A cross-industrial analysis on task content of trade

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Abstract

This paper estimates the task content of trade for Japanese manufacturing in terms of the number of employees using Japanese Input-Output Tables. The purpose of this paper is to examine the differences in task content of trade by flow, by task category, and by sector, and to reveal their determinants through descriptive and empirical analyses. For the estimation, the composite task index is calculated for five task categories. From the descriptive analysis, it is found that routine manual tasks are relatively large in the task content of imports of light industries. Another finding is that only machinery sectors have a trade surplus in terms of task content of trade, whereas the trade deficit of routine manual tasks tends to be large in light industries. In addition, empirical results reveal that the occupational structure and industrial characteristics explain the difference in task content of trade by sector.

Keywords: Trade; Task content of trade; Occupation; Task; Industrial characteristics
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1 Introduction

In recent years, the trade of 'task' has been a subject of controversy, in addition to the conventional approach of 'skill' and 'occupation'. Autor (2013) explains the difference between tasks and skills: "A task is a unit of work activity that produces output. A skill is a worker's *stock* of capabilities for performing various tasks." In other words, the nature of tasks lies in the work activities, while the nature of skills lies in the workers. Further, he adds that occupations can readily be conceptualized as bundles of tasks that workers are required to perform. In the empirical analyses, the skills have been widely used to measure the quality of labour.[1] Generally, an educational achievement such as an obtained college degree or the length of education is used as a proxy of skill levels. It is assumed that an education develops skills, because a skill is a worker's stock of capabilities, as Autor (2013) denotes. In contrast, the characteristics of tasks are based on the work activity.

This paper aims to estimate the "task content of trade" in terms of the number of employees required for the production of trade. In the previous studies, the factor content of trade has been estimated to "measure the amounts of labor and capital used to produce exports and imports" (Feenstra and Taylor, 2008, p.121), based on the Hecksher-Ohlin model. Estimation of task content of trade is an attempt to divide the amount of labour used for trade at the task level. Understanding the task content of trade rather than the factor content of trade is important in light of the global value chains (GVCs). Fragmentations in GVCs enable manufacturing companies to separate offshorable tasks and exchange intermediate goods in different tasks.

Autor, Levy, and Murnane (2003) is a pioneering study for investigating tasks quantitatively. They set task categories with a two-by-two matrix: one axis is routine versus nonroutine tasks, and the other axis is manual versus cognitive tasks. Routine tasks involve repetitive activities "following explicit rules", which can be substituted by machines. Nonroutine tasks, on the other hand, involve activities that require interaction with people or flexible judgment. Manual tasks involve physical work activities, whereas cognitive tasks involve the process of information and "problem-solving and complex communication activities". Autor et al. (2003) further divided nonroutine cognitive tasks into nonroutine analytical tasks and nonroutine interactive tasks. Eventually, they set

[1]For instance, the effect of trade on labour demand depends on the skill level of workers. This relation was examined by Hijzen, Görg, and Hine (2005) for the case of the UK, Kiyota and Maruyama (2017) for Japan, and Foster-McGregor, Stehrer, and de Vries (2013) as cross-country comparison.

five task categories including nonroutine analytical tasks, nonroutine interactive tasks, routine cognitive tasks, routine manual tasks, and nonroutine manual tasks.

Table 1 summarises the description of five task categories by Ikenaga and Kambayashi (2016) which followed Autor et al. (2003). Roughly speaking, tasks categorised as nonroutine analytical tasks are, for example, related to research and design activities. Nonroutine interactive tasks include tasks related to activities such as management and professional engineering. Routine cognitive tasks are related to clerical tasks. Routine manual tasks involve manufacturing process tasks. Nonroutine manual tasks are related to service activities. Meanwhile, actual occupations are assumed to bundle tasks from different task categories.

=== Table 1 ===

Some researchers attempt to explain the trade flows using the concept of tasks. Theoretically, Grossman and Rossi-Hansberg (2008) introduced offshoring and trade of tasks in the model of international division of labour. They focused on the differing effects of labour type. Becker, Ekholm, and Muendler (2013) and Baugmarten, Geishecker and Görg (2013) empirically tested the effect of offshoring and trade of tasks on the wage.

The most related analysis to this paper is Tomiura, Wakasugi and Zhu (2014). They estimated how tasks were traded quantitatively for the case of Japanese trade from 1995 to 2005 using Input-Output (IO) tables.[2] They expressed the task content of trade in terms of the number of workers with the original seven task categories. Composite task scores were calculated using scales from the US Occupational Information Network (O*NET). They revealed that Japan's net exports of technical tasks substantially declined between 1995 and 2005. In addition, they showed that electric appliances and computers were the major products driving the change in task trade.

Following the method of Tomiura et al. (2014), this paper estimates the task content of trade for Japanese manufacturing in terms of the number of employees using 2015 Input-Output Tables for Japan (hereafter 2015IO).[3] How is Japanese task content of trade

[2] As a preceding study, Wolff (2003) estimates skill content of US trade during the 1950 to 1990 period. Three composite measures of skill are calculated using information from the Dictionary of Occupational Titles (DOT). Using the information of workers by sector and the Leontief inverse matrix of IO tables, direct and indirect effects for employment are estimated.

[3] In this analysis, manufacturing sectors are focused on. Task content of trade for service sectors can also be estimated. There is, however, no export or import for some service sectors, and it makes it difficult to compare with manufacturing sectors. Manufacturing sectors include sectors of industrial code 111-391 for 2015 IO.

composed by task category? Is there any difference in task composition by industry?[4] Is there any difference by trade flow: between exports and imports, or between imports of final demand and imports of intermediate input? Among these questions, we particularly focus on the differences by industry. The differing importance and offshorability of tasks by industry would appear as a difference in the task content of trade. Therefore, the purpose of this paper is to examine the cross-industrial differences in the task content of trade and to reveal their determinants through descriptive and empirical analyses. From the analysis, we can understand which industries are affected, replaced, or supported by trade.

This paper employs five task categories proposed by Autor et al. (2003). There are several types or categories for measuring tasks, however, the use of different task categories makes it difficult to compare the results.[5] The reason for choosing the five task categories by Autor et al. (2003) is that there are several subsequent studies. Acemoglu and Autor (2011) describe how to calculate the composite task index for five categories. In addition, Komatsu and Mugiyama (2022) show an application of the method by Acemoglu and Autor (2011) for the Japanese labour market. These studies enable us to replicate task indices in this analysis.

This paper extends the analysis of Tomiura et al. (2014) in the following three points. First, job information from *Jobtag*, a Japanese version of O*NET, is used instead of the US O*NET. Second, the precise distinction between 'task' and 'skill' is introduced. Tomiura et al. (2014) constructed composite task indices using scales in the domain 'skills' from the O*NET. In contrast, Acemoglu and Autor (2011) and Komatsu and Mugiyama (2022) use the scales included in the domains 'Work contexts' and 'Work activities' in the O*NET which fit in the concept of task. Third, imports are separated into imports of final demand and imports of intermediate input. Tomiura et al. (2014) provided information on the task content of total imports, which is reported in the final demand sector as a deduction item in the basic table of IO tables. Using the import table of IO, imports of intermediate input and imports of final demand can be separated.

The contribution of this paper is summarized as follows. First, introducing information on Jobtag, task content of trade which reflects task evaluation in Japan is estimated.

[4]In this paper, both terms of 'sector' and 'industry' are used. The term 'sector' is used when we indicate sectors at a medium level of classification in 2015IO. The term 'industry' is used when we include broader and more aggregated levels of classification.

[5]For instance, Tomiura et al. (2014) use the original seven task categories. In addition, Wolff (2003) calculates three indices of substantive complexity, interactive skills, and motor skills. Yamaguchi (2018) uses two categories of motor and cognitive tasks for the analysis of Japanese employment.

It provides a more accurate picture of the Japanese labour structure. Second, task content of the imports of intermediate input is estimated.[6] Because value chains of Japanese companies are constructed globally, the imports of intermediate goods, which can be complemental to the production in Japan, are becoming more important.[7]

The rest of the paper is organized as follows. In section 2, the calculation of composite task indices and the estimation method of task content of trade are explained. Section 3 presents the results of descriptive analysis. Section 4 presents the estimation results of regression analysis. A summary of findings and concluding remarks are described in section 5.

2 Methodology

The calculation of task content of trade needs connected information by sector between production, employment, and trade. Therefore, IO tables are suitable for this analysis. The IO tables for Japan are prepared by the Statistics Bureau of Japan. In this analysis, values for domestic production and exports are obtained from *Basic Transaction Tables valued at producers' prices*. Supplemental tables of IO are also used. Import value separated into final demand and intermediate input is obtained from *Table on Imports*, and the number of employees by occupation is obtained from *Employment matrix*.[8]

The estimation of the task content of trade is divided into the following two parts. The first part is to calculate composite task indices according to the occupations of IO tables. The second part is to allocate employees into five task categories by sector using the composite task indices and the export or import ratio.

[6] A disadvantage of the separation of intermediate input and final demand is that direct/indirect effects using Leontief-inverse and input-output structure cannot be calculated, because imports of intermediate input are included in the internal sectors of IO tables.

[7] For instance, some of the "China shock" analyses separate imports of intermediate goods from imports of final goods. They find that the imports of intermediate goods from China tend to have a positive effect on employment in developed countries including Japan, whereas the imports of final goods tend to provide a negative effect on their employment (Wang, Wei, Yu and Zhu, 2018; Taniguchi, 2019; Kiyota, Maruyama and Taniguchi, 2021).

[8] The method of concordance between Jobtag and 2015IO is explained in Appendix A. Sectors for IO tables are aggregated at medium level, namely 107 sectors for 2015 IO.

2.1 Composite index of five task categories

For the calculation of the task index, job information of Jobtag is used.[9] Jobtag is intended to construct a Japanese version of US O*NET and the framework and indicators involved are generally common with O*NET. Therefore, using Jobtag, almost the same composite indices of five task categories with Acemoglu and Autor (2011) can be calculated.

In the process of calculating task composite indices at the occupational level of IO tables, the first challenge is that the classification for the occupations of the Jobtag is different from that of IO tables. Jobtag classification needs to be matched to IO classification.[10] There are 484 occupations in Jobtag. 69 Jobtag occupations lack necessary information, therefore, 415 Jobtag occupations are used in the analysis.[11] In addition, some IO occupations lack corresponding Jobtag-occupations. As for 2015IO, 52 occupations out of 227 are unavailable. As a result, composite task indices for 175 occupations for 2015IO are estimated. In the estimation results, employees of unavailable occupations are sorted in 'not specified'.

In the analysis of occupational composition in section 3, available 175 occupations of 2015IO are aggregated in 11 groups at 2-digit level (Table 2). As Table 2 shows, the largest occupation 'Manufacturing process workers' accounts for 66.0% of total employees in the manufacturing sector. Meanwhile, many employees in manufacturing are engaged in service activities, such as 'Clerical workers'(15.2%) or 'Professional/engineering workers'(7.3%).

=== Table 2 ===

As components of each task index, Acemoglu and Autor (2011) selected three or four scales included in the domains of 'Work activities' and 'Work Context Importance' of O*NET, see Table 3. For instance, the index of nonroutine analytical tasks is expressed as a composite index of three scales: "Analyzing data/information", "Thinking creatively", and "Interpreting information for others". The composite task index is calculated in the following manner. First, each scale is standardised to have a mean zero and a standard de-

[9] Jobtag is a database aiming to support job-seekers and companies by providing occupational information. It is operated by the Ministry of Health, Labor and Welfare. Datasets were collected and prepared by the Japan Institute for Labour Policy and Training (JILPT).

[10] Generally, Jobtag classification is more detailed than IO classification. When one occupation in the IO classification includes one or more occupations in the Jobtag classification, a simple average of Jobtag occupations is calculated. See Appendix Table A1 for an example of calculation.

[11] See Appendix Table B1.

viation one, using the number of employees by occupation as a weight.[12] This standardisation is due to make each component have the same range of value. Second, three/four standardised scales are added to generate a composite index. Third, the composite index is standardised again to have a mean zero and a standard deviation one. With this second standardisation, five task composite indices can have the same range and become comparable.

=== Table 3 ===

For the calculation of Japanese indices, Komatsu and Mugiyama (2022) follow the choice of scales by Acemoglu and Autor (2011). Scales are included in the domains of 'Work Activities' and 'Work Context' in the Jobtag.[13] Only scales for nonroutine manual tasks are different from those of Acemoglu and Autor (2011).[14] In Jobtag, each scale indicates a value from one to five; one means the work activity is not important, and five means it is very important.

The result of the calculation of five task indices is shown in Appendix Table A4, as a list of the top twenty occupations for each task category.

2.2 Task content of trade

The task content of trade is estimated following the calculation method by Tomiura et al. (2014). They assume that employees are generally engaged in tasks of all five categories.[15] The employees allocate their working hours into five categories based on the importance of each task category. With this assumption, the task content of trade is estimated with the following three steps. First, the importance of each task category is calculated by occupation. Second, task content for domestic production by sector is estimated. Third, the task content of trade is calculated using the ratio of exports or imports to domestic production.

[12] The number of employees used as a weight includes all the sectors.

[13] Scales in 'Work Activities' set up indicators for 41 activities that are abstracted to measure common elements of different tasks. Scales in 'Work Context' measure the interpersonal/physical/structural work environment with 37 indicators. In addition to these domains, Jobtag includes the following data domains: Job interest, Value to the job, Skills, Knowledge, Education and Training, and Detailed Tasks. Dataset ver.3.01 was downloaded on November 30, 2022. Link to Jobtag website (available only in Japanese) https://shigoto.mhlw.go.jp/User

[14] Three scales out of four used in nonroutine manual task in Komatsu and Mugiyama (2022) are common with scales for Offshorability index of Acemoglu and Autor (2011).

[15] This means that, for instance, Manufacturing process workers are engaged not only in tasks to produce manufacturing goods but also in tasks to provide services.

In the first step, the value of calculated composite task indices is regarded as a measure of importance. Composite task indices are normalised to have a range from zero to one. This enables us to add five indices as a positive value. Then, the ratio of each category to the sum of five categories is calculated. See Appendix A for more details.

In the second step, task content for domestic production by task category is estimated in terms of the number of employees. Based on the task importance ratio, employees by occupation are allocated into five task categories. Then, the number of employees in the same task categories is summed up by sector.

In the third step, the task content of trade is calculated using the ratio of exports or imports to domestic production. Task content of exports for task category j in sector i is obtained by multiplying task content for domestic production by the export ratio Xi/Yi. X and Y indicate exports and domestic production, respectively. Task content of exports (ET_{ij}) is expressed as follows:

$$ET_{ij} = \frac{X_i}{Y_i} \sum_k \frac{\tau_{jk}}{\sum_j \tau_{jk}} L_{ik} \tag{1}$$

where subscripts i, j, k, denote sector, task category, occupation, respectively. τ is task index, and L is the number of employees. Similarly, the task content of imports is calculated by multiplying the task importance ratio by the import ratio, Mi/Yi. With superscripts FD and IM, imports of final demand and imports of intermediate input are distinguished. Task content of imports of final demand (IT_{ij}^{FD}) and task content of imports of intermediate input (IT_{ij}^{IM}) are respectively expressed as follows:

$$IT_{ij}^{FD} = \frac{M_i^{FD}}{Y_i} \sum_k \frac{\tau_{jk}}{\sum_j \tau_{jk}} L_{ik} \tag{2}$$

$$IT_{ij}^{IM} = \frac{M_i^{IM}}{Y_i} \sum_k \frac{\tau_{jk}}{\sum_j \tau_{jk}} L_{ik} \tag{3}$$

Using eq.(1)-(3), the task content of net exports for each category can be calculated as $ET_{ij} - (IT_{ij}^{FD} + IT_{ij}^{IM})$. The estimated task content of trade for total manufacturing is analysed in Appendix B.[16]

It must be noted that the task content of imports for both types is calculated using the structure of Japanese production and employment. The estimated task content of imports provides the number of Japanese employees when the substitutive goods of imports are

[16] In Appendix B, estimation results using 2011IO are also provided as a reference.

produced in Japan. It can be regarded as missing employment by the replacement of domestic production with imports or as a supplement for a lack of labour with imports. At the same time, it is emphasized that it does not provide an actual number of foreign employees engaged in the production of imported goods.

2.3 Industrial features in the task content for domestic production

In the descriptive analysis of section 3, 53 manufacturing sectors are divided into six groups according to the similarity of products for rough comparison.[17] Six groups consist of (1) Basic materials – Light industry, (2) Basic materials – Heavy industry, (3) Machinery – Light industry, (4) Machinery – Heavy industry, (5) Daily necessities – Light industry, and (6) Daily necessities – Heavy industry, see Table 4 for the list of sectors. Group (1) includes products such as textile, wood/paper products, plastic products, and ceramic products, whereas Group (2) includes products such as organic chemical products, petroleum and coal products, and steel and metal products. Group (3) includes electric machinery such as home appliances, computers, semiconductors and electronic components. Group (4) mainly includes industrial machinery and transport equipment. Group (5) includes products such as foods and beverages, apparel, and leather. Group (6) consists of products such as synthetic resins and fibers, medical products, and other chemical final products.

=== Table 4 ===

Figure 1 shows task content for domestic production divided by manufacturing group. The comparison in Figure 1 reveals differences in the main tasks among manufacturing groups. First, Group (5) uses relatively larger task content in routine manual tasks than other manufacturing groups. Second, nonroutine analytical tasks are the largest category in Groups (2), (3), and (6). Third, routine cognitive task is the largest category in Groups (1), (4), and (5). These differences in the production structure also appear in the task content of trade as described later.

[17] Six grouping of manufacturing is done in two steps. We first classify sectors into three groups 'Basic materials', 'Machinery', and 'Daily necessities'. Then, each group is separated into 'Light industry' and 'Heavy industry'. Separation into three groups is often used in the analysis of *Updated Input-Output Tables* and *Census of Manufacture* by the Ministry of Economy, Trade and Industry (METI). As corresponding to three groups in this paper, METI uses 'Raw material products', 'Processed and assembled products', and 'Other products'. Roughly speaking, 'Raw material products', which we call 'Basic materials', tend to include capital-intensive sectors, while 'Processed and assembled products', which we call 'Machinery', tend to include labour-intensive sectors. 'Other products', which we call 'Daily necessities', include both labour-intensive and capital-intensive sectors.

=== Figure 1 ===

3 Descriptive analysis

In this section, the task content of trade divided into five task categories is analysed. In 3.1, the characteristics of six manufacturing groups are analysed. In 3.2, the occupational composition of six manufacturing groups is focused on.

3.1 Comparison of six manufacturing groups

Figure 2 shows the estimation results of task content of trade by manufacturing group and by trade flow. Based on the method of estimation, the task content of trade reflects the difference in trade volume by flow. There are three types. Concerning Groups (3) and (4), exports are much larger than both types of imports. Concerning Groups (1), (2), and (6), exports and imports of intermediate input are almost the same volume. Only Group (5) shows that imports of final demand are much larger than exports and imports of intermediate input.

=== Figure 2 ===

What is found as a difference by manufacturing group? The largest difference is the importance of routine manual tasks. A salient feature is observed in Group (5). In Group (5), routine manual tasks are the largest task category in both types of imports. Similarly, in Group (1), routine manual tasks are the second largest category in both imports. In other groups, nonroutine analytical tasks and routine cognitive tasks are the largest and the second largest categories. The sectors classified in Groups (1) and (5) are light industries which do not require high technology. In contrast, the routine manual tasks of Group (6) are the smallest both in imports of final demand and in imports of intermediate input.

As shown in Figure 2, trade volume is largely different by trade flow and by manufacturing group; this makes it difficult to highlight different features by industry. To eliminate this problem, the share of each task category is calculated as shown in Figure 3.[18] The main findings from these graphs are threefold. First, the share of routine manual tasks is larger in Groups (1) and (5) than in other groups, exceeding 20 per cent in all trade flows. Interestingly, the share of routine manual tasks of exports in Group (5) is

[18] Workers classified into 'Not specified' are excluded.

smaller than that of imports. Second, the share of routine manual tasks is the smallest in Group (6) in all trade flows in comparison to other categories. These two findings are in line with the results from Figure 2. Third, in Groups (3) and (5), there is a clear difference in task share by flow, as the three line charts are not overlapped. Concerning imports of final demand in Group (3), the share of routine manual tasks is smaller, and the share of nonroutine analytical tasks and nonroutine interactive tasks is larger. In contrast, Group (5) indicates the largest share of routine manual tasks in imports of final demand. Differences in task share depend on the aggregation by group because task importance ratio by sector used in estimation is common across trade flows. It reflects a difference in trade structure by sector within a manufacturing group.

=== Figure 3 ===

Next, the task content of net exports by manufacturing group is analysed. Panel (a) of Figure 4 shows the task content of net exports in terms of the number of workers. Panel (a) reveals that only Groups (3) and (4) have a surplus, and the rest of the groups have a deficit. Interestingly, net exports tend to show the largest trade deficit in routine manual tasks and the second largest level in routine cognitive tasks in Groups (1) and (5). As for Group (3), the largest surplus (not deficit) is also shown in routine manual tasks. These facts suggest that routine tasks are the most important tasks in the trade of light industries, even though the estimation is based on the Japanese production structure.

=== Figure 4 ===

Panel (b) of Figure 4 shows a ratio of net exports to total trade.[19] The calculation of ratios for panel (b) aims to eliminate different trade volumes among groups. Panel (b) reveals that Group (6) has a different structure of task trade by category. A higher degree of trade deficit in nonroutine analytical tasks and in nonroutine interactive tasks than in other tasks is observed. As for other manufacturing groups, routine manual task tends to show the largest gap between exports and imports.

To sum up, light industries tend to have relatively large imports of routine manual tasks, and it leads to a trade deficit in this category.

[19] Total trade is calculated as the sum of exports and imports.

3.2 Occupational composition of six manufacturing groups

The estimation of the task content of trade is based on the structure of employment and trade by sector. The occupational composition may explain the difference among manufacturing groups.

How are the employees in the six manufacturing groups composed by occupation? Figure 5 shows the occupational composition of six manufacturing groups. The employees in 175 occupations are aggregated into eight occupational groups at a 2-digit level of the occupational classification. Five occupations which account for less than one per cent of the total are further aggregated in 'Other workers' in the graph. From Figure 5, it is clear that 'Manufacturing process workers' is the largest occupational category in all groups. The second largest category is 'Clerical workers', and the third is 'Professional/engineering workers'. In Groups (3), (4), and (6), 'Professional/engineering workers' account for around ten per cent or more. This suggests that these three manufacturing groups tend to have a technology-intensive nature. On the other hand, Group (5) shows the smallest share of Professional/engineering workers (2.2%) and Clerical workers (10.8%), and the largest share of Manufacturing process workers. This suggests that Group (5) uses fewer cognitive tasks with the former two occupations.

=== Figure 5 ===

Next, we focus on the difference in task composition by occupation. Figures 6, 7, and 8 show the share of task categories by manufacturing groups for three major occupations, namely Manufacturing process workers, Professional/engineering workers, and Clerical workers, respectively. It is pointed out that the shapes of the line chart of the three occupations are clearly different. In Figure 6, the shape of the line for Manufacturing process workers tends to be more balanced than the shape for the other two occupations. In addition, the bottom of the pentagon in Figure 6 is wider, which means the share of two routine tasks is higher than the other categories, except Group (6). The shapes of the line chart of Figures 7 and 8 are more skewed. As for Professional/engineering workers in Figure 7, the shares of nonroutine analytical and interactive tasks, in other words, nonroutine cognitive tasks, are much higher than the other three tasks. As for Clerical workers in Figure 8, the shares of nonroutine analytical and interactive tasks as well as routine cognitive tasks are much higher than the other two manual tasks. These findings suggest that more resources are allocated to cognitive tasks in the industries where the ratios of Professional/engineering and Clerical workers are higher.

=== Figure 6 ===
=== Figure 7 ===
=== Figure 8 ===

The features of Manufacturing process workers by manufacturing group are summarised in the following three points. First, the share of routine manual tasks tends to be the largest in Groups (1) and (5), namely light industries. Second, both shares of routine cognitive tasks and routine manual tasks tend to be large in Groups (3) and (4) of machinery. Third, nonroutine analytical tasks tend to be large in Groups (2) and (6), namely heavy industries. Such differences among six manufacturing groups are not observed, or only minor differences are found for Professional/engineering and Clerical workers. This suggests that the tasks required for manufacturing process workers are diversified among industries. For instance, the share of nonroutine analytical tasks of Group (6) is much higher than other manufacturing groups. This means that activities such as "Analyzing data/information" or "Thinking creatively" are required of manufacturing process workers. Group (5), on the other hand, shows less share of nonroutine analytical and interactive tasks.

Our findings from the analysis of three major occupations are summarised as follows. First, the main task categories are different by occupation. Thus, the share of occupations can affect the difference in task content of trade of each sector. Second, the task trade of Manufacturing process workers shows different composition among manufacturing groups, whereas the other two major occupations have a common task structure across groups.

4 Empirical analysis

4.1 Framework

In the previous section, it is revealed that there are differences in task composition by manufacturing group. Moreover, the task category of importance is different by occupation. Considering these facts, the effect of the industrial characteristics and occupational composition by sector on the task content of trade is empirically tested in this section. A difference from the descriptive analysis is that industrial characteristics are expressed quantitatively in the regression analysis.

As a dependent variable, two types of indicators are employed. One is the task ratio by sector. It is calculated as a ratio of task content of trade by category to the sum of five categories. The ratios by category are the same across trade flows since the calculation of the task content of each trade flow is based on the task content for domestic production. Therefore, this test focuses on the differing effects by task category. Because the dependent variables are limited to the range between 0 and 1, the fractional logistic regression model is used for the regression.

The other dependent variable is net exports in terms of the number of employees by sector.[20] With this test, coefficients on five task categories are compared. The effect on the task content of trade by flow is not tested either. Because the task content of trade is calculated by the allocation using the ratio of exports or imports to domestic production, differences in volume among task categories within a sector are much smaller than differences among sectors. Net exports can be both positive and negative value, therefore, OLS is used for the regression.

Concerning explanatory variables, factors which indicate the occupational structure by sector and industrial characteristics are employed. As shown in 3.2, the task composition depends on the occupational structure. In the regression on the task ratios, the ratios of the following three major occupations are used as determinants: Professional/engineering workers (OCCRATIO02), Clerical workers (OCCRATIO03), and Manufacturing process workers (OCCRATIO08). From the findings in 3.2, it is expected that the larger the ratio of Manufacturing process workers is, the larger the task ratio of routine manual tasks is. In contrast, it is expected that the larger the ratio of Professional/engineering workers is, the larger the task ratio of nonroutine analytical tasks is. For the regression on net exports, the number of employees by occupation is also employed (OCCNUM02, OCCNUM03, OCCNUM08).

As a variable for the industrial characteristics, the ratio of part-time workers and capital-labour ratio are employed. The ratio of part-time workers (PARTTIME) aims to capture a demand for unskilled labour.[21] Sectors classified into the light industry, namely Groups (1), (3), and (5), tend to indicate a high ratio of part-time workers. In a sector which requires more part-time workers, it is expected to allocate more resources to routine

[20] Negative values of imports are provided in the sectors with scrap and by-products.

[21] Part-time workers here include part-time workers, contract workers, and temporary workers. The information is obtained from the supplementary table of 2015IO, *Table on Employees Engaged in Production Activities*. The term 'non-regular workers' is avoided, because the classification of regular workers in the 2015IO includes part-time workers and contract workers.

tasks. Capital-labour ratio (KLRATIO), calculated as a ratio of fixed capital divided by the total number of employees, aims to capture capital intensity. The larger the capital-labour ratio is, the more capital-intensive the sector is. A capital-intensive industry is expected to allocate fewer human resources to manual tasks. Three types of capital-labour ratios are calculated: (a) the total value of fixed capital (KL_SUM), (b) the selection of fixed capital for machinery (KL_MCN) and intellectual properties (KL_INT), and (c) dividing fixed capital into information and communication technology (ICT) and non-ICT (KL_ICT and KL_OTH).[22] Case (b) is intended to distinguish the effect of investment in tangible capital goods and that in intangible capital goods.[23] Case (c) aims to test the effect of the computerisation. In the model of ICT investment by Autor et al. (2003), it is expected that the more a sector is computerised, the lower the ratio of two routine tasks and the higher the ratio of two nonroutine cognitive tasks. [24]

The equation for the regression on the task ratio is expressed as follows.

$$TASKRATIO = \alpha + \sum_{k=02,03,08} \beta_k * OCCRATIO_k + \beta_4 * PARTTIME + \beta_5 * KLRATIO \quad (4)$$

The equation for the regression on net exports is expressed as follows.

$$NETEXPORT = \alpha + \sum_{k=02,03,08} \beta_k * OCCUPATION_k + \beta_4 * PARTTIME + \beta_5 * KLRATIO \quad (5)$$

OCCUPATION is an occupational variable. For this variable in each model, either OCCRATIO or OCCNUM is used. NETEXPORT and OCCNUM are expressed as a unit of 1000 persons.

53 manufacturing sectors for 2015IO are tested as a baseline. As a robustness check,

[22]The values of fixed capital are obtained from the supplementary table of 2015IO, *Fixed Capital Matrix*. Fixed capital for machinery includes items from 2911-011 to 3599-099. Fixed capital for intellectual properties includes items 5931-011, and from 6321-011 to 6322-011. Fixed capital for ICT includes items from 3411 to 3421 and 5931-011. Fixed capital for non-ICT covers all items excluding ICT items. The distinction of ICT/non-ICT depends on the analysis in *The White Paper on Information and Communications in Japan 2019* by the Ministry of Internal Affairs and Communications.

[23]Investment in intangible capital goods includes investment in software, infra- and extra-firm R&Ds.

[24]"As industries adopt computer technology, our model predicts that they will simultaneously reduce labor input of routine cognitive and manual tasks and increase labor input of nonroutine cognitive tasks." (Autor et al., 2003, p.1302)

data from 2011IO is added and tested as pooled data.[25] Concerning fixed capital, only case (a) and (c) are tested, because investment value for research and development, included in intellectual properties in case (b), is not available for 2011IO. For the additional regression with the pooled data, a year dummy of 2015 is introduced. The correlation matrix is shown in Table 5. Panel (a) presents correlation coefficients for 2015, and panel (b) presents those for the pooled data.

=== Table 5 ===

4.2 Effects on task ratio by sector

The regression results on task ratio with the 2015 data are shown in Table 6. Panel (a) of Table 6 shows the regression results with the capital-labour ratio of case (a). The main findings are threefold. First, the occupational composition affects the task ratio differently. The coefficient of ratios of Professional/engineering (OCCRATIO02) and Clerical (OCCRATIO03) workers on nonroutine analytical tasks are positive and statistically significant, whereas the coefficients of the ratios of these two occupations on routine and nonroutine manual tasks are negative and statistically significant. In contrast, the coefficient of the ratio of Manufacturing process workers (OCCRATIO08) on routine manual tasks is positive and statistically significant. The ratio of three major occupations does not explain the difference in task ratio for routine cognitive tasks, as no statistically significant coefficients are obtained. The results of regression confirm the relation between occupational composition and specific tasks.

=== Table 6 ===

Second, as for the ratio of part-time workers, only the coefficient of routine cognitive tasks is positive and statistically significant. This suggests that the ratio of routine cognitive tasks tends to be high in a sector with a high ratio of less skilled workers. It is interesting because no coefficients of the three major occupations are statistically significant for this task category.

[25]Using 2011IO data, task indices and the task content of trade of 2011 are estimated. However, these are not used for the main part of the study because of the special circumstances of the Japanese economy in 2011. In 2011, manufacturing production in Japan was at a low level for the reason of the Great East Japan Earthquake and massive floods in Thailand. Therefore, the estimated results for 2011 need to be carefully interpreted.

Third, the coefficient of the capital-labour ratio indicates positive and statistically significant effects on nonroutine analytical and nonroutine interactive tasks, namely nonroutine cognitive tasks. In contrast, negative and statistically significant effects are obtained on routine manual tasks. These indicate that the ratio of nonroutine analytical/interactive tasks tends to be high in the capital-intensive sectors and to be small in the labour-intensive sectors.

When the fixed capital is calculated in case (b), the effects of occupational composition are almost the same as in case (a). The effects of industrial characteristics are partly changed. First, as for the effect of part-time workers, the ratio of nonroutine manual tasks turns to negative and statistically significant results, although at a low level of significance. Second, the capital-labour ratio for machinery affects nonroutine analytical tasks positively, and nonroutine manual tasks negatively. Third, the capital-labour ratio for intellectual property affects routine cognitive tasks negatively, although the capital-labour ratio does not affect this task category in case (a).

When the fixed capital is divided into ICT and non-ICT as in case (c), the effects of occupational composition and the ratio of the part-time workers are almost the same as the cases (a) and (b). As for ICT capital, no coefficient is statistically significant. The effect of ICT capital is not clear from this analysis. As for the coefficient of non-ICT fixed capital, a common feature with case (a) is observed.

To sum up, the occupational composition affects the task ratio of five categories differently. The results suggest that the ratio of Professional/engineering and Clerical workers and that of Manufacturing process workers have opposite effects on routine manual tasks. As for industrial characteristics, the ratio of routine cognitive tasks tends to be large in the sector with a high ratio of less skilled workers. In contrast, the ratio of nonroutine analytical and interactive tasks, in other words, nonroutine cognitive tasks, tends to be large in the capital-intensive sectors.

Is this relation held when data for a different year is added? To answer this question, pooled data for 2011 and 2015 is examined. Table 7 shows regression results for case (a) and for case (c). As for occupational composition, the signs of statistically significant coefficients are almost the same as the regression results of 2015 data.

=== Table 7 ===

As for the ratio of part-time workers, more coefficients are statistically significant, in addition to routine cognitive tasks for 2015 results. The results suggest that the existence of less skilled workers has a different impact on routine and nonroutine tasks. The higher the ratio of part-time workers is, the larger the ratios of routine cognitive and routine manual tasks are. In contrast, the ratio of nonroutine analytical and nonroutine manual tasks tends to be smaller when the ratio of part-time workers is higher.

As for the capital-labour ratio, most of the coefficients in case (a) become statistically significant, and it is confirmed that the relation of the baseline result is robust. With the regression with pooled data, the effect of ICT capital is partly changed. The coefficient of fixed capital for ICT on nonroutine analytical tasks is positive and statistically significant. On the other hand, the coefficients on routine cognitive tasks are negative and statistically significant. These results are in line with the results from Autor et al. (2003).

Table 8 shows the estimation of average marginal effects from the fractional logistic regression. From the comparison among task categories, it is pointed out that the occupational composition of Professional/engineering and Clerical workers affects the ratio of nonroutine analytical tasks stronger than the ratio of nonroutine interactive tasks.

=== Table 8 ===

4.3 Effects on net exports by sector

The regression results on net exports of 2015 are shown in Table 9. The table includes both results for the occupation ratios (OCCRATIO) and the number of employees (OCCNUM).

=== Table 9 ===

The main findings are summarised in the following three points. First, the coefficients of occupational composition are not statistically significant at all. Second, the number of Clerical workers and Manufacturing process workers have opposite impacts. The coefficients of OCCNUM03 are positive and statistically significant, while the coefficients of OCCNUM08 are negative and statistically significant, in all the cases. This suggests that the increase in clerical workers tends to bring about a trade surplus, whereas the increase in manufacturing process workers tends to bring about a trade deficit. Third, sectors with a high ratio of part-time workers tend to have a larger trade deficit.

As for the capital-labour ratio in case (a), the statistical significance of the results depends on the choice of occupational variables. When the fixed capital is calculated as case (b), the coefficients of the capital-labour ratio for intellectual properties are negative and statistically significant, except for routine manual tasks, although at a 10% level of significance. When the fixed capital is divided into ICT and non-ICT in case (c), the coefficients of the capital-labour ratio for ICT investments are also negative and statistically significant. These facts suggest that sectors which invest more in intangible assets tend to have a larger trade deficit.

Table 10 shows regression results using pooled data for 2011 and 2015. The signs of statistically significant coefficients are almost the same as the regression results of the 2015 data. A difference from the regression with 2015 data is that the coefficients of OCCNUM02 are positive and statistically significant in all the cases. On the other hand, the capital-labour ratio for ICT investments is no longer able to explain the volume of net exports sufficiently.

=== Table 10 ===

To sum up, the number of Clerical workers and Manufacturing process workers rather than the occupational composition affects the volume of net exports. The ratio of part-time workers explains the volume of net exports well. It suggests that light industries tend to have a trade deficit.

5 Concluding remarks

This paper estimates the task content of trade for Japanese manufacturing in terms of the number of employees. Major findings from the descriptive analysis are summarized as follows. First, divided into six manufacturing groups, light industries tend to have relatively large imports of routine manual tasks. Especially in Group (5), routine manual tasks are the largest category both in imports of final demand and in imports of intermediate input. In contrast, in Group (6), routine manual tasks are the smallest category in both imports. This suggests that the importance of routine manual tasks is different between light industries and heavy industries.

Second, as for net exports of six manufacturing groups, only Groups (3) and (4) of machinery have a surplus, and the rest of the groups have a deficit. Light industries (1) and (5) have a common feature that the trade deficit of routine manual tasks tends to be large.

Third, the comparison of occupational composition suggests that the task structure of Manufacturing process workers is different among manufacturing groups, whereas the other two major occupations of Professional/engineering and Clerical workers have a common task structure across groups.

From the empirical analysis, major findings concerning the determinants of the task ratio are summarised as follows. First, the occupational composition affects the task ratio of nonroutine cognitive tasks and two manual tasks differently. Second, the ratio of routine cognitive tasks tends to be large in the sector with a high ratio of less skilled workers. Third, the ratios of nonroutine analytical and interactive tasks tend to be large in the capital-intensive sectors. These results suggest that the occupational structure and industrial characteristics explain the difference in the task content of trade by sector. Concerning the determinants of net exports, the main findings are twofold. First, the number of Clerical workers and Manufacturing process workers rather than the occupational composition affects the volume of net exports. Second, sectors with a high ratio of part-time workers such as light industries tend to have a larger trade deficit.

There are, however, some remaining issues. One is to improve the concordance between Jobtag and IO. Estimated results of task content of trade with 2005IO were not available in this analysis, because many occupations in 2005IO were unable to match to occupations in Jobtag. Information from the National Census may be useful for better matching. It will help to analyse changes over time.[26] Another issue is an estimation of task content of trade by gender. Komatsu and Mugiyama (2022) calculate the composite task index by gender and analyse the difference between male and female workers. IO tables do not involve the gender information of workers. Separation of employees by gender can be done through the concordance of IO with the National Census. In addition, an estimation would be applied to service sectors. In this paper, an estimated result of service sectors is not used, because it includes many non-trade sectors. Furthermore, additional determinants related to industrial characteristics need to be introduced. For explaining the task content of trade, especially imports of intermediate input, indicators for multinational enterprises or participation of global value chains will be available. These are the questions for future research.

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[26]See Appendix B for a comparison of aggregated value for 2005, 2011, and 2015.

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Appendix A: Data preparation and estimation of task content of trade

This appendix provides information and an example of estimating the task content of trade using Japanese data. As for a concordance of the Jobtag classification and 2015IO classification, an appendix of Komatsu and Mugiyama (2021) is referred to. When one IO-occupation includes more than two Jobtag-occupations, a simple average of scales for Jobtag-occupations is calculated. Because there is no information about the number of employees for occupations in the Jobtag, the weighted average cannot be calculated. Table A1 is an example of the calculation of a scale of composite task index, for the case of 'software creators', IO occupation code 0205017.

=== Table A1 ===

As explained in 2.2, the task content of trade is estimated with three steps. In the first step, the importance of each task category is calculated by occupation. Table A2 is an example of the calculation of the task importance ratio for the case of 'software creators'. The second row shows composite task indices by task category. The standardized index usually has a range from -3 to 3. The third row shows indices after normalization to have a range from 0 to 1. Using the sum of indices, the task importance ratio is calculated, as shown in the fourth row. For example, in the case of 'software programmer', the task index of nonroutine analytical tasks is 0.723 after normalisation. The sum of the five task indices for this occupation is 2.158. The task importance ratio of nonroutine analytical tasks is 33.8%, which suggests software programmers allocate 33.8% of their working hours to nonroutine analytical tasks.

=== Table A2 ===

In the second step of the estimation, the allocation of employees into the five task categories using the task importance ratio by occupation is applied in each sector. For instance, sector '111 Foods' which has 210 software creators allocates them into the five task categories as shown in the third row in Table A3. Similarly, sector '112 Beverage' allocates 67 software creators as shown in the fourth row.

=== Table A3 ===

Table A4 shows a list of the top twenty occupations out of 175 available occupations for 2015IO. Similar tables are provided in Komatsu and Mugiyama (2022). However, the results of this analysis and their results do not match, because there is unavailable information for some occupations in data provided online.

=== Table A4 ===

Appendix B: Shift of task content of trade

In Appendix B, the estimated task content of trade for 2005, 2011 and 2015 is overviewed. The estimated result for 2005 is not analysed in sections 3 and 4. The reason is that there are many occupations unable to connect the job information of Jobtag in manufacturing of 2005IO. As for 2005 IO tables, 96 occupations out of 269 are unavailable, and task composite indices are calculated for 173 occupations, see Table B1. Occupations which do not have matched information from Jobtag are summed in 'Not specified'. Because the amount of 'not specified' is large in some sectors in 2005, unavailable occupations are biased in some specific sectors. These conditions make it difficult to compare the estimations for 2005 and 2015. Although a detailed analysis with disaggregated data is inadequate, it is useful to understand the overall trend with aggregated data.

=== Table B1 ===

Figure B1 shows a comparison of export and import values of Japanese manufacturing. Three features are pointed out. First, exports exceed imports total, namely the sum of imports of final demand and imports of intermediate input. Second, imports of intermediate input exceed imports of final demand. Third, imports total in 2005 were smaller than exports, whereas imports in 2015 grew to be almost equivalent to exports.

=== Figure B1 ===

The estimation of task content of trade, which indicates trade volume in terms of the number of employees, provides a different picture from trade values. Figure B2 shows a comparison of exports and imports as the sum of the task content of trade. There are clear differences from Figure B1. First, imports total exceed exports. Second, imports of final demand exceed imports of intermediate input. Third, exports and imports total in 2005 were almost equivalent, however, imports in 2015 grew larger than exports. These differences suggest that products made in labour-intensive sectors are more imported as final products. In addition, imported goods tend to use a lot of labour force when they are produced in Japan.

=== Figure B2 ===

Figure B3 shows the estimation of task content of trade by task category and by trade flow. Note that 'Not specified' in 2005 is much larger than those in 2011 and in 2015, as explained. The main features from panels (a), (b), and (c) are threefold. First, routine cognitive tasks are the largest category, except imports of final demand in 2005. Second, nonroutine analytical tasks have grown to be almost equivalent to routine cognitive tasks from 2011. Third, routine manual tasks are relatively large for imports of final demand, and the gap from routine cognitive tasks is smaller than those in other trade flows.

=== Figure B3 ===

Panel (d) shows the shift in net exports. The trade deficit grew from 2005 to 2015. In 2005, a trade deficit was observed only for routine manual tasks, but all the task categories turned into a trade deficit in 2015.

Figures B4 to B6 are graphs using 2011, and they correspond to Figures 1, 2, and 4 for 2015 data. The task composition of 2011 is almost the same as in 2015. Figure B7 shows the growth from 2011 to 2015 in terms of trade volume. The volume of growth in Figure B7 shows a similar structure to the task content of trade. The growth is proportional to the task content of trade. Figure B8 shows the growth rate. From Figure 8, it is clear that imports of final demand for Groups (3) and (4) achieved high growth. Exports of Group (5) also indicate a high growth rate, however, they are at a low volume of growth as Figure B7 shows.

=== Figure B4 ===
=== Figure B5 ===
=== Figure B6 ===
=== Figure B7 ===
=== Figure B8 ===

Table 1. Description of five tasks by Ikenaga and Kambayashi (2016)

<table>
<tr><td></td><td>Cognitive</td><td>Manual</td></tr>
<tr><td rowspan="2">Non-routine</td><td>Nonroutine <u>analytical</u> tasks require highly specialized knowledge and the ability to solve problems using abstract thinking</td><td rowspan="2">Nonroutine manual tasks do not require a particularly high level of specialized knowledge, but involve physical work comprising nonroutine activities that require a flexible response to particular situations</td></tr>
<tr><td>Nonroutine <u>interactive</u> tasks create and provide value through complex interpersonal communication such as negotiation, management, and consulting activities</td></tr>
<tr><td>Routine</td><td>Routine cognitive tasks are clerical and information-processing tasks that follow explicit rules</td><td>Routine manual tasks can follow explicit rules, but generally comprise physical work such as production involving routine repetitive manual work or work involving the operation of machinery</td></tr>
</table>

(Source) Ikenaga and Kambayashi (2016)

Table 2. Occupational classification and composition of 2015IO

	2-digit groups	number of subgroups (7-digit code)	Share of employees in manufacturing (%)
01	Administrative and managerial workers	3	2.2
02	Professional and engineering workers	54	7.3
03	Clerical workers	12	15.2
04	Sales workers	10	3.6
05	Service workers	22	0.4
06	Security workers	6	0.1
07	Agriculture, forestry and fishery workers	5	0.0
08	Manufacturing process workers	29	66.0
09	Transport and machine operation workers	12	0.8
10	Construction and mining workers	12	0.2
11	Carrying, cleaning, packaging, and related workers	10	4.0

(Note) “Workers not classifiable by occupation”, which is omitted in the table, accounts for 0.3%.

(Source) 2015 Input-Output tables for Japan.

Table 3. Scales for five task categories

	Acemoglu and Autor (2011): O*NET	Komatsu and Mugiyama (2022): Jobtag
Nonroutine analytical	-- Analyzing data/information -- Thinking creatively -- Interpreting information for others	-- Analyzing data/information (WA) -- Thinking creatively (WA) -- Interpreting information for others (WA)
Nonroutine interactive	-- Establishing and maintaining personal relationships -- Guiding, directing and motivating subordinates -- Coaching/developing others	-- Establishing and maintaining personal relationships (WA) -- Guiding, directing and motivating subordinates (WA) -- Coaching/developing others (WA)
Routine cognitive	-- Importance of repeating the same tasks -- Importance of being exact or accurate -- Structured v. Unstructured work (reverse)	-- Importance of repeating the same tasks (WC) -- Importance of being exact or accurate (WC) -- Structured v. Unstructured work (reverse) (WC)
Routine manual	-- Pace determined by speed of equipment -- Controlling machines and processes -- Spend time making repetitive motions	-- Pace determined by speed of equipment (WC) -- Spend time making repetitive motions (WC) -- Controlling machines and processes (WA)
Nonroutine manual	-- Operating vehicles, mechanized devices, or equipment -- Spend time using hands to handle, control or feel objects, tools or controls -- Manual dexterity -- Spatial orientation	-- Performing general physical activities (WA) -- Handling and moving objects by using hands and arms (WA) -- Assisting and caring for others (WA) -- Performing for or working directly with the public (WA)

(Note) WA and WC stand for Work Activities and Work Context, respectively.

Table 4. 3-digit Industrial Classification for 2015IO and six manufacturing groups

(1) Basic materials -- Light industry	(2) Basic materials -- Heavy industry
151 Textile products	201 Chemical fertilizer
161 Lumber and wood products	202 Industrial inorganic chemicals
162 Furniture and fixtures	203 Petrochemical basic products
163 Pulp, paper, paperboard, coated and glazed paper	204 Organic chemical products (except petrochemical basic products or synthetic resins)
164 Paper products	211 Petroleum refinery products
221 Plastic products	212 Coal products
222 Rubber products	261 Pig iron and crude steel
251 Glass and glass products	262 Steel products
252 Cement and cement products	263 Cast and forged steel products (iron)
253 Pottery, china and earthenware	269 Miscellaneous iron or steel products
259 Miscellaneous ceramic, stone and clay products	271 Non-ferrous metals
	272 Non-ferrous metal products
	281 Fabricated constructional and architectural metal products
	289 Miscellaneous metal products
(3) Machinery -- Light industry	**(4) Machinery -- Heavy industry**
321 Electronic devices	291 General-purpose machinery
329 Miscellaneous electronic components	301 Production machinery
331 Electrical devices and parts	311 Business oriented machinery
332 Household electric appliances	351 Passenger motor cars
333 Applied electronic equipment and electric measuring instruments	352 Miscellaneous cars
339 Miscellaneous electrical machinery	353 Motor vehicle parts and accessories
341 Communication, image and audio equipment	354 Ships and repair of ships
342 Electronic computing equipment and accessory equipment of electronic computing equipment	359 Miscellaneous transportation equipment and repair of transportation equipment
(5) Daily necessities -- Light industry	**(6) Daily necessities -- Heavy industry**
111 Foods	205 Synthetic resins
112 Beverage	206 Synthetic fibers
113 Feeds and organic fertilizer, n.e.c.	207 Medicaments
114 Tobacco	208 Final chemical products (except medicaments)
152 Wearing apparel and miscellaneous ready-made textile products	
191 Printing, plate making and book binding	
231 Tanned leather, leather products and fur skins	
391 Miscellaneous manufacturing products	

Table 5. Correlation matrix

(a) 2015

	OCCRATIO02	OCCRATIO03	OCCRATIO08	OCCNUM02	OCCNUM03	OCCNUM08	PARTTIME	KL_SUM	KL_MCH	KL_INT	KL_ICT	KL_OTH
OCCRATIO02	1.0000											
OCCRATIO03	0.5053	1.0000										
OCCRATIO08	-0.6616	-0.7598	1.0000									
OCCNUM02				1.0000								
OCCNUM03				0.7883	1.0000							
OCCNUM08				0.5297	0.8512	1.0000						
PARTTIME	-0.3152	-0.3760	0.3591	0.0363	0.3715	0.5416	1.0000					
KL_SUM	0.5620	0.3419	-0.4312	-0.0290	-0.2645	-0.2979	-0.3824	1.0000				
KL_MCH	0.3076	0.2143	-0.2288	-0.1050	-0.2682	-0.2541	-0.4128	0.8361	1.0000			
KL_INT	0.6643	0.3388	-0.4953	0.1179	-0.1228	-0.2078	-0.1985	0.7881	0.3347	1.0000		
KL_ICT	0.7388	0.3436	-0.4974	0.0542	-0.1821	-0.2269	-0.1788	0.6257	0.3380	0.7334	1.0000	
KL_OTH	0.5098	0.3236	-0.4001	-0.0381	-0.2611	-0.2912	-0.3882	0.9950	0.8556	0.7536	0.5450	1.0000

(b) Pooled data of 2015 and 2011

	OCCRATIO02	OCCRATIO03	OCCRATIO08	OCCNUM02	OCCNUM03	OCCNUM08	PARTTIME	KL_SUM	KL_ICT	KL_OTH
OCCRATIO02	1.0000									
OCCRATIO03	0.4372	1.0000								
OCCRATIO08	-0.6357	-0.7280	1.0000							
OCCNUM02				1.0000						
OCCNUM03				0.7744	1.0000					
OCCNUM08				0.5435	0.8723	1.0000				
PARTTIME	-0.3049	-0.3253	0.2785	0.0381	0.3775	0.5160	1.0000			
KL_SUM	0.4660	0.2511	-0.3193	-0.0623	-0.2611	-0.2806	-0.3397	1.0000		
KL_ICT	0.5624	0.2113	-0.3146	-0.0341	-0.2397	-0.2513	-0.1588	0.6745	1.0000	
KL_OTH	0.4193	0.2418	-0.2995	-0.0632	-0.2480	-0.2676	-0.3491	0.9918	0.5747	1.0000

Table 6. The effects on task ratio, 2015

		Nonroutine analytical	Nonroutine interactive	Routine cognitive	Routine manual	Nonroutine manual
(a)	OCCRATIO02	0.472	0.112	0.156	-0.512	-0.424
		(0.137)***	(0.153)	(0.148)	(0.191)***	(0.242)*
	OCCRATIO03	0.603	0.529	0.074	-0.725	-0.736
		(0.312)*	(0.213)**	(0.188)	(0.32)**	(0.301)**
	OCCRATIO08	-0.137	-0.265	0.000	0.484	-0.133
		(0.124)	(0.159)*	(0.116)	(0.159)***	(0.17)
	PARTTIME	-0.170	-0.124	0.203	0.169	-0.171
		(0.134)	(0.121)	(0.079)**	(0.115)	(0.107)
	KL_SUM	0.003	0.004	-0.001	-0.004	-0.003
		(0.001)***	(0.001)**	(0.001)	(0.002)*	(0.002)**
	Intercept	-1.298	-1.421	-1.324	-1.568	-1.241
		(0.116)***	(0.128)***	(0.103)***	(0.135)***	(0.158)***
	No. of obs.	53	53	53	53	53
	Pseudo-R2	0.001	0.001	0.0001	0.003	0.0004
	loglikelihood	-28.224	-25.586	-27.894	-25.619	-24.848
(b)	OCCRATIO02	0.478	0.105	0.232	-0.483	-0.511
		(0.134)***	(0.158)	(0.156)	(0.203)**	(0.241)**
	OCCRATIO03	0.608	0.537	0.053	-0.739	-0.725
		(0.321)*	(0.221)**	(0.184)	(0.326)**	(0.309)**
	OCCRATIO08	-0.141	-0.265	-0.018	0.480	-0.112
		(0.131)	(0.164)	(0.119)	(0.162)***	(0.171)
	PARTTIME	-0.168	-0.129	0.236	0.177	-0.204
		(0.142)	(0.121)	(0.075)***	(0.115)	(0.121)*
	KL_MCH	0.005	0.005	0.001	-0.004	-0.007
		(0.002)**	(0.003)	(0.003)	(0.003)	(0.003)**
	KL_INT	0.003	0.004	-0.004	-0.005	0.001
		(0.002)	(0.003)	(0.002)**	(0.003)	(0.002)
	Intercept	-1.295	-1.419	-1.322	-1.568	-1.245
		(0.119)***	(0.128)***	(0.103)***	(0.137)***	(0.159)***
	No. of obs.	53	53	53	53	53
	Pseudo-R2	0.001	0.001	0.0001	0.003	0.0004
	loglikelihood	-28.224	-25.586	-27.893	-25.619	-24.848
(c)	OCCRATIO02	0.461	0.160	0.216	-0.555	-0.410
		(0.187)**	(0.207)	(0.176)	(0.253)**	(0.283)
	OCCRATIO03	0.605	0.521	0.066	-0.721	-0.738
		(0.31)*	(0.22)**	(0.193)	(0.329)**	(0.297)**
	OCCRATIO08	-0.137	-0.268	-0.003	0.486	-0.133
		(0.124)	(0.16)*	(0.117)	(0.161)***	(0.169)
	PARTTIME	-0.171	-0.116	0.213	0.163	-0.169
		(0.136)	(0.119)	(0.08)***	(0.116)	(0.111)
	KL_ICT	0.005	-0.003	-0.010	0.003	-0.005
		(0.014)	(0.015)	(0.01)	(0.021)	(0.015)
	KL_OTH	0.003	0.004	-0.001	-0.004	-0.003
		(0.001)***	(0.002)**	(0.001)	(0.002)*	(0.001)**
	Intercept	-1.298	-1.421	-1.325	-1.567	-1.241
		(0.116)***	(0.127)***	(0.104)***	(0.138)***	(0.158)***
	No. of obs.	53	53	53	53	53
	Pseudo-R2	0.001	0.001	0.0001	0.003	0.0004
	loglikelihood	-28.224	-25.586	-27.894	-25.619	-24.848

(Note) Heteroskedasticity robust standard errors in parentheses. ***, **, and * indicate the significant level at 1%, 5%, and 10%, respectively.

Table 7. The effects on task ratio, pooled data of 2011 and 2015

		Nonroutine analytical	Nonroutine interactive	Routine cognitive	Routine manual	Nonroutine manual
(a)	OCCRATIO02	0.608	0.176	0.185	-0.565	-0.639
		(0.113)***	(0.135)	(0.115)	(0.156)***	(0.194)***
	OCCRATIO03	0.479	0.505	0.118	-0.674	-0.644
		(0.19)**	(0.147)***	(0.138)	(0.229)***	(0.216)***
	OCCRATIO08	-0.132	-0.339	0.025	0.564	-0.177
		(0.081)	(0.108)***	(0.078)	(0.11)***	(0.129)
	PARTTIME	-0.257	-0.171	0.268	0.245	-0.192
		(0.106)**	(0.117)	(0.074)***	(0.11)**	(0.099)*
	KL_SUM	3.873	4.179	-1.692	-4.199	-3.040
		(0.848)***	(1.135)***	(0.941)*	(1.501)***	(1.066)***
	2015DUM	-0.013	-0.005	-0.013	0.010	0.021
		(0.013)	(0.016)	(0.013)	(0.018)	(0.017)
	Intercept	-1.266	-1.372	-1.343	-1.637	-1.232
		(0.078)***	(0.091)***	(0.074)***	(0.099)***	(0.125)***
	No. of obs.	106	106	106	106	106
	Pseudo-R2	0.0012	0.0011	0.0001	0.0029	0.0004
	loglikelihood	-56.261	-50.878	-55.952	-51.585	-49.669
(c)	OCCRATIO02	0.514	0.130	0.243	-0.503	-0.591
		(0.119)***	(0.147)	(0.125)*	(0.166)***	(0.211)***
	OCCRATIO03	0.474	0.503	0.122	-0.668	-0.641
		(0.184)***	(0.145)***	(0.14)	(0.225)***	(0.214)***
	OCCRATIO08	-0.140	-0.343	0.030	0.570	-0.173
		(0.079)*	(0.108)***	(0.077)	(0.109)***	(0.131)
	PARTTIME	-0.287	-0.185	0.286	0.264	-0.177
		(0.105)***	(0.118)	(0.074)***	(0.112)**	(0.1)*
	KL_ICT	19.533	11.787	-11.647	-15.807	-11.661
		(8.998)**	(10.949)	(6.049)*	(13.372)	(10.657)
	KL_OTH	2.174	3.360	-0.615	-2.939	-2.119
		(1.246)*	(1.538)**	(1.173)	(1.982)	(1.436)
	2015DUM	-0.004	-0.001	-0.018	0.004	0.017
		(0.014)	(0.017)	(0.014)	(0.019)	(0.019)
	Intercept	-1.254	-1.366	-1.351	-1.645	-1.238
		(0.077)***	(0.091)***	(0.074)***	(0.099)***	(0.126)***
	No. of obs.	106	106	106	106	106
	Pseudo-R2	0.0012	0.0011	0.0001	0.0029	0.0004
	loglikelihood	-56.260	-50.877	-55.952	-51.585	-49.669

(Note) Heteroskedasticity robust standard errors in parentheses. ***, **, and * indicate the significant level at 1%, 5%, and 10%, respectively.

Table 8. Marginal effect of fractional logistic regression
(a) 2015

		Nonroutine analytical	Nonroutine interactive	Routine cognitive	Routine manual	Nonroutine manual
(a)	OCCRATIO02	0.082 ***	0.017	0.027	-0.078 ***	-0.062 *
	OCCRATIO03	0.105 *	0.081 **	0.013	-0.111 **	-0.108 **
	OCCRATIO08	-0.024	-0.040 *	0.000	0.074 ***	-0.019
	PARTTIME	-0.030	-0.019	0.035 ***	0.026	-0.025
	KL_SUM	0.001 ***	0.001 **	0.000	-0.001 *	0.000 **
(b)	OCCRATIO02	0.083 ***	0.016	0.040	-0.074 **	-0.075 **
	OCCRATIO03	0.106 *	0.082 **	0.009	-0.113 **	-0.106 **
	OCCRATIO08	-0.025	-0.040	-0.003	0.073 ***	-0.016
	PARTTIME	-0.029	-0.020	0.040 ***	0.027	-0.030 *
	KL_MCH	0.001 **	0.001	0.000	-0.001	-0.001 **
	KL_INT	0.001	0.001	-0.001 **	-0.001	0.000
(c)	OCCRATIO02	0.080 **	0.024	0.037	-0.085 **	-0.060
	OCCRATIO03	0.105 *	0.080 **	0.011	-0.110 **	-0.108 **
	OCCRATIO08	-0.024	-0.041 *	0.000	0.074 ***	-0.020
	PARTTIME	-0.030	-0.018	0.036 ***	0.025	-0.025
	KL_ICT	0.001	-0.001	-0.002	0.001	-0.001
	KL_OTH	0.001 ***	0.001 **	0.000	-0.001 *	0.000 **

(b) Pooled data of 2011 and 2015

		Nonroutine analytical	Nonroutine interactive	Routine cognitive	Routine manual	Nonroutine manual
(a)	OCCRATIO02	0.105 ***	0.027	0.032	-0.087 ***	-0.094 ***
	OCCRATIO03	0.083 **	0.076 ***	0.020	-0.104 ***	-0.094 ***
	OCCRATIO08	-0.023	-0.051 ***	0.004	0.087 ***	-0.026
	PARTTIME	-0.045 **	-0.026	0.046 ***	0.038 **	-0.028 *
	KL_SUM	0.671 ***	0.632 ***	-0.291 *	-0.648 ***	-0.445 ***
	2015DUM	-0.002	-0.001	-0.002	0.002	0.003
(c)	OCCRATIO02	0.089 ***	0.020	0.042 *	-0.078 ***	-0.087 ***
	OCCRATIO03	0.082 ***	0.076 ***	0.021	-0.103 ***	-0.094 ***
	OCCRATIO08	-0.024 *	-0.052 ***	0.005	0.088 ***	-0.025
	PARTTIME	-0.050 ***	-0.028	0.049 ***	0.041 **	-0.026 *
	KL_ICT	3.386 **	1.783	-2.004 *	-2.438	-1.708
	KL_OTH	0.377 *	0.508 **	-0.106	-0.453	-0.310
	2015DUM	-0.001	0.000	-0.003	0.001	0.002

Table 9. The effects on net export by category, 2015

	Nonroutine analytical		Nonroutine interactive		Routine cognitive		Routine manual		Nonroutine manual	
(a) OCCRATIO02	0.293		0.251		0.342		0.282		0.265	
	(0.418)		(0.338)		(0.423)		(0.375)		(0.334)	
OCCRATIO03	-0.199		-0.186		-0.173		-0.100		-0.144	
	(0.529)		(0.434)		(0.602)		(0.614)		(0.491)	
OCCRATIO08	-0.212		-0.164		-0.224		-0.274		-0.201	
	(0.249)		(0.194)		(0.271)		(0.285)		(0.222)	
OCCNUM02		0.192		0.170		0.206		0.146		0.159
		(0.117)		(0.085)*		(0.115)*		(0.115)		(0.091)*
OCCNUM03		0.359		0.294		0.424		0.451		0.341
		(0.15)**		(0.101)***		(0.154)***		(0.18)**		(0.131)**
OCCNUM08		-0.056		-0.050		-0.074		-0.077		-0.059
		(0.019)***		(0.012)***		(0.018)***		(0.021)***		(0.015)***
PARTTIME	-0.900	-0.846	-0.770	-0.686	-1.023	-0.889	-1.005	-0.889	-0.844	-0.744
	(0.24)***	(0.298)***	(0.19)***	(0.206)***	(0.275)***	(0.313)***	(0.289)***	(0.364)**	(0.225)***	(0.265)***
KL_SUM	-0.678	-0.304	-0.569	-0.279	-0.708	-0.299	-0.605	-0.172	-0.551	-0.213
	(0.302)**	(0.242)	(0.244)**	(0.187)	(0.322)**	(0.237)	(0.297)**	(0.229)	(0.252)**	(0.19)
Intercept	30.919	8.986	25.783	7.733	32.807	9.480	33.364	8.620	27.783	7.852
	(20.02)	(2.94)***	(15.947)	(2.319)***	(22.193)	(2.919)***	(23.168)	(2.855)***	(18.19)	(2.416)***
No. of obs.	53	53	53	53	53	53	53	53	53	53
R-squared	0.287	0.494	0.338	0.573	0.322	0.534	0.307	0.467	0.328	0.520

(Note) Heteroskedasticity robust standard errors in parentheses. ***, **, and * indicate the significant level at 1%, 5%, and 10%, respectively.

Table 9. The effects on net export by category, 2015 (cont.)

	Nonroutine analytical		Nonroutine interactive		Routine cognitive		Routine manual		Nonroutine manual	
(b) OCCRATIO02	0.456		0.375		0.475		0.376		0.361	
	(0.412)		(0.333)		(0.424)		(0.374)		(0.33)	
OCCRATIO03	-0.251		-0.226		-0.218		-0.134		-0.177	
	(0.523)		(0.428)		(0.594)		(0.608)		(0.485)	
OCCRATIO08	-0.246		-0.189		-0.251		-0.292		-0.220	
	(0.26)		(0.203)		(0.281)		(0.295)		(0.231)	
OCCNUM02		0.246		0.214		0.255		0.179		0.194
		(0.108)**		(0.075)***		(0.11)**		(0.116)		(0.087)**
OCCNUM03		0.356		0.292		0.421		0.448		0.339
		(0.151)**		(0.102)***		(0.156)***		(0.181)**		(0.132)**
OCCNUM08		-0.061		-0.054		-0.079		-0.081		-0.063
		(0.019)***		(0.012)***		(0.018)***		(0.021)***		(0.016)***
PARTTIME	-0.841	-0.759	-0.726	-0.613	-0.976	-0.810	-0.973	-0.837	-0.811	-0.688
	(0.235)***	(0.305)**	(0.192)***	(0.208)***	(0.277)***	(0.323)**	(0.289)***	(0.381)**	(0.227)***	(0.274)**
KL_MCH	-0.436	0.279	-0.409	0.190	-0.587	0.220	-0.572	0.177	-0.479	0.154
	(0.396)	(0.263)	(0.332)	(0.208)	(0.436)	(0.264)	(0.406)	(0.264)	(0.347)	(0.224)
KL_INT	-1.308	-0.938	-1.044	-0.800	-1.206	-0.877	-0.946	-0.563	-0.909	-0.626
	(0.688)*	(0.484)*	(0.55)*	(0.378)**	(0.689)*	(0.464)*	(0.589)	(0.422)	(0.529)*	(0.367)*
Intercept	31.443	7.181	26.164	6.221	33.188	7.842	33.607	7.589	28.046	6.697
	(20.731)	(2.613)***	(16.454)	(1.997)***	(22.751)	(2.701)***	(23.637)	(2.914)**	(18.608)	(2.314)***
No. of obs.	53	53	53	53	53	53	53	53	53	53
R-squared	0.298	0.513	0.348	0.595	0.327	0.548	0.309	0.473	0.331	0.530

(Note) Heteroskedasticity robust standard errors in parentheses. ***, **, and * indicate the significant level at 1%, 5%, and 10%, respectively.

Table 9. The effects on net export by category, 2015 (cont.)

	Nonroutine analytical		Nonroutine interactive		Routine cognitive		Routine manual		Nonroutine manual	
(c) OCCRATIO02	0.784		0.641		0.798		0.652		0.619	
	(0.458) *		(0.371) *		(0.478)		(0.434)		(0.377)	
OCCRATIO03	-0.264		-0.237		-0.233		-0.149		-0.190	
	(0.621)		(0.507)		(0.688)		(0.685)		(0.558)	
OCCRATIO08	-0.240		-0.186		-0.250		-0.295		-0.221	
	(0.266)		(0.207)		(0.287)		(0.299)		(0.236)	
OCCNUM02		0.235		0.206		0.243		0.168		0.186
		(0.117)*		(0.082)**		(0.118)**		(0.123)		(0.093)*
OCCNUM03		0.336		0.274		0.404		0.439		0.327
		(0.156)**		(0.105)**		(0.161)**		(0.188)**		(0.136)**
OCCNUM08		-0.057		-0.051		-0.075		-0.078		-0.060
		(0.019)***		(0.013)***		(0.018)***		(0.021)***		(0.016)***
PARTTIME	-0.821	-0.798	-0.707	-0.645	-0.949	-0.847	-0.945	-0.864	-0.787	-0.714
	(0.227) ***	(0.309)**	(0.183) ***	(0.212)***	(0.268) ***	(0.326)**	(0.281) ***	(0.382)**	(0.219) ***	(0.276)**
KL_ICT	-8.137	-3.366	-6.496	-2.862	-7.627	-2.959	-6.234	-1.731	-5.934	-2.139
	(2.705) ***	(1.748)*	(2.166) ***	(1.353)**	(2.828) ***	(1.72)*	(2.641) **	(1.633)	(2.242) **	(1.355)
KL_OTH	-0.357	-0.065	-0.314	-0.078	-0.410	-0.091	-0.363	-0.050	-0.319	-0.063
	(0.244)	(0.166)	(0.2)	(0.133)	(0.266)	(0.167)	(0.251)	(0.162)	(0.211)	(0.136)
Intercept	30.102	8.566	25.134	7.379	32.049	9.114	32.747	8.405	27.193	7.588
	(22.96)	(2.842)***	(18.322)	(2.229)***	(25.005)	(2.862)***	(25.471)	(2.883)***	(20.372)	(2.388)***
No. of obs.	53	53	53	53	53	53	53	53	53	53
R-squared	0.329	0.505	0.382	0.587	0.352	0.541	0.325	0.470	0.355	0.526

(Note) Heteroskedasticity robust standard errors in parentheses. ***, **, and * indicate the significant level at 1%, 5%, and 10%, respectively.

Table 10. The effects on net export by category, pooled data

	Nonroutine analytical		Nonroutine interactive		Routine cognitive		Routine manual		Nonroutine manual	
(a) OCCRATIO02	0.248		0.219		0.284		0.213		0.216	
	(0.28)		(0.225)		(0.286)		(0.259)		(0.226)	
OCCRATIO03	-0.326		-0.300		-0.304		-0.211		-0.245	
	(0.265)		(0.214)		(0.307)		(0.325)		(0.253)	
OCCRATIO08	-0.228		-0.173		-0.243		-0.299		-0.217	
	(0.17)		(0.127)		(0.183)		(0.201)		(0.152)	
OCCNUM02		0.237		0.215		0.259		0.188		0.201
		(0.097)**		(0.074)***		(0.101)**		(0.103)*		(0.082)**
OCCNUM03		0.332		0.256		0.393		0.442		0.318
		(0.141)**		(0.099)**		(0.148)***		(0.173)**		(0.126)**
OCCNUM08		-0.055		-0.047		-0.072		-0.079		-0.058
		(0.019)***		(0.013)***		(0.02)***		(0.022)***		(0.016)***
PARTTIME	-0.937	-0.851	-0.805	-0.691	-1.077	-0.909	-1.051	-0.905	-0.885	-0.755
	(0.202)***	(0.234)***	(0.161)***	(0.163)***	(0.232)***	(0.247)***	(0.242)***	(0.285)***	(0.189)***	(0.208)***
KL_SUM	-0.509	-0.171	-0.432	-0.176	-0.535	-0.175	-0.442	-0.068	-0.413	-0.118
	(0.22)**	(0.2)	(0.179)**	(0.157)	(0.234)**	(0.201)	(0.213)**	(0.195)	(0.183)**	(0.162)
2015DUM	-1.012	-2.523	-0.734	-1.960	-1.110	-2.695	-1.516	-2.935	-1.037	-2.278
	(2.609)	(2.306)	(1.96)	(1.671)	(2.788)	(2.449)	(2.96)	(2.726)	(2.282)	(2.035)
Intercept	35.082	10.848	29.126	9.284	37.674	11.779	38.676	11.070	31.809	9.757
	(12.769)***	(3.518)***	(9.704)***	(2.548)***	(14.029)***	(3.639)***	(15.316)**	(4.022)***	(11.607)***	(3.04)***
No. of obs.	106	106	106	106	106	106	106	106	106	106
R-squared	0.270	0.479	0.315	0.542	0.303	0.517	0.292	0.460	0.310	0.505

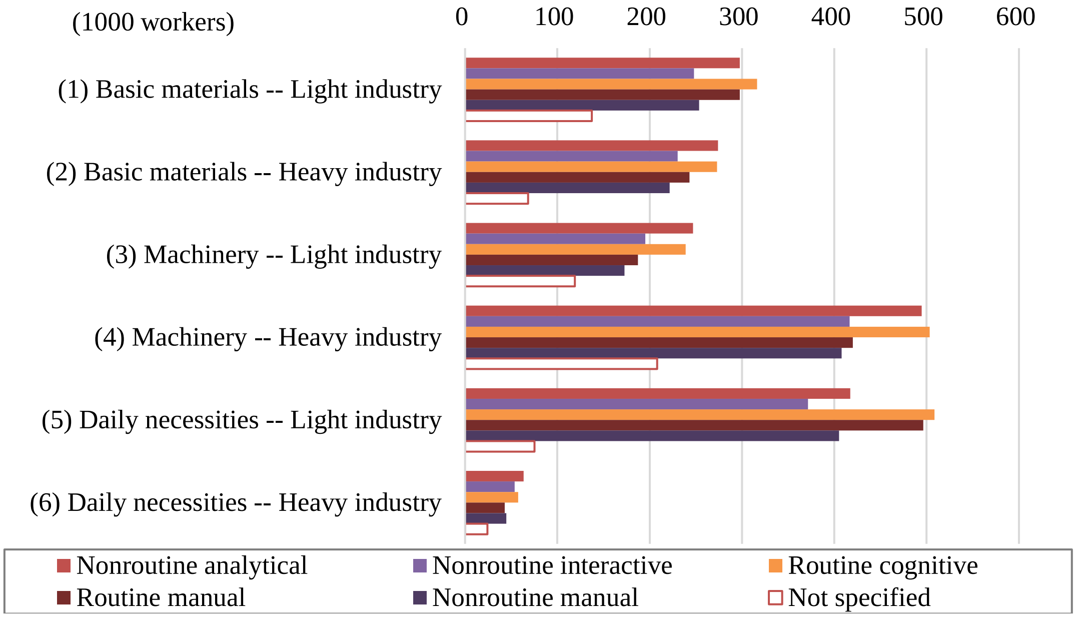
(Note) Heteroskedasticity robust standard errors in parentheses. ***, **, and * indicate the significant level at 1%, 5%, and 10%, respectively.

Table 10. The effects on net export by category, pooled data (cont)

	Nonroutine analytical		Nonroutine interactive		Routine cognitive		Routine manual		Nonroutine manual	
(c) OCCRATIO02	0.423		0.356		0.442		0.338		0.340	
	(0.3)		(0.242)		(0.31)		(0.28)		(0.244)	
OCCRATIO03	-0.315		-0.291		-0.294		-0.203		-0.237	
	(0.275)		(0.221)		(0.317)		(0.334)		(0.261)	
OCCRATIO08	-0.212		-0.160		-0.228		-0.288		-0.205	
	(0.171)		(0.128)		(0.184)		(0.202)		(0.153)	
OCCNUM02		0.260		0.234		0.279		0.201		0.217
		(0.097)***		(0.074)***		(0.102)***		(0.106)*		(0.083)**
OCCNUM03		0.319		0.245		0.382		0.434		0.310
		(0.143)**		(0.1)**		(0.151)**		(0.177)**		(0.128)**
OCCNUM08		-0.055		-0.047		-0.073		-0.079		-0.059
		(0.019)***		(0.013)***		(0.02)***		(0.022)***		(0.016)***
PARTTIME	-0.882	-0.810	-0.762	-0.655	-1.028	-0.872	-1.012	-0.882	-0.846	-0.728
	(0.196)***	(0.238)***	(0.16)***	(0.165)***	(0.23)***	(0.252)***	(0.239)***	(0.292)***	(0.187)***	(0.212)***
KL_ICT	-3.516	-1.816	-2.786	-1.606	-3.242	-1.674	-2.601	-0.990	-2.550	-1.248
	(1.88)*	(1.231)	(1.522)*	(0.989)	(1.937)*	(1.228)	(1.748)	(1.13)	(1.533)*	(0.973)
KL_OTH	-0.185	0.042	-0.178	0.009	-0.243	0.019	-0.208	0.052	-0.182	0.028
	(0.222)	(0.193)	(0.179)	(0.154)	(0.238)	(0.195)	(0.23)	(0.184)	(0.192)	(0.157)
2015DUM	-2.530	-3.342	-1.923	-2.672	-2.477	-3.441	-2.607	-3.394	-2.116	-2.840
	(2.842)	(2.355)	(2.132)	(1.707)	(3.06)	(2.496)	(3.263)	(2.789)	(2.504)	(2.08)
Intercept	32.854	10.758	27.381	9.206	35.668	11.696	37.076	11.019	30.224	9.695
	(12.879)**	(3.536)***	(9.799)***	(2.562)***	(14.183)**	(3.659)***	(15.438)**	(4.043)***	(11.717)**	(3.056)***
No. of obs.	106	106	106	106	106	106	106	106	106	106
R-squared	0.283	0.484	0.329	0.548	0.312	0.520	0.297	0.462	0.318	0.508

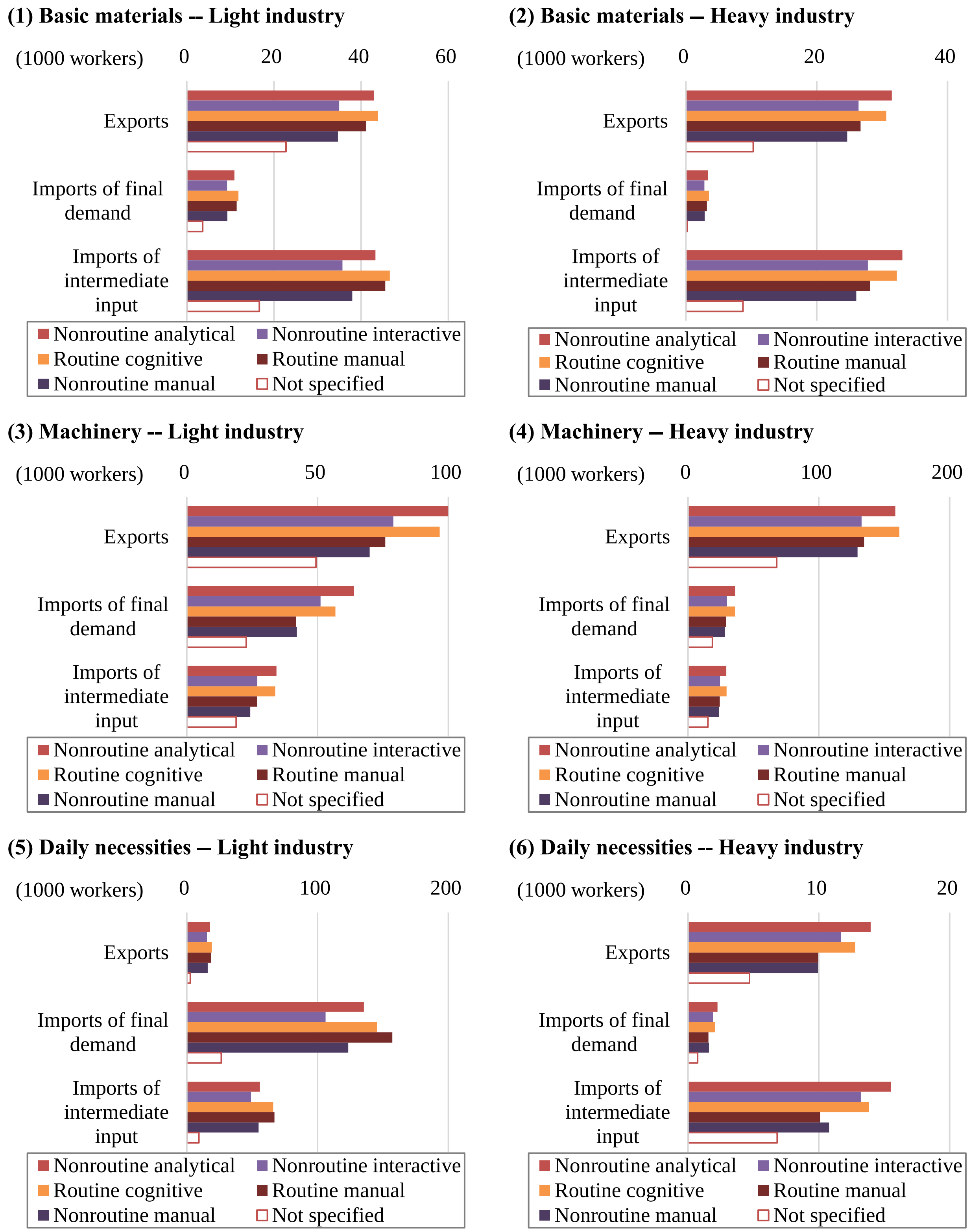
(Note) Heteroskedasticity robust standard errors in parentheses. ***, **, and * indicate the significant level at 1%, 5%, and 10%, respectively.

Figure 1. Task content for domestic production by manufacturing group, 2015



(Source) Author’s calculation.

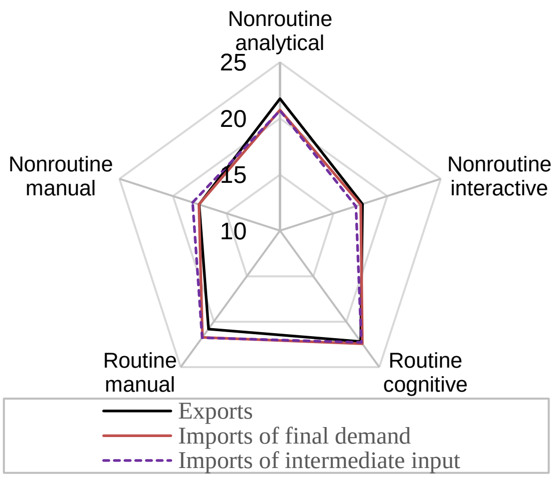
Figure 2. Task content of trade by manufacturing group, 2015



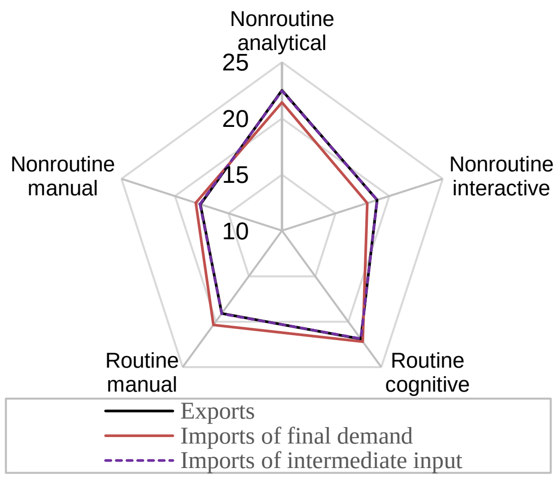
(Source) Author’s calculation.

Figure 3. Share of task categories by manufacturing group (%)

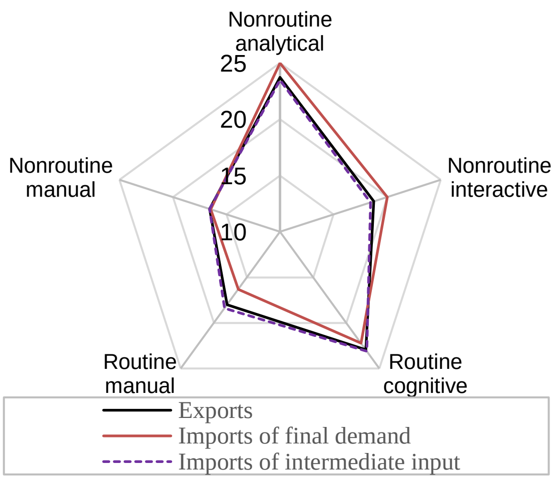
(1) Basic materials -- Light industry



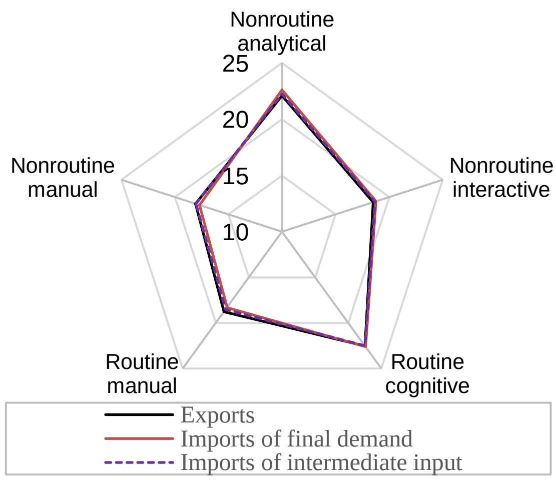
(2) Basic materials -- Heavy industry



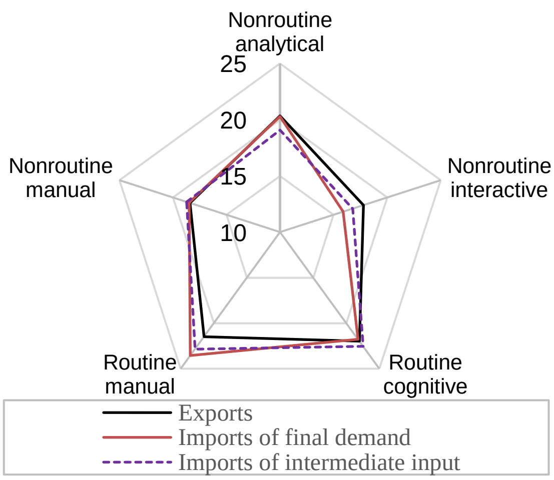
(3) Machinery -- Light industry



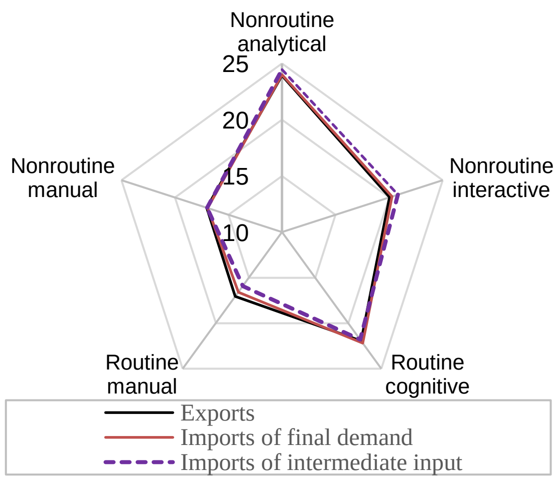
(4) Machinery -- Heavy industry



(5) Daily necessities -- Light industry



(6) Daily necessities -- Heavy industry

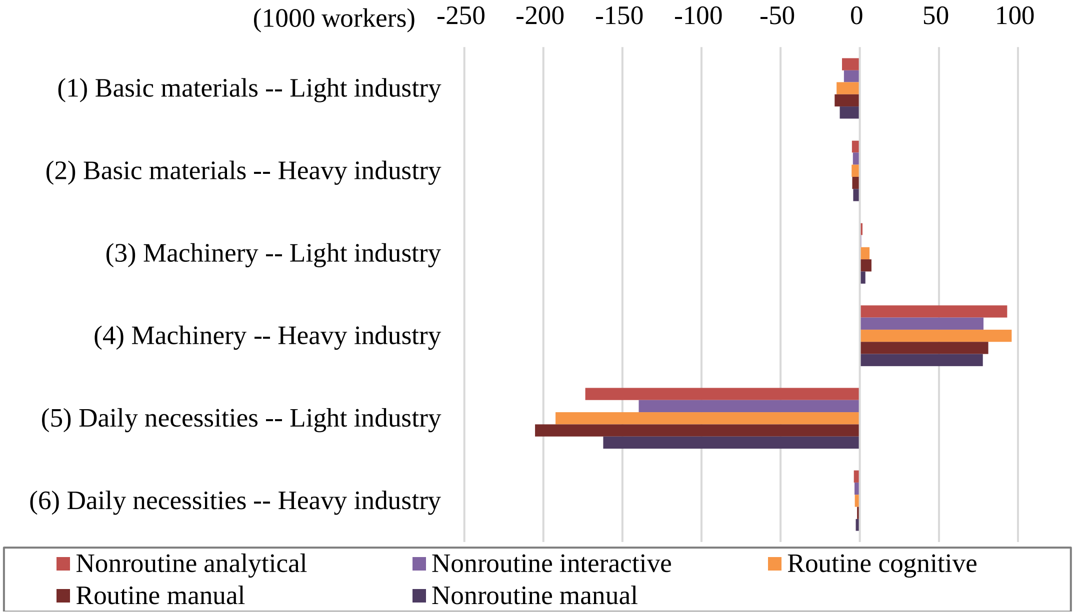


(Source) Author’s calculation.

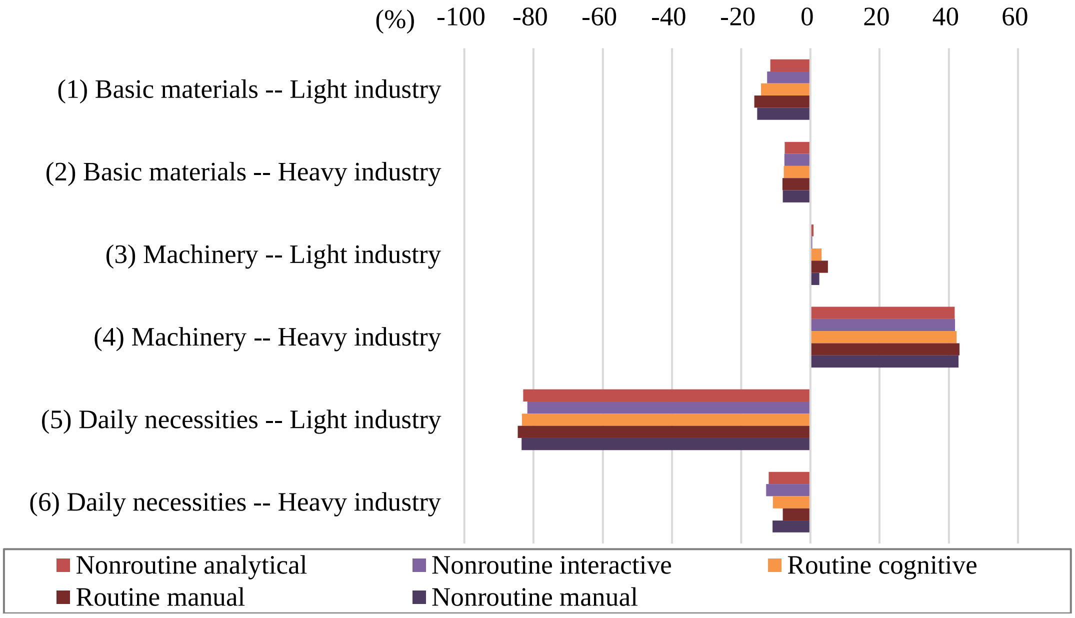
(Note) The origin of each chart is 10%. Workers classified into the group ‘Not specified’ are omitted.

Figure 4. Net exports of task content of trade by manufacturing group, 2015

(a) Volume (1000 workers)

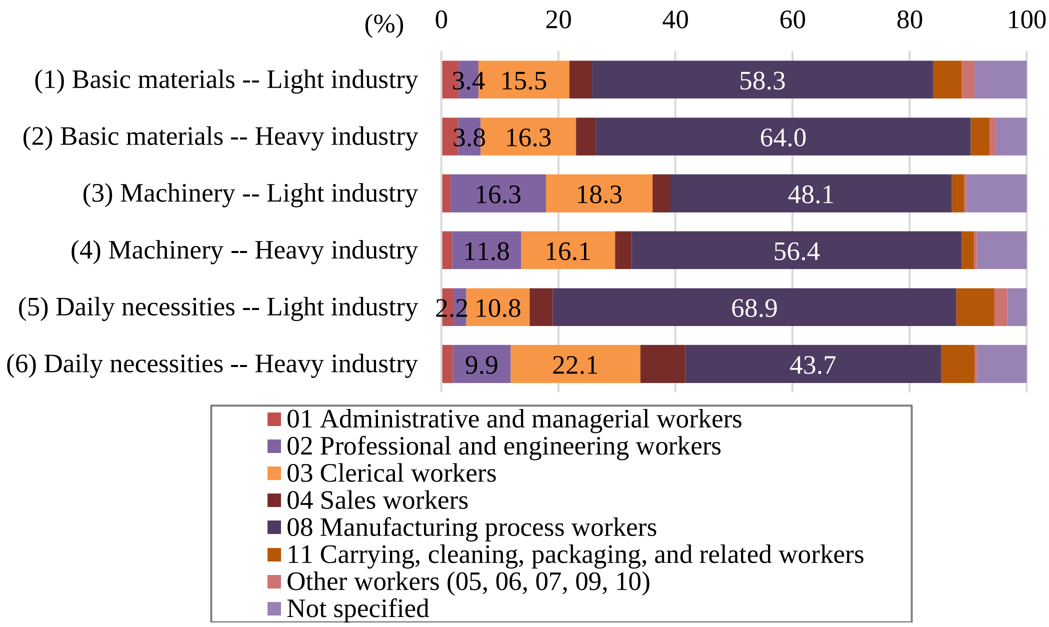


(b) Ratio to total trade (%)



(Source) Author’s calculation.

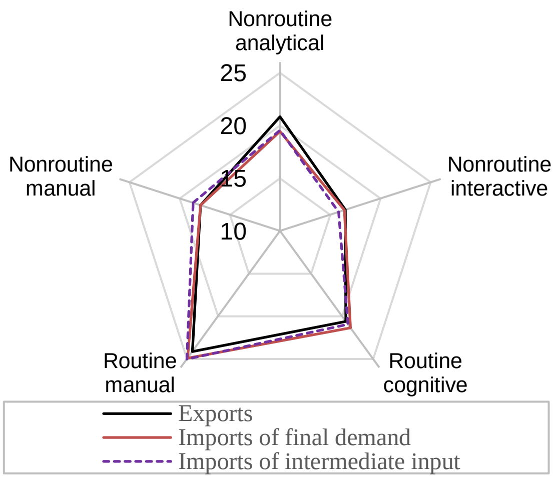
Figure 5. Occupational composition of six manufacturing groups, 2015



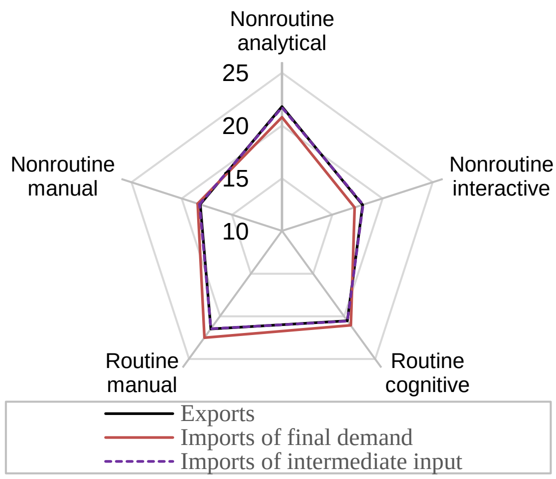
(Source) Author’s calculation.

Figure 6. Share of task categories by manufacturing group, 08 Manufacturing process workers

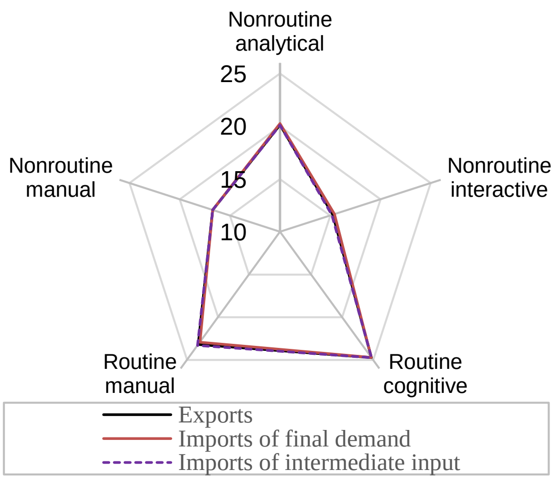
(1) Basic materials -- Light industry



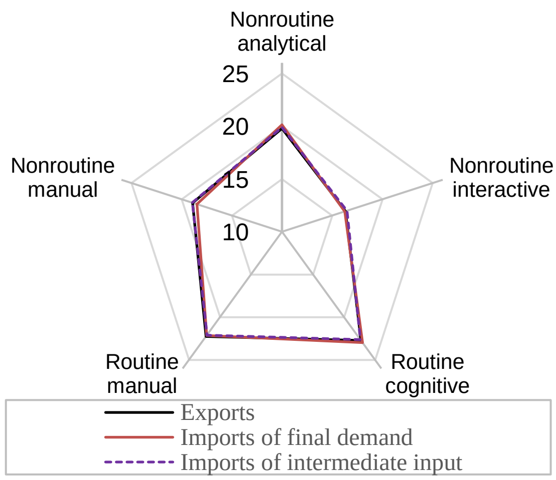
(2) Basic materials -- Heavy industry



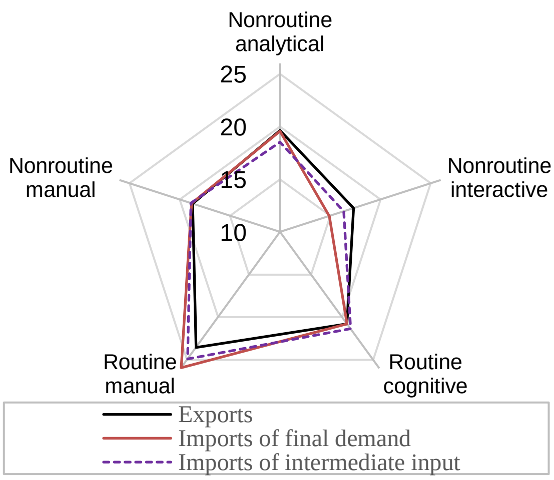
(3) Machinery -- Light industry



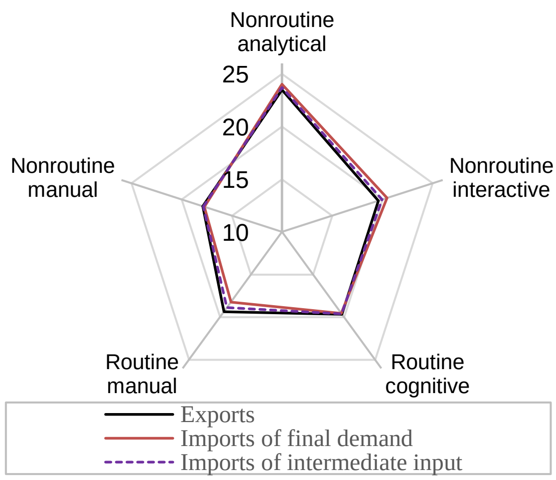
(4) Machinery -- Heavy industry



(5) Daily necessities -- Light industry



(6) Daily necessities -- Heavy industry

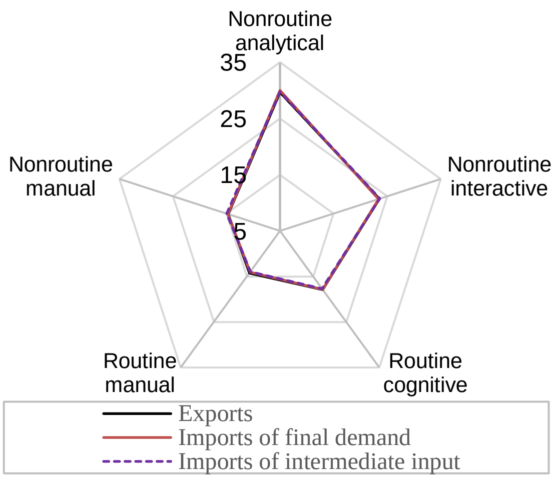


(Source) Author’s calculation.

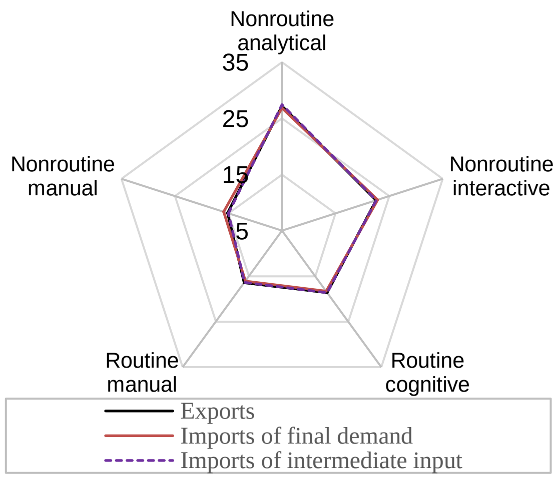
(Note) The origin of each chart is 10%.

Figure 7. Share of task categories by manufacturing group, 02 Professional and engineering workers

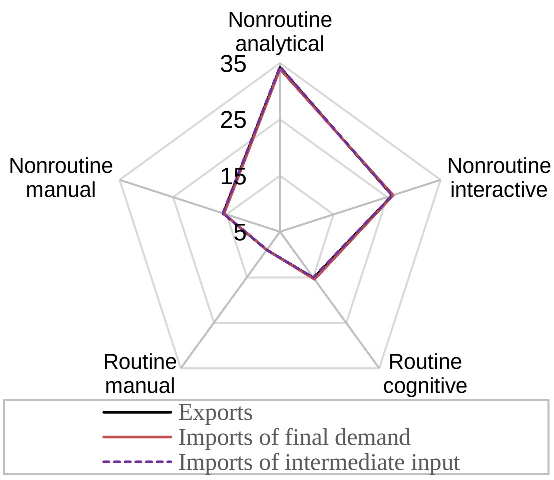
(1) Basic materials -- Light industry



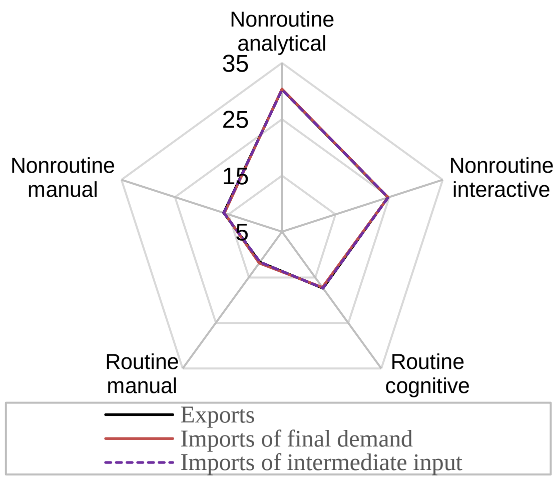
(2) Basic materials -- Heavy industry



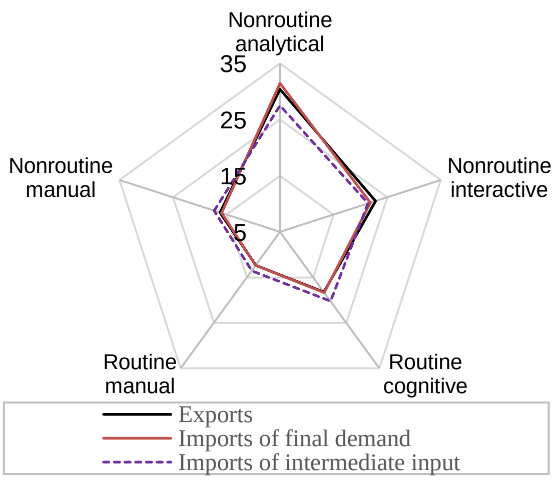
(3) Machinery -- Light industry



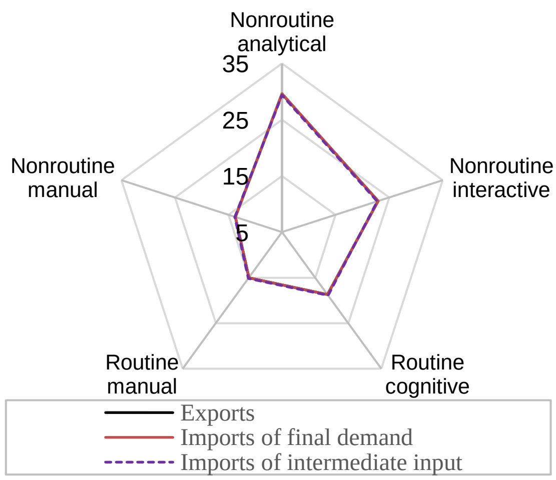
(4) Machinery -- Heavy industry



(5) Daily necessities -- Light industry



(6) Daily necessities -- Heavy industry

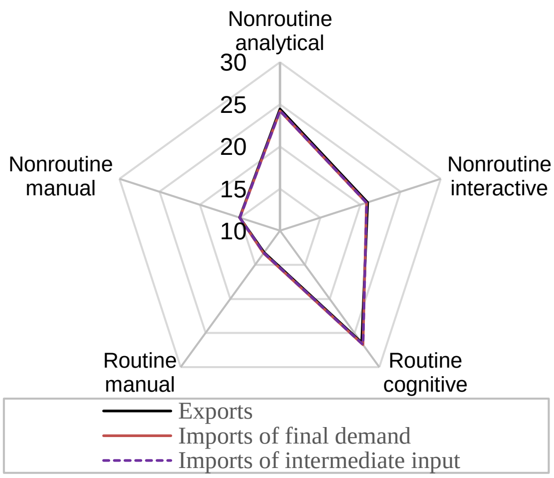


(Source) Author's calculation.

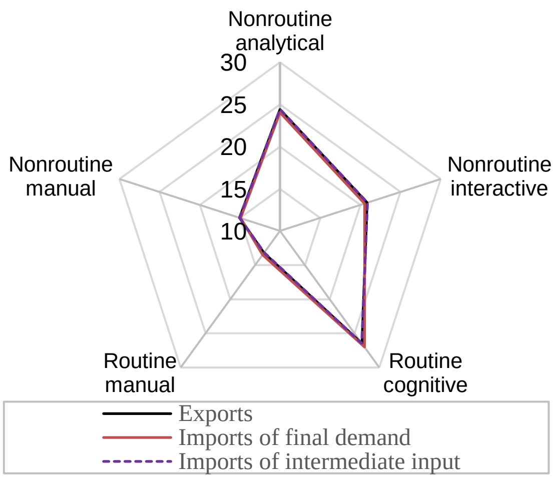
(Note) The origin of each chart is 5%.

Figure 8. Share of task categories by manufacturing group, 03 Clerical workers

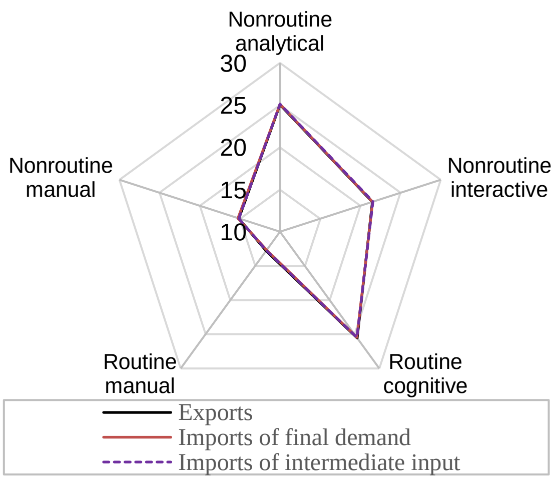
(1) Basic materials -- Light industry



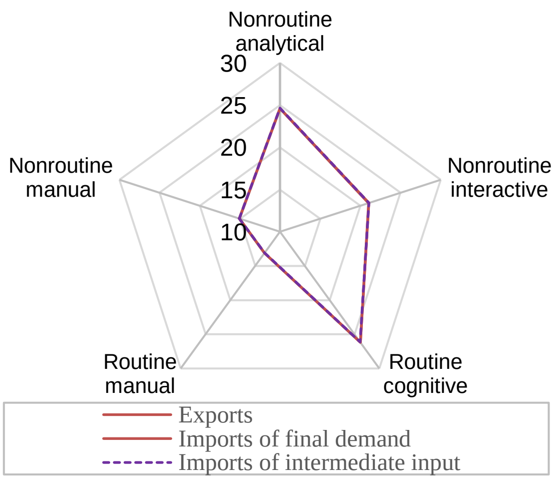
(2) Basic materials -- Heavy industry



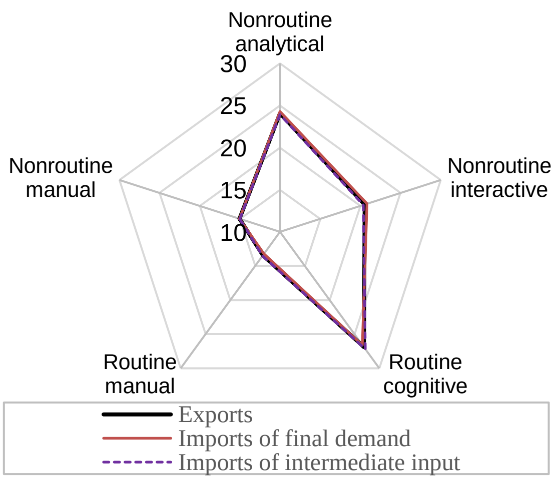
(3) Machinery -- Light industry



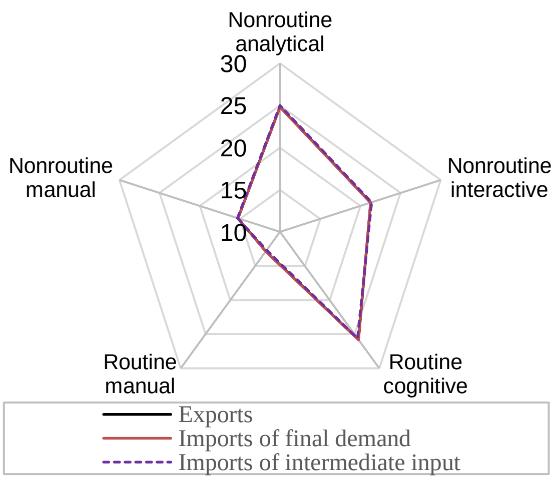
(4) Machinery -- Heavy industry



(5) Daily necessities -- Light industry



(6) Daily necessities -- Heavy industry



(Source) Author's calculation.

(Note) The origin of each chart is 10%.

Table A1. Example of occupational concordance and calculation of scale

	Occupations in the Jobtag classification corresponding to 2015IO occupation '0205017'	Scale for "Analyzing data/information"
312	System engineer of business-oriented system	3.164
313	Programmer	3.016
314	System engineer of website development	3.404
315	System engineer of embedded system/IoT	3.474
316	Software development of package software	3.222
317	Software development of smartphone app	3.143
0205017	Software creators	3.237 (simple average of 312-317)

(Source) Author's calculation.

Table A2. Importance of each task: Example of '0205017 Software creators'

	Nonroutine analytical	Nonroutine interactive	Routine cognitive	Routine manual	Nonroutine manual	Sum
Standardized Task index	1.3533	0.34281	-0.91579	-1.28852	-1.17409	
Normalized Task index	0.72947	0.52893	0.42241	0.18525	0.29176	2.15782
Task importance Ratio	**33.806**	**24.512**	**19.576**	**8.585**	**13.521**	100

(Source) Author's calculation.

Table A3. Allocation of employees: Example of '0205017 Software creators'

IO sectors	No. of employees 020517	Nonroutine analytical	Nonroutine interactive	Routine cognitive	Routine manual	Nonroutine manual
Task importance ratio (%)		**33.806**	**24.512**	**19.576**	**8.585**	**13.521**
111 Foods	**210**	71	51	41	18	28
112 Beverage	**67**	23	16	13	6	9
113 Feeds and organic fertilizer, n.e.c.	**0**	0	0	0	0	0
…	**…**					
354 Ships and repair o f ships	**84**	28	21	16	7	11
359 Miscellaneous trans portation equipment	**500**	169	123	98	43	68
391 Miscellaneous man ufacturing products	**849**	287	208	166	73	115

(Source) Author's calculation.

Table A4. The top twenty occupations for each task category, 2015

	Code	Occupation (2015IO)	Task Index
Nonroutine analytical task			
1	0204006	Natural science researchers	2.88148
2	0214059	Dancers, actors, directors and performers	2.21893
3	0212054	Journalists, editors	2.18262
4	0209041	Certified public accountants	2.17011
5	0205016	System consultants and designers	2.13363
6	0206029	Physiotherapists, occupational therapists	2.11946
7	0205013	Chemical engineers	2.01897
8	0425094	Medicine sales workers	2.00362
9	0208038	Judges, public prosecutors and attorneys	1.97438
10	0206024	Public health nurses	1.86027
11	0205009	Electrical, electronic, telecommunications engineers (except communication network engineers)	1.79545
12	0206035	Other health care workers	1.77442
13	0209044	Other management, finance, and insurance professionals	1.77279
14	0206025	Midwives	1.76030
15	0212053	Authors	1.74627
16	0213056	Designers	1.68463
17	0210049	Special needs education school teachers	1.64865
18	0205018	Other data processing and communication engineers	1.63595
19	0215068	Specialist professionals not classified elsewhere	1.63476
20	0215060	Librarians and curators	1.61446
Nonroutine interactive task			
1	0634129	Firefighters	2.89255
2	0206025	Midwives	2.71822
3	0841170	Transportation machinery maintenance and repair workers (except automobiles)	2.67251
4	0634128	Prison guards and other judicial police staff	2.50522
5	0103005	Administrative and managerial workers not classified elsewhere	2.45784
6	0103004	Administrative and managerial workers of corporations and organizations	2.45473
7	0531112	Restaurateurs, restaurant managers	2.45006
8	1050213	Railway line construction workers	2.29119
9	0634127	Police officers and maritime safety officials	2.28920
10	0206035	Other health care workers	2.11689
11	0210047	Junior high school teachers	1.99390
12	0634126	Self-defense officials	1.95125
13	0206029	Physiotherapists, occupational therapists	1.88241
14	0205016	System consultants and designers	1.87427
15	0425094	Medicine sales workers	1.85151
16	0209041	Certified public accountants	1.80920
17	0214059	Dancers, actors, directors and performers	1.75349
18	0206024	Public health nurses	1.74553
19	0206028	Clinical laboratory technicians	1.64683
20	0206026	Nurses (including assistant nurses)	1.64105
Routine cognitive task			
1	0945190	Railway drivers	4.69718
2	0948195	Conductors	3.30310
3	0634128	Prison guards and other judicial police staff	3.20673
4	0841170	Transportation machinery maintenance and repair workers (except automobiles)	3.16439
5	0206028	Clinical laboratory technicians	2.94913
6	0947194	Aircraft pilots	2.76996
7	1050213	Railway line construction workers	2.49613
8	0320079	Other outdoor service workers	2.37879
9	0206031	Dental hygienists	2.26610
10	0206027	Diagnostic radiographers	2.25420
11	0321080	Transport clerical workers	2.19926
12	0206023	Pharmacists	2.16644
13	0316071	Telephone receptionists	2.16358

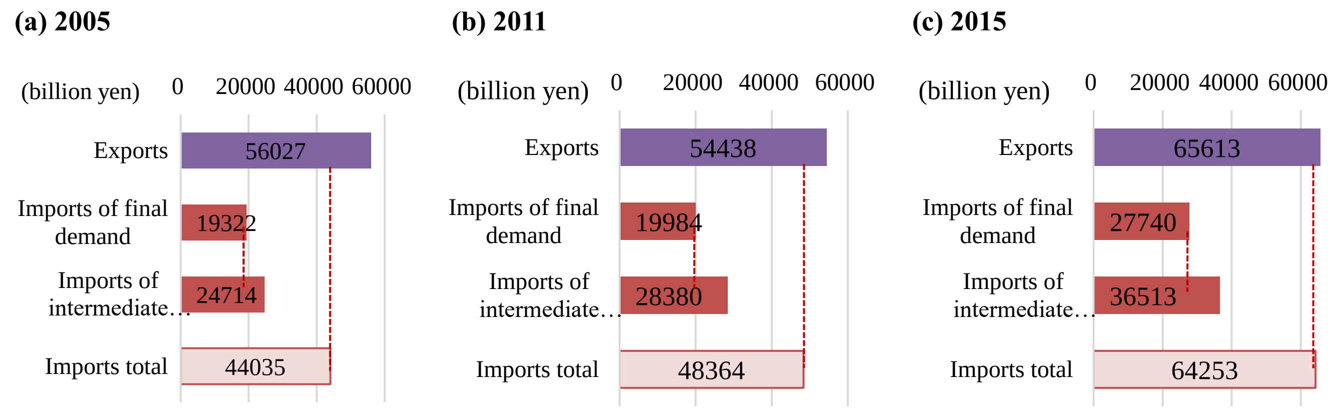
14	0634126	Self-defense officials	2.07960
15	0844188	Manufacturing-related workers (except painters, paint・signboard production)	2.06730
16	1155230	Packaging workers	1.98530
17	0317074	Accountancy clerks	1.97374
18	0634127	Police officers and maritime safety officials	1.86436
19	0206033	Nutritionists	1.83268
20	0206026	Nurses (including assistant nurses)	1.78349
Routine manual task			
1	0945190	Railway drivers	4.26518
2	0947194	Aircraft pilots	3.73458
3	0947193	Ships' chief engineers, engineers (except fishing boats)	3.52355
4	0529109	Launderers and fullers	3.41528
5	0206028	Clinical laboratory technicians	3.27794
6	0838146	Metal machine tools workers	2.66634
7	0949201	Construction, well-drilling machinery operators	2.54609
8	0206027	Diagnostic radiographers	2.50464
9	0841170	Transportation machinery maintenance and repair workers (except automobiles)	2.49934
10	0215067	Communication equipment operators	2.26050
11	0735133	Livestock farm workers	2.25500
12	0206021	Dental surgeons	2.17085
13	0948195	Conductors	2.13757
14	0839160	Rubber, plastic product manufacturing workers	2.09078
15	0839159	Printing and bookbinding workers	2.06705
16	0531112	Restaurateurs, restaurant managers	2.04822
17	0839156	Beverage and cigarette manufacturing workers	2.03018
18	0838148	Ironworkers, boilermakers	2.01544
19	0839155	Food manufacturing workers	1.95393
20	0841169	Automobile maintenance and repair workers	1.95382
Nonroutine manual task			
1	0206025	Midwives	3.25320
2	0634129	Firefighters	3.24385
3	0206029	Physiotherapists, occupational therapists	2.94723
4	0207036	Childcare workers	2.51884
5	0206026	Nurses (including assistant nurses)	2.40400
6	0210049	Special needs education school teachers	2.33402
7	0527102	Home visiting care workers	2.10950
8	0533120	Travel and tourist guides	2.10209
9	0528104	Other healthcare service workers	2.09604
10	0634127	Police officers and maritime safety officials	2.09038
11	0210045	Kindergarten teachers	1.87894
12	0206024	Public health nurses	1.82402
13	1050213	Railway line construction workers	1.81300
14	0526100	Other domestic support service workers	1.74152
15	0841170	Transportation machinery maintenance and repair workers (except automobiles)	1.73163
16	0206034	Masseurs, chiropractors, acupuncturists, moxacauterists and judo-orthopedists	1.61078
17	0207037	Other social welfare specialist professionals	1.54492
18	0206022	Veterinary surgeons	1.47353
19	0214059	Dancers, actors, directors and performers	1.41272
20	0206030	Certified orthoptists, speech therapists	1.40601

(Source) Author's calculation.

Table B1. The number of occupations in the datasets

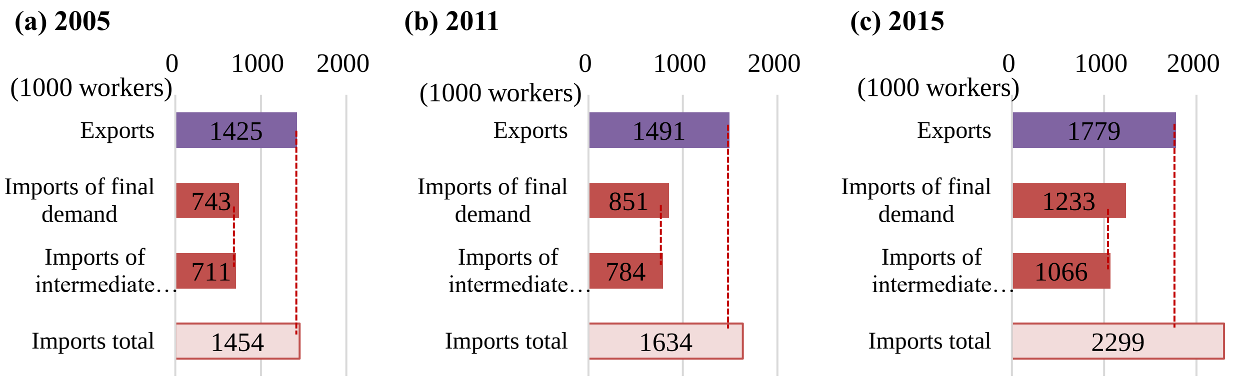
	Jobtag	2015 IO	2011IO	2005 IO
No. of occupation	484	227	227	269
No. of occupation with available information	415	175	175	173
No. of occupation with unavailable information	69	52	52	96
No. of sectors	--	107	108	108
No. of manufacturing sectors	--	53	54	55

Figure B1. Comparison of value of trade from 2005 to 2015



(Source) Author's calculation.

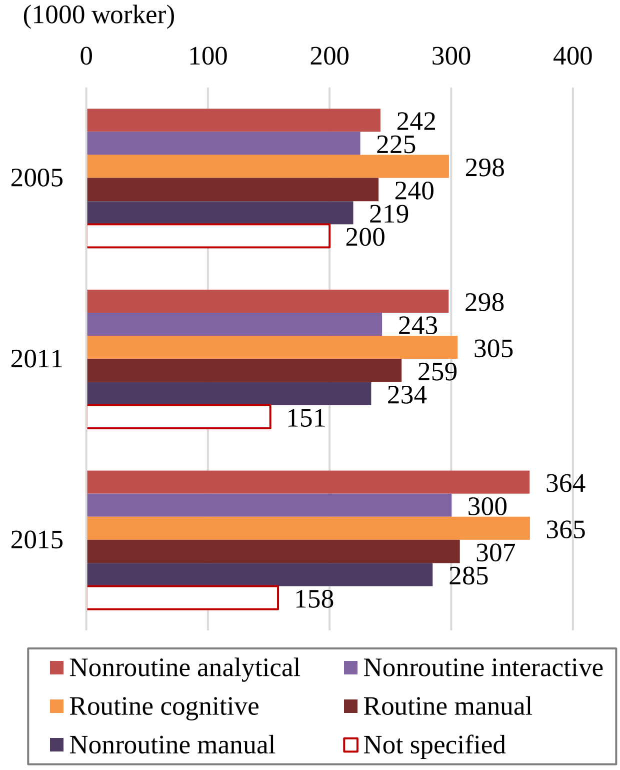
Figure B2. Comparison of the sum of task content of trade from 2005 to 2015



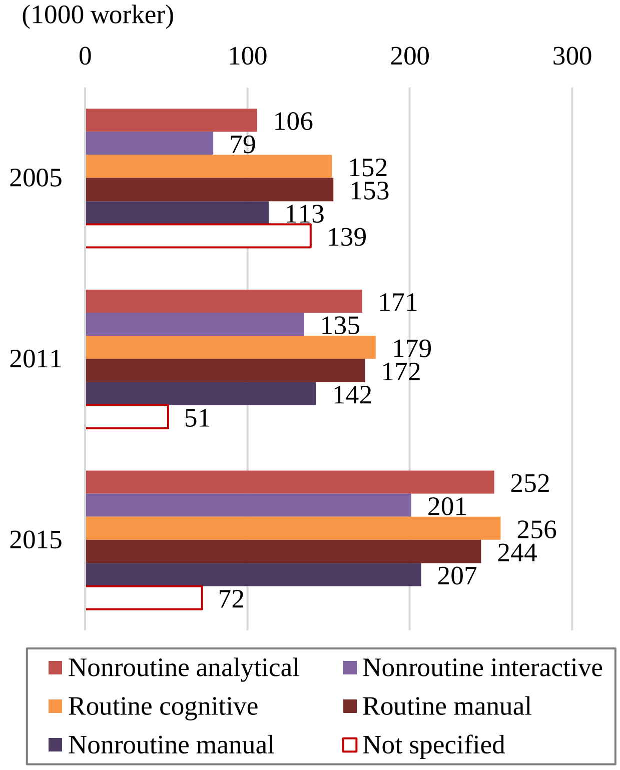
(Source) Author's calculation.

Figure B3. Task content of trade for manufacturing

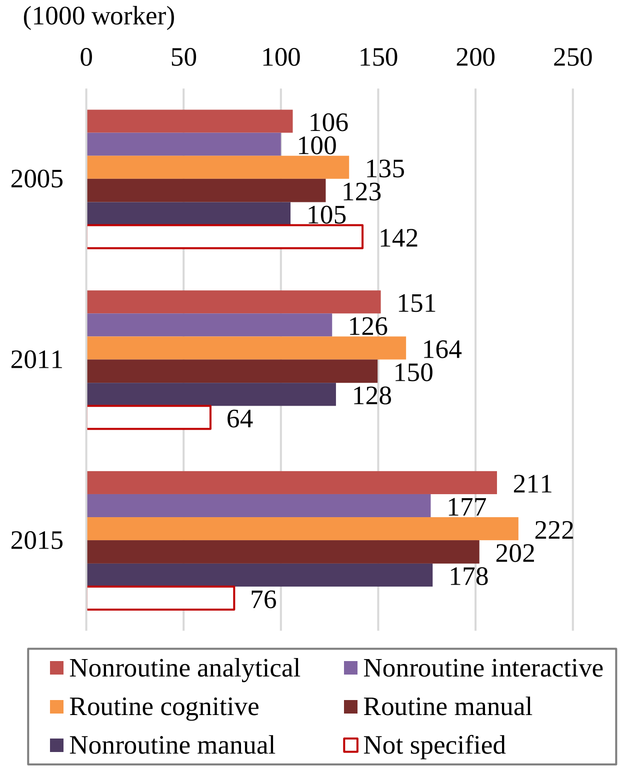
(a) Exports



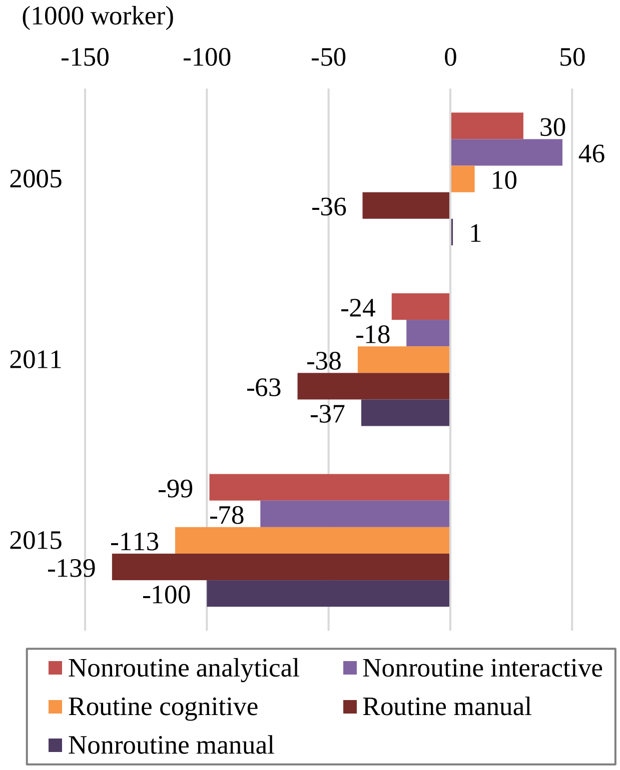
(b) Imports of final demand



(c) Imports of intermediate input

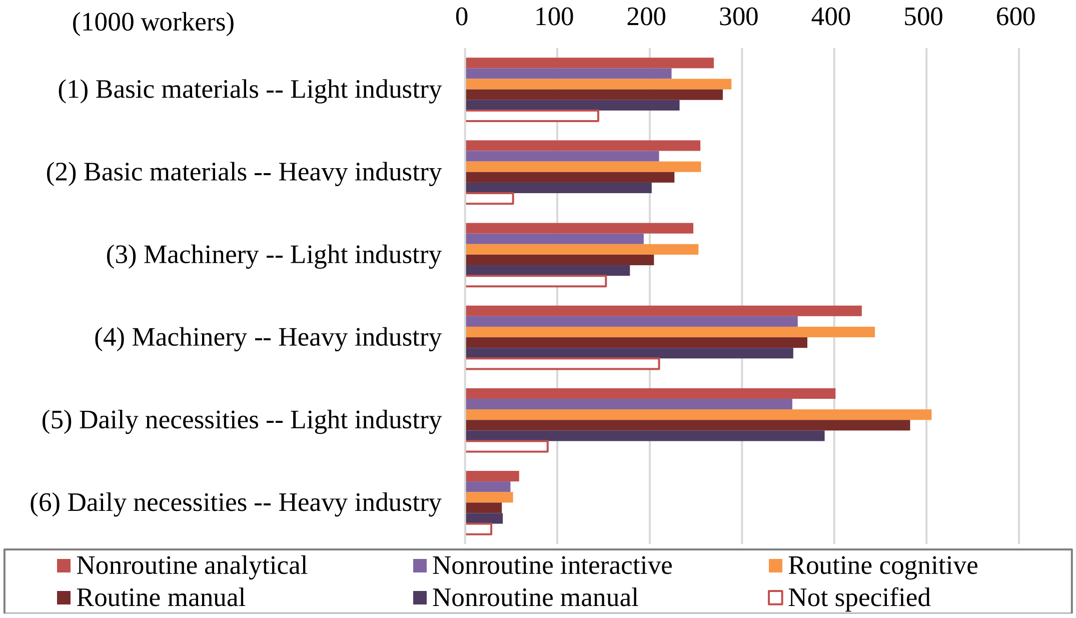


(d) Net exports



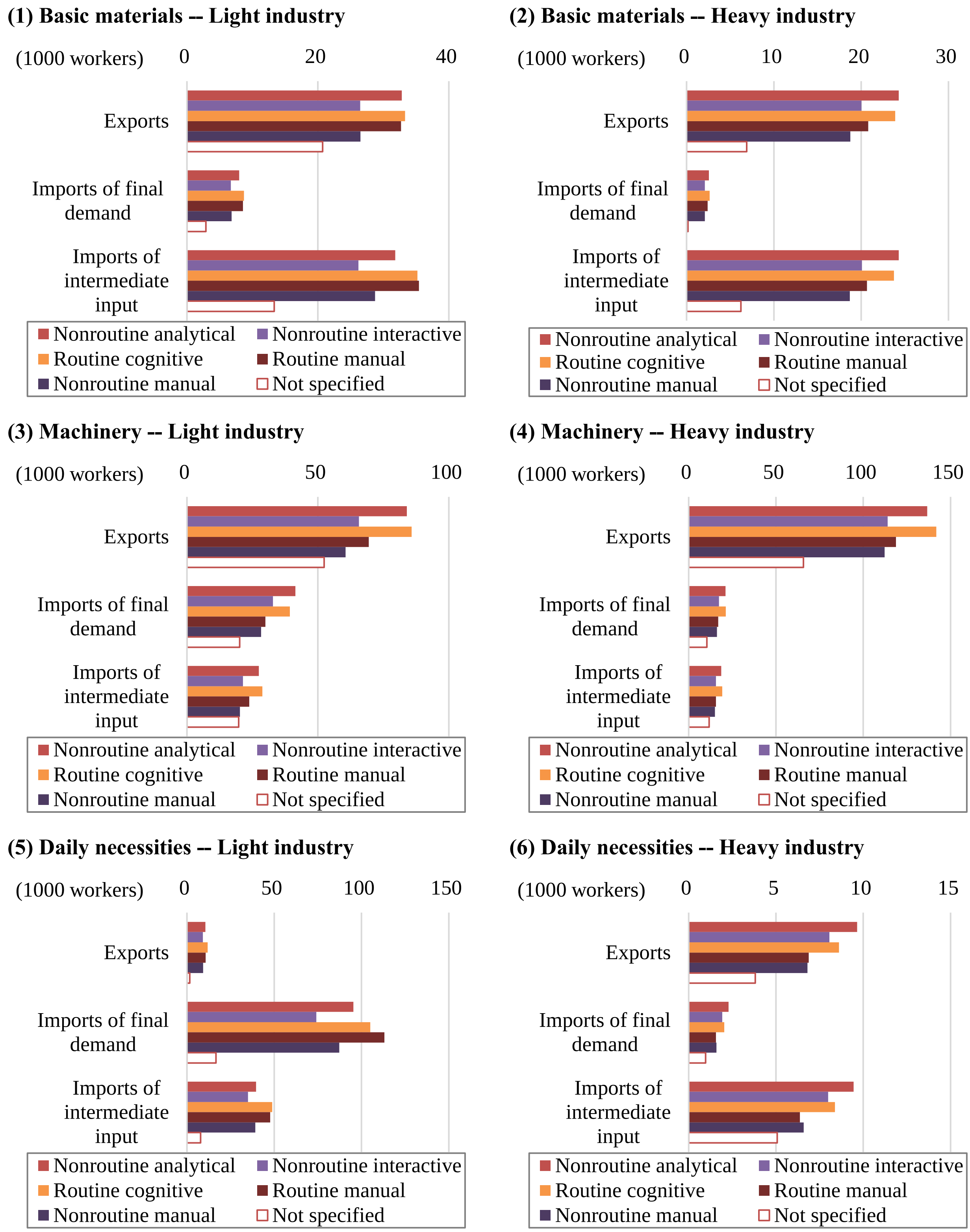
(Source) Author's calculation.

Figure B4. Task content for domestic production by manufacturing group, 2011



(Source) Author’s calculation.

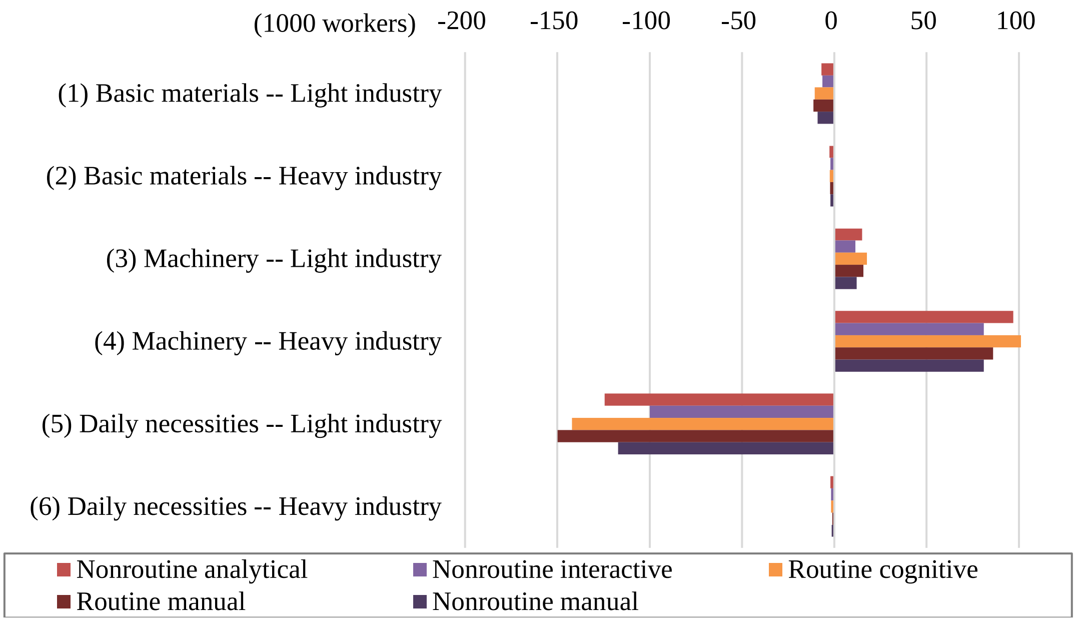
Figure B5. Task content of trade by manufacturing group, 2011



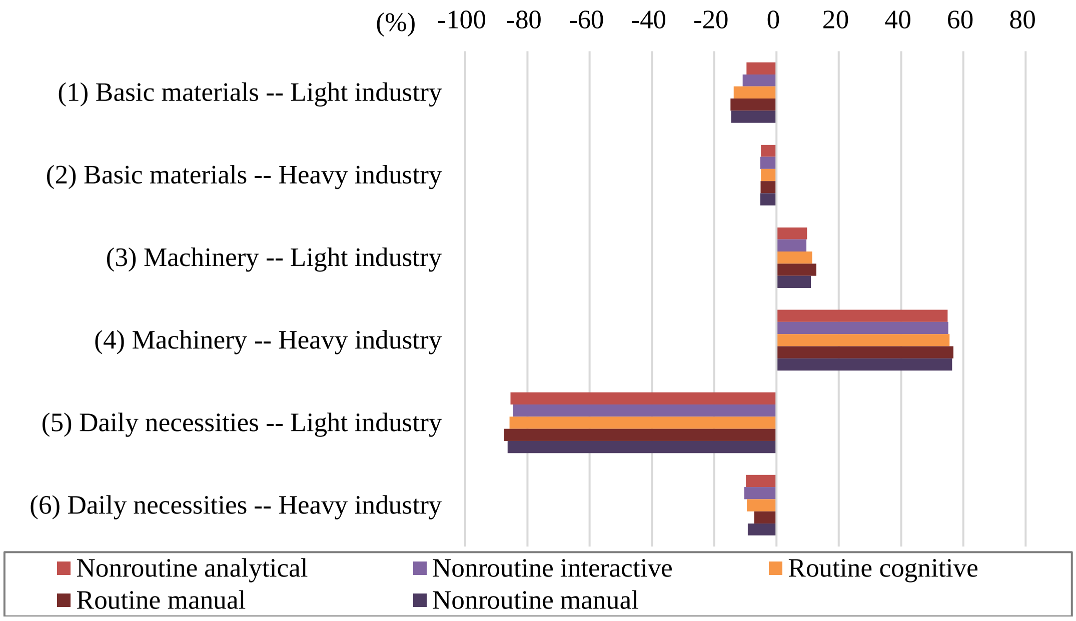
(Source) Author's calculation.

Figure B6. Net exports of task content of trade by manufacturing group, 2011

(a) Volume (1000 workers)

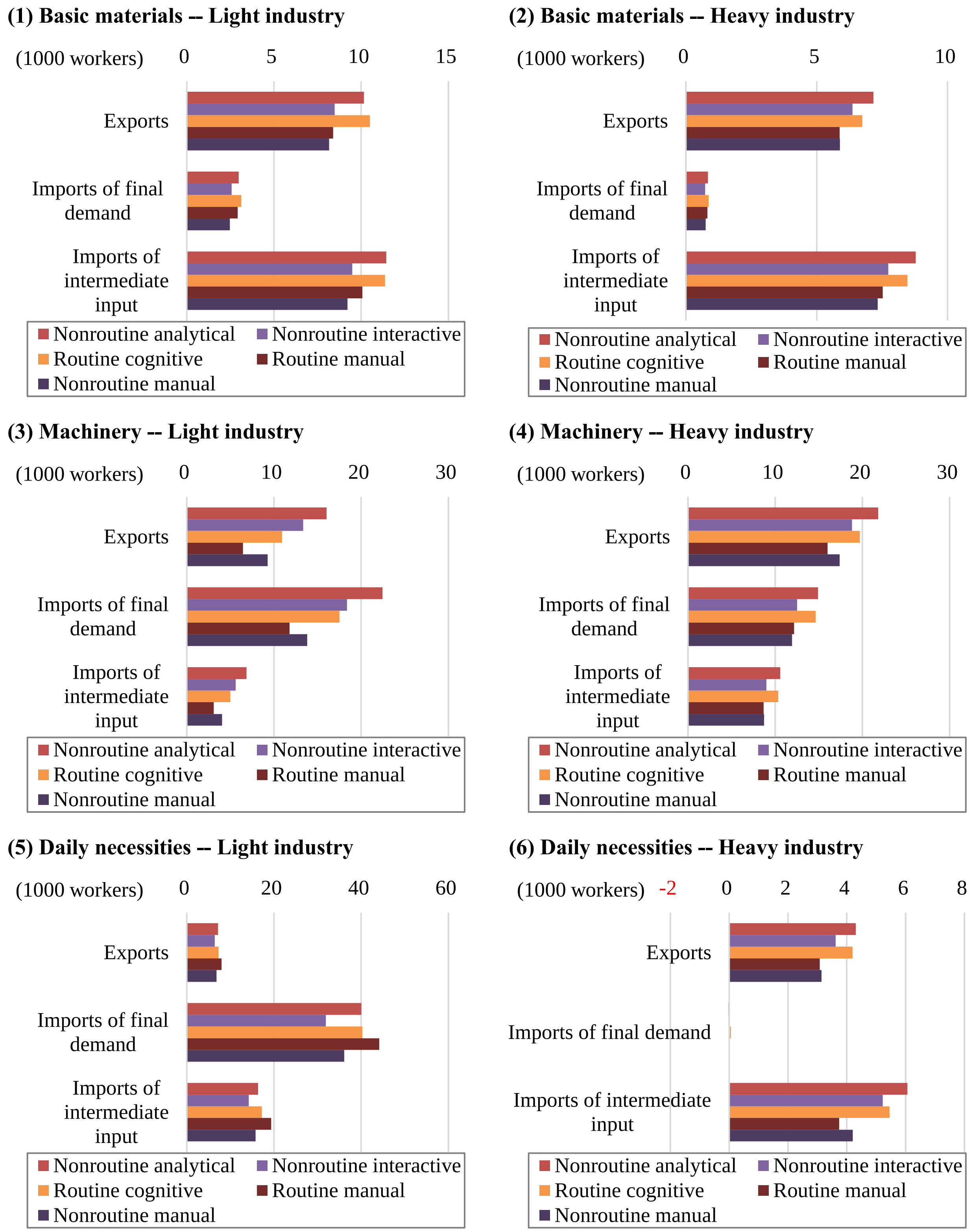


(b) Ratio to total trade (%)



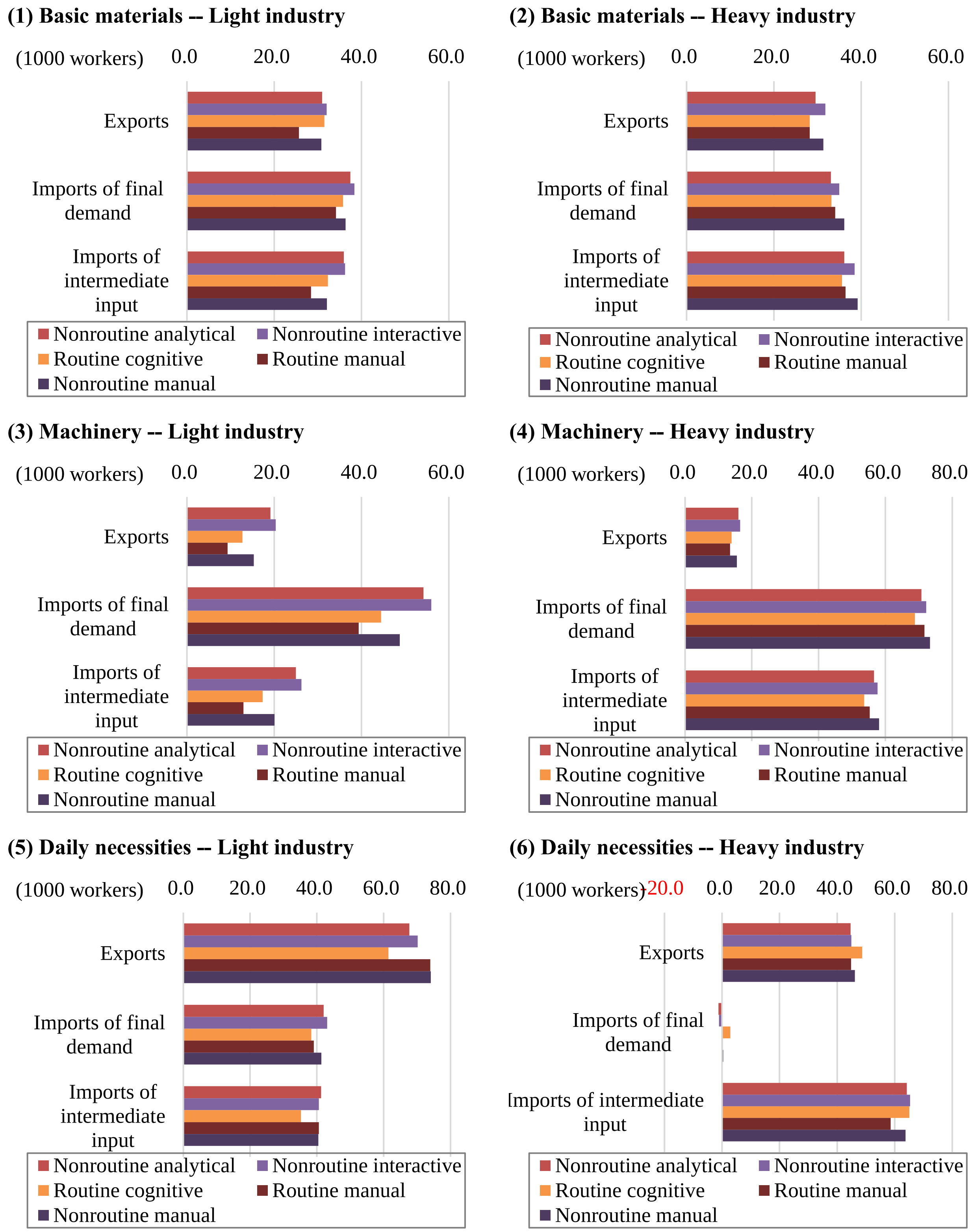
(Source) Author’s calculation.

Figure B7. Growth of task content of trade from 2011 to 2015 by manufacturing group



(Source) Author’s calculation.

Figure B8. Growth rate of task content of trade from 2011 to 2015 by manufacturing group



(Source) Author's calculation.