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Nonprofit/For-profit Facility and Difference of Wage Distribution: Evidence from the Japanese elderly care industry

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Nonprofit/For-profit Facility and Difference of Wage Distribution: Evidence from the Japanese elderly care industry[1]

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Abstract

This paper provides new estimation results for the impacts of operator types, nonprofit or for-profit, on earnings distribution by using employee-employer matched data in the Japanese elderly care sector. The ordinary least squares (OLS) and quantile regression results show that even if workers' and operators' basic characteristics are controlled, we can observe a nonprofit premium on average and in lower quantiles. However, in higher quantiles, we observe a negative premium (penalty) of nonprofit operators. Additionally, average and quantile decomposition results represent that, on average and in each quantile, a large part of a nonprofit premium can be explained by the difference of observable characteristics, especially the license acquisition rate and worker's tenure. The quantile decomposition results additionally show that a larger part of earnings gap in high quantiles can be explained by the difference of tenure than in lower quantiles.

Keywords: Nonprofit operator, Quantile decomposition, Wage gap

JEL classification: H11 J31

[1]This study is conducted as a part of the Project “A Socioeconomic Analysis of Households in Environments Characterized by Aging Population and Low Birth Rates” undertaken at Research Institute of Economy, Trade and Industry (RIETI). The data for this secondary analysis, "Statistical Survey on Nursing Home Employees," was provided by the Social Science Japan Data Archive, Center for Social Research and Data Archives, Institute of Social Science, The University of Tokyo.

1 Introduction

In recent year, the labor demand in the Japanese elderly care sector is rapidly increasing with the advancement of an aging society, while care workers is still undersupply[1]. Under these social backgrounds, the low-wage problem of Japanese care workers continues to attract attentions by not only researchers but also policymakers because they think that low wages are a reason for insufficient labor supply for the elderly care sector. The aim of this paper is to understand the roll of facility operation on workers' earnings, especially focus on the difference between nonprofit and for-profit operators.

Some papers (e.g., Leete 2001, Noguchi and Shimizutani 2007, and Pennerstorfer and Schneider 2010) already estimated the effect of operators' types and robustly funded a nonprofit wage premium; the average earnings in nonprofit operators is higher than in for-profit operators. They focused on only the average effects, however, economics theory predicts not only average earnings but also other "statistics" of the earnings distribution (e.g., variance and quantile) have non-trivial effects on labor supply decision-makings. In this paper, we then estimates the effects on the earnings distribution.

In this paper, we use the "Statistical Survey on Nursing Home Employees" in 2010, which has some advantages. First, this survey is large samples; there are 6850 samples of workers in nonprofit operators and 2953 samples in for-profit operators, which allows not only parametric but also nonparametric estimation approaches. Second advantage is that this survey includes detail and specific information of both workers and operators. Consequently, to remove the bias, we can control various characteristics in the regression.

From the descriptive statistics, we can easily find that the average earnings in nonprofit operator is higher than in for-profit operator. Moreover, the kernel estimation reports show that the earnings distribution in nonprofit is located to the right of the earnings distribution in for-profit. These results consistently shows that the earnings in nonprofit operators tend to be higher than in for-profit operators. However, other characteristics, such as the number of employment, location, and workers characteristics, are also totally different between nonprofit and for-profit. We then use more sophisticated approaches to understand the effects of operators' type.

First, we estimate the average effects of operators' type by using the OLS regression and the Oaxaca-Blinder decomposition. The regression results shows consistent results with previous papers; the estimation without

[1] For example, the average market tightness in the elderly care sector is 1.73, while average market tightness in all sector is 0.89.

any control variables shows the existence of a nonprofit premium on average earnings as 9.1%. This premium is still observed even if we incorporate workers' and operators' characteristics as control variables, but the size of the premium is decreased 66.5 %. Moreover, the Oaxaca-Blinder decomposition results show that 80.2% of a nonprofit premium can be explained by the difference of observable characteristics, especially by worker's tenure and skill, between nonprofit and for-profits operators. These results consistently show that large part of the average wage difference is coming from the difference of workers' and operators' characteristics.

Next, we estimate effects on each components of the earnings distribution by using the unconditional quantile regression and decomposition approaches offered by Firpo, Fortin, and Lemieux (2009). The estimation results show that the earnings premium declines along the earnings distribution. For example, without control variables, the estimated premium at the 90th quantile is less than at the 10th quantile as 61.6%. Moreover, at the high quantile, the negative premium (penalty) can be observed if we control some characteristics of workers and operators. The decomposition results show that a large part of the earnings premium in each quantile can be explained by the difference of observable characteristics, and the explanation power of observable characteristics is high in the lower and higher quantile.

Finally, the effect on the earnings distribution is estimated by using the counterfactual distribution approach offered by Dinardo, Fortin, and Lemieux (1996)[2]. In this approach, we estimate the counterfactual earnings distribution in which the characteristics distribution is totally same as in for-profit operators, but wage schedule (density) is according to non-profit operators. This result shows that the counterfactual distribution are still located to the right of the earnings distribution in for–profit operators. However, the location of the counterfactual distribution is the left of the original distribution in non-profit operators. Additionally, the comparison between actual and counterfactual distribution represents that the effect of nonprofit is more strong for workers with low and middle wages. This results implies that nonprofit operators have an effect as the compress the earnings distribution.

The estimation on the earnings distribution is then an important foundation to obtain policy implications. Our paper robustly finds a large nonprofit premium at mean and lower quantile but a small premium or penalty at higher quantile, which mean that nonprofit operators may reduce earning dispersion. Moreover, the wage gap between nonprofit and for-profit can be explained by the difference of observable characteristics, especially

[2]The method of Dinardo, Fortin, and Lemieux (1996) aleady applies for the analysis of Japanese labor market (see, for example, Hara and Kawaguchi 2008, Kambayashi, Kawaguchi, and Yokoyama 2008).

workers' tenure and licence acquisition. This paper then offer new policy implications for market competition policies in the care-industry.

In the rest of this paper, Section 2 describes data and descriptive statistics. In Section 3, the OLS and unconditional quantile regression results are shown, and Section 4 presents the decomposition results. Section 5 discusses policy implications.

2 Data

We use the "Statistical Survey on Nursing Home Employees" conducted by the Care Worker Support Center Foundation in 2010. This survey has large number of observations (workers) and is random sampling from all areas in Japan. One advantage of this survey is sample size; the number of observations as workers in for-profit and nonprofit operators are 2953 and 6850, respectively. Another advantage is to include detail information on characteristics of both workers and their operators.

In this study. we focus on full-time care workers, and following Noguchi and Shimizutani (2007), the explained variable is the logarithm of daily wages derived from available information of monthly wages and hours worked. In Figure 1, the kernel estimation of the log earnings distribution are shown[3]. This figure means existence of earnings gap on not only the mean but also on different parts of the distribution because the earnings distribution in nonprofit operators is located to the right of the distribution in for-profit operators.

[Figure 1]

Next, Table 1 gives some summary statistics for log earnings and other important variables[4]. Panel A and B show mean of each variable, and the final panel shows its' difference and statistical test results. This table first shows that the average earnings in for-profit operators is significantly lower than in nonprofit operators as 9.1%[5].

Table 1 also reports statistically significant difference for other variables. For example, the average age of workers is older in for-profit operators than in nonprofit operators, while the average tenure is shorter. The

[3] The epanechnikov kernel function is assumed, and the bandwidth is set as 0.038 for for-profit sub-sample and 0.034 for nonprofit sub-sample.

[4] In the Appendix, Table A1 shows the complete list of summarized statistics.

[5] Note that Noguchi and Shimizutani (2007) uses the same survey but in 2000 and reports that the average earings gap about home helpers and staff nurses is just one percent and not statistically significant.

licence acquisition rates are also significantly different. For the licences of the care-worker and the care-maneger, the acquisition rate is larger in nonprofit operators than in for-profit operators. However, for licences of first and second level home-helper, the acquisition rate in nonprofit operators is smaller than in for-profit operators.

We can also observe significant difference about operator's characteristics. Nonprofit operators has larger number of equipment and provide more kind of service[6] than for-profit operators on average. The average facility tenure of nonprofit operators is longer than for-profit operators. The trend about the facility size (the number of employee) is not monotonically: the share of middle size facility (the number of employee is between 50 and 499) is lager in nonprofit operators than in for-profit operators, while the share of smallest and largest facility (less than 49 and more than 500) is smaller. Finally, the facility of nonprofit operators tend to locate in small community, while the facility of for-profit locate in large cities.

[Table 1]

3 Regression analysis

In this section, we estimate effects of operator type by using the OLS and unconditional quantile regression approaches. First, to estimate the average effect, we suppose the linear population model as

$$\log w_i = \beta_1 T_i + \boldsymbol{X}_i \boldsymbol{\beta}' + u_i, \tag{1}$$

where $\log w_i$ is log daily earnings, T_i is the operator type dummy; $T_i = 0$ if the worker works in for-profit operator, and $T_i = 1$ if she/he works in nonprofit operator, and β_1 is it's coefficients. u_i represents effects of other factors, and in the following analysis, we assume the conditional mean zero assumption as $E\left[u_i | T_i, X_i\right] = 0$.

Additionally, $\boldsymbol{X}_i$ is the vector of constant term and control variables, and $\boldsymbol{\beta}'$ is the vector of its' coefficients. In this estimation, we control some worker's characteristics (gender, job tenure, and acquired licence) and operator's characteristics (the number of employee, years in business, equipment, providing services, and its' location[7]) are included in $\boldsymbol{X}_i$.

[6] The list of equipment and service are shown in Appendix as Table A0-1 and A0-2.

[7] We use three types of location variables as prefecture, city size (Tokyo/Ordinance-designated city, Other city, and Vil-

3.1 Unconditional Quantile Regression

Next, we estimate the effects on each components of the earnings distribution by using the unconditional quantile regression offered by Firpo, Fortin, and Lemieux (2009). In this approach, we first run a regression on the re-centered influence function (RIF). Let's denote the θth quantile of earnings w by Q_θ. The (population) RIF corresponding to an observed earnings w and Q_θ can be defined as

$$RIF(w : Q_\theta) = Q_\theta + IF\left(w : Q_\theta\right) = Q_\theta + IF\left(w : Q_\theta\right), \tag{2}$$

where

$$IF\left(w : Q_\theta\right) = \frac{\theta - I\left\{w \leq Q_\theta\right\}}{f\left(Q_\theta\right)},$$

$f\left(Q_\theta\right)$ is the density of w, and I is an indicator function; $I = 1$ if $w \leq Q_\theta$, and $I = 0$ if $w > Q_\theta$. $IF\left(w : Q_\theta\right)$ is called as the influence function, which measures a magnitude of a change of the distribution if we add an additional observation $i : w_i = w$. The important note that because $\int IF\left(w : Q_\theta\right) dF\left(w\right) = 0$, the expected value of $RIF\left(w : Q_\theta\right)$ is equal to Q_θ.

We estimate the conditional expectation of the RIF (2) which is denoted as $E\left[RIF\left(w : Q_\theta\right)|T, X\right]$. To simplify, $E\left[RIF\left(w : Q_\theta\right)|T, X\right]$ is specified as a simple linear function of the operator type dummy and control variables as

$$E\left[RIF\left(w : Q_\theta\right)|T, X\right] = \gamma_1\left(\theta\right) T_i + \mathbf{X}_i \boldsymbol{\gamma}\left(\theta\right)' + \varepsilon.$$

where $\gamma_1\left(\theta\right)$ and $\boldsymbol{\gamma}\left(\theta\right)$ are coefficients, and ε is the error terms and assumed $E\left[\varepsilon_i|T_i, X_i\right] = 0$. Note that above specification allows that the value of coefficients can be different in each quantile.

To get estimators about coefficients, estimators of $RIF\left(w : Q_\theta\right)$, denoted by $\widehat{RIF}\left(w : Q_\theta\right)$, are needed. From equation (2), the RIF includes two unknown parameter Q_θ and $f\left(Q_\theta\right)$. Fortunately, the estimator of Q_θ, denoted by $\hat{Q}_\theta$, can be obtained by Koenker and Bassett (1978) approach as

$$\hat{Q}_\theta \in \arg\min_Q \sum_i^N \left(\theta - I\left\{w \leq Q\right\}\left(w_i - Q\right)\right),$$

lage/Town), and the area classification for care compensation. Note that by regulation, "price" of care-service is determined according o located area.

and the estimator of $f(Q_\theta)$, $\hat{f}\left(\hat{Q}_\theta\right)$, can be yield by using the kernel estimation. $\widehat{RIF}(w:Q_\theta)$ is then estimated by plugging in $\hat{Q}_\theta$ and $\hat{f}\left(\hat{Q}_\theta\right)$ into equation (2).

Using $\widehat{RIF}(w:Q_\theta)$, the unbiased estimators of coefficients can be obtained by the OLS regression on following population model;

$$\widehat{RIF}(w:Q_\theta) = \gamma_1(\theta)T_i + \mathbf{X}_i\boldsymbol{\gamma}(\theta)' + \varepsilon_i.$$

Under the conditional mean zero assumption, we can obtain consistent estimators of $\hat{\gamma}_1(\theta)$ and $\boldsymbol{\gamma}(\theta)$. Moreover, because the expected value of $\widehat{RIF}(w;Q_\theta)$ is Q_θ, the value of unconditional quantile can be rewritten as

$$Q_\theta = E\left[\widehat{RIF}(w;Q_\theta)\right] = \hat{\gamma}_1(\theta)E[T_i] + E[X]\hat{\boldsymbol{\gamma}}(\theta)',$$

and $\hat{\gamma}_1(\theta)$ can be then interpreted as unconditional partial effects of small location shifts of operation type. In this case, $\hat{\gamma}_1(\theta)$ captures the marginal effect of an increasing in the probability that workers work in nonprofit operators.

3.2 Results

The key results of the OLS estimation for equation (1) are reported in Table 2. From this table, we can still observe the significant earnings gap between for-profit and nonprofit operators even if some characteristics are controlled, but it's size is dropped about 66.5% from descriptive earnings gap as shown in Table 1

[Table 2]

Key results of the unconditional quantile regressions are shown in Figure 2 (the full results are shown in Appendix as Table A3). This figure shows the size of coefficients of operator type dummy in each quantile. Blue line is estimated coefficients without control variables, while orange line is coefficients with control variables.

[Figure 2]

Figure 2 also shows some important results. First, for any quantile, the size of coefficients of nonprofit dummy is dropped by controlling workers' and operators' characteristics. More detail, the size of coefficients are largely dropped in higher quantile: in the 10th quantile, the drop rate is just 27.5%, while this rate is 148.8% in the 90th quantile.

The second important result is that the coefficients decline along the earnings distribution. This result implies that there exist larger gap in lower quantile than in higher quantile. For example, the drop rates between the 90th and 10th quantile are 61.6% if we do not control characteristics. Moreover, in top quantile, the earnings after controlling workers' and operators' characteristics are lower in nonprofit operators than in for-profit operators if we control characteristics. This down-sloping lines show that the dispersion of earnings is less in nonprofit operators than in for-profit operators.

4 Decomposition analysis

Table 1 and Figure 2 show that the earnings gap on average and at each quantile may be explained by the difference of observable characteristics because the size of coefficients of operator type are decreased by incorporating control variables. To obtain more clear evidence about which components mainly bring earnings gap, we next decompose the wage cap by using Oaxaca(1973) and Blinder(1973)'s parametric approach and DiNardo, Fortin and Lemieux (1996)'s nonparametric approach.

4.1 Empirical strategy

To conduct the Blinder-Oaxaca decomposition, we estimate the following population model by using subsample for workers in for-profit and nonprofit operators:

$$\log w_i = \boldsymbol{X}_i \boldsymbol{\beta}^{T\prime} + u_i, \text{ where } T \in \{1, 0\}.$$

From the conditional means zero assumption, $E\left(u_i | X_i^T\right) = 0$, we can then obtain consistent estimators of coefficients as $\hat{\boldsymbol{\beta}}^T$. Moreover, the average log daily wages can be characterized as

$$E\left[\log w_i | T\right] = E[\boldsymbol{X}_i | T] \boldsymbol{\beta}^{T\prime}.$$

The mean earnings gap difference between for-profit and non-profit operators can be then decomposed as

$$E\left[\log w_i | T = 1\right] - E\left[\log w_i | T = 0\right] = \left(\boldsymbol{\beta}^{1\prime} - \boldsymbol{\beta}^{0\prime}\right) E\left[X_i | T = 1\right] + \boldsymbol{\beta}^{0\prime}\left(E\left[X_i | T = 1\right] - E\left[X_i | T = 0\right]\right). \tag{3}$$

The first term in right-hand side of above equation is the contribution of difference of coefficients, which is called as the unexplained term. The second term represents the contribution of difference of observable characteristics, which is called as the explained terms.

Next, we decompose the earnings gap at each quantile by using Firpo, Fortin, and Lemieux (2009)'s approach. First, we run a OLS regression on the estimated RIF by using for-profit and nonprofit sub-samples. Let denotes $\hat{\boldsymbol{\gamma}}(\theta)^1$ and $\hat{\boldsymbol{\gamma}}(\theta)^0$ as estimated coefficients in for-profit and non-profit subsample. Using the conditional mean zero assumption, the conditional θth quantile of earnings can be written as

$$\begin{aligned} E\left[Q_\theta|T=1\right] &= E\left[X|T=1\right]\hat{\gamma}^1(\theta), \\ E\left[Q_\theta|T=0\right] &= E\left[X|T=0\right]\hat{\gamma}^0(\theta). \end{aligned}$$

The difference of the θth quantile of earnings can be decomposed as

$$E\left[Q_\theta|T=1\right]-E\left[Q_\theta|T=0\right]=E\left[X|T=1\right]\left(\hat{\gamma}^1(\theta)-\hat{\gamma}^0(\theta)\right)+\hat{\gamma}^0(\theta)\left\{E\left[X|T=1\right]-E\left[X|T=0\right]\right\}. \tag{4}$$

Similar to decomposition of mean wages, the first term can be interpreted as unexplained terms, while the second term represents the explained term. Note that the unexplained components can be interpreted as the gap of actual earnings in nonprofit operators and their counterfactual earnings based on the wage structure of for-profit operators (see Fortin, Lemieux, and Firpo 2010).

Finally, we nonparametrically evaluate the impacts of operator type by using the counterfactual distribution approach offered by DiNard, Fortin, and Lemieux (1996). The counterfactual distribution is defined as the earnings distribution if the operator changes from for-profit to nonprofit holding other characteristics constant.

The earnings distribution in nonprofit and for-profit operators can be defined as

$$f_1(w) = \int \omega_1(w|X)\,g_1(X)\,dX \tag{5}$$

$$f_0(w) = \int \omega_0(w|X)\,g_0(X)\,dX \tag{6}$$

where $f_1(\cdot)$ and $f_0(\cdot)$ are the earnings distributions, $\omega_1(w|X)$ and $\omega_0(w|X)$ are the wage determination structure which are density functions from workers' and operator's characteristics to wages density, and $g_1(X)$

and $g_0(X)$ are distributions of their characteristics in nonprofit and for-profit operators, respectively. The important implication of above definition is the earnings distribution are consisted by two density functions; the wage density function $\omega_T(w|X)$ and characteristics distribution $g_T(X)$.

The counterfactual distribution can be defined as

$$\tilde{f}_0(w) = \int \omega_0(w|X)\, g_1(X)\, dX. \tag{7}$$

Intuitively, the counterfactual distribution is that the characteristic distribution is same as in nonprofit, but the wage determination structure is same as in for-profit. The earnings gap between nonprofit and for-profit operators can be then decomposed as

$$\begin{aligned} f_1(w) - f_0(w) &= \left[f_1(w) - \tilde{f}_0(w)\right] \\ &\quad + \left[\tilde{f}_0(w) - f_0(w)\right]. \end{aligned}$$

The first blanket shows the contribution of the difference of wage determination structure, and the second blanket is the contribution of the difference of the characteristics distribution.

To obtain the decomposition results, we should estimate (7). Using the Bayes' rule, equation (7) can be rewritten as

$$\begin{aligned} \tilde{f}_0(w) &= \int \omega_0(w|X)\, \frac{g_1(X|T=1)}{g_0(X)} g_0(X)\, dX, \\ &= \int \omega_0(w|X)\, h(X)\, g_0(X)\, dX, \end{aligned} \tag{8}$$

where

$$h(X) = \frac{p(T=1|X)}{1-p(T=1|X)} \frac{1-p(T=1)}{p(T=1)}.$$

$p(T=1|x)$ is the conditional probability that operator type is nonprofit if characteristics are X, and $p(T=1)$ is the unconditional probability that the operator type is nonprofit. Equation (8) implies that the counterfactual distribution can be modified as for-profit's earnings distribution reweighted by $h(X)$. The counterfactual distribution can be then estimated as the reweighted earnings distribution in for-profit operators by using the reweighted factors $h(x)$.

From equation (8), the reweighting factor includes two unknowns; $p(T=1|X)$ and $p(T=1)$. Fortunately, the estimator of $p(T=1|X)$ can be obtained by the probit estimation of $\Pr[T=1|X]$, and the sample average of T can be used as the estimator of $\hat{p}(T=1)$. We can then estimate the reweighting factors as

$$\hat{h}(x) = \frac{\hat{p}(O=1|x)}{1-\hat{p}(O=1|x)} \frac{1-\hat{p}(O=1)}{\hat{p}(O=1)},$$

and the estimator of the counter factural distribution is

$$\tilde{f}_0(w) = \int \omega_0(w|X)\,\hat{h}(X)\,g_0(X)\,dX.$$

4.2 Results

[Table 3]

The results of the decomposition on the average earnings gap (equation (3)) are shown in Table 3. This table reports that large share (80.2%) of the average earnings gap between for-profit and nonprofit operators can be explained by explained components. Additionally, the contribution of each variables are reported in Table 3, and we can then find that tenure of workers and licence have large contribution (61.8% and 34.6% of total gap, respectively) on the total earnings gap.

[Figure 3]

Next, the main results of quantile decomposition are shown in Figure 3. The blue line shows the total earnings gap in each quantile, which is the down-sloping as pointed out in Figure 2. However, the trend of explained and unexplained components are totally different: explained components (shown by the orange line) has the U-shaped trend, which mean that in top and bottom quantile, there exist large earnings difference coming from the difference of observable characteristics.

Meanwhile, the unexplained components (shown by the gray line) has the inverse U-shaped trends. Thus, the earnings gap coming from the difference of the wage structure is largest in the middle earnings groups.

Additionally, in the highest quantile, the unexplained components turns to a negative value, which means that for high quantile groups, the for-profit operators pay more wages holding observable characteristics constant.

[Table 4]

Table 4 shows more detail results of the quantile decomposition. This results show that in each quantile, a large part of the earnings gap can be explained by differences of worker's tenure and licence acquisition rate. Moreover, the contribution of difference of worker's tenure is rapidly increasing along the earnings distribution. Recalling that Table 1 reports the average tenure in nonprofit operators is longer than in for-profit operators, the earnings gap in high quantile can be mostly explained by the long tenure in nonprofit operators.

[Figure 4]

Finally, Figure 4 shows the counterfactual distribution[8] by the green line in addition to the (descriptive) earnings distribution in for-profit and nonprofit operators (red and blue lines). This figure represents that the counterfactual distribution is located to the right of the earnings distribution in for–profit operators but the left of the distribution in nonprofit operators. This results also consist with results of the OLS regression because the coefficient of operator dummy in the estimation with control variables is negative, but the size of the coefficient is lower than it in the estimation without control variables.

Figure 4 additionally shows the heterogeneous effects of operator type. From the comparison of the earnings distributions between for-profit and counterfactual, the density of low earnings in the counterfactual distribution is smaller than in the earnings distribution in for-profit operators, while the density of middle earnings workers is larger. Finally, there are no large difference about the density of high earnings workers. These findings show that nonprofit operators reduce the small earnings workers while increases the share of middle earnings workers. This results are also consist with the RIF regression results because both results show that the dispersion of earnings is less in nonprofit operators than in for-profit operators.

5 Conclusion and policy discussion

In this paper, by using the OLS and the RIF regression, we first estimate the impacts of operator types on the earnings distribution. Regression results show a positive nonprofit earnings premium on average and in low

[8] Note that the bandwidth is choosen as 0.030.

and middle quantile, while in high quantile, a negative nonprofit premium is observed. Next, we decompose the earnings gap into various explanatory factors. The decomposition results show that on average and in each quantile, a large part of the earnings gap can be explained by the difference of licence equitation rates and tenure of workers in between nonprofit and for-profit operators. Moreover, the contribution of tenure is increasing along the earning distribution.

Finally, we discuss policy implications of above results with its' limitation. Regression results show that even if many characteristics are controlled, a nonprofit premium can be found in lower quantile. Moreover, decomposition results find that the difference of worker's tenure is important factor to explain the earnings gap, especially in higher quantile. In keeping with regression results, this decomposition results show the possible story to explain large earnings gap in high quantile; lower wages in low quantile lead to not only early job-leave but also decrease wages in high quantile because the number of long-tenured workers is less in for-profit operators than in nonprofit operators. Both interpretations imply the importance of policy or regulation to improve wages in lower quantile.

However, this paper also has some limitations. First is the endogeneity problem; in the real labor markets, workers endogenously determine to work in whether nonprofit or for-profit operators, which is a source of biased estimators. In this paper, we use just control variables to solve the endogeneity problem, but some bias may still remain. Another limitation is that our study focus on labor markets, but the quality of care service may be also different between for-profit and nonprofit operators. To obtain general policy implications, studies with more comprehensive comparison between nonprofit and for-profit operators are needed. Finally, this paper does not analyze the source of a nonprofit premium. One of potential source is public subsidies for nonprofit operators, and if so, more "equal" subsidy policy is important for solving earnings gap. There are important problems and should be overcome by future research.

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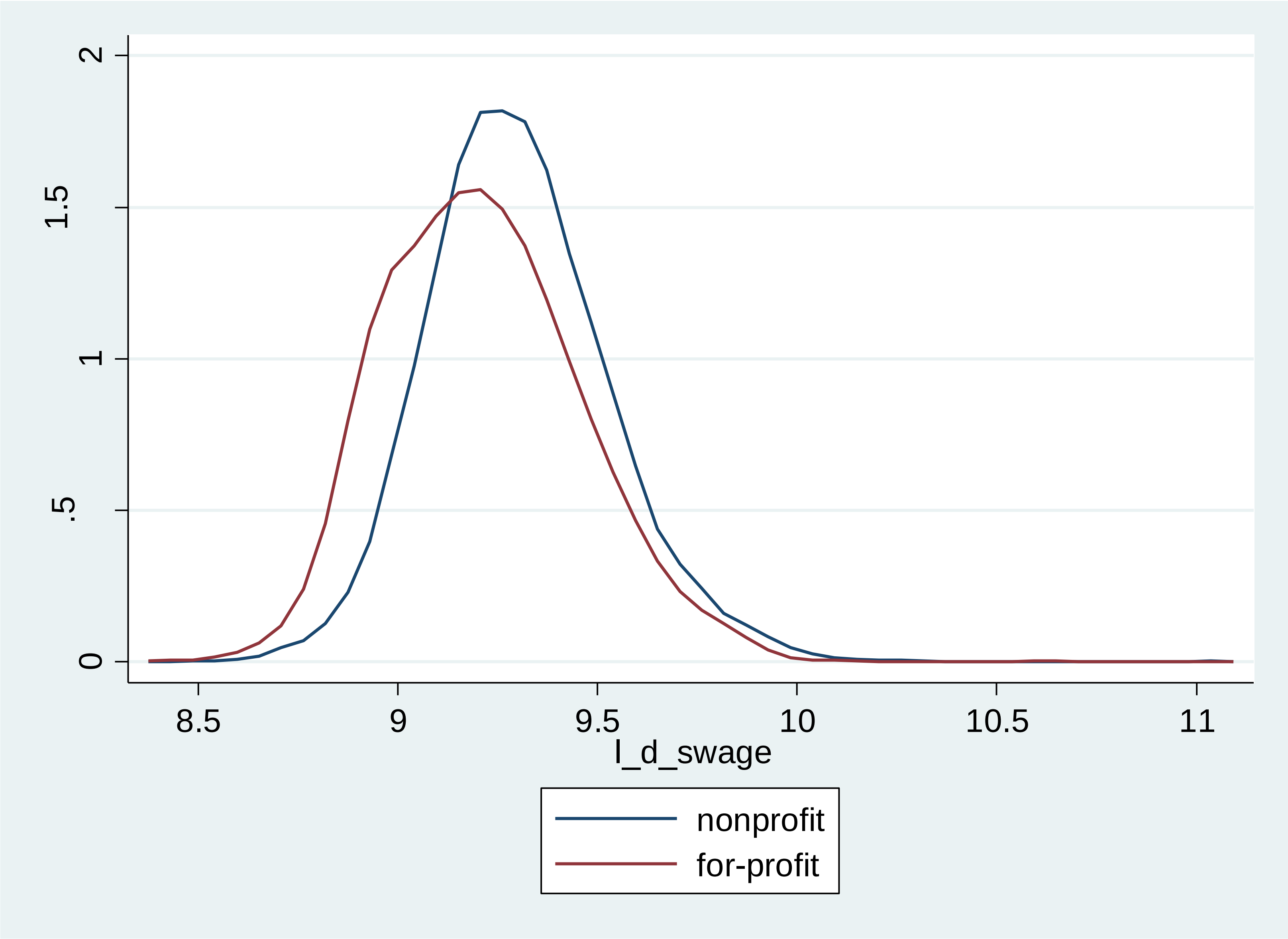

Figure1: Distribution of earnings

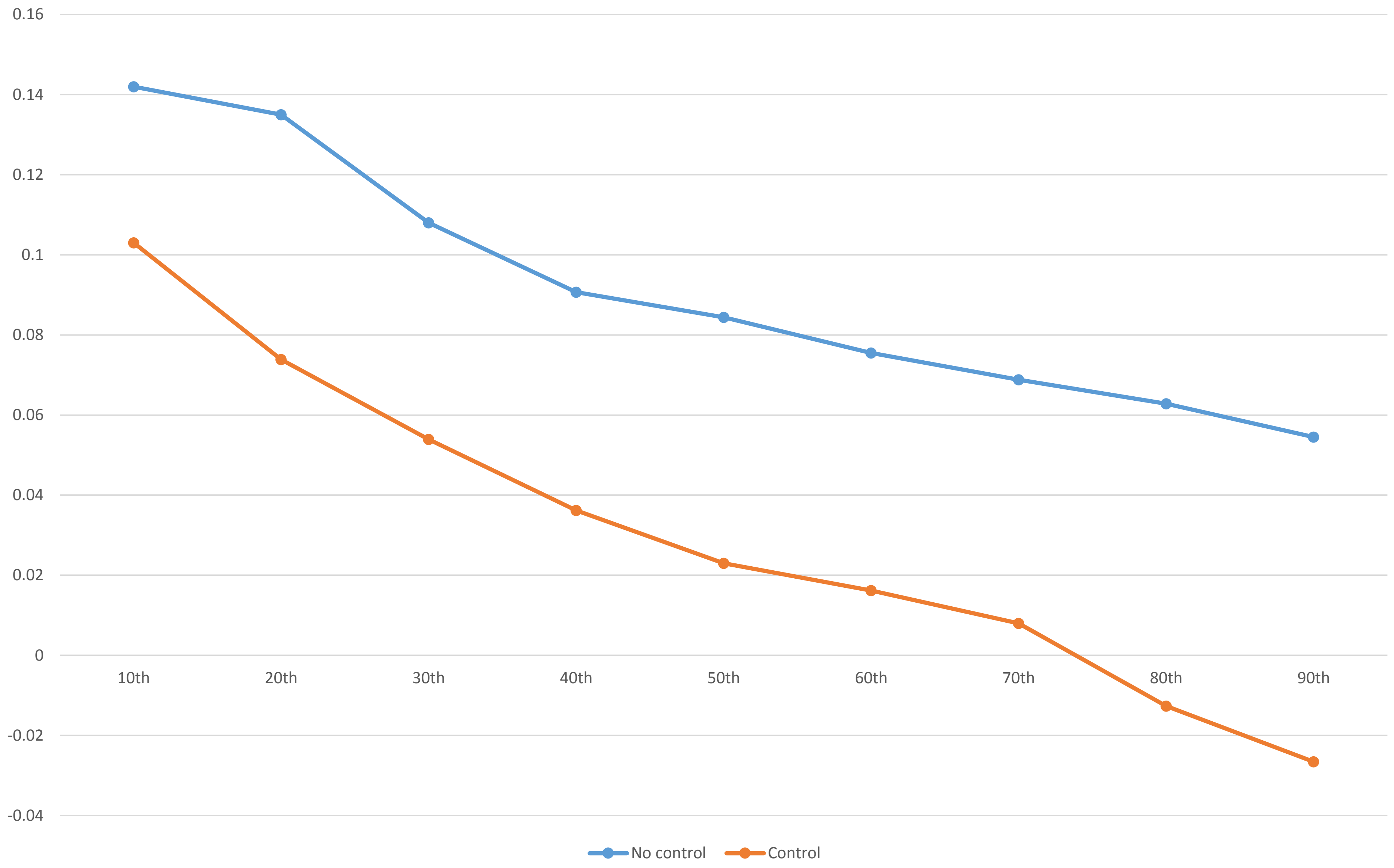

Figure2: Coefficients in the quantile regression

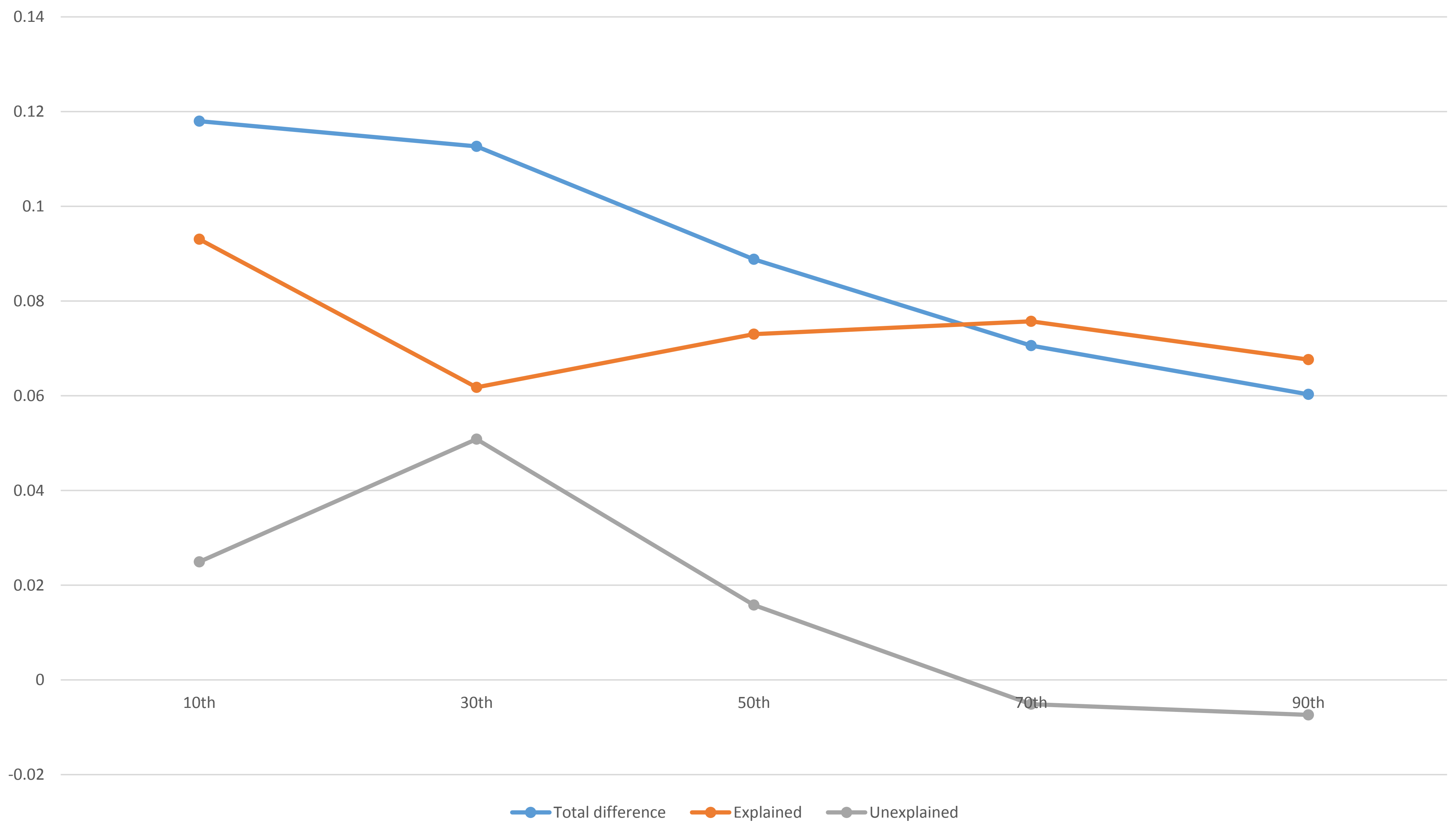

Figure3: Results of quantile decomposition

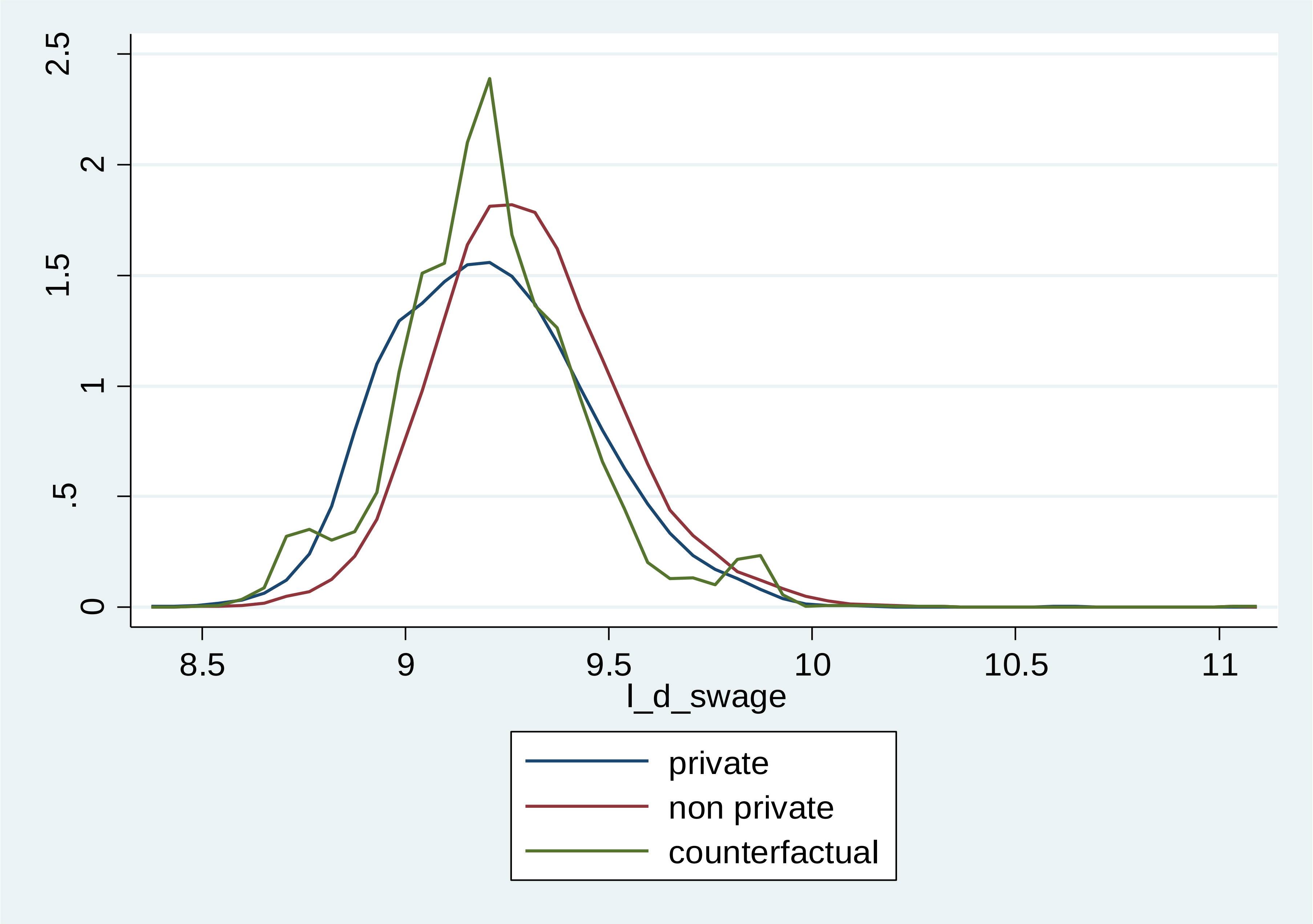

Figure4: Results of the counter factual analysis

Providing Service
Visiting care
Home-Visit Bathing Long-Term Care
Home nursing care
Home-Visit Rehabilitation
Guidance for Management of In-Home Medical Long-Term Care
VISITING CARE FACILITY
Outpatient Rehabilitation
Short-Term Admission for Daily Life Long-Term Care
Short-Term Admission for Recuperation
Long-Term Care Admitted to a Specified Facility
Rental Service of Equipment for Long-Term Care Covered by Public Aid
Sale of Specified Equipment Covered by Public Aid
Home-Visit at Night for Long-Term Care
Outpatient Long-Term Care for a Dementia Patient
Multifunctional Long-Term Care in a Small Group Home
Communal Daily Long-Term Care for a Dementia Patient
Daily Life Long-Term Care for a Person Admitted to a Community-Based Specified Facility
Community-Based Facility for the Elderly Covered by Public Aid Requiring Long-Term Care
In-Home Long-Term Care Support
Facility Covered by Public Aid Providing Long-Term Care to the Elderly
Long-Term Care Health Facility
Sanatorium Medical Facility for the Elderly Requiring Long-Term Care
Home-Visit Nursing Service for Preventive Long-Term Care
Home-Visit Bathing Service for Preventive Long-Term Care
Home-Visit Nursing Service for Preventive Long-Term Care
Home-Visit Rehabilitation Service for Preventive Long-Term Care
Management and Guidance for In-Home Medical Service for Preventive Long-Term Care
Outpatient Preventive Long-Term Care
Outpatient Rehabilitation for Preventive Long-Term Care
Short-Term Admission for Daily Preventive Long-Term Care
Short-Term Admission for Recuperation for Preventive Long-Term Care
Daily Preventive Long-Term Care Admitted to a Specified Facility
Equipment Rental for Preventive Long-Term Care Covered by Public Aid
Sale of Specified Equipment for Preventive Long-Term Care Covered by Public Aid
Preventive Long-Term Care for a Dementia Outpatient
Multifunctional Preventive Long-Term Care in a Small Group Home
Preventive Long-Term Care for a Dementia Patient in Communal Living
Preventive Support of Long-Term Care

Table A0-1: Name of Service and Equipments

Equipment
Mobile Lift for Nursing
Bed
Wheelchair with a Seat Surface Rising and Falling Position
Special Bathtub
Stretcher
Carrier for Shower
Lifting Apparatus
Wheelchair Scale
Nursing Care Robot

Table A0-2: Name of Service and Equipments

	A	B	
Variable	**Nonprofit**	**For-profit**	**Difference**
Log Daily Wage	9.302	9.211	0.0910***
Workers' characteristics			
Female Share	0.694	0.674	0.0206*
Age	36.675	38.120	-1.445***
Tenure	5.768	2.665	3.103***
Licence acquisition rates			
Care worker	0.679	0.315	0.364***
Home helper: 1st level	0.032	0.041	-0.00934*
Home helper: 2nd level	0.307	0.586	-0.279***
Care maneger	0.075	0.029	0.0458***
Operators' characteristics			
Number of equipments	4.418	3.012	1.406***
Number of providing service	5.434	2.685	2.748***
Facility tenure	13.718	5.708	8.009***
Firm size: less than 49	0.094	0.314	-0.219***
Firm size: 50 - 99	0.250	0.194	0.0553***
Firm size: 100 - 299	0.431	0.154	0.277***
Firm size: 300 - 499	0.113	0.050	0.0631***
Firm size: more than 500	0.112	0.288	-0.176***
City size: large city	0.160	0.308	-0.148***
City size: other city	0.665	0.618	0.0468***
City size: town and village	0.175	0.073	0.101***
Sample size	6850	2953	

Table 1: Descriptive Statistics

Notes that *** p<0.01, ** p<0.05, * p<0.1

	A	B	
Variable	**Nonprofit**	**For-profit**	**Difference**
Log Daily Wage	9.302	9.211	0.0910***
Worker Characteristics			
Female Share	0.694	0.674	0.0206*
Age	36.675	38.120	-1.445***
Tenure	5.768	2.665	3.103***
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Operator Characteristics			
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Number of Providing Service	5.434	2.685	2.748***
Facility Tenure	13.718	5.708	8.009***
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Firm Size: 50 - 99	0.250	0.194	0.0553***
Firm Size: 100 - 299	0.431	0.154	0.277***
Firm Size: 300 - 499	0.113	0.050	0.0631***
Firm Size: More than 500	0.112	0.288	-0.176***
City Size: Large city	0.160	0.308	-0.148***
City Size: Other City	0.665	0.618	0.0468***
City Size: Town and Village	0.175	0.073	0.101***
Area Classification: 1st level	0.036	0.074	-0.0384***
Area Classification: 2nd level	0.105	0.209	-0.104***
Area Classification: 3rd level	0.045	0.078	-0.0334***
Area Classification: 4th level	0.109	0.206	-0.0965***
Area Classification: 5th level	0.705	0.433	0.272***
Sample size	6850	2953	

Table A1: Detail Descriptive Statistics

Notes that *** p<0.01, ** p<0.05, * p<0.1

VARIABLES	
Non private	0.0305***
	-0.00555
Female Share	-0.0594***
	-0.00369
Age	0.00136***
	-0.000166
Tenure	0.0216***
	-0.00101
Tenure*Tenure	-0.000196***
	-5.01E-05
Care worker	0.0587***
	-0.00441
Home helper: 1st level	0.0139
	-0.00907
Home helper: 2nd level	-0.0300***
	-0.00424
Care Maneger	0.0796***
	-0.00847
Facility Tenure	0.000605***
	-0.000174
Firm Size: 50 - 99	0.0274***
	-0.00611
Firm Size: 100 - 299	0.0375***
	-0.00615
Firm Size: 300 - 499	0.0649***
	-0.00787
Firm Size: More than 500	0.0819***
	-0.00742
Location, Servise, and Equipments	Controled
Constant	9.047***
	-0.0195

Table 2: Average effect

Notes that *** p<0.01, ** p<0.05, * p<0.1

VARIABLES	10	20	30	40	50	60	70	80	90
Non private	0.142***	0.135***	0.108***	0.0907***	0.0844***	0.0755***	0.0688***	0.0628***	0.0545***
	-0.00901	-0.00767	-0.00655	-0.00626	-0.00628	-0.00628	-0.00666	-0.00753	-0.00928
Female Share									
Age									
Tenure									
Tenure*Tenure									
Care worker									
Home helper: 1st level									
Home helper: 2nd level									
Care Maneger									
Facility Tenure									
Firm Size: 50 - 99									
Firm Size: 100 - 299									
Firm Size: 300 - 499									
Firm Size: More than 500									
Location, Servise, and Equipments	Not controled								
Constant	8.885***	8.983***	9.071***	9.143***	9.203***	9.268***	9.337***	9.419***	9.537***
	-0.00833	-0.00685	-0.00568	-0.0053	-0.00522	-0.00514	-0.00537	-0.00599	-0.00731

Table A2-1: Quantile Effects without control

Notes that *** p<0.01, ** p<0.05, * p<0.1

VARIABLES	10	20	30	40	50	60	70	80	90
Non private	0.103***	0.0739***	0.0539***	0.0362***	0.0230***	0.0162**	0.00797	-0.0127	-0.0266**
	-0.0117	-0.00975	-0.00807	-0.00748	-0.00742	-0.00749	-0.00782	-0.00881	-0.0112
Female Share	-0.0447***	-0.0472***	-0.0458***	-0.0576***	-0.0620***	-0.0566***	-0.0635***	-0.0740***	-0.0860***
	-0.00652	-0.00579	-0.00509	-0.00496	-0.00515	-0.00542	-0.00596	-0.00714	-0.00951
Age	0.000283	0.000967***	0.00101***	0.00131***	0.00135***	0.00123***	0.00163***	0.00221***	0.00205***
	-0.000347	-0.000289	-0.000241	-0.000228	-0.000228	-0.000231	-0.000248	-0.000288	-0.000365
Tenure	0.0176***	0.0199***	0.0210***	0.0225***	0.0254***	0.0245***	0.0259***	0.0245***	0.0213***
	-0.0016	-0.00142	-0.00124	-0.0012	-0.00124	-0.0013	-0.00152	-0.00194	-0.00282
Tenure*Tenure	-0.000463***	-0.000482***	-0.000438***	-0.000410***	-0.000430***	-0.000296***	-0.000195***	-4.18E-06	0.000409***
	-6.38E-05	-5.80E-05	-4.91E-05	-4.75E-05	-5.16E-05	-5.62E-05	-7.08E-05	-9.57E-05	-0.000151
Care worker	0.0897***	0.0869***	0.0763***	0.0732***	0.0622***	0.0534***	0.0414***	0.0259***	0.0293***
	-0.00793	-0.00693	-0.00606	-0.00585	-0.00593	-0.00608	-0.00656	-0.00778	-0.0103
Home helper: 1st level	0.0335*	0.0353**	0.00658	0.00468	-0.000629	-0.0108	-0.0138	-0.0056	0.00929
	-0.0171	-0.0157	-0.0141	-0.0133	-0.0133	-0.0131	-0.0136	-0.0166	-0.0229
Home helper: 2nd level	-0.00916	-0.0197***	-0.0197***	-0.0259***	-0.0400***	-0.0425***	-0.0449***	-0.0514***	-0.0433***
	-0.00794	-0.0068	-0.00586	-0.0056	-0.00571	-0.00592	-0.0064	-0.00755	-0.00997
Care Maneger	0.0211***	0.0363***	0.0418***	0.0545***	0.0698***	0.0874***	0.102***	0.123***	0.159***
	-0.00789	-0.0085	-0.00856	-0.00895	-0.00996	-0.0109	-0.0129	-0.0172	-0.0261
Facility Tenure	0.000388	0.000216	0.000399*	0.000391	0.000498*	0.000920***	0.000863***	0.00115***	0.00148***
	-0.00031	-0.00028	-0.000242	-0.000245	-0.000261	-0.000273	-0.000296	-0.000351	-0.000481
Firm Size: 50 - 99	0.0520***	0.0519***	0.0407***	0.0291***	0.0290***	0.0142*	-0.00181	-0.00205	-0.00334
	-0.0145	-0.0117	-0.00945	-0.00861	-0.00819	-0.00805	-0.00828	-0.00935	-0.0111
Firm Size: 100 - 299	0.0730***	0.0849***	0.0640***	0.0517***	0.0315***	0.00755	-0.00965	0.00179	0.00669
	-0.0138	-0.0112	-0.00929	-0.00863	-0.00837	-0.00822	-0.00855	-0.00984	-0.0123
Firm Size: 300 - 499	0.0595***	0.0683***	0.0712***	0.0655***	0.0682***	0.0548***	0.0430***	0.0551***	0.0844***
	-0.0149	-0.013	-0.0111	-0.0107	-0.0109	-0.0113	-0.0126	-0.015	-0.0193
Firm Size: More than 500	0.0882***	0.104***	0.0942***	0.0937***	0.0832***	0.0659***	0.0477***	0.0544***	0.0828***
	-0.0141	-0.0123	-0.0105	-0.01	-0.01	-0.0102	-0.0109	-0.0127	-0.0163
Location, Servise, and Equipments	Controled								
Constant	8.643***	8.739***	8.849***	8.907***	8.964***	9.042***	9.109***	9.203***	9.377***
	-0.0316	-0.027	-0.0235	-0.0233	-0.0247	-0.0266	-0.0311	-0.0401	-0.0552

Table A2-2: Quantile Effects with control

Notes that *** p<0.01, ** p<0.05, * p<0.1

	Mean
Explained	80.2%
Licence	34.6%
Tenure of workers	61.8%
Worker's other characteristics	-4.8%
Operator's characteristics	32.2%
Location	-43.5%
Unexplained	19.8%
Licence	56.6%
Worker's other characteristics	60.1%
Operator's characteristics	194.4%
Location	-28.5%
Constant	-262.8%

Table3: Average Decomposition Results

	10th	30th	50th	70th	90th
Explained	78.9%	54.8%	82.2%	107.3%	112.2%
Licence	30.8%	29.8%	36.1%	41.8%	44.5%
Tenure of workers	30.5%	39.8%	65.7%	96.1%	132.3%
Worker's other characteristics	-2.3%	-3.1%	-4.9%	-7.1%	-9.2%
Operator's characteristics	41.1%	19.8%	30.5%	37.4%	18.6%
Location	-21.2%	-31.4%	-45.1%	-60.9%	-74.0%
Unexplained	21.1%	45.2%	17.8%	-7.3%	-12.2%
Licence	4.1%	53.5%	103.3%	93.6%	126.4%
Worker's other characteristics	34.1%	51.1%	71.8%	115.8%	-8.2%
Operator's characteristics	10.4%	329.8%	358.7%	-105.5%	276.4%
Location	-19.4%	-28.1%	-33.5%	-16.1%	-22.3%
Constant	-8.2%	-361.1%	-482.4%	-95.1%	-384.5%

Table 4: Quantile Decomposition Results