The Effect of Over-education and Overskilling on Economic Growth across States in Malaysia: An Empirical Evidence

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Abstract: This paper explores the incidence and the outcome of educational and skill mismatches in economic growth across state in Malaysia from 2006 and 2012. The mismatch indicators were gauged using the Job Analysis (JA) and the mode method. Using micro cross-section data from Labour Force Survey (LFS) between 2006 and 2012, overqualification (underqualification) and overskilling (underskilling) were reported between 13 (20) and 19 (34) percent. Results for Fixed Effect (FE) regression demonstrated overqualification and overskilling had a favourable impact on regional growth. By contrast, the growth was negatively associated with an increase in undereducation and underskilling incidence. The findings depict that the economic performance at the regional level in Malaysia is associated with an increase in overqualification and overskilling. The presence of such incidence, therefore, may not be a sign of inefficient public investment and resources allocated to education are in fact economically beneficial at a macro-level.

Keywords: over qualification, over skillin, economic growth, state, Malaysia

Introduction

Researchers in traditional labour market have argued that workers seek for jobs on the large or regional rather than small market due greater job opportunities provided in the former than in the latter. Yet, due to spatial mobility constraints experienced by some workers, they have looked for work on the local or small labour market (Hensen, de Vries, & Cörvers, 2009; Cabus & Somers, 2018). Job seekers who experienced flexibility limitation tend to end up in a local job that below than their actual education or skill background, resulting in overqualification (Büchel & Battu, 2002; Kulkarni, Lengnick-Hall & Martinez, 2015) or overskilling (Zakariya, Abdul, et al., 2017; Zakariya & Yin, 2017).

Assessments of the degree of the consequence of overqualification and overskilling between large and small labour market may seem decided for policymakers as such incidences are typically ending up in negative rather than positive outcome at an individual nor at a firm level.\textsuperscript{1} The negative outcome at both levels may drive down local economic performance and leads to an unequal distribution of economic development between smaller and larger region. This may seem to be truly in the context of Malaysia as differences in educational attainment, unemployment, occupation education and skills utilisation has led to regional income inequalities and unbalanced growth among states (Yussof & Kasim, 2003; Ragayah, 2008; Saari, Dietzenbacher, & Los, 2014; Abdullah, Doucouliagos, & Manning, 2014; Hutchinson, 2017; Zakariya, Hermansson, Yin, Fazlin, & Noor, 2019).

Nevertheless, if the supply of highly educated workers is not in line by demand at the state labour market, then the impact of education and skill on state Growth Domestic Product (GDP) may not as high as expected relative to if the state werefully utilised the education and skills of all the mismatched workers (McGowan and Andrews, 2017; Adrian, Desislava, Ganev, & Aleksiev, 2018).\textsuperscript{2} Yet, educational and skill mismatch incidences may also in turn lead to apposite outcome on state economic growth. This is because the overqualified and overskilled are typically have accumulated more schooling and skill, hence, more

\textsuperscript{1} At an individual-level study, both overeducated and overskilled earn significantly lower than their comparable well-matched (see review in Leuven & Oosterbeek, 2011) and greater job dissatisfaction (Fleming & Kler, 2008; Di Paolo & Mañé, 2016; Verhaest & Verhofstadt, 2016). Some studies found over-education at the workplace improves firm level productivity (Jones, Jones, Latreille, & Sloane, 2009; Kampelmann & Rycx, 2012; Mahy, Rycz, & Vermeulen, 2015; Philipp Grunau, 2016).

\textsuperscript{2} A study from Wald (2004) Canada showed that over-qualification resulted in approximately 2 percent or $20 billion reduction in the Canadian Gross Domestic Product (GDP) due to lower tax revenues among the overqualified workers.
productive than that of the well-matched group (Sloane, Battu, & Seaman, 1996; Chiswick & Miller, 2010; Sánchez-Sánchez, McGuinness, 2015). Consequently, they may have driven up local economic growth. Therefore, any economic impact of overqualification and overskilling at the regional level could be possible. As far as we are concerned, there has no study examined the link between educational-skill mismatch and economic growth. Instead, there has very few study examined the linkages between educational mismatch on growth (Ramos, Surinach, & Artús, 2012; Zakariya, Hermansson, Yin, Fazlin, & Noor, 2019). It should be acknowledged that both educational and skill mismatch are two difference phenomenon in the labour market as each incidence captures different dimension (Mavromaras, Mcguinness, O’Leary, Sloane, & Fok, 2010; Zakariya, Abdul Jalil, & Yin Yin, 2017; Zakariya & Yin, 2017).

Therefore, this paper aims to explore the incidence and the consequence of not only aggregate overqualification but also aggregate overskilling on economic growth across states in Malaysia between 2006 and 2012. If overskilling reduces workers’ own productivity, this negative outcome might be translated into decreasing output at macro-level, i.e. GDP growth, especially state with higher proportion of overskilling in the labour market. In doing so, the rest of the paper is structured as follows. Section two reviews past studies related to the outcomes of overqualification and overskilling at the aggregate level if any. Dataset, measurement and empirical method are outlined in section three. Section four focuses on empirical findings whereas section five highlights discussion and conclusion of the study.

**Overqualification, Overskilling and Regional Economic Growth**

The typical findings of negative outcomes of overqualification incidence on workers tend to have an adverse effect at a firm or a country-level. At the firm level, for example, Tsang (1987) revealed that over-education indirectly reduced firm productivity in Bell companies thru job dissatisfaction mechanism. A one-year increase in surplus education led to a losing in 8.4 percent firm output. In Germany, Philipp (2016) demonstrated that under-education rather than overeducation impair firm productivity. Other studies demonstrated that overqualification decreased workplace average pay (Belfield, 2010) and led to workplace dis-harmonization in terms of absenteeism and quit rate (Jones, Jones, Latreille and Sloane, 2009; Belfield, 2010).

There are few studies, however, found that overqualification results in workplace improvement with respect to financial performance (Jones et al., 2009) and firm productivity (Kampelmann & Rycx, 2012; Mahy et al., 2015). For instance, Mahy et al. (2015) found that higher incidence of over-education at workplaces tend to raise firm productivity, especially at firms with a greater proportion of high-skilled workers at the workplace in high-tech/knowledge-intensive industries. These may be due to the overeducated have more skills and greater educational attainment than their comparable well-matched, hence more productive (Hartog, 1988; Sloane et al., 1996; Hartog, 2000). This might have an impact on other workers’ productivities at the workplace, hence, improving establishment-level productivity. Battu et al. (2003) and Mohamed Noor et al. (2017) for example found workers who employed with co-workers who have more schooling than theirs boost own earnings. Indeed, few studies found firms in regions with greater proportion of human capital stocks are more productive than firms in regions with less one (Acemoglu & Angrist, 2001; Moretti, 2004; Liu, 2007; Sand, 2013; Mohamed Noor et al., 2017).

Up to a certain point, negative outcomes of over-education at the firm level may possibly reduce national income than would be the case if all the skills and knowledge of the overqualified or overskilled workers were fully exploited within the economy. Unfortunately, up to our knowledge, there is very little study available at a macro-level. McGowan and Andrews (2017) found overskilling decreases labour productivity across 19 OECD countries. Guiorgnet and Peypoch (2007) and Adrian et al., (2018) in their respective studies in France and European countries found skill mismatch tends to reduce a country’s aggregate productivity.

With respect to the outcomes of over-education on growth, there seems unconvincing findings. A study by Jaoul-Grammare and Guiorgnet (2009) provides a limited evidence of negative causality of over-education on France’s economic growth in the short run. Specifically, the study revealed that higher proportion of overeducated workers without degree in the workforce was negatively associated with growth in France. Instead, Ramos et al. (2012) demonstrated that all educational mismatch indicators, i.e. - over-education, overqualification and years of over-schooling are positively associated with growth, ranges from 3 to 13 percent across nine European countries. Of the three indicators, the effect was greater for the overeducation incidence

3 By contrast, the authors found no evidence of causality relationship for the three different groups of overeducation - the share of overeducated workers of the higher education (SOHE), overeducated workers of the Higher Education (OHE), and overeducated workers without any degree of higher education (OWHE)
In a recent study, Zakariya et al. (2019) examined the outcome of aggregate overqualification on growth across region in Malaysia from 2005 to 2017 using Dynamic Panel Data (DPD) time series analysis. In the study, the aggregate overqualification was measured as the fraction of workers with at least a bachelor’s degree qualification who were employed in an occupation below than the professional job level. The authors found strong evidence of negative outcome of the aggregate overqualification on growth across region in Malaysia although the magnitudes of the effect were smaller (between 0.02 and 0.03).

Perhaps, the inconclusive results may be partly explained by differences in the measurement, method and dataset employed. The mismatch could have different outcomes in developing economies due to lower income, but education levels are rising faster than the growth as noted earlier. Therefore, they might not reap as much benefit from higher education investment as they might hope for due to slower job creations leave the underutilisation of the highly educated person. Nevertheless, to some extent, the negative consequence of over-education on growth may depict there would be growth penalty for not being fully utilised the knowledge and skills of highly educated workers at the regional labour market.

Dataset, Measurement and Methodology of the Study

Dataset and Measurements of Aggregate Educational and Skill Mismatch

To measure educational and skill mismatch at aggregate level, we employed data from Labour Force Survey (LFS), 2006 – 2012 provided by Department of Statistics Malaysia (DoSM). The advantage of the LFS’s sample lies in the fact that a number of key variables such as educational and qualification level, occupations and types of industry are recorded using a homogeneous classification, allowing us to calculate the rate of educational and skill mismatch and other variables in a comparable way across 12 states and 2 federal territories (Kuala Lumpur and Labuan). This allows us to measure the rate of overqualification (underqualification) and overskilling (underskilling) using traditional method of the Job Analysis (JA) and the mode method. In particular, we calculate first both the educational and skill mismatch at the individual level, and subsequently aggregate them into regional level to obtain regional indicators of the incidence following Ramos et al. (2012). Meanwhile, macro level data, i.e. - GDP per capita ($Y$) and capital ($K$) across state, each was extracted from the DoSM and the Malaysia Investment Development Authority (MIDA). Both variables were measured in logarithm form based on 2010 constant price (Ringgit Malaysia).

<table>
<thead>
<tr>
<th>Table 1. Descriptive statistics of the key variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Year</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Inccap (lnK)</td>
</tr>
<tr>
<td>Schooling (sch)</td>
</tr>
<tr>
<td>aggunderq_ja (%)</td>
</tr>
<tr>
<td>agcoverq_mode (%)</td>
</tr>
</tbody>
</table>

4 Under the LFS, educational level and highest qualification attained are classified following the 1997 International Standard Classification of Education (ISCED) while occupations are classified in accordance with the 2008 International Standard Classification of Occupation (ISCO).
5 Details of the mode method are outlined in Ramos et al. (2012).
6 Due to data on capital formation was not available across state, the variable $K$ was measured using capital investment received by state following Gyimah-Brempong, Paddison and Mitiku (2006)(Zakariya et al 2019).
Table 1 presents the mean and standard deviations of some key variables used in the paper. On average, GDP per capita (lnY) is 10.36 (s.d: 1.07), capital per capita (lnK) and labour (lnL) per year is 20.56 (s.d – 2.43) and 13.16 (s.d:1.05) per year, respectively. With respect to human capital endowment, approximately workers have completed nearly 11 years (s.d: 0.89 year) of schooling.\(^7\) This was equivalent to SPM qualification. Turning to educational mismatch, in general, the proportion of aggregate overqualification was a bit higher for the mode (aggoverq_mode) than the JA method (aggoverq_ja) with the corresponding figure of 16% against 18% each. By contrast, the incidence of aggregate underqualification was a much lower for the latter (aggunderq_ja), roughly 20% relative to 33% for the former method (aggunderq_mode). With respect to skill mismatch, aggregate overskilling (aggversq) and underskilling (aggundersq) represented about 13.7% and 25% of the total employed person.

Looking first at the JA method, Figure 1 shows in general, the proportion of overqualification does not have a clear pattern. In some state, overqualification remained higher between 2006 and 2002 as illustrated in Perlis, Terengganu and Kuala Lumpur. Other states demonstrated a decline trend in Kedah, P. Pinang, N. Sembilan and Perak whereas the incidence remained lower and stable in Sarawak, Selangor, Sabah and Johor.

Turning to mode method (Figure 2), there seems a clear trend where the incidence of overqualification showed an increase trend between 2006 and 2009 in almost states and the incidence remained stable after cross all states (albeit for Kuala Lumpur and Labuan).

\(^7\)Following the 1997 ISCED, we converted levels of qualification among the employed persons (for example, UPSR, PMR/SRP and SPM) into number years of schooling completed. For instance, UPSR requires 6 years of education while SPM requires 11 years of education.
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Figure 2. The Proportion of Over and Under qualification under the Mode Method Across State (%)

With respect to underqualification, such incidence always outnumbered overqualification in almost all states regardless of measurements. In fact, Figure 2 shows underqualification was always greater than overqualification across all states over the period of 2006 – 2012.

Nevertheless, the proportion of overskilling demonstrates a steady increase across almost all states (albeit for WP Kuala Lumpur) between 2006 and 2012. Instead, the incidence of underskilling exhibits a decline trend over the same period for all states.

Figure 3. The Proportion of Over and Underskilling Across State (%)
Empirical Framework

Due to the nature of data used here, this paper employs fixed effect (FE) regression to ascertain the effect of educational and skill mismatch on growth. This is because the method permits us to control for unobservable heterogeneity through the inclusion of state and time-fixed effects. In particular, GDP per capita ($lnY$) between 2006 and 2009 and between 2006 and 2009 is regressed on the initial level of GDP per capita ($lnY_{t-2}$) and the educational-skill mismatch indicators for the different sets of regions both periods. Following Ramos et al., (2012), the model can be written as below:

\[
(lnY_{t,t-2})/x = \alpha + \beta \cdot lnY_{t,t-2} + \delta \cdot lnK_{i,t-2} + \eta \cdot lnsch_{i,t-2} + \gamma \cdot x_{i,t-2} + \eta + v(1)
\]

where $ln\text{gdp}_{it}$ is the natural log of real GDP per capita of region $i$ at year $t$; $lnK_{i}$ and $lnsch_{i}$ represent the natural log of real capital per capita and years of schooling of the working population in region $i$, respectively; $x_{i,t-2}$ denotes educational-skill mismatch indicators in state $i$ at year $t$; $\eta$ is a time-fixed effect; $\mu_{i}$, a region fixed effect; and $\epsilon_{i,t}$ is a random error term that varies across region and time periods.

Empirical Findings

Table 2 presents the results of Fixed Effect (FE) estimator across models with the different explanatory variables. In models (1), GDP per capita was regressed on initial GDP per capita and traditional growth model, i.e. $lnK$ and $lnS$. Indicators of educational and skill mismatch among the working population are included in models (2) to (4). Specifically, percentage of overqualification following objective method ($lnoe_{om}$) and mode method ($lnoe_{mm}$) is included in model (2) and model (3), respectively while in model (4), we controlled for percentage of overskilling ($lnper_{os}$). The significant of F-test across models indicating that the FE estimator is preferable than the Ordinary Least Square (OLS) estimator.

**Table 2. Growth effect of overqualification and overskilling with regional, industry and time fixed-effects**

<table>
<thead>
<tr>
<th>GDP per capita ($lnY$)</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial GDP per capita ($lnY_{t-2}$)</td>
<td>-0.2167***</td>
<td>-0.2081***</td>
<td>-0.2163***</td>
<td>-0.2078***</td>
</tr>
<tr>
<td></td>
<td>(0.0565)</td>
<td>(0.0593)</td>
<td>(0.0579)</td>
<td>(0.0587)</td>
</tr>
<tr>
<td>lncapital ($lnK$)</td>
<td>0.0122</td>
<td>0.0105</td>
<td>0.0125</td>
<td>0.0108</td>
</tr>
<tr>
<td></td>
<td>(0.0015)</td>
<td>(0.0014)</td>
<td>(0.0014)</td>
<td>(0.0015)</td>
</tr>
<tr>
<td>Years of schooling ($lnS$)</td>
<td>0.2012***</td>
<td>0.1228***</td>
<td>0.1698***</td>
<td>0.1977***</td>
</tr>
<tr>
<td></td>
<td>(0.0645)</td>
<td>(0.0586)</td>
<td>(0.0773)</td>
<td>(0.0632)</td>
</tr>
<tr>
<td>% overqualified workers ($lnoe_{om}$)</td>
<td>0.0610***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0127)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% overqualified workers ($lnoe_{mm}$)</td>
<td></td>
<td>0.0180***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0036)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% overskilled workers ($lnper_{os}$)</td>
<td></td>
<td>0.0500***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0112)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| N                      | 45      | 45      | 45      | 45      |
| Number of groups       | 15      | 15      | 15      | 15      |
| Adjusted R-square      | 0.9961  | 0.9961  | 0.9964  | 0.9961  |
| Rho ($\rho$)           | 0.956   | 0.956   | 0.963   | 0.956   |
| F-test (all $u_i=0$)   | 24.37***| 23.10***| 23.20***| 23.39***|

Note: *, ** and *** significant at 0.1, 0.05 and 0.01 respectively; Robust standard error in parenthesis
Results from the Table 2 reveals some interesting findings. The coefficient of initial GDP per capita \( \ln Y_{1,t-1} \) is negative and significant at 0.01 across all models, indicating that a process of regional convergence has occurred during the period under review. This process is still apparent when additional covariates are controlled for together. The effect of \( \ln K \) on growth is positive and statistically significantly different from zero at 0.01. Yet, the magnitude is very small, i.e. – less than 0.02. Likewise, the traditional indicator of human capital, i.e. \( \ln S \) across models is always positive and has a strong impact on economic growth. Other factors being held constant, an increase of additional one year of schooling completed among the working population leads to a raise in GDP per capita by approximately between 0.13 (e0.1228) and 0.22 (e0.2015) percent.⁸

Focus on our main variable interest, model (2) to model (4) show that the coefficients of overqualification and overskilling are positive and statistically significantly different from zero at the 1% level indicating that both incidences have a strong impact on regional economic growth. The magnitudes of the effects are however somewhat depending on measurement used. Using the objective method, the coefficient of \( \ln oe_{om} \) (model 2) is 0.0610, suggesting that one percent increase in the percentage of overqualified workers lead to an increase of approximately 0.06 percent in regional GDP per capita. Using the mode method (model 3), the coefficient of \( \ln oe_{mm} \) is 0.0180. Perhaps, lower return may reflect higher incidence of overqualification produced by the mode method as compared to the objective method. In model (4), the coefficient of \( \ln per_{os} \) is positive and statistically significant at the 1% level. One percent increase in the percentage number of overskilling at the regional level will lead to an increase of about 0.05 percent in GDP per capita.

Another point that emerging from Table 2 is that the impact of schooling on growth tends to decline once overqualification is included in the regression. For example, when \( \ln oe_{om} \) and \( \ln oe_{mm} \) is included together, respectively in the Model 2 and Model 3, the coefficient of \( \ln S \) is about 8 and 5 percentage points lower than the previous model. Two additional tests have been carried out in order to test the robustness of the results to changes in the econometric specification. First, we carried out the log likelihoods ratio test from both models and found that adding \( \ln oe_{om} \) in model 2 and \( \ln oe_{mm} \) in model 3 as a predictor variable result in a statistically significant improvement in model fit.

We also perform parameter test of schooling and overqualification and reject the null hypothesis that the coefficients for both parameters are jointly equal to zero. All these may indicate that overqualification effects pick up some of effects of schooling on GDP per capita. This may not be surprisingly due to the way overqualification is measured, i.e. - based mainly on years of education for any given occupation. By contrast, when overskilling is controlled for as (model 4), the growth impact of schooling does though remain similar to model 1.

In Table 3, we replace both overqualification and overskilling at the regional level with underqualification and underskilling. Threespecifications are examined. In model 5, the underqualification based on the objective method (\( \ln uoe_{om} \)) is added together with the basic model (Model 1) whereas in Model 6, underqualification is represented by the mode method (\( \ln uoe_{mm} \)). In Model 7, underskilling (\( \ln per_{us} \)) is replaced for underqualification. The results with respect to \( \ln Y_{1,t-1} \), \( \ln K \) and \( \ln S \) seem similar to Model 1 in terms of the sign and significant level with one exception where the coefficient of \( \ln S \) in Model 6 has now turned out to be negative but insignificant in both models. Therefore, the conclusions almost remain unchanged.

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⁸ Since the \( \ln S \)s in the natural logarithmic form, the percentage point effect (PE) is obtained using the following formula:

\[
PE = (e^\beta - 1) \times 100, \text{ where } \beta \text{ is the coefficient estimate.}
\]

The percentage point effect will be used throughout the discussion in this chapter. Instead, the coefficients of other variables represent the elasticity values.
Turning now on the effect of underqualification, the coefficient of \( lnue_{om} \) and \( lnue_{mm} \) respectively for Model 5 and 6 are negative and significantly with at least at the 5% level. This means that underqualification has unfavourable impact on growth. Yet, the impact is 3 times lower for the objective (Model 5) than for the mode measure (Model 6). Other factors being equal, one percentage point increase in aggregate underqualification, GDP per capita at the regional level will decline by around 0.08 percent for the former and about around 0.24 percent for the latter. Indeed, the growth impact of schooling has turned out to be negative, but not statistically significant. When underqualification is replaced with underskilling, Model 7 demonstrates that such variable \( (lnper_{us}) \) has also negatively associated with growth over the period of study. The GDP per capita at the regional level will be decreased by approximately 0.15 percent, all things equal.

**Discussion and Conclusion**

This study explored the incidence and the outcome of aggregate educational and skill mismatch among employed persons across region in Malaysia between 2006 and 2012. The study employs conventional methods of the objective and mode method in calculating the aggregate mismatch by using micro survey data, i.e – LFS and then aggregated into regional level. Between 13 and 18% (21 and 33%) of employed workers were deemed overqualified (underqualified) whereas around 14% were considered as being over skilled workers. Both incidences were comparable higher in K. Lumpur and Selangor than other states.

The findings somewhat contrast to our expectation as the developed state could experience a lower rate of aggregate mismatch than the less developed state due to the former rather than the latter can provide more suitable jobs for the highly educated person. Perhaps, the findings reflect larger numbers of vacancies in the developed states are offset by a larger number of job seekers (Mcgoldrick & Robst, 1996). This seems to be true as these states have as many as higher educational institutions relative to other states (Ministry of Higher Education Malaysia, 2018), therefore provide more highly educated job seekers.

After a range of statistical tests performed, we employed fixed effect panel data approach to investigate the growth outcome of educational and skill mismatch at the regional level. Two specifications were examined. In the first specification, we controlled for overqualification and overskilling as shown in Model 2 – Model 4. Regardless of any model, there was strong evidence of the positive impact of both incidences on regional growth. In specification 2, we replaced underqualification and underskilling for overqualification and overskilling, respectively. The results both incidences were negatively associated with regional economic

<table>
<thead>
<tr>
<th>GDP per capita (( lnY ))</th>
<th>Model 5</th>
<th>Model 6</th>
<th>Model 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial GDP per capita (( lnY_{t-1} ))</td>
<td>-0.2138 (0.0549)</td>
<td>-0.2367 (0.0560)</td>
<td>-0.2085 (0.0510)</td>
</tr>
<tr>
<td>Incapital (( lnK ))</td>
<td>0.0106 (0.0052) **</td>
<td>0.0155 (0.0090) *</td>
<td>0.0100 (0.057) *</td>
</tr>
<tr>
<td>Years of schooling (( lnS ))</td>
<td>0.2054 (0.0614) ***</td>
<td>-0.3634 (0.2230)</td>
<td>0.1476 (0.0688) **</td>
</tr>
<tr>
<td>Percentage of underqualified workers (( lnue_{om} ))</td>
<td>-0.0819 (0.0213) ***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percentage of underqualified workers (( lnue_{mm} ))</td>
<td>-0.2772 (0.1211) **</td>
<td></td>
<td>-0.1576 (0.0462) ***</td>
</tr>
<tr>
<td>Percentage of underskilled workers (( lnper_{us} ))</td>
<td>11.5950 (1.4706) ***</td>
<td>13.6998 (1.5221) ***</td>
<td>11.9833 (0.0142) ***</td>
</tr>
<tr>
<td>Constant</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of groups</td>
<td>45</td>
<td>45</td>
<td>45</td>
</tr>
<tr>
<td>Adjusted R-square</td>
<td>0.9964</td>
<td>0.9970</td>
<td>0.9964</td>
</tr>
<tr>
<td>Rho (( \rho ))</td>
<td>0.996</td>
<td>0.9969</td>
<td>0.9957</td>
</tr>
</tbody>
</table>

*Note: * ** and *** significant at 0.1, 0.05 and 0.01 respectively. Robust standard error in parenthesis.
growth. As such, our results with respect to over- and underqualification seem in line with finding from Ramos et al. (2012). The magnitudes of the impact were much higher for the mode than the objective method. This may reflect the mode tends to generate more (less) overqualified (underqualified) than the objective method.

Nevertheless, the positive impact of overqualification and overskilling may be partly due to the stylized fact that the overqualified and overskilled workers tend to earn a wage premium compared to their co-workers who have less schooling but in well-matched jobs (Sicherman & Galor, 1991).9 They might still more productive than the latter and this might have an impact on other workers’ effort. Battu et al. (2003) and Mohamed Noor et al. (2017) for example find that workers who employed with co-workers who have more schooling than theirs boost earnings. Otherwise, the overqualified workers tend to have accumulated more skills and greater educational attainment than their comparable well-matched, hence more productive (Hartog, 1988; Sloane et al., 1996; Hartog, 2000). As mentioned in human capital externality hypothesis, firms and regions with greater human capital stock tend to be more productive than firms and regions with less human capital stocks accumulation (Acemoglu & Angrist, 2001; Moretti, 2004; Liu, 2007; Sand, 2013; Mohamed Noor et al., 2017). This spillovers can be translated into improving establishment-level productivity, hence, contagious at macroeconomic level.

Moreover, the fact that the mismatched workers have accumulated more skill and schooling may suggest that the human capital of mismatched workers may contribute to public benefits associated with higher levels of the national human capital stock (Hartog, 1988; Sloane, Battu, & Seamian, 1996; Chiswick & Miller, 2010). A country with a high stock of human capital tends to exhibit higher labour productivity (Mankiw, Romer, & Weil, 1992; Hanushek & Wößmann, 2010; Breton, 2011; Hanushek, 2013), be more innovative (Lucas, 1988; Romer, 1990, 1994) and be better at adopting new technologies (Benhabib & Spiegel, 1994).

To some extent, the positive impacts of overqualification and overskilling on growth may not reflect a waste of investment in higher education in Malaysia. This is because the coefficient of schooling is always positively associated with growth regardless of the model specification even after controlling for both variables. Moreover, it is an exaggeration to say that the region with greater overqualified or overskilled worker may indicate higher levels of human capital accumulation, hence, higher labour productivity (Hanushek, Jamison, Jamison, & Woessman, 2008; Breton, 2011; Hanushek & Wößmann, 2010; Hanushek, 2013), increase the innovative capacity of the economy (Lucas, 1988; Romer, 1990, 1994) and transmission of knowledge and new technologies (Nelson & Phelps, 1966; Benhabib & Spiegel, 1994; Hanushek et al., 2015) than countries with lower levels of human capital stock.

Moreover, the findings from this paper may suggest that the growth may no longer a function solely of the supply side (educational attainment of workers) as done in many previous studies (Yussof & Zakariya, 2009; Hanushek, 2013; Amir, Khan, & Bilal, 2015; Dissou, Didic, & Yakautsava, 2016). Instead, the growth might be treated as a function of both the demand, i.e. job characteristics in which how workers are assigned in their jobs and supply side (attained education).

References


9Sicherman and Galor (1991) have observed two stylized facts of over and undereducation with respect to earnings outcomes: -

i. Workers in occupations that require less schooling than they actually have (overeducated) earn lower wages than workers with similar levels of schooling who hold jobs that require the level of schooling they have obtained. These overeducated workers, however, earn more than their co- workers who are not overeducated (i.e., who have the required and, there- fore, lower schooling).

ii. Workers in jobs that require more schooling than they have obtained (undereducated) receive higher wages than workers with the same level of schooling who work in jobs that require just their level of schooling. Undereducated workers, however, receive lower earnings that do their co-workers with the required and, therefore, higher schooling.
Skills Mismatches-An Impediment to the Competitiveness of EU Businesses. https://doi.org/10.2864/448258


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The Effect of Over-education and Overskilling on Economic Growth across States in Malaysia: An Empirical Evidence