# Essays in Labour Economics

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## Declaration

I, Minsok Chae confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

# Abstract

This thesis studies how the relaxation of various constraints can affect the labour market through the search and matching between firms and workers.

The first chapter shows that the skill requirements imposed by the training system adopted by large firms can explain a specific phenomenon in the Korean labour market that cannot be adequately explained by standard search models: the limited job-to-job transitions from SMEs to large enterprises despite workers strongly preferring the latter. Furthermore, a counterfactual analysis using a structural model shows relaxing the skill requirements reduces about 26∼38 percent of the wage gap between small and large firms.

The second chapter examines the impact of submitting referrals, which relax information constraints on applicants, on hiring outcomes. Using unique data from a private matching platform, I find that submitting referrals significantly increases the probability that an applicant is hired, but does not significantly change his or her wage once hired.

The final chapter suggests that firms' preference for experienced workers could be one of the causes of high youth unemployment. A counterfactual analysis shows that if companies do not prefer experienced workers, more than 40 percent of the unemployment gap between young workers and prime-age workers would disappear and the expected lifetime income of young unemployed people newly entering the labor market is expected to increase by 14 percent.

# Impact Statement

Academically, the paper contributes to future research on key issues in labour economics, such as matching between firms and workers, wage and unemployment gaps. It also has a number of non-academic implications, particularly for labour policy.

The first chapter presents findings and methodology that may be useful for future research on the wage gap or labour market duality. It also provides policy implications that reducing the wage gap between large and small firms in Korea requires detailed policies that take into account the differences in their recruitment and training practices, and that education policies aimed at fostering talent favoured by large firms may lead to a widening of the wage gap in the economy as a whole.

The second chapter contributes to the literature on matching between firms and workers by analysing the impact of providing additional information about applicants on hiring outcomes. The findings of this thesis suggest that efforts to increase matching efficiency by relaxing information constraints between firms and workers are necessary to expand employment.

High youth unemployment, the subject of the third chapter, is a topic of both academic and non-academic interest, as its impact is not only on the economy but also on society as a whole, and it can last not only in the present but also in the future. In particular, the results of the counterfactual analysis in this thesis have policy implications, as a stronger preference for career jobs by firms can significantly reduce the lifetime earnings of the most vulnerable among young people.

# Contents

# List of Figures

# List of Tables

# Chapter 1

# Limited Job-to-Job Transitions from SMEs to Large Enterprises in Korea

## Abstract

This paper studies the limited job-to-job transitions from small and medium enterprises (SMEs) to large enterprises in Korea. This phenomenon is not adequately explained by standard search models due to the strong preference of workers for large firms in the country. To explore the reasons behind this and its impact on the labour market, I introduce a search model with two types of workers and two types of firms. Wage and job mobilities are determined through a sequential auction process. The key assumption is the existence of a skill requirement by one type of firm, corresponding to large enterprises, where low-type workers can only be hired by the other type of firm, corresponding to SMEs. This sorting between worker type and firm size leads to infrequent cross-sectional job-to-job transitions from small to large firms. Regarding the application of the model, I decompose the wage gap between SMEs and large enterprises in Korea, which is significantly larger than in other countries. I attribute this wage gap to differences in productivity and the impact of the skill requirement. The skill requirement contributes to about 26$\sim$38% of the wage gap through two mechanisms. First, it leads to the sorting between firm size and worker type, resulting in different wages based on worker type.

Additionally, the skill requirement reduces competition for low-type workers, thereby widening the wage gap by worker type.

## 1.1 Introduction

In standard search models with on-the-job search, workers accept a new offer if it is better than their current job. As a result, the models predict frequent job-to-job transitions from less preferred firms to more preferred ones. However, job-to-job transitions between SMEs and large firms in Korea show the opposite phenomenon. Korean workers strongly prefer large firms to SMEs. According to a survey conducted by the Korea economic research institute (2021), 35.0% of college students and graduates prefer to work at large-sized firms, while only 11.9% of them prefer SMEs. Also, the number of job applications to large firms was more than thirty times that of hiring by the firms in 2013, while the ratio for SMEs was just about 6 to 1 (Korea enterprises federation (2013)). Despite this strong preference for large firms over SMEs, job-to-job transitions from the latter to the former are rare in Korea. Table 1.1 shows the job-to-job transitions by firm size calculated using the Korean Labor and Income Panel Study (KLIPS).[1] One can observe that the probability of job-to-job transitions from SMEs to large firms is only 0.06% per month, and, more importantly, it is lower than the probability of large firms-to-large firms transitions, which is 0.13%.

This is difficult to explain using standard search models because, on average, existing jobs in large firms are expected to be better than those in SMEs. Therefore, the probability of accepting a new offer is expected to be lower (higher) for employed workers in large firms (SMEs), as long as the distribution of new offers does not differ by current jobs. Meanwhile, the SMEs-to-large firms transition rate (S2C) can be lower than the Large firms-to-SMEs transition rate (C2S) in standard search models if the total number of postings by SMEs is far larger than that by large firms, for example, because the number of SMEs is far larger than that of large firms.

In addition, it is challenging to reconcile the job-to-job transitions between

[1] KLIPS and the exact definition of SMEs and the transition rates will be explained in detail below.

Table 1.1: Labour mobility by firm sizes

| | |
|---|---|
| SMEs-to-large firms transition rate(S2C) | 0.06% |
| Large firms-to-large firms transition rate(C2C) | 0.13% |
| Large firms-to-SMEs transition rate(C2S) | 0.12% |
| SMEs-to-SMEs transition rate(S2S) | 0.52% |

Note: Monthly

large firms and SMEs in Korea with the substantial wage gap by firm size in the country. According to the OECD (2017), the wage gap is significantly larger than in other countries. Cheon et al. (2018) claim that the wage ratio of large firms to SMEs is 1.7, and the wage premium of large firms over SMEs, controlling for gender, age, education, etc., is about 46%. In standard search models, if workers are inclined to prefer jobs with higher wages, the significant wage gap would encourage job transitions from SMEs to large firms. On the other hand, if there are other reasons that workers prefer large firms to SMEs given the same wage, large firms have an incentive to reduce their wages.

Therefore, this paper aims to study the reasons behind this phenomenon and its impact on the Korean labour market. I begin by introducing a search model in which there are two types of workers and two types of firms, and wage and job mobilities are determined by a sequential auction(Postel-Vinay and Robin (2002)). The key assumption is that there is a skill requirement by one type of firm, which would correspond to large enterprises in the end. Low-type workers can be hired only by the other type of firm, corresponding to SMEs. This sorting between worker type and firm size leads to rare cross-sectional job-to-job transitions from small firms to large firms.

To estimate the model, I use KLIPS. I estimate the parameters relating to workers' mobility mainly via indirect inference. Then, the rest of the parameters relating to vacancies can be estimated sequentially. The model fits the data well overall, and particularly, it successfully replicates the key feature of real data that motivates the paper: the 'SMEs-to-large firms' transition probability is lower, even than the 'large firms-to-large firms' transition probability.

Regarding the application of the model, I decompose the wage gap between SMEs and large enterprises into the difference in productivity and the impact of the skill requirement. The skill requirement causes about 26∼38%

of the wage gap in two ways. First, as mentioned above, it leads to the sorting between firm size and worker type, where wages differ by worker's type: it accounts for about 13∼25% of the gap by firm size. In addition, the skill requirement reduces competition for low-type workers, widening the wage gap by workers' type, and it widens the gap by firm size given the sorting between firm size and worker type: it accounts for about 13% of the gap by firm size. Another counterfactual analysis showed that if the number of highly capable workers increases through improved education, there will be no significant difference in the wage gap by company size, but the wage gap by ability may widen.

This paper makes a direct contribution to studies on the wage gap by presenting a new cause that can explain the wage difference by company size. However, a more significant contribution is that it can help explain wage gaps between various sectors because it presents a methodology that elucidates the wage gap and labour market duality simultaneously. In Korea, as large companies are recognized as having higher-quality jobs than SMEs, there have been many attempts to explain the wage gap between them through a dual structure of the labour market, based on theories provided by Doeringer and Piore (1970) or Cain (1976). For example, Kim (2007) argues that subcontracting relationships between large corporations and small and medium-sized enterprises are the main factors in the wage gap by firm size. As international competition to which large corporations are exposed intensifies, large firms demand lower delivery prices from subcontracted SMEs, leading to a decline in the productivity and wages of SMEs. Kim et al. (2017) also presents that wage increases at large companies that outsource production lead to downward pressure on wages at small and medium-sized companies that have contractual relationships with them. Jung (2007) argued that a policy response is necessary because the effect of fragmentation depending on company size is significant. Jeon (2018) also emphasized that the company size variable has a great influence on the wage determination process, and so it is the main cause of Korea's labour market fragmentation.

Although the disruption of mobility between sectors may be more important than the gap between sectors in studying the dual labour market, these studies have a limitation in that they tend to view the disruption of labour mobility as a given when analyzing the causes of the gap between sectors. Chung and Jung (2016) are one of the few studies on segmentation according to company size in Korea that deal with labour mobility, but they just analyzed that movement from the primary labour market to the secondary labour market has gradually decreased. Unlike the papers above, this paper focuses on the causes of labour movement restrictions and also explains the gap between the sectors through these causes. In other words, it simultaneously explains the mobility restrictions and wage gap between the two types of companies through realistic assumptions about the differences in recruitment procedures and training programs between large corporations and SMEs. In particular, this paper uses realistic but simple assumptions and introduces them into a structural model that allows counterfactual analyses. Therefore, it also has the advantage of being able to analyze the impact of the differences in recruitment procedures and training programs on the dual structure of the labour market and the wage gap between sectors in more detail. This contribution to research on the dual structure of the labour market means that, by changing the assumption slightly, one can use this study as a basis for explaining the wage gap between various sectors such as regular versus non-regular workers, professional versus non-professional, etc., in addition to large firms versus SMEs.

The rest of the paper is organized as follows. In Section 1.2, I introduce the structural model. In the following sections, I explain the data, estimation strategy, and estimation results. In Section 1.6, I use the model to decompose the wage gap between SMEs and large enterprises. Section 1.7 concludes.

## 1.2 Model

This section provides an extension of sequential auction framework(Postel-Vinay and Robin (2002)) in which there are two types of workers and two types of firms, and the offer arriving rates are determined endogenously. In other words, each firm maximizes its profits by choosing its type and the number of vacancies to be posted.

### 1.2.1 The Environment

Time is discrete, and the economy is in steady state.[2] There is a unit mass of workers and a continuum of firms, both infinitely lived, forward-looking, risk-neutral, and share a common exogenous discount rate of $\rho$. Workers are either high type('$h$') or low type('$\ell$'), where the fraction of high type worker is denoted as $\Omega$. Firms are either type '$s$,' representing SMEs, or type '$c$,' representing conglomerates. In the following section, I will show that, under an assumption, type $s$ and type $c$ will correspond to SMEs and large firms, respectively, because the number of postings per firm would be larger for the latter. The number of type $s$ and type $c$ firms is denoted as $n_s$ and $n_c$, respectively. Note that, since the number of workers is normalized to one, $n_k$ can be interpreted as the number of type $k$ firms per worker.

The timeline is as follows:

① At the beginning of every period, each firm chooses its type, considering the total expected profit from choosing each type.

② Given the type, each firm maximizes its profit by choosing the number of vacancies to be posted.

③ When a firm meets a worker, it draws a match-specific productivity, $p$, from the sampling distribution $F_k(p)$, which differs by firm type where $k \in \{s, c\}$.

④ Based on $p$ and the worker's type, the firm makes an offer, and the worker decides whether to accept it or not.

Note that ① means, theoretically, firms can change their type period by period, and in that case, the type of existing job positions would not be affected by the new choice. As it requires distinguishing firm type and vacancy type, it could be more appropriate to assume that firms choose the type of 'vacancies' to be posted in each period rather than the type of the firm. However, distinguishing firm type and vacancy type is meaningless because, as you can see below, each firm repeats the same static decision relating to the choice of the vacancy type in steady state, so it will choose the same vacancy type every

[2] In what follows I will therefore drop the time subscript 't'.

period. Therefore, it is enough to consider one kind of type only, and I call it the firm type. A vacancy would either be filled with a worker or disappear at the end of each period.

#### 1.2.1.1 The types of firms

The difference in firm type signifies variations in recruitment methods. Opting for type $c$ implies that the firm operates a specialized department responsible for hiring workers and developing training programs for the hired workforce. Conversely, selecting type $s$ indicates that the firm either temporarily assigns recruitment tasks to existing employees in addition to their original duties or outsources recruitment to an agency.

Type $c$ firms have their training programs, and members of the recruitment department are likely more specialized in hiring than other employees, possessing a better understanding of their firm compared to agencies. Therefore, type $c$ firms are expected to draw better match-specific productivity than type $s$ firms, i.e. $F_c(p)$ is anticipated to first-order stochastically dominate $F_s(p)$. However, there is a trade-off, namely the skill requirement imposed by the training program: a match between a type $c$ firm and a worker produces the drawn productivity $p$ if the worker is of high type, but otherwise, the level of production would be zero. In contrast, a match between a type $s$ firm and a worker produces $p$ regardless of the worker's type. Consequently, the type $c$ firms cannot make any meaningful offers to the low type workers, and it will be always rejected. As a result, the type $c$ firms can hire the high type workers only, while the type $s$ firms can hire both types of workers.[3]

Regarding costs, the type $c$ is assumed to incur higher fixed costs than the latter, attributable to maintaining the department, including wages, and developing training programs. For simplicity, I normalize the fixed cost of type $s$ as zero and denote the fixed cost for type $c$ as $\chi_j$, which is assumed to vary

[3]The model can be more generalized by taking less strict assumptions in terms of workers' type and skill requirement. For example, workers can be allowed to have continuous type (e.g. workers are heterogeneous in terms of their ability, $\epsilon$, where $\epsilon$ is normally distributed), and the production of match between a type $c$ firm and a worker is increasing in $\epsilon$, while the production of match with a type $s$ firm is not related to $\epsilon$. In this case, given the same match-specific productivity, the type $c$ firms are more likely to hire the workers with higher $\epsilon$, while the type $s$ firms do not care about workers' type. However, in this case the model cannot be fully identified unless workers' type is observed.

by firm. The difference in $\chi_j$ reflects that firms are ex-ante heterogeneous in terms of financial constraints, R&D capability, location, etc. As detailed in the following subsection, firms' choice of type is determined by $\chi_j$.

On the other hand, type $s$ would incur higher variable costs because assigning additional recruiting tasks to existing employees may disrupt their original work, or the agency fee might be quite high. Therefore, I denote the variable cost for type $s$ as $\kappa$ and that for type $c$ as $\theta\kappa$, where $\theta$ is expected to be lower than one.[4] Meanwhile, I assume that the marginal cost of posting increases with the number of postings of a firm $j$, denoted as $\zeta_j$. In summary, the cost for posting $\zeta_j$ vacancies is,

$$\chi_j + \theta\kappa\zeta_j^2 \text{ for type } c\text{, and}$$

$$\kappa\zeta_j^2 \text{ for type } s$$

#### 1.2.1.2 Job search

Workers can be either unemployed or employed by a firm, which can be either type $s$ or type $c$. The search is purely random, and on-the-job search is allowed, so all workers continue to search: unemployed (employed) workers receive job offers from the type $k$ firms at a probability $\lambda_{0k}$ ($\lambda_{1k}$) where $k \in \{s, c\}$, while a worker can receive at most one offer per period. The fact that $\lambda_{0k}$ and $\lambda_{1k}$ are different means that workers are assumed to have different search efforts by their employment status, while I normalized the search effort of unemployed workers as one. Additionally, from the fact that $\lambda_{1k}$ is the same for all employed workers, one can see that the job search effort of employed workers, denoted as $\tau$, is assumed to be the same regardless of not only their type but also the type of firm they are currently working for. This means the search effort is the same for workers hired in type $c$ firms and those hired in the type $s$ firms. It is a very strong assumption, especially because the overall productivity would be better for matches with type $c$ firms. However, allowing workers to have different search efforts by the type of firms that currently

[4] As one can see below, the difference in the number of vacancies to be posted between type $s$ and type $c$ firm is mainly determined by $\theta$ and the difference between $F_c(p)$ and $F_s(p)$ . Therefore, in the following section for the estimation, I assume $F_c(p)$ is is better enough than $F_s(p)$ in the sense of FOSD and/or $\theta$ is lower enough than one, so the number of postings per type $c$ firm is higher than that per type $s$ firm.

hire them makes the model much more complicated. More importantly, the assumption does not change the key predictions of the model regarding the limited job transitions from less preferred jobs to more preferred jobs. If the workers currently hired by type $s$ firms are allowed to have higher search effort because the overall match productivity is lower than those hired by type $c$ firms, standard search models would expect more frequent job transitions from type $s$ to type $c$ firms, which contradicts the real data. This means that when different search effort is allowed, the skill requirement by type $c$, which is the key assumption for explaining the limited job transitions, would have a stronger effect to fit the real data. In other words, as I assume the same search effort for all employed workers, the following results can be interpreted as a lower bound of the effect of the skill requirement. Note that the offer arriving rates are determined endogenously by the firms' choice of their type and the number of vacancies to be posted, as explained in detail below.

When a worker receives an offer, she will only accept it if the lifetime value of the offer is larger than what they enjoy in their current state. Therefore, employed workers will accept the new offer as long as it is better than the current job, and as a result, low-type workers will reject any offers from type $c$ firms because those firms cannot make any acceptable offers to low-type workers, as I discussed above. As for unemployed workers who receive unemployment benefits $b$, I assume that $b$ is low enough so that unemployed workers will accept all job offers unless it is an offer from type $c$ firms to low-type workers.

Employed workers lose their job at an exogenous probability $\delta_\epsilon$, where $\epsilon \in \{h, \ell\}$, while an employed worker can experience at most one event among the receipt of a new offer and the loss of the current job per period. However, right after the job destruction, 1-$\pi_\epsilon$ fractions of them are assumed to receive a substitute job offer, where $\epsilon \in \{h, \ell\}$. Note that the probability of job destruction and substitute job offers differ by workers' type. These assumptions are necessary not for the key predictions of the model regarding the limited job transitions but for improving the model fit, which requires that low-type workers have a higher probability of job destruction and substitute job offers, as one can see in the following sections. I admit that allowing a difference in $\pi_\epsilon$ by workers' type could seem to contradict the previous assumption that the search effort does not differ by workers' type. However, one can interpret it as a kind of social security: the government wants to protect workers who suffer frequent job destruction. More importantly, as I mentioned, this assumption does not change the key predictions of the model.

The substitute offers come from both types of firms: the fractions of offers from type $s$ and $c$ are $\frac{\lambda_{0s}}{\lambda_{0s}+\lambda_{0c}}$ and $\frac{\lambda_{0c}}{\lambda_{0s}+\lambda_{0c}}$ respectively, while a worker who loses her job during the period can receive at most one substitute offer. If the workers reject the substitute offers, then they will become unemployed.[5] Therefore, like other offers to usual unemployed workers, substitute job offers would be always accepted unless it is an offer from type $c$ firms to the low-type workers.

#### 1.2.1.3 Matching function

As for the matching function, I assume the standard Cobb-Douglas form. First, I define the total number of vacancies $\upsilon$ and effective workers $e$ as follows:

$$\upsilon = \upsilon_s + \upsilon_c = \sum_{j \in s} \zeta_j + \sum_{j \in c} \zeta_j$$

$$e = \tau_u e_u + \tau_s e_s + \tau_c e_c = (1 - e_s - e_c) + \tau e_s + \tau e_c$$

Note that $\upsilon_k$ is the total number of vacancies posted by all firms with type $k \in \{s, c\}$, which is the sum of the number of postings of each firm with the type, and $e_z$ is the fraction of workers whose employment status is $z \in \{u, s, c\}$, i.e. unemployed or employed at a firm with type $s$ or $c$. Therefore, $e_u + e_s + e_c = 1$. Also, $\tau_z$ is the search effort of workers whose employment status is $z$, and as I mentioned above, I normalize the search effort of unemployed workers as one and assume that the search effort of employed workers is the same for all employed workers, i.e. $\tau_u = 1$ & $\tau := \tau_s = \tau_c$.

Then, the number of matches $m$ is

$$m = \eta \upsilon^{\alpha} e^{1-\alpha}$$

Note that $\eta$ captures matching efficiency and $\alpha$ denotes the matching elasticity

[5] Therefore, the outside option for wage bargaining is unemployment in the following subsection.

with respect to vacant jobs. The offer arriving rate from type $k$ firms to an unemployed worker $\lambda_{0k}$ is

$$\lambda_{0k} = m * \frac{\upsilon_k}{\upsilon} * \frac{1}{e}$$

and, similarly, the offer arriving rate from type $k$ firms to a worker employed at a type $z$ firm is

$$\lambda_{1zk} = m * \frac{\upsilon_k}{\upsilon} * \frac{\tau_z e_z}{e} * \frac{1}{e_z} = \lambda_{0k} * \tau_z = \lambda_{0k} * \tau$$

As I discussed above, since I assume that the search effort is the same as $\tau$ for all employed workers, $\lambda_{1zk}$ is the same for all of them regardless of the type of firm they are currently hired by. Therefore, I will use the simpler notation $\lambda_{1k}$, rather than $\lambda_{1zk}$. Finally, the rate at which a firm contacts a worker with employment status $z \in \{u, s, c\}$ is $\gamma_z$, defined as follows:

$$\gamma_z = m * \frac{\tau_z e_z}{e} * \frac{1}{\upsilon}$$

Note that is the same for both types of firms since I assume purely random search.

### 1.2.2 Wage Determination and Job Mobility

As for wage determination and job mobility, I follow the sequential auction framework provided by Postel-Vinay and Robin (2002), but I extend it by allowing that there are two types of workers and two types of firms, as I discussed above. In this framework, all information, including each other's types, match-specific productivity, and outside opportunities, is assumed to be completely known to firms and workers, and wages can be renegotiated by mutual consent only.

Let's define $V(\epsilon, w, p, k)$ as the lifetime value of being employed at a type $k$ firm with wage $w$ and match-specific productivity $p$ and $U(\epsilon)$ as that of unemployment for $\epsilon$ type workers. Then, one can find that the lifetime value of a job for high-type workers does not differ by the type of firm that the worker is currently hired by because $\lambda_{1k}$ is the same for employees in type $s$ and type

$c$ firms. That means the value of the future opportunity does not differ by the type of firm that the worker is currently hired by. In addition, $V(\ell, w, p, c)$ can be ignored because the match between a type $c$ firm and a low-type worker is not available by the assumption of skill requirement. Therefore, in what follows, I will not consider the case of a match between a type $c$ firm and a low-type worker, and, instead of $V(\epsilon, w, p, k)$, I will use the notation $V(\epsilon, w, p)$, which is defined as follows:

$$V(h, w, p) := V(h, w, p, s) = V(h, w, p, c)$$

$$V(\ell, w, p) := V(\ell, w, p, s)$$

Let's consider the case in which an unemployed worker with type $\epsilon$ meets a potential employer, and they draw a match-specific productivity $p$.[6] Then, through a Rubinstein (1982)-type bargaining game, the workers is hired at a wage $\phi_0(\epsilon, p)$ such that:

$$V(\epsilon, \phi_0(\epsilon, p), p) = U(\epsilon) + \beta[V(\epsilon, p, p) - U(\epsilon)] \tag{1.1}$$

$\beta \in [0, 1]$ is the worker's bargaining power. Note that, similarly to the lifetime value, I use simpler notations for the wage as follows:

- $\phi_0(h, p)$: wage for unemployed high type workers who just met a firm and draw $p$. It does not differ by the type of firm.
- $\phi_0(\ell, p)$: wage for unemployed low type workers who just met a type $s$ firm and draw $p$.

When an employed worker meets a potential alternate employer, the employers compete with each other for the worker. As a result, the worker will choose the more productive match because each productivity is the maximum wage available from each match. The wage of the employed worker will be determined by the productivity of the current match, which would be the highest productivity among the productivities that the worker has experienced since the beginning of the employment spell, and the outside option, which would be the second-highest productivity.[7] For example, if a worker is employed

[6] When a low type worker meets a type $c$ firm, she will reject any offers from the firm and stay unemployed by the assumption of skill requirement.

[7] Note that the lifetime value from the match between a type $c$ firm and a low type worker

at a match with $p^+$ and has the outside option $p^-$, then she receives a wage $\phi(\epsilon, p^-, p^+)$ such that:

$$V(\epsilon, \phi(\epsilon, p^-, p^+), p^+) = V(\epsilon, p^-, p^-) + \beta[V(\epsilon, p^+, p^+) - V(\epsilon, p^-, p^-)] \quad (1.2)$$

Again, I use simpler notations for the wage as follows:

- $\phi(h, p^-, p^+)$: wage for high type workers who are employed at a firm with $p^+$ and has an outside option $p^-$ from another firm. It does not differ by the type of firm.
- $\phi(\ell, p^-, p^+)$: wage for low type workers who are employed at a type $s$ firm with $p^+$ and has an outside option $p^-$ from another type $s$ firm.

Note that now the maximum lifetime value available from the second most productive match, i.e. the value for the worker when she receives $p^-$, becomes the threat point for the bargaining.

To consider job and wage mobility in detail, let's suppose a type $\epsilon$ worker earning $w$ at a match with productivity $p$. One can define $q(\epsilon, w, p)$ such that:

$$\phi(\epsilon, q, p) = w \Leftrightarrow V(\epsilon, w, p) = \beta V(\epsilon, p, p) + (1 - \beta)V(\epsilon, q, q) \quad (1.3)$$

i.e. $q(\epsilon, w, p)$ is the outside option that justifies current wage $w$ from the match given $\epsilon$ and $p$. When the worker meets a potential alternate employer and the productivity of the new match is $p'$, one of the following three situations can happen[8]:

① $p' \leq q(\epsilon, w, p)$: Nothing happens;

② $q(\epsilon, w, p) < p' \leq p$: The worker stays at the match with $p$ and gets a higher wage $\phi(\epsilon, p', p)$, i.e. she renegotiate with current employer.;

③ $p < p'$: The worker moves to the match with $p'$ for a wage $\phi(\epsilon, p, p')$.

Then, for $\epsilon$ type workers, the lifetime value of being employed at the match with wage $w$ and productivity $p$ can be formally written down as follows:

is always lower than the value from being unemployed. Therefore, any productivity from the the match between a type $c$ firm and a low type worker cannot be the outside option.

[8]Again, the new offer from a type $c$ firm can lead neither a job transition nor a renegotiation if the worker is low type.

$$
\begin{aligned}
\rho V(\epsilon,w,p) &= w + \delta_\epsilon \pi_\epsilon [U(\epsilon) - V(\epsilon,w,p)] \\
&+ \delta_\epsilon (1-\pi_\epsilon)[\tfrac{\lambda_{0s}}{\lambda_{0s}+\lambda_{0c}} \textstyle\int_{\underline{p}}^{\bar{p}} (\beta V(\epsilon,x,x) + (1-\beta)U(\epsilon))dF_s(x) \\
&\quad + \tfrac{\lambda_{0c}}{\lambda_{0s}+\lambda_{0c}} \mathbb{1}(\epsilon = h) \textstyle\int_{\underline{p}}^{\bar{p}} (\beta V(\epsilon,x,x) + (1-\beta)U(\epsilon))dF_c(x) - V(\epsilon,w,p)] \\
&+ \lambda_{1s} [\textstyle\int_{p}^{\bar{p}} (\beta V(\epsilon,x,x) + (1-\beta)V(\epsilon,p,p))dF_s(x) \\
&\quad + \textstyle\int_{q(\epsilon,w,p)}^{p} (\beta V(\epsilon,p,p) + (1-\beta)V(\epsilon,x,x))dF_s(x) \\
&\quad - \textstyle\int_{q(\epsilon,w,p)}^{\bar{p}} V(\epsilon,w,p)dF_s(x)] \\
&+ \mathbb{1}(\epsilon = h)\lambda_{1c} [\textstyle\int_{p}^{\bar{p}} (\beta V(\epsilon,x,x) + (1-\beta)V(\epsilon,p,p))dF_c(x) \\
&\quad + \textstyle\int_{q(\epsilon,w,p)}^{p} (\beta V(\epsilon,p,p) + (1-\beta)V(\epsilon,x,x))dF_c(x) \\
&\quad - \int_{q(\epsilon,w,p)}^{\bar{p}} V(\epsilon,w,p)dF_c(x)] \qquad (1.4)
\end{aligned}
$$

The worker becomes unemployed with probability $\delta_\epsilon \pi_\epsilon$, or she faces a reallocation shock, i.e., loses her job and immediately receives a substitute job offer from a type $s$ firm with probability $\delta_\epsilon(1-\pi_\epsilon)\frac{\lambda_{0s}}{\lambda_{0s}+\lambda_{0c}}$ or from a type $c$ firm with probability $\delta_\epsilon(1-\pi_\epsilon)\frac{\lambda_{0c}}{\lambda_{0s}+\lambda_{0c}}$. The latter will always be rejected if the worker is a low type, but otherwise, she will always accept the substitute offer and bargain with the new employer, having unemployment as an outside option. With probability $\lambda_s$ ($\lambda_c$), the worker receives a new job offer from a type $s$ ($c$) firm and draws a match-specific productivity $p$ from $F_s$ ($F_c$). She will move to the new match if it is more productive than the current match. Otherwise, she will stay but renegotiate with the current employer if the new match is more productive than the current outside option $q(\epsilon, w, p)$. However, again, the new offer from a type $c$ firm can lead neither to a job transition nor to a renegotiation if the worker is a low type.

Also, the lifetime value of being unemployed for $\epsilon$ type workers can be formally written down as follows:

$$
\begin{aligned}
\rho U(\epsilon) &= b + \lambda_{0s} \textstyle\int_{\underline{p}}^{\bar{p}} \beta[V(\epsilon,x,x) - U(\epsilon)]dF_s(x) \\
&\quad + \mathbb{1}(\epsilon = h)\lambda_{0c} \int_{\underline{p}}^{\bar{p}} \beta[V(\epsilon,x,x) - U(\epsilon)]dF_c(x) \qquad (1.5)
\end{aligned}
$$

Finally, the wage for $\epsilon$ type workers who are employed at the match with productivity $p^+$ and have the outside option $p^-$ can be formally written down as follows:

$$\phi(\epsilon, p^-, p^+) = p^+ - (1-\beta)\int_{p^-}^{p^+} \frac{\rho + \delta_\epsilon + \lambda_{1s}\bar{F}_s(x) + \mathbb{1}(\epsilon = h)\lambda_{1c}\bar{F}_c(x)}{\rho + \delta_\epsilon + \beta(\lambda_{1s}\bar{F}_s(x) + \mathbb{1}(\epsilon = h)\lambda_{1c}\bar{F}_c(x))} dx \tag{1.6}$$

[9]

### 1.2.3 Firms' choice

Each firm chooses its type, and given the type, it determines the number of vacancies to be posted, where each firm's revenue and cost for posting $\zeta_j$ vacancies are as follows:

$$\text{Total revenue for type } c = E(\text{profit per posting} \mid c)\zeta_j$$

$$\text{Total revenue for type } s = E(\text{profit per posting} \mid s)\zeta_j$$

$$\text{Total cost for type } c = \chi + \theta\kappa\zeta_j^2$$

$$\text{Total cost for type } s = \kappa\zeta_j^2$$

Note that

$$\begin{aligned}
&\text{E(profit per posting|type-k)} \\
&= \gamma_u \int_p [Pr(\epsilon = h|u)J(h, \phi_0(h,p), p) \\
&\qquad + \mathbb{1}(k = s)Pr(\epsilon = \ell|u)J(\ell, \phi_0(\ell,p), p)]dF_k(p) \\
&\quad + \gamma_s \int_p \int_q [Pr(\epsilon = h|s)J(h, \phi(h,q,p), p)dL(q|\epsilon = h, s) \\
&\qquad + \mathbb{1}(k = s)Pr(\epsilon = \ell|s)J(\ell, \phi(\ell,q,p), p)dL(q|\epsilon = \ell, s)]dF_k(p) \\
&\quad + \gamma_c \int_p \int_q J(h, \phi(h,q,p), p)dL(q|c)dF_k(p)
\end{aligned}$$

Here, $\gamma_z$ is the rate at which a firm contacts a worker with employment status $z$, and $Pr(\epsilon = h|z)$ and $Pr(\epsilon = \ell|z)$ are the fractions of high and low type workers, respectively, among workers with employment status $z$, where

[9]Note that $\phi_0(\epsilon, p) = \phi(\epsilon, p_{inf}, p)$, where
$p_{inf} = b + \int_{p_{inf}}^{\bar{p}} \frac{\beta((\lambda_{0s}-\lambda_{1s})\bar{F}_s(x)+\mathbb{1}(\epsilon=h)(\lambda_{0c}-\lambda_{1c})\bar{F}_c(x))}{\rho+\delta+\beta(\lambda_{1s}\bar{F}_s(x)+\mathbb{1}(\epsilon=h)\lambda_{1c}\bar{F}_{1c}(x))} dx$
However, in the estimation, for convenience, I assume that the unemployment benefit $b$ satisfies that $\phi_0(\epsilon, p) = \phi(\epsilon, \underline{p}, p)$.

$z \in \{u, s, c\}$.[10] Also, $J(\epsilon, w, p)$ is the value of a filled job with a $\epsilon$ type worker, productivity $p$ and wage $w$. The formal expression of $J(\epsilon, w, p)$ can be found in the Appendix. Finally, $L(q|\epsilon, k)$ is the cross-sectional distribution of productivity among the jobs created from the match between type $\epsilon$ workers and type $k$ firms.

Then the firm's choice of type and the number of vacancies can be solved backward. Let's suppose a firm has already chosen type $c$. Then the number of vacancies $\zeta_j$, which maximizes the firm's profit, should equalize the marginal revenue and the marginal cost. Marginal revenue would be the expected profit per posting since it is fixed from the individual firm's point of view, and the marginal cost is $2\theta\kappa\zeta_j$. Therefore, $\zeta_j$ for type $c$ can be achieved by solving the following:

$$E(\text{profit per posting} \mid c) = 2\theta\kappa\zeta_j \tag{1.7}$$

Similarly, profit maximizing $\zeta_j$ for type $s$ should satisfy the following:

$$E(\text{profit per posting} \mid s) = 2\kappa\zeta_j \tag{1.8}$$

Therefore, firms chose type $c$ have lower marginal cost of hiring and better productivity draws, but they face a fixed cost of hiring and they cannot hire low-type workers. Note that the profit-maximizing $\zeta_j^*$ is the same for all firms with the same type: let's denote them as $\zeta_s^*$ and $\zeta_c^*$, respectively. The difference between $\zeta_s^*$ and $\zeta_c^*$ is determined by $\theta$ and the difference between $F_c(p)$ and $F_s(p)$, so one can find the following proposition is true.

**Proposition 1.** *If $F_c(p)$ is better enough than $F_s(p)$ in the sense of first-order stochastic dominance(FOSD) and/or $\theta$ is lower enough than one, the number of postings per firm with type* c *is higher than firm with type* s*, i.e. $\zeta_c^* > \zeta_s^*$.*

The proposition can be proved by dividing equation (1.7) by equation (1.8), i.e.

$$\frac{E(\text{profit per posting} \mid c)}{E(\text{profit per posting} \mid s)} \frac{1}{\theta} = \frac{\zeta_c^*}{\zeta_s^*} \tag{1.9}$$

As $E(\text{profit per posting} \mid j)$ is positively related to $F_j(p)$, the first part of the left-hand side of equation (1.9) increases as $F_c(p)$ is significantly better than $F_s(p)$ in the sense of FOSD, while it is obvious that the second part increases

[10] Note that $Pr(\epsilon = h|c) = 1$.

as $\theta$ decreases.

Given that $\zeta_k^*$ would be the number of postings for all type $k$ firms, each firm chooses its type by comparing the total expected profit from choosing each type. In other words, firm $j$ will choose type $c$ if

$$\begin{aligned} &\mathrm{E}(\text{profit per posting}|\mathrm{c})\zeta_c^* - \chi_j - \theta\kappa\zeta_c^{*2} \\ &\qquad > E(\text{profit per posting} \mid \mathrm{s})\zeta_s^* - \kappa\zeta_s^{*2} \end{aligned} \tag{1.10}$$

Otherwise, it will chooses type $s$. In other words, while firms are ex-ante heterogeneous in terms of $\chi_j$, there will be a threshold value, $\chi^*$, and all firms with $\chi_j$ lower than $\chi^*$ will choose type $c$, and vice versa.

## 1.3 Data

I use the Korean Labor and Income Panel Study (KLIPS), which has been conducted annually since 1998 by the Korea Labor Institute (KLI) with the approval of the national government. The same set of survey questions is repeatedly posed to a sample covering 5,000 households and all members of these households, totaling 13,000 individuals. The sample population comprises members of general households residing in the territory of Korea, and the samples are drawn using methods designed to ensure representativeness. Additionally, to maintain representativeness against panel attrition, samples were extended in 2009 and 2018. Consequently, the sample can be assumed to be representative of the Korean population.

KLIPS data sets consist of three parts: the Household data set, the Individual data set, and the Work History data set. For the estimation of the model, I combine the Individual data set and the Work History data set. The former provides information about individuals' characteristics (i.e., age), job status at the time of each survey, and recent experiences of job search. On the other hand, the Work History data set, compiled against all jobs ever held by an individual, provides information about the existence and date of job changes, and wages in each job, not only at the time of the survey but also at the start and end of each job.

As indicated below, I set a period as a month for the estimation. Therefore, I construct monthly data from annual data that covers from 2003 to 2018. In other words, I extract information about workers' characteristics and job status in the months between two consecutive surveys from the results of the yearly survey. The reason I do not use data from the early stage of the survey is because some essential questions, such as the one about the size of employers, were not asked at the early stage of the survey.

For the construction of data on job mobility, I primarily use the answers to two sets of questions. The first set of questions pertains to previous jobs and is directed at individuals who were employed at the time of the last survey:

(1) Are you still working in that job?

(2) (If not,) When did you quit this job?

The second set of questions concerns new jobs that started after the last survey:

(1) Since the last survey, did you get a new job that you held for more than a week?

(2) (If yes,) When did you start this job?

(3) Are you still working in that job?

(4) (If not,) When did you quit this job?

However, when categorising workers according to their employment status, it is important to consider how to deal with the self-employed, as there are many of them in Korea. Self-employed workers are expected to differ from wage-paid workers in terms of on-the-job search. Therefore, for the correct estimation of job-to-job transition rates, I include self-employed workers as unemployed workers. While this may lead to an overestimation of the unemployment rate[11], it is the simplest way to deal with self-employed workers, focusing on job-to-job transition rates among wage-paid workers. In addition, only full-time workers are treated as employed workers, and part-time workers are included as unemployed workers. This approach is necessary for the

[11] It may underestimate unemployment-to-employment transition rate since self-employed workers are less likely to search hard for the wage-paid job opportunity. On the other hand, employment-to-unemployment transition rate would be overestimated since it additionally includes transitions from wage-paid jobs to self-employment.

correct estimation of job-to-job transition rates because most workers may prefer full-time jobs to part-time jobs, and the preference for different-sized firms could be vague among part-time jobs. On the other hand, individuals who have never had a full-time job during the whole sample period are considered as economically inactive population and are dropped from the data for the estimation. This is due to the limitation of available information on workers' job-seeking activity. For example, in the case of workers who lose their jobs between two consecutive surveys, KLPS does not provide any information about whether they have searched for a new job or not. The lack of information on workers' job-seeking activity makes it impossible to distinguish between unemployed workers and the economically inactive population using general definitions. Therefore, I assume that because the economically active population is always looking for full-time work, they will eventually secure a full-time job at least once in the long run. As a result, under the additional assumption that the sample period is sufficiently long, individuals who have never been employed in a full-time job are treated as the economically inactive population. Meanwhile, I restrict the sample to workers aged 25-55, considering that the model does not reflect changes in job preferences as retirement approaches. One limitation of KLIPS is that it provides information on wages only at the time of survey, job finding, and job loss. In other words, it is impossible to construct monthly wages. Therefore, I treat the average wage of the employed people interviewed each month as the wage of all employed people in that month, assuming that who would be interviewed each month is determined randomly, regardless of their wage level, etc.[12] Meanwhile, there is no problem in calculating the average wages of people who have just become employed from the unemployed because, as mentioned above, KLIPS provides information on wages at the time of job finding.

Table 1.2 provides summary statistics on the (unbalanced) panels of individual labour market histories, constructed according to the above rules and used for the estimation of the model. There are 866,782 observations from 9,948 workers. The number of employment spells is 17,997, and employment at SMEs accounts for more than seventy percent. As for job changes, there are 2,529 cases, and SMEs-to-SMEs transitions are the most frequent cases,

[12]Therefore, in the estimation process below, when calculating the average wage of all employed people from simulation data, the average wage of all employed people is used without the process of extracting a sample who was interviewed each month.

accounting for about eighty percent. The numbers of other kinds of job change are similar, about two hundred. There is a similar number of job findings and job losses, 5,398 and 5,259 respectively. In both transitions, into-and-out of SMEs cases account for more than eighty-five percent.

Table 1.2: Summary Statistics

| | |
|---|---|
| Number of observations | 866,782 |
| Number of workers | 9,948 |
| Number of employment spell | 17,997 |
| At SMEs | 13,466 |
| At large firms | 4,531 |
| Number of unemployment spell | 9,602 |
| Number of job changes | 2,529 |
| SMEs-to-large firms transitions | 210 |
| Large firms-to-large firms transitions | 175 |
| Large firms-to-SMEs transitions | 163 |
| SMEs-to-SMEs transitions | 1,981 |
| Number of job findings | 5,398 |
| Unemployment-to-SMEs transitions | 4,595 |
| Unemployment-to-large firms transitions | 803 |
| Number of job losses | 5,259 |
| SMEs-to-unemployment transitions | 4,554 |
| Large firms-to-unemployment transitions | 705 |

## 1.4 Estimation strategy

### 1.4.1 Further assumptions and calibration

For the model estimation, I introduce additional assumptions. Firstly, the type of firm is not directly observable. To address this, and based on Proposition 1, I assume that $F_c(p)$ is significantly better than $F_s(p)$ in the sense of FOSD, and/or $\theta$ is significantly lower than one, ensuring that the number of postings per type $c$ firm consistently exceeds that of type $s$ firm. While this allows for a partial identification of firm types through size, a full identification is necessary. Therefore, by taking things further, I assume that all large firms are type $c$ firms, and all SMEs are type $s$ firms.[13] Although this is a strong assumption, it is essential for the estimation and aligns with the reality that most large firms have a dedicated HR department and conduct in-house employee training, unlike many SMEs. Under this assumption, subsequent sections distinguish firms by their size rather than their type. Large firms and SMEs are defined following the general criteria commonly used in research on Korean firms (e.g. Kim et al. (2017), Jeon (2018), etc.): SMEs are enterprises with fewer than 300 employees, and the remaining firms are classified as large enterprises. [14] Note that, According to a report by the Korean Ministry of Employment and Labor on the state of vocational training in companies, 51.9% of companies with 300 or more employees have a department dedicated to training and 80.1% have a person in charge of training. On the other hand, only 13.1% and 35.3% of companies with less than 300 employees have a dedicated training department and a person in charge of training, respectively(Ministry of Employment and Labor (2022)), which shows that my assumption is in line with reality. Meanwhile, the unobservable nature of worker types does not pose a challenge for model estimation. As mentioned earlier, the "strict" skill requirement assumption, where low-type workers are never hired by type $c$ firms, allows for partial identification of worker types. Specifically, it is known that all employees in type $c$ firms are high type. Combining this information with the conditions for steady state, I can calculate the fraction of high-type workers among unemployed workers, among employees in type $s$ firms, and among all workers, respectively. For further details, refer to the following and the Appendix.

Second, I introduce a parametric assumption regarding the sampling distribution of productivity for both types of firms: $ln(p_k - \underline{p})$ is assumed to be normally distributed with mean $\mu_k$ and variance $\sigma_k$, where $p_k$ is the productivity drawn for matches with type $k$ firms. Additionally, the fixed cost $\chi_j$ incurred by firm $j$ when choosing type $c$ is assumed to follow a uniform distribution within the range $[0,\bar{\chi}]$. As for the calibration, I define a period as a month, set $\underline{p}$ as nine hundred thousand won to reflect the average monthly minimum wage during the sample period, and establish a monthly discount

[13] Note that it is more than a stricter assumption on $F_c(p)$, $F_s(p)$ and/or $\theta$, because I additionally assume that there is no overlap in terms of firm size between type $c$ and $s$ firms.

[14] Note that the legal and administrative definitions of SMEs are complex, considering various features such as the number of employees, total assets, and sales, and vary by industry.

rate $\rho$ of 0.8 percent. Also, considering the results from other researches, I set the bargaining power $\beta$ at 0.3 (e.g. Bagger et al. (2014)) and the matching elasticity with respect to vacant jobs at 0.5 (Petrongolo and Pissarides (2001)). The number of type $s$ and type $c$ firms are set as 0.0624 and 0.00016, respectively, based on the number of SMEs and large firms per worker in Korea. Finally, instead of directly calibrating the matching efficiency $\eta$, I normalize the optimal number of posting per SME $\zeta_s^*$ as one. Consequently, the value of $\eta$ can be derived from the matching function, given the estimation results, as elaborated below. Thus, $\zeta_c^*$ should be interpreted as the number of postings per large firm relative to that of SMEs.

### 1.4.2 Estimation procedure

There are fifteen parameters to be estimated: $\lambda_{0k}$, $\tau$, $\Omega$, $\delta_\epsilon$, $\pi_\epsilon$, $\mu_k$, $\sigma_k$, $\kappa$, $\theta$ and $\bar{\chi}$ where $k \in \{s,c\}$ and $\epsilon \in \{h,\ell\}$.[15] I estimate these parameters through three steps. First, some parameters can be directly estimated from empirical moments. Since any offers from SMEs would always be accepted by unemployed workers, regardless of their type, $\lambda_{0s}$ can be estimated from the empirical moments of 'unemployment-to-SMEs' transition (U2S) rates, i.e., the average monthly U2S rates over the sample period as follows:

$$\hat{\lambda_{0s}} = \frac{1}{T-1}\sum_{t=2}^{T} U2S_t = \frac{1}{T-1}\sum_{t=2}^{T} \frac{\sum_i \mathbb{1}\{ES_{i,t-1}=0, EC_{i,t-1}=0, ES_{i,t}=1\}}{\sum_i \mathbb{1}\{ES_{i,t-1}=0, EC_{i,t-1}=0\}}$$

Here, $ES_{i,t}$ ($EC_{i,t}$) is the indicator function that is equal to one if the individual $i$ is employed by a SME (large firm) in period $t$ and zero otherwise. Also, as all employees in large firms are assumed to be high type, $\delta_h\pi_h$, the probability that high-type employed workers lose their job, can be estimated from the empirical moments of 'large firms-to-unemployment' transition (C2U) rates, i.e.

$$\hat{\delta_h \pi_h} = \frac{1}{T-1}\sum_{t=2}^{T} C2U_t = \frac{1}{T-1}\sum_{t=2}^{T} = \frac{\sum_i \mathbb{1}\{EC_{i,t-1}=1, ES_{i,t}=0, EC_{i,t}=0\}}{\sum_i \mathbb{1}\{EC_{i,t-1}=1\}}$$

The second step involves estimating most of the parameters related to job mobility and wages via indirect inference (Gourieroux et al. (1993)). Be-

[15] Note that $\zeta_c^*$ and $\chi^*$ are determined endogenously.

fore doing that, I reduce the number of parameters to be estimated by using steady-state conditions. First, from the flow-balance equations for unemployed workers with each type, $\Omega$ can be expressed as follows (See the Appendix for the derivation):

$$\Omega = \frac{(\delta_h \pi_h + \lambda_{0s} + \lambda_{0c})(\delta_\ell \pi_\ell (1 - Pr(u)) - \lambda_{0s} Pr(u))}{\delta_\ell \pi_\ell (\lambda_{0s} + \lambda_{0c}) - \delta_h \pi_h \lambda_{0s}}$$

Also, the average probability of 'employment-to-unemployment' transition (E2U) among all employed workers, which can be directly estimated from the data, is the weighted average of $\delta_h \pi_h$ and $\delta_\ell \pi_\ell$. Therefore, $\delta_\ell \pi_\ell$ can be expressed as functions of the estimates of $\delta_h \pi_h$ and E2U among all workers, and other parameters to be estimated.

Therefore, in the second step, I estimate $\lambda_{0c}$, $\lambda_{1s}$, $\pi_\ell$, $\pi_h$, $\mu_s$, $\sigma_s$, $\mu_c$ and $\sigma_c$ while it is obvious that $\delta_h = \frac{\delta_h \pi_h}{\pi_h}$, $\delta_\ell = \frac{\delta_\ell \pi_\ell}{\pi_\ell}$ and $\tau = \frac{\lambda_{1s}}{\lambda_{0s}}$. For the estimation, I target the following nineteen moments. First, I target average monthly rates of job-to-job transitions by firm size: 'SMEs-to-SMEs' transition rate (S2S), 'SMEs-to-large firms' transition rate (S2C), 'large firms-to-SMEs' transition rate (C2S), and 'large firms-to-large firms' transition rate (C2C), where monthly K2K' for K, K' $\in \{S, C\}$ is

$$K2K'_t = \frac{\sum_i \mathbb{1}\{EK_{i,t-1} = 1, EK'_{i,t} = 1, Stay_{i,t} = 0\}}{\sum_i \mathbb{1}\{EK_{i,t-1} = 1\}}$$

Here, $Stay_{i,t}$ is the indicator function that is equal to one if individual $i$ has the same job in both periods *t-1* and *t*, and zero otherwise. Second, I target the average monthly fraction of workers who are employed by large firms and SMEs, respectively. Third, I target the average monthly mean, median[16], and standard deviation of log wages for large firms and SMEs employees, respectively. Additionally, I target the difference in the average monthly mean of log wages between large firms and SMEs and weight it five times to emphasize the importance of the wage gap. Finally, I target the average monthly mean, standard deviation, and median of log wages for workers who just moved from unemployment to large firms and SMEs, respectively. Note that the first group of moments mainly contributes to identifying $\lambda_{1s}$, $\pi_\ell$ and $\pi_h$, the second group to identifying $\lambda_{0c}$, and the third group to identifying $\mu_s$, $\sigma_s$, $\mu_c$ and $\sigma_c$. See

[16]More precisely, when I target the mean or median of log wages below, I target the difference between them and $ln(\underline{p})$, the log wage from a match with the lowest productivity, in order to target the part that is only determined by the parameters to be estimated.

the Appendix for the identification.

As for the third step, I calculate the remaining parameters sequentially as follows. First, note that $\zeta_s^*$ is normalized as one, and $\zeta_c^*$ can be calculated from the matching function given the above estimation results and empirical moments, as follows:

- From $\lambda_{0k} = \eta \upsilon^\alpha e^{1-\alpha} * \frac{\upsilon_c}{\upsilon} * \frac{1}{e}$, one can find that $\upsilon_s = \frac{\lambda_{0s}}{\lambda_{0c}} \upsilon_c$.
- Using the result, $\lambda_{0c}$ can be written as

$$\lambda_{0c} = \eta \upsilon^\alpha e^{1-\alpha} * \frac{\upsilon_c}{\upsilon} * \frac{1}{e} = \eta \upsilon_c \frac{(\upsilon_c + \frac{\lambda_{0s}}{\lambda_{0c}} \upsilon_c)^{\alpha-1}}{(1+(\tau-1)(e_s+e_c))^\alpha}$$ [17]

- Finally, as the profit maximization leads $\upsilon_k = \sum_{j \in k} \zeta_j = n_k \zeta_k^*$,

$$\lambda_{0c} = \eta (n_c \zeta_c^*)^\alpha \frac{(1+\frac{\lambda_{0s}}{\lambda_{0c}})^{\alpha-1}}{(1+(\tau-1)(e_s+e_c))^\alpha}$$

  , which gives the value of $\zeta_c^*$ given the estimation results on $\lambda_{0s}$, $\lambda_{0c}$ and $\tau$ from the previous steps, and empirical moments for the employment share by large firms and SMEs. Note that $n_s$ and $\alpha$ are calibrated, and $\eta$ can be calculated from

$$\lambda_{0s} = \eta (n_s \zeta_s^*)^\alpha \frac{(1+\frac{\lambda_{0s}}{\lambda_{0c}})^{\alpha-1}}{(1+(\tau-1)(e_s+e_c))^\alpha}$$

  , by using the normalization, $\zeta_s^* = 1$.

Therefore, by putting the value of $\zeta_s^*$, which is normalized as one, into Eq(1.8), the equation for the optimal choice of the number of vacancies per SME, $\kappa$ can be achieved. Then, given $\kappa$, by putting the value of $\zeta_c^*$ into Eq(1.7), the equation for the optimal choice of the number of vacancies per large firm, $\theta$ can be achieved. Also, given those results, $\chi^*$ can be calculated by equating the total expected profit from becoming a large firm and that from becoming an SME, i.e., by equating the RHS and LHS of Eq(1.10). Then, $\bar{\chi}$ can be achieved from $\frac{\chi^*}{\bar{\chi}} = \frac{n_c}{n_c+n_s}$ since $\chi_j \sim$ U$[0,\bar{\chi}]$

[17] Note that

$$e = \tau_u e_u + \tau_s e_s + \tau_c e_c = 1 - e_s - e_c + \tau e_s + \tau e_c = 1 + (\tau - 1)(e_s + e_c)$$

## 1.5 Estimation results

### 1.5.1 Model fits

#### 1.5.1.1 Labour mobility

Table 1.3 compares monthly transition probabilities from the real data with those from simulated data. Overall, the structural model fits the observed job-to-job transition probabilities well. This alignment is evident in Figure 1.1, which illustrates the gap in J2J transition probabilities between real and simulated data, accompanied by 95% confidence intervals obtained through bootstrapping. Notably, the model successfully reproduces a key feature of the real data that motivates the paper: the 'SMEs-to-large firms' transition probability is lower, even than the 'large firms-to-large firms' transition probability. Furthermore, the model provides a reasonable fit for 'employment-to-unemployment' and 'unemployment-to-employment' transition probabilities. Note that U2S, E2U, and C2U are targeted in the 1st step of the estimation, while U2C is targeted via the calculation of $\Omega$ using the steady state condition. However, S2U is not targeted.

Table 1.3: Labour mobility by firm sizes

| | Real | Simulated |
|---|---|---|
| SMEs-to-large firms transition rate(S2C) | 0.06% | 0.06% |
| Large firms-to-large firms transition rate(C2C) | 0.13% | 0.14% |
| Large firms-to-SMEs transition rate(C2S) | 0.12% | 0.09% |
| SMEs-to-SMEs transition rate(S2S) | 0.52% | 0.51% |
| Unemployment-to-SMEs transition rate(U2S) | 1.33% | 1.33% |
| Unemployment-to-large firms transition rate(U2C) | 0.23% | 0.22% |
| Employment-to-unemployment transition rate(E2U) | 1.04% | 1.04% |
| Large firms-to-unemployment transition rate(C2U) | 0.53% | 0.53% |
| SMEs-to-unemployment transition rate(S2U) | 1.22% | 1.27% |

Note: Monthly

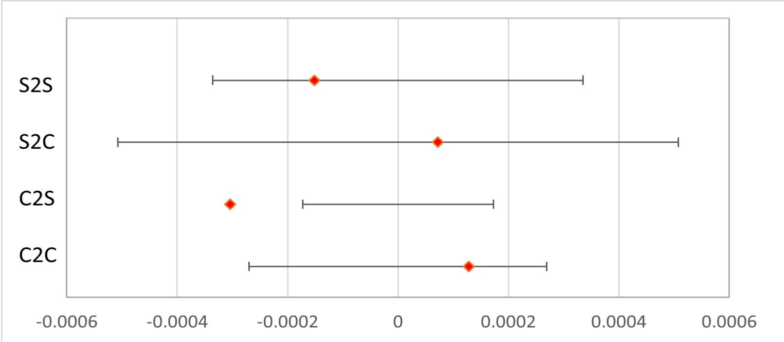


Figure 1.1: The gap in J2J between real and simulated data
Note: The boundary shows 95% confidence interval

#### 1.5.1.2 Employment share

The model's prediction on the share of employed workers by SMEs suggests a smaller proportion than observed in the real data, while it predicts a larger share for large firms. In Table 1.4, the difference between the real and simulated data may not appear substantial; however, Figure 1.2 illustrates that the gap is considerably larger than the 95% confidence intervals.

Table 1.4: Employment share by firm sizes

| | Real | Simulated |
|---|---|---|
| Share of employees in SMEs | 0.4433 | 0.4106 |
| Share of employees in large firms | 0.1569 | 0.1887 |
| Share of unemployed workers | 0.3998 | 0.4008 |

Note: Unemployed workers include self-employed workers, etc.

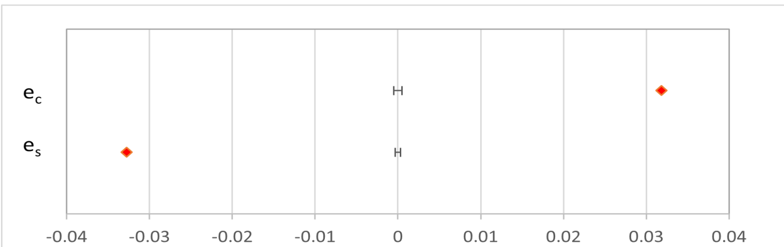


Figure 1.2: The gap in employment share between real and simulated data
Note: The boundary shows 95% confidence interval

#### 1.5.1.3 Wage moments

As evident from Table 1.5 and Figure 1.3, half of wage moments are fitted well, but the rest are located outside of 95% confidence intervals. An explanation for predicting a lower median than the actual data, despite accurately fitting the mean wages of workers in both large and small firms, could be attributed to the prevalence of 'Salary Step System' in South Korea, combined with a low job-to-job transition rate (i.e., a low probability of receiving new job offers). While the number of firms adopting a salary step system has been steadily declining, about 40 percent of firms still use it. Firms employing a salary step system typically have a predetermined plan for wage changes based on years of service, applying the same plan uniformly to all employees. Consequently, in reality, the wages of all workers under the salary step system increase annually. In contrast, the probability of wage growth in the model is lower, reflecting the lower likelihood of job-to-job transitions in reality, resulting in many wages clustered below the mean, i.e., a lower median. The reason why the standard deviation of wages in large firms in the real world is lower than in the model is likely related to the relatively small number of large firms. This is because the wage differential between workers within a firm is likely to be smaller than the wage differential between firms. Meanwhile, despite the fact that the average wage of all workers and the average wage of newly hired workers are influenced by the same productivity distribution, only the latter in real data, is lower than the corresponding value from the simulated data. This difference may be attributed to the weaker bargaining power of newly hired workers in reality, even though the model assumes their bargaining power to be the same as that of existing workers.

Despite the imperfect fit for certain wage moments arising from disparities between the model and reality, a crucial observation is that the mean of log wages for both large firms and SMEs is remarkably well-fitted. As detailed in the subsequent section, my primary focus for the application of the model lies in these specific moments.

### 1.5.2 Parameter estimates

Table 1.6 presents the estimation results. Firstly, the results indicate that the offer arriving rate from SMEs and large firms is nearly identical. However, with the fraction of high-type workers $\Omega$ hovering around 40%, the actual probability of being hired by large firms is significantly lower than that of being hired by SMEs, as shown in Table 1.3. The relatively small $\Omega$ contributes

Table 1.5: Wage moments

| | Real | Simulated |
|---|---|---|
| Log wages, among all employees, | | |
| Mean of employees in SMEs(E($W\|s$)) | 2.7860 | 2.7820 |
| Mean of employees in large firms(E($W\|c$)) | 3.2875 | 3.2719 |
| Standard deviation of employees in SMEs(SD($W\|s$)) | 0.5285 | 0.5347 |
| Standard deviation of employees in large firms(SD($W\|c$)) | 0.6002 | 0.7350 |
| Median of employees in SMEs(MED($W\|s$)) | 2.7841 | 2.6043 |
| Median of employees in large firms(MED($W\|c$)) | 3.3438 | 3.2039 |
| Log wages, among employees who were unemployed last month, | | |
| Mean of employees in SMEs(E($W\|u2s$)) | 2.5165 | 2.6253 |
| Mean of employees in large firms(E($W\|u2c$)) | 2.6817 | 2.7576 |
| Standard deviation of employees in SMEs(SD($W\|u2s$)) | 0.4715 | 0.3976 |
| Standard deviation of employees in large firms(SD($W\|u2c$)) | 0.5531 | 0.5187 |
| Median of employees in SMEs(MED($W\|u2s$)) | 2.4965 | 2.4996 |
| Median of employees in large firms(MED($W\|u2c$)) | 2.6506 | 2.5915 |

to transitions from SMEs to large firms being infrequent, even though the average productivity of large firms is higher than that of SMEs.[18] Regarding worker heterogeneity, low-type workers experience job loss approximately four times more frequently than high-type workers. However, over half of low-type workers facing job destruction promptly receive substitute job offers, whereas the probability of high-type workers receiving such offers is only around 7 percent. Consequently, the 'SMEs-to-unemployment' transition rate is slightly more than twice the 'large firms-to-unemployment' transition rate, as observed in Table 1.3.

Now, let's look at the parameters related to vacancies. Firstly, under the normalization of the number of postings per SME as one, the matching efficiency is approximately 5.6%. The number of postings per large firm exceeds that of SMEs by more than four hundred times. To maintain consistency with this substantial gap, the variable cost per posting for large firms is only 0.16% of SMEs' cost.[19] On the other hand, the fixed cost for large firms is huge, admittedly. However, this is unavoidable given the considerable disparity in

[18] If the most of workers are high type, then there should be many high type employees in SMEs as well. Therefore, if large firms' average productivity is higher then SMEs', there would be frequent SMEs-to-large firms transitions in spite of the skill requirement by large firms. In other words, if $\Omega$ is large, higher average productivity of large firms cannot be compatible with rare SMEs-to-large firms transitions.

[19] Note that the interpretation of $\kappa$ is meaningless because it's level is determined by $\zeta_s$, which is already normalized as one.

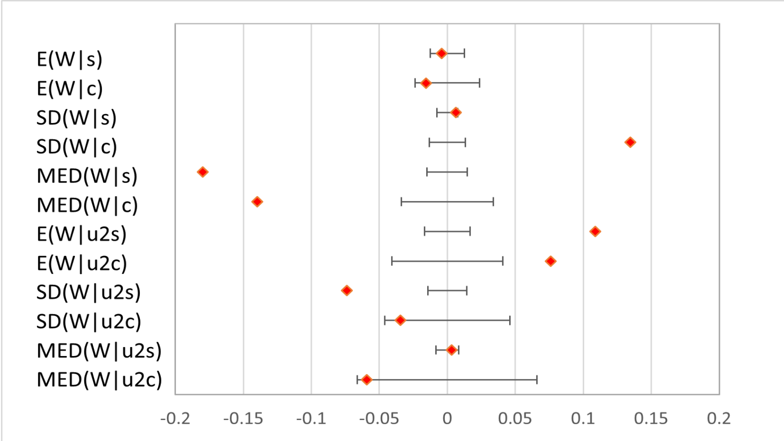


Figure 1.3: The gap in wage moments between real and simulated data
Note: The boundary shows 95% confidence interval

the number of firms between SMEs and large firms.

Table 1.6: Estimation results

| | | |
|---|---|---|
| $\lambda_{0s}$ | 0.0133 | (0.0003) |
| $\lambda_{0c}$ | 0.0145 | (0.0010) |
| $\lambda_{1s}$ | 0.0029 | (0.0001) |
| $\pi_\ell$ | 0.4727 | (0.0265) |
| $\pi_h$ | 0.9306 | (0.0529) |
| $\mu_s$ | 2.5661 | (0.0774) |
| $\sigma_s$ | 1.0981 | (0.0567) |
| $\mu_c$ | 3.2144 | (0.1604) |
| $\sigma_c$ | 1.0771 | (0.0576) |
| $\Omega$ | 0.3908 | (-) |
| $\tau$ | 0.2162 | (-) |
| $\delta_h$ | 0.0056 | (-) |
| $\delta_\ell$ | 0.0222 | (-) |
| $\eta$ | 0.0562 | (-) |
| $\kappa$ | 34.1409 | (-) |
| $\theta$ | 0.0016 | (-) |
| $\bar{\chi}$ | 3.9103e+06 | (-) |
| $\zeta_c$ | 425.6263 | (-) |
| $\chi^*$ | 1.0004e+04 | (-) |

Note: Standard errors in parentheses. $\Omega$, $\delta_h$, $\delta_\ell$, $\tau$, $\eta$, $\kappa$, $\theta$ and $\bar{\chi}$ are calculated from other parameters, empirical moments and the equilibrium conditions for the firms' choice of type and the number of vacancies, e.g. $\tau = \frac{\lambda_{1s}}{\lambda_{0s}}$. Also, $\zeta_c^*$ and $\chi^*$ are determined endogenously.

## 1.6 Applications

### 1.6.1 Decomposition of wage gap

In the model, the wage gap between SMEs and large firms is determined by two factors: the gap in match-specific productivity and the skill requirement effect. The first part can be understood as the impact of firm heterogeneity. This is because, for any 'existing' matches that meet the skill requirement, the production does vary not by firm size but by match-specific productivity. The primary focus lies in the second part, which originates from worker heterogeneity but influences the wage gap between SMEs and large firms solely through the skill requirement. Essentially, wages differ based on worker types due to variations in the probability of job destruction. The average wage of high-type employees, less prone to falling to the bottom of the job ladder through job loss, is higher than that of low-type workers. This disparity can contribute to the wage gap between SMEs and large firms because the skill requirement by large firms results in the sorting between firm size and worker type.

However, this is not the whole story. The skill requirement not only allows the difference in job destruction rates to impact the wage gap between SMEs and large firms but also reinforces this effect by creating variations in competition for low-type and high-type workers. Employers of low-type workers would face less intense competition for their employees, as low-type workers can receive meaningful offers only from SMEs, not from large firms. This dynamic enlarges the wage gap between low- and high-type workers, consequently widening the gap between SMEs and large firms as well.

As a result, the wage gap between SMEs and large firms can be decomposed into three parts: ① the effect of the productivity gap, ② the 'indirect' effect of skill requirements originating from the difference in job destruction rates by workers' type and ③ the 'direct' effect of skill requirements originating from the difference in competition for workers by their type. To eliminate the effect of the difference in productivity distribution from the wage gap, I simulated the model under the restriction that the sampling distribution of productivity is the same for SMEs and large firms. The second column of Table 1.7 shows the results, while the first column provides original moments, i.e., the results when there is no restriction. As seen from the first row, the wage gap between SMEs and large firms under the restriction of the same productivity distribution is about 38% of the original wage gap. This implies that 62% of the wage gap between SMEs and large firms can be explained by firm heterogeneity in terms of productivity distribution, while the rest is due to worker heterogeneity that can be effective and amplified by skill requirements.

The fourth column shows the simulated wage moments under the additional restriction that the job destruction rate does not differ by worker type. In other words, it only shows the direct effect of skill requirements caused by lower competition for low-type workers: it accounts for about 13% of the original wage gap between SMEs and large firms, which means the indirect effect of the skill requirement (i.e., worker heterogeneity) accounts for about 25% of the original wage gap.

Note that the effect of firm heterogeneity and the indirect effect of skill requirement may vary in magnitude depending on which effect is calculated first, while the direct effect (i.e., differences in competition for workers due to skill requirements) does not. As shown in the third column of the table, the wage gap under the restrictions that the job destruction rate does not differ by workers' type but the sampling distribution of productivity does differ by firm type is about 87% of the original wage gap. It means that, when I calculate the wage gap explained by worker heterogeneity first, the result is about 13%. In addition, as the sum of the effect of firm heterogeneity and the direct effect is about 87%, by subtracting the magnitude of the direct effect, which is about 13% as shown in the fourth column, one can find that the effect of firm heterogeneity is about 74%. Note that, although the absolute magnitudes have changed, the fact remains that firm heterogeneity contributes the most.

Meanwhile, the average wage of low-type workers is also lower than that of high-type workers for three reasons: ① all of them are working for SMEs, while some high-type workers are working for large firms, where the average match-specific productivity in large firms is higher than that in SMEs, ② they have a higher job destruction rate, and ③ the level of employers' competition for low-type workers is lower than that for high-type workers. The lower part of Table 1.7 shows the decomposition of the wage gap between high and low-type workers. From the second column, which suppresses the first reason for the wage gap by workers' type by eliminating the difference in productivity between large firms and SMEs, I conclude that about 26% of the wage gap comes from the difference in average productivity of firms that each type of workers is eligible for. Also, by comparing the second and fourth columns, one can conclude that about 50% of the wage gap between low and high-type workers is due to the difference in job destruction rate, and 24% of the gap is due to the difference in competition for workers by their type. However, if I calculate the effect of the difference in job destruction rate first, it explains about 25% of the wage gap, while the difference in productivity by firm type explains about 51%.

### 1.6.2 Effect of education on wage gap

Generally, employment outcomes of graduates are considered as a part of the criteria for assessing the performance of universities. Therefore, many schools try to develop curriculums designed to help students acquire the abilities necessary for being hired by preferred firms. Sometimes schools directly

Table 1.7: Decomposition of wage gap

| | Basic | $F_s$=$F_c$ | $\delta_\ell$=$\delta_h$ | $F_s$=$F_c$ & $\delta_\ell$=$\delta_h$ |
|---|---|---|---|---|
| Expected wage gap by firm size | 0.4899 | 0.1862 | 0.4284 | 0.0615 |
| | (100.0%) | (38.0%) | (87.4%) | (12.6%) |
| Expected wage in large firms | 3.2719 | 3.2954 | 3.3197 | 3.3529 |
| Expected wage in SMEs | 2.7820 | 3.1092 | 2.8913 | 3.2914 |
| Expected wage gap by worker type | 0.4121 | 0.3068 | 0.3095 | 0.0980 |
| | (100.0%) | (74.4%) | (75.1%) | (23.8%) |
| Expected wage of high type workers | 3.1231 | 3.2987 | 3.1763 | 3.3590 |
| Expected wage of low type workers | 2.7110 | 2.9919 | 2.8668 | 3.2610 |

collaborate with firms on curriculum development, and educational authorities encourage educational-industrial cooperation.

In the model, the impact of such curriculums can be partly examined by considering the case when $\Omega$, the fraction of high-type workers, is higher than in reality. The second column of Table 1.8 shows the wage gap when the fraction of high-type workers is 60%, increased by about 50% from the estimation result. From the upper part, one can see that the wage gap between large firms and SMEs is roughly the same as in the original scenario. However, the lower part shows that the wage gap between high and low-type workers is about 26% higher than in the original scenario because the wage of high-type workers is increased while that of low-type workers decreased slightly. This is because the higher fraction of high-type workers means a higher probability of filling the vacancies in large firms, leading to a higher number of total vacancies in large firms in two ways. First, as large firms' expected profit per posting is higher, each of them posts more vacancies. Second, it means the total expected profit from being a large firm is higher, so the number of large firms is also higher than in the case with a lower fraction of high-type workers. As it means that the competition for high-type workers is stronger, their wage is higher than in reality.

If the fraction of high-type workers among SMEs' employees is the same, the wider wage gap between high and low-type workers leads to a wider gap between large firms and SMEs as well. However, the higher fraction of high-type workers means more opportunity for SMEs to hire high-type workers, as one can see from the bottom of the table, and it increases the average wage of

SME employees. As the two effects offset each other, the impact of the change in $\Omega$ on the wage gap between large firms and SMEs is small.

The results imply that the efforts of universities and educational authorities to increase the number of graduates who are qualified for preferred firms can increase the number of employees in those firms and improve their compensation. However, it can widen the wage gap between high and low-type workers. The implications can be confirmed through another counterfactual analysis considering the opposite case, as the last column of Table 1.8 shows. When the fraction of high-type workers is 20%, decreased by about 50% from the estimation result, the wage gap between high and low-type workers is smaller as the wage of high-type workers is lower. However, again, the wage gap between large firms and SMEs' employees is not that different from the original scenario.

Table 1.8: Effect of education

| | Basic | More $h$-workers | Fewer $h$-workers |
|---|---|---|---|
| | ($\Omega = 0.3908$) | ($\Omega = 0.6$) | ($\Omega = 0.2$) |
| Expected wage gap by firm type | 0.4899 | 0.4936 | 0.4679 |
| | (100.0%) | (100.8%) | (95.5%) |
| Expected wage in large firms | 3.2719 | 3.3116 | 3.2269 |
| Expected wage in SMEs | 2.7820 | 2.8180 | 2.7590 |
| Expected wage gap by worker type | 0.4121 | 0.5221 | 0.2852 |
| | (100.0%) | (126.7%) | (69.2%) |
| Expected wage of high type workers | 3.1231 | 3.2221 | 3.0054 |
| Expected wage of low type workers | 2.7110 | 2.7000 | 2.7202 |
| $\Pr(\epsilon = h \mid s)$ | 0.3382 | 0.4047 | 0.3158 |

## 1.7 Conclusion

This paper aims to examine a specific phenomenon in the Korean labour market that cannot be adequately explained by standard search models: the limited job-to-job transitions from SMEs to large enterprises despite workers strongly preferring the latter. The study employs a search model featuring two types of workers and two types of firms, where wage and job mobilities are determined by sequential auctions. In the model, one type of firm, which corresponds to large enterprises, can only produce if they hire high-type workers. Consequently, low-type workers can only be hired by the other type of firms, representing SMEs. Due to the sorting between worker type and firm size, cross-sectional job-to-job transitions from SMEs to large firms become rare. The model successfully replicates a key feature of real data: the lower probability of 'SMEs-to-large firms' transitions compared to 'large firms-to-large firms' transitions. In the next step, a counterfactual analysis is performed to decompose the wage gap between SMEs and large enterprises, which is significantly larger in Korea than in other countries, into the difference in productivity and the impact of skill requirements. Skill requirements can contribute to the wage gap in two ways. First, since wages differ by worker type, the sorting between firm size and worker type caused by skill requirements can widen the wage difference between large firms and SMEs. Second, due to skill requirements, competition for low-type workers weakens, leading to a wider wage gap by worker type, consequently widening the gap by firm size given the sorting between firm size and worker type. The first way explains about 13∼25% of the gap by firm size, while the second one explains about 13% of the gap. In another counterfactual analysis, it is shown that an increase in the number of highly capable workers through improved education may not significantly alter the wage gap by company size, but it may widen the wage gap by ability.

## 1.8 Appendix

### 1.8.1 The Value of a Filled Job

The value of a filled job with a high type worker, productivity $p$ and wage $w$ can be formally written down as follows:

$$\rho J(\epsilon = h, w, p) = p - w - \delta_h J(h, w, p)$$
$$+\lambda_{1s}[\int_{q(h,w,p)}^{p} J(h, \phi(h, x, p), p) dF_s(x) - \int_{q(h,w,p)}^{\bar{p}} J(h, w, p) dF_s(x)]$$

$$+\lambda_{1c}[\int_{q(h,w,p)}^{p} J(h, \phi(h,x,p), p)dF_c(x) - \int_{q(h,w,p)}^{\bar{p}} J(h,w,p)dF_c(x)]$$

Similarly, the value of a filled job with a low type worker, productivity $p$ and wage $w$ can be formally written down as follows:

$$\rho J(\epsilon = \ell, w, p) = p - w - \delta_\ell J(\ell, w, p)$$

$$+\lambda_{1s}[\int_{q(\ell,w,p)}^{p} J(\ell, \phi(\ell,x,p), p)dF_s(x) - \int_{q(\ell,w,p)}^{\bar{p}} J(\ell,w,p)dF_s(x)]$$

### 1.8.2 Steady-state Distributions

#### 1.8.2.1 Distributions of workers' type

The type of workers is not observable. However, under the 'strict' skill requirement assumption that low type workers never be hired by type large firms, the fraction of high type workers among unemployed workers, among employees in type $s$ firms and among all workers can be identified respectively. Let's start from the fraction among unemployed workers, $Pr(\epsilon = h|u)$. The flow-balance equation for unemployed high type workers is

$$(\lambda_{0s} + \lambda_{0c})e_u Pr(\epsilon = h|u) = \delta_h \pi_h (e_s Pr(\epsilon = h|s) + e_c) \tag{1.11}$$

and that for unemployed low type workers is

$$\lambda_{0s} e_u (1 - Pr(\epsilon = h|u)) = \delta_\ell \pi_\ell e_s (1 - Pr(\epsilon = h|s)) \tag{1.12}$$

By solving the two equation, one can find followings:

$$Pr(\epsilon = h|u) = \frac{\delta_h \pi_h (\delta_\ell \pi_\ell (1 - e_u) - \lambda_{0s} e_u)}{\delta_\ell \pi_\ell e_u (\lambda_{0s} + \lambda_{0c} - \frac{\delta_h \pi_h}{\delta_\ell \pi_\ell} \lambda_{0s})} \tag{1.13}$$

$$Pr(\epsilon = h|s) = 1 - \frac{\lambda_{0s} e_u (1 - Pr(\epsilon = h|u))}{\delta_\ell \pi_\ell e_s} \tag{1.14}$$

Also, the fraction of high type workers among all workers is the weighted sum of the fraction among unemployed workers, among employees in type $s$ and $c$ firms, i.e.

$$Pr(\epsilon = h|u)e_u + Pr(\epsilon = h|s)e_s + e_c = Pr(\epsilon = h) := \Omega \tag{1.15}$$

By putting the Eq(1.15) into Eq(1.11) one can find

$$(\lambda_{0s} + \lambda_{0c})e_u Pr(\epsilon = h|u) = \delta_h \pi_h (\Omega - Pr(\epsilon = h|u)e_u) \tag{1.16}$$

and, by combining with Eq(1.13), the equation can be solved for $\Omega$ as follows:

$$\begin{aligned}\Omega &= \frac{(\delta_h \pi_h + \lambda_{0s} + \lambda_{0c})}{\delta_h \pi_h} e_u Pr(\epsilon = h|u) \\ &= \frac{(\delta_h \pi_h + \lambda_{0s} + \lambda_{0c})(\delta_\ell \pi_\ell - (\delta_\ell \pi_\ell + \lambda_{0s})e_u)}{\delta_\ell \pi_\ell (\lambda_{0s} + \lambda_{0c}) - \delta_h \pi_h \lambda_{0s}} \end{aligned} \tag{1.17}$$

#### 1.8.2.2 Cross-sectional Distributions of Productivity

Let's consider outflow and inflow of high type workers who are employed by small firms and its match-specific productivity is $p$. As for the outflow, they would lose their current job at a probability of $\delta_h$, or they can receive a new offer from type $s(c)$ firms at a probability of $\lambda_{1s}(\lambda_{1c})$ and accept it if the new match is more productive than $p$. As for the inflow, there are four sources: 1) unemployed high type workers who receive an offer from type $s$ firms at a probability of $\lambda_{0s}$, 2) high type employed workers who lose their job and immediately receive a substitute job offer from type $s$ firms at probability of $\delta_h(1-\pi_h)\frac{\lambda_{0s}}{\lambda_{0s}+\lambda_{0c}}$, 3) high type employees with a match-specific productivity lower than $p$ in type $s$ firms and 4) those in type $c$ firms who receive a new offer from type $s$ firms at probability of $\lambda_{1s}$. They become the inflow if they pick a match-specific productivity $p$ from $F_s$. Therefore, the flow-balance equations are:

$$\begin{aligned}&[\delta_h + \lambda_{1s}\bar{F}_s(p) + \lambda_{1c}\bar{F}_c(p)]\ell(p|h,s)Pr(\epsilon = h|s)e_s \\ &\quad = [\lambda_{0s} Pr(\epsilon = h|u)e_u + \{\lambda_{1s} L(p|h,s) + \delta_h(1-\pi_h)\frac{\lambda_{0s}}{\lambda_{0s}+\lambda_{0c}}\}Pr(\epsilon = h|s)e_s \\ &\qquad + \{\lambda_{1s} L(p|c) + \delta_h(1-\pi_h)\frac{\lambda_{0s}}{\lambda_{0s}+\lambda_{0c}}\}e_c]f_s(p)\end{aligned} \tag{1.18}$$

Similarly, the flow-balance equations for high type employees with match-specific productivity $p$ in large firms are

$$[\delta_h + \lambda_{1s}\bar{F}_s(p) + \lambda_{1c}\bar{F}_c(p)]\ell(p|c)e_c$$

$$= [\lambda_{0c}Pr(\epsilon = h|u)e_u + \{\lambda_{1c}L(p|h,s) + \delta_h(1-\pi_h)\frac{\lambda_{0c}}{\lambda_{0s}+\lambda_{0c}}\}Pr(\epsilon = h|s)e_s$$

$$+\{\lambda_{1c}L(p|c) + \delta_h(1-\pi_h)\frac{\lambda_{0c}}{\lambda_{0s}+\lambda_{0c}}\}e_c]f_c(p) \quad (1.19)$$

and that for low type employees with match-specific productivity $p$ in small firms are

$$[\delta_\ell + \lambda_{1s}\bar{F}_s(p)]\ell(p|\ell,s)Pr(\epsilon = \ell|s)e_s$$

$$= [\lambda_{0s}Pr(\epsilon = \ell|u)e_u + \{\lambda_{1s}L(p|\ell,s) + \delta_\ell(1-\pi_\ell)\frac{\lambda_{0s}}{\lambda_{0s}+\lambda_{0c}}\}Pr(\epsilon = \ell|s)e_s]f_s(p) \quad (1.20)$$

where $L(x|\epsilon,k)$ is the cross-sectional CDF of productivity among type $\epsilon$ employees in type $k$ firms and $\ell(x|\epsilon,k) = dL(x|\epsilon,k)/dx$. From the Eq(1.20) one can find that

$$L(p|\ell,s) = \frac{[\pi_\ell + (1-\pi_\ell)\frac{\lambda_{0s}}{\lambda_{0s}+\lambda_{0c}}]F_s(p)}{1 + \frac{\lambda_{1s}}{\delta_\ell}\bar{F}_s(p)} \quad (1.21)$$

Also, from Eq(1.18) and Eq(1.19), $L(p|h,s)$ and $L(p|c)$ can be solved as functions of $F_s(p)$, $F_c(p)$ and other parameters to be estimated.

### 1.8.3 Identification of the 2nd step of estimation

As the unemployment benefit is assumed to be low enough, high type unemployed workers would always accept offer from large firms. Also, from the assumption of skill requirement, one can know that the workers who have been hired by large firms before is high type workers. Combining these two results, $\lambda_{0c}$, the offer arriving rate from large firms to unemployed workers can be identified from average monthly U2C rates among unemployed workers who have been hired by large firms before,[20] i.e.

$$\hat{\lambda_{0c}} = \frac{1}{T-1}\sum_{t=2}^{T}\frac{\sum_i \mathbb{1}\{ES_{i,t-1}=0, EC_{i,t-1}=0, ECP_{i,t-1}=1, EC_{i,t}=1\}}{\sum_i \mathbb{1}\{ES_{i,t-1}=0, EC_{i,t-1}=0, ECP_{i,t-1}=1\}}$$

where $ECP_{i,t}$ is the indicator function which is equal to one if the individual $i$ has been hired by large firms before the period $t$[21], and zero otherwise. Then, given $\hat{\lambda_{0c}}$ and the results from the 1st step[22], $\tau$, $\delta_\ell$, $\delta_h$, $\mu_s$, $\sigma_s$, $\mu_c$ and $\sigma_c$ can be identified from following eight moments:

$$\text{C2C rate} = \tau\lambda_{0c}\int_{\underline{p}}^{\bar{p}} \bar{F}_c(p)dL(p|c) + \delta_h(1-\pi_h)\frac{\lambda_{0c}}{\lambda_{0s}+\lambda_{0c}} \tag{1.22}$$

$$\text{S2C rate} = Pr(\epsilon = h|s)[\tau\lambda_{0c}\int_{\underline{p}}^{\bar{p}} \bar{F}_c(p)dL(p|h,s)+\delta_h(1-\pi_h)\frac{\lambda_{0c}}{\lambda_{0s}+\lambda_{0c}}] \tag{1.23}$$

$$\text{C2S rate} = \tau\lambda_{0s}\int_{\underline{p}}^{\bar{p}} \bar{F}_s(p)dL(p|c) + \delta_h(1-\pi_h)\frac{\lambda_{0s}}{\lambda_{0s}+\lambda_{0c}} \tag{1.24}$$

$$\begin{aligned}\text{S2S rate} &= Pr(\epsilon = h|s)[\tau\lambda_{0s}\int_{\underline{p}}^{\bar{p}} \bar{F}_s(p)dL(p|h,s) + \delta_h(1-\pi_h)\frac{\lambda_{0s}}{\lambda_{0s}+\lambda_{0c}}] \\ &+(1-Pr(\epsilon = h|s))[\tau\lambda_{0s}\int_{\underline{p}}^{\bar{p}} \bar{F}_s(p)dL(p|\ell,s) + \delta_\ell(1-\pi_\ell)\frac{\lambda_{0s}}{\lambda_{0s}+\lambda_{0c}}] \\ &= Pr(\epsilon = h|s)[\tau\lambda_{0s}\int_{\underline{p}}^{\bar{p}} \bar{F}_s(p)dL(p|h,s) + \delta_h(1-\pi_h)\frac{\lambda_{0s}}{\lambda_{0s}+\lambda_{0c}}] \\ &+(1-Pr(\epsilon = h|s))[\delta_\ell\{\frac{(\delta_\ell+\tau\lambda_{0s})\Pi_\ell}{\tau\lambda_{0s}}\log(\frac{\delta_\ell\Pi_\ell+\tau\lambda_{0s}}{\delta_\ell\Pi_\ell})-1\}+\delta_\ell(1-\pi_\ell)\frac{\lambda_{0s}}{\lambda_{0s}+\lambda_{0c}}]\end{aligned} \tag{1.25}$$

where $\Pi_\ell := \pi_\ell + (1-\pi_\ell)\frac{\lambda_{0s}}{\lambda_{0s}+\lambda_{0c}}$[23]

$$E(w|U2C) = E_{p\sim F_c}(p) + E_{p\sim F_c}(\text{A}) \tag{1.26}$$

$$E(w|U2S) = E_{p\sim F_s}(p) + E_{p\sim F_s}(\text{B}) \tag{1.27}$$

[20]From the flow-balance equations for unemployed workers with each type, $\lambda_{0c}$ can be expressed as functions of $\Omega$ and other parameters. Therefore, instead of $\lambda_{0c}$, one can identify $\Omega$ using asymptotic assumption, i.e from the fraction of workers who have been hired by large firms at least once during whole sample period.

[21]Note that it can include the work experience before the beginning of the sample period by using data from retrospective response.

[22]I.e. $\hat{\lambda_{0s}}$ and $\widehat{\delta_h\pi_h}$. Also, as mentioned in the main text, note that $\delta_\ell\pi_\ell$ can be expressed as functions of other parameters and moments.

[23]The last line shows that S2S rate among low type workers is

$$\delta_\ell\{\frac{(\delta_\ell+\tau\lambda_{0s})\Pi_\ell}{\tau\lambda_{0s}}\log(\frac{\delta_\ell\Pi_\ell+\tau\lambda_{0s}}{\delta_\ell\Pi_\ell})-1\}+\delta_\ell(1-\pi_\ell)\frac{\lambda_{0s}}{\lambda_{0s}+\lambda_{0c}}$$

As the rate is not related with the distributions of productivity, the identification becomes more clear if I assume that workers who never been hired by large firms during the whole sample period are low type and use the empirical S2S rate among them.

$$Var(w|U2C) = Var_{p\sim F_c}(p) + Var_{p\sim F_c}(\text{A}) + 2Cov_{p\sim F_c}(p, \text{A}) \tag{1.28}$$

$$Var(w|U2S) = Var_{p\sim F_s}(p) + Var_{p\sim F_s}(\text{B}) + 2Cov_{p\sim F_s}(p, \text{B}) \tag{1.29}$$

, where $\text{A} = -(1-\beta)\int_{\underline{p}}^{p} \frac{\rho+\delta_h+\lambda_{1s}\bar{F}_s(x)+\lambda_{1c}\bar{F}_c(x)}{\rho+\delta_h+\beta(\lambda_{1s}\bar{F}_s(x)+\lambda_{1c}\bar{F}_c(x))}dx$, and

$\text{B} = Pr(\epsilon = h|u)\text{A} - (1 - Pr(\epsilon = h|u))(1-\beta)\int_{\underline{p}}^{p} \frac{\rho+\delta_\ell+\lambda_{1s}\bar{F}_s(x)}{\rho+\delta_\ell+\beta\lambda_{1s}\bar{F}_s(x)}dx.$[24][25]

[24]Note that $E_{p\sim F_k}(p) = exp(\mu_k + \frac{\sigma_k^2}{2})$ and $Var_{p\sim F_k}(p) = [exp(\sigma_k^2) - 1]exp(2\mu_k + \sigma_k^2)$ for $k \in \{s, c\}$

[25]As the wage of low type workers is not a function of $F_c$, again, the identification becomes more clear if I assume that workers who never been hired by large firms during the whole sample period are low type, i.e. if I use the empirical moments of wage among workers who never been hired by large firms and just experienced U2S transition.

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# Chapter 2

# The Effect of Referrals on Employment Outcome


## abstract

This paper examines the impact of referrals on the probability of hiring and wage levels. I utilize unique data from a private matching platform, where applicants can choose whether to submit a referral, typically in the form of a letter from an acquaintance. The estimation method takes into account the endogeneity of referral use and the selection issues related to wage data. The results of the estimation indicate that firms are more inclined to hire applicants with a referral. This suggests that referrals provide hiring firms with positive information about applicants' productivity that would not be available otherwise. However, there is no discernible difference in wage levels between applications with and without a referral. These seemingly contradictory results hold even for referrals with stronger signals or evaluations, despite their more pronounced effect on the probability of being hired. Therefore, the lack of a significant effect on wages does not appear to be attributable to weak signals from referrals.

## 2.1 Introduction

Recruiting can be viewed as a game with incomplete information between workers and firms. From the firm's perspective, certain worker attributes, such as responsibility, diligence, and cooperativeness, are challenging to observe. This limitation prompts firms to heavily rely on informal hiring methods. According to a survey cited by Marsden (2001), 37% of US employers frequently seek new employees through the social networks of their current employees. Another survey used by Miller and Rosenbaum (1997) in the Chicago area reveals that over 65% of employers use employee referrals in their recruitment processes. Additionally, in many countries, conducting reference checks through letters from previous employers or phone calls is a common recruiting practice.

Therefore, examining the effect of referrals becomes crucial in understanding the role and impact of incomplete information in the matching process. This study aims to address questions such as "How do firms value additional information on potential employees?" and "What benefits do workers derive from the reduction of information restrictions?"

To investigate this topic, I use new data from a private company providing a matching platform for workers and firms. Notably, when a worker applies for job positions through this platform, they can choose whether or not to submit a referral from someone they know. It's important to note that the definition of a referral in this paper differs from most literature on the subject. Rather than focusing on cases where hiring firms ask current employees for referrals, here, a referral refers to a letter from one of the applicant's acquaintances describing or commenting on the worker's attributes and abilities. The study examines the effect of referrals on employment outcomes by comparing the results of applications with a referral to those without one.

The paper begins by introducing the background and key features of the data. Besides information on the use of referrals, the dataset includes valuable details on worker- and job-specific characteristics. Notably, the minimum intended wage for each posted job, provided by firms to the platform, is a key element used to control for job-specific effects in both wage and hiring decisions.

In terms of the estimation method, two critical issues are addressed. First, there is a censoring issue in wage data, as demonstrated by Heckman (1979), where wages are observable only when the application is successful. Additionally, the possibility of endogeneity in the use of referrals cannot be ruled out. Following Kim (2006), the paper extends Heckman's two-step method. The use of referral and hiring equations are estimated as a bivariate probit model in the first step, and the wage equation is estimated by OLS with selection effect correction terms.

The estimation results reveal that the use of a referral significantly increases the probability of being hired, indicating that hiring firms value the information provided by referrals. However, when considering the wage level, no significant difference is observed based on the use of referrals. It is challenging to attribute this seemingly contradictory result to weak signals from referrals that may not be captured by the estimation. This is because the effect on wage remains insignificant even for referrals with higher quality in terms of praise or length. Therefore, the paper concludes that an alternative explanation, such as a combination of weak credibility of referrals and wage rigidity, needs to be explored and verified.

This paper contributes to the literature examining the role of referrals in reducing information friction in the hiring process. Dustmann et al. (2015) extend Jovanovic (1979)'s learning-matching model, demonstrating that workers hired through referrals earn higher wages and are less likely to leave their firms, with these effects diminishing over tenure. Unlike they use co-nationals in a firm as a proxy for referrals, Glitz and Vejlin (2019) employ the presence of a former coworker at the time of hiring as a proxy for referrals, finding similar outcomes. Galenianos (2013) presents a more general setting where firms endogenously choose search methods with analogous predictions about the impact of referrals.

However, as noted by Brown et al. (2016), learning models of referrals yield mixed predictions regarding relative hiring probabilities. In response, they and Burks et al. (2015) conduct empirical work based on alternative approaches following Montgomery (1991) and Galenianos (2014), using actual referral data rather than proxies. Their results indicate that firms are more likely to hire applicants referred by existing employees than non-referred applicants.

In contrast to these studies focusing on employee referrals, where hiring firms seek referrals from existing workers, this paper investigates referrals where the referrers are not current employees of the hiring firms.[1] One advantage of studying 'external' referrals instead of employee referrals is the ease of considering the quality of referrals. However, to my knowledge, only a few papers have examined external referrals. Pallais (2014), in a study on the inefficient hiring of inexperienced workers, explores the differences in subsequent employment outcomes between workers with no evaluation, those with coarse public evaluations, and those with detailed evaluations. Experimental data show that workers with evaluations are more likely to be hired than those without evaluations. Providing workers with detailed evaluations also increases their earnings, contingent on good performance. However, due to the primary focus and data characteristics, she concentrates on inexperienced workers and temporary jobs. In contrast, this paper encompasses both experienced and inexperienced workers, considering regular jobs. Additionally, various methods to control the quality of referrals are explored.

The remainder of the paper is organized as follows: Section 2.2 describes microdata from a private matching platform between firms and workers. Section 2.3 outlines the empirical strategy. In Section 2.4, the estimation results of referrals' effects on hiring and wages are presented. Finally, Section 2.5 concludes.

## 2.2 Data

### 2.2.1 Description of the data

To estimate the effect of referrals, I utilize new data obtained from a Korean private company. This company has been operating a matching platform connecting workers and firms since 2016. Firms seeking to hire workers can post job advertisements on the platform, providing details such as the firm's introduction, position information, main tasks, qualifications, and non-wage

[1] Note that the relationship between referrers and applicants could be the same.

benefits. Notably, hiring firms also specify the minimum and maximum levels of wages they are willing or intend to pay for the position.[2] The actual wage is expected to be determined within this range, primarily based on the workers' abilities, qualifications, and other factors.

Registered platform users, who are workers, can freely apply to the posted positions. A distinctive feature of the application process is that workers have the option to submit a referral, which is a letter describing or commenting on the worker's attributes and abilities. Workers can request referrals from their acquaintances at any time, and once obtained, referrals can be used freely. This means a referral can be utilized multiple times if the applicant deems it helpful for securing a position, or not at all otherwise. Recognizing that the use of referrals may enhance the probability and quality of matching, the platform incentivizes applicants to utilize referrals by offering financial rewards for both the referrer and the applicant in the case of a successful match. Meanwhile, applicants provide individual information, including education, employment history, years of work experience, etc.

In the event of a successful match, the hiring firm pays a fee proportional to the annual wage offered to the hired applicant. Therefore, when a firm decides to hire one of the applicants, it informs the platform not only about the hiring decision but also the level of wage to be paid.

As a result, I have access to valuable information on offered positions, applicants, and application outcomes. Nevertheless, there are some limitations that I have attempted to address. Firstly, the platform does not collect information on the gender of users.[3] Recognizing that gender could be a significant factor explaining differences in both wages and the use of referrals, I imputed gender primarily from applicants' names. For those with gender-neutral names, I utilized the length of university years for gender imputation, considering that most Korean men undergo military service during this period.[4] Additionally, I cannot directly observe the employment status of each applicant at the time of application, which may impact wage levels and the use of referrals. To address this, I inferred employment status from the provided employment history information. Another limitation arises from the possi-

[2]These are not open to applicants.
[3]It is related to belief of people operating the platform on the ideal recruiting.
[4]The methods for imputing gender are explained in detail in Appendix.

bility of the same position being posted more than once for various reasons, such as expansion, turnover, or layoffs. In this case, those postings should be treated as different postings for different positions in my estimation,[5] but, unfortunately, the platform does not distinguish between such postings, using the same 'position ID.' To handle this, I employed a series of application timestamps for each position ID. If the gap between two consecutive applications for a position exceeds two months, I treat the applications before and after the gap as applying for two distinct postings.

Before proceeding to the next subsection, it is crucial to acknowledge that the data may not be representative of the entire Korean labor force. Unlike the official Korean Labor Force Survey, it lacks sampling methods and weights that consider the overall demographics of the population. Furthermore, as evident from the job opening statistic below, positions matched through the platform are more likely to be related to information technology (IT), such as computer programmers and web designers, rather than traditional manufacturing or service industries. However, this can be advantageous for hiring research, given the significant increase in IT job openings in Korea and the high job-to-job transition rate in this sector. Most importantly, despite its weaknesses in representativeness, the data offers unique insights into the use of referrals, justifying its use for research purposes.

### 2.2.2 Statistics

Table 2.1 presents descriptive statistics for application cases and workers in the data from January 2017 to April 2019.[6] While a total of 260,781 applications were made by 32,761 workers during this period, some cases lack the necessary variables for estimating the effect of referrals. Therefore, the analysis focuses on 191,398 application cases with complete information about applicants and positions[7], involving 21,633 workers. Approximately 80% of

[5]It is necessary to calculate the total number of applicant for the position, which is an important variable as one can see in the empirical strategy.

[6]While the platform started the service since 2016, I do not use the application cases of 2016. As the service was in its early stage in 2016, there were several big changes in operating policy. Therefore, the data from the period have some noises while the number of application cases is quite small compare to the years after that.

[7]Note that the distributions of education, gender, and the employment status are quite similar between before and after the selection. On the other hand, the ratio of workers with zero work experience is lower after the selection, which indicates that one must be careful

the applicants have at least a college degree, and male applicants outnumber female applicants. Around 58% of applicants were employed at the time of their first application through the platform, and nearly 80% have at least one year of work experience.

Referrals were submitted for about 5% of application cases in the regression sample. Notably, the ratio of successful matches (i.e., hired cases) is 0.8%[8] for all application cases in the regression sample. However, for cases with a referral, this ratio more than doubles to 1.66%. This suggests a positive effect of referrals on the probability of hiring, as further supported in the following section. On the other hand, the number of applicants who have used referrals at least once is 1,241, representing about 5.7% of all applicants in the regression sample. Previous research indicates that the use of referrals is influenced by worker characteristics, such as education level, job status, and gender(Topa (2011)). A t-test between applicants with and without referral experience reveals a higher tendency for referral use among applicants with a college degree or above. Additionally, the table indicates that employed applicants or those with work experience are more likely to use referrals in job searches. However, there is no significant difference in the distribution of gender between applicants using referrals and others. The formal examination of the tendency of referral use based on workers' characteristics will be explored in the main estimation, with some results potentially differing from those mentioned above.

Table 2.2 provides insights into the positions posted in the regression sample, totaling 13,350.[9] Notably, the majority of these positions are related to information technology, with a significant portion(40%) seeking computer programmers. Additionally, approximately 11% of positions are for web or mobile design. Positions related to business planning and marketing strategies each account for about 14%. Approximately 8% of positions are associated with sales and customer service. On average, about 19 workers have applied for

about the interpretation of zero work experience. First, some of applicants who do not want to provide their information to the platform may answer that they have zero work experience. In addition, not only the workers who have never been employed but also some of workers who just started their current job can say that they have zero work experience.

[8]The ratio is quite low. It can be explained by 1) there are many applicants for those positions through channels other than the platform that the data come from, 2) some positions fail to find a proper worker, etc.

[9]In the case of repeated postings for the same position, I counted them as different positions.

each position, and the average annual wage in the case of a successful match is approximately £26,900.

Table 2.1: Descriptive Statistics: Application cases & Workers

| | All | | Regression Sample | | | |
|---|---|---|---|---|---|---|
| | | | All | | Referral used | |
| | Obs | Share(%) | Obs | Share(%) | Obs | Share(%) |
| <Application cases> | | | | | | |
| All | 260,871 | | 191,389 | | 9,502 | (4.96)# |
| Hired | 2,049 | (0.79) | 1,528 | (0.80) | 158 | (1.66)** |
| <Applicants> | | | | | | |
| All | 32,761 | | 21,633 | | 1,241 | (5.74)# |
| College or above | 19,981 | (79.65) | 17,425 | (80.55) | 1,030 | (83.00)* |
| Junior college | 4,246 | (16.93) | 3,534 | (16.34) | 180 | (14.50) |
| High school | 859 | (3.42) | 674 | (3.12) | 31 | (2.50) |
| Male | 17,785 | (57.87) | 12,615 | (58.31) | 703 | (56.65) |
| Female | 12,948 | (42.13) | 9,018 | (41.69) | 538 | (43.35) |
| Employed | 13,337 | (57.51) | 12,439 | (57.50) | 783 | (63.09)** |
| Unemployed | 9,853 | (42.49) | 9,194 | (42.50) | 458 | (36.91)** |
| Experience>=1 | 24,590 | (75.70) | 17,468 | (80.75) | 1,070 | (86.22)** |
| (Ave. years) | 5.19 | | 5.31 | | 5.31 | |
| Experience=0 | 7,895 | (24.30) | 4,165 | (19.25) | 171 | (13.78)** |

Note: 'Share' means the each entry's share of application cases or applicants in each column, except for ones marked with #, which means the referral used sample's share of all regression sample. 'Employed' means that the worker were employed at the time of his first application thorough the platform. As for the results of t-test between referral used application cases/applicants and the others in regression sample, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 2.2: Descriptive Statistics: Positions

| | Obs | Share |
|---|---|---|
| All | 13,350 | |
| Programmer | 5,433 | (40.70) |
| Designer(web, industrial, graphic) | 1,511 | (11.32) |
| Business(plan maker) | 1,959 | (14.67) |
| Marketing | 1,885 | (14.12) |
| Sales & customer service | 1,141 | (8.55) |
| Others | 1,421 | (10.64) |
| (Ave. annual wage, pound) | 26,900 | |
| (Ave. # of applications) | 19.39 | |

Note: In the case of repeated postings for the same position, I considered them as different positions.

## 2.3 Empirical strategy

### 2.3.1 Two issues

The primary objective of this paper is to study the impact of using referrals on the probability of being hired and the level of wage upon being hired. Specifically, the focus is on "decent" referrals, referring to those that applicants actually use. Notably, applicants can review the content of referrals before deciding whether to submit them, implying that the submission of a referral indicates that it speaks positively enough about the applicant. Therefore, the effect of using referrals is expected to be positive.

However, two issues make it impractical to study these effects through simple probit estimation of the hiring equation and OLS estimation of the wage equation separately. Firstly, there is a censoring problem with wage data, where wage information is observable only when the application is successful. Additionally, there may be unobservable factors influencing both the hiring decision and wage levels. For instance, workers' abilities which are unobservable to researchers, may impact both the probability of worker hire and the wage level. In such cases, the residuals in hiring and wage equations become positively correlated, leading to downward biased estimates of the effect on wage in OLS estimation, as shown by Heckman (1979). To address this, Heckman proposes a two-step method treating selection bias as an omitted variable to consistently estimate the effect on wages. The first step in Heckman's method involves probit estimation of the selection equation. However, my empirical strategy differs due to the second issue: the potential endogeneity of using referrals. For instance, the likelihood of receiving a decent referral may be higher for applicants with positive attributes, which are often unobservable to researchers. However, if some of these attributes are visible to hiring firms during the recruitment process, even without referrals, and positively influence hiring and wage, then the effect of referrals might be overestimated in probit estimation. Conversely, a negative correlation between the use of referrals and residuals in the hiring and wage equation is also plausible. For example, while a worker's personality is generally unobservable, shy individuals may find it challenging to fully showcase their abilities during a job interview. If shy individuals are more inclined to use referrals to compensate for their perceived weaknesses, the effect of referrals might be underestimated in probit estimation. Regardless of the direction of this correlation, it is imperative to consider the potential endogeneity of using referrals in the analysis.

### 2.3.2 Methods

Kim (2006) introduces a method to study a sample selection model with a common endogenous dummy regressor for the selection and censored equation. The method is a generalization of Heckman's approach: the first step involves a bivariate probit estimation of selection and the endogenous dummy regressor, representing the use of referrals in my case. Following his method, there are three estimating equations for studying the effect of referrals as follows:

$$R_i = 1[Z_{1i}'\gamma_1 + \epsilon_{1i} > 0] \tag{2.1}$$

$$H_i = 1[Z_{2i}'\gamma_2 + R_i\beta_2 + \epsilon_{2i} > 0] \tag{2.2}$$

$$W_i = H_i * [Z_{3i}'\gamma_3 + R_i\beta_3 + \epsilon_{3i}] \tag{2.3}$$

where each i represents an application by a worker for a job position. $H_i$ is an indicator of the hiring decision, equal to 1 if the application was successful, i.e., the applicant is hired for the position. $W_i$ is the log annual wage of the worker when $H_i$ is equal to 1. $R_i$ is an indicator taking the value 1 if the worker submitted a referral during the application process. The key coefficients of interest are $\beta_2$ and $\beta_3$, where $\beta_2$ measures the effect of referrals on the hiring decision, and $\beta_3$ measures the effect on the log wage.

In addition, I assume the following[10] [11]:

$$\begin{pmatrix} \epsilon_1 \\ \epsilon_2 \end{pmatrix} \sim N(0, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix})$$

$$E(\epsilon_3 \mid \epsilon_1, \epsilon_2) = \delta_1\epsilon_1 + \delta_2\epsilon_2$$

Then the conditional expectation of wage is

$$E(W_i \mid Z_i, R_i, H_i = 1) = Z'_{3i}\gamma_3 + R_i\beta_3 + R_iE(\epsilon_{3i} \mid Z_i, R_i = 1, H_i = 1)$$
$$+(1 - R_i)E(\epsilon_{3i} \mid Z_i, R_i = 0, H_i = 1) \qquad (2.4)$$

where $Z_i = (Z'_{1i}, Z'_{2i}, Z'_{3i})'$. Similarly to Poirier (1980), one can find

$$E(\epsilon_{3i} \mid Z_i, R_i = 1, H_i = 1) = (\delta_1{+}\rho\delta_2)[\frac{\phi(Z'_{1i}\gamma_1)\Phi((Z'_{2i}\gamma_2 + \beta_2 - \rho Z'_{1i}\gamma_1)/\sqrt{1-\rho^2})}{\Phi(Z'_{1i}\gamma_1, Z'_{2i}\gamma_2 + \beta_2; \rho)}]$$
$$+(\delta_2 + \rho\delta_1)[\frac{\phi(Z'_{2i}\gamma_2 + \beta_2)\Phi((Z'_{1i}\gamma_1 - \rho(Z'_{2i}\gamma_2 + \beta_2))/\sqrt{1-\rho^2})}{\Phi(Z'_{1i}\gamma_1, Z'_{2i}\gamma_2 + \beta_3; \rho)}] \qquad (2.5)$$

$$E(\epsilon_{3i} \mid Z_i, R_i = 0, H_i = 1) = -(\delta_1{+}\rho\delta_2)[\frac{\phi(Z'_{1i}\gamma_1)\Phi((Z'_{2i}\gamma_2 - \rho Z'_{1i}\gamma_1)/\sqrt{1-\rho^2})}{\Phi(-Z'_{1i}\gamma_1, Z'_{2i}\gamma_2; -\rho)}]$$
$$+(\delta_2 + \rho\delta_1)[\frac{\phi(Z'_{2i}\gamma_2)\Phi((-Z'_{1i}\gamma_1 + \rho Z'_{2i}\gamma_2)/\sqrt{1-\rho^2})}{\Phi(-Z'_{1i}\gamma_1, Z'_{2i}\gamma_2; -\rho)}] \qquad (2.6)$$

Let's define $\alpha \equiv (\gamma_1, \gamma_2, \beta_2, \rho)$, $C_{11i}(\alpha) \equiv \frac{\phi(Z'_{1i}\gamma_1)\Phi((Z'_{2i}\gamma_2+\beta_2-\rho Z'_{1i}\gamma_1)/\sqrt{1-\rho^2})}{\Phi(Z'_{1i}\gamma_1, Z'_{2i}\gamma_2+\beta_2;\rho)}$, $C_{12i}(\alpha) \equiv \frac{\phi(Z'_{2i}\gamma_2+\beta_2)\Phi((Z'_{1i}\gamma_1-\rho(Z'_{2i}\gamma_2+\beta_2))/\sqrt{1-\rho^2})}{\Phi(Z'_{1i}\gamma_1, Z'_{2i}\gamma_2+\beta_3;\rho)}$, $C_{01i}(\alpha) \equiv -\frac{\phi(Z'_{1i}\gamma_1)\Phi((Z'_{2i}\gamma_2-\rho Z'_{1i}\gamma_1)/\sqrt{1-\rho^2})}{\Phi(-Z'_{1i}\gamma_1, Z'_{2i}\gamma_2;-\rho)}$, $C_{02i}(\alpha) \equiv \frac{\phi(Z'_{2i}\gamma_2)\Phi((-Z'_{1i}\gamma_1+\rho Z'_{2i}\gamma_2)/\sqrt{1-\rho^2})}{\Phi(-Z'_{1i}\gamma_1, Z'_{2i}\gamma_2;-\rho)}$ to simplify the notation.

As the correction terms $C_{11i}$, $C_{12i}$, $C_{01i}$ and $C_{02i}$ become feasible when $\alpha$ is known, the initial step involves estimating a bivariate probit model. In essence, I estimate $\alpha$, which encompasses the effect of referrals on the probability of being hired, by maximizing the following log-likelihood:

[10] Note that these are weaker than assuming $(\epsilon_1, \epsilon_2, \epsilon_3)$ to be jointly normally distributed.

[11] Kim (2006) allows the correlations between $\epsilon_1$, $\epsilon_2$ and $\epsilon_3$ can be switched depending on the value of the endogenous dummy regressor.

$$lnL(\alpha) = \sum_{i=1}^{n} [R_i H_i ln\Phi(Z_{1i}'\gamma_1, Z_{2i}'\gamma_2 + \beta_2; \rho) + R_i(1-H_i) ln\Phi(Z_{1i}'\gamma_1, -Z_{2i}'\gamma_2 - \beta_2; -\rho)$$

$$+(1-R_i)H_i ln\Phi(-Z_{1i}'\gamma_1, Z_{2i}'\gamma_2; -\rho) + (1-R_i)(1-H_i) ln\Phi(-Z_{1i}'\gamma_1, -Z_{2i}'\gamma_2; \rho)] \tag{2.7}$$

Given $\hat{\alpha}$ from the first step, the effect of referrals on wage can be estimated by regressing $W_i$ on $(Z_{3i}, R_i, R_i C_{11i}(\hat{\alpha}) + (1-R_i)C_{01i}(\hat{\alpha}), R_i C_{12i}(\hat{\alpha}) + (1-R_i)C_{02i}(\hat{\alpha}))$ using the subsample where $H_i = 1$. In other words, the equation to be estimated in the second step is:

$$W_i = Z_{3i}'\gamma_3 + R_i\beta_3 + \mu_1(R_i C_{11i}(\hat{\alpha}) + (1-R_i)C_{01i}(\hat{\alpha})) + \mu_2(R_i C_{12i}(\hat{\alpha}) + (1-R_i)C_{02i}(\hat{\alpha})) + \eta_i \tag{2.8}$$

### 2.3.3 Exclusion restrictions and regressors

When implementing this two-step estimation method in practice, two exclusion restrictions are necessary to avoid the multicollinearity problem. Firstly, at least one element (referred to as the first instrumental variable, IV1 in the following) of $Z_1$, the vector of regressors in the referral equation, should not be present in $Z_2$, the vector of regressors in the hiring equation. As found by Han and Vytlacil (2017), IV1 plays a crucial role in identifying the parameters in the first step, i.e., bivariate probit with a dummy endogenous regressor. Additionally, at least one element (IV2 in the following) of $Z_2$, the vector of regressors in the selection equation, should not be present in $Z_3$, the vector of regressors in the wage equation. Similar to the usual Heckman correction, it is essential to avoid multicollinearity in the second step, especially when the regressors do not vary much in the sample. In the following, I explain which variable I use as IV1 and IV2 and why, along with the introduction of other regressors.

Let me begin by explaining $Z_3$, the vector of regressors in the wage equation, as it is the smallest group of regressors. The most significant variable in $Z_3$ is the log of the minimum level of wage that the firm 'intends to pay.' It is introduced as a proxy for job-specific factors, such as job-specific productivity, which would be the sole determinant of the wage when the applicant's qualifications have the lowest value acceptable for the job. Therefore, one can expect that the minimum intended wage can be a key control for job-specific effects in both wage and hiring decisions. $Z_3$ also includes other job characteristics, such as occupation dummies and the minimum requirement of work experience. As for worker-specific variables, the level of education, years of work experience and its square, a variable indicating whether the applicant is employed or not at the time of application, and an indicator of gender are present in $Z_3$ as well.

To satisfy the exclusion restrictions on the regressors in the hiring equation and those in the wage equation, the former includes the total number of applicants for the same job position as IV2. While it is straightforward that the probability of being hired would decrease as the number of applicants for the same position increases, doubts could arise about the assumption that the number of applicants is not directly related to wage. One might argue that higher wages lead to a larger number of applicants because people may prefer jobs that provide higher wages. However, I control for these factors by introducing the minimum level of intended wage, as mentioned earlier. Therefore, it is acceptable to assume that the level of wage cannot directly affect the number of applicants. On the other hand, concerns may arise that more applicants for a given job will increase the firm's bargaining power and result in lower wages. However, this channel can be ruled out by assuming a standard no-commitment approach, following Blanchard and Diamond (1994). According to this assumption, even if a candidate agrees to take a job at a lower wage because of weak bargaining power due to the presence of other candidates, the hired worker will try to renegotiate the wage as soon as the other candidates leave, knowing that they have been eliminated. This is consistent with the real-world hiring process, where wage negotiations generally take place between the successful applicant and the employer after the outcome of the application is known to both the successful and unsuccessful applicants.[12]

The final point I would like to explain in this section is IV1, the regressor included in the referral equation but not in the hiring equation. For IV1, I use the indicator of whether the applicant chooses to use a 'service' that finds potential referrers using information about her current or past working

[12]Note that I also include the square of the total number of applicants into the hiring equation in order to allow non-linear relationship. Similarly, I control the square of years of work experience in both equations. The reason that the non-linearity does matter for those two variables is their relatively larger variance while other variables are dummy variables or logged value.

experience. If she does, the platform automatically finds and shows registered users who have worked for the same company and choose to use the same service as well. Once she finds some suitable referrers among them, it is quite straightforward to ask them to write referrals through the platform. On the other hand, if an applicant does not use the service, she has to find referrers herself and ask for referrals by sending a link through a short message service (SMS). In this case, the referrer has to register as a user of the platform before writing requested referrals, unless he is an existing user already. Using the service can increase the probability of using referrals for two reasons: it is easier to find potential referrers for applicants using the service, and the procedure for writing referrals is likely to be simpler when applicants find referrers through the service. On the other hand, I assume that the use of the service does not directly affect hiring decisions for the following reasons.[13] As there are incentive to try to achieve referrals[14], an applicant will choose to use the service unless she is reluctant to reveal to her co-workers that she is a user of the platform[15], which may mean that she is looking for a new job. It would be reasonable to assume that the reluctance does not directly affect the probability of being hired. In addition, firms cannot observe whether applicants are using the service or not.

## 2.4 Results

### 2.4.1 Basic results

Table 2.3 presents the results from the first step, i.e., the bivariate probit estimation of equations (2.1) and (2.2), where the dependent variables are the indicator for the use of a referral ('Referral use') and the hiring decision ('Hiring'). My preferred specification is (2), which includes more information on the posted job position, such as occupation dummies. According to specifica-

[13]For the same reason, I assume that it does not affect the level of wage either.

[14]First of all, this platform provides financial rewards for successful application with a referral, while applicants can choose to whether or not to submit referrals after checking the contents of them, i.e. there is no penalty from getting bad referrals. In addition, the availability of referrals, which is uniqueness of the platform, may be one of the reason why the applicants are looking for jobs through the platform.

[15]Note that the applicants who choose to use the service would show up on the list of potential referrers for her co-workers.

tion (2), the use of a decent referral can significantly increase the probability of being hired. Using the descriptive statistics in Section 2.2.2, let's consider an average job position: a programmer position that requires at least 3 years of experience, with the minimum wage the company is willing to pay for the position being £26,900 per year, and a total of 20 applicants applied. An average applicant who is male graduated from college, has 5.31 years of work experience, is currently employed by another company, and decides not to use a referral according to equation (2.1) has a 1.4 percent chance of being hired for this position. However, in the counterfactual case where this applicant uses a referral, the probability increases to 25.3 percent.

This is a very large effect, much higher than that in the case of simple probit estimation in Heckman's method.[16] This is related to the fact that the correlation between the unobservables in the equation for the use of referrals and that for being hired, is significantly negative. It can be interpreted as follows: applicants who are more likely to be undervalued in hiring decisions tend to use referrals more frequently to make up for their weaknesses. Unlike a simple probit, which does not take this tendency into account, my method does, explaining why the effect of referrals on hiring probability is estimated to be much stronger. Additionally, the fact that Korean firms are having a harder time identifying the right people for their jobs due to the upward leveling of qualifications on applicants' resumes and the increased sharing of information on interview tips, etc. may have contributed to the large effect of referrals, providing information that only someone who has been with the applicant for a long time can know. As a result, one can conclude that decent referrals, at least in part, provide hiring firms with positive information regarding applicants' productivity that they otherwise would not have.

Let's take a closer look at the results of estimating the equation for the use of referrals. As expected, the use of the referrer-finding service is strongly correlated with referral use. Meanwhile, one can observe variation in the use of referrals by some demographic characteristics that have been mentioned in many literatures. For example, Datcher (1983) reports more frequent use of informal contacts for less educated job seekers, and one theoretical explanation is that less educated workers have a stronger incentive to join a network

[16]The coefficient on the referral in the probit estimation with the same regressors is just 0.2875.

Table 2.3: The use of referrals and hiring probability

| | (1) | | (2) | |
|---|---|---|---|---|
| | Referral use | Hiring | Referral use | Hiring |
| Referral use | - | 2.5330** | - | 1.5297** |
| | - | (0.3682) | - | (0.5450) |
| High school | 0.1267** | -0.1431** | 0.1203** | -0.2060** |
| | (0.0260) | (0.0554) | (0.0265) | (0.0605) |
| Junior college | -0.0307* | -0.1187** | -0.0523** | -0.1620** |
| | (0.0131) | (0.0264) | (0.0134) | (0.0276) |
| Experience | 0.0291** | 0.0271** | 0.0314** | 0.0377** |
| | (0.0034) | (0.0066) | (0.0035) | (0.0070) |
| Experience$^2$ | -0.0025** | -0.0024** | -0.0026** | -0.0029** |
| | (0.0002) | (0.0005) | (0.0002) | (0.0005) |
| Employment status | -0.0168 | -0.0066 | -0.0083 | -0.0117 |
| | (0.0099) | (0.0183) | (0.0101) | (0.0192) |
| Gender | -0.0201* | -0.0913** | -0.0140 | -0.1411** |
| | (0.0102) | (0.0186) | (0.0108) | (0.0204) |
| Min. intended wage | 0.0481** | -0.0355 | 0.0511** | -0.0590* |
| | (0.0174) | (0.0325) | (0.0192) | (0.0366) |
| Referrer finding service | 0.1826** | - | 0.1855** | - |
| | (0.0195) | - | (0.0198) | - |
| #Applicants | 0.0001 | -0.0030** | 0.0001 | -0.0029** |
| | (0.0002) | (0.0003) | (0.0002) | (0.0003) |
| #Applicants$^2$ | -5.45e-7 | 5.51e-6** | -5.02e-7 | 5.49e-6** |
| | (4.04e-7) | (7.94e-7) | (4.12e-7) | (8.38e-7) |
| Occupations, etc. | - | - | ✓ | ✓ |
| $\rho$ | -0.7619** | | -0.4858* | |
| obs | 192683 | | 191389 | |

Note: Standard errors in parentheses. $^{**}p < 0.01$, $^{*}p < 0.05$

that can be helpful for job search because they face a higher probability of job loss (see Topa (2011)). On the other hand, more educated people may have a social network with a larger size and better quality. Both predictions can be encompassed by the result in Table 3, which shows that, compared to college graduates, high school graduates are more likely to use referrals, while junior college graduates are less likely to use them. Regarding gender differences, the results are insignificant, similar to the mixed evidence in previous literatures: e.g., Rosenbaum et al. (1999) find that women tend to use informal contacts less than men, while Moore (1990) shows that most gender differences in personal networks disappear or are considerably reduced when information about employment, age, and family is controlled. In addition, the tendency to use referrals increases with the years of work experience, which may be due to the increase in the size of the social network, albeit at a decreasing rate. The positive coefficient on the minimum level of intended wage may reflect that applicants use referrals more frequently when they apply for more desirable jobs.

Before discussing the effect on wages, let's look at the effect of other variables on the hiring decision. First, one can see that the probability of being hired significantly decreases with the number of total applicants for that firm, which supports the use of the variable as an IV2 for the estimations. College graduates enjoy a higher probability of being hired than high school or junior college graduates. The years of work experience also significantly increase the hiring probability but at decreasing rates. Therefore, one can say that these results are consistent with the usual predictions about the effect of abilities or qualifications.[17]

According to Table 2.4, which summarizes the results of the second step for estimating the wage equation, the effect of referrals on the level of wage is insignificant.[18] It is unexpected and quite hard to explain given its positive effect on hiring probability. One possibility could be too small an effect of the information conveyed by referrals on productivity to be captured by the estimation. I will partially test this explanation in the next subsection.

Before going to the next subsection, one can find the effect of other variables on wages. Similarly to the effect on hiring, the level of education and the years of work experience are positively related to the level of wage. On the other hand, the effect of employment status is different between hiring and wage, as the wage of currently employed applicants is higher than that of the unemployed. Currently employed applicants may have a higher reservation wage and productivity[19] compared to unemployed applicants, so the

[17]One thing somewhat hard to explain is the effect of the indicator for gender equal to 1 if the applicant is male and 0 otherwise. According to the results, the probability of hiring is significantly low for male applicants while there is no gender difference in wage, as you can see in the Table 2.4. One possible explanation can come from the industrial characteristics of the sample. The most of applications are for firms related to information technology, in which female workers are relative rare in general. Therefore, if firms take account of gender ratio for some reasons which are not directly related to the production, e.g. pursuing diversity, they can prefer female applicants to male as long as they have similar productivity (and reservation wage).

[18]As for the standard errors of the wage equation coefficients, I use the bootstrap method with 100 replications. However, the results are robust when I use the numerically calculated asymptotic standard errors following Kim (2006). As for the results with asymptotic standard errors, see the Appendix.

[19]E.g. One can assume that currently employed workers are quicker to adapt themselves to new jobs compare to unemployed workers.

Table 2.4: The effect on wage

| | (1) | (2) |
|---|---|---|
| | ln(Wage) | ln(Wage) |
| Referral use | 0.2793 | -0.1381 |
| | (0.3812) | (0.3865) |
| High school | -0.1351** | -0.1563** |
| | (0.0302) | (0.0272) |
| junior college | -0.0919** | -0.0984** |
| | (0.0172) | (0.0202) |
| Experience | 0.0800** | 0.0811** |
| | (0.0049) | (0.0046) |
| Experience$^2$ | -0.0019** | -0.0021** |
| | (0.0003) | (0.0003) |
| Employment status | 0.0598** | 0.0478** |
| | (0.0103) | (0.0103) |
| Gender | 0.0407** | 0.0011 |
| | (0.0118) | (0.0149) |
| Min. intended wage | 0.2595** | 0.1910** |
| | (0.0314) | (0.0384) |
| $C_1$ | -0.0867 | 0.0369 |
| | (0.0981) | (0.1333) |
| $C_2$ | 0.1244* | 0.1547** |
| | (0.0588) | (0.0570) |
| Occupations, etc. | - | ✓ |
| obs | 192683 | 191389 |

Note: Bootstrapped(rep.100) standard errors in parentheses. $^{**}p < 0.01$, $^{*}p < 0.05$

employed would get a higher wage when they achieve a new job. However, if the difference in reservation wage between the employed and the unemployed is similar to the difference in productivity, then, as for the hiring decision, firms would be indifferent between the employed and the unemployed. Finally, the minimum level of the intended wage is strongly and positively related to the level of wage, as expected.

### 2.4.2 Exploiting the quality of referrals

How the basic results, where the use of a referral increases the probability of being hired but does not affect the level of wage, can be explained? It could be attributed to limitations in the estimation, i.e. while applicants with decent referrals are expected to lead to higher productivity, the difference from those without referrals might be too small to be accurately captured by the estimation. If it is true, it would be possible to find a positive effect on wage in the case of more decent referrals, i.e. referrals convey stronger evaluations/signals. To further investigate this, it is essential to consider the quality of referrals.

One way to assess this is by examining the kinds of words used in each referral.[20] As I mentioned earlier, referrals with evaluations positive enough to encourage workers to submit them for applications are considered. However, the strength of positiveness can vary across referrals. In other words, while all referrals include some positive words describing workers, some of them can include higher praises. Therefore, referrals are divided into two groups: one containing words like 'exceptional' and 'the best', and another with words like 'fine' and 'good'. The estimation method is extended accordingly, using a bivariate 'ordered' probit in the first step, and amending the correction terms in the second step. [21]

Table 5 presents the effect of referrals with and without high praise. Note that both specification (1) and (2) include all other regressors included in the specification (2) of Table 2.3 and 2.4.[22] Specification (1) estimates the effect of each group of referrals separately, while specification (2) estimates the 'additional' effect of referrals with high praises compared to referrals without them. The results of specification (1) show that the effect on hiring is significant, but the effect on wages remains insignificant regardless of the level of praise. Notably, the positive effect of referrals with high praises on hiring probability is significantly higher than the effect of referrals without them in the specification (2), suggesting that the former includes stronger evaluations/signals than the latter. Therefore, the insignificant effect on wages is challenging to explain as a result of too weak signals from referrals to be estimated.

Similar results are obtained when controlling for the quality of referrals in another way, such as considering the length of referrals. As I consider referrals with evaluations that are positive enough to make workers submit them for applications, longer length may mean more specific praises. In the specifications in Table 2.6, referrals are divided into two groups: one with more than

[20]As for statistics regarding the quality of referrals, see the Appendix.

[21]The details are explained in Appendix.

[22]I omit the estimation results with respect to the other regressors as they are very similar to the results in Table 2.3 and 2.4.

Table 2.5: The effect of referrals with high praises

| | (1) | | (2) | |
|---|---|---|---|---|
| | Hiring | ln(Wage) | Hiring | ln(Wage) |
| RF w/ High praises | 1.6918** | -0.1129 | 0.2677* | 0.0673 |
| | (0.6113) | (0.4187) | (0.1105) | (0.0722) |
| RF w/o High praises | 1.4241** | -0.1802 | - | - |
| | (0.5175) | (0.3565) | - | - |
| All RF | - | - | 1.4241** | -0.1802 |
| | - | - | (0.5175) | (0.3365) |
| $C_1$ | - | 0.0410 | - | 0.0410 |
| | - | (0.1250) | - | (0.1198) |
| $C_2$ | - | 0.1531* | - | 0.1531* |
| | - | (0.0711) | - | (0.0604) |
| $\rho$ | -0.4781* | - | -0.4781* | - |
| obs | 191,389 | 1,528 | 191,389 | 1,528 |

Note: Additional regressors included are a education dummy, years of work experience and its square, a dummy indicating current employment status, a gender dummy, log of minimum level of intended wage, total number of applicants and its square, occupation dummies and minimum requirement of work experience. Standard errors in parentheses for Hiring. Bootstrapped(rep.100) standard errors in parentheses for Wage. $^{**}p < 0.01$, $^{*}p < 0.05$

500 letters and another with equal or fewer than 500 letters. The effects on wage are still insignificant for both long and short referrals, while the former increases the hiring probability significantly more than the latter, with the difference being even more substantial than that in Table 2.5.

Table 2.6: The effect of long referrals

| | (1) | | (2) | |
|---|---|---|---|---|
| | Hiring | ln(Wage) | Hiring | ln(Wage) |
| Long RF | 2.3344** | 0.1110 | 0.6992** | 0.1271 |
| | (0.5614) | (0.4513) | (0.0955) | (0.0882) |
| Short RF | 1.6352** | -0.0161 | - | - |
| | (0.4860) | (0.3671) | - | - |
| All RF | - | - | 1.6352** | -0.0161 |
| | - | - | (0.4860) | (0.3825) |
| $C_1$ | - | -0.0182 | - | -0.0182 |
| | - | (0.1170) | - | (0.1183) |
| $C_2$ | - | 0.1536* | - | 0.1536* |
| | - | (0.0721) | - | (0.0611) |
| $\rho$ | -0.5599** | - | -0.5599** | - |
| obs | 191,389 | 1,528 | 191,389 | 1,528 |

Note: Long RF means the group of referrals with more than 500 letters, while Short RF means those with equal or less than 500 letters. Additional regressors included are a education dummy, years of work experience and its square, a dummy indicating current employment status, a gender dummy, log of minimum level of intended wage, total number of applicants and its square, occupation dummies and minimum requirement of work experience. Standard errors in parentheses for Hiring. Bootstrapped(rep.100) standard errors in parentheses for Wage. $^{**}p < 0.01$, $^{*}p < 0.05$

## 2.5 Conclusion

This paper utilizes distinctive data from a private matching platform to examine the impact of referrals from applicants' acquaintances, distinct from those originating from existing employees of hiring firms. The findings reveal that applicants with a referral are more likely to be hired. However, concerning the level of wage, there is no discernible difference based on the use of referrals. The results suggest that hiring firms place value on the additional information about applicants provided by referrals, yet applicants seem to reap the benefits of reduced information frictions primarily in terms of hiring probability.

As the results remain consistent for referrals with stronger signals/evaluations, where they exhibit a more potent effect on hiring probability, the paper concludes that the insignificant effect on wage is not attributable to weak signals from referrals. Then, what can explain the seemingly contradictory results? One can find a clue in the fact that the data is from a platform that serves as a pioneer for referrals in Korea, where there is virtually no established tradition of referrals. This implies that the credibility of referrals may be still low in Korea. A plausible explanation for the lack of impact on wages could be the combination of weak credibility of referrals and wage rigidity towards downward adjustments. In such a scenario, even if the expected productivity of applicants with referrals is higher, hiring firms might prefer to reflect it in wages only after thorough verification, given the difficulty of modifying wages if the information turns out to be untrue. The verification of this theory remains a potential avenue for future research.

## 2.6 Appendix

### 2.6.1 The methods for imputing gender of applicants

One of the limitations of the data is that it does not include the information on gender of applicants. As many studies have shown that wages and the use of referrals can vary by gender, I have imputed it from other information on applicants. First, I used their given name. Even I considered Korean applicants only, there are three kinds of names: 1) Korean name written in Korean alphabet, 2) Korean name written in alphabet, 3) English name. As for the third case, it is quite straightforward to classify them into groups by gender. However, as for many Korean names, it is not that clear to classify. Therefore, after translating the second case into Korean alphabet, I classified them based on information from a web site, kimkkikki (). Using data from the Supreme Court of Korea about names of newborn baby, the web site informs the number of times that each name has been used for boys and girls since 2008. Based on the information, I have classified a name as male(resp. female) name if the number of times it has been used for boys(resp. girls) is more than twice that for girls(resp. boys).

By the method using name, I have imputed gender of 29,722 applicants, which is equivalent to more than 90 percent of 32,761 applicants. In order to increase the number of regression sample as much as possible, I have applied another imputing method to the gender-neutral names, i.e. names with similar frequency of use between boys and girls. The most of Korean men are under obligation to go to army for about two years, and many of them fulfill the duty during their university years. As a result, one can expect that the length of university years of men would be equal or longer than six years. Therefore, for the applicants who have a gender-neutral name and graduated a university in Korea[23], I have classified them as male(resp. female) if the length of university years is longer(resp. shorter) than six years.[24] As a result, I have imputed gender of 30,733 applicants, which is equivalent to about 94 percent of 32,761 applicants.

### 2.6.2 Statistics regarding the quality of referrals

Table 2.7 shows statistics of referral used for the regression sample. One can find that about 40 percent and 22 percent of them are classified as high quality referrals in Section 2.4.2 when I consider the degree of praises and the length of referrals, respectively.

Table 2.7: Statistics: Referrals by quality

| | Obs | Share(%) |
|---|---|---|
| All | 1,406 | |
| w/ High praises | 564 | (40.11) |
| Longer than 500 letters | 315 | (22.40) |
| (Ave. length) | 374.16 | |

### 2.6.3 The estimation methods with two groups of referrals

As there are two groups of referrals, I extend the estimation method as follows:

$$LR_i = 1[\tau > Z'_{1i}\gamma_1 + \epsilon_{1i} > 0] \tag{2.9}$$

$$HR_i = 1[Z'_{1i}\gamma_1 + \epsilon_{1i} > \tau] \tag{2.10}$$

$$H_i = 1[Z'_{2i}\gamma_2 + LR_i\beta_2 + HR_i\beta_3 + \epsilon_{2i} > 0] \tag{2.11}$$

$$W_i = H_i * [Z'_{3i}\gamma_3 + LR_i\beta_4 + HR_i\beta_5 + \epsilon_{3i}] \tag{2.12}$$

where $LR_i$ (resp. $HR_i$) is an indicator taking the value 1 if the worker submitted a referral with low (resp. high) quality in the process of the application, and other terms are the same with the section 2.3.2. Note that the use and its quality of referrals are assumed to be determined by ordered probit now.

[23]Note that I did not apply the method to applicants who graduated foreign universities because they are more likely to go to army after the graduation.

[24]Note that I left applicants with six years of university life as unidentified cases.

In addition, I assume followings as before:

$$\begin{pmatrix} \epsilon_1 \\ \epsilon_2 \end{pmatrix} \sim N(0, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix})$$

$$E(\epsilon_3 \mid \epsilon_1, \epsilon_2) = \delta_1 \epsilon_1 + \delta_2 \epsilon_2$$

Then the conditional expectation of wage is

$$\begin{aligned} E(W_i \mid Z_i, LR_i, HR_i, H_i = 1) = Z'_{3i}\gamma_3 + LR_i\beta_4 + HR_i\beta_5 + HR_i E(\epsilon_{3i} \mid Z_i, HR_i = 1, LR_i = 0, H_i = 1) \\ + LR_i E(\epsilon_{3i} \mid Z_i, HR_i = 0, LR_i = 1, H_i = 1) \\ + (1 - HR_i)(1 - LR_i) E(\epsilon_{3i} \mid Z_i, HR_i = 0, LR_i = 0, H_i = 1) \end{aligned} \tag{2.13}$$

And similarly to the section 3.2., one can find followings:

$$E(\epsilon_{3i} \mid Z_i, HR_i = 1, LR_i = 0, H_i = 1) = (\delta_1 + \rho\delta_2) C_{111i}(\alpha) + (\delta_2 + \rho\delta_1) C_{112i}(\alpha)$$

$$E(\epsilon_{3i} \mid Z_i, HR_i = 0, LR_i = 1, H_i = 1) = (\delta_1 + \rho\delta_2) C_{101i}(\alpha) + (\delta_2 + \rho\delta_1) C_{102i}(\alpha)$$

$$E(\epsilon_{3i} \mid Z_i, HR_i = 0, LR_i = 0, H_i = 1) = (\delta_1 + \rho\delta_2) C_{001i}(\alpha) + (\delta_2 + \rho\delta_1) C_{002i}(\alpha)$$

where I define $\alpha \equiv (\gamma_1, \gamma_2, \beta_2, \beta_3, \tau, \rho)$ and the correction terms for the selection effects:

$$C_{111i}(\alpha) \equiv \frac{\phi(Z'_{1i}\gamma_1 - \tau)\Phi((Z'_{2i}\gamma_2 + \beta_3 - \rho(Z'_{1i}\gamma_1 - \tau))/\sqrt{1-\rho^2})}{\Phi(Z'_{1i}\gamma_1 - \tau, Z'_{2i}\gamma_2 + \beta_3; \rho)},$$

$$C_{112i}(\alpha) \equiv \frac{\phi(Z'_{2i}\gamma_2 + \beta_3)\Phi((Z'_{1i}\gamma_1 - \tau - \rho(Z'_{2i}\gamma_2 + \beta_3))/\sqrt{1-\rho^2})}{\Phi(Z'_{1i}\gamma_1 - \tau, Z'_{2i}\gamma_2 + \beta_3; \rho)},$$

$$C_{101i}(\alpha) \equiv \frac{\phi(Z'_{1i}\gamma_1)\Phi(\frac{Z'_{2i}\gamma_2 + \beta_2 - \rho(Z'_{1i}\gamma_1)}{\sqrt{1-\rho^2}}) - \phi(Z'_{1i}\gamma_1 - \tau)\Phi(\frac{Z'_{2i}\gamma_2 + \beta_2 - \rho(Z'_{1i}\gamma_1 - \tau)}{\sqrt{1-\rho^2}})}{\Phi(Z'_{1i}\gamma_1, Z'_{2i}\gamma_2 + \beta_2; \rho) - \Phi(Z'_{1i}\gamma_1 - \tau, Z'_{2i}\gamma_2 + \beta_2; \rho)},$$

$$C_{102i}(\alpha) \equiv \frac{\phi(Z'_{2i}\gamma_2 + \beta_2)\Phi(\frac{-(Z'_{1i}\gamma_1 - \tau) + \rho(Z'_{2i}\gamma_2 + \beta_2)}{\sqrt{1-\rho^2}}) - \phi(Z'_{2i}\gamma_2 + \beta_2)\Phi(\frac{-Z'_{1i}\gamma_1 + \rho(Z'_{2i}\gamma_2 + \beta_2)}{\sqrt{1-\rho^2}})}{\Phi(Z'_{1i}\gamma_1, Z'_{2i}\gamma_2 + \beta_2; \rho) - \Phi(Z'_{1i}\gamma_1 - \tau, Z'_{2i}\gamma_2 + \beta_2; \rho)},$$

$$C_{001i}(\alpha) \equiv -\frac{\phi(Z'_{1i}\gamma_1)\Phi((Z'_{2i}\gamma_2 - \rho Z'_{1i}\gamma_1)/\sqrt{1-\rho^2})}{\Phi(-Z'_{1i}\gamma_1, Z'_{2i}\gamma_2; -\rho)},$$

$$C_{002i}(\alpha) \equiv \frac{\phi(Z'_{2i}\gamma_2)\Phi((-Z'_{1i}\gamma_1 + \rho Z'_{2i}\gamma_2)/\sqrt{1-\rho^2})}{\Phi(-Z'_{1i}\gamma_1, Z'_{2i}\gamma_2; -\rho)}$$

Then, the first step is to estimate a bivariate ordered probit model. In other words, I estimate $\alpha$, which includes the effect of referrals on the probability of being hired, by maximizing the following log likelihood:

$$lnL(\alpha) = \sum_{i=1}^{n}[HR_i H_i ln\Phi(Z'_{1i}\gamma_1 - \tau, Z'_{2i}\gamma_2 + \beta_3; \rho)$$

$$+HR_i(1 - H_i)ln\Phi(Z'_{1i}\gamma_1 - \tau, -Z'_{2i}\gamma_2 - \beta_3; -\rho)$$

$$+LR_i H_i ln(\Phi(Z'_{1i}\gamma_1, Z'_{2i}\gamma_2 + \beta_2; \rho) - \Phi(Z'_{1i}\gamma_1 - \tau, Z'_{2i}\gamma_2 + \beta_2; \rho))$$

$$+LR_i(1 - H_i)ln(\Phi(Z'_{1i}\gamma_1, -Z'_{2i}\gamma_2 - \beta_2; -\rho) - \Phi(Z'_{1i}\gamma_1 - \tau, -Z'_{2i}\gamma_2 - \beta_2; -\rho))$$

$$+(1 - HR_i)(1 - LR_i)H_i ln\Phi(-Z'_{1i}\gamma_1, Z'_{2i}\gamma_2; -\rho)$$

$$+(1 - HR_i)(1 - LR_i)(1 - H_i)ln\Phi(-Z'_{1i}\gamma_1, -Z'_{2i}\gamma_2; \rho)] \qquad (2.14)$$

Given $\hat{\alpha}$ from the first step, the effect of referrals on wage can be estimated by OLS $W_i$ on $(Z_{3i}, HR_i, LR_i, HR_i C_{111i}(\hat{\alpha}) + LR_i C_{101i}(\hat{\alpha}) + (1 - HR_i)(1 - LR_i)C_{001i}(\hat{\alpha}), HR_i C_{112i}(\hat{\alpha}) + LR_i C_{102i}(\hat{\alpha}) + (1 - HR_i)(1 - LR_i)C_{002i}(\hat{\alpha}))$ using the subsample with $H_i = 1$. In other words, the equation to be estimated in the second step is

$$W_i = Z'_{3i}\gamma_3 + LR_i\beta_4 + HR_i\beta_5 + \mu_1(HR_i C_{111i}(\hat{\alpha}) + LR_i C_{101i}(\hat{\alpha}) + (1 - HR_i)(1 - LR_i)C_{001i}(\hat{\alpha}))$$

$$+\mu_2(HR_i C_{112i}(\hat{\alpha}) + LR_i C_{102i}(\hat{\alpha}) + (1 - HR_i)(1 - LR_i)C_{002i}(\hat{\alpha})) + \eta_i \quad (2.15)$$

### 2.6.4 The effect on wage with asymptotic standard errors

Table 2.8: The effect on wage

| | (1) | (2) |
|---|---|---|
| | log wage | log wage |
| Referral use | 0.2793 | -0.1381 |
| | (0.3561) | (0.4077) |
| High school | -0.1351** | -0.1563** |
| | (0.0291) | (0.0312) |
| junior college | -0.0919** | -0.0984** |
| | (0.0172) | (0.0180) |
| Experience | 0.0800** | 0.0811** |
| | (0.0042) | (0.0046) |
| Experience$^2$ | -0.0019** | -0.0021** |
| | (0.0003) | (0.0003) |
| Employment status | 0.0598** | 0.0478** |
| | (0.0109) | (0.0107) |
| Gender | 0.0407** | 0.0011 |
| | (0.0122) | (0.0145) |
| Min. intended wage | 0.2595** | 0.1910** |
| | (0.0316) | (0.0343) |
| $C_1$ | -0.0867 | 0.0369 |
| | (0.0853) | (0.1372) |
| $C_2$ | 0.1244* | 0.1547** |
| | (0.0602) | (0.0600) |
| Occupations, etc. | - | ✓ |
| obs | 192,683 | 191,389 |

Note: Numerically calculated standard errors in parentheses. $^{**}p < 0.01$, $^{*}p < 0.05$

Table 2.9: The effect of referrals with high praises on wage

| | (1) | (2) |
|---|---|---|
| | ln(Wage) | ln(Wage) |
| RF w/ High praises | -0.1129 | 0.0673 |
| | (0.4652) | (0.0821) |
| RF w/o High praises | -0.1802 | - |
| | (0.3913) | - |
| All RF | - | -0.1802 |
| | - | (0.3913) |
| $C_1$ | 0.0410 | 0.0410 |
| | (0.1386) | (0.1386) |
| $C_2$ | 0.1531* | 0.1531* |
| | (0.0599) | (0.0599) |
| obs | 1,528 | 1,528 |

Note: Additional regressors included are a education dummy, years of work experience and its square, a dummy indicating current employment status, a gender dummy, log of minimum level of intended wage, total number of applicants and its square, occupation dummies and minimum requirement of work experience. Numerically calculated standard errors in parentheses. $^{**}p < 0.01$, $^{*}p < 0.05$

Table 2.10: The effect of long referrals on wage

| | (1) | (2) |
|---|---|---|
| | ln(Wage) | ln(Wage) |
| Long RF | 0.1110 | 0.1271 |
| | (0.4606) | (0.0858) |
| Short RF | -0.0161 | - |
| | (0.3836) | - |
| All RF | - | -0.0161 |
| | - | (0.3836) |
| $C_1$ | -0.0182 | -0.0182 |
| | (0.1177) | (0.1177) |
| $C_2$ | 0.1536* | 0.1536* |
| | (0.0599) | (0.0599) |
| obs | 1,528 | 1,528 |

Note: Long RF means the group of referrals with more than 500 letters, while Short RF means those with equal or less than 500 letters. Additional regressors included are a education dummy, years of work experience and its square, a dummy indicating current employment status, a gender dummy, log of minimum level of intended wage, total number of applicants and its square, occupation dummies and minimum requirement of work experience. Numerically calculated standard errors in parentheses. $^{**}p < 0.01$, $^{*}p < 0.05$

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# Chapter 3

# Firms' preference for experienced workers

## abstract

This paper aims to examine the large unemployment gap between young workers and prime-age workers, an important issue in Korea and many other countries. I hypothesize that companies will prefer experienced workers due to the additional training costs required when hiring inexperienced workers. Under this hypothesis, a search model in which wage and job mobilities are determined by sequential auction reproduces the large unemployment gap well. Especially in a counterfactual analysis, the model shows that more than 40 percent of the unemployment gap can be explained by firms' preference for experienced workers over inexperienced workers. In addition, if companies do not prefer experienced workers, the expected lifetime income of young unemployed people newly entering the labor market is expected to increase by 14 percent. On the other hand, the frequent job search of employed people, which can be another reason for the high unemployment rate of young workers, is found to cause an increase in the overall unemployment rate and does not explain why the unemployment rate gap between young workers and others is large.

## 3.1 Introduction

Naturally, the unemployment rate among young workers is higher than the unemployment rate among prime-age workers because young people have only just started looking for work. However, the unemployment gap between young workers and others has recently become an important issue in many countries as it has grown excessively. In particular, in the case of Korea, although the overall unemployment rate fell gently from 4.4% in 2000 to 3.8% in 2019, the unemployment rate for those aged 20 to 29 steadily increased from 7.5% to 8.9%.[1] Since then, the unemployment rate has decreased somewhat due to the impact of COVID-19, but the employment situation felt by young people is still not good.

One reason for the huge unemployment gap between young workers and prime-age workers could be firms' preference for experienced workers over inexperienced workers because young workers are more likely to have no work experience. According to a survey, firms answered that they prefer experienced workers because training costs can be saved, and the workers can start to work immediately after hiring. As a result, more and more job positions are opened to workers with work experience rather than those without experience. It means that young workers who just enter the labor market face fewer opportunities for getting their first job. Delay of the first job would increase the unemployment rate among young workers. In addition, it can affect young workers' lifetime income because they would start to climb the job ladder late.

Therefore, the main aim of this paper is to examine those impacts. In other words, I study how much of the unemployment gap between young workers and others can be explained by firms' preference for experienced workers over inexperienced workers. In addition, the impact of firms' preferences on workers' lifetime income is also examined. As a first step, I introduce a simple structural search model in which there are two types of unemployed workers and two types of vacancies, and wage and job mobilities are determined by sequential auction. I assume that higher training costs are required when hiring inexperienced workers, so firms prefer experienced workers to inexperienced workers.

[1] In Korea, the college entrance rate is very high and it is common to start looking for a job after graduation. Therefore I looked at the unemployment rate after the age of 20.

The estimation results show that firms' preference for experienced workers can explain well the higher youth unemployment rate. A counterfactual analysis is conducted to determine how much of the difference in unemployment rates between young and prime-age workers can be explained by the company's preference for experienced workers. As a result, it was found that about 40 percent of the difference was due to the company's preference for experienced workers. In addition, as a result of a counterfactual simulation assuming that companies treat experienced and inexperienced workers equally, the expected lifetime income of young unemployed people newly entering the labor market was found to increase by about 14 percent. This is because young unemployed people begin to climb the job ladder more quickly as they gain access to more job opportunities, increasing not only the expected length of work before retirement but also the maximum achievable wage level.

Meanwhile, the frequent job search of employed people is also considered one of the factors that can increase youth unemployment. However, simulation results assuming that employed people search for new jobs more diligently show that the unemployment rate of not only young workers but also prime-age workers increases because the probability of finding a job decreases for all unemployed people regardless of experience. Thus, I conclude that the large gap in unemployment rates is mainly due to the additional training costs required when hiring an inexperienced worker rather than the frequent job searches of employed workers.

There have been many attempts to explain why youth unemployment is high. Using a panel of 15 OECD countries over the period 1970-1994, Korenman and Neumark (1997) show that youth unemployment increases relative to the unemployment rate of the elderly as the youth population share increases. Jimeno and Rodriguez-Palenzuela (2002) demonstrate similar results using data for 19 OECD countries over the period 1960-1996. These findings can be supported by the theoretical explanation that an increase in labor supply leads to a decrease in wages, and a decrease in wages leads to an increase in unemployment through a decrease in the job search efforts of the unemployed.

However, this cannot explain the rise in youth unemployment since the 1990s amidst a declining youth population share. Using state-level data for the United States over a similar period, Shimer (2001) shows the opposite result:

the higher the youth population share, the lower the youth unemployment rate. This can be explained by a search model that allows for on-the-job search. Young people who have just started looking for a job are more likely to accept a new job offer, as they are more likely to be unemployed or have poor job conditions, such as wage levels. More people like them mean easier recruitment for businesses, so they can create more new jobs, leading to a lower unemployment rate.

However, this theory predicts that a decrease in the proportion of young people in the population will lead to an increase in the unemployment rate of prime-age people as well as the unemployment rate of young people. Therefore, it cannot explain a situation where the unemployment rate of young people increases while the unemployment rate of prime-age people decreases, such as in the case of South Korea mentioned above. One of the contributions of this paper is to explain this phenomenon through a realistic assumption of firms' preference for experienced workers. Furthermore, through simulations using a theoretical structural model, it numerically verifies how much of the difference in unemployment rates between young and prime-age workers is explained by firms' career preferences, and its impact on lifetime income is also examined.

The remainder of the paper is organized as follows. In the following section, I introduce the structural model. In sections 3.3 and 3.4, I explain the data and estimation strategy. Next, the estimation results and counterfactual analysis using them follow. Section 3.7 concludes.

## 3.2 Model

This section suggests an extension of the sequential auction model(Postel-Vinay and Robin (2002)) in which there are two types of unemployed workers and two types of vacancies, and the offer arriving rates are determined endogenously. In other words, each firm that posts one vacancy per period maximizes its profits by choosing the type of vacancy to be posted. The key assumption is the higher cost required to hire inexperienced workers.

### 3.2.1 The Environment

Time is discrete, and the economy is in steady state.[2] There is a unit mass of workers and a continuum of firms, and both are infinitely lived, forward-looking, risk-neutral and have a common exogenous discount rate of $\rho$.

Workers are either unemployed or employed by a firm. Additionally, there are two types of workers: those who have worked before (:='$EXP$') and those who have not worked so far (:='$NEXP$'). Therefore, unemployed workers are either EXP or NEXP, where the fraction of EXP workers among unemployed workers is $\Omega$. On the other hand, by definition, all employed workers are EXP, i.e., an NEXP worker becomes an EXP worker as soon as she gets the first job. Also, with a probability $\pi$, workers retire. There are two additional assumptions related to retirement. First, the same number of workers newly enter the market immediately. Second, among the new workers, a fraction of workers, 1-$\chi$, are employed, and the others are unemployed and NEXP. While these assumptions do not change the key predictions of the model, the first one makes the model simpler, and the second one improves the model fit. Additionally, the second assumption is acceptable considering the situation in Korea: 1) many university students postpone their graduation until they have jobs, so in the data, they are counted as non-participants until they have jobs, 2) workers from colleges specialized for some occupations, e.g., doctors, nurses, teachers, soldiers, etc., can easily get employed straight after graduation.

Firms are ex-ante homogeneous. Every period, each firm posts one vacancy, and vacancies are either type '$A$' or type '$B$' while the types are explained in detail below. A vacancy would either be filled with a worker or disappear at the end of each period. The number of type $A$ and type $B$ vacancies is $n_A$ and $n_B$ respectively.[3]

The timeline is as follows:

① At the beginning of every period, each firm posts one vacancy after choosing the type of vacancy[4], considering the expected profit from choosing each type.

[2] In what follows I will therefore drop the time subscript 't'.

[3] Since the number of workers is normalized as one, $n_k$ can be interpreted as the number of type $k$ vacancies per worker.

[4] Note that firms can change their choice period by period.

② When a vacancy meets a worker, it draws a match-specific productivity, $p$, from the sampling distribution $F(p)$, which is common for both types of vacancies.

③ Based on $p$ and the type of worker and vacancy, the firm makes an offer, and the worker decides whether to accept it or not.

#### 3.2.1.1 The types of vacancy

The difference in the type of vacancy means the difference in the training program for newly hired workers, which has to be prepared in advance. Choosing type $A$ means that the firm prepares a training program available for both types of workers. Therefore, a match between a type $A$ vacancy and a worker produces the drawn productivity $p$, regardless of the type of worker. On the other hand, choosing type $B$ means that the firm prepares a training program available for EXP workers only. Therefore, a type $B$ vacancy produces $p$ only if it is filled with an EXP worker. Otherwise, it produces zero because its training program is not available for NEXP workers. As a result, a type $B$ vacancy cannot make any meaningful offers to the NEXP workers, and it will always be rejected. In other words, type $B$ vacancies can be filled with EXP workers only, while type $A$ vacancies can be filled with both types of workers.

As for the cost of posting a vacancy, which includes the cost of preparing the training program in advance, NEXP workers would need to be taught many things over a longer period before starting to work. Therefore, the cost of posting a type $A$ vacancy is assumed to be higher than that of posting a type $B$ vacancy. As I normalize the latter as zero, for convenience, the cost of posting a type $A$ vacancy, $\theta$, should be interpreted as the additional cost.

Note that type $A$ vacancies are different from type $B$ vacancies only in terms of the training program and posting cost that has to be paid in advance. Therefore, except for matches between a type $B$ vacancy and an NEXP worker, the production of a match does not depend on the type of vacancy but depends on the match-specific productivity $p$.

#### 3.2.1.2 Workers and job search

The search is random and on-the-job search is allowed, so all workers continue to search: unemployed (employed) workers receive job offers from the type $k$ vacancies at a probability $\lambda_{0k}$ ($\lambda_{1k}$) where $k \in \{A, B\}$, while it is assumed that a worker can receive at most one offer per period. The difference between $\lambda_{0k}$ and $\lambda_{1k}$ means that the search effort is assumed to vary by workers' employment status. For convenience, I normalize the search effort of unemployed workers as one and notate that of employed workers as $\tau$. On the other hand, $\lambda_{0k}$ is the same for all unemployed workers regardless of workers' type, which means that the search effort of unemployed workers is assumed to be the same for both types. While it is a strong assumption, it could be acceptable because the following two effects, which are not explicitly considered in the model, cancel each other out: 1) NEXP workers have an incentive not to search hard for jobs because the return to search is low, 2) on the other hand, in the real world, the longer a worker delays getting her first job, the harder it can be to get a job, so younger workers are likely to search harder. Also, I assume that the search effort of employed workers does not vary by the types of vacancies that they currently fill because the production does not depend on the type. Note that the offer arriving rates are determined endogenously by the firms' choice of vacancy type, as explained in detail below.

When a worker receives an offer, she will only accept it whenever the lifetime value from the offer is larger than what she enjoys in their current state. Therefore, employed workers will accept the new offer as long as it is better than the current job. As for unemployed workers who receive unemployment benefits $b$, I assume that it is low enough, so unemployed workers will accept all job offers unless it is an offer from the type $B$ vacancies to NEXP workers. Note that NEXP workers will reject any offers from the type $B$ vacancies because those vacancies cannot make any acceptable offers to NEXP workers, as I discussed above.

Finally, employed workers lose their jobs and become unemployed EXP workers at an exogenous probability $\delta$, where I assume that an employed worker can experience at most one event among the receipt of a new offer and the loss of the current job per period.

#### 3.2.1.3 Matching function

As for the matching function, I assume the standard Cobb-Douglas form. First, I define the total number of vacancies $\upsilon$ and effective workers $e$ as follows:

$$\upsilon = \upsilon_A + \upsilon_B$$

$$e = \tau_{0,NEXP}U_{NEXP} + \tau_{0,EXP}U_{EXP} + \tau E = (1 - E) + \tau E$$

where $\upsilon_k$ is the total number of posted vacancies with type $k \in \{A, B\}$. Also, $U_{NEXP}(U_{EXP})$ is the fraction of NEXP(EXP) unemployed workers among total workers and E is that of employed workers.[5] Also, $\tau_{0,NEXP}(\tau_{0,EXP})$ is the search effort of NEXP(EXP) unemployed workers, and as I mentioned above, I normalize the search effort of unemployed workers as one regardless of their type(i.e. $\tau_{0,NEXP} = \tau_{0,EXP} = 1$), where $\tau$ is the search effort of employed workers.

Then, the number of matches $m$ is given by:

$$m = (\eta \upsilon^{\alpha} e^{1-\alpha})$$

where $\eta$ captures matching efficiency and $\alpha$ denote the matching elasticity with respect to vacant jobs. The offer arriving rate from type $k$ vacancies to an unemployed worker with type $\epsilon$ is:

$$\lambda_{0\epsilon k} = m * \frac{\upsilon_k}{\upsilon} * \frac{1}{e}$$

As $\lambda_{0\epsilon k}$ is the same for all unemployed workers regardless of their type, I will use simpler notation $\lambda_{0k}$, rather than $\lambda_{0\epsilon k}$.

Similarly, the offer arriving rate from type $k$ vacancies to an employed worker is

$$\lambda_{1k} = m * \frac{\upsilon_k}{\upsilon} * \frac{\tau E}{e} * \frac{1}{E} = \lambda_{0k} * \tau$$

$\gamma_{0\epsilon}$, the rate at which a vacancy contacts an unemployed $\epsilon$-type worker is

$$\gamma_{0\epsilon} = m * \frac{U_{\epsilon}}{e} * \frac{1}{\upsilon} = \gamma_0 * (\mathbb{1}(\epsilon = EXP)\Omega + \mathbb{1}(\epsilon = NEXP)(1 - \Omega))$$

[5] Therefore, $U_{NEXP} + U_{EXP} + E = 1$

where $\gamma_0$ is the rate at which a vacancy contacts an unemployed worker regardless of her type and $\Omega$ is the fraction of EXP type among unemployed workers. Finally, $\gamma_1$, the rate at which a vacancy contacts an employed worker is

$$\gamma_1 = m * \frac{\tau E}{e} * \frac{1}{v}$$

Note that the contact rates do not vary by the types of vacancies since I assume purely random search.

### 3.2.2 Wage Determination and Job Mobility

As for wage determination and job mobility, I follow the sequential auction framework provided by Postel-Vinay and Robin (2002), but I extend it by allowing that there are two types of workers and two types of vacancies, as discussed above. In this framework, all information, including each other's types, match-specific productivity, and outside options, is assumed to be completely known to firms and workers, and wages can be renegotiated by mutual consent only. Let's define $V(w, p)$ as the lifetime value of being employed with wage $w$ and match-specific productivity $p$. Note that it is a function of neither the type of workers nor that of vacancies from the following assumptions, which have already been discussed above. First, the match between a type $B$ vacancy and an NEXP worker is not available. Second, as soon as an NEXP workers is hired by a type $A$ vacancy, she becomes EXP. Third, except for matches between a type $B$ vacancy and an NEXP worker, the production of a match does not depend on the type of vacancy. Finally, the search effort of employed workers does not vary by the types of vacancies that they currently fill. On the other hand, the lifetime value of being unemployed, $U(\epsilon)$, is a function of the type of worker $\epsilon$.

Let's consider the case in which an unemployed worker with type $\epsilon$ meets a potential employer, and they draw a match-specific productivity $p$. Then, by a Rubinstein (1982)-type bargaining game, unless it is the match between an NEXP worker and a type $B$ vacancy, the worker is hired at a wage $\phi_0(\epsilon, p)$ such that:

$$V(\phi_0(\epsilon, p), p) = U(\epsilon) + \beta[V(p, p) - U(\epsilon)] \tag{3.1}$$

where $\beta \in [0, 1]$ is the worker's bargaining power. Note that the wage is not a function of the type of vacancies for the same reasons mentioned above.

When an employed worker meets a potential alternate employer, the employers compete with each other for the worker. As a result, the worker will choose the more productive match because each productivity is the maximum wage available from each match. The wage of an employed worker will be determined by the productivity of the current match, which would be the highest productivity among the productivities that the worker has experienced since the beginning of the employment spell, and the outside option, which would be the second-highest productivity. For example, if a worker is employed at a match with $p^+$ and has the outside option $p^-$, then she receives a wage $\phi(p^-, p^+)$ such that:

$$V(\phi(p^-, p^+), p^+) = V(p^-, p^-) + \beta[V(p^+, p^+) - V(p^-, p^-)] \tag{3.2}$$

In other words, now the maximum lifetime value available from the second most productive match becomes the threat point for bargaining. Note that now the wage is a function of neither the type of vacancies nor that of workers because all employed workers are EXP.

To consider job and wage mobility in detail, let's suppose an employed worker earning $w$ at a match with productivity $p$. One can define $q(w, p)$ such that:

$$\phi(q, p) = w \Leftrightarrow V(w, p) = \beta V(p, p) + (1 - \beta)V(q, q) \tag{3.3}$$

In other words, $q(w, p)$ is the outside option that justifies the current wage $w$ from the match given $p$. When the worker meets a potential alternate employer and the productivity of the new match is $p'$, one of the following three situations can happen:

① $p' \leq q(w, p)$: Nothing happens;

② $q(w, p) < p' \leq p$: The worker stays at the match with $p$ and gets a higher wage $\phi(p', p)$, i.e., she renegotiates with the current employer.;

③ $p < p'$: The worker moves to the match with $p'$ for a wage $\phi(p, p')$.

Then, the lifetime value of being employed at the match with wage $w$ and productivity $p$ can be formally written down as follows:

$$\begin{aligned}
\rho V(w,p) = {} & w + \delta[U(EXP) - V(w,p)] - \pi V(w,p) \\
& +(\lambda_{1A} + \lambda_{1B})[\textstyle\int_{p}^{\bar{p}} (\beta V(x,x) + (1-\beta)V(p,p))dF(x) \\
& \quad + \textstyle\int_{q(w,p)}^{p} (\beta V(p,p) + (1-\beta)V(x,x))dF(x) \\
& \quad - \textstyle\int_{q(w,p)}^{\bar{p}} V(w,p)dF(x)]
\end{aligned}$$

An employed worker becomes an unemployed EXP worker with probability $\delta$, or she retires with probability $\pi$, or she receives a new job offer from a type $A(B)$ vacancy with probability $\lambda_{1A}(\lambda_{1B})$ and draws a match-specific productivity $p$ from $F$. She will move to the new match if it is more productive than the current match. Otherwise, she will stay but renegotiate with the current employer if the new match is more productive than the current outside option $q(w,p)$. Also, the lifetime value of being unemployed for $\epsilon$ type workers can be formally written down as follows:

$$\rho U(\epsilon) = b - \pi U(\epsilon) + (\lambda_{0A} + \mathbb{1}(\epsilon = EXP)\lambda_{0B}) \textstyle\int_{\underline{p}}^{\bar{p}} \beta[V(x,x) - U(\epsilon)]dF(x)$$

Note that unemployed EXP workers can be hired for both types of vacancies, while NEXP workers can be hired for A-type vacancies only.

Finally, the wage for $\epsilon$ type workers who are employed at the match with productivity $p^+$ and have the outside option $p^-$ can be formally written down as follows:

$$\phi(p^-, p^+) = p^+ - (1-\beta) \int_{p^-}^{p^+} \frac{\rho + \delta + (\lambda_{1A} + \lambda_{1B})\bar{F}(x)}{\rho + \delta + \beta(\lambda_{1A} + \lambda_{1B})\bar{F}(x)} dx^{6} \qquad (3.4)$$

### 3.2.3 Firms' choice

Each firm chooses the type of vacancy and posts one, where the expected profit from posting a type-$k$ vacancy is as follows:

[6] Note that $\phi_0(\epsilon,p) = \phi(p^{\epsilon}_{inf}, p)$, where
$p^{\epsilon}_{inf} = b + \int_{p^{\epsilon}_{inf}}^{\bar{p}} \frac{\beta((\lambda_{0A} + \mathbb{1}(\epsilon = EXP)\lambda_{0B} - \lambda_{1A} - \lambda_{1B})\bar{F}(x)}{\rho + \delta + \beta(\lambda_{1A} + \lambda_{1B})\bar{F}(x)} dx$
However, in the estimation, for convenience, I assume that $\phi_0(\epsilon,p) = \phi(\underline{p}, p)$.

E(profit | choosing type-A)

$$=\gamma_0 \int_p [\Omega J(\phi_0(EXP, p), p) + (1-\Omega) J(\phi_0(NEXP, p), p)] dF(p)$$

$$+\gamma_1 \int_p \int_q J(\phi(q, p), p) dL(q) dF(p) - \theta$$

E(profit | choosing type-B)

$$=\gamma_0 \int_p \Omega J(\phi_0(EXP, p), p) dF(p) + \gamma_1 \int_p \int_q J(\phi(q, p), p) dL(q) dF(p)$$

where $\gamma_0(\gamma_1)$ s the rate at which a firm contacts an unemployed (employed) worker, and $\Omega$ is the fraction of EXP workers among unemployed workers. Additionally, $J(w, p)$ represents the value of a filled job with productivity $p$ and wage $w$. Finally, $L(q)$ denotes the cross-sectional distribution of productivity among existing matches.

In equilibrium, firms are indifferent between posting an A-type vacancy and posting a B-type vacancy, i.e.

$$E(profit \mid \text{choosing type-A}) = E(profit \mid \text{choosing type-B}) \tag{3.5}$$

Given the above assumptions on search efforts, matching function, etc., offer-arriving rates are determined endogenously from the equilibrium condition.

## 3.3 Data

To estimate the model, I use data called Korean Labor and Income Panel Study (KLIPS). KLIPS has been conducted annually since 1998 by the Korea Labor Institute (KLI) with the approval of the national government. KLI asks the same set of questions every year to the 5,000 households, which are selected in a way that ensures the representativeness, about 13,000 people belonging to the households.

KLIPS comprises three parts: Household data, Individual data, and Work History data. For model estimation, I utilize the second and third datasets. The Individual data provides information on individuals' characteristics, job status at each survey, recent job search experiences, etc. The Work History data, which includes information on all jobs ever held by an individual, provides information about whether the worker changed jobs, and if so, when, and what she was paid at the time of the survey, and the start and end dates of each job.

For model estimation, I define a period as a month. Monthly data is derived from annual surveys conducted between 2003 and 2021. In other words, I extract information about job status, wage, etc., in the months between two consecutive surveys from the results of the yearly survey. Note that I do not use data from the early stage of the survey because some essential questions were not asked at the early stage of the survey.

The extraction of the information on monthly employment status and job changes mainly relies on the answers to two sets of questions. The first set is about previous jobs and is asked to individuals who were employed at the time of the last survey:

(1) “Are you still working in that job?”

(2) (If not,) “When did you quit this job?”

The second set is about new jobs that started after the last survey:

(1) “Since the last survey, did you get a new job that you held for more than a week?”

(2) (If yes,) “When did you start this job?”

(3) “Are you still working in that job?”

(4) (If not,) “When did you quit this job?”

An important issue in the process is how to deal with self-employed people because there are many self-employed workers in Korea. I excluded all workers who had ever experienced self-employment during the sample period because it is the simplest method while ensuring accurate estimation of the unemployment-to-employment transition rate, one of the most important moments. Additionally, only full-time workers were classified as employed, and part-time workers were classified as unemployed. This is to avoid overestimating the probability of finding a job for inexperienced workers, considering that many inexperienced workers who cannot secure a full-time job may be forced to temporarily take part-time jobs. There are differences between full-time and part-time jobs in terms of qualifications and the difficulty of the process that must be passed to get a job. One limitation of KLIPS is that it only inquires about job search activity if the person is unemployed at the time of the survey. Considering this limitation, I assume that workers who were employed at the time of the previous survey but lost their jobs before the next survey continued their job search activities immediately after losing their jobs. Another constraint of KLIPS lies in its provision of wage information only at the time of survey, job finding, and job loss, which makes it unfeasible to construct monthly wages. Consequently, I consider the average wage of individuals employed and interviewed each month as representative of the wage for all employed individuals in that month. This assumes that those selected for interviews each month are chosen randomly, regardless of their wage levels, etc. [7] On the other hand, there is no issue in determining the average wages of individuals who have recently transitioned from unemployment to employment since, as previously noted, KLIPS furnishes information on wages at the time of job finding. The sample is restricted to workers aged 20-55, assuming that elderly workers nearing retirement age would not substitute for young or prime-aged workers. Additionally, for use in estimating models, I define youth workers as those whose years since entering the job market (:= year since the completion date of each worker's final education) are equal to or less than five years, considering followings: 1) youth workers are formally defined as workers under the age of 29, 2) most Koreans [8] attend college until the age of 23 for women and 25 for men, including military service.

Table 3.1 presents summary statistics for the monthly panel data, constructed by the aforementioned rules and utilized in estimating the model. The dataset comprises 756,545 observations. The average monthly workforce is 3,535, of which 562 are young and 2,973 are prime aged.[9] Additionally, the average monthly count of unemployed individuals is 426, encompassing 94 young workers and 332 prime-aged workers, revealing a higher unemployment rate among the younger demographic. As anticipated, the proportion of un-

[7] Therefore, in the subsequent estimation process, when calculating the average wage of all employed individuals from simulation data, the average wage of the entire employed population is utilized, without the step of extracting a sample interviewed each month.

[8] More than 85% of Koreans graduate from college.

[9] Note that it is unbalanced panel data.

employed individuals lacking previous work experience is greater among young unemployed individuals than among their prime-aged counterparts. To elaborate, among the 332 prime-aged unemployed individuals, 87 had no previous work experience, while 245 did. Conversely, among the 94 young unemployed individuals, 41 lacked previous work experience, while 53 had some. The dataset includes 16,266 employment spells and 7,351 unemployment spells. Notably, there are 2,700 instances of job changes. Regarding job findings, there are 3,176 cases, with 2,595 arising from workers with prior work experience and 581 from those without such experience. Consequently, finding employment is more challenging for individuals without work experience than for those with prior experience. Lastly, there are 4,964 cases of job losses.

Table 3.1: Summary Statistics

| | |
|---|---|
| Number of observations | 756,545 |
| Monthly average number of workers | 3,535 |
| Young workers | 562 |
| Prime age workers | 2,973 |
| Monthly average number of unemployed workers | 426 |
| Young workers | 94 |
| w/ previous work experience | 53 |
| w/o previous work experience | 41 |
| Prime age workers | 332 |
| w/ previous work experience | 245 |
| w/o previous work experience | 87 |
| Number of employment spell | 16,266 |
| Number of unemployment spell | 7,351 |
| Number of job changes | 2,700 |
| Number of job findings | 3,176 |
| Among workers w/ previous work experience | 2,595 |
| Among workers w/o previous work experience | 581 |
| Number of job losses | 4,964 |

## 3.4 Estimation strategy

### 3.4.1 Further assumption and calibration

For the estimation of the model, I make a parametric assumption on the sampling distribution of productivity: $ln(p - \underline{p})$ follows a normal distribution with a mean $\mu$ and variance $\sigma^2$, where $p$ represents the productivity drawn when a vacancy meets a worker.

In terms of calibration, I define a period as a month, setting $\underline{p}$ at eleven hundred thousand won to reflect the average monthly minimum wage during the sample period. The monthly discount rate $\rho$ is established at 0.8 percent. Additionally, guided by findings in other studies, I fix the bargaining power $\beta$ at 0.3 (e.g. Bagger et al. (2014)) and set the matching elasticity with respect to vacant jobs to 0.5. (Petrongolo and Pissarides (2001)) Finally, I set the total number of vacancies at 0.59, derived from the number of job postings per worker in Korea.

### 3.4.2 Estimation procedure

There are ten parameters to be estimated: $\lambda_{0A}$, $\lambda_{0B}$, $\delta$, $\Omega$, $\pi$, $\tau$, $\mu$, $\sigma$, $\theta$ and $\eta$. I employ a three-step process for estimating these parameters. Initially, some parameters are directly estimated from empirical moments. Specifically, as unemployed NEXP workers would accept all offers from type A vacancies but reject any offers from type B vacancies, $\lambda_{0A}$ can be estimated from the empirical moments of 'unemployment-to-employment transition rates among workers who have never been employed so far'(:=$U2E_1$), i.e. the average of monthly $U2E_1$ over the sample period as follows:

$$\hat{\lambda_{0A}} = \frac{1}{T-1}\sum_{t=2}^{T} U2E_{1,t} = \frac{1}{T-1}\sum_{t=2}^{T} \frac{\sum_i \mathbb{1}\{EM_{i,t} = 1, \sum_{s=-\infty}^{t-1} EM_{i,s} = 0\}}{\sum_i \mathbb{1}\{\sum_{s=-\infty}^{t-1} EM_{i,s} = 0\}}$$

[10] where, $EM_{i,t}$ is the indicator function, equal to one if the individual $i$ is employed in period $t$ and zero otherwise.

[10]Note that the moment can be calculated from the first sample period using the retrospective information.

Likewise, for unemployed EXP workers, who would always accept any offers irrespective of the type of vacancy, $\lambda_{0A} + \lambda_{0B}$ can be estimated from the empirical moments of 'unemployment-to-employment transition rates among workers who have been employed before' (:=$U2E_2$), i.e. the average of monthly $U2E_2$ over the sample period as follows:

$$\hat{\lambda_{0A}}+\hat{\lambda_{0B}} = \frac{1}{T-1}\sum_{t=2}^{T} U2E_{2,t} = \frac{1}{T-1}\sum_{t=2}^{T} \frac{\sum_i \mathbb{1}\{EM_{i,t}=1, EM_{i,t-1}=0, \sum_{s=-\infty}^{t-2} EM_{i,s}>0\}}{\sum_i \mathbb{1}\{EM_{i,t-1}=0, \sum_{s=-\infty}^{t-2} EM_{i,s}>0\}}$$

Therefore, $\hat{\lambda_{0B}}$ can be obtained by calculating the difference between the average of monthly $U2E_1$ and the average of monthly $U2E_2$.

Additionally, $\Omega$, representing the fraction of EXP workers, can be estimated from the empirical fraction of workers who have been employed before among unemployed workers, i.e.

$$\hat{\Omega} = \frac{1}{T-1}\sum_{t=2}^{T} = \frac{\sum_i \mathbb{1}\{EM_{i,t}=0, \sum_{s=-\infty}^{t-1} EM_{i,s}>0\}}{\sum_i \mathbb{1}\{EM_{i,t}=0\}}$$

The second step involves estimating most of the parameters related to job mobility and wages through indirect inference (Gourieroux et al. (1993)). However, before proceeding, I reduce the number of parameters to be estimated by using the following flow-balance equations for NEXP workers and unemployed EXP workers:

$$(\lambda_{0A} + \pi) * (1 - \Omega) * U = \pi * \chi \tag{3.6}$$

$$(\lambda_{0A} + \lambda_{0B} + \pi) * \Omega * U = \delta(1 - U) \tag{3.7}$$

It is worth noting that the first equation assumes that, immediately after retirement, the same number of NEXP workers enter the market, with a fraction of $1 - \chi$ being employed and the remaining fraction being unemployed and NEXP. From these equations, $\chi$ and $\delta$ can be expressed as functions of $\pi$, the unemployment rate U, which can be calculated from the data, and other parameters already estimated above.

Therefore, in the second step, I estimate $\pi$, $\tau$, $\mu$ and $\sigma$ by targeting the following seven moments. First, I target the unemployment rates of youth and prime-age workers, respectively. It's important to note that in the data section, youth workers are defined as those whose years since entering the market (:= years since the completion date of each worker's final education) are equal to or less than five years. Since these two unemployment rates are the most important moments, they are weighted three times. Second, I target the average monthly rates of job-to-job transactions (J2J), where monthly J2J is

$$J2J_t = \frac{\sum_i \mathbb{1}\{EM_{i,t} = 1, EM_{i,t-1} = 1, Stay_{i,t} = 0\}}{\sum_i \mathbb{1}\{EM_{i,t-1} = 1\}}$$

Here, $Stay_{i,t}$ is the indicator function, equal to one if the individual $i$ has the same job in both periods *t-1* and $t$, and zero otherwise. Finally, I target the average monthly mean, median[11], and standard deviation of log wages for all employees and workers who just moved from unemployment to employment, respectively. Note that the first group of moments mainly contributes to identifying $\pi$, the second group to identifying $\tau$, and the third group to identifying $\mu$ and $\sigma$. See the Appendix for the identification.

For the third step, I calculate the remaining parameters, $\eta$ and $\theta$ sequentially. First, as outlined below, $\lambda_{0A}$ and $\lambda_{0B}$, which are estimated in the first step, can be used to calculate $\eta$ and $\upsilon_A$:

- $\lambda_{0A} = \eta \upsilon^{\alpha-1} e^{-\alpha} * \upsilon_A$
- $\lambda_{0B} = \eta \upsilon^{\alpha-1} e^{-\alpha} * (\upsilon - \upsilon_A)$

  (Note that $\upsilon$ is calibrated and $e$ can be obtained from $\tau$, which is estimated in the second step, and the empirical unemployment rate.)

Then, by substituting the value of $\upsilon_A$ into Eq(3.5), the equilibrium condition relating to the optimal choice of vacancy type, $\theta$ can be determined.

[11]More precisely, when I target the mean or median of log wages, I target the difference between them and $ln(\underline{p})$, the log wage from a match with the lowest productivity, in order to target the part that is only determined by the parameters to be estimated.

## 3.5 Estimation results

### 3.5.1 Model fits

Table 3.2 compares the targeted moments from the real data with those from the simulated data. First, the structural model fits well the observed unemployment rates of youth and prime-age workers, respectively. Therefore, it can be concluded that the model explains the higher youth unemployment rate by incorporating firms' preferences for experienced workers due to lower training costs. Additionally, the moments related to log wages for all employees and recently hired workers are well-fitted overall. On the other hand, the model's predictions for the job-to-job transition probability is somewhat lower than the real data, although the level of difference is deemed acceptable.

Table 3.2: Model fits

| | Real | Simulated |
|---|---|---|
| Youth unemployment rate($U_y$) | 16.50% | 16.06% |
| Prime age unemployment rate($U_o$) | 11.19% | 10.58% |
| Job-to-job transition rate($J2J$) | 0.43% | 0.29% |
| Among all employees, | | |
| Mean of log wages (E($lnW$)) | 3.1141 | 3.1840 |
| Median of log wages (MD($lnW$)) | 3.1135 | 3.0480 |
| Standard deviation of log wages (SD($lnW$)) | 0.5230 | 0.6277 |
| Among employees who were unemployed last month, | | |
| Mean of log wages (E($lnW|U2E$)) | 2.7359 | 2.7749 |
| Median of log wages (MD($lnW|U2E$)) | 2.7081 | 2.6535 |
| Standard deviation of log wages (SD($lnW|U2E$)) | 0.4195 | 0.3564 |

Note: Monthly

### 3.5.2 Parameter estimates

Table 3.3 presents the estimation results. Firstly, it reveals a clear preference among firms for experienced workers over inexperienced workers. According to the results, the offer arrival rate for unemployed workers with previous work experience is approximately 4.09% per month, while that for unemployed workers without prior work experience is 2.34% per month. In other words, unemployed workers with previous work experience, constituting over 70% of the unemployed workforce, have a roughly 75% higher chance of securing a job compared to those without work experience. The search effort of employed workers is found to be about 17% of that of unemployed workers. 0.5% of the total population retires each month. Although the same number of new workers immediately enter the labor market, 81% of them enter the labor market having a job already.

As for the parameters related to vacancies, the cost of posting a job available for both experienced and inexperienced workers, which is assumed to include training costs, is approximately three hundred thousand won higher than that for posting a job available only for experienced workers. While this may be lower than anticipated, it is partly acceptable, considering the substantial heterogeneity in training costs. It's noteworthy that smaller-sized firms tend to be more cautious when investing in training. The matching efficiency is estimated to be about 2.9%.

Table 3.3: Estimation results

| | | |
|---|---|---|
| $\lambda_{0A}$ | 0.0234 | (0.0012) |
| $\lambda_{0B}$ | 0.0175 | (0.0011) |
| $\Omega$ | 0.7172 | (0.0093) |
| $\tau$ | 0.1680 | (0.0025) |
| $\mu$ | 3.3467 | (1.4807) |
| $\sigma$ | 0.7980 | (1.0890) |
| $\pi$ | 0.0052 | (0.0000) |
| $\theta$ | 3.0911 | (-) |
| $\eta$ | 0.0291 | (-) |
| $\delta$ | 0.0045 | (-) |
| $\chi$ | 0.1864 | (-) |

Note: Standard errors in parentheses. $\theta$, $\eta$, $\delta$ and $\chi$ are calculated from other parameters, empirical moments and the equilibrium conditions for the firms' choice of type of vacancy.

## 3.6 Applications

### 3.6.1 Effect of training cost

In the model, a key assumption is that firms prefer experienced workers and are willing to forgo the chance to hire inexperienced workers due to the higher training costs associated with the latter. Consequently, if the training costs for hiring inexperienced workers decrease, it could result in more job opportunities for these workers, potentially leading to a lower unemployment rate among young workers as they are more likely to be inexperienced.

To explore the impact of training costs on the unemployment gap between young workers and others, the case of no preference for experienced workers is considered. In this scenario, all firms choose to post a type A vacancy, which is available for both experienced and inexperienced workers, as the additional training costs for hiring inexperienced workers become low enough. First, the calculation of $\theta_{min}$, representing the level of additional cost for a type A vacancy that all firms would choose to post a type A vacancy below, is done using equations (3.5), (3.6), and (3.7). $\theta_{min}$ is found to be 1.9191, approximately 40 percent lower than the baseline, the original estimation result.

The second column of Table 3.4 presents the simulation results with $\theta_{min}$ while the first column shows the baseline. Comparing these two columns reveals that the unemployment gap between youth workers and others decreases from 5.5 percentage points in the baseline scenario to 3.2 percentage points in the case with no preference for experienced workers. In other words, more than 40 percent of the unemployment gap can be explained by firms' preference for experienced workers over inexperienced workers. Conversely, the third column of Table 3.4 explores the opposite case, where the additional cost for posting a type A vacancy is 40 percent higher than the baseline. It is observed that the unemployment gap increases by about 20%, from 5.5 percentage points to 6.6 percentage points.

As a next step, the impact of additional training costs on workers' lifetime income is examined. These costs can reduce lifetime income in two ways: by decreasing the total years of employment and by lowering the lifetime maximum wage. When firms avoid hiring inexperienced workers due to higher training costs, the duration of unemployment before obtaining the first job increases, leading to a reduction in total years of employment. Additionally, as young workers start climbing the job ladder later, the lifetime maximum wage is expected to decrease. To study these impacts, a simulation is conducted with a group of new workers over 30 years under different scenarios.[12] The upper part of Table 3.5 provides information on employed years, personal maximum log wage, and lifetime income that new workers can expect upon entering the labor market. Comparing columns 1 and 2, it is observed that when there is no preference for experienced workers, the expected value of lifetime income increases by 2%. This increase is primarily attributed to the rise in the average working period by 0.4 years, while the personal maximum wage increases by 0.5%.

It's important to note that the impact on lifetime income may seem smaller than expected, but the effect is concentrated on new workers entering the market without a job, while approximately 80% of new workers enter the labor market already employed. The bottom part of Table 3.5 shows that when there is no preference for experienced workers, new workers entering the market without a job are expected to work about 1.5 years longer and, consequently, have about 14% higher expected lifetime income. On the other hand, comparing columns 1 and 3 of the table, it is evident that as the preference for experienced workers becomes stronger, the challenges for workers entering the market without a job intensify. Specifically, the reduction in the expected working period is close to 2 years, and the reduction in lifetime income is about 14%. Therefore, policymakers need to consider that the negative impact of firms' preference for experienced workers can be concentrated on some vulnerable workers.

### 3.6.2 Effect of search effort

The higher search effort among employed workers could be another factor contributing to the higher unemployment rate among inexperienced and/or youth workers. The societal perspective on job changes has shifted from negative to positive in Korea. In the past, individuals sought lifelong employment

[12]For those simulations, I assume that there is no retirement for the 30 years just because it would be helpful to see the difference between the scenarios more clearly.

Table 3.4: Effect of training cost on unemployment gap and wage distribution

| | Baseline | $\theta_{new} = \theta_{min}$ | $\theta_{new} = 1.4 * \theta$ |
|---|---|---|---|
| $U_y$ | 16.06% | 12.96% | 18.37% |
| $U_o$ | 10.58% | 9.81% | 11.76% |
| $J2J$ | 0.29% | 0.29% | 0.28% |
| E($lnW$) | 3.1840 | 3.1839 | 3.1784 |
| MD($lnW$) | 3.0480 | 3.0464 | 3.0343 |
| SD($lnW$) | 0.6277 | 0.6318 | 0.6234 |
| E($lnW\|U2E$) | 2.7749 | 2.7683 | 2.7771 |
| MD($lnW\|U2E$) | 2.6535 | 2.6454 | 2.6581 |
| SD($lnW\|U2E$) | 0.3564 | 0.3546 | 0.3517 |

Note: Monthly

Table 3.5: Effect of training cost on newly entered workers

| | Baseline | $\theta_{new} = \theta_{min}$ | $\theta_{new} = 1.4 * \theta$ |
|---|---|---|---|
| Among all workers newly entered, | | | |
| E(Employed years) | 26.5958 | 26.9110 | 26.1979 |
| E(Personal maximum log wage) | 3.7936 | 3.8110 | 3.7801 |
| E(Life-time income) | 320.6956 | 327.8667 | 313.7233 |
| Among workers newly entered as unemployed, | | | |
| E(Employed years) | 23.9855 | 25.4488 | 22.1222 |
| E(Personal maximum log wage) | 3.7402 | 3.7829 | 3.6915 |
| E(Life-time income) | 245.9992 | 281.1814 | 211.5284 |

and changed jobs only when it was unavoidable, resulting in lower job change rates. However, in contemporary times, workers view job changes as opportunities to increase their wages and advance their careers. This shift has led to more frequent job changes, potentially impacting job-finding opportunities for inexperienced workers in two ways. Firstly, from the employers' perspective, the incentive to hire novices and invest in training them diminishes, as there is an increased likelihood that individuals will change jobs after receiving training, while it becomes easier for employers to hire workers currently employed by another company. Consequently, firms will reduce the number of job postings available for inexperienced workers. Secondly, even for the reduced job postings, inexperienced workers face fiercer competition because employed individuals are more proactive in searching for new opportunities. It is important to note that the second effect applies to all unemployed individuals, regardless of whether they have work experience or not.

To assess whether higher job search efforts among employed workers contribute to the unemployment gap between young workers and others, two scenarios were simulated: one with job search efforts 50% higher than the baseline and another with efforts 50% lower than the baseline. Table 3.6 confirms that the unemployment rate among young workers increases when employed individuals search more eagerly for new jobs, rising from 16.1% in the baseline scenario to 17.3%. Conversely, the rate decreases to 14.0% in the scenario with lower search effort. However, a similar pattern is observed for the unemployment rate among prime-age workers. Their unemployment rate increases from 10.6% in the baseline scenario to 12.0% with higher search effort and decreases to 8.5% with lower search effort. Consequently, the unemployment gap remains relatively stable at around 5 percentage points in both cases. The reason for this stability lies in the dominance of the second path among the two paths through which an increase in employed workers' job search effort lowers the probability of inexperienced workers finding a job. In other words, when employed individuals search more eagerly for new jobs, the job-finding opportunity for inexperienced workers decreases primarily due to fiercer competition for posted jobs, which reduce the opportunity of unemployed workers with previous work experiences as well, rather than the decrease of the number of job postings available for inexperienced workers.

In summary, according to this model, both the additional training costs required when hiring an inexperienced person and the frequent job searches of employed people can explain the high unemployment rate of young workers. However, only the former explains the large unemployment rate gap between young workers and others. Therefore, it can be concluded that the significant gap in unemployment rates is primarily due to the former rather than the latter.

Table 3.6: Effect of search effort on unemployment gap and wage distribution

| | Baseline | $\tau_{new} = 0.5 * \tau$ | $\tau_{new} = 1.5 * \tau$ |
|---|---|---|---|
| $U_y$ | 16.06% | 13.98% | 17.25% |
| $U_o$ | 10.58% | 8.53% | 11.99% |
| $J2J$ | 0.29% | 0.19% | 0.35% |
| E($lnW$) | 3.1840 | 3.1382 | 3.2109 |
| MD($lnW$) | 3.0480 | 2.9821 | 3.1289 |
| SD($lnW$) | 0.6277 | 0.5492 | 0.6818 |
| E($lnW\|U2E$) | 2.7749 | 2.8787 | 2.6883 |
| MD($lnW\|U2E$) | 2.6535 | 2.7784 | 2.5480 |
| SD($lnW\|U2E$) | 0.3564 | 0.3603 | 0.3532 |

Note: Monthly

Table 3.7: Effect of search effort on newly entered workers

| | Baseline | $\tau_{new} = 0.5 * \tau$ | $\tau_{new} = 1.5 * \tau$ |
|---|---|---|---|
| Among all workers newly entered, | | | |
| E(Employed years) | 26.5958 | 27.1937 | 26.1279 |
| E(Personal maximum log wage) | 3.7936 | 3.6457 | 3.8856 |
| E(Life-time income) | 320.6956 | 326.6658 | 316.1554 |
| Among workers newly entered as unemployed, | | | |
| E(Employed years) | 23.9855 | 25.1706 | 22.9988 |
| E(Personal maximum log wage) | 3.7402 | 3.6125 | 3.8189 |
| E(Life-time income) | 245.9992 | 266.3233 | 230.9303 |

## 3.7 Conclusion

This paper studies a significant phenomenon in Korea and many other countries—the notably higher unemployment rate among young workers compared to prime-aged workers. The central assumption is that companies prefer experienced workers due to the higher training costs associated with hiring inexperienced workers. This assumption is incorporated into a search model featuring two types of unemployed workers and two types of vacancies. Wage and job mobilities are determined by a sequential auction process. The model aligns well with moments derived from real data, effectively reproducing the observed large unemployment gap. In subsequent counterfactual analyses, the model suggests that if companies do not favor experienced workers as the additional training costs for hiring inexperienced workers become low enough, the unemployment gap could be reduced by 40 percent. Additionally, the expected lifetime income of young unemployed individuals entering the labor market is anticipated to increase by 14 percent. This increase is attributed to a longer working period and a higher maximum wage, both resulting from an earlier start in climbing the career ladder. While considering the frequent job searches of employed people as another potential reason for the large gap in unemployment rates, it is noted that this factor leads to lower job finding opportunity for all unemployed individuals, irrespective of their experience. Consequently, it is shown to elevate not only the unemployment rate of young workers but also that of other workers. As a result, the paper concludes that the substantial gap in unemployment rates is primarily due to the additional training costs required when hiring inexperienced workers rather than the frequent job searches of employed workers.

## 3.8 Appendix

### 3.8.1 Steady-state Cross-sectional Distribution of Productivity

Let's consider outflow and inflow of workers who are employed at a match-specific productivity $p$. As for the outflow, they would lose their current job at a probability of $\delta$, or they would retire at a probability of $\pi$, or they can receive a new offer from type $A(B)$ vacancies at a probability of $\lambda_{1A}(\lambda_{1B})$ and accept it if the new match is more productive than $p$. As for the inflow, there are three sources: 1) unemployed NEXP workers who receive an offer from type $A$ vacancies at a probability of $\lambda_{0A}$, 2) unemployed EXP workers who receive an offer from any type of vacancy at a probability of $\lambda_{0A} + \lambda_{0B}$, 3) employed workers with a match-specific productivity lower than $p$ and receive a new offer from any type of vacancy at a probability of $\lambda_{1A} + \lambda_{1B}$. They become the inflow if they pick a match-specific productivity $p$ from $F$. Therefore, the flow-balance equations are:

$$
\begin{aligned}
&[\delta + \pi + (\lambda_{1A} + \lambda_{1B})\bar{F}(p)]\ell(p)(1-U) \\
&= [\lambda_{0A}\Omega U + (\lambda_{0A} + \lambda_{0B})(1-\Omega)U + (\lambda_{1A} + \lambda_{1B})L(p)(1-U)]f(p) \\
&= [(\delta+\pi)(1-U) + (\lambda_{1A} + \lambda_{1B})L(p)(1-U)]f(p) \qquad (3.8)
\end{aligned}
$$

Note that the last line used the following flow-balance equation for unemployed workers:

$$\lambda_{0A}\Omega U + (\lambda_{0A} + \lambda_{0B})(1-\Omega)U = (\delta+\pi)(1-U)$$

Then, by cancelling out $1-U$ from the both sides of the equation (3.8) and dividing them by $\delta+\pi$, one can get

$$[1 + \kappa\bar{F}(p)]\ell(p) = [1 + \kappa L(p)]f(p)$$

, where $\kappa \equiv \frac{\lambda_{1A}+\lambda_{1B}}{\delta+\pi}$. Finally, by rearranging the equation and integrating it over p, the cross-sectional distribution of productivity can be achieved as follow:

$$L(p) = \frac{F(p)}{1+\kappa\bar{F}(p)} \qquad (3.9)$$

which is the same with standard sequential auction model except for the definition of $\kappa$.

### 3.8.2 Identification of the 2nd step of estimation

First, $\pi$ can be identified from the youth unemployment rate, $U_y$. Keeping in mind that $\pi$ new young workers enter the market each month, and that they become prime age workers after 60 months, let's define $Y^s$ as the number of young workers who have been in the labour market for s months. Given that the retirement rate is $\pi$, $Y^s$ can be calculated as follows:

$$Y^s = \pi(1-\pi)^s$$

where $s = 0, 1, ...60$. In addition, total number of young workers, Y would be

$$Y = \sum_{s=0}^{60} Y^s = 1 - (1-\pi)^{61}$$

Also, if we define $U_y^s$ as the unemployment rate among young workers who have been in the labour market for s months, it can be calculated as follows:

$$U_y^0 = \chi$$

$$\begin{aligned} U_y^s &= \frac{Y^{s-1}(U_y^{s-1}(1-\pi-\Omega^{s-1}\lambda_{0B}-\lambda_{0A})+(1-U_y^{s-1})\delta)}{Y^s} \\ &= \frac{U_y^{s-1}(1-\pi-\Omega^{s-1}\lambda_{0B}-\lambda_{0A})+(1-U_y^{s-1})\delta}{1-\pi} \end{aligned}$$

, for $s = 1, ...60$, where $\Omega^s$, the fraction of experienced workers among unemployed workers who have been in the labour market for s months can be calculated as follows:

$$\Omega^0 = 0$$

$$\begin{aligned} \Omega^s &= \frac{Y^{s-1}(U_y^{s-1}\Omega^{s-1}(1-\pi-\lambda_{0B}-\lambda_{0A})+(1-U_y^{s-1})\delta)}{U_y^s Y^s} \\ &= \frac{U_y^{s-1}\Omega^{s-1}(1-\pi-\lambda_{0B}-\lambda_{0A})+(1-U_y^{s-1})\delta}{U_y^s(1-\pi)} \\ &= \frac{U_y^{s-1}\Omega^{s-1}(1-\pi-\lambda_{0B}-\lambda_{0A})+(1-U_y^{s-1})\delta}{U_y^{s-1}(1-\pi-\Omega^{s-1}\lambda_{0B}-\lambda_{0A})+(1-U_y^{s-1})\delta} \end{aligned}$$

Since $U_y$ is the weighted average of $U_y^s$ for $s = 0, ...60$, i.e.

$$U_y = \frac{1}{Y} \sum_{s=0}^{60} Y^s U_y^s = \frac{1}{1-(1-\pi)^{61}} \sum_{s=0}^{60} \pi(1-\pi)^s U_y^s$$

$\pi$ can be expressed as functions of $U_y$ and other parameters estimated from the 1st step. (Note that, from the equation (3.6) and (3.7), $\chi$ and $\delta$ can be expressed as functions of $\pi$, total unemployment rate U and other parameters estimated from the 1st step.)

Given $\pi$, $\tau$ can be identified from the average job-to-job transition rate under the steady-state assumption:

$$J2J = (\lambda_{1A}+\lambda_{1B}) \int_{\underline{p}}^{\bar{p}} \bar{F}(p) dL(p) = (\delta+\pi)\{\frac{(\delta+\pi+\lambda_{1A}+\lambda_{1B})}{\lambda_{1A}+\lambda_{1B}} \log(\frac{\delta+\pi+\lambda_{1A}+\lambda_{1B}}{\delta+\pi}) - 1\} \tag{3.10}$$

because $\lambda_{1A} + \lambda_{1B} = \tau(\lambda_{0A} + \lambda_{0B})$.

Then, given $\pi$, $\tau$ and the results from the 1st step, $\mu$ and $\sigma$ can be identified from the mean and variance of wage.

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