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Are Part-time Employees Underpaid or Overpaid? Productivity–wage gaps in Japan

MORIKAWA Masayuki
RIETI

The Research Institute of Economy, Trade and Industry
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MORIKAWA Masayuki (RIETI)

Abstract

This study presents empirical findings on productivity-wage gaps among certain groups of Japanese employees. More specifically, we estimate the productivity and wage equations of part-time workers, females, and employees with a university education in order to determine whether they are underpaid or overpaid relative to their productivity. The results indicate that the wage levels of part-time workers and females reflect their contribution to firm productivity. Since the estimations are based on mean values, overpaid and underpaid workers may co-exist at the micro level. However, the parity between mean productivity and wages suggests that firms do not discriminate against these types of employees, and set wages efficiently under market competition. In order to reduce the overall inequality in wages, investments in human capital to enhance the productivity of the lower end of the productivity distribution are essential.

Keywords: Productivity‐wage gap, Part-time, Female, University graduate
JEL Classification: J31, J71, D22

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Are Part-time Employees Underpaid or Overpaid?
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1. Introduction

This study presents new evidence on the relationship between the productivity and wages of employees of Japanese firms. Specifically, we estimate the productivity–wage gaps for part-time workers, females, and employees with higher education.

The principle of "equal pay for equal work" has been discussed for a long time, but the fundamental difficulties in executing this principle are the definition and practical application of "equal work." Large variations in wages are evident in all countries, but whether these wage disparities are rational market outcomes or due to irrational discrimination cannot be judged by simply comparing wage levels among workers. From the viewpoint of economic efficiency, the key is whether wages accurately reflect workers' contributions to productivity. From an economics perspective, an ideal definition of "same work" might be that workers provide the same level of productivity. Altonji and Blank (1999) review representative theoretical and empirical studies on discrimination by race and gender, and state that "we define labor market discrimination as a situation in which persons who provide labor market services and who are *equally productive* in a physical or material sense are treated unequally in a way that is related to an observable characteristic such as race, ethnicity, or gender."

When the wage levels of non-standard workers, such as part-time workers, contract workers, and temporary agency workers, are low relative to their productivity, closing the gaps in relation to the wages of standard workers is desirable from both an efficiency and an equity point of view. On the other hand, if the current wage levels of these workers do reflect their productivity, an increase in their wages causes inefficiency in the labor market. In such a case, it is essential that their productivity improve in order to reflect the increase in their wages. Since the number and proportion of non-standard workers are both high in the service industries, productivity–wage gaps for these workers are closely related to the policy issue of improving productivity in the service industries.

Wage differentials by individual characteristics such as gender, age, education, and type of employment have been widely studied by estimating Mincerian wage functions using individual-level micro data.[1] Such studies have made clear how much of the observed wage differentials can be explained by these individual characteristics. More recently, detailed analyses have considered the effects of statistically unobservable characteristics, such as individual ability and skill.[2]

However, studies on *productivity* differences by individual characteristics are scarce, despite its practical importance to formulating policies. The major reason for this scarcity is that it is extremely difficult to measure the productivity of individual workers accurately in most occupations. Individual-level productivity can be measured for some types of workers, for example, professional sports players or operators of call centers, but such occupations are rare.[3]

Although the measurement of individual-level productivity is difficult, estimating firm- or establishment-level productivity is possible using micro data of businesses. If the composition of employees, such as the proportions of non-standard employees, females, and employees with a university education, at the firm- or establishment-level are available, we can infer a productivity–wage gap for a category of employees by comparing their contributions to productivity and wages.

However, in general, official statistics on firms and establishments do not contain detailed information about employee characteristics. One way to overcome this limitation is to construct a matched employer–employee data set by linking firm- or establishment-level statistics and individual-level statistics. Then, by estimating the association between the composition of workers (by gender, race, age classes, or education) and their productivity, as well as their association with mean wages, enables us to compare types of workers' contributions to productivity and wages. In this manner, as described in the next section, several studies have estimated productivity–wage gaps, beginning with Hellerstein and Neumark (1995).[4] However, most studies focus on productivity–wage gaps by age, gender, or race. Studies based on non-standard workers are scarce, in spite of the growing importance of non-standard workers in the labor markets of advanced economies.

Against this background, this study links original survey data with government statistics on

[1] See, Willis (1986) for a survey.
[2] See, for example, Lemieux (2006) and Chen (2008).
[3] In the case of school teachers, an improvement in students' test scores can be used as a measure of teachers' productivity. The productivity of researchers, including university professors, can be measured by counting their academic publications and citations.
[4] In Japan, such studies are scarce, although there are exceptions, such as Kawaguchi *et al.* (2007). However, past studies on Japan tend to use data from over a decade ago and, thus, do not reflect recent structural changes in the labor market.

Japanese firms in order to estimate productivity-gaps of part-time workers, females, and university graduates. The main results of this study are as follows. The wage levels of part-time workers and female employees are, on average, balanced in terms of their contribution to firm productivity. However, university graduates are underpaid relative to their contribution to productivity. Since these productivity–wage gaps are estimated as mean values, some part-time (or female) employees are underpaid, while others are overpaid at the micro-level. However, the parity between mean productivity and wages suggests that, in general, firms do not discriminate against part-time and female workers, and set their wages efficiently under market competition.

The rest of this paper is structured as follows. Section 2 provides an overview of the existing literature on productivity–wage gaps and describes the contribution of this study. Section 3 presents the data and the method of analysis used in this study, and Section 4 reports the empirical findings. Lastly, Section 5 concludes the paper, including the policy implications of the findings.

2. Literature Review

In most countries, data on individual employees' characteristics in official statistics of firms and establishments are limited. As a result, in order to measure types of employees' contributions to firm productivity, we need to construct a linked employer–employee data set. Estimations of productivity–wage gaps using such linked data have been conducted since the original works of Hellerstein and Neumark (1995, 1999), based on the manufacturing industry in Israel, and Hellerstein *et al*. (1999), based on the U.S. manufacturing industry. The worker characteristics analyzed in these studies include age, gender, race, and education.

Table 1 summarizes the estimations of productivity–wage gaps of representative past studies. Earlier studies analyze productivity–wage gaps in the manufacturing industry, while more recent studies examine both the manufacturing and service industries. In this table, "P ≈ W" means there is no statistically significant gap between the productivity and wages for a category of workers. Then, "P > W" or "P < W" indicate a significant positive or negative gap for a category of workers, respectively. The results on whether categories of workers are underpaid or overpaid vary by country, period of analysis, and method of analysis.[5]

[5] While not reported in this table, a similar approach has been applied to the productivity–wage gap of immigrants (Bartolucci, 2014) and to the impact of training on productivity and wages (Konings

A relatively large number of studies adopt the production function approach to estimate the marginal product of a category of workers, where firms' gross output or value-added are used as dependent variables. However, other studies employ an approach to explain total factor productivity (TFP) by the composition of the workforce, where the TFP is estimated separately in advance (Ilmakunnas *et al*., 2004; Ilmakunnas and Maliranta, 2005). The method of analysis in this study belongs to the latter approach.

Kawaguchi *et al*. (2007) and Asano and Kawaguchi (2007) are two of the few studies that compare productivity and wages in the Japanese labor market. Kawaguchi *et al*. (2007) construct a linked employer–employee data set from the Census of Manufacturers (Ministry of Economy, Trade and Industry) and the Basic Survey on Wage Structure (Ministry of Health, Labour and Welfare) for the period 1993 to 2003. Then, using these data, they estimate age–wage and age–productivity profiles for Japan. Their results show that the wage profile is steeper than the productivity profile, suggesting that younger workers are underpaid, while elderly workers are overpaid. They also show that the contributions of workers' years of schooling to productivity and wages are balanced. Although female and part-time workers are not the main subjects of their study, their results suggest that female and part-time workers are underpaid relative their contribution to productivity (P > W). Asano and Kawaguchi (2007), using panel data from the Basic Survey of Japanese Business Structure and Activities (BSJBSA) for the period 1992 to 2000, estimate the relative marginal productivity and relative wages of female workers compared to those of male workers.[6] Importantly, in addition to manufacturing firms, the BSJBSA covers wholesale, retail, and some services firms. Their analysis indicates that part of the male–female wage differential cannot be explained by the productivity differential (P > W). However, both studies are based on data until the early 2000s. Since the numbers of female and non-standard workers are increasing rapidly in Japan, and the "equal work, equal pay" rule is being hotly debated among policymakers, there is a need for empirical studies on productivity–wage gaps using more recent data.

Note that worker-level statistics used to construct linked employer–employee data sets typically adopt a sampling framework and, thus, do not include all employees of firms or establishments. As a result, studies using such data assume that the individual characteristics of matched workers represent those of all workers in a firm, but the validity of this assumption is not necessarily

and Vanormelingen, 2015).

[6] Unfortunately, the number of employees by gender was dropped from the BSJBSA in 2001.

guaranteed.[7]

Against this background, this study conducts an original firm survey on the composition of their overall workforce, and then links these data with official firm-level statistics (BSJBSA). Using this matched cross-sectional data set for 2015, we estimate productivity–wage gaps by employment type (full-time/part-time), gender, and education. With regard to part-time workers, we conduct a supplementary analysis using panel data on all BSJBSA firms for the period 2010 to 2015 (about 37,000 firms). In this case, we estimate the productivity–wage gap of part-time workers by accounting for firm fixed effects.

The major contributions of this study are as follows: 1) the use of recent data, including both manufacturing and service firms; 2) avoiding possible sampling errors by using firm-side data on the composition of workforces; and 3) the accurate measurement of the labor inputs of part-time workers using the full-time equivalent number of part-time workers available from the BSJBSA.

3. Data and Method of Analysis

The data used in this study are taken from the Survey of Corporate Management and Economic Policy (Research Institute of Economy, Trade and Industry: RIETI), linked with the BSJBSA (Ministry of Economy, Trade and Industry: METI) for 2015.

The BSJBSA is annual government statistics on about 30 thousands firms that have 50 or more regular employees, and include mining, manufacturing, electricity and gas, wholesale, retail, and several service industries. The purpose of this survey is to capture a comprehensive picture of Japanese firms, including their financial information (sales, costs, profits, book value of capital, etc.), number of employees, R&D expenditure, international trade, and foreign direct investment. In this study, we use data from the 2015 Survey. We calculate the firm-level TFP and the mean wages (both expressed in logarithmic form) from the BSJBSA, and use these as dependent variables.

The TFP is calculated non-parametrically using the index number approach, which uses a hypothetical representative firm as a reference. Specifically, the input and output of the

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[7] For example, the mean proportion of workers in the sample of Hellerstein *et al*. (1999), a representative study in this field, is 12%. In Japan, the Basic Survey of Wage Structure determines the sampling proportion based on the size of establishments, with the proportion decreasing with establishment size.

hypothetical firm are calculated as the geometric means of the inputs and outputs of all firms, while the cost shares of labor and capital are calculated as arithmetic means. The TFP for each firm is calculated relative to the hypothetical representative firm. This cost-share-based index number approach has frequently been applied to BSJBSA data in calculating TFP (e.g., Nishimura *et al*., 2005; Fukao and Kwon, 2006; Morikawa, 2016).[8] An advantage of this method is that it does not assume a specific functional form of production. The output in this study is value-added, calculated as the sum of operating profit, rent, wages, welfare expenses, depreciation, and tax paid. Value-added includes wages and bonuses, as well as retirement allowances and social insurance payments borne by firms. Capital is the book value of tangible assets, taken from the BSJBSA.

As mentioned in the previous section, an advantage of this study is its use of the full-time equivalent number of part-time employees to measure the part-time labor input. Since 2007, the BSJBSA has collected data on the full-time equivalent number of part-time workers, in addition to raw data on all part-time workers. Since the working hours of full-time workers are not surveyed, industry-level working hour data from the Monthly Labor Survey (Statistics Bureau, Ministry of Internal Affairs and Communications) are used as the mean working hours of full-time workers. Mean wages are calculated as the sum of wages and welfare expenses (labor costs) divided by the sum of full-time workers and full-time equivalent part-time workers. In calculating TFP, we use total working hours, calculated as the sum of full-time and part-time working hours, as the labor input, and total labor costs are used to calculate the labor share. Therefore, the contributions of part-time workers to productivity and wages can be compared consistently based on their working hours.

The Survey of Corporate Management and Economic Policy, planned by the author and conducted by RIETI in 2015, is designed to be linked to the BSJBSA. We randomly chose 15,000 firms from the registered list of the BSJBSA, excluding firms classified as mining and utilities, and sent them the questionnaire. A total of 3,438 firms responded to the survey (22.9% response rate). With regard to the composition of firms' employees, the survey collects information about the number of employees by gender, type of employment (standard and non-standard employees), mean age of standard employees, and the proportion of standard employees with a university education or higher.[9] The breakdown of firms by industry is as follows: manufacturing 48.1%,

[8] For example, Morikawa (2016) describes the measurement procedure in detail in the appendix.
[9] The questionnaires of the Survey of Corporate Management and Economic Policy include the

ICT 5.8%, wholesale 18.6%, retail 11.8%, services 11.5%, and other industries 4.2%.[10]

Table 2 shows the mean values of the major characteristics (firm size, firm age, the proportion of part-time employees, TFP, and mean wages) of the firms that responded to the survey, and the mean values for all BSJBSA firms. The table shows that there is little difference between the major firm characteristics of the sample and those of all BSJBSA firms. Of the 3,438 firms that responded to the survey, 3,138 firms can be matched with the BSJBSA, but after eliminating firms that lack data necessary for this study (particularly TFP), the final sample is reduced to 2,417 firms. A relatively large number of firms are available to calculate mean wages, but we exclude firms where we are unable to calculate their TFP in order to ensure comparability.

Using this data set, we run simple firm-level OLS regressions to explain the TFP and mean wages by the composition of firms' workforces. The workforce characteristics used in the analysis are the proportion of part-time employees (available from the BSJBSA), the proportion of females, mean age, and the proportion of employees with a university education or higher (taken from the Survey of Corporate Management and Economic Policy).[11] The estimations include three-digit industry dummies. In another specification, firm size (log number of employees) and firm age (years from establishment) are added as control variables, but as shown later, the results remain essentially unchanged. In addition to the analysis using the whole sample, estimations for the subsamples of manufacturing and service firms are conducted.[12] The variables used in the analysis and their summary statistics are presented in **Table 3**.

We are interested in whether the wage premiums (or discounts) of part-time, female, and educated workers accurately reflect their contributions to firm productivity, which we measure as the quantitative difference between the estimated coefficients of the productivity and wage equations. However, we need to be careful, because it is inappropriate to simply compare the raw coefficients obtained from the two equations. Thus, we divide the estimated coefficients for the proportions of specific types of workers (e.g., the proportion of part-time workers) in the productivity equation by the labor share before comparing them to the coefficients of the wage equation (Ilmakunnas *et al*., 2004; Ilmakunnas and Maliranta, 2005; Vandenberghe, 2013).[13]

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proportion of employees with a postgraduate education, but this study does not use this survey item.

[10] The industry classifications of 11 firms are unknown. The percentages by industry are calculated by excluding "unknown" firms from the denominator.

[11] The mean age and the proportion of university graduates are those of standard employees.

[12] The service industries included in this study are wholesale, retail, information and communications, and other (narrowly defined) service industries.

[13] Assuming profit maximization behavior of firms, the equilibrium condition is expressed as

With regard to the productivity–wage gap of part-time workers, in addition to the analysis explained above, we conduct fixed-effects (FE) estimations using panel data of the BSJBSA for the period 2010 to 2015. Although we cannot use the proportions of females and workers with a university education in this case, we can control for unobservable time-invariant firm characteristics. In this analysis, the number of sample firms and observations are about 37,000 and 163,000, respectively.

4. Results

4.1. Worker Characteristics and Productivity–wage Gaps

The OLS estimation results used to explain the TFP and mean wages at the firm-level by the composition of the workforce are reported in **Table 4**. According to the result for all industries (column (1)), the coefficients for the proportion of part-time employees are large and negative for both TFP and wages. Thus, firms with a high proportion of part-time employees are less productive and their mean wages are lower. Although the results are qualitatively the same for the subsamples of manufacturing and service industries (columns (2) and (3)), the absolute values of the coefficients are larger among service firms. Since we calculate the TFP and mean wages using the full-time equivalent number of part-time employees, the estimated productivity and wage discounts are not resulting from the relatively short working hours of part-time workers in the service sector. The contribution of part-time workers to firm productivity is lower for service firms than it is for manufacturing firms and, thus, their wages are lower in the service sector.[14]

The absolute sizes of the coefficients for the proportion of part-time workers is greater in the productivity equation than in the wage equation. However, as explained in the previous section, it is inappropriate to simply compare the raw coefficients obtained from the two equations. **Table 5** reports the relative contributions of the types of employees to TFP and mean wages, expressed

$(\partial ln\mathrm{Y} \div \partial \mathrm{q}) \div (1 - \mathrm{S}) = (\partial ln\mathrm{w} \div \partial \mathrm{q})$,

where Y, w, q, and (1 – S) are the value-added, wages, quality of workers (worker characteristics), and the labor share, respectively.

[14] Because the figures for the proportions of females and employees with university education or higher are those of the standard (full-time) employees, the estimated coefficients for part-time workers reflect the differences to all full-time workers, unadjusted for gender and education.

as percentages, after adjusting the coefficients of TFP divided by the labor share. The mean labor shares of costs are 0.721 (all industries), 0.736 (manufacturing industry), and 0.708 (service industry). The table indicates that when the proportion of part-time employees is one percentage point higher, the firm's TFP and wages become 0.50% and 0.48% lower, respectively. Furthermore, the resulting productivity–wage gap of part-time workers is -2.1% (P < W) (column (1)). The productivity–wage gaps are +0.8% (P > W) in the manufacturing and -3.2% (P < W) in the service sector (columns (2) and (3), respectively). Interestingly, the productivity–wage gaps of part-time workers are quantitatively very small, irrespective of the industry.

Figure 1 indicates the point estimates (dots) and the 95% confidence intervals (bars) of the above estimation results. While the confidence intervals are relatively wide for the contribution to TFP, the wage discounts of part-time workers lie within the range of their productivity discounts. This result holds for both the manufacturing and service sectors. In short, for the data used in this study, the wage level of part-time workers is, on average, an reflection of their contribution to productivity.

Next, we interpret the estimated coefficients for the proportion of females. The coefficients of the estimations for the overall sample and for the subsample of manufacturing firms are negative and significant for both TFP and wages (columns (1) and (2) of **Table 4**, respectively). However, the coefficients are statistically insignificant for the service firms; that is, productivity and wage discounts are not detected for female employees in the service sector (column (3) of **Table 4**). Similarly to the procedure applied to part-time workers, the adjusted labor share figures, expressed as percentages, are reported in the second row of **Table 5**. Female workers' productivity–wage gaps are –3.3% and –4.7% (P < W) for the whole sample and for the manufacturing subsample, respectively.

Taken at face value, female workers seem to be overpaid. However, it is evident from the point estimates and from the 95% confidence intervals depicted in **Figure 2** that the ranges of wage discounts are within those of productivity discounts. The relationships are essentially the same in the subsamples of the manufacturing and service industries. Thus, we interpret this result to mean that, on average, the wage level of female workers reflects their contribution to productivity.[15]

[15] The female wage discount estimated in this study is smaller than the figures for Japan estimated from worker-level data, such as the Basic Survey of Wage Structure. Possible reasons for this, in addition to the different coverage of firms/establishments, are that 1) this study estimates the gender wage gap by including part-time workers, whose gender gap is small, and 2) the proportion of females is higher among younger full-time workers, where the gender wage gap is relatively small.

Note that we do not have data on the working hours of full-time employees by gender. If full-time females work fewer hours than males do, the contributions of female workers to productivity and their mean wages may be underestimated on a per hour basis. In fact, according to the Basic Survey of Wage Structure (Ministry of Health, Labour and Welfare) in 2015, the working hours of female full-time (standard) employees are 5.5% shorter than those of their male counterparts. Therefore, considering the different working hours by gender, the productivity/wage discounts of females relative to males reported above may be reduced somewhat. However, since the reductions in the discounts are applied to both productivity and wages, the resulting productivity–wage gap remains unchanged.

The coefficients for the mean age of employees are generally larger for wages than they are for productivity (the third row of **Table 5**). However, they are statistically insignificant, with the exception of the wage equation for the overall sample. For the data used in this study, we do not detect significant relationships between the average age of employees and their productivity or wages. However, average age is a very crude measure of the age composition of the workforce.[16] Unfortunately, detailed data on the number of employees by age class are not available. Thus, we note the limitation of the analysis on the productivity–wage gap by the age structure of workers, and do not pursue this further in this study.

The coefficients for the proportion of employees with a university education or higher are statistically significant on productivity and mean wages for the overall sample and for the subsample of manufacturing firms (the last row of **Table 5**). According to the results for the overall sample, a one percentage point higher proportion of educated workers is associated with 0.18% and 0.10% higher TFP and mean wages, respectively, with a resulting productivity–wage gap of +7.9%. In the case of manufacturing firms, the productivity and wage premiums of university graduates are larger, with an estimated productivity–wage gap of +13.5% (P > W).[17]

The estimated wage premiums of university education (9.5% for the whole sample and 17.5% for the subsample of manufacturing firms) are smaller than those generally obtained from standard wage function estimations based on worker-level data (e.g., Kawaguchi and Mori, 2016). One

[16] When the square term of the mean age is added as an explanatory variable, the coefficients are statistically insignificant.

[17] Some may argue that the positive productivity–wage gap (underpayment) for employees with a university education or higher may be compensated for by higher future earnings as a result of their higher probability of promotion and/or greater retirement allowances. We cannot deny such possibilities. However, this study uses labor costs, which is the sum of wages and welfare expenses, including retirement allowances.

reason for this is that the comparison group (less than four years university) in this study includes two-year college and occupational school graduates.

The point estimates and 95% confidence intervals are shown in **Figure 3**. As shown, highly educated workers' contributions to TFP lie above the wage premium, with the exception of service firms, although most of the ranges overlap. Highly educated workers are, on average, likely to be underpaid relative to their contribution to productivity, possibly because of the compressed wage structure among Japanese firms.

The results presented above are controlled using three-digit industry dummies only. The estimation results including firm size (i.e., log number of regular employees) and firm age (i.e., years since establishment) as additional explanatory variables are reported in **Table 6**. Although not reported in this table, the estimated coefficients for firm size are generally positive and statistically significant in both the TFP and the wage equations. The results are essentially similar to those found in the baseline estimations.

Based on these estimations, **Table 7** reports the relative contributions to TFP and mean wages by the types of employees, expressed as percentages, after adjusting the coefficients of TFP divided by the labor share of costs. For the overall sample (column (1)), the productivity–wage gap of part-time workers is -5.5% (P < W). The gaps for female and educated workers are -3.9% (P < W) and +6.4% (P > W), respectively. Although the negative gap (overpayment) for part-time workers is larger than that in the baseline results, and the positive gap for educated workers is smaller than that in the baseline results, the general conclusions are unaffected by the inclusion of firm size and firm age.

4.2. Productivity–Wage Gap of Part-Time Workers: Panel Estimations

The results of the previous subsection depend on the one-time cross-sectional data. Although the analysis is restricted to part-time workers, we conduct similar estimations using a panel of all firms in the BSJBSA for the period 2010 to 2015. In this case, the numbers of sample firms and observations are about 37,000 and 163,000, respectively, which are far larger than the data used in the previous subsection. More importantly, by using panel data, we can control for unobservable firm characteristics using fixed-effects (FE) estimators. In the OLS estimations, year dummies and three-digit industry dummies are included as control variables. In the FE estimations, year dummies are included.

The OLS and the FE estimation results for the overall sample, and the subsamples of manufacturing and service firms are reported in **Table 8**. In the OLS and FE estimations, the coefficients for part-time workers are negative and significant at the 1% level for both productivity and wages. The coefficients are larger than those of the previous subsection, mainly because the effects of gender and education (i.e., a higher proportion of females and a lower level of education of part-time workers) are reflected in the coefficients for part-time workers. The result of the larger productivity and wage discounts in the service sector than those in the manufacturing sector (columns (3)–(6)) is the same as the previous finding from the matched data set.

Table 9 reports the relative contributions to TFP and mean wages for part-time workers, expressed as percentages, after adjusting the coefficients on TFP divided by the labor share of costs. The productivity–wage gaps of part-time workers in the OLS estimation are -1.1%, -1.5%, and -1.1% for the overall sample, manufacturing industry, and service industry, respectively (panel A, column (3)). Thus, small negative gaps (P < W) are observed. On the other hand, the gaps calculated from the FE estimations by industry are +1.1%, +3.1%, and -0.1%, respectively (panel B, column (3)). Here, the gaps become positive (P > W) for the overall sample and for the manufacturing subsample. However, irrespective of the estimations, the productivity–wage gaps of part-time workers are quantitatively very small.

The point estimates and 95% confidence intervals are shown in **Figure 4**. According to the OLS estimations, the ranges of wages lie above those of TFP, meaning that part-time workers are somewhat overpaid (**Figure 4-A**). On the other hand, the relative positions of TFP and wages are reversed in the FE estimations, but the confidence intervals of productivity and wages mostly overlap (**Figure 4-B**). To summarize, the productivity–wage gap of part-time workers, if any, is quantitatively very small. On average, part-time workers are not significantly overpaid or underpaid in the current Japanese labor market.

5. Conclusions

This study presents empirical findings on productivity–wage gaps in the Japanese labor market. Specifically, we estimate production and wage functions to determine whether part-time, female, and highly educated employees are underpaid or overpaid, relative to their productivity.

The analysis presented here shows that the wage levels of part-time and female employees reflect their contribution to firm productivity. On the other hand, employees with a university education or higher are underpaid, relative to their contribution to productivity. Since the estimation results indicate mean values, overpaid and underpaid employees may co-exist at the micro-level. Therefore, the results do not deny the importance of efforts to realize the “equal pay for equal work” principle at the firm-level.

However, the parity between the mean productivity and wages of part-time and female workers suggests that firms do not discriminate against these types of employees, and instead set wages efficiently under market competition. From the employees’ standpoint, some part-time and female workers will gain, while others will lose if complete “equal pay for equal work” is achieved. Therefore, in order to narrow the overall inequality in wages, investments in human capital to enhance the productivity of the lower end of the productivity distribution are essential. Thus, wage levels and equal opportunities for education and training should be discussed when formulating policies. However, human resources management to use skills acquired through investments in human capital and to allocate job opportunities equally are also important.

The analysis of this study has several limitations. First, it depends on data sets that do not contain enough information on the composition of the workforce, such as the number of employees by age class and by tenure. Second, among various types of non-standard employment, this study only deals with part-time workers. Further analyses using rich data containing detailed worker characteristics and covering non-standard workers other than part-time workers are left for future research.

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Table 1. Empirical Studies on Productivity-wage Gaps.

	Country, industry	Elderly, long-tenure	Female	University graduates	Part-time
Hellerstein and Neumark (1995)	Israel, manufacturing	P ≈ W			
Hellerstein and Neumark (1999)	Israel, manufacturing		P ≈ W		
Hellerstein *et al*. (1999)	U.S., manufacturing	P ≈ W	P > W		
Ilmakunnas *et al*. (2004)	Finland, manufacturing	P < W		P ≈ W	
Ilmakunnas and Maliranta (2005)	Finland	P < W	P < W	P > W	
Hellerstein and Neumark (2007)	U.S., manufacturing	P < W	P > W	P < W	
Haltiwanger *et al*. (2007)	U.S.	P < W	P > W		
van Ours and Stoeldraijer (2011)	The Netherlands	P ≈ W	P ≈ W		
Vandenberghe (2013)	Belgium	P ≈ W	P < W		
Cardoso *et al*. (2011)	Portugal	P > W			
Garnero *et al*. (2014)	Belgium		P > W		P > W
Rycx *et al*. (2015)	Belgium			P > W	
Kawaguchi *et al*. (2007)	Japan, manufacturing	P < W	P > W	P ≈ W	P > W
Asano and Kawaguchi (2007)	Japan		P > W		

Notes: "P ≈ W" means no statistically significant gap between productivity and wages for the categories of workers. "P > W" and "P < W" indicate significant positive and negative gaps for the categories of workers, respectively.

Table 2. Comparison of the Sample Firms and the All BSJBSA firms.

	(1) Sample firms			(2) BSJBSA firms			(3) Diff.
	Nobs.	Mean	Std. Dev.	Nobs.	Mean	Std. Dev.	Mean
Firm size log)	3138	5.124	0.953	30033	5.253	1.059	-0.128
Firm age	3138	46.4	20.7	30033	44.6	21.1	1.754
Ratio of part-time	3138	0.174	0.237	30033	0.170	0.233	0.003
TFP (log)	2873	-0.099	0.452	27142	-0.060	0.499	-0.040
Mean wages (log)	3037	-6.017	0.417	28970	-5.992	0.464	-0.024

Notes: Firm size is the log of the number of regular employees. The BSJBSA firms in this table exclude firms classified in electricity, gas, and water.

Table 3. Summary Statistics by Industry.

	(1) All industries			(2) Manufacturing			(3) Services		
	Mean	SD	Nobs.	Mean	SD	Nobs.	Mean	SD	Nobs.
Ratio of part-timers	0.171	0.233	2,417	0.119	0.167	1,115	0.215	0.269	1,294
Female ratio	0.297	0.201	2,417	0.276	0.192	1,115	0.316	0.208	1,294
Mean age	40.63	4.28	2,417	40.79	4.01	1,115	40.48	4.50	1,294
Ratio of university graduates	0.377	0.267	2,417	0.324	0.247	1,115	0.422	0.275	1,294
Cost share of labor	0.721	0.261	2,417	0.736	0.326	1,115	0.708	0.187	1,294
Firm size (log)	5.093	0.919	2,417	5.007	0.797	1,115	5.168	1.004	1,294
Firm age (log)	47.20	20.01	2,417	50.81	19.72	1,115	44.10	19.75	1,294
TFP (log)	-0.1108	0.4445	2,417	-0.1092	0.4207	1,115	-0.1116	0.4635	1,294
Mean wages (log)	-6.0191	0.4085	2,417	-6.037	0.3771	1,115	-6.003	0.433	1,294

Note: The service industries include wholesale, retail, information and communications, and other (narrowly defined) service industries.

Table 4. Estimation Results on the Relationships between the Composition of Employees and Productivity/Wages.

A. TFP

	(1) All		(2) Manufacturing		(3) Services	
Part-time	-0.4982	***	-0.3189	***	-0.5937	***
	(0.0542)		(0.0864)		(0.0706)	
Female	-0.0802	*	-0.1806	***	-0.0079	
	(0.0470)		(0.0692)		(0.0640)	
Mean age	0.0000		-0.0045		0.0031	
	(0.0022)		(0.0032)		(0.0029)	
University graduates	0.1161	***	0.1988	***	0.0631	
	(0.0354)		(0.0523)		(0.0479)	
Industry dummies	Yes		Yes		Yes	
Nobs.	2417		1115		1294	
Adj. R^2	0.0708		0.0568		0.0851	

B. Mean wages

	(1) All		(2) Manufacturing		(3) Services	
Part-time	-0.6500	***	-0.4461	***	-0.7676	***
	(0.0426)		(0.0716)		(0.0529)	
Female	-0.0749	**	-0.1873	***	0.0101	
	(0.0370)		(0.0574)		(0.0479)	
Mean age	0.0029	*	0.0004		0.0046	**
	(0.0017)		(0.0026)		(0.0022)	
University graduates	0.0911	***	0.1617	***	0.0481	
	(0.0278)		(0.0434)		(0.0359)	
Industry dummies	Yes		Yes		Yes	
Nobs.	2417		1115		1294	
Adj. R^2	0.3201		0.1936		0.4122	

Notes: OLS estimations with standard errors in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5. Productivity‐wage Gaps by Types of Workers and by Industry.

	(1) All			(2) Manufacturing			(3) Services		
	TFP	Wage	Diff.	TFP	Wage	Diff.	TFP	Wage	Diff.
Part-time	-49.9%	-47.8%	-2.1%	-35.1%	-36.0%	0.8%	-56.8%	-53.6%	-3.2%
Female	-10.5%	-7.2%	-3.3%	-21.7%	-17.1%	-4.7%	-1.1%	1.0%	-2.1%
Mean age	0.0%	0.3%	-0.3%	-0.6%	0.0%	-0.6%	0.4%	0.5%	0.0%
Educated	17.5%	9.5%	7.9%	31.0%	17.5%	13.5%	9.3%	4.9%	4.4%

Notes: Calculated from the estimation results reported in Table 4. The TFP premiums/discounts are adjusted by labor share.

Table 6. Estimation Results on the Relationships between the Composition of Employees and Productivity/Wages.

A. TFP

	(1) All		(2) Manufacturing		(3) Services	
Part-time	-0.6061	***	-0.3930	***	-0.7237	***
	(0.0534)		(0.0839)		(0.0696)	
Female	-0.0762	*	-0.1562	**	-0.0113	
	(0.0455)		(0.0670)		(0.0611)	
Mean age	0.0018		-0.0020		0.0049	
	(0.0021)		(0.0031)		(0.0028)	
University graduates	0.0935	***	0.1836	***	0.0377	
	(0.0343)		(0.0506)		(0.0460)	
Industry dummies	Yes		Yes		Yes	
Nobs.	2417		1115		1294	
Adj. R^2	0.1320		0.1209		0.1660	

B. Mean wages

	(1) All		(2) Manufacturing		(3) Services	
Part-time	-0.7205	***	-0.5012	***	-0.8415	***
	(0.0428)		(0.0702)		(0.0539)	
Female	-0.0630	*	-0.1617	***	0.0157	
	(0.0365)		(0.0561)		(0.0474)	
Mean age	0.0038	**	0.0022		0.0051	**
	(0.0017)		(0.0026)		(0.0022)	
University graduates	0.0718	***	0.1476	***	0.0272	
	(0.0275)		(0.0423)		(0.0357)	
Industry dummies	Yes		Yes		Yes	
Nobs.	2417		1115		1294	
Adj. R^2	0.3407		0.2332		0.4258	

Notes: OLS estimations with standard errors in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. In addition to the three-digit industry, firm size and firm age are controlled for.

Table 7. Productivity-wage Gaps by Types of Workers and by Industry.

	(1) All			(2) Manufacturing			(3) Services		
	TFP	Wage	Diff.	TFP	Wage	Diff.	TFP	Wage	Diff.
Part-time	-56.9%	-51.3%	-5.5%	-41.4%	-39.4%	-1.9%	-64.0%	-56.9%	-7.1%
Female	-10.0%	-6.1%	-3.9%	-19.1%	-14.9%	-4.2%	-1.6%	1.6%	-3.2%
Mean age	0.3%	0.4%	-0.1%	-0.3%	0.2%	-0.5%	0.7%	0.5%	0.2%
Educated	13.8%	7.4%	6.4%	28.3%	15.9%	12.4%	5.5%	2.8%	2.7%

Notes: Calculated from the estimation results reported in Table 6. In addition to the three-digit industry, firm size and firm age are controlled for. The TFP premiums/discounts are adjusted by the labor share.

Table 8. The Proportion of Part-Time Workers and Productivity/Wages from the BSJBSA Panel Data.

A. TFP

	(1)		(2)		(3)		(4)		(5)		(6)	
	All				Manufacturing				Services			
	OLS		FE		OLS		FE		OLS		FE	
Part-time ratio	-1.1748	***	-0.7484	***	-1.1257	***	-0.5794	***	-1.2096	***	-0.8512	***
	(0.0071)		(0.0118)		(0.0117)		(0.0211)		(0.0091)		(0.0143)	
Year dummies	Yes		Yes		Yes		Yes		Yes		Yes	
Industry dummies	Yes		No		Yes		No		Yes		No	
Firm FE	No		Yes		No		Yes		No		Yes	
Nobs.	162,791		162,791		72,649		72,649		85,092		85,092	
Adj. R^2/R^2 (within)	0.1524		0.035		0.1174		0.0221		0.1809		0.055	

B. Mean wages

	(1)		(2)		(3)		(4)		(5)		(6)	
	All				Manufacturing				Services			
	OLS		FE		OLS		FE		OLS		FE	
Part-time ratio	-1.5594	***	-1.0602	***	-1.4505	***	-0.8486	***	-1.6193	***	-1.1778	***
	(0.0053)		(0.0101)		(0.0090)		(0.0170)		(0.0068)		(0.0128)	
Year dummies	Yes		Yes		Yes		Yes		Yes		Yes	
Industry dummies	Yes		No		Yes		No		Yes		No	
Firm FE	No		Yes		No		Yes		No		Yes	
Nobs.	162,791		162,791		72,649		76,409		85,092		85,092	
Adj. R^2/R^2 (within)	0.5885		0.0823		0.4258		0.0452		0.6634		0.1168	

Notes: OLS and fixed-effects (FE) estimations with standard errors in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Panel data of the BSJBSA for the period 2010 to 2015 are used. Explanatory variables include year dummies and three-digit industry dummies in the OLS estimations and year dummies in the fixed-effects estimations.

Table 9. Productivity‐wage Gaps of Part-Time Workers from the BSJBSA Panel Data.

A. OLS estimations

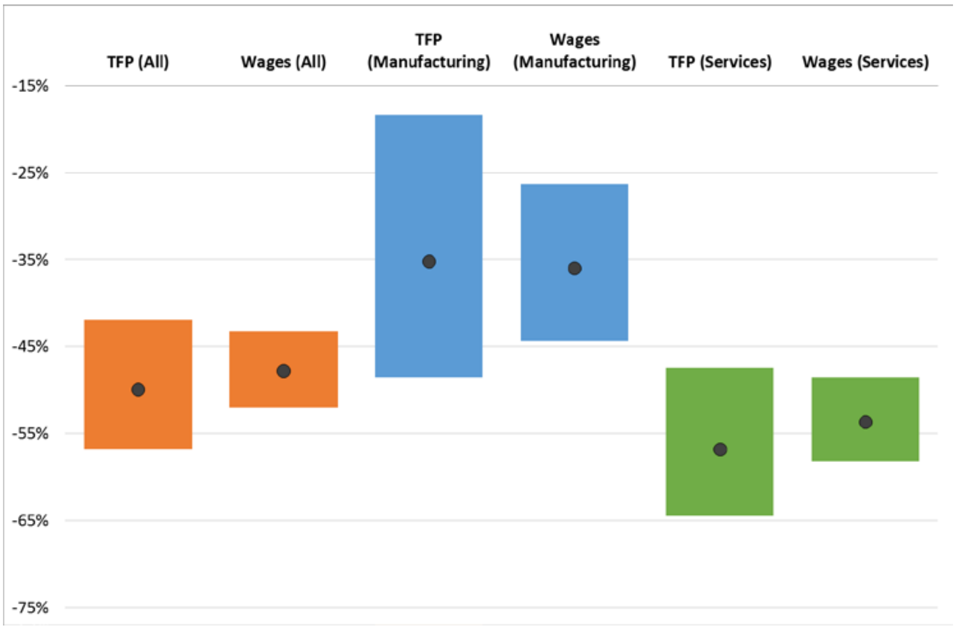
	(1) TFP	(2) Wages	(3) Diff.
A. All	-80.1%	-79.0%	-1.1%
B. Manufacturing	-78.1%	-76.6%	-1.5%
C. Services	-81.3%	-80.2%	-1.1%

B. FE estimations

	(1) TFP	(2) Wages	(3) Diff.
A. All	-64.2%	-65.4%	1.1%
B. Manufacturing	-54.2%	-57.2%	3.0%
C. Services	-69.3%	-69.2%	-0.1%

Notes: Calculated from the estimation results using the panel data from the BSJBSA reported in Table 8. The TFP premiums/discounts are adjusted by the cost share of labor.

Figure 1. Productivity‑wage Gaps of Part-Time Workers.



Notes: The bars indicate 95% confidence intervals and ● at the center of the bars are the point estimates. When the TFP is placed above (below) the mean wages, workers are underpaid (overpaid). The TFP premium/discount is adjusted by the cost share of labor.

Figure 2. Productivity–wage Gaps of Female Workers.

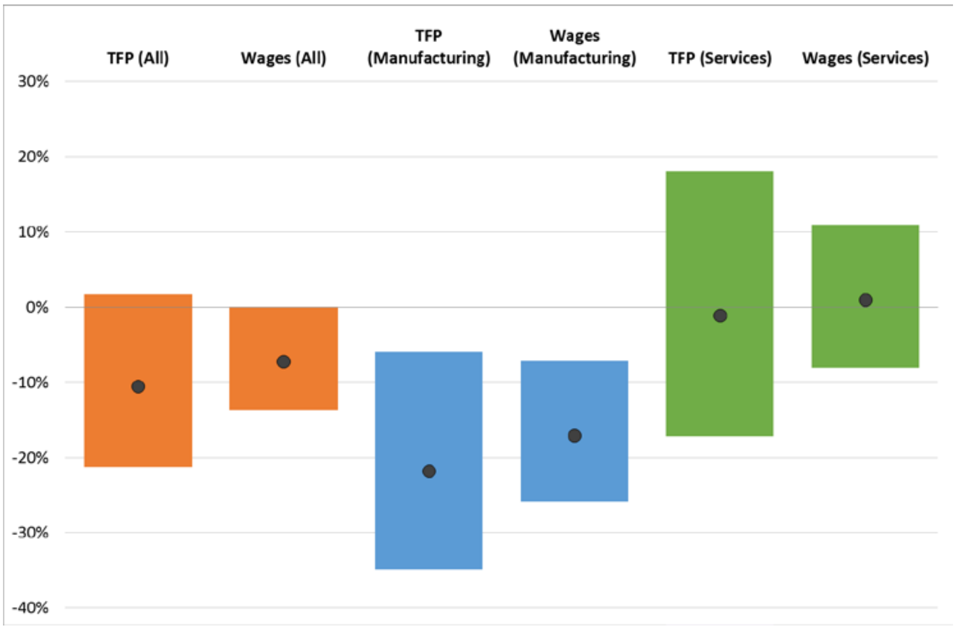


Figure 3. Productivity–wage Gaps of Workers with University or Higher Education.

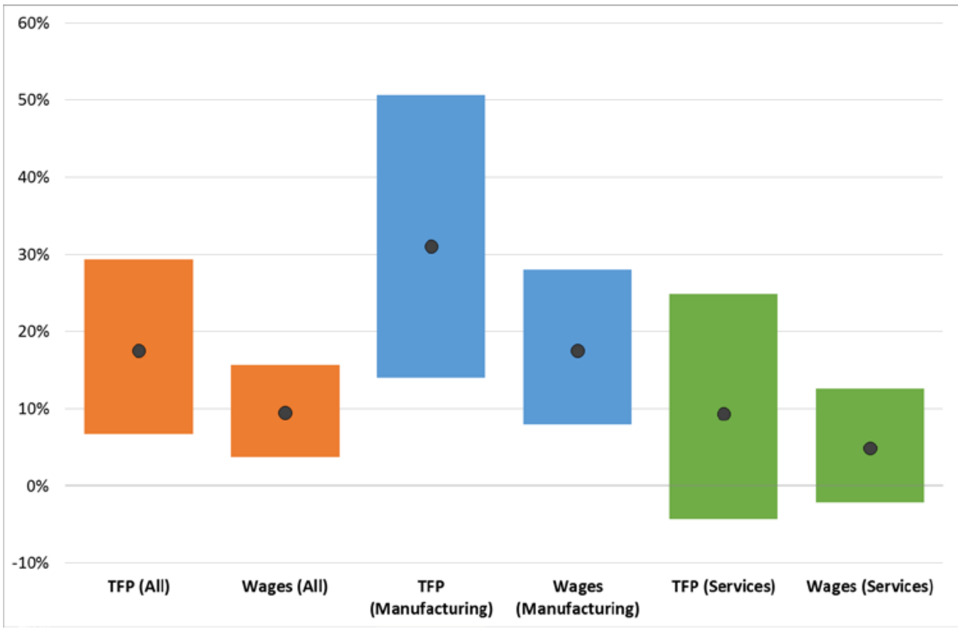
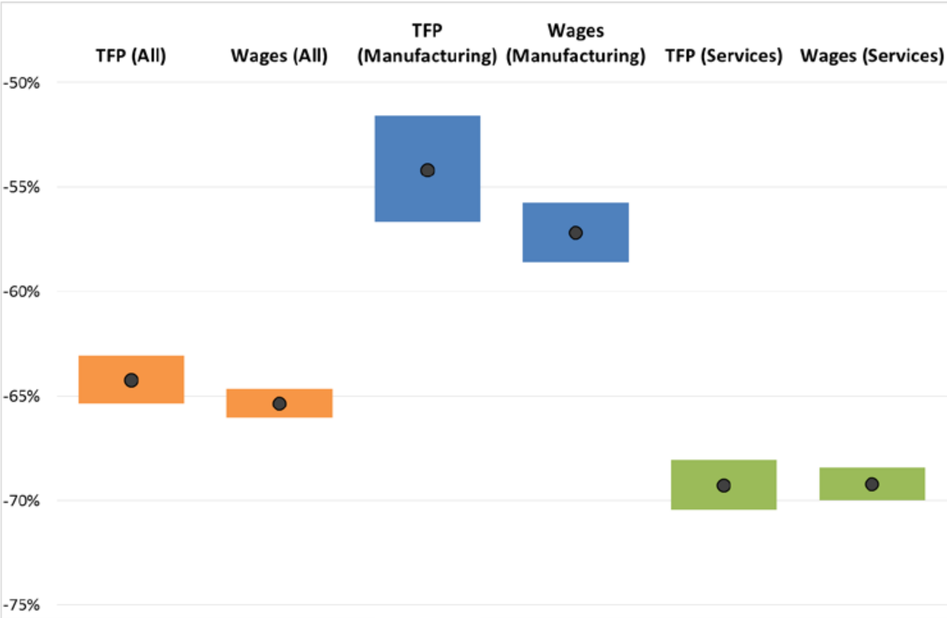


Figure 4. Productivity-wage Gaps of Part-Time Workers (The whole BSJBSA firms).

A. OLS estimations

Notes: Panel data of the BSJBSA for the period from 2010 to 2015 are used. Explanatory variables include year dummies and three-digit industry dummies.

B. Fixed-effects estimations



Notes: Panel data of the BSJBSA for the period from 2010 to 2015 are used. Explanatory variables include year dummies.