Impact of education-job mismatches on wage:The case of university graduates in Cambodia

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Abstract

This article analyzes the wage impacts of educational mismatches among university graduates in Cambodia by considering the both forms of mismatches (vertical and horizontal forms) and the possibility of their combination (double mismatch). This research uses two-stage least square regression to deal with the endogenous problem of education-job mismatches, while sample selection bias owing to non-employed graduates was also considered. Results prove that wage penalties exist with the strongest impacts for the case of double mismatch, following by overeducation and horizontal mismatch. The findings underline the importance of improvement in the quality of higher education in Cambodia. At the same time, creating the occupational counseling for students to consult would be also helpful to orientate students to the majors strongly needed by the labor market.

Keywords: higher education, overeducation, horizontal mismatch, double mismatch, wage differentials, two-stage least square regression, endogeneity and sample selection bias.
JEL Codes: I23, I26, J24, J31.

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1 Introduction

The average level of education has risen successively and considerably worldwide during the past several decades (Barro & Lee, 2001 ; OECD, 2014). This increase in educational levels has positively contributed to individual earnings and economic growth as predicted by the human capital theory (Becker, 1964) and endogenous growth theory (Lucas, 1988), yet vertical education-job mismatch or overeducation also has emerged as a serious concern, particularly in developed countries. Overeducation refers to an excess of education, beyond the level needed to perform a certain job (Rumberger, 1981 ; Hartog, 2000). Besides overeducation, horizontal mismatch also exists when people's occupations do not match their fields of education (Robst, 2007). The existence of these mismatches raise questions on the positive effects of education on individual outcomes in the labor market.

From the theoretical point of view, there exists a consensus on the negative impact of mismatches on wages. First, workers may prefer a mismatched job to their qualification with lower wages offered, in compensation for other job attributes such as career promotion and perspectives (Sicherman & Galor, 1990) or less job pressures and stress for which they may have stronger preferences (McGuinness & Sloane, 2011). Second, workers accept a mismatched job because they do not have other choices as the job opportunities are limited given an excessive supply of high educated persons, but working in this unfit job would not allow them to exploit their potential skills, and consequently they would be less productive and earn less than if they were employed in a matched occupation (Thurow, 1976 ; Sattinger, 1993).

Yet, several limits exist in the empirical studies. First, there is no consensus even though most research finds a wage penalty as a consequence of working in a mismatched job (see literature reviews of Leuven et al., 2011 and McGuinness et al., 2017). Second, most of researches assume that mismatches are exogenous (Tsai, 2010), while they are more likely endogenous (Dolton & Vignoles, 2000) and the endogeneity of mismatches in the combination of their two forms (the case of a double mismatch[1]) was not generally considered in the literature. Third, less researches take into account the effects of unemployment when analyzing the impacts of mismatches on wages (Ordine & Rose, 2015), while the scarring effects from staying unemployed for a long time before finding a job may affect wages, and unemployment itself may also constitute another form of mismatches in case some workers prefer to be unemployed than to work in a mismatched job, thus, a selection bias problem may exist. Fourth, little researches analyze developing countries. For instance, Quinn & Rubb (2006), Filiztekin (2011) and Reis (2017) find that the returns for overeducation are about a half of required education in Mexico, Turkey

[1] A double mismatch refers to the combination of vertical and horizontal mismatches

and Brazil, respectively. Pholphirul (2017) focuses on both forms of mismatches and finds the negative impacts of horizontal mismatches on workers' incomes in Thailand (-7.2%) but with a weaker effect than vertical mismatches (-18.6%).[2]

None of research in developing countries focus on a low income country though. For example, Cambodia, a country in Southeast-Asia, has known a remarkable rise in the enrollment rate in higher education but with an increasing concerns on unemployment and education-job mismatches (ADB and ILO, 2015). For instance, the enrollment rate in higher education has increased from just 2.5% in 2000 to 15.9% in 2011 (World Bank's website[3]) with the number of students rises from 20,000 in 2001 to 250,000 in 2014 (Un, 2015). Nevertheless, the unemployment rate of graduates is much higher, 7.7% in 2012, than people with only secondary education, 2.7% (NIS, 2012). Given that Cambodia tries to promote the higher education sector to boost its economic development, the negative impacts associated with educational mismatches may discourage people from investing in higher education, which likely will constraint the future economic growth and hinder its ambitions to upgrade to more technology-based industrial structures.

The objective of this article is accordingly to investigate if educational mismatches generate a wage penalty for Cambodian university graduates. This research contributes to the prior literature on three main points. First, it analyzes another case of developing country, namely Cambodia, while the existing studies focus on relatively more advanced economies. Second, it analyzes the combination effects of vertical and horizontal mismatches that previous researches in developing countries have not done yet. Third, we take into account the selection bias problem and also the endogeneity of education-job mismatches by firstly estimating the propensity to work for each individual before incorporating this probability into the two-stage least square regression that treats the endogenous problem of mismatches. This regression model is applied on a survey data financed by the French-speaking University Agency, known as AUF, and conducted by the French cooperation at the Royal University of Law and Economics among nineteen higher education institutions in Cambodia in 2011.

[2]Pholphirul (2017) did not, however, consider the possible combination of these two mismatches.
[3]Data link: `https://data.worldbank.org/indicator/SE.TER.ENRR?locations=KH`

2 Data

The French cooperation at the Royal University of Law and Economics in Cambodia conducted the survey that informs this research by phone in 2011, among Cambodian graduates who had received their bachelor's degrees in 2008. The 4,025 observations are randomly selected and representative of nineteen higher education institutions in Phnom Penh, capital of Cambodia. The current study excludes self-employed people from the initial data set, because there are no detailed information available to evaluate the required schooling for their jobs, and thus impossible to define their education-job match status.[4] Observations that offered no information on occupation, earnings and other key variables were also dropped. The final sample thus contains 1,957 university graduates, who are representative of the study population,[5] in which 92 graduates were unemployed at the moment of interview.

To measure the incidence of mismatches, we employ the job analysis (JA) that is known as an objective measure. Based on the JA measure, each occupation classified by the International Standard Classification of Occupations Code (1-digit) is assigned to the required level of education mentioned in the International Standard Classification of Education (ISCED). For example, graduates working in the positions classified as managers, professionals, and technicians/associate professionals, are considered as matched workers because these positions require tertiary education. Other occupational levels such as clerical support workers and elementary occupations do not require higher education. Consequently, graduates in these occupations will be considered as overeducated.[6]

The data also include information about the specialty of each bachelor's degree acquired from the different universities, which supports an objective determination of the presence of a horizontal mismatch. By reviewing the study program and job prospect of each specialty offered by each university, the author compares these descriptions with each individual occupation to discern if each graduate's job corresponds with his or her field of study.[7]

Our results indicate that 32.2% and 33.3% of graduates are overeducated and horizontally mismatched, respectively. We also find that 16.9% of graduates suffer a double mismatch. The incidence of educational mismatches for each category of mismatch is provided in the figure 1.

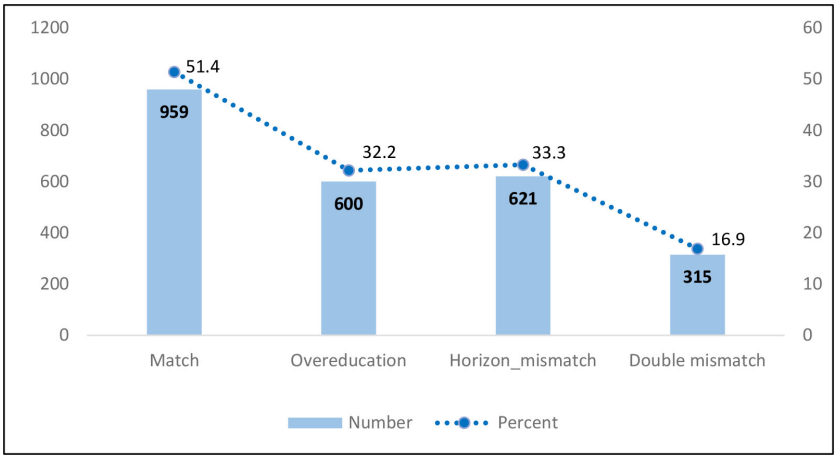
[4] In Cambodian language, when people say they are self-employed, it can refer to owning a small grocery shop in the informal sector or a formal complex business. Without detailed information on their business size and activities, the author cannot define if their jobs match their educational level and fields or not (234 graduates declared they were self-employed).

[5] By comparing the means and standard deviations of all variables used in our analysis before and after the eliminations of those observations, we do not remark any important gaps to consider.

[6] Tables that specify the process of matching the occupational class to the educational level required, are in the Appendix: A.

[7] The matching table can be found in the Appendix: B.

Figure 1: Number and percent of graduates
by category of education-job mismatch



Based on the figure 1, we observe that only a half of graduates work in a matched job to their education, while the rest faces at least one type of educational mismatch. Thus, education-job mismatch could be a problem to carefully consider. Additionally, the incidence of horizontal mismatch is comparable to the vertical form, hence, the literature that focuses solely on overeducation may neglect another important source of mismatches. More importantly, 16.9% of graduates suffer both types of mismatches that can be a serious problem we should not ignore.

To estimate the impacts of education-job mismatches on wages, several variables related to individual attributes (birthplace, gender, marital status, age, family head), education background (fields of study, type of university, double training), professional background (internship, job experiences, previous unemployment duration), individual ability (study scholarship status), job search channel (informal network, online application) and firm characteristics (sector, work contract, firm size) are needed to be controlled because those variables may affect both wages and probability of accepting a mismatched job in the previous literature (see literature reviews of McGuinness, 2006; Sala et al., 2011; Leuven et al., 2011; Quintini, 2011; McGuinness & Pouliakas, 2017).

The survey questionnaire also provides information regarding the workers' preferences on several job attributes such as job autonomy, job stability, opportunities to learn new things, job challenge, career perspective, high salary, good social status, possibility to do something useful for the society, possibility to reconcile working and family time, and job leisure. Given that some workers may accept a mismatched job and are paid less in compensation for some of these job attributes for which they have stronger preferences (McGuinness & Sloane, 2011), being able to control the workers' preferences on these job attributes could make our estimation more robust than the majority of previous researches.

3 Descriptive statistics

Table 1 contains the descriptive statistics for all variables included in the analysis in relation to wages and education-job mismatches. For continuous variables (age at the end of study, monthly work experience and unemployment duration), observed mean wages are evaluated for the two last quartiles of each variable.

Table 1: Descriptive statistics

				Category of Mismatch:			
	TOTAL			Match	Verti. Mismatch	Horiz. Mismatch	Double Mismatch
VARIABLES	Mean	Std. dev.	Observed mean wage	Mean	Mean	Mean	Mean
Dependent variable							
Wages (log)	5.34	0.64		5.33	5.39	5.26	5.29
Individual attributes							
Male	0.64	0.48	5.36	0.58	0.25	0.32	0.14
Age at the end of study	22.08	4.08	5.26	22.46	21.53	22.03	21.94
Married	0.29	0.45	5.33	0.56	0.28	0.33	0.17
Being born in Phnom Penh	0.46	0.50	5.33	0.50	0.33	0.34	0.17
Family head	0.52	0.50	5.28	0.49	0.33	0.33	0.16
Educational background							
Law-Eco-Management	0.46	0.50	5.41	0.41	0.47	0.32	0.21
Social Science English	0.14	0.35	5.48	0.54	0.27	0.34	0.14
Engineering	0.07	0.26	5.94	0.81	0.06	0.18	0.05
Public university	0.42	0.49	5.35	0.53	0.32	0.30	0.15
Double training	0.63	0.48	5.38	0.50	0.34	0.32	0.17
Study scholarship	0.10	0.30	5.18	0.56	0.27	0.31	0.14
Internship during study	0.51	0.50	5.42	0.53	0.32	0.32	0.17
Professional background							
Monthly work experiences	26.2	8.41	5.36	0.50	0.32	0.34	0.16
Monthly unemployment	2.09	5.48	5.40	0.50	0.33	0.32	0.14
Job search channel							
Informal job network	0.32	0.47	5.35	0.50	0.35	0.34	0.18
Online application	0.16	0.37	5.53	0.44	0.41	0.35	0.20
Observations		1957		959	600	621	315

Table 1: Descriptive statistics-continued

				Category of Mismatch:			
	TOTAL			Match	Verti. Mismatch	Horiz. Mismatch	Double Mismatch
VARIABLES	Mean	Std. dev.	Observed mean wage	Mean	Mean	Mean	Mean
Dependent variable							
Wages (log)	5.34	0.64		5.33	5.39	5.26	5.29
Firm characteristics							
Public sector	0.26	0.44	4.68	0.65	0.18	0.30	0.12
Private sector	0.58	0.49	5.57	0.46	0.39	0.35	0.20
Fixed-terms contract	0.25	0.43	5.63	0.48	0.33	0.36	0.16
Permanent contract	0.33	0.47	5.46	0.49	0.37	0.33	0.19
Work in a small firm	0.35	0.48	5.39	0.51	0.33	0.34	0.18
Work in a medium firm	0.15	0.36	5.36	0.56	0.31	0.30	0.17
Preferences for job attributes							
Job autonomy	0.77	0.42	5.31	0.53	0.31	0.32	0.16
Job stability	0.56	0.50	5.23	0.54	0.28	0.32	0.15
Chance to learn new things	0.85	0.36	5.34	0.51	0.33	0.32	0.16
Job challenge	0.71	0.45	5.30	0.52	0.31	0.33	0.16
Career perspective	0.79	0.49	5.33	0.51	0.32	0.33	0.17
High salary	0.80	0.40	5.35	0.51	0.33	0.32	0.17
Good social status	0.82	0.38	5.32	0.52	0.31	0.33	0.16
Doing useful things for society	0.88	0.33	5.32	0.52	0.31	0.33	0.16
Having time for family	0.78	0.41	5.30	0.53	0.31	0.33	0.17
Job leisure	0.74	0.44	5.29	0.54	0.30	0.32	0.16
Observations		1957		959	600	621	315

Based on the descriptive statistics, we observe that several variables may affect both mismatches and wages. Nevertheless, we cannot rely on these statistics to conclude any relations between these variables. An econometric estimation is needed.

4 Method

The descriptive statistics have shown that many variables can affect both wages and risks of educational mismatches. Thus, to identify the impacts of mismatches on wages, we need to control the endogeneity of education-job mismatches process.

The two-stage least square regression (2SLS) offers the following estimation:
First, we regress the endogenous variable, $mismatches_i$ (overeducation or horizontal mismatch or double mismatch), on a set of exogenous variables x_i (individual attributes, educational and professional backgrounds, individual ability, job search channel, firm characteristics and graduates' preferences on different job attributes, described in the Table 1) and instrumental variables m_i:

$$mismatches_i = \gamma_1^{'} x_i + \gamma_2^{'} m_i + e_i \tag{1}$$

Second, we calculate the predicted values $\widehat{mismatches_i}$ from the equation (1) and substitute them in the main equation model:

$$log\_wage_i = \alpha^{'} x_i + \beta^{'} \widehat{mismatches_i} + u_i \tag{2}$$

Nevertheless, to employ this regression model, we need an instrumental variable that has to fill two conditions: 1- instrument relevance and 2- instrument exogeneity (Wooldridge, 2012, p.514). The relevance of instrument implies that it must be correlated with the endogenous variable. The exogeneity assumption requires that the instrument must be exogenous (uncorrelated with the error term) and not a direct cause of the dependent variable.

There exist evidences that the education of parents can influence the risks of mismatches among graduates (e.g., Hansen & Mastekaasa, 2006, Torche, 2011, Capsada-Munsech, 2015). Their arguments are that educated parents are likely better informed and share more knowledge with their children since their early age. However, there is no evidence that the parents' education can directly affect the graduates' wages. Thus, we use the level of parents' education as the instrumental variable in the regression model. To test the quality of this instrument, we use the Cragg-Donald Wald test and the results show that our instrumental variable is not weak.[8]

Besides the endogenous problem of mismatches, we may also confront another issue called the selection bias problem. Indeed, it is possible that some high skilled graduates prefer to stay unemployed than to work if the wage offered is not high enough to exceed their reservation wages

[8]We will report the test result in the Table 4 below.

(Jovanovic, 1979). However, it is also possible that some graduates who fail to find a decent job, prefer to stay unemployed than to be mismatched (McCormick, 1990). Thus, ignoring the non-employed graduates from the analysis can lead to a sample selection bias (Nicaise, 2001). Consequently, considering the unemployed graduates' characteristics seems to be also crucial (Caroleo & Pastore, 2018).

To take into account this selection bias problem, first, we regress with a probit model the graduate's employment status (employed or unemployed) on a set of exogenous variables x_i such as individual attributes, educational background and individual preferences on some job attributes that may affect the individual decision to work or not, with the following equation:

$$work_i = \alpha^{'} x_i + a_i \tag{3}$$

Next, we predict the likelihood that a graduate is employed conditional on those observable characteristics x_i. Then, we incorporate this probability into the equations (1) and (2) above. This will help to isolate the effects of selection bias on the risks of education-job mismatches and on wages.

The regression results are reported in the Tables below.

4.1 Results

Table 2 presents the factors that affect the probability that a graduate is employed from the equation (3) above.

Table 2: Factors affecting the likelihood of being employed

VARIABLES	Coefficient	Robust standard errors
Individual attributes		
Male	0.079	0.109
Age at the end of study	0.029	0.019
Married	0.256*	0.148
Birthplace	0.069	0.103
Family head	0.250**	0.100
Educational background		
Law-Economics-Management	-0.257**	0.122
Social sciences in English	0.584**	0.284
Engineering	-0.207	0.222
Public university	0.169	0.121
Double training	0.084	0.117
Internship	0.173	0.106
Study scholarship	0.285	0.233
Individual preferences for		
High salary	-0.226	0.156
Having time for family	-0.021	0.127
Observations		1957

*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

According to the Table 2, married people and family head are more likely to work than to stay unemployed because of their family's charge perhaps. Graduates in Law-Economics-Management are less likely to be employed due to the excessive supply of graduates in this field (Madhur, 2014), while graduates in English have more chances. We expect that graduates with strong preferences for high wages and reconciliation the working and family time may have higher reservation wages, and consequently, they are more likely to be unemployed (Jovanovic, 1979), but despite the negative coefficients as predicted, we do not find statistical significant effects.[9] Next, we predict the probability that a graduate is employed conditional on those observable characteristics, and then, we control this probability in the Model 2 of the Table 3 to correct the possible sample selection bias owing to the sample of non-employed graduates.

[9]We do not control for graduates' preferences on other job attributes because we have no theoretical supports that they can affect the probability of being employed, but only the type of jobs that graduates may choose.

Table 3 shows the impacts of education-job mismatches on wages by treating the endogenous problem of mismatches in the Model I and plus the possible sample selection bias in the Model II. In each model, we estimate the impacts of mismatches separately for overeducation (1), horizontal mismatch (2) and double mismatch (3). For the presentation convenience, only significant variables in at least one model are reported in the Table 3, while the list of all control variables can be found in the Table 1 above.

Table 3: Impact of education-job mismatches on individual wages

VARIABLES	**Model I(1)**	**Model I(2)**	**Model I(3)**	**Model II(1)**	**Model II(2)**	**Model II(3)**
Probability to work				-1.541	-0.337	-2.491*
				(1.241)	(1.158)	(1.465)
Category of mismatches						
Overeducation	-1.044**			-1.032**		
	(0.454)			(0.449)		
Horiz. Mismatch		-0.976**			-0.973**	
		(0.406)			(0.407)	
Double Mismatch			-1.277**			-1.255**
			(0.546)			(0.534)
Individual attributes						
Age at the end of study	0.004	0.003	0.006	0.007	0.004	0.011**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Married	0.087**	0.102***	0.131***	0.118***	0.109**	0.181***
	(0.039)	(0.034)	(0.035)	(0.043)	(0.042)	(0.046)
Family head	-0.030	-0.043	-0.075*	0.003	-0.035	-0.019
	(0.032)	(0.032)	(0.039)	(0.041)	(0.041)	(0.041)
Educational background						
Law-Eco-Management	0.228**	-0.066	0.050	0.186***	-0.074	-0.014
	(0.089)	(0.059)	(0.037)	(0.085)	(0.063)	(0.050)
Social Science English	0.175***	0.117**	0.127**	0.214***	0.126*	0.191***
	(0.052)	(0.054)	(0.054)	(0.061)	(0.064)	(0.060)
Engineering	0.311**	0.317***	0.343***	0.286**	0.311***	0.303**
	(0.123)	(0.119)	(0.110)	(0.129)	(0.118)	(0.122)
Public university	0.141***	0.031	0.065*	0.160***	0.035	0.098**
	(0.042)	(0.037)	(0.033)	(0.048)	(0.042)	(0.037)

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Notes: Robust standard errors are in brackets.

Table 3: Impact of education-job mismatches on individual wages (continued)

VARIABLES	**Model I(1)**	**Model I(2)**	**Model I(3)**	**Model II(1)**	**Model II(2)**	**Model II(3)**
Professional background						
Monthly work experiences	0.001	0.004*	0.002	0.001	0.004*	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Monthly unemployment	-0.018***	-0.012**	-0.016***	-0.018***	-0.012**	-0.016***
	(0.006)	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)
Firm characteristics						
Public sector	-0.898***	-0.893***	-0.825***	-0.901***	-0.893***	-0.830***
	(0.070)	(0.068)	(0.063)	(0.070)	(0.068)	(0.062)
Fixed-terms contract	0.273***	0.299***	0.279***	0.271***	0.298***	0.275***
	(0.045)	(0.042)	(0.044)	(0.044)	(0.042)	(0.043)
Permanent contract	0.190***	0.166***	0.196***	0.191***	0.166***	0.197***
	(0.037)	(0.035)	(0.037)	(0.037)	(0.035)	(0.037)
Preferences for job attributes						
Job stability	-0.202***	-0.139***	-0.171***	-0.196***	-0.138***	-0.163***
	(0.049)	(0.034)	(0.040)	(0.048)	(0.034)	(0.039)
Chance to learn new things	0.224***	0.095*	0.138**	0.222***	0.095*	0.137**
	(0.072)	(0.054)	(0.055)	(0.072)	(0.053)	(0.055)
High salary	0.106**	0.014	0.055	0.079	0.008	0.011
	(0.052)	(0.044)	(0.045)	(0.053)	(0.048)	(0.050)
Endogenous variables: $Mismatch_i$						
Probability to work				-0.884	0.298	-1.484**
				(0.835)	(0.881)	(0.751)
Individual attributes						
Male	-0.153***	-0.039	-0.063***	-0.145***	-0.041*	-0.050**
	(0.022)	(0.023)	(0.019)	(0.023)	(0.025)	(0.020)
Family head	-0.008	-0.021	-0.042**	0.011	-0.028	-0.009
	(0.022)	(0.023)	(0.018)	(0.028)	(0.030)	(0.024)
Educational background						
Law-Eco-Management	0.176***	-0.113***	0.004	0.153***	-0.105***	-0.034
	(0.034)	(0.029)	(0.023)	(0.034)	(0.037)	(0.029)
Engineering	-0.227***	-0.237***	-0.160***	-0.242***	-0.231***	-0.186**
	(0.037)	(0.045)	(0.031)	(0.039)	(0.048)	(0.034)
Public university	0.062***	-0.045*	-0.008	0.073***	-0.049*	0.010
	(0.023)	(0.025)	(0.020)	(0.026)	(0.027)	(0.022)
Double training	-0.026	-0.060**	-0.040*	-0.016	-0.063**	-0.024
	(0.024)	(0.026)	(0.021)	(0.026)	(0.028)	(0.022)

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Notes: Robust standard errors are in brackets.

Table 3: Impact of education-job mismatches on individual wages (continued)

VARIABLES	**Model I(1)**	**Model I(2)**	**Model I(3)**	**Model II(1)**	**Model II(2)**	**Model II(3)**
Job search channel						
Informal network	0.043*	0.005	0.023	0.044*	0.005	0.024
	(0.023)	(0.025)	(0.020)	(0.023)	(0.025)	(0.020)
Professional background						
Monthly work experiences	-0.001	0.002*	0.001	-0.001	0.002*	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Firm characteristics						
Private sector	0.070**	0.009	0.064**	0.068*	0.010	0.060**
	(0.035)	(0.036)	(0.026)	(0.035)	(0.036)	(0.026)
Work in a medium firm	0.010	-0.070**	0.001	0.008	-0.070**	-0.002
	(0.028)	(0.031)	(0.025)	(0.029)	(0.031)	(0.025)
Preferences for job attributes						
Job autonomy	-0.001	-0.056*	-0.016	-0.001	-0.056*	-0.018
	(0.030)	(0.032)	(0.025)	(0.030)	(0.032)	(0.025)
Job stability	-0.074***	-0.014	-0.036*	-0.071***	-0.015	-0.032
	(0.025)	(0.025)	(0.020)	(0.025)	(0.026)	(0.020)
Chance to learn new things	0.114***	-0.009	0.020	0.114***	-0.009	0.026
	(0.039)	(0.042)	(0.034)	(0.039)	(0.042)	(0.034)
High salary	0.061*	-0.029	0.009	0.045	-0.024	-0.016
	(0.032)	(0.034)	(0.027)	(0.035)	(0.037)	(0.030)
Having time for family	0.108***	0.025	0.069**	0.104***	0.026	0.062*
	(0.037)	(0.042)	(0.033)	(0.037)	(0.042)	(0.033)
Job leisure	-0.077**	-0.042	-0.030	-0.078**	-0.042	-0.032
	(0.035)	(0.040)	(0.033)	(0.035)	(0.040)	(0.033)
Instrumental variable						
High educated parents	-0.070***	-0.075***	-0.057***	-0.071***	-0.075***	-0.058***
	(0.021)	(0.023)	0.017)	(0.021)	(0.023)	(0.017)
Test for the quality of instrument						
(H_0: The Instrument is weak)						
Wald F-statistic	10.419***	10.480***	10.559***	10.556***	10.429***	10.870***
Test for endogeneity of mismatches						
(H_0: $Mismatch_i$ is exogenous)						
Robust score chi2	9.834***	8.088***	8.828***	9.727***	8.007***	8.699***
Observation	1865	1865	1865	1865	1865	1865

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Notes: Robust standard errors are in brackets.

Based on the Table 3 above, we observe that our mismatch indicator is really endogenous as the robust score chi2 is highly significant at 1% level, rejecting the null hypothesis that mismatch is exogenous. Regarding the quality of instrument, the Wald F-statistic also indicates a significant value higher than 10 conforming to what proposed by Staiger & Stock (1994) and Stock et al. (2002) as enough to reject the null hypothesis that our instrument is weak.

Several variables are found to affect both the probability of being mismatched and wages. First, we observe that female tend be more mismatched than male in almost all models (McGoldrick & Robst, 1996). Graduates with economics-management degree tend to be more overeducated but less horizontal mismatched. There exists an oversupply of graduates in this discipline that exceeds the demand around 2.5 times between 2009 and 2014, but as it is a more generalize discipline, graduates in this field may fit to various fields of studies (D'Amico, 2010). In contrast, graduates in engineering are less mismatched than non-engineering graduates. This is in line with some previous research (e.g., Dolton & Vignoles, 2000 ; Morano, 2014), more scientific (e.g., engineering) and specific (e.g., medicine, architecture) disciplines are less likely to suffer the risk of mismatches. Using the informal job network increases the risk of overeducation. Meliciani & Radicchia (2014) argue that using the family/friends network limits the extent of job search, thus reducing spatial flexibility to find a suitable job. Graduates' preferences for different job attributes are also found to affect the risks of mismatches. We observe that graduates who prefer to a chance to learn new things are more likely overeducated as predicted by the career mobility theory that accepting an overeducated position might be necessary to acquire specific skills related to the job. Then, graduates who need to reconcile the family tasks and working time are more likely to suffer a double mismatch. Perhaps their family tasks constraint them to limit the areas of their job search, making them more difficult to find a matched job. Finally, our instrumental variable, the level of education of parents does influence the probability of mismatch, with higher educated parents, lower risks of mismatches. As Hansen & Mastekaasa (2006), Torche (2011), and Capsada-Munsech (2015) suggest, graduated parents likely are better informed and share more knowledge with their children.

Regarding the impacts on wages, educational background emerges as a good indicator to explain the gap in wages. Graduates in engineering and social sciences in English tend to enjoy higher wages owing to a high demand for these graduates in the Cambodian labor market. Firm characteristics also influence wages, such as working in public sector earns less, while people with work contracts earn better than people without work contracts. Considering the

low salary of public staff and a large presence of informal sector, these results are not surprising.

Some more interesting results are worst to note. First, the unemployment duration decreases wages. Thus, the literature should also consider the scarring effects of unemployment period when estimating the impacts of mismatches on wages. The preferences for job attributes also affect wages given people prefer to job stability tend to be less paid in compensation perhaps for this job attribute. Then, people who prefer to learn new things tend to enjoy greater wages even though they are likely to be overeducated as we mentioned previously.

Finally, we observe that all mismatch indicators are found to reduce wages in all models with the strongest impact from double mismatch, following by vertical and horizontal mismatches. This confirms the job competition and assignment models (Thurow, 1976 ; Sattinger, 1993) that working in mismatched job would not allow them to exploit their potential skills, and consequently they would be less productive and earn less. Our results suggest that educational mismatch is a main issue that is needed to be carefully considered in Cambodia because with lower return, younger generation might have less incentives to work hard or invest in their education in the future, which could block Cambodia in the middle-income trap.

5 Conclusion

This article analyzes the wage impacts of educational mismatches among university graduates in Cambodia. This research distinguishes from the literature with different key points: 1- We analyze the case of a low income country that previous researches focus on more advanced economies, 2- We analyze education-job mismatches in their both forms (vertical and horizontal forms) and the possibility of their combination (double mismatch), which remains limited in the literature, 3- We take into account the effect of unemployment duration, the endogenous problem of education-job mismatches and sample selection bias owing to non-sample graduates, which is still scarce in the analyses of previous studies.

Results confirm that wage penalties exist with the strongest impacts for the case of double mismatch, following by overeducation and horizontal mismatch. The negative impacts may discourage young generation to invest their time and efforts on education, which could be bad for the society and economic development. Thus, Cambodia should pay more attention to the quality of its education system as found by other researches as a main determinant of education-job mismatches. Then, the policy makers in Cambodia should focus not only on the unemployment rate of their graduates, but also the quality of their jobs, thus education-job mismatches, when they analyze the labor market outcomes of Cambodian graduates.

This research, however, faces some limits. First, we do not have precise data allowing us to measure education-job mismatches with other methods to compare with our result. Second, we do not have panel data to isolate unobserved characteristics of graduates, which may affect our result. These limits are needed to overcome in the future researches concerning Cambodia and other developing countries.

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Appendix: A

Table 4: Correspondence between occupational class and educational level

ISCO-08 occupational class	ILO skill level	ISCED-97 educational level
1. Manager	3 + 4	6, 5a and 5b
2. Professionals	4	6 and 5a
3. Technicians	3	5b
4. Clerks	2	4, 3 and 2
5. Service and sales	2	4, 3 and 2
6. Skilled agricultural	2	4, 3 and 2
7. Craft and related	2	4, 3 and 2
8. Plant and machine operators	2	4, 3 and 2
9. Elementary occupations	1	1

Source: ISCO-08, volume I

Table 5: Description of educational level required for each skill level

Skill level	Educational level	Description of educational level
4	6	Second stage of tertiary education (advanced research qualification)
	5a	First stage of tertiary education, 1st degree (medium duration)
3	5b	First stage of tertiary education (short or medium duration)
2	4	Post-secondary, non-tertiary education
	3	Upper secondary level of education
	2	Lower secondary level of education
1	1	Primary level of education

Source: ISCO-08, volume I

Notes: One limit of using this measure to estimate the rate of overeducation is that the same job title may not mean that workers are performing the same tasks, and thus workers can be required to possess different educational levels. Nevertheless, other measures of overeducation also possess other drawbacks (please see the literature review of McGuinness (2006) and Sala et al. (2011) for a further discussion on this matter). Additionally, the use of this measure is also constrained by the data availability. For instance, previous researches on this issue in developing countries, including Cambodia, conducted by the International Labour Organization and Asian Development Bank also employ this same method by assigning the ISCO with 1 digit level to the ISCED (e.g., Sparreboom & Staneva, 2014 ; ILO and ADB, 2015).

Appendix: B

Table 6: Field of education and Matching jobs

Field of education	Matching jobs (ISCO-08 3-digit codes)
Economics and Management	112, 121, 122, 134, 143, 231, 232, 241, 242, 243, 262, 263, 264, 331, 332, 333, 334, 411, 412, 413, 421, 431, 432, 522
Engineering and Architecture	132, 214, 215, 216, 231, 232, 233, 311, 312, 313, 315, 515
Social sciences in English language	111, 112, 121, 122, 133, 134, 141, 143, 216, 231, 232, 233, 241, 242, 261, 262, 263, 264, 265, 334, 341, 343, 351, 352, 411, 412, 413, 511, 521, 522, 524
Sociology, Humanities and Arts	112, 216, 231, 232, 233, 234, 262, 263, 264, 265, 341, 511
Sciences	211, 212, 231, 232, 233, 311, 331, 421, 431
Information and Computer Technologies	112, 121, 133, 134, 231, 232, 233, 251, 252, 351, 352, 524
Tourism and Hospitality	112, 122, 134, 141, 231, 232, 243, 264, 341, 343, 441, 511
Law and Public Affairs	111, 121, 231, 232, 242, 261, 262, 263, 264, 334, 335, 341

Table source: Author's estimation by reviewing the job prospects described for each specialty in each university, then comparing with individual occupation.