Labor Market Polarization in Japan
– Changes in Tasks and the Impact of the Introduction of IT –

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Abstract

The purpose of this paper is to examine the reasons for the polarization in Japan's labor market observed in recent years. To this end, five different types of tasks following the theoretical framework of Autor, Levy and Murnane (2003) are distinguished. Doing so shows that employment both in relatively high-skill high-wage tasks and in relatively low-skill low-wage tasks increased. To investigate the underlying reasons for these trends, the roles of education, structural change, and the spread of information technology (IT) in the demand for and supply of workers of different types of skills are empirically examined. Among other things, the results show that IT is complementary to nonroutine analytic tasks, while it substitutes for workers performing routine tasks. The spread of IT therefore appears to have contributed to the polarization in Japan's labor market by increasing the demand for workers performing – typically high-skill – nonroutine analytic tasks and decreasing the demand for workers performing – typically low-skill – routine tasks.

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1. Introduction

Recent years have seen growing evidence of a polarization in labor markets in advanced economies around the world. On the one hand, there has been a marked increase in the number of those working in high-income jobs requiring a high degree of specialization; on the other, this has been accompanied by a rise in the number of those who have little choice but to work in unstable low-income jobs that require few skills. These developments reflect long-term trends observed in countries such as the United States, the United Kingdom, and Germany of a polarization of tasks at the workplace that is characterized by an increase in high-skill tasks that require specialized expertise and abilities as well as in manual tasks that require relatively few skills but are difficult to mechanize, and a simultaneous decrease in intermediate tasks. Underlying this trend, it has been argued, are developments such as the ongoing computerization at the workplace and the shift to a service economy.

Research on this issue so far has largely concentrated on advanced Western economies. Against this background, the purpose of this study is to examine whether similar long-term trends can also be observed in Japan. Specifically, the aim is to investigate whether in Japan, too, there has been a parallel increase in high-skill tasks and in low-skill manual tasks that are difficult to mechanize, and a decrease in intermediate clerical tasks and manufacturing tasks; and, moreover, whether and how such trends are related to the introduction of information technology (IT) at the workplace.

In the United States, evidence of a polarization in the labor market has been observed since the 1980s. Aspects of this is increasing wage inequality as well as the growing employment shares of those in high-wage or low-wage jobs and a shrinking share of those in-between. These developments gave rise, in the 1990s, to the hypothesis of skill-biased technical change (SBTC), which argues that an important reason for the increase in wage differentials is technological innovation, exemplified by the introduction of computer-technology, which increases the relative demand for high-skill workers. Some scholars, such as Card and DiNardo (2002) and Lemieux (2006) among others, have questioned the SBTC hypothesis, however. They argue that the increase in wage differentials in the 1980s was a temporary phenomenon that reflects factors other than technological innovation (such as the decline in the real minimum wage and the decrease in unionization rates) and changes in the composition of the labor force (such as in terms of educational attainment and experience). As an expansion of the SBTC hypothesis, Autor, Levy and Murnane (2003; referred to as ALM hereafter) developed a theoretical model to examine how computer technology changes the demand for labor. Classifying tasks in terms of whether they are, for example, routine or nonroutine and intellectual or physical, ALM distinguish five different types of tasks, namely nonroutine analytic tasks, nonroutine interactive tasks, routine cognitive tasks, routine manual tasks and nonroutine manual tasks. Doing so, they showed that computerization on the one hand substitutes for manual and routine cognitive tasks and reduces the demand for labor performing such tasks, but on the other was complementary to nonroutine analytic and nonroutine interactive tasks and increased the demand for labor performing such tasks.

The ALM framework has subsequently been applied in studies on other countries. Focusing on the United Kingdom, Goos and Manning (2007), for example, showed that ALM's model provided a good explanation of the job polarization observed over the past 25 years. Similarly, applying ALM's framework, Spitz-Oener (2006) showed that trends in West Germany resembled those in the United States, with the spread of the computer in the workplace substituting for workers performing routine manual and cognitive tasks and complementing analytic and interactive tasks. Dustmann, Ludsteck and Schoenberg (2007) also looked at West Germany and found that wage inequality grew during the 1980s, but only at the top of the distribution, while in the early 1990s, wage inequality started to rise also at the bottom of the distribution. Developments during the early 1990s, however, were due to temporary factors such as acceleration in the decline in the unionization rate and the influx of low-skilled workers from Eastern Europe and East Germany.

To the author's best knowledge, there are so far no studies that have directly applied the ALM framework to Japan. Yet, the available evidence suggests that similar long-term trends to those in the United States, the United Kingdom, and Germany can be found. For instance, in Japan, too, the demand for and supply of high-skill, high-wage labor is increasing as a result of changes in industrial structure, rising education levels, technological innovation and other factors. (see, e.g., Ministry of Health, Labour and Welfare, 2006), while at the same time, the number of workers in low-skill, low-wage employment is increasing. In this context, Sakurai (2004), focusing on employment in Japan's manufacturing sector during the period 1985-2000, found that technological progress, represented by investment in computers and research and development (R&D), played an important role in the shift in demand toward workers with higher levels of educational attainment. Similarly, using data from the manufacturing sector for 1998 to 2003, Sasaki and Sakura (2004) showed that a higher R&D share in an industry as well as a higher ratio of imports from East Asia and a higher overseas production ratio were associated with a shift in labor demand toward more highly-educated workers, thus illustrating the role played by technological change and economic globalization. Meanwhile, Abe (2005), based on a questionnaire survey of firms and their white-collar permanent employees, found that the introduction of information and communication technology in firms on the one hand digitized routine jobs and led to their outsourcing and, on the other hand, further boosted the importance of analogue skills that cannot be performed by information and communication equipment. Finally, Yamada (2007) pointed out that among those who had graduated only from elementary, junior high, or high school, employment in relatively low-wage occupational categories requiring physical strength such as “protective and guarding service occupations” and “laborers” was increasing.

Against this background, the purpose of this study is to investigate whether there are signs of a polarization in the Japanese labor market and to analyze the relationship between related trends and the introduction of IT. Specifically, based on ALM’s theoretical framework, the detailed job classifications of the *Population Census* are divided into the five categories of nonroutine analytic, nonroutine interactive, routine cognitive, routine manual, and nonroutine manual tasks, and employment trends in these categories from 1980 to 2005 are examined. The next step then is an investigation into the factors determining these labor market trends by focusing on both supply-side aspects (e.g., the secular rise in educational attainment and changes in preferences regarding particular tasks) and demand-side aspects (changes in industrial structure and in the demand for specific tasks within individual industries). Finally, the relationship between the above five tasks and the introduction of IT is examined by regressing changes in the composition of tasks by industry on changes in the IT capital stock by industry.

The results of the analysis show that in Japan, just as in other countries, a parallel increase in knowledge-intensive nonroutine analytic tasks and relatively low-skill nonroutine manual tasks on the one hand and a decrease in routine tasks on the other can be observed. In addition, it is found that, generally speaking, an increase in knowledge-intensive (nonroutine analytic) tasks and a decrease in routine (cognitive as well as manual) tasks can be observed in industries where investment in IT is particularly active.

The remainder of the paper is organized as follows. Section 2 provides a simple examination of trends in the wage distribution and employment structure in Japan. Section 3 presents the empirical analysis, for which job categories are divided into tasks along the lines proposed by ALM and Spitz-Oener (2006). Changes in employment in these task categories are then regressed on supply-side factors (e.g., the rise in education levels), demand-side factors (e.g., changes in industry structure), and IT capital, representing the spread of IT in the workplace. Finally, Section 4 concludes and discusses future research tasks.

2. Trends in the wage distribution and employment structure

To begin the examination of whether a polarization in Japan's labor market can be observed, trends in the wage distribution and in the job structure are examined.

2.1 Wage distribution

Let us begin with trends in the wage distribution. Table 1, based on data from the *Basic Survey on Wage Structure*, shows the relative monthly scheduled cash earnings of regular employees (at enterprises with 10 or more regular employees) for various categories of workers for selected years from 1980 to 2007. Overall, the figures fluctuate within relatively narrow ranges without displaying a clear trend, and no conspicuous polarization is observed. This observation is line with the findings of preceding studies. Ohtake (2005), for example, examining the statistical evidence for the period from 1980 to around 2000, concluded that there has been no large increase in wage inequality. Meanwhile, Kambayashi, Kawaguchi and Yokoyama (2007) suggest that wage differentials actually shrank from 1989 to the mid-1990s, remained largely unchanged until the end of the 1990s, and then increased from 2000 onward for men.

Next, to examine developments in wages in more detail, Figure 1 presents the trend in earnings by wage bracket and by educational attainment. More specifically, the figure depicts the monthly scheduled cash earnings of regular employees for the same period (firms with 10 or more regular employees, real values, 2005 prices) converted to an index of hourly earnings,[1] with the left-hand panels showing the trend in the median wage and the wages of the top and bottom deciles, and the right-hand panels showing the trend for workers with different levels of educational attainment. The left-hand panel illustrates that until 2000, wages increased uniformly across the board. Since 2000, however, wage growth has slowed substantially, and while the top decile continued to register some wage growth, the wages of the bottom decile more or less stagnated. These patterns are quite similar for both men and women, although in the case of women, the increase in wages and the divergence between the top and the bottom decile are more pronounced.

The patterns are somewhat less uniform in the right-hand panels showing the trend in wages for workers with different levels of educational attainment. Until 2000,

[1] Hourly earnings are calculated as monthly earnings divided by monthly working hours. Aggregate data only provide a cross tabulation of monthly working hours by sex and educational attainment and a cross tabulation of monthly scheduled cash earnings of the 1st decile, the 1st quartile, median, the 3rd quartile and the 9th decile by sex and educational attainment respectively. Thus, working hours by income quartile are not available and are therefore set to be equal across income quartiles.

the indexes for the different groups all are very close to each other, moving in a similar fashion, with the exception of male graduates of higher professional schools and junior colleges. Since then, however, the wage growth for both male and female high school graduates slackened, while wages for junior high school graduates generally declined.

Figure 2 provides a close-up of the period from 2000 to 2007 to examine the most recent trends in more detail. Beginning with the left-hand panels, it can be seen that for men, wages moved in tandem until 2004, registering very little change, but then diverged somewhat, with the bottom decile recording a decrease and the top decile a further increase. Among women, similar, though again more pronounced, developments can be observed. Wages continued to increase for all brackets until 2004, but then declined for the bottom decile, while increasing further for the top decile. Turning to the right-hand panels for wage trends by workers' educational attainment and beginning with men, it can be seen that university graduates and graduates of higher professional schools and junior colleges continued to enjoy small increases in wages. On the other hand, high school graduates saw no growth in wages, while workers that only graduated from junior high school suffered a pronounced decline in wages. Among women, both graduates of higher professional schools and junior colleges and university graduates enjoyed an increase in wages, with wage growth for the former in fact outstripping that for the latter. For junior high and high school graduates, wages have been on a downward trend from around 2004/2005.

Next, Figures 3 and 4 show the change between 2002 and 2007 in the total number of workers (at firms with more than 5 employees) by wage bracket. Figure 3 depicts the change in the number of regular full-time workers grouped in terms of their (nominal) monthly scheduled cash earnings. The figure shows that, overall, the number of regular full-time workers has declined, and that while the numbers of those employed in the lowest and highest earnings brackets saw small increases, there were large decreases in the numbers of those in the middle brackets. Figure 4 similarly depicts the change in the number of part-time workers grouped in terms of their (nominal) hourly scheduled cash earnings. The figure shows that the number of part-time workers has increased and, moreover, that there has been a rise in the number of male part-time workers in the lowest wage group such as those earning less than 800 yen an hour.

Overall, the trends can be summarized as follows. Between 1980 and around 2000, the wages of the highest wage earners and those with a high educational attainment increased absolutely and also, to some extent, relative to that of lower-wage earners. However, because the wages of the lowest-wage earners also increased and therefore managed to keep up to some extent, a striking polarization in wages was not observed. Since around 2000, however, trends have diverged somewhat: the wages of those in the lowest wage group and those with the lowest levels of educational attainment have stagnated or even fallen, while the wages of those in the highest wage group and those with higher levels of educational attainment have continued to increase somewhat or at least have generally held up, leading to an increase in wage inequality. Moreover, looking at changes in the number of workers by wage bracket between 2002 and 2007, a substantial decrease in the number of those in the middle wage brackets can be observed. This latter pattern is particularly pronounced among men.

2.2 Changes in employment structure by type of job

Let us now look at changes in the employment structure by type of job. Table 2 shows those jobs among the 142 job categories distinguished in the *Basic Survey of Wage Structure* that saw the greatest percentage increase or decrease in labor input between 1995 and 2007.[2] Job categories that saw particularly large increases in labor input are those related to health and welfare services (care managers, home helpers, therapists) and researchers, while job categories that saw the most pronounced decreases in labor input were related to industries that contracted during this period, such as coal mining and clothing and textiles (e.g., miners, sewing machine workers, weavers). Another pattern shown in the table is that although knowledge-intensive jobs (researchers, academics, pilots) saw increases in labor input, the fastest growth can be found in service jobs that are labor intensive and not particularly high-skill, especially nursing-related jobs. However, the level of pay in such nursing-related jobs registering high rates of labor input growth is relatively low (prime examples are home helpers and caregivers at welfare facilities), thus providing one possible explanation for the increase in the number of workers in the low-wage brackets shown in Figure 3.

3. Empirical analysis

The simple analysis of labor market trends in the preceding section suggests that Japan – like advanced Western economies – has experienced a parallel increase high-skill, high-income jobs and in low-skill, low-income jobs. In order to examine this potential polarization in the labor market more rigorously and determine the contributing factors, this section provides an empirical analysis of the observed trends following the framework suggested by ALM. To this end, jobs are divided into five task categories (nonroutine analytic, nonroutine interactive, routine cognitive, routine manual, and nonroutine manual), and changes in the employment in these task categories is then examined taking supply-side and demand-side aspects into account. Supply-side aspects considered include the secular rise in workers' level of education

[2] The 142 job categories consist of the 129 job categories in the 2007 edition of the *Basic Survey* and 13 discontinued job categories. For job categories that were added or deleted during the 1995-2007 period, the annual rate of change for the period for which data are available is used.

over time and changes in the preference for tasks, while demand-side aspects include changes in industrial structure as well as changes in the demand for specific tasks within individual industries.[3] Finally, based on ALM's model, the relationship between the use of IT in the workplace and changes in employment in different types of tasks are examined.

3.1 Changes in tasks

3.1.1 Classification of jobs into task categories

For the analysis, the detailed job classifications of the *Population Census*, which is published every five years, are divided into the five task categories distinguished by ALM.[4] Jobs are allocated into one of the five task categories by referring to the Career Matrix prepared by the Japan Institute for Labour Policy and Training and to the Occupational Information Network (O*Net) being developed under the sponsorship of the Employment and Training Administration of the U.S. Department of Labor (USDOL/ETA) through a grant to the North Carolina Employment Security Commission. Definitions of the five tasks, important keywords, and example tasks are shown in Table 3 (for details of the classification method refer to Appendix 1).

3.1.2 Employment trends by task type

Let us begin by looking at the employment trends for each task category. In Figure 5, employment for each task category is expressed as an index, which is set to 100 for the year 1980. As can be seen, there has been a steep increase in the number of those employed in nonroutine analytic tasks, reflecting the rapidly growing employment

[3] Because it was impossible to cross-tabulate job classifications, industries, and educational attainment, the relationship between educational attainment and tasks is examined without controlling for industries and that between industries and tasks is examined without controlling for education.

[4] Regarding changes in detailed job classifications during the observation period, the following procedure was used. First, where individual classifications changed, these were linked wherever possible and summarized in the 244 job categories. Second, in cases where the name of job classifications changed, the most recent name was used.

in job categories such as IT engineers, electrical and electronics engineers, and researchers in the humanities and social sciences. On the other hand, employment in nonroutine interactive tasks and routine cognitive tasks grew much more slowly until 1995 and has in fact declined or stagnated since. This pattern is different from the one observed by ALM for the United States in that it is nonroutine interactive tasks that registered the highest rate of growth, exceeding that in nonroutine analytic tasks, and employment in routine cognitive tasks has been consistently shrinking since the 1990s.

Looking in more detail at nonroutine interactive tasks, there are many job categories that have seen an increase in employment, such as social welfare professions, pharmacists, and professional athletes. However, much of this increase was offset by remarkable decreases in employment in job categories such as civil servants in managerial positions and workers in managerial occupations at firms and organizations (summarily labelled "public and private sector managers" below)[5] and wholesale and retail shop owners. Similar offsetting trends can be observed for routine cognitive tasks. On the one hand, there have been large decreases in job categories such as stenographers, typists, and word processor operators, but on the other, other job categories generally experienced an increase. This is particularly the case for the job category of general office workers, who make up more than half of those working in tasks classified as routine cognitive tasks. However, the reason for this increase likely is that the tasks performed by general office workers have become more diversified and at least some of these tasks are not necessarily routine.

The figure also shows that employment in routine manual tasks has declined. Again, a closer look shows countervailing trends. While employment in labor-intensive

[5] In Japan, there has been a remarkable decline in the number of self-employed since the 1980s, which is also notable in comparison with other OECD countries.

industries that are no longer internationally competitive (e.g., clothing and textiles, daily-use and household articles, and mining) has fallen, employment in delivery services and cleaners and garbage collectors registered substantial rises. Turning finally to nonroutine manual tasks, a steady upward trend can be observed. Job categories that saw a rise include those related to personal services, such as nursing, as well as caretakers (e.g., of buildings, parking lots, and apartment blocks), protective and guarding service personnel, attendants at amusement facilities, and beauticians. At the same time, employment in traditional service job categories (e.g., hotel staff, train conductors, and geisha and dancers) registered a large decrease.

It goes without saying that to some extent the classification of job categories into the five task types represents an oversimplification. In practice, most jobs consist of a combination of the different types of tasks. Especially in the case of broadly defined job categories, such as manufacturing and general office work, respectively classified as falling under routine manual and routine cognitive tasks, workers perform a variety of tasks, including nonroutine tasks. Moreover, the relative importance of individual task types within job categories may change over time. However, data limitations make it difficult to take these aspects into account. Keeping these caveats in mind, the approach adopted in this study therefore is to classify each job category into one of the five task types on the basis of the one task type that is considered to be the most characteristic of a particular job category.

3.1.3 Changes in employment by task type and supply-side factors: Educational attainment and task preferences

The stage is now set to begin the empirical analysis. The first issue to be addressed is the supply-side factors contributing to changes in the employment in different task types. Two supply-side factors are considered: the secular rise in education levels and changing preferences regarding the different types of tasks. Looking at the composition of educational attainment of workers in each of the five task types, the pattern observed conforms to expectations: in nonroutine analytic tasks, those with tertiary education (i.e., university and higher professional school and junior college) make up the largest share (52.9 percent in 2000); in contrast, in routine and nonroutine manual tasks, those with only elementary or junior high school education account for relatively large shares - 30.5 percent and 23.9 percent respectively in 2000, compared with a share of less than 10 percent in other tasks."

It is generally thought that the increase in employment in nonroutine analytic tasks is a reflection of the increase in the number of those with a high level of educational attainment. However, the share of those with a high level of educational attainment employed in routine and manual tasks is also increasing, which is likely to be the result of the secular rise in education levels overall. To investigate these issues more rigorously, the relationship between the changes in educational attainment (*e*) and task preferences (*P*) on the one hand and the change in the number of those employed (*T*) in each of the five tasks (*k*) on the other is examined empirically using data from the *Population Census* for the period 1980-2000. The following specification is used:

$$\Delta T_k = \sum_{e}^{n} \Delta T_e \overline{P}_{ek} + \sum_{e}^{n} \Delta P_{ek} \overline{T}_e$$

where

e=1, …n (educational attainment)[6] (n=5)

ΔT_k : Change in the number of workers in task *k* from 1980 to 2000.

[6] The educational attainment categories are: elementary and junior high school (1980: elementary and junior high school, schools in the prewar period including higher elementary school, and school for youth outside secondary education, unschooled; 2000: elementary and junior high school, unschooled); high school, former middle school, junior college, and higher professional school graduates; university graduates; and other (currently enrolled students and school type unknown).

$\overline{P}_{ek}$: Period average of the share of those with educational attainment level *e* employed in task *k* (representing task preferences).

ΔT_e: Change in the number of workers with educational attainment *e* from 1980 to 2000 (representing the change in the composition of educational attainment).

$\overline{T}_e$: Period average of the number of workers with educational attainment *e* (representing the composition of educational attainment).

ΔP_{ek} : Change in the share of those with educational attainment *e* employed in task *k* from 1980 to 2000 (representing the change in task preferences).

The first term shows the change in the number of workers due the change in education levels (the spread of higher levels of education), while the second term shows the change in the number of workers as a result of changes in task preferences.[7]

The results of the estimation are shown in Table 4 and suggest that the increased employment in nonroutine analytic tasks is due both to the rise in education levels and changes in task preferences. In contrast, in the case of nonroutine interactive and routine cognitive tasks, only the rise in education levels made a positive contribution to the increase in employment, which was partly offset by the negative contribution of changes in task preferences. Next, the decline in employment in manual tasks is almost entirely attributable to the rise in education levels, although changes in task preferences also made a small negative contribution. Finally, the increase in nonroutine manual tasks is entirely due to changes in task preferences, with the rise in education levels having no impact. In sum, the results suggest that the rise in education levels

[7] To check the robustness of the results, the exercise was repeated using the task preferences and composition of educational attainment in 1980 and 2000 instead of period averages. In both cases, the results obtained are essentially the same as when using period averages.

contributed to the increase in nonroutine analytic, nonroutine interactive, and routine cognitive tasks, i.e., so-called white collar tasks, while changes in task preferences contributed only to increases in employment in nonroutine analytic and nonroutine manual tasks.

3.1.4 Changes in employment by task type and demand-side factors: The shift between and within industries in the demand for tasks types

Next, demand-side factors contributing to changes in employment in the different task types are considered. Specifically, the analysis focuses on changes in the structure of the economy overall, that is, the shift in the relative weight of and, hence, labor demand from different industries (the "between shift"), as exemplified by the shift from manufacturing to services, and the changing demand for different task types within each industry (the "within shift"). Using data for employment by industry and detailed job category from the *Population Census*,[8] the following specification is used for the empirical analysis:

$$\Delta P_k = \sum_{j}^{n} \Delta S_j \overline{P}_{kj} + \sum_{j}^{n} \Delta P_{kj} \overline{S}_j \qquad j = 1,\ldots, n \text{ industry} \quad (n\text{=78})$$

where

$P_{kj} = L_{kj} / L_j$: Labor share of task k in industry j.

$S_j = L_j / L$: Share of workers in industry j in total workers.

Upper bars denote period averages.

ΔP_k denotes the change in the share of workers in task k in total workers within the

[8] To be able to examine the role of IT later, the industry categories of the Japan Industrial Productivity Database 2006 (JIP Database) published by the Research Institute of Economy, Trade and Industry (108 industries) and the *Population Census* 1980: 199 industries; 1990: 213; 2000: 223; and 2005: 225) are aggregated into 78 industries.

period, while the first term represents the change due to the change in industrial structure (between shift) and the second term represents the change due to the change in tasks performed within each industry (within shift).[9]

The results are presented in Table 5 and suggest that for employment in nonroutine analytic tasks, the shift within industries is more important than that between industries, particularly during the 1980s, when the within-industry shift made a large positive contribution. On the other hand, the increase in employment in nonroutine interactive tasks is entirely due to the between-industry shift, while the within-industry shift actually made a negative contribution. As for routine cognitive tasks, both the between- and the within-industry shift made a positive contribution, although the size of the former is greater. Meanwhile, the decline in employment in routine manual tasks is largely due to the between-shift, with the within-shift making only a comparatively small contribution. Finally, the increase in employment in nonroutine interactive tasks is largely due to the between-industry shift.

Summarizing the results, it can be said that the between-industry shift has had a considerably greater impact on employment in the various tasks than the between-industry shift. That is, changes in industrial structure, such as the shift to services, has resulted in an increase in employment in nonroutine analytic, nonroutine interactive, routine cognitive, and nonroutine manual tasks (i.e., tasks associated with so-called white collar jobs) and a decrease in employment in routine manual tasks (i.e., tasks associated with so-called blue collar jobs). However, the one task category that stands out in that the within-shift (i.e., changes in the demand for different task types within an industry) is more important than the between-shift is nonroutine analytic tasks,

[9] Again, as in Section 3.1.3, to check the robustness of the results, instead of period averages, the values at the beginning and at the end of each period for the labor share of a particular task in a particular industry and for the share of workers in a particular industry in total workers were used. Although the sizes of coefficients differed to some extent, the results were essentially the same in terms of the sign of coefficients and the relative size of the intra-industry and inter-industry effects.

indicating that the demand for such tasks has generally increased across all industries.[10]

3.2 Computerization and task input

3.2.1 Theoretical considerations

The next issue to be considered is the link between the use of IT at the workplace and changes in employment in different task categories. This is done by employing the model developed by ALM. The model assumes a Cobb-Douglas production function, in which product *Q* is produced using two task inputs, routine tasks and nonroutine tasks. Routine tasks are supplied by labor L_R and computer capital *C*, while nonroutine tasks are supplied by labor L_N, that is:

$$Q = (L_R + C)^{1-\beta} L_N^{\beta}, \beta \in (0,1)$$

where labor L_R and computer capital *C* are perfect substitutes, and the wage paid for routine tasks measured in efficiency units, w_R, and the price of computer capital, ρ, are equal in equilibrium, i.e. $w_R = \rho$.

Further assumptions are that routine and nonroutine tasks are q-complementary to each other (that is, an increase in routine tasks raises the marginal productivity of nonroutine tasks) and that the price of computer capital decreases exogenously through technological progress, pushing down the wage for routine tasks one-to-one and expanding the demand for them. Because an increase in routine tasks raises the marginal productivity of nonroutine tasks, the relative wage paid for nonroutine tasks increases and workers chose nonroutine tasks. Therefore, an increase in demand for routine tasks will be met not by an increase in workers but by an increase in computer capital.

Based on this reasoning assuming that all industries use a technology of

[10] While ALM find that for routine tasks (routine cognitive and routine manual tasks) the within-industry decline in demand for such tasks dominates, the analysis here finds hardly any negative contribution of within-industry changes. The reason for this is likely to be the data issues with regard to routine tasks already mentioned in Section 3.1.2.

Cobb-Douglas form, the production function of industry *j* is:

$$q_j = r_j^{1-\beta_j} n_j^{\beta_j}, \beta_j \in (0,1)$$

where q_j denotes the output of industry *j*, r_j stands for the routine task input in industry *j* (with the input by workers and computer capital expressed in efficiency units), and n_j is the nonroutine task input. β_j stands for the factor share of nonroutine tasks to capture industry characteristics, implying that the smaller β_j, the more routine task-intensive is the industry. By deriving factor demand from the profit maximization condition, the following two hypotheses can be posited based on the model (see Appendix A.2 for details):

<u>Hypothesis 1</u>: All industries face the same decrease in the price of computer capital and introduce computer capital, but the extent to which they do so is greater the higher the degree of routine task intensity (the smaller β_j).

<u>Hypothesis 2</u>: Through the complementarity of computer capital and nonroutine task input, a decrease in the price of computer capital increases the demand for nonroutine task input (along with the demand for routine task input). However, because increased demand for routine tasks is met by an increase in computer capital, labor input in nonroutine tasks increases and that in routine tasks decreases in those sectors that have invested more in computer capital.[11]

3.2.2 Data

The extent to which industries have introduced IT capital is measured by the IT capital stock[12] by industry (in 1995 prices) for the years 1980, 1990, 2000, and 2004 from the Japan Industrial Productivity Database 2006 (JIP Database) compiled and published in collaboration by the Research Institute of Economy, Trade and Industry

[11] ALM additionally posit a third hypothesis, namely that the above-mentioned industry-level discussion can also be applied to the job level. However, because in this paper, each job corresponds to one of these five task types, it is not possible here to distinguish tasks within each job category.

[12] The IT capital stock in the JIP Database consists of the following items: copying machines; other business equipment; electric audio equipment; TVs; radios; computer-related equipment; wired and wireless electronic communication equipment; video and associated electronic equipment; electric measuring equipment, cameras, other optical equipment, machinery for physics and chemistry, analyzers, testing machines, gauges, finders and medical equipment; and order-made software.

(RIETI) and Hitotsubashi University.

3.2.3 Estimation method and results

To start with, Hypothesis 1 is examined, namely, whether the use of IT capital is greater the more routine-task intensive an industry is. The observation period is 1980 to 2004, and the following relationship is obtained:

$$\Delta \ln(IT_{jstock} / L_j)_{1980-2004} = 0.0345 + 0.0864 RS_{j1980}$$

(0.015) (0.021) (Figures in parentheses are standard errors.) (n=78, Adjusted R^2 = 0.179)

where:

$\Delta \ln(IT_{jstock} / L_j)_{1980-2004}$: Annual rate of change (1980-2004) in real IT capital stock per worker in industry *j*.

RS_{j1980} : Share of routine tasks in industry *j* in 1980 [(Routine cognitive tasks + Routine manual tasks)/Total of the 5 tasks].

The estimation shows that industries that were more routine task intensive in 1980 were indeed more active in introducing computer capital (the coefficient is positive and significant at the 1 percent level); however, a 1 percent higher share in routine tasks in 1980 is associated only with a 0.09 percent higher annual growth rate in capital stock in the period 1980-2004.[13]

Next, Hypothesis 2, namely whether labor input in nonroutine tasks increased and that in routine tasks decreased in those industries in which the use of IT capital increased, is tested. To do so, the relationship between the change in employment in

[13] Re-estimating the equation employing weighted least squares and using period average employment shares as weights, the size of the coefficient increases somewhat, but remains small:

$\triangle \mathrm{Ln}\ (IT_{jstock}/L_j)_{1980\text{-}2004} = 0.1169 + 0.1169 RS_{j1980}$

(0.009) (0.014) (Figures in parentheses are standard errors.)

(n=78, Adjusted R^2 = 0.4605)

task k (k=nonroutine analytic, nonroutine interactive, routine cognitive, routine manual, and nonroutine manual tasks[14]) in industry j (78 industries) from 1980 to 2005 and the introduction of IT capital in that industry is examined. Specifically, using the annual rate of change in employment in task k in industry j from 1980 to 1990, from 1990 to 2000, and from 2000 to 2005 as the dependent variable, pooled estimations for these three periods as well as for the two periods of 1980-1990 and 1990-2000 are conducted.[15] The use of IT capital is measured by the real IT capital stock per worker (and per man-hour), and for comparison, various specifications using different measures of capital, such as the non-IT capital stock and the capital equipment ratio for capital stock, were also estimated.

In order to remove common time trends, period dummies for 1990-2000 and for 2000-2005 are used, meaning that 1980-1990 is the base case. Because there are large variations across industries in terms of the number of persons employed, the estimation is conducted using weighted least squares utilizing the period average of industries' share in total employment as weights. Thus, the specification to be estimated is as follows:

$$\Delta T_{jk\tau} = \alpha + \beta \Delta IT_{j\tau} + \gamma \Delta NonIT_{j\tau} + D_{time} + u_{jk\tau}$$

where

$\Delta T_{jk\tau} = T_{jk\tau} - T_{jkt}$: Change in labor input in task k in industry j during the period t to τ.

$\Delta IT_{j\tau}$: Annual rate of change in real IT capital in industry j during the period t to τ.

$\Delta NonIT_{j\tau}$: Annual rate of change in real capital other than IT in industry j during the

[14] With regard to nonroutine manual tasks, ALM argue that computer capital is unlikely to substitute for, or be complementary to, such tasks in any substantial way. They therefore do not posit any hypothesis on such tasks, nor do they include them in their estimation. However, since Autor, Katz and Kearney (2006) subsequently discussed possible q-complementarity between computer capital and nonroutine manual tasks, the estimation for nonroutine manual tasks is included in this paper for reference.

[15] For real IT capital stock, non-IT capital stock, and real IT investment, data for 2004 are used to substitute for 2005 data. Because data for man-hours and real net capital stock are available only up to 2002, pooled estimations only for the two periods of 1980-1990 and 1990-2000 were conducted.

period t to τ.

D_{time} : Period dummies.

$u_{jk\tau}$: Error term.

The results are presented in Table 6. As can be seen, in the estimation for nonroutine analytic tasks, the coefficient on real IT capital stock is significant and positive, indicating that employment in these tasks increased in industries where there was greater investment in computer capital. The estimation results in Table 6 also show that, in the estimations for both routine manual and routine cognitive tasks, the coefficient on real IT stock is negative and significant, indicating that employment in these tasks decreases the more an industry relies on the use of computer capital. Comparing the two tasks, this effect is stronger for nonroutine manual tasks. Finally, for nonroutine interactive tasks, the coefficient on real IT stock is statistically insignificant.

Looking at the coefficients for other variables, those on non-IT capital stock and the capital equipment ratio with regard to capital stock overall are significantly negative in many cases. Further, the coefficients on the dummies for 1990-2000 and 2000-2005 are significantly negative in all cases, indicating that there was a strong underlying trend of a slowdown in labor input growth. Overall, these results support the hypothesis that nonroutine analytic tasks are complementary to IT capital, while routine manual and routine cognitive tasks are being substituted by it.

At this point, it is interesting to briefly focus on one job category in particular, namely public and private sector managers. As mentioned above, this is a job category falling under the heading of nonroutine interactive tasks that has seen a substantial decline in employment in Japan. A possible explanation for this decline is that many of these jobs may have disappeared as a result of the flattening of organizational structures through the introduction of IT and the increased speed of communication. Rerunning the regression just for this job category in order to examine this issue, the coefficient on real IT capital stock is found to be significantly negative (Table 6(c)), indicating that indeed the use of IT at least to some extent appears to have contributed to the decline in employment in this job category. The trend in Japan contrasts sharply with that in the United States, where employment in business management occupations has generally increase since the latter half of the 1980s (see, e.g., Ministry of Health, Labour and Welfare, 2001), the reason for which, it is generally believed, is that in the United States, those in managerial jobs accumulate experience in specialized skills through changing jobs and there is strong demand for managers that can play an active strategic role in their organization.[16] In contrast, in Japan, the role of managers is to mediate and transmit internal information based on experience in a wide range of postings within a firm, and it has been conjectured that it is for this reason that the increased use of IT has resulted in a reduction of such jobs.[17] Examining this issue empirically represents an interesting topic for future research.

Finally, a comment on the result for nonroutine manual tasks. Autor, Katz and Kearny (2006) suggest that computers have little adverse effect on the quantity of nonroutine manual task input.[18] In the empirical analysis here, however, the coefficient on IT capital stock in the estimation for nonroutine manual tasks was significantly negative. This is likely to be a spurious result, a possible explanation for which is that against the backdrop of an increase in nonroutine manual work for reasons other than IT, it was impossible or uneconomical to replace tasks with IT in industries where nonroutine manual work increased and the adoption of IT in these industries hence was

[16] See, e.g., Sato (2002), Morishima (2002) and Kato (2002), who compare management practices in Japan, the United States and Germany based on a survey among large firms in the countries conducted by the Japan Institute of Labour.

[17] Of course, in the United States, too, there has been a reduction in middle-management employment due to re-engineering linked to the use of information equipment, which has led to a restructuring of what is done within firms and what is outsourced, and of different positions within firms (see, e.g., Takayama, 2001).

[18] Similarly, Goos and Manning (2007) observe that Baumol’s (1967) argument that technological progress brings about a shift in employment to occupations with low productivity growth in which it is difficult to use technology continues to be applicable today, and that technological progress brings about an increase in low-wage, low-skill jobs (“lousy jobs”, mainly in the service sector).

comparatively slow.

4. Conclusion

The purpose of this study was to investigate whether there are signs of a polarization in the Japanese labor market, to identify factors determining these labor market trends by focusing on both supply and demand aspects, and to analyze the relationship between the related trends and the introduction of IT. The analysis, following the theoretical framework of Autor, Levy and Murnane (2003), focused on five task categories, consisting of nonroutine analytic, nonroutine interactive, routine cognitive, routine manual, and nonroutine manual tasks.

This study finds little evidence of a polarization in wages across different earnings groups or by educational attainment in the period from 1980 to 2007 as a whole. That being said, however, since 2000, a stagnation or even decline in the real wages of the bottom decile of wage earners and of workers who only completed junior high or high school can be observed. Especially male junior high school graduates have seen a clear decrease in wages. What is more, the number of men falling into the lowest wage groups has increased as much, or even more than, that of women.

Next, in order to determine whether there has been a polarization in tasks in Japan – that is, an increase in employment in high-skill and low-skill tasks and a decrease in employment in medium-skill tasks – employment trends in different job categories were examined. It was found that, indeed, employment in both knowledge-intensive jobs (such as researchers and engineers) and jobs that are labor intensive and do not require a high level of skill (such as nursing and home helping services and cleaning and garbage collection) registered large increases, while employment in jobs where demand declined as a result of economic and structural changes such as international competition and the introduction of new technology (e.g., clothing, textiles, and light industries, mining operations, telephone operators, stenographers, and typists.) registered a large decrease. Looking at the past 10 years, for which job and income data are available, it is clear that jobs that have seen the highest rates of increase in employment are not necessarily ones that pay particularly high wages.

Further, following ALM's framework, jobs were divided into the five task categories of nonroutine analytic, nonroutine interactive, routine cognitive, routine manual, and nonroutine manual tasks. It was found that during the period 1980–2005, there was a large increase in employment in nonroutine analytic tasks. Moreover, employment in nonroutine manuals tasks also increased, while that in routine manual tasks decreased.

Looking at the relationship between changes in employment the five tasks and changes in supply-side factors (worker characteristics) and demand-side factors (industry demand for tasks), it was found that the secular rise in education levels and changes in preferences, as well as changes in industrial structure (such as the shift to services) and the move to higher value-added tasks that is common to all industries, contributed to an increase in employment in high-skill white collar nonroutine tasks in all industries and to a decrease in employment in blue collar routine manual tasks.

Next, concerning the relationship between changes in employment in the five tasks and the use of IT, the estimation results suggest that the more routine-task intensive an industry was, the more active was the introduction of IT capital in that industry. Furthermore, they indicate that nonroutine analytic tasks are complementary to IT capital, while routine manual and routine cognitive tasks are being substituted by it. Overall, the results can be interpreted as implying that the more routine task-intensive an industry, the more active it tends to have been in introducing IT; moreover, by substituting for routine tasks and complementing nonroutine analytic tasks, the increase in IT capital stock has given rise to a labor shift from routine task intensive-industries to nonroutine task-intensive industries (the "between industries shift") as well as an increase in employment in nonroutine analytic tasks observed across all industries that introduced IT capital (the "within industries shift").

Overall, it appears that in Japan, too, a polarization in labor markets can be observed, with a simultaneous trend toward high-wage high-skill (knowledge-intensive) jobs on the one hand and low-wage low-skill (manual) jobs on the other. A backdrop to the increase in employment in nonroutine manual tasks is the large increase in services tasks, a prime example of which is the rapid rise in home help and nursing services. These occupations are mostly low-paid and make up the lower stratum of such a polarized labor market. Whether further strong demand for such tasks will eventually raise wages depends on the relative impact of the supply of and demand for low-skill jobs. At a time that inequality and poverty are issues of growing social concern in Japan, more research is necessary to gain a better understanding of the demand and supply factors underlying the increase in low-skill jobs and wage trends.

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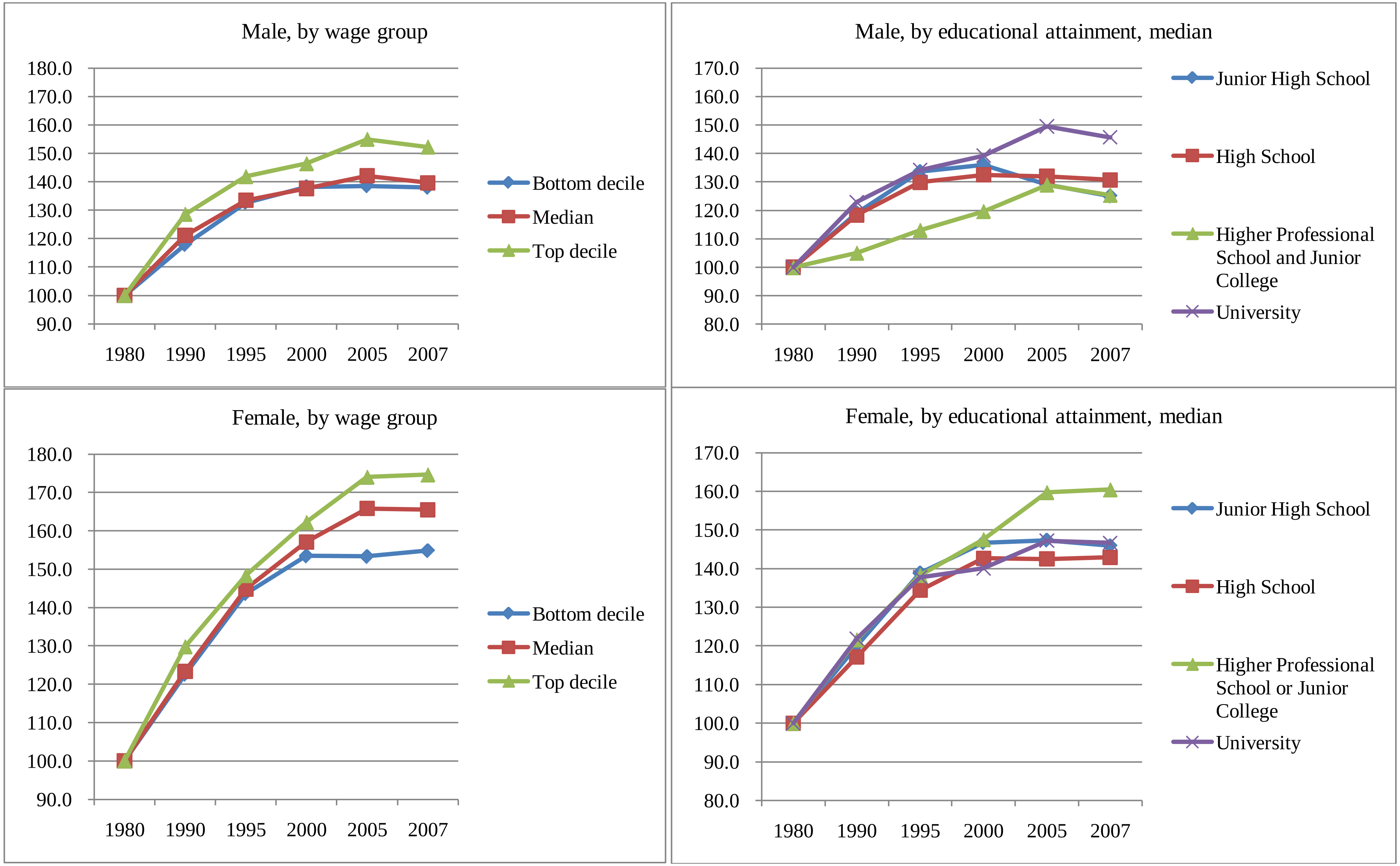
Table 1. Relative Monthly Scheduled Cash Earnings by Category

		1980	1990	1995	2000	2005	2007
Total for both sexes, all age and educational groups	10/50	0.586	0.592	0.615	0.619	0.597	0.606
	90/50	1.756	1.872	1.849	1.829	1.862	1.853
Male, all age and educational groups	10/50	0.626	0.609	0.622	0.628	0.610	0.618
	90/50	1.627	1.727	1.729	1.730	1.774	1.774
Female, all age and educational groups	10/50	0.712	0.707	0.706	0.695	0.658	0.666
	90/50	1.549	1.629	1.587	1.599	1.626	1.635
Male, high school graduates, 40-44 years old	10/50	0.694	0.682	0.680	0.664	0.658	0.662
	90/50	1.451	1.411	1.412	1.400	1.420	1.446
Male, university graduates, 40-44 years old	10/50	0.705	0.700	0.707	0.689	0.673	0.663
	90/50	1.365	1.429	1.484	1.462	1.484	1.548
Male university/ high school	Median	1.202	1.248	1.242	1.264	1.362	1.339
Female university/ high school	Median	1.308	1.361	1.341	1.284	1.352	1.342
Male university/ high school, 40-44 years old	Median	1.465	1.381	1.304	1.338	1.431	1.477

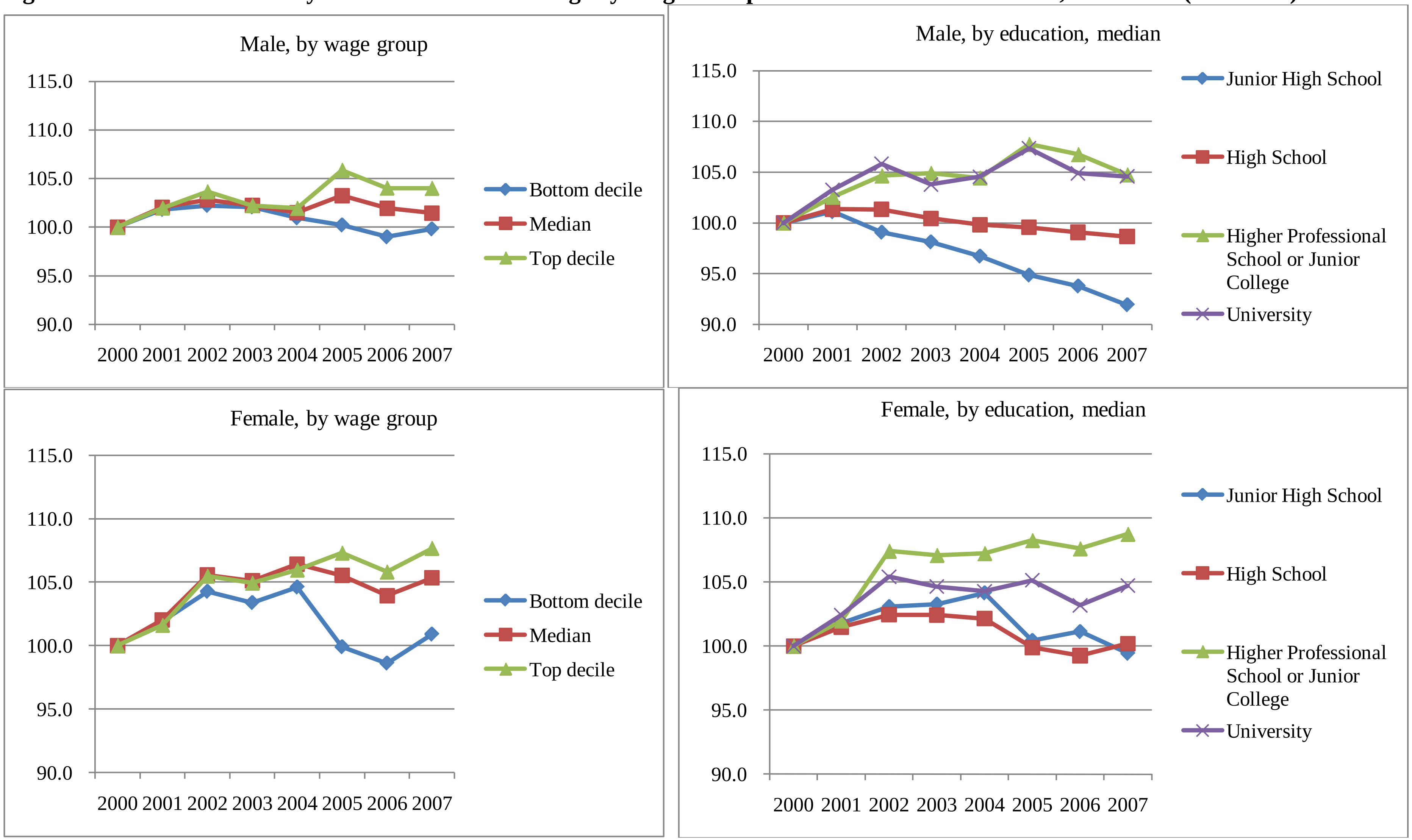
Source: Author's calculations based on the *Basic Survey on Wage Structure* (various issues).
Note: 10/50 and 90/50 refer to the earnings of the bottom decile and the top decile relative to the median.

Figure 1. Index of Real Hourly Scheduled Cash Earnings by Wage Group and Educational Attainment (1980=100)



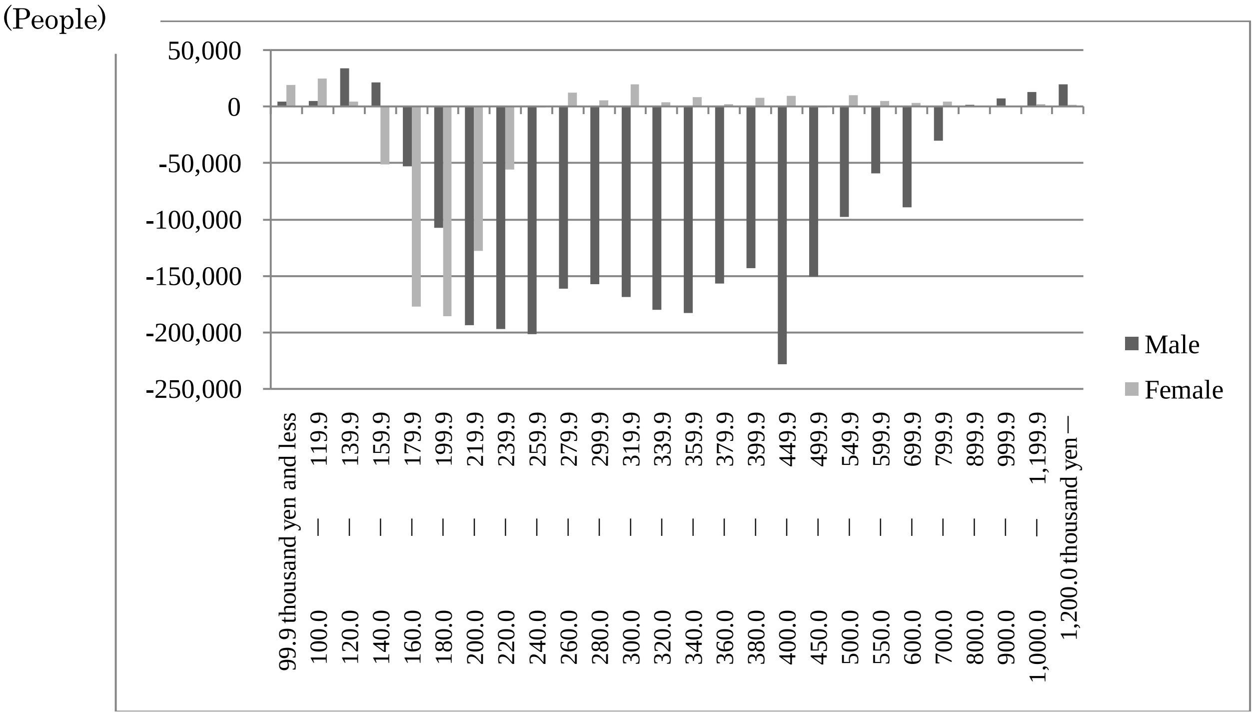
Source: See Table 1.

Figure 2. Index of Real Hourly Scheduled Cash Earnings by Wage Group and Educational Attainment, 2000-2007 (2000=100)



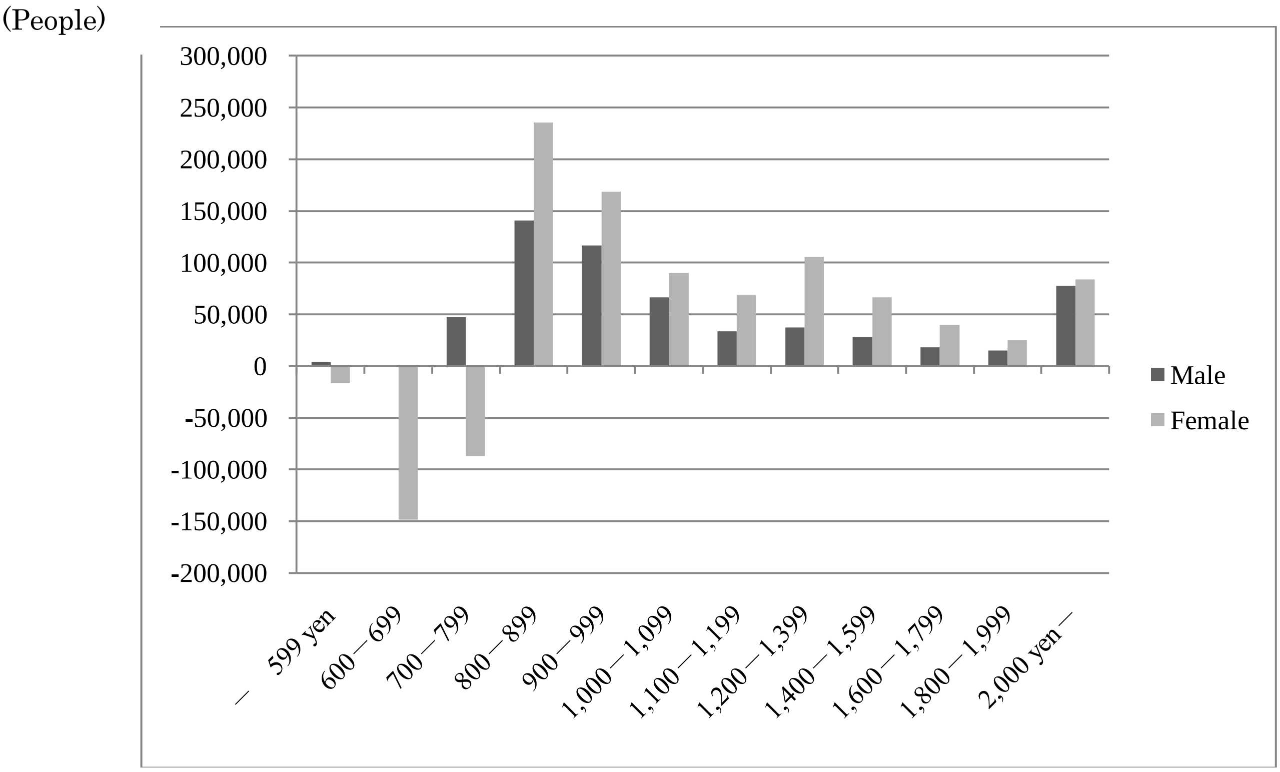
Source: See Table 1.

Figure 3. Changes in the Number of Ordinary Workers by Monthly Scheduled Cash Earnings Group (2002-2007)



Source: See Table 1.

Figure 4. Changes in the Number of Part-time Workers by Hourly Scheduled Cash Earnings Group (2002-2007)



Source: See Table 1.

Table 2. Top Ten and Bottom Ten Occupations by Labor Input Growth Between 1995 and 2007 (Ordinary Workers)

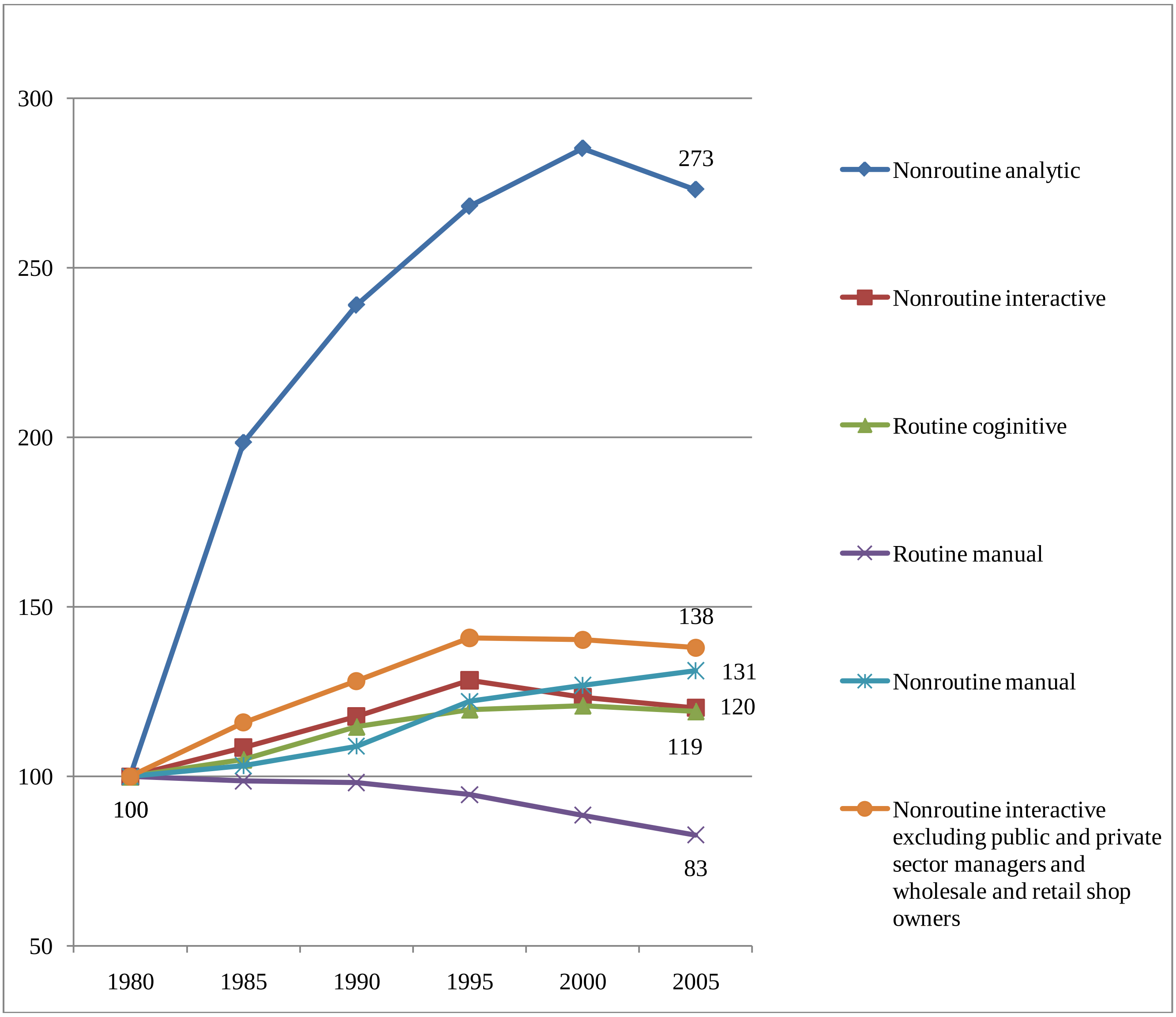
Top10			(for Reference)	Bottom10			(for Reference)
	Growth in labor input (%, annual change in employment)	Growth in labor input share (percentage points)	Hourly Scheduled Cash Earnings in 2007 (yen)		Growth in labor inputs (%, annual change in employment)	Growth in labor input share (percentage points)	Hourly Scheduled Cash Earnings in 2007 (yen)
Total occupations	−1.7		1814	Total occupations	−1.7		1814
1. Care managers*1)	16.1	0.1	1535	1. Miners (digger)*2)	−34.3	-0.3	2263
2. Home helpers*1)	16.1	0.1	1198	2. Radio, television assemblers*2)	−20.6	0.0	1212
3. Physical therapists & Occupational therapists*1)	12.2	0.1	1615	3. Miners (pitmen)*2)	−17.4	0.0	1822
4. Natural science researchers	11.1	0.2	2530	4. Carpenters	−12.9	-1.0	1599
5. Welfare facility workers*1)	11.0	0.8	1209	5. Internal line operators	−12.8	-0.6	1218
6. Automobile assemblers	10.0	0.3	1572	6. Sewing machine workers	−11.4	-0.1	828
7. Univ. associate professors	7.9	0.1	3280	7. Earth workers	−11.1	-0.3	1429
8. Univ. professors	6.7	0.1	4157	8. Metal fusing workers*3)	−10.9	0.0	1755
9. Pilots	4.1	0.0	5978	9. Weavers	−10.8	-0.1	1236
10. Electroplating workers	3.5	0.1	1568	10. Pipe fitters	−10.6	0.0	1514

Note: 1) Change between 2001 and 2007.
2) Change between 1995 and 2004. The amount of hourly scheduled cash earnings is that in 2004. (The average for all occupations in 2004 is 1,817 yen.)
3) Change between 1995 and 2000.
4) The amount of hourly scheduled cash earnings is that in 2000. (The average for all occupations in 2000 is 1,810 yen).
5) Gray areas indicate occupations for which wages are below the average for all occupations.
6) Labor input is monthly labor input= working hours ×number of workers.
Source: See Table 1.

Table 3. Definition of Five Task Types

Category	Definition	Keywords	Example tasks
Nonroutine analytic tasks	Problem solving with high-level expertise and abstract thinking, including researching, analyzing, planning, designing	Mathematics, science, logical thinking and analyzing	Research, investigation, design
Nonroutine interactive tasks	Creating value with high-level personal communication, including negotiating, coordinating, teaching, training, selling, advertising, presenting, directing or managing, leading or instructing or consulting	Coordination with others, social perceptiveness, active listening, speaking, **persuasion**, **negotiation**	Legal, control and management, consulting, education, art, sales and marketing
Routine cognitive tasks	Clerical work requiring precise attainment of predetermined standards, including calculating, measuring, monitoring, data-processing, dealing with customers	Operation and control, operation monitoring	Clerical work, desk work, accounting, monitoring and inspection
Routine manual tasks	Physical work requiring rapid and accurate attainment of predetermined standards, including regular and repetitive production work by hand or by operating and controlling machinery	Operation and control, operation monitoring , troubleshooting	Agriculture, forestry and fisheries, manufacturing
Nonroutine manual tasks	Physical work not requiring a high-level of expertise but a flexible response depending on circumstances	Coordination with others, social perceptiveness, active listening, speaking, **service orientation**	Service, entertainment, beauty services, security, driving transportation machinery, repairing or renovating

Figure 5. Trends in Tasks Measured in Labor Input (Number of Workers in 1980=100)



Source: *Population Census*.

Table 4. Decomposition of Employment Changes by Task: Demand Factors (1980-2000)

	Nonroutine analytic	Nonroutine interactive	Routine cognitive	Routine manual	Nonroutine manual
Total	185	23	21	-11	27
Educational changes	83	31	32	-9	0
Task selection propensity changes	102	-7	-11	-2	27

Note: Figures represent the change in the employment index, with1980 as 100.

Table 5. Decomposition of Employment Changes by Task: Supply Factors (1980-2000)

Changes (%)		1980-2005	1980-1990	1990-2000	2000-2005
Nonroutine analytic	Total	2.13	1.67	0.52	-0.07
	Between industry	0.72	0.48	0.23	0.05
	Within industry	1.41	1.20	0.29	-0.12
Nonroutine interactive	Total	2.40	1.71	0.74	-0.05
	Between industry	4.22	1.75	1.69	0.62
	Within industry	-1.86	-0.05	-0.96	-0.69
Routine cognitive	Total	1.80	0.82	0.73	0.24
	Between industry	1.13	0.83	0.54	-0.17
	Within industry	0.62	-0.01	0.17	0.39
Routine manual	Total	-9.78	-4.39	-4.09	-1.30
	Between industry	-9.32	-3.83	-4.00	-1.56
	Within industry	-0.47	-0.56	-0.09	0.25
Nonroutine manual	Total	1.99	-0.16	1.44	0.70
	Between industry	1.71	0.42	0.86	0.55
	Within industry	0.28	-0.58	0.58	0.15

Note: See Table 4.

Table 6. Employment Changes and Computerization (Weighted Least Squares)
[Dependent variable: Annual change in the number of workers]

(a)1980-2005

	△Nonroutine analytic		△Nonroutine interactive		△Routine cognitive		△Routine manual		(for Reference) △Nonroutine manual	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
$\Delta Ln(K_{it}/L)$	0.383*** (0.061)		-0.039 (0.025)		-0.065** (0.031)		-0.112*** (0.034)		-0.190*** (0.043)	
$\Delta Ln(K_{nonit}/L)$	-0.760*** (0.099)	-0.720*** (0.102)	-0.230*** (0.045)	-0.373*** (0.041)	-0.193*** (0.049)	-0.266*** (0.050)	-0.587*** (0.067)	-0.697*** (0.057)	-0.775*** (0.075)	-1.068*** (0.074)
1990-2000dummy	-0.032*** (0.009)	-0.082*** (0.006)	-0.017*** (0.003)	-0.020*** (0.003)	-0.015*** (0.004)	-0.011*** (0.003)	-0.027*** (0.005)	-0.018*** (0.004)	-0.022*** (0.006)	-0.026*** (0.006)
2000-2005dummy	-0.056*** (0.009)	-0.115*** (0.007)	-0.030*** (0.003)	-0.035*** (0.003)	-0.026*** (0.004)	-0.022*** (0.003)	-0.045*** (0.006)	-0.032*** (0.004)	-0.050*** (0.007)	-0.054*** (0.007)
Constant	0.055*** (0.010)	-0.052* (0.031)	0.0274*** (0.003)	-0.045*** (0.013)	0.027*** (0.004)	0.003 (0.014)	0.045*** (0.006)	0.007 (0.012)	0.054*** (0.005)	-0.091*** (0.027)
Adj. R^2	0.603	0.582	0.313	0.387	0.212	0.202	0.440	0.424	0.457	0.471
No. of Obs.	231	231	234	234	234	234	234	234	234	234

Note: 1) Standard errors are in parentheses. *, **, *** mean that the coefficients are significant at the 10%, 5%, and 1% level, respectively.
2) K_{it} : Real IT capital stock (1995 prices), K_{nonit} : Real non-IT capital stock (1995 prices), L : Number of workers.
3) Figures for K_{it}, K_{nonit} are for 2004.

(b) 1980-2000

	△Nonroutine analytic			
	(1)	(2)	(3)	(4)
$\Delta Ln(K_{it} / L)$	0.178*** (0.068)	0.252*** (0.073)		
$\Delta Ln(K_{nonit} / L)$	-1.177*** (0.126)			
$\Delta Ln(K / L)$		-1.063*** (0.143)		
$\Delta Ln(K_{it} / MH)$			0.158** (0.070)	0.222*** (0.075)
$\Delta Ln(K_{nonit} / MH)$			-1.068*** (0.115)	
$\Delta Ln(K / MH)$				-1.009*** (0.131)
1990-2000dummy	-0.055*** (0.009)	-0.054*** (0.010)	-0.056*** (0.009)	-0.057*** (0.010)
Constant	0.101*** (0.012)	0.095*** (0.013)	0.104*** (0.013)	0.101*** (0.014)
Adj. R^2	0.641	0.586	0.635	0.589
No. of Obs.	153	153	153	153

	△Nonroutine interactive			
	(1)	(2)	(3)	(4)
$\Delta Ln(K_{it} / L)$	-0.035 (0.027)	-0.043 (0.027)		
$\Delta Ln(K_{nonit} / L)$	0.037 (0.060)			
$\Delta Ln(K / L)$		0.079 (0.060)		
$\Delta Ln(K_{it} / MH)$			-0.037 (0.026)	-0.447 (0.027)
$\Delta Ln(K_{nonit} / MH)$			0.009 (0.062)	
$\Delta Ln(K / MH)$				0.056 (0.063)
1990-2000dummy	-0.014*** (0.003)	-0.013*** (0.003)	-0.139*** (0.003)	-0.014*** (0.003)
Constant	0.019*** (0.004)	0.018*** (0.004)	0.020*** (0.037)	0.019*** (0.004)
Adj. R^2	0.110	0.117	0.111	0.115
No. of Obs.	156	156	156	156

	△Routine cognitive			
	(1)	(2)	(3)	(4)
$\Delta Ln(K_{it}/L)$	-0.069* (0.038)	-0.074* (0.039)		
$\Delta Ln(K_{nonit}/L)$	-0.053 (0.067)			
$\Delta Ln(K/L)$		-0.019 (0.070)		
$\Delta Ln(K_{it}/MH)$			-0.066* (0.038)	-0.071* (0.039)
$\Delta Ln(K_{nonit}/MH)$			-0.042 (0.070)	
$\Delta Ln(K/MH)$				-0.004 (0.073)
1990-2000dummy	-0.014*** (0.004)	-0.015*** (0.004)	-0.014*** (0.004)	-0.014*** (0.004)
Constant	0.024*** (0.005)	0.024*** (0.005)	0.024*** (0.005)	0.023*** (0.006)
Adj. R^2	0.061	0.057	0.054	0.052
No. of Obs.	156	156	156	156

	△Routine manual			
	(1)	(2)	(3)	(4)
$\Delta Ln(K_{it}/L)$	-0.139*** (0.039)	-0.155*** (0.040)		
$\Delta Ln(K_{nonit}/L)$	-0.418*** (0.093)			
$\Delta Ln(K/L)$		-0.356*** (0.096)		
$\Delta Ln(K_{it}/MH)$			-0.127*** (0.041)	-0.144*** (0.042)
$\Delta Ln(K_{nonit}/MH)$			-0.411*** (0.100)	
$\Delta Ln(K/MH)$				-0.345*** (0.104)
1990-2000dummy	-0.028*** (0.005)	-0.297*** (0.005)	-0.024*** (0.005)	-0.026*** (0.005)
Constant	0.042*** (0.006)	0.044*** (0.006)	0.041*** (0.007)	0.042*** (0.007)
Adj. R^2	0.343	0.317	0.309	0.285
No. of Obs.	156	156	156	156

(for Reference)

	△Nonroutine manual			
	(1)	(2)	(3)	(4)
$\Delta Ln(K_{it} / L)$	-0.160*** (0.043)	-0.163*** (0.043)		
$\Delta Ln(K_{nonit} / L)$	0.037 (0.093)			
$\Delta Ln(K / L)$		0.059 (0.094)		
$\Delta Ln(K_{it} / MH)$			-0.150*** (0.042)	-0.155*** (0.043)
$\Delta Ln(K_{nonit} / MH)$			0.108 (0.095)	
$\Delta Ln(K / MH)$				0.130 (0.096)
1990-2000dummy	0.001 (0.005)	0.002 (0.005)	0.004 (0.005)	0.004 (0.005)
Constant	0.020*** (0.005)	0.020*** (0.005)	0.017*** (0.006)	0.016*** (0.006)
Adj. R^2	0.083	0.085	0.074	0.077
No. of Obs.	156	156	156	156

Note: 1) Standard errors are in parentheses. *, **, *** mean that the coefficients are significant at the 10%, 5%, and 1% level, respectively.

2) K_{it} : Real IT capital stock (in 1995 prices), K_{nonit} : Real non-IT capital stock (in 1995 prices), L : Number of workers, MH : Man hours (1000 × annual total hours worked).

3) Figures for K_{it} and K_{nonit} are for 2004.

(c) Public and private sector managers

1980-2005		
	(1)	(2)
$\Delta Ln(K_{it}/L)$	-0.591** (0.029)	
$\Delta Ln(K_{nonit}/L)$	-0.331*** (0.055)	-0.370*** (0.055)
1990-2000dummy	-0.032*** (0.004)	-0.028*** (0.003)
2000-2005dummy	-0.008* (0.005)	-0.002 (0.004)
Constant	0.013*** (0.004)	0.005 (0.015)
Adj. R^2	0.396	0.386
No. of Obs.	234	234

1980-2000				
	(1)	(2)	(3)	(4)
$\Delta Ln(K_{it}/L)$	-0.080** (0.034)	-0.077** (0.034)		
$\Delta Ln(K_{nonit}/L)$	-0.175** (0.073)			
$\Delta Ln(K/L)$		-0.157** (0.075)		
$\Delta Ln(K_{it}/MH)$			-0.072** (0.034)	-0.071** (0.035)
$\Delta Ln(K_{nonit}/MH)$			-0.126 (0.078)	
$\Delta Ln(K/MH)$				-0.106 (0.080)
1990-2000dummy	-0.034*** (0.004)	-0.034*** (0.004)	-0.032*** (0.004)	-0.033*** (0.004)
Constant	0.012** (0.005)	0.012** (0.005)	0.010* (0.005)	0.009* (0.006)
Adj. R^2	0.360	0.354	0.336	0.333
No. of Obs.	156	156	156	156

APPENDIXES

A.1 Classification of job categories into tasks

The purpose here is to explain in greater detail how the detailed job categories in the *Population Census* were classified into the five types of tasks distinguished in the ALM framework. The first thing to note is that, as mentioned above, each job to some extent contains elements of each of the five task types and the relative weight of these tasks within a particular job may change over time. However, because it was impossible to devise a consistent methodology to incorporate intertemporal changes in the weight of tasks within jobs, job categories were classified into one of the five principle tasks at the beginning of the observation period and then remain within that task type throughout.

Definitions of the five task groups and examples of individual tasks therein are provided by ALM and Spitz-Oener and the classification of job categories here follows these definitions. The classification of job categories relies on the Career Matrix published by the Japan Institute for Labour Policy and Training. For each of the 503 job categories, this provides a list of 35 skills (such as logic and analysis, negotiation, operation and control, gauge monitoring, and service mindedness) and their importance for the execution of that particular job on a five-step scale. For the analysis here, those among the 35 skills were chosen that seemed to most clearly represent the five task types based on the definition of the task types and task examples. (In Table 3, keywords that are particularly representative of a particular task type are underlined.)

The Career Matrix also contains a table that classifying these 503 job categories into the Classification of Occupations for Employment Services (ESCO) compiled by the Ministry of Labour (the predecessor of the Ministry of Health, Labour and Welfare). Using this and comparing it with the Japan Standard Occupational Classification and the *Population Census*, the 503 job categories are then, where possible, matched with the 244 detailed job categories of the *Population Census*, and, based on the skills that are assumed to be important for each job, these jobs are then classified into the five task types. Jobs in the *Population Census* that are not included in the Career Matrix and for which therefore no skill score is available, are classified based on other information associated with the job descriptions and key concepts presented by ALM and Spitz-Oener.

In principle, the 244 job categories in the *Population Census* were each assigned to one task type only. However, for the following job categories, the number of workers were partitioned out to different task types:

- Jobs in technical areas involve activities such as planning and design and accordingly were classified as nonroutine analytic tasks. However, because for many architect-engineers and civil engineers, a large part of their job consists of instruction (supervision, tutoring), their numbers were allocated 50-50 to nonroutine analytic and nonroutine interactive tasks.

- The job category of general office workers includes a wide variety of workers, such as general office staff, planning staff, receptionists, secretaries, other general duty employees, staff at production facilities, freight-handling personnel, sales and marketing personnel, and other management, sales and marketing employees. Based on the definitions shown in Table 3, sales and marketing personnel are classified as falling into the nonroutine interactive tasks category, while all other general office workers fall under routine cognitive tasks. However, because a breakdown for general office workers in the *Population Census* was not available, data from the *Employment Security Service Statistics* were used. The *Employment Security Service Statistics* provide data on the number of workers (regular workers, including part-timers) working as general office staff, production-related office staff, and management and sales-related staff. Using these data, the share of management and sales-related staff is calculated (it is about 10 percent) and used to partition out the number of general office workers.

Finally, while Autor and Dorn (2007) take the category of cleaning and garbage collection as an example of a nonroutine manual task, this is classified as a routine manual task here since it consists of activities that use machinery and tools at a specific place and do not really require a flexible response.

A.2 Industry-level production function and factor demand

Following ALM, the production function for industry *j* is given by:

$$q_j = r_j^{1-\beta_j} n_j^{\beta_j}, \beta_j \in (0,1)$$

where q_j is the output of industry *j*, r_j is the input of routine tasks in industry *j*, and n_j is the input of nonroutine tasks in industry *j*.

Consumers' utility function is given by:

$$U(q_1, q_{2.} ...., q_j) = (\sum_j q_j^{1-\upsilon})^{1/(1-\upsilon)} \qquad 0 < \upsilon < 1$$

The elasticity of demand for each good is $-(1/\upsilon)$ and market-clearing prices are inversely related to output, i.e.,

$$p_j(q_j) \propto q_j^{-\upsilon}$$

The first-order condition for profit maximization yields

$$\rho = n_j^{\beta_j} r_j^{-\beta_j} (1-\beta_j)(1-\upsilon)(n_j^{\beta_j} r_j^{1-\beta_j})^{-\upsilon}$$

$$w_N = n_j^{\beta_j - 1} r_j^{1-\beta_j} \beta_j (1-\upsilon)(n_j^{\beta_j} r_j^{1-\beta_j})^{-\upsilon}$$

From this, factor demand is then derived as follows:

$$n_j = w_N^{-1/\upsilon} (\beta_j (1-\upsilon))^{1/\upsilon} \left(\frac{w_N}{\rho} . \frac{(1-\beta_j)}{\beta_j} \right)^{((1-\beta_j)(1-\upsilon))/\upsilon}$$

$$r_j = \rho^{-1/\upsilon}((1-\beta_j)(1-\upsilon))^{1/\upsilon}\left(\frac{w_N}{\rho}.\frac{(1-\beta_j)}{\beta_j}\right)^{(\beta_j(\upsilon-1))/\upsilon}$$

As stated in the main text, the expansion in demand for routine tasks brought about by the decrease in the price of computer capital will be met by an increase in computer capital. However, the extent of the increase in computer capital will be greater, the higher the routine task intensity (prior to the introduction of computer capital). This leads to Hypothesis 1, namely that all industries face the same decrease in the price of computer capital and introduce computer capital, but the extent to which they do so is greater the higher the degree of routine task intensity (the smaller β_j):

$$\frac{\delta \ln r_j}{\delta\rho} = \frac{\beta_j(1-\upsilon)-1}{\upsilon\rho} < 0 \qquad \frac{\delta^2 \ln r_j}{\delta\rho\delta\beta_j} = \frac{1-\upsilon}{\upsilon\rho} > 0$$

Further, through the complementarity of computer capital and nonroutine tasks, a decrease in the price of computer capital will increase the demand for nonroutine task input (as well as for routine task input), and this will be greater the higher the routine task intensity:

$$\frac{\delta \ln n_j}{\delta\rho} = \frac{(\beta_j-1)(1-\upsilon)}{\upsilon\rho} < 0 \qquad \frac{\delta^2 \ln n_j}{\delta\rho\delta\beta_j} = \frac{1-\upsilon}{\upsilon\rho} > 0$$

This shows that the demand for labor input in nonroutine tasks will increase and the demand for labor input in routine tasks will decrease in sectors with more computer capital input. This leads to Hypothesis 2: Through the complementarity of computer capital and nonroutine task input, a decrease in the price of computer capital increases the demand for nonroutine task input (along with the demand for routine task input). However, because increased demand for routine tasks is met by an increase in computer capital, labor input in nonroutine tasks increases and that in routine tasks decreases in those sectors that have invested more in computer capital.