THREE ESSAYS ON EMPIRICAL STUDIES OF WAGES IN THE KOREAN LABOR MARKET

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Kihong Park

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As members of the Dissertation Committee, we certify that we have read the dissertation prepared by Kihong Park
entitled Three Essays on Empirical Studies of Wages in the Korean Labor Market
and recommend that it be accepted as fulfilling the dissertation requirement for the Degree of Doctor of Philosophy.

____ Date: 09/30/11
Ronald L. Oaxaca, PhD
McClellan Professor

____ Date: 09/30/11
Price V. Fishback, PhD
Thomas R. Brown Professor

____ Date: 09/30/11
Mark Stegeman, PhD
Associate Professor of Economics

____ Date: 09/30/11
Stanley S. Reynolds, PhD
Eller Professor of Economics

Final approval and acceptance of this dissertation is contingent upon the candidate's submission of the final copies of the dissertation to the Graduate College.

I hereby certify that I have read this dissertation prepared under my direction and recommend that it be accepted as fulfilling the dissertation requirement.

____ Date: 09/30/11
Dissertation Director: Ronald L. Oaxaca, PhD
McClellan Professor

STATEMENT BY AUTHOR

SIGNED: Kihong Park

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ABSTRACT

My dissertation follows a coherent theme on three important and interesting issues for the Korean labor market as follows: Chapter 1 using data from the 2008 Panel Survey of Employment for the Disabled (PSED) investigates gender wage differentials among the disabled. The selectivity corrected decomposition framework is employed to examine what factors - endowments, discrimination, and selectivity - account for the wage gap. The main results are as follows: (1) the gender wage gap among the disabled is sizable: (2) the wage gap is significantly attributable to discrimination: (3) the endowments factor plays an important role in explaining gender wage differentials, as well: and (4) the presence of selection effects raises the observed wage gap. Such evidence suggests that Korean disabled female workers are more likely to be disadvantaged than their male counterparts in terms of wages.

Chapter 2 using the 2007 Korea Labor and Income Panel Survey (KLIPS) examines the impact on wages of skills-job mismatch between acquired and required English language proficiency in Korean workplaces. The main findings of this study reveal (1) job mismatch in terms of English language skills has a strong statistically significant impact on wages: (2) the returns to over-skilling are negative (the wage penalty), while the returns to under-skilling are positive (the wage premium): and (3) the wage penalty associated with over-skilling is stronger than the wage premium associated with under-skilling.

Chapter 3 using the KLIPS data from 1998 through 2008 investigates the causal relationship between veteran status and post-service labor market outcomes by examining

the wage experience of veterans and nonveterans. The major empirical findings can be summarized as follows: (1) contrary to the general perception, veteran status has a significant positive impact on wages after completion of military service, inducing a veteran wage premium: and (2) in terms of the veteran wage premium in subgroups based on educational attainment at the time of entry into military service, less-educated veterans have a greater wage premium relative to their nonveteran counterparts of similar backgrounds than is the case for more-educated veterans. It suggests that military service could be particularly important for less-educated veterans.

CHAPTER 1. GENDER WAGE DIFFERENTIALS AMONG DISABLED PEOPLE: EVIDENCE FROM SOUHT KOREA[1]

1.1. Introduction

Discrimination occurs when individuals or groups are treated unfairly when compared to similarly situated individuals or groups because of personal characteristics such as race, color, religion, gender, or disability. The 2009 U.S. State Department report on human rights notes that South Korea (hereafter denoted as Korea) generally respects the human rights of its citizens; however, women, persons with disabilities, and minorities continued to face societal discrimination due to traditional attitudes that limit opportunities for women, persons with disabilities, and ethnic minorities. This report suggests that Korean women with disabilities may be experiencing "double discrimination", being female as well as disabled. In that sense, disabled female workers could be considered a special concern in the Korean labor market.

Feminist disability scholars have begun to conceptualize the relationship between sexism and "disablism" of women with disabilities as "double discrimination" while discussing the overlap in personal and political issues for disabled females (e.g., Fine & Asch, 1988; Londsdale, 1990; Morris, 1996). Based on the assumption that disability is always inextricably linked to other social markers, such as gender, race, and social class, they have shown that women with disabilities experience a dual form of discrimination with respect to both gender and disability. That is, the results suggest that disabled female

[1] Chapter 1 has been published in the journal *Asian Women:* Park, Kihong (2011). Gender Wage Differentials among Disabled People: Evidence from South Korea, *Asian Women, 27* (1), 65-93.

workers may be treated less favorably than not only their non-disabled female counterparts but also their male counterparts in the labor market when “double discrimination” based on both gender and disability occurs. Despite the progress made over the last three decades in this area, most previous studies on the status of disabled females with respect to “double discrimination” have been mainly focused in terms of social welfare administration/policy without economic perspectives (Priestley, 2003). It may in part reflect that the research in this area has not extended economic analysis to examine labor market consequences experienced by disabled female workers.

In the mean time, the dual form of discrimination against disabled females (i.e., disability and gender) has traditionally been addressed separately in the economic literature. Regarding disability issues, in particular, numerous studies have examined the impact of disability status by comparing labor market outcomes between the disabled and the non-disabled with increasing attention. For instance, the U.K. and the U.S. have experienced a substantial increase in publication on such issues since the U.K. Disability Discrimination Act 1995 (DDA) and the U.S. Americans with Disability Act of 1990 (ADA) respectively (e.g., Baldwin, Johnson & Watson 1995, 2000; DeLeire, 2001; Jones, Latreille & Sloane, 2006; Kidd, Sloane & Ferko, 2000).

In contrast, there has been relatively little empirical research on gender issues of disabled females within the labor market. Indeed, the research on gender discrimination among the disabled has been relatively ignored in Korea, given gender differences in labor market outcomes among the disabled.[2] To my knowledge, the only economic analysis of wage discrimination against disabled female workers published in a journal to date in Korea is that by Jung (2010) which used data from the 2008 Panel Survey of Employment for the Disabled (hereafter denoted as PSED). Moreover, there has been relatively little policy interest in disabled female issues in Korea. This may in part reflect the situation that dealing with gender issues among disabled people has been almost overtaken by the gender mainstreaming approach. For instance, while the Korean government established the Ministry of Gender Equity in 2001 to ensure that gender perspective is introduced in all government policies and has made significant achievements in gender-related issues, they still have failed to implement a comprehensive strategy addressing discrimination against disabled females.

In the light of the results by Jung (2010), this paper using data from the 2008 PSED attempts to provide new empirical evidence on gender wage differentials among the disabled working population in Korea. The PSED dataset used in the present study is a unique Korean data set on individuals who are registered as disabled. This study in particular focuses on gender wage discrimination against disabled female workers. This is because the relative position of females in the labor market in general is inferior to that of males, at least in terms of wages, thus it is clearly of interest to ascertain whether disabled females are similarly disadvantaged relative to disabled males (e.g., Jones et al., 2006).

[2] The employment rate for the disabled females is just 23.7 percent, compared to the rate of 47.6 percent for the disabled males and disabled female workers earn on average approximately 56 percent less than their male counterparts, according to the 2008 National Survey on Persons with Disability in Korea, released in 2009.

As stated, disabled female workers may be experiencing “double discrimination”, being female as wells as disabled. Since this paper focuses on gender discrimination among the disabled, it is difficult to understand in what ways disabled females experience the double aspect of the discrimination. Without this type of empirical analysis, however, one may be clearly aware of the fact that disabled females would have a lower wage rate than their non-disabled counterparts. And discrimination based on disability would play an important role in explaining the wage gap between disabled and non-disabled female workers.[3]

Jung (2010) claims that selection bias turns out to be empirically unimportant in her case because the inverse mills ratio term is not statistically significant. There are, however, some issues that need to be clarified with respect to this claim. First, the author does not mention exactly what selection is being examined. Presumably it is employed vs. not employed. In her case, does not employed mean unemployed or does it include those who are out of the labor force? Second, one does not know how the probit equation was specified. This should be made explicit and the results reported otherwise one cannot ascertain if there were any exclusion restriction problems.

To address the above deficiencies, this study incorporates the probability of employment into the analysis and the wage equations are corrected for selectivity using the Heckman procedure (i.e., the Heckman selection model). Subsequently, the selectivity corrected decomposition approach suggested by Neuman & Oaxaca (2004)

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[3] One may want to understand “to what extent” gender discrimination of the disabled is different from those of the non-disabled. This paper presents comparisons of gender discrimination of the disabled and the non-disabled by reviewing literature surveys that are already published in the Results and Discussion section.

decomposes gender wage differentials in mean observed wages into 'endowments' (a part attributed to differences in productivity), 'discrimination' (a part attributed to gender discrimination), and 'selectivity' (a part attributed to selection bias) components.

There are several contributions made by this new analysis. First, this paper advances the literature on gender wage discrimination against disabled female workers in Korea, by considering decompositions with selectivity correction. If selection effects have significant implications in the form of gender wage discrimination, this paper determines whether such economic consequences exist. Second, the PSED used in this study is a unique dataset aimed at addressing the economic activities of a sample of respondents with disabilities. Accordingly this survey provides an opportunity for researchers not to concern about justification bias in terms of defining disability and thus has an advantage over researcher defined disability. In other words, the disability classifications in this study are superior to other studies at least in that the PSED survey adopts some definition of disability to identify disabled people from the population and researchers do not need to craft their own definitions to apply to a general sample of the population. Since there are no socially or conventionally acceptable measures of disability, many previous studies in the literature on discrimination have their own subjective criteria to identify disabled people in the survey. Finally, this study contributes to future research investigating many other disabled female-related labor market issues such as employment participation. In particular there has been relatively little empirical work on the labor market status of disabled females in Korea, though the literature on the labor market discrimination has grown in the last 10 years. This paper and future research will narrow this gap.

The main results presented in this study are as follows. First, the wage gap between disabled male and female workers is sizable at 43 percent. Second, the gender wage gap among the disabled is significantly associated with discrimination (49-66 percent). Third, the endowment factor plays an important role in explaining gender wage differentials as well (34-51 percent). Finally, the presence of selection effects raises the observed gender wage gap among the disabled in this analysis. In addition, the estimated discrimination and endowment components can vary based on assumptions about how or whether to incorporate selection effects. The allocation of all selection effects yields similar or lower estimates of discrimination in general but raises the estimate of endowments. Even a partial allocation of selection effects raises (lowers) the estimate of discrimination (endowments). Such evidence suggests that Korean disabled female workers are more likely to be disadvantaged than their male counterparts in terms of wages. Thus, national policies, regulations or laws against gender discrimination (e.g., the U.K. Disability Discrimination Act 1995 (DDA), the U.S. Americans with Disabilities Act of 1990 (ADA)) and additional supports beyond prohibiting discrimination (e.g., vocational training, on-the-job training) are needed to enhance the labor market status of disabled female workers in Korea.

1.2. Methodology

1.2.1. Selection Issues on Estimating Wage Equations

When examining the disabled working population, there would be a strong presumption that selection effects are at work with respect to labor force participation. Under such circumstances, a simple ordinary least squares (OLS) model is expected to provide biased estimates of wage equations. This is because wages are usually estimated from a censored sample that includes only employed disabled workers, i.e., the observed wages. The present study thus employs the Heckman's two-step procedure (hereafter denoted as Heckman model) to correct sample selection bias caused by the absence of information on offer wages to non-workers. In the first stage, consider the traditional reduced form labor force participation equation (selection equation) in given by

$$E_{i,j}^{*} = \gamma_j Z_{i,j} + \mu_{i,j} \quad (j = m \text{ or } f) \tag{1}$$

where $E_{i,j}^{*}$ is a latent index that can be thought of as representing the difference between the employer's wage offer and his or her reservation wage.[4] $Z_{i,j}$ is a vector of observed variables determining labor force participation such as conventional human capital variables. Only an indicator variable for employment is observed, defined as $E = 1$ if $E_i^{*} > 0$ and $E = 0$ otherwise.[5]

In the second stage, the wage equation (outcome equation) is

$$lnW_{i,j} = \beta_j X_{i,j} + \mu_{i,j} \quad (j = m \text{ or } f) \tag{2}$$

[4] The 'offered wage' is defined as the maximum wage rate at which an employer is willing to pay a worker. And the 'reservation wage' is defined as the minimum wage rate at which an individual will accept employment.

[5] The employment variable (E) takes the value 1 if the disabled individual participates in the labor force ('labor force participation') and 0 if the disabled individual is not in the labor force ('not participating'). In other words, the reference group includes potential workers who choose not to seek employment, and so are counted as 'out of the labor force' in official employment statistics, i.e., the reference group ('not participating') = the unemployed + out-of-the labor force.

where $lnW_{i,j}$ is the log of hourly (offer) wage of the individual worker i, m and f denote disabled males and females respectively, $X_{i,j}$ is a vector of observed variables related to productivity characteristics, β_j is the returns on characteristics, and $\mu_{i,j}$ includes all unobserved determinants of wages. The wage equation (2) assumes that W is observed only for employed workers. That is, W is observed if the individual accepts employment in case the employer's offered wage exceeds their reservation wage, i.e., $E = 1$.

The probit estimates of γ_j from the employment equation (1) are used to construct consistent estimates of the inverse Mills ratio term ($\lambda_{i,j}$, hereafter denoted as *IMR*) that is used as an additional regressor to correct for selection bias in the wage equation (2), which is

$$lnW^*_{i,j} = \beta_j X_{i,j} + \theta_j \lambda_{i,j} + \mu_{i,j} \quad (j = m \text{ or } f) \tag{3}$$

where lnW^*_i is the log hourly wage of the individual worker i and the variable $\lambda_{i,j}$ is the bias correction term/selectivity variable created to account for selection bias in the sample wage respondents. The wage equation (3) is estimated by ordinary least squares (OLS) in the second stage. The second step is carried out only for the uncensored observations and provides consistent and asymptotically normal estimators for β_j and θ_j.

1.2.2. Identification Issues

In the first stage of the Heckman model (the employment equation), the dependent variable is a dummy indicating whether or not the disabled individual participates in the labor force. And the estimates of the probit model are used to construct the *IMR* for the selectivity corrected wage equations in the second stage of Heckman model (the wage equation). Then the gender wage gap from the selectivity corrected wage equations are decomposed into three components: endowments, discrimination, and selectivity.[6]

In the present paper, two dummy variables indicating the presence of other labor market income earner (*OEARNER*) and dependent children under the age of 18 (*CHILD*) in the household are incorporated as exclusion restrictions for identification. Stated another way, identification is obtained by including these two dummy variables in the employment equation and excluding them from the wage equation. This is based on the following assumption that for disabled individuals those two excluded variables sometimes called instrumental variables (IV) contribute to determining the propensity to employment but are not related to wages.[7]

In addition to this, like many previous studies in this area, age and its square also appeare in the selection equations, but potential labor market experience and its square are in the wage equations (e.g., Jones et al., 2006; Neuman & Oaxaca, 2005). Clearly labor market characteristic variables in the wage equation are not observed in the

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[6] The employment equation includes: age and age squared, marital status, region, severity of disability, educational attainment, other labor market income earner in the household, and the presence of dependent children under the age of 18. The wage determination equations follow the Mincerian type wage specification. The log of hourly wages is regressed against a linear combination of socio-demographical characteristics, conventional human capital variables, and labor market characteristics. The wage equation includes: marital status, region, severity of disability, (maximum) potential labor market experience and experience squared, educational attainment, labor union membership, part-time employment contract, public-sector employment, occupation, and industry with addition of *IMR*.

[7] It seems reasonable to assume that the factors influencing the value of time (e.g., presence of children, exogenous income, nonwage income, etc) play an important role in determining whether individuals participate in the labor force or not, but do not directly affect the wages of workers. Some previous studies, in particular, use a dependent children dummy and a dummy indicating the presence of other labor market income earner in the household as exclusion restrictions (e.g., Heckman, Lyons & Todd, 2000; Jones et al., 2006). For instance, Jones et al. (2006) find the evidence that for disabled individuals the presence of other labor market income earner in the household discourages employment participation. They also claim that disabled males (females) with dependent children under age 18 are more (less) likely to be employed that their counterparts without dependent children.

employment equations, since such information is not available for individuals who are not employed. As Jones et al. (2006) note that this could influence the correction for selectivity bias in the equations. Additionally, the sample selectivity variable (*IMR*) is also excluded from the employment equations.

1.2.3. Decomposing Gender Wage Differentials

The standard wage decomposition methodology by Blinder (1973) and Oaxaca (1973) is widely used in the literature to examine gender discrimination in the labor market. It decomposes gender wage differentials into 'explained' and 'unexplained' components. The latter (former) is conventionally interpreted as a discrimination (human capital) portion. The standard decomposition approach, however, ignores the presence of sample selection in the stage of decomposing wage differentials (e.g., Baldwin, Butler & Johnson, 2001; Baldwin et al., 1995, 2000; Kidd et al., 2000; Jones et al., 2006; Jung, 2010). The present study thus adopts the selectivity corrected decompositions approach suggested by Neuman & Oaxaca (2004) to consider selectivity bias in estimating a part of wage differentials attributed to discrimination. This methodological framework can be applicable under the condition when the bias correction term is included in the wage equation, i.e., the decomposition extension of Heckman model.

In this paper, the selectivity corrected decomposition methodology decomposes gender wage differentials among the disabled into three components: 'endowments', 'discrimination', and 'selectivity'. The 'endowments' component represents a part of the difference attributable to productivity-related characteristics. The 'discrimination' component is the ‘unexplained’ residual that is traditionally defined as a discrimination portion.[8] The ‘selectivity’ component measures the contribution of selection effects to the observed wage differential. This technique allows policy-makers to identify the relative importance of differences of different factors that contribute to the observed gender wage gap and to develop a more effective approach for eliminating gender wage discrimination against disabled female workers.

In estimating the contributions of the three components in gender wage differentials, selectivity corrected wage equations (equation (3)) yield the following decomposition in assuming that the *m* (male) wage structure is the norm as the nondiscriminatory, like much of the literature:

$$\overline{W}_m - \overline{W}_f = \underbrace{\bar{X}'_f(\hat{\beta}_m - \hat{\beta}_f)}_{\text{Discrimination}} + \underbrace{(\bar{X}_m - \bar{X}_f)'\hat{\beta}_m}_{\text{Endowments}} + \underbrace{(\hat{\theta}_m\hat{\lambda}_m - \hat{\theta}_f\hat{\lambda}_f)}_{\text{Selectivity}} \tag{4}$$

This approach is implied to identify the overall selection component as a category apart from discrimination and endowments effects. The decomposition defined by equation (4) is labeled as ‘decomposition #1’. In the case in which policy makers are primarily interested in direct pay equity, decomposition #1 would provide the relevant target adjustment. This is because decomposition #1 offers policy implications regarding

[8] It is a pure measure of discrimination only if the productivity-related characteristics fully capture all productivity differences. This study, however, refers to the ‘unexplained’ differential as discrimination, like conventional studies in this area. In addition, the estimated ‘unexplained’ gap could be an underestimate as well as an overestimates of discrimination. This is because any omitted variable bias depends on the correlations between the omitted and the included variables (Oaxaca & Ransom, 2003). That is, what I call ‘discrimination’ in this paper is just a part of non-observable items. More generally, one has to be careful about arguing that the estimated ‘unexplained’ gap is a biased estimate of discrimination due to omitted variable bias. In general, the same set of variables belongs in both wage equations. So if one uses the standard set of variables that are used in wage regressions a la Mincer, and one believes there is omitted variable bias, then the Mincerian type wage specification is flawed for (disabled) males as wells as (disabled) females.

the elimination of wage discrimination against employed disabled females. In decomposition #1, the only term that is explicitly associated with labor market inequality is the first term that reflects gender differences in the returns to the observable characteristics (Neuman & Oaxaca, 2005).

As noted by Neuman & Oaxaca (2004), if one believes that gender differences in the probit selection parameter for employment represent discrimination and that gender differences in personal attributes that determine the probability of employment are simply endowment differences, the resulting decomposition would be:

$$\overline{W}_m - \overline{W}_f =$$

$$\underbrace{\bar{X}'_f(\hat{\beta}_m - \hat{\beta}_f) + \hat{\theta}_m\left(\hat{\lambda}_f^o - \hat{\lambda}_f\right)}_{\text{Discrimination}} + \underbrace{(\bar{X}_m - \bar{X}_f)'\hat{\beta}_m + \hat{\theta}_m(\hat{\lambda}_m - \hat{\lambda}_f^o)}_{\text{Endowments}} + \underbrace{(\hat{\theta}_m - \hat{\theta}_f)\hat{\lambda}_f}_{\text{Selectivity}} \qquad (5)$$

where $\hat{\lambda}_f^o$ is the mean value of the *IMR* if disabled females faced the same selection equation that disabled males face. The decomposition defined by equation (5) is labeled as ‘decomposition #2’. Decomposition #2 indicates that antidiscrimination policy would entail the elimination of the hiring discrimination against disabled females seeking employment in addition to the elimination of wage discrimination against already employed disabled female workers (Neuman & Oaxaca, 2005).

An alternative would be to regard gender differences in the wage effects of selectivity as one contribution to the endowments component:

$$\overline{W}_m - \overline{W}_f =$$

$$\underbrace{\bar{X}'_f(\hat{\beta}_m - \hat{\beta}_f) + \hat{\theta}_m\left(\hat{\lambda}_f^o - \hat{\lambda}_f\right)}_{\text{Discrimination}} + \underbrace{(\bar{X}_m - \bar{X}_f)'\hat{\beta}_m + \hat{\theta}_m(\hat{\lambda}_m - \hat{\lambda}_f^o) + (\hat{\theta}_m - \hat{\theta}_f)\hat{\lambda}_f}_{\text{Endowments}} \qquad (6)$$

The decomposition defined by equation (6) is labeled as ‘decomposition #3’. The policy implications for decomposition #3 are the same as for decomposition #2. Finally, the most encompassing view of discrimination is:

$$\overline{W}_m - \overline{W}_f = \underbrace{\bar{X}'_f(\hat{\beta}_m - \hat{\beta}_f) + \hat{\theta}_m\hat{\lambda}_f^o - \hat{\theta}_f\hat{\lambda}_f}_{\text{Discrimination}} + \underbrace{(\bar{X}_m - \bar{X}_f)'\hat{\beta}_m + \hat{\theta}_m(\hat{\lambda}_m - \hat{\lambda}_f^o)}_{\text{Endowments}} \qquad (7)$$

The decomposition defined by equation (7) is labeled as ‘decomposition #4’. Although decomposition #4 is the most inclusive of the decompositions as far as measuring discrimination is concerned, it would not necessarily yield the largest estimate of discrimination. As Neuman & Oaxaca (2004) note that decomposition #1 is noncommittal regarding the role of selection effects in labor market discrimination and the decomposition expressed in (5), (6), and (7) involve varying degrees of assignment of selection effect decompositions to discrimination and endowment components.

1.3. The Concept of Labor Market Discrimination[9]

Altonji & Blank (1999) define labor market discrimination as a situation in which persons who provide labor market services and who are equally productive in a physical or material sense are treated unequally in a way that is related to an observable characteristic such as race, ethnicity, or gender. By “unequal” they mean these persons receive different wages or face different demands for their services at a given wage. Let the wage Y equal

$$Y = X\beta + \alpha Z + e$$

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[9] The primary reference for this section is Altonji & Blank (1999).

where X is a vector of exogenous productivity characteristics that are observable by firms, β is the vector of related coefficients, and Z is an indicator variable for membership in a minority group. Assuming that $X\beta$ fully captures the set of productive characteristics and their returns and/or Z is uncorrelated with e, then discrimination is a case where $\alpha < 0$.

As Cain (1986) discusses in some detail, there are difficulties just using this simple definition of "equally productive". First, 'productivity' may directly depend on Z. For instance, physical beauty may be rewarded in the entertainment industry. If customers prefer to watch white actresses or handsome newscasters, is this a legitimate component of productivity or sources of labor market discrimination against other racial groups or less handsome people? Second, there is also the issue of whether the production technology that determines β is truly exogenous. For instance, changes in technology in the fire fighting industry and in the military have altered the effects of physical strength on productivity and increased the average productivity of women relative to men. Finally, the *X's* could also be endogenous. That is, pre-labor market discrimination may reduce the productivity characteristics (the *Xs*) among the minority groups. For instance, discrimination in housing or in educational access among earlier generation may lower current education levels among minorities. And current labor market discrimination may also influence X. If minority groups believe that they will have difficulty being accepted in a particular profession, they are less likely to invest in the skills necessary for the profession.

Although such issues above may be hard to examine directly or whether or not these are relevant in this paper, it can still be the case that $\alpha < 0$ conditional on both X and

β, which would constitute discrimination in the labor market. When measuring discrimination with decomposition techniques here, all that is being estimated is direct labor market discrimination, though the size of the 'unexplained' (discrimination) differential identified in a decomposition analysis may be affected from the various other factors such as socio-cultural background, labor market structure, law, etc. That is, conditioning on the observed characteristics is there any wage differential attributed solely to gender. So differences in characteristics that are due to societal discrimination are not measured.[10]

1.4. Data

1.4.1. Panel Survey of Employment for the Disabled (PSED)

The Employment Development Institute (EDI) under the supervision of the Korea Employment Promotion Agency for the Disabled, an affiliate of the Ministry of Labor initiated the PSED in 2007 with the aim of addressing the economic activities of a selection of respondents with disabilities. The PSED is designed as a longitudinal survey of income activities of a representative sample of Korean households and individuals with disability. This dataset is a unique Korean dataset on individuals who are registered as disabled. The data source used in the present study is the 2008 PSED. The targets of the 2008 PSED survey are registered disabled persons who were selected in late 2007 for the PSED. This dataset consists of 5,092 registered disabled people and the sub group is

[10] The major sources of labor market discrimination are as follows. Besides Becker taste driven discrimination on the part of employers, there could be fellow worker or consumer taste for discrimination (Becker, 1971). There could also be monopsony (Ransom & Oaxaca, 2010). There could be statistical discrimination as well (Phelps, 1972). For hierarchical discrimination see Baldwin et al. (2001).

designed to measure economic activity and employment characteristics of the disabled from the age of 15 to 75.

The PSED in general is highly useful for academic research and policy development for disabled people in Korea as it contains a rich variety of information focusing on registered disabled people. That is, this dataset can serve as a valuable data source for not only examining disability-related issues in research studies but also designing/implementing the right set of disability-related labor policies and regulations. In research, the PSED dataset has a particular strength in that researchers at least do not need to have their own subjective definition of disability to identify disabled individuals from survey data, unlike much of the literature on discrimination. Since there is no clear and widely accepted definition of disability, defining disability has been a fairly subjective issue in disability-related studies. To identify people with disabilities, some have drawn upon the distinction made by the World Health Organization (WHO) between disability, impairment and handicap. Others have used self-reported health status, work/functional limitations, or specific impairments. It suggests that the results of studies (e.g., disability prevalence estimates) and their interpretation could be different depending on definitions by researchers.

1.4.2. Descriptive Statistics

The original 2008 PSED dataset used in this study is for 5,092 registered disabled people. I restrict the original dataset to salary workers from the age of 15 to 60, so self-employed and unpaid family-employed workers are not included in decomposition analysis. Table 1-2 presents the summary statistics (mean and standard deviation) for the estimation sample. Most variables conform to usual predictions. Several important differences between disabled males and females are worthy of note. In panel *A*, disabled female workers typically earn less than their male counterparts, as would be expected. The log of hourly wages is 8.843 for disabled male workers and 8.414 for disabled female workers, yielding approximately 43 percent gender wage differentials. In other words, disabled female workers received, on average, nearly 43 percent lower wages than their male counterparts. It indicates that the relative position of disabled female workers may be inferior to that of disabled male workers in the Korean labor market, at least in terms of wages.

In addition to this, the results presented in panel *D* once again suggest that for disabled individuals gender differences in labor market characteristics could in part be associated with a gender wage differential in Korea. Specifically, disabled female workers are less likely to be union members (3.6 percent vs. 9.7 percent), more likely to work part-time (22.4 percent vs. 13 percent), and more likely to be employed in the public sector (11.2 percent vs. 8.2 percent) than their male counterparts, which could be one possible explanation for their lower wage levels. Moreover, disabled females are more likely to be employed in relatively low-wage occupations where the majority of workers make lower wages than their male counterparts. For instance, the employment rate in laborer occupations (managerial, senior official, or professional occupations) for disabled female workers is 59.6 percent (4.7 percent), compared to 43.7 percent (0.4

percent) for disabled male workers. Such findings indicate that disabled female workers may be disadvantaged relative to disabled male workers in the Korean labor market.

1.5. Results and Discussion

1.5.1. Probit Estimates of the Employment Equation

The employment function based on the equation (1) provides information on the relationship between the employment probability and observed variables influencing a worker's employment participation decision. Table 1-3 reports the probit estimates of the employment equation by gender. The gender specific probit estimates are presented in column (2) for disabled males and column (3) for disabled females respectively. In column (2), all variables show statistically significant effects on employment participation of disabled males. For disabled females most findings also show statistically significant employment effects in column (3), with the exception of three variables – marital status (*MARRIED*), rural region (*RURAL*), and less than high school graduates (*HSDROP*). The signs of all coefficients, however, are still consistent with usual predictions in column (3)

Regarding hypothesis testing of coefficients, obviously the likelihood ratio test rejects the null hypothesis that all coefficients in each regression are jointly statistically insignificant (all slope coefficients are zero) at all conventional significance levels in both male and female categories. On the whole, in addition, the coefficient estimates shows different qualitative effects on the employment probability for disabled males and females. Indeed, the χ^2 test rejects the null hypothesis of parameter homogeneity (equality) among gender groups of the disabled, as would be expected.

Turning to the specific coefficient estimates, most findings are in accordance with the usual expectations. Begin with the socio-demographic characteristics in panel *A*. There are strong age effects, with positive and negative signs on the coefficients of the linear (*AGE*) and quadratic terms (*AGESQ*) respectively for both male and female categories. For disabled males being married (living in rural areas; *RURAL*) has a statistically significant positive (negative) effect on employment participation but has no statistically significant effect on disabled females. The estimates for the dummy variables of marital status (*MARRIED*) reflect conventional household roles. Regarding severity of disability, for both disabled males and females mild disability individuals (*MILD*) are more likely to be employed than their severe disability counterparts. Such findings are once again in accordance with the results found in numerous previous studies. For instance, Rigg (2005) shows that the employment rate is lower for more-severely disabled individuals, compared to less-severely disabled people.

In terms of educational attainment in panel *B*, both disabled males and females with relatively high educational qualifications (e.g., more than a 2-year college degree; *COLLEGE*) are more likely to be employed than those with relatively low educational qualifications (e.g., high school diploma; the omitted group), while relatively low educational attainment (e.g., less than a high school diploma; *HSDROP*) reduces the likelihood of employment for both male and female cases of the disabled, as would be expected. For disabled females, in particular, the marginal effect of higher education on employment participation (*COLLEGE*) is stronger than that of their male counterparts. It suggests that for disabled females education may be a particularly important factor for higher employment in Korea.

In panel *C*, for both disabled males and females the presence of other labor market income earner in the household (*OEARNER*) has a positive employment effect. And disabled males (females) with dependent children under the age of 18 (*CHILD*) are more (less) likely to be employed than their counterparts without dependent children. Such findings also confirm the results of previous studies in this area (e.g., Heckman et al., 2000; Jones et al., 2006).

1.5.2. Selectivity Corrected Estimates of the Wage Equation

In Table 1-4, the selectivity corrected estimates based on the wage equation (3) are presented in column (2) for disabled males and column (3) for disabled females respectively. Most variables have statistically significant effects in the wage equations for disabled males, while a relatively small number of coefficient estimates are statistically significant in the model for disabled females. For disabled females the lack of statistical significance may in part be explained by the relatively small number of observations, however all findings have the same signs with the results for disabled males.

In terms of the specific coefficient estimates, these are once again in accordance with usual predictions based on the traditional labor market analysis. As regards the socio-demographic characteristics in panel *A*, the marital status variable agrees with what most studies seem to show: being married (*MARRIED*) has positive returns for men and generally has little or no effect for women. As might be expected, the regional dummy shows that given the omitted category (urban region), living in rural areas (*RURAL*) is associated with lower wages for both disabled male and female categories, though there is no statistically significant impact for disabled males. For both disabled males and females mild disability (*MILD*) is also positively related to wages.

Regarding human capital characteristics in panel *B*, there is a positive wage effect of potential labor market experience (*EXP*), though this effect is not statistically significant for disabled females. It indicates that potential labor market experience has no effect on higher wages for disabled females. For both disabled male and female workers higher education and job tenure (years in the current job) are generally associated with higher wages. Such findings are in accordance with the usual predictions in that disabled people with higher levels of human capital accumulation are paid more than those with lower levels of human capital traits. In particular, the presence of more than a 2-year college degree (*COLLEGE*) has a strong positive effect on wages: disabled male (female) workers with more than a 2-year college degree paid on average approximately 14.1 (45.6) percent more that their high school graduate counterparts (omitted group; *HSCHOOL*). It suggests that higher education may be a particularly important factor in wage determination for disabled people.

Turning to labor market characteristics in panel *C*, members of labor unions (part-time employees) generally earn more (less) than their non-union (full-time) counterparts, as would be expected, but there is no statistically significant effect on the wages of disabled female (male) workers. Interestingly, being employed in the public sector

(*PUBLIC*) is associated with significantly higher wages for both disabled male and female categories, though there is no statistically significant effect for disabled males. Such findings, however, also confirm the results of some previous studies in this area (e.g., Jones et al., 2006).

As regards occupation and industry, all variables are statistically significant positive and of plausible relative magnitudes given the omitted groups (laborer occupation; *OCC6*), with just one exception - disabled females employed in the managerial, senior official, or professional occupations (*OCC1*). For both disabled male and female workers the average wage level employed in secondary and tertiary industries is higher than that of the omitted group (the primary industry; *IND1*), but there are no significant industry effects on wages of disabled females.

Finally, *IMR* (the selectivity correction term) has a negative sign and is statistically significant for both disabled males and females, as would be expected. It suggests that some non-employed disabled people may not be able or willing to work due to their disabilities, or may not be able to access employment due to prejudice among employers. Taken at face value, the sample selection bias in the employment process has significant influence on wages of disabled male and female workers. It indicates that unobservables captured by the error term, which encourage participation in the wage sector, are associated with lower wages. Thus, some disabled people who do not work may have higher potential wages than those who work.

1.5.3. Decomposing Gender Wage Differentials

Table 1-5 summarizes the results of analysis of gender wage differentials among the disabled. In panel *A*, observed gender wage differentials are presented. The first and second rows provide the mean prediction of log hourly wages for disabled males and females respectively. The third row indicates gender wage differentials yielding from the first and second rows. Panel *B* provides the results of four alternative decompositions incorporating selection effects as a portion of the gender wage gap. Four selectivity corrected decompositions decomposition #1-4 are labeled corresponding to equations (4), (5), (6), and (7) respectively. The standard decomposition model without selectivity correction is used as a benchmark, labeled as 'Standard Oaxaca'.

In terms of gender wage differentials, panel *A* reports an estimated gender wage gap of approximately 43 percent among the disabled in the Korean labor market. It indicates that disabled female workers earned 70 percent as much as their male counterparts. This figure is somewhat interesting when comparing the size of gender wage differentials among the general working population in Korea. The OECD report released in 2009 using data collected targeting 21 OECD member countries during 2006 and 2008 notes that Korean female workers earn, on average, approximately 38 percent less than their male counterparts and this is the largest gender wage gap among the OECD countries. The average gender wage gap is 17.6 percent for the OECD countries. Moreover, the result also suggests that for disabled people 43 percent of the gender wage differential in Korea could be relatively larger than the wage gap in other countries. The gaps are 24.7-32.9 percent in the U.K. (Jones et al., 2006), 42.6 percent in the U.S. (Baldwin et al., 1995), etc.

A particular focus of this study is to investigate what factors - ‘endowments’, ‘discrimination’, and ‘selectivity’ - account for the gender wage differentials among the disabled. First, the endowment component in column (1) of panel *B* reflects the mean increase in disabled female workers’ wages if they had the same characteristics (e.g., human capital accumulation) as their male counterparts. That is, the increase of 0.146-0.219 indicates that gender differences in the endowment characteristics among the disabled account for amount ranging from 34 percent to 51 percent of gender wage differentials. The portion explained by differences in characteristics is smallest under ‘Standard Oaxaca’ and largest under ‘decomposition #3’. The results indicate that disabled male workers, on average, have more characteristics with higher wages than their female counterparts. And the endowments (explained) component is one important factor to explain gender wage differentials among the disabled in the Korean labor market.

Next, the discrimination component presented in column (2) of panel *B* quantifies the change in disabled female workers’ wages when applying coefficients of disabled males to the characteristics of disabled females. The results show that all of the decompositions employed yield positive estimates of discrimination against disabled female workers. Specifically, the positive portion of wage differentials explained by the discrimination component (0.210–0.282) is regarded as the magnitude of gender wage differentials among the disabled due to discrimination. In addition, discrimination explains the gender wage gap among the disabled between 49 percent under decompositions #2-3 and 66 percent under Standard Oaxaca. On the whole, such findings are consistent with the results of previous studies in other countries in that the discrimination (unexplained) component plays a significant role in explaining gender wage differentials among the disabled. For instance, the estimates of the gender wage gap attributable to discrimination are 39-59 percent and 62 percent in the U.K. (Jones et al., 2006) and U.S. (Baldwin et al., 1995) respectively.

The gender wage gap of 43 percent among the disabled discussed above is sizable. This figure, however, provides nothing regarding the relative importance of the residual/unexplained factor (i.e., discrimination) between the disabled and general working population, though many believe that the wage gap could be a good measure of the extent of gender wage discrimination. This is because the PSED dataset cannot answer the following question: “To what extent” gender wage discrimination of the disabled is different from those of the general working population. To compare gender wage discrimination of the disabled and the general working population, however this paper reviews literature surveys. By and large, the comparisons indicate that the extent of gender wage discrimination among the disabled is similar to or relatively larger than that of the general working population (e.g., 49-67 percent vs. 49-62 percent for Yoo & Hwang (2005)). The results suggest that the discriminator factor could play a bigger role in explaining gender differentials than the endowment factor, as is the case with the general working population in Korea.

Finally, the selection effects estimates presented in column (3) of panel *B* have positive signs and are statistically significant. They indicate that selection bias has a negative impact on gender wage differentials among the disabled in Korea. That is, the presence of selection effects raises the observed gender wage gap among the disabled. This may in part reflect that potential disabled females with relatively lower wages are employed. In addition to this, the estimates in column (1) for the endowments component and column (2) for discrimination component vary across alternative decompositions, as a result of the imputation of gender differences in the selectivity term. This variation, as stated earlier, is not simply statistical variation but rather the consequences of what policy makers choose to label as ‘discrimination’ or ‘endowments’.

1.6. Summary and Conclusions

Numerous previous studies in the literature on discrimination using decomposition approaches have focused on examining the disability effects on labor market outcomes comparing differences in likelihood of employment and levels of wages between the disabled and the non-disabled (or the general working population). In particular, the research on the comparison of gender differences among the disabled within the labor market has been relatively neglected in Korea, in both the theoretical and empirical aspects. Thus, this paper using data from the 2008 PSED (a unique Korean data set on individuals who are registered as disabled) attempts to examine gender wage differentials among the disabled working population in the Korean labor market.

A particular focus of this study is to determine the relative importance of the endowment (explained) and discrimination (unexplained) factors in the gender wage gap among the disabled in Korea. For this reason, this paper employs selectivity corrected decompositions framework suggested by Neuman & Oaxaca (2004) to examine what factors - endowments, discrimination, and selectivity - account for the gender wage gap. The main evidence presented in this study is as follows. First, the wage gap of 43 percent between disabled male and female workers is substantial in Korea. Second, the estimated size of the gender wage gap among the disabled attributable to discrimination accounts for between 49 and 66 percent. It suggests that for disabled people the portion of gender wage discrimination may be relatively larger than the gender wage gap explained by the endowments (explained) component. Such findings indicate that disabled female workers relative to disabled male workers may suffer significant gender-based wage discrimination in the Korean labor market.

Regarding the issue of selection bias, this paper suggests that ignoring the selection bias may be likely to produce bias estimates of gender wage differentials among the disabled when wage equations suffer from the sample selection bias. In this analysis, the presence of selection effects raises the observed gender wage differentials among the disabled. That is, selection effects do impact the portion of gender wage discrimination against disabled female workers in the Korean labor market. This evidence is once again in accordance with the usual expectation in that using decomposition methods with selectivity correction in the presence of the selection bias is appropriate (e.g., Neuman & Oaxaca, 2005).

The findings discussed above suggest that disabled females hold with a (potential) wage disadvantage relative to comparable disabled males and thus have the following important policy implications for combating disabled female workers' inferiority in the labor market. Since gender wage discrimination could reduce disabled females' incentives to work, in particular, the government and management try to find corrective measures that must be taken immediately to eliminate obstacles for full labor market participation of disabled females. National policies/regulations, laws against discrimination such as the U.K. Disability Discrimination Act 1995 (DDA), the U.S. Americans with Disabilities Act of 1990 (ADA), etc are necessary to enhance labor market status of disabled female workers in Korea, though this is highly controversial. Such anti-discrimination policies/laws can help reduce disability-based discrimination in the workplace including denial of employment, negative work performance evaluations, unjust denial of promotion and/or tenure, and sexual harassment, particularly disabled female workers.

In addition to anti-discrimination policies/laws, a wide variety of factors (e.g., educational level, labor market experience, etc.) could impact gender wage differentials among the disabled. The evidence presented in this paper suggests that the endowments component plays an important role in explaining the gender wage gap among the disabled in Korea (38-44 percent) and may point to the importance of additional supports beyond prohibiting discrimination against disabled females. Thus, for disabled females the government and management must also adopt additional policies (environments) to improve work abilities/skills (develop human resources) such as on-the-job-training (vocational education and training) respectively. Such policies/regulations can help enhance disabled females' human capital stock and thus reduce the gender wage gap among the disabled through induced labor productivity growth of disable females.

This paper focuses on the gender discrimination among the disabled in the Korean labor market. Future research could seek a decomposition comparison between the disabled and non-disabled groups as a whole or even a cross-country comparison with the differences among the disabled. Under such circumstances, one could consider the possibility that the markets for the disabled work very differently than the markets for the non-disabled or there are the differences between Korean market and markets in other countries. Exploring these institutional differences would be an interesting way to compare outcomes for the disabled.

In addition to this, when measuring discrimination with decomposition analysis in the present study, differences in characteristics that are due to societal discrimination are not measured. In reality, however, the feedback effect of anticipated labor market discrimination could lead women to invest less in human capital than they otherwise would. With a different type of data, thus one could also attempt to estimate the effect of current and recent past labor market discrimination on gender differences in (human capital) investments in education, on-the-job training, etc.

CHAPTER 2. ENGLISH LANGUAGE AND SKILL MISMATCH IN KOREA

2.1. Introduction

Job mismatch is one of the most widely-studied topics in modern labor economics. A large part of this literature has focused mainly on the concept of over- and under-education, i.e., workers are usually denoted as over-educated (under-educated) if they have higher (lower) educational qualifications than an applicant would be required to get their job. Much attention in the empirical literature on educational mismatch is given to the basic relation between over- and under-education and several labor market outcomes such as wages, job satisfaction, and mobility, etc. In particular, most prior research in this area has investigated the impact on wages of the mismatch between a worker's attained level of education (years of schoolings) and the level of education required for a job, e.g., Hartog (2000). Some of the more recent publications discuss on-the-job mismatch in terms of the field of study among college graduates, by considering whether college major is related to the current job, e.g., Robst (2007).

Special emphasis has been given to job mismatch issues with regard to education, particularly on the concept of over-education, while the topic of skills-job mismatch in terms of skill utilization has received relatively little attention in the economic literature. However, since there could exist significant variability in terms of skill endowments or ability among workers with similar educational attainment, one may need to investigate skills and their utilization. In such cases the over- and under-education conceptual framework can still be applied to other forms of human capital skills influencing labor market success such as computer skills, language skills, etc. For instance, Chiswick and Miller (2007) examine variations in the wage impact of job mismatch in terms of English language skills among immigrants according to skills required for a job in the U.S. labor market and conclude that the methodology of the over- and under-education literature is also useful in study of language skills and labor market outcomes.

In light of the results by Chiswick and Miller (2007), this paper examines whether the impact of over- and under-qualifications related to English language skills reflects the limits placed on opportunities for skill utilization in South Korea (hereafter denoted as Korea). That is, this work advances the research on skills-job mismatch between acquired and required English language proficiency, by considering natives in a non-English speaking country, while Chiswick and Miller (2007) focus only on immigrants in native-English speaking countries. Recently English language skills have become one of the most important key tools in terms of labor market success for not only immigrants in native-English speaking countries but also for natives in non-English speaking countries. However, empirical studies of language skills-job mismatch have not expanded the concept of labor market consequences experienced among natives in non-English speaking countries. To my knowledge, an economic analysis of the impact on wages of skills-job mismatch related to English language proficiency in non-English speaking countries has not been published in a journal. Thus, this paper attempts to fill this gap by assessing the association between wages and the degree to which English as a foreign language is utilized in Korean workplaces.

The three main research questions this study seeks to address are: (1) does the job mismatch in terms of English language skills exhibit significant impacts on wages in a non-English speaking country: (2) if so, is the wage impact positive or negative: and (3) what type of skill mismatch, i.e., over- and under-skilling, leads to greater impacts on wages. These questions may be more relevant today than ever before in Korea. This is in part because English language skills have become increasingly important in Korean workplaces. The ability to utilize acquired English language proficiency in future employment can be regarded as one aspect of labor market success. If skills-job mismatch with respect to workers' acquired English language proficiency level relative to required job level has significant economic implications in the form of a wage premium or penalty, this paper determines whether such economic benefits or costs exist in the Korean labor market.

The data used in this empirical analysis is the 2007 Korea Labor and Income Panel Survey (hereafter denoted as KLIPS). The 2007 KLIPS is a unique and appropriate Korean dataset for the present study, as it contains relevant information on the English language proficiency of workers and the degree to which this is necessary for the job they hold. Two different measurement techniques, i.e., the direct self-assessment (DSA) and the indirect self-assessment (ISA) measures, are used to identify over- and under-skilled workers in this analysis: These two different approaches provide a much richer analysis.

This study employs the random effects generalized least squares (GLS) model to consider the nature of cross-sectional data drawn from populations with a grouped structure. It is possible that more than one random group effect exists in cross-sectional grouped data regression models, and these group effects could be correlated, both across groups and among levels with a group. Under these circumstances, the regressor errors are often correlated within groups, and such intra-group error correlation can be incorporated into error components or random coefficient models for the disturbance (Moulton, 1986)**.** The standard approach, such as ordinary least squares (OLS) estimation, is to assume such random group effects are uncorrelated, although this assumption of independent errors is usually incorrect in many grouped data situations. Thus, the random effects GLS approach leads in many situations to less biased estimates than OLS, when estimating wage equations in the presence of random group effects. Incorporating group effects may result in not only possibly correct statistical inferences, but it also uses a potentially interesting piece of information in the analysis.

The main findings in this study are consistent with the stylized facts of the assignment theory (Sattinger, 1993) literature as follows: (1) the job mismatch in terms of English language skills is significantly associated with wages in Korean workplaces: (2) there exist substantial differences in the wage impact between over- and under-skilling related to English language proficiency the returns to over-skilling (i.e., skill under-utilization) are negative (the wage penalty), while returns to under-skilling (i.e., skill deficit) are positive (the wage premium): (3) the wage penalty for over-skilled workers is larger than the wage premium for under-skilled workers in the Korean labor market: (4) the sign and significance of the parameters associated with the wage impact are robust over the different measures of skills-job mismatch: and (5) these results once again confirm the fact that the conceptual framework of the over- and under-education literature is also useful when examining the impact of skills-job mismatch on the returns to English language proficiency in non-English speaking countries.

2.2. Background[11]

If skills-job mismatch affects wages, is the impact positive or negative? If there is a wage premium or penalty related to skills-job mismatch, what causes it? The general consensus in the literature on the relationship between skills-job mismatch and wages is that over-skilled workers suffer a wage penalty, while a wage premium exists for under-skilled workers. There are several theories to explain the observed wage effects of over- and under-skilling: Human capital theory (Becker, 1962) assumes that individuals invest in their human capital to maximize expected lifetime utility. Firms are, in turn, willing to fully utilize their employees' knowledge and skills by adapting appropriate production technologies in response to changes in skilled labor availability. Under such circumstances, an individual's particular level of human capital will provide a certain level of productivity regardless of the job in which that individual works, and thus workers are rewarded according to their marginal product determined by the human capital or skill level they have accumulated rather than their job characteristics. This supply-side oriented approach takes into account only differences in individual characteristics, when explaining wage differentials.

Several economists, using the Mincer wage function based on human capital theory, call into question these assumptions and have developed alternative theoretical

[11] The primary references for this section are Allen and van der Velden (2001) and Di Pietro and Urwin (2006).

assumptions and frameworks to investigate whether individuals' wages are determined by both their individual and job characteristics, or if productivity solely depends on human capital (e.g., Duncan and Hoffman, 1981; Hartog and Oosterbeek, 1998; Rumberger, 1987). They argue that the observed wage differentials for jobs below and above workers' own skill level might just as easily reflect individual differences in human capital, which are roughly sorted according to job level. The research in this area has found that over-skilled (under-skilled) workers earn less (more) than their adequately skilled counterparts. According to this alternative human capital approach, over-skilled workers (those working 'below their own level') are in that case less productive on average than adequately matched workers (those working 'at their own level'), not because the job imposes limitations on their productivity, but because they have less human capital on average to begin with. Similarly, under-skilled workers (those working 'above their own level') have according to this view more human capital on average than adequately matched workers (Allen and van der Velden, 2001).

Institutional theory (Thurow, 1975) provides another possible explanation for the same wage impact of skills-job mismatch. This theory is demand-side oriented and stresses differences in job characteristics as prime determinants of individual's wages, suggesting that the level of wages of individual workers is solely determined by job characteristics (i.e., job skill requirements), rather than their individual characteristics (i.e., the productivity of workers). The rationale behind this approach is based on the assumption that since employers have difficulty quantifying individual productivity in general, they often use easily observable characteristics of employees or jobs, rather than individual performance, to make inferences regarding productivity and wages of workers. This is one form of statistical discrimination. From such a perspective, the observed wage differences could be accounted for by the fact that the level of skills required for a job is frequently incorporated in wage scales as determined in collective and individual bargaining agreements, and the differences may not reflect individual differences in productivity, but rather the value assigned to skills and job categories in such agreements.

If the employers' demand for different levels of skill is not matched by equivalent levels of supply of skills, some mismatching in general is inevitable (Mavromaras *et al*, 2010). In order to explain the existence of skills-job mismatch in the labor market, it has become conventional to use assignment theory (Sattinger, 1993) in the literature. The assignment theory approach emphasizes that both individual (supply) and job (demand) characteristics of the labor market should be taken into account when explaining wage differentials. In this context, there exists a certain skill level required for a job irrespective of the attributes of individual employees who are employed in it, and individual workers are then assigned to these jobs based on their characteristics. In addition to this, the actual level of productivity realized is determined by the match between acquired and required levels of human capital, although higher average human capital raises overall productivity in general.

According to the assignment theory, working in a job below one's skill level (over-skilling) may impose a limitation on the utilization of skills. The lower level of the job in effect imposes a ceiling on the worker's productivity, resulting in lower wages. Conversely, working in a job above one's skill level (under-skilling) in effect raises this productivity ceiling, allowing workers to be more productive than they would be when working at their actual skill level. In the former case, the job imposes limitations on their productivity (i.e., skill under-utilization measured by over-skilling), while in the latter case the worker's own abilities are the main factor limiting productivity (i.e., skill deficit measured by under-skilling). Since workers employed in a job at their own level are already performing at a level close to their own individual productivity ceiling, the wage premium of over-skilled workers is generally modest.

The conceptual framework employed in this paper is based on the assignment theory proposed by Sattinger (1993). This study attempts to examine whether the central premise of the assignment theory literature carries across to the analysis of job mismatch in terms of English language skills in a non-English speaking country (Korea). The main objectives of this work are to test the following three hypotheses generated from research questions stated in the earlier section.

Hypothesis 1: The skills-job mismatch related to English language proficiency has a significant impact on wages.
Hypothesis 2: The wage returns to over-skilling are negative, while the wage returns to under-skilling are positive.
Hypothesis 3: The wage premium for under-skilled workers is smaller than the wage penalty for over-skilled workers.

Even though this paper does not employ longitudinal data, the set of hypotheses above can be tested based on a proper nationally representative dataset (the 2007 KLIPS). If the assignment theory is valid in this work, over-skilled workers are underutilizing their knowledge or skills, resulting in a wage penalty, while under-skilled workers lack some of their knowledge or skills for optimal job performance, resulting in a wage premium. In addition to this, the assignment explanation also predicts that the returns to over-skilling are smaller than returns to under-skilling.

2.3. Data

2.3.1. Korean Labor and Income Panel Survey (KLIPS)

This paper uses survey data obtained by KLIPS in 2007. The Korea Labor Institute (KLI) under the supervision of the Ministry of Labor initiated the KLIPS in 1998 with the main objective of providing comprehensive information and national-level estimates for Korea resident population and subgroups regarding labor force behavior and other associated events. The KLIPS is designed as a longitudinal survey, a nationally representative sample of Korean households and individuals and is conducted annually on a sample of 5,000 urban households and members of the households (all members of the 5,000 households) 15 years of age or older distributed nationwide. Currently the KLIPS is the nation’s only labor-related panel survey (time-series and cross-sectional data) in Korea.

The KLIPS is highly useful for academic research and policy development in Korea, as it contains a rich variety of information about the Korean population, including household demographics, economic activities and labor market mobility, income activities and consumption, education, vocational training, and social activities of individuals. For the present study the 2007 KLIPS is particularly suitable because it includes questions concerning private education for English and the respondent's English proficiency. In other words, the 2007 KLIPS (wave 10) is a unique Korean dataset that provides relevant information on using English language, although previous surveys have been conducted since 1998 (wave 1). In the 2007 KLIPS, 5,069 households were successfully surveyed and the total number of individual respondents was 11,855. I restrict the 2007 KLIPS to salary workers from the age of 15 to 65, so that self-employed and unpaid family-employed workers are not included in the sample. The entire sample is 36.6 percent of the 2007 KLIPS with 4,344 valid responses (male 2,644; female 1,700).[12]

2.3.2. Main Variables

The 2007 KLIPS is a nationally representative cross-section dataset in Korea. It includes unique information on the individual worker's acquired English language proficiency and the level of English language skills required for a job. The responses to the following three key survey questions asked in the 2007 KLIPS are used to identify the existence of over-skilled and under-skilled workers. The first question relates to the individual worker's self-assessed English language proficiency:

In your view, what is the proficiency of your spoken English?

(1) Can hardly speak English
(2) Limited to very simple communication
(3) Able to carry on everyday conversation
(4) Able to conduct business with foreigners in English
(5) Fluent, able to interpret

[12] Due to the nature of cross-sectional data, it is not possible to consider the dynamics or persistence of skill mismatch in this paper.

The second question is about the level of English language skills to which this is necessary for a job:

What is the level of spoken English proficiency required by your current job?

(1) Almost none

(2) A little

(3) Substantially

The third question asked respondents directly whether they are over- or under-skilled for the job in terms of the level of English language proficiency they acquired is stated as follows:

What is the proficiency of your spoken English, compared to the level required in the workplace?

(1) Very low

(2) Relatively low

(3) Relatively high

(4) Very high

The comparison between acquired and required English language skills leads to two possible definitions of skills-job mismatch in the analysis, i.e. over-skilling (skill under-utilization) and under-skilling (skill deficit). Individuals are denoted as over-skilled workers if their English language proficiency exceeds the required English language skills for a job. Similarly, if individuals have less English language skills than those required for the job, they are then classified as under-skilled workers.

The measures of skills-job mismatch can be classified into four broad categories in the literature: (1) Direct self-assessment (DSA); (2) Indirect self-assessment (ISA); (3)

Job analysis (JA); and (4) Realized matches (RM).[13] Due to the availability of the relevant data, the DSA and the ISA procedures are employed to create two skills-job mismatch variables (i.e., over- and under-skilling) in this work. The DSA method is based on workers' self-reports of their level of skills for the job: Respondents are asked directly whether they are over- or under-skilling for the work they do. In the ISA method, the self-reported level of required skills is compared to the worker's acquired skill level: Respondents are asked the level of skills required for their job, and over- and under-skilling is then measured by comparing this required skill level with the acquired skill level.

The two sets of information collected in the first and second questions are used to assess skills-job mismatch variables in the ISA measure. The variable for over-skilling (*ISA_OVER*) takes the value of 1 if the worker reports *(1) Almost none* or *(2) A little* as the level of required English language skills in the current job and feels that his or her English language proficiency is *(3) Able to carry on everyday conversation*, *(4) Able to conduct business with foreigners in English* or *(5) Fluent in his/her English language ability*, 0 otherwise. The variable for under-skilling (*ISA_UNDER*) takes the value of 1 if the workers feels that the level of required English language skills in the current job is *(3) Substantial* and claims that his or her English language proficiency is *(1) Can hardly speak English*, *(2) Limited to very simple communication* or *(3) Able to carry on everyday conversation*, 0 otherwise. The responses to the third question are used in the DSA measure as follows: Individuals claiming *(3) Relatively high* or *(4) Very high* are classified as over-

[13] For details on these measurement techniques, see Groot and Maassen van den Brink (2000).

skilling (*DSA_OVER*) and those selecting *(1) Very low* or *(2) Relatively low* as under-skilling (*DSA_UNDER*).

The procedures used to identify skills-job mismatch variables in this study are based on subjective evaluation. Subjective evaluations may seem not related to the actual condition or response bias could exist. For instance, individuals could answer the questions in a way that makes their answers seem more in agreement. In the context of this study, workers whose English skills are not very good may be more disposed to downplay the importance of English language skills for their job, even if it is actually important. However, as pointed out by Jones and Sloane (2010), there is no obvious evidence that employees would consistently overestimates or underestimates their own skills or demands to the extent to which the job requires the level of skills they possess. In addition to this, Di Pietro and Urwin (2006) argue that the self-reported 'subjective' measures of skill mismatch can be reliably compared to the jobholder's judgment concerning the degree of utilization of employees' knowledge and skills. Indeed, subjectively measured skills-job mismatch variables have been used in much of the previous literature. Thus, while the responses to the cited questions are subjective, the individual assessments are expected to provide the substance (important information) of the present study.[14]

2.4. Methodology

[14] None of measurement methods is free of critique in general. In addition to this, Hartog (2000) argues that the basic relationship between skills-job mismatch and wages seems not to be influence by the measurement method, suggesting the robustness of the results for the different types of measures.

As is well known, grouped data estimation of well-specified linear models yields unbiased and consistent estimates of the parameters (e.g., Cramer, 1964; Haitovsky, 1973; Prais and Aitchison, 1954). Since the regression errors are often correlated within the groups when data used in a regression model are drawn from populations with a grouped structure, error component and random coefficient regression models are considered as models of intra-group correlation (e.g., Dickens, 1985; Moulton, 1986; Randolph, 1985). Researchers tend to view random effects models, especially two-way random group effects, as applying to situations using panel data. In such cases the random group effects typically refer to individual i and time t (i.e., the component errors: $\varepsilon_{ij} = u_i + v_t + w_{it}$), and these effects are commonly assumed to be uncorrelated. Several previous studies, however, focus on the use of group effects models in regression analysis of cross-sectional data and prove that random effects are also important in cross-sectional grouped data models (e.g., Conway and Houtenville, 1999; Moulton, 1986, 1987; Pakes 1983; Phfeffermann and Smith, 1985; Shore-Sheppard, 1996). In this study, I consider groups appearing in the data on age, educational attainment, firm size, and occupation.

As discussed by Conway and Houtenville, (1999), cross-sectional data is often drawn from populations with well-defined groups (such as location, industry, occupation, and level of education), and a sample may frequently contain repeated observations from each group. It is also possible to have more than one grouping structure present in the data and thus more than one random effect. In general, these random group effects could be correlated, unlike the panel data set. For instance, the wage data in this work could contain both education and occupation effects, and these two effects could be correlated. Thus, when grouped data models are used in regression analysis of cross-sectional data, it is commonly the case that the assumption of uncorrelated regression errors is not valid due to intra-group error correlation, and so it is usually necessary to take account of group effects either in the specification of the regressors or in the stochastic structure of the errors, when analyzing cross-sectional grouped data (Moulton, 1986).

In the context of OLS estimation, the consequences of the failure to incorporate group effects have been previously recognized. For instance, Shore-Sheppard (1996) notes that correlated errors arise most commonly when data are obtained using cluster sampling methods, and if the intra-group error correlation is ignored and standard estimation procedures are performed, (then) inefficient coefficient estimation and biased standard errors will results. Moulton (1986) using the 1982 Current Population Survey (CPS) examines the effects of ignoring the problem of the grouped structure in the analysis of Mincer-type wage functions and shows a substantial downward bias in estimated standard errors and thereby artificially inflating their statistical significance. In particular, he argues that even with a small intra-group correlation, the use of OLS regression may generate inefficient coefficient estimation and biased standard errors, while the magnitude of the bias is likely to vary. However, little attention has been paid to the consequences of such correlation errors for standard approaches appropriate for data with independent errors, e.g., Di Pietro and Urwin (2006).

Consider the following simple case of two-variable model to illustrate the implication of the use of ordinary least squares (OLS) in the presence of correlated disturbances:[15]

$$y_{ij} = \beta_0 + \beta_1 x_{ij} + \varepsilon_{ij},$$

where y_{ij} is the dependent variable, x_{ij} is a regressor, and ε_{ij} is the error for unit (observation) *i* in group j. The errors are composed of a group-specific component u_j and an individual-specific component v_{ij} (i.e., $\varepsilon_{ij} = u_j + v_{ij}$), and they are assumed to be equicorrelated within groups with ρ (i.e., $\text{corr}(\varepsilon_{ij}, \varepsilon_{kj}) = \rho$ for $i \neq k$), and the error variance, σ^2, known. Denote the group sizes by $m_1, \ldots, m_q$ where q is the number of groups and $\sum m_j$ = n.

Then the covariance matrix of the errors, *V*, has the form

$$E(\varepsilon\varepsilon') = V = \sigma^2 diag\{(1-\rho)I_{m_j} + \rho e_{m_j} e_{m_j}'],$$

where e_{m_j} is an m_j vector of ones. Let $\beta = (\beta_0, \beta_1)'$ and *X* be the n×2 regressor matrix. The true covariance matrix for the OLS coefficient estimator (if intra-group error correlation exists), $\hat{\beta}$, is given by

$$var(\hat{\beta}) = \sigma^2 (X'X)^{-1} X'VX (X'X)^{-1}.$$

This can be compared with the unadjusted (misspecified) covariance matrix

$$\widetilde{\text{var}}(\hat{\beta}) = \sigma^2 (X'X)^{-1}.$$

[15] This part is from Moulton (1986; 387-388).

An examination of the ratio of the true covariance of the OLS coefficient estimator to its misspecified variance provides the estimates of the magnitude of the potential understatement.

$$\frac{var(\widehat{\beta_1})}{\widetilde{var}(\widehat{\beta_1})} = 1 + [\frac{var(m_i)}{\bar{m}} + \bar{m} + 1]\,\rho_x\rho,$$

where ρ_x is the intra-group correlation of x_{ij}. The greater the magnitude of the ratio of var($\widehat{\beta_1}$)/$\widetilde{\text{var}}$($\widehat{\beta_1}$), the more the standard errors have been understated. The efficiency loss tends to be larger, the larger are ρ, $\bar{m}$ (the average group size), and $var(m_i)$.

Since the explanatory variables in this study are all categorical (see Table 2-1), one can think of wage differentials as reflecting changes in the wages received from different groups (i.e., between-group effects) and wage changes within those groups (i.e., within-group effects). Thus, a grouped regression model with cross-sectional data should be considered when estimating wage equations. In order to consider the nature of the sample as there is both a between-establishment error term variance and a within-establishment error term variance, this paper employs the random effects GLS estimation in the analysis. The random effects GLS approach would yield less biased results than OLS regression (e.g., Dickens, 1985; Jones and Sloane, 2010; Moulton, 1986, 1987; Randolph, 1985).

Of course, one could capture group-specific effects by allowing each group to have its own dummy variable that is treated as a fixed parameter (i.e., the dummy variable model), not random variables drawn from a distribution. This treatment, however, typically preclude the estimation of the effects of observed factors that vary across groups, and the regression errors are correlated within groups (i.e., intra-group correlation). Under such circumstances one may be able to specify the unobserved group-specific effects as random to explicitly model the variation between groups, and the intra-group error correlation can be incorporated into the specification using error components and random coefficient model for disturbance (Moulton, 1986).

2.5. The Empirical Model

This section presents empirical models to examine the wage impact of skills-job mismatch related to English language skills. Three models are specified for the empirical analysis (see Table 2-3). Begin with Model 1 comprising a large number of control variables in the wage equation, including indicators of socio-demographic characteristics (age, marital status, region), with human capital endowments (educational attainment, job tenure) and labor market related variables (union membership, full-time employment, permanent employment contract, public sector employment, occupation, industry). The random effects model specification estimated in this study, following Allen and Van der Velden (2001), Di Pietro and Urwin (2006), and Green and McIntosh (2007), is of the following general form:

$$Y = X\beta + +Z_1\delta_1 + Z_2\delta_2 + \cdots + \ Z_c\delta_c + \varepsilon, \quad (1)$$

where Y is a $n\times 1$ vector of log hourly wages, $X\beta$ is an $n\times p$ matrix of known constants (control variables stated above), β is p vector of unknown parameters, and Z_i is an $n\times q_i$ matrix of dummy variables for each of the q_i levels of the i^{th} grouping, δ_i is a $q_i\times 1$

vector random variables with assumed mean zero and covariance ${\delta_i}^2 I$, c is the number of grouping variables or effects, and ε is the typical white noise error. In this study, n is the number of individuals (observations), the number of grouping variables c is 15, and q_i is the number of levels for each group. The definition and summary statistics of the full set of variables used in the analysis are presented in Table 2-1 and Table 2-2, respectively.

Models 2 and 3 incorporate measures for skills-job mismatch variables, i.e., over- and under-skilling, which are of central interest to this study. These variables allow this work to ascertain the impact of the job mismatch in terms of English language skills on wages after controlling for the same level of educational attainment. Model 2 expands Model 1 by adding skill mismatch measures based on responses to the first and second questions, i.e., the ISA method.

$$Y = \text{Model 1} + \gamma_1 ISA\_OVER + \delta_1 ISA\_UNDER + \varepsilon \tag{2}$$

where *ISA_OVER* (*ISA_UNDER*) is a dummy variable indicating if the worker's level of English language proficiency is considered higher (lower) than the level of English language skills required for a job, 0 otherwise.

Model 3 replaces the terms representing over-skilling (*ISA_OVER*) and under-skilling (*ISA_UNDER*) in Model 2 by the respondents' direct judgments of under-utilization of skills (*DSA_OVER*) and skill deficits (*DSA_UNDER*), as measured by the responses to the third question, i.e., the DSA method. The model specification is given by:

$$Y = \text{Model 1} + \gamma_2 DSA\_OVER + \delta_2 DSA\_UNDER + \varepsilon \tag{3}$$

where *DSA_OVER* (*DAS_UNDER*) is a dummy variables indicating if a worker feels his or her acquired level of English language proficiency is higher (lower), compared to the required level of English language skills for a job, 0 otherwise.

In Models 2 - 3, hypotheses 1 and 2 can be tested by examining the signs and significance of the coefficients of the over- and under-skilling variables: The assignment theory perspective expects a negative wage impact of over-skilling (i.e., skill under-utilization). Similarly the assignment theory leads to the prediction of a positive wage impact of under-skilling (i.e., skill deficit), i.e., $\gamma_1 < 0$, $\delta_1 > 0$, and $\gamma_2 < 0$, $\delta_2 > 0$. For hypothesis 3 a comparison between over- and under-skilling measures for the absolute value provides an indication of which type of skills-job mismatch has a stronger wage impact. The assignment theory argument predicts that the absolute magnitude of the returns to under-skilling is smaller than the returns to over-skilling. Thus, the absolute value of the coefficient of over-skilling is expected to be greater than that of under-skilling in Models 2 - 3, i.e., $|\gamma_1| > |\delta_1|$ and $|\gamma_2| > |\delta_2|$.

2.6. The Impact of Skill Mismatch on Wages

Table 2-3 presents estimates of the impacts of English language skills-job mismatch on wages. The standard OLS estimates of Model 1 are reported in column (1). The results based on the random effects GLS regression for different specifications of the wage equation in columns (2) - (4). Columns (2), (3), and (4) correspond to Models 1, 2, and 3, respectively. As regards hypothesis tests on the regression coefficients in Models 1 - 3, obviously Wald χ^2 tests for the random effects GLS estimation reject the null hypothesis that all slope coefficients in each regression are jointly zero at all conventional significance levels. For the variance components specification in Models 1 - 3, the Lagrange multiplier (LM) tests reject the null hypothesis in each regression at all conventional significance levels indicating that the assumption of uncorrelated errors is not consistent with the data. In columns (1) - (2), a comparison between OLS and random effects GLS estimates shows relatively large differences in several parameters such as *AGE1*, *MARRIED*, *URBAN*, *FULL*, *PERT*, etc.

In Model 1, most findings are consistent with the previous literature on conventional labor market analysis, although the estimates are presented based on a large number of variables. In panel *A* (socio-demographic characteristics), female workers are paid on average less than their male counterparts. All age groups enjoy a wage premium relative to a reference group (workers age 60 and older). Being married and living in the urban area have positive returns. In panel *B* (human capital endowments), workers with relatively low educational attainment suffer a wage penalty relative to their counterparts with a 4-year college degree or higher. Wages increase with job tenure, indicating the expected U-shaped pattern. In panel *C* (labor market related variables), members of labor unions are paid more than their non-union counterparts. A full-time employment and a permanent employment contract dummies are associated with higher wages. The indicators for public sector employment, firm size, occupation, and industry also confirm the stylized facts from traditional labor market analysis.

On the whole the addition of the control for skills-job mismatch in Models 2 - 3 (i.e., *ISA_OVER* and *ISA_UNDER* for Model 2; *DSA_OVER* and *DSA_UNDER* for

Model 3) does little to change the effects of the measured variables in Model 1, indicating there is no significant change in coefficient estimates and their statistical significance across Models 1 - 3. Turning to specific coefficient estimates of the job mismatch in terms of English language skills in panel *D*, the results are broadly the same with each of the two measurement methods, i.e., the DSA and the ISA measures. In addition to this, the findings presented in this work conform to the usual results found in numerous previous studies on skill mismatch based on the assignment theory as below.

Regarding hypothesis 1, the skills-job mismatch variables have statistically significant impacts on wages, suggesting that there is a strong association between the job mismatch in terms of English language skills and wages in Korea. As regards hypothesis 2, the signs of the coefficients of skills-job mismatch variables are negative and positive for over-skilling (i.e., skill under-utilization) and under-skilling (i.e., skill deficit), respectively. It indicates that over-skilled workers suffer a wage penalty, while under-skilled workers enjoy a wage premium in Korean workplaces. This is in line with the predictions of the assignment theory adapted in this study. In terms of hypothesis 3, the coefficients of the over-skilling variables are greater than those of the under-skilling variables in absolute value, as would be expected. Such findings also agree with the general results found in the literature on skill mismatch based on the assignment theory approach, indicating that the returns to over-skilling are stronger than the returns to under-skilling. The results show that in each case over-skilled (under-skilled) workers suffer (enjoy) a wage penalty (premium) of approximately 24 (12) percent and 20 (16) percent for Model 2 and Model 3, respectively.[16]

2.7. Summary and Conclusions

Most prior research addressing the topic of the job mismatch focuses on educational mismatch, while the economic analysis of skill mismatch has received relatively little attention in the literature. This paper using the 2007 KLIPS examines the impact on wages of the job mismatch in terms of English language skills in Korean workplaces. Two measurement techniques, i.e., the DSA and the ISA methods, are used to identify over- and under-skilled workers in the analysis. Special attention is given to the research design and estimation approach: Based on the assignment theory proposed by Sattinger (1993), this paper explores whether the evidences supporting conventional studies on skills-job mismatch carry to the non-English speaking country, i.e., Korea. Unlike conventional studies on cross-sectional grouped data, this paper employs a random effects GLS regression framework rather than the traditional OLS estimation method to take account of intra-group error correlation, when estimating wage equations.

The main results presented in this paper confirm the validity of the assignment theory, which asserts that the returns to additional investment in human capital appear to depend in part on the quality of the assignment of heterogeneous workers to heterogeneous jobs, and thus returns to investment in skills are limited by how well jobs exploit workers' skills (Sattinger, 1993). Specifically (1) job mismatch in terms of

[16] For dummy variables, $[e^{(\text{the coefficients for variables})}-1]\times 100$ yields the percent change in wages.

English language skills is reported to have a strong statistically significant impact on wages, suggesting that English language skills-job mismatch may be one of the major causes of wage differentials in the Korean labor market: (2) the returns to over-skilling are negative (wage penalty), while the returns to under-skilling are positive (wage premium): and (3) the wage penalty associated with over-skilling is stronger than the wage premium associated with under-skilling. Finally, the signs and significance of the wage impact of skill mismatch are generally robust over the different two measurement techniques, i.e., the DSA and the ISA measures.

Due to the nature of cross-sectional data, this paper focuses solely on a single snapshot in one year of a dynamic process. That is, this study considers only a static labor market with no upward job mobility, where people are stuck in the same job forever. Thus, future research could study how English language skills-job mismatch influences wage growth or career advancement, when multi-years datasets are available. In addition, future research could also explore within specific age groups and turn these into estimates for different age cohorts. Since different age groups in general have quite different access to English language education in Korea, the relationship between English language skills and labor market outcomes may vary across age groups.

CHAPTER 3. THE LABOR MARKET RETURNS TO COMPULSORY MILIITYAR SERVICE IN KOREA

3.1. Introduction

Compulsory military service has traditionally been a very sensitive social and legal issue in South Korea (hereafter denoted as Korea). One important reason is that conscription most often occurs when young adults are making important decisions related to various facets of life such as education, employment, marriage, etc. For instance, most Korean males are typically called for military service during a period of their lives which they would otherwise devote to higher education, when aged 20-25 coinciding with the college years. In this case, the time spent in the military means that men who served in the military as conscripts (hereafter denoted as veterans) graduate from a higher educational facility at a later age than men who were exempted from military service (hereafter denoted as nonveterans). This trend is more relevant today than ever before. According to the 2008 Defense White Paper by the Korean Ministry of National Defense, released in 2009, about 82 percent of servicemen enlist in the army during their college years.

Another critical reason why conscription has been highly controversial in Korea is that most young men tend to believe that the cost of compulsory military service from the individual's perspective generally exceeds the benefit. This is in part due to the possibility that human capital stock previously accumulated through education and work experience prior to military service will depreciate, or the human capital accumulation process will be interrupted while on their military duty. Moreover, since the conscription law currently in effect applies only to men, veterans usually believe that they have much more to lose by serving in the military relative to women. In order to such issues, the Korean government introduced a “point system” in 1969. This system provided veterans as conscripts’ compensation in the form of (free) extra points on civil service examinations for lower-grade jobs (rank 7th and 9th). In December 1999, the “point system” was abolished upon the Korean Constitutional Court’s ruling that it is disadvantageous to women and the disabled. Most recently, however, the issue of the “point system” has been raised again.

The economic analysis of the consequences of compulsory military service within the labor market has been relatively neglected in Korea, given the large number of individuals who have served in the military.[17] To my knowledge, the only study to examine the effect of compulsory military service on subsequent civilian wages published in a journal to date in Korea is that by Eom (2009), who used data from the 2007 Korea Labor and Income Panel Survey (hereafter denoted as KLIPS). Contrary to what one would expect, the author finds that veteran status has a statistically significant positive impact on subsequent civilian wages. It indicates that on average, veterans receive higher market wages than their nonveteran counterparts in Korea, suggesting a wage premium associated with veteran status.

In light of the results discussed by Eom (2009), this paper attempts to find new evidence on the labor market returns to compulsory military service in Korea, by

[17] This may in part reflect a lack of data on military service. However, the widespread availability of databases including information related to military service (such as Graduate Occupation Mobility Survey and KLIPS) makes such excuse increasingly inadequate.

examining the wages experience of veterans and nonveterans. The present study in part adopts the approach in Eom (2009), but extends this earlier work in several respects. First, while Eom (2009) considers all male veterans including men who served as professional military personnel in the analysis, this study focuses on men who served as conscripts, when examining wage equations. It would help in evaluating more accurate measures of the impact of veteran status on wages after completion of military service. Second, this analysis advances Eom (2009)' study by implementing a control for reasons for exemption from military service that may be linked to wages of nonveterans such as physical inadequacies, insufficient educational background, and various other domestic reasons (e.g., the age limit, dual citizenship, homosexuality, etc). This approach would help control for possible selectivity among nonveterans and test whether selection bias is considered the principal culprit in generating the significant effect of veteran status on subsequent civilian wages.[18]

In this work, I utilize individual data obtained by the KLIPS for the years 1998 - 2008, whereas Eom (2009) had only cross-sectional data from the 2007 KILPS. The panel data set used in this paper is a representative sample of the Korean workforce, containing time series observations on a number of individuals. Eom (2009) appears to be using a panel data set but only one wave of that panel, even though the relevant information on military service is available in more than one wave. It does not justify the use of cross-section data which only shows the association between veteran status and

[18] Although this paper attempts to correct or account for selection bias that can affect the results of the study, it is not possible to consider all potential sources of selectivity in the wage equation. This is in part because it requires access to data that is not available in this study. For instance, the KLIPS survey does not contain data on military ranks, types of branches (The Army, Air Force, Navy, and Marine Corps), and fields/occupations (armor, artillery, engineering, infantry, etc). It might be a limitation of this study.

subsequent civilian wages. The estimation in his work does not control for any unobserved individual heterogeneity between veterans and nonveterans in the analysis, and this relegates the estimation results to the state of "association" and not "effects". Panel data in general contains more degrees of freedom and more sample variability. Moreover, it has greater capacity for controlling for the complexity of human behavior than single cross-sectional data. Thus, panel data provides an opportunity to account for unmeasured individual characteristics which may lead to biased results in the analysis. This analysis would have more precise estimates of model parameters than the case of cross-sectional data.

This paper extends Eom (2009)'s study by exploring variations in the veteran wage premium according to the level of educational attainment at the time of entry into military service, while controlling for other well-known determinants of wages, i.e., more-educated veterans (at least a high school diploma or above) vs. less-educated veterans (less than a high school diploma). The basic idea is that the relationship between compulsory military service and subsequent economic performance depends on the social context and the socio-economic background of veterans such as race, ethnicity, and level of education. Some previous research has indeed shown that the impact of veteran status on subsequent civilian wages is not uniform for all veterans: Racial and ethnic minorities and men with less education are more likely to benefit from time spent in the military than other veterans (e.g., Berger and Hirsch, 1983; Hisnanick, 2003; Teachman and Tedrow, 2007; Xie, 1992). Thus, this approach would be more informative not only to individuals, but also to policymakers.

Although the results presented in this paper only refer to Korea, there is still informational content in both research and policy work that may apply beyond Korea. The major findings of this study can be summarized as follows: (1) contrary to what one would expect, veteran status has a significant positive impact on subsequent civilian wages, indicating that veterans enjoy a wage premium after completion of military service. It suggests that veteran status could be one of the most important positive determinants of subsequent civilian wages levels in the Korean labor market, like other various human capital attributes such as education, job experience, etc: (2) consistent with the "bridging environment" hypothesis of military service, there exists strong empirical evidence that less-educated veterans have higher subsequent civilian wages relative to their civilian counterparts than is the case for more-educated veterans. The finding indicates that the economic consequences associated with compulsory military service vary according to the level of educational attainment at the time of entry into military service.[19] The latter finding suggests that for less-educated veterans employers view veteran status as the more significant factor relative to the case of more-educated veterans in the Korean labor market.

3.2. Background

One of the classic topics in the literature on military service is given to the economic costs of conscription. Much previous research in the literature has focused on

[19] Teachman and Tedrow (2007) note that some literature, using the term "bridging environment", has argued that military provides lessons about the value of discipline, timeliness, and personal responsibility, and for men from resource poor surroundings (such as racial/ethnic minorities, low-educated individuals, etc.), an ability to understand and operate in a highly structured bureaucratic environment that can be translated to success in the civilian labor market.

the estimation of the implicit income tax placed on people who serve in the military. The previous research suggests that compulsory military service imposes opportunity costs on conscripts which do not show in fiscal budgets and the social cost of conscription is sizeable (e.g., Bauer *et al*., 2009; Kerstens and Meyermans, 1993; Lau *et al*., 2004).[20] For instance, Lau *et al*. (2004) show that the opportunity costs imposed on conscripts exceed budgetary costs by the maximum amount conscripts are willing to pay to avoid conscription in Germany. Bauer *et al*. (2009) argue that the voluntary military system should be preferred due to structural inefficiencies and potential long-run costs that may arise in the compulsory military system, although conscription is an inexpensive way for the government to provide military service. Another strand of study in this area is the relationship between compulsory military service and schooling, which has mainly investigated the effect of conscription on college enrollment/graduation rates (e.g., Angrist and Chen, 2008; Card and Lemieux, 2001; Cipollone and Rosolia; 2007; Maurin and Xeogiani, 2007). Most of the studies on that subject typically find empirical evidence supporting the hypothesis that compulsory military service has an adverse effect on schooling in the form of the detrimental effect on the demand for higher education.

In the meantime, special attention has been paid to the topic of labor market implications of compulsory military service. There has been a substantial increase in the number of publications in the United States following the elimination of compulsory military service in 1973 (e.g., Angrist, 1990; Angrist and Krueger, 1994; Card, 1983; De Tray, 1982; Fredland and Little, 1985; Little and Fredland, 1979; Martindale and Poston,

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[20] The implicit income tax is conceptualized as the difference between the income that those who serve could earn in the civilian labor market and (usually lower) income from military service.

1979; Teachman, 2003). A large part of the study in this area has focused on the impact of compulsory military service on subsequent civilian wages. Much of this literature agrees that veteran status is one of the major determinants of wage levels in the civilian labor market. The existing literature, however, has produced mixed results, i.e., the wage premium vs. the wage penalty, associated with veteran status.

On the one hand, many previous studies have found that veteran status exerts a negative influence that leads to a wage penalty for veterans after completion of military service (e.g., Buonanno, 2006; Bauer *et al*.; 2009; Imbens and vad der Klaauw, 1995; Keller *et al*., 2009; Martindale and Poston, 1979; Schwarts, 1986). For instance, Angrist (1990) using the Vietnam draft lottery as a natural experiment finds that compulsory military service reduced wages by about 15 percent for American conscripts relative to their nonveteran counterparts of the same cohort in the United States. Angrist and Krueger (1994) argue that WWII veterans earn less than non-veterans in the United States. Imbens and van der Klaauw (1995) show that conscription in the Netherlands reduced wages for conscripts by about 8 percent when compared to the earnings of non-drafted men during the 1980s and early 1990s. Buonanno (2006) and Bauer *et al* (2009) claim that compulsory military service generated a negative effect on subsequent civilian wages for the United Kingdom and Germany, respectively.

On the other hand, some research has provided empirical evidence of opposite trends that veterans have relative monetary advantages, compared to their nonveteran counterparts in the civilian labor market, indicating a wage premium associated with veteran status (e.g., Berger and Hirsch, 1985; De Tray, 1982; Fredland and Little, 1979, 1985; Hisnanick, 2003; Teachman and Tedrow, 2007; Xie, 1992). That is, the analysis shows that there exists a strong positive relationship between veteran status and subsequent civilian wages, suggesting veterans enjoy a wage premium, compared to their nonveteran counterparts. In light of such studies, some empirical studies have emphasized the possibility that the wage impact of military service may often vary significantly depending on socio-economic characteristics of veterans such as age, race, and education (e.g., Angrist, 1989; Berger and Hirsch 1985; Fredland and Little, 1985; Martindale and Poston, 1979; Schwartz 1986; Teachman and Tedrow, 2007). Most empirical research in this area has tested the hypothesis that military service acts as a bridge to more favorable labor market conditions after discharge in creating a wage premium, and has found evidence supporting a “bridge environment’ hypothesis that racial/ethnic minorities or men with less education are more likely to benefit from the time spent in the military than other veterans (e.g., Berger and Hirsch, 1983; Hisnanick, 2003; Teachman and Tedrow, 2007; Xie, 1992).

There are several ways to explain the causes of a veteran wage premium or penalty in the civilian labor market. One may argue that employers could use veteran status as a positive or negative productivity screen, commonly known as signaling. The basic idea is that employers, provided with limited information about employees, often rely on veteran status as an easily observed characteristic in the determination of wages, rather than on individual productivity or job performance. This is an example of statistical discrimination. De Tray (1982) argues that veteran status often sends favorable signals to employers, indicating relatively high productivity of veterans, because veterans must pass minimum mental and physical standards to serve, or they served successfully for at least one tour of duty in the military. If veteran status reliably indicates high (low) productivity relative to nonveterans, employer will pay veterans higher (lower) wages to compensate for increased (decreased) productivity from military experience. Under such circumstances, the existence of a veteran wage premium (penalty) may be a consequence of screening through favorable (unfavorable) signals from veteran status to employers, respectively.

An alternative perspective is that the military experience-enhanced productivity/human capital could be a major cause of wage differentials between veterans and nonveterans. In this context, the positive wage returns to military service depend mostly on a consequence of enhanced productivity growth during military service. If education or training received in the military improves conscripts' productivity that can transfer to the civilian labor market through increased skills, then there would be a veteran wage premium. But, if military experience is not considered as equivalent to labor market experience by civilian employers, then veterans would suffer a wage penalty. Bryant and Wilhite (1990) note that outside of the public education system, the military is probably the largest institutionalized source of training. It may suggest that compulsory military service could be one of the most valuable vocational training opportunities for veterans in Korea. Indeed, Korean young men can acquire marketable skills that would be valued by civilian employers through vocational training in their military occupational specialties (MOS). For instance, on-the-job training in military occupations provides conscripts with opportunities to hone professional and technical skills in their fields such as signal, electronics, intelligence analysis, logistics, medical care, etc.

3.3. Data

3.3.1. Korea Labor and Income Panel Survey (KLIPS)

The Korea Labor Institute (KLI) under the supervision of the Ministry of Labor initiated the KLIPS in 1998 with the aim of observing economic activities of individuals and households to understand and evaluate the impact of public policies on the Korean labor market. Starting in 1998, the KLIPS is conducted annually on a sample of 5,000 households and members of households 15 years of age or older distributed nationwide. It has been completed up to the 11th wave in 2008 and the 2008 KLIPS was released in 2010. The KLIPS is the nation's only labor-related panel survey in Korea. It provides comprehensive information and national-level estimates for the Korean resident population and subgroups regarding labor force behavior and other associated events, as a representative sample of Korean households and individuals. The KLIPS is highly useful for academic research and policy development and analysis within the Korean labor market.

For the present study the KILPS has particular advantages over other surveys in Korea. First, this is a unique Korean survey simultaneously containing information on military service records and labor market activities for respondents. Second, the KLIPS contains relatively detailed information on military service of the respondents. For instance, a set of retrospective questions concerning dates of military service allow this study to determine for each person year whether the respondent was in the military or had become a veteran. Using information regarding the reasons for exemption from military service and the level of educational attainment at the time of entry into military service, this study may be able to control for selectivity and a source of diversity among nonveterans and veterans, respectively. Third, the baseline survey consists of 5,000 nationally representative households and collects data on the characteristics of households and all eligible members of sampled households. The dataset used in this study thus includes a number of brother pairs. Such information, as well as the repeated measures for each respondent, could be used to control for constant household-specific and person-specific unmeasured factors that might bias the wage effect of veteran status after completion of military service.

3.3.2. Descriptive Statistics

In order to create the dataset used for this analysis, I impose several restrictions on the KLIPS data covering the periods from the 1998 through 2008. First, this study restricts the sample to men who are at least age 20 between the years 1998 and 2008. Since the current effective conscription law applies only to males, women are not included in the sample. The men thus were interviewed a maximum of 11 times over a period of 11 years. Second, veterans who served in the military as professional military personnel are excluded in the analysis. This restriction helps to identify the causal relationship between veteran status and subsequent civilian wages in the analysis. Third, the sample consists only of salaried workers so that self-employed and unpaid family-employed workers are excluded from the sample. The sample contains 21,796 Korean males: There are 17,971 (3,825) individuals for veterans (nonveterans) with about 82.5 (17.5) percent of the sample.

Table 3-1 provides definitions of the full set of variables used in this work. The descriptive statistics for veterans and nonveterans are presented in Table 3-2 and Table 3-3, respectively. Several important differences between veterans and nonveterans are worthy of note. As shown in panel *A* of Tables 3-2 and 3-3, the comparison with the log hourly wages (*LNHRW*) shows that the raw wage differential between veterans and nonveterans is positive over the entire period 1998-2008, indicating that veteran individuals earn more than their nonveteran counterparts. It suggests that veteran workers are more likely to enjoy higher wages than their nonveteran counterparts, and the relatively position of nonveteran workers may be inferior to that of veteran workers in Korea, at least in terms of wages.

As regards the length (duration) of time spent in the military (*MILEXP*) in panel *A* of Table 3-2, veterans served an average of about 28 months (2 years and 4 months) for their military draft. It indicates that the burden of conscription in term of time is not negligible. This is in part because Korean men are typically drafted to do their military duty during the critical period of their lives which they would otherwise devote to education or gathering their first work experience. During 1998-2008, a relatively small number of veterans (approximately 16.3 percent) had less than a high school diploma at the time of entry into military service (i.e., less-educated veterans; *VETERAN_LESSEDU*). In addition, the percentage recorded as less-educated veterans in the same period 1998-2008 has fallen by 7 percent points from 19.6 in 1998 to 12.7 percent in 2008. It is in part related to the fact that the gross enrollment rate in higher education has increased sharply during the last two decades. As of 2010, in higher education enrollment rates, Korea ranks second in the world after Finland. Approximately 2 million students are enrolled in four-year and 700,000 are enrolled in junior colleges. This is over one half of young people aged between 18 and 21 in Korea. According to reasons for exemption from military service in panel *A* of Table 3-3, nonveterans are divided into three groups - about 69 percent for physical inadequacies (*EXEMPT_PHY*), 4 percent for insufficient education (*EXEMPT_EDU*), and 27 percent for other domestic reasons (*EXEMPT_OTHER*), respectively. As would be expected, the exemption from military service is associated with physical or medical limitations in many cases, but there are various other factors.

Turning to other variables in panels *B* - *D* of Tables 3-2 - 3-3, the results may suggest that veteran-nonveteran differences in human capital endowments, socio-demographic characteristics, and labor market related variables could be associated with the veteran-nonveteran wage differential in Korea, discussed above. Specifically, in terms of human capital endowments of panel *B*, on the whole veterans are more qualified than their nonveteran counterparts. For instance, veterans have higher (lower) rates of 4-year college graduates or above (less than high school graduates) than nonveterans. Nonveterans in general have less job tenure than their veteran counterparts. Regarding labor market related variables in panel *D*, veterans are once again more likely to have better labor market status than nonveterans. Veteran workers are more likely to be union members and more likely to have full-time jobs than their nonveteran counterparts. Moreover, veterans are more (less) likely to be employed in relatively high-wage (low-wage) jobs such as managerial & professional occupations (laborer jobs) than their nonveteran counterparts, respectively.

3.4. Methodology

Measuring the wage impact of veteran status after completion of military service presents one of a classical treatment evaluation problem. Under the counterfactual framework (the potential outcome model) developed by Rubin (1974), let V_i be a binary treatment indicator that equals 1 if the treatment is applied (individual i served in the military as a conscript; veteran), and is 0 otherwise (individual i with no military experience; nonveteran). That is, $V_i = 1$ denotes treatment and $V_i = 0$ otherwise. The variable Y_i denotes potential outcomes (i.e., subsequent civilian wages) for an individual veteran i. Y_{1i} (Y_{0i}) is potential outcome under (without) the treatment, respectively. Each individual has an outcome either Y_{1i} or Y_{0i}.

The goal of this paper is to examine the effect of compulsory military service (the treatment) on subsequent civilian wages (the outcome) for individual i. Thus, the present study is primarily interested in estimating the average treatment effect on the treated (ATE) as follows:

$$\Delta_i = E\{Y_{1i}|V_i = 1, X\} - E\{Y_{0i}|V_i = 1, X\} \quad (2)$$

Δ_i is defined as the outcome differences between treated and untreated states. In this analysis, equation (2) indicates a veteran wage premium or penalty in the civilian labor market. However, Δ_i can never be identified because individuals cannot be simultaneously observed in both states above, i.e., individuals are either V_i = 1 or V_i = 0. Since $E\{Y_{oi}|V_i = 1, X\}$ cannot be observed, Δ_i is not directly observable. This is a missing counterfactual problem in treatment evaluations in this work.

The equation (2) can be rewritten as:

$$\Delta_i = [E\{Y_{1i}|V_i = 1, X\} - E\{Y_{0i}|V_i = 0, X\}] + [E\{Y_{0i}|V_i = 0, X\} - E\{Y_{0i}|V_i = 1, X\}] \quad (3)$$

There are two terms on the right-hand side of the equation (3). Both components in the first term ($E\{Y_{1i}|V_i = 1, X\}, E\{Y_{0i}|V_i = 0, X\}$) are observable, whereas the unobservable counterfactual situation ($E\{Y_{0i}|V_i = 1, X\}$) exists in the second term, often called selection bias. The key to effective treatment evaluations is to solve the problem of selection bias in the second term.

From a theoretical perspective, individuals who are randomly assigned to treatment or control groups are free from the troublesome selection bias issues. The randomization of individuals into a treatment (V_i= 1) and a control (comparison) group (V_i= 0) solves the missing counterfactual problem under the following assumption: $E\{Y_{oi}|V_i = 1, X\} = E\{Y_{0i}|V_i = 0, X\}$. In such situations, the control (comparison) group serve as a perfect counterfactual and thus the potential outcomes for individual *i* are given by

$$\Delta_i = E\{Y_{1i}|V_i = 1, X\} - E\{Y_{0i}|V_i = 0, X\} \quad (4)$$

The sample of veterans, however, is not a random sample of the total working population in this study. Veterans are individuals who selected for military service because they are actually screened and are only deemed qualified for military service if they meet some criteria such as physical or psychological impairments, educational or behavioral standards, etc. In order to address the issues of selection bias discussed above, this paper, following Allison (1994) and Teachman and Tedow (2007), employs the fixed effects (panel data) model, when estimating wage equations. As pointed out by Allison (1994), the fixed effects model is a powerful tool in examining the effect of an event (i.e., compulsory military service) on subsequent outcomes (i.e., civilian wages). Moreover, the sample used in this study contains information on respondents who are followed over time, as well as many men from the same household. Under such circumstances, the fixed effects procedure can control for all constant personal-specific and household-specific factors characteristics that might otherwise bias results (Teachman and Tedow, 2007). Further, the fixed effects model makes it possible to take into account unmeasured individual heterogeneity referring to unobserved differences between individuals in the analysis. Thus, the fixed effects approach would produce more precise and credible estimates of treatment impacts in this work than other simpler alternative estimation methods such as OLS, Differences-in-Differences (DID), etc.

Instrument variables (IV) and propensity-score matching (PSM) methods could be considered alternative treatment effects approaches. Some previous studies in the literature have relied on the IV method to solve the problem of selection bias (e.g., Angrist, 1990; Angrist and Krueger, 1994; Imbens and van der Klaauw, 1995). The IV estimation, however, often has a challenge to control the impact of unobserved individual heterogeneity that might bias the wage impact of veteran status after completion of military service. More generally, it is hard to find suitable instruments, which are correlated with veteran status, but do not directly affect subsequent civilian wages in this study. In the case of the United States, conscripted military service was not universal but was the results of a draft lottery plus deferments and exemptions. The lottery aspect is an advantage because the control group is more likely random assignment (see Angrist, 1990). The PSM technique is a very useful method when there are many potential characteristics to match individuals between the treatment (veterans) and control/comparison (nonveterans) groups. This approach, however, also does not completely address the issue of selection bias in many cases due to unobservables. In the case whether someone is drafted for military service is partially determined by factors which are directly related to subsequent civilian wages but unobservable such as health status, the treatment is non-random and thus PSM estimates of Δ_i in the equation (3) is biased since $E\{\varepsilon|V_i\} \neq 0$.

3.5. The Empirical Model

This section provides empirical models to investigate the causal relationship between veteran status and subsequent civilian wages. Since the Mincer-style human capital wage equation is a highly stylized model with the wage effect of military service in the literature (Angrist and Chen, 2008), this paper estimates Mincerian wage regressions in the analysis. The basic assumption underlying the estimation procedure is that compulsory military service affects the human-capital stock of conscripts and thus influences their subsequent civilian labor market performance. If conscription increases or decreases the productivity of conscripts, then their subsequent civilian wages reflect that change. This approach would highlight important channels through which military service might affect subsequent civilian wages in this study. The Mincerian wage specification employed in this analysis is of the following general form:

$$lnY_{it} = \beta X_{it} + \gamma Z_i + \delta VETERAN_{it} + \alpha_i + \mu_{it} \quad (5)$$

where i and t index individuals and time periods respectively. The dependent variable lnY_{it} is the log hourly wage of the individual worker i. X_{it} (Z_i) is a vector of time-varying (time-invariant) regressors. β and γ are vectors of unknown parameters to be estimated. $VETERAN_{it}$ is a time-varying dummy variable indicating whether respondent i is a veteran as of the beginning of person year t, and δ is a coefficient. α_i represents unobserved and constant individual-specific and time-invariant error component across respondents. μ_{it} is a conventional mean zero disturbance.

The specification of the wage equations comprises a large number of control variables including military service related variables (veteran status, reasons for exemption from conscription, and the level of educational attainment among veterans at the time of entry into military service), socio-demographic characteristics (age, marital status, and region), human capital endowments (educational attainment and job tenure), and labor market related variables (labor union, full-time employment contract, public sector employment, occupation, and industry).

Since the estimates in Table 3-4 are obtained by using a fixed effects procedure, the model does not include any fixed characteristics of respondents that do not vary within the groups (i.e., time invariant characteristics). In particular, this paper uses the fact that the interaction of time-invariant variables with time-varying parameters yields a time-varying characteristic, and it is estimable in a fixed effects framework. For instance, an interaction between veteran status and educational background at the time of entry into military service takes the value of zero until the respondent becomes a veteran, after which the interaction takes a value equal to the respondent's score on educational background at the time of entry into military service (Teachman and Tedrow, 2007).

Model 1 is a simple linear regression model including the veteran status indicator (*VETERAN*) as a single regressor. It shows a simple casual relationship between veteran status and subsequent civilian wages. Model 2 expands Model 1 by including the measure of veteran status (*VETERAN*) which is of central interest to this study, with a large set of control variables used in the conventional labor market analysis. The research question of whether a veteran wage premium or penalty exists will be answered in Model 2. In addition to this, Model 2 also implements a control for whether a respondent is a nonveteran who was exempted from military service due to a variety of domestic reasons domestic reasons (*EXEMPT_OTHER*) such as the age limit, dual citizenship, difficulties in maintaining household, homosexuality, etc., not physical inadequacies (*EXEMPT_PHY*) or insufficient educational background (*EXEMPT_EDU*). Since the rationale for this control is based on the assumption that nonveterans who were exempted from military service due to various domestic reasons are more likely to share with veterans than nonveterans who were exempted from military service due to physical inadequacies or insufficient education unmeasured characteristics concerning the relative value of labor market activities, this study would expect to see a coefficient more in line with the coefficient for being a veteran (Teachman and Tedrow, 2007).

In order to test the hypothesis that the effect of veteran status on subsequent civilian wages is not uniform between more- and less-educated veterans, and compulsory military service plays a more important role for less-educated veterans' careers as a "bridging environment", an extra dummy variable indicating whether the veteran had less than a high school education at the time of entry into military service (*VETERAN_LESSEDU*) is added in Model 3. This additional variable which is another key variable of interest in this study would help control for the source of diversity among veterans. Finally, Model 4 elaborates Model 3 by incorporating further dummy variables representing occupation and industry as control variables. This approach helps control for the effects of occupation and industry characteristics on wage differentials between veterans and nonveterans. One would expect that Model 4 can reduce the residual of veteran-nonveteran wage differentials.

3.6. Results and Discussion

The empirical estimates of wage equations for Models 1 - 4 are presented in Table 3-3.[21] As regards hypothesis testing for coefficients, obviously the likelihood-ratio test rejects the null hypothesis that all slope coefficients in each regression are jointly zero at

[21] The Hausman-type specification test rejects the null hypothesis that the unobserved personal specific random effects are significantly uncorrelated with the other regressors in the model, suggesting that the random effects estimator would be inconsistent. In addition, the F test for fixed effects vs. pooled OLS rejects the null hypothesis that the cross-sectional effects are correlated with the regressors in the model. It indicates that the fixed effects are correlated with the group means of the regressors, and thus the fixed effects model would be more efficient than the pooled OLS model.

all conventional significance levels. While coefficient estimates are presented based on a large number of variables (military service related variables, socio-demographic characteristics, human capital endowments, and labor market related variables), most findings are consistent with the results from conventional labor market studies. In terms of the effect of veteran status on subsequent civilian wages, the findings are very robust across all Models 1-4 in that the veteran status dummies (*VETERAN*) have a positive and statistically significant effect, i.e., the veteran wage premium. The results presented in this paper are in accordance with the findings from a number of previous studies in the literature such as Fredland and Little (1985), Hisnanick (2003), Little and Fredland (1979), Teachman and Tedrow (2007), etc.

In Model 1, veteran status is clearly associated with a 27.1 percent pay raise in the civilian labor market.[22] It indicates the raw wage differentials between veterans and nonveterans. Similarly, veterans are paid on average 14.1 percent more than their nonveteran counterparts in Model 2. Although Model 3 still shows the existence of a significant positive wage premium for veterans, the percentage of a veteran premium is reduced to 11.1 percent. It suggests that the control for less-educated veterans (*VETERAN_LESSEDU*) explains 21.3 percent of the veteran wage premium. When controls for occupation and industry are added, the veteran wage premium is being smaller from 11.1 percent for Model 3 to 7.1 percent for Model 4. Apparently veteran status is associated with more favorable occupation and industry affiliations and higher wages within occupation and industry in this study. This would indicate that veteran

[22] For dummy variables, $[e^{(\text{the coefficients of variables})}-1] \times 100$ yields the percent change in wages.

status enhances the occupation/industry affiliation of low wage workers. Controlling for this positive effect is what lowers the pure wage premium.[23]

Contrary to conventional wisdom, the findings discussed above suggest that compulsory military service may be effectively efficient for Korean males and thus veteran status could to be one of the key factors in wage determination. One possible explanation is that the veteran wage premium exists as a consequence of enhanced productivity during the military draft. The basic idea is based on the following human capital approach that if compulsory military service has a positive effect on conscripts' general/specific human capital stock such as punctuality, discipline, teamwork, and communication skills, then enhanced human capital stock through military experience increases (labor) productivity of veterans. Given individuals are paid the value of their marginal product, which is determined by their human capital, the expected returns to compulsory military service would be positive in the civilian labor market.

Most conscripts, regardless of military branches/fields, can acquire general human capital (such as relationship skills accumulated through dedication, teamwork, positive work ethic, etc.) during their military duty, and such general human capital which is most valued by all potential employers holds 'transferable' characteristic across occupations and industries. Moreover, since the work environment is traditionally male-dominated in Korea, the leadership experience, including personal responsibility and self-sacrifice from working in teams/a strict hierarchical structure during military service, in particular seems to make veterans more desirable assets to businesses and government agencies.

[23] Basically, this indicates that 11.1 - 7.1 = 4 percentage points of the 11.1 % veterans premium is associated with better occupation/industry employment.

Furthermore, compulsory military service generally can offer conscripts the opportunity to accumulate specific human capital through training and working experience on knowledge or skills specific to a job/task because each of military fields/occupations provides their own work-related/special skills (such as construction, electronics, logistics, etc.) directly translatable into subsequent civilian employment. For instance, conscripts who serve in combat support & combat service support forces such as signal, transportation, engineers, finance, medical services, ordnance, intelligence, etc. can have marketable technical skills that would be rewarded in the civilian labor market.

In an alternative explanation, wage differentials between veterans and nonveterans could be attributed to the use of veteran status as a (positive or negative) productivity screen by employer. De Tray (1982) claims that employers tend to assume that veterans on average have higher labor productivity than their nonveteran cohort because all veterans have passed minimum standards/requirements for military service (e.g., mental and physical tests) and have met minimum performance and behavior standard in order to be honorably discharged. Under such circumstances, veteran status conveyed by successful completion of military service is valuable to employers as a positive productivity signal of an ability to successfully complete a job. From such a perspective, employers can use veteran status as an easily observed indicator of potential productivity. If it does, veteran status is a meaningful signal to employers as a screening device. In this work, employer may use veteran status as a positive productivity screen, resulting in positive statistical discrimination in favor of veterans. This preferential treatment that former conscripts may potentially receive in the civilian labor market could be translated into a veteran wage premium associated with veteran status.[24] Indeed, many Korean employers, even in the public sector, usually take into consideration the individual's participation in military service, when hiring or determining wages. It may suggest that failure to complete the service could result in labor market discrimination in the Korean labor market.

Regarding selectivity among nonveterans in Models 2-4, there appears to have a significant negative relationship between being a nonveteran due to a variety of domestic reasons (*EXEMPT_OTHER*) and wages. It may suggest that the impact of veteran status on subsequent civilian wages is not due to selectivity, as would be expected. If nonveterans due to a variety of domestic reasons (*EXEMPT_OTHER*) are more like veterans on unmeasured characteristics than are other nonveterans such as nonveterans due to physical inadequacies (*EXEMPT_PHY*) or insufficient educational background (*EXEMPT_EDU*) but do not share any of the effects of having served in the military, a coefficient for nonveterans due to a variety of domestic reasons (*EXEMPT_OTHER*) would be more in line with the coefficient for being an veteran (*VETERAN*), as stated before. This is based on the assumption that health or education concerns for nonveterans due to a variety of domestic reasons are less likely than nonveterans due to physical inadequacies or insufficient education to limit productivity in the civilian labor market.

One of the important goals of this study is to see whether the wage impact of veteran status differs among subgroups of veterans with different levels of educational attainment at the time of entry into military service, i.e., less-educated vs. more-educated

[24] The KLIPS data does not identify volunteers from conscripts. If it is possible, it would be potentially a different signal.

veterans. The basic idea is based on the following assumption: If compulsory military service affects the subsequent civilian wages of veterans, those effects impact certain groups of veterans more than others. Models 3 - 4 explore the possibility that the veteran wage premium varies according to educational background achieved prior to military service. This approach in part tests whether compulsory military service provides less-educated veterans with a “bridging environment” which facilitates the movement of veterans from pre-conscription life to post-conscription civilian life. It reflects the idea that military service can be a second chance, a place of equal acceptance and involvement despite prior social disadvantages, a chance to get ahead and an avenue for social and career mobility (Hisnanick, 2003).

The analysis in Models 3 - 4 finds empirical evidence that less-educated veterans are more likely than more-educated veterans to experience higher subsequent civilian wages relative to their civilian counterparts. The variable denoting less-educated veterans (*VETERAN_LESSEDU*) shows a positive and statistically significant effect with 22.1 (13.3) percent without (with) controlling for occupation and industry in Model 3 (Model 4). It suggests that the impact of compulsory military service does not yield uniform results for all types of veterans (heterogeneous treatment effects across subgroups of veterans), emphasizing that higher uniform wage levels are more likely to benefit men who would otherwise be at a disadvantaged in the civilian labor market, e.g., less-educated veterans. One may argue that for less-educated males compulsory military service could represent an important opportunity to overcome the limitations imposed by a deprived background (i.e., relatively low levels of educational attainment), and veteran status could be more likely used as a better indicator of potential labor productivity in Korea. These findings are generally consistent with those from several previous studies on the bridging hypothesis of military service such as Angrist (1998), Berger and Hirsch (1983), Binkin *et al*. (1982), De Tray(1982), Sampson and Laub (1996), Seeborg (1994), Xie (1992), etc.

3.7. Summary and Conclusions

Recently the issue of veterans incentives associated with a “point system” has received considerable attention in Korea. In fact, the economic challenges facing veterans are a recurrent theme in the mass media. However, empirical analysis on the economic consequences of compulsory military service has been relatively neglected. In particular, far less attention is paid to the costs or benefits of serving in the military for the conscripts themselves in the civilian labor market. This paper using the Korea Labor and Income Panel Survey (KLIPS) data from the 1998 through 2008 attempts to investigate the causal relationship between veteran status and post-service labor market outcomes by examining the wages experience of veterans and nonveterans. It contributes to economic research on the impact of compulsory military service within the labor market in Korea.

The major empirical findings are summarized as follows: Contrary to the general perception, veteran status has a significant positive impact on wages after completion of military service, indicting a veteran wage premium. It suggests that for veterans the benefits of compulsory military service are far from negligible in Korea. In addition, the findings presented in this study also indicate that there may exist overall differences in subsequent civilian wages between veterans and nonveterans in the Korean labor market. In terms of the veteran wage premium in subgroups based on educational attainment at the time of entry into military service, less-educated veterans have a greater wage premium relative to their nonveteran counterparts of similar backgrounds than is the case for more-educated veterans. This evidence of the heterogeneous wage effect of veteran status suggests that military service could be particularly important for less-educated veterans. In other words, the relatively higher wage premium among less-educated veterans may explain the belief that military service can provide minority veterans with a "bridging environment" between early experience and subsequent civilian work in Korea.

This paper does not consider the long-term effect of veteran status on subsequent civilian wages. Since a number of previous studies of job training programs show that the positive effects tend to decline over time, future research based on decisions of individuals over the life cycle could seek the dynamic effect of compulsory military service on wages after completion of military service. This approach allows the researcher not only to determine if the initial wage benefits for veterans attenuate over time, but also to find empirical evidence on the long-term benefits or costs of conscription in Korea. The results of this paper might seem like compulsory military service for veterans offers them opportunities they would not have known about (otherwise they could have voluntarily served in the military). However, it may be that even with the knowledge of the enhanced civilian wages after completion of military service, many Korean young men would be reluctant to serve in the army. This is in part because either the life style or exposure to danger during military service would offset any subsequent wages increase. In addition, young men in Korea would also still regard compulsory military service as one form of disruption/distortion of human capital accumulation and investment.

The results of this study suggest a number of policy implications for Korea. First, since the military service is compulsory and generally the socially disadvantaged are exempt from the service in many cases, those exempt persons could already have lower wages from the beginning. Thus, readers may need to be careful before accepting the conclusion that the military service seems to have positive effect on wages in Korea. Second, more active and effective policies/incentives that would motivate young males to compulsory military service should be introduced, although there are limited incentive programs available at this time. The incentives could include offering higher monetary compensations, training in marketable skills which are more easily transferable to civilian occupations, tuition credits, the point system, etc.[25] Third, a well-organized advertising campaign is also needed to emphasize the economic benefits of compulsory military service such as a wage premium and better employment opportunities. Finally, it is important to stress that irrespective of economic benefits, veterans can also learn a variety of lessons during their military service such as leadership skills, personal responsibility, self-sacrifice, operating within a bureaucratic environment, and how to live in a social organization/community.

[25]About 83 percent of Korean citizens agreed that those who have fulfilled their military duties should be offered benefits, showed a recent survey conducted by the Ministry Manpower Administration in November-December 2009. Among the 1,500 respondents, 87.1 percent of the men and 78.7 percent of the women supported policies to offer social or financial benefits to veterans, editorial, *The Korea Herald* (Seoul), March 30, 2010.

APPENDIX A: TABLES

Table 1-1: Definition of Variables

Variables	**Definitions**
Panel A: Dependent Variables	
EMPL	Dummy variable: 1 if the worker is employed, 0 otherwise
LNHRW	The natural logarithm of hourly wages
Panel B: Socio-Demographic Characteristics	
AGE	Workers age (years)
AGESQ	The square of *AGE*/100
MARRIED	Dummy variable: 1 if the worker is married, 0 otherwise
RURAL	Dummy variable: 1if the worker lives in the rural area, 0 otherwise
MILD	Dummy variable: 1 if degree of disability≥3th; (3th~6th), 0 otherwise
Panel C: Human Capital Variables	
EXP	Potential labor market experience (Age - 6 - years of schooling)
EXPSQ	The square of *EXP*/100
HSDROP	Dummy variable: 1 if the worker is less than high school graduates and high school dropouts, 0 otherwise
HSCHOOL	Dummy variable: 1if high school diploma, 0 otherwise
COLLEGE	Dummy variable: 1if 2-year college degree or above, 0 otherwise
TENURE	Workers Job tenure (years)
Panel D: Labor Market Characteristics	
UNION	Dummy variable: 1 if member of labor unions, 0 otherwise
PART	Dummy variable: 1if part-time employment, 0 otherwise
PUBLIC	Dummy variable: 1if employed in the public sector, 0 otherwise
OCC 1	Dummy variable: Managerial, senior official, and professional occupations
OCC 2	Dummy variable: Clerical, administrative, and secretarial occupations.
OCC 3	Dummy variable: Services, sales, and customer Services occupations.
OCC 4	Dummy variable: Associated professional and technical occupations.
OCC 5	Dummy variable: Process, plant, and operative occupations.
OCC 6	Dummy variable: Laborer occupations.
IND 1	Dummy variable: Primary industry (such as agriculture and fishing).
IND 2	Dummy variable: Secondary industry (approximately manufacturing).
IND 3	Dummy variable: Tertiary industry (known as the service sector/industry).
Panel E: Other Variables:	
OEARNER	Dummy variable: 1 if other salary worker in the household, 0 otherwise
CHILD	Dummy variable: 1 if dependent children under the age of 18, 0 otherwise

Table 1-2: Summary Statistics

Variables	**Male**	**Female**
Panel A: Dependent Variable:		
LNHRW (The natural logarithm of hourly wages)	8.925(0.025)	8.386 (0.043)
Panel B: Socio-Demographic Characteristics:		
AGE (Individual age; years)	46.355(0.356)	47.379 (0.599)
AGESQ (The square of *AGE*/100)	22.510(0.317)	23.439 (0.535)
MARRIED (Married individual)	0.821 (0.014)	0.895 (0.018)
RURAR (Rural region)	0.579 (0.017)	0.603 (0.029)
MILD (Mild disability)	0.752 (0.015)	0.751 (0.026)
Panel C: Human Capital Variables:		
EXP (Potential labor market experience; years)	29.106(0.393)	30.863 (0.678)
EXPSQ (The square of *EXP*/100)	9.714 (0.218)	10.795 (0.379)
HSDROP (Less than a high school diploma)	0.442 (0.018)	0.610 (0.029)
HSCHOOL (High school graduates)	0.399 (0.017)	0.300 (0.028)
COLLEGE (2-year college degree or above)	0.147 (0.012)	0.083 (0.017)
TENURE (Job tenure; years)	7.625 (0.304)	3.960 (0.274)
Panel D: Labor Market Characteristics:		
UNION (Labor union Membership)	0.097 (0.010)	0.036 (0.011)
PART (Part-time employment contract)	0.130 (0.012)	0.224 (0.025)
PUBLIC (Public sector employment)	0.082 (0.010)	0.112 (0.019)
OCC1 (Managerial, senior official, or professional occupation)	0.047(0.007)	0.004 (0.004)
OCC2 (Clerical, administrative, or secretarial occupation)	0.099 (0.011)	0.116 (0.019)
OCC3 (Services, sales, or customer services occupation)	0.106 (0.011)	0.195 (0.024)
OCC4 (Associated professional or technical occupation)	0.058 (0.008)	0.029 (0.010)
OCC5 (Process, plant, or operative occupation)	0.251 (0.015)	0.058 (0.014)
OCC6 (Laborer)	0.437 (0.017)	0.596 (0.030)
IND1 (Primary industry)	0.021 (0.005)	0.047 (0.013)
IND2 (Secondary industry)	0.443 (0.018)	0.264 (0.027)
IND3 (Tertiary industry)	0.534 (0.018)	0.690 (0.028)
PANEL E: OTHER VARIABLES		
OEARNER (Other labor market income earner)	0.473 (0.017)	0.516 (0.030)
CHILD (Dependent children under the age of 18)	0.535 (0.013)	0.458 (0.027)

Notes: In all cases figures relate to the estimation samples used.
Standard errors are in parentheses.

Table 1-3: Probit Estimates of Labor Force Participation

Variables (1)	**Male (2)**	**Female (3)**
Panel A: Socio-Demographic Characteristics:		
AGE (Individual age; years)	0.043 (0.016)***	0.069 (0.026)***
AGESQ (The square of *AGE*/100)	-0.081 (0.017)***	-0.097 (0.027)***
MARRIED (Married individual)	0.513 (0.085)***	0.194 (0.149)
RURAL (Rural region)	-0.206 (0.054)***	-0.036 (0.078)
MILD (Mild disability)	0.705 (0.053)***	0.678 (0.081)***
Panel B: Human Capital Variables:		
HSDROP (Less than a high school diploma)	-0.118 (0.056)**	-0.111 (0.089)
COLLEGE (2-year college degree or above)	0.159 (0.094)*	0.414 (0.170)**
Panel C: Other Variables		
OEARNER (Other labor market income earner)	0.145 (0.055)***	-0.336 (0.082)***
CHILD (Dependent children under the age of 18)	0.561 (0.074)***	-0.325 (0.080)***
Constant	-1.112 (0.348)***	-2.265 (0.057)***
Sample Size (Observations)	2849	1677
Log Likelihood	-1618	-766.4
χ^2 p-value	0.000	0.000
Pseudo R-squared	0.169	0.099

Notes: Data are unweighted.
Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1
The χ^2 statistic is a test that all slope coefficients are zero.
Pseudo-R^2 is McFadden's measure (1983), defined as 1- the ratio of the maximized log-likelihood from the regression to that a regression including the optimal constant only.

Table 1-4: Selectivity Corrected Estimates of Wage Equations

Variables (1)	**Male (2)**	**Female (3)**
Panel *A*: Socio-Demographic Characteristics:		
MARRIED (Married individual)	0.164 (0.097)*	0.064 (0.187)
RURAR (Rural region)	-0.014 (0.048)	-0.157 (0.077)**
MILD (Mild disability)	0.257(0.054)***	0.160 (0.093)*
Panel *B*: Human Capital Variables:		
EXP (Potential labor market experience; years)	0.023 (0.018)**	0.002 (0.033)
EXPSQ (The square of *EXP*/100)	-0.032(0.019)***	-0.009 (0.036)
HSDROP (Less than a high school diploma)	-0.001 (0.056)	-0.005 (0.101)
COLLEGE (2-year college degree or above)	0.141 (0.077)*	0.456 (0.178)**
TENURE (Job tenure)	0.011(0.003)***	0.006 (0.009)
Panel *C*: Labor Market Characteristics:		
UNION (Labor union Membership)	0.247(0.084)***	0.185 (0.218)
PART (Part-time employment contract)	-0.035 (0.069)	-0.229 (0.093)**
PUBLIC (Public sector employment)	0.269 (0.155)*	0.556 (0.620)
OCC1 (Managerial, senior official, or professional occupation)	0.680(0.128)***	0.963 (0.645)
OCC2 (Clerical, administrative, or secretarial occupation)	0.514(0.095)***	0.705(0.156)***
OCC3 (Services, sales, or customer services occupation)	0.200 (0.084)**	0.290(0.109)***
OCC4 (Associated professional or technical occupation)	0.398(0.105)***	0.597 (0.253)**
OCC5 (Process, plant, or operative occupation)	0.211(0.060)***	0.305 (0.174)*
IND2 (Secondary industry)	0.432(0.163)***	0.031 (0.211)
IND3 (Tertiary industry)	0.340 (0.164)**	0.074 (0.206)
IMR	-0.361(0.105)***	-0.576(0.232)**
Constant	7.725(0.441)***	8.593(0.783)***
Sample Size (Observations)	805	277
R-squared (R2)	0.320	0.274
Adjusted R2	0.303	0.220
Log Likelihood	-773.9	-250.4
F (p-value)	0.000	0.000

Notes: Data are unweighted.
Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1
The F test is a test that all slope coefficients are zero.

Table 1-5: Gender Wage Decompositions

Panel *A*: Gender Wage Differentials		
Mean Prediction of log hourly wages	Disabled Male	8.843
	Disabled Female	8.414
Log Wage Differentials		**0.429**

Panel *B*: Selectivity Corrected Wage Decompositions			
Decomposition Methods	**Endowment (1)**	**Discrimination (2)**	**Selectivity (3)**
Standard Oaxaca	0.162 (37.76%)	0.267 (62.24%)	0.000 (0.00%)
Decomposition #1	0.146 (34.03%)	0.279 (65.04%)	0.004 (0.93%)
Decomposition #2	0.147(34.27%)	0.210 (48.95%)	0.072 (16.78%)
Decomposition #3	0.219 (51.05%)	0.210 (48.95%)	0.000 (0.00%)
Decomposition #4	0.147 (34.27%)	0.282 (65.73%)	0.000 (0.00%)

Table 2-1: Definition of Variables

Variables	Definitions
Panel *A*: Dependent Variables	
LNHRW	Log hourly wages; Hourly wage = Monthly wage / (average worked days per month×average worked hours per day)
Panel *B*: Socio-Demographic Characteristics	
FEMALE	Dummy variable: 1 if female, 0 otherwise.
AGE 1	Dummy variable: 1 if the worker's age is between 18 and 19, 0 otherwise.
AGE 2	Dummy variable: 1 if the worker's age is between 20 and 21, 0 otherwise.
AGE 3	Dummy variable: 1 if the worker's age is between 22 and 29, 0 otherwise.
AGE 4	Dummy variable: 1 if the worker's age is between 30 and 39, 0 otherwise.
AGE 5	Dummy variable: 1 if the worker age is between 40 and 49, 0 otherwise.
AGE 6	Dummy variable: 1 if the worker age is between 50 and 59, 0 otherwise.
AGE 7	Dummy variable; reference group: 1 if the worker age is 60 and over, 0 otherwise.
MARRIED	Dummy variable: 1 if married (including separated/divorced), 0 otherwise.
URBAN	Dummy variable: 1 if the worker lives in urban areas, 0 otherwise.
Panel *C*: Human Capital Endowments	
HSDROP	Dummy variable: 1 if the worker is less than high school graduates and high school dropouts, 0 otherwise.
HSCHOOL	Dummy variable: 1 if high school diploma, 0 otherwise.
SCOLLEGE	Dummy variable: 1 if some college degree, 0 otherwise.
COLLEGE	Dummy variable; reference group: 1 if 4-year college degree or above, 0 otherwise.
TEN 1	Dummy variable; reference group: 1 if the worker has been working in the current job for less than 1 year, 0 otherwise.
TEN 2	Dummy variable: 1 if the worker has been working in the current job for between 1 and 2 years, 0 otherwise.
TEN 3	Dummy variable: 1 if the worker has been working in the current job for between 3 and 5 years, 0 otherwise.
TEN 4	Dummy variable: 1 if the worker has been working in the current job for between 6 and 10 years, 0 otherwise.
TEN 5	Dummy variable: 1 if the worker has been working in the current job for more than 10 years, 0 otherwise.
Panel *D*: Labor Market related Variables	
UNION	Dummy variable: 1 if member of labor unions, 0 otherwise.
FULL	Dummy variable: 1 if full-time employment, 0 otherwise.
PERT	Dummy variable: 1 if permanent employment contract, 0 otherwise.

PUBLIC	Dummy variable: 1 if employed in the public sector, 0 otherwise.
FIRM SIZE 1	Dummy variable; reference group: 1 if firm size is less than 10 employees, 0 otherwise.
FIRM SIZE 2	Dummy variable: 1 if firm size is between 10 and 99 employees, 0 otherwise.
FIRM SIZE 3	Dummy variable: 1 if firm size is between 100 and 299 employees, 0 otherwise.
FIRM SIZE 4	Dummy variable: 1 if firm size is between 100 and 299 employees, 0 otherwise.
OCC 1	Dummy variable: 1 if managerial, senior official, and professional occupations, 0 otherwise.
OCC 2	Dummy variable: 1 if clerical, administrative, and secretarial occupations, 0 otherwise.
OCC 3	Dummy variable: 1 if services, sales, and customer services occupations, 0 otherwise.
OCC 4	Dummy variable: 1 if associated professional and technical occupations, 0 otherwise.
OCC 5	Dummy variable: 1 if process, plant, and operative occupations, 0 otherwise.
OCC 6	Dummy variable; reference group: 1 if laborer, 0 otherwise.
IND 1	Dummy variable; reference group: 1 if primary industry (extraction such as mining, agriculture and fishing), 0 otherwise.
IND 2	Dummy variable: 1 if secondary industry (approximately manufacturing), 0 otherwise.
IND 3	Dummy variable: 1 if tertiary industry (known as the service sector or the service industry), 0 otherwise.
Panel *E*: Skill Mismatch Variables	
DSA_OVER	Dummy variable: 1 if the worker feels that his/her English language proficiency is (3) *Relatively high* or (4) *Very high*, compared to the level required for a job, 0 otherwise.
DSA_UNDER	Dummy variable: 1 if the worker feels that his/her English language proficiency is (1) *Very low* or (2) *Relatively low*, compared to the level required for a job, 0 otherwise.
ISA_OVER	Dummy variable: 1 if the worker claims that the level of required English language in his/her current job is (1) *Almost none* or (2) *A little* and feels that his/her English language proficiency is (3) *able to carry on everyday conversation*, (4) *Able to conduct business with foreigners in English*, or (5) *Fluent in his/her English language ability*, 0 otherwise.
ISA_UNDER	Dummy variable: 1 if the worker claims that the level of required English language in his/her current job is (3) *substantially* and feels his/her English language proficiency is (1) *Can hardly speak English*, (2) *Limited to very simple communication* or (3) *Able to carry on everyday conversation*, 0 otherwise.

Table 2-2: Summary Statistics

Variables	Mean	Std. Errors
Panel *A*: Dependent Variable		
LNHRW (The natural logarithm of hourly wages)	9.029	0.015
Panel *B*: Socio-demographic Characteristics		
FEMALE (Female workers)	0.392	0.008
AGE 1 (Ages 18-19)	0.010	0.001
AGE 2 (Ages 20-21)	0.022	0.002
AGE 3 (Ages 22-29)	0.181	0.006
AGE 4 (Ages 30-39)	0.362	0.007
AGE 5 (Ages 40-49)	0.247	0.007
AGE 6 (Ages 50-59)	0.133	0.006
AGE 7 (Age 60 and over)	0.045	0.003
MARRIED (Married workers)	0.664	0.007
URBAN (Urban area)	0.454	0.008
Panel *C*: Human Capital Endowments		
HSDROP (Less than high school graduates)	0.144	0.005
HSCHOL (High school diploma)	0.399	0.008
SCOLLEGE (Some college degree)	0.181	0.006
COLLEGE (4-year college degree or above)	0.276	0.007
TEN 1 (Job tenure of less than 1 year)	0.139	0.005
TEN 2 (Job tenure of 1-2 years)	0.313	0.007
TEN 3 (Job tenure of 3-5 years)	0.213	0.006
TEN 4 (Job tenure of 6-10 years)	0.164	0.007
TEN 5 (Job tenure over 10 years)	0.171	0.006
Panel *D*: Labor Market related Variables		
UNION (Members of labor unions)	0.212	0.005
FULL (Full-time employment)	0.740	0.004
PERT (Permanent employment contract)	0.702	0.007
PUBLIC (Public sector employment)	0.127	0.005
FIRM SIZE 1 (Employed in job with less than 10 people)	0.276	0.007
FIRM SIZE 2 (Employed in job with 10 to 99 people)	0.374	0.007
FIRM SIZE 2 (Employed in job with 100 to 299 people)	0.112	0.004
FIRM SIZE 4 (Employed in job with 300 or more people)	0.238	0.007

OCC1 (Managerial/senior official, or professional occupation)	0.141	0.005
OCC2 (Clerical, administrative, or secretarial occupation)	0.161	0.006
OCC3 (Services, sales, or customer services occupation)	0.180	0.006
OCC4 (Associated professional or technical occupation)	0.141	0.006
OCC5 (Process, plant, or operative occupation)	0.266	0.007
OCC6 (Laborer)	0.111	0.005
IND1 (Primary industry)	0.038	0.001
IND2 (Secondary industry)	0.242	0.007
IND3 (Tertiary industry)	0.720	0.007
Panel *E*: Skill Mismatch Variables		
DSA_OVER (Over-skilling under the DSA measure)	0.278	0.004
DSA_UNDER (Under-skilling under the DSA measure)	0.190	0.006
ISA_OVER (Over-skilling under the ISA measure)	0.251	0.004
ISA_UNDER (Under-skilling under the ISA measure)	0.179	0.005
Sample Size (Observations)	4344	

Table 2-3: The Impact of the Skills-Job Mismatch on Wages

Variables	**OLS**	**Random Effects GLS**		
	Model 1	**Model 1**	**Model 2**	**Model 3**
	(1)	**(2)**	**(3)**	**(4)**
Panel *A*: Socio-demographic Characteristics				
FEMALE (Female workers)	- 0.277(0.030)***	- 0.240(0.028)***	- 0.238(0.027)***	- 0.233(0.028)***
AGE 1 (Ages 18-19)	0.038 (0.183)	0.306 (0.183)*	0.319 (0.177)*	0.318 (0.177)*
AGE 2 (Ages 20-21)	0.410(0.084)***	0.389(0.084)***	0.386(0.084)***	0.386(0.084)***
AGE 3 (Ages 22-29)	0.512(0.077)***	0.505(0.151)***	0.497(0.150)***	0.493(0.151)***
AGE 4 (Ages 30-39)	0.534(0.078)***	0.508(0.077)***	0.499(0.076)***	0.506(0.076)***
AGE 5 (Ages 40-49)	0.491(0.076)***	0.489(0.075)***	0.486(0.075)***	0.489(0.075)***
AGE 6 (Ages 50-59)	0.512(0.077)***	0.488(0.076)***	0.485(0.075)***	0.488(0.076)***
MARRIED (Married workers)	0.054 (0.076)	0.060 (0.034)*	0.063 (0.034)*	0.061 (0.034)*
URBAN (Urban area)	0.312(0.077)***	0.110(0.029)***	0.095(0.029)***	0.106(0.029)***
Panel *B*: Human Capital Endowments				
HSDROP (Less than high school graduates)	- 0.259 (0.053)***	- 0.234 (0.053)***	- 0.212 (0.053)***	- 0.216 (0.053)***
HSCHOL (High school diploma)	- 0.227 (0.038)***	- 0.235 (0.037)***	- 0.206 (0.038)***	- 0.210 (0.038)***
SCOLLEGE (Some college degree)	- 0.097 (0.041)**	- 0.080 (0.040)**	- 0.066 (0.040)**	- 0.069 (0.040)**
TEN 1 (Job tenure of less than 1 year)	0.126(0.042)***	0.091 (0.041)**	0.096 (0.041)**	0.095 (0.041)**
TEN 2 (Job tenure of 1-2 years)	0.219(0.046)***	0.174(0.045)***	0.177(0.045)***	0.180(0.045)***
TEN 3 (Job tenure of 3-5 years)	0.256(0.050)***	0.190(0.048)***	0.193(0.048)***	0.197(0.048)***
TEN 4 (Job tenure of 6-10 years)	0.587(0.055)***	0.533(0.053)***	0.538(0.053)***	0.539(0.053)***
Panel *C*: Labor Market related Variables				
UNION (Members of labor unions)	0.140(0.046)***	0.105(0.045)***	0.098(0.045)***	0.109(0.045)***
FULL (Full-time employment)	0.093 (0.061)	0.464(0.058)***	0.473(0.058)***	0.465(0.058)***

PERT (Permanent employment contract)	- 0.042 (0.034)	0.146(0.033)***	0.138(0.033)***	0.141(0.033)***
PUBLIC (Public sector employment)	- 0.282 (0.044)***	- 0.254 (0.044)***	- 0.252 (0.044)***	- 0.248 (0.044)***
FIRM SIZE 2 (Employed in job with 10 to 99 people)	0.127(0.034)***	0.094(0.034)***	0.091(0.034)***	0.094(0.034)***
FIRM SIZE 2 (Employed in job with 100 to 299 people)	0.250(0.049)***	0.208(0.048)***	0.200(0.048)***	0.204(0.048)***
FIRM SIZE 4 (Employed in job with 300 or more people)	0.380(0.037)***	0.355(0.037)***	0.338(0.037)***	0.344(0.037)***
OCC1 (Managerial/senior official, or professional occupation)	0.540(0.060)***	0.435(0.059)***	0.396(0.059)***	0.415(0.059)***
OCC2 (Clerical, administrative, or secretarial occupation)	0.430(0.057)***	0.365(0.056)***	0.341(0.056)***	0.353(0.056)***
OCC3 (Services, sales, or customer services occupation)	0.331(0.056)***	0.261(0.055)***	0.246(0.055)***	0.254(0.055)***
OCC4 (Associated professional or technical occupation)	0.052 (0.055)	0.047(0.054)	0.047(0.053)	0.046(0.053)
OCC5 (Process, plant, or operative occupation)	0.260(0.050)***	0.238(0.049)***	0.233(0.049)***	0.237(0.049)***
IND2 (Secondary industry)	0.584(0.147)***	0.425(0.144)***	0.424(0.144)***	0.416(0.144)***
IND3 (Tertiary industry)	0.646(0.145)***	0.509(0.142)***	0.506(0.142)***	0.501(0.142)***
<u>Panel *D*: Skill Mismatch Variables</u>				
DSA_OVER (Over-skilling under the DSA measure)			- 0.215(0.035)***	
DSA_UNDER (Under-skilling under the DSA measure)			0.110(0.172)***	
ISA_OVER (Over-skilling under the ISA measure)				- 0.178(0.056)***
ISA_UNDER (Under-skilling under the ISA measure)				0.144(0.076)***
Constant	7.450(0.172)***	7.100(0.172)***	7.069(0.172)***	7.082(0.172)***
R-squared (overall)	0.270	0.291	0.305	0.305
F-test	51.44 [0.000]	-	-	-
Wald χ^2	-	1638.00 [0.000]	1668.96 [0.000]	1662.48 [0.000]
Number of Observations		4,344		

Note: Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 3-1: Definition of Variables

Variables	**Definitions**
Panel *A*: Dependent Variable:	
LNHRW	The natural logarithm of hourly wages
Panel *B*: Military Service related Variables:	
VETERAN	Dummy variable: 1 if veteran status, 0 otherwise.
MILEXP	Length of military experience (months)
EXEMPT_PHY	Dummy variable: 1 if nonveterans due to physical inadequacies, 0 otherwise.
EXEMPT_EDU	Dummy variable: 1 if nonveterans due to insufficient educational background, 0 otherwise.
EXEMPT_OTHER	Dummy variable: 1 if nonveterans due to domestic reasons, 0 otherwise.
VETERAN_LESSEDU	Dummy variable: 1 if less-educated veteran, 0 otherwise.
Panel *C*: Human Capital Endowments:	
HSDROP	Dummy variable: 1 if the worker is less than high school graduates and high school dropouts, 0 otherwise.
HSCHOOL	Dummy variable; reference group: 1 if high school diploma, 0 otherwise.
SCOLLEGE	Dummy variable: 1 if some college degree, 0 otherwise
COLLEGE	Dummy variable: 1 if 4-year college degree or above, 0 otherwise
TENURE	Workers Job tenure (years)
TENURESQ	The square of *TENURE*/100
Panel *D*: Socio-Demographic Characteristics:	
AGE	Workers age (years)
AGESQ	The square of *AGE*/100
MARRIED	Dummy variable: 1 if the worker is married, 0 otherwise.
URBAN	Dummy variable: 1if the worker lives in urban areas, 0 otherwise.
Panel *E*: Labor Market related Variables:	
UNION	Dummy variable: 1 if member of labor unions, 0 otherwise.
FULL	Dummy variable: 1 if full-time employment contract, 0 otherwise.
PUBLIC	Dummy variable: 1if employed in the public sector, 0 otherwise.
OCC1	Dummy variable: 1 if managerial, senior official, and professional occupations, 0 otherwise.
OCC2	Dummy variable: 1if clerical, administrative, and secretarial

	occupations, 0 otherwise.
OCC3	Dummy variable: 1if services, sales, and customer services occupations, 0 otherwise.
OCC4	Dummy variable: 1 if associated professional and technical occupations, 0 otherwise.
OCC5	Dummy variable: 1 if process, plant, and operative occupations, 0 otherwise.
OCC6	Dummy variable; reference group: 1 if laborer, 0 otherwise
IND1	Dummy variable: 1 if primary industry (extraction such as mining, agriculture and fishing), 0 otherwise.
IND2	Dummy variable; reference group: 1 if secondary industry (approximately manufacturing), 0 otherwise.
IND3	Dummy variable: 1 if tertiary industry (known as the service sector or the service industry), 0 otherwise.

Table 3-2: Summary Statistics for Veteran Sample

Variables	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**
Panel *A*: Military Service related Variables:											
LNHRW (The natural logarithm of hourly wages)	8.682	8.588	8.705	8.714	8.868	8.972	9.077	9.158	9.212	9.270	9.346
MILEXP (Length of military experience in months)	28.914	28.689	28.666	28.672	28.446	28.365	28.257	28.104	27.921	27.907	27.872
VETERAN_LESSEDU (Less-educated veteran)	0.196	0.186	0.189	0.187	0.178	0.168	0.149	0.145	0.137	0.129	0.127
Panel *B*: Human Capital Endowments:											
HSDROP (Less than high school graduates)	0.122	0.137	0.108	0.126	0.105	0.099	0.093	0.098	0.092	0.088	0.086
HSCHOOL (High school diploma)	0.466	0.478	0.479	0.461	0.478	0.437	0.426	0.418	0.416	0.398	0.387
SCOLLEGE (Some college degree)	0.152	0.148	0.157	0.170	0.169	0.186	0.187	0.192	0.203	0.198	0.214
COLLEGE (4-year college degree or above)	0.260	0.237	0.256	0.243	0.248	0.278	0.294	0.292	0.289	0.316	0.313
TENURE (Job tenure; years)	7.530	6.241	6.766	6.618	6.594	6.625	6.601	6.791	6.673	6.792	6.822
TENURESQ (The square of *TENURE*/100)	1.118	0.885	0.990	0.978	0.980	0.988	0.970	1.017	1.001	1.023	1.018
Panel *C*: Socio-Demographic Characteristics:											
AGE (Workers Age; years)	37.231	36.816	37.532	37.922	38.286	38.291	38.629	38.985	39.105	39.432	39.868
AGESQ (The square of *AGE*/100)	14.586	14.366	14.922	15.254	15.558	15.572	15.848	16.152	16.248	16.508	16.907
MARRIED (Married)	0.755	0.745	0.739	0.755	0.745	0.742	0.740	0.737	0.762	0.742	0.708
URBAN (Urban region)	0.450	0.464	0.119	0.429	0.435	0.418	0.445	0.434	0.449	0.454	0.472
Panel *D*: Labor Market related Variables:											
UNION (Labor union membership)	0.218	0.193	0.237	0.277	0.257	0.270	0.265	0.264	0.253	0.252	0.245
FULL(Full-time employment contract)	0.826	0.811	0.814	0.869	0.875	0.829	0.828	0.799	0.780	0.782	0.799
PUBLIC (Public sector employment)	0.220	0.159	0.178	0.144	0.168	0.141	0.151	0.163	0.171	0.154	0.167
OCC1(Manager, senior official, professional)	0.116	0.095	0.075	0.095	0.103	0.131	0.123	0.132	0.127	0.133	0.137

OCC2 (Clerical, administrative, secretarial)	0.149	0.218	0.210	0.194	0.185	0.198	0.191	0.189	0.185	0.196	0.204
OCC3 (Services, sales, customer services)	0.238	0.145	0.142	0.148	0.149	0.147	0.166	0.164	0.173	0.167	0.174
OCC4 (Associated professional, technical)	0.072	0.088	0.086	0.092	0.102	0.095	0.091	0.093	0.096	0.098	0.093
OCC5 (Process, plant, operative)	0.359	0.392	0.412	0.390	0.382	0.361	0.355	0.343	0.346	0.335	0.328
OCC6 (Laborer)	0.066	0.062	0.075	0.081	0.079	0.068	0.074	0.079	0.073	0.071	0.064
IND1 (Primary industry)	0.024	0.026	0.027	0.024	0.028	0.027	0.024	0.025	0.024	0.027	0.028
IND2 (Secondary industry)	0.287	0.312	0.310	0.303	0.297	0.299	0.292	0.291	0.284	0.286	0.286
IND3 (Tertiary industry)	0.689	0.662	0.663	0.673	0.675	0.674	0.684	0.684	0.692	0.687	0.686
Sample Size (Observations)	1,384	1,671	1,582	1,642	1,515	1,749	1,685	1,526	1,763	1,726	1,728

Table 3-3: Summary Statistics for Nonveteran Sample

Variables	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**
Panel *A*: Military Service related Variables:											
LNHRW (The natural logarithm of hourly wages)	8.484	8.392	8.470	8.561	8.716	8.718	8.840	8.953	8.992	8.981	9.133
EXEMPT_PHY (Nonveterans due to physical inadequacy)	0.681	0.687	0.642	0.657	0.658	0.684	0.703	0.723	0.745	0.732	0.710
EXEMPT_EDU (Nonveterans due to insufficient education)	0.027	0.044	0.040	0.047	0.042	0.042	0.037	0.036	0.033	0.036	0.041
EXEMPT_OTHER (Nonveterans due to domestic reasons)	0.292	0.269	0.318	0.296	0.300	0.274	0.260	0.241	0.222	0.232	0.249
Panel *B*: Human Capital Endowments:											
HSDROP (Less than high school graduates)	0.390	0.366	0.382	0.368	0.398	0.369	0.361	0.359	0.332	0.335	0.319
HSCHOOL (High school diploma)	0.473	0.483	0.484	0.482	0.452	0.468	0.455	0.459	0.436	0.483	0.492
SCOLLEGE (Some college degree)	0.074	0.080	0.067	0.063	0.054	0.056	0.068	0.074	0.092	0.079	0.087
COLLEGE (4-year college degree or above)	0.063	0.071	0.067	0.087	0.096	0.107	0.116	0.108	0.140	0.103	0.102
TENURE (Job tenure; years)	6.243	4.822	5.532	5.408	5.630	5.953	6.493	6.380	6.289	6.556	6.787
TENURESQ (The square of *TENURE*/100)	0.950	0.682	0.834	0.802	0.859	0.907	1.010	0.974	0.944	1.025	0.125
Panel *C*: Socio-Demographic Characteristics:											
AGE (Workers Age; years)	37.596	37.624	37.990	39.059	39.872	40.988	41.091	41.651	42.069	43.002	43.789
AGESQ (The square of *AGE*/100)	14.884	14.881	15.195	16.091	16.788	17.704	17.831	18.301	18.658	19.429	20.128
MARRIED (Married)	0.733	0.725	0.732	0.735	0.722	0.730	0.720	0.720	0.726	0.737	0.746
URBAN (Urban region)	0.369	0.436	0.435	0.402	0.403	0.392	0.399	0.416	0.432	0.418	0.438
Panel *D*: Labor Market related Variables:											
UNION (Labor union membership)	0.188	0.117	0.117	0.131	0.199	0.110	0.125	0.108	0.123	0.105	0.097
FULL(Full-time employment contract)	0.741	0.718	0.692	0.799	0.752	0.736	0.688	0.632	0.657	0.628	0.644
PUBLIC (Public sector employment)	0.122	0.081	0.100	0.103	0.090	0.095	0.093	0.097	0.074	0.086	0.077

OCC1(Manager, senior official, professional)	0.063	0.070	0.057	0.081	0.081	0.112	0.111	0.099	0.097	0.090	0.079
OCC2 (Clerical, administrative, secretarial)	0.094	0.070	0.097	0.097	0.072	0.077	0.096	0.111	0.110	0.119	0.114
OCC3 (Services, sales, customer services)	0.086	0.074	0.067	0.081	0.081	0.071	0.065	0.075	0.082	0.064	0.080
OCC4 (Associated professional, technical)	0.051	0.084	0.067	0.062	0.063	0.059	0.054	0.050	0.056	0.050	0.061
OCC5 (Process, plant, operative)	0.545	0.548	0.555	0.523	0.531	0.518	0.501	0.482	0.481	0.477	0.455
OCC6 (Laborer)	0.161	0.154	0.157	0.156	0.172	0.163	0.173	0.183	0.174	0.200	0.211
IND1 (Primary industry)	0.024	0.013	0.017	0.019	0.021	0.018	0.020	0.022	0.013	0.019	0.019
IND2 (Secondary industry)	0.313	0.340	0.331	0.326	0.342	0.290	0.261	0.274	0.274	0.271	0.257
IND3 (Tertiary industry)	0.663	0.647	0.652	0.655	0.637	0.692	0.719	0.704	0.713	0.710	0.724
Sample Size (Observations)	278	318	335	321	299	353	337	413	391	419	361

Table 3-4: The Effect of Veteran Status on Subsequent Civilian Wages

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Panel *A*: Military Service related Variables:				
VETERAN (Veteran Status)	0.240(0.017)***	0.132 (0.023)**	0.105(0.019)***	0.069(0.016)***
EXEMPT_OTHER (Nonveterans due to domestic reasons)		-0.123 (0.050)***	-0.136 (0.050)***	-0.117 (0.048)***
VETERAN_LESSEDU (Less-educated veteran)			0.200(0.019)***	0.125(0.020)***
Panel *B*: Human Capital Endowments:				
HSDROP (Less than high school graduates)		-0.236 (0.021)***	-0.238 (0.020)***	-0.155 (0.051)***
SCOLLEGE (Some college degree)		0.194(0.019)***	0.083(0.022)***	0.065(0.004)***
COLLEGE (4-year college degree or above)		0.342(0.017)***	0.209(0.021)***	0.187(0.005)***
TENURE (Job tenure; years)		0.048(0.003)***	0.048(0.003)***	0.044(0.003)***
TENURESQ (The square of *TENURE*/100)		-0.070 (0.010)***	-0.070 (0.010)***	-0.073 (0.010)***
Panel *C*: Socio-Demographic Characteristics:				
AGE (Workers Age; years)		0.085(0.006)***	0.085(0.019)***	0.075(0.006)***
AGESQ (The square of *AGE*/100)		-0.101 (0.007)***	-0.101 (0.007)***	-0.086 (0.007)***
MARRIED (Married)		0.159(0.017)***	0.158(0.017)***	0132(0.017)***
URBAN (Urban region)		0.072(0.013)***	0.066(0.013)***	0.047(0.013)***
Panel *D*: Labor Market related Variables:				
UNION (Labor union membership)		0.061(0.018)***	0.069(0.018)***	0.078(0.018)***
FULL(Full-time employment contract)		0.246(0.034)***	0.245(0.034)***	0.224(0.033)***
PUBLIC (Public sector employment)		-0.041 (0.020)**	-0.037 (0.020)*	-0.055(0.020)***
OCC1(Manager, senior official, professional)				0.596(0.029)***
OCC2 (Clerical, administrative, secretarial)				0.464(0.027)***

OCC3 (Services, sales, customer services)				0.389(0.027)***
OCC4 (Associated professional, technical)				0.235(0.030)***
OCC5 (Process, plant, operative)				0.237(0.023)***
IND1 (Primary industry)				-0.282(0.071)***
IND3 (Tertiary industry)				0.085(0.123)***
Constant	8.779(0.015)***	6.709(0.124)***	6.743(0.123)***	6.638(0.123)***
Adjusted R^2	0.050	0.172	0.187	0.201
Log Likelihood	-25,660	-23,935	-23,882	-23,610
F-statistics (p-value)	197.8 (0.000)	246.4 (0.000)	239.5 (0.000)	197.4 (0.000)

Note: Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.
Sample Size: 21,796 (Veterans 17,971, Nonveterans 382).

APPENDIX B: COMPULSORY MILITAYR SERVICE IN KOREA

Compulsory military service is legislated in Korea as one of the Four Constitutional Duties (along with taxes, education, and labor) for all citizens. Article 39 of the 1987 Constitution states "(1) All citizen shall have the duty of national defense under the conditions a prescribed by Act. (2) No citizen shall be treated unfavorably on account of the fulfillment of his obligation of military service." The current Military Service Act, however, requires only Korean male citizens of a particular birth cohort serve a military duty: "Men of Korean nationality must fulfill their military service obligation in a satisfactory manner. Women may also accomplish their active duty if they so desire".

In principle, the conscription laws and regulations are simple. All Korean men are automatically registered as conscripts in the year they turn 18 and called up for mandatory medical examinations (including psychological, physical and general education tests) takes place at the age of 19. Based on these examinations, most of them are categorized as being fit for service and a relatively small number of men exempt from military service in general. The exemption is limited to physical inadequacies, insufficient educational background, or domestic reasons such as the age limit, homosexuality, dual citizenship, significant criminal records, etc., with no exemption provisions for conscientious objectors (Article 11 and 12 of the Military Service Act). Service can be started after turning 19. The duty to enlist in the Armed Forces lasts until the age of 31, with an exception for draft evader, for whom it last until they reach 36 (Article 18 of the Military Service Act).

Currently Korea has among the longest conscription term in the world, ranked just behind Israel. The duration of military service varies according to branch involved as follows: 21 months for the Army and Marin Corps, two years and 24 months for the Air force, and 23 months for the Navy, as of May 2011. Currently, the Korean Armed Forces rely heavily on conscripts, who account for around 75 percent of the approximately 650,000 armed forces. The remaining 25 percent are commissioned and non-commissioned officers (i.e., professional soldiers), account for around 8 percent and 17 percent respectively. According to the “Defense Reform Plan 2020”, the number of professional soldiers will be increased to 40 percent by 2020.

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