UNIVERSITY OF ABERDEEN

CELMR

Business School

Department of Economics

Centre for European Labour Market Research

Overskilling and Overeducation In Malaysia

Harminder Battu and Zainizam Zakariya

Discussion Paper in Economics No 15-20

December 2015

ISSN 0143-4543

Overskilling and Overeducation in Malaysia

Harminder Battu[a], Zainizam Zakariya[b]

[a] *Department of Economics, Business School, University of Aberdeen , Aberdeen, UK, AB24 3QY*

[b] *Department of Economics, Faculty of Management and Economics, Universiti Pendidikan Sultan Idris, 35900 Tanjung Malim, Perak, Malaysia*

Dec 2015

ABSTRACT

Using a workplace survey from Malaysia (the 2007 Productivity Investment Climate Survey), this paper examines the incidence, determinants and consequences of overskilling in the Malaysian manufacturing sector. The degree of overskilling is found to be low relative to other comparable countries and lower among the more highly educated but higher among those who are overeducated. Workplace characteristics such as share of workforce with university qualifications, hiring practices, capital intensity, and degree of competition, all seem to have an impact on the probability of overskilling. Overskilling is also found to reduce an individual's earnings and has a negative impact upon firm performance.

Keywords: overskilling, overeducation, earnings, Malaysia

JEL Classifications: J24, J31

1. Introduction

Over the last thirty years, many low or middle income countries have invested heavily in their educational systems. Though educational attainment has risen there has been limited attention paid to the quality of match between a worker's education and skills and that required in the workplace (Mehta *et al*., 2010). Indeed, the vast bulk of research on the utilisation of education and skills in the labour market focuses on the developed countries with the various reviews by Hartog (2000), Sloane (2003), McGuiness (2006), Oosterbeek and Leuven (2011) making little or no mention of matching in low or middle income labour markets.[1] The stems principally from a lack of data in these countries on the education or skills required to perform in a job (Mehta *et al.,* 2010).

This study examines match quality in Malaysia. Malaysia is a middle-income country which has, since the 1970s, moved from being a primary goods exporter to one that is much more reliant on manufacturing and services. Education has played a pivotal role in this transformation with higher levels of investment and educational attainment (UNDP, 2009). As the proportion of the population with secondary and tertiary education has increased significantly from 46% in 1985 to 77% in 2004, doubts have been inevitably raised about the quality of matching in the Malaysian labour market (Lim et al. 2008; World Bank, 2009).

A unique workplace dataset from 2007 (Productivity Investment Climate Survey) is utilised and this offers a number of key advantages. First, it contains extensive information on the skills and educational requirements of jobs allowing for an analysis of both overeducation and overskilling. Traditionally the mismatch literature has focused on overeducation (i.e. comparing actual educational attainment with the formal education required in the job) though it is broadly acknowledged that this is a far too narrow indicator of mismatch (Mavromaras *et al*. 2009). Overskilling (the extent to which workers are not able to utilise all their skills and knowledge in their current employment) is a broader concept going beyond formal educational qualifications and is perhaps better at controlling for unobserved individual differences in skills, ability and knowledge (Mavromaras *et al*. 2009, 2010). Second, overskilling allows us to investigate the quality of an employer–employee match across the whole spectrum of educational attainment. This is not feasible when we use formal education qualifications, as being overeducated makes little sense for the large number of workers with low or minimal educational qualifications. Third, having a matched employer-

[1] This is somewhat surprising since Blaug (1973) in his classic study, identified graduates in India as accepting lower paid jobs that were incompatible with their educational qualifications.

worker dataset allows for an analysis of matching at both an individual and workplace level allowing us to ascertain how firm-level characteristics influence match quality and how match quality impacts on firm performance. As far as we are aware, overskilling has only seriously been examined at the individual level (Allen and van der Velden, 2001; Mavromaras *et al*., 2009; Mavromaras *et al*., 2010; McGuinness and Sloane, 2010) though a small literature has examined overeducation at the workplace level (Battu *et al*., 2003). An exception is a study by Belfield (2010) which examines overskilling at the workplace level using UK data.

Given this we have four sets of objectives. First, we document the extent of educational and skills mismatch for individuals. Second, we investigate the determinants of overskilling not only across workers but also across workplaces, i.e. the determinants of workplace overskilling. Specifically, we investigate the extent to which overskilling is influenced by workplace hiring practices, firm size, capital intensity and the presence of competitors. Here, we investigate whether the overeducated are also more likely to be overskilled. Third, we explore the effect of overskilling on earnings from the perspective of both the individual and the workplace. Fourth, we examine whether there are externalities associated with overskilling by examining the effects of overskilling on a firm's performance in terms of absenteeism, quit rates, productivity, total output and sales.

This paper is organised as follows. Section 2 outlines our data, presents some descriptive statistics and outlines how we measure match quality. Section 3 focuses on our empirical findings focusing on the determinants of individual and workplace overskilling, the effects of match quality on earnings and the effects of overskilling on a firm's performance. The final section provides a few concluding remarks.

2. The Data

The data used in this paper is taken from the second survey of the Malaysian Productivity Investment Climate Survey (PICS-II) which was carried out in 2007.[2] This is a workplace survey and a collaborative effort between the World Bank and the Malaysian Government. The survey attempts to understand the investment climate faced by enterprises and how this impacts upon business performance. The survey provides information on a wide

[2] The first (PICS-I) was administered in 2002, and though it contained an individual and firm survey, we have no access to the individual-level data.

range of workplace and firm characteristics, product market characteristics, workplace performance and management practices.

PICS-II covers the manufacturing and business support services sectors with 1,115 firms in the former (across nine industries) [3] and 303 firms in the latter. Here we focus on the manufacturing sector since this is representative of the manufacturing sector as a whole (World Bank, 2009).[4,5] For each of the workplaces, structured interviews were conducted with the Chief Executive Officers (CEOs), general managers or business owners. In addition, the management were asked to arrange for the completion of a "Workplace Characteristics Questionnaire" seeking data, for example, on the level and composition of employment. Self-administered questionnaires were also distributed to up to ten random samples of full-time employees at all workplaces where the senior manager had agreed to employee involvement. This sought information on the usual array of demographic and work-related information as well as human capital endowments (i.e. earnings, previous and current job, education, skills, training, and work experience). The response rate here is high with the target number of ten full-time workers being successfully interviewed in 94% of workplaces.

The individual and workplace surveys are merged so that the information set is rich in details on multiple workers per workplace. We confined our attention to respondents who were in full-time employment, aged between 15 and 64, who reported positive earnings and to workplaces where more than four workers had responded to the worker survey. Since we are only interested in Malaysian workers, we excluded foreign workers from the analysis.[6] This leaves us with 9,078 workers (split evenly by gender) across 1,043 manufacturing firms.

Table 1 provides some descriptive statistics focusing on a set of key variables. Respondents are on average 35 years of age and reported to have about 10 years of schooling which is equivalent in Malaysia to upper secondary qualifications. They have also accumulated on average around 14 years of work experience (equivalent to 165 months), 7.6

[3] The nine are food processing, textiles, garments, wood and furniture, chemical and chemical products, rubber and plastics, machinery and equipment, electrical and electronics, motor vehicles and parts.

[4] According to the World Bank (2009, p. 170): " …. the sampling methodology of PICS-II: (1) generates a sample representative of the whole economy that substantiates assertions about the manufacturing and business support services sectors; and (2) generates large enough sample sizes for selected industries to conduct statistically robust analyses." However, since business services are only a subset of the service sector we exclude them from our analysis. Appendix 1 assesses the representativeness of PICS-II through a comparison with other Malaysian data sources.

[5] According to 2014 Malaysian Labour Force Survey around 17% of Malaysian jobs in 2013 were in manufacturing with around half in services.

[6] Foreign workers account for nearly 12% of the total sample in the manufacturing sector. The majority of foreign workers were attached to unskilled jobs and most of them come from Asian countries such as Indonesia, Bangladesh and India.

years of job tenure within firms and 42% had once attended a training course. Women are slightly younger than men (34 versus 36 years) and men have more work experience and job tenure than women (15 years and 8 years respectively versus 12.4 years and 7 years respectively). However, women are slightly better educated with 24% holding higher educational qualifications (both diploma and university qualifications) relative to 19% amongst men. Though a quarter of women occupy higher job levels (management and professional) compared to 22% of men, women are twice as likely as men to be working in unskilled jobs. Men work on average two hours longer per week than women and earn around 20% more than women in terms of hourly earnings.[7] With respect to firm characteristics, on average, firms are well established and mature, with an average life of 33 years. Around 40% of the firms have less than 50 employees with 30% being wholly or partly foreign owned.

As stated earlier, the PICS-II allows us to examine various types of match quality. Overskilling measures are constructed using respondents responses to the following two statements:

i. *Your current job offers you sufficient scope to use your knowledge and skills*[8]

and

ii. *You would perform better in your current job if you possess additional knowledge and skills*

For both statements, four responses were available: do not agree at all, somewhat agree, agree and agree completely (Table 2). Around 70% of respondents agreed or completely agreed with statement one with similar responses across gender. To aid our later empirical estimations, we collapsed the four responses into three to create a new variable, termed overskilling (see bottom panel of Table 2). Those with response 1 are classified as severely over-skilled, those with response 2 are classified as moderately over-skilled, and those with responses 3 or 4 are classified as well-matched. The extent of overskilling (both severely and moderate) is around 31% and this is low compared to the 53% (severe and

[7] Information on income is available on a monthly basis. However, since there is information on hours of work per week we can calculate hourly earnings by dividing the monthly salary by 4.3 and then further dividing it by the average number of hours worked per week (World Bank, 2009).

[8] This statement is similar to that used elsewhere. Allen and van der Velden (2001) measure overskilling from the statement: "My current job offers me sufficient scope to use my knowledge and skills". Green and McIntosh (2002) combine responses to two statements: "In my current job I have enough opportunity to use the knowledge and skills that I have"; and "How much of your past experience, skills and abilities can you make use of in your present job?"

moderate) reported for the UK by Belfield (2010) and the 44% for Australia found in Mavromaras *et al*. (2010).[9]

The responses to statement *ii* are also set out in Table 3. Again we collapsed the four responses into three with responses 1 and 2 being classified as well-matched, response 3 as moderately underskilled and response 4 as severely underskilled. The extent of skills deficit at around 80% seems high relative to other countries.[10] For the UK, Green and McIntosh (2007) find that nearly two-thirds of workers have a skill deficit though severe underskilling is only 13% compared with our estimate of 26%. Allen and van der Velden (2001) in the Netherlands report an underskilling incidence for workers of 50% though they focus only on graduate workers.

More conventional overeducation measures are constructed using the following statements:

iii. *According to you, what is the most appropriate level of education for the work you are doing?*

iv. *According to you, what is the most appropriate field of education for the work you are doing?*

Under statement *iii*, there are six educational levels to choose from, from (1) degree, to (6) informal/no qualification. By comparing the survey respondents' actual educational attainment with the perceived appropriate education required for the job,[11] we derived conventional estimates of overeducation and these are presented in Table 4. Less than a fifth (18.5%) of workers are overeducated, whilst 52% are adequately matched, and about 30% are undereducated. It is difficult to compare these estimates with those found elsewhere since there is considerable variation in the incidence of overeducation across the different measures used. Nevertheless, the incidence of overeducation in Malaysia seems to be at the lower end of the existing estimates. Groot and Maassen van den Brink (2000) undertake a meta-analysis based on data from 25 overeducation studies and find that the incidence of overeducation varies from 10% to 42% with the unweighted average for overeducation standing at 23.3%. A recent review by Leuven and Oosterbeek (2011) reports a mean overeducation rate across

[9] McGuinness and Wooden (2007) and Mavromaras *et al.* (2009) for Australia report a rate of severe overskilling of up to 15% and moderate overskilling of up to 29%.

[10] The problem of skills deficits is acknowledged by a recent World Bank report (World Bank, 2010), which stated that "despite Malaysia's impressive development in the last few years, many Malaysians have not been able to fully benefit from the country's growth. One major challenge is that many workers lack the necessary skills to be productive in the fast changing and increasingly competitive labor market".

[11] We are assuming that the appropriate level of education equates with the minimum education required for the job.

studies of 30% with self-assessment approaches having an average overeducation rate of 37%.[12]

For statement *iv*, there are four options available: (1) only your own field; (2) related to my field; (3) completely different from my field; and (4) no specific fields are required for this job. Over half of the respondents (Table 5) were reported to be working in jobs unrelated to their field of education and only 7% of workers were matched to their own specific field of education. These findings are close to those found in Allen and van der Valden (2001) for the Netherlands but higher than that found in Robst (2008) for the US, where only 20% of the sample reported that their field of study and work were not related. The differences may reflect the use of different samples (i.e. a graduate sample versus a sample of the whole workforce).[13] For convenience purpose, we categorised the four responses into two categories – only your/related to your field (response 1 and 2) and outside own field (response 3 and 4).

The correlation between the overskilling and overeducation measures is found to be low indicating that the two matching measures are quite different entities (Table 6). Of those who are overeducated, about a third are considered to be overskilled (a quarter are moderately overskilled and less than ten percent are severely overskilled). This compares with an equivalent figure of half found in Green and McIntosh (2007) and Mavromaras *et al.* (2009). Similarly, only around one in five of the moderately overskilled and one in four of the severely overskilled (Table 7) are identified as overeducated (using the level of education measure), though a larger proportion of overskilled workers (i.e. over 60%) are identified as overeducated under the field of study measure (statement *iv*). A simple Spearman rank order test reveals a positive correlation between overeducation and both moderately and severely overskilled, though the correlation coefficient is not strong, at less than 0.1.[14]

[12] As stated earlier, there are very few comparable middle or developing country studies. Hung (2008), using data for Taiwan, finds an overeducation rate of 46% using a measure which is similar to ours while Yue and Yang (2005) find that 21% of Chinese graduates in 2003 were overeducated.

[13] Indeed, when we restrict our sample to graduate workers (diploma and university qualifications), our estimates are in line with Robst (2008) with about 21% of graduates working in jobs which are not related to their field of study.

[14] A similar weak correlation between overeducation and overskilling was found by Green and McIntosh (2007) and Allen and van der Valden (2001) with the former finding a correlation of 0.2.

3. Empirical Results and Discussion

3.1 Determinants of Worker Overskilling

Here we examine the factors that potentially drive individual worker overskilling in the labour market. For this purpose, we employ a multinomial logit regression model for both severe and moderate overskilling for males and females. Table 8 reports the marginal effects estimated from the multinomial logit at the sample means.[15] The effects of a range of demographic, human capital and workplace characteristics are assessed.

With respect to our demographic variables, we find that gender and marital status play no discernible role in determining the degree of overskilling. However, the presence of children under 12 years of age in a household does matter in that it boosts the likelihood for women being in matched jobs. This seems a little counterintuitive since one would expect the presence of children to be a greater constraint for females perhaps generating more mismatch via a more narrowly defined spatial job search (Frank, 1978; Mincer, 1978). With regards to ethnicity, being Chinese and Indian female significantly increases the risk of moderate overskilling relative to being in the majority ethnic Malay group.

A range of human capital variables are included and our general finding is that overskilling is lower for those with higher qualifications with this effect being more evident for those qualifications that are more closely aligned with the labour market. Other factors being equal, having a college diploma reduces the risk of being severely overskilled (moderately overskilled) by between 3.7 and 5.4% (between 4.7% and 10.5%) regardless of gender. This is perhaps not surprising since college diplomas are more closely tied to job requirements and are offered in Malaysia by polytechnic institutions, vocational training centres and private colleges. In contrast, many University degree qualifications are not occupation specific. In line with Belfield (2010) and Mavromaras *et al*. (2009), increased training (with current or previous firm) is found to reduce the possibility of being in a moderately overskilled position although this holds only for males. Similarly, the incidence of moderate overskilling is reduced by 4.7 percentage points amongst those with additional

[15] The marginal effects are calculated by first working out predicted probabilities on the basis of certain default characteristics and then varying each of the characteristics in turn to see how the predicted probability changes.

professional certification, but again, this is evident for men only. Professional certification refers to additional qualifications from polytechnics and vocational training institutes.

Now, we focus our attention on the effects of a range of workplace characteristics. For this, we re-estimated Table 8 by including a vector of workplace characteristics and the results are presented in Table 9. The log-likelihood ratio test is found to be statistically significantly different from zero so that the full model (the model with the inclusion of workplace characteristics) is preferable over the model without workplace characteristics.[16]

In line with our previous findings on individual education, we find that workplaces that employ more educated workers have lower overskilling. Perhaps workplaces that are skewed towards hiring more educated workers have better scope for improving match quality. In particular, our results reveal that firms where graduate workers, particularly the male sample account for over 50% of the workforce have a lower risk of workers being severely overskilled.[17] With respect to firm size, one argument may be that larger firms may be more likely to employ graduates and where they do they may find it easier to accommodate their skills and education. However, we find no discernible relationship between firm size and skills mismatch. Firms with higher foreign ownership (i.e. workplace is more than 30% foreign owned) are associated with increased moderate overskilling (albeit only for the pooled and male sample). Firms with less than 30% foreign ownership decrease the risk of severe overskilling.

One may also argue that capital intensive-firms may require more highly skilled workers relative to labour-intensive firms so that skills underutilisation may be more evident in the latter. Following Battu *et al.* (2003) and Belfield (2010), firms where labour costs account for less than 25% of total costs are assumed to be capital intensive while an establishment where labour costs denote over 75% of total costs is classified as labour-intensive. Our results here support this basic hypothesis. In particular, a higher risk of severe overskilling is prevalent for labour-intensive firms (labour costs account for over 75%) as revealed in the male samples.

Our results also reveal that the extent of skill mismatch differs by how much competition a firm faces. A higher number of competitors (i.e. more than 25) decreases (increases) the likelihood of males being severely (moderately) overskilled compared to a monopoly position (i.e. no competitors). Increased competition perhaps keeps firms more "on

[16] The coefficients on the covariates already discussed remain largely unchanged in terms of sign and statistical significance.

[17] This variable is obtained using managers' statement on the percentage of workforce with some university and other qualifications.

their toes" in terms of ensuring good matches. Our results here contrast with Belfield (2010) who finds no effect via competition.

Belfield (2010) also argues that workplace mismatch may be higher where firms have weak hiring systems and where they do not properly check worker capabilities before hiring. Here, we have information on the key factors that employers consider when hiring ("hiring practices") and in particular managers were asked to list the important criteria used to hire workers. The three that were deemed the most important for hiring employees were education, work experience, and technical skills. Other factors such as loyalty and interpersonal skills were seen as less important. We therefore control for these three criteria in hiring and ascertain their impact on overskilling. The results are not clear cut and do vary by gender. Where education is emphasised in hiring workers there is a lower risk of severe overskilling (pooled and male samples) and a higher risk of moderate overskilling (pooled and female samples). When work experience is used as the main criteria for hiring, this raises the risk of moderate and severe overskilling in general and moderate overskilling for females only. In contrast, an emphasis on technical skills based hiring results in a fall in severe overskilling. Finally, there is some evidence that firms providing on-the-job training at the workplace (albeit only for the female sample) increase the workers' odds of being in jobs that correspond to their skills. This is in line with our earlier finding that workers with greater participation in on-the-job training have a better job-match quality.[18]

In Table 10, we summarise our results with respect to the relationship between overeducation and overskilling and the extent to which overskilling is determined by overeducation. We run a multinomial logit regression estimate (marginal effects) with our overeducation terms included as covariates. These are entered separately and in specification 3 entered jointly. The other covariates are similar to those in Table 8 and 9, and the results are broadly in line with both the tables and so not reported here.

There are three key findings. First, workers working in jobs below their own level (overeducated) or outside their own field (outside own field) have a higher probability of being overskilled. Second, the effects are stronger when educational mismatch is measured

[18] A number of effects are not reported in our tables and are worth mentioning. A higher share of females at the workplace reduces the probability for workers to be moderately overskilled, especially amongst females themselves. There is also some modest evidence that where firms are experiencing staff shortages this increases the probability of moderate overskilling (albeit only for females). This is somewhat surprising since one might expect that firms that face difficulties in filling vacancies may upgrade the job tasks for their current workers and so reduce the extent of overskilling. Furthermore, a well-matched job seems more likely for firms listed in the Kuala Lumpur Stock Exchange (KLSE).

via field of education. In particular, working "outside own field" results in higher severe and moderate overskilling across all three samples. Third, the penalties are higher in terms of moderate overskilling. To some extent, these results suggest that educational mismatch seems to be a sufficient if not necessary condition for explaining the phenomenon of skill underutilisation. This is because working outside one's own field of study or below the respondents' actual educational level to some extent limits the workers' ability or opportunity to use their knowledge and skills thus resulting in overskilling.

3.2 Determinants of Workplace Overskilling

Here, we examine the determinants of overskilling at the level of the workplace. Three separate regressions are run with our dependant variable being the percentage of the workforce who are overskilled, moderately overskilled and severely overskilled (calculated using workers' responses) and these are regressed against the same workplace characteristics as before (taken from the managerial survey) with the results being presented in Table 11. In terms of the educational composition of the workforce and training the results are in line with those from the worker responses. Workplaces where more than 50% of workers have university qualifications have lower general and severe overskilling and workplaces that provide on-the-job training programmes have lower general and moderate overskilling. The results with respect to firm size, degree of foreign ownership, labour costs and hiring practices reveal little. There is some evidence that large firms (more than 150 employees) have lower overskilling at the workplace. With respect to hiring practices systems, education-based hiring is the only recruitment practice with a significant relationship, i.e. it lowers the rate of severe overskilling at the workplace.

3.3 The Effect of Overskilling and Overeducation on Earnings

Table 12 provides the results from two sets of estimations examining the effects of moderate and severe overskilling on individual earnings. Specification 1 controls for only individual-level characteristics (human capital endowments, demographic characteristics and job attributes) and specification 2 incorporates workplace-specific level variables such as the type of industry, firm size, firm ownership, hiring practices, labour costs and the educational composition of the workplace.

Both OLS and random effects estimates are provided. OLS requires us to neglect the hierarchical character of the data we are dealing with here, in which all workers are grouped into larger units, i.e. workplaces. As pointed out by Wooden and Bora (1999), individuals from the same workplace have to some extent similar characteristics when compared with those from other workplaces. Given the fact that not all these characteristics can be measured empirically, it follows that the disturbances might be correlated. In that case, this would violate the assumption of independence. A more appropriate error structure is then given by:

$$Inw_{ij} = \alpha_0 + \alpha_1 X_{ij} + \gamma_1 MOS_{ij} + \gamma_2 SOS_{ij} + \delta Z_j + \varepsilon_{ij} \quad (1)$$

$$\varepsilon_{ij} = e_i + \mu_{ij} \quad (2)$$

i= 1, . . . individual N $\qquad$ j= 1, . . . firm J

where ln$w$ is the natural logarithm of hourly earnings, X is a vector of explanatory variables, *MOS* and *SOS* respectively denote dummies for moderate and severe overskilling and Z_j is a set of characteristics describing the workplace at which individual i is employed. The composite error term ε_{ij} consists of two components, e_i which is an individual-specific error component, varying independently across individuals both within and across firms, and μ_{ij} which is the combined individual and firm error component, i.e. it differs across firms but is presumably constant for individuals within the same establishment. This error structure captures the random effects model. The usual assumptions under the random effects model are:

$$e_i \sim N(0, \sigma_e^2)$$
$$\mu_{ij} \sim N(0, \sigma_\mu^2)$$
$$E(e_i \mu_{ij}) = 0 \qquad E(e_i e_l) = 0 \qquad (i \neq l)$$
$$E(\mu_{ij}\mu_{is}) = E(\mu_{ij}\mu_{nj}) = E(\mu_{ij}\mu_{sn}) = 0 \qquad (j \neq s; i \neq n)$$

that is, the individual error components are not correlated with each other and are not auto-correlated across individuals and workplaces. As a result of these assumptions, all disturbances have the following variance:

$$E(\varepsilon_{ij}) = 0 \quad (3)$$

$$Var\ (\varepsilon_{ij}) = \sigma^2 = \sigma_e^2 + \sigma_\mu^2 \quad (4)$$

but for a given j, the disturbances for different individuals are correlated because of their common component, λ_j. As such, an efficient estimator is possible using the generalised least squares method. We should also note that any workplace and firm effects not captured in Z_j are assumed to be random and hence merged with the disturbance term.

We can make a number of remarks about the OLS estimates. First, being employed in jobs which underutilise one's skills generates a wage penalty for individual workers. Second, this penalty is larger for those who are severely overskilled, approximately 9 ($e^{-0.099} - 1$) to 11% ($e^{-0.116} - 1$).[19] The corresponding penalty associated with moderate overskilling is much lower at around 2 percent but the coefficients here are statistically significant at 0.1. The earnings losses reported here, particularly for the combined sample, are in line with Mavromaras *et al.* (2009; 2010) who find earnings penalties that range from 2% (moderate overskilling) to 16% (severe overskilling) using Australian data. Third, controlling for workplace and firm-specific characteristics (specification 2), reduces the pay penalty for severely overskilled workers to around 9% ($e^{-0.099} - 1$). Fourth, females experience a lower penalty than men (Table 13) from being severely overskilled and this is in line with Mavromaras *et al.* (2010) again using Australian data.

The RE estimates reveal a greater pay penalty for severely and moderated overskilled workers compared to the OLS estimates. The penalty for severe overskilling still exceeds that of moderate overskilling though the gap between them is narrower and there is no gender difference in the overskilling penalty. Using the lagrange multiplier (LM) test, suggests that the random effect estimates are more appropriate than OLS.[20]

Let us turn to how the wage penalty differs across different educational levels. In particular, we estimate separately the earnings penalty from overskilling across different educational levels.[21] Both OLS and RE estimates are generated and these results are presented in Table 14. Looking first at the OLS, though the earnings penalty does differ considerably by qualification level, the penalty is not evident across all levels of educational attainment. Indeed, there is no evidence that overskilling significantly reduces the hourly wage for those with university degrees. As such, our results are out of kilter with those of Mavromaras *et al.* (2009; 2010). However, severely overskilled workers do receive a wage penalty when they possess mid-level qualifications. In particular, being severely overskilled

[19] Since the earnings regression specification is in semi-logarithmic form, the percentage point effect (PE) is obtained using the following formula:

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

[20] The LM test is designed to test random effects. The null hypothesis of the one-way random group effect model is that variances of groups are zero. If the null hypothesis is accepted, the pooled regression model is appropriate.

[21] Due to the small number of observations reported for those with no/ informal qualification (Table 1), this group is combined with group of workers with primary education for easy interpretation.

(controlling for both individual and firm characteristics) leads to a reduction in earnings of 16% ($e^{-0.178} - 1$) and 12% ($e^{-0.125} - 1$) for those with lower secondary and college diploma qualifications respectively. The RE estimates are similar with a higher earnings loss being reported for severely overskilled workers with lower secondary qualifications and college diploma. Approximately 60% of "unskilled" workers in our dataset possess lower secondary qualifications or below and these individuals may be concentrated in sectors where there is little in the way of an effective wage floor as there is no minimum wage regulation in Malaysia.[22] Furthermore, the presence of foreign unskilled workers may also be exerting further downward pressure on wages though we do not test explicitly for this. The overskilling pay penalty for those with a college diploma is perhaps explained by the fact that they may be crowded into lower level jobs which offers fewer opportunities for a successful skills match.[23]

Previously we found a low degree of correlation between overskilling and overeducation. Here we consider what happens to the wage penalty from being overskilled when controlling for educational mismatch (i.e. overeducation). Overeducation is measured as before using both educational level and field of study. Four sets of specifications are estimated using OLS and RE as presented in Table 15. Specification 1 reproduces our previous estimates from Table 12 (Spec 2) which focuses on the effects of skills mismatch. The next three specifications add our measures of educational mismatch separately and collectively. The reason why we controlled for both measures of overeducation in the regression is mainly due to the fact that they capture different things – one focuses on level or quantity of education and another one focus on type or field of education. By doing so, this allows us to estimate the earnings outcomes of educational mismatch by comparing individuals with surplus education who employed in jobs unrelated to their level of education to overeducated workers who employed in jobs not correspond to their field of study.The penalty from being severely overskilled remains remarkably unchanged across the various specifications. Under OLS estimates (top table) the pay penalty from being severely overskilled is between 8 ($e^{-0.080} - 1$) and 9.5% ($e^{-0.099} - 1$) and the equivalent RE estimates are between 8.5 ($e^{-0.089} - 1$) and 10.5% ($e^{-0.112} - 1$). The penalty accruing to moderately overskilled workers where it exists (the RE estimates) is considerably smaller and this declines a little with the inclusion of our educational mismatch terms. The overkilling penalty

[22] The extent to which workers are skilled is gauged from the employer survey.

[23] Our raw data reveals that 30% of workers with diploma qualifications have ended up in non-production and unskilled jobs.

dominates the penalty from being overeducated when one measures overeducation via those who work outside their own field. Where overeducation is measured via levels of education, the pay penalty for severe overskilling and overeducation are similar.

The finding of a robust overskilling penalty is found elsewhere (Mavromaras *et. al.* 2010) implying that the reason for the wage penalty is not due to educational mismatch, at least not to any significant extent. There could be an argument with respect to unobserved individual heterogeneity, following the lines that the overskilled may be less able than the well-matched workers in some unobserved respect. The data at hand, however, does not allow us to evaluate this since the PICS-II is not a panel data.[24] Nevertheless, the fact that overskilling has a strongly negative and significant impact on wages implies that it does contain important information.

We also should acknowledge that apart from overeducation and overskilling, we also controlled for undereducation and underskilling (moderately and severely underskilled) in the earnings regression. Regardless of OLS or RE estimates, the general findings (not reported here) are undereducation leads to a greater wage premium, at around 9 to 11% whereas there has no evidence of wage premium for underskilling. Therefore, we choose to ignore the discussion of the results due to our main interested in overeducation and overskilling parameters.[25]

3.4. The Effect of Overskilling on Firm Performance

As acknowledged above there is a small literature focusing on the effects of mismatch on firm performance though few of these studies focus on overskilling. Here we explore the effects of overskilling on a range of firm performance measures including average pay, absenteeism, quit rates, labour productivity, output per worker and sales per worker. Since the focus is on workplace performance, we use a measure of workplace overskilling, and here we follow Belfield (2010) where the percentage overskilled is calculated as the average probability of being overskilled within the workplace using worker responses. The extent of overskilling is similar to that reported at the individual level with approximately 31% of the workforce across workplaces being overskilled (23% are moderately overskilled and 8% are severely overskilled).

[24] Indeed, Mavromaras *et al*. (2010) find that a substantial wage penalty of the overskilled group remains after all unobserved time-invariant heterogeneity has been controlled for (using a fixed effect regression).

[25] The results are available upon request.

Following Belfield (2010), we calculate average workplace pay for all the workers who responded to the survey (i.e. monthly earnings reported by respondents) and average workplace pay as reported by the manager (i.e. based on a report for all workers at the firm, irrespective of whether they were surveyed or not).[26] The average workplace pay is in Malaysian dollars (RM) 1,621 using the workers' responses, and RM 1,725 using the managers' statement with a high degree of correlation between the two measures at 0.88. As expected, average workplace pay differs considerably across industry, firm size and extent of foreign ownership. For example, higher average workplace pay is reported among firms in the chemical industry whereas lower pay is reported in the garment industry (RM 2,229 against RM 946).

Mismatch may also reduce work effort and boost absence and quit rates. We measure absence rates in terms of the number of man-days lost.[27] Specifically, the manager was asked, *'Approximately, how many man-days if any did you lose in 2006 due to workers' due to following ..."* with worker absenteeism being one of the options.[28] On average, firms reported losing about 21 days in 2006 with the number of days lost higher in the rubber and plastic industry (40), large firms and firms who were more than 30% foreign-owned.

The third measure of firm performance used is the quit rate, which is calculated using responses to the questions, *"How many employees resigned in 2006?"* and *"How many employees left for other reasons in 2006?"* Using these two questions, we calculate the percentage quit rate across workplaces.[29] On average, the quit rate was around 13% with considerable variation across industry and is higher in larger firms and firms who are more than 30% foreign-owned.

Following Jones *et al.* (2009) and the World Bank (2009), we also use labour productivity as a measure of firm performance. The argument here is that working in jobs which do not correspond to respondents' actual skills may reduce workers' productivity since part of their accumulated skill and knowledge is not fully utilised. In the PICS-II, labour

[26] In particular, the managers were asked to give information on total remuneration (wages and salaries in 2006) for permanent workers. For this, we compute the average workplace pay by dividing the total remuneration (wage and salary) by the number of permanent workers for each workplace.

[27] Our measure differs from Belfield (2010) and Jones *et al.* (2009) who using the 2004 WERS for the UK, measure the absence rate in terms of the percentage absent in the last 12 months.

[28] Other available options are – (i) strikes, (ii) other stoppages, (iii) worker slowdowns, (iv) alcoholism, (v) drug abuse, (vi) reported sickness, (vii) other labor related causes, (viii) civil unrest, (x) other

[29] Quit rates are calculated by dividing the number of employees who resigned or left for other reasons in 2006 with the number of permanent workers reported at the end of fiscal year of 2006.

productivity is defined as value-added per worker in Malaysian dollars.[30] Labour productivity in 2006 for the manufacturing sector as a whole is RM 180,974 with this being considerably higher in the chemical industry (RM 485,398). Labour productivity was also found to be higher in larger firms and firms who have less than 30% foreign-owned (relative to those wholly domestically owned).

Another firm performance indicator used is total production per worker. The argument here is if mismatch reduces workplace productivity, this may also be reflected in a fall in total output (production). Tsang (1987) finds in the context of the US that overeducation reduces firm output via reduced job satisfaction. In the PICS-II, there is information on total output produced in 2006 and we can calculate average output per worker by dividing total output by the total number of permanent workers for each workplace. Average output per worker in 2006 is found to be nearly RM 300,000 and the chemical industry has an output per worker which is up to four times higher than other industries.

Our final indicator of firm performance is sales per worker and this is generated via information provided by managers. Here we use total sales per worker (in RM) and average total sales per worker for each workplace are RM 364,324 with the highest average sales reported in the chemical industry and the lowest in the garment industry (RM 934,207 versus RM 56,632).

Our empirical results are presented in Table 16 to 19 and our results in general are supportive of the view that overskilling is deleterious to firm performance. First, we discuss the influence on average workplace pay based both upon the workers' and managers' responses and these results are presented in Table 16. There are three specifications. In specification 1, we control for skills mismatch alongside workplace characteristics. Here we find that the higher the presence of severe overskilling at the workplace, the lower is the average workplace pay. Moving from a firm with no overskilled workers to another where all the workers are severely overskilled reduces the log average pay by about 17 ($e^{-.186}$-1) and 30% ($e^{-.355}$-1), respectively, using manager' and workers' statements. The negative effects are in line with those reported by Belfield (2010) for the UK, where the pay penalty from overskilling is between 17 and 26%.

In specification 2, we substitute percentage of educational mismatch for percentage of skills mismatch and there are differing results depending on how one measures educational

[30] For details, see the World Bank (2009), Appendix Annex 2 (p. 206).

mismatch. Under our first measure (percentage overeducated), we find that workplace overeducation lowers average pay at the workplace and this is evident using both workers' and managers' statements (the magnitude of the effects are larger under the former). Indeed, going from an establishment with no overeducation to one with a higher fraction of overeducation reduces workplace average pay by 20($e^{-.220}$-1) (managers response) and 34% ($e^{-.419}$-1) (workers response). Under the second measure, we find that a greater proportion of workers employed in jobs outside their own field actually leads to lower average workplace pay by 19($e^{-.209}$-1) and 23% ($e^{-.261}$-1), respectively using employers and employees response. In specification 3, we control for both educational and skills mismatch percentages and the results are similar to the above albeit the negative effects for severe overskilling are smaller with larger negative effects being evident from being mismatched by education (both overeducation and working outside own field).

The effects on workers' absenteeism are reported in Table 17 and there is no evidence that skills mismatch at the workplace increases the absence rate (specification 1). This is line with Jones *et al.* (2009) and Belfield (2010) who find no significant impact of overskilling on the risk of absenteeism using the 2004 WERS. By contrast, workplace overeducation is associated with a higher probability of absenteeism (specifications 2 and 3). The results on quit rates are also reported in Table 17 and here we do not find any statistically significant association between overskilling and the quit rate. This is somewhat surprising since both Jones *et al.* (2009) and Belfield (2010) find evidence that a higher overskilling increases the quit rate at the establishment level though the latter is only the case for the private sector. [31] However, educational mismatch (measured via overeducation) does boost quit rates.

Table 18 reports the results for labour productivity and there is no discernible relationship between overskilling and labour productivity or production (per worker) and as such this is line with the findings of Jones *et al.* (2009) for the UK. However, we do find that workplace overeducation reduces both workplace productivity and production per worker. For instance, specification 2 reveals that moving from a workplace with no overeducation to another where all workers are considered overeducated leads to a 36% ($e^{-0.451}$-1) reduction in log labour productivity and a 46.5% ($e^{-0.626}$-1) fall in output per worker. Finally, we find that greater workplace overeducation also strongly reduces firm performance in terms of sales per worker (Table 19). This is clearly evident in specifications 2 and 3. Any negative effects of

[31] We also did another regression where actual number of workers who quit from firms due to resignation or other reasons was used as the dependant variable. There is still no evidence that mismatch incidences increase the number of workers who quit across the workplace.

workplace overskilling in terms of sales are only evident in specification 1 and this effect dissipates with the inclusion of our educational mismatch terms (specification 3).

To summarise, we can say that there are negative externalities from having overskilled and overeducated workers in the workplace. Severe overskilling reduces average workplace pay. However, the effects of overeducation are more severe and wide ranging with lower average workplace pay, higher absenteeism, lower labour productivity, output and sales per worker.

4. Conclusions

This paper represents an attempt to fill a long standing gap in the literature on educational and skills mismatch by examining the incidence, determinants, and effects of overskilling in the context of a developing country such as Malaysia. We have at our disposal a unique workplace dataset that contains extensive individual and workplace level information allowing an important focus on workplace characteristics.

Using workers' own self-assessment of their skills, we find overskilling to be less of a problem in Malaysia compared to other countries. Nearly a third of our sample is overskilled but only 8% are severely overskilled. The degree of overskilling is also found to be lower among those who possess higher qualifications, particularly a college diploma. With respect to educational mismatch, we find an overeducation rate of 18.5% with the majority of workers being well matched in terms of education. However, where overeducation is measure via field of education, we find that 57% of workers are believed to be employed in jobs that do not correspond to their fields of study. Contrary to our findings with respect to overskilling, the degree of overeducation is higher among the highly educated workers. Workplace characteristics such as the educational composition of the workforce, labour intensity, degree of competition and an emphasis on technical skills in hiring all boost overskilling. Though the degree of correlation between overskilling and overeducation is found to be low we do find that increased overeducation (both measures) does boost overskilling.

The main finding from the earnings regressions is that whilst the degree of severe overskilling is low the penalties in terms of loss in earnings are quite large compared to that for the moderately overskilled and well-matched. Indeed, moderate overskilling does not translate into a significant disadvantage in terms of pay. The negative effect of overskilling on individual's earnings is also translated into a reduction in average workplace pay. However, the effects of overeducation are more acute with overeducation resulting in lower average workplace pay, higher absence rates, lower labour productivity, output per worker and sales per worker.

References

Allen, J., and van der Velden, R. (2001). Educational mismatches versus skill mismatches: Effects on wages, job satisfaction, and on-the-job search. *Oxford Economic Papers, 53*(3), 434-452.

Battu, H., Belfield, C. R., and Sloane, P. J. (2003). Human capital spillovers within the workplace: Evidence for Great Britain. *Oxford Bulletin of Economics and Statistics, 65*(5), 575-594.

Battu, H. (2008) Overeducation amongst the young, Report for the OECD.

Bauer, T. K. (2002). Educational mismatch and wages: A panel analysis. *Economics of Education Review, 21*(3), 221-229.

Belfield, C. (2010). Over-education: What influence does the workplace have? *Economics of Education Review, 29*(2), 236-245.

Blaug, M. (1973). *Education and the employment problem in developing countries*. Geneva: International Labour Office.

Bloom, D. E., Freeman, R. B., and Korenman, S. D. (1988). The labour-market consequences of generational crowding. *European Journal of Population, 3*(2), 131-176.

Büchel, F., and Mertens, A. (2004). Overeducation, undereducation, and the theory of career mobility. *Applied Economics, 36*(8), 803-816.

Bygren, M. (2010). The gender composition of workplaces and men's and women's turnover. *European Sociological Review, 26*(2), 193-202.

Daly, M. C., Büchel, F., and Duncan, G. J. (2000). Premiums and penalties for surplus and deficit education: Evidence from the united states and germany. *Economics of Education Review, 19*(2), 169-178.

Green, F., and McIntosh, S. (2007). Is there a genuine under-utilization of skills amongst the over-qualified? *Applied Economics, 39*(4), 427-439.

Hartog, J., and Oosterbeek, H. (1988). Education, allocation and earnings in the Netherlands: 0verschooling? *Economics of Education Review, 7*(2), 185-194.

Jajri, I., and Ismail, R. (2006). Elasticity of substitutions between foreign and local workers in the Malaysian manufacturing sector. *Pertanika Journal of Social Science and Humanities, 14*(1), 63-76.

Jones, M. K., Jones, R. J., Latreille, P. L. and Sloane, P. J. (2009), Training, Job Satisfaction, and Workplace Performance in Britain: Evidence from WERS 2004. LABOUR, 23: 139–175

Lim, H. E., Rich, J., and Harris, M. N. (2008). Employment outcomes of graduates: The case of Universiti Utara, Malaysia. *Asian Economic Journal, 22*(3), 321-341.

Mavromaras, K., McGuinness, S., and Fok, Y. K. (2009). Assessing the incidence and wage effects of overskilling in the australian labour market. *Economic Record, 85*(268), 60-72.

Mavromaras, K., McGuinness, S., O'Leary, N., Sloane, P., and Fok, Y. K. (2010). The problem of overskilling in Australia and Britain. *Manchester School, 78*(3), 219-241.

McGuinness, S., (2006). "Overeducation in the Labour Market." *Journal of Economic Surveys* 20(3): 387-418.

McGuinness, S., and Sloane, P. J. (2010). Labour market mismatch among UK graduates: An analysis using REFLEX data. *Economics of Education Review,* 30, 130-145.

Mehta, Aashish, Felipe, Jesus, Quising, Pilipinas, and Camingue, Shiela. (2010). Overeducation in Developing Economies: How can we test for it, and what does it mean?. UC Santa Barbara: Global and International Studies. Retrieved from http://www.escholarship.org/uc/item/6b07h5p5

Leuven, Edwin and Oosterbeek, Hessel. (2011). Overeducation and Mismatch in the Labor Market IZA DP No. 5523.

Reskin, B. (1993). Sex segregation in the workplace. *Annual Review of Sociology, 19*, pp. 241-270.

Robst, J. (2008). Overeducation and college major: Expanding the definition of mismatch between schooling and jobs. *Manchester School, 76*(4), 349-368.

Sattinger, M. (1993). Assignment models of the distribution of earnings. *Journal of Economic Literature, 31*(2), pp. 831-880.

Sicherman, N., and Galor, O. (1990). A theory of career mobility. *The Journal of Political Economy, 98*(1), pp. 169-192.

Sicherman, N. (1990). 'Overeducation' in the labour market. *Journal of Labour Economics*, 9(2), 101–22

Sloane, P. J., Battu, H., and Seaman, P. T. (1999). Overeducation, undereducation and the British labour market. *Applied Economics, 31*(11), 1437-1453.

Voon, D., and Miller, P. W. (2005). Undereducation and overeducation in the Australian labour market. *Economic Record, 81*(SUPPL. 1)

Wald, S., and Fang, T. (2008). Overeducated immigrants in the Canadian labour market: Evidence from the workplace and employee survey. *Canadian Public Policy, 34*(4), 457-479.

Wooden, Mark and Bora, Bijit. (1999). Workplace Characteristics and Their Effects on Wages. Australian Evidence. *Australian Economic Papers*, *38 (3), 276 - 289.*

Appendix 1

Here we check the representativeness of PICS-II through a comparison with other Malaysian data sources including the 2008 Labour Force Survey (LFS) and the 2008 Annual Survey of Manufacturing (ASM). In particular, we consider reported earnings, hours of work per week, educational attainment, marital status, gender and ethnicity.

With respect to earnings, the PICS-II data is close to the 2008 AMS. The average monthly income among respondents was RM 1,633 using the PICS-II and RM 1,810 using the AMS. Unfortunately, the LFS has no information on respondents' income. In terms of hours of work per week, the PICS-II reports that workers spend on average 45 hours at work per week which is close to that reported by the ILO (2008) and LFS (2008), approximately 46 and 48 hours per week respectively. With respect to educational attainment, the PICS-II is generally representative of the Malaysian workforce as a whole. According to the 2008 LFS, the majority of workers in 2007 were secondary school-leavers (56%) and a fifth had tertiary education (21%) with the corresponding figures of 58% and 22% in the PICS-II.

It is a mixed bag with respect to the demographic variables. In terms of marital status we have consistency with the 2008 LFS. 34% and 65% of respondents in the manufacturing sector in the PICS-II are single and married respectively and the equivalent proportions are 34% and 63% in the 2008 LFS also for manufacturing. However, there are differences with respect to gender and ethnic group composition. The 2008 LFS reports that about 20% of the women employed in 2007 were in the manufacturing sector with a corresponding figure of 17% for men. In the PICS-II, women account for nearly half of the respondents. The PICS-II also seems to over-represent Chinese ethnics relative to the 2008 LFS (35% against 26%). The proportion of Chinese employed in the manufacturing sector is also higher in the PICS-II, roughly 35% with a corresponding figure of 28% in the LFS.

Table 1

Descriptive statistics of selected key variables (mean and standard deviation)

Variable	All		Male		Female	
	Mean	SD	Mean	SD	Mean	SD
Age of respondent	34.89	9.83	35.86	9.99	33.91	9.56
Years of schooling completed	10.35	3.52	10.21	3.63	10.92	3.34
Education attainment						
No/informal qualification	0.03	0.18	0.04	0.21	0.02	0.14
Primary education	0.12	0.33	0.13	0.33	0.12	0.33
Lower secondary	0.25	0.43	0.28	0.45	0.21	0.41
Upper secondary	0.38	0.49	0.36	0.49	0.41	0.49
Diploma	0.13	0.34	0.11	0.31	0.15	0.36
Degree	0.09	0.29	0.08	0.29	0.09	0.29
Prof cert (professional certificate)	0.11	0.32	0.11	0.31	0.13	0.34
Exp (month)	165.45	120.05	181.26	123.15	149.38	114.61
Tenure (year)	7.60	7.02	7.98	7.36	6.95	6.56
Train	0.42	0.49	0.43	0.50	0.40	0.49
Female	0.55	0.45				
Married	0.65	0.48	0.68	0.47	0.62	0.49
Children under 12 years	0.94	1.18	1.02	1.23	0.87	1.12
Ethnicity						
Malay	0.55	0.50	0.58	0.49	0.52	0.50
Chinese	0.35	0.48	0.33	0.47	0.39	0.49
Indian	0.10	0.29	0.09	0.29	0.10	0.30
Occupation						
Managerial	0.15	0.36	0.13	0.33	0.17	0.38
Professional	0.08	0.28	0.09	0.28	0.08	0.27
Skilled job	0.37	0.48	0.45	0.50	0.28	0.45

Clerical/Non-production	0.23	0.42	0.22	0.41	0.24	0.43
Unskilled job	0.17	0.38	0.12	0.32	0.23	0.42
Hours of work (weekly)	45.82	12.23	46.81	12.56	44.81	11.81
Earnings (hourly)	13.96	29.12	15.22	30.10	12.69	28.03
Firm age	33.34	4.57	33.39	4.74	33.13	5.96
Firm size						
Firm size less than 50	0.40	0.49	0.43	0.50	0.37	0.48
Firm size 50 to 150	0.31	0.46	0.30	0.46	0.32	0.47
Firm size more than 150	0.29	0.45	0.27	0.44	0.31	0.46
Ownership						
Purely domestically-owned	0.68	0.47	0.68	0.47	0.68	0.47
Less than 30% foreign-owned	0.05	0.21	0.05	0.22	0.04	0.21
More than 30% foreign-owned	0.27	0.45	0.27	0.44	0.28	0.45
Share of workforce with university qualifications						
Graduates less than 25%	0.76	0.42	0.76	0.43	0.77	0.42
Graduates 25 to 50%	0.19	0.39	0.18	0.38	0.19	0.39
Graduates more than 50%	0.05	0.22	0.06	0.23	0.04	0.20
Share of labour cost of the total cost						
Labour cost less than 25%	0.64	0.48	0.65	0.48	0.63	0.48
Labour cost 25 to 50%	0.26	0.44	0.25	0.43	0.28	0.45
Labour cost 51 to75%	0.07	0.25	0.07	0.26	0.07	0.25
Labour cost more than 75%	0.03	0.16	0.04	0.17	0.02	0.15
Firm train (firm providing on-the-job training)	0.52	0.49	0.49	0.50	0.55	0.50

Table 2

The incidence of overskilling across workers

	All (n = 10,302)	Male (n = 5,610)	Female (n = 4,692)
	%	%	%
Statement 1*			
Do not agree at all	8.1	8.8	7.3
Somewhat agree	22.9	23.5	22.1
Agree	54.7	53.0	56.7
Agree completely	14.3	14.7	13.9
Total	**100**	**100**	**100**
Overskilling			
Well-matched	69.0	67.7	70.6
Moderately overskilled	22.9	23.5	22.1
Severely overskilled	8.1	8.8	7.3
Total	**100.0**	**100.0**	**100.0**

Source: Productivity Climate Investment Survey 2007 (PCIS-2)

* Your current job offers you sufficient scope to use your knowledge and skills.

Table 3

The incidence of underskilling across workers

	All	Male	Female
	%	%	%
Statement 2*			
Do not agree at all	3.9	4.0	3.7
Somewhat agree	15.8	17.0	14.4
Agree	55.8	55.3	56.5
Agree completely	24.5	23.7	25.4
Total	**100.0**	**100.0**	**100.0**
Underskilling			
Well-matched	19.7	21.0	18.1
Moderately underskilled	55.8	55.3	56.5
Severely underskilled	24.5	23.7	25.4
Total	**100.0**	**100.0**	**100.0**

Source: Productivity Climate Investment Survey 2007 (PCIS-2)

* You would perform better in your current job if you possess additional knowledge and skills.

Table 4

Education required for current job and the incidence of over-education using conventional measure (percentage)

	All (n = 10,302)	**Male** (n = 5,610)	**Female** (n = 4,692)
Statement 3*			
Degree	11.7	12.9	10.5
Diploma	19.1	18.0	20.2
Upper secondary	37.0	36.9	37.2
Lower secondary	21.0	20.9	21.1
Primary	7.0	6.5	7.5
Informal/no qualification	1.8	1.8	1.8
Total	**100.0**	**100.0**	**100.0**
Educational mismatch			
Well-matched	51.9	48.7	55.7
Overeducated	18.5	18.5	18.6
Undereducated	29.6	32.8	25.7
Total	**100.0**	**100.0**	**100.0**

Source: Productivity Climate Investment Survey 2007 (PCIS-2)

*According to you, what is the most appropriate level of education for the work you are doing?

Table 5

Field of education required to do current job (percentage)

	Pooled **(n = 10,302)**	**Male** **(n = 5,610)**	**Female** **(n = 4,692)**
Statement 4*			
Only your own field	6.7	7.0	6.3
Related to your field	36.7	35.2	38.5
Completely different from your field	17.3	17.8	16.6
No specific field is required for this	39.3	39.9	38.6
Total	**100.0**	**100.0**	**100.0**
Field of education			
Only your/related to own field	43.4	42.3	44.8
Outside of own field	56.6	57.7	55.2
Total	**100.0**	**100.0**	**100.0**

Source: Productivity Climate Investment Survey 2007 (PCIS-2)

* According to you, what is the most appropriate field of education for the work you are doing?

Table 6

Percentage of Overskilled by Overeducation

Skills utilisation	**Educational mismatch**	
	Overeducated	**Outside own field**
Pooled		
Skill-matched	65.4	65.9
Moderately overskilled	24.7	25.0
Severely overskilled	9.9	9.1
Total	***100.0***	***100.0***
Male		
Skill-matched	64.6	66.8
Moderately overskilled	26.6	24.9
Severely overskilled	8.8	8.3
Total	***100.0***	***100.0***
Female		
Skill-matched	66.1	65.1
Moderately overskilled	23.0	25.1
Severely overskilled	10.9	9.8
Total	***100.0***	***100.0***
Total	**17.5**	**48.9**

Table 7

Percentage of Overeducation by Overskilling

Educational mismatch	**All**		**Male**		**Female**	
	Moderately Overskilled	**Severely Overskilled**	**Moderately Overskilled**	**Severely Overskilled**	**Moderately Overskilled**	**Severely Overskilled**
Overeducated	20.0	25.7	21.0	23.4	19.1	28.1
Outside of own field	62.8	73.5	62.9	71.0	62.7	75.7

Table 8

Determinants of overskilling among workers - marginal effects

	Pooled		Male		Female	
	Moderately-overskilled	**Severely-overskilled**	**Moderately-overskilled**	**Severely-overskilled**	**Moderately-overskilled**	**Severely-overskilled**
Demographic backgrounds						
Female	0.001	0.005				
	0.009	*0.005*				
Married	-0.002	-0.004	-0.009	-0.007	0.002	-0.001
	0.010	*0.005*	*0.015*	*0.007*	*0.015*	*0.006*
Child12	-0.010 **	-0.007 ***	-0.013 **	-0.006	-0.007	-0.007 **
	0.004	*0.003*	*0.006*	*0.004*	*0.007*	*0.003*
Race (ref – Malay)						
Chinese	0.036 ***	0.000	0.030 *	0.002	0.040 ***	-0.001
	0.011	*0.005*	*0.016*	*0.008*	*0.015*	*0.007*
Indian	0.035 **	-0.010	0.019	-0.012	0.055 **	-0.011
	0.016	*0.009*	*0.023*	*0.014*	*0.022*	*0.010*
Educational attainment (ref - no/primary education*)*						
Lower secondary	0.009	-0.025 ***	0.017	-0.013 *	0.003	-0.036 ***
	0.013	*0.006*	*0.018*	*0.008*	*0.021*	*0.008*
Upper secondary	-0.045 ***	-0.037 ***	-0.049 ***	-0.031 ***	-0.038 *	-0.037 ***
	0.014	*0.006*	*0.018*	*0.008*	*0.021*	*0.008*
Diploma	-0.078 ***	-0.049 ***	-0.047 *	-0.037 **	-0.105 ***	-0.054 ***
	0.020	*0.010*	*0.028*	*0.015*	*0.029*	*0.013*
Degree	-0.022	-0.038 ***	-0.027	-0.029	-0.015	-0.047 ***
	0.022	*0.013*	*0.033*	*0.019*	*0.032*	*0.016*
Exp (month)	0.000 *	0.000	0.000	0.000	-0.001 ***	0.000 *
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*

Training	-0.015	-0.020 ***	-0.015	-0.036 ***	-0.013	0.000
	0.010	*0.005*	*0.014*	*0.008*	*0.014*	*0.007*
Prof cert	-0.047 ***	0.000	-0.052 **	0.008	-0.033	-0.006
	0.016	*0.009*	*0.021*	*0.011*	*0.024*	*0.013*
N	9,971		5,380		4,591	
Pseudo R-sq	0.071		0.086		0.068	
Log-likelihood	-7358.2		-3989.7		-3309.3	

Robust standard error in italics

Other covariates – household size, region (5), work distance (km), job tenure, unionisation and number of job held in the past

, **, and * respectively 0.1, 0.05 and 0.01*

Table 9

Workplace characteristics and the determinants of overskilling (marginal effects)

	All		Male		Female	
	Moderately-overskilled	**Severely-overskilled**	**Moderately-overskilled**	**Severely-overskilled**	**Moderately-overskilled**	**Severely-overskilled**
Share of workforce with university qualifications (ref – Graduates less than 25%)						
Graduates 25 to 50%	-0.017	-0.005	-0.022	-0.001	-0.011	-0.009
	0.012	*0.006*	*0.017*	*0.008*	*0.018*	*0.008*
Graduates more than 50%	-0.025	-0.052 ***	-0.029	-0.062 ***	-0.030	-0.035 *
	0.022	*0.014*	*0.028*	*0.018*	*0.034*	*0.021*
Firm size (ref - firm size less than 50)						
Firm size 50 to 150	-0.006	0.011 **	-0.006	0.019 **	-0.009	0.001
	0.011	*0.005*	*0.016*	*0.008*	*0.017*	*0.007*
Firm size more than 150	-0.008	-0.002	-0.001	0.015	-0.016	-0.014
	0.014	*0.007*	*0.020*	*0.010*	*0.020*	*0.009*
Ownership (ref –Purely domestically-owned)						
Less than 30% foreign-owned	-0.021	-0.058 ***	-0.018	-0.053 ***	-0.067 **	-0.072 **
	0.022	*0.017*	*0.032*	*0.020*	*0.031*	*0.029*
More than 30% foreign-owned	0.039 ***	-0.007	0.042 ***	-0.008	0.038 **	-0.004
	0.011	*0.005*	*0.016*	*0.008*	*0.017*	*0.007*
Share of labour cost of the total cost (ref - Labour cost less than 25%)						
Labour cost 25 to 50%	0.014	0.004	0.019	0.006	0.008	0.000
	0.010	*0.005*	*0.015*	*0.006*	*0.015*	*0.006*
Labour cost 51 to75%	0.022	-0.003	0.025	-0.023 *	0.023	0.007
	0.017	*0.008*	*0.023*	*0.012*	*0.027*	*0.009*

Labour cost more than 75%	0.022	0.012	0.049	0.032 **	-0.001	-0.017
	0.027	*0.012*	*0.035*	*0.015*	*0.042*	*0.019*
Number of competitors (ref – No competitor)						
Competitor less than 25	0.029	-0.012	0.093 **	-0.018	-0.010	-0.003
	0.022	*0.008*	*0.037*	*0.013*	*0.027*	*0.009*
Competitor more than 25	0.025	-0.024 **	0.125 ***	-0.042 ***	-0.058 *	-0.001
	0.026	*0.010*	*0.041*	*0.016*	*0.034*	*0.012*
Hiring practice						
Education-based	0.023 **	-0.010 **	0.008	-0.012 **	0.038 ***	-0.009
	0.009	*0.004*	*0.013*	*0.006*	*0.014*	*0.005*
Work exp-based	0.022 *	0.010 *	0.007	0.010	0.039 **	0.010
	0.012	*0.006*	*0.017*	*0.007*	*0.019*	*0.008*
Technical-based	-0.010	-0.010 **	-0.004	-0.010	-0.019	-0.009
	0.011	*0.005*	*0.015*	*0.007*	*0.016*	*0.006*
Firm train	-0.014	-0.007	0.007	-0.005	-0.032 **	-0.009
	0.011	*0.005*	*0.015*	*0.007*	*0.016*	*0.006*
No. of observation	**9,814**		**5,285**		**4,529**	
No. of firm	1,013		1,013		1,013	
Pseudo R-sq	0.081		0.092		0.083	
Log-likelihood	-7147.5		-3850.5		-3207.6	
Log likelihood ratio test (χ)	426.2 ***		278.4 ***		203.4 ***	

Robust standard error in italics

Other covariates- firm age, share of women workers of the total workforce (3), share of foreign skilled workers of the total skilled (3) worker and over-staffed firm

, **, and * respectively 0.1, 0.05 and 0.01*

Table 10

The effects of educational mismatch on worker overskilling - marginal effects

	Spec 1		**Spec 2**		**Spec 3**	
	Moderately-overskilled	**Severely-overskilled**	**Moderately-overskilled**	**Severely-overskilled**	**Moderately-overskilled**	**Severely-overskilled**
All						
Overeducated	0.029 **	0.021 ***			0.023 *	0.017 ***
	0.012	*0.005*			*0.012*	*0.005*
Outside of own field			0.052 ***	0.036 ***	0.049 ***	0.032 ***
			0.010	*0.005*	*0.010*	*0.005*
N	9700		9700		9700	
Pseudo R-sq	0.088		0.091		0.094	
Log-likelihood	-7008.1		-6987.1		-6965.3	
Log likelihood ratio test (χ)	278.88 ***		320.8 ***		364.4 ***	
Male						
Overeducated	0.048 ***	0.017 **			0.043 ***	0.012 *
	0.017	*0.007*			*0.017*	*0.007*
Outside of own field			0.049 ***	0.038 ***	0.044 ***	0.034 ***
			0.014	*0.006*	*0.014*	*0.006*
N	5217		5217		5217	
Pseudo R-sq	0.114		0.112		0.116	
Log-likelihood	-3755.7		-3747.3		-3732.3	
Log likelihood ratio test (χ)	189.6 ***		206.4 ***		236.4 ***	
Female						
Overeducated	0.001	0.021 ***			-0.006	0.019 ***
	0.018	0.006			0.018	0.006

Outside of own field		0.059 ***	0.026 ***	0.058 ***	0.023 ***
		0.014	*0.006*	*0.014*	*0.006*
N	4483	4483		4483	
Pseudo R-sq	0.092	0.094		0.097	
Log-likelihood	-3148.0	-3138.9		-3130.7	
Log likelihood ratio test (χ)	119.2 ***	137.4 ***		153.8***	

Robust standard error in italics

, **, and * respectively 0.1, 0.05 and 0.01*

Table 11

The determinants of workplace mismatch

	Overskilling	Moderate overskilling	Severe overskilling
Share of workforce with university qualifications (ref – Graduates less than 25%)			
Graduates 25 to 50%	-0.054 *	-0.034	-0.02
	0.029	*0.025*	*0.017*
Graduates more than 50%	-0.098 **	-0.019	-0.079 ***
	0.044	*0.039*	*0.024*
Firm train	-0.054 **	-0.034 *	-0.019
	0.023	*0.02*	*0.014*
Firm size (ref –firm size less than 50 emp)			
Firm size 50 to 150 emp	-0.031	-0.028	-0.003
	0.025	*0.022*	*0.016*
Firm size more than 150 emp	-0.051 *	-0.035	-0.016
	0.027	*0.025*	*0.016*
Ownership (ref – purely domestically-owned)			
Less than 30% foreign-owned	-0.036	0.007	-0.043 ***
	0.033	*0.032*	*0.013*
More than 30% foreign-owned	0.03	0.031	-0.001
	0.023	*0.021*	*0.012*
Share of labour cost of the total cost (ref - Labour cost less than 25%)			
Labour cost 25 to 50%	0.013	0.005	0.020
	(0.011)	(0.004)	(0.016)
Labour cost 51 to75%	0.009	-0.002	0.011
	(0.019)	(0.008)	(0.027)
Labour cost more than 75%	0.012	0.019	0.034
	(0.030)	(0.013)	(0.041)

Hiring practice

	Education-based	0.03	0.012	0.018
		0.025	*0.023*	*0.015*
	Work exp-based	-0.012	0.01	-0.022 *
		0.02	*0.018*	*0.012*
	Technical-based	-0.034	-0.021	-0.013
		0.024	*0.021*	*0.014*
_cons		0.444 ***	0.246 ***	0.199 ***
		0.072	*0.063*	*0.049*
No. of firm		1,013	1,013	1,013
R-square		0.117	0.058	0.096
Adjusted R-sq		0.081	0.019	0.059

Robust standard error in italics

Other explanatory variables – female workforce composition (3), firm competitors (3), labour cost (4), firm age and dummies for under-staffed and over-staffed firm.

, ** and *, respectively denote 0.1, 0.05, and 0.01*

Table 12

The effects of overskilling on earnings across workers

log wage (hourly)	**OLS**		**RE**	
	Spec 1	**Spec 2**	**Spec 1**	**Spec 2**
Skill utilisation (ref - well-matched)				
Moderately overskilled	-0.022 *	-0.023 *	-0.055 ***	-0.053 ***
	0.012	*0.012*	*0.013*	*0.013*
Severely overskilled	-0.116 ***	-0.099 ***	-0.123 ***	-0.112 ***
	0.017	*0.017*	*0.020*	*0.021*
Individual characteristic	*Yes*	*Yes*	*Yes*	*Yes*
Workplace attributes	*No*	*Yes*	*No*	*Yes*
N	**9,952**	**9,787**	**9,952**	**9,787**
No. of firms			1,034	1,019
R-sq	0.677	0.691		
adj. R-sq	0.676	0.689		
R-sq – overall			0.672	0.687
Rho (ρ)			0.326	0.317
		603.09 ***		
LM test			1719.3 ***	4017.4 ***

Notes: Other explanatory variables are individuals' characteristics (education and work experience) demographic characteristics (race, gender, marital status, children and household member) spatial elements (region, work distance and commuting time), last unemployed, job attributes (occupational level, tenure, hours of work, number of job held and union member) and the workplace characteristics - firm size (3), industry (9), firm ownership (3), hiring system (3), labour cost (4), firm age, KLSE, firm provided training and workforce composition (university, secondary, female and foreign skilled workers)

Robust Standard errors in parentheses

** , **, and *** denote 0.1,0.05, and 0.01, respectively*

Table 13 Wage effects of overskilling by gender

	OLS		RE	
	Male	**Female**	**Male**	**Female**
Skills mismatch (ref-well-matched)				
Moderately-overskilled	-0.024	-0.023	-0.050 ***	-0.052 ***
	0.017	*0.016*	*0.018*	*0.018*
Severely-overskilled	-0.103 ***	-0.083 ***	-0.094 ***	-0.106 ***
	0.024	*0.026*	*0.025*	*0.029*
Cons	3.198 ***	2.729 ***	3.112 ***	2.782 ***
	0.089	*0.090*	*0.123*	*0.117*
N	**5,273**	**4,514**	**5,273**	**4,514**
No. of firm			972	934
R-square	0.685	0.702		
Adjusted R-sq	0.681	0.697		
Overall R-sq			0.681	0.699
Rho (ρ)			0.359	0.354
LM test		1508.470 ***		1317.660 ***

Robust Standard errors in parentheses

** , **, and *** denote 0.1,0.05, and 0.01, respectively*

Table 14

The effect of overskilling on earnings across education levels

Log hourly wage	**No/primary**	**Lower secondary**	**Upper secondary**	**Diploma college**	**University degree**
OLS					
Skills mismatch (ref-Well-matched)					
Moderately-overskilled	0.032	-0.042 *	-0.013	-0.010	-0.058
	0.026	*0.024*	*0.020*	*0.037*	*0.041*
Severely -overskilled	-0.045	-0.178 ***	-0.015	-0.125 *	-0.070
	0.034	*0.033*	*0.029*	*0.068*	*0.066*
Cons	3.455 ***	3.035 ***	3.177 ***	3.534 ***	3.910 ***
	0.162	*0.140*	*0.102*	*0.156*	*0.226*
N	**1,536**	**2,457**	**3,766**	**1,191**	**837**
R-square	0.683	0.627	0.661	0.702	0.7
Adjusted R-square	0.668	0.616	0.655	0.683	0.673
RE					
Skills mismatch (ref-Well-matched)					
Moderately-overskilled	-0.007	-0.042 *	-0.052 **	-0.030	-0.060
	0.029	*0.025*	*0.021*	*0.037*	*0.044*
Severely -overskilled	-0.049	-0.144 ***	-0.055 *	-0.134 **	-0.074
	0.038	*0.038*	*0.031*	*0.062*	*0.059*
Cons	3.400 ***	3.143 ***	3.001 ***	3.446 ***	3.901 ***
	0.193	*0.180*	*0.132*	*0.170*	*0.238*
N	**1,536**	**2,457**	**3,766**	**1,191**	**837**
No. of firm	531	767	908	564	400

Overall R-sq	0.673	0.623	0.656	0.697	0.698
Rho (ρ)	0.573	0.319	0.389	0.381	0.13
LM test	361.64 ***	576.15 ***	783.52 ***	41.65 ***	16.93 ***

Robust Standard errors in parentheses

** , **, and *** denote 0.1,0.05, and 0.01, respectively*

Table 15

The effect of overskilling and over-education on individual earnings

log hourly earnings	Spec 1	Spec 2	Spec 3	Spec 4
OLS				
Educational mismatch				
Overeducated		-0.077 ***		-0.074 ***
		0.013		*0.013*
Outside of own field			-0.041 ***	-0.027 ***
			0.010	*0.010*
Skills mismatch				
Moderately-overskilled	-0.023 *	-0.017	-0.020 *	-0.015
	0.012	*0.012*	*0.012*	*0.012*
Severely-overskilled	-0.099 ***	-0.084 ***	-0.093 ***	-0.080 ***
	0.017	*0.017*	*0.017*	*0.017*
N	9,787	9,787	9,787	9,787
R-square	0.691	0.696	0.692	0.696
Adjusted R-sq	0.689	0.693	0.689	0.693
RE				
Educational mismatch				
Overeducated		-0.094 ***		-0.088 ***
		0.013		*0.013*
Outside of own field			-0.061 ***	-0.045 ***
			0.013	*0.012*
Skills mismatch				
Moderately-overskilled	-0.053 ***	-0.047 ***	-0.048 ***	-0.043 ***
	0.013	*0.013*	*0.013*	*0.013*
Severely-overskilled	-0.112 ***	-0.094 ***	-0.103 ***	-0.089 ***

	-0.021	*0.021*	*0.021*	*0.020*
N	9,787	9,787	9,787	9,787
No. of group	1,019	1,019	1,019	1,019
Overall R-sq	0.687	0.691	0.687	0.692
Rho (ϱ)	0.317	0.320	0.319	0.321
LM test	4017.4***	4051.5***	4039.2***	4072.7***

Source: Productivity Climate Investment Survey 2007 (PCIS-2)

Robust Standard errors in parentheses

** , **, and *** denote 0.1,0.05, and 0.01, respectively*

Table 16

The effect of workplace mismatch on workplace average pay

Log average pay	**Respondents' response**			**Managers' response**		
	Spec 1	**Spec 2**	**Spec 3**	**Spec 1**	**Spec 2**	**Spe**
Skill mismatch						
Moderate overskilling (%)	-0.034		-0.017	0.028		0.04
	0.087		*0.085*	*0.071*		*0.07*
Severe overskilling (%)	-0.355 ***		-0.281 ***	-0.186 ***		-0.13
	0.111		*0.111*	*0.078*		*0.07*
Educational mismatch						
Overeducation (%*)*		-0.419 ***	-0.399 ***		-0.220 ***	-0.21
		0.087	*0.087*		*0.069*	*0.06*
Outside of own field (%)		-0.261 ***	-0.239 ***		-0.209 ***	-0.20
		0.057	*0.056*		*0.044*	*0.04*
Cons	8.704 ***	8.862 ***	8.886 ***	6.566 ***	6.722 ***	6.671
	0.186	*0.194*	*0.198*	*0.154*	*0.165*	*0.17*
-----------	--------- ----	--------- ----	--------- ---	---------- ---	---------- ---	----------
N	1,003	1,003	1,003	1,003	1,003	1,00
R-square	0.307	0.330	0.340	0.302	0.324	0.32
Adjusted r-sq	0.274	0.299	0.306	0.269	0.293	0.29

*Robust Standard error in parenthesis; *, **, and ***, respectively donate 0.1, 0.05, and 0.01*

Notes: other controlled variables – log (K), log (L), firm's competitors (3), the percent of female workforce composition, dummy KLSE, dummies for over-staffed and under-staffed firm, hiring practice (education, experience and technical) and labour cost (4).

Table 17

The effect of workplace overskilling/over-education on absenteeism and quite rate

	Log absenteeism			Quit rate		
	Spec 1	**Spec 2**	**Spec 3**	**Spec 1**	**Spec 2**	**Spec 3**
Skill mismatch						
Moderate overskilling (%)	0.108		0.115	0.141		0.157
	0.205		*0.202*	*0.195*		*0.195*
Severe overskilling (%)	0.516		0.530	-0.038		0.003
	0.330		*0.326*	*0.285*		*0.290*
Educational mismatch						
Overeducation (%)		0.732 ***	0.703 ***		0.250	0.278
		0.249	*0.249*		*0.238*	*0.238*
Outside of own field (%)		-0.208	-0.246 *		-0.220	-0.201
		0.142	*0.143*		*0.141*	*0.142*
Cons	0.316	0.266	-0.064	0.096 *	0.088 *	0.072
	0.530	*0.593*	*0.599*	*0.049*	*0.051*	*0.053*
----------	---------- ---	---------- ---	---------- ---	---------- ---	---------- ---	---------- ---
N	1,020	1,020	1,020	1,021	1,021	1,021
R-square	0.093	0.100	0.103	0.120	0.120	0.123
Adjusted R-sq	0.051	0.059	0.058	0.089	0.088	0.093

*Robust standard error in parenthesis; *, ** and ***, respectively denote 0.1, 0.05, and 0.01*

Notes: other controlled variables - firm competitors (3), the percent of female workforce composition, dummy KLSE, dummies for over-staffed and under-staffed firm, hiring practice (education, experience and technical) and labour cost (4).

Table 18

The effects of workplace mismatch on productivity and production per worker

	Log productivity			Log production per worker		
	Spec 1	**Spec 2**	**Spec 3**	**Spec 1**	**Spec 2**	**Spec 3**
Skill mismatch						
Moderate overskilling (%)	-0.230		-0.223	-0.036		-0.024
	0.143		*0.140*	*0.166*		*0.163*
Severe overskilling (%)	-0.229		-0.205	0.052		0.155
	0.218		*0.221*	*0.244*		*0.242*
Educational mismatch						
Overeducation (%)		-0.451 ***	-0.435 ***		-0.626 ***	-0.629 ***
		0.163	*0.163*		*0.200*	*0.200*
Outside of own field (%)		-0.067	-0.086		-0.123	-0.126
		0.101	*0.102*		*0.117*	*0.117*
_cons	10.940 ***	10.843 ***	11.107 ***	12.550 ***	12.291 ***	12.500 ***
	0.403	*0.426*	*0.442*	*0.650*	*0.668*	*0.677*
-----------	--------- ----	--------- ----	--------- ---	---------- ---	---------- ---	---------- ---
N	1,016	1,016	1,016	847	847	847
R-square	0.257	0.260	0.263	0.698	0.702	0.702
Adjusted R-sq	0.218	0.222	0.222	0.681	0.685	0.684

*Robust standard error in parenthesis; *, ** and ***, respectively denote 0.1, 0.05, and 0.01*

Notes: other controlled variables - log (K), log (L), firm's competitors (3), the percent of female workforce composition, dummy KLSE, dummies for over-staffed and under-staffed firm, hiring practice (education, experience and technical) and labour cost (4).

Table 19

The effect of workplace overskilling/over-education on sales (RM)

Log value sales per worker (RM)	**Spec 1**	**Spec 2**	**Spec 3**
Skill mismatch			
Moderate overskilling (%)	-0.125		-0.103
	0.149		*0.148*
Severe overskilling (%)	-0.366 *		-0.277
	0.195		*0.196*
Educational mismatch			
Overeducation (%)		-0.601 ***	-0.578 ***
		0.158	*0.157*
Outside of own field (%)		-0.179 *	-0.023
		0.100	*0.102*
_cons	12.565 ***	12.582 ***	12.764 ***
	0.552	*0.580*	*0.582*
-----------	--------- ----	--------- ----	--------- ----
N	**1,024**	**1,024**	**1,024**
R-square	0.710	0.711	0.714
Adjusted R-sq	0.655	0.654	0.658

*Robust standard error in parenthesis; *, ** and ***, respectively denote 0.1, 0.05, and 0.01*

Notes: other controlled variables - log (K), log (L), firm's competitors (3), the percent of female workforce composition, dummy KLSE, dummy for over-staffed and under-staffed firm, hiring practice (education, experience and technical) and labour cost (4).

Appendix

Variable Definitions

Variable	Definition
Educational attainment	
No/Primary education	= 1 if no/primary education, 0 otherwise
Lower secondary	= 1 if lower secondary education, 0 otherwise
Upper secondary	= 1 if upper secondary education, 0 otherwise
Diploma	= 1 if college diploma, 0 otherwise
Degree	= 1 if university degree, 0 otherwise
Exp (month)	= Potential work experience, age minus the number of years of formal education minus 6.
Train	= 1 if a worker receive a formal training, 0 otherwise
Prof cert	= 1 if a worker has a professional or skills training certification, 0 otherwise
Female	= 1 if female, 0 otherwise
Married	= 1 if married, otherwise
Child12	= The number of household members less than 12 years-old
Race	
Malay	= 1 if Malay, 0 otherwise
Chinese	= 1 if Chinese, 0 otherwise
Indian	= 1 if Indian, 0 otherwise
Educational-skills mismatch	
Overeducated	= 1 if overeducated, 0 otherwise
Undereducated	= 1 if under-educated, 0 otherwise
Outside of own field	= 1 if a worker is employed outside own field/unrelated to their field of study, 0 otherwise
Moderately overskilled	= 1 if moderately overskilled, 0 otherwise
Severely overskilled	= 1 if severely overskilled, 0 otherwise

Firm age	= Age of firm
Share of workforce with a university qualification	
Graduates less than 25%	= 1 if the share is less than 25%, 0 otherwise
Graduates 25 to 50%	= 1 if the share is between 25% and 50%, 0 otherwise
Graduates more than 50%	= 1 if the share is more than 50%, 0 otherwise
Firm size	
Firm size less than 50 emp	= 1 if firm has less than 50 employees
Firm size 50 to 150 emp	= 1 if firm between 50 and 50 employees, 0 otherwise
Firm size more than 150 emp	= 1 if firm has more than 150 employees, 0 otherwise
Firm ownership –P	
Purely domestically-owned	= 1 if firm is purely domestically owned
Less than 30% foreign-owned	= 1 if foreign ownership is less than 30%, 0 otherwise
more than 30% foreign-owned	= 1 if foreign ownership is more than 30%, 0 otherwise
Share of labour cost of firm total cost	
Labour cost less than 25%	= 1 if labour cost less than 25% of total cost, 0 otherwise
Labour cost 25 to 50%	= 1 if labour costs between 25 and 50% of total cost, 0 otherwise
Labour cost 51 to 75%	= 1 if labour costs between 51 and 75% of total cost, 0 otherwise
Labour cost more than 75%	= 1 if labour costs more than 75% of total cost, 0 otherwise
Hiring system	
Education-based	= 1 if education is the most important considerations in recruiting, 0 otherwise
Work exp-based	= 1 if work experience is the most important considerations in recruiting, 0 otherwise
Technical-based	= 1 if technical skills is the most important considerations in recruiting, 0 otherwise
Firm competitor	
No competitor	= 1 if firm has no competitor
Competitor less than 25	= 1 if firm has less than 25 competitors, 0 otherwise
Competitor more than 25	= 1 if firm has more than 25 competitors, 0 otherwise
Firm train	= 1 if firm providing training programmes at the workplace, 0 otherwise

LogL	= Total number of employees in 2006 (in log)
LogK	= Total cost paid for rent capital in 2006 (machinery, building or land)

Source: 2007 Productivity Climate Investment Survey