#### Jurnal Ekonomi Malaysia 58(1) 2024 77-90 http://dx.doi.org/10.17576/JEM-2024-5801-6

# Knowledge Spillovers and Workers' Absorptive Capacity in Manufacturing Industry

## (Limpahan Pengetahuan dan Kapasiti Penyerapan Pekerja dalam Industri Pembuatan)

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#### ABSTRACT

This article examines the relationship between FDI and workers' absorptive capacity on knowledge spillovers by constructing an augmented human capital model based on their education and job training experience. Employing a quantile regression estimator, the model scrutinises the knowledge flow from multinational corporations (MNCs) via labour mobility spillovers. This study use Malaysian manufacturing industry data from 2000 to 2019. The results of the study revealed that the Malaysian manufacturing industry has the potential to receive more than 30% of knowledge spillovers from FDI if the level of absorptive capacity of degree and diploma-educated workers reaches the highest quantile. The locally trained workers' absorptive capacity to exploit the foreign knowledge spillovers transferred from skilled workers who have worked in MNCs is assimilated only at the 25th quantile of the conditional knowledge spillovers of FDI distributions. This study suggests creating a lucrative reward system for those who successfully transfer the technological knowledge learned while working in multinational companies to employees in local firms. In addition, large-scale training institutions with comprehensive training programs need to be established at all levels of education, especially for the younger generation.

Keywords: Knowledge spillovers; multinational corporations; human capital; absorptive capacity; quantile regression

ABSTRAK

Kajian ini menganalisis hubungan antara pelaburan langsung asing dengan kapasiti penyerapan pekerja terhadap limpahan pengetahuan menerusi model modal manusia yang ditambah baik berdasarkan tingkat pendidikan dan pengalaman dalam latihan. Menggunakan penganggar regresi kuantil, model itu meneliti aliran pengetahuan daripada syarikat multinasional melalui limpahan mobiliti buruh. Kajian ini menggunakan data dari industri pembuatan dari 2000 hingga 2019. Keputusan kajian mendedahkan bahawa industri pembuatan Malaysia berpotensi untuk menerima lebih daripada 30% limpahan pengetahuan daripada pelaburan langsung asing jika tahap kapasiti penyerapan pekerja yang berpendidikan ijazah dan diploma mencapai kuantil tertinggi. Keupayaan penyerapan pekerja terlatih tempatan untuk mengeksploitasi limpahan pengetahuan asing yang dipindahkan daripada pekerja mahir yang telah bekerja di syarikat multinasional dapat diasimilasi hanya pada kuantil ke-25 limpahan pengetahuan. Kajian ini mencadangkan supaya diwujudkan suatu sistem ganjaran yang lumayan kepada mereka yang berjaya memindahkan pengetahuan teknologi yang dipelajari semasa bekerja di syarikat multinasional kepada pekerja di firma tempatan. Selain itu, suatu institusi latihan berskala besar dengan program latihan yang komprehensif perlu diperluaskan kepada semua peringkat pendidikan, khususnya generasi muda.

Kata kunci: Limpahan pengetahuan; syarikat multinasional; modal manusia; kapasiti penyerapan; regresi kuantil JEL: F20, F35, J24, C21, L6

Received 5 May 2023; Revised 5 February 2024; Accepted 30 April 2024; Available online 7 May 2024

#### INTRODUCTION

Multinational corporations (MNCs) undoubtedly contribute a combination of technology and knowledge spillovers through their investments, but many host countries, especially developing countries, no longer prioritise attracting foreign direct investment (FDI) inflows (Behera 2015; Nguyen et al. 2009; Yunus & Abdullah 2022a). Recently, attention has turned to the degree to which the spillovers brought by FDI can be assimilated



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and exploited by local workers. This is to ensure the host country could gain from the flow of superior technology, capital, know-how, and improved managerial skills (Blalock & Gertler 2009; Girma & Görg 2005; Nguyen et al. 2009; Shamsub 2014; Yunus et al. 2014, 2015). Based on the latest FDI inflow statistics, Malaysia continues to record high FDI inflows, reflecting the country's secure economic investment cycle during the COVID-19 pandemic (MIDA 2020)<sup>1</sup>. Concerns abound over how the technology and knowledge spillovers brought in by FDI can be applied and exploited by local workers in Malaysia, which is closely related to the concept of 'absorptive capacity'. We consider in this context through a broader sense, as one of the factors affecting a firm's capacity for absorption (e.g., Girma et al. 2001; Girma & Görg 2005; Yunus & Abdullah 2022a, 2022b). The term 'absorptive capacity', especially for domestic firms, can be defined as their capacity to increase productivity by utilising spillovers from multinational corporations (Girma & Görg 2005). Empirical studies have also proven that the recipient countries of FDI will reap greater benefits depending on the firm's and workers' ability to assimilate FDI spillovers. Absorptive capacity is a crucial element that can raise any company's productivity, and it is connected to dimensional operations, which include acquisition, assimilation, transformation, and exploitation (Mohammad et al. 2019; Vega-Jurado et al. 2008; Zahra & George 2002).

In Malaysia, there is a concern about the absorptive capacity of workers to exploit FDI technology and knowledge within the industry. This concern emerges because MNCs rate the level of absorptive capacity among qualified workers in the manufacturing industry as relatively low, despite a growing number of highly educated graduates and the implementation of skills upgrading programs by employers in their firms (Yunus & Abdullah 2022a; Yunus & Hamid 2017, 2019). A recent study by Yunus and Abdullah (2022a) showed that the technology brought in by foreign firms was not fully assimilated by workers in the local firms, as their technical skills were below the median level of absorptive capacity. Even though this concern is relatively important, the extent to which highly educated workers can transfer the knowledge and technological skills they acquired while working in MNCs to local workers has not explicitly been gauged.

Similarly, Mangematin and Nesta (1999) discovered that greater worker absorptive capacity would boost a firm's ability to employ more fundamental (as opposed to applied) knowledge. Furthermore, the firm's ability to learn is considered an idiosyncrasy resulting from 'competitive resources', which in this study is viewed as an overflow of external knowledge from MNCs (Hamel & Prahalad 1990). Therefore, this study contributes significantly to the body of knowledge because it differs from existing studies in at least three ways.

First, this study investigates knowledge spillovers from MNCs by considering the absorption of external knowledge. Since FDI is recognised as a crucial avenue for knowledge spillovers, most literature often disregards the knowledge absorption perspective (Foss & Pedersen 2002; Ghauri & Yamin 2009; Liu & Zou 2008; Yunus 2023). Absorptive capacity has only recently gained attention in FDI research, and yet, most research mainly focused on 'technology' as opposed to 'knowledge' spillovers (Ali et al. 2017; Yunus & Abdullah 2022b). In the Malaysian context, studying the relationship between FDI and absorptive capacity is essential because the actual spillover effects, involving the transfer of new knowledge from FDI to the local firm's production process and management, are not fully understood. An increasing number of local workers in MNCs further necessitates a numerical analysis of FDI knowledge spillover effects.

Second, while most studies treated human capital as a supplementary proxy in absorption capacity studies (e.g., Khordagui & Saleh 2016; Yunus & Abdullah 2022a), the current research focuses on human capital as a channel of absorptive capacity. Even though the study revisits and extends upon the studies by Fatima (2017), Girma and Görg (2005), and Yunus and Abdullah (2022a), it differs in its examination of the roles played by two human capital proxies, namely educational qualifications and job training.

Currently, there is limited understanding of the extent to which knowledge acquired by workers with different academic qualifications and the skills levels obtained through in-job training can be 'adapted' and 'assimilated'. This is crucial to absorb the foreign knowledge brought by MNCs into the constantly evolving technological progress (Szulanski 1996; Von Hippel 1994; Gupta & Govindarajan 2000; Foss & Pedersen 2002; Yunus & Abdullah 2022a). The emphasis on human capital is essential since knowledge is transferred between people. However, research in this area is still limited, especially since Cohen and Levinthal (1990) hypothesised that technological knowledge attributes (usability and complexity) influence the firms' ease of learning. The existing conceptual models examine how different aspects affect firms' development of absorptive capacity. Most models, however, exclude the extent to which the workers' knowledge and skills can accelerate the firms' adaptation of outward knowledge. Acknowledging the scarcity, this study focuses on the aspect of human capital.

Lastly, recent studies reported mixed evidence of absorptive capacity and FDI in terms of their magnitude and direction (Fatima 2017; Girma et al. 2001; Yunus & Abdullah 2022a). However, the evidence on knowledge spillovers from FDI relative to absorptive capacity is still inconclusive. Hence, this study utilises quantile regression since it can gauge the extent of absorptive capacity and is not widely applied in FDI spillover studies. Additionally, the study views it as the best estimator to assess the assimilation process of knowledge FDI inflows based on the level of skilled and educated workers' absorptive capacity in the host industry. The study thus recommends an alternative calculation method for the absorptive capacity model of human capital. This method permits us to characterise knowledge spillovers as a non-linear process. Hence, the coefficient values of the workers' absorptive capacity level will appear either negative or positive due to the different workers' absorptive capacity across the quantiles of FDI distributions (Girma et al. 2001; Girma & Görg 2005). By applying these calculations, we can make certain generalisations regarding the pattern of FDI inflows based on the level of absorption capability in the host country. Therefore, findings from this estimation method will elucidate the role of absorptive capacity, relative to the workers' knowledge and skills, in enhancing a firm's ability to absorb more benefits via the horizontal mechanism of FDI spillovers. A horizontal mechanism occurs when domestic firms benefit from foreign firms operating within the same industry through the movement of labour or direct competition. This will have practical implications for managers to help enhance their firm's competitiveness.

The remainder of the paper is structured as follows: Section 2 discusses the literature on absorptive capacity and FDI spillovers. Section 3 explains the data and methodology employed in this study, including the scope of the study, the definition of variables, and the estimation of the quantile model. Section 4 reports the validity test and discusses the results derived from the quantile analysis. Finally, the study concludes in Section 5 with some recommendations.

#### LITERATURE REVIEW

Cohen and Levinthal (1990) first introduced the concept of research and development (R&D) investments as a proxy in absorptive capacity studies in 1990. Since then, it has remained a popular proxy and has been widely used (Cohen & Levinthal 1990; Kinoshita 2009; Vega-Jurado et al. 2008). The discussion on absorptive capacity has since extended to its role in the context of FDI spillover. Studies applying R&D proxy to explore the relationship between absorptive capacity and technology spillovers of FDI were carried out in various contexts but mainly focused on technology effects. For instance, Barrios and Strobl (2002) used R&D stocks at the firm level for Spanish firms, while Behera (2015) applied it in the Indian manufacturing context, and Kinoshita (2001) conducted one within the Czech manufacturing firms. These studies unanimously concluded that firms with greater absorptive capacity benefitted more from foreign-owned presence than other domestic firms involved in R&D. Meanwhile, Mowery and Oxley (1995) found that R&D intensity did not positively affect external learning capability.

Human capital is significant in exploiting in-house and extraneous knowledge that enables firms to maintain competitiveness via higher productivity (Tu et al. 2006). Nevertheless, only a handful of recent FDI overflow studies employed human capital as the primary proxy

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of absorptive capacity at firm levels, such as Vu (2018) in Vietnam, Lopez-Garcia and Montero (2012) in Spain, and Khordagui and Saleh (2016) in Emerging and Middle Eastern Economies at the sector level. These studies, however, utilised elemental educational attainment proxies for human capital. Yunus and Abdullah (2022a) examined workers' academic qualifications, which were treated as an agent of absorptive capacity. They scrutinised the assimilation of technological impact brought by the presence of MNCs in high- and low-technology industries in Malaysia. They found that the absorptive capacity of degree-holder workers could potentially increase FDI inflows by around 44.0% at the median quantile. Diplomaeducation workers' absorptive capacity decreased from the median and subsequent quantile and was insignificant at the 75th and 90th quantiles. The result also implied that firms would benefit more from FDI technology effects if the workers' absorptive capacity levels reached at least the median quantile. Hence, they suggested that educational digitisation efforts to increase quality human capital should be intensified to equip workers with the latest knowledge and skills.

Meanwhile, Ali et al. (2017) investigated the interrelation between absorptive capacity, international knowledge overflow, and total factor productivity (TFP) in the Indian manufacturing sector from 2000 to 2016. They utilised imports and FDI as the two main channels of knowledge spillovers. The human capital aspect in R&D was categorised according to the workers' education level and used as a proxy for domestic absorption capacity. Using pooled linear regression estimators, they found that the absorptive capacity of human capital positively moderated the import spillovers for productivity growth. No moderating effect was found for R&D in the hightechnology sector, but opposite results were observed in the low- and medium-technology sectors. They also noted that the spillover effects of FDI and imports were positive and significant on TFP growth only in the hightechnology industry.

Recently, there has been a growing interest in studies examining the impact of FDIs on productivity, particularly about absorptive capacity. However, studies on FDIs' knowledge spillover on productivity are still scant (Foss & Pedersen 2002; Liu et al. 2001; Osabutey et al. 2014; Yunus & Abdullah 2022a, 2022b). Research examining the effects of knowledge overflow from FDI inflows and their relationship with absorptive capacity is even more limited. Most of the emerging studies examining FDI knowledge overflow and absorptive capacity focused on the variables' relationship and its impact on (i) the host country's economic growth (Silajdzic & Mehic 2015), (ii) total factor productivity (Ali et al. 2017; Liao et al. 2012), (iii) productivity growth (Roy & Paul 2022), and (iv) performance or capacity of innovation at the regional and industrial levels (Buckley et al. 2007; Chunying 2011).

Only a few studies applied quantile regression to explore knowledge overflow. These studies, however, were not specific on either FDI overflow or absorptive capacity itself. For instance, Aldieri and Vinci (2017) explored the extent to which knowledge spillover effects are sensitive to different levels of innovation. They reported a significant heterogeneity of technology spillovers across quantiles where the maximum value of spillovers is observed at the minimum quantile of innovation distribution. To investigate the spilloverproductivity relationship across countries and quantiles in France and Italy, Cardamone (2021) employed a quantile regression approach by differentiating between the sources of knowledge overflow. A distinction was made between R&D overflow from firms in similar sectors but different regions and similar geographical regions but different sectors. The study found heterogeneity across countries and quantiles.

Based on the literature mentioned earlier, this study contributes to the existing research that explores the role of absorptive capacity, represented via educational attainment and job training proxies. Empirical studies have suggested that these proxies potentially encouraged FDI inflows and their complementarity (Ndikumana & Verick 2008; Yunus et al. 2015; Yunus 2020). However, these proxies are underutilised in econometric analysis that examines the association between absorptive capacity and FDI, particularly for studies at the industry level in developing countries (Girma et al. 2001; Vu 2018; Yunus & Abdullah 2022a).

#### METHODOLOGY

#### DATA AND SCOPE OF THE STUDY

This study's main data sources are the manufacturing surveys from 2010 to 2019 conducted by the Department of Statistics Malaysia (DOSM), taking into account a balanced panel at the 2-digit aggregate level for all variables employed in this study. The period was chosen because the quantity of FDI influxes and the number of Malaysian workers working in MNCs are considered significant during this period. This aligns with the government's efforts to further promote FDI inflows as one of the strategies to assist industry players in adopting advanced technological knowledge to produce more sophisticated products, especially the Electronics and Electrical industry (E&E) (MIDA 2020). After 2019, the absence of complete and balanced data for all the variables used is one of the limitations in this study, considering the COVID-19 pandemic in 2020; which may contribute to the inaccuracy of the analysis in this study. Moreover, the required quality, i.e., technology transfer, enhancing management skills, and potential for forward and backward linkages with domestic suppliers, are not brought into Malaysia by FDI after post-COVID-19 (Jusoh 2020).

The manufacturing industries were chosen since technology spillovers have long been associated with the manufacturing sector, which has received the highest volume of FDI and continues to be the critical industry driving FDI to Malaysia. In reality, most MNCs are stepping up their R&D and design and development (D&D) efforts in high-tech manufacturing sectors, particularly in the machinery and E&E industries. Likely due to the manufacturing sector's efforts to increase the knowledge of highly skilled workers through learning and training programmes, the knowledge spillovers to local workers from MNCs' activities through the 'learning effect' are more significant for high-tech industries (Mohammad et al. 2018; Yunus 2023). This is because skilled workers in the manufacturing sector are conceived to have better absorptive capacity. Training and learning are intended to ensure that personnel in the industrial industry can keep up with the rapidly evolving technological advances and bridge a wide technological gap between domestic and foreign technology (Yunus & Abdullah 2022a). Consequently, the advantages of the most recent technological advancements learned throughout training make it possible for trained workers to benefit from the most recent wave of technological advancement and use it to produce and develop new products in domestic enterprises as demanded by the MNCs.

Based on the latest and balanced panel data, this study focuses on 11 manufacturing industries at twodigit industry level, namely (i) Food and Beverage, (ii) Textiles, (iii) Wood, (iv) Publishing, Paper, and Printing, (v) E&E, (vi) Chemical, (vii) Machinery and Equipment, (viii) Transport Equipment, (ix) Furniture, (x) Rubber, and (xi) Manufacturing of other non-metallic mineral products.

#### THE DEFINITION OF VARIABLES

In this study, the dependent variable is the number of local workers in the MNCs, representing knowledge spillovers (*KS\_FDI*), assuming that local workers in foreign MNCs possess higher skills and knowledge overflow than those with no experience working in foreign companies. In line with evolutionary theory, the knowledge spillover of MNCs occurs through the horizontal channels of 'training', 'demonstration-imitation', and 'mobility spillovers' transferred from local workers in MNCs. This transfer will expedite the process of knowledge absorption by local workers because workers could easily absorb knowledge from their colleagues compared to industry providers (Mullen & Noe 1999).

FDI knowledge spillovers *ln(KS\_FDI*) is gauged using the following formula:

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$$ln(KS\_FDI_{it}) = \sum_{i}^{N} KS_{it} ln\left(\frac{1}{KS_{it}}\right)$$
(1)

Where,  $KS_{it}$  is the number of Malaysian workers working in MNCs hired by local companies as 'mobility spillovers' in the process of assimilation of knowledge from MNCs towards the local manufacturing industry, *i* in a year, *t* (Bwalya 2006).

Both human capital variables, educational attainments and job training, are proxies of absorptive capacity (ABC). These proxies' interactions would capture the knowledge effects from MNCs, characterised by the knowledge assimilation of Malaysian workers who previously worked in foreign-owned companies. Therefore, this study extends the absorptive capacity

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models by Yunus and Abdullah (2022a) and Girma and Görg (2005) to measure workers' absorptive capacity by three levels of academic qualifications and how effective locally trained workers are in capturing foreign knowledge brought by the MNCs from equation (1). There are three different educational levels, namely: (i) degree and above (*ABC\_EMP\_DEGREE*<sub>*i*,*t*</sub>), (ii) diploma and Malaysian Higher School Certificate (*ABC\_EMP\_DIP\_HSC\_*<sub>*i*,*t*</sub>) and (iii) Malaysian Certificate of Education/Vocational (*ABC\_EMP\_MCE\_MCEV*<sub>*i*,*t*</sub>) and the locally trained workers' absorptive capacity (*ABC\_TRAIN*<sub>*i*,*t*</sub>) are measured using the following formula:

$$ABC\_EMP\_DEGREE_{i,t} = Degree \times \frac{KS\_FDI_{i,t}}{Max(KS\_FDI_{i,t}) \times KS\_FDI_{i,t-1}}$$
(2)

$$ABC\_EMP\_DIP\_HSC_{i,t} = Diploma \times \frac{KS\_FDI_{i,t}}{Max(KS\_FDI_{i,t}) \times KS\_FDI_{i,t-1}}$$
(3)

$$ABC\_EMP\_MCE\_MCEV_{i,t} = MCE\_MCEV \times \frac{KS\_FDI_{i,t}}{Max(KS\_FDI_{i,t}) \times KS\_FDI_{i,t-1}}$$
(4)

$$ABC\_TRAIN_{i,t} = TRAIN \times \frac{KS\_FDI_{i,t}}{Max(KS\_FDI_{i,t}) \times KS\_FDI_{i,t-1}}$$
(5)

Where *Degree* is the number of workers with a degree and above qualifications from total employment in the manufacturing sector. The Diploma is the number of workers with certificates of diploma and Malaysian Higher School from total employment in the manufacturing sector. The MCE\_MCEV is the number of workers with Malaysian Educational/Vocational Certificates from total employment in the manufacturing sector. TRAIN is the percentage of training costs invested per worker by employer in the local establishment firm in manufacturing industries. Max (KS\_FDI) is the highest number of Malaysian workers in the MNCs capturing two-digit sectors (industry leaders) present in the sector in a specific year.  $KS_FDI_{i,t-1}$  is the lagged of FDI knowledge spillovers. Similar to Girma and Görg (2005), the measure of ABC is the distance between a firm's productivity and that of its industry leader. Including the one-period lagged FDI knowledge spillovers, considering the process of FDI spillover effects, which involves generating and disseminating technological knowledge, is a relatively lengthy procedure (Zhang et al. 2020). From the four equations, namely, (2), (3), (4) and (5) above, this study extended the parameters capturing the degree of absorptive capacity by adding the squared terms according to the three levels of education and job training. The squared terms employed in this study also capture the possible non-linearity of knowledge FDI effects.

From an economic perspective, absorptive capacity is considered a non-linear process due to its mechanism, which includes identifying, assimilation, and applying external knowledge to individuals. These processes are different in each absorption phase and are primarily related to the productive traits of the workers, such as their educational attainment and work experience (Falaris 2008; Aribi & Dupout 2016). The process of workers' absorptive capacity to capture advanced technologies from FDI will occur gradually, leading to a non-linear relationship. This is because FDI also transfers technological knowledge that will progressively increase labour skills while developing human capital in recipient nations, as outlined in the endogenous model of FDI (Lucas Jr 1988). When absorption capacity exceeds the turning point, it will decline and may even become negative at high levels of foreign control (Girma & Görg 2005). Employees' ability to absorb the productivity spillover of FDI will also start to decline at that point.

There is more flexibility in the quadratic specification, as it demonstrates the level of knowledge spillovers transmitted by workers from FDI companies, either positively or negatively, proportionate to the absorptive capacity of skilled and trained workers in the hosting industry. Positive values of coefficients indicate that the knowledge brought in by workers previously trained by MNCs equals the current local workers' capacity (Nunemkamp 2004; Nguyen et al. 2009). Since we expect a non-linear-relationship, the square term of absorptive capacity should not be estimated separately. Its inclusion will represent the quadratic effects of employee absorptive capacity variables to calculate the possible non-linearity of FDI. The nonlinear model provides a better fit because it is unbiased and produces smaller residuals (Alejo et al. 2016). Therefore, we combined the two workers' absorptive capacity models, ABC, according to the three levels of educational attainment and work training experience, with their quadratic effects represented by  $\eta$ . These were combined with other proxies of absorptive capacity ( $X_{it}$ ) that potentially enhances external knowledge spillovers.

These variables, namely, R&D investment ( $R\&D\_EXP$ ), ICT investment ( $ICT\_EXP$ ), domestic investment from Malaysian investors ( $DOM\_INV$ ), and firm size (FS), in one equation to present a non-linear equation as follows:

$$lnKS\_FDI_{it} = B_1 + B_2ABC\_EMP\_Degree_{it} + B_3ABC\_EMP\_DIP\_HSC_{it} + B_4ABC\_EMP\_MCE\_MCEV_{it} + B_5TRAIN_{it} + B_6\etaABC\_degree_{it}^2 + B_7\etaABC\_Diploma_{it}^2 + B_8\etaABC\_MCE\_MCEV_{it}^2 + B_9\etaABC\_TRAIN_{it}^2 + B_{10}lnX_{it} + \mu_{it}$$

#### THE MODEL ESTIMATION

Based on the theoretical framework from Girma and Görg (2005) and Yunus and Abdullah (2022a), quantile regression was employed to gauge the level of workers' absorptive capacity, which embodied skills and experience together with other variables to help firms assimilate and exploit FDI knowledge from MNCs. The quantile regression has also become a popular alternative to least squares regression for modelling heterogeneous data, as it is less sensitive to the presence of outliers in the dependent variable and yields a more robust and efficient alternative to OLS when the error term is non-normal. Thus, the present study opted for quantile regression since the establishment level of FDI knowledge did not appear to be (log) normally distributed, as indicated by the normality test in Figure 1 (Buchinsky 1998; Koenker & Machado 1999; Fatima 2017). As shown in Figure 1, there is a stark difference in the curves of Kernel density and the corresponding normal density estimates of log FDI knowledge spillovers.

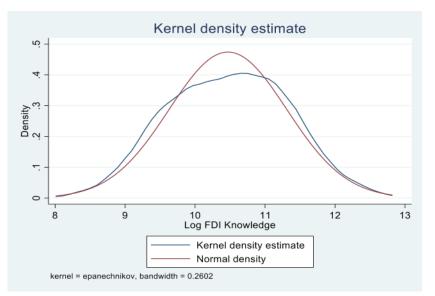


FIGURE 1. Kernel density estimate for log FDI knowledge spillovers

As the study utilised manufacturing industrylevel data, quantile regression was adopted to address persistent heterogeneity across firms (Falaris 2008; Girma et al. 2001). Quantile regression allowed us to explore whether Malaysian workers' absorptive capacity in the manufacturing industry and other factors helped the assimilation process of knowledge spillovers from FDI and whether they affected knowledge absorption at particular points of the conditional knowledge spillovers of FDI distributions. Quantile regression was estimated at five different quantiles: the 10th, 25th, 50th (median), 75th, and 90th percentiles of the FDI knowledge spillover distribution. Through quantile regression, the workers' ability to absorb knowledge from FDI spillovers could be differentiated according to workers' and industry's absorptive capacity level, even within a particular conditional quantile. From equation (6), this study follows Koenker and Bassett (1978) and Yunus and Abdullah (2022a) to estimate the model using a quantile regression estimator as follows:

$$KS\_FDI_{it} = R'_{it}B_{\theta} + \mu_{\theta i}; Quant_{\theta} (KS\_FDI_{it}/R_{it}) = R'_{it}B_{\theta}$$
(7)

(6)

Where R' is a set of regressors, including workers' absorptive capacity y and other determinants influencing the assimilation of knowledge overflow from Malaysian workers in foreign companies transferred to local firms.  $B_{\theta}$  is the slope coefficient quantifying the level of absorptive capacity proxies on FDI knowledge spillover assimilation into local firms at quantile  $\theta$ .  $Quant_{\theta}$  ( $KS_FDI_{it}/R_i$ ) is the conditional quantile of FDI knowledge spillovers.  $\mu$  is the error term.

Quantile regression estimator involves minimisation of sample size; 1/n, and it also minimises the weighted absolute values of the residuals using all the available data (Buchinsky 1998; Koenker & Bassett 1978) as presented in equation (8) with the  $\theta$ th quantile regression solving  $0 < \theta < 1$ 

$$Min\frac{1}{n}\left(\left|KS\_FDI_{it} - R_{it}^{'}B\right| + \sum_{i,t:KS\_FDI < R_{B}^{'}B}(1-\theta)\left|KS\_FDI_{it} - R_{it}^{'}B\right|\right)$$
(8)

Where:  $KS\_FDI \ge R' B$  and  $KS\_FDI < R' B$  are indicators function, which describes a positive and a negative value of residuals contingent on the value of  $\theta$ . As one quantile continues to increase from 0 to 1, one can detect the entire conditional distribution of knowledge FDI, which is conditional on the regressors of absorptive capacity. Instead of squaring all errors, this method gives a weight of  $\theta$  to positive and (1- $\theta$ ) to negative residuals.

### **RESULTS AND DISCUSSIONS**

The analysis will be presented in two parts. The first part discusses the validity test for multicollinearity using correlation analysis. Next, the skewness and kurtosis normality tests for the log FDI knowledge spillovers are discussed. The second part discusses the quantile regression analysis results at five different quantiles to gauge the extent to which the workers' knowledge and skills can accelerate the firms' adaptation of knowledge FDI spillovers in the Malaysian manufacturing industry.

# VALIDITY TEST FOR MULTICOLLINEARITY AND NORMALITY

Before the quantile regression results were analysed, the correlation analysis was performed for two purposes: (i) validity tests of the proxies used for absorptive capacity and (ii) multicollinearity test. The former was necessary due to the lack of studies that performed validity tests of absorptive capacity, particularly in the context of FDI (Vu 2018). As shown in Table 1, except for direct domestic investment, the value of the positive coefficient proves that all the independent variables indicated positive values. The proxies are thus considered good for absorptive capacity in influencing FDI knowledge spillovers in the manufacturing industry.

As for the multicollinearity test, the correlation coefficient was less than 0.8, thus indicating the absence

of a high correlation between the independent variables of absorptive capacity used in this study. Two normality tests, one following Shapiro and Francia (1972) and the other based on D'Agostino et al. (1990), were performed for skewness and kurtosis to prove that the FDI knowledge spillovers as dependent variables used in this study's analysis are normally distributed (Fatima 2007). As shown in Table 2, both normality tests were performed together with other summary statistics for FDI knowledge, which include the mean, standard deviation, skewness, kurtosis, and five quantiles developed in this study. Based on the p-values for both normality tests in Table 2, the null hypothesis that log FDI knowledge spillovers are normally distributed at a 5% level of significance was rejected (D'Agostino et al. 1990; Shapiro & Francia 1972).

#### QUANTILE REGRESSION ANALYSIS

The estimation results of quantile regression at five quantiles of FDI knowledge spillovers in the manufacturing industry are presented in Table 3. The absorptive capacity of workers at all education levels and their quadratic effects were reported to be significant from the 10th quantile of the conditional knowledge FDI distribution. Regarding the impact of FDI knowledge spillovers exploited by workers according to their education credentials and their quadratic effects, a positive and statistically significant result was found at the 10th quantile. The higher knowledge absorption from degree-qualified workers is consistent with the theory of evolution and human capital, which states that workers with higher education can better integrate with international and domestic partners to access practical technological knowledge (Blomstrom & Kokko 1998; Cantwell 2000).

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1.000     0.789     1.000       0.789     1.000       0.736     0.728       0.736     0.728       0.739     1.000       0.734     0.534       0.534     0.538       0.514     0.388       0.739     0.779       0.739     0.779       0.734     0.714       0.734     0.714       0.734     0.714       0.734     0.714       0.734     0.714       0.734     0.714       0.734     0.714       0.734     0.714       0.734     0.714       0.734     0.712       0.735     0.172       0.736     0.712       0.736     0.713       0.366     0.719       0.366     0.721       0.366     0.719       0.366     0.719       0.366     0.719       0.366     0.721       0.366     0.721       0.366     0.719 <t< th=""><th></th><th>FDI KNOW</th><th><math>ABC\_EMP</math> DEG</th><th>ABC_EMP_ DIP_HSC</th><th>ABC_MCE_ MCEV</th><th><math>ABC_{-}</math> TRAIN</th><th><math>DEGREE^2</math></th><th>ABC*DEGREE<sup>2</sup></th><th>ABC*DIP/ HSC<sup>2</sup></th><th>ABC*MCE/ MCEV<sup>2</sup></th><th><math>ABC^{*}_{TRAIN^{2}}</math></th><th><math>R\&amp;D_{-}</math></th><th><math>\frac{ICT}{EXP}</math></th><th></th><th>FS</th></t<>		FDI KNOW	$ABC\_EMP$ DEG	ABC_EMP_ DIP_HSC	ABC_MCE_ MCEV	$ABC_{-}$ TRAIN	$DEGREE^2$	ABC*DEGREE <sup>2</sup>	ABC*DIP/ HSC <sup>2</sup>	ABC*MCE/ MCEV <sup>2</sup>	$ABC^{*}_{TRAIN^{2}}$	$R\&D_{-}$	$\frac{ICT}{EXP}$		FS
0.789     1.000       0.736     0.728     1.000       0.734     0.534     0.539     0.052     1.000       0.738     0.514     0.338     0.176     1.000       0.734     0.729     0.729     0.729     0.729     0.729     0.724     0.065     1.000       0.734     0.714     0.724     0.388     0.508     1.000     1.000       0.734     0.714     0.724     0.723     0.386     0.747     1.000       0.734     0.714     0.724     0.723     0.182     0.409     0.713     0.412     1.000       0.734     0.714     0.723     0.733     0.736     0.712     0.732     0.731     0.732     1.000       0.346     0.352     0.337     0.732     0.732     0.732     0.732     1.000       0.564     0.472     0.532     0.747     0.352     0.741     0.561     0.698     1.000       0.506     0.617     0.755     0.747     0.352     <	FDI_KNOW	1.000													
0.736     0.728     1.000       0.554     0.539     0.052     1.000       0.358     0.514     0.388     0.176     1.000       0.738     0.514     0.388     0.176     1.000       0.784     0.729     0.779     0.388     0.508     1.000       0.784     0.714     0.724     0.045     0.386     0.747     1.000       0.734     0.714     0.724     0.045     0.386     0.747     1.000       0.747     0.710     0.723     0.182     0.409     0.073     0.412     1.000       0.514     0.724     0.723     0.747     1.000     0.522     0.178     1.000       0.564     0.412     0.514     0.386     0.525     0.178     1.000       0.564     0.472     0.528     0.749     0.525     0.178     0.522     1.000       0.504     0.514     0.555     0.719     0.525     0.178     0.508     0.506     0.506     0.506     0.506     <	ABC_EMP_DEGREE	0.789	1.000												
0.554     0.539     0.052     1.000       0.358     0.514     0.388     0.176     1.000       0.784     0.779     0.388     0.508     1.000       0.784     0.779     0.388     0.508     1.000       0.734     0.714     0.729     0.388     0.508     1.000       0.734     0.714     0.724     0.045     0.386     0.747     1.000       0.734     0.714     0.723     0.182     0.409     0.073     0.412     1.000       0.579     0.412     0.51     0.723     0.182     0.409     0.073     0.412     1.000       0.564     0.412     0.755     0.178     0.522     1.000     1.000       0.564     0.472     0.523     0.514     0.525     0.178     1.000       0.505     0.756     0.719     0.525     0.721     0.522     1.000       0.506     0.068     0.617     0.525     0.144     0.561     0.698     1.000       0.	ABC_EMP_DIP_HSC	0.736	0.728	1.000											
	ABC_EMP_MCE/MCEV	0.554	0.539	0.052	1.000										
	ABC_TRAIN	0.358	0.514	0.388	0.176	1.000									
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	ABC*DEGREE <sup>2</sup>	0.784	0.729	0.779	0.388	0.508	1.000								
$EV^2$ $0.579$ $0.412$ $0.651$ $0.723$ $0.182$ $0.409$ $0.073$ $0.412$ $1.000$ $0.346$ $0.352$ $0.387$ $0.172$ $0.753$ $0.514$ $0.386$ $0.522$ $0.178$ $1.000$ $0.564$ $0.472$ $0.528$ $0.344$ $0.486$ $0.719$ $0.525$ $0.171$ $0.352$ $0.522$ $1.000$ $0.505$ $0.726$ $0.619$ $0.134$ $0.542$ $0.7756$ $0.719$ $0.555$ $0.144$ $0.561$ $0.698$ $1.000$ $0.006$ $-0.068$ $-0.064$ $0.539$ $-0.062$ $-0.064$ $0.228$ $0.403$ $0.235$ $0.096$ $-0.064$ $0.098$ $-0.098$ $-0.098$ $0.204$ $0.245$ $0.09$ $0.228$ $0.403$ $0.235$ $0.089$ $0.247$ $0.232$ $0.407$ $0.398$ $0.072$	ABC*DIP_HSC2	0.734	0.714	0.724	0.045	0.386	0.747	1.000							
0.346     0.352     0.387     0.172     0.753     0.514     0.386     0.522     0.178     1.000       0.564     0.472     0.528     0.344     0.486     0.719     0.525     0.721     0.352     1.000       0.564     0.472     0.528     0.344     0.486     0.719     0.525     0.721     0.352     1.000       0.505     0.756     0.514     0.542     0.756     0.517     0.352     0.501     0.698     1.000       0.006     -0.064     0.053     0.259     -0.062     -0.064     0.657     0.221     -0.098     -0.072       0.204     0.245     0.235     0.089     0.247     0.320     0.308     0.364	ABC*MCE_MCEV <sup>2</sup>	0.579	0.412	0.651	0.723	0.182	0.409	0.073	0.412	1.000					
>     0.564     0.472     0.528     0.344     0.486     0.719     0.525     0.721     0.352     0.522     1.000       0.505     0.756     0.619     0.134     0.542     0.756     0.617     0.755     0.144     0.561     0.698     1.000        0.006     -0.064     0.053     0.259     -0.062     -0.064     0.055     0.098     -0.072        0.204     0.245     0.235     0.235     0.089     0.247     0.398     0.364     0.398     0.364	$ABC^*_{TRAIN^2}$	0.346	0.352	0.387	0.172	0.753	0.514	0.386	0.522	0.178	1.000				
0.505     0.756     0.134     0.542     0.756     0.617     0.755     0.144     0.561     0.698     1.000       0.006     -0.068     -0.053     0.259     -0.08     -0.062     -0.055     0.221     -0.098     -0.072       0.204     0.245     0.228     0.403     0.235     0.089     0.247     0.322     0.364     0.398     0.364	R&D_EXP	0.564	0.472	0.528	0.344	0.486	0.719	0.525	0.721	0.352	0.522	1.000			
$M\_INV = 0.006 -0.068 -0.064 = 0.053 = 0.259 -0.08 -0.062 -0.064 = 0.055 = 0.221 -0.098 -0.072 = 0.204 = 0.245 = 0.09 = 0.228 = 0.403 = 0.235 = 0.089 = 0.247 = 0.232 = 0.407 = 0.398 = 0.364 = 0.244 = 0.245 = 0.09 = 0.228 = 0.403 = 0.235 = 0.089 = 0.247 = 0.232 = 0.407 = 0.348 = 0.364 = 0.008 $	ICT_EXP	0.505	0.756	0.619	0.134	0.542	0.756	0.617	0.755	0.144	0.561	0.698	1.000		
0.204 $0.245$ $0.09$ $0.228$ $0.403$ $0.235$ $0.089$ $0.247$ $0.232$ $0.407$ $0.398$ $0.364$	ANI_MOD	0.006	-0.068	-0.064	0.053	0.259	-0.08	-0.062	-0.064	0.055	0.221	-0.098	-0.072	1.000	
	FS	0.204	0.245	0.09	0.228	0.403	0.235	0.089	0.247	0.232	0.407	0.398	0.364	0.171	1.000

TABLE 1. Correlation matrix between independent variables

TABLE 2 Summar	y statistics for log FDI knowledge spillovers in	n the Malaysian manufacturing industry
In IDEE 2. Outilitiat	buildies for log i bi knowledge spino (ers n	in the management management industry

	6 ,
All Observations	Value
Normality Test (Shapiro and Francia, 1972)	0.013
Skewness and kurtosis test for normality (D'Agostino et al.,1990)	0.021
Mean	11.031
Standard Deviation	0.564
Skewness	0.273
Kurtosis	0.161
10th Quantile	0.104
25th Quantile	0.339
Median Quantile	0.502
75th Quantile	0.047
90th Quantile	0.314

The study also revealed a positive trend of workers' absorptive capacity from all education levels across all conditional quantiles specifications, except for workers with secondary education at the 75th and 90th quantiles. The negative absorption capacity detected among secondary-educated workers could indicate situations where they could not exploit the knowledge overflow of FDI and adapt to high-skill-based technological changes in the manufacturing industry. Nonetheless, based on the coefficient values of degree-and diploma-educated workers and their quadratic effects, FDI knowledge spillovers in manufacturing firms, on average, the manufacturing sector will receive more than 30% of knowledge spillovers from FDI if these educated workers can capture FDI knowledge at the 90th quantile. Based on our findings, it can be concluded that the coaching sessions by experienced workers who have worked in MNC companies could encourage knowledge spillovers via 'learning effects' and the imitation-demonstration process. This also echoes past research that supports the idea that knowledge can be absorbed through sharing experiences between people (Davenport & Prusak 1998; Leonard & Sensiper 1998).

Job training differs from other investments, remarkably, as the effect differs from education because it can be transferred and taught to others (Deborah 1993). Therefore, this study's subsequent analysis measured the absorptive capacity of trained workers in absorbing and imitating foreign knowledge from their colleagues who previously worked in MNCs. Two notable findings could serve as benchmarks for employers to gauge the effectiveness of their skill-development training courses.

First, the study discovered that the ability of trained workers was significant and positive in encouraging the influx of foreign knowledge FDI at the 10th and 25th quantiles. The coefficient results indicate that the FDI inflows are expected to increase by 22.58% between these two quantiles. These results can help forecast whether the knowledge brought in from foreign companies will match the current level of workers' knowledge in the host's manufacturing industry. In exploiting the knowledge overflow, however, the result showed that the workers' absorptive capacity rates were only achievable up to the 25th quantile.

This finding suggests that the job training implemented by internal employers was likely ineffective, as most employers tend to focus on general training, and the primary goal of training programmes is to improve workers' efficiency and the profitability of their company (Farjad 2012). Conversely, the job training provided by the MNCs usually adheres to the global standard of training programmes (Moumita & Zaman 2013). Thus, the differences in the nature and the contents of training between the two training providers could explain the local workers' low absorption of the advanced knowledge brought into local firms.

Dependent variable: EDI Knowledge			Quantile		
Dependant variable: FDI Knowledge spillovers	10th	25th	50th (median)	75th	90th
ABC_EMP_DEGREE	0.328**	0.373***	0.335**	0.364**	0.342***
	(0.031)	(0.001)	(0.001)	(0.003)	(0.001)
ABC_EMP_DIP_HSC	0.225*	0.243**	0.245**	0.269*	0.346**
	(0.004)	(0.007)	(0.021)	(0.012)	(0.021)
ABC_EMP_MCE_MCEV	0.124*	0.117**	0.164*	-0.149*	-0.153**
	(0.005)	(0.008)	(0.022)	(0.013)	(0.022)
ABC_TRAIN	0.124*	0.152*	-0.154**	-0.170	-0.224***
	(0.073)	(0.100)	(0.018)	(0.108)	(0.019)
ABC*DEGREE <sup>2</sup>	0.030**	0.125*	0.215*	0.325*	0.310*
	(0.002)	(0.004)	(0.010)	(0.005)	(0.010)
ABC*DIP_HSC <sup>2</sup>	0.143***	0.127**	0.152**	0.294*	0.321****
	(0.002)	(0.004)	(0.011)	(0.006)	(0.011)
ABC*MCE_MCEV <sup>2</sup>	0.169*	0.131	0.135**	-0.205	-0.211*
	(0.026)	(0.050)	(0.014)	(0.016)	(0.014)
ABC*_TRAIN <sup>2</sup>	0.119***	0.128**	-0.174**	-0.151	-0.215**
	(0.027)	(0.026)	(0.041)	(0.025)	(0.042)
R&D_EXP	0.330**	0.338***	0.367	0.382*	-0.279
	(0.024)	(0.023)	(0.022)	(0.026	(0.018)
ICT_EXP	0.300*	0.312***	0.327*	0.358*	-0.249**
	(0.029)	(0.043)	(0.032)	(0.028)	(0.072)
DOM_INV	0.383*	0.378*	0.352**	0.362***	-0.341**
	(0.041)	(0.003)	(0.045)	(0.049)	(0.046)
FS	0.185***	0.191***	0.277***	0.374**	0.481**
	(0.123)	(0.124)	(0.106)	(0.173)	(0.106)
Constant	24.648**	24.864**	25.631*	26.765*	24.207**
	(0.086)	(0.080)	(0.084)	(0.878)	(0.053)
Observations	220	220	220	220	220
Pseudo R <sup>2</sup>	0.768	0.784	0.815	0.797	0.823

TABLE 3. Quantile regression results for the manufacturing industry, 2000-2019

*Notes:* The dependent variable for the quantile regression is FDI knowledge spillovers. Entries in parentheses are robust standard errors, and all variables are transformed into natural log. \*\*\* p<0.01, \*\* p<0.05, \* p<0.01

Second, this study found that at the median quantile and beyond, the capacity of trained workers and their quadratic effects to absorb external technological knowledge were negative and achieved an insignificant relationship at the 75th quantile, implying the nonlinearity between FDI knowledge spillovers and trained workers' absorptive capacity. These findings suggest that knowledge spillovers from FDI are a non-linear process, meaning that the interaction between training, its squared and FDI knowledge spillovers exhibits an inverted U-shaped relationship (Yunus & Abdullah 2022a; Girma & Görg 2005). This assumption follows the endogenous model of FDI, which states that foreign companies also transfer technological expertise to gradually increase the recipient country's labour skills in developing human capital (Lucas Jr. 1988). Hence, the non-linearity found in the situation of trained workers contradicts human capital theory, which assumes work-related training is associated with significantly higher firm productivity. Training, nevertheless, makes innovation profitable, thus encouraging firms to be more innovative in capturing external knowledge (Booth & Snower 1996).

This study also found that trained workers could not take advantage of knowledge and innovations during their training, especially those related to digital knowledge content, despite the latest requirements of The Fourth Industrial Revolution (IR4.0) in the manufacturing industry. This negatively affects conditional FDI knowledge distribution at the higher quantile. These concerns are not addressed in current research due to the limitations of the current panel data. Past studies, however, have examined the causes of low knowledge absorption. For instance, in the case of online training conducted by internal employers as well as by MNCs within firms, low absorptive capacity was associated with difficulty in attracting workers to e-learning content, poor quality of training content, communication problems and language barriers, and the lack of independence and selfawareness among the workers and trainers themselves. When workers were reluctant to learn new knowledge, the trainers' lack of encouragement exacerbated the situation (Mathieu et al. 1992; Ramayah et al. 2012).

Another notable finding is that in-house investment substantially helps firms to absorb technological knowledge from FDI. The results confirmed that from the 10th to the 75th quantile, the firms' absorptive capacity related to the investment activities in R&D, FDI, and direct domestic investment is significant and positive. The result in Table 3 projected that if there is a 1% increase in the firm's capability of absorption through investment activities in R&D, ICT, and direct domestic investment, knowledge overflow from FDI will reach 38.2%, 35.8%, and 36.2% respectively at the 75th quantile of the conditional FDI knowledge distribution.

These findings indicate a complementary relationship between intra-industry-domestic investments and foreign investment from MNCs. Therefore, domestic investors should be provided with more investment funds in technological know-how to generate higher profits, resulting in a high return on capital for FDI. Hence, FDI can help the development of domestic industry through complementarity, either in production or through interaction with superior technological knowledge and the host's human capital.

Considering the perks of complementary relationships, local firms should collaborate with foreign investors through partnerships. Partnerships could widen market access for local firms, as foreign investors usually have existing commercial arrangements and distribution channels worldwide. The negative relationship attained at the 95<sup>th</sup> quantile for in-house investments can be attributed to the technological knowledge gap between experienced and skilled workers working in foreign companies and local workers.

The training could also be flawed, thus complicating learning new skills and external spillover knowledge. The absence of technological expertise prevented the firms from operating in high-value-added innovation and R&D activities. Moreover, the competition between the MNCs operating in Malaysia could cause excessive dissemination of knowledge, thus demanding local workers to practice various forms of knowledge. Local workers might feel inundated by the knowledge, as each requires new skills for advanced tasks. Hence, this could explain the negative coefficient found at the highest distribution level of FDI knowledge.

The result also reveals that firm size capability as the assimilator of FDI inflows into the manufacturing industry yielded positive significance across quantiles from the lowest to the highest levels in attracting FDI. This study shows that firms operating on a larger scale are associated with higher levels of productivity, which increase innovation activities and increase the firm's ability to capture foreign technological knowledge efficiently.

#### CONCLUSION

This study proposed two human capital models to assess how workers can use and adapt their knowledge and skills to absorb the knowledge spillovers from their colleagues working in foreign companies. Utilising these models, the quantile regression results pointed to three notable findings.

First, the capacity of degree- and diploma-holding employees to assimilate foreign knowledge in the firm through the process of 'learning by doing' via labour mobility spillovers from ex-Malaysian workers working in MNCs shows a positive effect from the lowest quantile to the highest quantile. This finding reveals an increase in skills and knowledge among workers resulting from the industrial training required for graduates and an increase in the collaboration network between higher education and industry, even though the rate of knowledge absorption is less than 50%. It also points to the willingness of foreign expatriates in MNCs to disseminate knowledge to local employees.

Second, the ability of workers who have MCE/MCEV to absorb the influx of foreign knowledge is still low. However, the knowledge requires higher skills relative to the workers' current ability. This could be countered if employers in local firms are open to providing informal training, as specific industries still use unskilled labour to perform simple work related to assembly or resource extractive activities. Another measure to address this is by introducing a training policy for all levels of education, particularly for the younger generation. Related policies should not only focus on higher education graduates but also include school leavers to reduce their risk of unemployment.

Third, this study finds that the ability of trained workers gained from the training programmes organised by the employers is still insufficient to absorb the overflow of foreign knowledge. It was significant and positive in encouraging the influx of foreign knowledge FDI from the 10th to 25th quantiles. This finding shows that job training carried out by internal employers is still less able to improve workers' skills, which may be due to the difference in programmes provided by MNCs and local employers. We suggest that this gap can be bridged by providing comprehensive and extensive large-scale training institutions according to the level of education and absorption of workers.

Through the absorptive capacity coefficient value obtained, for industry stakeholders, this study can be beneficial as a screening tool for identifying highquality graduates, as assessing the ability of employees to adapt to foreign technologies is one of the signals that can contribute towards the achievement of higher productivity in the manufacturing industry. Our findings also benefit the industry by considering the participation of local managers in MNC activities. The involvement of local managers in MNCs may facilitate the rapid transfer of technological knowledge within the Malaysian manufacturing industry. Hence, skilled local managers should be encouraged to work in MNCs.

Since mentoring could be a practical approach to ensuring the transmission of skills from one worker to another to increase the flow of knowledge among workers working in MNCs, we suggest the industry consider increasing the existing reward system given to workers who successfully train and impart knowledge to their coworkers in the industry. When the pioneer workers quit, they would bring their expertise with them. Firms should, therefore, acknowledge that a transfer of skills could offset severe losses. These people's skills and knowledge will be helpful to the new company when they work for other companies.

Recognising that research that examines knowledge spillover effects from FDI inflows and their relationship with absorptive capacity is more limited; we thus contribute to the extending argument in the FDI and knowledge spillover literature. We provide current theoretical and empirical knowledge into the role of human capital as a knowledge spillover mechanism through labour mobility, considering that human capital tends to be 'treated' as a supplementary variable of absorption capacity. Our findings are broadly consistent with the endogenous theory, which reveals that human capital plays a significant role in knowledge transfer from the movement of workers from MNCs to local firms and increases the productivity of local workers. We can conclude that knowledge flow from FDI has greater beneficial effects in the Malaysian manufacturing industry if the level of absorptive capacity of educated workers through the process of 'learning by doing' and the coupled effects of in-house investment from R&D, ICT, and domestic investors are at the 75th quantile of the conditional FDI knowledge distribution.

Future studies could measure the absorptive capacity of workers who have undergone skills development training according to the workers' education levels. Such studies could inform educational institutions of the effectiveness of their curriculum. As this study did not delve into the financial benefit of job training, future research could focus on this aspect. Lastly, a rigorous assessment and evaluation of real organisational learning gains obtained from e-training is essential to help firms adapt to the ever-changing technological changes.

#### NOTES

Total foreign direct investment (FDI) and domestic direct investment (DDI) in 2021 exceeded expectations, up 83.1% from that recorded in 2020. In 2021, FDI contributed the bulk of total investments approved, RM208.6 billion (68.1%), a jump of 224.9% from RM64.2 billion in 2020, while DDI contributed the remaining RM97.9 billion (31.9%).

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