Jurnal Ekonomi Malaysia 48(1) 2014 133 - 142

Do Cost of Training, Education Level and R&D Investment Matter towards Influencing Labour Productivity?

(Adakah Kos Latihan, Tahap Pendidikan dan Pelaburan R&D Penting ke Arah Mempengaruhi Produktiviti Buruh?)

Norhanishah Mohamad Yunus
Universiti Sains Malaysia

Rusmawati Said
Department of Economics
Universiti Putra Malaysia

Law Siong Hook
Department of Economics
Universiti Putra Malaysia

ABSTRACT

Firms that invest in knowledge introduce more technological advances, while firms that innovate have greater labour productivity. This study aims to investigate the impact of the cost of training, level of educational attainment and research and development (R&D) investment on labour productivity in Malaysia's manufacturing industry. Using 3 digit levels of panel data set from 53 manufacturing industries, this study applies the System-Generalized Method of Moments (SYS-GMM) estimator technique to capture the effects of human capital variables on productivity. The study finds that the cost of training sponsored by a firm, level of educational attainment and R&D investment are significant and influence labour productivity. This study also finds that the level of education attained by employees significantly influences labour productivity. However, employees whose educational credentials do not proceed further than diploma and SPM level education remain insignificant in influencing labour productivity. The results are consistent with the objectives of the Economic Transformation Programme of the Malaysian government, which aims to enhance the quality of skilled labour to successfully develop a high income economy. In order to attain the status of a high income economy, 60 percent of jobs in Malaysia must consist of skilled workers and quality skilled workers, which are crucial to accelerating economic development. Consequently, manufacturing industries could improve their competitive position by raising their respective employment shares of high-skilled labour.

Keywords: Education; GMM-SYS; human capital; labour productivity; R&D expenditures; training.

ABSTRAK

Firma yang membuat pelaburan berasaskan pengetahuan memperkenalkan lebih banyak perkembangan teknologi yang baru manakala firma yang berasaskan inovasi pula lebih cenderung kepada peningkatan produktiviti buruh. Kajian ini bertujuan mengkaji kesan kos latihan, tahap pencapaian pendidikan, dan pelaburan aktiviti pembangunan dan penyelidikan ke atas produktiviti buruh dalam industri pembuatan di Malaysia. Dengan menggunakan data panel 3 digit yang berasaskan 53 industri pembuatan, kajian ini mengaplikasikan teknik penganggaran System-Generalized Method of Moments (SYS-GMM) untuk mengkaji kesan pembolehubah modal insan ke atas produktiviti. Kajian ini mendapati bahawa kos latihan yang ditanggung oleh sesebuah firma, tahap pencapaian pendidikan, dan pelaburan aktiviti penyelidikan dan pembangunan mempunyai kesan yang signifikan dan mempengaruhi produktiviti buruh. Hasil kajian juga mendapati pencapaian pendidikan pekerja juga mempunyai kesan yang signifikan dan mempengaruhi produktiviti buruh. Walau bagaimanapun, pekerja yang mempunyai pencapaian pendidikan sehingga ke peringkat SPM dan diploma sahaja, memberi kesan yang tidak signifikan terhadap produktiviti buruh. Hasil kajian yang diperolehi adalah seiring dengan objektif Program Transformasi Ekonomi Kerajaan Malaysia yang bertujuan meningkatkan kualiti buruh berkemahiran bagi membentuk ekonomi berpendapatan tinggi. Dalam usaha mencapai status ekonomi berpendapatan tinggi, pekerjaan di Malaysia perlu memiliki 60 peratus pekerja berkemahiran. Pekerja berkemahiran yang berkualiti adalah penting untuk menjana pertumbuhan ekonomi yang pesat. Kesannya, industri pembuatan boleh mempertingkatkan kedudukan kompetitif mereka dengan meningkatkan komposisi pekerja berkemahiran tinggi.

Kata kunci: GMM-SYS; latihan; Modal insan; pendidikan; perbelanjaan R&D; produktiviti buruh.

INTRODUCTION

In order to become a high income country, Malaysia emphasises human capital and R&D (research and development) in their long and medium term plans. The two elements are recognised as an engine to achieve a productivity driven economy (Ninth Malaysia Plan (9MP), 2006-2010 & Tenth Malaysia Plan (10MP) 2011-2015. The importance of human capital and research and development (R&D) on productivity is documented in many empirical studies and applies to both macro and microeconomic studies (Fischer et al. 2009; Redding 1996). In line with endogenous growth theory, improvements in productivity are linked to a faster pace of innovation and more investment in human capital. In extant literature, education and training are the main variables that contributes to the productivity of a firm (Ballot et al. 2001; Corvers 1997). Thus, a skill shortage can be reduced by increasing the amount and effectiveness of education and training (Haskel & Martin 1993). The theory of endogenous growth model assigns a substantial role to R&D as an engine of productivity (Griliches 1979).

Numerous studies focus on the investment in human capital that is measured by educational attainment and linked with R&D. Few studies explore the effect of training sponsored by firms (Ballot et al. 2001). However, most of the studies are not considered the cost of training in their analyses. In order to estimate the impact of productivity, the present study uses the cost of training. The cost of training is not only important to decisions made by employers concerning whether workers need to be trained, but also to determine what kinds of training should be provided to employees. Given that the impact of training upon productivity is highly dependent upon the type of training program utilised, the possibility of employers providing varying types of training is hypothesised a being dependent upon the relative costs and benefits of investing in training in relation to the skills needed to enhance labour productivity (Tan & Batra 1995).The present article contributes to existing literature by presenting new evidence at the industry level. The effects of human capital investment are investigated in terms of skills, education and links with R&D investment on labour productivity in manufacturing industries. The study seeks to answer the question of whether the three types of investments are needed to increase labour productivity.

The remainder of this article is organized as follows. In the second section, a background of human capital, R&D and labour productivity in Malaysia is provided; and the theoretical background and related empirical literature are discussed. The third section discusses the data sources and variable concepts. In the fourth and fifth sections, the methodology and econometric strategy are presented, respectively. The results of the econometric exercises are reported in section six. These results include the robustness of the results in relation to the inclusion of the ancillary variables. Concluding remarks are presented in section seven.

HUMAN CAPITAL, R&D INVESTMENTS AND LABOUR PRODUCTIVITY IN MALAYSIA

The interrelationship between investments in human capital, R&D and productivity is likely to be a major issue in Malaysia due to the role of enhancing labour productivity growth. Labour productivity in Malaysia grew at a rate of 3.1% in 2000 and 3.6% in 2008. Such labour growth demonstrates an increasing trend, but the changes is slow compared to labour productivity growth in other Asian countries during the same period, such as China (8.3% - 10.7%), India (3.6% - 5.4%), Sri Lanka (2.5% - 4.7%), and Cambodia (3.5% - 6.3%). Vietnam and Myanmar decreased in terms of labour productivity growth (4.8% to 4.3% and 10.8% to 5.0%, respectively).

Malaysian investments in human capital and R&D have been increasing compared to other countries such as Thailand and Indonesia. The government development allocation on education, R&D and venture capital increased by 40% in Tenth Malaysia Plan (10MP, 2011-2015) as compared with 21.8% in Ninth Malaysia Plan (9MP, 2006-2010). Public expenditures on education, as a percentage of gross domestic product (GDP), for Malaysia is higher than in the other selected countries. For instance, Malaysian expenditures on education were equivalent to 4.7% of GDP in 2006 compared to those of Thailand (4.3%), Hong Kong (3.9%), Indonesia (3.6%), India (3.1%) and the Philippines (2.6%) (World Bank 2010).

Other indicators of human capital, such as the growth of enrolment in Higher Education Institutions for all levels of study, increased by 47.6% during the period of 2006-2010. The empirical study also indicates that an increase in the average level of formal education or educational attainment leads to enhanced labour quality and contributes to aggregate productivity growth (Mason & Finegold 1997). However, the contribution of education to Malaysian output remained unchanged (0.3%) between the periods of 1987-1997 and 1998-2007. As such, continuous efforts have been undertaken to establish several advanced skills training institutes linked with foreign institutions, such as the German-Malaysian Institute Malaysian-France Institute, Japanese-Malaysian Technical Institute, British-Malaysian Institute and Malaysian Spanish Institute (9MP, 2006-2010).

The Malaysian government recognises the importance of joint investments in human capital and R&D to enhance productivity growth, which is reflected by provision in the annual budget of the Malasyian government for R&D activities. In addition, greater participation from the private sector in investing in R&D activities was encouraged. In terms of the gross expenditure on R&D as a percentage of GDP, the Malaysian expenditure on R&D was higher than in selected Asian countries. For instance, Malaysian R&D expenditures of 0.47% in 2000 were higher than in Indonesia (0.07%) and Thailand (0.25%). In 2006, Malaysian R&D expenditures increased to 0.64%. However, the increment in R&D expenditures is still comparatively lower than key Asian competitors, such as Korea (3.01%), Singapore (2.52%), China (1.42%) and Hong Kong (0.81%).

LITERATURE REVIEW

The role of human capital and R&D are presently attracting considerable attention in theoretical works geared towards determining productivity growth (Redding, 1996). Productivity is often seen as the real driver of growth. Productivity is directly linked to education, training, R&D, innovation and technology, as well as strategic investments in physical capital, human capital, public capital, and labour division (Romer 1990). Human capital theory posits that formal education is highly instrumental and necessary to improve the production capacity of a population. In short, human capital theorists argue that educated people are a productive population (Schultz 1961). Education increases the productivity and efficiency of workers by increasing the level of cognitive stock of economically productive human capability. Human capital has a direct effect on value added as an input, either through a higher direct productivity, particularly from the educated workers, or because of the role of the employer in making better decisions and their capability to organize or supervise the work (Gemmell 1997).

Black and Lynch (1996) conclude that a positive relationship exists between workers' years of schooling and productivity, particularly in firms that have a higher average employee education level. A recent study of 198 European regions, which uses tertiary education as a proxy for human capital, finds that a 10% increase in human capital will lead to a 1.3% increase, on average, in the final period level of labour productivity (Fischer et al. 2009). Moretti (2004) examines the effect of college education on plant level productivity growth during the period of 1982 to 1992. The study shows that a 1% increase in the percentage of college educated workers leads to an increase in plant productivity by 0.6 – 0.7%, with higher returns for high technology industries.

Jajri and Ismail (2010) show that the effect of quality labour (measured by level of education) is not significant compared to capital stock and capital-labour ratio in determining labour productivity in Malaysia for the period of 1981 to 2007. The finding is attributed to the fact that the numbers of workers (senior officials and managers, professionals, technicians and associate professional) have been growing slowly.

The human capital accumulated from education and training contributes to a firm's productivity by providing useful knowledge and skills (Ballot et al. 2001; Corvers 1997). A study by Mason and Finegold (1997) in the United States and Britain supports the positive relationship between human capital and firm performance. The study finds that education and training are more important than physical capital in determining productivity. Other US and Canadian studies show that highly educated workers are more likely to participate in training than those with little education, suggesting a complementary relationship between human capital acquired through the education system and that acquired through in-house training (Lynch 1992). The effects of particular forms of training can lead to higher productivity. More specifically, an increase of 10 hours per year of for the training of all employees leads to an increase in current productivity by 0.6% (Ballot et al. 2001). A study by Barrett and O'Connell (2001) also shows that training leads to a significant positive change in labour productivity, whether it is specific or general training. These findings are supported by (Tan & Batra 1995).

Similar results are found in the context of Malaysia. Training expenditures in Small and Medium Enterprises (SMEs) have a significant impact on labour productivity because an increase in the level of productivity reflects an increase in the efficiency of inputs (Ismail 2000). However, Malaysian training expenditures at the industry level are comparatively lower than expenditures for training in the US (Karuppiah 2004). Tan & Batra (1995), found that only 35% of Malaysian firms conducted formal training and the firms focussed only upon specific training related to their firms' needs. Meanwhile, in the manufacturing industry, training provided by employers also varies according to firm size. For small manufacturing establishments, the proportion of training has changed largely in recent years. Training declined from 34 percent in 1997 to 25 percent in 2002, but recovered to 31 percent in 2007. Meanwhile, for medium-sized manufacturing establishments, incidents of training increased from 56 percent in 1997 to 57 percent in 2002 and 72 percent in 2007. The amount of training provided in Malaysia was the highest compared with other selected countries, such as Colombia, Indonesia, Mexico and Taiwan. The survey conducted by Tan & Batra, (1995) covers a wide range of firms with different characteristics in relation to age, location, firm size, foreign capital, export orientation and industry.

The effects of training can be beneficial for firms. According to Booth and Snower (1996), training and innovation are inextricably linked; and reinforce each other due to the impact of training enhancing the profitability of innovation and encouraging firms to be more innovative. Firms active in R&D tend to implement more training programmes and consequently generate more productivity growth (Baldwin & Johnson 1996). For instance, Ballot et al. (2001) finds that the effects of training among French and Swedish firms reveals that firm sponsored training and R&D expenditures are significant. However, only training has a positive effect on the profitability of a firm.

With regards to the productivity an d R&D issues, the relationship between productivity and R&D expenditure is well documented in economic literature. The first study pertaining to the role of R&D in determining productivity growth was pioneered by (Griliches 1979), who finds that R&D has a positive and significant impact on productivity growth at the firm, sectoral and national levels. Empirical literature reveals that between 1% and 25% of the variance in actual productivity across firms can be explained by differences in R&D investment (Hall, Mairesse, & Mohnen, 2010). However, Chang and Robin (2008) analyse the impact of being an innovator on total factor productivity TFP in Taiwan between 1997 and 2003 across 23 industries. The results reveal a significant negative effect of being an innovator on TFP in most industries, both before and after 1999.

A recent study by Bravo-Ortega and García Marín (2011) use a 65-country panel for the period between 1965 and 2005 and analyse the relationship between R&D and productivity. The findings indicate that a 10% increase in R&D per capita generates an average increase of about 1.6% in long-run TFP. Mario (2009) analyses the relationship between productivity growth and levels of R&D investment and finds that more than 65 % of the productivity growth variance is determined by gross domestic expenditure on R&D (GERD). In addition, when the range of GERD is between 2.3% and 2.6 %, productivity growth is maximized and productivity and technology improvements are sustained.

METHODOLOGY

DATA

The data used in the present study were obtained from the Malaysian Department of Statistics (MDOS) based upon a manufacturing survey on industries including the following variables: training cost expenditures; formal educational attainment; value added; and gross fixed capital formation. The dataset contains R&D expenditure information gathered from the National Survey of Research and Development that was conducted by the Malaysian Science and Technology Information Centre (MASTIC) and MDOS. Data required to measure labour productivity were provided by the Malaysian Productivity Corporation (MPC). Data concerning the firms are classified by type of activity in accordance with the "Malaysian Industrial Classification System" (MSIC) at three-digits and only focuses on manufacturing industries, because R&D activities and innovation has been associated with the manufacturing sector for a long period of time (MASTIC 2008).

The present study examines the period of 2000-2008. The limitation of the temporal scope of the present study is due to the industrial classification system (previously known as the Malaysia Industrial Classification (MIC), 1972: revised in 1979). After 2008, the MSIC code was revamped by DOS. However, the period is selected because investment in human capital is considered to be large during this period. In addition, the data from 2008provides comprehensive information on the status of R&D in Malaysia (MASTIC 2008).

Labour productivity is measured by value added per worker because the measurement of labour productivity reflects the combined effects of changes in capital inputs, intermediate inputs and overall productivity, without leaving out any direct effects of technical change, whether such effects are embodied or disembodied. The advantages of this measurement are that the results are easy and readable (OECD 2001). Human capital is a proxy by training and level of education. Training refers to the cost of training sponsored by the industry. Investment in training is calculated in aggregate form and includes in-house training and on-the-job training.

The cost of training also includes the training of all workers because of the non availability of data disaggregating training costs according to forms of training, job classification and skill group. Educational attainment is divided into 3 categories based upon the classification criteria of MDOS. In Malaysia, the data for educational attainment are categorized as University degree and above; Diploma/STPM or equivalent; and SPM/SPVM or equivalent, which describe tertiary, secondary and primary education, respectively. Investment in R&D is measured by R&D expenditure, where the R&D expenditure is treated as an investment, rather than as an expense (Parham 2006). Expenditure can be divided into 2 categories: current expenditures and capital expenditures. Current expenditures consist of labour costs and operating costs, while capital expenditures consist of land, building and other structures; and vehicles, plants, machinery and equipment.

MODEL SPECIFICATION

The purpose of this section is to estimate the impact of both investments of human capital and R&D on labour productivity for the period of 2000-2008. The estimation of the labour productivity model is based on the Cobb Douglas production function. In the present study, a combination of model specification of Bronzini and Piselli (2009) and that of Ballot et al. (2001) is used to examine the interaction between investments in human capital and R&D on the productivity of firms. The model estimated by Bronzini and Piselli (2009) focuses on the impact of human capital in terms of educational attainment (proxy average years of schooling), R&D and public capital infrastructure.

The present study eliminates public capital infrastructure as an independent variable due to data limitations. To measure the effect of educational attainment on labour productivity, the present study follows the approach of Corvers (1997) by defining workers based upon their educational attainment. This study includes educational attainment in the model to demonstrate the impact of human capital in terms of knowledge, combined with training and R&D investment, on labour productivity. The present study combines all models to investigate the effects of human capital in terms of skills, education and links with R&D investment on labour productivity in manufacturing industries. The basic model can be expressed as follows:

$$\ln Y_{it} = \ln A_{it} + B_1 \ln\left(\frac{K}{L}\right)_{it} + B_2 \ln EDU_{it} + B_3 \ln TRAIN_{it} + B_4 \ln RD_{it} + B_5 \ln X_{it} + \varepsilon_{it} \quad (1)$$

Where *i* and *t* are industry index and time index; *Y* refers to labour productivity per value added; $\frac{K}{L}$ denotes the ratio of capital to worker or capital intensity, *EDU* refers to the level of educational attained by employees, *TRAIN* is cost of training per employee and *RD* represents R&D investment. *X* represents other factors commonly considered in the literature on labour productivity including industrial sales revenue of the sub-sector (which is calculated by dividing such revenue by the number of total firms) (Ballot et al. 2001) and ICT investment (share of ICT to GDP)(Belorgey et al. 2006). ε_{it} is an error term that captures the time varying firm specific productivity shocks.

ECONOMETRIC STRATEGY

The present study employs the Generalized Method of Moments (GMM) technique, as proposed by Arellano and Bover (1995), to estimate the labour productivity function during the period of 2000-2008. The data covers 53 industries in the manufacturing sector. Two techniques of GMM exist: difference GMM (DIFF-GMM) and system GMM (SYS-GMM). The first DIFF-GMM was introduced by (Arellano & Bond 1991; Arellano & Bover 1995). Blundell and Bond (1998) extended the technique by introducing SYS-GMM. Both estimators limit the number of instruments and have their advantages for the control of unobserved heterogeneity and simultaneity, especially as both problems are present in the OLS estimator.

However, it is well documented that the first-differenced GMM estimator has very poor finite sample properties in terms of bias and precision. Consequently, Blundell and Bond (1998) propose the use of extra moment conditions in the SYS-GMM estimator due to a lower bias and higher efficiency than all the other estimators analysed, including the standard first-difference GMM estimator. In addition, the basic advantages of the SYS-GMM, as compared with the DIFF-GMM, are due to the valid instrumental variables for the untransformed equations in levels. The SYS-GMM not only increases the efficiency of the estimates, but also allows for the exploitation of all of the variable information at the level and difference equations (Arellano & Bover 1995). In the present study, the application of the SYS-GMM is more appropriate than the DIFF-GMM since the number of time series observations is small (477 observations) and consists of a short panel (N=53).

The estimation of the labour productivity function in Equation (4.0) yields biased results because an endogeneity problem exists in the present study. More specifically, the presence of endogeneity is due to unobserved time invariant heterogeneity (Dearden, Reed, & Van Reenen, 2000; Dearden et al., 2006). The occurrences of unobserved time-invariant heterogeneity due to the training offer by firms may be structurally more or less productive. In addition, the endogeneity of a firm's decision is also influenced by other factors, such as management quality; technical change; industrial relationships; personnel department activity; management-employee relationships; and technological levels (Colombo & Stanca 2008). Consequently, unobserved heterogeneity between firms leads to a correlation between formal training and the error term (Griliches & Mairesse 1998), as the result impacts the explanatory variables and value added at the same time (Huselid & Becker 1996). Firms do not decide randomly how many employees need to be trained. Thus, training is not a strictly exogenous variable in the productivity equation. The endogeneity also emerged in R&D firms due to decisions of R&D firms regarding output and investment (Griliches 1979).

To solve the problem of endogeneity, the SYS-GMM estimators are applied, which takes the 1st differences and lagged instruments of training and R&D investments to eliminate unobserved industry specific effects and time invariant characteristics. These techniques are more effective in remedying the shortcomings of the fixed effect model. The efficiency in short panel estimates can also be increased since the sample of firms only covers 9 years and 53 manufacturing industries (Blundell and Bond (1998).

In the model estimation, the presence of heteroscedasticity of an unknown form and the instrument variable estimates of the standard errors are inconsistent. Hence, the two-step SYS-GMM with a robust technique is adopted due to the presence of heteroscedasticity and the serial correlation consistent estimate of the weighting matrix, taking the residuals from the one-step estimate(Davidson & MacKinnon 2004). GMM allows for the use of orthogonality conditions for efficient estimation in the presence of the heteroscedasticity of an unknown form (Hansen 1982).

A simultaneity problem also exists for future labour productivity output, in which the value added depends on past R&D. R&D, in turn, depends on both past outputs and the expectations concerning R&D in future, as discussed by (Griliches & Mairesse 1998). The effect of current R&D on productivity is not prompt and the impact can be seen after several years due to the time required for R&D

development. Hence, assumptions are made concerning the relevant lag structure (Griliches 1979). To address the problem of simultaneity and the correlation between labour productivity and the error term, the equation is lagged with at least one lagged dependent variable on the right-hand side. The lagged level of the regressor is utilized as an instrument (Arellano & Bond 1991).

This is valid under the assumption in the present model that the error term is not serially correlated and the lag of the variables are weakly exogenous. To increase the efficiency of the lagged levels of a series, appearing as weak instruments in the first difference, the present study implements the extended SYS-GMM estimator by taking into account additional non-linear moment conditions that correspond with adding T–2 equations in levels to the system (Blundell & Bond 1998), in which pre-determined and endogenous variables in levels are instrumented with suitable lags of their own differences.

In the present analysis, the instrument set is lagged at two periods, particularly for the variables representing training, R&D and ICT investments, due to the fact that returns on investment occur many years in the future. For instance, the impact of the R&D investment on labour productivity at the aggregate firm level is faced with several lags because of many projects that started at different dates and that are in different stages of fruition (Griliches, 1979). Firms may choose to invest in R&D, which, on average, will increase their future productivity whether they innovate in t-1 and t. The returns on R&D are subject to uncertainty, reflecting the fact that some R&D projects ultimately fail (Griliches 1979). This technique not only addresses the endogeneity problem, but also corrects for bias arising from transitory measurement error in both the dependent variable and the regressors.

As the present study is based upon a DPD model, one issue with regard to DPD GMM still remains problematic: the fact that the number of instruments grows with T. The presence of too many instruments results in GMM becoming inconsistent due to generating endogenous variables that can be over-fitted. Hence, the power of the Hansen test to detect instruments joint-validity can be weakened (Calderon, Chong & Loayza 2002). Therefore, the present study implements the "collapsing" technique to overcome the problem of too many instruments, due to the small sample size used in the present study. This technique provides a few advantages that provide a basis for certain minimal arbitrary robustness and specification tests for SYS-GMM.

EMPIRICAL RESULTS

In this section, the results are discussed based upon the estimation in Equation (1.0) by using the SYS-GMM estimator with the first difference transformation. The results reported are as shown in Appendix (Table A.2) for the robustness test. The analysis begins without the inclusion of educational attainment to examine the impact of investment in training and R&D on labour productivity. Columns (1) and (2) report that the results reveal only training assert a significant impact without the inclusion of the impact of educational attainment into the model. The other variables remain statistically insignificant for influencing labour productivity for one and two step variants. However, the influence of R&D on labour productivity at the two-step GMM estimators is shown in column (2). The two-step estimates of the standard errors tend to be downward biased (Arellano & Bond 1991; Blundell & Bond 1998).

The present study study re-estimates the model by including educational attainment as shown in Columns (3) and (4) in Table A.2 in the Appendix. The results demonstrate that, following the inclusion of educational attainment into the model, only training; educational attainment with degree; and ICT investment are significant at one-step and two-step GMM estimators. R&D investment; educational attainment with a diploma and SPM levels; capital intensity; and firm size fail to achieve significance at one and two-step variants. However, the results presented in Columns (1) to (4) suffer a problem of instruments proliferation due to generating a very high number of instruments proliferations. As the Hansen test (p value) equal to 1 this results indicate that the instruments are endogenous and statistically insignificant.

Therefore, the present analysis applies the "collapsing" technique to reduce the number of instruments following a novel procedure, as suggested by Calderon et al. (2002). The results of the analysis are presented in Table 1. Columns 1 and 2 in Table 1 show the effects of ICT investment and firm size variables are considered in the model. The results indicate that ICT investments affect capital intensity. Both variables appear to have a similar impact on labour productivity, especially to those employees with degree education levels. However, by including both variables together in the model, the results in Column (3) indicate that R&D becomes significant. This results consistents with the previous literature such as Cohen & Klepper (1996) and Lichtenberg & Siegel, (1991) where there are strong association exists between R&D and firm size). Firm size is considered as important factor that influences R&D activities (Kafouros & Wang 2008). In another study, R&D and ICT strongly influence labour productivity (THIa & Martin 2011).

It is interesting to note that the cost of training; R&D; and educational attainment with degrees levels are jointly significant and influence labour productivity. The findings are supported by Booth and Snower (1996), who argue that training and R&D are inextricably linked to determine productivity growth. In the case of Malaysia, the effort of made by the government is demonstrated by financial investments made to financially support education and training initiatives. For example, the Ministry of Human Resources has established a number financial grant

TABLE 1. Labour productivity, SYS-GMM Estimator with "Collapsing Technique"

Variable	1		2		3	
	Alternative SYS-GMM					
	Two-Step					
	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
Lagged labour productivity	0.127	0.293 (0.644)**	0.508	0.175 (0.004)*	0.365	0.171 (0.030)*
Share of training cost per employee	0.004	0.002 (0.047)*	0.002	0.002 (0.088)**	0.002	0.001 (0.082)**
R&D Expenditure	–0.054	0.040 (0.169)	–0.055	0.061 (0.366)	–0.010	0.044 (0.022)*
Edu_Degree	0.472	0.246 (0.055)**	0.622	0.323 (0.054)**	0.636	0.226 (0.005)*
Edu_Diploma	–0.414	0.139 (0.195)	–0.358	0.477 (0.452)	–0.369	0.355 (0.299)
Edu_SPM	–0.473	0.473 (0.435)	0.015	0.729 (0.983)	–0.138	0.504 (0.783)
Firm Size	0.193	0.193 (0.180)	–	–	0.151	0.113 (0.186)
Share ICT/GDP	–	–	–0.096	0.085 (0.263)	–0.101	0.056 (0.075)**
Capital Intensity	0.041	0.125 (0.742)	0.187	0.095 (0.051)**	0.098	0.106 (0.355)
AR(20 Test	0.244		0.844		0.556	
Hansen/Sargan Test (p-value)	0.527		0.631		0.655	
Observation	53		53		53	
Instrument	29		29		32	

The figures in parentheses represent standard error.
All variables are transform into natural log.
* denote significant at 5%
** denotes significant at 10%

categories in the Human Resource Development Fund (HRDF) for training and upgrading of employee skills. Firms that have contributed to this fund are eligible for grants to defray the costs incurred in training and re-training their workforce. Realising that financing is a key enabling factor for innovation, a total of RM116 million under the Human Resource Development Programme has been allocated to fund for specialist and consultant training, as well as attachments for researchers. To further enhance productivity and technological development, centres of excellence in emerging technology and research institutions have been upgraded and coupled with industrial collaborations with the industry to generate technologies required for product and process innovation (EPU 2006, 2010).

The effect of training and R&D emerged after controlling for unobserved heterogeneity. The effect is found to be more robust after using the "collapsing" technique to eliminate the problem of too many instruments. The role of educated workers and highly skilled labour, which are employees with a college degree, are found to be positively associated with the firm productivity indicators (Black & Lynch 1996; Moretti 2004). More highly skilled workers are found to be a direct source of innovation (Romer 1990). More importantly, the model cannot be rejected on the basis of either the Hansen's test or second-order serial correlation. No evidence exists of instrument proliferation as the number of instruments appears to be substantially smaller than *N*.

Educational attainment with diploma and SPM levels remains insignificant in influencing labour productivity. This is because workers believe that they need a university degree and on-the job training to do their jobs properly (EPU & Bank 2007). This result parallels the current situation, which reflects that the numbers of firm involved with on the-job training increased dramatically from 1.2 million firms in early 2000 to 2.5 million firms in 2005.

CONCLUSION

The investigations of the effects of human capital and and R&D investments on labour productivity on 51 manufacturing industries finds that investments in R&D and training have a significant impact in influencing labour productivity in Malaysia during the period of 2000-2008. In line with the 10MP, the focus of the Malaysian government on skill development to enhance the skills of workers, as well as the upgrading of the existing workers, will facilitate industries to drive productivity growth and speed up the value chain. The present study expands on earlier research by combining the impact of training and education attainment jointly with the R&D investment in influencing labour productivity. Consistent with Said et al. (2008), the influence of educational attainment on labour productivity is confirmed for workers with university degrees. To enhance the productivity of workers with diploma and SPM education levels, employers need to increase their investments in on-the-job training and learning-by-doing. Employers also need to focus more on specific worker training. The present study suggests that policy makers should focus on both human capital and R&D in order to assist the nation to become a developed nation.

The present study contributes to literature in the field by applying the first difference SYS-GMM with the "collapsing" technique to alleviate the first different technique overcoming the simultaneous problem; and utilizing the "collapsing" technique to resolve the proliferation problem. Both problems have emerged in other estimators, including the standard GMM.

REFERENCES

Arellano, M., & Bond, S. 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies* 58(2): 277.

Arellano, M., & Bover, O. 1995. Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics* 68(1): 29-51.

Baldwin, J., & Johnson, J. 1996. Human capital development and innovation: A sectoral analysis. In *The Implications of Knowledge-Based Growth for Micro-Economic Policies*. Edited by P. Howitt, 83-110. Calgary: University of Calgary Press.

Ballot, G., Fakhfakh, F., & Taymaz, E. 2001. Firms' human capital, R&D and performance: a study on French and Swedish firms. *Labour Economics* 8(4): 443-462.

Barrett, A., & O'Connell, P. J. 2001. Does training generally work? The returns to in-company training. *Industrial and Labour Relations Review*: 647-662.

Bartel, A. P., & Lichtenberg, F. R. 1987. The comparative advantage of educated workers in implementing new technology. *The Review of Economics and Statistics* 49(1): 1-12.

Belorgey, N., Lecat, R., & Maury, T.-P. 2006. Determinants of productivity per employee: An empirical estimation using panel data. *Economics Letters* 91(2): 153-157.

Bishop, J. 1994. *The Impact of Previous Training on Productivity and Wages*. Chicago: University Of Chicago Press.

Black, S. E., & Lynch, L. M. 1996. Human-capital investments and productivity. *The American Economic Review* 86(2): 263-267.

Blundell, R., & Bond, S. 1998. Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics* 87(1): 115-143.

Booth, A. L. & Snower, D. J. 1996. *Acquiring Skills: Market Failures, Their Symptoms and Policy Responses*. Cambridge: Cambridge University Press.

Bravo-Ortega, C., & García Marín, Á. 2011. R&D and productivity: A two way avenue? *World Development* 39(7): 1090-1107.

Bronzini, R., & Piselli, P. 2009. Determinants of long-run regional productivity with geographical spillovers: The role of R&D, human capital and public infrastructure. *Regional Science and Urban Economics,* 39(2): 187-199.

Calderon, C., Chong, A., & Loayza, N. 2002. Determinants of current account deficits in developing countries. *Contributions to Macroeconomics* 2(1): 2.

Chang, C. L. & Robin, S. 2008. Public policy, innovation and total factor productivity: An application to Taiwan's manufacturing industry. *Mathematics and Computers in Simulation* 79(3): 352-367.

Cohen, W. M., & Klepper, S. 1996. Firm size and the nature of innovation within industries: the case of process and product R&D. *The Review of Economics and Statistics*: 232-243.

Colombo, E., & Stanca, L. 2008. The impact of training on productivity: evidence from a large panel of firms.

Corvers, F. 1997. The impact of human capital on labour productivity in manufacturing sectors of the European Union. *Applied Economics* 29(8): 975-987.

Davidson, R., & MacKinnon, J. G. 2004. *Econometric Theory and Methods*. New York: Oxford University Press New York.

Dearden, L., Reed, H., & Van Reenen, J. 2000. Who gains when workers train? Training and corporate productivity in a panel of British industries.

Dearden, L., Reed, H., & Van Reenen, J. 2006. The Impact of Training on Productivity and Wages: Evidence from British Panel Data*. *Oxford Bulletin of Economics and Statistics* 68(4): 397-421. doi: 10.1111/j.1468-0084.2006.00170.x

EPU. 2006. *Ninth Malaysia Plan, 2006-2010*. Kuala Lumpur: Percetakan Nasional Malaysia Berhad.

EPU. 2010. *Tenth Malaysia Plan 2011-2015*. Putrajaya: EPU, Prime Minister's Department.

EPU & Bank, W. 2007. *Productivity and investment climate survey*. Malaysia.

Fischer, M., Bartkowska, M., Riedl, A., Sardadvar, S., & Kunnert, A. 2009. The impact of human capital on regional labour productivity in Europe. *Letters in Spatial and Resource Sciences* 2(2): 97-108.

Gemmell, N. 1997. Externalities to higher education: A review of the new growth literature. *Report* 8: 5-9.

Griliches, Z. 1979. Issues in assessing the contribution of research and development to productivity growth. *Bell Journal of Economics* 10: 92-116.

Griliches, Z., & Mairesse, J. 1998. Production functions: The search for identification. In *Econometrics and Economic Theory in the 20th Century*, edited by S. Strøm. Cambridge: Cambridge University Press.

Hall, B. H., Mairesse, J., & Mohnen, P. 2010. *Measuring the Returns to R&D*: CIRANO.

Hansen, L. P. 1982. Large sample properties of generalized method of moments estimators. *Econometrica: Journal of the Econometric Society*: 1029-1054.

Haskel, J., & Martin, C. 1993. Do skill shortages reduce productivity? Theory and evidence from the United Kingdom. *The Economic Journal* 103(417): 386-394.

Huselid, M. A., & Becker, B. E. 1996. Methodological issues in cross-sectional and panel estimates of the human resource firm performance link. *Industrial Relations: A Journal of Economy and Society* 35(3): 400-422.

Ismail, R. 2000. Human Resource Development and SMEs' Performance. *Akademika* 57: 41-66.

Jajri, I., & Ismail, R. 2010. Impact of labour quality on labour productivity and economic growth. *African Journal of Business Management* 4(4): 486-495.

Kafouros, M. I., & Wang, C. 2008. The role of time in assessing the economic effects of R&D. *Industry and Innovation* 15(3): 233-251.

Karuppiah, K. 2004. *Education and Training Practices in Four Selected Malaysian Manufacturing Companies.* Serdang: Universiti Putra Malaysia.

Lichtenberg, F. R., & Siegel, D. 1991. The impact of R&D investment on productivity–New evidence using linked R&D–LRD data. *Economic Inquiry* 29(2): 203-229.

Lynch, L. M. 1992. Private-sector training and the earnings of young workers. *The American Economic Review* 82(1): 299-312.

Mario, C. 2009. What is the optimal rate of R&D investment to maximize productivity growth? *Technological Forecasting and Social Change* 76(3): 433-446.

Mason, G., & Finegold, D. 1997. Productivity, machinery and skills in the United States and Western Europe. *National Institute Economic Review* 162(1): 85.

MASTIC. (2008). *National survey of research and development*: Malaysian Science and Technology Information Centre, Ministry of Science,Technology and Innovation.

Moretti, E. 2004. Workers' education, spillovers, and productivity: evidence from plant-level production functions. *American Economic Review*: 656-690.

Nelson, R. R., & Phelps, E. S. 1966. Investment in humans, technological diffusion, and economic growth. *The American Economic Review* 56(1/2): 69-75.

OECD. 2001. *Measuring Productivity: Measurement of Aggregate and Industry-Level Productivity Growth: OECD Manual*: Organisation for Economic Co-operation and Development.

Parham, D. 2006. *Empirical Analysis of The Effects of R&D on productivity: Implications for Productivity Measurement*.

Redding, S. 1996. The low-skill, low-quality trap: Strategic complementarities between human capital and R & D. *The Economic Journal*: 458-470.

Romer, P. 1990. Endogenous technological change. *Journal of Political Economy* 98(2): 71-102.

Roodman, D. 2009. A Note on the theme of too many instruments. *Oxford Bulletin of Economics and Statistics* 71(1): 135-158.

Said, R., Haris, A., & McNabb, R. 2008. Changes in relative demand for labour in Malaysia (1984-1997) using a decompsition approach. *International Journal of Economics and Management* 2(1): 157-178.

Schultz, T. W. 1953. *The Economic Organization of Agriculture*. New York: McGraw-Hill New York.

Schultz, T. W. 1961. Investment in human capital. *The American Economic Review* 51(1): 1-17.

Tan, H. & Batra, G. 1995. *Enterprise Training in Developing Countries: Incidence, Productivity Effects and Policy Implications*. Private Sector Development Dept., World Bank.

THIa, T. U. N., & Martin, L. 2011) The Relationship between innovation and productivity conditional to R&D and ICT use. An empirical analysis for firms in Luxembourg. *Working Papers*.

Wolff, E. N. 2000. Human capital investment and economic growth: exploring the cross-country evidence. *Structural Change and Economic Dynamics* 11(4): 433-472.

World Bank. 2010. *World Development Indicators*. http://data.worldbank.org/.

Norhanishah Mohamad Yunus
Universiti Sains Malaysia

Rusmawati Said*
Department of Economics
Universiti Putra Malaysia
rusmawatisaid@gmail.com

Law Siong Hook
Department of Economics
Universiti Putra Malaysia

*Corresponding author

APPENDIX

TABLE A.1. Summary Statistic

Variable	Obs	Mean	Std. Dev	Min	Max
Share of training cost per	53	1.72	1.29	9.39	18.50
R&D Expenditure	53	15.40	1.90	8.41	20.44
Edu_Degree	53	5.98	5.54	0.79	90.40
Edu_Diploma	53	10.98	5.25	0.18	35.22
Edu_SPM	53	83.12	9.71	3.71	96.52
Firm Size	53	16.73	1.03	14.04	19.13
Share ICT/GDP	53	–1.90	1.44	–6.91	4.61
Capital Intensity	53	2.038	1.084	–3.83	6.1

TABLE A.2. Labour Productivity, Robustness Test by using SYS-GMM Estimator

Variable	1		2		3		4	
	SYS-GMM				SYS-GMM with Education Attainment			
	One-Step		Two-Step		One-Step		Two-Step	
	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
Lagged labour productivity	0.444	0.270 (0.035)*	0.451	0.321 (0.033)*	0.533	0.157 (0.001)*	0.565	0.147 (0.000)*
Share of training cost per employee	0.003	0.001 (0.001)*	0.003	0.002 (0.000)*	0.002	0.001 (0.037)**	0.001	0.001 (0.075)*
R&D Expenditure	0.515	0.052 (0.121)	0.057	0.057 (0.060)	–0.036	0.031 (0.198)*	–0.052	0.034 (0.136)
Edu_Degree	–	–	–	–	0.339	0.156 (0.023)*	0.399	0.116 (0.028)*
Edu_Diploma	–	–	–	–	–0.235	0.170 (0.344)	–0.239	0.171 (0.402)
Edu_SPM	–	–	–	–	–0.032	0.509 (0.950)	–0.109	0.965 (0.991)
Firm Size	–0.015	0.049 (0.151)	–0.022	–	0.011	0.054 (0.951)	0.027	0.045 (0.556)
Share ICT/GDP	–0.044	0.057 (0.448)	0.043	0.063 (0.057)**	–0.071	0.056 (0.092)**	–0.076	0.048 (0.072)**
Capital Intensity	0.229	0.218 (0.174)	0.170	0.169 (0.130)	0.222	0.164 (0.182)	0.215	0.139 (0.128)
AR(20 Test	0.427		0.390		0.587		0.697	
Hansen/Sargan Test (p-value)	0.979		0.979		0.985		0.985	
Observation	53		53		53		53	
Instrument	78		78		80		80	

The figures in parentheses represent standard error.
All variable are transform into natural log
* denote significant at 5%
** denotes significant at 10%