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An Interval Regression Analysis for Tenures of Japanese Elder Care Workers Using Matched Employer-Employee Data

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Abstract

This paper analyzes job tenures of Japanese elder care workers in the home care service sector, using an econometric framework that can fully utilize information of available data. This sector reveals a large between-firm difference in workers' separation rates, despite a regulation policy that induces a limited wage dispersion. I rationalize this puzzling observation by a screening model in which firms try to avoid adverse selection caused by information asymmetry regarding workers' motivation. My model induces a separating equilibrium in which several firms cover training costs for general human capital accumulation of workers. To examine a testable implication of my screening model, I construct an interval regression model using cross-section data with matched employer-employee information. A standard Bayesian estimation provides empirical results that support my economics model.

JEL classification; C11; J13; M53

Keyword; Interval regression; Bayesian statistics; Employer-employee match data; Elder care; Firm-provided training; Screening model

1 Introduction

This paper analyzes labor economics of care workers for the elderly in Japan. Japan suffers from a worldwide problem of short job tenures among care workers. As a face-to-face service, stable relationships between workers and the elderly are an important factor to achieve reasonable quality of care. However, short

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job tenures prevent workers from accumulating this firm-specific human capital. To address this problem, many studies investigate elements that affect the job tenures of care workers; in particular, the effect of wages is analyzed.

With respect to the wage effect, the Japanese labor market for home care workers presents a unique natural-experimental situation. Under the national insurance program, rewards for most care services are fixed. This policy induces a small wage divergence between firms. However, there is still a wide difference in separation rates between firms. Thus, my research objective is to identify what factors affect the job tenures of care workers, except wages.

I focus on the effect of a firm-provided training on the accumulation of general human capital(GHC). The GHC in this paper is an occupational certification which is widely recognized in the care service sector. However, Becker (1964) indicated that it would be impossible for firms to provide such training. Acemoglu and Pischke (1998) challenged this claim and showed a possibility of firm-provided training with an appropriate rent collection mechanism.

To rationalize the firm-provided training for GHC, this paper extends the screening model of Autor (2001) in which the rent collection mechanism in this model is a combination of information asymmetry regarding labor quality and a time-lag until workers' skills are revealed to outside firms. I make several changes to Autor (2001)'s model to reflect the circumstances of Japanese elder care workers. As a source of information asymmetry, I adopt unobservable motivations of workers that affects separation. The resulting model has a separating equilibrium in which several firms offer the training while the others do not, and this difference of firms' attitudes toward the training creates the between-firm divergence of job tenures.

The testable implication from my model is that receiving the firm-provided training increases workers' job tenures. For an empirical evaluation of this hypothesis, however, there is a problem of data availability because these two elements are not observed at the same time. This paper proposes a new method based on available cross-section data of establishments with matched employer-employee information. Using counts of completed separations that are aggregated at the establishment level, I construct an interval regression model. In addition, using censored observations from matched worker data, I obtain an additional inequality restriction.

The interval regression models were analyzed by Manski and Tamer (2002) as an example of partially identified models, which do not always have point identification, but have set identification. The novel contribution of this paper is that I propose a means of combining aggregated data with individual information. This approach is a similar to Berry et al. (2004) in the industrial organization for point-identified models. In their paper, firm-level aggregate data can achieve identification, as suggested by Berry et al. (1995), but data of individual consumers provide information gains. My study collects such supplemental information from matched employer-employee data, which are popular in labor economics (Abowd and Kramarz, 1999).

To address the data availability problem, there are two existing approaches that are different from the interval regression. A popular approach is to concentrate on rates of separation using only establishment data. This approach is taken by many papers, such as Powers and Powers (2010) for U.S. data and Hanaoka (2011) for Japanese data. Another approach is provided by Abrevaya (1999) and Honoré and Hu (2010) using the rank estimation method for transformation models. If applied to my situation, this method utilizes only workers data. In contrast, my interval regression approach allows the use of information from both data sources.

For econometric models with set identification, several studies such as Chernozhukov et al. (2007) incorporated classical confidence set estimation using the subsampling. The subsampling is a resampling method applicable to such situations as the set estimation, where the standard bootstrap does not work because of a lack of smoothness. The subsampling estimators are constructed using resamples with a smaller size than the original sample. However, it is difficult to determine the sample size for the subsampling in my case because my data have two distinct populations of establishment data and worker data.

On the other hand, Beresteanu and Molinari (2008) proposed a different classical method without subsampling via the theory of a set-valued random variable. However, this method requires a special treatment if there is a discrete explanatory variable. Because my main interest is in the coefficient of a binary variable for the firm-provided general human capital training, I do not employ this approach.

Instead, this paper adopts a Bayesian approach[1]. Because Bayesian estimation needs to evaluate the likelihood function, it requires a distributional assumption. With the appropriate choice of a distributional assumption and

[1] Moon and Schorfheide (2012) compared the classical and Bayesian estimation for this field.

prior distributions, I can implement an efficient estimation procedure via the Gibbs sampler.

In the empirical analysis, a preliminary result shows that my dataset is fragile if one uses an ad-hoc choice of variables within the inequality restriction. Thus, a robust estimation method is required. In the interval regression analysis, the estimation result shows that provision of the training for GHC increases job tenures of workers, as suggested by my screening model. The other coefficient estimates also have reasonable interpretations. A convergence diagnosis for my Gibbs sampler demonstrates efficiency of my computational method.

The organization of this paper is as follows. In Section 2, I provide an overview of the Japanese labor market for elder care workers and propose the theoretical model of the market. Section 3 presents an econometric framework to examine the validity of my economic model. Empirical results are reported in Section 4. Section 5 concludes the paper.

2 Economic model

This section provides an economic theoretical model for home care for the elderly in Japan. The first part of this section presents a brief review of the labor market. Next, I proceed to the construction of my screening model.

2.1 Japanese labor market for elder care

To address the growing demand for long-term care caused by rapid population aging, the Japanese government has launched a national program of long-term care insurance (LTCI) in the year 2000. Before the implementation of the LTCI, elder care was provided informally by family members and by limited formal care sectors for poor individuals, as part of the national welfare program, and for wealthier consumers, such as private nursing homes.

The LTCI has drastically changed the situation of elder care. One of the main policy objective is the "Socialization of Care," which requests a shift of the workforce from the family to formal sectors. To achieve this purpose, the LTCI does not provide per-capita cash transfers to elders, which is allowed in a precedent program in Germany, but covers only realized service costs. To satisfy the considerable demand induced by this policy, the elder care sector has instantaneously grown into a large industry.

Among the wide range of care sectors that the LTCI covers, this paper focuses on the service sector of home care. This sector targets elders with relatively light care needs and provides care at their home. The Survey on Institutions and Establishments for Long-Term Care(Japan Ministry of Health, Labor and Welfare, 2007) indicate the following basic characteristics of this sector. In 2006, the year my empirical study analyzes in the later section, there were approximately 1.3 million users per month, which corresponds to one third of all LTCI users. The LTCI for the first time allows for-profit firms to enter the market, and today, these for-profit firms already make up approximately half of the firms. In addition, one fourth of the firms are a government-sponsored non-profit organizations, so-called social welfare corporations(*Shakai Fukushi Kyougikai*). The remaining firms are various types of non-profit providers, such as medical corporations and co-operatives.

Hotta (2007) provides a general review of the labor market of the home care sector. In 2006, there were approximately 400,000 workers, which corresponds to one fourth of the total workforce of formal elder care. This labor force includes a large fraction of non-regular workers. Approximately, 70% are temporary part-time(*touroku-gata*) workers. In this paper, I construct an economic model that describes the situation of the temporary part-time workers.

This sector has two types of workers; direct care workers and Service Delivery Supervisor(*service teikyou sekinin-sha*). Direct care workers needs a Grade Two Helper certification, which requires no exam but only lectures, training and a practicum[2]. Service Delivery Supervisors have a responsibility for the teamed provision of services and generally receive additional salary. The requirements to be Service Delivery Supervisors are explained later.

As a result of the rapid change caused by the LTCI, there are many regulations in elder care sectors: Some old regulations are heritage from the previous schemes, while other regulations are newly established to protect the infant industry. In this paper, I focus on a new regulation of fixed rewards. Similar to the medical care in Japan, the LTCI adopts a detailed remuneration point system for services to determine rewards of elder care. Because there are only five regional variations of the exchange rate between point and money, this system leads to a slight divergence of wages among firms.

There is a discussion whether these wages are sufficient to attract workers.

[2]There will be a change of requirements from April 2013, which assigns an exam and more training.

One opinion states that these wages are higher than the average wage of part-time female workers, which are a typical workforce in this fields. This statement implies that these wages are sufficient as a replacement cost. As supporting evidence of this claim, there has been a monotonically growing supply of new workers after 2000, which is a rare tendency in the Japanese labor markets that has experienced a long recession. Another popular opinion is that these wages are too low considering workloads. In economic terms, efficiency wages might be much higher than current wages, if they reflect the physical and mental burdens in poor work environments. As supporting evidence of this opinion, we can observe high separation rates in Japanese firms.

As reviewed in Knapp and Missiakoulis (1983) and Castle and Engberg (2005), high separation rates of workers lower the quality of care via many channels. In terms of labor economics, it is important that short job tenures prevent workers from accumulating firm-specific human capital, which is critical in elder care. A stable relationship between workers and elders is useful to grasp the preferences of elders. Furthermore, frequent changes of care givers cause care recipients to experience a mental stress.

There is abundant literature on the reasons for the short job tenures of care workers. Many studies, such as Powers and Powers (2010), targeted the effect of wages on separation rates. Due to an obvious endogeneity between wages and separations, the primary issue in this literature is a choice of instruments. In contrast, in Japan, there is the puzzling observation that in spite of a small wage disparity, there is a wide variety in separation rates between firms. Particularly, a press report from the Ministry of Health, Labor and Welfare(Japan Ministry of Health, Labor and Welfare, 2008) showed that while 45% of home care establishments have separation rates of less than 10%, more than 20% of all establishments have separation rates higher than 30%. To address this puzzle, we need to consider other reasons of separations than wages.

This paper considers a firm-provided on-the-job training for GHC as a determinant of job tenures. As GHC, I adopt the certification of Care Worker(*Kaigo fukushi-shi*)[3]. This is a national occupational certification which is observable to outside firms. There are three paths to obtain this certification. The first path requires passing an exam that can be taken after three years of work experience. Approximately 60% of all certifications are issued via this first path.

[3]Yamada and Sekiya (2003) provided a detailed review of occupational licenses and certifications in the Japanese care sector.

The second path requires no exam but does require graduation from professional universities or junior colleges. Approximately 40% of all certificate holders take this path. The third path requires passing an exam which can be taken after graduation from professional high schools. Only a small number of people follow the third path. I focus on the first path in my model.

Holders of the Care Worker certificate can become Service Delivery Supervisors in the home care sector if the certification is obtained via the second or third path. In contrast, workers with three years of work experience can become Service Delivery Supervisors without the certification. Because this paper considers only the first path, the GHC in this paper is not a license for any particular work.

2.2 A screening model with firm-provided training for general human capital

In this subsection, I provide a screening model for the labor market and its testable implication. I begin with assuming that the economy continues for three periods $t = 1, 2, 3$. There are many firms that operate their business only in the first two periods, and there are many new workers who live for all three periods. Firms need to employ a worker for both periods. For simplicity, I assume that the time-discount factors of firms and workers are zero.

There is an asymmetric information problem that workers completely know their type but firms do not. There are two types of workers, $T \in \{L, H\}$. $T = L$ represents a worker with low motivation, while $T = H$ represents a worker with high motivation. Workers with low motivation are willing to work as part-time. These workers quit for exogenous reasons at rate μ, and do not want to become a Service Delivery Supervisor. In contrast, highly motivated workers do not quit for exogenous reasons, and want to become a Service Delivery Supervisor, if possible.

Workers have the following marginal productivity per period. In period one, all new care workers start their job of direct care and produce q. Previous experience does not affect this productivity of newly hired workers, because in direct care, only human relationships matter as firm-specific human capital. In period two, incumbent direct care workers produce $(1 + \delta)q$, regardless of their type, where $\delta > 0$ measures the firm-specific human capital. This firm-specific human capital can increase the productivity even under fixed rewards, because the good human relationships can lead to an efficient provision of services. In period three, Service Delivery Supervisors produce $\bar{q}$, which is higher than the productivity of mature direct care workers, i.e., $\bar{q} > (1+\delta)q$.

In addition, I assume that there is a pool of secondhand workers. The workers in this pool works only for one-period with productivity q and quit before they accumulate the firm-specific human capital. Firms can always hire a shot-term worker from this pool, and new workers can enter this pool at any time.

To manage adverse selection, firms offer a package of the GHC training and wages. Firms choose the amount of GHC training $\tau \geq 0$. The cost of the firm-provided training is $c(\tau)$, which is paid in period one. I assume $c(0) = 0$ and $c'(\tau) > 0$ for $\tau > 0$. For simplicity, I assume that workers without the firm-provided training cannot afford self-training. This assumption is justified by a situation in which severe working conditions prevent direct care workers from training by themselves, without allowances of firms. Type H workers can pass the exam for the certification with a probability $p(\tau)$ after completing training, but type L workers cannot pass the exam even with training. I assume $p(0) = 0$ and $p'(\tau) > 0$ for $\tau > 0$.

Corresponding to the training level, firms offer wages $w_t(\tau)$ for $t = 1, 2$ and I let $\boldsymbol{w}(\tau) = [w_1(\tau), w_2(\tau)]'$. I assume that the firm's offer is with commitment. In period three, workers who have the certification become a Service Delivery Supervisor, for which there is a competitive labor market. The market wage is determined as $\bar{q}$ from the zero-profit condition. In contrast, workers without certification enter the secondhand worker pool, regardless of their type. This behavior is explained by the burnout of veteran direct care workers. I also assume that there is a competitive labor market for these secondhand workers with a market wage q. This wage is greater than the one-period reservation utility $\underline{u}$.

My model has two large differences to Autor (2001). First, to incorporate the divergence of job tenures into my model, I define worker types differently. Autor (2001) assumed the same rate of exogenous separations and different productivities for distinct types. On the other hand, I assume type-specific differences in exogenous separation rates as a source of divergence of job tenures. Furthermore, I assume that only relationships between workers and elders, which are always established for incumbent workers, can affect productivity of direct care works under the fixed reward mechanism. Then, I do not adopt type-specific productivity differences.

Second, for secondhand workers, I adopt a uniform productivity. Autor (2001) considered that the worker pool has both types of workers and that their wage is endogenously determined by outside firms. My simplification is technically required to adopt the dynamic nature of firm-provided human capital and type-specific exogenous separations.

The sequence of events in this model is as follows:

1. At the beginning of period one, firms offer a package of τ and $\boldsymbol{w}(\tau)$ with a commitment to new workers, and new workers choose a firm after seeing all the offers. Workers also have the option to enter the secondhand worker pool and work under a short-term contract with wage q.

2. During period one, all workers produce q for firms. Firms with $\tau > 0$ provide the training and pay the cost $c(\tau)$.

3. At the end of period one, exogenous separations occur for type L workers with a probability μ. Endogenous separations into the secondhand worker pool also occur for both types, if any. If a separation occurs, the firm supplements a short-term worker from the secondhand worker pool.

4. During period two, incumbent workers produce $(1+\delta)q$ regardless of their type, and secondhand workers produce q with the wage q.

5. At the end of period two, incumbent firms close their business. Type H workers with training obtain the certification. All workers without training and workers who fail the exam enter the secondhand worker pool.

6. In period three, workers with the certification earn $\bar{q}$, while workers without the certification earn q.

In the above screening model, I have a separating equilibrium under conditions described in Appendix A. In the equilibrium, all type H workers choose training firms, while all type L workers choose non-training firms. There is no endogenous separation of workers. Both training and non-training firms exist.

The resulting equilibrium has the following properties. First, similar to the model of Autor (2001), the total wages in training firms are lower than total wages in nontraining firms, due to the training cost. Second, although the equilibrium wage in non-training firms is same as the secondhand wage, non-training firms earn a higher profit than do firm that hires secondhand workers from the beginning. The source of the additional profit is the rent from incumbent workers who accumulate the firm-specific human capital. Third, training firms can achieve the same profit as non-training firms, even though they pay for the training cost, because the firm-provided training can attract more highly motivated workers who generate higher expected productivities from the firm-specific human capital than low-motivated workers in non-training firms.

From the above separating equilibrium, I have the testable implication that the firm-provided GHC training increases workers' job tenure. Let t^* be the job tenure. Because all the highly motivated workers receive the training and low-motivated workers do not, I have

$$E[t^*|\tau > 0] = E[t^*|T = H] = 2 \geq E[t^*|\tau = 0] = E[t^*|T = L] = 2 - \mu$$

There are several observations that indicate the possibility of adverse selection in the Japanese labor market for home care workers. First, there is only a low barrier to enter the labor market of direct care workers. Then, the absence of skill signals such as education is likely to produces adverse selection regarding labor quality. Second, the irregular work conditions of temporary part-time workers induce a difficulty of peer monitoring for labor quality. Under such circumstances, a truth-telling mechanism, such as the one in my screening model, is required to validate the motivation of workers.

3 Econometric method

This section provides an econometric framework to examine the testable implication of the screening model. I first describe details of the available data, which induce restrictions for my econometric modeling. Subsequently, I construct my econometric model that consists only of inequality restrictions. The later part of this section proposes a method for standard Bayesian estimation.

3.1 Available data

Examining the implication of the screening model, we face a data availability problem. The testable implication is that the firm-provided GHC training has a positive effect on job tenures of workers. However, it is difficult to simultaneously observe these two elements. The job tenures are observable only with data of labor dynamics. An example is a panel dataset of workers, such as the Survey of Income and Program Participation(SIPP) used in Baughman and Smith (2012). Another possibility is a cross-section data of separated workers with retrospective questions on previous job tenures. In contrast, my screening model is based on a specific situation of temporary part-time workers in the home care sector. Thus, required data must be specific to this labor force, and the inclusion of other workers would distort an empirical analysis. To the best of my knowledge, there are no data that satisfy both requirements simultaneously.

This paper presents an econometric framework using available cross section data. I use the Working Conditions Survey in Long-Term Care, which is an annually repeated cross-section survey that started in 2002 and collected by an the Long-Term Care Labor Assurance Center. The questionnaires have year-by-year differences, and I use the dataset of 2006 that contains the necessary questions for this study. This dataset consists of an establishment survey and a labor survey. This study utilizes only the establishment survey because the labor survey does not ask questions regarding the GHC training. The establishment survey is accompanied with matched employer-employee information because each establishment is asked to provide information on its workers.

Unlike the panel data, my cross-section data cannot reveal the true tenures of workers. As a disadvantage of my data, this problem of incomplete observations requires a complicated econometric framework, which is described below. In contrast, an advantage of my data is that we have enough observations of temporary part-time workers in the home care sector who are the objects of my screening model.

In the separating equilibrium of my screening model, workers and firms make their decisions based on information at the time of the contract. Therefore, in an empirical analysis, explanatory variables that affect the job tenure must be measured at that point in time. The problem is that we only observe information at the time of the survey, not at the time of the job matching. In the later empirical section, I try to resolve this problem by an appropriate choice of explanatory variables.

3.2 An interval regression model with supplemental information

I begin with considering a possibility to examine the testable implication of the screening model using worker data from the matched employer-employee information. The sample from the worker data consists of J_W establishments, where the jth establishment has $N_{j,W}$ individual workers. The total sample size is $N_W = \sum_j N_{j,W}$.

The ideal dependent variable is the true job tenure t^*_{ij}. This variable represents the length of working years until separation. To analyze the effect of the firm-provided GHC training on t^*_{ij}, I adopt the following log-linear functional form:

$$\log t^*_{ij} = \boldsymbol{x}'_{ij}\boldsymbol{\beta} + \boldsymbol{z}_j\boldsymbol{\gamma} + \epsilon_{ij}, \tag{3.1}$$

where $\boldsymbol{x}_{ij}$ and $\boldsymbol{z}_j$ are observable characteristics of a worker and an establishment, and ϵ_{ij} is an unobserved characteristic. Note that $\boldsymbol{z}_j$ contains our main explanatory variable, a dummy variable indicating whether a firm provides the GHC training or not.

The problem is that t^*_{ij} is not observable in my cross-section dataset. Instead, I can obtain a variable of the ongoing tenure, which I denote y_{ij}. This variable represents the length of working years until the survey year and is essentially right-censored as a proxy for t^*_{ij}. For example, suppose that the ith individual has the true tenure $t^*_{ij} = 3$. If the survey is conducted two years after from the job matching, we observe $y_{ij} = 2$. On the other hand, if the survey is conducted four years after the job matching, the ith individual is not observed. Because of such an attrition for completed tenures, all the observed ongoing tenures are right-censored.

Due to the incomplete observation, I cannot employ a regression analysis of (3.1). Instead, the right-censoring property induces the following inequality restriction:

$$\log y_{ij} \leq \boldsymbol{x}'_{ij}\boldsymbol{\beta} + \boldsymbol{w}_j\boldsymbol{\gamma} + \epsilon_{ij}. \tag{3.2}$$

Next, I investigate how to use establishment data. Similar to the worker data, I assume that the sample consists of J_W establishments and that the jth establishment reports $N_{j,E}$ workers.

For the job tenures, establishment data have variables that are essentially free from the right-censoring, because establishments can report completed separations. However, there still is a problem of incomplete observations because we can observe only aggregated categorical variables for tenures.

The specific question is that “for the workers with separation last year, how long had they worked for your establishment? Answer the numbers of workers for categories; (1) Tenure < 1 or (2) $1 \leq$ Tenure < 3." We can also construct the number of separated workers with three years or more tenures, using another question that asks about the total number of the workers who separated in the last year.

To use these categorical variables, I take the mean of both hand sides on (3.1) with respect to $i = 1, ..., N_{j,E}$ and obtain

$$\overline{\log t^*}_j = \bar{\boldsymbol{x}}_j \boldsymbol{\beta} + \boldsymbol{w}_j \boldsymbol{\gamma} + \bar{\epsilon}_j, \tag{3.3}$$

where bar variables represent sample averages. Using the aggregated categorical variables, I can construct a lower bound v_{0j} and an upper bound v_{1j} for $\overline{\log t_j^*}$ as

$$\begin{cases} v_{0j} = & \log(1/365) \times (\#\text{tenure} < 1) + \log(1) \times (\#1 \leq \text{tenure} < 3) \\ & + \log(3) \times (\#\text{tenure} > 3), \\ v_{1j} = & \log(1) \times (\#\text{tenure} < 1) + \log(3) \times (\#1 \leq \text{tenure} < 3) \\ & + \log(\text{Years from opening}) \times (\#\text{tenure} > 3). \end{cases} \tag{3.4}$$

In the definition of v_{0j}, I use 1/365 year, or one day, as a lower bound of the tenures of less than one year. In this equation, I implicitly assume that if a worker separates without staying for one day, the establishment does not recognize it as hiring.

Combining the above discussions regarding worker and establishment data, I obtain three inequality restrictions. Two restrictions come from the establishment data as

$$v_{0j} \leq \bar{\boldsymbol{x}}_j \boldsymbol{\beta} + \boldsymbol{w}_j \boldsymbol{\gamma} + \bar{\epsilon}_j \leq v_{1j}. \tag{3.5}$$

One can consider a rough and easy regression analysis based on (3.3) by using some representative values of the dependent variable as a proxy for $\overline{\log t_j^*}$, such as v_{0j}, v_{1j} or their median. However, as shown in the latter empirical analysis, my data are sensitive to the choice of such values. Thus, a more robust econometric framework is required for our situation.

As a candidate of a robust framework, I adopt an interval regression model, where the right-hand side variable on (3.3) is bounded by v_{0j} and v_{1j}. Manski and Tamer (2002) showed that the interval regression model can be analyzed using a set estimation methodology. In addition to the basic two inequalities

(3.5) for the interval regression, I have another inequality restriction (3.2) from the worker data.

3.2.1 An estimation procedure via a standard Bayesian approach

Although they have the same origin, I treat the establishment and worker data as two distinct populations, for two reasons. First, the number of establishments is differently defined. For worker data, J_W is defined as the number of all establishments. On the other hand, for establishment data, J_E is defined as the number of establishments with at least one realized separation. This requirement is necessary to have well-defined values of the aggregated categorical variables. Second, there are many missing observations for tenure variables in the establishment data, as described in the later empirical analysis. As a result, I cannot relate the two populations, and they are treated as independent samples with size J_E and N_W.

The existence of two populations makes it difficult to employ a conventional classical estimation via the subsampling. Thus, I adopt a Bayesian estimation for an econometric model defined by inequality restrictions (3.2) and (3.5). With an appropriate choices of a distributional assumption and prior distributions, we can implement an efficient Gibbs sampler as follows.

To employ Bayesian estimation, we need a distributional assumption on the error terms in the inequalities. In this paper, I assume that the error terms follow independent and identical normal distributions:

$$\epsilon_{ij} \sim \text{IID } N(0, \sigma^2). \tag{3.6}$$

This distributional assumption implies that $\bar{\epsilon}_j = N_{j,E}^{-1} \sum_{i=1}^{N_{j,E}} \epsilon_{ij} \sim N(0, \sigma^2/N_{j,E})$. Furthermore, I introduce new sample-specific parameters as

$$\begin{aligned} 0 \leq \lambda_j^L &= \bar{\boldsymbol{x}}_j' \boldsymbol{\beta} + \boldsymbol{w}_j' \boldsymbol{\gamma} + \bar{\epsilon}_j - v_{0j}, \\ 0 \leq \lambda_j^U &= v_{1j} - \bar{\boldsymbol{x}}_j' \boldsymbol{\beta} - \boldsymbol{w}_j' \boldsymbol{\gamma} - \bar{\epsilon}_j, \\ 0 \leq \lambda_{ij}^W &= \boldsymbol{x}_{ij}' \boldsymbol{\beta} + \boldsymbol{w}_j' \boldsymbol{\gamma} + \epsilon_{ij} - \log y_{ij}. \end{aligned}$$

Then I set the following conjugate the prior distributions:

$$
\begin{aligned}
(\boldsymbol{\beta}', \boldsymbol{\gamma}') &\sim N(\boldsymbol{\mu}_0, \Sigma_0),\ \sigma^2 \sim \mathrm{IG}(\alpha_{10}/2, \alpha_{20}/2), && (3.7)\\
\lambda_j^{\Upsilon} &\sim \mathrm{TN}_{[0,\infty)}[\mu_{\lambda_j^{\Upsilon}0}, \sigma^2_{\lambda_j^{\Upsilon}0}],\ \Upsilon \in \{L, U\},\ j = 1, ..., J_E, && (3.8)\\
\lambda_{ij}^{W} &\sim \mathrm{TN}_{[0,\infty)}[\mu_{\lambda_{ij}^{W}0}, \sigma^2_{\lambda_{ij}^{W}0}],\ j = 1, ..., J_W,\ i = 1, ..., N_{j,W}, && (3.9)
\end{aligned}
$$

where IG denotes inverse gamma and $\mathrm{TN}_{[S]}$ denotes the truncated normal distribution whose support is restricted to S. The conditional posterior distributions are described in Appendix B. Because the conditional posterior distributions have familiar forms, we can implement the Gibbs sampler for estimation.

The above Bayesian estimation procedure yields a point identification for the interval regression model for the following reason. As mentioned in Manski and Tamer (2002), the partial identification problem shifts to the incidental parameter problem by introducing appropriate latent variables. However, a Bayesian method can explicitly estimate these latent variables, or sample-specific nuisance parameters, because it can work for small samples. Thus, the incidental parameter problem is not essential in Bayesian statistics. This approach is also employed in other papers by the author (Sugawara and Omori, 2012, 2013).

4 Empirical analysis

4.1 Detailed data definitions

Among various care sectors in the Working Conditions Survey in Long-Term Care, I restrict my attention to temporary part-time workers in the home care sectors. In the matched employer-employee information, the number of workers is determined as follows: If an establishment has fewer than 20 workers, it reports on all workers. If an establishment has 20 workers or more, it randomly chooses 20 workers to report on. The sample sizes for establishment data and worker data are $J_E = 68$ and $N_W = 10,319$. For the main econometric model consisting of (3.2) and (3.5), the sample size is $2J_E + N_W$, because we have two inequalities for each establishment and an inequality for each worker.

The sample size for the establishment data is small. As mentioned above, there are many missing observations of tenure variables in the establishment data. Specifically, we have 4,980 home care establishments in the original data, but 3,310 of these establishments do not report the number of separated workers.

Furthermore, 1,118 establishments are also eliminated from my study, because they do not have any separated worker in the survey year. From the remaining 558 establishments, I eliminate those with missing information for the other variables and obtain $J_E = 68$. In contrast, the number of the separated workers does not affect the worker data due to its construction.

Regarding boundaries of dependent variables, upper and lower bounds for the establishment data are defined as (3.4). The upper bound for the worker data is the logarithm of the ongoing tenure. Several workers report their ongoing tenure as zero, but this value leads to a problem when we take its logarithm. I define the lower bound as $\log(1/365)$, similar to the definition of v_{0j} in (3.4).

The explanatory variables are defined as follows. For workers' characteristics $\boldsymbol{x}$, worker's age at the job matching(**Age**) and a logarithm of he monthly wage (**Wage**) are adopted. The monthly wage is defined as the total wage paid in September 2006. The variable **Wage** has two problems. First, I do not control the obvious endogeneity between wage and job tenure. Second, I use the observation at the time of the survey, but my screening model requires this variable to be measured at the time of the job matching, which is a time of decision making. Thus, the resulting coefficient estimator might be biased, but I do not pursue its precision because the wage effect is not our main interest.

For establishment characteristics $\boldsymbol{z}$, our main target is a dummy variable for firm-provided training for the Care Worker certification(**Training**). This variable takes unity if the establishment provides training to obtain occupational certifications and pays all or part of the training cost. I further adopt the following establishment variables. Considering a behavioral difference between nonprofit and for-profit firms, I introduce a dummy variable that takes unity if the establishment is operated by a for-profit firm(**For-Profit**). Another establishment characteristics is a dummy variable that takes unity when the establishment was build before the launch of the LTCI(**Old Establishment**). I adopt this variable to reflect possible differences of new and mature firms. To control for various forms of compensations for workers, I adopt three dummy variables for the existence of raises in salary, bonuses, and periodical checkups for temporary part-time workers(**Raise in Salary**, **Bonus** and **Checkup**).

To reflect regional differences, I also include the regional averages of monthly wages for female part-time workers(**Regional Wage**). The monthly wage is defined as follows using average regional values from the Basic Survey of Wage Structure(Japan Ministry of Health, Labor and Welfare, 2006). I first define a scheduled monthly wage as the number of working days in June times the scheduled working hours per day times the scheduled hourly wage. Next, I calculate the annual wage by multiplying the scheduled monthly wage times twelve and adding the annual bonus. Dividing this annual wage by twelve, I finally obtain the monthly wage. The regional unit is a prefecture, which is the largest subnational jurisdiction in Japan. This value is measured for the year of the survey and shares the timing problem with **Wage**. Due to small variations in regional wages, I use the standardized values for estimation to stabilize results. Table 1 shows descriptive statistics for these variables.

Table 1 is here

4.2 Estimation result

Table 2 is here

Before reporting the main estimation results, I show preliminary regression results in which some representative values are used as dependent variables. In Table 2, the first three columns use the lower bounds v_0, the median $(v_0+v_1)/2$ and the upper bound as dependent variables for the establishment data. The last column uses the logarithm of the ongoing tenure $\log y$ as a dependent variable for worker data. All regression coefficients are estimated using a classical ordinary least square. It is important to note that coefficients for **Training** have different significance levels, according to the choice of a dependent variable. These results clearly indicate the danger of an ad-hoc choice of a dependent variable.

Next, I report the estimation result for the interval regression model. In my implementation of the Gibbs sampler, 50,00 posterior samples are generated after discarding 5,000 initial samples of the burn-in period. I adopt the following hyperparameters to induce flat prior distributions that reflect my lack of subjective knowledge.

$$
\begin{aligned}
\boldsymbol{\mu}_0 &= \mathbf{0},\ \Sigma_0 = 1000\boldsymbol{I},\ \alpha_{10} = \alpha_{20} = 0.001, \\
\mu_{\lambda_j^U 0} &= \mu_{\lambda_j^L 0} = \mu_{\lambda_{ij}^W 0} = 0,\ \text{for all } i, j, \\
\sigma^2_{\lambda_j^U 0} &= \sigma^2_{\lambda_j^L 0} = \sigma^2_{\lambda_{ij}^W 0} = 10,\ \text{for all } i, j,
\end{aligned}
$$

Table 3, Figures 1 and 2 are here.

Table 3 presents the estimation result of my standard Bayesian approach. The first column shows 95% credible intervals. I also present posterior means and standard deviations in the second column. These values are identified under the standard Bayesian approach, unlike the classical estimation that has only set identification. Figure 2 plots kernel density estimators of posterior samples. As shown in the figure, estimated posterior densities have unimodal shapes without flat surfaces for all parameters. These shapes of densities can indicate the information gain of my method which utilizes all information from available data.

Before analyzing the details of estimates, I examine the performance of my estimation procedure. The last column in Table 3 reports statistics for this purpose, inefficiency factors (IF) of Chib (2001). The inefficiency factors are 1.928 to 4.148, implying that we would obtain the same variance for the posterior sample means from $5,000/4.148 \fallingdotseq 1250$ uncorrelated draws in the worst case. Furthermore, Figure 1 plots posterior sample paths, which clearly show that the chain mixes well for all parameters. These results indicate that my Gibbs sampler performs well.

The most important result in my estimation is that my main variable of interest, **Training**, has a positive coefficient. This result implies the validity of our screening model, and has rich policy implications. For workers, obtaining GHC increases their future wages. For firms, under the tight budget constraint caused by the fixed rewards mechanism, the provision of GHC training is a rare feasible method to extend tenures of workers. However, it is possible that this circumstance produces an unfair competition, because larger firms should have benefit more from scale effects to reduce training costs. Considering workers' sensitivity to their lifetime wage, deregulation of the fixed rewards mechanism can create healthy competition.

The other coefficients are naturally interpreted as follows. The positive effect of **wage** on tenures is a natural finding, but it must be carefully interpreted because I do not control the endogeneity. The negative effect of **For-Profit** indicates the existence of a nonprofit premium for working conditions, which was also suggested by Noguchi and Shimizutani (2007). The positive sign of **Old Establishment** implies that establishments with longer tenures can survive for a long time. The positive effect of **Bonus** indicates that bonuses are useful benefits to extend the workers' tenures. The negative effect for **Regional wage** shows that the existence of attractive outside options encourage workers to exit from the home care sector.

To examine the robustness of my estimation results, I also adopt a hyperparameter $\sigma^2_{\lambda^W_{ij}0} = 1000$. Because the inequality from the worker data (3.2) does not have the lower bound, it is possible that λ^W_{ij} to take an extremely small value, and this hyperparameter allows such an extreme value. Using this hyperparameter, I obtain the same signs of boundaries of 95% credible intervals of all coefficients as the above main results. Thus, my main results are robust to the choice of this hyperparameter.

5 Conclusion

This paper has investigated determinants of job tenures of elder care workers in Japan. I have adopted firm-provided general human capital training as a non-wage element that affects the job tenures. This hypothesis has formally been incorporated into a screening model with a separating equilibrium. To examine the validity of the model, I have constructed an interval regression framework that overcomes the data restriction. I have proposed a simple estimation procedure using a standard Bayesian approach. The empirical result supports my hypothesis.

Due to the rapid emergence of a new market, today's Japanese elder care sector has many regulations. Those regulations have helped the countrywide diffusion of the new policy, but certain regulations might already be outdated to current standard. Considering that ongoing aging is depressing the fiscal budget, inefficient regulations must be removed to keep the program sustainable. As an example of such a regulation, the fixed rewards mechanism should once have been attractive for consumers who were unfamiliar with the emerging sector, because it guarantees a unified standard with fixed prices. However, my study suggests that a deregulation of this mechanism can produce healthy competition.

A disadvantage of my Bayesian estimation is its requirement of a distributional assumption. To remove this restriction, one needs to extend the frontier of econometrics. As a possible direction, the author proposes a quasi-Bayesian method with Bayesian justification for its credible interval estimator in Sueishi and Sugawara (2013). However, this approach is based on a unconditional moment inequality, while my model with (3.2) and (3.5) induces conditional inequalities. In contrast, Kim (2009) proposes a classical method with subsampling for the conditional moment inequalities. The combination of these two approaches might produce a robust method for my problem, but such a study is beyond the scope of this paper.

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References

Abowd, J. M. and F. Kramarz (1999) "The analysis of labor markets using matched employer-employee data," in Ashenfelter, O. C. and D. Card eds. *Handbook of Labor Economics 3B*, Amsterdam: North-Holland, pp. 2629-2710.

Abrevaya, J. (1999) "Rank estimation of a transformation model with observed truncation," *Econometrics Journal*, Vol. 2, pp. 292-305.

Acemoglu, D. and J.-S. Pischke (1998) "Why do firms train? Theory and evidence," *Quarterly Journal of Economics*, Vol. 113, No. 1, pp. 79-119.

Autor, D. (2001) "Do temporary help firms provide free general skills training?" *Quarterly Journal of Economics*, Vol. 116, No. 4, pp. 1409-1448.

Baughman, R. A. and K. E. Smith (2012) "Labor mobility of the direct care workforce: Implications for the provision of long-term care," *Health Economics*, Vol. 21, pp. 1402-1415.

Becker, G. S. (1964) *Human capital*, Chicago: The University of Chicago Press.

Beresteanu, A. and F. Molinari (2008) "Asymptotic properties for a class of partially identified models," *Econometrica*, Vol. 76, No. 4, pp. 763-814.

Berry, S., J. Levinsohn, and A. Pakes (1995) "Automobile price in market equilibrium," *Econometrica*, Vol. 63, No. 4, pp. 841-890.

Berry, S., J. Levinsohn, and A. Pakes (2004) "Differentiated products demand systems from a combination of micro and macro data: The new vehicle market," *Journal of Political Economy*, Vol. 112, pp. 68-105.

Castle, N. G. and J. Engberg (2005) "Staff rurnover and quality of care in nursing homes," *Medical Care*, Vol. 43, No. 6, pp. 616-626.

Chernozhukov, V., H. Hong, and E. Tamer (2007) "Estimation and confidence regions for parameter sets in econometric models," *Econometrica*, Vol. 75, No. 5, pp. 1243-1284.

Chib, S. (2001) "Markov chain Monte Carlo methods: computation and inference," in Heckman, J. J. and E. Leamer eds. *Handbook of Econometrics 5*, Amsterdam: North Holland.

Doornik, J. A. (2011) *Object-Oriented Matrix Programming Using Ox*, London: Timberlake Consultants Press and Oxford, 6th edition.

Hanaoka, C. (2011) "Care staff turnover in long-term care services for older people: how does the effect of relative wages on turnover vary by tenure? (in Japanese)," *Iryou Keizai Kenkyuu*, Vol. 23, No. 1, pp. 39-57.

Honoré, B. E. and L. Hu (2010) "Estimation of a transformation model with truncation, interval observation and time-varying covariates," *Econometrics Journal*, Vol. 13, pp. 127-144.

Hotta, S. (2007) "Toward maintaining and improving the quality of long-term care: The current state and issues regarding home helpers in Japan under the Long-Term Care Insurance system," *Social Science Japan Journal*, Vol. 10, No. 2, pp. 265-279.

Japan Ministry of Health, Labor and Welfare (2006) "Basic Survey of Wage Structure," Tokyo.

Japan Ministry of Health, Labor and Welfare (2007) "Survey on institutions and establishments for long-term care (Kaigo sabisu sisetsu jigyousho chousa, in Japanese)," Tokyo.

Japan Ministry of Health, Labor and Welfare (2008) "Report of study group for serurity and stability of care workers(in Japanese)," Tokyo. http://www.mhlw.go.jp/houdou/2008/07/dl/h0729-2a.pdf.

Kim, K. I. (2009) "Set estimation and inference with models characterized by conditional moment inequalities." Working paper.

Knapp, M. and S. Missiakoulis (1983) "Predicting turnover rates among the staff of English and Welsh old people's homes," *Social Science and Medicine*, Vol. 17, No. 1, pp. 29-36.

Manski, C. and E. Tamer (2002) "Inference on Regressions with Interval Data on a Regressor or Outcome," *Econometrica*, Vol. 70, pp. 519-547.

Moon, H. R. and F. Schorfheide (2012) "Bayesian and frequentist inference in partially identified models," *Econometrica*, Vol. 80, No. 2, pp. 755-782.

Noguchi, H. and S. Shimizutani (2007) "Nonprofit for-profit status and earning differentials in the Japanese at-home elderly care industry: Evidence from micro-level data on home helpers and staff nurses," *Journal of the Japanese and International Economies*, Vol. 21, pp. 106-120.

Powers, E. T. and N. J. Powers (2010) "Causes of Caregiver Turnover and Potential Effectiveness of Wage Subsidies for Solving the Long-Term Care Workforce 'Crisis,'," *The B.E. Journal of Economic Analysis and Policy*, Vol. 10, No. 1.

Sueishi, N. and S. Sugawara (2013) "Bayesian empirical likelihood for moment inequality models." mimeo.

Sugawara, S. and Y. Omori (2012) "Duopoly in the Japanese airline market: Bayesian estimation for entry games," *Japanese Economic Review*, Vol. 63, No. 3, pp. 310-332.

Sugawara, S. and Y. Omori (2013) "An econometric analysis of insurance markets with separate identification for moral hazard and selection problems." Working paper.

Yamada, Y. and M. Sekiya (2003) "Licensing and training requrements for direct care workers in Japan," *Journal of Aging and Social Policy*, Vol. 15, No. 4, pp. 113-129.

A Separating conditions for the screening model

This appendix presents conditions to guarantee the existence of a separating equilibrium for my screening model that is described in Section 2.2. In the separating equilibrium, given the equilibrium belief π^*, there are firms with training level τ^* and firms without training, who earn the same equilibrium profit $\underline{\Pi} > 0$. The property of this equilibrium profit is described in Autor (2001, Footnote 17). Given equilibrium values of τ^* and w^*, there is no endogenous separation of workers for both types. All type H workers work for training firms, while all type L workers work for non-training firms. The equilibrium belief is as follows:

$$\begin{aligned}\pi^*(T = H,\ \text{no endogenous separation}; \tau = \tau^*) &= 1,\\ \pi^*(T = L,\ \text{no endogenous separation}; \tau = 0) &= 1.\end{aligned}$$

To derive the separating condition, I first consider the equilibrium behavior of nontraining firms. The optimization problem is given as

$$\max_{\boldsymbol{w}(0)} (1-\mu)[q + (1+\delta)q - w_1(0) - w_2(0)] + \mu[q - w_1(0)],$$

subject to participation constraints:

$$\begin{aligned}w_t(0) &\geq \underline{u},\ t = 1, 2\\ w_2(0) + q &\geq 2q,\\ w_1(0) + w_2(0) + q &\geq 3q,\end{aligned}$$

and the truth-telling mechanisms:

$$w_1(0) + w_2(0) + q \geq w_1^*(\tau^*) + w_2^*(\tau^*) + q, \tag{A.1}$$

$$w_1(0) + w_2(0) + q \geq w_1^*(\tau^*) + q + q. \tag{A.2}$$

I firstly ignore the truth-telling mechanisms and verify them later. There is a solution $\boldsymbol{w}^*(0) = (\underline{u}, 2q - \underline{u})'$, which gives the equilibrium profit as

$$\underline{\Pi} = (1-\mu)q\delta + \mu(q - \underline{u}),$$

where the right-hand side is positive from assumptions of the model.

Given these equilibrium wages of non-training firms, the optimization problem for training firms is given as

$$\max_{\tau>0,\boldsymbol{w}(\tau)} q+(1+\delta)q-w_1(\tau)-w_2(\tau)-c(\tau),$$

subject to participation constraints:

$$\begin{aligned} w_t(\tau) &\geq \underline{u},\ t=1,2 && \text{(A.3)} \\ w_2(\tau)+p(\tau)\bar{q}+[1-p(\tau)]q &\geq 2q, \\ w_1(\tau)+w_2(\tau)+p(\tau)\bar{q}+[1-p(\tau)]q &\geq 3q. \end{aligned}$$

Under the above participation constraints with equilibrium nontraining wages $\boldsymbol{w}^*(0)$, truth-telling mechanisms for highly motivated workers are automatically satisfied and are abbreviated here. To solve the optimization problem, I first assume the existence of $\tau^*>0$ and find the equilibrium wage for the fixed τ^*. As a result, the first and second period wages are not separately determined, but their total is given by $w_1^*(\tau^*)+w_2^*(\tau^*)=2q-p(\tau^*)(\bar{q}-q)$ subject to (A.3) and

$$w_2^*(\tau^*)\geq q-p(\tau^*)(\bar{q}-q). \tag{A.4}$$

Furthermore, the resulting equilibrium wages can verify a truth-telling condition for type L workers (A.1). To satisfy another condition (A.2), I need an additional condition:

$$w_1^*(\tau^*)\leq q. \tag{A.5}$$

To guarantee the existence of the equilibrium wages that satisfy (A.3), (A.4) and (A.5), we need the following:

$$\underline{u}\leq\bar{q}-\frac{p(\tau^*)(\bar{q}-q)}{2}. \tag{A.6}$$

With these equilibrium wages, the equilibrium profit of training firms is

$$\underline{\Pi}=\delta q+p(\tau^*)(\bar{q}-q)-c(\tau^*).$$

Equating the profits for training and non-training firms, we have

$$\mu(q-u)-q\delta=p(\tau^*)(\bar{q}-q)-c(\tau^*). \tag{A.7}$$

Consequently, the separating conditions are given by the existence of $\tau^* > 0$, which satisfies (A.6) and (A.7).

B The conditional posterior distributions for Bayesian estimation

This appendix describes the functional forms of the conditional posterior densities which are used in the Bayesian estimation procedure in Section 3.2.1. Under the distributional assumption (3.6), I have a closed form of the likelihood function as

$$
\begin{aligned}
&\pi(\boldsymbol{v}_0, \boldsymbol{v}_1, \boldsymbol{y} | \boldsymbol{\beta}, \boldsymbol{\gamma}, \sigma^2, \boldsymbol{\lambda}^U, \boldsymbol{\lambda}^L, \boldsymbol{\lambda}^W) \\
&\propto \quad (\sigma^2)^{-(2J_E+N_W)/2} \exp\Bigg\{ -\frac{1}{2\sigma^2} \Big[\sum_{j=1}^{J_E} N_{j,E} (v_{0j} + \lambda_j^L - \bar{\boldsymbol{x}}_j' \boldsymbol{\beta} - \boldsymbol{w}_j' \boldsymbol{\gamma})^2 \\
&\qquad + \sum_{j=1}^{J_E} N_{j,E} (v_{1j} - \lambda_j^U - \bar{\boldsymbol{x}}_j' \boldsymbol{\beta} - \boldsymbol{w}_j' \boldsymbol{\gamma})^2 + \sum_{j=1}^{J_W} \sum_{i=1}^{N_j} (\log y_{ij} + \lambda_{ij}^W - \boldsymbol{x}_{ij}' \boldsymbol{\beta} - \boldsymbol{w}_j' \boldsymbol{\gamma})^2 \Big] \Bigg\}.
\end{aligned}
$$

Under the prior distributions (3.7), (3.8) and (3.9), straight-forward calculations yield conditional posterior distributions as

$$
\begin{aligned}
(\boldsymbol{\beta}', \boldsymbol{\gamma}') | \boldsymbol{v}_0, \boldsymbol{v}_1, \boldsymbol{y}, \sigma^2, \boldsymbol{\lambda}^U, \boldsymbol{\lambda}^L, \boldsymbol{\lambda}^W &\sim N(\boldsymbol{\mu}_1, \Sigma_1), \\
\sigma^2 | \boldsymbol{v}_0, \boldsymbol{v}_1, \boldsymbol{y}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\lambda}^U, \boldsymbol{\lambda}^L, \boldsymbol{\lambda}^W &\sim \mathrm{IG}(\alpha_{11}/2, \alpha_{21}/2), \\
\lambda_j^X | \boldsymbol{v}_0, \boldsymbol{v}_1, \boldsymbol{y}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \sigma^2 &\sim TN_{[0,\infty)}(\mu_{\lambda_j^\Upsilon 1}, \sigma^2_{\lambda_j^\Upsilon 1}), \ \Upsilon \in \{L, U\}, \\
\lambda_{ij}^W | \boldsymbol{v}_0, \boldsymbol{v}_1, \boldsymbol{y}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \sigma^2 &\sim TN_{[0,\infty)}(\mu_{\lambda_{ij}^W 1}, \sigma^2_{\lambda_{ij}^W 1}),
\end{aligned}
$$

where

$$
\begin{aligned}
\Sigma_1 &= \Big(\sigma^{-2}\boldsymbol{X}'\boldsymbol{X} + \Sigma_0^{-1}\Big)^{-1},\ \mu_1 = \Sigma_1\Big(\sigma^{-2}\boldsymbol{X}'\boldsymbol{y}^* + \Sigma_0^{-1}\boldsymbol{\mu}_0\Big),\\
\alpha_{11} &= 2J_E + N_W + \alpha_{10},\\
\alpha_{21} &= \Big(\boldsymbol{y}^* - \boldsymbol{X}(\boldsymbol{\beta}',\boldsymbol{\gamma}')'\Big)'\Big(\boldsymbol{y}^* - \boldsymbol{X}(\boldsymbol{\beta}',\boldsymbol{\gamma}')'\Big) + \alpha_{20},\\
\sigma^2_{\lambda_j^{\Upsilon}1} &= \left(\frac{N_{j,E}}{\sigma^2} + \frac{1}{\sigma_{\lambda_j^{\Upsilon}}0}\right)^{-1},\ \ \sigma^2_{\lambda_{ij}^W 1} = \left(\frac{1}{\sigma^2} + \frac{1}{\sigma_{\lambda_{ij}^W}0}\right)^{-1},\\
\mu_{\lambda_j^L 1} &= \sigma^2_{\lambda_j^L 1}\left(\frac{N_{j,E}(-v_{0j} + \bar{\boldsymbol{x}}_j'\boldsymbol{\beta} + \boldsymbol{w}_j'\boldsymbol{\gamma})}{\sigma^2} + \frac{\mu_{\lambda_j^L 0}}{\sigma^2_{\lambda_j^L 0}}\right),\\
\mu_{\lambda_j^U 1} &= \sigma^2_{\lambda_j^U 1}\left(\frac{N_{j,E}(v_{1j} - \bar{\boldsymbol{x}}_j'\boldsymbol{\beta} - \boldsymbol{w}_j'\boldsymbol{\gamma})}{\sigma^2} + \frac{\mu_{\lambda_j^U 0}}{\sigma^2_{\lambda_j^U 0}}\right),\\
\mu_{\lambda_{ij}^W 1} &= \sigma^2_{\lambda_{ij}^W 1}\left(\frac{-\log y_{ij} + \boldsymbol{x}_{ij}'\boldsymbol{\beta} + \boldsymbol{w}_j'\boldsymbol{\gamma}}{\sigma^2} + \frac{\mu_{\lambda_{ij}^W 0}}{\sigma^2_{\lambda_{ij}^W 0}}\right),
\end{aligned}
$$

in which

$$
\boldsymbol{X} = \begin{pmatrix}
\sqrt{N_{1,E}}\bar{\boldsymbol{x}}_1' & \sqrt{N_{1,E}}\boldsymbol{w}_1' \\
\vdots & \vdots \\
\sqrt{N_{J_E,E}}\bar{\boldsymbol{x}}_{J_E}' & \sqrt{N_{J_E,E}}\boldsymbol{w}_{J_E}' \\
\sqrt{N_{1,E}}\bar{\boldsymbol{x}}_1' & \sqrt{N_{1,E}}\boldsymbol{w}_1' \\
\vdots & \vdots \\
\sqrt{N_{J_E,E}}\bar{\boldsymbol{x}}_{J_E}' & \sqrt{N_{J_E,E}}\boldsymbol{w}_{J_E}' \\
\boldsymbol{x}_{1,1}' & \boldsymbol{w}_1' \\
\boldsymbol{x}_{2,1}' & \boldsymbol{w}_1' \\
\vdots & \vdots \\
\boldsymbol{x}_{N_{J_W},J_W}' & \boldsymbol{w}_{J_W}'
\end{pmatrix},\ \ \boldsymbol{y}^* = \begin{pmatrix}
\sqrt{N_{1,E}}v_{0,1} + \sqrt{N_{1,E}}\lambda_1^L \\
\vdots \\
\sqrt{N_{J_E,E}}v_{0,J_E} + \sqrt{N_{J_E,E}}\lambda_{J_E}^L \\
\sqrt{N_{1,E}}v_{1,1} - \sqrt{N_{1,E}}\lambda_1^U \\
\vdots \\
\sqrt{N_{J_E,E}}v_{1,J_E} - \sqrt{N_{J_E,E}}\lambda_{J_E}^U \\
\log y_{1,1} + \lambda_{1,1}^W \\
\log y_{2,1} + \lambda_{2,1}^W \\
\vdots \\
\log y_{N_{J_W},J_W} + \lambda_{N_{J_W},J_W}^W
\end{pmatrix}.
$$

C Tables and Figures

		Mean	S.D.
Establishment data			
	v_0	-2.809	(2.882)
	v_1	0.830	(1.012)
$\boldsymbol{x}$	Wage	11.079	(0.507)
	Age	45.732	(6.907)
$\boldsymbol{z}$	Training	0.221	(0.418)
	For-Profit	0.471	(0.503)
	Old Establishment	0.559	(0.500)
	Raise in Salary	0.412	(0.496)
	Bonus	0.324	(0.471)
	Checkup	0.559	(0.500)
	Regional Wage	11.226	(0.070)
J_E	Sample size	68	
Worker data		Mean	S.D.
	Ongoing Tenure	3.101	(2.253)
$\boldsymbol{x}$	Wage	10.988	(0.664)
	Age	47.735	(9.693)
$\boldsymbol{z}$	Training	0.212	(0.409)
	For-Profit	0.564	(0.496)
	Old Establishment	0.498	(0.500)
	Raise in Salary	0.381	(0.486)
	Bonus	0.278	(0.448)
	Checkup	0.565	(0.496)
	Regional Wage	11.228	(0.071)
N_W	Sample size	10319	

Table 1: Descriptive statistics. Standard deviations in parentheses.

Variables	Establishment Data v_0	Median	v_1	Worker data $\log y$
Training	1.348	0.774**	0.777**	0.293***
	(0.877)	(0.378)	(0.368)	(0.045)
Wage	0.752	0.318	0.298	0.409***
	(0.613)	(0.229)	(0.215)	(0.032)
Age	-0.042	-0.010	-0.008	0.003
	(0.053)	(0.016)	(0.014)	(0.002)
For-Profit	-0.739	-0.170	-0.127	-0.358***
	(0.793)	(0.254)	(0.232)	(0.041)
Old Establishment	1.036	0.628**	0.635**	0.417***
	(0.813)	(0.279)	(0.254)	(0.040)
Raise in Salary	0.475	0.230	0.225	-0.209***
	(0.846)	(0.286)	(0.262)	(0.042)
Bonus	0.226	0.001	-0.0249	0.067
	(0.901)	(0.338)	(0.319)	(0.042)
Checkup	-0.853	-0.218	-0.171	-0.020
	(0.789)	(0.274)	(0.256)	(0.040)
Regional Wage	0.300	0.198	0.203*	-0.123***
	(0.407)	(0.130)	(0.119)	(0.020)
Constant	-9.523	-3.217	-2.539	-4.189***
	(6.838)	(2.431)	(2.253)	(0.371)
Sample size	68	68	68	10,319

Table 2: Preliminary regression results by the classical OLS. Robust standard errors in parentheses. $***$, $**$ and $*$ denotes $p < 0.01$, $p < 0.05$ and $p < 0.1$, respectively.

	95% Interval	Posterior Mean	IF
Training	[0.065, 0.367]	0.217(0.079)	4.148
Wage	[0.428, 0.613]	0.519(0.048)	2.013
Age	[-0.004, 0.009]	0.002(0.003)	2.185
For-Profit	[-0.862, -0.587]	-0.722(0.071)	2.440
Old Establishment	[0.641, 0.906]	0.774(0.069)	1.569
Raise in Salary	[-0.238, 0.036]	-0.095(0.069)	1.973
Bonus	[0.213, 0.505]	0.359(0.074)	2.322
Checkup	[-0.156, 0.107]	-0.024(0.068)	2.886
Regional Wage	[-0.214, -0.086]	-0.150(0.033)	2.528
Constant	[-3.870, -1.723]	-2.798(0.549)	1.928
σ^2	[6.600, 7.346]	6.961(0.193)	2.114

Table 3: Standard Bayes estimation result. Standard deviations in parentheses. The sample size is $N_W + 2J_E = 10,455$.

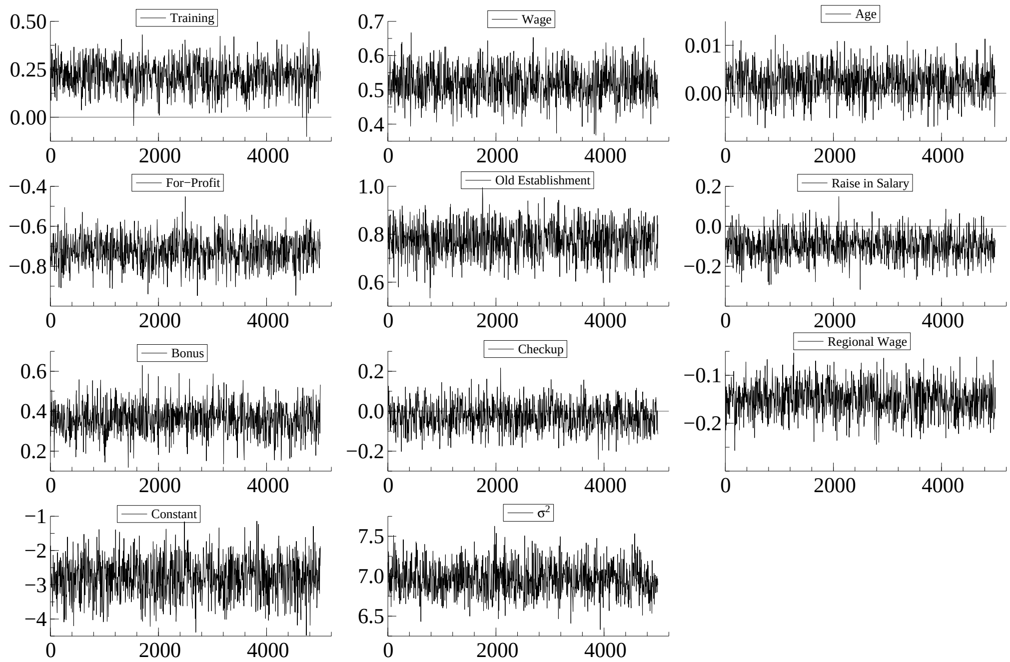

Figure 1: Posterior sample paths

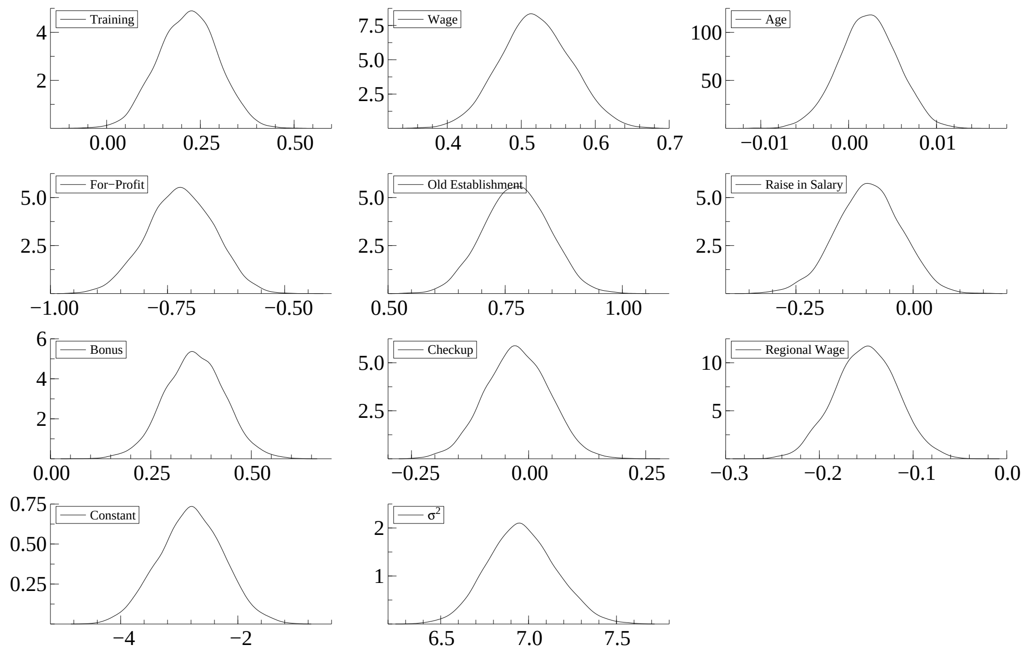

Figure 2: Posterior density plots