Measuring mismatch unemployment in the Malaysia labour market

Rusmawati Said, Salwaty Jamaludin*, Normaz Wana Ismail and Norashidah Mohamed Nor

Faculty of Economics and Management, Universiti Putra Malaysia, Malaysia
Email: rusmawati@upm.edu.my
Email: salwaty.jamaludin@gmail.com
Email: nwi@upm.edu.my
Email: norashidah@upm.edu.my
*Corresponding author

Chen Chen Yong

Faculty of Economics and Administration, and UM STEM Centre, University of Malaya, Malaysia
Email: ccyong@um.edu.my

Abstract: Despite its low unemployment rate, the Malaysia labour market is currently sending signals of mismatch, a misallocation between demand and supply that may occur in the form of educational, skills, geographical, occupational, and industrial mismatches. Failure to identify the right type of mismatches will lead to ineffective policies to solve the unemployment issue. Using matching function, this study aims to calculate the labour mismatch index and measure the contribution of mismatch unemployment to the rise of unemployment rate. Employing various sources of data from the Department of Statistics Malaysia, Ministry of Human Resource Malaysia and Bank Negara Malaysia, this study found the presence of skills mismatch in the Malaysia labour market, with the mismatch index gradually increased from 0.108 in 2007 to 0.273 in 2017. Mismatch unemployment explained at most half of the total observed increase in unemployment rate, signalling severe mismatch in the Malaysia labour market.

Keywords: mismatch; unemployment; vacancies; matching models; Malaysia.


Biographical notes: Rusmawati Said is an Associate Professor at the Faculty of Economics and Management, Universiti Putra Malaysia. She received her PhD in Economics from the Cardiff University, UK. Her research interests include labour economics and development economics particularly in human capital development, minimum wages, demand and supply forecasting (manpower forecasting), unemployment insurance, poverty and green jobs.
Salwaty Jamaludin has graduated from the Universiti Putra Malaysia in Master of Economics. She is currently pursuing her PhD in Economics at the Universiti Putra Malaysia. Her research interests include labour economics, development economics and environmental economics.

Normaz Wana Ismail is an Associate Professor at the Faculty of Economics and Management, Universiti Putra Malaysia and the Deputy Director of the Institute of Agricultural and Food Policy Studies, Universiti Putra Malaysia. She received her PhD from the University of Southampton, UK. Her research interests include ASEAN studies, particularly issues related to intra-regional trade, foreign direct investment, convergence and economic growth.

Norashidah Mohamed Nor is an Associate Professor at the Faculty of Economics and Management, Universiti Putra Malaysia. She received her PhD from the Universiti Putra Malaysia and has completed her Post Doctorate from the Queensland University, Australia. Her research interests include health economics and development economics.

Chen Chen Yong is an Associate Professor at the Faculty of Economics and Administration, University of Malaya, Malaysia. She received her PhD in Economics from the Universiti Putra Malaysia. Her research interests include international trade and human capital development.

1 Introduction

Structural unemployment or labour mismatch refers to the inefficient allocation of resources between supply and demand in the labour market and it may occur in the form of educational or skills; geographical or regional; occupational, and industrial mismatches (Sahin et al., 2014; Adams et al., 2000). It could arise from several circumstances. Firstly, the technology shock that could change the skill set demanded by the employer (Bauer and Bender, 2004; Goldin and Katz, 2008). Secondly, the job seekers are not located in areas where jobs are available (Erken et al., 2015) and lastly, lucrative unemployment benefits (Rothstein, 2011; Nickell et al., 2003).

Of course labour market would demonstrate certain level of mismatch or else job vacancies would fill up instantly. However, any rise of mismatch above its usual level makes it tougher than usual for unemployed to find a job and more expensive for firms to fill a vacancy (Daly et al., 2012). The issue should not be ignored as it could impede the long-term productivity and economic growth as a whole. Labour mismatch also causes other issues, such as long unemployment spell (Grosen and Potter, 2003; Domadenik and Pastore, 2006). Even though Freeman (1976) stressed that mismatch is a temporary phenomenon, when an individual experiences unemployment in the early stage of his career development, he would have a high chance of facing long unemployment spell later on in his life. Other social issues, such as criminal activities, would also emerge due to the positive correlation between unemployment and crime (Fougère et al., 2009).

The labour market may signal the presence of mismatch in five ways. Firstly, the Beveridge curve that shows the negative correlation between job vacancies and unemployment. At one point, there will be more job openings, which may surpass the number of unemployment, and vice versa at another point. According to Wall and Zoega (2002) and Shibata (2013), an outward shift in the Beveridge curve suggests a potential
mismatch in the labour market. For Malaysia, Subramaniam and Baharumshah (2011) found a positive correlation between vacancies and unemployment, suggesting that the theory of Beveridge curve does not apply for this country.

Secondly, high percentage of unemployed with tertiary education and youth unemployed. The percentage of graduated unemployed significantly raise to 35% (of total unemployed) in 2017, which is 20% higher compared to the last ten years (DOSM, 1982–2017). While, for the rate of youth unemployment, has reached up to 10%, which is more than three times higher than the national unemployment rate (BNM, 2017). This issue, if remain neglected, would reduce the value of education, that resulting in an insufficient integration from educational institution to the labour market (Shkodinsky et al., 2019).

Thirdly, despite of the growing number of graduates, most job vacancies are concentrated in low-skilled jobs. In 2006, there were 834,675 job vacancies are reported in the market. However, looking at the distribution of job vacancies, 60% of the job vacancies were low-skilled jobs, 36% were middle-skilled jobs and only 5% were high-skilled jobs. Even in 2017, with 1,473,376 job vacancies was recorded, the proportion of low-skilled job still the highest with 77%, followed by middle-skilled jobs and high-skilled jobs with 19% and 5% respectively.

Fourthly, slow growth of wages for workforce with tertiary education. A joint study by the Ministry of Human Resources and The World Bank in 2016 revealed that wage growth for educated workers may slow down due to skills mismatch. BNM (2018) had stated that local employees are still being paid less than employees in benchmark economies (such as Singapore and Australia), even after accounting for the different productivity levels across countries. The report also suggests that Malaysia’s current wage productivity levels are not matching.

To make it clear, for an output worth USD1,000 produced by Malaysian labour, they will be paid USD340 for it. The corresponding wage received by a worker in benchmark economies for producing the same output worth USD1,000 is much higher, which is USD510. This is supported by the study done by Said et al. (2009) that showed the return for each level of qualification declined especially at the higher levels (diploma and degree). Recent study by Yunus and Said (2016) stated that the declining returns education for degrees’ holders is closely associated with the fall in the value of a degree, particularly for young graduates who fail to get a graduate-level job.

Fifthly, the difficulty in filling jobs or long duration needed to fill up the vacancy. The Productivity and Investment Climate Survey (The World Bank, 2009) reported that employers found it difficult finding the sought-after skills. Around 40% of firms stated that the average time to fill a vacancy was about four weeks in Malaysia. This is long compared to other countries, for instance, in Indonesia and India, it takes less than two weeks to fill a vacancy for professional posts in the manufacturing sector.

Motivated by the above issues, this study attempts to calculate the mismatch index and measure the contribution of mismatch in increased of the unemployment rate in the Malaysia labour market. Developed countries such as the USA, the UK, Japan, Netherlands and Sweden have taken the approach to measure the mismatch index in order the disentangle the unemployment issue. Notably, all these countries have experienced a remarkable decline in unemployment rate after the measurement of the index. For example, the unemployment rate in the USA declined from 7.9% in 2013 to 3.9% in 2017, while that in Japan declined from 4.0% to 2.4% during the same period (The World
Thus, this study is a first attempt to measure the mismatch index for the case of developing countries regards of our knowledge.

This paper organised as follows, Section 2 explain the literature review and Section 3 describe data and methodology. Section 4 present the empirical and Section 5 draws the conclusions from the results of the analysis and suggests some solutions to improve the Malaysia labour market.

2 Literature review

2.1 Matching function

The matching function plays a key role in the equilibrium unemployment theory. Generally, the function describes the connection between job seekers and firms advertising the vacancy. The former’s application for the vacancies form the productive matches. This is the interchange process by a well-behaved function, given the vacancies created in the market and the available supply actively looking for jobs.

Based on Petrongolo and Pissarides (2001), this matching function is basically derived from the production function and can be expressed as:

\[ H = m(U, V) \]  \hspace{1cm} (1)

where

- \( H \) new hires
- \( m \) matching efficiency
- \( U \) number of unemployed
- \( V \) number of vacancies.

The function is homogeneous of degree 1 with constant returns to scale.

The new hires or successful match may depend on the type of matching model in the labour market. For instance, the random matching model which is based on the assumption that job seekers take and apply for a vacancy at random. However, because of the heterogeneity of agents, not all hires could be formed.

2.2 Mismatch index

In the real world, not all employers are looking to hire a worker and not all job seekers find employers, thus some job opening remains unfilled and job seekers remain unemployed (Daly et al., 2012). Because of this misallocation, the term ‘mismatch’ emerges in the labour market.

A considerable body of literature has attempted to measure the level of mismatch. Among the earliest studies to calculate a mismatch index was Jackman and Roper (1987). The authors used a matching model with unemployment and vacancies as the main variables. They defined mismatch as structural imbalances (SU) due to the job seekers’ poor match with vacant jobs in terms of sector, skills or region, experience and so on. SU is defined as:
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\[ SU = \frac{1}{2} U \sum [u_i - v_i] \]  \hspace{1cm} (2)

where \( U \) is total unemployed, \( u_i \) and \( v_i \) is the number of unemployed and vacancies in the specific sector, skills or region. Then, from equation (2), they derived the mismatch index that measures the proportion of the unemployed in the wrong sector, skills or region. The value of 1 indicates maximal mismatch, whereas the value of 0 indicates no mismatch. The index is expressed as:

\[ m_1 = \frac{SU}{U} = \frac{1}{2} \sum [u_i - v_i] \]  \hspace{1cm} (3)

\[ m_2 = \frac{SU}{L} = \frac{1}{2} \frac{U}{L} \sum [u_i - v_i] \]  \hspace{1cm} (4)

where \( L \) is the size of labour force.

However, \( m_1 \) and \( m_2 \) do not measure the mismatch that could contribute to \( SU \). Assuming the hiring function is a Cobb-Douglas function, the authors injected the element of elasticity, which is 0.5. Thus, the \( m_3 \) defines the level of unemployment and vacancies at structural balance:

\[ m_3 = 1 - \sum \left( \frac{u_i v_i}{u v} \right)^{\frac{1}{2}} \]  \hspace{1cm} (5)

Three years later, Jackman et al. (1990) developed another index that focuses on the differences in unemployment rate between or within sectors. The authors assumed that the optimal unemployment rate could be obtained if and only if unemployment rates are similar across sectors. The index measures the dispersion of unemployment rate across sectors:

\[ m_4 = \frac{1}{2} \text{var} \frac{u_i}{u} \]  \hspace{1cm} (6)

where \( u_i \) is the unemployment rate in sector \( i \) and \( u \) is the mean of the sector-specific unemployment rate.

Next, Evans (1993) develop \( m_5 \) based on the UK scenario. It measures imbalances as a share of the sectoral labour force, as the author assumed that labour force imbalances across the region could affect region imbalance. The index is as follows:

\[ m_5 = \frac{1}{2} \sum l_i \left| (u_i - v_i) - (u - v) \right| \]  \hspace{1cm} (7)

where \( l_i \) is the share of labour force in sector \( i \).

Focusing on skills mismatch, Peters (2000) developed an index to measure the gap between the demand and supply of skills in the UK, economy:

\[ m_6 = SMI_e = \sum_{j=1}^{3} (S_{\beta} - M_{\beta})^2 \]  \hspace{1cm} (8)
$S_{jt}$ is the supply of each skill while $M_{jt}$ is the skill demanded proxy by share of the employee in the respective industry. His work has been adopted by Estevao and Tsounta (2011) and Dao et al. (2014) to measure mismatch in the USA and South Korea.

The latest mismatch index was developed by Sahin et al. (2014) for the USA. This index measures the fraction lost to misallocation. Compared to past indexes, this study provided in-depth analysis by considering matching efficiency, labour market tightness, job finding rate and job separation rate to measure the magnitude of mismatch unemployment. The index is expressed as:

$$m_7 = 1 - \sum_{i=1}^{I} \left( \frac{\Phi_i}{\Phi_j} \right) \left( \frac{V_{it}}{V_j} \right)^{\alpha} \left( \frac{u_{it}}{u_j} \right)^{1-\alpha}$$

where $\Phi$ is the element of matching efficiency and $\alpha$ is the element of elasticity. Their evidence suggested that industrial and occupational mismatches contribute to one-third of the overall unemployment rate.

Several studies have adopted the Sahin et al.’s (2014) mismatch index such as Marthin (2012) for Sweden, Patterson et al. (2013) for the UK, Shibata (2013) for Japan and recently Erken et al. (2015) for Netherlands. In Sweden, the author observed that geographic mismatch contributed to 30% of current unemployment. Meanwhile, in Japan, Shibata (2013) found that occupational mismatch accounted for nearly 20%–40% in the latest surge of unemployment rate. In Netherlands, Erken et al. (2015) concluded that the Dutch labour market was severely affected by sectoral mismatch during the Great Recession, while occupational and geographical mismatches had no significant effect.

Canon et al. (2013) employed $m_1, m_2, m_3$ ($m_7$), $m_4, m_5$ to calculate the mismatch index for the USA. For the industrial mismatch, the authors found $m_1$ and $m_3$ ($m_7$) showed a similar pattern, while the index from $m_2$ shared similar pattern with $m_5$. In terms of occupational mismatch, most of the indexes followed similar trends with their respective industry indexes. Besides that, for the counterfactual unemployment, the authors revealed that an increase of mismatch unemployment contributed at 2.72% out of 5.30% increase in the unemployment rate from May 2005 to November 2009.

3 Data and methodology

3.1 Data

The analysis was carried out using annual time series data from 2006 to 2017. The data included information of the unemployed, vacancies and new hires collected from the Department of Statistics Malaysia (DOSM), Ministry of Human Resources Malaysia (MOHR) and Bank Negara Malaysia (BNM). These institutions are authorised to capture the data at the national level.

Following Marthin’s (2012) definition, the number of the unemployed included all unemployed persons, who do not have a job but are interested to work. This definition is quite different from that of Sahin et al. (2014) as the authors only considered the unemployed with work experience. The number of unemployed persons, disaggregated by education level, was obtained from DOSM’s labour force survey.
Labour force survey is conducted by DOSM every month on households to obtain data on the structure of employment and unemployment. This survey reports the principal statistics of the labour force for the working age population (15–64) as well as their socioeconomic characteristics, such as sex, age group, educational attainment, occupation and industry.

In order to compute the skills mismatch index, this study will match the data for unemployed to represent the supply side with the data of vacancies, which based on MASCO code to represent the demand side. Table 1 describes the mapping of occupational group’s classifications and their corresponding level of education. However, following the practices of International Labour Organization (ILO), the group of Managers will be included in the high-skilled worker category.

<table>
<thead>
<tr>
<th>Group of occupation</th>
<th>Skill level</th>
<th>Educational level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Professionals</td>
<td>High-skilled</td>
<td>Fourth Tertiary education leading to a university or postgraduate university degree</td>
</tr>
<tr>
<td>Technicians and associate professionals</td>
<td>Third</td>
<td>Tertiary education leading to an award not equivalent to a first university level</td>
</tr>
<tr>
<td>Clerical support workers</td>
<td>Middle-skilled</td>
<td>Second Secondary or post-secondary education</td>
</tr>
<tr>
<td>Service and sales workers</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Skilled agricultural, forestry and fishery workers</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Craft and related trades workers</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Plant and machine-operators and assemblers</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elementary occupations</td>
<td>Low-skilled</td>
<td>First Primary education</td>
</tr>
</tbody>
</table>

Source: Malaysia Standard Classification of Occupations (MASCO) 2013

The data for vacancies, new hires and their corresponding skills levels (high-skilled, middle-skilled, and low-skilled) were obtained from the MOHR and BNM. Vacancies refer to job listings posted by select public employers and private businesses registered in the JobsMalaysia database.

JobsMalaysia is an automated online job matching system developed and managed by MOHR. It is one of the three core modules of the Electronic Labour Exchange (ELX). Basically, this portal allows job seekers to find suitable jobs and for employers to recruit the right candidates. Job seekers can apply through the portal while employers can manage the applications on it. The list of job vacancies included non-substantive vacancies such as salesperson, promoter, insurance agent, part-time workers and foreign workers.

The means of the unemployed, vacancies and new hires are presented in Table 2.
Table 2  Average number of new hired, vacancies and unemployed

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>High-skilled</td>
<td>6,862</td>
<td>118,387</td>
<td>121,925</td>
</tr>
<tr>
<td>Middle-skilled</td>
<td>14,730</td>
<td>340,680</td>
<td>24,149</td>
</tr>
<tr>
<td>Low-skilled</td>
<td>3,612</td>
<td>859,625</td>
<td>38,791</td>
</tr>
</tbody>
</table>

Source: The Department of Statistics Malaysia (DOSM), Ministry of Human Resources Malaysia (MOHR) and Bank Negara Malaysia (BNM).

3.2 Methodology

The empirical strategy followed two steps. First, the calculation of the mismatch index and second involved the measurement of contribution of mismatch to the rise in unemployment rate in Malaysia.

3.3 Mismatch index

Sahin et al. (2014) has developed the calculation of mismatch to measure the fraction of lost hires resulting from misallocations in the labour market. The authors argued that the market could be divided into several dimensions (industrial, skills and regional) with a certain number of vacancies and aggregate matching efficiency. In each dimension, the number of matches is established by the individual market matching function:

$$h_{it} (v_{it}, u_{it}) = \phi \Phi_{it} \left( v_{it} \right)^\alpha \left( u_{it} \right)^{1-\alpha}$$

where

- $h_{it}$ hires in sector, $i$
- $\phi$ aggregate matching efficiency
- $\Phi_{it}$ market-specific matching efficiency
- $v_{it}$ number of vacancies in the market, $i$, in period, $t$
- $u_{it}$ number of unemployed persons in the market, $i$, in period, $t$
- $\alpha$ share/elasticity of vacancies.

The mismatch index estimates the fraction of hires lost in the labour market or

$$\frac{h_{it}}{h_{it}^*}$$

where, $h_{it}$ denotes the total number of hires, and $h_{it}^*$ denotes its efficient counterpart.

The aggregate number of new hires is expressed as:

$$h_i = \Phi_i \left( v_i \right)^\alpha \left( u_i \right)^{1-\alpha} \left[ \sum_{j=1}^{l} \Phi_j \left( \frac{v_{ij}}{v_i} \right)^\alpha \left( \frac{u_{ij}}{u_i} \right)^{1-\alpha} \right]$$
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Under the assumptions of homogenous productivities and job separation, the optimality condition to allocate unemployed market between market $i$ and $j$ is:

$$\Phi_i \left( \frac{v_i}{u_i} \right) = \Phi_j \left( \frac{v_j}{u_j} \right)$$

(12)

The optimal hires can be attained by allocating $u_t$, which denotes available unemployed workers across the sector:

$$h_t^* = \Phi_j v_t u_t^{1-\alpha} \left[ \sum_{i=1}^I \Phi_i \left( \frac{v_i}{v_i} \right)^{\alpha} \left( \frac{u_i}{u_i} \right)^{1-\alpha} \right]$$

(13)

By substitute equation (12) into equation (13), the heterogeneous mismatch index, $M_{\Phi}$, thus, takes the following form:

$$M_{\Phi t} = \frac{h_t^* - h_t}{h_t^*}$$

(14)

$$M_{\Phi t} = 1 - \sum_{i=1}^I \left( \frac{\Phi_i}{\Phi_j} \right) \left( \frac{v_i}{v_i} \right)^{\alpha} \left( \frac{u_i}{u_i} \right)^{1-\alpha}$$

(15)

where aggregate matching efficiency becomes:

$$\Phi_j = \left[ \sum_{i=1}^I \Phi_i \left( \frac{v_i}{v_i} \right)^{\alpha} \left( \frac{u_i}{u_i} \right)^{1-\alpha} \right]$$

(16)

and $\Phi_i$ is the market-specific efficiency.

It is assumed that there is no heterogeneity in the productivity and rate of job separation throughout the market, as there are limited data to support this claim. Also, this assumption does not produce a significant difference in effect (Shibata, 2013).

However, for the absence of heterogeneity in the matching efficiency, the mismatch index becomes homogenous, $M_t$:

$$M_t = 1 - \sum_{i=1}^I \left( \frac{v_i}{v_i} \right)^{\alpha} \left( \frac{u_i}{u_i} \right)^{1-\alpha}$$

(17)

Three characteristics of the index should be noted. First, $M_{\Phi}$ should be between zero and one. Zero indicates no mismatch and one indicates maximum mismatch. Second, the index is invariant to ‘pure’ aggregate shocks that shift the total number of vacancies and unemployed persons up or down, but leave the vacancy and unemployment shares across markets unchanged. Third, the index increases upon disaggregation (Sahin et al., 2014).

3.4 Mismatch contribution

The contribution of mismatch on the rise of unemployment rate can be calculated using the mismatch index in equation (15). From the definition, mismatch unemployment refers to the disparity between actual and counterfactual unemployment, where the counterfactual situation reflects the optimal number of hires achieved.
Following Sahin et al. (2014) and Shibata (2013), in order to obtain the rate of counterfactual unemployment, the counterfactual job-finding rate and job-finding rate should be measured first. Counterfactual job-finding rate can be denoted as:

\[ f_t^* = f_t \frac{1}{1 - M_{\Phi t}} \left( \frac{u_t}{u_t} \right)^{\alpha} \]  

(18)

While, job-finding rate is denoted by:

\[ f_t = \frac{h_t}{u_t} = (1 - M_{\Phi t}) \Phi_t \Phi_t \left( \frac{v_t}{u_t} \right)^{\alpha} \]  

(19)

Thus, to estimate the changes of counterfactual unemployment, this study followed the calculations of Erken et al. (2015). The changes of counterfactual unemployment, can be expressed as:

\[ U_{t+1}^* = U_t^* + s_t \left( E_t + \left( U_t - U_t^* \right) \right) - f_t^* U_t^* \]  

(20)

where

- \( U \) number of unemployed persons
- \( E \) number of employed persons
- \( s_t \) job separation rate
- \( f_t \) job finding rate.

With an initial value of counterfactual unemployment, this equation can be iterated forward to acquire a path for counterfactual unemployment without mismatch.

3.5 Robustness check

Two steps were carried out to check the robustness of the results. For the first robustness check, the elasticity of vacancy was amended to 0.5, assuming the elasticity of matched was similar with respect to both vacancy and unemployed (Erken et al., 2015). For the second robustness check, since managers groups was introduced into the vacancy data as the initial mismatch index, the managers group was excluded from the estimation. As mentioned in MASCO, the concept of skill level is not applicable to managers group as the skill level concept does not reflect the main skill requirements for distinguishing them from other groups. Sahin et al. (2014) adopted the same technique to study the issue of discouraged workers. When the proxy is amended, there is quantitatively insignificant variance between the modified and original mismatch indexes.

4 Findings and discussion

4.1 Mismatch index

Table 3 demonstrates the index of skills mismatch in the Malaysia labour market. Overall, both homogenous and heterogeneous skills mismatch indexes showed an upward
trend throughout these ten years. In 2007, both homogenous and heterogeneous skills mismatch index was only around 0.108 and this index reached up to 0.273 in 2017, which indicates in 2017, there were 27% of hires lost due to misallocation in the labour market. This measurement is large compared to other developed country, perhaps due to the inefficient of matches in the Malaysia labour market.

<table>
<thead>
<tr>
<th>Year</th>
<th>Homogenous skills mismatch index ($\alpha = 0.7$)</th>
<th>Heterogenous skills mismatch index ($\alpha = 0.7$)</th>
<th>Homogenous skills mismatch index ($\alpha = 0.5$)</th>
<th>Heterogenous skills mismatch index ($\alpha = 0.5$)</th>
<th>Homogenous skills mismatch index (exclude manager)</th>
<th>Heterogenous skills mismatch index (exclude manager)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2007</td>
<td>0.109</td>
<td>0.108</td>
<td>0.123</td>
<td>0.121</td>
<td>0.100</td>
<td>0.098</td>
</tr>
<tr>
<td>2008</td>
<td>0.170</td>
<td>0.169</td>
<td>0.192</td>
<td>0.191</td>
<td>0.169</td>
<td>0.167</td>
</tr>
<tr>
<td>2009</td>
<td>0.135</td>
<td>0.145</td>
<td>0.152</td>
<td>0.169</td>
<td>0.139</td>
<td>0.165</td>
</tr>
<tr>
<td>2010</td>
<td>0.166</td>
<td>0.165</td>
<td>0.187</td>
<td>0.185</td>
<td>0.151</td>
<td>0.148</td>
</tr>
<tr>
<td>2011</td>
<td>0.158</td>
<td>0.157</td>
<td>0.177</td>
<td>0.175</td>
<td>0.115</td>
<td>0.113</td>
</tr>
<tr>
<td>2012</td>
<td>0.165</td>
<td>0.164</td>
<td>0.185</td>
<td>0.184</td>
<td>0.161</td>
<td>0.159</td>
</tr>
<tr>
<td>2013</td>
<td>0.214</td>
<td>0.213</td>
<td>0.244</td>
<td>0.242</td>
<td>0.205</td>
<td>0.203</td>
</tr>
<tr>
<td>2014</td>
<td>0.231</td>
<td>0.229</td>
<td>0.257</td>
<td>0.256</td>
<td>0.213</td>
<td>0.211</td>
</tr>
<tr>
<td>2015</td>
<td>0.208</td>
<td>0.207</td>
<td>0.231</td>
<td>0.230</td>
<td>0.204</td>
<td>0.202</td>
</tr>
<tr>
<td>2016</td>
<td>0.201</td>
<td>0.200</td>
<td>0.222</td>
<td>0.221</td>
<td>0.196</td>
<td>0.194</td>
</tr>
<tr>
<td>2017</td>
<td>0.274</td>
<td>0.273</td>
<td>0.308</td>
<td>0.306</td>
<td>0.258</td>
<td>0.256</td>
</tr>
</tbody>
</table>

As many as 1,473,376 vacancies were documented during the year, with almost 70,000 vacancies for high-skilled jobs and 175,800 unemployed graduates with tertiary education, high-skilled unemployed were unable to be absorbed into the labour market. This can be explained why the data shows tremendous percentage of unemployed for those with tertiary education.

Based on the current situation in the Malaysia, sheepskin effects, or credential effects, which is the increase in labour market earnings related to the completion of a diploma or degree, will be dismissed (Hungerford and Solon, 1987) and the validity of human capital theory has been challenged (Sicherman, 1991). Surprisingly, in the case of Malaysia, Zulkifly et al. (2010) found an increase of investment in human capital would only increase the number of unemployed persons with higher education attainment, leading to job mismatch. With the asymmetric information in the labour market, the circumstances of mismatch are becoming worse (Osman and Shahiri, 2013).

As time goes by, graduates might also become trapped in McJobs that are associated with mediocre salary, as well as job status (Lindsay and McQuaid, 2004), as job creation in the market is more concentrated on middle-skilled and low-skilled jobs.

With the increasing percentage of low-skilled job vacancies, it seems like the demand side of the labour market do not correspond with the signal from the supply side. Even Malaysia is among the major recipients of Foreign Direct Investment (FDI) in the world and this circumstances could act as catalysts for job creation, however there are negative correlation between FDI and skilled labour demand (Yunus et al., 2015). This circumstances shows that, even we solve the issue of unbalance supply side alone, it does
not eliminate the whole problem of unemployment, since it also has entangled with the issue of unbalance demand side (Kopycinska, 2008).

4.2 Robustness check

As shown in Figures 1 and 2, the outcomes were robust on the overall although they are subjected to some restrictions. Insignificant differences were found between the reanalysed and original indexes, with a contribution of mismatch unemployment, which constructed from the indexes, difference of only 0.008 on average.

Figure 1  Homogenous skills mismatch index (see online version for colours)

![Figure 1](image1.png)

Figure 2  Heterogeneous skills mismatch index (see online version for colours)

![Figure 2](image2.png)

4.3 Mismatch unemployment in Malaysia

Figure 3 displays the unemployment rate in Malaysia (exclude those with no formal education) and its counterfactual unemployment rate. By eliminating the skills mismatch, the unemployment rate would drop significantly. For instance, in 2017, the unemployment rate was 3.45, would drop to 2.95 with the absence of mismatch. In
Measuring mismatch unemployment in the Malaysia labour market

In general, from 2007 to 2017, on average, the unemployment rate would decrease by 0.31 compared to the stated unemployment rate of the particular year.

**Figure 3** Actual unemployment rate vs. counterfactual unemployment rate (see online version for colours)

While, Table 4 exhibits the influence of mismatch on the increasing unemployment rate in Malaysia. The skills mismatch accounted for 40% and 50% in the rise of unemployment rate from 2007 to 2009 and 2013 to 2017, respectively. This situation is due to the discrepancy between the supply and demand in labour market. From the supply side, the training provider and curriculum design do not match with the demand side or requirements of firms. New program or curriculum designed by the training provider is always hindered by time-consuming bureaucracy and accreditation procedures that must be fulfilled before it can be offered to firms, resulting in a gap between training provider from the supply side and firms from the demand side. These circumstances were among the reasons of high percentage of unemployed graduates, as shown by the statistics.

**Table 4** Contribution of skills mismatch to the rise of the unemployment rate in Malaysia

<table>
<thead>
<tr>
<th>Year</th>
<th>Changes in unemployment rate</th>
<th>Changes in counterfactual unemployment rate</th>
<th>Percentage explained</th>
</tr>
</thead>
<tbody>
<tr>
<td>2007–2009</td>
<td>0.483</td>
<td>0.191</td>
<td>39.5%</td>
</tr>
<tr>
<td>2013–2017</td>
<td>0.237</td>
<td>0.119</td>
<td>50.2%</td>
</tr>
</tbody>
</table>

5 Conclusions

This paper measures the mismatch index and contribution of mismatch unemployment in the Malaysia labour market. Mismatch index has gradually increased throughout the years. In 2017, heterogeneous skills mismatch is 0.273, indicating 27% of hires were lost due to misallocation respectively. Mismatch unemployment contributed around 40–50% to the rise of unemployment in 2007–2009 and 2013–2017. From the results, it can be suggested that the formal education system in Malaysia is not responsive to the demands of the labour market.

In order to reduce unemployment rate and mismatch, the government could learn from past experiences. For example, in the Fourth Malaysia Plan, the government aimed
to transform the Malaysian economy from agriculture-based to manufacturing-based. While in the Sixth Malaysia Plan, the government targeted to increase the volume of manufacturing products by attracting more foreign direct investments. Low-skilled workers have been imported to increase production, as Malaysia was among the countries that implemented low-wage policies in ASEAN. Perhaps unintentionally, this policy has resulted in the inflation of low-skilled labour in the market, which in turn created a large gap between the number of low-skilled and high-skilled jobs. The emphasis towards human capital was only highlighted in the Ninth Malaysia Plan. Now, as the nation progresses towards a knowledge economy amidst Industrial 4.0, the engagement of local human capital with the labour market should be enhanced to fully utilise the available resources.

The government also needs to create more skilled jobs and on-the-job training to match the excessive supply of graduates with tertiary education. Undeniably, the government has launched tons of initiatives to reduce mismatch, such as 2u2i: a four-year learning program where participants learn in university for two years and industry for two years; Skim Latihan 1 Malaysia (SL1M): a program aimed at enhancing the employability of graduates by improving their capabilities and skills; and the critical occupations list (COL): a set of occupations in demand in order to promote better coordination of human capital policies aimed at attracting, nurturing and retaining talent. Whether the program has reached the target group and implemented effectively, however, are another issue that must be considered. In addition, re-skilling and up-skilling low- and middle-skilled workers should not be neglected as it is not possible that the demand for these workers to disappear.

Aside from that, the government also could offer incentives for both job seekers and employers. For example, after the job seekers, especially young fresh graduates, found secure jobs, they would receive wage incentives for a certain period. While for the employers, by hiring the targeted group, they could receive tax exemption or hiring incentives. This kind of incentives could also be granted to firms for hiring Technical and Vocational Education and Training (TVET) graduates, women, and local workers to increase these groups’ participation in the labour market. This win-win situation would reassure the job seekers to enter the formal labour market.

The employers also should promote job vacancies and ensure that the information of vacancies reach job seekers. The current hiring practices should be enhanced to avoid the destruction of human capital in the long-term. In the meantime, the graduates must also improve their own added values. They should not solely depend on the learning process in the class, but must also develop their soft skills, such as communication, second or third language, and entrepreneurial skills, all of which would enable them to create their own job opportunities. Accompanied with the rise of gig economy, the job seekers could explore more chances to learn new experiences that would aid them in the future.

This study is constrained by some limitations, mainly in terms of data. Since the government does not collect the data on previous employment, the occupational and industrial mismatch indexes could not be measured. While, as for the skills mismatch, it is possible that vacancies are measured with some errors, since vacancies are severely underreported and not all hires are done through formal advertisement. However, these problems are prevalent in all matching function studies (Ilmakunnas and Pesola, 2003).
Acknowledgements

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References


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Notes

1 Malaysia Standard Classification of Occupations (MASCO) 2013, have nine groups of occupations at one-digit level to describe the labour market. Groups 1, 2 and 3 are considered high-skilled workers with tertiary level of education, groups 4, 5, 6, 7 and 8 are known as middle-skilled workers with secondary and post-secondary level of education and group 9 is low-skilled workers with at least primary education.

Appendix 1

Descriptive statistics

This segment provides the background information about the Malaysia labour market. First, the vacancy-unemployment relationship. In Figure 4, despite the increasing number of high-skilled unemployed persons, the number of vacancies for this group dropped in 2011 and has remained stagnant until recently. However, a different situation can be said for the low-skilled group. The number of unemployed persons has decreased, while the number of vacancies keeps increasing.
Appendix 2

_Beveridge curve_

Beveridge curve is one of the indicators of mismatch. Figure 5 plotted the pattern of Beveridge curve for Malaysia which suggested a potential mismatch in the labour market.
Appendix 3

Job-finding rate

The job-finding rate is expressed as the number of unemployed persons who manage to secure a job divided by the total number of unemployed persons. Generally, the job-finding rate would increase when there are fewer unemployed workers and more job vacancies, which would create more new successful matches. Figure 8 shows the job-finding rate in Malaysia. In 2014, the job-finding rate was the highest, as that year recorded the highest number of successful new matches compared to other years.
Appendix 4

Matching function estimation

Matching efficiency is the efficiency of the system to match job seekers with open positions in the industry (Hall and Schulhofer-Wohl, 2018). The vacancy share was estimated using pooled least square (POL) regression (Marthin, 2012; Erken et al., 2015):

\[
\ln \left( \frac{H_{i,t}}{U_{i,t}} \right) = c + (\phi) + (\Phi_i) + \alpha \ln \left( \frac{V_{i,t}}{U_{i,t}} \right) + \epsilon_t
\]

(21)

where

\( \phi \) aggregate matching efficiency

\( \Phi_i \) skills-specific matching efficiency.

The matching efficiency was estimated using stochastic frontier analysis (SFA). Ilmakunnas and Pesola (2003) and Němec (2015) have employed SFA to respectively calculate the matching efficiency for the Finnish and Czech labour markets. Following Coelli (1996), the SFA model is as follows:

\[
y_i = \gamma + \gamma_1 x_i + \epsilon_i
\]

\( i = 1, \ldots, N \)

\( \epsilon_i = p_i - q_i \)

\( p_i \sim N(0, \sigma_p^2) \)

\( q_i \sim F \)

(22)

where

\( \gamma \) constant

\( \gamma_1 \) vector of unknown parameter

\( \epsilon_i \) sum (or the difference) of a normally distributed disturbance

\( p_i \) random (stochastic) variables assumed to be \( N(0, \sigma_p^2) \) and independent of the \( q_i \)

\( q_i \) non-negative random variables assumed to account for the cost of inefficiency in production, which are often assumed to be \( \sim F(0, \sigma_q^2) \)

\( y_i \) vector of output

\( x_i \) vector of input.

Prediction of specific efficiency are defined as

\[
EFF_i = \frac{E(y_i q_i, x_i)}{E(y_i | u_i = 0, x_i)}
\]

(23)

\( EFF_i \) will take a value between one and infinity and can be defined as
The value of efficiency would be \( 0 < \text{EFF}_i < 1 \).

For the robustness check, the matching efficiency was reanalysed using data envelopment analysis (DEA). Following the regression, the estimated elasticity of vacancy was found to be around 0.695 (SFA) and 0.631 (DEA).

Table 5 shows the estimated elasticity of vacancy and the magnitude of matching efficiency for Malaysia labour market.

The elasticity of matches with respect to (registered) vacancies for the Malaysia labour market was found to be 0.7, which was relatively larger than that of the US (\( \alpha = 0.5 \)) and Japanese (\( \alpha = 0.4 \)) labour markets. However, the elasticity ranged between 0.5 to 0.7 is acceptable and commonly used in the literature (Petrongolo and Pissarides, 2001).

### Table 5

<table>
<thead>
<tr>
<th>Matching efficiency</th>
<th>High-skilled</th>
<th>Middle-skilled</th>
<th>Low-skilled</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.722</td>
<td>0.725</td>
<td>0.720</td>
</tr>
</tbody>
</table>

Matching efficiency

<table>
<thead>
<tr>
<th>Year</th>
<th>Efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>2007</td>
<td>0.819</td>
</tr>
<tr>
<td>2008</td>
<td>0.807</td>
</tr>
<tr>
<td>2009</td>
<td>0.757</td>
</tr>
<tr>
<td>2010</td>
<td>0.617</td>
</tr>
<tr>
<td>2011</td>
<td>0.658</td>
</tr>
<tr>
<td>2012</td>
<td>0.536</td>
</tr>
<tr>
<td>2013</td>
<td>0.877</td>
</tr>
<tr>
<td>2014</td>
<td>0.932</td>
</tr>
<tr>
<td>2015</td>
<td>0.913</td>
</tr>
<tr>
<td>2016</td>
<td>0.796</td>
</tr>
<tr>
<td>2017</td>
<td>0.724</td>
</tr>
</tbody>
</table>

Notes: Significant at *10%, **5%, ***1%.

The matching efficiency for middle-skilled worker was higher than that of other skills. This is due the percentage of new hired was the highest for this type of skilled. In average, 57% of new hired was from the middle-skilled category, followed by high-skilled and low-skilled category, which indicated 28% and 15% of new hired respectively. Meanwhile, the yearly matching efficiency was high during the economic recession (2008, 2009, 2013 and 2014) as in recessions, it is easier for employers to fill a vacancy, and hence matches are made quicker (Marthin, 2012).