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Native-immigrant Wage Differentials in Malaysia

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Abstract

This paper utilizes Productivity and Investment Climate Survey (PICS) 2007 data to explore native and immigrant wage differentials in Malaysia. An Oaxaca decomposition analysis was conducted by adapting Oaxaca and Ransom (1994) and Fortin's (2008) approach using quantile regression to identify the non-discriminatory wage structure and the components of the wage differentials along the income distribution. The findings of the study suggest that most of the native-immigrant wage gap can be explained by differences in endowments. This study also shows discrimination contributes to the wage gap by increasing the native wage by 15.4% above the non-discriminatory wage structure and reducing the immigrant wage by 13.3%.

Keywords

Migration; wage differentials; native-immigrant wage differentials

Introduction

In the last two decades, Malaysia has become a major host country to foreign workers in Asia (Athukorala & Devadason, 2012). There is a growing number of immigrant workers in Malaysia due to the excess demand for labor, rapid economic growth, and industrialization (Noor, Isa, Said & Jalil, 2011). Recently, studies have been conducted in Malaysia to discover the impact of immigrant workers on various aspects of its society and economy, e.g. Narayanan and Lai (2014), Athukorala and Devadason (2012), and Noor et al., (2011).

In developed countries, many researchers have concentrated on wage differentials between natives and immigrants due to mass migration. The increasing interest in immigrant-native wage differentials in the United States and in European countries has heightened the need for an investigation into this issue in the Malaysian labor market. Most labor market studies in Malaysia have focused only on gender wage differentials (Ismail, 2011; Ismail & Jajri, 2012; Schafgans, 1998). As the number of immigrant workers in Malaysia has been increasing every year, there is a need to address the immigrant[i]-native[ii] wage differential in the Malaysian labor market.

[i] The term "immigrant" is defined here as a person who has citizenship in a country other than Malaysia and works in the formal sector.

[ii] The term "native" is defined here as a Malaysian worker who works in the formal sector.

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Labor migration occurs across various types of countries and occurs regardless of the level of economic development in the host and home countries as long as the expected salary in the host country is greater than the salary in the home country (Debrah, 2002). In the case of labor migration in Malaysia, most immigrants come from developing countries, especially Indonesia and the Philippines. The number of immigrant workers has continuously increased to fill the labor demand gap in the Malaysian labor market.

Most previous studies have found that immigrants earn significantly less than natives. One of the main reasons for this is that human capital, such as education, skills, and experience acquired abroad, is imperfectly transferable across countries due to the differences in economic development between hosts and home countries. However, there is a lack of studies investigating labor migration across developing countries. This study will address this issue and explore the wage determinants of immigrants and natives in the Malaysian labor market by estimating the return to human capital and other individual characteristics. Additionally, non-economic factors, such as discrimination, need to be considered when studying wage differentials between native and immigrant workers.

This study will formulate a wage equation for native and immigrant workers to identify wage determinants and wage differentials between natives and immigrants. The decomposition method proposed by Oaxaca and Ransom (1994) and Fortin (2008) will be applied to further explore the components of these wage differentials. This method should allow for the identification of factors that cause wage differentials between native and immigrant workers.

Literature Review

Wages should be paid based on the productivity of workers. In the labor market, elements of human capital, such as education, skills, and experience, are used as indicators of the productivity of the workers, which in turn determine their wages (Becker, 1964). However, information on the personal productivity of workers is costly for employers to identify, thus personal identity or inherited traits, such as gender, nationality, and race, are used as productivity indicators.

The issue of native-immigrant wage differentials has been debated widely in European countries and the United States. There have been numerous empirical studies conducted, and most of these find evidence of a wage gap. For example, Nielsen, Rosholm, Smith and Husted (2004) have highlighted the fact that an immigrant in a host country receives a lower wage rate than a native worker. A recent study by Brenzel and Reichelt (2015) utilised 2007 and 2008 survey data for 10,177 individuals to study immigrant and native wage differentials in Germany. Among other results, the study suggests that there is wage inequality between immigrant and native workers. There are many other empirical studies exploring wage differentials in the labor market, especially in the United States (e.g. Butcher & DiNardo, 1998; Cohen & Haberfeld, 1991; Parrott, 2014; Pitts, Orozco-Aleman & Rezek, 2014) and European countries (e.g. Aldashev, Gernandt & Thomsen, 2008; Brenzel & Reichelt, 2015; Canal-Domínguez & Rodríguez-Gutiérrez, 2008; Joona, 2010; Karamessini & Ioakimoglou, 2007; Lehmer & Ludsteck, 2011). However, very few studies discuss native-immigrant wage differentials in Southeast Asian countries.

Differences in the human capital of individuals cause wage differentials (Brenzel & Reichelt, 2015). There are two main sources of human capital, experience in the labor market and level of education (formal and informal) attained (Savvides & Stengos, 2008). In human capital theory, workers with the same level of human capital should be paid the same salary because human capital is a signal of the productivity of workers. Differences in human capital are one of the main reasons for wage differentials (Borjas, 2002). However, the return on human capital might not be the same for natives and immigrants in the labor market. This could be because the education and experience that immigrants have acquired abroad is not perfectly transferable across countries (Chiswick, 1978).

The existence of the wage gap could also be due to the fact that an immigrant's human capital from their country of origin is not relevant or is not adaptable to the destination country (Chiswick & Miller, 2009). An immigrant from a developing country, for example, may have difficulties in using other countries' knowledge or skills obtained in his home country (Barth, Bratsberg & Raaum, 2012). Nielsen et al. (2004) suggest that immigrants receive lower pay than natives because of differences in the 'standard' of human capital.

Therefore, the return on immigrants' human capital also depends on the applicability of human capital in the host country. As discussed in previous studies, some countries, especially developed ones, have a 'standard' human capital (Nielsen et al., 2004). In this case, the wage gap between natives and immigrants will be greater in the long term because immigrants' earnings growth is flatter than that of natives.

Immigrants who have been assimilated into a country should be able to adapt their human capital in the labor market and thus reduce the native-immigrant wage gap. However, in segmented labor market (SLM) theory, the assimilation of an immigrant into the labor market and the equalisation of the wage differentials between natives and immigrants are not applicable. SLM theory posits that labor markets are never perfectly competitive and that workers are not able to choose jobs based on preferences or abilities (Leontaridi, 1998). In SLM theory, there are two segments of the labor market, competing and non-competing (Anderson, 2015). Segmentation occurs when some workers are eligible for a job and others are not and it does not correspond to the abilities or skills of the workers. This theory can be useful when explaining non-economic factors or discrimination that contributes to wage differentials between natives and immigrants.

Discrimination exists because of imperfect information about an individual's productivity (Arrow, 1973). Grenier (1984) explains that imperfect information can be considered in two ways: from the point of view of employers and from that of employees. Employers face difficulties when they have imperfect information about workers, especially when hiring immigrants who speak different languages. To avoid additional expense, they may only hire natives, and the immigrants will lose out on the position. Further, if the employer does decide to hire immigrants, they may offer them a lower salary because they need to pay extra to yield information about the employee. This discrimination occurs in the labor market when the employer uses nationality to predict productivity (Lundberg, 1991). In the case of an employee, if imperfect information occurs, the employee will not have full information about jobs and the labor market. This is likely to be more common amongst immigrant workers because they are more likely to lack knowledge about the labor market in their destination country.

According to previous empirical studies, the assimilation of immigrants into the labor market takes place after a certain period, and this assimilation increases the immigrant's wages and closes the wage gap. However, even in a 'perfect assimilated state' the wage gap will always occur (Nielsen et al., 2004) due to discrimination in the labor market.

In earlier empirical studies, discrimination in the labor market was calculated by applying the standard decomposition. Oaxaca (1973) studied the gender wage gap in the U.S. labor market. He found that the wage gap between females and males is quite large. In the same year, Blinder (1973) exploited U.S. data to explore the gender and race wage gap. He concluded that there is a difference in wages across different genders and races. Both studies focused on the contribution of discrimination to wage differentials in the labor market. Since then, many more empirical studies have applied the Blinder-Oaxaca decomposition analysis to explore various aspects of discrimination. Thus, this method is arguably the most prominent for analysing immigrant-native wage differentials in the Malaysian labor market.

Methodology

The previous section shows that native-immigrant wage differentials are a crucial issue in the labor market. Wage differentials continue to exist for many reasons, which can be grouped into economic and non-economic factors.

This study used cross-sectional data obtained from the Productivity and Investment Climate Survey (PICS) 2 for 2007 collected by the Economic Planning Unit and Department of Statistics Malaysia in collaboration with the World Bank. The PICS includes 1,200 firms in the manufacturing sector and 300 establishments in the service sector. The PICS contains random samples of 13,533 workers that work in formal sectors in various sized firms.

Native and immigrant wage differentials

In investigating native-immigrant wage differentials, it is important to identify wage determinants. Therefore, the first step is comparing the wage determinants of natives and immigrants by estimating the standard Mincer earnings equation (Canal-Domínguez & Rodríguez-Gutiérrez, 2008), using single and separate earning equations for native and immigrant workers (Zangelidis, 2008).

The analysis begins by estimating the relationship between wage and explanatory variables. In a single-equation approach, the dummy variable 'immigrant' is included in the estimation to categorise workers by citizenship. In this method, all explanatory variables (except 'immigrant') are assumed to have the same effect on wages regardless of the citizenship of the workers (Smith, 2011). Consider the following equation:

$$Wage_i = \beta_0 + \delta_0 immigrant + \beta_1 HC_i + \beta_2 DC_i + \beta_3 EC_i + \mu_i \quad (1)$$

where the dependent variable is the natural logarithm of the hourly wage rate. 'Immigrant' is a dummy variable that refers to the citizenship of the workers (1 for immigrant and 0 for native workers). HC refers to human capital, which consists of level of education, training, potential experience and its square, and tenure and its square. DC represents socio-demographic characteristics such as gender, marital status, and citizenship, while EC represents employment characteristics, consisting of type of job (management, professional, skilled or unskilled workers) and membership of a trade union. B_i is the coefficient vector and μ is the error term or the individual unobserved characteristics, which are expected to be zero.

The problem of applying single equation estimation is when the dummy variable ('immigrant') is a confounding factor in the equation. However, if 'immigrant' is not a confounding factor, it will give biased estimates and also produce a large error in the estimation. To avoid these problems, a separate equation should be applied by assuming that native and immigrant estimations are independent, meaning both equations have a different slope (thus are not parallel to each other) and also have different intercepts (Ahn, 2002; Smith, 2011). Consider the following equations (2) and (3):

$$Wage_{ni} = \beta_{n0} + \beta_{n1}HC_{ni} + \beta_{n2}DC_{ni} + \beta_{n3}EC_{ni} + \mu_n \quad (2)$$

$$Wage_{mi} = \beta_{m0} + \beta_{m1}HC_{mi} + \beta_{m2}DC_{mi} + \beta_{m3}EC_{mi} + \mu_m \quad (3)$$

where the dependent variable is the individual log hourly wage rate, for native, n and immigrant, m.

Oaxaca decomposition analysis on native-immigrant wage differentials

This study will apply Oaxaca decomposition to explore native-immigrant wage differentials. The Oaxaca (1973) decomposition formula is as follows:

$$G = \frac{\overline{W}_n - \overline{W}_m}{\overline{W}_m} \quad (4)$$

where G is the native-immigrant wage gap and $\overline{W}_n$ and $\overline{W}_m$ are the average wages of natives and immigrants, respectively. The Ordinary Least Square (OLS) estimation of the logarithmic wage equation in equation (4) is as follows:

$$\ln(\overline{W}_n) = \overline{X}_n\widehat{\beta}_n$$
$$\ln(\overline{W}_m) = \overline{X}_m\widehat{\beta}_m$$

The wage differentials can be written as:

$$\ln(G+1) = \overline{X}_n\widehat{\beta}_n - \overline{X}_m\widehat{\beta}_m \quad (5)$$

and suppose that

$$\Delta\overline{X} = \overline{X}_n - \overline{X}_m$$
$$\Delta\widehat{\beta} = \widehat{\beta}_m - \widehat{\beta}_n$$

Thus,

$$\ln(G+1) = (\overline{X}_n - \overline{X}_m)\widehat{\beta}_m - (\widehat{\beta}_m - \widehat{\beta}_n)\overline{X}_n \quad (6)$$

In equation (6), $(\overline{X}_n - \overline{X}_m)\widehat{\beta}_m$ is the component of the wage differentials between natives and immigrants due to differences in their characteristics. The second term, $(\widehat{\beta}_m - \widehat{\beta}_n)\overline{X}_n$, represents the effect of discrimination on wage differentials. Thus, using the Oaxaca decomposition, the wage differentials can be divided into two components, the effect of the varying characteristics of workers and the effect of the coefficient.

However, Oaxaca and Ransom (1994) claim that discrimination in the labor market not only affects the minority group (immigrants) but also influences the wage of the majority group (natives). Discrimination will lower the wage of the minority group and at the same time increase the wage of the majority group.

Neumark (1988) and Oaxaca and Ransom (1994) use an estimation from the pooled model to derive the counterfactual coefficient of vector $\grave{\beta}$. However, Fortin (2008) argues that a pooled model will overstate the effect of variables with a large difference between the two groups. Pooled coefficients only capture part of the "between" overpaid and underpaid effect. In addition, if the advantage (overpayment) and disadvantage (underpayment) effects are not equal, the value of the non-discriminatory wage structure is negated.

To overcome this issue, Fortin (2008) proposed that the study include citizenship intercept shifts and identification restriction in the regression calculation of natives and immigrants pooled together. Consider the equation of natives and immigrants as follows (Fortin, 2008):

$$\overline{\ln W_n} = \widehat{\gamma}_0 + \widehat{\gamma}_{0n} + \overline{X}_n\widehat{\gamma} + E(v_i|M_i=0) \quad (7)$$

$$\overline{\ln W_m} = \widehat{\gamma}_0 + \widehat{\gamma}_{0m} + \overline{X}_m\widehat{\gamma} + E(v_i|M_i=1) \quad (8)$$

Then,

$$\overline{\ln W_n} - \overline{\ln W_m} = (\overline{X}_n - \overline{X}_m)\widehat{\gamma} + (\widehat{\gamma}_{0n} - \widehat{\gamma}_{0m}) + [E(v_i|M_i=0) - E(v_i|M_i=1)] \quad (9)$$

In equation (9), under the zero mean assumption, $((E(v_i|M_i=0)-E(v_i|M_i=1)=0)$, $(\overline{X}_n-\overline{X}_m)\widehat{\gamma}$ is the wage differential due to the difference in the characteristics of the workers. $(\widehat{\gamma}_{0n}-\widehat{\gamma}_{0m})$ is the wage differential due to the coefficient effect, where $\hat{\gamma}_{0n}$ represents the advantage of the majority group (native workers) and $\hat{\gamma}_{0m}$ represents the disadvantage of minority group (immigrant workers) in the labor market. The value of the immigrant coefficient, $\hat{\gamma}_{0m}$, will be negative.

Therefore, this study applies the wage gap decomposition analysis introduced by Oaxaca and Ransom (1994) by pooling the data. This approach is implemented together with the approach proposed by Fortin (2008).

In addition, the quantile regression decomposition method is applied to further explore the wage differentials between native and immigrant workers across the income distribution. The quantile regression decomposition cannot be done first because quantiles do not generate an exact result for wage decomposition. The wage decomposition proposed by Fortin (2008) is applied and can be written as:

$$\overline{\ln W_n} - \overline{\ln W_m} = \left(\overline{X}_n - \overline{X}_m\right)\hat{\gamma} + \left(\hat{\gamma}_{0n} - \hat{\gamma}_{0m}\right) + [E(v_i|M_i=0) - E(v_i|M_i=1)] \quad (10)$$

Canal-Domínguez and Rodríguez-Gutiérrez (2008) point out that the wage equation estimation is subject to the log wage being equal to its unconditional quantile of order θ, $\ln W_i = \ln \omega_\theta$, because the previous outcome cannot be obtained in quantile regression due to the wage decomposition (Machado & Mata, 2005). Thus, the quantile regression decomposition can be written as follows:

$$\begin{aligned}\overline{\ln W_n} - \overline{\ln W_m} &= \begin{bmatrix} (\overline{X}_n | \ln W_i = \ln \omega_\theta) \\ -(\overline{X}_m | \ln W_i = \ln \omega_\theta) \end{bmatrix} \hat{\gamma} + \left(\hat{\gamma}^{\theta}_{0n} - \hat{\gamma}^{\theta}_{0m}\right) \\ &+ \left[E\left(v^{\theta}_n \middle| \ln W_i = \ln \omega_\theta\right) - E\left(v^{\theta}_m \middle| \ln W_i = \ln \omega_\theta\right)\right]\end{aligned} \quad (11)$$

where $\left[E\left(v^{\theta}_n \middle| \ln W_i = \ln \omega_\theta\right) - E\left(v^{\theta}_m \middle| \ln W_i = \ln \omega_\theta\right)\right]$ cannot be explained by the quantile regression.

Results

This section will explain the results obtained. The analysis consisted of two stages: first, identifying the wage determination for immigrant and native workers, and second, analysing the composition of the wage differentials in the Malaysian labor market.

Table 1 shows the results obtained from the regression analysis, which was conducted based on equation (1). As shown in the table, the model indicates that about 36% of the variation in wages is explained by factors controlled for in the model, and the remaining 64% is explained by other factors. All the variables included in the estimation have the expected sign (as in previous studies), and this is in line with the aforementioned theories. Table 1 indicates, as expected, that human capital indicators, such as education, training, and potential experience, have a positive relationship with wage in this study. Similarly, socio-demographic (i.e. gender, and marital status) and employment characteristic indicators (i.e. type of job) as included in the estimation have the expected sign. For instance, males earn more than females. Many factors, such as discrimination in the workplace, cause the gender wage gap as female human capital is not fully realised (Arrow, 1973).

All variables were found to be statistically significant at the 1% level, except for skilled production job. The immigrant coefficient in Table 1 indicates that the citizenship gap remains unexplained. Immigrant workers earn significantly lower wages in comparison with native workers. Considering this result, we can infer that immigrant workers are treated unfairly in the labor market.

The potential experience and tenure variables have a non-linear relationship with wages, therefore the optimum level of these two variables should be calculated. Based on the coefficient of potential experience and potential experience squared as presented in Table 1, an increase in one year of experience should yield a positive change in hourly wages by 3.1%, while the maximum return on education occurs when a worker has about 28.28 years of experience[iii], assuming all other variables are constant. The coefficient on tenure implies a worker with one additional year of tenure can expect a rise in his hourly wage of 2.2% if he decides to remain in the company. However, the tenure squared figure is statistically insignificant.

Based on the coefficients of experience and tenure as shown in Table 1, these variables do not explain much when determining the wage of workers. Similarly, López-Bazo and Motellón (2012) note that experience and tenure only play a minor role in wage setting. The negative sign on potential experience squared indicates that the incremental return of experience on wage decreases as age increases. Thus, differences in human capital lead to differentials in wage (López-Bazo & Motellón, 2012).

Table 1: OLS regression output for wage equation of pooled samples

	Log hourly wage
Immigrant	-0.286***
	(-12.17)
Degree	0.956***
	(35.97)
Diploma	0.648***
	(28.41)
Upper secondary	0.228***
	(14.25)
Training	0.003***
	(4.02)
Potential experience	0.031***
	(14.03)
Potential experience squared	-5.5e-04***
	(-12.04)
Tenure	0.022***
	(7.25)
Tenure squared	-1.24e-04
	(-1.14)
Male	0.191***
	(15.05)
Married	0.088***
	(5.75)
Management	0.354***
	(15.24)
Professional	0.354***
	(14.26)
Skilled	-0.008
	(-0.46)
Unskilled	-0.232***
	(-11.44)
Union	-0.008***
	(-4.39)
Constant	1.074***
	(40.55)

iii $\left(\dfrac{\delta \log \text{hourly wage}}{\delta \text{ potential experience}} = 0.031 + 2(-0.00055) PotentialExperience\right)$

R^2	0.36
N	13,310
Prob > F	0.000

Notes: (1) *Numbers in parentheses are t-values.*
(2) *Reference group of education is Lower education*
(3) *Reference group of type of job is Nonproduction and apprentice jobs*
(4) * *Statistically significant at p<0.1*
(5) ** *Statistically significant at p<0.05*
(6) *** *Statistically significant at p<0.01*

As discussed in the methodology section, a single equation approach could give biased estimates if the dummy variable ('immigrant') is a confounding factor. Thus, separate equations should be used. In this way, workers are divided into two groups, native and immigrant. The purpose of this analysis is to identify the wage determinant for native and immigrant workers separately. This involves comparing the coefficient of native and immigrant estimates as shown in the third column of Table 2. The null hypothesis is:

$$H_0 = \beta^n = \beta^m \tag{12}$$

where β^n is the estimated coefficient for native, and β^m is the estimated coefficient for immigrant. Table 2 shows that degree of education, upper secondary education, and management jobs are statistically significant at 1%. Potential experience and union are significant at the 5% level, while training is statistically significant at the 10% level. The results indicate that the estimated coefficient for native, β^n, and for the six variables are significantly different from the coefficient of immigrant, β^m. However, other variables are not significant. This suggests that the coefficients native and immigrant might be similar.

Table 2: OLS regression output for wage equations of native and immigrant subsamples

	Native (β^n)	Immigrant (β^m)	Test $\Pr(\beta^n - \beta^m = 0)$
Degree	0.988***	0.534***	***
	(36.40)	(4.33)	
Diploma	0.667***	0.478***	
	(28.75)	(3.36)	
Upper secondary	0.244***	0.053	***
	(14.50)	(0.99)	
Training	0.003***	-0.001	*
	(4.08)	(0.54)	
Potential experience	0.033***	0.012	**
	(14.07)	(1.24)	
Potential experience squared	-0.001***	-3.8e-04	
	(11.94)	(1.48)	
Tenure	0.022***	0.015	
	(7.02)	(1.57)	
Tenure squared	-1.46e-04	1.3e-05	
	(1.28)	(0.04)	
Male	0.190***	0.160***	
	(14.61)	(3.05)	
Married	0.090***	0.091**	
	(5.49)	(2.03)	
Management	0.341***	1.103***	***
	(14.59)	(4.65)	
Professional	0.344***	0.502***	
	(13.72)	(3.09)	
Skilled	-0.002	-0.042	
	(0.08)	(0.43)	
Unskilled	-0.247***	-0.128	
	(11.67)	(1.39)	
Union	-0.009***	0.009	**
	(4.58)	(1.16)	
Constant	1.042***	1.074***	
	(38.35)	(8.29)	
R^2	0.34	0.15	
N	12,103	1,207	
Prob > F	0.000	0.000	

Notes: (1) Numbers in parentheses are t-values.
(2) Reference group of education is Lower education
(3) Reference group of type of job is Nonproduction and apprentice jobs
*(4) * Statistically significant at p<0.1*
*(5) ** Statistically significant at p<0.05*
*(6) *** Statistically significant at p<0.01*

The first column in Table 2 confirms that all independent variables of native workers are statistically significant at a 1% level except for skilled production job and tenure squared. The immigrant wage estimations in the second column show that there are six variables that are statistically significant at the 1% level and one variable that is significant at the 5% level. However, the F-statistics show that both models fit the data well. All the independent variables for native and immigrant estimations are jointly significant when explaining changes in the hourly wage.

As displayed in Table 2, the magnitude and direction of the coefficients on the independent variables for both native and immigrant are as predicted, and the result is comparative with the single-equation estimate as presented in Table 1.

In the separate regression analysis of immigrant and native, it can be concluded that the return on education, experience, and tenure is greater for natives compared to immigrants. On the other hand, the returns on management and professional jobs are higher for immigrants than natives.

Decomposition of native-immigrant wage differentials

Previous analysis posits that there is a gap between immigrant and native wages. This gap might be due to differences in human capital, socio-demographic characteristics, labor market characteristics, or other factors. There are also other unobserved factors that could contribute to the wage gap. This section analyses the unobserved factors that cannot be explained by economic reasoning and that contribute to native and immigrant wage differentials in the labor market. Unexplained components such as discrimination increase the wage gap between natives and immigrants. To identify the unexplained component effect on the wage gap, the Oaxaca Decomposition analysis will be applied.

The Oaxaca Decomposition analysis can divide the effect of explanatory variables on the dependent variable into two components, Explained and Unexplained (Jann, 2008). The Explained component refers to the effect of all explanatory variables in the wage estimation. The Unexplained component refers to factors that cannot be accounted for, such as discrimination (Jann, 2008). For example, the coefficient immigrant in Table 1 could be one indication of discrimination. This coefficient allows us to determine that being an immigrant could result in a wage reduction of 28.6% relative to natives. However, this explanation is questionable as the wage gap also might occur due to a misspecification or omitted variables (Canal-Domínguez & Rodríguez-Gutiérrez, 2008). To specify this effect, the Oaxaca decomposition approach is applied to divide the Unexplained factor.

Before conducting the standard decomposition, it's useful to compare the coefficient for natives and immigrants, and also the coefficient when natives and immigrants are pooled together based on Oaxaca and Ransom (1994) and Fortin's (2008) approach. Column three of Table 3 shows the coefficient calculated by the Oaxaca and Ransom (1994) approach, and the fourth column indicates the result of applying Fortin's (2008) approach. As Fortin (2008) stated, the problem of Neumark (1988) and Oaxaca and Ransom (1994) is that the pooled coefficient overstates the effect of variables and magnifies citizenship differences because the pooled coefficient captures the part 'between' the native and immigrant effect. In column three, there are five variables that show that the coefficient of the pooled samples based on Oaxaca and Ransom's (1994) approach is greater than of the native and immigrant subsamples. For example, the coefficient of the pooled samples for diploma (0.680) is larger than the native (0.667) and immigrant (0.478) coefficients. Other variables, such as upper secondary, tenure, married, and unskilled, also show that the pooled samples have greater coefficients than the native and immigrant subsamples. However, when the citizenship intercept is included in the estimation along with the restriction ($\gamma_{0m} + \gamma_{0n} = 0$) (in the fourth column) as suggested by Fortin (2008), it shows that aside from male and married, all coefficients of the variables are between the native and immigrant coefficients. Although two variables of the pooled samples have greater coefficients than the coefficients of the native and immigrant subsamples, those coefficients show only small differences between pooled samples and native and immigrant subsamples. This suggests that Fortin's (2008) approach is feasible when applied to Malaysian labor market data.

Table 3: Estimated regression coefficient of Oaxaca and Ransom (1994) and Fortin (2008) approaches

Log hourly wage	**Immigrant**	**Native**	**Oaxaca and Ransom (1994)**	**Fortin (2008)**
Degree	0.534***	0.988***	0.988***	0.956***
	(0.123)	(0.027)	(0.027)	(0.027)
Diploma	0.478***	0.667***	0.680***	0.648***
	(0.142)	(0.023)	(0.023)	(0.023)
Upper secondary	0.053	0.244***	0.256***	0.228***
	(0.053)	(0.017)	(0.016)	(0.016)
Training	-0.001	0.003***	0.003***	0.003***
	(0.002)	(0.001)	(0.001)	(0.001)
Potential experience	0.012	0.033***	0.028***	0.031***
	(0.010)	(0.002)	(0.002)	(0.002)
Potential experience squared	-3.8E-04	-0.001***	4.74E-04***	-0.001***
	(2.57E-04)	(4.71E-05)	(4.47E05)	(4.55E-05)
Tenure	0.015	0.022	0.026	0.022
	(0.009)	(0.003)	(0.003)	(0.003)
Tenure squared	1.28E-05	-1.45E-04***	-2.41E-04***	-1.24E-04***
	(3.46E-04)	(1.13E-04)	(1.08E-04)	(1.09E-04)
Male	0.160**	0.190***	0.162***	0.191***
	(0.052)	(0.013)	(0.013)	(0.013)
Married	0.091**	0.090***	0.103***	0.088***
	(0.045)	(0.016)	(0.015)	(0.015)
Management	1.103	0.341***	0.356***	0.354***
	(0.237)	(0.023)	(0.023)	(0.023)
Professional	0.502**	0.344***	0.358***	0.354***
	(0.162)	(0.025)	(0.025)	(0.025)
Skilled	-0.042	-0.002	-0.012***	-0.008
	(0.098)	(0.019)	(0.018)	(0.018)
Unskilled	-0.128	-0.247***	-0.268***	-0.232***
	(0.092)	(0.021)	(0.020)	(0.020)
Union	0.009	-0.009***	-0.008***	-0.008***
	(0.008)	(0.002)	(0.002)	(0.002)
Immigrant				-0.143***
				(0.012)
Native				0.143***
				(0.012)
Constant	1.074***	1.042***	1.039***	0.931***
	(0.130)	(0.027)	(0.026)	(0.028)

Notes: *(1) Numbers in parentheses are standard errors.*
(2) Reference group of education is Lower education
(3) Reference group of type of job is Nonproduction and apprentice jobs
*(4) * Statistically significant at $p<0.1$*
*(5) ** Statistically significant at $p<0.05$*
*(6) *** Statistically significant at $p<0.01$*

Table 4: Regression-compatible decomposition of the immigrant-native wage gap

	Coefficient	Exp (β)
Native	2.079***	7.996***
	(0.008)	(0.062)
Immigrant	1.378***	3.966***
	(0.021)	(0.082)
Raw log wage gap	0.701***	2.016***
	(0.022)	(0.045)
Difference in characteristics/ Explained ($\Delta\bar{X}'\hat{\gamma}$)	0.415***	1.515***
	(0.015)	(0.022)
as percentage of raw gap	59.20%	
Discrimination/ Unexplained	0.286***	1.331***
($\gamma_{0n} - \gamma_{0m}$)	(0.023)	(0.031)
as percentage of raw gap	40.80%	
Advantage of native (γ_{0n})	0.143***	1.154
	(-0.012)	
Disadvantage of immigrant (γ_{0m})	-0.143***	0.867
	(-0.012)	

Notes: (1) * *Statistically significant at p<0.1*
(2) ** *Statistically significant at p<0.05*
(3) *** *Statistically significant at p<0.01*

Finally, Table 4 shows the regression compatible decomposition as proposed by Fortin (2008) to explore the wage differentials between the native and immigrant variables. The decomposition here is more sensible if the data of the dependent variable is expressed in the actual value. The output in Table 4 is based on the estimation of the equation (11) with the restriction $\gamma_{0m} + \gamma_{0n} = 0$.

As shown in Table 4, when the coefficient is transformed into the exponential form, the mean wages are 7.996 (Ringgit Malaysia) for native and 3.966 (Ringgit Malaysia) for immigrant. Thus, the wage difference between natives and immigrants is 101.6%. Table 4 also provides information about the effect that differences in characteristics or Explained factors have on immigrant-native wage differentials. Based on the information presented in the table, it can be supposed that immigrant endowments are adjusted to the same level as native workers. In this case, the wages of an immigrant will increase by 51.5%. The Unexplained component is 33.1% resulting from the effect of discriminatory and other components on the wage differentials.

The Oaxaca decomposition can be used to divide the effect of discrimination into an advantaged group, referring to natives with a higher wage, and a disadvantaged group, referring to immigrants earning wages below the non-discriminatory wage structure. When the Unexplained component is divided into two, it can be seen that the wage differential due to the contribution of the advantage to natives is 15.4% and the disadvantage to immigrants is 13.3%.

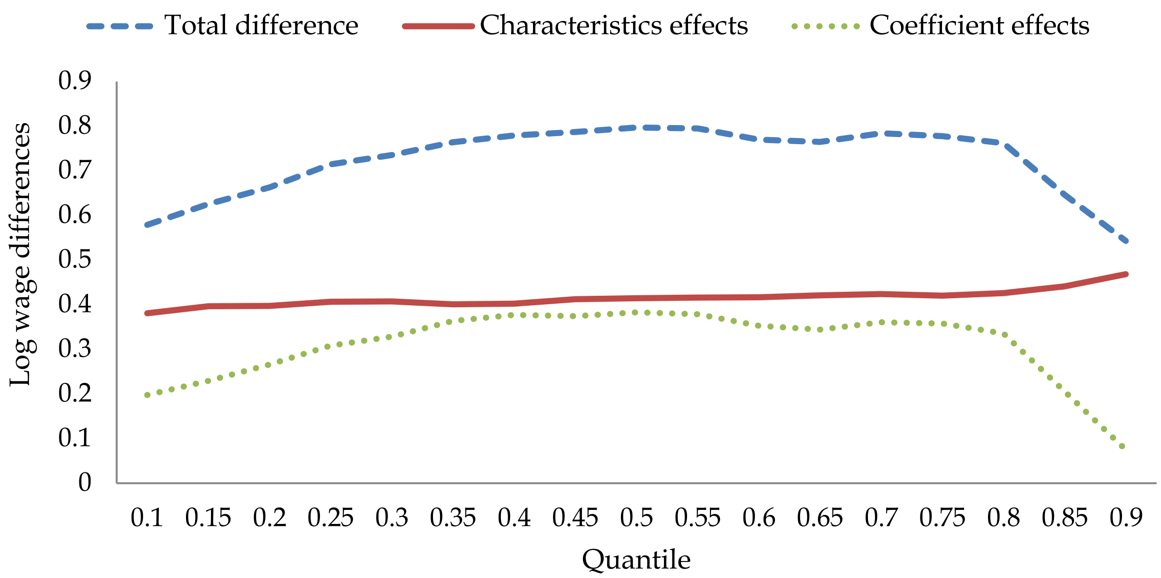
In Table 4, 59.2% of the difference in the raw log wage gap between natives and immigrants can be explained by differences in their characteristics. The wage differentials due to discrimination and other components contribute to 40.8% of the native-immigrant wage differential. Table 4 shows that decomposition analysis is plausible because the coefficient of the Unexplained components is comparable to the total sum of the advantage and disadvantage effects. It is also compatible with the coefficient of immigrant as shown in the regression analysis presented in Table 1.

Table 5: Quantile regression decomposition of the wage gap between native and immigrant workers

Components	Quantile									
	OLS	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Wage differentials	0.701	0.579	0.663	0.735	0.779	0.797	0.770	0.784	0.762	0.543
Characteristics	0.415	0.381	0.397	0.407	0.402	0.414	0.417	0.424	0.426	0.468
Coefficient	0.286	0.198	0.266	0.328	0.377	0.383	0.353	0.360	0.336	0.075
% of discrimination and unexplained	40.80	34.19	40.08	44.61	48.38	48.02	45.84	45.97	44.06	13.75

Notes: Quantile regression decomposition using Fortin (2008) estimator.

Figure 1: The decomposition of differences in distribution



The result of the decomposition of differences along income distribution from the 10th to 90th percentile is shown in Figure 1. Based on this figure, the Total difference and Coefficient effect curves show the same movement along the distribution. The highest wage differential is between the 78th and 80th percentile. This figure shows that Characteristic effects dominate Coefficient effects. This result is in line with Lehmer and Ludsteck (2011) who concluded that immigrant-native wage differentials are mainly explained by disadvantageous characteristics of workers.

Figure 1 shows that wage differentials in the low-income group are smaller compared to the high-income group. This result is similar to a study by Nicodemo and Ramos (2012) who found the discriminatory effect to be smaller for the low-income group than for the high-income group in the distribution. There are many possible explanations for this. Firstly, the wages of workers doing basic jobs are hard to justify because all of them are doing the same task (Melly, 2005). Secondly, the low-income group experience less discrimination because most of the workers are immigrants (Joona, 2011; Melly, 2005). Thirdly, immigrants in the lower income decile may have a higher education level than natives in the same decile (Joona, 2011). Thus, it is more difficult to discriminate against immigrants (Canal-Domínguez & Rodríguez-Gutiérrez, 2008). Fourth, minimal immigrant-native wage differentials could be due to the compressive effect exerted by labor market institutions, such as the minimum wage (Joona, 2011) and collective agreements (Antón, de Bustillo & Carrera, 2010).

On the other hand, there is an enormous immigrant-native wage gap in the middle of the income distribution. This huge gap could be due to levels of human capital or, specifically, the relative education level of natives and immigrants. However, education levels are in fact the same, meaning immigrants are being discriminated against. The size of the gap could also be attributable to the fact that the reservation wage of immigrants is lower than that of natives, or that immigrants face a lack of alternative job options (Joona, 2011). Whereas, at the higher income distribution, there is a minimal wage gap because most workers are professional and managerial workers have more education and training. This result is in line with Green, Heywoody and Theodoropoulos (2014) who found racial wage differentials shrinking at higher income distributions due to the role of bonuses among managerial and supervisory workers. To sum up, wage differentials are more intense at the middle-income distribution than at the lower and higher income distributions.

Discussions and Conclusions

This study was conducted to estimate the wage determination and wage differentials between immigrants and natives in the Malaysian labor market. Overall, it shows that the results are in line with relevant theories and previous empirical studies on immigrant-native wage differentials. The findings in this study provide empirical support for the idea that human capital for immigrants and natives in the Malaysian labor market is positively related to wage.

By applying the Mincer earning equation, it is revealed that the returns on education, experience, and tenure for natives are greater than for immigrants. Previous studies give some explanation for this. Firstly, most studies agree that human capital from developing countries is imperfectly transferred to the host country (Basilio, Bauer & Kramer, 2017; Chiswick & Miller, 2009). Immigrants' human capital also depreciates during the migration process (Brenzel & Reichelt, 2015). There is also the possibility that immigrants have difficulty integrating into the Malaysian market (Chiswick & Miller, 2009). Further, SLM theory explains that labor market segmentation might exist (Leontaridi, 1998). When segmentation exists, it gives an advantage to native workers because they do not have to compete with immigrant workers to find jobs. Moreover, immigrant workers are disadvantaged because they are not eligible for employment in posts reserved for native workers. On the other hand, immigrants yield a higher return than natives for management and professional jobs when these jobs require specific skills. Immigrants with specific skills will earn higher salaries than natives. However, this result could be biased as only 4% of immigrants from the sample were working in management and professional jobs.

The decomposition analysis shows that there are two main components of the wage gap, the explained and unexplained components. The explained component refers to the endowments or the characteristics of the workers, whereas the unexplained component relates to discrimination and other factors that cause the wage gap. The decomposition analysis also shows that natives earn above the non-discriminatory wage structure while immigrants earn below this structure. This study reveals that most of the wage gap between natives and immigrants is explained by the difference in endowments, which is in line with other empirical studies of developed countries (e.g. Aldashev et al., 2008; Lehmer & Ludsteck, 2011; Nielsen et al., 2004). However, discrimination and other components must also be considered as they explain almost half of the wage differentials.

To further explore immigrant-native wage differentials, a Quantile regression decomposition was conducted. The analysis shows that immigrant-native wage differentials vary across income distribution. The Characteristics effect is fairly constant, while the Coefficient effect lays below the Characteristics effect's line. Thus, by comparing the trend of the Total wage difference and the Coefficient effects, it can be concluded that the Coefficient effects drive the changes in the total wage gap across the income distribution.

In summary, this research has helped to identify discrimination in the Malaysian labor market between natives and immigrants. It has also found that most immigrant-native wage differentials can be explained by the difference in endowments, which is in line with previous studies. However, the difference due to discrimination should be stressed since this unexplained component contributes a large portion of the wage gap. The different return on endowments between natives and immigrants could be due to the imperfect transferability of immigrants' human capital. The findings of this study indicate that migration across developing countries has the same effect as migration across different levels of economic development.

There are some limitations to this study. First, it employs cross-sectional data from the manufacturing and service sectors only, and these represent just 32.1% and 12% of the population, respectively. Thus, future research should use a larger sample to obtain more precise and decisive findings on the immigrant-native wage gap.

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