THE EFFECTS OF OVER-EDUCATION ON JOB MOBILITY
: EVIDENCE FROM KOREAN FEMALE GRADUATES

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Abstract:

This paper examines the incidence and the impact of educational mismatch on job mobility using the Graduates Occupational Mobility Survey (GOMS) data covering Korean female graduates making their transition from university to labor market. Contrary to most prior research in the literature, I account for individual heterogeneity in perceived skills mismatch when measuring over-educational mismatch. The results presented in this paper give support to previous studies: over-education is associated with a significant impact on job mobility. This positive correlation remains the same even if I estimate an augmented specification where graduate over-education is disaggregated according to perceived skills mismatch. High job turnover is clearly related to over-education jointly either with matched in skills or over-skilling. Moreover, in line with Chevalier (2003), Green and Zhu (2010) and Mavromaras et al. (2013), there is a clear message that the over-educated and over-skilled workers are more likely to switch their employers than their formal over-educated counterparts. The formal over-education has a relatively little correlation with job turnover.

Keywords: Over-Education, job turnover, female, graduates

I. Introduction

This paper is motivated by a significant increase in a number of female students with qualifications in the Korean labor market. Since the early 1990s, in many parts of the world, female students have begun switch places with their male counterparts as the most dominant gender in terms of higher education participation. In South Korea (hereafter denoted as Korea) 65.4 percent of female high school graduates entered college, while 7.0.4 percent of male graduates did so a decade earlier. In 2010, however, female high school students surpassed male students in the higher education entry ratio with 80.5 percent to 77.6 percent. During the period 2000 -2013, the number of women enrolled in higher education institutes has also steadily increased (for details, see Table 1). In 2013, women made up 42.2 percent of students enrolled in higher educational institutions. This spreading out of higher education to Korean female students has naturally given rise to concerns whether the economy can successfully provide enough positions to accommodate all college graduates (i.e., education-job mismatch). Unfortunately, as pointed by Cho and Lee (2014), there is a little attention to economic analysis to qualification-job mismatch in Korea, particular for young female college graduates, although numerous news ad research institutes reports on labor market mismatch and its costs.

<Insert Table 1 here>

Since the seminar work by Richard Freeman (1976), there has been a growing literature on qualification-job mismatch. Most of this literature has focused on over-education and under-education (i.e., educational mismatch) as the difference between a worker's attained or completed level of education and the level of education required for the job workers holds, while the topic of over-skilling and under-skilling (i.e., skill mismatch) has received relatively little attention to date. This asymmetric is in part due to the unavailability of data on skill mismatch. One of the major concerns in the empirical educational mismatch literature is that the measurement method to define educational mismatch. As regards this issue, most prior research has assumed that workers with a given level of schoolings may be homogeneous in terms of skills. However, some previous studies have already supported the view that education and skill mismatch are distinct phenomena with a variety of labor

market outcomes, e.g., Mavromaras et al. (2013). Some over-educated workers, for instance, may have lower skill levels for their educational attainment, compared to their peers and thus unable to obtain a job commensurate with their attained level of education. In such a case, educational mismatch does therefore not necessarily imply skill mismatch. Accordingly, the inability of the educational mismatch measures to account for skill mismatch may produce biased estimates of the incidence and the effects of education-job mismatch in the labor market.

Using two periods' panel data from the Graduates Occupational Mobility Survey (GOMS), this paper examines the incidence and effects of over-education on job mobility. The GOMS survey is particularly suitable for this analysis because it includes appropriate information on both educational and skill mismatches for young female graduates. Moreover, contrary to most prior research in the literature, I account for individual heterogeneity in perceived skills mismatch when measuring over-educational mismatch and, therefore, address the measurement issue discussed above. An alternative method used in this study incorporates information on both educational and skill requirements in the workplace into an improved measured of over-education. To do this, I make use of questions in recent data sets, namely the 2009 GOMS survey which both ask respondents about the extent they are able to use their previously acquired education and skills on the job. This alternative measure of over-education seems less likely to be biased through failure to control for skill utilization differences. Since I focus on female college graduates in this work, under-education is not possible, as this group has the highest level of education. Thus possible categories of education-job matching are limited to:[1]

(i) *Formal matched*: matched in education, but over-skilled

(ii) *Real* matched: matched in both education and skills (i.e., neither over-educated nor over-skilled)

(iii) *Formal matched*: over-educated, but matched in skills

(iv) *Real matched*: over-educated and over-skilled (i.e., mismatched in both education and skills)

Finally, the topic discussed here in this paper of paramount importance in the Korean setting. According to recent data from the Organization for Economic Cooperation and Development

[1] When defining educational mismatch in this study, I follow the terminology in using the term formal/real duality introduced by Green and Zhu (2010), for more details see Chapter II-2, Definitions of main variables.

(hereafter denoted as OECD), the employment rate of Korean female college graduates ranked at the bottom among a group of the world's advanced nations. Only 60.1 percent of female college graduates were employed as of 2011 in Korea, making the lowest rate among 33 OECD member countries surveyed. This figure was far cry from the OECD average of 78.8 percent. Moreover, the OECD data also shown that Korea's women part-time workers accounted for 27.2 percent of the country's entire female workforce, topping the OECD list 22 countries with such data available. The figure was a sharp contrast to the OECD average of 12.5 percent. Since the young female group experiences a weaker position in different aspects of their participation in the labor market compared to the average attainments of all individuals, they tend to be the ones who invest additional human capital and change jobs more frequently. For the most skilled female workers it may suggest that over-qualification in early careers is a voluntary choice to accumulate work experience until when they get the best job offer they can.

II. Data

1. Graduates Occupational Mobility Survey (GOMS)

For the empirical analysis, I use the data from the Graduates Occupational Mobility Survey (GOMS). The GOMS is a nationally representative survey of Korean young graduates of 2-to3-year college or higher education institutions in a given survey year. This survey is the largest short-term panel survey conducted annually by Korean Employment Information Service (KEIS) which aims to provide basic information to policy makers and researchers so it could be used for employment policy making and in-depth studies of highly educated unemployment problem.

The first wave of 2005 GOMS initiated in 2006 was conducted on a sample of 25,000 young persons (approximately 5 percent of the population). In 2009, the survey design was modified to short-term longitudinal survey. Beginning with the 2007 GOMS, the survey has performed for each subject on the next calendar year of graduation. The sample of the GOMS is composed of 4 percent of all college graduates who graduated from a 2-3 year college or higher education institution, which corresponds to 18,000 persons. In the first-wave survey, all graduates having successfully completed a

degree in a recognized tertiary or higher education institution are asked to complete a questionnaire one year after graduation. Only graduates who participated in the first wave survey are asked to take part in a second wave survey two years later. Since the GOMS contains extensive information concerning youths' labor market behavior and educational experience, one and three years after graduation, it in particular facilitates this study that investigates characteristics of the transition the youths makes from school to the labor market.

In this study, I make use of data from the GOMS among the cohort graduated in the year 2009. This cohort having been surveyed a first time in 2010 and a second time in 2012. The 2009 GOMS data used here is restricted to a balanced panel of female salaried graduate employees graduated in the year 2009 who provide valid information for the variables of interest, so that self-employed and unpaid family-employed workers at the time of both surveys are excluded in the analysis. These restrictions result in a final sample of 5,760 (resp. 4,966) Korean female graduates in 2010 (resp. 2012). Summary mean statistics of the variables used in this study are provided in Table 2.

<Insert Table 2 here>

2. Definition of Main Variables

As noted by Groot and Maassen van den Brink (2000), broadly speaking the following four measures of educational mismatch are used in the literature. (1) Direct self-assessment; (2) Indirect self-assessment; (3) Job analysis; (4) Realized matches. Among these four categories of measures, like most previous studies, this paper employs the Direct self-assessment method to define educational mismatch. The other methods for measuring over-education are indeed difficult to be implemented on the basis of the GOMS data.

The 2009 GOMS data provides information on both educational and skill mismatches as the basis for the present study. Specifically, the following two survey questions are used to collect these two sets of information. The first (resp. second) question is related to self-assessed educational mismatch (resp. skill mismatch). Specifically, respondents were asked directly whether they are over- and under-

education (resp. over- and under-skilling) for the work they do as follows.

What is the level of education (resp. skills) required by your current job, compared to your education (resp. skill) level?

(1) Very low

(2) Low

(3) Appropriate

(4) High

(5) Very high

As a conventional measure of educational mismatch, individual are defined as being over-educated if they claimed that a below level of education is most appropriate for their current job. The responses to the first question are used for identifying those over-educated. Individuals claiming *(1) Very* low or *(2) Low* as the level of required education level in the current job, comparing to their education level acquired are classified as over-educated and those selecting *(3) appropriate* as matched in education. As noted earlier, the approach taken here assumes that over-educated graduates are homogeneous in terms of skills. In order to account for workers heterogeneity in terms of perceived skills utilization this paper attempts to adopt an improved concept of educational mismatch that combine the subjective measure of education-job mismatch from the first question with the self-reported of skill-job mismatch from the second question. Thus, the second question on skill-job mismatch is also used. The self-assessed measure of skill-job mismatch is used for identifying whether skills among over-educated graduates do or do not correspond to the job. In the second question, individuals selecting 1 or 2 (resp. 3) on the scale are classified as over-skilled (resp. matched in skills).

Some previous studies have already attempted to make progress by disaggregating the over-education variable. Chevalier (2003) distinguished between genuine and apparent over-education by considering job satisfaction as a possible way of showing the degree of match between workers and jobs. Green and Zhu (2010) distinguished between real and formal mismatch according to whether or not this was accompanied by skills under-utilization. Mavromaras et al. (2013) also considered three possible categories of over-education as follows: only over-educated; only over-skilled; over-educated

and over-skilled. In this paper I following Green and Zhu (2010) consider four types of matching status: (i) formal matched (matched in education, but over-skilled), (ii) real matched (matched in both education and skills), (iii) formal over-educated (over-education and matched in skills), and (iv) real over-educated (over-educated and over-skilled). Table 3 summarizes how the subject measure of educational mismatch is disaggregated into four possible categories.

<Insert Table 3 here>

The procedure used here to create educational mismatch variables is open to criticism as it is based on subjective evaluation, which could not be related to the actual conditions. The existing literature, however, provides conclusion about the reliability of self-reported measures, and the workers' self-assessed qualification-job mismatch has been still used in much of the literature. Jones and Sloane (2010) argue that there is no obvious evidence that employees would consistently overestimates or underestimates their own skills or demand to the extent to which the job requires the level of skills they possess. Di Pietro and Urwin (2006) also claim that the self-reported 'subjective' measures of education and skill mismatch are reliably compared to the jobholder's judgment concerning the degree of utilization of employees' knowledge and skills. Chevalier (2003) in particular emphasize that the subjective method has the advantage of adjusting the measure of over-education to the specific requirements of the job, while objective and statistical methods assume that all jobs within a given occupation have the same requirements. Thus, the individual's subjective assessment adopted in the analysis would also be expected to provide the substance (important information) of the present paper, even though it could be generally the weakness of the study.

III. Empirical Model and Methodology

This study aims to analyze the relationship between job mobility and educational mismatch, particularly for over-education. In order to achieve the goal I run a Probit regression in which job mobility is regressed on a vector of characteristics for individual *i*. The regression model estimated in this study is of the following general form:

$$Prob(JM_i) = \Phi(\alpha + \beta_1 X_i + \beta_2 Z_j)$$

where *i* and *j* index individuals and workplace respectively. The dependent variable JM_i corresponds to job mobility of the individual worker *i*. The dependent variable 1 if, in 2011, a person worked or an employer different from that in 2009 and 0 if the person worked for the same employer. X_i is a set of individual demographic variables, Z_j is a set of employment characteristics. β_1 and β_2 are vectors of unknown parameters to be estimated. I control for a number of characteristics of individuals (age, marital status, educational attainment, and location) and their jobs (firm size, union membership, public sector employment, full-time employment contract). Table 4 provides the definition of all variables used in the analysis.

<Insert Table 4 here>

For the empirical analysis, two models are provided to identify the correlation between educational mismatch and job mobility, conditional on employment. Model 1, as a benchmark, incorporates a dummy variable indicating over-education (*OE*) in the basic equation above.

$$Prob(TURNOVER_i) = \Phi(\alpha + \beta_1 X_i + \beta_2 Z_j + \gamma OVER_EDU_{ij})$$

This specification with a single dummy for over-educated individuals is a special case of the one proposed by Verdugo and Verdugo (1989) which includes both dummies for being over- and under-educated. In Model 1, over-educated graduates are compared to graduates who are matched in education, i.e., adequately educated being the reference category.

Model 2 replaces the indicator representing over-education (*OE*) in Model 1 by a vector of dummies including different type of mismatch. To some extent, this paper relies on a similar equation that incorporates an alternative measure of educational mismatch.

$$Prob(TURNOVER_i) = \Phi(\alpha + \beta_1 X_i + \beta_2 Z_j + \gamma_1 formal_MATCH_{ij} + \gamma_2 formal_OE_{ij} + \gamma_3 real_OE_{ij})$$

where *formal_MATCH* is a dummy for formal matched (matched in education, but over-skilled), *formal_OE* dummy for formal over-education (over-education and matched in skills), and *real_OE* dummy for real over-education (over-educated and over-skilled). Formal matched, formal over-

educated, and real over-educated graduates are thus compared to graduates who are real matched (matched in education, but over-skilled).

In general, the choice of one out of J unordered alternatives can be driven by a latent variable, often interpreted as indirect utility. For this study, the indirect utility V_{ij}^{*} of an individual i being two alternative j = 1, 2 is

$$V_{ij}^{*} = X_i'\beta_j + \varepsilon_{ij}$$

where the reference group is a person worked for the same employer between 2010 and 2012 (j=2) and the other parameter of the Probit model is the person worked for an employer different from that between 2010 and 2012 (j=1). There are 2 error terms ε_{ij} for any individual i. The exogenous variables X_{ij} = (X_j^1, X_i^2) can be divided into variables that depend only on the individual, X_i^2, only on the alternative, X_j^1.

Let Y_i be a random variable that indicates the alternatives made. The probability that an individual i chooses alternative j conditional on a vector of characteristics X_i is

$$\begin{cases} \mathrm{P}_{i2} = \text{ Prob } (Y_i = 2 \mid X_i) = \dfrac{1}{1 + \sum_{k=1}^{2} e^{\beta_k' X_i}} \\ \mathrm{P}_{i1} = \text{ Prob } (Y_i = 1 \mid X_i) = \dfrac{e^{\beta_k' X_i}}{1 + \sum_{k=1}^{2} e^{\beta_k' X_i}} \end{cases}$$

IV. Results and Discussion

The aim of this section is twofold. First, I analyze the incidence of educational mismatch in the Korean labor market among young female graduates. Second I analyze the relationship between job mobility and educational mismatch using the GOMS 2009 data. For both purpose I consider two measurers of graduates mismatch: a conventional method based on self-assessed over-education only and an alternative measure derived from a combination of self-reported over-education and perceived skill mismatch.

1. Incidence of Educational Mismatch

In order to achieve the first goal, I rely on the 2009 GOMS data including individuals graduated in the year 2009. This cohort having been interviewed a first time in 2010 and a second time in 2012. As noted earlier, this selected sample consists of salaried workers reporting valid information for the variables of interest. Table 5 present how the incidence of educational mismatch evolves one and three years after graduation. The upper (resp. lower) part of this table show proportions derived from the conventional (resp. alternative) measure.

According to the conventional measure, the majority (resp. minority) of workers are adequately educated (over-educated) and their proportion is approximately 19 (resp. 71) percent. The proportion of over-educated employees has significantly decreased by about 4 percent points two years later. At least one out of ten graduates is over-educated in 2012. This proportion of over-educated workers appears comparable to or smaller than the overall means reported by other existing studies of graduate over-education. For instance, Green and Zhu (2010) found that the proportion of over-educated workers is ranging between 23 percent and 33 percent among U.K. graduates. This pattern is also consistent with the findings of Frenette (2004) showed that at least 30 percent of Canadian graduates are over-educated. For Australian graduates Mavromaras et al. (2013) provided rates of over-education ranging between 14 percent and 23 percent. In sum, the finding presented in Table 5 suggest that among young Korean female graduates, the proportion of over-educated workers is non-negligible, although the magnitude is similar to lower than that reported in the developed countries such as U.S. and U.K.

<Insert Table 5 here>

When over-educated graduates are disaggregated depending on perceived skills mismatch, previous results based on conventional measure of educational mismatch are clearly overestimated. It turns out that around a third are in a situation of real over-educated (approximately 7 percent), most of this group being then apparently overeducated (approximately 11 percent) among the whole group of overeducated workers. Besides, the extent of real over-educated has remained stable since 2010,

indicating that there is no significant change in the prevalence of real over-education between 2010 and 2012. The low proportion of real over-educated workers (approximately 6%) is in line with the fact that there is a shortage of skilled/qualified labor in Korea. Interestingly, these proportions of real over-educated graduates are comparable to those of other developed countries such as found U.K. (Chevalier, 2003; Green and Zhu, 2010) and Australia (Mavromaras et al., 2013).

In order to achieve the second goal, I examine the dynamic relationship between over-education and job turnover. In the second interview in 2012, respondents are asked directly to answer the following question: Do you still have the same job since the first interview? The job turnover is then defined as changing employers between two interviews in the analysis. Using cross-sectional data, I estimate a Probit model for each measure of educational mismatch. The Probit regressions results are presented in Table 6, where the dependent variable is a binary indicator of job mobility takes value 1 in case of a job change occurring since graduation, 0 otherwise (i.e., job turnover).[2] The first (resp. second) column of Table 6 presents estimates from the conventional (resp. alternative) measure of graduate mismatch.

<Insert Table 6 here>

According to the conventional measure, the estimation results indicate that self-assessed over-education only (i.e., over-educated) is positively associated with the probability of a subsequent job change. When over-education is combined with perceived skills mismatch (i.e., an alternative measure), the coefficients on each type of mismatch are significantly positive in the Probit model. Importantly, the association between real over-education and job turnover (i.e., real over-educated) is being the largest in magnitude, suggesting that the probability of job turnover is the highest among graduates who are mismatched in both education and skills (i.e., real over-education) at the start of their career. Specifically, workers who report as real over-educated in 2012 are approximately 45 percent points more likely to switch employers.

[2] It should be noted that this study does not able to separate voluntary from involuntary job change, because the 2009 GOMS data did not ask about the reason for leaving his or her job.

V. Summary and Conclusion

Does educational mismatch affect job mobility at all? If so, what type of mismatch is particularly concerned? In order to answer these questions, this paper examines the incidence and the impact of educational mismatch on job mobility using the Graduates Occupational Mobility Survey (GOMS) data covering Korean female graduates making their transition from university to labor market.

The earlier literature on graduate mismatch was constrained by the unavailability of data on skill mismatch, particularly for over-skilling. Since the GOMS data used here includes questions on both educational and skill mismatches, this paper considers a more detailed definition of educational mismatch than continued in the earlier literature with a mismatched worker being analyzed according to whether he or she is either over-educated. The presence of a question on skill mismatch enables this study to consider an improved measure of over-education that accounts for graduate heterogeneity in perceived skills mismatch.

Conventional measures of over-education in most previous studies exclusively refer to the concept of excess schooling, in the more general case where workers can be both over- and under-qualified for their jobs (vertical qualification-job mismatch) or have different qualifications (horizontal qualification-job mismatch), and as skill gap to refer to employed workers whose education/skills acquired are lower than those required by their jobs. In the analysis, I following Green and Zhu (2010) consider four types of matching status: ‘formal matched’ (i.e., matched in education, but over-skilled); ‘real matched’ (i.e., matched in both education and skills); ‘formal over-educated’ (over-educated, but matched in skills); ‘real over-educated’ (i.e., over-educated and over-skilled). Given that real over-educated graduates cannot use most of their skills acquired in the workplace compared to their formal over-educated counterparts (i.e., skill under-utilization), this distinction is particularly important when estimating the effects over-education on job mobility. It may suggest that real over-educated individuals are more likely to change their current jobs than their formal over-educated counterparts.

Whatever which measure of mismatch is applied, the results presented in this paper give support to previous studies: over-education is associated with a significant impact on job mobility. This positive correlation remains the same even if I estimate an augmented specification where graduate

over-education is disaggregated according to perceived skills mismatch. High job turnover is clearly related to over-education jointly either with matched in skills (i.e., formal over-educated) or over-skilling (i.e., real over-educated). However, in line with Chevalier (2003), Green and Zhu (2010) and Mavromaras et al. (2013), there is a clear message that the real over-educated workers are more likely to switch their employers than their formal over-educated counterparts. The formal over-education has a relatively little correlation with job turnover.

The findings of the present paper suggest that job-worker mismatch between workers' level of education/skills acquired and job requirement has an adverse effect on the labor market efficiency, raising employee turnover. Economists generally believe that labor markets adjust to job-worker mismatch, especially over time. But it is also possible that such mismatches can persist for many years or decades. Under such circumstances, adverse equilibria characterized by higher level of structural unemployment, long-term unfilled vacancies may arise. For employers the cost of employee turnover is also high. Due to the productivity losses when someone leaves a job, it is costly to replace workers, the costs of hiring and training a new employee, and the slower productivity until the new employee is fully to speed in the workplace. Labor market policies that change or improve job-employee matching processes can help reduce turnover costs in such cases because the efficient job-worker matching process will determine how efficiently workers find new jobs. Thus, the efficiency with which human resources are developed in the education system and used on the labor market must become a priority concern for policy makers.

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Table 1: Number of Female Students in Higher Education Institutes

Classification	Higher Education Graduates	Universities	University of Education	Industrial University	Graduate school	Junior College	Other
2013	1,574,495	835,703	11,828	20,320	158,952	303,169	244,523
2012	1,574,076	821,875	12,751	26,319	159,032	307,350	246,749
2011	1,571,909	802,075	13,765	34,430	158,523	310,247	252,869
2010	1,524,603	778,186	14,712	36,565	152,367	304,846	237,927
2009	1,483,536	749,329	15,335	38,258	146,090	301,395	233,129
2008	1,455,962	727,178	16,244	40,785	141,672	305,701	224,382
2007	1,436,730	712,735	17,658	41,962	137,118	308,453	218,804
2005	1,399,931	684,238	17,856	46,382	124,930	316,326	210,199
2000	1,286,762	596,389	15,032	38,232	80,072	339,233	217,804

Sources: KEDI, Korean MOE, Korean National Statistical Office.

Table 2: Summary Mean Statistics

Variables	**2010**	**2012**
Panel A: Dependent Variable:		
TURNOVER	-	0.025 (0.002)
Panel B: Educational Mismatch Variable:		
OVER_EDU	0.186 (0.005)	0.135 (0.005)
MATCH_EDU	0.713 (0.006)	0.767 (0.006)
formal_MATCH	0.051 (0.006)	0.694 (0.002)
real_MATCH	0.652 (0.002)	0.046 (0.002)
formal_OE	0.114 (0.005)	0.072 (0.005)
real_OE	0.065 (0.003)	0.055 (0.005)
Panel *C*: Individual Demographic Variables:		
AGE	25.156 (0.071)	28.181 (0.078)
AGESQ	7.131 (0.094)	8.246 (0.059)
UNIVERSITY	0.612 (0.006)	0.642 (0.007)
MARRIED1	0.094 (0.004)	0.171 (0.005)
MARRIED2	0.005 (0.001)	0.007 (0.001)
CAPITAL	0.512 (0.107)	0.538 (0.007)
Panel D: Employment Characteristics Variables:		
FULL	0.401 (0.007)	0.437 (0.007)
UNION	0.053 (0.003)	0.077 (0.004)
PUBLIC	0.084 (0.004)	0.083 (0.004)
MIDDLE	0.342 (0.006)	0.307 (0.007)
LARGE	0.171 (0.005)	0.351 (0.007)
Sample Size (Observations)	5760	4966

Notes: Standard errors in parentheses**.**

Table 3: Identification of Skill Mismatch

Categories		Educational Mismatch	
		(1) or (2) = Over	(3) = Match
Skill Mismatch	(1) or (2) = Over	**Real Over-Educated**	Formal Matched
	(3) Match	Formal Over-Educated	**Real Matched**

Note: Over denotes the over-skilled/educated and Match denotes the adequately matched respectively.

Table 4: Definition of Variables

Variables	Definitions
Panel *A*: Dependent Variable:	
TRUNOVER	Dummy variable: 1 if, in 2012, a person worked for an employer different from that in 2009, 0 if the person worked for the same employer.
Panel *B*: Educational Mismatch Variables:	
OVER_EDU	Dummy variable: 1 if an individual is matched in education, but over-skilled, 0 otherwise.
MATCH_EDU	
formal_MATCH	Dummy variable: 1 if an individual is matched in education, but over-skilled, 0 otherwise.
real_MATCH	Dummy variable: 1 if an individual is matched both in education and skills, 0 otherwise. <Reference group>
formal_OE	Dummy variable: 1 if an individual is over-educated, but matched in skills, 0 otherwise.
real_OE	Dummy variable; 1 , if an individual is over-educated and over-skilled, 0 otherwise
Panel *C*: Individual Demographic Variables:	
AGE	Workers age (years)
AGESQ	The square of *AGE*/100
COLLEGE	Dummy variables: 1 if 2-to-3-year college degree, 0 otherwise. <Reference group>
UNIVERSITY	Dummy variable: 1if 4-year college degree, 0 otherwise
SINGLE	Dummy variable: 1 if the worker is single, 0 otherwise. <Reference group>
MARRIED1	Dummy variable: 1 if the worker is married with spouse, 0 otherwise.
MARRIED2	Dummy variable: 1 if the worker is married without spouse, 0 otherwise.
CAPITAL	Dummy variable: 1if the worker lives in Seoul and Gyeonggi-do, 0 otherwise.
Panel *D*: Employment Characteristics Variables:	
FULL	Dummy variable: 1 if full-time employment, 0 otherwise..
UNION	Dummy variable: 1 if member of labor unions, 0 otherwise.
PUBLIC	Dummy variable: 1 if employed in the public sector, 0 otherwise.
SMALL	Dummy variable: 1 if firm has less than 30 employees, 0 otherwise. <Reference group>
MIDDLE	Dummy variable: 1 if firm has 30 to 299 employees, 0 otherwise.
LARGE	Dummy variable: 1 if firm has more than 300 employees, 0 otherwise.

Table 5: The Incidence of Change of Educational Mismatch

Year Sample	2010	2012
Panel A: conventional measure:		
Over-Educated	0.186	0.135
Adequately Educated	0.713	0.767
Panel B: Alternative measure:		
(1) Real Over-Educated	0.065	0.055
(2) Formal Over-Educated	0.114	0.072
(3) Real Matched	0.652	0.694
(3) Formal Matched	0.051	0.046
Sample Size	5,760	4,966

Source: 2009 GOMS, data is unweighted.

Table 6: The Effects of Over-Education on Job Mobility

Variables	**Conventional Measure**		**Alternative Measure**	
Panel A: Skill Mismatch related Variables:				
OE	0.235	(0.049)***	-	-
formal_MATCH	-	-	0.189	(0.083)**
formal_OE	-	-	0.235	(0.125)*
real_OE	-	-	0.450	(0.216)**
Panel B: Individual Demographic Variables:				
AGE	-0.097	(0.029)***	-0.095	(0.029)***
AGESQ	0.107	(0.039)***	0.104	(0.039)***
UNIVERSITY	-0.099	(0.042)**	-0.098	(0.042)**
MARRIED1	0.228	(0.050)***	-0.265	(0.059)***
MARRIED2	0.160	(0.230)	0.155	(0.230)
CAPITAL	0.075	(0.037)**	0.073	(0.037)**
Panel C: Employment Characteristics Variables:				
FULL	-0.541	(0.087)***	-0.538	(0.087)***
UNION	-0.577	(0.073)***	0.575	(0.073)***
PUBLIC	0.042	(0.067)	0.042	(0.067)
MIDDLE	-0.172	(0.046)***	-0.173	(0.046)***
LARGE	-0.219	(0.046)***	-0.223	(0.046)***
Constant	2.592	(0.510)***	2.554	(0.510)***
Sample Size	5,760		4,966	
Log-Likelihood	-3,304		-3,302	
Pseudo R-square	0.0450		0.0456	

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