1.10	0.98	0.98	0.91	1.04	1.19	0.96
Public health and medical workers	29.3	21.1	-8.2	0.99	0.99	1.01	1.02	1.01	0.97	1.00	1.02	1.00	1.01
Scientific researchers	1.8	1.2	-0.6	1.04	0.94	1.01	1.09	0.93	1.10	0.96	0.98	1.06	0.88
Musicians and stage artists	2.4	1.5	-0.9	0.98	1.00	1.01	1.02	1.01	0.91	0.99	1.03	1.05	1.06
Bottom ten occupations	100.0	100.0											
Mining workers	2.1	0.8	-1.3	0.99	0.99	1.02	1.01	1.00	0.96	0.98	1.02	1.01	1.04
Forestry workers	2.3	1.3	-1.0	0.98	1.00	1.01	1.01	1.02	0.96	1.00	1.02	1.01	1.02
Textile workers	6.3	3.9	-2.4	0.97	0.98	1.02	1.04	1.00	0.98	0.96	1.06	1.04	0.98
Agricultural workers	74.1	65.7	-8.4	1.00	1.00	1.00	1.00	1.00	1.01	1.01	0.99	0.99	1.00
Wood, bamboo, grass and vine products workers	4.4	6.3	1.9	1.00	0.99	1.01	1.00	1.00	1.00	0.96	1.03	1.02	1.00
Fisheries workers	3.2	4.9	1.8	0.96	0.99	1.01	1.02	1.04	0.99	0.95	1.04	1.07	0.97
Leather and leather products workers	0.5	0.8	0.3	1.01	1.00	1.00	0.99	1.00	0.90	1.04	1.04	0.97	1.09
Clothing and textile products workers	4.7	10.3	5.6	1.03	1.02	0.98	0.95	1.02	0.98	1.02	1.04	0.93	1.05
Metal material workers	2.0	5.0	3.0	0.99	0.98	1.02	1.01	1.01	0.96	0.93	1.08	1.08	0.97
Workers operating marine and air transport equipment	0.4	0.9	0.5	0.96	0.97	1.04	1.04	1.02	0.95	0.95	1.05	1.06	1.01

Source: See Figures 1 and 7

Appendix Figure 1(a): Skill score of 35 skills for social and welfare workers

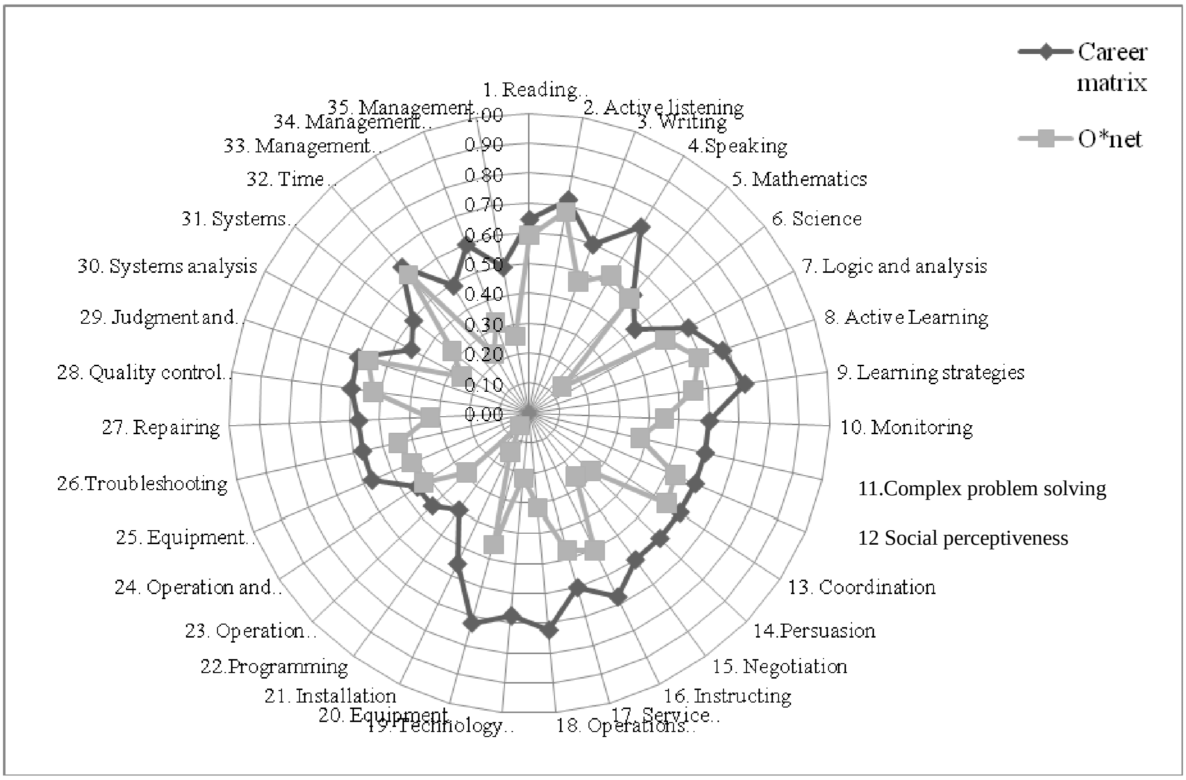


Appendix Figure 1(b): Task intensity in 1960 for social and welfare workers

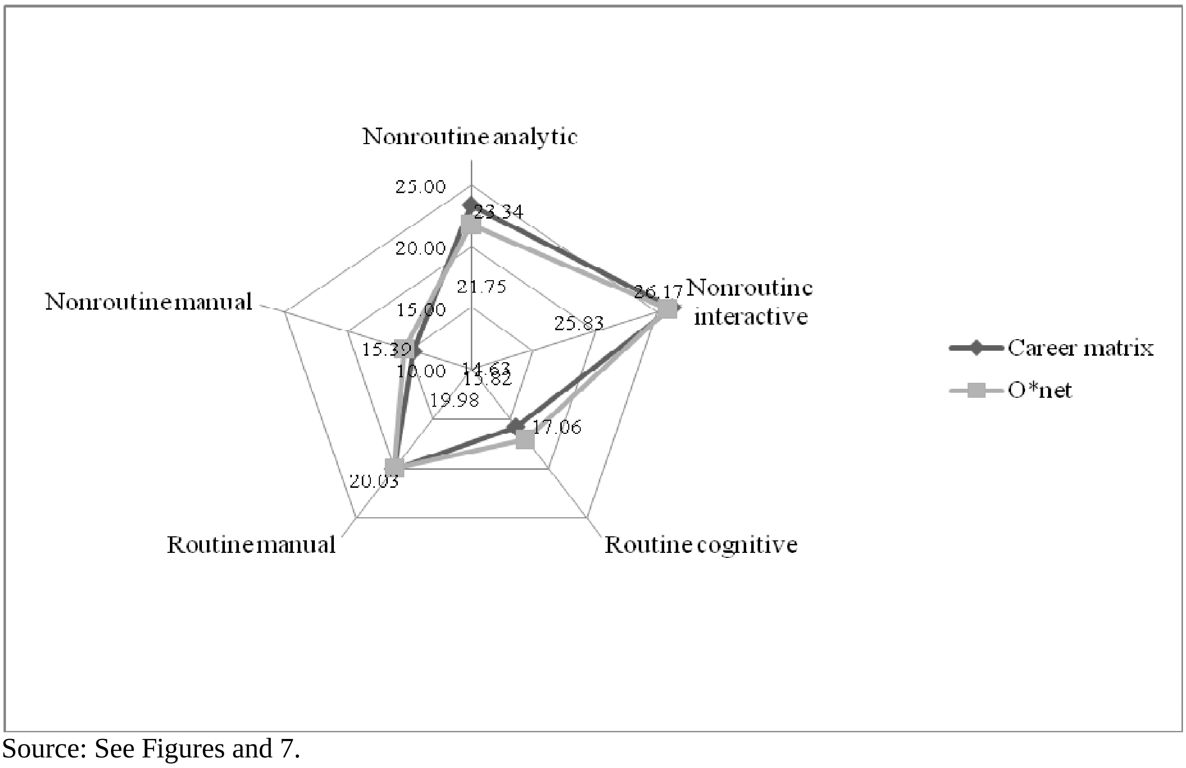


Source: See Figures and 7.

Appendix Figure 2(a): Skill score points of 35 skills for clothing and textile products workers



Appendix Figure 2(b): Task intensity in 1960 for clothing and textile products workers



Source: See Figures and 7.

Appendix Table 4: Summary statistics

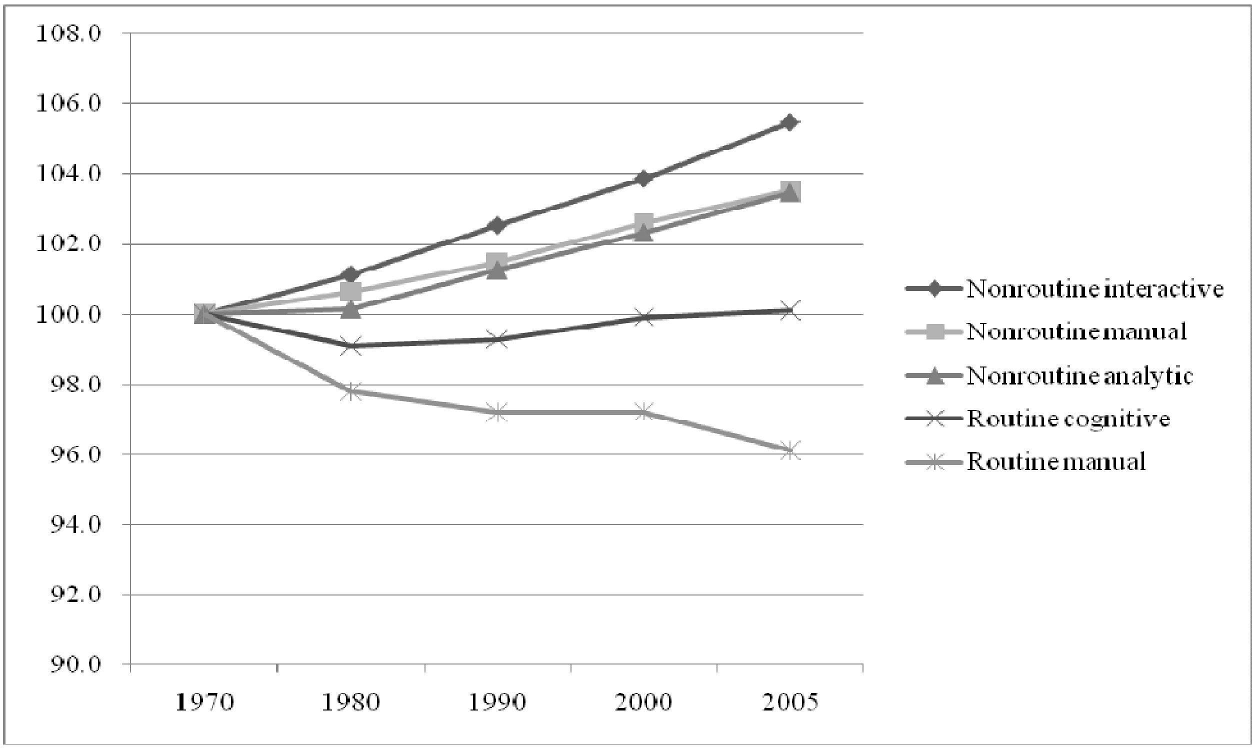
	Variable	Observations	Mean	S.D.	Min.	Max.
Log of hourly scheduled wage (Nominal)		984	6.918	0.715	4.615	9.031
Log of hourly scheduled wage (Real)		984	7.143	0.412	5.715	9.076
Task intensity	Nonroutine analytic	984	24.180	2.644	17.232	29.489
	Nonroutine interactive	984	28.270	2.779	21.546	36.844
	Routine cognitive	984	17.333	1.518	12.627	21.837
	Routine manual	984	21.544	2.688	13.743	28.865
	Nonroutine manual	984	15.941	1.266	12.074	19.281
Composition of occupation	Average age	979	38.195	7.061	19.500	58.800
	Average tenure	924	9.733	4.072	0.600	29.300
	Percentage of college graduates	725	10.401	18.748	0.000	96.275
	Female dummy	984	0.362		0	1
Year dummy	1970	984	0.167		0	1
	1980	984	0.160		0	1
	1990	984	0.161		0	1
	2000	984	0.249		0	1
	2005	984	0.261		0	1
Difference from overall average	Hourly scheduled wage	984	-105.000	656.628	-1091.572	6928.689
	Nonroutine analytic	984	-0.103	2.649	-7.098	5.289
	Nonroutine interactive	984	-0.630	2.773	-7.424	7.874
	Routine cognitive	984	0.546	1.523	-4.233	4.817
	Routine manual	984	1.374	2.691	-6.647	7.955
	Nonroutine manual	984	-0.010	1.264	-3.896	3.311
	Average age	979	-0.076	6.533	-21.200	19.200
	Average tenure	924	-1.000	3.906	-11.400	17.300
	Percentage of college graduates	725	-3.423	18.405	-19.330	82.185
	Female dummy	984	0.052	0.482	-0.326	0.702

Appendix Table 5: Correlations between task intensities

	Nonroutine analytic	Nonroutine interactive	Routine cognitive	Routine manual	Nonroutine manual
Nonroutine analytic	1.000				
Nonroutine interactive	0.870	1.000			
Routine cognitive	0.775	0.586	1.000		
Routine manual	0.544	0.225	0.898	1.000	
Nonroutine manual	0.799	0.928	0.730	0.409	1.000

Source: Authors' calculation.

Appendix Figure 3: Trends in task input in Japan using data from the *Basic Survey on Wage Structure*



Source: Authors' calculation.