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ICT, Offshoring, and the Demand for Part-time Workers: The Case of Japanese Manufacturing*

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Abstract

This paper examines the effects of information and communication technology (ICT) and offshoring on the skill demand in Japanese manufacturing. One of the contributions of this paper is that we focus explicitly on the demand for low-wage part-time workers (i.e., low skilled workers). Estimating a system of variable factor demands for the period 1980–2011, we found that industries with higher ICT stock shifted demand from middle-low to middle-high skilled workers. Offshoring is associated with the increasing demand for high skilled workers but it has insignificant effects on the demand for middle-high, middle-low, and low skilled workers. The results together suggest that the increasing demand for low-wage part-time workers can be attributable to ICT in Japan.

Key words: Offshoring; Information and Communication Technology; Skills; Part-time Workers; Polarization
JEL classification codes: F14; J31

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1 Introduction

With the growing demand for skilled workers relative to unskilled workers, the wage inequality between skilled and unskilled workers is increasing in many countries. Theoretically, the increases in the relative demand for skilled workers can be explained by both offshoring and skill-biased technological change due to the use of computers and other high-tech equipment (Feenstra, 2010).[1] Determining which of these explanations account for the changes is an empirical question.[2] Accordingly, several studies have examined the effects of skill-biased technological change and offshoring on skill demand.

Along this line of the literature, this paper examines the effects of information and communication technology (ICT) and offshoring on the skill demand in Japanese manufacturing. Our motivation for this research comes from two strands of the literature. The first strand is the studies that estimate the system of labor demands, controlling for the effects of skill-biased technological change and offshoring simultaneously.[3] This approach was first proposed by Hijzen et al. (2005) that examined the skill demand in the United Kingdom. Ahn et al. (2008) applied this framework to Japan and Korea.[4] Using detailed industry data in Japan and Korea between 1988 and 2002, they found that the labor demand shifted to skilled workers in Japanese manufacturing due to offshoring.

Their study did not explicitly focus on low-wage part-time workers although their study contributes to the literature. As we will see in Section 3, the average wages of the Japanese

[1] Throughout this paper, we abuse terminology and freely interchange the terms "international (or foreign) outsourcing" and "offshoring," as has been the practice in the empirical studies on this issue although, strictly speaking, they are slightly different concept. For more detail, see (Feenstra, 2010, pp.5–6).

[2] See Berman et al. (1998) and Feenstra and Hanson (1999) for the theoretical explanation on the effects of offshoring and skill-biased technological change on the relative labor demand (and relative wages).

[3] Another approach is to estimate a single cost function rather than the system of cost functions. See, for example, Sasaki and Sakura (2005) and Yamashita (2008). This paper focuses on the system of cost functions because the demand for skilled and unskilled workers is determined simultaneously.

[4] A more recent study by Foster-McGregor et al. (2013) examined the labor demand for 40 countries, including Japan. However, because their main interest is on the cross-country comparisons, they did not focus explicitly on Japan.

manufacturing workers can be classified into four groups: 1) university graduates; 2) college or high school graduates; 3) junior-high school graduates; and 4) part-time workers. Because the share of part-time workers is increasing while the growth of their wages remains low, including part-time workers is important in the context of Japanese labor market.

The other strand of the literature is the study of part-time workers. Several studies examined the supply and wages of part-time workers in Japan. However, only a few studies focused on the demand for them. An example of such study is Gaston and Kishi (2007). One of their research questions is why firms *increasingly* employ part-time workers in jobs traditionally offered to full-time workers. Using the establishment data for the period between 1999 and 2001, they found that "manufacturing firms are outsourcing in lieu of hiring domestic part-time workers" (p. 435). Although their study presented interesting finding, their study did not control for the effect of technological change. Besides, it is not clear why the demand for part-time workers *increased* rather than *decreased*, despite the fact that manufacturing firms increased outsourcing.

Building upon these two strands of literature, this paper examines the effects of offshoring and skill-biased technological change on skill demand in Japanese manufacturing. Our study extends the previous studies in four ways. First, our study utilized more detailed skill classification than that of previous studies. Specifically, we focus explicitly on low-wage part-time workers, which is, to the best of our knowledge, the first attempt in the literature on the effect of offshoring and skill-biased technological change on skill demand.

Second, this paper improves the measurement of skill-biased technological change. Several studies including Ahn et al. (2008) utilized R&D expenditure for the proxy of skill-biased technological change.[5] However, R&D expenditure is not necessarily an appropriate proxy the use of computers or other high-tech equipment. One of the reasons is that R&D ex-

[5]Foster-McGregor et al. (2013) utilized industry-country specific time trend to control for the effect of technological change.

penditure is generally measured by flow while computer equipment is measured by stock. Theoretically, the inputs of the production function should be measured by stock. If R&D is measured by flow, the accumulation of experience and knowledge from R&D in the previous years will be ignored completely. To overcome this problem, a more recent study by Michaels et al. (2014) utilized information and communication technology (ICT) stock as a proxy for skill-biased technology change. ICT stock is a more appropriate proxy for skilled biased technological change because it includes both computers and other high-tech equipment and it is measured by stock. Following Michaels et al. (2014), we utilize ICT capital stock as a proxy.[6]

Third, we tested various measures of offshoring to check the robustness of the results.[7] This allows us to enhance the credibility of our analysis. Finally, our study covers the longer period (i.e., from 1980 to 2011) than that of other studies, including more recent years. Our study presents a comprehensive picture of the Japanese manufacturing for the last 30 years. Moreover, our study is the latest update of the studies on the effects of ICT and offshoring on the skill structure in Japan.

The rest of the paper is organized as follows. Section 2 describes the empirical framework. Section 3 explains the data used in this paper. In Section 4, we present the estimation results. A summary and concluding remarks are presented in Section 5.

[6]Michaels et al. (2014) also examined the effects of offshoring and skill-biased technological change for 11 countries, including Japan. However, their analysis is based not on system but on a single factor demand function.

[7]Note that Michaels et al. (2014) applied the US import-use matrix in 1987 to other countries in other years. This is a problem because the import-use structure is basically constant over the period. We relax this assumption in our empirical analysis, allowing for the changes in import-use matrix over the period.

2 Econometric Methodology

2.1 Model

Let i be the index of industry ($i = 1, ..., N$); j be the index of factor ($j = 1, ..., J$); k be the index of fixed input or output ($k = 1, ..., K$); and r be the index of proxy for technological change ($r = 1, ..., R$). For the ease of presentation, we omit time subscript t, unless otherwise noted. Assume that the industry cost function can be represented by a translog form, which is twice differentiable, linearly homogenous, and concave in factor prices. The cost function of industry i, C_i, can be represented as follows:

$$
\begin{aligned}
\ln C_i(w, x, z) &= \alpha_0 + \sum_{j=1}^{J} \alpha_j \ln w_{ij} + \sum_{k=1}^{K} \beta_k \ln x_{ik} + \sum_{r=1}^{R} \gamma_r z_r \\
&+\frac{1}{2}\sum_{j=1}^{J}\sum_{s=1}^{J} \alpha_{ij} \ln w_{ij} \ln w_{is} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{kl} \ln x_{ik} \ln x_{il} + \frac{1}{2}\sum_{r=1}^{R}\sum_{q=1}^{R} \gamma_{rq} z_{ir} z_{iq} \\
&+\frac{1}{2}\sum_{j=1}^{J}\sum_{k=1}^{K} \delta_{jk} \ln w_{ij} \ln x_{ik} + \frac{1}{2}\sum_{j=1}^{J}\sum_{r=1}^{R} \delta_{jr} \ln w_{ij} z_{ir} + \frac{1}{2}\sum_{k=1}^{K}\sum_{r=1}^{R} \delta_{kr} \ln x_{ik} z_{ir}, \qquad (1)
\end{aligned}
$$

where w_{ij} is factor prices for factor j in industry i; x_{ik} is fixed input or output k in industry i; z_{ir} is technological change for proxy r.

Assume the constant returns to scale technology. The variable cost function is then linearly homogeneous in variable factor prices:

$$\sum_{j=1}^{J} \alpha_j = 1 \text{ and } \sum_{j=1}^{J} \alpha_{js} = \sum_{s=1}^{J} \alpha_{sj} = \sum_{j=1}^{J} \delta_{jk} = \sum_{j=1}^{J} \delta_{jr} = 0. \qquad (2)$$

Without loss of generality, symmetry implies $\alpha_{js} = \alpha_{sj}$. Differentiating the translog cost function with respect to factor prices, we have the cost share of factor j in total variable costs:

$$S_{ij} = \alpha_j + \sum_{j=1}^{J} \alpha_{js} \ln w_{ij} + \sum_{j=1}^{J} \delta_{jk} \ln x_{ik} + \sum_{r=1}^{R} \alpha_{jr} z_{ir}, \tag{3}$$

where $S_{ij} = \partial \ln C_i / \partial \ln w_{ij} = (w_{ij}/C_{ij})(\partial C_i / \partial w_{ij}) = w_{ij} x_{ij} / C_i$ and $\sum_{j=1}^{J} S_{ij} = 1$.

Adding time subscript t and error term μ_{ijt} and taking into account the industry-factor specific fixed effects α_{ij}, regression equation is written as:

$$S_{ijt} = \alpha_{ij} + \sum_{j=1}^{J} \alpha_{js} \ln w_{ijt} + \sum_{j=1}^{J} \delta_{jk} \ln x_{ikt} + \sum_{r=1}^{R} \alpha_{jr} z_{irt} + d_t + \mu_{ijt}. \tag{4}$$

Following Hijzen et al. (2005), we use skilled and unskilled labor inputs as well as intermediate inputs as for variable factors. The definition of skilled and unskilled labor is defined in the next section. For fixed inputs x_{ikt}, we use the non-ICT capital stock. For skill-biased technological change z_{irt}, we focus on the change due to offshoring and the ICT capital stock. A full set of time dummies d_t is included to capture the economy-wide technological change over time.

2.2 Elasticities

The elasticity of factor demand j with respect to a change in factor prices is:

$$\varepsilon_{js} = \frac{\partial \ln v_j}{\partial \ln w_s} = \frac{\hat{\alpha}_{js}}{s_j} + s_s - \phi_{js}, \tag{5}$$

where $\phi_{js} = 1$ if $j = s$, $\sum_{j=1}^{N} \varepsilon_{js} = 0$, and $\hat{\alpha}_{js}$ is an estimated parameter value in equation (4). The elasticity of factor demand j with respect to a change in non-ICT capital stock or output is:

$$\varepsilon_{jk} = \frac{\partial \ln v_j}{\partial \ln x_{sk}} = \frac{\hat{\delta}_{jk}}{s_j}, \tag{6}$$

where $\sum_{k=1}^{M} \varepsilon_{jk} = 1$ and $\hat{\delta}_{jk}$ is an estimated parameter value in equation (4). The elasticity of factor demand with respect to skill-biased technological change due to offshoring is:

$$\varepsilon_{jr} = \frac{\partial \ln v_j}{\partial z_r} = \frac{\hat{\alpha}_{jr}}{s_r}, \tag{7}$$

where $\sum_{r=1}^{R} \varepsilon_{jr} = 1$ and $\hat{\alpha}_{jr}$ is an estimated parameter value in equation (4).

3 Trends in Labor Markets, ICT, and Offshoring in Japan

3.1 Data

Outputs and inputs

Data on outputs, inputs, and their prices are obtained from the Japan Industrial Productivity database 2014 (JIP database 2014), which was compiled as part of a research project at the Research Institute of Economy, Trade and Industry (RIETI). The database is constructed to estimate total factor productivity (TFP). The database includes detailed information on sectoral outputs, inputs, and their prices. The database runs annually from 1970 to 2011, consisting of 52 manufacturing and 56 nonmanufacturing industries.[8]

From the JIP database 2014, we use gross outputs, ICT capital stock, non-ICT capital stock, and intermediate inputs.[9] All of these variables are valued at constant prices (year 2000). We also obtain nominal intermediate inputs from the database to compute the cost shares. Labor inputs are also obtained from the database. The labor inputs consist of

[8] The database is downloadable from `http://www.rieti.go.jp/en/database/JIP2014/index.html` For more details about the JIP database, see Fukao et al. (2007).

[9] ICT capital stock and non-ICT capital stock are used as fixed inputs because the user cost of capital is not available by the type of capital. Besides, it is common to assume that capital is (quasi-)fixed input in estimating a production function. See, for example, Kiyota et al. (2009) and Dobbelaere et al. (2015) for the case of Japanese firms.

the following six categories: 1) university graduates or higher; 2) college graduates; 3) high school graduates; 4) junior high school graduates; 5) part-time workers; and 6) self-employed workers. The educational level of the last two categories is not available.

Figure 1 presents the disparities in average wages per hour across the above six worker categories in Japanese manufacturing in 1980 and 2011.[10] Each category is represented by a horizontal line segment, the length of which indicates the worker share of the labor force. The average hourly wage is indicated by the vertical position.

=== Figure 1 ===

There are three notable findings. First, the average wages are different across educational level and worker types. Figure indicates that, in 2011, the workers can be classified into four groups: 1) high wage category that consists of university graduates (4,159 JPY); 2) middle-high wage category that consists of high school and college graduates (2,954 JPY and 2,859 JPY, respectively); 3) middle-low wage category that consists of junior-high school graduates (2,320 JPY); and 4) low wage category that consists of part-time workers and self-employed workers (923 JPY and 792 JPY, respectively). The average wages of part-time and self-employed workers is less than half of that of junior-high school graduates. Difference between high school and college graduates and junior-high school graduates is also not negligibly small in 2011.

Second, the share of part-time workers in manufacturing employment expanded significantly. The employment share of part-time workers grew from 7.7 percent in 1980 to 17.7 percent in 2011.[11] Noting that the share of university graduates was 18.5 percent in 2011, the size of part-time workers is not negligible in Japanese manufacturing employment.

Third, both the share of the highest wage category (i.e., university graduates) and that of the lowest wage categories (i.e., self-employed and part-time workers) increased from 1980

[10] Detailed description about the data is provided in Section 3.

[11] Figure A1 presents the share of workers, by education and type of workers from 1970 to 2011 in more detail.

to 2011. On the flipside, the share of the middle wage categories (i.e., college, high-school, and junior high-school graduates) declined over the period. This result may imply the "job polarization" of the labor market, where there is a simultaneous growth of high-education, high-wage jobs at one end and low-education, low-wage jobs at the other end, both at the expense of middle-wage, middle education jobs (Goos and Manning, 2007).

Figure 2 presents the average wage per hour, by above six categories from 1970 to 2011. The wage is valued at current prices. We highlight two points. First, the average hourly wages of part-time and self-employed workers are almost constant from the early 1990s even though that of junior-high school graduates grew in the 1990s (and gradually decline afterward). Assuming that the average hourly wages reflect the marginal product of labor, these results imply that the part-time and self-employed workers are different from other worker categories. Combining the part-time and self-employed workers with other worker categories would thus be a problem in analyzing the skill demand in Japanese manufacturing.

=== Figure 2 ===

Second, the wage gap between college/high school graduates and junior-high school graduates starts expanding from the 2000s. The average wage of junior-high school graduates was almost the same as that of college and high-school graduates from 1990 to 2000, but it gradually declined from 2000. As a result, the average wage of junior-high school graduates was 20 percent lower than that of college/high school graduates in 2011. This result also implies that it is important to cover the 2000s to examine the recent expansion of wage gap between college/high school graduates and junior-high school graduates.

Note that self-employed workers are employer rather than employee. It is not clear whether the demand for employers can be estimated in the same framework as the demand for employees. Based on these observations, this paper classifies labor inputs into four groups: 1) High skilled workers which are defined as university graduates; 2) Middle-high skilled workers which are defined as college or high school graduates; 3) Middle-low skilled workers which are defined as junior-high school graduates; and 4) Low skilled workers which are defined as part-time workers. We exclude self-employed workers from the analysis for the reason noted above.

Offshoring

The offshoring is computed using import-use matrices of input–output tables for manufacturing industries between 1980 and 2011.[12] The input–output table is available every five year between 1980 and 2005, and 2011. Unlike Michaels et al. (2014) that applied the US import-use matrix in 1987 to other countries in other years, we allow the import-use matrix changes over the period.[13]

There are two types of offshoring in the literature. One is the narrow offshoring $S^N_{O,jt}$ and the other is the broad offshoring $S^B_{O,jt}$. The narrow offshoring is defined as the imported intermediate inputs in an industry i from the same industry (which corresponds to diagonal terms of the import-use matrix) divided by the industry j's tradable intermediate inputs M_{jt}:

$$S^N_{O,jt} = \frac{O_{i=j,t}}{\sum_{i=\text{tradables}} M_{ijt}}, \tag{8}$$

where $O_{i=j,t}$ stands for imported intermediate inputs in industry j in year t only; and M is intermediate inputs from industry i to industry j in year t. Tradable intermediate inputs mean both domestic and imported intermediate inputs from agricultural and manufacturing industries.[14] Feenstra and Hanson (1999) called this measure of offshoring as narrow measure

[12]The construction of the import-use matrices are explained in the Appendix.

[13]Note that the import-use matrix is not available in every year in many countries. Some studies such as Hijzen et al. (2005) and Ahn et al. (2008) employed linear extrapolation (or interpolation) for the missing years to fill the gaps. In this paper, however, we do not employ the linear extrapolation (or interpolation). The changes in imports seemed to be non-linear because the missing years include such years as the Asian financial crisis in 1997 and the global financial crisis in 2008–09.

[14]For some industries such as Seafood products and Livestock products, inputs mainly come from agricultural industries. If we focus on manufacturing intermediate inputs, these industries tend to show high

of offshoring.[15]

The broad measure is defined as all the imported intermediate inputs in an industry j divided by the industry j's total tradable intermediate inputs M_{jt}:

$$S^B_{O,jt} = \frac{\sum_{i=1}^{J} O_{ijt}}{\sum_{i=\text{tradables}} M_{ijt}}. \tag{9}$$

Feenstra and Hanson (1999) prefers the narrow measure to the broad measure because the essence of fragmentation, which necessarily takes place within the industry, is closer in the narrow measure to the broad measure. In the baseline model of our analysis, we utilize the narrow definition of offshoring. In Section 5, we also use the broad measure to check the robustness of our results.

3.2 Descriptive statistics

Tables 1 and 2 report some summary statistics for the labor market and production data for 1980–2011. Table 1 presents the average cost shares of high skilled, medium-high skilled, medium-low skilled, and low skilled workers (s_H, s_{MH}, s_{ML}, and s_L, respectively) and intermediate inputs (s_M) at the level of the industry (52 manufacturing industries from 1980 to 2011). The major findings are twofold. First, on average, intermediate inputs indicate the largest cost shares, accounting for 76.4 percent of total variable costs. Second, the cost share of the labor inputs varies across groups, ranging from 1.5 percent for low skilled to 12.5 percent for middle-high skilled workers.

=== Tables 1 & 2 ===

offshoring index because their manufacturing inputs are low. In the baseline model, therefore, we take into account agricultural intermediate inputs. To check the robustness of our results, Section 4.2 utilizes different measures of denominator.

[15] Strictly speaking, Feenstra and Hanson (1999) utilized non-energy intermediate inputs for the denominator.

Table 2 presents average annual changes for the quantities and prices of inputs and output between 1980 and 2011. Two messages stand out from this table. First, the cost shares were fairly stable over the sample period. The annual percentage change is less than 1 percent for all the cost shares. This result is quite similar to that in the United Kingdom reported in Hijzen et al. (2005). Second, however, some of the input quantities and flexible factor prices indicate large change. The demand for high skilled worker grew at 1.3 percent per year whereas the demand for the middle-low skilled workers declined at 7.7 percent per year. The average wage grew at around 1.7 percent for middle-low, middle-high, and high skilled workers whereas at 1.3 percent for low skilled workers. As a result, as we confirmed in Figure 1, the wage gap between low skilled and other types of workers expanded from 1980 to 2011.

Table 3 presents descriptive statistics for broad and narrow offshoring and the share of the ICT capital stock. We also report the difference between the broad and narrow measures. This represents the intermediate inputs from other industries in foreign countries. There are three notable findings. First, the narrow offshoring increased steadily from 2.1 percent in 1980 to 5.7 percent in 2005, although it declined slightly to 5.3 percent in 2011. This implies the increasing importance of offshoring from the mid-1980s. Second, differential and broad offshoring shows slightly different trend. Both measures increased steadily throughout the period. This implies that the results of our analysis may be sensitive to the measurement of offshoring. Although we utilize the narrow definition of offshoring in the baseline model in Section 4.1, we examine how the results are sensitive to the measurement of the offshoring in Section 4.2.

=== Table 3 ===

Finally, the share of the ICT capital stock to total capital stock increased rapidly. The ICT capital share increased from 2.4 percent in 1980 to 12.2 percent in 2005, although it declined to 8.4 percent in 2011. Because the ICT capital stock and offshoring increased over the period, the increase in the relative demand for skilled labor can be explained by offshoring or skill-biased technological change (or both). We now turn to the econometric analysis.

4 Results

4.1 Baseline model

Table 4 presents the estimation results of equation (4). Due to the symmetry constraint, some of the coefficients such as the coefficients of w_{MH} in L_H equation and w_H in L_{MH} equation are the same. We test the null hypothesis that the error terms across equations are contemporaneously uncorrelated, using the Breusch–Pagan test. The null hypothesis is rejected at the 1 percent level. Because the error terms across equations are correlated with each other, the system of equations should be estimated by the SUR. We also test the null hypothesis that the fixed effect equals zero, which is rejected at 1 percent level in all equations. This implies that the SUR with fixed effects performs better than the SUR without fixed effect. It is important to control for unobserved industry heterogeneity in estimating labor demand.

=== Table 4 ===

Table 5 presents the estimated elasticities of factor demands. The elasticities are computed, using the estimated parameters and simple average cost shares across industries and years. Four findings are evident from this table. First, the own price elasticities are negative and generally statistically significant (in italic in Table 5). This means that, on average, a necessary (but not sufficient) condition for concavity in factor prices is satisfied. In other words, the cost functions are well behaved in the sense that they are consistent with a standard economic theory (Hijzen et al., 2005, p.870). Second, regardless of the skill types, increases in wages have positive effects on the demand for materials. This implies that labor and material substitute for each other.

=== Table 5 ===

Third, the offshoring has significantly positive effects on the demand for high skilled workers. However, the effect of offshoring on the demand for low, middle-low, and middle-high skilled workers is insignificant. This result suggests that the offshoring is not harmful for workers although only high skilled workers can have benefit from it. The result is consistent with the findings of the previous studies such as Kambayashi and Kiyota (2015) and Yamashita and Fukao (2010) which found that the negative effects of foreign direct investment on employment were, if any, rather small in Japan.

Finally, the effect of the ICT capital on the demand for middle-high, middle-low, and low skilled workers is significantly positive, significantly negative, and significantly positive, respectively. This result implies that ICT has different effects across skills: it complements the middle-high and low skilled workers but substitutes for the middle-low skilled workers. Industries with higher ICT stock shifted demand from middle-low skilled workers to middle-high skilled and low skilled workers.

The insignificant effect of the ICT capital on the demand for high skilled workers is a bit puzzling. One possible reason may be that the university graduates work for variety of tasks due to their growing supply and tight job market in the lost two decades. Some engage in high skilled non-routine tasks but others engage in less skilled routine tasks. Such heterogeneity in the university graduates may offset the effects of the ICT capital with each other.

In sum, the effects of ICT and offshoring are different across skill types. The demand for middle-low skilled workers has negative effects from ICT. The middle-high and low skilled workers have positive effects from ICT while the high skilled workers have benefits from offshoring. The result is consistent with ICT–based "job polarization."[16] A part of the growing demand for part-time workers thus can be explained by the expansion of ICT.

4.2 Robustness check

In the baseline model, we found that offshoring was not harmful for workers. However, one may be concerned that our results are sensitive to the measurement of the offshoring, sample selection, or additional control variables. This section addresses some of these issues.

4.2.1 Alternative measures of offshoring

First, one may be concerned that our results are attributed to the measurement of the offshoring variable because the trend of the narrow offshoring is slightly different from that of the broad offshoring (Table 3). To address this concern, we estimate equation (4), replacing the narrow offshoring variable with the broad offshoring. All the other independent variables and the estimation method are the same as the baseline model.

The second row in Tables 6 and 7 present the estimation results of offshoring elasticity and ICT capital stock elasticity, respectively. Other elasticities are reported in Table A2. The second row in Table 6 indicates that the offshoring has significantly positive effects on the demand for high skilled workers while significantly negative effects on the demand for middle-high skilled workers. There is no significant effect on the demand for middle-low and low skilled workers.

=== Tables 6 & 7 ===

The second row in Table 7 presents that the ICT capital stock has positive effects on the demand for middle-high and low skilled workers whereas it has negative effects on the

[16] Similarly, Autor (2015) pointed out that "automation and new technology were going to wipe out large numbers of middle class jobs" (p. 3). Ikenaga (2009) also found that the ICT complemented workers with non-routine analytic tasks while substituting them with routine tasks. However, her study did not take into account the effects of offshoring.

demand for middle-low skilled workers. No significant effect is confirmed on the demand for high skilled workers. These results suggest that major messages of the baseline model remain unchanged even when we employ a broad measure of offshoring.

Another concern may be that our results are sensitive to the measurement of the denominator. Although we use total tradable intermediate inputs as denominator, the results may be sensitive to how to measure the denominator. To check the robustness of our results, we use all intermediate inputs and gross output. All the variables and the estimation method are the same as the baseline model (i.e., narrow offshoring).

The third and fourth rows present the results of all intermediate inputs and gross output, respectively. Other elasticities are reported in Tables A3 and A4. The results are generally the same as those of baseline results. The effect of offshoring is significantly positive on the demand for high skilled workers although it turns to be insignificant in the case of the use of gross output. The effect of the ICT capital stock is significantly positive for the demand for middle-high and low skilled workers while significantly negative for the demand for middle-low skilled workers. We thus can conclude that the results are generally robust to the measurement of the denominator of offshoring variable.

4.2.2 Additional control variable

Michaels et al. (2014) found that the effects of offshoring became insignificant once the initial R&D intensity, measured by R&D expenditure to value added ratio, was controlled for. Because our analysis is based on the fixed effect SUR model, the effects of the industry-specific time-invariant factors such as the initial R&D intensity are absorbed by the fixed effect. Nevertheless, one may be worried about whether the technology change z_{ir} can be attributable to offshoring and year fixed effects.

To address this concern, we assume that the technology change z_{ir} depends not only on offshoring but also on R&D intensity, and estimate the regression equation, adding R&D

intensity variable. Due to the difficulty in obtaining R&D stock, following Michaels et al. (2014), we use R&D investment. R&D investment is obtained from the Research and Development, Innovation and Productivity (RDIP) database developed by the National Institute of Science and Technology Policy. In the RDIP database, both nominal and real R&D investment is available for 1973–2008, by the same industry classification as the JIP database. The real R&D investment is valued at 2000 constant prices. We calculate R&D intensity for each industry-year, which is defined as the real R&D investment divided by the real value added. Because the RDIP database is not available after 2008, we focus on the period between 1980 and 2008.[17]

The fifth row in Tables 6 and 7 show the estimation results. Other elasticities are presented in Table A5. Notable findings are twofold. First, the effect of offshoring is significantly positive for high skilled workers and insignificant for middle-high, middle-low, and low skilled workers. This pattern is the same as that in the baseline results.

Second, the effect of ICT is positive for middle-high and low skilled workers, negative for middle-low skilled workers, and insignificant for high skilled workers. This result is also the same as the baseline model. The results suggest that the effects of offshoring and ICT on labor demand are not sensitive to the inclusion of R&D intensity.

4.2.3 Excluding low skilled workers

One may further ask how the results change if we drop low skilled workers. Note that low skilled workers (defined as part-time workers) are classified by the occupational type while middle-low/high and high skilled workers are classified by educational level. Because part-time workers may include all of university, college/high school, and/or junior-high school graduates, strictly speaking, the classification is not consistent with each other. To answer above question, we estimate equation (4), excluding low skilled workers (defined as part-time

[17]Because the RDIP database is not available after 2008 and the (time invariant) initial R&D can be controlled for by the fixed effects, we did not include R&D intensity in the baseline model.

workers) from the sample.[18]

The seventh row in Tables 6 and 7 presents the results of offshoring and ICT capital elasticities, respectively, Table A7 reports other elasticities. The effect of offshoring is significantly positive for high skilled workers. The effect of ICT is significantly positive for middle-high skilled workers while significantly negative for middle-low skilled workers. The results are qualitatively the same as the baseline results. Note, however, that we confirmed significantly positive effects of ICT and offshoring on part-time workers. Without including these workers, one may conclude that both offshoring and ICT have negative effects on the demand for part-time workers because they can be classified as unskilled workers. The result suggests the importance of including low-wage part-time workers in the sample in analyzing the effects of offshoring and ICT.

In sum, we asked whether our results are sensitive to the use of different measures of offshoring, the inclusion of an additional control variable, and the exclusion of low skilled part-time workers. We confirmed the positive and significant effects of offshoring on the demand for high skilled workers in most specifications. We also confirmed that the effect of ICT is significantly positive for middle-high and low skilled workers while significantly negative for middle-low skilled workers in all specifications. Moreover, the effects of offshoring on the demand for low skilled workers are insignificant in all specifications. We thus can conclude that our main messages are generally robust.

5 Concluding Remarks

With the growing demand for skilled workers relative to unskilled workers, the wage inequality between skilled and unskilled workers is increasing in many countries. Determining which of these explanations account for the changes is an empirical question. It is widely believed

[18]The total cost and cost share of variable factors are recalculated accordingly

that low skilled workers are significantly affected by the information and communication technology (ICT) and offshoring in Japan. To answer this question is very important for workers as well as policy makers in Japan.

This paper examines empirically the link between ICT, offshoring, and the skill structure of labor demand in Japan. One of the contributions of this paper is that we focus explicitly on the demand for low-wage part-time workers. Offshoring is calculated using import-use matrices of input-output tables for manufacturing industries between 1980 and 2011. Estimating a system of variable factor demands, we found that offshoring was associated with the increasing demand for high skilled workers. We also found insignificant effects of offshoring on middle-high, middle-low, and low skilled workers. Industries with higher ICT stock shifted demand from middle-low workers to middle-high and low skilled workers, which is consistent with the ICT–based "job polarization." These results are generally robust even when we use different measures of offshoring or we include an additional control variable. The results together suggest that the increasing demand for low-wage part-time workers are attributable to ICT in Japan.

While we found significantly positive effects of ICT on the demand for part-time workers, we could not find the rapid growth of their wages. This is puzzling because, as Autor (2015, p. 5) pointed out, the polarization of the labor market typically associated with the disproportional wage gains to those at the top and at the bottom of the income and skill distribution. Based on the fact that the share of part-time workers is increasing rapidly, clarifying the demand for part-time workers is an important question. This question will be clarified in our future research.

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Appendix: Data

Sources

Data for estimating imported input are obtained from the Input-Output (IO) tables by Ministry of International Affairs and Communications (various years) and the Japan Industrial Productivity (JIP) database. The IO tables, issued every five year by the Statistics Bureau of Japan, include the nominal value of imported inputs. The JIP database provided by the Research Institute of Economy, Trade and Industry is used for deflating from nominal to the real prices. We prepared imported inputs data in every five year between 1980 and 2005, and 2011.

The construction of the import-use matrices

Offshoring variables are calculated from the import-use matrices of IO tables for manufacturing industries between 1980 and 2011. Imported inputs data are provided in the Basic Transaction Matrix of IO table in which the basic sector consists of items with 6-digit column and 7-digit row codes. The transaction of intermediate inputs is reported for domestic and imported inputs separately.

To match the IO industry classification with the JIP industry classification, we aggregate imported input data into 52 manufacturing sectors (i.e., JIP industry classification). The concordance of two classifications relies on "the industry concordance with JSIC, Japan

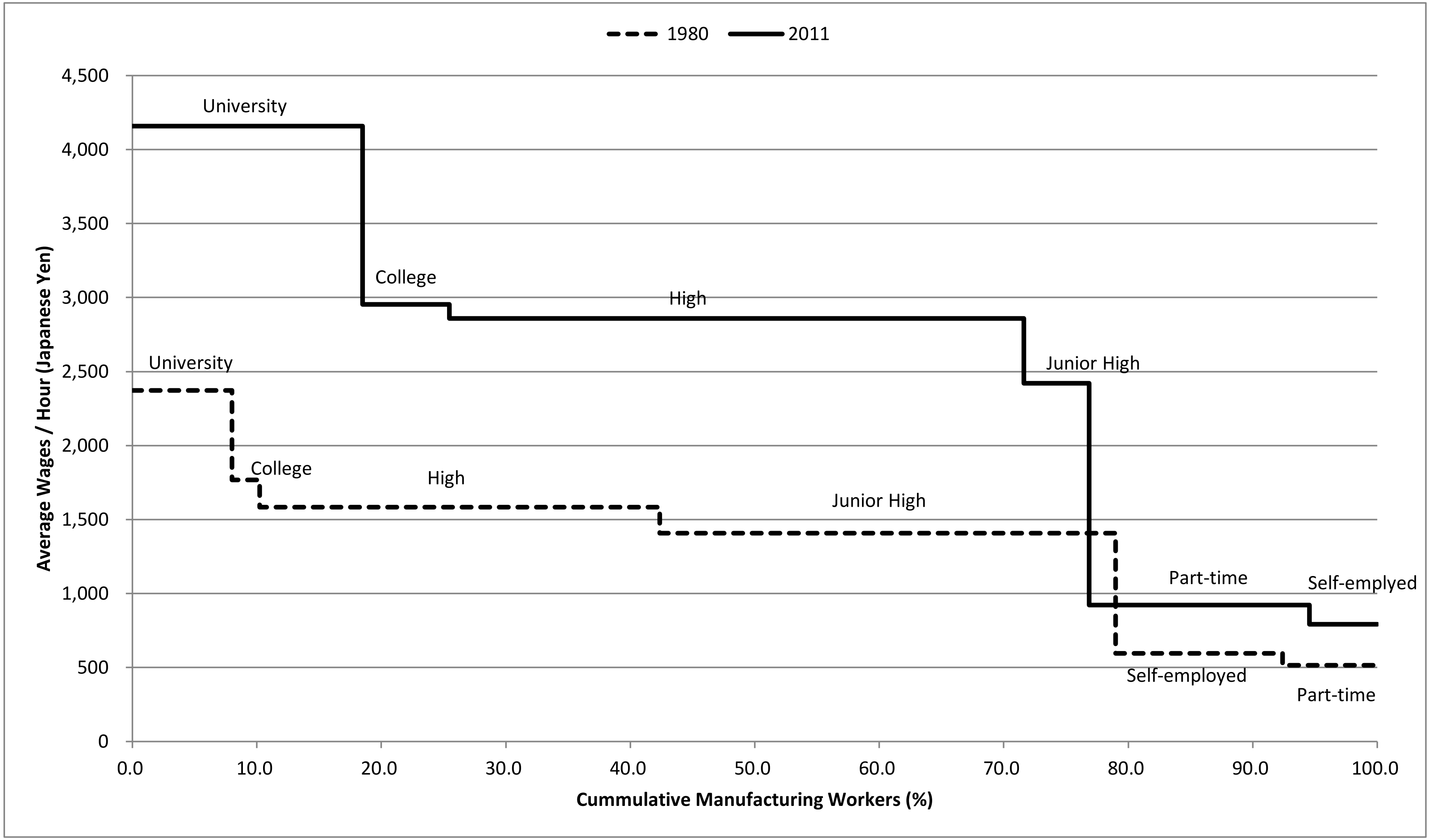
Standard Industrial Classification, and ISIC" provided in the JIP database 2011. The benchmark year of IO basic sector classification for the concordance is 1995 with the table of 403 columns and 519 rows. We modify concordance for other years in order to reflect the revision of the basic sector classification. As for 1980 IO table, "Automobile" and "Automobile parts and accessories" are integrated in one industry. We estimate the import values of these sectors, applying the rate of change from 1985 to 1990 in the same sectors.

In the IO table, only nominal imported inputs are available. We first calculate the share of imported intermediates to total intermediate inputs and then multiply the real total intermediate inputs from the JIP database. Specifically, let θ_{ijt} be the share of nominal imported intermediate inputs of industry j from industry i in year t to nominal total intermediate inputs of industry j,. Denote the real total intermediate inputs of industry j in year t as M_{jt}. To obtain the real imports of industry i from industry j, we use the following calculation:

$$O_{ijt} = \theta_{ijt} \times M_{jt},$$

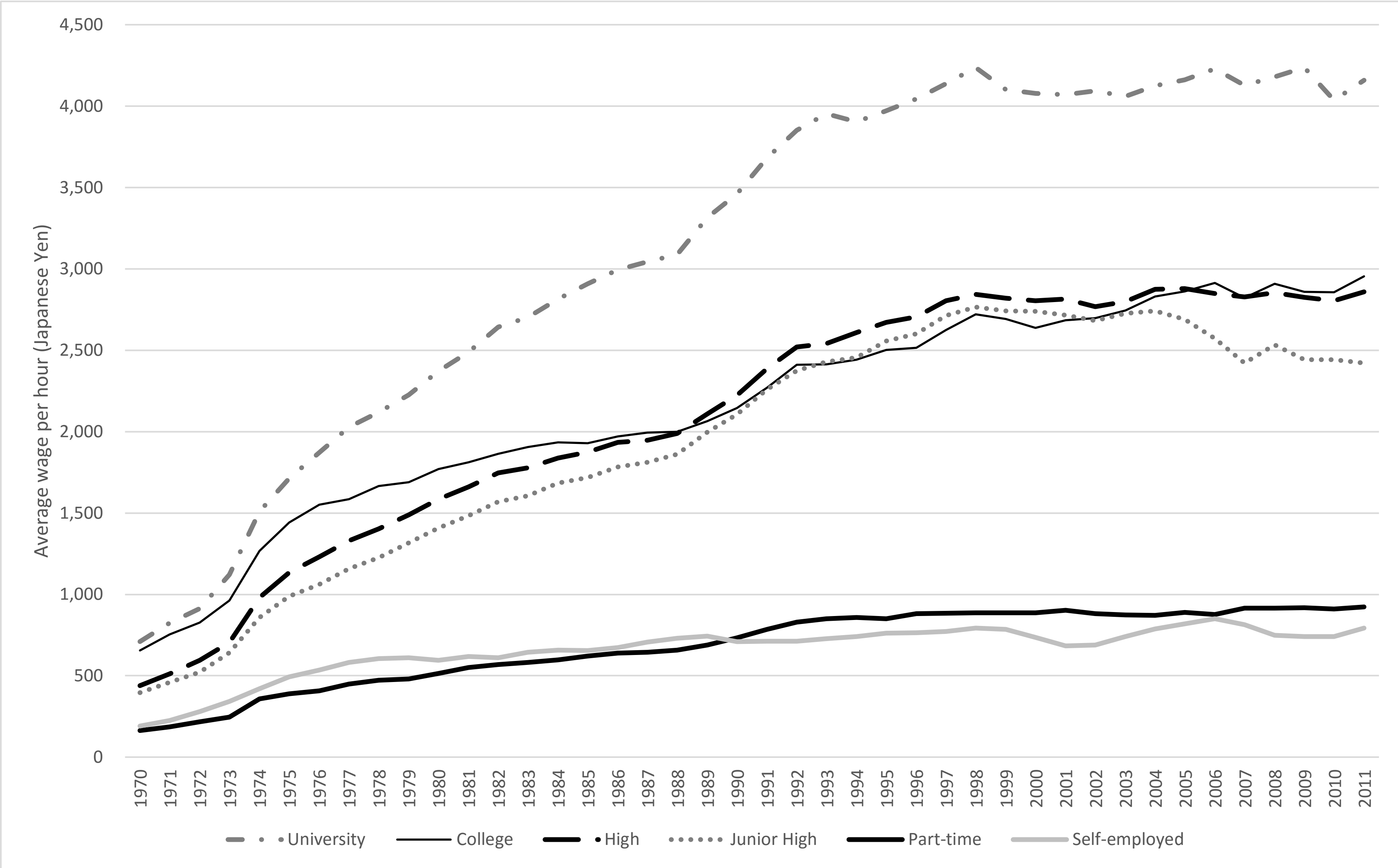
where θ_{ijt} and M_{it} are obtained from the IO table and the JIP database, respectively.

Figure 1. Average Wages in Japanese Labor Markets, 1980 and 2011



Note: More detailed figures on the average wage and the employment share of each group are reported in Figure 2 and Figure A1, respectively.
Source: JIP database 2014.

Figure 2. Average Wage per Hour, by Education and Type of Workers: Manufacturing in Japan



Source: JIP database 2014.

Table 1. Average Cost Shares, 1980-2011

	N	Mean	Std. Dev.	Min	Max
s_H	364	0.050	0.030	0.003	0.171
s_{MH}	364	0.124	0.058	0.007	0.320
s_{ML}	364	0.046	0.037	0.001	0.187
s_L	364	0.007	0.006	0.000	0.033
s_M	364	0.773	0.098	0.509	0.988

Source: JIP database 2014.

Table 2. Annual Percentage Change, 1980-2011

	N	Mean	Std. Dev.	Min	Max
Cost shares					
s_H	52	0.001	0.001	0.000	0.003
s_{MH}	52	0.002	0.001	-0.001	0.005
s_{ML}	52	-0.002	0.001	-0.005	0.000
s_L	52	0.000	0.000	0.000	0.001
s_M	52	-0.001	0.001	-0.004	0.003
Input quantities					
L_H	52	0.013	0.021	-0.038	0.076
L_{MH}	52	0.000	0.020	-0.058	0.054
L_{ML}	52	-0.077	0.020	-0.144	-0.028
L_L	52	0.016	0.021	-0.032	0.076
M	52	0.004	0.025	-0.040	0.077
Flexible factor prices					
w_H	52	0.018	0.007	-0.013	0.038
w_{MH}	52	0.018	0.007	-0.013	0.036
w_{ML}	52	0.016	0.008	-0.018	0.035
w_L	52	0.018	0.008	-0.008	0.044
p_M	52	-0.001	0.012	-0.041	0.028
Fixed input and output quantities					
ICT capital stock	52	0.065	0.031	-0.033	0.129
Non-ICT capital stock	52	0.024	0.020	-0.020	0.095
Output	52	0.021	0.065	-0.093	0.282

Source: JIP database 2014.

Table 3. Offshoring and ICT, 1980-2011

	Offshoring			ICT capital share
	Narrow	Differential	Broad	
1980	0.021	0.053	0.074	0.024
1985	0.024	0.055	0.079	0.056
1990	0.030	0.061	0.091	0.074
1995	0.042	0.061	0.103	0.085
2000	0.047	0.078	0.124	0.118
2005	0.057	0.097	0.154	0.122
2011	0.053	0.110	0.163	0.084

Note: "Differential" is defined as the difference between the broad and narrow definition. ITC capital share is the share of IT capital stock to total capital stock.
Source: Ministry of International Affairs and Communications (various years).

Table 4. Regression Results, 1980-2011

Fixed effects SUR	L_H	L_{MH}	L_{ML}	L_L
w_H	0.003*	0.004	-0.013***	0.006**
	(0.002)	(0.003)	(0.004)	(0.003)
w_{MH}	0.004	-0.052**	0.042**	0.012
	(0.003)	(0.022)	(0.017)	(0.011)
w_{ML}	-0.013***	0.042**	0.019	-0.018
	(0.004)	(0.017)	(0.020)	(0.012)
w_L	0.006**	0.012	-0.018	0.033***
	(0.003)	(0.011)	(0.012)	(0.011)
Offshoring	0.001***	-0.005**	0.010***	-0.002
	(0.000)	(0.002)	(0.003)	(0.002)
ICT capital	-0.001	0.013***	-0.026***	-0.000
	(0.001)	(0.004)	(0.006)	(0.003)
Non-ICT capital	-0.002***	-0.003	-0.010***	0.003*
	(0.000)	(0.002)	(0.003)	(0.002)
Output	0.006	-0.017	0.032	0.045**
	(0.005)	(0.028)	(0.037)	(0.019)
N	364	364	364	364
R-squared	0.960	0.954	0.985	0.980
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Notes: Figures in parentheses are standard errors. ***, **, and * indicate statistically significance at 1%, 5%, and 10% levels, respectively. The null hypothesis that the fixed effect equals zero is rejected at 1% level in all equations. Shaded coefficients are constrained by symmetry constraints.

Source: JIP database 2014 and Ministry of International Affairs and Communications (various years).

Table 5. Factor Demand and Other Elasticities, 1980-2011: Baseline Results

	L_H	L_{MH}	L_{ML}	L_L	M
w_H	*-0.291*				
	(0.217)				
w_{MH}	-1.986	*-0.726****			
	(1.933)	*(0.165)*			
w_{ML}	6.270	8.443***	*-2.087****		
	(4.866)	(3.056)	*(0.484)*		
w_L	17.887**	-12.820***	13.493	*-0.550***	
	(8.141)	(4.348)	(9.489)	*(0.255)*	
p_M	0.153*	0.688***	0.811***	0.816***	*-0.406****
	(0.087)	(0.068)	(0.142)	(0.170)	*(0.056)*
Offshoring	0.907**	0.256	-0.372	0.797	-0.085
	(0.375)	(0.300)	(0.615)	(0.616)	(0.063)
ICT capital	-0.049	0.080***	-0.115**	0.201***	-0.005
	(0.030)	(0.024)	(0.050)	(0.051)	(0.005)
Non-ICT capital	-0.000	-0.212***	0.288***	-0.155	0.019*
	(0.059)	(0.047)	(0.097)	(0.098)	(0.010)
Output	0.062*	-0.084***	-0.066	-0.215***	0.015***
	(0.032)	(0.026)	(0.053)	(0.053)	(0.005)

Notes: Figures in parentheses are standard errors. ***, **, and * indicate statistically significance at 1%, 5%, and 10% levels, respectively. Offshoring is measured by narrow measure. The own price elasticities are reported in italic.
Sources: JIP database 2014 and Ministry of International Affairs and Communications (various years).

Table 6. Robustness Check: Offshoring Elasticity

	L_H	L_{MH}	L_{ML}	L_L	M
Baseline	0.907**	0.256	-0.372	0.797	-0.085
	(0.375)	(0.300)	(0.615)	(0.616)	(0.063)
Broad measure	0.568**	-0.549***	0.380	-0.145	0.030
	(0.256)	(0.204)	(0.421)	(0.423)	(0.043)
Relative to all	1.321**	0.316	-0.577	1.414	-0.115
intermediate inputs	(0.598)	(0.478)	(0.982)	(0.983)	(0.100)
Relative to gross	0.646	-0.455	-1.355	-0.034	0.112
output	(0.910)	(0.725)	(1.485)	(1.491)	(0.152)
Adding R&D as a	0.626*	-0.016	-0.086	0.554	-0.038
control variable	(0.343)	(0.301)	(0.586)	(0.669)	(0.064)
Excluding low skilled	0.918**	0.263	-0.371		-0.080
workers	(0.374)	(0.306)	(0.615)		(0.061)

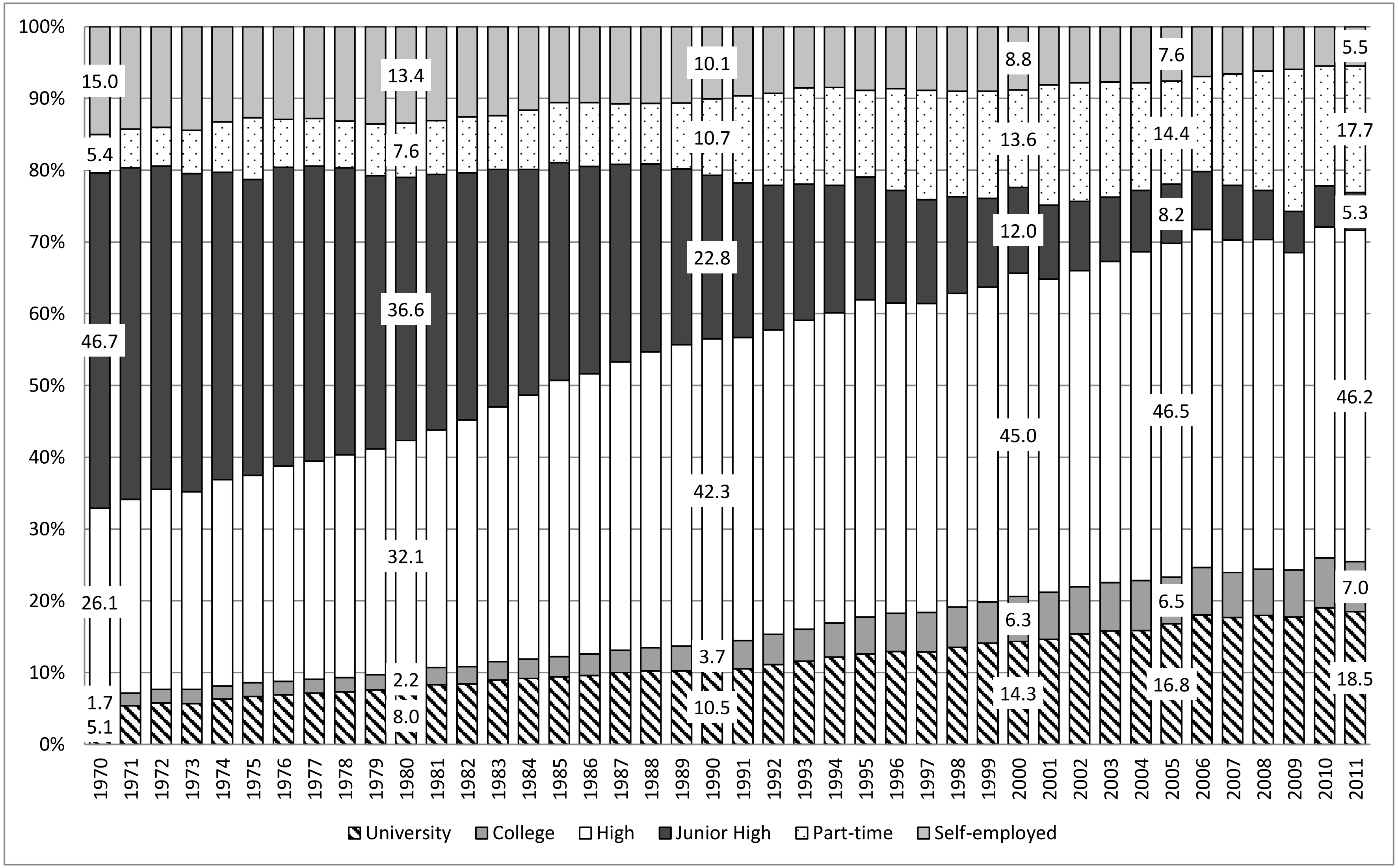
For notes and sources, see Table 5.

Table 7. Robustness Check: ICT Capital Stock Elasticity

	L_H	L_{MH}	L_{ML}	L_L	M
Baseline	-0.049	0.080***	-0.115**	0.201***	-0.005
	(0.030)	(0.024)	(0.050)	(0.051)	(0.005)
Broad measure	-0.049	0.088***	-0.123**	0.211***	-0.006
	(0.030)	(0.024)	(0.050)	(0.050)	(0.005)
Relative to all	-0.048	0.081***	-0.115**	0.201***	-0.005
intermediate inputs	(0.030)	(0.024)	(0.050)	(0.051)	(0.005)
Relative to gross	-0.044	0.082***	-0.114**	0.208***	-0.006
output	(0.030)	(0.024)	(0.050)	(0.051)	(0.005)
Adding R&D as a	-0.027	0.116***	-0.318***	0.231***	-0.000
control variable	(0.032)	(0.028)	(0.056)	(0.064)	(0.006)
Excluding low skilled	-0.045	0.080***	-0.112**		-0.003
workers	(0.030)	(0.025)	(0.050)		(0.005)

For notes and sources, see Table 5.

Figure A1. Share of Workers, by Education and Type of Workers: Manufacturing in Japan



Source: JIP database 2014.

Table A1. Offshoring, 1980-2011, by Industry

Industry	1980	1985	1990	1995	2000	2005	2011
Chemical fertilizers	0.013	0.007	0.033	0.116	0.176	0.312	0.228
Basic inorganic chemicals	0.070	0.084	0.097	0.091	0.096	0.163	0.176
Textile products	0.048	0.067	0.086	0.095	0.105	0.139	0.175
Organic chemicals	0.051	0.077	0.085	0.100	0.113	0.131	0.152
Leather and leather products	0.044	0.045	0.079	0.106	0.145	0.164	0.138
Lumber and wood products	0.013	0.028	0.044	0.068	0.095	0.106	0.131
Smelting and refining of non-ferrous metals	0.086	0.086	0.147	0.160	0.081	0.107	0.123
Seafood products	0.003	0.053	0.089	0.151	0.127	0.139	0.112
Livestock products	0.027	0.069	0.061	0.087	0.094	0.106	0.107
Other transportation equipment	0.033	0.090	0.081	0.064	0.114	0.102	0.100
General industry machinery	0.010	0.013	0.016	0.020	0.052	0.067	0.088
Miscellaneous foods and related products	0.115	0.052	0.050	0.059	0.052	0.077	0.086
Semiconductor devices and integrated circuits	0.009	0.029	0.060	0.062	0.056	0.124	0.085
Miscellaneous chemical products	0.016	0.024	0.040	0.029	0.033	0.044	0.079
Plastic products	0.003	0.005	0.015	0.020	0.038	0.060	0.075
Electronic data processing machines, digital and analog computer equipment and accessories	0.060	0.094	0.070	0.114	0.053	0.047	0.070
Pulp, paper, and coated and glazed paper	0.077	0.080	0.116	0.122	0.102	0.081	0.069
Special industry machinery	0.011	0.007	0.022	0.029	0.063	0.069	0.066
Miscellaneous ceramic, stone and clay products	0.020	0.019	0.003	0.030	0.062	0.074	0.060
Electronic parts	0.011	0.009	0.005	0.028	0.072	0.121	0.058
Pharmaceutical products	0.119	0.019	0.021	0.099	0.022	0.028	0.053
Electrical generating, transmission, distribution and industrial apparatus	0.009	0.012	0.015	0.024	0.048	0.052	0.050
Miscellaneous manufacturing industries	0.036	0.018	0.022	0.023	0.017	0.056	0.044
Pig iron and crude steel	0.031	0.051	0.065	0.095	0.053	0.077	0.043
Beverages	0.003	0.006	0.012	0.008	0.012	0.021	0.040
Precision machinery & equipment	0.028	0.029	0.045	0.102	0.154	0.034	0.038
Non-ferrous metal products	0.000	0.002	0.007	0.005	0.013	0.030	0.036
Electronic equipment and electric measuring instruments	0.024	0.028	0.020	0.011	0.031	0.027	0.036
Furniture and fixtures	0.007	0.008	0.027	0.026	0.044	0.058	0.035
Miscellaneous electrical machinery equipment	0.036	0.016	0.020	0.048	0.060	0.077	0.034
Household electric appliances	0.004	0.004	0.011	0.028	0.051	0.033	0.029
Motor vehicle parts and accessories	0.000	0.001	0.002	0.004	0.007	0.019	0.026
Glass and its products	0.007	0.028	0.007	0.002	0.003	0.005	0.023
Miscellaneous fabricated metal products	0.003	0.002	0.006	0.009	0.009	0.020	0.020
Miscellaneous machinery	0.012	0.006	0.005	0.009	0.029	0.022	0.016
Miscellaneous iron and steel	0.003	0.012	0.021	0.018	0.013	0.013	0.015
Rubber products	0.006	0.007	0.009	0.014	0.013	0.017	0.014
Office and service industry machines	0.005	0.005	0.010	0.020	0.033	0.025	0.012
Petroleum products	0.010	0.024	0.016	0.031	0.003	0.007	0.007
Cement and its products	0.000	0.003	0.009	0.003	0.007	0.007	0.005
Communication equipment	0.000	0.000	0.000	0.002	0.003	0.002	0.004
Fabricated constructional and architectural metal products	0.000	0.000	0.000	0.000	0.000	0.003	0.003
Coal products	0.002	0.000	0.000	0.000	0.000	0.000	0.003
Printing, plate making for printing and bookbinding	0.000	0.001	0.002	0.002	0.001	0.002	0.003
Flour and grain mill products	0.000	0.000	0.000	0.000	0.000	0.001	0.002
Basic organic chemicals	0.000	0.002	0.002	0.001	0.001	0.001	0.002
Pottery	0.005	0.001	0.005	0.001	0.002	0.003	0.002
Prepared animal foods and organic fertilizers	0.000	0.008	0.018	0.035	0.056	0.066	0.001
Motor vehicles	0.000	0.000	0.000	0.000	0.000	0.000	0.001
Paper products	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Tobacco	0.002	0.023	0.007	0.002	0.010	0.000	0.000
Chemical fibers	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Outsourcing is based on narrow definition. Sorted by the descending order in 2011.
Source: JIP database 2014.

Table A2. Robustness Check 1: Broad Offshoring

	L_H	L_{MH}	L_{ML}	L_L	M
w_H	*-0.239*				
	(0.211)				
w_{MH}	-3.015	*-0.592*** **			
	(1.897)	*(0.162)*			
w_{ML}	7.310	7.207**	*-1.999*** **		
	(4.823)	(3.022)	*(0.484)*		
w_L	15.529*	-11.206***	11.758	*-0.549** *	
	(8.066)	(4.323)	(9.427)	*(0.254)*	
p_M	0.212**	0.640***	0.845***	0.810***	*-0.379*** **
	(0.090)	(0.070)	(0.146)	(0.175)	*(0.055)*
Offshoring	0.568**	-0.549***	0.380	-0.145	0.030
	(0.256)	(0.204)	(0.421)	(0.423)	(0.043)
ICT capital	-0.049	0.088***	-0.123**	0.211***	-0.006
	(0.030)	(0.024)	(0.050)	(0.050)	(0.005)
Non-ICT capital	0.018	-0.238***	0.307***	-0.168*	0.021**
	(0.060)	(0.048)	(0.099)	(0.099)	(0.010)
Output	0.044	-0.073***	-0.071	-0.218***	0.015***
	(0.033)	(0.026)	(0.054)	(0.054)	(0.006)

For notes and sources, see Table 5.

Table A3. Robustness Check 2: Relative to All Intermediate Inputs

	L_H	L_{MH}	L_{ML}	L_L	M
w_H	*-0.306*				
	(0.217)				
w_{MH}	-1.952	*-0.726*** **			
	(1.932)	*(0.165)*			
w_{ML}	6.456	8.405***	*-2.093*** **		
	(4.876)	(3.063)	*(0.486)*		
w_L	17.743**	-12.910***	13.941	*-0.556** *	
	(8.136)	(4.350)	(9.514)	*(0.255)*	
p_M	0.157*	0.689***	0.809***	0.821***	*-0.407*** **
	(0.087)	(0.068)	(0.142)	(0.170)	*(0.056)*
Offshoring	1.321**	0.316	-0.577	1.414	-0.115
	(0.598)	(0.478)	(0.982)	(0.983)	(0.100)
ICT capital	-0.048	0.081***	-0.115**	0.201***	-0.005
	(0.030)	(0.024)	(0.050)	(0.051)	(0.005)
Non-ICT capital	-0.003	-0.213***	0.289***	-0.157	0.019*
	(0.059)	(0.047)	(0.097)	(0.098)	(0.010)
Output	0.058*	-0.085***	-0.064	-0.219***	0.016***
	(0.032)	(0.026)	(0.053)	(0.053)	(0.005)

For notes and sources, see Table 5.

Table A4. Robustness Check 3: Relative to Gross Output

	L_H	L_{MH}	L_{ML}	L_L	M
w_H	*-0.309*				
	(0.217)				
w_{MH}	-1.723	*-0.747****			
	(1.927)	*(0.164)*			
w_{ML}	5.902	8.563***	*-2.084****		
	(4.869)	(3.049)	*(0.484)*		
w_L	17.638**	-12.587***	12.996	*-0.548***	
	(8.130)	(4.336)	(9.483)	*(0.255)*	
p_M	0.158*	0.689***	0.816***	0.821***	*-0.409****
	(0.088)	(0.069)	(0.142)	(0.170)	*(0.056)*
Offshoring	0.646	-0.455	-1.355	-0.034	0.112
	(0.910)	(0.725)	(1.485)	(1.491)	(0.152)
ICT capital	-0.044	0.082***	-0.114**	0.208***	-0.006
	(0.030)	(0.024)	(0.050)	(0.051)	(0.005)
Non-ICT capital	-0.008	-0.213***	0.292***	-0.161	0.019*
	(0.059)	(0.047)	(0.097)	(0.098)	(0.010)
Output	0.062*	-0.089***	-0.075	-0.220***	0.017***
	(0.033)	(0.027)	(0.055)	(0.055)	(0.006)

For notes and sources, see Table 5.

Table A5. Robustness Check 4: R&D Intensity

	L_H	L_{MH}	L_{ML}	L_L	M
w_H	*-0.512***				
	(0.229)				
w_{MH}	-1.784	*-0.649****			
	(2.077)	*(0.198)*			
w_{ML}	6.751	2.230	*-1.002**		
	(5.648)	(3.892)	*(0.593)*		
w_L	14.627	-6.169	-4.350	*-0.665***	
	(9.160)	(5.227)	(12.739)	*(0.299)*	
p_M	0.409***	0.881***	0.544***	1.166***	*-0.290****
	(0.098)	(0.084)	(0.166)	(0.227)	*(0.067)*
Offshoring	0.626*	-0.016	-0.086	0.554	-0.038
	(0.343)	(0.301)	(0.586)	(0.669)	(0.064)
ICT capital	-0.027	0.116***	-0.318***	0.231***	-0.000
	(0.032)	(0.028)	(0.056)	(0.064)	(0.006)
Non-ICT capital	0.041	-0.152***	0.309***	-0.060	0.004
	(0.057)	(0.050)	(0.098)	(0.112)	(0.011)
Output	0.031	-0.128***	-0.096*	-0.267***	0.027***
	(0.032)	(0.028)	(0.056)	(0.063)	(0.006)
R&D intensity	0.935**	-0.662*	-0.382	-0.586	0.074
	(0.456)	(0.399)	(0.778)	(0.889)	(0.085)

For notes and sources, see Table 5.

Table A6. Robustness Check 5: Excluding Low Skilled Workers

	L_H	L_{MH}	L_{ML}	L_L	M
w_H	*-0.199*				
	(0.212)				
w_{MH}	-2.223	*-0.801****			
	(1.924)	*(0.167)*			
w_{ML}	6.887	8.798***	*-2.110****		
	(4.831)	(3.072)	*(0.486)*		
w_L					
p_M	0.204**	0.650***	0.850***		*-0.412****
	(0.083)	(0.067)	(0.137)		*(0.056)*
Offshoring	0.918**	0.263	-0.371		-0.080
	(0.374)	(0.306)	(0.615)		(0.061)
ICT capital	-0.045	0.080***	-0.112**		-0.003
	(0.030)	(0.025)	(0.050)		(0.005)
Non-ICT capital	-0.009	-0.209***	0.282***		0.017*
	(0.059)	(0.048)	(0.097)		(0.010)
Output	0.060*	-0.087***	-0.066		0.014***
	(0.032)	(0.026)	(0.053)		(0.005)

For notes and sources, see Table 5.