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Note on alternative work arrangements, tasks, and compensations: Evidence from a quasi-natural experiment

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Note on alternative work arrangements, tasks, and compensations: Evidence from a quasi-natural experiment

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Abstract

This note estimates a Mincerial equation to disentangle the effect of alternative work arrangements on wage premiums using an anonymized microdata and a quasi-experimental event of labor market deregulation in Japan. This study focuses on tasks of workers. The estimation results indicate that (i) alternative work arrangements equalize wage premiums between major metropolitan areas and other areas, (ii) alternative work arrangements equalize negative female premiums between routine-manual tasks and other tasks, and (iii) alternative work arrangements don't affect the returns to education and work experience.

Keywords: Alternative work arrangements, tasks, wage premium

1 Introduction

Alternative work arrangements provide flexibility for rigid labor markets. For example, temporary employment facilitates active matching in labor markets and shortens the searching-and-matching period for both labor supply and demand sides. Accordingly, it helps to improve the efficiency of labor markets. On the other hand, temporary employment has negative aspects. For example, employers may not evaluate skills and education of temporary workers. If so, it reduces the incentives for temporary workers to accumulate their human capitals. Further, temporary workers tend to lack opportunity to enhance skills through on-the-job training. These disadvantages may fix the polarization of the labor markets.

This study examines how alternative work arrangements affect labor markets in general and how they affect the market evaluation of employees in specific. To this end, I use the labor market deregulation in Japan in 2003 as a quasi-natural experimental opportunity and estimate changes in excess wage premiums on education, work experience, gender, location, and other attributes using a large-scale anonymized micro-dataset of the Japan's government ("Employment Status Survey").

Among other studies, this study is different in focusing on tasks of workers. Acemoglu and Autor (2011) suggest that we can gain a better understanding of the labor

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market when looking occupations through the lens of tasks. In line with Autor, Levy and Murnane (2003), Acemoglu and Restrepo (2020) construct a task-based model of endogenous growth and the analyze the impact of automation on the labor market. This paper conducts two kinds of analyses by focusing on tasks. First, I estimate changes in excess wage premiums between similar-task workers in industries subject to deregulation and those in industries not subject to deregulation. Second, I estimate changes in wage premiums between occupations (tasks) subject to deregulation and those not subject to deregulation within same industries.

The estimation results are as follows. First, from the first exercise, I find that alternative work arrangements equalize wage premiums between major metropolitan areas and other areas. It is considered that, after the deregulation, the wage equalization pressure becomes harsh in urban area where the labor supply is relatively abundant. Second, alternative work arrangements equalize the negative female premiums between routine-manual tasks and other tasks. It is considered that a flexible work arrangement enables female workers to demonstrate the abilities through diverse work styles. Third, alternative work arrangements don't affect the returns to education and work experience.

After the seminal work by Mincer (1974), a vast amount of studies contribute to the literature on the estimation of wage premium.[1] The estimation of the Mincer equation in Japan has been surveyed by Sano and Yasui (2009). The current study contributes to this literature through the lens of tasks using the quasi-natural experimental opportunity of deregulation in 2003. The empirical evaluation of the Japan's labor-market deregulation in 2003 includes Kambayashi and Mizumachi (2014), which comprehensively assesses the impact of deregulation in 2003.[2][3] Kambayashi and Mizumachi (2014) conclude that the wage rate of temporary workers declined during the period between 2002 and 2007. Different from this previous study, the current study estimates a Mincerian equation with focusing on the tasks subject to deregulation and examines the effect of alternative work arrangements on wage premiums.

The organization of this study is as follows. Section 2 describes the detail of the deregulation in 2003 and presents the estimation strategy. Section 3 describes the dataset. Section 4 presents the estimation results. Section 5 is the conclusion.

2 Research design

2.1 Deregulation of alternative work arrangements in Japan

The Worker Dispatching Act in Japan, which was enacted in 1986, was amended in 2003. The act regulates the operations of temporary work agencies in Japan. Before the amendment in 2003, temporary work agencies were prohibited from dispatching their workers

[1] See Psacharopoulos and Patrinos (2018) for a comprehensive survey of the literature.

[2] Okudaira, Ohtake, Kume and Tsuru (2013) and Esteban-Pretel, Nakajima and Tanaka (2011) analyze the transition from temporary workers to regular workers in Japan. Chino (2020) examines the effect of alternative work arrangements on costs of equity.

[3] Flexible staffing and alternative work arrangements have been analyzed by many studies such as Autor (2001), Houseman (2001), and Autor and Houseman (2010). See Mas and Pallais (2020) for a comprehensive survey of the literature.

to production lines in manufacturing plants. Following Autor et al. (2003), this study categorizes tasks of (temporary) workers in production lines into routine-manual tasks. And then, the current study uses this opportunity to compare differences of wage premiums on routine-manual tasks in manufacturing and other industries before and after the deregulation. Further, this study also compares differences of wage premiums on routine-manual tasks and other tasks within manufacturing industries before and after the deregulation. By doing so, this analysis disentangles the effect of exogenously-introduced alternative work arrangements on wage premiums.

2.2 Estimation strategy

When estimating a wage equation using cross sectional dataset, I have to cope with potential biases caused by endogenous labor supply decision. In response, this study applies the Heckman's two stage estimation method.[4] Specifically, I estimate the following "Mincerial" equation (*c.f.* Mincer (1974)) as a benchmark specification,

$$\begin{aligned}
\log(w_i) &= \text{constant} + \beta_1 \times education_i + \beta_2 \times age_i + \beta_3 \times age_i^2 + \beta_4 \times tenure_i + \beta_5 \times tenure_i^2 \\
&+ \beta_6 \times female_i + \beta_7 \times city_i + \beta_7 \lambda_i + \epsilon_i, \\
&\Leftrightarrow \\
\log(\boldsymbol{w}) &= \boldsymbol{\beta}' \boldsymbol{X} + \boldsymbol{\epsilon}, \qquad (1)
\end{aligned}$$

where w, *education*, *age*, *tenure*, *female*, *city*, and λ are the wage rate per hour, age, years of tenure, a female dummy, a dummy of the three largest metropolitan area, and the inverse Mill's ratio obtained from the first stage regression, respectively. A subscript i for each variable and $\boldsymbol{X}$ denote an individual respondent i and the matrix of the covariates. I also denote the number of samples is N. Following the convention in the literature, I add the quadratic terms of age and tenure years to cope with the potential nonlinear effects of these variables.

To compare between control and treatment groups, I extend the benchmark equation as follows,

$$\log(\boldsymbol{w_s}) = \boldsymbol{\beta}' \boldsymbol{X_s} + \boldsymbol{\gamma}'_{manufact} \boldsymbol{X_s} \circ \boldsymbol{D}_{manufact} + \boldsymbol{\epsilon_s}, \qquad (2)$$

$$\log(\boldsymbol{w_m}) = \boldsymbol{\beta}' \boldsymbol{X_m} + \boldsymbol{\gamma}'_{task} \boldsymbol{X_m} \circ \boldsymbol{D}_{task} + \boldsymbol{\epsilon_m}, \qquad (3)$$

where subscript s and m represent the sets of individuals whose occupations belong to the *routine-manual* task group and who work in the manufacturing industries, respectively; D_s and D_m represent the $N \times K$ dummy matrixes of routine-manual tasks and the manufacturing, respectively; $\circ$ represents the Hadamard (element-by-element) product. The covariates are the same of those used in (1).

In (2) and (3), $\boldsymbol{\gamma}_{manufact}$ and $\boldsymbol{\gamma}_{task}$ are excess premium on respective attributes. Specifically, the former represents the excess premiums payed to routine-manual-task workers in manufacturing industries relative to routine-manual-task workers in other industries,

[4] As a first stage regression, this study estimates a probit model, whereby the dependent variable is the employment dummy, and covariates are years of education, the head-of-the-house dummy, and the dummy of employment status in the last year. See the appendix for the detail of the regression results.

and the latter represents the excess premiums payed to routine-manual-task workers in manufacturing industries relative to other-task workers in the same industries.

Because the purpose of this study is the comparison of excess premium before and after the deregulation, I estimate (2) and (3) two times using the 2002 survey and the 2007 survey. Then, I examine whether each excess premium has changed after 2003 using the χ^2 test. It may well to consider that the design of the current study is a quasi difference in difference approach using the repeated cross section dataset.

3 Data

This section presents the definition and descriptive statistics of the dataset.

3.1 Definition of variables

All the data used in this study is the anonymized microdata from the "employment status survey" conducted by the Statistics Bureau of Japan. To examine the compensation determined in the market, I drop respondents if (i) main earnings are pension and benefits; (ii) the occupational status is either student, self-employed, assistant of the self-employed, homework, or the unidentified.

The wage rate (per hour) is defined as a compensation to an individual divided by the number of work days in a year times the daily work hours.[5] This study converts all the categorical data into the consecutive value using a medium of the category's range. The years of education are 9, 12, 14, 16, and 18 for elementary/junior high school, high school, junior college/technical college, university, and graduate school, respectively. In case that the university and graduate school are in one category, I assign 16.

While referring to the previous studies such as Autor et al. (2003), I classify the following occupations as occupations of routine-manual tasks; Metal Material Worker, Chemical Product Workers, Ceramic and Stone Product Workers, Metalworking Workers, General machinery and equipment assembler/repairer, Electrical machinery and apparatus assembler/repairer, Transportation machinery assemblers and repairers, Measurement and optical machinery and equipment assemblers and repairers, Food product manufacturers, Beverage and tobacco manufacturers, Textile workers, Garment and textile product manufacturers, Wood, bamboo, grass, and vine product manufacturers, Pulp, Paper, and Paper Product Workers, Printing and bookbinding workers, Rubber and plastic product manufacturers, Leather and Leather Products Workers, Other Manufacturing and Production Workers, Mining Workers, Construction Workers, Transport laborers, and Other laborers.

Finally, I categorize the following as manufacturing industries; Food, Beverage and Tobacco Manufacturing, Textile industry and textile product manufacturing, Wood, Wood Products and Furniture Manufacturing, Pulp, Paper and Paper Products Manufacturing, Printing and Related Industries, Chemical, Petroleum and Coal Manufacturing, Plastics and Rubber Products, Ceramic, Clay and Stone Products, Iron and Steel, Non-ferrous

[5] To calculate the daily work hours, I divide the weekly work hours by 5.

Metals, Metal products, General machinery and apparatus, Electrical machinery and apparatus, Information and Communication, Machinery and Equipment, Electronic Components and Devices, Transportation Machinery and Equipment, Manufacture of precision machinery and equipment, Other manufacturing industries, Food, Beverage, and Tobacco Manufacturing, Textile industry and textile products manufacturing, Wood, Wood Products and Furniture Manufacturing, Pulp, Paper, and Paper Products Manufacturing, Printing and Related Industries, Chemicals, Petroleum and Coal, Plastics and Rubber Products, Ceramic, Clay and Stone Products, Iron and Steel, Non-ferrous Metals, Metal products, General machinery and apparatus, Electrical machinery and apparatus, Information and Communication Machinery and Equipment, Electronic Components and Devices, Transportation Machinery and Equipment, Manufacture of precision machinery and equipment, Other manufacturing industries.

3.2 Descriptive Statistics

Table 1 reports the descriptive statistics of the data. The number of samples is over 300,000 for both 2002 and 2007. The mean and standard deviation of variables are almost balanced between the sample of 2002 and 2007. The fraction of respondents in manufacturing industries and that in occupations of routine-manual tasks are approximately 15 and 20 percent, respectively.

It is also worth reporting that 51-52 percent of routine-manual workers are in manufacturing industries and 69-70 percent of workers in manufacturing industries are engaged in routine-manual tasks. Therefore, the size of control and treatment groups are large enough to withstand empirical analysis.

4 Results

Table 2 is the preliminary benchmark results. Most covariates are statistically significant. The statistically significant inverse Mill's ratios suggest that endogeneity in labor supply decision making would affect the results when estimated without using the two stage estimator. The returns to education are 6.5-7.2 percent in overall, whereas they are relatively lower and 2.8-3.6 percent in routine-manual tasks. The negative female premium is greater in the routine-manual tasks.

Table 3 presents the main results. The estimated parameters are basically statistically significant. In the first three columns, this study compares the excess premium on routine-manual tasks in manufacturing before and after the deregulation. The key parameters are the cross terms presented in 8-14th rows. It is interesting that the excess negative premium on the location ($city \times manufact$) is almost doubled after the deregulation. The χ^2 test in the third column shows that this difference is statistically significant. After the deregulation, wage-equalization pressure between manufacturing and other industries becomes harsh. However, these pressures are effective only in urban areas because job opportunities in the urban area are concentrated in a relatively small area, and hence, labor supply is relatively abundant. The χ^2 tests in the third column also report that the other parameters such as the excess return to education, the excess return to the work experience

Table 1: Descriptive statistics

	N	Mean	S.D.	Min	Max
		2002			
log(*wage*)	313126	-1.8677	0.7032	-4.9628	3.2321
age	481169	46.6586	16.6308	17	87
tenure	329639	12.1970	10.8898	0	33
education	478725	12.2691	2.2463	9	16
female	481169	0.5285	0.4992	0	1
city	481169	0.2979	0.4573	0	1
work	481169	0.9817	0.1342	0	1
head house	481169	0.4150	0.4927	0	1
work last year	477512	0.6871	0.4637	0	1
manufact	481169	0.1497	0.3567	0	1
Routine manual	481169	0.2023	0.4017	0	1
		2007			
log(*wage*)	322265	-1.9334	0.7037	-5.1889	3.8430
age	482834	48.2111	16.6612	17	87
tenure	335865	12.5397	11.1079	0	33
education	473097	12.6145	2.2496	9	18
female	482834	0.5352	0.4988	0	1
city	482834	0.2944	0.4558	0	1
work	482834	0.9803	0.1390	0	1
head house	482834	0.4171	0.4931	0	1
work last year	475106	0.7001	0.4582	0	1
manufact	482834	0.1467	0.3538	0	1
Routine manual	482834	0.1985	0.3988	0	1

Table 2: Benchmark results

	2002				2007			
	Overall	Routine/Manual			Overall	Routine/Manual		
		All	Manufact.	The other		All	Manufact.	The other
age	0.032***	0.038***	0.033***	0.042***	0.034***	0.036***	0.033***	0.041***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
age^2	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
tenure	0.028***	0.023***	0.025***	0.020***	0.021***	0.017***	0.020***	0.013***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
$tenure^2$	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000	-0.000	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
education	0.072***	0.036***	0.033***	0.033***	0.065***	0.028***	0.028***	0.024***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
female	-0.257***	-0.452***	-0.527***	-0.384***	-0.223***	-0.396***	-0.470***	-0.333***
	(0.003)	(0.005)	(0.006)	(0.008)	(0.003)	(0.005)	(0.006)	(0.008)
city	0.139***	0.140***	0.121***	0.148***	0.172***	0.156***	0.127***	0.181***
	(0.002)	(0.004)	(0.005)	(0.006)	(0.002)	(0.004)	(0.006)	(0.006)
λ	-3.035***	-0.687***	-1.112***	-0.455***	-3.286***	-0.633***	-1.431***	-0.372***
	(0.051)	(0.043)	(0.081)	(0.049)	(0.050)	(0.050)	(0.112)	(0.053)
const	-3.569***	-3.294***	-3.082***	-3.448***	-3.529***	-3.191***	-3.017***	-3.368***
	(0.015)	(0.024)	(0.033)	(0.034)	(0.015)	(0.026)	(0.035)	(0.038)
N	310797	89969	47079	42890	314764	88430	46934	41496
R^2	0.341	0.326	0.415	0.242	0.283	0.259	0.346	0.186

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

(years of tenure), and the negative female premium are unchanged after the deregulation ($education \times manufact$, $tenure \times manufact$, $tenure^2 \times manufact$).

The last three columns of Table 3 compare the compensation gaps within manufacturing industries before and after the deregulation. Again, the key parameters here are the cross terms presented in 15-21st rows. The parameters show that the age is more evaluated in routine-manual tasks while education premium is less evaluated in these tasks. An important change after the deregulation is the negative female premium ($\times routine, manual$). It drops from -10.8 percent to -5.1 percent after the deregulation. The χ^2 test in the last column reports this difference is statistically significant. The flexible labor market allows alternative work arrangements and enables female workers to demonstrate the abilities through diverse work styles. In the meanwhile, alternative work arrangements do not change the returns to education and work experience ($education \times routine, manual$, $tenure \times routine, manual$, $tenure^2 \times routine, manual$).

5 Conclusion

This study estimates a Mincerial equation to disentangle the effect of alternative work arrangements on wage premiums using an anonymized microdata and a quasi-experimental event of labor market deregulation in Japan. One feature of this note is the focus on tasks of workers. The estimation results indicate that (i) alternative work arrangements equalize

Table 3: Main results

	Routine-manual tasks			Manufacturing		
	2002	2007	χ^2-test (p-value)	2002	2007	χ^2-test (p-value)
age	0.037***	0.036***		0.021***	0.021***	
	(0.001)	(0.001)		(0.001)	(0.001)	
age^2	-0.000***	-0.000***		-0.000***	-0.000***	
	(0.000)	(0.000)		(0.000)	(0.000)	
tenure	0.020***	0.013***		0.024***	0.018***	
	(0.001)	(0.001)		(0.001)	(0.001)	
$tenure^2$	-0.000***	-0.000*		-0.000***	-0.000	
	(0.000)	(0.000)		(0.000)	(0.000)	
education	0.027***	0.019***		0.056***	0.053***	
	(0.001)	(0.001)		(0.002)	(0.002)	
female	-0.378***	-0.326***		-0.417***	-0.414***	
	(0.006)	(0.007)		(0.008)	(0.008)	
city	0.147***	0.180***		0.174***	0.195***	
	(0.006)	(0.006)		(0.007)	(0.008)	
$age \times manufact$	0.002	0.003*	[0.5557]			
	(0.001)	(0.001)				
$age^2 \times manufact$	-0.000***	-0.000***	[0.5679]			
	(0.000)	(0.000)				
$tenure \times manufact$	0.005***	0.007***	[0.3470]			
	(0.001)	(0.001)				
$tenure^2 \times manufact$	0.000**	0.000	[0.4336]			
	(0.000)	(0.000)				
$education \times manufact$	0.012***	0.013***	[0.6581]			
	(0.002)	(0.002)				
$female \times manufact$	-0.149***	-0.149***	[0.9890]			
	(0.008)	(0.008)				
$city \times manufact$	-0.026**	-0.052***	[0.0242]**			
	(0.008)	(0.008)				
$age \times routine, manual$				0.015***	0.014***	[0.8564]
				(0.001)	(0.001)	
$age^2 \times routine, manual$				-0.000***	-0.000***	[0.6870]
				(0.000)	(0.000)	
$tenure \times routine, manual$				0.001	0.001	[0.9472]
				(0.002)	(0.002)	
$tenure^2 \times routine, manual$				0.000	0.000	[0.7390]
				(0.000)	(0.000)	
$education \times routine, manual$				-0.021***	-0.025***	[0.2904]
				(0.002)	(0.002)	
$female \times routine, manual$				-0.108***	-0.051***	[0.0002]***
				(0.009)	(0.010)	
$city \times routine, manual$				-0.053***	-0.068***	[0.2786]
				(0.009)	(0.010)	
λ	-0.703***	-0.673***		-1.196***	-1.635***	
	(0.039)	(0.046)		(0.071)	(0.097)	
const	-3.262***	-3.185***		-3.155***	-3.054***	
	(0.022)	(0.024)		(0.027)	(0.028)	
N	89969	88430		68908	67348	
R^2	0.340	0.279		0.450	0.401	

Standard errors in parentheses and p-value in square brackets

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

wage premiums between major metropolitan areas and other areas; (ii) alternative work arrangements equalize negative female premiums between routine-manual tasks and other tasks; (iii) alternative work arrangements don't affect the returns to education and work experience.

There are several reservations about the analysis in this study. First, the analysis is not a difference-in-difference design in the strict sense because the micro-dataset used is repeated cross section data. Thus, unobserved heterogeneity may affect the estimation results. Second, although the most significant change in Japan's labor markets between 2002 and 2007 was the deregulation on temporary employment in the manufacturing industry, other events may have affected the results.

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A Appendix: first stage probit model

The followings are estimation results of the first stage probit models.

Table 4: Heckit first stage: 2007

	Overall	Routine/Manual		
		All	Manufacturing	The other
education	0.038***	0.077***	0.071***	0.074***
	(0.002)	(0.005)	(0.010)	(0.006)
head house	0.511***	0.542***	0.504***	0.630***
	(0.011)	(0.019)	(0.035)	(0.023)
work last year	-0.381***	0.666***	0.620***	0.678***
	(0.012)	(0.026)	(0.045)	(0.034)
α	1.718***	0.164*	0.585***	-0.055
	(0.025)	(0.066)	(0.126)	(0.077)
N	467279	93362	48463	44899
R^2				

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Heckit first stage: 2002

	Overall	Routine/Manual		
		All	Manufacturing	The other
education	0.035***	0.078***	0.097***	0.065***
	(0.002)	(0.005)	(0.009)	(0.006)
head house	0.525***	0.579***	0.550***	0.656***
	(0.011)	(0.019)	(0.034)	(0.023)
work last year	-0.300***	0.720***	0.746***	0.677***
	(0.011)	(0.024)	(0.040)	(0.031)
α	1.723***	0.134*	0.158	0.110
	(0.024)	(0.063)	(0.115)	(0.075)
N	475405	96287	49076	47211
R^2				

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$