Asian Journal of Empirical Research
Volume 12, Issue 2 (2022): 54-61.

http://www.aessweb.com/journals/5004

INNOVATION AND PRODUCTIVITY IN THE MALAYSIAN FOOD PROCESSING INDUSTRY: AN EMPIRICAL ANALYSIS USING A SYSTEM GENERALISED METHOD OF MOMENTS APPROACH

Sarah Nursyazmin Mohamad Kamal[a]
Normaz Wana Ismail[b] †
Shaufique Fahmi Ahmad Sidique[c]

[a, c]*Laboratory of Agricultural and Food Policy Studies, Institute of Tropical Agriculture & Food Security, Putra Universiti Malaysia, Malaysia.*
[b]*School of Business and Economics, Putra Universiti Malaysia, Malaysia.*

† ✉ nwi@upm.edu.my (Corresponding author)

Article History
Received: 24 January 2022
Revised: 21 February 2022
Accepted: 7 March 2022
Published: 28 March 2022

Keywords
Food industry
Innovation
Manufacturing
Panel data
SYS-GMM.

ABSTRACT
The food processing industry was reviewed as a top priority for industrial development and targeted to lead greater growth in Malaysia's Industrial Masterplan (NIMP). Leading to industrial development, this paper highlighted the relationship between innovative activities (R&D expenditure and ICT expenditure) and productivity with other variables like the presence of skill intensity, capital intensity, export intensity, foreign-owned firms and imported intermediate input. This hypothesis is examined for a panel dataset of the food processing industry in Malaysia from 2000 until 2015 (according to Economic Census- Manufacturing). Using a System Generalised Method of Moments (GMM) approach, empirical analysis suggests that innovators performed better than non-innovators in terms of labour productivity. Innovative activity and ICT expenditure along with skilled intensity and capital intensity seem to be the main determinants of subsector's productivity, whereas R&D expenditure has mixed results from the estimation output.

Contribution/Originality: The novelty of this research is the analysis of the dynamic model between innovation and productivity. This study is expected to shed light on industry players within the Malaysian food processing industry and contribute to productivity growth as well as better industrial planning in near future.

DOI: 10.55493/5004.v12i2.4453
ISSN(P): 2306-983X/ ISSN(E): 2224-4425
How to cite: Sarah Nursyazmin Mohamad Kamal --- Normaz Wana Ismail --- Shaufique Fahmi Ahmad Sidique (2022) Innovation and Productivity in the Malaysian Food Processing Industry: An Empirical Analysis using a System Generalised Method of Moments Approach. *Asian Journal of Empirical Research*, 12(2), 54-61. 10.55493/5004.v12i2.4453

1. INTRODUCTION

Malaysia enjoys a relatively solid and competitive position in manufacturing and the use of technology on a global scale. The Global Competitive Report 2019 ranked Malaysia 27th among 141 countries where several competitiveness index components show a significant score. Malaysia's scores include ICT adoption (71.6), skills (72.5) and innovation capability (55). At the industry level, Malaysia's labour productivity increased from RM75,634 per worker in 2015 to RM81,268 in 2017, representing an average annual growth of 3.7%. Referring to the National Industrial Masterplan (NIMP), the food processing industry was reviewed as a top priority for industrial development and targeted to lead greater growth in higher value-added, technology, exports, and knowledge content. Hence, agro-food subsectors were identified under Malaysian Productivity Blueprint (MPB) in 2017 as priority subsectors to drive productivity in their respective productivity nexus because the food processing industry relies on agro-food commodities.

It is widely known that the food manufacturing industry is often associated with Small Medium Enterprises (SMEs) that uses a low level of technologies and are relatively more labour intensive in their operations or production.

According to Shafii and Ismail (2015) and Shah and Ahmad (2015), the SMEs sector has contributed by creating more job opportunities, increasing the volume of production, increasing exports, and stimulating the growth of gross domestic products. There is a positive increasing trend in foreign and domestic markets for food industry sectors. However, SMEs specifically in the food and beverages sector faced external challenges such as technological developments, increasing production costs, the shift in demand and taste, an increasing number of competitors. The utilization of technology in producing products is still low in Malaysia. The adaptation of technology are occur at a slow rate as it requires a high amount of capital, a high level of knowledge and expertise. The industry is facing serious challenges to compete in global SMEs caused by a shortage of raw materials, lack of technology, limited research and development (Nor, Bhuiyan, Said, & Alam, 2016). There are also a few problems with the food industry where the majority of these problems influenced productivity and efficiency in the industry (Afrooz, Rahim, Noor, & Chin, 2010).

This paper contributes to the literature by analysing the empirical relationship between innovation inputs (R&D expenditure and ICT expenditure) and productivity in the presence of skill-intensive firms. Subsectors in the food processing industry highly assume acquiring knowledge and technology through R&D because R&D and innovation activities raise productivity in various ways. This can be done by generating new knowledge and bringing new products to a firm and market (Segarra-Blasco, 2010). Firms with low productivity mean the production processes are inefficient while a country with a high level of productivity implies that the input in the firms are utilized efficiently and the operation is on the right track in achieving its objectives. Therefore, understanding the link between innovation and productivity level could eventually lead to the formulation of appropriate policies that could help the domestic SMEs in the manufacturing industry, especially the food industry. Hence, innovation and research and development activities as instruments to create new knowledge and escalate productivity which spills over to other firms or industries (O'Mahony & Vecchi, 2005; Parisi, Schiantarelli, & Sembenelli, 2006). At the industry level, Edquist and Henrekson (2017) found evidence that investing in R&D show impacts on productivity through the more efficient organisation of production and higher product quality in the short run.

A broad literature associates productivity growth with an investment in information and communication technologies (ICTs), and most growth derives from industries that produced and used ICT intensively. Adopting the ICT brought benefits, especially among the small and medium enterprises (SMEs); new business opportunities, access to market information and knowledge, speedy, and reliable business communications (Tan, Chong, Lin, & Eze, 2009). The OECD (2003) stated that investment in technology adds to the capital stock available for workers and thus helps raise labour productivity. Furthermore, the use of ICT enhances efficiency and innovation where firms expand their product range, customise their services, or respond better to demand. ICT also served as a particular case of new technologies that enable technologies to lead to even further innovation (Cardona, Kretschmer, & Strobel, 2013). According to Venturini (2009), ICT needs a long time to yield positive returns against productivity because its adoption by firms is usually accompanied by organisational restructuring, complementary investment, or, more generally, adjustment costs. Besides that, several pieces of literature prove that R&D and ICT were complements each other in reducing inefficiencies within production (Ding, Levin, Stephan, & Winkler, 2010; Pieri, Vecchi, & Venturini, 2018). ICT brought a broad positive impact across sectors which by contrast, spillovers from R&D spread within. This is possible because of knowledge spillovers and similarities in digital technologies between firms operating in the same sector (Pieri et al., 2018).

Most early studies related to exporting activities with foreign ownership, such as Xiaonan and Junjie (2011) explore the exporting pattern of different firm ownership, foreign-owned firms and state-owned enterprises (SOEs). Hence, they found that foreign-owned exporters seem to be more export-oriented, while state-owned exporters focus more on the domestic market. Hence, foreign investors may bring a difference in performance through superior technology, marketing networks, and better resource allocation skills (Lemi & Wright, 2020). Additionally, the relationship between exporting and productivity were further explored by Newman, Rand, Tarp, and Anh (2014) with the impact of characteristics and behaviour of firms. This relationship shows the greater impact on initial years for foreign-owned firms but cannot be associated with learning effects while it does not persist with years of experience on export markets. Hence, exporters are more productive than non-exporters and most likely to self-select into the export market (Girma, Greenaway, & Kneller, 2004; Wagner, 2007). On the other hand, Bigsten and Gebreeyesus (2009) found the opposite as it proved that Ethiopian manufacturing learning-by-exporting with the size of the firm and state ownership positively affect export participation. Pär and Nan Nan (2004) assumed that productivity differences within industries mean that fit holds greater superiority in productivity and work their way as exporters, while less productive firms will produce only for the domestic market. Mixed evidence also stipulate that effects vary by unique characteristics in the economic environment (Bigsten & Gebreeyesus, 2009).

Given what is currently known from the literature, the current paper attempts to fill the gap in existing research on innovation and productivity regarding the Malaysian food manufacturing industries. To do so, this paper is organised as follows: Section 2 briefly introduces the model specification, estimation technique and describes the dataset used in the econometric model. Section 3 presents the main results and discusses the robustness test conducted. Finally, section 4 concludes the paper.

2. EMPIRICAL APPROACH

2.1. Data Sources

This paper used an aggregated panel dataset from the Economic Census - Manufacturing Sector, specifically on Manufacture of Food Products (Group 10) and Beverages (Group 11) for four periods: 2000, 2005, 2010 and 2015. This census was conducted by the Department of Statistics Malaysia (DOSM) and data were collected every five years which covers all establishments involved in manufacturing activities based on the five digits of DOSM (2008).

2.2. Empirical Model and Estimation Technique

According to, productivity is commonly measured as a ratio between the output volume and the volume of inputs. In other words, it measures how efficiently production inputs, such as labour and capital, are being used in an economy to produce a given level of output. Thus, empirical models are formed to investigate the impact of innovation in enhancing productivity in the food processing industry. This is similar to the empirical model presented in Yang and Chen (2012) and Malikane and Chitambara (2017). Our core empirical model is given by Equation 1.

$$LP_{it} = \beta_0 + \beta_1 CAPR_{it} + \beta_2 INNO_{it} + \beta_3 DIMP_{it} + \beta_4 EXPR_{it} + \beta_5 SKILLR_{it} + \beta_6 DFOR_{it} + \varepsilon_{it} \quad (1)$$

Where dependent variable, LP_{it} indicates labour productivity of subsector i in year t. Meanwhile, the explanatory variables include capital intensity ($CAPR_{it}$), innovation inputs ($INNO_{it}$), import of intermediate input ($DIMP_{it}$), export intensity ($EXPR_{it}$), skill intensity($SKILLR_{it}$), and foreign ownership ($DFOR_{it}$).

The dependent variable is labour productivity (LP) measured by total sales of manufactured (proxy of gross output) per total number of employees in a subsector i in time t, as suggested by Shafi'i and Ismail (2015), Lee (2011) and Damijan, Kostevc, and Polanec (2008). The main variable of interest is innovation (INNO) which is expected to have a positive impact on productivity significantly. According to Shafi'i and Ismail (2015) innovation can be divided into input innovation and output innovation. Input innovation refers to spending on Research and Development, meanwhile, output innovation is proxy by several patents granted. In this study, we used input innovation namely R & D expenditure and ICT expenditure. Supporting empirical evidence such as (Segarra-Blasco, 2010); Shafi'i and Ismail (2015); Calza, Goedhuys, and Trifković (2019) and Chandran, Rasiah, and Lim (2020) conquered with the results that innovation plays a significant role towards the productivity in the food manufacturing industry. A positive and significant coeffi of innovation indicates that the firms are involvectttt in high investment technology and together with the support of high quality of labour they can improve the production process and add value to their existing product. This would eventually boost firms' productivity. Thus, innovation is expected to have a positive impact on productivity.

Another control variable, namely capital intensity (CAPR), is measured by capital expenditure per salaries/wages for each of the sub-sectors, i. According to Yang and Chen (2012) capital intensities exhibit a significant positive impact on labour productivity. This implies that firms with higher capital intensities have greater performance on labour productivity due to the saving on labour utilisation. However, how capital intensity affects export behaviour is uncertain. Variable DIMP denotes import of intermediate input measured by a dummy that equals one if a subsector has the positive import of intermediate input and 0 for domestic sourcing. Sjöholm and Takii (2008) study on foreign ownership and imports of intermediate products. They found clear evidence that foreign-owned plants are more likely to start exporting, however, the coefficient for imports is not statistically significant. Hence, this study might find a plausible reason that the presence of foreign firms causes both quality upgrading and variety expansion in the local input market simultaneously.

Another control variable is export intensity (EXPR) measured by the total value of export per sale of manufactured, which is expected to have a positive significance on productivity. The increase in export intensity is mainly due to the higher export intensity of incumbent firms rather than the effect of the entry of more export-oriented firms. To control for foreign ownership, DFOR denotes a dummy that takes the value of 1 if the subsectors with at least 5% of the accumulated number of firms owned by foreigners (and 0 otherwise). Other control variables are also included in the model namely skill intensity (SKILLR) measured by tertiary education per total number of employee proxy for skilled workers. According to Yang and Chen (2012) skill-intensive or capital-intensive firms are more aggressive to engage in R&D activity to develop new products and manufacturing processes, which translate to high productivity performance.

The analysis will be carried out using static and dynamic panel data estimation in determining the impact of innovation on labour productivity. In static panel data, estimation commenced with traditional panel models; standard ordinary least squares or pool,ed OLS (POLS), fixed and random effects estimator. Estimation of pooled OLS brought a few statistical issues in heterogeneity failure and absence of autocorrelation. Breusch-Pagan lagrangian multiplier (LM) test are employed under the null hypothesis that $\sigma_u^2 = 0$. LM test were employed and prove the suitability of random effect estimator over pooled OLS estimator (Refer Table 1A). Rejection of the null hypothesis proposes the existence of individual heterogeneity. Meanwhile, Hausman specification test were employ in distinguishing hypothesis of correlation between u_i and x_{it} . Based on Table 1A, negative sign of the Hausman test statistic were taken by absolute value and not rejecting the null hypothesis (Schreiber, 2008). This implies that random effects are preferred over fixed effect estimator under null hypothesis, u_i is not correlated with x_{it}.

Given the problem of endogeneity and biasness of static model estimation in the panel data modelling, this paper utilized the generalized method of moment (GMM) estimators design by Holtz-Eakin, Newey, and Rosen (1988) as extended by Arellano and Bond (1991), Arellano and Bover (1995), and Blundell and Bond (1998).Thus, Equation 1 may be written as follow:

$$lnLP_{it} = \beta_0 + \beta_1 lnLP_{it-1} + \beta_2 CAPR_{it} + \beta_3\, lnRD_{it} + \beta_4\, lnICT_{it} + \beta_5 SKILLR_{it} + \beta_6 EXPR_{it} + \beta_7 DIMP_{it} + \beta_8 DFOR_{it} + \mu_i + \varepsilon_{it} \quad (2)$$

Where μ_i and ε denotes the country-specifics effect and error term, respectively. While, the lagged dependent variable ($lnLP_{it-1}$) refers to dynamic effect, where the existence of the labour productivity relies on itself in the previous year, and the coefficient must be less than 1 because of the persistency of the variable to be statistically significant.

There are two GMM estimators for dynamic panel data modelling, namely the first difference GMM estimator and the system GMM estimator which are typically applied in one- and two-step variants. These two estimators also share the common feature instrument usage to address the endogeneity issue. On the latter note, if the difference GMM estimate obtained is close to being below the fixed effects estimate, this suggests that the former estimate is downward biased because of weak instrumentation, and a system GMM estimator should be used instead. Hence, this paper uses the system GMM estimator based on the argument that it is consistent and relatively more efficient as compared to the first difference GMM estimator. System GMM were to resolve issues of instrument weakness and the loss of information in the level of the variables in the first difference GMM. Likewise, standard errors in finite samples tend to be downward biased. The conventional approach by practitioners in such circumstances is to use the Windmeijer (2005) adjustment to correct for such small sample downward bias, where corrected variance of the two-step GMM estimator were a much accurate inference compared to the standard two-step Wald test.

3. RESULTS & DISCUSSION

This section lays out the estimation results of innovation's impact on productivity within the food processing industry in Malaysia, highlighting 53 selected subsectors over the years 2000-2015(strongly balanced panel data). The dynamic panel modelling in this study focuses on short panels where the numbers of selected subsector (cross-sectional unit) are greater than time-series observation or (N>T). Table 1 shows the estimation outcome resulting from the one-step system GMM, two-step system GMM and two-step system GMM with Robust SE. Labour productivity is used as a dependent variable, and lagged dependence is significant at a 1% level in all econometric approaches, which justify the model are dynamic. Before the dynamic analysis, the Pooled OLS, fixed effect and random estimation were carried out, and the results reported in the appendix (Table 1B).

Estimation outputs in the model (1), (2) and (3) shows that ICT expenditure is statistically significant at a 5% level. Innovation input, ICT displays a positive relationship with productivity. Meanwhile, R & D expenditure (RD) is negative but insignificant. The result is against the findings from previous literature (Pieri et al., 2018; Venturini, 2009), who found that ICT and R&D go complementarily towards productivity growth. Meanwhile, having a significant effect on ICT particularly does not mean that subsectors can increase productivity. ICT must be embedded in complementary organisational investments, skills, and industry structures (Cardona et al., 2013). Thus, econometric evidence on the nexus between ICT capital and industry labour productivity growth is still mixed (Venturini, 2009).

Table 1. Impact of innovation on productivity: Generalised method of moments (GMM) estimations.

Dependent variable: Labour productivity(LP)			
Variable	**One-step Sys. GMM(1)**	**Two-step Sys. GMM(2)**	**Two-step Sys. GMM with Robust SE(3)**
Lagged labor productivity	0.901 (0.0508)***	0.908 (0.0499)***	0.908 (0.0590)***
CAPR Capital intensity	0.231 (0.1146)**	0.229 (0.1158)**	0.229 (0.1134)**
RD R&D expenditure	-0.045 (0.0420)	-0.037 (0.0321)	-0.037 (0.0336)
ICT ICT expenditure	0.069 (0.0343)**	0.059 (0.0283)**	0.059 (0.0286)**
EXPR Export intensity	-0.373 (0.3675)	-0.264 (0.2697)	-0.264 (0.2917)
SKILLR Skill intensity	6.238 (2.2664)***	5.859 (1.7470)***	5.859 (2.1164)***
DFOR Foreign ownership	0.213 (0.1973)	0.295 (0.1365)**	0.295 (0.1651)*
DIMP Imported intermediate input	0.028 (0.2205)	-0.074 (0.1795)	-0.074 (0.2213)
No. of observation	100	100	100
No. of groups	45	45	45
No. of instrument	12	12	12
Sargan Test(p-value)	0.2727	0.7212	-

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Capital is an essential indicator in drivers of production. The result shows that capital intensity has positive sign and is statistically significant at a 5% level. Capital intensity also increases once firms start exporting where exporters spent higher wages and gained more total sales (Van Biesebroeck, 2005). However, econometric outputs in Table 1 shows no impact of export intensity in boosting labour productivity. According to Greenaway, Gullstrand, and Kneller (2005), firms must become more efficient and productive *before* entry and self-select into export markets. Thus, potential exporters are becoming more productive before they export.

On the other hand, two intensities were cast to enrich further the comparisons; capital intensities and skill intensities. Hence, skill intensity is statistically significant at a 1% level. The coefficients estimated were positive in all econometric approaches used. These results support the finding in Yang and Chen (2012) which conclude that skill-intensive or capital-intensive firms are more aggressive in engaging in R&D activity to develop new products and manufacturing processes. Furthermore, Espinoza and Vandeweyer (2019) show that Malaysia needs to move to a higher-skills equilibrium. Strategies to boost productivity are beyond improving the education system and matching skills in the economy. Further efforts need to be put in motion; foreign direct investment promotes entrepreneurship and encourages the adoption of technology.

Table 2 presents robustness findings using the two-step system GMM with robust standard error. Xun and White (2014) mentioned that a robustness check involves examining how certain "core" regression coefficient estimates behave when the regression specification is modified by adding or removing regressors. In model (1), we put a basic regression model of capital intensity, R&D expenditure and skill intensity as an explanatory variable to labour productivity. Estimation result shows that R&D expenditure is significant but negatively affect productivity. The analysis proceeded with removing and adding other control variables to observe the impact of R&D on productivity, all results show a negative and significant. The results implied that the innovation in the food processing industry will be costly, especially among the SMEs which mostly operate based on labour-intensive production. Our results support findings from Nor et al. (2016) that the utilization of technology and innovation in the food industry in Malaysia is still low and limited compared to other manufacturing sectors (Shafi'i & Ismail, 2015) statistically significant in the model with the absence of foreign ownership and imported intermediate variable. This implies that labour productivity in the Malaysian food processing industry is greatly impacted by internal R&D rather than adopting foreign technology. Subsequently, ICT expenditure was added to the regression model. A robustness check on this model found that innovative activities (R&D and ICT) work together in raising labour productivity.

Table 2. Impact of innovation on productivity: Robustness check using two-step system GMM with robust SE.

Dependent variable: Labour productivity (LP)							
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Lagged labor productivity	1.004 (0.0395)***	0.938 (0.0636)***	0.939 (0.0630)***	0.910 (0.0592)***	0.908 (0.0590)***	0.918 (0.0549)***	1.004 (0.0513)***
CAPR Capital intensity	0.214 (0.1147)**	0.222 (0.1110)**	0.200 (0.1139)**	0.220 (0.1176)*	0.229 (0.1134)**	0.215 (0.1174)*	0.185 (0.1283)
LRD R&D expenditure	-0.078 (0.0308)***	-0.071 (0.0334)**	-0.066 (0.0355)*	-0.036 (0.0337)	-0.037 (0.0336)	-0.032 0.0340	-0.054 (0.0315)*
LICT ICT expenditure	-	0.051 (0.0292)*	0.052 (0.0289)*	0.052 (0.0264)**	0.059 (0.0286)	0.064 (0.0296)**	-
EXPR Export intensity	-	-	-0.266 (0.2942)	-0.240 (0.3031)	-0.264 (0.2917)	-0.326 (0.3090)	-0.290 (0.2763)
SKILLR Skill intensity	5.813 (2.4535)***	6.808 (2.2872)***	6.890 (2.1543)***	5.958 (1.9337)***	5.859 (2.1164)***	5.552 (2.1271)***	5.275 (2.7723)
DFOR Foreign ownership	-	-	-	0.321 (0.1920)*	0.295 (0.1651)*	0.308 (0.1524)**	0.236 (0.1772)
DIMP Imported intermediate input	-	-	-	-	-0.074 (0.2213)	-0.067 (0.2215)	-0.011 (0.2507)
DSME Presence of SME	-	-	-	-	-	-0.244 (0.1565)	-0.205 (0.1579)
No of observation	110	110	110	110	110	110	110

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

On the other hand, export intensity shows an insignificant relationship with productivity, indicating that productivity gains in the food processing industry do not come from an exporting effect. Xiaonan and Junjie (2011) also stated that if knowledge spill over from foreign counterparts is the main force behind productivity improvement, foreign-owned firms have already benefited from such spillovers internally. Hence, food processing industries could be increasing their productivity to become exporters. Greenaway et al. (2005), in stark contrast with the rest of the literature, find that exporters' productivity growth does not appear to differ significantly from non-exporters either in the periods leading up to or after entry. This is a finding that the coefficients do not change much is taken to be evidence that these coefficients are robust.

Meanwhile, there is a robust, positive and statistically significant relationship between labour productivity and skill intensity. The estimation results consistently support our previous arguments that building up a workforce with a tertiary education level may help technology adoption and digitalisation raise productivity. On the other hand, imported intermediate input is not statistically significant, meaning that having local source input may boost productivity. As mentioned in Productivity Report 2020, facilitating better matching along the supply chain is the best initiative to improve the subsector's productivity and reduce the food processing value chain gap. On a side note, these estimation results clash with findings from Amiti and Konings (2007) highlighted that lowering the input tariff led to cheaper imported inputs, which helps raise productivity. The extended equation with the presence of SMEs also shows an insignificant relationship with productivity. This implies that labour productivity in SMEs lags behind that of larger firms, particularly in the food processing industry.

4. CONCLUSION AND RECOMMENDATION

In this study, our objective was to empirically investigate the relationship between innovative activities (R&D expenditure and ICT expenditure), among other factors, in boosting labour productivity within subsectors of the Malaysian food processing industry. Using the System Generalised Method of Moments (GMM), we estimate the labour productivity model and test for robustness check with an extended model. Study results show that innovators performed better than non-innovators in terms of labour productivity, during 2000- 2015 in the Malaysian food processing industry. Innovative activity; ICT expenditure jointly with skilled intensity and capital intensity seems to be the main determinants of subsector's productivity, whereas R&D expenditure has mixed results from the estimation output. This implies that ICT works as a tool of digitalisation in influencing subsectors to be more productive.

The positive relationship between skill intensity and labour productivity was consistent in all estimation outputs since the tertiary education level in Malaysia is quite comparable to other OECD countries. However, the quality level of skilled labour remains an issue in expanding the Malaysian education system towards productivity growth. The performance gap in international assessments between Malaysia's education system and other countries can affect Malaysia's long-run relative competitiveness. Hence, the government should prioritise investments at the lower levels of education, namely primary and secondary education. In the meantime, export activity, imported intermediate input, and firm size (SME) do not positively impact and are not statistically significant for productivity. Additionally, foreign ownership is statistically significant in the presence of ICT expenditure, skilled labour and capital. Eventually, these results provide important insights for industry players and other researchers to design strategic planning and find gaps for future research regarding productivity growth at the industry level.

Funding: This research is supported by Universiti Putra Malaysia (Grant number: GP-IPB/2017/9542301).
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study.

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APPENDICES

Table 1A. Definition of variables.

Variable name	Definition	Data stream code
LP	Labour productivity; Sales of manufactured per total number of employee	2001,1419,1439
CAPR	Capital intensity; Capital expenditure per salaries/wages	0299,0399,0499,1839
RD	R&D expenditure; Total value spent on R&D (RM)	2112
ICT	ICT expenditure; Total value spent on ICT in subsector j (RM)	2119
DIMP	Imported intermediate input, which is measured by a dummy variable: 1 if subsector import intermediate input is greater than 5%, 0 if sources locally	1572,1672
SKILLR	Skill intensity; Tertiary education per total number of employee	1506,1501,1502,1606,1601, 1602, 1419,1439
EXPR	Export intensity; Total value of export per sales of manufactured	4660,2001
DFOR	Foreign ownership, which is measured by a dummy variable: 1 if the share of foreign ownership is greater than 5%; and 0 if otherwise	0045
DSME	Small and medium enterprise, which is measured by a dummy variable: 1 if the SME is presence in subsector; and 0 if otherwise	1419,1420 1439

Sources: Economic Census- Manufacturing, DOSM.

Table 1B. Impact of innovation on productivity: POLS, RE and FE.

Dependent Variable: Labour productivity(LP)			
Variable	**POLS (1)**	**RE(2)**	**FE(3)**
CAPR Capital intensity	0.3299 (0.0825)***	0.0811 (0.0445)*	0.0595 (0.0453)
RD R&D expenditure	0.0666 (0.0317)**	0.0331 (0.0186)*	0.0207 (0.0195)
ICT ICT expenditure	0.0881 (0.0292)***	0.0565 (0.0160)***	0.0514 (0.0164)***
EXPR Export intensity	0.1372 (0.2981)	-0.2707 (0.1889)	-0.3418 (0.1978)*
SKILLR Skill intensity	4.4576 (1.2714)***	6.6484 (0.9511)***	6.6795 (1.1055)***
DFOR Foreign ownership	0.5804 (0.1566)***	0.2474 (0.0916)***	0.1843 (0.0947)*
DIMP Imported intermediate input	0.1468 (0.1477)	0.0435 (0.0958)	-0.0195 (0.1023)
Constant	9.7023 (0.3627)***	10.7161 (0.2611)***	11.0351 (0.2678)***
R-squared	0.5322	0.5243	0.4893
Breusch Pagan Test	-	0.0000	
Hausman Test	-	-24.96	
No. of observation	132	132	132

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.