Research article

The Effect of Educational Mismatch on Wages: A Comparative Study of Migrant and Native Workers

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Abstract: One of the important issues in the Indonesian labor market is an educational mismatch. And one of the implications caused by educational mismatch is that the wages received are unsuitable with the educational qualifications have. This study attempts to relate the educational mismatch phenomenon to the issue of internal migration. Hence, this study aimed to reveal the effect of educational mismatch on the earning of workers, especially migrant and native workers. The discussion of educational mismatch was more specific to migrant workers and native workers because these two types of workers had quite different potential earnings. The data used in this research were gained from the National Labor Force Survey (SAKERNAS) in August 2019. The unit of analysis used was workers with labor/employees' status other than TNI/POLRI aged 15-64 years and over. The results showed that migrant workers were more likely to experience over education than native workers, and native workers were more likely to experience undereducation than migrant workers. Then, based on the results of the multiple linear regression analysis, it was found that migrant workers encountered greater wage penalties than native workers.

Keywords: education, migrant worker, native worker, wage

JEL Classification: J22, J61, J64

Abstrak: Ketidaksesuaian antara kualifikasi pendidikan dan pekerjaan (educational mismatch) adalah isu yang masih sering terjadi di pasar kerja Indonesia. Salah satu implikasi yang dihasilkan dari educational mismatch adalah pendapatan yang diterima tidak sesuai dengan kualifikasi pendidikan yang dimiliki. Studi ini mencoba mengkaitkan fenomena educational mismatch dengan isu migrasi internal. Sehingga studi ini bertujuan untuk mempelajari pengaruh educational mismatch pada pendapatan pekerja lebih khusus pekerja pendatang dan lokal. Pembahasan educational mismatch lebih spesifik pada pekerja pendatang dan pekerja lokal karena kedua jenis pekerja ini memiliki potential earning yang cukup berbeda. Data yang digunakan dalam penelitian ini berasal dari Survey Angkatan Kerja Nasional (Sakernas) Agustus 2019. Unit analisis yang digunakan yaitu pekerja berstatus buruh/pegawai selain TNI/ POLRI berusia 15-64 tahun ke atas. Hasil penelitian menunukkan bahwa pekerja pendatang lebih cenderung mengalami overeducation dibandin pekerja lokal dan sebaliknya pekerja lokal lebih cenderung mengalami undereducation dibanding pekerja pendatang. Kemudian dari hasil analisis regresi linier berganda ditemukan bahwa pekerja pendatang mengalami wage penalty yang lebih besar dibanding pekerja lokal.

Kata Kunci: pendidikan, pekerja migran, pekerja lokal, upah

1. INTRODUCTION

Migration is a socio-economic phenomenon that frequently occurred in many countries, including Indonesia. Occasionally, the main motive for a person to migrate is economic (Lee, 1966; Todaro, 1969). Migration is also a component of population dynamics that is closely related to employment. By migrating someone hopes to improve his economic conditions by working or looking for a better job outside the area of his residence. A consideration that there will be a higher expectation gain than staying in a hometown may trigger a person to migrate (Harris & Todaro, 1970). In this case, the benefit mentioned is that they will get better wages by working in the destination area than staying in their hometown.

Based on the data from the National Labor Force Survey (Sakernas), it is known that the trend of migrant workers has tended to increase in the last three years. Migrant workers are defined as workers with the status of recent migrants where residence 5 years ago is different from their current residence. The presence of migrants in an area creates socio-economic dynamics. The migrant adds the supply of residents in an area. One of the possible consequences of having a migrant in an area is that it can increase the competence or competition for job opportunities not only between native residents and migrants but also between fellow migrant workers. An increase in the number of workers, especially at a certain level of education without being accompanied by good absorption in the labor market, will cause problems. The arisen problems include triggering high open unemployment, inequality in income distribution, and increasing labor mismatch (Safuan & Nazara, 2005). Later, Verhaest et al. (2017) and Puspasari (2019) state that the imbalance of supply and demand reflected in the number of job seekers and job opportunities can cause job mismatches. Imbalance in the labor market structure where job opportunities are limited so that many workers choose to accept jobs that are not following their level and educational background rather than bear the risk of unemployment.
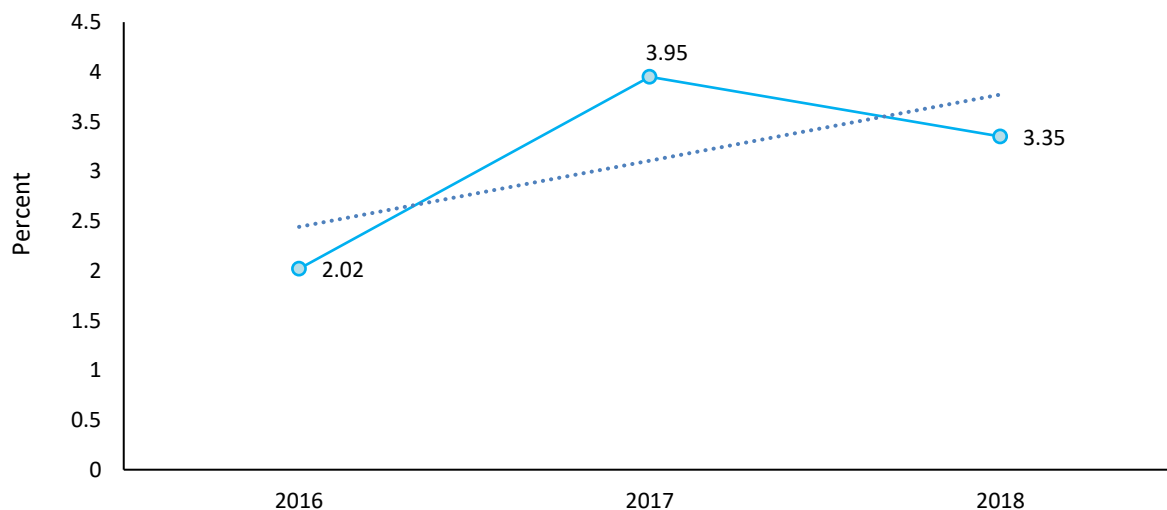

Figure 1. The Percentage of Migrant Workers in Indonesia, 2016-2018
Source: BPS (2017, 2019)

Not only being influenced by supply and demand dynamics in the labor market but labor mismatch is also influenced by individual experiences in the labor market. Mismatch at work occurs partly due to imperfect information received by workers (Allen & van der Velden, 2001; Piracha & Vadean, 2012). In job search theory there are many frictions in the labor market such as a lack of information from employers and potential job candidates so it takes time for workers to find suitable jobs (Jovanovich, 1979). Thus, prospective workers choose to work as quickly as possible to not be unemployed. Job mismatch due to information asymmetry is also relevant for migrant workers. Migrant workers are still studying the structure of the labor market, especially those who are in the early stages of being settled (Piracha & Vadean, 2012).

The educational mismatch is one of the problems frequently encountered in the job market in Indonesia. Based on a study from ILO (2017a) it was found that the mismatch rate in Indonesia has relatively not changed significantly in the last 10 years wherein 2006 the mismatch rate was 37 percent and in 2016 it slightly decreased to 36,2 percent. It can be concluded that more than a third of workers in Indonesia have inadequacy between the level of education and jobs they have.
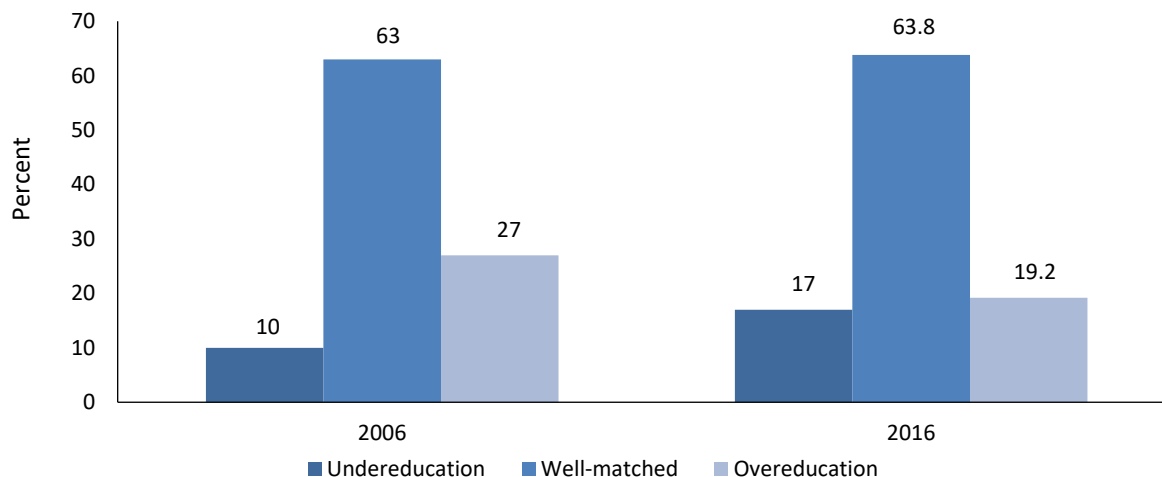

Figure 2. The Percentage of Educational Mismatches in Indonesia, 2006-2016
Source: ILO (2017a), Compiled from Sakernas 2006 and 2016

The existence of educational mismatch may cause disadvantages in the short and long-term, both in terms of workers and employers. In the short term, workers may receive undue wages that are unsuitable with the qualifications the workers have while employers may lose potential productivity from unqualified workers. In the long term, educational mismatch eventually can increase unemployment (Sattinger, 2012). In addition, Montt (2015) states that educational mismatch occurred in individuals influences job stability and job dissatisfaction.

Several previous studies have proven the effect of educational mismatch on workers' wages. The condition of overeducation in workers has a negative sign and significant effect on wages received while undereducation has a positive effect on wages (Montt, 2015). The existing studies mostly discuss the issue of educational mismatch that exists in the job market generally. However, studies focusing on the issue of educational mismatch correlated with the phenomenon of internal migration have not been widely conducted in Indonesia. Therefore, this study aimed more specifically to reveal the effect of educational mismatch on the wages of migrant and native workers.

To measure educational mismatch, there are two methods generally used, namely vertical and horizontal. The vertical mismatch method is carried out by comparing the level of education the workers have with the level of education required for the jobs. Meanwhile, the horizontal mismatch method is carried out by comparing the field of study the workers have with the field of study required for the type of the jobs (ILO, 2017b). This study only focused on vertical mismatch.

In vertical mismatch, there are three approaches used to measure educational mismatch, namely the normative approach, statistics, and self-assessment (ILO, 2018). Each method has advantages and disadvantages. This study used statistical methods to measure educational mismatch. Statistical methods are easy to apply with the core variables present in the household-based employment survey. In addition, it can also be compared between countries because it uses a more universal unit, namely the length of schooling variable. The statistical method is obtained by comparing the distribution of workers' education level viewed from the length of schooling with the distribution of the length of schooling for each type of job minus the standard deviation. A worker is called to be overeducation or undereducation if the average length of schooling is higher or lower than the average length of school minus one standard deviation of the type of job the worker has (ILO, 2017b).

There have been many studies conducted on the educational mismatch issue. A study conducted by Pholphirul (2017) examined educational mismatch in the labor market in Thailand using the vertical mismatch method. The results of the study showed that male workers who experience over education have lower wages (wage penalty) by 18,3 percent compared to workers who have jobs that match their qualifications while female workers $A = \pi r^2$ 18,1 percent.

A similar study to examined the effect of overeducation and undereducation on wages among workers in Indonesia. By using the statistical method approach, it was found that the overeducation on workers has a negative sign and significant effect on wages in which workers who experience overeducation encounter wage penalty of Rp. 231.447,00. Meanwhile, undereducation among workers has a positive effect on wages, in which undereducation workers receive a wage of Rp. 157.721,00 higher than well-matched workers.

Another study was conducted by Li et al. (2015) who conducted a job mismatch study on university graduates in the United States. By using the data gained from the American Community Survey, it was found that 5,7 percent of business faculty graduates experienced overeducation in the job market. The implication is that there are wage penalties that vary between majors in which the lowest wage penalty is received by general business graduates of -4,4 percent and the highest is experienced by accounting graduates at -13,8 percent. Another empirical research is conducted by Allen & van der Velden (2001). This study uses data from the "Higher education and graduate employment in Europe" project. In this study, it was found that the effect of overeducation was greater than the effect of undereducation. Each additional year of overeducation (working below one level) causes a decrease in income of 8,1 percent and each additional year of undereducation causes an increase in income of 3,6 percent.

The wages received by individuals are also influenced by the characteristics of the individual and the characteristics of the job. In terms of individual characteristics, the age variable has a positive effect on wages, whereas the age increases, the work experience increases so that it contributes to increasing wages (Van ours & Stoeldraijer, 2010). However, after a certain point, the increasing age will have a negative correlation with wages (Willis, 1986). Length of schooling also plays a role in increasing wages (Becker 1964); Gabriel & Schmitz 2005). Likewise, with gender, there is still a wage gap between men and women (Mardiana, 2014). Meanwhile, Carlino (1986) and Bucci (1993) state that wages in urban areas is higher than in rural areas. This is to compensate for the higher life necessities in urban areas than those in rural areas.

In terms of job characteristics, in the field of business variable, the agricultural sector is the sector with the smallest wages compared to the other sectors. It may be due to the differences in human capital in each sector (Young, 2013). Viewed from the type of jobs, empirical studies found that white-collar workers have the highest average wages compared to gray-collar and blue-collar workers (Fox, 2009). In addition, working time has a role in determining the number of wages received. Other study found that adding 1 hour of working time would increase wages by 1-2 percent. Furthermore, the training factor also has a positive relationship with the wages received. It is because training can increase the marginal product of workers so that it can increase incentives for companies (Konings & Vanormelingen, 2010). The labor union variable, based on empirical studies, has a positive effect on wages (Bitzan & Bahrami, 2010; Bryson, 2014; Card, 2001; Ge, 2014).

2. RESEARCH METHODS

2.1. Data

This study used raw data gained from the results of the Labor Force Survey (SAKERNAS). The unit of analysis in this study was migrant and native workers of productive age that is 15-64 years old and status as labor/employees other than TNI/POLRI. The unit analysis of labor/employees was chosen because the value wages could be consistently obtained. Meanwhile, migrant workers are chosen based on workers who are recent migrants. The spatial dynamics of population mobility are more depicted in recent migration than in lifelong migration (Wajdi, 2010). Recent migration is a type of migration characterized by the last residence in the past five years that is different from the

residence when the Sakernas survey was conducted in August 2019. The number of observation analysis units for migrant and native workers were 10.408 people and 165.125 people, respectively.

2.2. Model

To find out the effect of the educational mismatch variable on wages, the analysis method used was the Ordinary Least Square (OLS) regression analysis in which the function of wage refers to Mincer (1974) wage equation model. Estimation of wages on the mincer's earning function using the OLS method cannot be carried out directly because it can produce biased estimation. This is because the sampling process only considers the individuals who are labor/employees who earn wages. To overcome the problem of selectivity bias, the first step conducted is to create a working probability function for workers with labor/employee/employees' status using Heckman's two-step procedure based on certain characteristics of the workers (Heckman, 1979).

Work participation model used in individuals aged 15-64 years who work used a probit probability model. The probit model of work participation is a normal cumulative function that has an average of 0 and standard deviation of 1 so that it can be written with the following equation:

$$F(Zi) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{Zi} e^{(zi^2)/2} \, dZi \tag{1}$$

The work participation model in this study is as follows:

$$Zi = \beta_0 + \beta_1 age + \beta_2 age2 + \beta_3 gender + \beta_4 \, marital \, status +$$
$$\beta_4 length \, of \, schooling + \beta_5 \, area \tag{2}$$

To accommodate selectivity bias, Heckman (1979) introduced the inverse mills variable which is denoted by (λ). The value (λ) obtained is as follows:

$$\lambda = \frac{f(Zi)}{1 - F(Zi)} = \frac{f(Zi)}{F(-Zi)} \tag{3}$$

The operational definitions of all variables used in this study are presented more concisely in Table 1 below:

The model form is a modified model of the Mincer earning equation with independent variables in the form of educational mismatch, individual characteristics, and job characteristics and by adding the inverse mills variable derived from two-step Heckman correction. This wages equation was made separately between migrant workers and native workers. The model used based on the variables used from the function of wage is as follows:

$$Ln \, wage \, of \, migrant = \beta_0 + \beta_1 \, OE + \beta_2 \, UE + \sum_i^n \beta_i X_i + \lambda i + \varepsilon i \tag{4}$$

$$Ln \, wage \, of \, native = \beta_0 + \beta_1 \, OE + \beta_2 \, UE + \sum_j^n \beta_j X_j + \lambda j + \varepsilon j \tag{5}$$

where: Ln wage is the natural logarithm of workers' wages; OE is overeducation variable; UE is undereducation variable; Xi and Xj are control variables consisting of age, age square, length of schooling, gender, area of residence, type of jobs, the field of business, working time, training experience, and labor union; λij and λij are the inverse mills ratio variables.

Table 1. List of variables and the categorization

Variables	Symbol	Operational Definition	Category
Dependent Variable			
Wage	Ln Wage	Wages received during the last month either in the form of money or goods	Quantitative
Independent Variable			
Educational Mismatch:			
- Well-matched	1. Match	The status of *educational mismatch* in workers	1. Under; 0. Others
- Undereducation	2. Under		
- Overeducation	3. Over		1. Over; 0. Others
Age	Age	The age of workers based on their last birthday	Quantitative
Age Square	Age^2	Age square	Quantitative
Length of schooling	LS	Length of schooling of the workers (years)	Quantitative
Gender	G	Gender of the workers	0. Female*, 1. Male
Regional Classification	Reg.	Residential area	0. Rural*
			1. Urban
Business Fields:			
- Agriculture	1. Agriculture	The workers' business field	1. Industry; 0. Others*
- Industry	2. Industry		
- Service	3. Service		1. Service; 0. Others*
Types of Job:			
- Blue collar	1. BC		1. Gray-collar; 0. Others*
- Gray collar	2. GC	The workers' job type	
- White collar	3. WC		1. White-collar; 0. Others*
Working Time	WT	Working time during a week ago	Quantitative
Training	Training	Certified training that has been participated	0. Never participating*
			1. Participating
Labor Union	LU	The participation in labor union	0. Joining a labor union*;
			1. Never joining a labor union

Note: * is the reference of category

3. RESULTS AND DISCUSSION

3.1. General Description of Workers in Indonesia

Based on the previous explanation, the overall total of the analyzed sample was 175.533 individuals divided into two parts, namely 10.408 migrant workers and 165.125 native workers. In terms of the individual characteristics, migrant workers were more concentrated in the young age group (25-34 years) with the proportion reaching 40,16 percent. Rogers & Castro (1981) states that the population aged 20-30 years is the peak age with the highest mobility. Whilst the distribution of the age group among native workers was fairly even in the 25-54 year age group. However, in the 55-64 year age group, the percentage of migrant workers was smaller than that of native workers because the motive for migration decreases along with old age. In terms of gender, both migrant workers and native workers were dominated by male workers that their percentage reached more than 60 percent. Based on the regional classification, the migrant population was mostly found in urban areas by 65,58 percent compared to rural areas that were only 34,32 percent. The differences in the level of the economy between rural and urban areas indicate more labor market opportunities in urban areas so that workers decide to make rational decisions that can maximize present value.

Table 2. Number and Percentage of Labor based on Individual Characteristics and Migration Status

Characteristic	Migrant Worker		Native Worker	
	Total	Percent	Total	Percent
Age Group				
15-24	2.702	25,96	27.601	16,72
25-34	4.180	40,16	44.056	26,68
35-44	2.127	20,44	45.922	27,81
45-54	1.076	10,34	34.955	21,17
55-64	323	3,10	12.591	7,63
Gender				
Male	6.538	62,82	104.438	63,25
Female	3.870	37,18	60.687	36,75
Level of Education				
Low	1.504	14,5	34.650	21,0
Secondary	5.318	51,1	84.584	51,2
High	3.586	34,5	45.891	28,2
Region				
Urban	6.836	65,68	93.777	56,79
Rural	3.572	34,32	71.348	43,21
Total	10.408	100,00	165.125	100,00

Source: Sakernas August 2019 (author's calculation)

Table 3. Number and Percentage of Labor based on Job Characteristics and Migration Status

Characteristics	Migrant Worker		Native Worker	
	Total	Percent	Total	Percent
Business Fields				
Agriculture	847	8,14	15.947	9,66
Industry	2.512	24,14	45.090	27,31
Service	7.049	67,73	104.088	63,04
Types of Job				
Blue-Collar	3.989	38,33	73.467	44,49
Gray-Collar	3.406	32,72	46.879	28,39
White-Collar	3.013	28,95	44.779	27,12
Working Time				
<35 hours	1.358	13,05	29.251	17,71
35-40 hours	2.407	23,13	39.425	23,88
>40 hours	6.643	63,83	96.449	58,41
Training Experience				
Never participating	8.065	77,49	133.273	80,71
Participating	2.343	22,51	31.852	19,29
Labor Union				
Not participating	8.680	83,40	133.533	80,87
Participating	1.728	16,60	31.592	19,13
Total	10.408	100,00	165.125	100,00

Source: Sakernas August 2019 (author's calculation)

In terms of educational attainment, migrant workers have a better level of education than native workers in which the percentage of migrant workers who have higher education is 34,5 percent and of native workers is 28,2 percent. Migrant workers are relatively better than non-migrant workers. Migrant workers in general are highly selected individuals in the sense that those who migrate are individuals who tend to have better performance / human capital. Thus, in the

destination area, migrant workers have better potential earnings than native workers (Nasrudin & Resosudarmo, 2019). Based on the business field, both migrant workers and native workers showed the same distribution, namely more in the service sector. Likewise, it is also viewed from the types of job that shows the same distribution, but native workers are more likely to be in blue-collar than migrant workers who are more in gray-collar and white-collar.
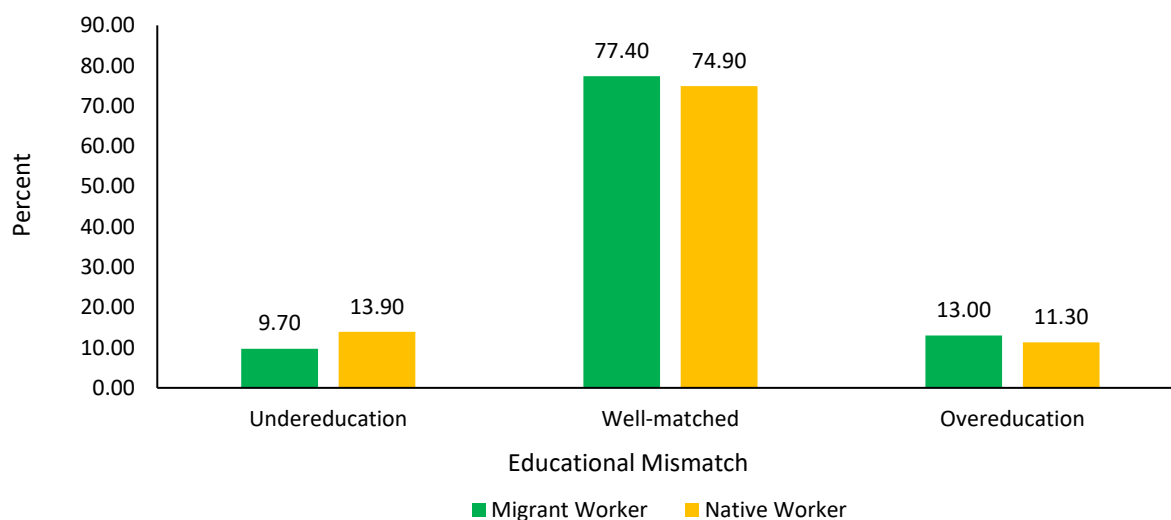

Figure 3. Percentage of Educational Mismatch on Laborers/Workers in Indonesia, 2019
Source: National Labor Force Survey 2019 (author's calculation)

The percentage of overeducation among migrant workers is higher than native workers in the same type of job. The rate of overeducation among migrant workers was 13 percent and among native workers was 11,3 percent. Based on the Unadjusted Odds Ratio (UOR) value, the UOR value was 1,17. It means that before it is controlled by other factors, the migrant population in Indonesia is 1,17 times more likely to experience over education than native residents in the same type of job. The UOR value obtained is as follows:

$$UOR = \frac{^{13}/_{(100-13)}}{^{11,3}/_{(100-11,3)}} = \frac{^{13}/_{87}}{^{11,3}/_{88,7}} = 1,17 \tag{6}$$

The high level of overeducation among migrant workers is related to their relatively better education compared to non-migrant workers in an area in the same type of job (Villareal, 2016). These results are in line with studies from Kalfa & Piracha (2017); Villareal (2016) & Visintin et al. (2015).

3.2. The Probability of Work Participation

Before applying the OLS regression analysis model on the Mincer wage function, the first step conducted was to calculate the individual's opportunity to enter the labor market. In the work participation probit model, the unit of analysis was the labor force. This is because the choices to work and not work come from the labor force. The total workforce in this study was 532.213 individuals. This stage generated the correction factor (λ) used in the revenue function.

Table 4 reports the work participation probability model. The results of chi-square obtained were the value of prob> chi2 of 0,000 so that the probit model formed is statistically significant or in other words, all independent variables could be inputted together. The work participation probability model presented in Table 4 as follows:

Table 4. Work Participation Probability Functions

Variable	Coefficient	S.E.	Significance
Constant	-1,090	0,016	
Age	0,036	0,001	0,000
Age Square	-0,0004	0,000	0,000
Gender			
Male	0,299	0,004	0,000
Marital Status			
Married	0,096	0,006	0,000
Length of Schooling	0,040	0,000	0,000
Regional Classification			
Urban	0,421	0,004	0,000

Source: Sakernas August 2019 (author's calculation)

The correlation between individual characteristics on the probability of working can be seen from the sign of the regression coefficient. The variables of age, gender, marital status, length of schooling and region were positively related to the probability of working. For example, it can be defined that longer education will increase the probability of working.

To know the influence of each independent variable, it can be seen from the marginal effects in Table 5. Individuals who are male have a probability of working 11,4 percent higher than those who are female. Those who have been married have a probability of working 3,7 percent higher than those who have never been married. The age squared variable shows a negative relationship with work participation. This means that at a certain age, work participation will decrease. The most dominant variable affecting work participation regional classification. Individuals who live in urban areas have a 15,7 percent higher probability of working than those who live in rural areas. This is also in line with studies conducted by Mardiana (2014).

Table 5. Marginal Effects of Work Participation Probability Function

Variable	dy/dx	S.E.	Significance
Age	0.014	0.000	0.000
Age Square	-0.0002	0.000	0.000
Gender			
Male	0.114	0.001	0.000
Marital Status			
Married	0.037	0.002	0.000
Length of Schooling	0.015	0.000	0.000
Regional Classification			
Urban	0.157	0.001	0.000

Source: Sakernas August 2019 (author's calculation)

3.3. The Effect of Educational Mismatch on Wages

This study used multiple linear regression analysis to examine the effect of educational mismatch on income. The first regression model formed was a model of wages for all workers. From the F- statistical test, it was obtained that the p-value is 0,000. The result was that the regression coefficient simultaneously has a significant effect on wages at the level of $\alpha = 0,05$. The coefficient value (R^2) obtained was 0,3448, meaning that 34,48 percent of the variation in workers' wages can be explained by the independent variables in the model while the rest is explained by other variables that have not been included in the model. Based on the result of the partial test, the main independent variables, namely overeducation and undereducation, have a significant effect on the overall wages of workers.

The coefficient value on overeducation was –0.0392, which means that the wages of overeducation workers tends to be 3,9 percent lower (wage penalty) than the wages of workers

with the same qualifications but working in jobs that are in accordance with the level of education required (well-matched) after being controlled for the independent variables of individual and job characteristics. In contrast, the coefficient value of undereducation was positive that was 0,0175, meaning that workers with undereducation characteristics receive 1,7 percent higher wages than workers with the same qualifications but working in jobs that match the level of education required (well-matched). These results are in line with the findings of studies conducted by Allen & Velden (2001), Safuan & Nazara (2004) and Pholphirul (2017).

Table 6. Estimation Model Result of Educational Mismatch and Wages for All Workers

Variable	Coefficient	S.E.	Significance
Constant	11,64	0,106	0,000*
Educational Mismatch			
Overeducation	−0,0392	0,0061	0,000*
Undereducation	0,0175	0,0071	0,013*
Age	0,048	0,002	0,000*
Age Square	−0,0004	0,00002	0,000*
Length of Schooling	0,067	0,0017	0,000*
Gender			
Male	0,44	0,012	0,000*
Regional Classification			
Urban	0,33	0,016	0,000*
Business Fields			
Industry	0,009	0,0063	0,151
Service	−0,255	0,0066	0,000*
Types of Job			
Gray Collar	0,099	0,0055	0,000*
White Collar	0,134	0,0071	0,000*
Working Time	0,016	0,0001	0,000*
Training Experience			
Participating	0,145	0,005	0,000*
Labor Union			
Never participating	−0,491	0,005	0,000*
Lambda	0,603	0,074	0,000*
Prob > F	0,000		
R^2	0,345		

Information: * = p-value < 0,05
Source: *Sakernas* August 2019 (author's calculation)

Furthermore, seen from the independent control variables, it was found that the variables of age, lenght of schooling, gender, regional classification, industrial business field, types of job, working time, training experience and participation in trade union had a significant positive effect on income at 5 percent. While the variable age squared significant negative effect on overall income. The age variable shows a positive relationship to income where an increase in age of one year will increase income by 4,8 percent. This result is in line with the findings of Van ours & Stoeldraijer (2010). Although age is positively related to income, at a certain point age will show a quadratic relationship which means that at a certain point the addition of age will be negatively related to income (Willis, 1986). The regression results show that the age variable squared is negatively related to income. In terms of gender, male workers have a 44 percent higher income than female workers.

The second and third regression models formed are wages models for migrant workers and native workers. From the F− statistical test in both models, it was found that the regression coefficient significantly affects wages at a level of α = 0,05. Based on the result of the partial test, the main independent variables, namely overeducation and undereducation, have significant effect on the wages of native workers. However, in the native worker wages model, only the overeducation

variable has significant effect on wages. Whilst, for the undereducation variable it has not been found sufficient statistical evidence to say that it influences wages. The proportion of undereducation workers was only 9,7 percent of the total sample of 10.408 migrant workers. It means that there are only 1.009 individual undereducation workers from migrant workers that have been examined its effect on wages. This relatively small number of individuals may not be strong enough to explain the effect on the wages of migrant workers. Estimation results of the educational mismatch effect on migrant workers presented in Table 7.

The wages of migrant workers with overeducation tended to be 6,4 percent lower (wage penalty) than those of migrant workers with the same qualifications but working in jobs that are in accordance with the level of education required (well-matched) after controlling for the independent variables of individual characteristics and job characteristics. Meanwhile, under education workers received 5,1 percent higher wages than workers with the same qualifications but working in jobs that are in accordance with the level of education required (well-matched). The variable length of schooling shows a positive effect to the income of migrant workers where an increase in the length of schooling by one year will increase income by 7,9 percent percent. This result is in line with the findings of Schmidt & Strauss (1975) and Gabriel & Schmitz (2005). Judging from the training experience, it was found that migrant workers who had attended training had 11,7 percent higher income than migrant workers who had never attended training. This is also in line with studies conducted by Konings & Vanormelingen (2010) and Dearden et al. (2006).

Table 7. Estimation Results of Educational Mismatch and Wages for Migrant and Native Workers

Variables	Migrant Workers			Native Workers		
	Coefficient	S.E.	Sig.	Coefficient	S.E.	Sig.
Constant	11.098	0.420	0.000*	11.645	0.110	0.000*
Educational Mismatch						
Overeducation	−0.064	0.024	0.007*	−0.037	0.006	0.000*
Undereducation	0.051	0.032	0.107	0.015	0.007	0.035*
Age	0.065	0.008	0.000*	0.048	0.002	0.000*
Age Square	−0.001	0.000	0.000*	−0.000	0.000	0.000*
Length of Schooling	0.079	0.007	0.000*	0.066	0.002	0.000*
Gender						
Male	0.550	0.046	0.000*	0.430	0.012	0.000*
Regional Classification						
Urban	0.516	0.063	0.000*	0.320	0.017	0.000*
Business Fields						
Industry	−0.092	0.028	0.001*	0.016	0.006	0.015*
Service	−0.370	0.028	0.000*	−0.248	0.007	0.000*
Types of Job						
Gray Collar	0.099	0.022	0.000*	0.099	0.006	0.000*
White Collar	0.135	0.028	0.000*	0.133	0.007	0.000*
Working Time	0.012	0.000	0.000*	0.016	0.000	0.000*
Training Experience						
Participating	0.117	0.017	0.000*	0.146	0.005	0.000*
Labor Union						
Not Participating	−0.455	0.019	0.000*	−0.494	0.005	0.000*
Lambda	1.196	0.295	0.000*	0,588	0.076	0.000*
Prob > F	0.000			0.000		
R^2	0.316			0.347		

Note: * = p-value < 0, 05
Source: *Sakernas* August 2019 (author's calculation)

In terms of business fields, the income of migrant workers in the industrial sector is 9,2 percent lower than in the agricultural sector and the income of migrant workers in the service sector is 37

percent lower than in the agricultural sector. The results of the descriptive analysis found that income in the agricultural sector dominates in the occupational classes such as managers, administrative staff, sales personnel, processing workers and manual workers. For example, in upper-level positions such as managers, migrant workers in the agricultural sector have an average income of Rp. 12.736.00,00 per month, while those in the industrial and service sectors are Rp. 11.474.375,00 and Rp. 7.108.571,00. Meanwhile, in the lowest level positions such as unskilled workers, the income of migrant workers in the agricultural sector got a higher value, reaching Rp. 2.346.444,00 and in the industrial and service sectors, Rp. 2.269.882,00 and Rp. 1.792. 347,00. The effect of educational mismatch on native workers can be stated in a regression equation presented in Table 7.

The wages of native workers with overeducation tended to be 3,7 percent lower than that of migrant workers with the same qualifications but working in jobs that are in accordance with the level of education required (well-matched) after controlling for the independent variables of individual characteristics and job characteristics. Meanwhile, undereducation workers received 1,5 percent higher wages than workers who are well-matched. The variable working time shows a positive effect to the income of native workers where an increase in working time by one hour will increase income by 1,6 percent. This result is in line with the findings of Mardiana (2014) who concluded that working time is positively related to income. Judging from participation in trade unions, it was found that native workers who did not join a trade union had 49,4 percent lower income than native workers who joined a trade union. This is also in line with studies conducted by Bitzan & Bahrami (2010), Bryson (2014), and Ge (2014).

The results of inferential analysis proved that overeducation has a negative effect on wages for both migrant workers and native workers. Even though it has the same direction, the coefficient of over education among migrant workers was greater (–0,064) than that of native workers (–0,037). It means that the wage penalty received by migrant workers is greater than that experienced by native workers, namely 6,4 percent compared to 3,7 percent. The amount of wage penalties for migrant workers can be due to the higher proportion of overeducation among migrant workers in blue collar (21,89%) and gray collar (7,63%) jobs compared to native workers in which the proportion in blue collar jobs was 18,31 percent and gray collar of 5,58 percent. This findings in line with this study, Sanroma et al. (2008) in their study conclude that the wage penalty experienced by migrant workers in Spain has been greater than that of native workers. However, the wage penalty for migrant varies depending on the region of origin. Another study conducted by Sharaf (2013) revealed that migrant workers in Canada have received a wage penalty of 8 percent.

4. CONCLUSIONS

The aim of this study was to compare educational mismatches among migrant and native workers. Based on the discussion in descriptive analysis, it was found that the occurrence of overeducation was more encountered by migrant workers than native workers. On the other hand, the occurrence of undereducation was mostly experienced by native workers. This difference was due to the significant difference in human capital between the two types of workers. One-third of migrant workers have had a diploma or higher education and this proportion was higher than that of native workers. On the other hand, those at primary school level and below were dominated by native workers compared to migrant workers. Based on the descriptive analysis, it was found that the level of conformity was higher for female workers than for male workers, both for migrant workers and native workers. In addition, based on age groups, workers in the younger age group had a higher percentage of experiencing overeducation, but in the younger age group, workers with undereducation were more dominant. In terms of residential area, the phenomenon of overeducation was more common in urban areas and vice versa, undereducation was more common in rural areas. It applied to both types of workers. Another interesting finding was that the percentage of overeducation of migrant workers who were absorbed in blue collar was quite high when compared to native workers. On the other hand, native workers who were undereducation were more likely to be white collar workers than migrant workers. The implication that can arise

from this mismatch is that the wages is not in accordance with the education owned.

To address the effect of educational mismatch on migrant and native workers, separate models for the two types of workers were developed. Based on the inferential analysis on the wages function of both migrant and native workers, it showed the same direction. The existence of undereducation had a positive effect on wages for both migrant workers and native workers. It means that workers experience a wage gain in the presence of undereducation. On the other hand, overeducation had a negative effect on wages for both types of workers. It means that the implication of overeducation is wage penalty. Based on the result of regression analysis, it was found that migrant workers experienced greater wage penalties than native workers, namely –6.4 percent for migrant workers and –3.7 percent for native workers. The greater wage penalty for migrant workers is likely because migrant workers are more absorbed in blue collar and gray collar types of job than native workers. The existence of overeducation in these workers indicates an inefficiency in the human capital of workers because they work in jobs that are not in accordance with their educational qualifications so that their wages tend to be lower when compared to workers with the same attributes but working at the appropriate wages.

To minimize the occurrence of educational mismatches in workers, it is necessary to have a system that can assist workers in optimizing the job search process. The government and the private sector can provide more detailed job information such as the educational qualifications required, and the amount of salary offered. In addition, this information must be up to date and accessible to the wider community. It is expected that the optimal job search system can suppress the information asymmetry between workers and employers, especially for migrant workers from regions who still lack information and experience in the labor market. Furthermore, because overeducation is more common in the younger age group, most of whom are fresh graduate workers, the government can encourage job providers to provide 'on the job training' that is relevant to company needs. It may add young workers' experiences and participations in training that empirically are proven to be able to increase workers' wages.

The phenomenon of undereducation was more common in rural areas than in urban areas. It means that there are many jobs in rural areas carried out by workers whose qualifications are below the required requirements. Thus, the government can work with job providers to focus on providing training and similar counseling to workers who are undereducation so that the lack of educational qualifications for workers can be covered by the skills and experience gained from the training provided. In determining the average length of schooling, this study used an indirect approach, namely through the highest degree completed. The measurement of the average length of schooling is more optimal if it considers the highest class completed. In Sakernas, the information related to the highest class is not available so that in further research it will be better to consider the highest class in viewing educational attainment. In conducting comparison between migrant workers and native workers, this study used cross section data. Motives to migrate for the reasons of working and looking for work cannot be identified in this study. Thus, to enrich the analysis in future studies, longitudinal data can be used to enrich information related to labor migration and its correlation to educational mismatch.

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