The Latent Structure of the Japanese Labor Market and the Type of Employment: Latent Class Analysis with Finite Mixture Model

SUZUKI Kyoko

This paper aims to present the "latent" structure of the labor market and clarify the impact of the type of employment on wage disparities. Based on the Employment Status Survey (2002), the results demonstrates that the Japanese labor market is not a single entity, nor is it composed of more than three segments, but consists of two heterogeneous segments corresponding to different wage-determining systems. The type of employment does not directly determine wage level, but affects wages by choosing the wage-determining systems. The division line of these two segments does not exactly coincide with the division line by regular/non-regular employees: regular employees span two different wage-determining systems, while all non-regular employees follow a single, more disadvantaged wage-determining system. This finding prompts a reconsideration of the common view that the Japanese labor market is prevailingly divided into regular and non-regular employees. This structure can be regarded as being continuous since the 1980s, implying that non-regular employment has expanded in line with the existing division and has contributed to maintaining it in turn.

I. Introduction

1. Type of employment, quality of jobs, and latent structure

The rise of nonstandard employment has been a commonplace in most developed economies, and this trend raises a concern for the quality of jobs. Nonstandard types of employment are not necessarily meant to be low quality of jobs, but it has been clarified that the quality of jobs actually has a strong relationship with type of employment in many countries (Kalleberg et al. 2000; Kambayashi and Kato 2016).

Japan is known as a country where the relationship between type of employment and job quality is direct and straightforward (OECD 2019). It is widely believed that the Japanese labor market is divided into two distinctive categories, "regular employees" and "non-regular employees," and that they directly link to job quality. "Regular employees" and "non-regular employees" are the terms used in Japan to refer to standard and nonstandard types of employment, particularly with connotations that are deeply rooted in its employment systems (Gordon 2017; Kambayashi 2013).[1] Regular employees are considered as members of the corporate "community" in the traditional Japanese employment system, while non-regular employees are those who are excluded from it (Inagami and Whittaker 2005; Osawa 2001). This means that regular employees enjoy higher wages with career advancement within a company, whereas non-regular employees earn low wages without any prospects for pay increases and work with no job security. These disparities between the two categories have attracted much attention and has become a major policy issue for the government (OECD 2019). It is widely believed that the "type of employment" is the most significant factor dividing the labor market, directly determining the quality of jobs.

However, this article challenges the view above and argues that categories of regular and non-regular employees are not the most significant division in the Japanese labor market. In fact, there is a hidden structure in the labor market that we cannot reach if we hold on to the dichotomy of regular and non-regular employment. This invisible "latent structure" can be obtained with an analytical method using a latent class analysis.

A "latent class" is a structure that is estimated endogenously from the data rather than defined by certain observable variables. Researchers have tried to identify segments of "good jobs" and "bad jobs," suggested by dual labor market theory, using variables such as industry and occupations. This approach did not work effectively due to the problem of inaccurate classification and selection biases. However, with a latent class approach, segments can be estimated so that they best fit to the data, without a prior choice of criteria by the analyst (Dickens and Lang 1985). The results prompt us to reconsider the widely promulgated view of the Japanese labor market: the division between regular and non-regular employment.

In defining the quality of jobs, this article focuses on "wage-determining systems." These are functions that define how each individual's attributes determine wages, and are represented by Mincer-type wage equations. Two persons with the same attributes would have different wage profiles, if they are assigned to different wage-determining systems, and therefore to different segments in the labor market in terms of job quality.

This article demonstrates three findings. First, the Japanese labor market consists of two heterogeneous wage-determining systems, and not a single entity or more than three. Second, the "type of employment" does not directly determine wage level, but affects wages by choosing the wage-determining system. Third, the division line of these two segments does not exactly coincide with that of regular and non-regular employees. In fact, the division line exists within regular employees, and this situation has been continuous in the labor market since the 1980s (Ishikawa and Dejima 1994). By re-discovering this dual structure, this article presents a new perspective on how we can understand regular/non-regular employees, and the employment system in Japan.

2. The effect of type of employment on wage differentials

(1) "Regular" and "non-regular" employment in Japan

How are the categories of "regular/non-regular employees" defined in Japan? Kambayashi (2013) explores three different ways of categorizing nonstandard employment in official statistics in Japan: by working hours, by length of labor contract, and by title at workplace. What people mean by "regular/non-regular employees" corresponds to the categorization defined by title at workplace, namely, whether they are called either "regular employees" or "non-regular employees." It seems tautological but explains exactly how situations are in Japan. The categorization by title at workplace strongly determines job quality including working conditions such as wages and job security (Kambayashi 2013). However, this categorization does not have any concrete criteria to differentiate regular and non-regular form of employment. In other words, there is no clear explanation of what determines whether the person is called as either a regular or non-regular employee. Sometimes they work for similarly long hours, both with open-ended contracts, and even engage in exactly the same tasks next to each other in the same workplace (Nitta 2011; Osawa 2001). Despite such situations, everyone seems to understand how they should identify themselves, as either regular or non-regular employees, and official statistics that quantify types of employment rely on these self-identified answers (Nitta 2011). In this respect, we could argue that the categories of regular/non-regular employees are socially constructed. Nevertheless, some research found that the categorization by title at workplace, rather than the work contract or the working hours of the employee, is the key element that strongly influences the wage differentials (Kambayashi and Kato 2016).

(2) Wage-determining systems and the criteria for the divide

There are two approaches in research on wage differentials between regular/non-regular employees: the first is to focus on wage levels, and the second is to focus on wage-determining systems. The first approach is the "neoclassical" view, which assumes a single labor market with a single mechanism of wage determination. Wage differentials can be explained as the results of having different individual attributes such as education, tenure, and experience, among which the type of employment is included. The second approach can be called the "segmented labor market" view, which considers wage differentials to be the result of different wage-determining systems. This approach maintains that wage differentials cannot be explained by workers' attributes, since the returns for them are different between regular and non-regular employees.

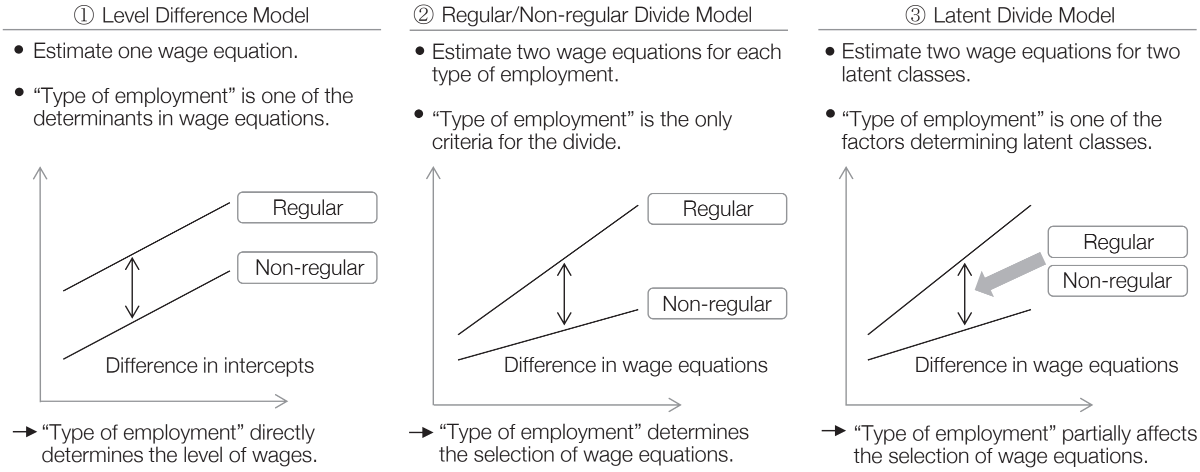
Assuming that we adopt the "segmented labor market" view, the next question is what should be the criteria for the divide. This approach draws on "dual labor market" theory, which considers the labor market to consist of two heterogeneous segments: one with better pay and favorable working conditions (the primary sector), and the other with inferior pay and precarious conditions (the secondary sector) (Doeringer and Piore 1971; Berger and Piore 1980). The question of how we should identify the two sectors empirically has been a controversial issue (Hodson and Kaufman 1982). Some have attempted to split jobs in a sample into two sectors on the basis of occupation and industry, but this approach has been criticized for inaccuracy. Any industries or occupations include many different jobs and positions within them, which results in anomalies in classification (Dickens and Lang 1985). A considerable advance to this problem was made by Dickens and Lang (1985), who developed an approach to estimate two segments endogenously as "latent classes," rather than having researchers determine two segments using specific criteria. With this approach, analysts can estimate two segments and two wage equations simultaneously, in the way they best fit to the actual data.

This approach is useful in analyzing the Japanese case, as we can easily take many factors into account to determine the structure of the labor market without knowing which variables are more important. The dualism in the Japanese labor market has evolved over time, involving several key factors such as company size, gender, and type of employment (Gordon 2017). The "dualism by company size," i.e., disparities between large companies and small or medium-sized companies, was a major issue in the 1960s (Ujihara 1966), and dualism was seen in gender wage differentials in the 1980s (Horn-Kawashima 1985; Osawa 1993). More recently it has been applied to regular/non-regular disparities (Genda 2008, 2011; Sato and Imai 2011; Gordon 2017). By adopting latent class analysis, we will be able to assess the impact of these varied factors on the current dualism in the labor market.

(3) Three analytical models

Three analytical models to estimate the structure of the labor market, corresponding to the discussion above, are presented in Figure 1. In these models, the wage-determining systems are specified as wage functions.

The first is the "level difference model," which estimates a single wage equation, using the type of employment as an explanatory variable. In this model, type of employment directly determines the wage level, with the coefficient accounting for the average wage differences for two groups. The second is the "regular/non-regular divide model," which assumes two different wage-determining systems corresponding to each type of employment. The data is divided into two groups, solely based on the type of employment.



Source: Created by the author.

Figure 1. Three models for the labor market structure

The third is the "latent divide model." This model also assumes two different wage equations, but they do not correspond to the dividing line of regular/non-regular employment. Instead, two segments are estimated endogenously as latent classes, using type of employment together with other factors affecting the class assignment (Dickens and Lang 1985; Ishikawa and Dejima 1994). The third model also can be extended into a model with more than three segments.

In the next section, I will analyze wage data using these three models and evaluate which would be the best to explain actual data. The results will tell us how we can understand the structure of the labor market as well as the impact of the type of employment on wages.

II. Data, variables, and models

1. The data

This article uses the anonymized data of the Employment Status Survey (2002) by the Ministry of Internal Affairs and Communications, with the sample limited to both male and female workers from ages 20 to 59, excluding company directors, the self-employed, and family employees. Workers not working regularly or working less than 200 days a year are also excluded. The sample size to be analyzed is 243,632, for which descriptive statistics are reported in Table 1. Note that all estimates in this paper are weighted by the sample multiplier.

2. Variables

Table 2 summarizes the variables used in the four models (the three models presented in Figure 1, plus a baseline model). All models include Mincer-type wage equations with exactly the same variables. The dependent variable is the log of annual income,[2] and its distribution was checked to see if it was normal. Explanatory variables for the wage equations include[3] "education (college or above)," "tenure (years of service)" and its square term, "experience"[4] and its square term, "company size," "gender," "marital status," and "working hours."[5]

The difference among these models lies in how to locate the type of employment. Model 0 is the baseline model and does not contain type of employment in any equation. Model 1, the level difference model, includes type of employment in the single wage equation. Model 2, the regular/non-regular divide model, includes type

Table 1. Sample from the Employment Status Survey (2002)

		Gender: Male	Gender: Female	Total
Sample size		143,467	100,165	243,632
Weighted by sample multiplier		17,651,543	11,441,728	29,093,272
Proportion		60.7%	39.3%	—
Age	20–29	22%	26%	23%
	30–39	29%	23%	27%
	40–49	25%	25%	25%
	50–59	25%	26%	25%
	Average	39.8	39.6	39.7
	s.d.	10.7	11.2	10.9
Education	College or above	34%	14%	26%
	Middle/High/Vocational Schools	66%	86%	74%
Tenure (Years of services)	Average	14.4	8.9	12.2
	s.d.	10.8	8.4	10.3
Experience (Outside the company)	Average	6.4	12.0	8.6
	s.d.	8.5	10.9	9.9
Company size	Large (employees 300+)	51%	41%	47%
	Medium/Small (employees <300)	49%	59%	53%
Marital status	Married	66%	58%	63%
	Unmarried	34%	42%	37%
Type of employment	Regular Employees	94%	57%	80%
	Non-regular Employees	6%	43%	20%

Source: Anonymized data of the Employment Status Survey (2002), Ministry of Internal Affairs and Communications.

Table 2. Variables used in the model

Variables	Models	⓪ Baseline Model Wage eq. (X)	① Level Difference Model Wage eq. (X)	② Regular/Non-regular Divide Model Wage eq. (X)	② Regular/Non-regular Divide Model Class eq. (Z)	③ Latent Divide Model Wage eq. (X)	③ Latent Divide Model Class eq. (Z)
Intercepts		✓	✓	✓	✓	✓	✓
Education	College or above dummy	✓	✓	✓		✓	✓
Tenure	Years of services	✓	✓	✓		✓	
	Years of services (squared)	✓	✓	✓		✓	
Experience	Outside the company	✓	✓	✓		✓	
	Outside the company (squared)	✓	✓	✓		✓	
Company size	Large company (employees 300+) dummy	✓	✓	✓		✓	✓
Gender	Female dummy	✓	✓	✓		✓	✓
Marital status	Married dummy	✓	✓	✓		✓	✓
	Female * Married	✓	✓	✓		✓	✓
Working hours	Working hours per week	✓	✓	✓		✓	
Type of employment	Non-regular employees dummy		✓		✓	✓	✓

Source: Created by the author.

of employment in the classification equation but not in the wage equations. Model 3, the latent divide model, also includes type of employment in the classification equation, but together with other covariates. Note that this model also puts type of employment into wage equations so that it could affect the wage level within each class.

For the covariates in the classification equation of Model 3, education and company size are included, given that these two factors have played an essential role in the Japanese employment system (Ujihara 1966; Ishikawa and Dejima 1994). Gender and marital status are included as well, as these two factors are also critical for explaining the composition of non-regular employees (Horn-Kawashima 1985; Osawa 2001).[6] On the other hand, tenure and experience should not be included, as these variables do not influence the allocation of classes when people first enter the labor market (Ishikawa and Dejima 1994). Model 0 and Model 1 both estimate a single wage equation, while Model 2 and Model 3 estimate two wage equations and one classification equation. Model 3 can be extended into models with more than three classes.

3. Model and hypotheses

The model used in this paper is called a Finite Mixture Model (FMM), a kind of latent class analysis. This is the same model as that referred to as a “switching model with unknown regimes” in Dickens and Lang (1985) and Ishikawa and Dejima (1994).[7]

In specifying a FMM, the analyst needs to set the number of latent classes to be estimated. The model will then consist of wage equations, the number of which is equal to the number of latent classes, as well as one classification equation that determines the allocation of individuals to the estimated classes. The likelihood function is derived from these two kinds of equations, and the model is simultaneously estimated with Maximum Likelihood Estimation (MLE).

The detailed specification is presented below (Greene 2012; Vermunt and Magidson 2013). The subscript i for each variable represents an individual and the subscript k represents the class to be assigned.

Wage equations of individual i in class k are expressed as:

$$f\,(lnW_i|k)=X_i\beta_k+u_{ki} \tag{1}$$

where W_i is the wages for each individual, X_i is a vector for explanatory variables, β_k is a vector for parameters, u_{ki} is an error term (normally distributed), and σ_k^2 is the variance of error terms.

The classification equation, determining the probabilities of individual i assigned to class k, is:

$$y_{ki}{*}=Z_i\gamma_k+\varepsilon_{ki} \tag{2}$$

where $y_i{*}$ is a latent variable determining class assignment, Z_i is a vector for explanatory variables, γ_k is a vector for parameters, and ε_i is an error term.

We have two random variables of wage (lnW_i) and probability of class assignment (y_{ki}^*), and the marginal density of individual i can be considered as a mixture of joint distribution, consisting of conditional densities (1) weighted by classification probabilities (2), which can be expressed as follows:

$$f\,(lnW_i|Z_i,X_i)=\sum_{k=1}^{K}Pr\left(class_i=k|Z_i\right)\cdot f\,(lnW_i|class_i=k,X_i) \tag{3}$$

To parameterize classification probabilities (2), conditioned on the individual characteristics (i.e., covariates Z_i in equation (2)), we assume multinominal distribution on ε_i, and then equation is expressed as follows:

$$Pr\left(class_i=k|Z_i\right)=Pr\left(\varepsilon_i>-Z_i\gamma_k|Z_i\right)=\frac{\exp\left(Z_i\gamma_k\right)}{\sum_{k=1}^{K}\exp\left(Z_i\gamma_k\right)} \tag{4}$$

Similarly, to parameterize the wage equation, conditioned on class k (1), we assume a normal distribution for u_{ki}, and the equation can be expressed as follows, using the variance of the error term σ_k^2:

$$f(lnW_i|class_i = k, X_i) = N\left(X_i\beta_k, \sigma_k^2\right) = \frac{exp\left[-\frac{1}{2}\left(lnW_i - X_i\beta_k\right)^2/\sigma_k^2\right]}{\sigma_k\sqrt{2\pi}} \tag{5}$$

where k=1, 2, ..K.

Therefore, by substituting these two parameterized equations (4) and (5) into equation (3), the marginal density of individual i is defined as:

$$f(lnW_i|Z_i, X_i) = \sum_{k=1}^{K}\left\{\frac{\exp\left(Z_i\gamma_k\right)}{\sum_{j=1}^{K}\exp\left(Z_i\gamma_j\right)}\cdot\frac{exp\left[-\frac{1}{2}\left(lnW_i - X_i\beta_k\right)^2/\sigma_k^2\right]}{\sigma_k\sqrt{2\pi}}\right\} \tag{6}$$

Then, the log-likelihood is defined as:

$$lnL = \sum_{i=1}^{n} ln\left[\sum_{k=1}^{K}\left\{\frac{\exp\left(Z_i\gamma_k\right)}{\sum_{j=1}^{K}\exp\left(Z_i\gamma_j\right)}\cdot\frac{exp\left[-\frac{1}{2}\left(lnW_i - X_i\beta_k\right)^2/\sigma_k^2\right]}{\sigma_k\sqrt{2\pi}}\right\}\right] \tag{7}$$

Using this log-likelihood function (7) with observed data of lnW_i, X_i, Z_i, we can simultaneously estimate parameter β_k, γ_k, as well as the variance σ_k^2, with MLE. Class assignments are influenced by the individual characteristics as well as by the fit to wage equations.

In Model 0 and Model 1 in Table 2, wage equations are reduced to a single equation, with the classification equation disappearing due to the equality constraint of parameters, β_1=β_2. In Model 2 and Model 3, the model consists of two different wage equations and one classification equation, with parameters $\beta_1 \neq \beta_2$. Constraints of perfect classification according to the type of employment are imposed on Model 2, while there is no constraint on Model 3.[8]

Three questions will be addressed using the model specified above. First, which of the three models in Figure 1 will be the best to explain the impact of type of employment on wages? Second, if we adopt models with two or more classes, what characteristics do these wage equations have? Third, which factors determine the classification of individuals to latent classes? Answering these questions will help to clarify the latent structure of the labor market in Japan.

III. The results

1. Which model best explains the data?

The methods to evaluate the validity of FMM can be broadly divided into two categories: the first employs testing procedures, while the second uses information criteria (IC). While the Likelihood Ratio Test is a standard procedures for MLE in the first category, the method cannot be applied to FMM due to the lack of regularity conditions (Chen et al. 2001; Morduch and Stern 1997; Günther and Launov 2012).[9] However, we can rely on the approaches in the second category using information criteria. Based on the discussion of Tuma and Decker (2013) that provide simulation studies of various criteria, BIC and AIC3 were chosen as evaluation criteria in this paper.[10]

The first question is which of the three models in Figure 1 can best explain the data to capture the effect of type of employment on wages. Table 3 shows the estimation results for the models specified in Table 2.[11] The results shows that the Model 3 can best explain the data among the three models. Model 1, the level difference model, has better goodness of fit, compared to Model 0, the baseline model. Similarly, Model 2, the regular/non-regular divide model, also has better goodness of fit compared to Model 0. These results tell us that the

Table 3. Results of model estimations (goodness of fit)

Models		⓪ Baseline Model	① Level Difference Model	② Regular/ Non-regular Divide Model	③ Latent Divide Model		
Use of "type of employment"	Wage eq.	—	✓	—	✓		
	Class eq.	—	—	✓	✓		
Number of wage equations		1	1	2	2	3	4
LL		−18,411,121	−15,485,838	−14,606,103	−12,937,873	−12,101,170	—
AIC3		36,822,277	30,971,715	29,212,282	25,875,841	24,202,493	—
BIC		36,822,448	30,971,899	29,212,636	25,876,295	24,203,217	—
(Ratio of Decrease)					(−16%)	(−6%)	—
Number of parameters		12	13	25	32	51	69
Class errors		0	0	0	0.118	0.194	—
R^2		0.650	0.714	0.723	0.770	0.799	—

Source: Created by the author based on the estimation results.

type of employment has impacts on wages in both models. Comparing these two models indicates that Model 2 fits the data better, which suggests that the type of employment affects the wage through choosing different wage-determining systems rather than directly determining the wage level. Further comparison of Model 2 and Model 3 indicates that the fit significantly improves with Model 3, suggesting that the dividing line of two different wage-determining systems is not the same as the divide by the type of employment.

On adopting Model 3, it becomes necessary to answer to the question of how many segments, or different wage-determining systems, should be assumed. The calculation did not converge when more than four classes are assumed. Both BIC and AIC3 are better in a three-class model than in a two-class model, but the difference is not as large as that of the change from one-class model to two-class model. Since a large sample is used in this analysis, which means it tends to detect even small heterogeneity in the data, we should determine an appropriate number of classes not only by the statistical significance, but also by the substance of each class. In the next section, we will adopt a three-class model to discuss the characteristics of the estimated equations, and then consider if it is appropriate to assume the third class.

2. What are the characteristics of the wage equations?

Table 4 summarizes the estimation results for Model 1, the level difference model, and Model 3, the latent divide model (with three classes). The results for Model 1 should be interpreted similarly to OLS. For Model 3, the three columns on the left report the coefficients for wage equations, while the three columns on the right report the coefficients for the classification equation. The "Compositions (%)" rows show the size of each latent class: Class 1 accounts for 55%, Class 2 for 36%, and Class 3 for 9%.[12] The "Error variance" and "R^2" rows tell us the goodness of fit for the wage equations within each class. The error variance for Class 3 is larger than that for Class 1 and Class 2, while R^2 is smaller for Class 3 than Class 1 and Class 2. These two statistics suggest that Class 1 and Class 2 are cohesive segments with substantial size, while Class 3 is much smaller and less concentrated. Thus, caution is required in regarding Class 3 as an independent segment.

How can we characterize the wage-determining system for each class? Figure 2 visualizes the returns for individual attributes for each class. The upper bar graph shows the effects of education, tenure, experience, and company size. The lower graph shows the effects of gender and marital status, having unmarried males as the base category.

The wage-determining system for Class 1 has higher returns for college graduates and large premiums for working for large companies. It also has a high return for tenure but less for experience outside the company.

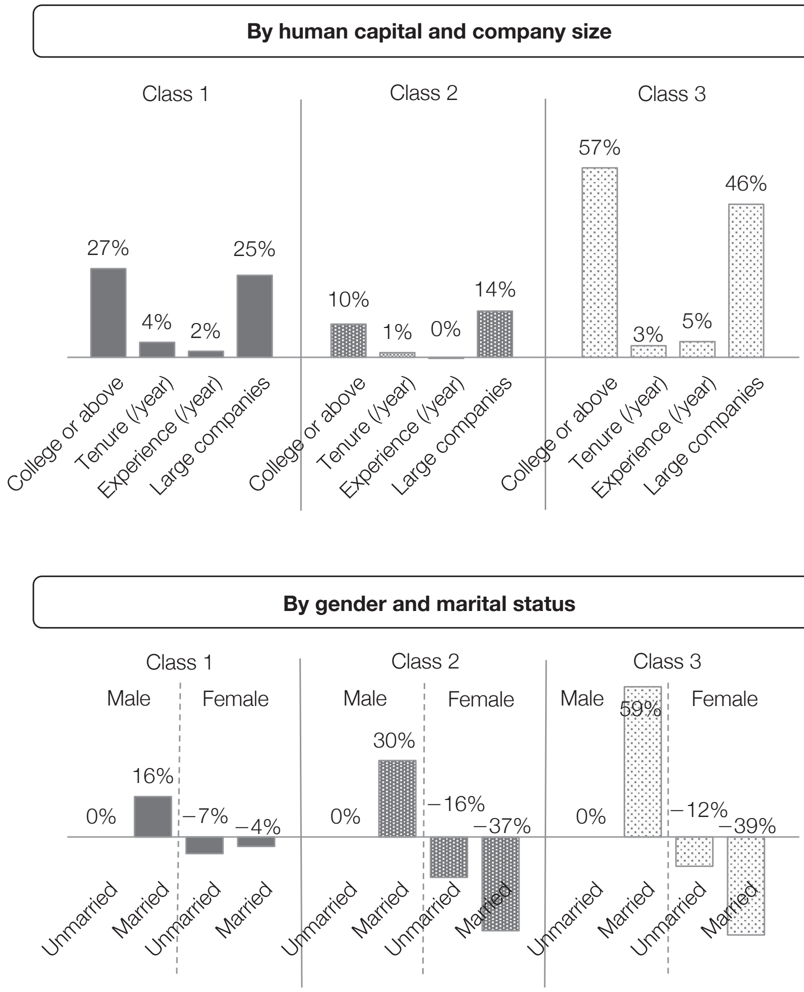
Table 4. Estimation results for Model 1 and Model 3

	① Level Difference Model (One class)	③ Latent Divide Model (Three classes)					
		Wage equation			Classification equation		
		Class 1	Class 2	Class 3	Class 1	Class 2	Class 3
Intercepts	14.020 ***	14.176 ***	14.437 ***	13.738 ***	0.828 ***	0.578 ***	−1.406 ***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.004)	(0.004)
Human capital							
College or above dummy	0.232 ***	0.236 ***	0.095 ***	0.450 ***	0.785 ***	−2.065 ***	1.280 ***
	(0.000)	(0.000)	(0.003)	(0.002)	(0.004)	(0.008)	(0.006)
Tenure	0.029 ***	0.044 ***	0.014 ***	0.034 ***			
	(0.000)	(0.000)	(0.000)	(0.000)			
Tenure (squared)	0.000 ***	0.000 ***	0.000 ***	−0.001 ***			
	(0.000)	(0.000)	(0.000)	(0.000)			
Experience	0.007 ***	0.018 ***	−0.003 ***	0.046 ***			
	(0.000)	(0.000)	(0.000)	(0.000)			
Experience (squared)	0.000 ***	0.000 ***	0.000 ***	−0.001 ***			
	(0.000)	(0.000)	(0.000)	(0.000)			
Company size							
Large company dummy	0.288 ***	0.220 ***	0.130 ***	0.378 ***	1.339 ***	−0.722 ***	−0.617 ***
	(0.000)	(0.000)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
Gender							
Female dummy	−0.078 ***	−0.068 ***	−0.174 ***	−0.123 ***	−0.355 ***	0.353 ***	0.002 ***
	(0.000)	(0.000)	(0.001)	(0.002)	(0.003)	(0.004)	(0.005)
Marital status							
Married dummy	0.210 ***	0.148 ***	0.264 ***	0.466 ***	−0.327 ***	0.281 ***	0.046 ***
	(0.000)	(0.000)	(0.001)	(0.002)	(0.003)	(0.004)	(0.004)
Female * Married	−0.375 ***	−0.118 ***	−0.553 ***	−0.833 ***	0.249 ***	−0.612 ***	0.364 ***
	(0.000)	(0.001)	(0.001)	(0.006)	(0.004)	(0.006)	(0.007)
Type of employment							
Non-regular dummy	−0.655 ***	−1.150 ***	−0.407 ***	−0.773 ***	−3.171 ***	1.559 ***	1.612 **
	(0.000)	(0.001)	(0.001)	(0.004)	(0.011)	(0.005)	(0.010)
Working hours							
Working hours/week	0.013 ***	0.008 ***	0.008 ***	0.008 ***			
	(0.000)	(0.000)	(0.000)	(0.000)			
Compositions (%)	100%	55%	36%	9%			
(Regular employees)	(80%)	55%	21%	5%			
(Non-regular employees)	(20%)	1%	15%	5%			
Average wage (Annual income, JPY)	3,558,501	5,004,009	2,248,559	2,249,571			
Error variance	0.170	0.073	0.121	0.570			
R^2	0.714	0.709	0.718	0.553			
N (weighted)	29,067,129		29,067,129				
Log-likelihood	−15,485,838		−12,101,170				

Source: Created by the author based on the estimation results.
Notes: 1. "Compositions" are calculated as averaged probabilities of assignments to each latent class.
2. "Average wage" is the averaged predicted value of wages. JPY: Japanese yen.
3. Estimation is weighted with the sample multiplier.
*** p<0.001, ** p<0.01, * p<0.05

The penalties for being female, especially married female, are not evident. These characteristics, estimated from the data, correspond to those of the traditional "Japanese employment systems." On the other hand, the wage-determining system for Class 2 has low returns for college degree and working for large companies. The returns for tenure and experience are also negligible. These characteristics of Class 2 are similar to the image of the peripheral/secondary sector suggested by dual labor market theory. As for gender, our estimated results show that there are much larger penalties for being female, and especially married female, in Class 2.

Figure 3 shows the wage distributions for each class, having each observation assigned exclusively to one of the three classes. While there is a significant difference between the medians, the lower half of Class



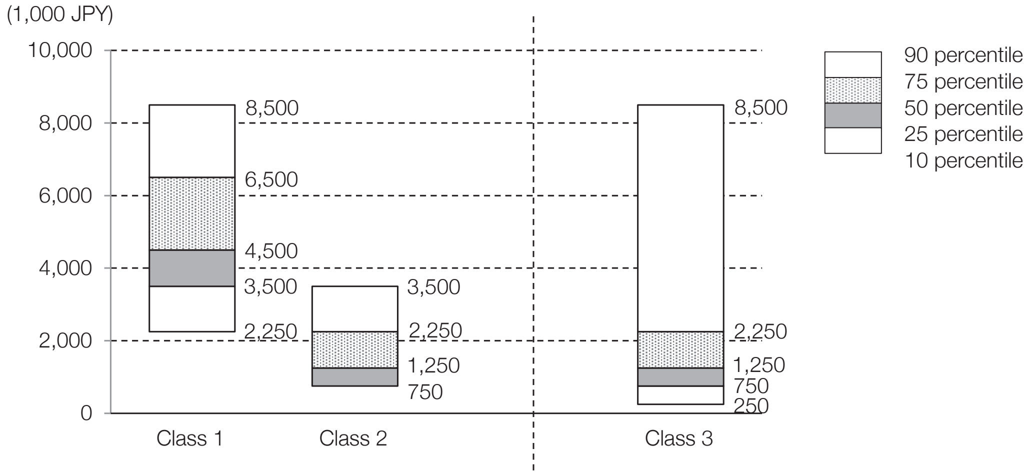
Source: Based on the coefficients in Table 4 .
Notes: 1. Estimated coefficients are converted to exponential form and displayed in %.
2. "Large companies" refer to companies with 300 employees or more.

Figure 2. Characteristics of the wage-determining systems

1 largely overlaps the upper half of Class 2. The distribution for Class 3 ranges from the lowest of Class 2 to the highest of Class 1.

Note that the type of employment is included both in the wage equations as well as in the classification equation, which means it could directly affect the wage level within each class. From the coefficients of Table 4, the wage of non-regular employees is 68% lower than regular employees in Class 1, and 33% lower in Class 2,[13] suggesting that type of employment also influences wage level within each class.

The intercepts of the wage equations can be understood as the wage level at one's entry into the labor market if we evaluate tenure and experience at zero. Although the intercept is larger in Class 2 than Class 1, the predicted wage will be higher in Class 1 than in Class 2, if we evaluate other variables at mean within each class.[14] In this case, we can consider that the initial wage level is also higher in Class 1 compared to Class 2.



Source: Created by the author based on the estimation results.
Note: Each observation is assigned to one class for which the classification probability is highest among the three.

Figure 3. Wage distributions by class

3. What determines the classification into two classes?

The next question will be what determines the assignment of each worker into estimated classes. To answer this question, we need to look at the effects of each variable on the probabilities of assignment, holding other variables constant. Partial Effect at Average (PEA) can be obtained as a difference between "probability of belonging to Class k, given the variable=1" and "probability of belonging to Class k, given the variable=0":

$$PEA=\Pr(class_i=k \mid Z_i\gamma, z_j=1)-\Pr(class_i=k \mid Z_i\gamma, z_j=0)$$

where k=1, 2..K, and z_j is the variable for which the effect is calculated.

Table 5 shows the PEA for each variable, calculated based on the coefficients for the classification equation in Table 4.

Looking at the PEA for Class 1, type of employment has the most significant impact on the allocation to Class 1. If a person is a non-regular employee, the probability of being Class 1 decreases by 74%. Company size and education, which have been long regarded as essential factors in the dualism in Japan, increase the probability of allocation by 46% and 32%, respectively, but the effects are smaller than that of the type of employment. On the other hand, the effects of gender and marital status on class allocation, independently of other factors, are relatively small, which contradicts the common view. Since this is an important aspect to clarify the role of the type of employment, I will examine it further in the next section.

IV. Discussion

1. How many segments are there in the labor market?

It is now necessary to answer a question that we have deferred so far: How many segments should we identify in the labor market? First, we can confirm that Class 1 and Class 2 are independent segments, because the class errors are small (see Table 4) and their estimated characteristics correspond to findings from other research. These two classes have much in common with those estimated by Ishikawa and Dejima (1994), who examined the structure of the labor market for regular employees in the 1980s and 1990s, using the same analytical model. They concluded that the estimated two segments correspond to those suggested by dual labor market theory: primary sector with high returns on education and tenure; and a secondary sector

Table 5. Partial Effect at Average for classification probabilities

		Mean	Class 1				Class 2				Class 3			
			Coef.	x=1	x=0	PEA	Coef.	x=1	x=0	PEA	Coef.	x=1	x=0	PEA
Intercepts			0.828				0.578				−1.406			
Education	(College or above dummy)	0.263	0.785	74%	42%	32%	−2.065	5%	51%	−46%	1.280	20%	7%	13%
Company size	(Large companies dummy)	0.474	1.339	79%	33%	46%	−0.722	15%	51%	−35%	−0.617	5%	16%	−11%
Gender	(Female dummy)	0.393	−0.355	47%	62%	−15%	0.353	42%	27%	14%	0.002	11%	10%	1%
Marital status	(Married dummy)	0.632	−0.327	52%	65%	−13%	0.281	37%	25%	12%	0.046	11%	10%	2%
	(Female * Married dummy)	0.230	0.249	66%	53%	13%	−0.612	20%	37%	−17%	0.364	14%	10%	4%
Type of employment	(Non-regular employees dummy)	0.203	−3.171	3%	77%	−74%	1.559	72%	17%	55%	1.612	25%	6%	19%

Source: Based on the coefficients in Table 4.
Note: PEA refers to Partial Effect at Average. In calculating the partial effects, other variables are evaluated at mean across the whole sample.

with less/no return on these factors. Our results for Class 1 and Class 2 also agree with these points. For example, education, company size, tenure, and experience have higher returns on wages in Class 1 (and the primary sector) than Class 2 (and the secondary sector), with the same order of their size of effects. With the classification equation, being male, in a large company, and a college graduate increases the probability of belonging to Class 1 (the primary sector). The question then becomes whether the third class, Class 3, can be regarded as an eligible segment.

There are broadly two perspectives maintaining that the Japanese labor market should consist of three tiers/segments rather than two. The first view suggests that an intermediate layer came to exist between regular and non-regular employees, as companies began to "internalize" some part of non-regular employment (Inagami 1999; Genda 2008). If Class 3 accords with this type of segment, the coefficients of the wage equations should fall somewhere between Class 1 and Class 2. However, the results do not support this: some coefficients are larger than Class 1, while others are even smaller than Class 2. Therefore, this perspective does not explain the results for Class 3, though the argument is most likely empirically valid.

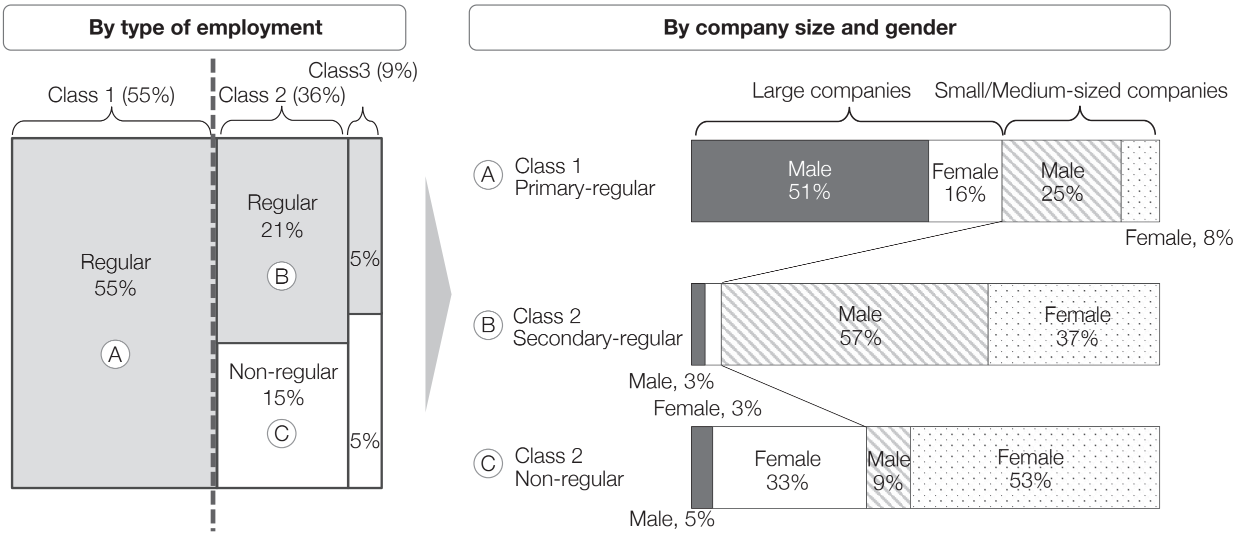
The second view is to conceptualize the third segment as being qualitatively different from the existing two. A good example of this is the well-known proposal "Japanese-style Management in a New Era" published by Nikkeiren (Japan Federation of Employers' Associations) in 1995 (Nikkeiren 1995). This report proposed that Japanese companies should manage their human resources with three different types of workforce: "long-term skill accumulation," "flexible employment," and "highly specialized skills." We can recognize the parallels between the long-term skill accumulation type and Class 1, as well as between the flexible type and Class 2. However, the estimated Class 3 does not seem to correspond to the highly specialized skills type in terms of wage level as well as the characteristics of wage-determining systems. It is reasonable to conclude that a segment of highly specialized skills type has not been emerged yet in the 2000s.

It seems more appropriate to consider the estimated Class 3 as being the residuals of Class 1 and Class 2 rather than as an independent segment, given that the goodness of fit for the wage equations are small and that the class errors are large (Table 4). This view can also explain some of the extreme values for coefficients for Class 3 (Figure 2).

Therefore, we can conclude that the Japanese labor market is not a single homogeneous entity, nor is it divided into more than three segments, but consists of two different segments, or wage-determining systems, which have continued from the 1980s and 1990s.

2. How does the type of employment relate to latent classes?

How does the type of employment relate to these two latent segments in the labor market? Figure 4 represents the breakdown of compositions by type of employment as well as company size and gender. The chart on the left shows that the division of the latent classes does not coincide with the division by the type of employment. Class 1 consists exclusively of regular employees, whereas Class 2 includes all non-regular



Source: Created by the author based on the estimation results.
Notes: 1. Figures in the left-hand chart represent percentages of the total.
2. Figures are based on the estimation results of the three-class model in Table 4.
3. (Right) Each observation is assigned to the one from among the three classes for which the estimated probabilities are highest.

Figure 4. Class assignment and its breakdown by attributes

employees (15% of the total) plus a significant part of regular employment (21% of the total). The division of the latent classes (the dotted vertical line in the chart) cuts through the regular employees and merges a quarter of this type with non-regular employees. These workers (segment B in the chart) are more like non-regular employees in terms of wage-determining systems despite being called "regular employees." Segment A can be called "primary-regular" and segment B can be called "secondary-regular."

Then, what kind of people are secondary-regular (B), i.e., regular employees but assigned to Class 2? The bar graph on the right shows the composition by company size and gender for each segment (A, B, C) in the chart on the left. Compositions broadly differ across segments. Segment A, primary-regular, is dominated by males, and especially those at large companies, while Segment B, secondary-regular, mostly consists of workers at small or medium-sized companies, also dominated by males. Segment C, non-regular, is mainly composed of females at both large and small or medium-sized companies. These compositions suggest that the findings by Ishikawa and Dejima (1994) identifying gender and company size as key factors in class allocation are still unchanged. It appears odd that gender has a strong relationship with class allocation, since it contradicts the findings in Table 5 that gender and marital status only have modest partial effects on allocation. The reason for this puzzle is obvious from the bar graph on the right. It shows that gender effectively exercises strong influences on class allocation through closely relating to the type of employment.[15] We can consider type of employment to be a "pipeline" that mediates women (especially married women) to the disadvantaged class in the labor market.

There is another finding regarding the influence of gender. While Ishikawa and Dejima (1994) found larger disparities between men and women in the primary sector, our results indicate more significant penalties for women (especially married women) in Class 2. It is not clear why penalties for married women are strong in Class 2. Given that the annual wages of workers allocated to Class 2 amount to around 1.25 million JPY (See Figure 3), which is limit for the spousal tax deduction, we can assume they control their working hours so that their income will not exceed it. In sum, married women are brought into Class 2 by taking employment as non-regular employees, and then choose to keep their income low, which in turn realizes severe penalties for married women in Class 2.

3. How can we understand the impact of type of employment on wages?

The commonly accepted belief that the wages of non-regular employees are lower than regular employees is correct, because the type of employment also directly affects the wage level within each class (see Table 4), resulting in wage levels in the order A > B > C in Figure 4. What is new here is that the prevailing division line exists within regular employees, between primary-regular and secondary-regular, which has continued since the 1980s.

While Ishikawa and Dejima (1994) estimated the size of the primary sector in the 1980s as 14 million,[16] here the size of Class 1 in the 2000s is roughly estimated as 16 million.[17] This implies that there has not been a large change in the size of the primary-regular employees segment, and that the division line between the two segments basically continued into the 2000s. Secondary-regular employees, many of whom work for small or medium-sized companies, also continue to exist in the 2000s, and the quality of these jobs cannot be differentiated from those of non-regular employees.

The results also demonstrate that non-regular employees, who rapidly expanded through the 1990s, have been allocated exclusively in what was called the "secondary sector." All non-regular employees follow a single wage-determining system in spite of their considerable heterogeneity. Viewed from the present point in time, it might seem natural and reasonable that non-regular employees are located exclusively in Class 2. However, this was not an inevitable result, given that a three-sector model was once a reasonable plan for the Japanese labor market where some type of non-regular employees should have been better off (Nikkeiren 1995). Nonetheless, non-regular employees have expanded in line with the existing division in the labor market.

Our analysis has revealed that this latent division, existing under the observable layer of regular and non-regular employees, has supported the continuing disparities in the employment system. In turn, the categories of regular and non-regular employees that can be regarded as socially constructed have played a critical role in maintaining this structural division in the workplace.

V. Conclusion

This paper has examined the structure of the labor market and the impact of the type of employment on wage disparities. The results indicate that the type of employment influences wages by choosing different wage-determining systems rather than by directly determining the wage level. Also, the labor market is not a single homogenous entity, nor does it consist of more than three segments, but is divided into two heterogeneous wage-determining systems. The division line between two latent classes does not coincide with the division line by regular/non-regular employees, though they partly overlap. This finding requires reconsideration of the prevailing view that the Japanese labor market is divided into regular and non-regular employees.

The two estimated segments are differentiated in terms of the wage-determining system. Class 1 has a higher return for education, company size, and tenure on wages, corresponding to the traditional "Japanese employment systems." More than half of regular employees are allocated to this segment. Class 2 has small returns for those factors and severe penalties for married women. All the non-regular employees are allocated exclusively in this segment. The rest of the regular employees, who mostly work for small or medium-sized companies, are also allocated to this segment, and the quality of their jobs is not differentiated from those of non-regular employees.

The most significant factor affecting the class allocation is the type of employment, but education and company size also have some impacts. Gender and marital status demonstrate strong relationships with class allocation, but only through the mediation of the type of employment. In this respect, type of employment works as a pipeline that transfers people with specific attributes (women in general, and especially married women) to the disadvantaged wage-determining system.

This divide can be regarded as a continuation of one found in the 1980s through the 1990s, suggesting that non-regular employment has expanded in line with the existing division and has contributed to maintaining it in turn.

This research relies on data from a single year more than ten years ago. It cannot demonstrate the transition of the labor market, and we may find new developments in the labor market today. We should not blindly rely on the category of regular and non-regular employees, but should be aware of the structure that exist latently but substantively in the labor market. We need to consider how we could resolve these disparities and realize more fairness in the Japanese labor market.

* This paper was originally a submission paper accepted by *The Japanese Journal of Labour Studies* in 2018 (printed in its September 2018 issue, vol. 60, no. 698) and has been revised and edited in line with the gist of Japan Labor Issues. The data used in this analysis is anonymized data from the Employment Status Survey (2002) by the Ministry of Internal Affairs and Communications, and was provided under Statistics Act by the National Statistics Center. I would like to thank many people for their supports in advancing the research. I wish to thank Professor Kazuo Yamaguchi, Professor Ryo Kambayashi, and Professor Takehiko Kariya, for their helpful comments, which improved the quality of this paper.

Notes

1. Gordon (2017) gives an extensive account of how the category of "non-regular employees" has emerged in the context of enduring dual structure of the Japanese labor market. Kambayashi (2013) analyses three definitions of the term in government statistics, which helps us to understand how the term is used differently from other countries.
2. The highest category of income is top-coded. The average value for that category is estimated using the quantile method (Ligon 1989) to be 18 million yen.
3. Variables for the Mincer wage equation were chosen according to Kawaguchi (2011).
4. Years of external experience=Age−(Years of education＋6)−Years of service
   This formula assumes that workers continue working after graduation, suggesting there would be measurement errors in cases of being unemployed or not in the labor force. Age is only provided as categories of 5-year intervals, and the median of each category is used.
5. Coefficients for "hours of work per week" are constrained to be equal across classes, while coefficients for other variables in wage equations are assumed to be different. This makes it easier to compare coefficients across estimated latent classes (Yamaguchi 2017).
6. Including marital status in the classification equation suggests that a person should be re-allocated when he/she gets married. This may not be realistic for men, who do not usually change jobs at marriage. However, this does happen for women: many choose to leave the labor market due to marriage or childbirth, and then re-enter it several years later. These women become excluded from their original status and are forced to enter peripheral jobs in the labor market.
7. Hori (2012) and Yamaguchi (2017) discussed the same model, and this paper refers to their suggestions on model specifications and evaluations. This model differs from what is now generally called a "switching regression." The structural forms of the specification model look similar for these two models, but there are some differences in objective of the models as well as in the technical aspects. The former is used to correct biases, when the choice of class is correlated with the outcome of the equations. In estimating the classification equation, a manifest variable is used as the dependent variable. On the other hand, the latter is used to detect heterogeneity (more than one distribution) in the data. A latent variable is used as the dependent variable of the classification function.
8. There is a possibility of sample selection bias from the unobserved wages of people who are not in the sample, since people with fewer working days or irregular work patterns are excluded. Günther and Launov (2012) proposed a modified model for correcting sample-selection bias, but its implementation is not available with standard software. The sample selection bias in the FMM is an issue to be dealt with in the future.
9. Some proposed alternative methods include modified LRT using statistics from a modified likelihood function (Chen et al. 2001), or a Bayesian approach using posterior predictive evaluation (Morduch and Stern 1997).
10. Tuma and Decker (2013) provided a review of simulation studies that evaluated the effectiveness of these criteria and found that many of them consider AIC3 to be the best. Also, they found that BIC is widely adopted as a criterion for model selection in empirical studies using FMM.
11. Latent Gold Ver. 5.0 was used for estimation.
12. The estimated latent classes are not observable segments in the labor market, but are constructs to represent the heterogeneity in the data, and each observation belongs to each class with specific probabilities rather than belonging exclusively to any single class.

13. Class 1: exp (−1.150)=0.32; Class 2: exp (−0.1407)=0.67. However, Class 2 is a mixture of regular/non-regular employment, whereas Class 1 has almost no non-regular employment.
14. There are three different approaches in evaluating variables: (1) Evaluate variables at zero; (2) evaluate variables at mean across all classes (as in Table 5); (3) evaluate variables at mean within each class. Option (1) means we would assume a typical worker to be "a high school graduate, working for a small/medium-sized company, unmarried, male, and a regular employee," which is not a very useful assumption. Also, it is a more realistic assumption to use individual attributes (3) averaged within each class rather than (2) averaged across all classes.
15. This point is one of the central issues in Yamaguchi (2017), but the same conclusions were reached in this paper despite the difference in data and model specifications.
16. From the results of Ishikawa and Dejima (1994) in Table 6-1, the number of general workers is 24.7 million people (36.3 million×67.8%) for males, and 10.02 million people (24.1 million×42.0%) for females, leading to 34.8 million people in total. Dividing this by the size of sectors in Table 6-6 (primary : secondary=27.5 : 41.3), the size of the primary sector will be 14.0 million people. This composition was based on the assumption that non-regular employees are included.
17. The estimated population using sample weights is 29 million people, as seen in Table 1. If we divide this number by the composition rate for Class 1, 55%, we obtain the result of 16 million people as workers in the primary sector. We should stop at comparison of "primary sector" and "Class 1" and should not go further, as people working with fewer days are excluded from the sample in this paper, and also "part-timers" are excluded from the sample in Ishikawa and Dejima (1984), leaving the size of the secondary/Class 2 sector undecided.

References

Berger, Suzanne, and Michael J. Piore. 1980. *Dualism and Discontinuity in Industrial Societies*. Cambridge: Cambridge University Press.

Chen, Hanfeng, Jiahua Chen, and John D. Kalbfleisch. 2001. "A Modified Likelihood Ratio Test for Homogeneity in Finite Mixture Models." *Journal of the Royal Statistical Society: Series B* (*Statistical Methodology*) 63, no. 1 (January): 19–29.

Dickens, William T., and Kevin Lang. 1985. "A Test of Dual Labor Market Theory." *The American Economic Review* 75, no. 4: 792–805.

Doeringer, Peter B., and Michael J. Piore. 1971. *Internal Labor Markets and Manpower Analysis*. Lexington, MA: D.C. Heath and Company and Heath Lexington Books.

Furugori, Tomoko. 1997. *Hiseiki rodo no keizai bunseki* [Economic analysis of non-regular employment]. Tokyo: Toyo Keizai Shinpo-sha.

Genda, Yuji. 2008. "Naibu rodo shijo kaiso to shiteno hiseiki" [Non-regular employees constituting a lower layer of the internal labor market]. *Economic Review* (*Keizai Kenkyu*) 59, no. 4: 340–356.

———. 2011. "Niju kozo ron: Saiko" [Double structure theory: Reconsideration]. *Japanese Journal of Labour Studies* 53, no. 4: 2–5.

Gordon, Andrew. 2017. "New and Enduring Dual Structures of Employment in Japan: The Rise of Non-Regular Labor, 1980s–2010s." *Social Science Japan Journal* 20, no. 1: 9–36.

Günther, Isabel, and Andrey Launov. 2012. "Informal Employment in Developing Countries: Opportunity or Last Resort?" *Journal of Development Economics* 97: 88–98.

Greene, William H. 2012. *Econometric Analysis*. 7th ed. Upper Saddle River, NJ: Prentice Hall.

Hodson, Randy, and Robert L. Kaufman. 1982. "Economic Dualism: A Critical Review." *American Sociological Review* 47, no. 6: 727–739.

Hori, Haruhiko. 2012. " 'Niju rodo shijo' to chingin kakusa" [Dual labor market and the wage disparities]. Section I, chap. 5 in *JILPT tayo na shugyo jittai chosa*, *data nijibunseki kekka houkokusho* [Report on secondary analysis of data from JILPT fact-finding survey on diversified employment types] JILPT Research Report no. 143, 134–163. Tokyo: JILPT.

Horn-Kawashima, Yoko. 1985. *Joshi rodo to rodo shijo kozo no bunseki* [Analyses on female labor and structure of labor market]. Tokyo: Nihon Keizai Hyoronsha.

Inagami, Takeshi. 1999. "Soron: Nihon no sangyo shakai to rodo" [Introduction: Japanese industrial society and labor]. Koza shakaigaku, vol. 6, Rodo [Socialogy of work (Sociology in Japan 6)], edited by Takeshi Inagami and Takashi Kawakita, 1–31. Tokyo: University of Tokyo Press.

———, and D. Hugh Whittaker. 2005. *The New Community Firm: Employment*, *Governance and Management Reform in Japan*. Cambridge: Cambridge University Press.

Ishikawa, Tsuneo, and Takahisa Dejima. 1994. "Rodo shijo no niju kozo" [Dual structure of the labor market]. In *Nihon no shotoku to tomi no bunpai* [Distribution of Japanese income and wealth], edited by Tsuneo Ishikawa, 169–209. Tokyo: University of Tokyo Press.

Kalleberg, Arne L., Barbara F. Reskin, and Ken Hudson. 2000. "Bad Jobs in America: Standard and Nonstandard Employment Relations and Job Quality in the United States." *American Sociological Review* 65, no. 2: 256–278.

Kambayashi, Ryo. 2013. "Differences in Definitions of Non-Regular Employees in Government Statistics." *Japan Labor Review* 10, no. 4: 55–66.

———, and T. Kato. 2016. “Good Jobs and Bad jobs in Japan: 1982–2007.” Working Paper Series no. 348, Center on Japanese Economy and Business, Columbia Business School.

———, 2017. *Seiki no sekai*, *Hiseiki no sekai: Gendai nihon rodo keizaigaku no kihon mondai* [The world of regular employment and non-regular employment: Basic problems of contemporary Japanese labor economics]. Tokyo: Keio University Press.

Kawaguchi, Daiji. 2011. “Minsa gata chingin kansu no nihon no rodo shijo e no tekiou” [Application of Mincer-type wage function to the Japanese labor market]. RIETI Discussion Paper Series 11-J-026, the Research Institute of Economy, Trade and Industry, Tokyo.

Ligon, Ethan. 1989. *The Development and Use of a Consistent Income Measure for the General Social Survey*. GSS Methodological Report no. 64. Chicago: NORC.

Loskin, Michael, and Zurab Sajaia. 2004. “Maximum Likelihood Esimation of Endogenous Switching Regression Models.” *Stata Journal* 3, no. 4: 282–289.

Maddala, Gangadharrao S. 1986. *Limited-dependent and Qualitative Variables in Econometrics*. Cambridge: Cambridge University Press.

Morduch, Jonathan J., and Hal S. Stern. 1997. “Using Mixture Models to Detect Sex Bias in Health Outcomes in Bangladesh.” *Journal of Econometrics* 77: 259–276.

Nikkeiren (Japan Federation of Employers' Associations). 1995. *Shinjidai no nihonteki keiei* [Japanese-style management in a new era]. Tokyo: Nikkeiren.

Nitta, Michio. 2011. “Hiseiki koyo no niju kozo” [Dual structure of non-regular employment in Japan], *Journal of Social Science* 62, no. 3–4: 3–23.

OECD (Organization for Economic Co-operation and Development). 2019. *OECD Economic Surveys of Japan 2019*. Paris: OECD Publishing https://www.oecd.org/economy/surveys/Japan-2019-OECD-economic-survey-overview.pdf.

Osawa, Mari. 1993. *Kigyo chushin shakai o koete: Gendai nihon o 'jenda' de yomu* [Beyond a corporate-centric society: Understanding contemporary Japan with gender perspective]. Tokyo: Jiji Press.

———. 2001. People in irregular modes of employment: Are they really not subject to discrimination?. *Social Science Japan Journal*, vol. 4(2): 183–199.

Sato, Yoshimichi, and Jun Imai eds. 2011. *Japan's New Inequality: Intersections of Employment Reforms and Welfare Arrangement*. Balwyn North, Victoria: Transpacific Press.

Tuma, Michael, and Reinhold Decker. 2013. “Finite Mixture Models in Market Segmentation: A Review and Suggestions for Best Practices” *Electronic Journal of Business Research Methods* 11, no. 1: 2–15.

Ujihara, Shojiro. 1966. *Nihon rodo mondai kenkyu* [Research on labor issues in Japan]. Tokyo: University of Tokyo Press.

Vermunt, Jeroen K., and Jay Magidson. 2013. *Technical Guide for Latent GOLD 5.0*. Belmont, MA: Statistical Innovations.

Yamaguchi, Kazuo. 2017. “Chingin kozo no senzaiteki tayosei to danjo chingin kakusa: Rodo shijo no niju kouzou bunseki saihou” [Latent diversity of wage structure and gender wage disparity: A double-structure analysis of the labor market]. RIETI Discussion Paper Series 17-J-057, The Research Institute of Economy, Trade and Industry, Tokyo.

SUZUKI Kyoko

Ph.D. Student, Graduate School of Interdisciplinary Information Studies, The University of Tokyo.