THE EFFECT OF DIGITAL SPILLOVERS

AND FIRM CHARACTERISTICS

ON INNOVATION AND PRODUCTIVITY

IN MALAYSIAN MANUFACTURING SECTOR

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ABSTRACT

THE EFFECTS OF DIGITAL SPILLOVERS AND FIRM CHARACTERISTICS ON INNOVATION AND PRODUCTIVITY IN MALAYSIAN MANUFACTURING SECTOR

Liew Feng Mei

The productivity of Malaysia's manufacturing sector remains a key government concern, given its role as the backbone of the economy. The emergence of Industry 4.0 has driven the sector to enhance its digital and innovation capabilities to adopt intensive disruptive technologies. Nevertheless, the impact of digitalisation and innovation on Malaysian manufacturing firms remained underexplored. Moreover, limited studies have examined the externalities of digitalisation, potentially leading to an underestimation of the full effect of digitalisation. Thus, this research is motivated to explore the relationships between digital spillovers, innovation and firm productivity in the Malaysian manufacturing sector. The Crepon-Duguet-Mairesse (CDM) model is applied as it allows the analysis of firm-level data. The Heckman selection model, Probit model, and OLS estimator are applied at different stages of the CDM model due to the different nature of the data. The data sample includes a total of 14,723 manufacturing firms, extracted from the Economic Census 2015. These unpublished firm-level data were provided by the Department of Statistics Malaysia upon request in 2020. The estimation results show that the firm characteristics, internal and horizontal digital spillovers are positively related to the innovation activities and firm productivity, as opposed to the forward digital spillover. Meanwhile, the backward digital spillover has a positive impact on the innovation output given the presence of absorptive capacity but exerts a negative effect on the firm productivity. These results reveal that manufacturing firms have lower incentives to conduct innovation when they can receive customers' feedback quickly via digital platforms. Moreover, manufacturing firms have to readjust and reallocate resources to integrate innovation into production and operations, aligning with supplier requirements and customer demands. These processes might slow down the firm productivity in the short term.

Keywords:

CDM Model; Digital Spillover; Firm Productivity; Innovation; Malaysia; Manufacturing Firm

Subject Area: HD56-57.5 Industrial productivity

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
CDM Model	Crepon-Duguet-Mairesse Model
DOSM	Department of Statistics Malaysia
FDI	Foreign Direct Investment
GDP	Gross Domestic Product
ICT	Information and Communications Technology
IO Table	Input-Output Table
IoT	Internet of Things
IR 4.0	Industry Revolution 4.0
IT	Information Technology
OECD	Organisation for Economic Cooperation and Development
OLS Estimator	Ordinary Least Square Estimator
R&D	Research and Development
SMEs	Small and Medium Enterprises

CHAPTER 1

INTRODUCTION

1.1 Development of the Manufacturing Sector in Malaysia

Since gaining independence in 1957, the manufacturing sector has been a crucial driver of economic growth in Malaysia. The sector's development must consistently align with global advancements to uphold its international competitiveness. This section begins by explaining the importance of the manufacturing sector to Malaysia's economic growth. Then, the following section illustrates the key policies implemented in the manufacturing sector, providing insights into the gradual development of this sector. Lastly, the section delves into the latest advancements in the manufacturing sector, i.e. its embracement of the concept of Industry 4.0 which evolved from the Industrial Revolution 4.0

1.1.1 Importance of Manufacturing Sector in Malaysia

The importance of the manufacturing sector can be viewed from the perspective of its contribution to Malaysian gross domestic product (GDP), employment and exports. Since Malaysia's independence in 1957, the contribution of the manufacturing sector to GDP has shown an upward trend, as illustrated in Table 1.1. The 10-year average rate has increased from 10.78% in the 1960s to the highest of 27.94% in the 2000s. Nonetheless, the rate has dropped by almost 5.5% in the recent decade and kept constant at approximately 23% in the last few years.

Table 1.1: Contribution of Manufacturing Sector to GDP (Percentage share to GDP, %)

Year	Contribution of the Manufacturing Sector (Percentage share to GDP on average, %)
1960-1969	10.78
1970-1979	17.76
1980-1989	20.66
1990-1999	27.05
2000-2009	27.94
2010-2019	22.45
Year	**Contribution of the Manufacturing Sector (Percentage share to GDP, %)**
2020	22.23
2021	23.39
2022	23.39

Source: World Bank Indicators, Malaysia (World Bank Group, 2024)

Aside from the sector's contribution to GDP, the manufacturing sector is vital in supporting Malaysian economic growth when there is an external shock. In the latest attack of the Covid-19 pandemic, the world has witnessed economic contraction as a result of global lockdown measures, including Malaysia. All sectors in Malaysia have recorded negative growth rates in 2020 due to the implementation of various rounds of movement control orders (MCO), as shown in Table 1.2 (Economic Planning Unit [EPU], 2023). However, the recovery from the Covid-19 pandemic favoured the growth of the manufacturing sector, which recorded a big jump to 9.5% and 8.1% respectively, in 2021 and 2022. The average growth rate of production in response to the Covid-19 pandemic even recorded the highest value of 4.95%.

Table 1.2: Growth rate of sectoral production (%) in Malaysia during the Covid-19 pandemic

National Sector	2020	2021	2022	Average growth rate
National	-5.46	3.30	8.65	2.16
Agriculture	-2.43	-0.11	0.07	-0.82
Mining and Quarrying	-9.73	0.9	2.65	-2.06
Manufacturing	**-2.74**	**9.50**	**8.10**	**4.95**
Construction	-19.32	-5.09	5.01	-6.47
Services	-5.23	2.17	10.92	2.62

Source: *Annual National Accounts Gross Domestic Product (GDP), Malaysia (EPU, 2023)*

In terms of job creation, the manufacturing sector has provided approximately 26% of the total employment (DOSM, 2023c). The data in Table 1.3 shows that even though the manufacturing sector is not as significant as the service sector in creating jobs, the percentage share of employment in the manufacturing sector is increasing after the period of post-COVID-19 pandemic. This statistic, once again, proves that the manufacturing sector is important for the recovery from external shock.

Table 1.3: Annual Percentage Share of Jobs by Sector (%)

National Sector	2015	2016	2017	2018	2019	2020	2021	2022
Agriculture	5.7	5.6	5.7	5.6	5.6	5.6	5.5	5.4
Mining and Quarrying	1.0	1.0	1.0	1.0	1.0	0.9	0.9	0.9
Manufacturing	**26.3**	**26.2**	**26.2**	**26.2**	**26.4**	**26.7**	**27.2**	**27.6**
Construction	15.5	15.7	15.7	15.4	15.4	15.2	14.7	14.3
Services	51.5	51.5	51.4	51.8	51.6	51.6	51.7	51.8

Source: *Employment Statistics (DOSM, 2023c)*

Regarding labour productivity growth, the manufacturing sector showed a decreasing trend starting in 2017. Nevertheless, the average growth rate of the manufacturing sector from 2016 to 2022 is the highest, i.e.,2.8%, compared to other economic sectoral and national performance. Similar to the production performance, there was negative national and sectoral labour productivity growth in 2020 due to the Covid-19 pandemic, as shown in Table 1.4.

Even though experiencing a challenging period, the manufacturing sector has rebounded sharply from the recovery of the Covid-19 pandemic and recorded the highest labour productivity in 2021. In contrast, other economic sectors have undergone a recovery path in the following year. It has proven the manufacturing sector's capacity to support economic growth during external shocks.

Table 1.4: Performance of Labour Productivity (Value Added per Employment) Growth (%) in Malaysia for the Years 2016 to 2022

National Sector	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**Average growth rate**
National	3.1	3.8	2.4	2.2	-5.3	2.0	5.4	1.9
Agriculture	1.8	2.2	-0.1	0.3	-2.0	-0.5	0.8	0.4
Mining and Quarrying	5.9	-4.8	4.0	-0.3	-7.6	-0.8	1.4	-0.3
Manufacturing	**3.8**	**3.9**	**2.4**	**1.7**	**-2.7**	**6.7**	**4.1**	**2.8**
Construction	8.8	6.8	3.4	3.6	-15.6	-4.1	5.2	1.2
Services	2.0	4.3	3.5	2.9	-5.7	0.7	6.5	2.0

Source: Labour Productivity First Quarter 2023 (Department of Statistics Malaysia[DOMS], 2023a)

Lastly, the manufacturing sector plays the role of a key exporter in Malaysia as it takes up more than 65% of the merchandise exports (World Bank

Group, 2024). The contribution of the manufacturing sector to export was low, i.e. less than 50%, in the 1970s and 1980s. Nevertheless, the manufacturing sector experienced a substantial surge of 40% in manufacturer exports over 20 years starting from 1990. Thereafter, the export rate fluctuates between 65% and 73%.

Table 1.5: Contribution of Manufacturing Sector to GDP (Percentage share to GDP, %)

Year	**Manufactures exports (% of merchandise exports, average rate)**	**Medium and high-tech export (% of manufactured export, average rate)**
1970-1979	13.20	N/A
1980-1989	30.81	N/A
1990-1999	70.76	65.17
2000-2009	73.34	70.39
2010-2019	65.24	61.83
Year	**Manufactures exports (% of merchandise exports)**	**Medium and high-tech export (% of manufactured export)**
2020	73.13	65.17
2021	70.28	62.00
2022	66.60	N/A

Source: World Bank Indicators, Malaysia (World Bank Group, 2024)

In addition, more than 60% of the manufactured exports are medium and high-tech exports, highlighting the strength and resilience of the manufacturing sector in Malaysia. According to the definition of World Bank Group (2024), high-tech products refer to merchandise that is characterized by a significant emphasis on research and development (R&D), for instance, aircraft, computers and pharmaceuticals. Meanwhile, medium-tech exports encompass motor vehicles, most chemicals, basic metals etc.

Furthermore, the Malaysia Industry-Government Group for High Technology (MIGHT) stressed the contribution of the high-tech manufacturing industry as high-tech exports once reached the highest rate of 36% of the total merchandise exports in 2018 (MIGHT, 2019). The high-tech products exported by Malaysia are mainly the intermediate products of electronics integrated circuits and information and communication technology (ICT) devices, for example, microprocessors, light-emitting diodes, semiconductor media, computer storage units etc. These products require additional value-added processes to manufacture the intended final products.

1.1.2 Key Policies in the Manufacturing Sector

As one of the core sectors in Malaysia, the manufacturing sector has undergone several rounds of transformation via the implementation of different policies (Ministry of Economy, 2024; Ministry of Investment, Trade and Industry [MITI], 2023). These policies successfully transformed Malaysia from an agricultural reliance to a manufacturing-reliance economy during the 1970s and 1980s. Then, the manufacturing sector started to focus on exporting high-tech products, with primary support from labour productivity during the 1990s and 2000s. In the recent eras, the government focused on the development of specific high-value-added manufacturing industries, along with the application of digital technologies and automation to further boost the contribution of the manufacturing sector to Malaysian GDP.

Backed to the early 1970s, the second Malaysia Plan (RM2) has focused on the development of electrical and electronics, petrochemical and chemical industries, intending to increase the contribution of the manufacturing sector to Malaysian GDP (Ministry of Economy,2024). Then, the third and fourth Malaysia Plans directed the manufacturing sector to produce high-value-added and high-tech products respectively. These developments were promoted to align with the implementation of an export-oriented industrial strategy in the 1980s (MITI, 2019).

In 1986, the Industrial Master Plan (IMP) was launched to pursue export-led industrialization in the manufacturing sector (MITI, 2019). The measures used in export-led industrialization encompass attracting foreign direct investment (FDI) to the manufacturing sector and providing investment incentives to these foreign investors. In addition, the government has also set up industrial free trade zones and given export incentives to the local exporters to encourage manufactured export.

The production and export of high-valued added and high-tech products have become the core targets for the manufacturing sector in the subsequent Malaysia Plans (Ministry of Economy, 2024). In 2006, the government presented the idea of a “Knowledge-Based Economy” during the introduction of the Ninth Malaysia Plan, intending to grow a country that is led by knowledge, creativity and innovation as well as boosting the export capabilities within the high-technology-related industries.

In 2018, the government introduced the National Industry 4.0 Policy Framework (Industry4WRD) to prepare the manufacturing sector to embrace "Industry 4.0" (MITI, 2018). The Industry4WRD has outlined strategies for helping manufacturing firms, especially small and medium firms (SMEs), in adopting digital technologies and automation. Under this framework, the manufacturing sector aims to achieve the following targets in the year 2025 by using the year 2016 as the benchmark year : (i) increase productivity by 30% ; (ii) increase total production by 54% ; (iii) improve the international innovation ranking index and (iv) increased high-skilled employment by 32% (World Bank Group, 2018).

To achieve the targets mentioned above, there are a total of 13 broad strategies being illustrated in the Industry4WRD to progress the adoption of new technologies in the manufacturing sector, together with the aims of producing high-value-added products and attracting high-tech investments. In response to the call of Malaysia Productivity Blueprint (Economic Planning Unit, 2017) and the report of Readiness for the Future of Production Kearney (2018), the Industry4WRD also focuses on developing the current and future high-skilled labour pool as well as upgrading the innovation capabilities.

To further strengthen the development of the manufacturing sector, the Malaysian government has also initiated the New Investment Policy (NIP) in 2022 (Malaysia Investment Development Authority [MIDA], 2024a). The main objective of NIP is to position Malaysia as the preferred investment recipient in the region of Southeast Asia and attract high-quality investments to all sectors in Malaysia. MIDA has been appointed as the principal agency in promoting the NIP, together with its workforce units, i.e. Project Acceleration and Coordination Unit (PACU) and Investment Promotion Agencies (IPAs).

Under the NIP, MIDA has acknowledged specific industries as the investment priorities in the manufacturing sector due to their notable comparative advantages. These industries consist of electronic and electrical (E&E), pharmaceuticals, digital economy, aerospace, and chemicals. Among the industries, E&E and aerospace were also identified as the high-potential industries driving economic growth under the 12th Malaysia Plan (MIDA, 2024a).

Last but not least, the New Industrial Master Plan (NIMP) 2030 was embarked on by the government under the Madani Economic Blueprint (MIDA, 2024b). The NIMP 2030 is the fourth revision of the Industrial Master Plan (IMP). Distinguished from previous IMPs, it adopts a mission-based approach to transform the manufacturing sector, with a targeted annual increase of 6.5% in the total output of the manufacturing sector. Furthermore, the NIMP 2030 seeks to expand the spectrum of manufactured exports by capitalizing on global market opportunities through the enhancement of value-added capabilities among manufacturing firms.

In addition, the government has also integrated the Sustainable Development Goals (SDGs) into the NIMP 2030 (MIDA, 2024b). For instance, the Industrial Development Fund (NIDF) under NIMP 2030 offers financial incentives to SMEs to boost their competitiveness, collectively strengthening the overall sectoral competitiveness on the global platform. By encouraging sustainable practices in the manufacturing sector, NIMP 2030 promotes socio-economic growth, industry innovation as well as responsible consumption and production, which fulfil various SDGs.

1.1.3 Embracing Industry 4.0: Digital Evolution in Manufacturing Sector

In the 21st century, the world has entered the Fourth Industrial Revolution era (IR4.0). IR 4.0 is considered the new era rather than the continuation of the Third Industrial Revolution (IR3.0) due to the sheer pace and breadth of the technological breakthrough (World Economic Forum, 2019). The heavy use of disruptive technologies such as the Internet of Things (IoT), robotics, artificial intelligence (AI), and cloud computing in IR4.0 has made it different from IR3.0, which mainly applied information technology (IT) and computers. These disruptive technologies change our daily lives and business operations. Thus, IR4.0 is also known as the “Digital Revolution”.

Under the IR 4.0, the sub-concept of “Industry 4.0” has been introduced (World Economic Forum, 2019). Industry 4.0 mainly promotes the computerisation of manufacturing technologies, as well as the integration of automation in the operation systems and production processes. Different sub-concepts, such as smart manufacturing, smart factory and IoT for the manufacturing sector, are introduced under Industry 4.0 (World Economic Forum, 2019). These sub-concepts have encouraged the massive use of machines embedded with sensors connected to the centralised system of manufacturing factories.

The manufacturing sector is affected by the concept of Industry 4.0 because the business landscape and production methods have to be reshaped within the sector. The manufacturing sector has to undergo a structural change, especially from the aspect of digital transformation. A study carried out by Huawei Technologies Co., Ltd and Oxford Economics (Xu & Cooper, 2017) mentioned the emergence of the “+Intelligence” process in response to the evolution of Industry 4.0. The “+Intelligence” process means improving the intelligence level of a firm in its daily operation and management, which ultimately stimulates innovation and productivity by transforming disruptive technologies into the firm’s competitive strength.

Given the pivotal role of the manufacturing sector in driving Malaysia's economic growth, its development must align with the evolution of Industry 4.0

to sustain its international competitiveness (MITI, 2018). The digital transformation in Malaysia’s manufacturing sector is inevitable and the heavy application of disruptive technologies has forced the manufacturing firms to enhance their technological capabilities to keep up with this sectoral transformation. To guide manufacturing firms in adopting digital technologies gradually, especially IoT technologies, the government has introduced the National Industry 4.0 Policy Framework to ease the digital transformation (MITI, 2018). The targets and objectives of this framework are illustrated in the previous section.

Aside from the application of disruptive technologies, the utilization of information and communication technology (ICT) also promotes digitalisation in the manufacturing sector (Zhu et al., 2021; Marsh et al.,2017). By looking at the manufacturing sector's information and communication technology (ICT) usage, its performance outperformed the national and other economic sectoral levels. Based on the available statistics, the manufacturing sector has the highest computer and internet usage percentage from 2015 to 2019, as shown in Table 1.6 (DOSM, 2021).

Table 1.6: ICT Usage in Malaysia by Economic Sectors

	National	Agriculture Sector	Mining and Quarrying Sector	Manufacturing Sector	Construction Sector	Services Sector
Computer Usage						
2015	73.5%	69.2%	88.3%	**91.8%**	73.4%	72.4%
2017	78.9%	73.4%	89.6%	**92.9%**	88.9%	77.6%
2019	86.2%	78.8%	91.5%	**93.8%**	93.1%	85.3%
Internet Usage						
2015	61.5%	49.4%	75.5%	**88.1%**	67.7%	59.8%
2017	73.3%	61.2%	78.6%	**89.7%**	85.6%	71.9%
2019	85.2%	72.0%	81.7%	**92.3%**	92.2%	84.4%
Web Presence Usage						
2015	28.4%	8.5%	25.0%	16.6%	12.2%	**30.2%**
2017	37.8%	14.2%	28.8%	26.5%	29.5%	**39.4%**
2019	53.9%	47.1%	34.8%	**59.9%**	38.9%	55.0%

Source: Malaysia Digital Economy (DOSM, 2021)

Nonetheless, the manufacturing sector mainly uses the Internet for sending and receiving emails and handling online banking-related matters, compared to other purposes such as exchanging information with other parties, sales and customer services, and staff development. For web presence usage, even though it was lower in 2015 and 2017, the percentage has increased by 126% and scored the highest among the sectors in 2019 due to the improvement in the presence on own and other companies' websites, social media and platform for e-commerce (DOSM, 2021).

In 2019, a new type of statistic, i.e., the data on digital technology adoption, was released. The manufacturing sector adopted the most in the website, social media and management software (DOSM, 2021). However, improvements are needed in adopting cloud computing, data analytics and online collaborative platforms because these digital technologies are closely related to the adoption of Industry 4.0, together with the IoT, robotics and artificial intelligence (World Economic Forum, 2019).

These statistics have shown that the manufacturing sector is undergoing digital transformation at the sectoral level as it has proactively applied ICT applications as compared to other economic sectors. Yet, the sector has to diligently work towards digital transformation, especially the adoption of disruptive technologies such as cloud computing and data analytics. The acceleration of digitalisation in the manufacturing sector not only eases the transformation to Industry 4.0, but it helps in improving innovation performance and firm productivity, as outlined as the targets of the National Industry 4.0 Policy Framework (Industry4WRD) (MITI, 2018).

Table 1.7: Digital Technologies Adoption in Malaysia by Economic Sectors in the Year 2019

	National	Agriculture Sector	Mining and Quarrying Sector	Manufacturing Sector	Construction Sector	Services Sector
Website	48.5%	51.8%	19.2%	**53.1%**	34.95	49.4%
Social media	60%	56.7%	46.1%	**73.0%**	47.5%	60.4%
Mobile internet and technologies	63.8%	54.7%	24.6%	62.7%	55.9%	**64.9%**
Cloud computing	46.8%	56.8%	**60.8%**	46.3%	48.8%	46.4%
Data analytics	6.3%	**9.0%**	3.4%	4.3%	2.8%	6.8%
Management software	41.1%	35.7%	32.8%	**47.9%**	29.0%	41.9%
Online collaborative platforms	11.4%	13.6%	**27.7%**	8.5%	5.4%	12.1%
No digital technology adoption	18.3%	7.7%	11.1%	12.3%	12.1%	**19.5%**

Source: Malaysia Digital Economy (DOSM, 2021)

1.2 Innovation Performance in Malaysia

Innovation plays a role in enhancing firm productivity. Oslo Manual has illustrated the importance of digitalisation in enhancing a country's innovation capability (OECD, 2018). Likewise, the Malaysian government has aimed to achieve dual objectives concurrently, i.e. digitalisation transformation and innovation enhancement, as facilitated by the Industry4WRD (MITI, 2018). The innovation performance of Malaysia can be studied from the ranking of international innovation indices, such as the Bloomberg Innovation Index and

Global Innovation Index. These international innovation indices measure the innovation performance of each country from different perspectives, such as research and development, technological advancements, innovation output, knowledge creation etc (Jamrisko et al., 2021; World Intellectual Property Organization, 2022).

Based on the latest available statistics from the Bloomberg Innovation Index, Malaysia's ranking has dipped continuously for three years, from 26th in 2019 to 27th in 2020 and 29th in 2021 (Jamrisko et al., 2021; Jamrisko et al., 2019). Besides, the difference between Malaysia's score and the maximum score of the year has been enlarged from 2016 to 2018. Even though the situation was improved in 2019, the difference in the scores continued to widen in 2020 and 2021. The drop in the ranking was caused by the weak performance in productivity, high-tech density, tertiary efficiency and research concentration (Jamrisko et al., 2021). The tertiary efficiency performed the worst as it dropped by 26 positions, from rank 26 in 2017 to 50 in 2021. The details of Malaysia's ranking on the Bloomberg Innovation Index and Global Innovation Index are shown in Table 1.8 and Table 1.9 respectively.

The results of these international innovation indices have pointed out some implications. First, Malaysia needs to improve its production of the innovation outputs, such as patent filings. Second, the volume of research and development activities and the collaboration between tertiary education institutions and industries need to be increased in supporting innovation activities in local markets. Thirdly, the number of skilled labourers, such as professionals, experienced technicians, and postgraduate students who engage in R&D, must be increased to boost innovation activities.

Table 1.8: Malaysia's Ranking on the Bloomberg Innovation Index

	2021	2020	2019	2018	2017
Maximum score of the particular year	90.49	88.21	87.38	89.30	89.00
Malaysia's score	69.68	68.28	67.61	64.79	66.98
Difference	20.81	19.93	19.77	24.51	22.02
The Sub-category of Index (Ranking)[1]					
R&D intensity	24	23	23	26	27
Manufacturing value added	10	9	9	17	12
Productivity	46	46	46	36	37
High-tech Density	27	25	21	24	21
Tertiary Efficiency	50	41	37	36	26
Researcher Concentration	42	40	40	33	34
Patent Activity	31	38	41	34	33

Source: Bloomberg Innovation Index (Jamrisko et al., 2021; Jamrisko et al., 2019)

[1] The definitions of the sub-categories of Bloomberg Innovation Index are as following:

i) R&D intensity : Research and development expenditure, as % GDP
ii) Manufacturing value-added : MVA, as % GDP and per capita ($PPP)
iii) Productivity : GDP and GNI per employed person age 15+ and 3Y improvement
iv) High-tech density : Number of domestically domiciled high-tech public companies, such as aerospace and defence, biotechnology, hardware, software, semiconductors, Internet software and services, and renewable energy companies—as % domestic publicly listed companies and as a share of world's total public high-tech companies.
v) Tertiary Efficiency: Total Enrolment in tertiary education, regardless of age, as % of the post-secondary cohort; gross graduation ratio of first-degree earners, share of labour force with advanced level of education; annual new science and engineering graduates as % total tertiary graduates and as % of labour force.
vi) Researcher Concentration: Professionals, including postgraduate PhD students, engaged in R&D per population.
vii) Patent Activity: Resident patent filings, total patent grants , patent in force and growth in filings, per population, filings per GDP and total grants and filing growth by country as a share of world total

Table 1.9: Malaysia's Ranking on the Global Innovation Index

	2022	2021	2020	2019	2018	2017
Global Innovation Index						
Maximum score of the particular year	64.62	65.5	66.1	67.24	68.40	67.69
Malaysia's score	38.72	41.9	42.4	42.68	43.16	42.72
Difference	**25.9**	**23.6**	**23.7**	**24.56**	**25.24**	**24.98**
Innovation Efficiency Ratio						
Maximum score of the particular year	0.91	0.89	0.90	0.88	1.0	1.0
Malaysia's score	0.61	0.68	0.62	0.61	0.66	0.68
Difference	**0.30**	**0.22**	**0.28**	**0.27**	**0.34**	**0.32**
Innovation Input Sub-index[2]						
Maximum score of the particular year	67.56	68.9	69.4	72.15	74.2	72.3
Malaysia's score	48	49.8	52.2	52.93	52.07	50.94
Difference	**19.56**	**19.1**	**17.2**	**19.22**	**22.13**	**21.36**
Innovation Output Sub-index[3]						
Maximum score of the particular year	61.7	62.0	62.80	63.45	67.1	65.8
Malaysia's score	29.45	33.9	32.6	32.42	34.26	34.49
Difference	**32.25**	**28.1**	**30.2**	**31.03**	**32.84**	**31.31**

Source: *Global Innovation Index (WIPO, 2022)*

Even though skilled labourers are vital in promoting innovation activities, the statistics provided by the DOSM (2022) in Table 1.10 show that Malaysia's manufacturing sector highly depends on semi-skilled labour, which accounts for three-quarters of the total employment. Yet, the skilled labour job is less than 20%, lower than the mining and quarrying sector (around 30%) and the services sector (more than 30%). Moreover, MITI (2018) mentioned that only 7.5% of the total employed in the manufacturing sector obtained the qualification of a

[2]The Innovation Input Sub-index is measured from the perspectives of institutions, human capital and research, infrastructure, market sophistication and business sophistication

[3] The Innovation Output Sub-index is measured from the perspectives of knowledge and technology outputs and creative outputs.

university degree and above, 12% achieved a diploma or STPM level, and the majority (80.5%) gained SPM level or below, based on the data collected in Economic Census 2016.

Table 1.10: Employment in the Manufacturing Sector Based on Skill from 2018 to 2022

	2018	2019	2020	2021	2022
Skilled labour	18.8%	17.9%	17.5%	17.7%	17.8%
Semi-skilled labour	73.9%	75.1%	75.1%	75.0%	75.1%
Low-skilled labour	7.3%	7.0%	7.4%	7.3%	7.1%

Source: Employment Statistics, Fourth Quarter 2022 (DOSM, 2022)

1.3 Problem Statement

The development of the manufacturing sector is a main concern to the Malaysian government and society because it is a key driver of economic growth. It has contributed approximately 23% of the GDP in recent years and it is the principal exporter of high-value-added products (World Bank Group, 2024). Even though this sector holds significant importance, its contribution to GDP was not as high as in the 1990s and 2000s (around 27%).

In addition, the growth in labour productivity has not been sustained since 2018 and has not reached the revised target growth rate of 3.9% annually set under the Mid-Term Review of Eleventh Malaysia Plan (11MP MTR) (Malaysia Productivity Corporation, 2019). Although there was a sharp rebound from the recovery of Covid-19 in 2021, the growth rate declined again in 2022. In terms of exports, the manufacturing sector is a key exporter but the percentage of manufacturing exports and medium and high-tech exports was not able to keep consistent has been inconsistent and has not demonstrated sustained improvement (World Bank Group, 2024).

1.3.1 Practical Problems

The fluctuating performance of the manufacturing sector poses challenges for the government, at the same time, concerned with managing the transition to Industry 4.0. World Economic Forum (2019) commented that digital and technological transformation is important for countries to implement Industry 4.0 and strengthen their international competitiveness. Nonetheless, the adoption rate of modern digital technologies in the manufacturing sector is beyond the desired outcomes (MITI,2018).

The Malaysia Enterprise Survey has revealed that the adoption of automation and modern technology in most manufacturing firms is less than 50% (Economic Planning Unit, 2017). This statement is tallied with the statistics[4] of digital technology adoption published in the report of Malaysia Digital Economy (DOSM, 2021). Even though the manufacturing sector has the highest percentage of adopting social media, mobile internet and technologies, and websites, the adoption rate of technologies that are related to automation and

[4] The detailed statistics can be viewed on Table 1.6 and 1.7 at Section ***1.4 Embracing Industry 4.0 : Digital Evolution in Manufacturing Sector.***

modern technology, such as cloud computing, data analytics and management software, was lower than 50%.

The Malaysia Enterprise Survey explained that the slow adoption of Industry 4.0 technologies in the manufacturing sector is caused by the high cost of adoption and longer payback period, based on the feedback given by the industry players (Economic Planning Unit, 2017). Moreover, the industry players also commented that there are insufficient solution providers for the key technologies and a lack of infrastructure, such as high-speed broadband, available in critical industrial locations. Furthermore, the inadequacy of government financial support and skilled labour are also the obstacles that prevent the digitalisation of businesses in the manufacturing sector (Economic Planning Unit, 2017).

Not only that, the digital adoption among small and medium enterprises (SMEs) in the manufacturing sector raised heightened concerns among stakeholders. The adoption rate was even lower, reaching only approximately 20% (Malaysia Productivity Corporation [MPC], 2018; MITI, 2018).MITI (2018) mentioned that SMEs are more reluctant to apply the ICT tools in their daily business activities and are involved less in online businesses because most of the SME owners are not aware of the impact and necessity of applying Industry 4.0 technologies in their business model.

Despite that, the performances of SMEs in the manufacturing sector are critical because they account for more than 97% of the manufacturing sector (Economic Planning Unit, 2021; Ministry of Investment, Trade and Industry,2018). Moreover, they contributed approximately 7.7% to the national GDP and 46% of total employment in the manufacturing sector from 2015 to 2020, according to National Accounts Small & Medium Enterprises 2020 (DOSM, 2021). As a result, a slow adoption rate of modern digital technologies among SMEs could prolong the implementation of Industry 4.0 in the manufacturing sector.

From another perspective, the prolonged journey towards digitalisation adversely affects the innovation capability of Malaysia. Innovation capability is essential in promoting innovation activities and creating sustainable industries (Griggs et al., 2013). The innovation capability of a firm or nation is established upon a robust financial foundation, ample technological-advanced physical capital and competitive human capital. All these resources contribute to the research and development projects and the innovation process.

Malaysia's innovation capability has not improved and sustained, as shown by the international innovation indices. In the manufacturing sector, the innovation capability of SMEs is lagged behind those of large firms, similar to the state of digitalisation (MPC, 2019). The SMEs found difficulty in recruiting high-performing talents and obtaining sufficient funding to conduct innovation activities (MITI,2018). Likewise, they also have limited access to research collaboration with external parties. The lower exposure to the innovation possibilities has made the productivity of SMEs three times lower than that of large firms (MPC, 2019).

The accomplishment of digitalisation and innovation highly depends on the accumulation of physical capital and human capital (Ministry of Economic Affairs,2018). The report "Readiness for the Future of Production" prepared by the World Economic Forum advocates that a country which plans to embrace Industry 4.0 should focus on developing technology, human capital and institutional frameworks (Kearney, 2018). A country that abounds with cheap labour, especially low-skilled labour, could lose its competitive advantages on the international stage because the tasks performed by these labourers are replaced by automatised machines and disruptive innovations gradually.

The physical and human capital form the absorptive capacity of a firm or a nation. Absorptive capacity is defined as the ability of a firm to recognise and assimilate new information, subsequently transforming external ideas into innovation and commercialising them to achieve a dynamic organisational capacity (Zahra & George, 2002). However, Malaysia's manufacturing sector lacks the absorptive capital.

The Midterm Review of the 11th Malaysia Plan report shows that the manufacturing sector often lacks capital investment in automated machinery and equipment and highly depends on low-skilled foreign workers Ministry of Economic Affairs (2018). MITI (2018) also mentioned that there is a mismatch of skilled labour and a shortage of experts in applying the concept of Industry 4.0 technologies in the manufacturing sector, especially in IoT, robotics and AI. In addition, there is also a lack of cyber-security experts, which plays a vital role in protecting the technology applications mentioned.

Furthermore, the high dependency on semi and low-skilled labour has made the manufacturing sector focus more on the low-value-added market segments than those with high value-added (Ministry of Economic Affairs, 2018; EPU, 2017). This employment condition, together with the loss of competitive advantage of low-cost labour, has put Malaysia at the risk that less FDI would be attracted to the manufacturing sector (Ministry of Investment, Trade and Industry,2018).

From another point of view, the lack of required human capital has caused limited cooperation between local and foreign firms in the innovation activities in the Malaysian manufacturing sector. Baskara (2017) discovered that multinational corporations in Malaysia prefer to recruit personnel from their parent company or subsidiaries outside Malaysia instead of local labour for innovation activities. This condition creates a vicious cycle in Malaysian human capital accumulation because it has limited the knowledge spillover from international companies to domestic businesses.

Moreover, there is also a limited knowledge spillover from the universities to the industries in carrying out innovation activities and promoting the implementation of Industry 4.0. MPC (2019) mentioned that limited collaboration is being carried out between industries and local higher education institutions. There are also limited scientists and engineers sourced to the manufacturing firms from the local labour market because the syllabus and pedagogy of Science subjects provided by universities are incompatible with the needs of Industry 4.0 (MPC, 2019).

The issues of digital technology adoption, innovation capability and absorptive capacity are not independent, but interrelated in developing the manufacturing sector. The absorptive capacity could advance the digital technology adoption and innovation capability, at the same time, digitalisation helps in innovation activities. Ultimately, manufacturing firms can enhance their productivity and competitiveness. As a result, if one of the issues here is not attended to, it would negatively affect the whole reaction chain.

Given the importance of these factors in affecting firm productivity, this research aims to study the relationships between the factors. As digitalisation transformation, innovation capability, and absorptive capacity vary from firm to firm, the heterogeneity of firm characteristics is also included in this study to examine the relationships. To have a clearer picture of these relationships under different contexts of firm characteristics, the CDM model founded by Crépon et al. (1998) is used in this study because it is a model designed for firm-level study. The CDM model is a recursive model, which investigates the process from the intention of a firm to carry out innovation to the effect of innovation on firm productivity.

1.3.2 Theoretical Problems

To comprehend the study on digitalisation, this research has also incorporated the idea of "digital spillover effects" proposed in a study conducted by Huawei Technologies Co., Ltd and Oxford Economics (Xu & Cooper, 2017). Xu and Cooper (2017) discovered that digital spillover happens when digital technologies expedite information sharing, knowledge transfer, and innovation activities among firms, industries, and countries. This is because the usages of digital technologies are different from the conventional capital. After all, there is no constraint on geographical mobility. Thus, the impact of digitalisation can be more significant than conventional capital.

Xu and Cooper (2017) revealed that the indirect return on the digital investments caused by the digital spillover effects can surpass the direct return in their study and urged the importance of incorporating digital spillover effects in the study of digitalisation. Nonetheless, these indirect effects have been overlooked by previous researchers. In addition, Fu et al. (2021) stressed that digital platforms could bring multiplier effects to the economic development in developing countries. Thus, if the indirect effects of digitalisation are overlooked by the researchers, there is also a potential for underestimation of the multiplier effects.

On the other hand, Marsh et al. (2017) also proposed the significance of absorptive capacity in grasping the ICT spillover effects because the digital spillover effects could be under-utilised when there is a shortage of skilled labour or experts. As a result, the role of the absorptive capacity has to be considered in the analysis of digital spillover effects. Due to the significance of digital spillover effects in the study of digitalisation, these variables are also considered in the formation of research objectives on top of the variables mentioned above.

1.4 Research Objectives

Based on the issues discussed in the problem statement, the research objectives of this study are formed.

General Objective:

This study is aimed to examine the interrelationships among firm characteristics, digital spillover effects, innovation and labour productivity in the Malaysian manufacturing sector.

Specific Objectives:

Research Objective 1:
To examine the influences of firm characteristics and digital spillover effects on innovation input in the Malaysian manufacturing sector.

Research Objective 2:
To investigate the impacts of innovation input, firm characteristics and digital spillover effects on innovation output in the Malaysian manufacturing sector.

Research Objective 3:
To evaluate the associations between digital spillover effects, innovation output and firm productivity in the Malaysian manufacturing sector.

In corresponding to the research objectives, three research questions have been set and listed as follows.

Research Question 1:
Do firm characteristics and digital spillover effects influence innovation input in the Malaysian manufacturing sector?

Research Question 2:
Do innovation input, firm characteristics and digital spillover effects impact innovation output in the Malaysian manufacturing sector?

Research Question 3:
Do digital spillover effects and innovation output affect the firm productivity in the Malaysian manufacturing sector?

1.5 Research Scope

This research studies the effects of firm characteristics, digital spillover effects and innovation on the firm productivity in Malaysia's manufacturing sector. As the CDM model is employed in this research, the firm-level study is carried out.

The research scope is limited to the manufacturing firms in Malaysia's manufacturing sector, regardless of the firm size. In this study, the firm-level data provided by DOSM upon official request is used for the data analysis because the firm-level was not published publicly. The firm-level data was extracted from the Fourth Economic Census[5], the Economic Census 2016, with the reference year of 2015 because that was the latest Economic Census that was available when the DOSM officer provided the data in March 2020. The author has submitted two rounds of official requests in 2022 and 2024 respectively to get the latest firm-level data, but the DOSM officer has informed that the firm-level data are not ready to given to the public. The details on the data selection and data sources can be referred to in Section 3.6.

These manufacturing firms cover 67 industry groups, in the classification follows the Malaysia Standard Industrial Classifications 2008 Version 1.0 (MSIC) (DOSM, 2015). The description of these industry groups can be referred to in Appendix 2. There are 24 of out 67 groups are categorized as high-productive groups, i.e. the groups which recorded a gross output of RM10 billion and above, according to the Economic Census of Manufacturing 2016 (DOSM,2017). Furthermore, there is a total of 14,723 manufacturing firms covered in this study, consisting of 548 large firms, 935 medium firms and 13,240 small firms.

[5] The Economic Census published by Department of Statistics entails a thorough enumeration of all "business entities" and 'non-profit organizations' in Malaysia. The survey is conducted at a five-year interval. The Fifth Economic Census is the Economic Census 2023, with the reference year of 2022, which is not available as at December 2023 (DOSM, 2024) .

1.6 Significance of Study

In this section, the contributions of this study are discussed from the perspectives of academia, policymakers, as well as the stakeholders of the manufacturing sector and firms.

1.6.1 Academia

This study aims to contribute to the literature on innovation and productivity, especially in the context of the CDM model. The CDM model was founded by Crépon et al. (1998) to study the relationship between innovation and productivity using firm-level data. This model has been used widely in the past literature because it can show the interactions between the innovation input, innovation output and productivity sequentially. A vast amount of literature has focused on the effect of firm characteristics on innovation, but little attention has been devoted to the impact of digital spillover effects on innovation and productivity.

The study of the digital spillover effect is essential in the new literature because it is the better indicator to measure the return on digital investment induced by digital transformation (Xu & Cooper, 2017). Nowadays, digital transformation is an irresistible trend and has been spread across all spectrums of an economy, especially after the universal usage of the internet and the popularisation of smartphones and computers. It accelerates the information flow in an economy and revolutionises production and consumption processes (Xu & Cooper, 2017).

The digital spillover effect happens when digital technologies expedite information sharing, knowledge transfer and innovation activities among firms, industries and even countries, and thus, it helps increase productivity (Marsh et al., 2017; Xu & Cooper, 2017). This is the reason that the indirect return on digital investments surpassed the direct return, as revealed by the study conducted together by Huawei Technologies Co., Ltd and Oxford Economics, the first research that called for studying the digital spillover effect (Xu & Cooper, 2017). As a result, this study intends to fill this literature gap by incorporating the digital spillover effect into the CDM model.

In addition, there is also limited study that employed the CDM model in the context of the Malaysian manufacturing sector. To the author's knowledge, only Shafi'I and Ismail (2015) studied the relationship between innovation and productivity in the Malaysian manufacturing sector using the CDM model. Nonetheless, they used only nine targeted sub-sectors as the research scope and employed the data extracted from the Annual Survey of Manufacturing 2008. In this study, the research scope is extended to include 67 sub-sectors using the data extracted from the Economic Census 2016 on the manufacturing sector.

Finally, this study also intends to contribute empirical evidence on the effect of absorptive capacity on innovation and productivity. Past studies, for instance, Sun et al. (2020), Shafi'I and Ismail (2015), Nitzsche et al. (2016), and Cohen and Levinthal (1990) have extensively used the number of skilled labour and educational level of labour to proxy the development and accumulation of human capital. In this study, absorptive capacity is not only a proxy by the skilled labour but also measured in the interaction term between skilled labour and digital spillover to examine the degree of digital spillover effect reaped by the skilled labour. Thus, it can provide insights into the interaction between skilled labour and digital technology adoption.

1.6.2 Policymakers

This research could provide insights to the Malaysian government on the relationships among digital technology adoption, innovation and productivity in the manufacturing sector. It is essential to focus on the development of the manufacturing sector because it remains the driving force of economic growth. As the adoption of Industry 4.0 in the Malaysian manufacturing sector is still early, multiple reviews on the National Industry 4.0 Policy Framework are needed. Thus, this study can serve as a reference to the Malaysian government in designing relevant policies to make digital technology adoption in the manufacturing sector more effective and efficient.

In addition, the analysis of the effect of firm characteristics on innovation investment and innovation output could give a formal and scientific approach to the government to identify the appropriate incentives given to the local firms in promoting innovation activities, especially the small and medium firms, because they formed the majority in the manufacturing sector. Furthermore, the government can design effective initiatives and provide the appropriate incentives to develop compatible human capital. Compatible human capital accumulation is needed to absorb and internalise the external knowledge transmitted via digital technology, which is then transformed into innovation and productivity. Thus, the digital spillover effect could be fully utilised, and digital dividends could be maximised.

1.6.3 Manufacturing Sector and Firms

The manufacturing sector is studied in this research because the manufacturing sector is always the first sector that experiences technological transformation whenever there is an industrial revolution (World Economic Forum, 2019). The arrival of Industrial Revolution 4.0 and Industry 4.0 has required Malaysian manufacturing firms to undergo technological transformation by heavily applying disruptive technologies, such as the Internet of Things (IoT), robotics, artificial intelligence (AI) and cloud computing.

For the stakeholders of the manufacturing sector, this study can serve as a guideline to the owner and management team of manufacturing firms to enhance their internal strength to conduct innovation activities and boost the firm productivity. The manufacturing firms' owner and management team can get insights into the effects of firm characteristics and digital adoption on innovation effectiveness from this study and prepare themselves to implement the technological transformations required in Industry 4.0.

Besides, this study gives an intuition to the firms, especially SMEs, on restructuring the existing resource allocation. The SMEs can reallocate the ratio of labour and capital, especially the digital technology adoption, in the production process. SMEs can consider the possibility of innovation activities by utilising digital technology, especially internet usage. The owners can consider process innovation, marketing innovation or operation innovation using the internet but not limit themselves to product innovation, which requires vast amounts of funding and expensive equipment and machinery. The SMEs should fully utilise computer and internet usage if facing financial difficulty because the costs are cheaper as these two materials are popularised. Thus, the productivity of SMEs could be enhanced as the large firms.

1.7 Definition of Terms

The definitions of some jargon, such as innovation input, innovation output, and digital spillover effect, are explained as follows. The detailed definition of these terms can be referred to in section 3.2.

Table 1.11: Brief Definition of Jargon

Term	Definition
Digital spillover effect	The externality of digitalisation, in the form of external knowledge created. The spillover effects happen when there is information flow that is transferred via digital platforms, which can be enjoyed by any economic agents, aside from the investors of digital technologies.
Firm characteristics	The attributes of a company, such as firm size, market share held, and industry groups that belong to.
Firm productivity	Efficiency of a firm in turning its resources into production.
Innovation activity	The action or event that creates the intention for a firm to implement or has implemented the innovation.

Table 1.11 (Continued) : Brief Definition of Jargon

Term	Definition
Innovation expenditures	The costs incurred during innovation activities, include research and development (R&D), creative work development, human capital development, information and communication technology (ICT) development, marketing-relevant expenditures, intellectual property-relevant expenditures and capital accumulation.
Innovation input	The resources and capabilities owned by a company in conducting innovation activities.
Innovation output	The outcome of innovation input where the implementation of a novel or upgraded product, service, process or business operation method in a company which is beneficial to the stakeholders of the organisation
Patent	An exclusive right granted by the government to help a firm enjoy the dividend bought by its novel product or/and process invention for a certain period.

1.8 Organisation of Thesis

There are a total of five chapters in this study.

Chapter 1: Introduction

This chapter presents the motivation and core idea of this research, starting from the research background to the problem statement. Next, the research objectives and the corresponding research questions are outlined. Finally, the significance of the study and chapter layout are presented.

Chapter 2: Literature Review

The literature reviews on the relationship between firm characteristics, innovation and productivity based on the CDM model are presented. Besides, the effects of digital spillovers on innovation and productivity are also outlined in this chapter. In addition, relevant theories are explained to support the validation of the empirical model in Chapter 3.

Chapter 3: Methodology

This chapter explains the data description and research methodologies. It includes an explanation of the estimation techniques of binary dependent variables and the relevant least squares method.

Chapter 4: Data Analysis

The empirical results of model estimation are reported in this chapter. Arguments and empirical evidence are given in support of the empirical results.

Chapter 5: Discussion, Conclusion and Implication

The final chapter highlights the major findings and implications of this study, which is then followed by the policy suggestions. Finally, the limitations of the study and recommendations for future research are discussed.

1.9 Concluding Remark

The arrival of Industrial Revolution 4.0 and Industry 4.0 is an impending development that is reshaping the competitive landscape and resource allocation in the manufacturing sector nationally and globally. The pace of changes is rapid and inevitable, with transformations taking place swiftly (World Economic Forum, 2019). As a result, Malaysia could not sit on the sidelines and neglect the transformation needed in the manufacturing sector. Otherwise, it would impair the productivity of the manufacturing sector and lose its competitiveness on the world stage.

This chapter starts with an illustration of the importance of the manufacturing sector to the Malaysian economy. The development of the manufacturing sector is vital to Malaysia because it has contributed an average of 23% of the total GDP in the last decades and remains the driving engine of economic growth in Malaysia (Economic Planning Unit, 2017). Nonetheless, labour productivity in the manufacturing sector has shown a decreasing trend starting from the year 2017 (DOSM, 2022). It raised the concern whether labour productivity can sustain the contribution of the manufacturing sector to Malaysia's GDP.

The problem statement has explained the inadequacy of digital technology adoption and innovation performance in stimulating labour productivity in the manufacturing sector. It is observed that the situations of digitalisation and innovation vary from firm to firm due to different firm characteristics. Notwithstanding, Xu and Cooper (2017) advocated that examining the direct impact of digitalisation on productivity alone is not adequate to understand the total effect of digitalisation. Instead, the indirect effects have to be considered together in the research. The indirect effects of digitalisation refer to the digital spillover effects, i.e. the widespread exchange of information and knowledge sharing via digital platforms and channels. Given the importance of these variables, this study explores the roles of firm characteristics and the digital spillover effects in stimulating innovation activities and firm productivity in the Malaysian manufacturing sector.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

In response to the research objectives of this study, this chapter outlines the literature review on innovation, digital spillovers and productivity. The effect of innovation on productivity has been mentioned in theories, such as endogenous growth theory, and has been proven by empirical studies. As innovation requires the acquisition of formal and tacit knowledge, digital spillover effects are believed to be an essential channel in transferring relevant technology and knowledge acquired by a firm.

This chapter starts with a theoretical review of the Endogenous Growth Theory and Schumpeter's Theory of Innovation. After that, the development of the CDM model, which describes the relationship between innovation input, innovation output and productivity, is discussed. Next, the literature review on digital spillover effects is presented as digital spillover is treated as one of the diffusion channels of knowledge. Lastly, a summary of chapter two and the research gap are elaborated.

2.2 Theoretical Review: Endogenous Growth Theory

The theory of economic growth generally focuses on measuring the actual and potential growth in the wealth and living standards of a nation in both the immediate and distant future. Over time, the theory of economic growth has evolved from exogenous growth to an endogenous growth model. Furthermore, the seminars of Schumpeter (1942) and Solow (1956) have asserted the importance of technology and innovation in promoting economic growth. Soon after, the endogenous growth theory advocated that long-term productivity growth is influenced by the accumulation of physical and human capital as well as the rate of innovation and technological change (Roa et al., 2001).

Based on the neoclassical economic theories, the savings rate and technical progress rate determine the long-run economic growth exogenously, as illustrated in the Harrod-Domar and Solow models, respectively. The Solow model was the first model which incorporated technological advancement in studying economic growth (Solow, 1956). The production function was designed based on his belief that economic growth is affected by the accumulation of capital and labour as well as the improvement in productivity of these inputs. The production function was shown as $Q = f(K, L; t)$, in which the output or profit (Q) was the function of capital (K) and labour (L). Meanwhile, the t represented the time needed for technological change, a proxy for the improvement in productivity of the inputs. Solow's (1956) study on the United States discovered that the productivity of the US economy was derived from technological change and savings. Still, the study was not able to explain part of the exogenous growth in output, which was termed as “Solow residual”.

The unexplained rate of technological progress has urged researchers to develop a model — the endogenous growth model, which explicitly embeds the critical determinants of growth. The endogenous growth theory advocates that economic growth is significantly contributed by the development of human capital, the transmission of knowledge as well as the creation of innovation. The endogenous growth model can be a simple model which only considers the constant return to scale in the production as demonstrated by the AK model or the complex version associated with positive externalities caused by the knowledge spillover effects.

The AK model, $Y=AK^{\alpha}L^{(1-\alpha),}$ is the most elementary endogenous model, in which A measures the technological progress and/or innovation while the α and 1- α estimate the output elasticity of capital and labour respectively (Romer, 1986). The model assumes that the labour is growing at a constant rate with no depreciation in capital, and thus, the value of α ranges from zero to one. In other words, the model implies that the output per capita is determined by capital per capita, and there is an absence of diminishing returns to scale in the capital inputs, which could lead to endogenous growth.

The absence of diminishing returns to scale and the assumption of holding constant returns to scale in the endogenous growth model is the strongest distinctness of the exogenous growth model. The endogenous-growth-favoured researchers did not hold the view of diminishing returns to scale by explaining that the improvements in technological progress, as well as the positive spillovers of capital investment, could increase production. Romer (1990) has viewed technological advancement as the by-product of capital investments. He also stated that positive spillovers happen when technological knowledge is increasing because new technical knowledge emerges from the process of learning by doing, and this knowledge acts as the free input in another wave of production. Thus, costs of production could be reduced, and at the same time, the marginal productivity of capital is improved.

Nonetheless, another group of researchers have suggested the incorporation of factors that encourage technological progress, such as research and development (henceforth R&D) (Grossman & Helpman, 1991; Lucas, 1988; Romer, 1986) and imperfect markets (Aghion & Howitt, 1990) in the growth model. Romer (1986) and Lucas (1988) perceived that the investment in human capital is an essential contributor to internal growth because the integration of advanced technological innovation in the production processes is highly relied upon by qualified labour. The interconnection between technological progress, innovation and qualified labour leads to the full utilisation of the physical capital, at the same time boosting productivity and minimising the diminishing returns to scale on the capital accumulation.

From another perspective, although the endogenous growth model holds the assumption of constant returns to scale at an aggregate level, it does not indicate that the productivity of big firms is higher than that of small firms. As there is no significant difference between big firms and small firms, the endogenous growth model could be constructed in the context of perfect competition. Nonetheless, this assumption has been relaxed in many models as some degree of monopoly power is allowed (Aghion et al., 1998; Grossman & Helpman, 1994).

By relating the endogenous growth theory to firm productivity, Aghion et al. (1998), as well as Grossman and Helpman (1994) argued that a firm that faces intense competition is forced to make continuous innovation to maintain their competitiveness, which in passing increases their company growth. This is because the monopoly power of a firm comes from its ability to achieve economies of scale and hold a higher market share. Otherwise, the firm possesses some competitive edge, such as patents, which make it gain more profit and sustain the business (allowed (Aghion et al., 1998; Grossman & Helpman, 1994).

In the endogenous growth model, the achievement of long-run economic growth is derived from the firm productivity collectively. It highly depends upon the policy measures which encourage the accumulation of physical and human capital, at the national and firm level, and the creation of innovation. For instance, providing education and training to the firm labourers as well as giving the subsidy and grants for research and development to individual firms for promoting innovation activities. Besides, Howitt (2007) stated that the policy design should also embrace openness and competition to enjoy long-term prosperity because the overprotection of particular firms and industries limits efficiency improvement and innovation.

Even though the endogenous growth model is a popular model for researchers studying the topic of economic growth, critics were given by other researchers. Sachs and Warner (1997) and Parente (2001) have commented that the empirical studies of endogenous growth models are unable to explain the conditional convergence as well as income disparity between advanced and developing countries. Furthermore, Krugman (2013) stated that the endogenous growth theory is vulnerable in the sense of making too many assumptions about the interactions of the unmeasurable variables. Thus, the theory is difficult to prove by the empirical literature.

2.3 Theoretical Review: Schumpeter's Theory of Innovation

In the early stage of the economics domain, the research on innovation emphasised the invention as well as the research and development of technology at the macro- and micro-level rather than the diffusion of innovations, which was focused on by the sociology researchers. From the late 1980s till now, the scope of study in innovation economics has been extended to entrepreneurship, the determinants of developing innovation, as well as the effect of innovation on economic growth, welfare and market competition (Sundbo, 2015).

In the 1890s, Gabriel Tarde was the pioneer who presented the idea of innovation. His idea was then been extended by Joseph Schumpeter, who was named the father of innovation theory in the field of economics (Sundbo, 2015). Schumpeter (1934) perceived that innovation is the outcome of R&D, and it is an essential element for a firm to increase the efficiency of factors of production and improve the production processes. As a result, a firm can retain its competitive advantage in the market. Collectively, innovation can achieve the long run industrial growth as well as economic growth.

The theory of innovation introduced by Schumpeter has been documented in two parts, Schumpeter I and Schumpeter II. In the early theory of Schumpeter I, it is said that the alteration of the market system and economic growth are driven by the entrepreneurs (Schumpeter, 1934, 1939). Schumpeter described an entrepreneur as an innovator who actively manages his business activities in production and marketing based on a new idea or invention, even if the idea or invention is not originated by the entrepreneur, that enables him to dominate and control the market.

In the later theory of Schumpeter II, Schumpeter (1939) advocated that the changes in the market and production system are related to the market structures instead of the entrepreneurial activities. This is because the higher the market share owned by the firm, the higher its influence on affecting the decisions of the small firms on their market and production activities. For instance, small firms follow the price range set by the large firms on their products. To retain and secure market power in the market, the firms which have higher market share are motivated to make investment decisions on innovation to keep their competitiveness advantage no matter whether the innovation is technological or non-technological. These innovations, especially technological ones, grant a firm a temporary monopoly position in the market, which enables it to enjoy supernormal profit even though this monopoly power is only held for a short term. The long-term supernormal profit is hard to sustain in the market because the innovation of a firm could be imitated or competed away by rivals in a short period.

The theory of Schumpeter II implies that the more monopolistic firms have a higher tendency in investing R&D activities because they own a solid financial background and limited rivalry. This theory is supported by Gilbert and Newbery (1982), who mentioned that the dominant firms in the market are likely to carry out innovation to keep their monopolistic position. However, research done by Arrow (1972) argued that the firms in competitive markets tend to innovate because the monopolist has no competition in the market and, thus, no external pressure to force it to innovate. Meanwhile, Loury (1979) and Dasgupta and Stiglitz (1980) have discovered that competitive firms are likely to commit excess investment in research and development.

A new model has been developed by Aghion et al. (2001) and Aghion and Griffith et al. (2006) in response to the Schumpeter-Arrow debate. They have assumed that there are two types of firms in a competitive market:

Type 1: Firms which have a small technological gap with their competing firms and try to innovate to escape from the competition.

Type 2: Firms which are located far away from the technology frontier and have a low incentive to carry out innovation.

They found that there is an inverted U-shaped relationship between competition and innovation activity. This relationship indicates that when the competition level is lower, the intense competition increases the reward of innovation, and vice versa.

Besides the theory of Schumpeter I and II, Schumpeter has also introduced the idea of "creative destruction", which is an extension of the work of Karl Marx (Schumpeter, 1942). Schumpeter described the innovations initiated by entrepreneurs as the disruptive forces which are needed to achieve sustainable economic growth. This is because Schumpeter believed that the swarms of innovations perpetually revolutionised the economic structure by continuously creating the new and destroying the old system. Besides, he is also concerned about the influence of innovation on democracy, i.e., if the innovation leads to capitalism or socialism.

By looking at the evolution of innovation economics, contemporary theory has shifted the focus from the R&D process to the diffusion of knowledge, especially the scientific knowledge that forms the foundation of technological innovation (Nonaka & Takeuchi, 1995). The research on knowledge diffusion emphasises the learning and utilisation of formal and informal knowledge by a firm to create innovation by a firm. Besides, researchers suggested that the firms acquire the research results externally for their innovations rather than invest the R&D internally as the knowledge bases (e.g., the universities, research centres, laboratories, etc.) are getting broadened in this era that is full of information.

At a later date, the theory of innovation evolved by diverting the focus to the concept of absorptive capacity. The evolutionary innovation theory has now speculated the ability of a firm to absorb external knowledge and internalise it in the innovation process. The theory of absorptive capacity is then emerged (Cohen & Levinthal, 1990). The level of absorptive capacity of a firm is highly correlated with the education level of the labour as well as the development of human capital because the labourers are required to learn the knowledge transferred externally through consultancy results, FDI spillover, digital spillover and other channels, and transform it into the new product or process.

2.4 Conceptual Framework: Extended CDM Model

Empirically, the early studies on the relationship between innovation and productivity were mainly macroeconomic analyses due to the availability of national and sectoral data as well as the measurement issue of the variables (Hall, 2011). The pioneer researchers in this area have faced the challenges of measuring the technical change on productivity as it is hard to quantify and measure.

In the early years, Solow (1957) treated technological innovation as residual in the estimation of long-run economic growth, i.e., the technological change is treated exogenously and estimated in the augmented labour productivity function. As more and more research on innovation has been carried out to identify its importance to productivity and economic growth, technological innovation has evolved to become an endogenous variable, together with the inclusion of physical and human capital in the estimation model (Romer, 1986).

Eventually, some researchers have used R&D as the proxy of technological progress to overcome the limitation on measurement as R&D is easily calculated quantitatively, yet this remedy has been questioned many times (Griliches, 1978, 1998). Grilinches (1979) used the knowledge production function to examine the determinants of innovation and applied the augmented output production function to study the effect of innovation on productivity.

Nevertheless, the existence and availability of micro-level data have brought a new wave of studying the relationship between innovation and productivity because innovation surveys can quantify innovation activities. Besides, the innovation survey covered a wide range of firm-level information, which was essential in determining the firms' innovation activities.

Crépon et al. (1998) first utilised the data in the Innovation Survey and developed a model known as the CDM model to examine the relationships between innovation and productivity by including a broader set of variables at the firm level rather than just incorporating R&D expenditures in the production function. Their study found that higher innovation output leads to firm productivity positively in France.

After that, the CDM model became popular among researchers because it provides more insights into the interaction between a firm's innovation and productivity as well as unbiased estimates of the elasticities. The search for the elasticity of the firm productivity to the innovation input and output has become the central research question in the field of the R&D-innovation-productivity relationship (Brostrom & Karlsson, 2017).

The CDM model describes the process from the propensity of a firm to carry out innovation until the effect of innovation on productivity. The model is generally estimated in a recursive system, which consists of three blocks of equations, as illustrated in Figure 2.1. (Crépon et al.,1998). The first stage is the innovation input function, used to study the propensity of a firm to invest in R&D expenditure as well as the level of R&D expenditure. The second stage is the innovation output equation, used to examine the effect of investment in innovation on the realization of innovation activity. Lastly, the productivity function is used to investigate the relationship between innovation output and productivity.

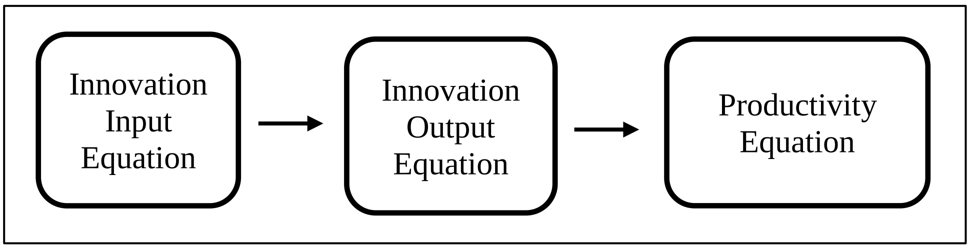


Figure 2.1: General structure of CDM model (Crépon et al., 1998)

The CDM has been revised and continuously extended by the researchers in corresponding to their research objectives and interests. At the early stage, Griffith *et al*. (2006) and Lee (2011) modified the first equation in the CDM model, the innovation input function, by incorporating the firm's size and the demand-pull factor. Meanwhile, some researchers extended the CDM model by incorporating environmental elements into innovation activities and productivity, for example, Garcia-Pozo (2018), Yuan and Xiang (2018), Marin (2014) and Horbach (2008).

Due to the generalisation of computers and the internet in recent decades, information and communication technology (ICT) has become another favourite element of CDM researchers' focus. Hall et al. (2013) pioneered the ICT investment and R&D in the modified CDM model, followed by Skorupinska et al. (2014), who considered the ICT infrastructure and management quality. Lately, Kijek and Kijek (2018) and Zhu et al. (2021) investigated the impact of ICT investment on innovation and productivity in Polish and Chinese firms, respectively. These authors have validated the importance of incorporating ICT expenditure in the CDM model.

Nonetheless, the recent study conducted by Huawei Technologies Co. Ltd and Oxford Economics Ltd has expanded the ICT investment to digital investment due to the intensive use of digital technologies in the current era (Xu & Cooper, 2017). Xu and Cooper (2017) also mentioned that studying digital investment itself is not sufficient to know the total impact of digital investment because digital applications nowadays are spread to a broader spectrum and speed up the information flow. Thus, the indirect impact, i.e. the digital spillover effects, should be incorporated into the study of digitalisation.

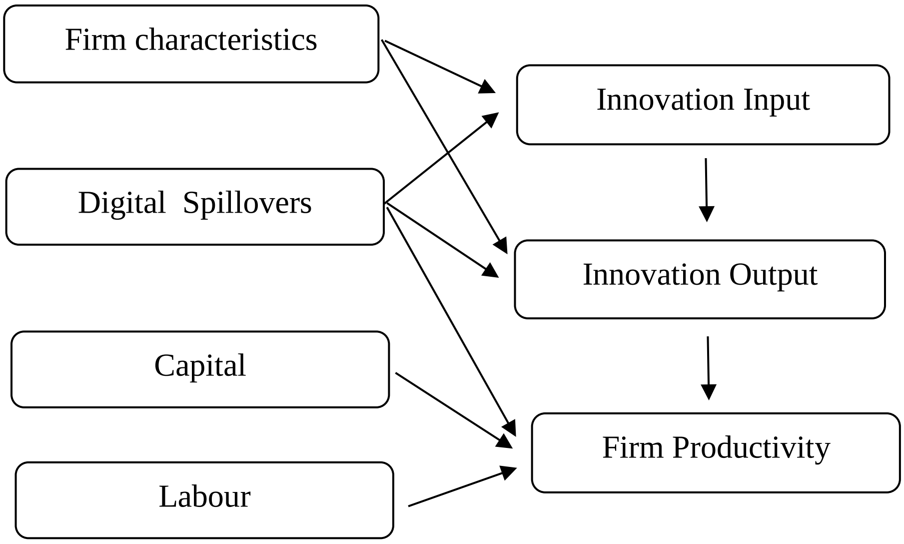
The digital spillover effect is defined as the externalities of digitalisation expenditure, i.e., the creation of external knowledge that is brought by digitalisation (Xu & Cooper, 2017). When a firm invests in digital spending, the application of digitalisation could create a certain level of external knowledge that could be enjoyed by the firm itself, its suppliers, customers and other stakeholders. The internal digital spillover effect means the information flow within a firm. Meanwhile, the external digital spillover effects happen when there is external knowledge created from the digital platform used by the competitor (horizontal spillover), supplier (backward spillover) and consumer (forward spillover).

Paunov and Rollo (2016) also supported that the application of digital technologies has broken the limitation of the conventional knowledge spillover, which is the geographical proximity because the knowledge transferred via digital platforms is not constrained by any geographical distance. Thus, digital spillover is more remarkable in transferring knowledge than other types of knowledge spillover channels. In addition, the OECD (2018) has supported the role of information flow in promoting innovation activities and firm productivity. As a result, researchers should consider the information flow via digital platforms to understand the total impact of digitalisation.

In this study, the CDM model is extended with digital spillover effects, as proposed by Xu and Cooper (2017), to capture the full impact of digitalisation on innovation activities and productivity. To the best knowledge of the author, Xu and Cooper (2017) were the first researchers to use the term “digital spillover” in their study and the past literature on “digital spillover” is limited. As Xu and Cooper (2017) used ICT capital stock as the proxy of digital assets to calculate the digital spillover effects, this section considers “digital expenditure”, “ICT expenditure”, “digital spillover”, and “ICT spillover” when carrying out the literature review.

Aside from the digital spillover effects, this study also aims to investigate the effect of the interaction between absorptive capacity and digital spillover effects on innovation and firm productivity. Thus, the digital spillover effects will be replaced by the interaction term between digital spillover effects and absorptive capacity in both innovation output and production function. Then, these equations are re-estimated to study the differences in the inclusion of interaction terms. The conceptual framework of the extended CDM model is illustrated below.

Conceptual Framework: Extended CDM Model



Recursive system:

1st stage: Estimation of R&D intensity:
R&D intensity = *f* (firm characteristic, digital spillover effects*)

2nd stage: Estimation of Innovation Output:
Innovation output = *f* (estimated R&D intensity, firm characteristic, digital spillover effects*)

3rd stage: Estimation of Productivity:
Productivity = *f* (estimated innovation output, capital, labour, digital spillover effects*)

Remark:
The digital spillover effects will be replaced by the interaction term between digital spillover effects and absorptive capacity under the extended equations.

Figure 2.2: Conceptual Framework of Study (Developed by the author)

2.5 Innovation Input Function

The innovation input function measures two aspects: (i) the intention that firms invest in innovation input and (ii) the intensity of the innovation input investment. Based on the conceptual framework, the dependent variable of innovation input is investment injected into the innovation activities by a firm meanwhile the independent variables include firm characteristics and digital spillover effects.

2.5.1 Relationship between Firm Characteristics and Innovation Input

The innovation input refers to the resources and capabilities owned by a company in conducting innovation activities (Mohnen & Hall, 2013). The decision to inject innovation investment is a crucial concern to a firm because it is a double-edged knife (Griliches, 1979). If the innovation investment can be transformed into innovation output, the firm can improve its productivity by using this competitive advantage. Otherwise, the firm has to bear a substantial cost or even a negative return if the project is failed. In short, a firm would choose to invest in innovation if the return gained from the innovation investment is higher than the costs incurred.

Crépon et al. (1998) mentioned that the firm characteristics determine a firm's intention to invest in innovation activities and the amount of the investment. The heterogeneity of firm characteristics forms the differences among the firms, which affects the firms' behaviours differently. Even though various proxies can be chosen to fulfil distinguished research objectives, some variables have been frequently used by the researchers, as revealed by Lööf et al. (2017) and Teplykh (2016) who did the meta-analyses on the CDM model. These variables are related to the possession of firm resources and Schumpeter's Theory of Innovation (Schumpeter, 1934, 1939), which include firm size, industry cluster, market structure etc.

Firm size is a principal variable examined by researchers in the work-study of innovation. The early adopters of the CDM model have argued that the firm size has a high correlation with the R&D expenditure injected by the firm, such as Crépon et al. (1998) and Cohen and Levin (1989). The same conclusion has been reached by recent researchers, such as Giotopoulos et al. (2023), Ouyang et al. (2022), and Ma et al. (2022). These researchers argued that large firms are more likely to invest in innovation activities because they have strong financial backgrounds which support them in absorbing the costs of innovation activities, including the fixed costs as well as the sunk cost which is irrecoverable. In addition, large firms have more access to financing channels, which grants them the ability to recruit the resources for innovation.

Nevertheless, there were studies argued that that small and medium firms tend to have higher R&D intensity because they want to increase their productivity through innovation. Baumann and Kritikos (2016) validated that the micro and small firms in Germany which successfully translate the R&D investment into innovation output can increase their productivity as those large firms. Similarly, a negative relationship between firm size and innovation input was found in Brazilian manufacturing firms (Viglioni & Calegario, 2021) and Nigerian firms (Edeh & Acedo, 2021). On the other hand, both Zhang and Islam (2022) and Zhu et al. (2021) discovered that the firm size affects only the firm's intention in investing R&D, but has no impact on the R&D intensity. In contrast, Audretsch and Belitski (2020) discovered that the R&D intensity is not affected by the firm size.

On the other hand, an industry group is found to affect the innovation input significantly. OECD has categorized manufacturing industries, based on the intensity of R&D investment, into low-, medium- and high technological groups (Kirner et al., 2009). The high technological manufacturing industries tend to realise the innovation output because these are the industries which require the latest technical knowledge, and thus, heavy R&D investment is needed. In addition, large firms in the high-technological industries tend to turn product innovation into their business success and firm sustainability while low and medium-technological firms prefer to acquire existing technologies but not opts for innovation (Audretsch & Belitski, 2020; Mariev et al.,2022).

Meanwhile, some researchers have categorized the manufacturing industries into high-and low-productive industries where the high-productive industries are usually abundant with resources and talents which allow them to carry out innovation activities (Ong et al.,2019; Na & Kang, 2019). Ong et al. (2019) and Na and Kang (2019) explained that highly productive manufacturing industries are usually the industries that require the latest technical knowledge and thus innovation input is needed to keep up with the latest technology. Moreover, Yin and Sheng (2019) discovered that the intensity of the innovation input depends on the resource abundance of the industry cluster, as shown by the consistent increase in innovation input in the technology-intensive and capital-intensity industries. In general, the high-technological, high-productive and capital-intensive industries tend to have higher R&D intensity due to the industry requirement.

By referring to the Theory of Innovation, Schumpeter (1939) has advocated that a firm which has a higher market share is motivated to make investment decisions on innovation to keep its competitiveness advantage no matter whether the innovation is technological or non-technological to secure its market position and market power. This argument has then been supported by Aghion et al. (2018), Crepon et al.(1998) and Montégu et al. (2022), who proposed a positive association between market share and R&D intensity. In Malaysia, Shafi'I and Ismail (2015) have confirmed that the market share exerts a significant positive effect on the propensity of R&D expenditure as well as the intensity of R&D invested by the firm.

A similar reason is applied to the exporter. The exporter tends to carry out innovation activities to secure its competitive edge on the international stage but the level of R&D intensity depends on the type of innovation. Jitsutthiphakorn (2021) and Fedyunina and Radosevic (2022) found empirical evidence that the export-intensive firms tend to invest higher R&D expenditure in the context of ASEAN and Central and Eastern Europe countries respectively. Nonetheless, the R&D intensity is higher for an exporter that focuses on product innovations, rather than the process and organisational innovations (Fedyunina & Radosevic, 2022).

There is another perspective that the investment in R&D expenditure depends on the destination of the exporting activities. Younas and ul-Husnain (2022) mentioned that the Pakistani firms which export to the US to European countries tend to invest in innovation, as compared to the exporters to South Asian countries. This phenomenon happened because there are higher requirements imposed by the developed countries, and thus R&D expenditure is needed to enhance the knowledge and skills possessed by the labour. This view is supported by Tuncel and Oktay (2022) who perceived that firms which learn by exporting activities tend to increase its innovation investment.

In a nutshell, firm characteristics play an essential role in determining the intensity of innovation input, i.e., R&D expenditure or innovation investment, of a firm. The firm’s decision to inject innovation investment is affected by the marginal return gained by a firm. In other words, if the marginal benefit of innovation investment is higher than the marginal cost, there is a high possibility that a firm invests in innovation. The firm characteristics are heterogeneous among firms in terms of the firm size, role as an exporter, market share and firm industry. Among these variables, mixed results on the relationship with innovation input have been revealed by past researchers.

2.5.2 Relationship between Digital Spillover Effects and Innovation Input

The digital spillover effects are the externalities created via the application of digital technologies. Xu and Cooper (2017) and Marsh et al. (2017) refer digital spillover effect as the external knowledge created through the information flow on the digital channels. OECD (2018) and Silva (2021) has stressed the importance of digitalisation on innovation input because digitalisation promotes the information flow inside and outside the firm which is vital in affecting the firm's decision to carry out innovation activities. Xu and Cooper (2017) have categorised digital spillover effects into internal and external spillovers.

The internal digital spillover effect is proxy by digital expenditure or ICT expenditure per worker because the digital expenditure spent by a firm stimulates the information flow within a firm (Xu & Cooper, 2017). The internal digital spillover effect is expected to have a positive impact on the decision of a firm in investing R&D expenditure and the level of R&D expenditure because the digital applications used in a company help in sharing information among employees, especially for firms that have subsidiaries in different locations and countries, which in turn encourage discussion and brainstorming that could lead to innovation activities (Marsh et al., 2017; Mun & Nadiri, 2002; Xu & Cooper, 2017).

For the external digital spillover effects, there is an underlying presumption that vertical digital spillovers have a positive influence on the investment in innovation activity because they encourage the imitation and invention of technological innovation carried out by the firm when the firm knows its suppliers and customers better via digital channels (Karhade & Dong, 2021; Paunov & Rollo; 2016). Nonetheless, Gong and Wang (2022) discovered that firms tend to increase the R&D propensity and intensity when the firms have stronger ties with clients, but the opposite for the suppliers. Meanwhile, the horizontal digital spillover is relatively weak in promoting innovation input because there is a tendency for the firm competitor to keep its business secret to maintain its market share (Paunov & Rollo, 2016).

Empirically, Karhade and Dong (2021) explained that the external digital spillover effects can affect innovation activities in three dimensions. Firstly, the firm can better know their customers' behaviour and needs via various digital sources, such as big data, the internet and social media, to produce desirable product innovation (Karhade & Dong, 2021; Saldanha et al., 2017). Next, the firm can understand the timely market demand and supply conditions to respond to the demand for innovation (Gómez et al., 2017). Lastly, ICT helps the firm to launch and promote innovative products at the right time and location (Tambe et al., 2012). In addition, Yang and Wang (2022) also mentioned that the information flow on R&D elements and technology licensing transfer via the regional ICT spread helps in knowledge diffusion and forming an innovation system.

In short, the empirical studies on the relationship between digital spillover effects and innovation input are relatively limited, as compared to the studies focused on the effect of digital spillover effects on innovation output. Theoretically, the external knowledge created by the application of digital technologies positively affected the firm's intention in investing innovation, as well as the level of innovation investment, because the information flow via the digital channels helps the firm enhance internal communication within a firm, understanding the customers and market demand better, facilitating the innovation activities with the firm operation.

2.6 Innovation Output Function

In the second stage of the CDM model, the innovation output function is investigated. Innovation output is the outcome of innovation investment

(Crépon et al.,1998) According to the conceptual framework, the innovation output is influenced by the innovation input, firm characteristics and digital spillover effects.

2.6.1 Relationship between Innovation Input and Innovation Output

The CDM model allows the estimation of the direct effect of innovation input on innovation output (Crépon et al., 1998). Innovation input is the resources and monetary funding required for initiating innovation activities (OECD, 2018). Generally, past studies found a positive relationship between the innovation input and innovation output. This positive relationship was not only discovered in developed countries (Audretsch & Belitski, 2020; García-Pozo et al.,2018; Giotopoulos et al.,2023) but also the developing countries (Khachoo et al.,2018; Younas & ul-Husnain, 2022; Zhu et al., 2021). In the context of Malaysia, Shafi'i and Ismail (2015) and Lee (2009) have also validated this positive relationship within the manufacturing firms in Malaysia.

The influential resources for innovation activities include personnel with high technical skills and educational qualifications, private investment in fixed capital, R&D expenditure and others (OECD, 2018). Among these variables, R&D expenditure is the most popular proxy under the CDM model, see Crespi & Zuniga, 2012; Jitsutthiphakorn,2021, Zhu et al., 2021). The significance of the R&D expenditure on the innovation output is different, and it is highly dependent on the type of innovation output. Furthermore, Yuan and Xiang (2018) revealed that the impact of the R&D expenditure shows delay and sequential progression, meaning the innovation input can have a long-term effect on the innovation output.

The R&D expenditure is found to be relatively important when a firm needs to realise a product innovation, rather than a process innovation because the creation of a new product requires more funding (Audretsch & Belitski 2020; Edeh & Acedo, 2021; Zhu et al., 2021). This statement is supported by Busom and Vélez-Ospina (2017) and Edeh and Acedo (2021) who found that the process innovation is not significantly affected by the R&D investment, but the enhancement in soft skills and managerial techniques of a firm. Meanwhile, Khalifa (2023) and Zhu et al. (2021) discovered that ICT investment is more significant in carrying out process and organisational innovation while R&D investment has a stronger effect on product innovation.

Nonetheless, the idea that R&D expenditure is only significant for product innovation is opposed by García-Pozo et al. (2018) and Acosta et al. (2015). They gave an example that even if the organisational innovation is not technological and does not require R&D expenditure, the organisational innovation could be a by-product of R&D investment as this type of investment not only helps in technological advancements but also induces managerial innovations. Similarly, Edeh and Acedo (2021) also revealed that R&D

expenditure spent on product innovation might be split to marketing innovation in Nigerian firms. Nonetheless, Taveira et al. (2019) mentioned that investment in technological workers is more important in promoting product innovation, rather than the investment in internal and external R&D activities.

In general, innovation input has a positive effect on innovation output because resources and funding are vital to acquire the necessities for innovation activities. However, it is found that innovation input is more significant to product innovation than the process, organisational and marketing innovation This is because the non-product innovations require more on the invisible attributes, such as soft skills and managerial techniques, rather than the financial sources.

2.6.2 Relationship between Firm Characteristics and Innovation Output

Similar to the innovation input, firm characteristics are deemed to have a relationship with the realization of innovation output (Crépon et al., 1998). Firm size remains the significant factor in realizing innovation output because firm size affects access to funding for innovation projects. Conte and Vivaralli (2014) discovered that large firms in Italian manufacturing companies find it relatively easy to fund their innovation activities and secure technology acquisition, which makes them more likely to succeed in product innovation. The same result was obtained by Giotopoulos et al. (2023) in Greek manufacturing firms and Zhu et al. (2021) in Chinese manufacturing firms. For the early studies, Crespi et al. (2010) and Benavente (2006) also found that firm size imposes influential power on innovation output in Latin American countries.

Meanwhile, in the context of Malaysia, the positive relationship between firm size and innovation output is also validated by Ong et al. (2019), Ooi et al. (2018), and Shafi'I and Ismail (2015). Ong et al. (2019) stated that innovation of manufacturing firms is positively caused by firm size, foreign ownership and involvement in publicly funded programs while Ooi et al. (2018) confirmed that the firm size and absorptive capacity of cloud computing technology positively affect the innovation of Malaysian manufacturing firms.

Aside from firm size, the type of industry that a firm belongs to also affects the tendency of innovation performance. Ong et al. (2019) and Shafi'I and Ismail (2015) explained that the Malaysian manufacturing firms attached to the high-technological industries are likely to be involved in innovation because these industries are gifted with abundant resources and talents. Correspondingly, Crespi et al. (2010) and Mariev et al.(2022) said that the large firms which conducted innovation activities are primarily located in the high-technological industries and the return on R&D investment on these firms is the largest.

Likewise, Na and Kang (2019) revealed that positive result between product innovation and sales growth happens only in high-tech manufacturing industries, whereas process innovation brings a negative impact to the low-tech and medium-tech industries in three Southeast Asian countries. Similarly, Santamaría et al. (2009) discovered that low-tech and medium-tech manufacturing industries tend not to invest in innovation projects, but they usually fully utilise the knowledge diffused from high-tech industries or adapt their innovation. In short, the high-technological industries possess more resources to make innovation happen and have more buffer to absorb the failure of innovation activities.

In terms of market share, the market concentration of an industry has a different influence on the innovation activities that are carried out by a firm. Schumpeter (1939) argued that a monopolist is likely to innovate to retain its market share and market power. This statement is supported by Aghion et al. (2018) who said that productive firms tend to innovate to deal with the tough competition to maintain their market share. Ugur (2024) revealed that market power and innovation exhibit a mutually reinforcing positive relationship, i.e. bidirectional positive relationships, among OECD countries. Likewise, Ong et al. (2019) and Lee (2004) also discovered that firms located in highly competitive market structures are likely to conduct innovation activities in the context of Malaysian manufacturing firms. In short, the sustainability of the market position and competitiveness drive the firms to deliver on innovation promises.

By looking at the relationship between exporting firms and innovation output, a similar reason as the innovation input is concluded. The exporter tends to spend more effort and resources to realise the innovation output to enhance and secure its market share in the international market (Aghion et al.,2018; Jitsutthiphakorn, 2021; Tuncel & Oktay, 2022). Empirically, the positive relationship between export intensity and innovation output is found by Kale and Rath (2018) and Sharma (2017) in India, Van Beveren and Vandenbussche (2010) in Belgium, and Lee (2011) and Shafi'I and Ismail (2015) in Malaysia.

Some researchers have identified the impact of the role of an exporter on the type of innovation. Fedyunina and Radosevic (2022) revealed that exporters tend to focus more on product and process innovation, as compared to organisational innovation, and these exporters are keen on patenting activities. Meanwhile, Zhu et al. (2021) stated that the exporter tends to introduce product innovation, instead of process innovation.

Nonetheless, Ong et al.(2019) found that the exporting firm in the Malaysian manufacturing sector has a negative relationship with innovation activities. They argued that the exporting manufacturing firms were demotivated to carry out innovation because strict criteria for custom clearance were imposed for the exported goods from other countries. Thus, the manufacturing firms which serve the domestic market are likely to innovate because of fewer rules on the production criteria. These studies show that exporting firm tends to transform the R&D investment into innovation output, but the transformation process can be restrained by the external environment such as the rules and regulations of international trade set by the government.

2.6.3 Relationship Between Digital Spillover Effects on Innovation Output Function

Similar to the section on innovation input, the effects of internal and external digital spillovers on the innovation output are discussed in this section. For the internal digital spillover effect, a vast literature has studied the digital-innovation nexus since the introduction of computers, but the effects are relatively mixed (Khalifa,2023; Marsh et al.,2017; Zhu et al., 2021).

The digital spending invested by a firm shows its importance in promoting innovation activities because digitalisation encourages information flow within a firm (Silva, 2021; OECD, 2018). It was found that the impact of digital investment on innovation activities could be mediated through various digitalization channels, such as cross-border e-commerce and big data analytics (Koh & Liu, 2024; Rampersad & Troshani, 2020; Saleem et al., 2021).

In addition, Kijek and Kijek (2018) have proven the moderating effect of ICT on process innovation, which in turn reflects on the improvement in labour productivity in Polish manufacturing firms. Meanwhile, Gómez et al. (2017) found that ICT investment encourages the innovation outcome on patents in Spanish manufacturing firms. There is research which found the complementary effects between R&D and ICT investment in increasing the likelihood of realizing an innovation output, for example, Khalifa (2023) and Zhu et al. (2021).

In addition, by incorporating ICT investment in the modified CDM model, Hall et al. (2013) commented that R&D and ICT are crucial to innovation and productivity, while Zhu et al. (2021) discovered that both product innovation and process innovation are affected by ICT investment positively. The early research done by Polder et al. (2009) revealed the complementarity effect between ICT and innovation in the Netherlands service sector, even though the magnitude is minimal.

From another perspective, past studies have shown that the firm needs to have compatible capabilities to turn the digital investment into the realisation of innovation, or else the digital investment has only weak significance on the innovation. Sherif et al. (2006) stated that the firm needs to go through a big scale of organisational adjustments in response to the extensive digital adoption, and these high integration costs might hinder innovation activities. Aral and Weill (2007) supported this finding by saying that organisational ICT capabilities are essential in commercialising product and service innovation in the marketplace.

In addition, the firm's innovation efficiency can be derived from the firm's absorptive capacity, i.e. the development of human capital. Audretsch and Belitski (2020) explained that the absorptive capacity is essential in utilizing the knowledge spillovers and, at the same time, determining the period needed for realizing an innovation. Sun et al. (2020) showed evidence that human capital has a high correlation with high-quality patent activities. Similarly, Lund-Vinding (2006) and Nitzsche et al. (2016) discovered that a firm's innovative performances are contributed by the higher number of employees with higher educational levels and mature management skills in human resources, as well as close external linkage with universities and research institutions. However, the recent studies done by Shi et al. (2019) in China revealed that the collaboration between universities and industry contributed negatively to the firm's innovation efficiency at the early stage, but it turns out to have positive impacts when the collaboration becomes deeper.

Likewise, Ma et al. (2019) emphasised that innovation-related training and worker participation significantly contribute to product innovation. Meanwhile, Crowley and McCann (2018) commented that the accumulation of physical capital and the development of human capital contribute substantially to product and process innovations in European countries, no matter if they are innovation-driven countries or those in the transition to this path. Similarly, Waheed (2017) also discovered that the contribution of highly educated workers is more critical to product innovation in Bangladesh as compared to process innovation.

Even though the digital expenditure spent by a firm enhances the realization of innovation investment and brings pecuniary benefit to the firm, there is a chance that the firms face uncertainty that goes against the desired outcome. This phenomenon happens when there is an occurrence of overbudget on the innovation project as well as high costs spent on the repeated failure of the experiment (Kohli & Melville, 2019; Ebersberger et al., 2012). Past studies have revealed that the high costs associated with digital investment always come from the adoption of new ICT operation systems, data management, internalisation of the previous outsourcing ICT operation, as well as the governance and coordination costs (Karhade & Dong, 2021; Williams & Karahanna, 2013; Barthélemy, 2001)

Compared to digital-innovation nexus literature, the literature focusing on the relationship between external digital spillover effects and innovation is relatively scarce. Paunov and Rollo (2016) and Conley and Udry (2010) mentioned that a firm not only benefitted from its internet investment but also from the internet investment made by the industry due to the spillover effect. This is because adopting the Internet at the industry level increases the communication between firms in the same industry. For instance, a firm can look for information about the best practices of its competitors through the Google or Firefox search engine as a reference in carrying out their product and organisational innovation (Marsh et al., 2017).

In addition, the internet and social media usage have also reduced the cost of disseminating knowledge and made the less innovative firms have higher access to new knowledge (Paunov & Rollo,2016). The process of sharing and gathering information improves the new knowledge and technology diffusion among firms and industries. Likewise, Gong and Wang (2022) found that the firms that have stronger ties with their customers, the likelihood of promoting innovation patents is high.

However, the horizontal digital spillover could cause a competition effect or crowding-out effect. Yang and Wang (2022) explained that the information flow via the ICT spillover effect makes other firms mimic innovation behaviours and create competition in the market. The competition is not limited to the competition on the innovation output but also the competition on the resources of innovation activities, such as materials, labour, technology, etc. This competition makes the original, innovative firm find it challenging to make the required innovation profits and subsequently reduce its incentives for reinvesting the innovation activities. The worst scenario of the dilemma is the crowding-out effect, in which the original innovative firm discontinues R&D activities (Spencer, 2008; Yang & Wang, 2022).

Meanwhile, Paunov and Rollo (2016) commented that the horizontal ICT spillover could be weak when the competitors intend to keep their business secret to maintain their market share. In contrast, Audretsch and Belitski (2020) mentioned that a firm tends to outsource the innovation activities or imitate the realised innovation if there is an alliance formed with the firm’s competitor.

On the other hand, past research has also confirmed the vertical digital spillover on the innovation activities, i.e. learning the external knowledge created by their suppliers and customers (Mendoza, 2024; Vo et al., 2023). A firm can learn the latest technology developed by the suppliers and apply it to its production process or products for value-added purposes (Paunov & Rollo, 2016). Empirically, when studying the multinational corporations’ (MNCs) innovation activities in the host country, Vo et al. (2023) discovered that an MNC's success in realizing innovation increases with a deeper understanding of its local suppliers and customers.

Nevertheless, Mendoza (2024) mentioned that both backward and forward digital spillover can be limited if the absorptive capacity is absent. However, Hioki and Ding (2023) opposed the findings of Mendoza (2024) and treating absorptive capacity as a neutral factor. They discovered that the firms engaged in international trade can enhance their innovation performance by leveraging knowledge from customers in less developed countries, even with low absorptive capacity. However, this positive effect is not observed when firms acquire knowledge from suppliers in developed countries, even when the firm exhibits a higher absorptive capacity.

Meanwhile, Audretsch and Belitski (2020) commented that the firms which absorb the knowledge spillover from the upstream suppliers are less likely to realise innovation because the knowledge learnt from the suppliers is readily integrated into the existing production process without any need to find the know-how. Similarly, Gong and Wang (2022) also revealed that construction firms in China are less likely to realise innovation patents when the tie between the firms and their suppliers is very strong.

In terms of the forward digital spillover effect, the firm can use ICT to know their customers better in their preferences and behaviours so that they can carry out the relevant innovation activities in response to these demands (Karhade & Dong, 2021; Paunov & Rollo,2016). For example, the firm could also apply big data analytics to study the customer's behaviours and provide relevant services and products to increase the firm sales (Karhade & Dong, 2021; Niebel et al., 2019). This forward digital spillover has given confidence to the firm in carrying out innovation activities because the major obstacle for firms to be involved in innovation is the uncertainty and unknown about future market demands (Collard-Wexler et al., 2011). Younas and ul-Husnain (2022) provided empirical studies that employing the website for client communication positively affects product innovation.

In a nutshell, the study on the relationship between digital spillover and innovation activities (both innovation input and output) is limited, and a consensus on the relationship is not achieved yet. The innovation activities are positively affected by digital spillover effects because the digital investments made by the firm's stakeholders help the firm understand the market demand better and facilitate innovation activities. However, the negative relationship is possible due to the repeated failure in the innovation experiment, which makes digital investment unrealised and other higher costs associated with the digital investment, which is hardly borne by the firm. In addition, literature tends to validate the role of vertical digital spillover in stimulating innovation activities because firms can have better ideas about their innovation activities by learning from their customers and suppliers. Nonetheless, the proof of the effect of horizontal spillover is limited because innovation is one of the business secrets that a firm needs to maintain its market position, and thus, only limited information flow happens.

2.7 Production Function

In the last stage of the CDM model, the production function is investigated. Based on the conceptual framework, the production function follows the form of the Cobb-Douglas function. The firm productivity is affected by the accumulation of labour and capital, as well as the innovation output and digital spillover effects.

2.7.1 Relationship between Factor Inputs and Firm Productivity

The study on the impact of factor inputs (both labour and capital) on firm productivity has been a focal point of research for decades. Various studies have been examining this complex interaction from different dimensions and different levels. This section focuses on reviewing the literature that examines the relationship between factor inputs and productivity at the firm level as this research employs the CDM model.

The economic growth theories explain that the factor inputs are able to increase the level of output directly as well as boost the rate of productivity indirectly via innovation and diffusion of new technologies (Solow, 1956; Romer, 1986). Empirically, both labour and capital are found to be positively affecting firm productivity in vast studies, such as Baum et al. (2016), Morris (2018), Zhu et al. (2021) etc. In the context of Malaysia, positive relationships within manufacturing firms have been found by Shafi'i and Ismail (2015) and Lee (2011).

The positive relationship revealed by the past studies is understandable because the possession of factor input directly represents the strength of a firm in realizing productivity (Kijek & Kijek, 2018). In addition, the firm productivity can be further enhanced if the firm focuses on the optimal allocation of capital and labour, as mentioned by Dai and Sun (2021). They discovered that the optimal resource allocation is not only able to realise both innovation efficiency and firm productivity among Chinese manufacturing firms, but in turn, improves the aggregate industry's productivity collectively.

Nonetheless, past studies also revealed that the significances of labour and capital are inconclusive when the firm conditions are varied, such as the difference in the firm ownership, firm size, firm age etc. For instance, Zhu et al. (2021) revealed that capital intensity is more important in boosting the productivity of state-owned enterprises and large firms in China, but Howell (2020) discovered that large private-owned firms benefited more from capital intensity in enhancing firm productivity.

The insignificance of the labour and capital on the firm productivity could be caused by the abundance of the resources within the industry that the firm belongs to because the little variation in the factor input is unable to reflect the changes in firm productivity. For example, Baum et al. (2016) explained that the significance of human capital could be reduced or be insignificant if the firms are located in an industry that requires talent pools because the addition of human capital has a weak impact on changing the firm productivity. Likewise, Carvalho and Avellar (2017) commented that physical capital investment is more important in driving the productivity of low and medium-technological firms instead.

From another perspective, some researchers have viewed labour and capital as the proxy of absorptive capacity, which stimulates productivity indirectly via innovation and technology diffusion. Ramírez et al. (2020) and Sweet and Eterovic (2019) revealed that labour intensity in R&D activities encourages patent issuance, which in turn boosts the firm productivity. Similarly, Khachoo et al. (2018) mentioned that Indian manufacturing firms that possess better technological resources benefit more from the FDI, which helps in creating patents and increasing firm productivity. The same conclusion has been reached by Morris (2018) who studied the cross-country panel dataset that consists of a total of 40,577 firms.

In short, labour and capital are generally found to have a positive effect on the firm productivity at firm-level study. The factor inputs can enhance the firm productivity in two directions: i) direct effect through the increase in scale of resources, and ii) indirect effect via innovation and technology diffusion. Under the indirect effect, the factor inputs are viewed as the proxy of absorptive capacity. Nonetheless, the significance of these two factor inputs on the firm productivity might change due to the firm heterogeneity and the quantity of the resources flown to the industry that the firm belongs to.

2.7.2 Relationship between Innovation Output and Firm Productivity

The empirical evidence has shown that the level of innovation activities in the world is highly uneven across countries or economic blocs, at the same time, there is growing literature showing geographical productivity differences (Crowley & McCann, 2018). Cirera and Muzi (2016) pointed out that the innovation activities in developing countries tend to be more incremental and less radical, i.e. improving or enhancing the innovation or technology transferred from developed countries instead of creating something brand new. Even within a country, Crespi and Zuniga (2012) found that the productivity gaps between innovative and non-innovative firms in developing countries are more significant than those in developed countries.

Past studies have shown that the effect of innovation on productivity is transmitted through a few channels (Hall, 2011, Hu et al.,2020; Zhang & Islam, 2022). Hall (2011) discovered that resources become more efficient through the implementation of innovation, which in turn creates sustainable competitive advantages for a company and thus increases the firm productivity. This idea is supported by Hu et al. (2020), who confirmed that product and process innovation has secured substantial profit for the innovative hotel businesses in Ghana. Meanwhile, Zhang and Islam (2022) stressed the importance of institutional innovation, as compared to technological innovation, in enhancing productivity in ASEAN countries.

Besides, innovation leads to the development of new industries, the shift in production structures and specialisation areas, as well as the growth in knowledge-intensive activities (Alvarez et al., 2015). These changes not only enhance the productivity of the firms and sectors but also create more job opportunities, as shown in the study done by Wadho et al. (2019) in Pakistan. Meanwhile, Mariev et al.,(2022) discovered that the positive impact of innovation on productivity is more essential among the firms in the high-technological industries. Furthermore, Santana et al. (2011) discovered that the positive effect of innovation on productivity is more intensive in the industries which are active in international trading in Brazil.

Vast studies have found positive relationships between innovation and productivity in different regions. For instance, Asian countries (Aw et al., 2011; Dai & Sun, 2021; Hegde & Shapira, 2007; Khachoo et al., 2018), Latin American countries (Alvarez & Crespi, 2015; Crespi & Zuniga, 2012; Grazzi et al., 2016; Ramírez et al.,2020) and Caribbean countries (Crespi et al., 2017). In addition, the degree of the positive impact would change due to different situations. For example, Giotopoulos et al. (2023) found that the positive relationship is constrained only to large firms in Greek manufacturing firms when there is an external shock or economic crisis. Meanwhile, Fu et al. (2018) found that formal firms do not exhibit significant innovative behaviours than informal firms, but the impacts of innovation on the productivity of formal firms are relatively significant.

Moreover, Morris (2018) also discovered that innovation output and productivity are changing simultaneously and affecting each other. In the case of Canada and the United States, Ranasinghe (2017) revealed that innovation positively affects productivity, and the differences in the innovation level in these two countries have led to productivity differences between them. Shafi'i and Ismail (2015) who studied the manufacturing sector in Malaysia also confirmed that innovation has a positive relationship with productivity.

Generally, innovation increases the productivity of the firm as the innovation increases the efficiency of the factors of production and thus more production is produced. The positive effect of innovation output on productivity is more significant in formal firms and sectors that are actively involved in international trade as shown by past research because these firms eagerly improve their skills and technology to maintain their competitiveness in the local and international markets.

On the other hand, some researchers did not study innovation per se but studied different types of innovations and their effects on productivity. Griffith et al. (2006) and Hall et al. (2009) studied innovation activities by categorising them into product innovation and process innovation. The product innovation enables the firm to expand the existing production range and diversify the production risk. Moreover, the increased production capacity gives the opportunity to the firm to enjoy economies of scale, which reduces the cost of production. Furthermore, product innovation also attracts more customers to purchase the products of the firm (Griffith et al., 2006).

Meanwhile, process innovation enhances the efficiency of the production factors, i.e., it reduces the cost of production because less labour and capital are needed to produce the same amount of output. Besides, process innovation increases the demand for existing products as the quality of existing goods and services is improved (Hall et al., 2009). The association of increased sales revenue and reduction in cost of production indicates an improvement in productivity. Thus, innovating firms have a larger room for growth as compared to non-innovative firms and are more likely to drive out inefficient firms (Griliches, 1998; Hall, 2011).

The impacts of product innovation and process innovation on productivity are different. By applying the CDM model, Hall et al. (2009) discovered that process and product innovation have affected the firm's productivity in the Italian manufacturing sector. However, Damijan et al. (2012) discovered that product and process innovation have a strong relationship with productivity levels but not productivity growth. On the other hand, Goedhuys and Veugelers (2012) mentioned that product innovation tends to influence the sales growth of Brazilian manufacturing firms, but the combined impact of process and product innovation is also statistically significant. Moreover, Crespi et al. (2017) discovered that the product innovation effect on firm productivity is two times higher as compared to the process innovation among manufacturing firms in Latin America.

Nonetheless, the study on Ireland conducted by Roper et al. (2008) showed that product and process innovations have a negative effect on productivity. They explained that this negative effect might be caused by the natural product life cycle disruptions, i.e. the introduction of new products has diversified the existing resource allocation, which in turn disrupts the product process and decreases productivity. Likewise, Mohnen and Hall (2013) stated that the time lags due to learning have caused this adverse effect.

From another perspective, some researchers only discovered that either type of innovation is significant. Past studies have found that process innovation is relatively significant in affecting productivity as compared to product innovation (Jitsutthiphakorn, 2021; Cefis et al., 2020; Waheed, 2017). Jitsutthiphakorn (2021) has reached the same conclusion in the context of six ASEAN countries. Likewise, Cefis et al. (2020) argued that the risk of carrying out process innovation is relatively lower than product innovation, especially during the period of economic crisis. Meanwhile, Waheed (2017) commented that product innovation takes a longer time for people to accept but the cost reduction due to the process innovation reflects rapidly on productivity enhancement.

Likewise, Mohnen and Hall (2013) argued that the difference in the impact of product and process was caused by the market share gained by the firm and the demand curve faced by the company. If the company is facing an inelastic demand, the revenue productivity decreases even if the improved efficiency has lowered the price because the quantity demanded is not increased at the higher percentage change. Meanwhile, Hall (2011) indicated that the impact of process innovation has higher variability as compared to product innovation. He also mentioned that the variation in the results might be caused by the measurement error in the innovation variables that were captured via the questionnaires or surveys.

Empirically, in the context of European countries, the positive impact of process innovation on the productivity and survival of Italian manufacturing firms during the period of economic crisis has been found by Cefis et al. (2020). Besides, Kijek and Kijek (2018) realised that process innovation can moderate the effect of information and communication technology in increasing productivity in the Polish manufacturing sector. Moreover, Griffith *et al*. (2006), Parisi et al. (2006), and Chudnovsky et al. (2006) discovered that the relationship between process innovation and productivity is significant in France, Italy and Argentina respectively. For other economic regions, Vakhitova and Pavlenko (2010) and Wahed (2017) found similar results in Ukrainian and Bangladeshi manufacturing firms respectively.

However, the contradicting result has been revealed by Mairesse and Robin (2009), who stated that process innovation has no relationship but product innovation has a significant effect on labour productivity. A similar result has been reached by Baumann and Kritikos (2016) and Berger (2010) who studied the labour productivity in German and Thai manufacturing firms respectively. Besides, Griffith *et al*. (2006) discovered that the relationship between product innovation and productivity is positive in France, Spain and the UK. Moreover, Benavente (2006) found that process innovation and productivity have no relationship in Chile and the same results were reached by Chudnovsky et al. (2006) and Raffo et al. (2008) in the study of Argentina. Furthermore, past studies showed that process innovation has an insignificant effect if investment intensity is used as the proxy for physical capital (Haet al. al, 2009).

In short, past researchers also studied the effect of different types of innovation on productivity aside from looking at the effect of innovation per se on productivity. The studies concluded that the impact of process innovation is positive and more significant in affecting productivity as compared to product innovation because improvement or enhancement in the production process takes a relatively shorter time to implement and the relevant cost is relatively lower. In short, the risk of process innovation is lower than product innovation.

2.7.3 Relationship between Digital Spillover Effects and Firm Productivity

The earliest discussion on the association between digital assets and productivity was made on the “Solow Paradox”, which concluded that the impact of ICT in driving productivity growth at the national level is minimal (Solow, 1987). Correspondingly, the early ICT literature showed insignificant or weak associations between ICT and firm productivity, for instance, Wilson (1995), Margetts and Willcocks (1993) and Roach (1987). In the recent literature, a similar observation was also detected by Zhu et al. (2021), who pointed out that ICT investment directly impacts innovation but not productivity. Paunov and Rollo (2016) explained that the Internet cannot boost productivity directly once it is invested because it takes time to adjust the organisational resources to utilise the benefit brought by the Internet. Meanwhile, Han et al. (2017) explained that there is a dynamic U-shaped relationship between digital assets and productivity, i.e., going down first and then going up later. This result responds to Engelbrecht and Xayavong (2006), who mentioned that the different impact of ICT on productivity depends on the time period.

Nonetheless, recent literature also opposed the “Solow Paradox” and proved the positive relationship between digital assets and productivity, i.e. proven the significance of internal digital spillover in boosting productivity. Khalifa (2023) and Kretschmer (2012) have discovered that ICT investment can enhance productivity indirectly via innovation activities or by linking the new technology with R&D and absorptive capacity. Meanwhile, Lee et al. (2020)

found that ICT helps the ageing labourers in Japan and Korea in increasing their productivity, especially those low-educated workers. A similar result has been found by Chung (2018), who incorporated the investment-specific technological change in the ICT-productivity relationship in Korea.

Likewise, Gal et al. (2019) also confirmed the positive influence of digital adoption on the productivity of productive firms and those firms with heavily routine activities. Besides they also revealed the complementary relationship between digital assets and intangible capital. Bresnahan et al. (2002) stated that the firm productivity could be increased by applying ICT and organisational design. Similarly, Skorupinska et al. (2014) also discovered that ICT infrastructure and management quality positively correlate with labour productivity. Hall et al. (2013), Cardona et al. (2013), and Li and Wu (2008) have also reached the same conclusion in the context of Italian, US and Chinese firms, respectively.

Overall, the early literature supported the "Solow Paradox", which shows the weak relationship between digital investment and productivity. Even though some of the recent literature has also found similar results, most of them discovered that the adoption of digital investment on productivity exhibits a dynamic U-shaped. In other words, it needs time to reap the benefit of the digital investment in increasing production efficiency. Due to this reason and the extensive usage of ICT, the common trend of the latest literature shows a positive relationship between digital investment and productivity, especially when firms are equipped with sufficient high-quality labour.

In the context of Malaysia, Yap et al. (2020) revealed a positive association between ICT support and Malaysian SME firm performance. In addition, they commented that the impact on the firm performance would be amplified if the firm has relative strength in coordinating and utilising the sources compared to their competitors. A similar result has been reached by Liew et al. (2012) in Malaysian service sectors but the degree of the effect varies among industries. The ICT-intensive industry benefited the most from the ICT investment as compared to others.

On the other hand, Teoh et al. (2018) found that IT capability does not significantly affect firm performance but strategic agility. In other words, even though the firm's ability to manage and deploy IT-based resources does not affect the firm performance directly, this ability makes the firm respond fast to the rapid change in external market conditions, which in turn indirectly contributes to the firm performance, especially with the employment of experienced IT staffs. This view is supported by Liew et al. (2012), saying that that the organisational adjustments, operational changes and training of ICT proficient staff are needed to integrate the ICT components in daily operations to increase the firm productivity.

In Malaysia, there is limited studies have been carried out to study the relationship between digital expenditure, innovation and productivity. Regardless of the methodology and proxies used in the analyses, these studies done by previous researchers show the convergent result that digital assets do matter in improving the firm productivity, and the effect is larger and more significant when the firm is equipped with sufficient high-skilled and ICT-proficient labourers to operate and manage the ICT components.

By looking at the channels of external digital spillover, the prominent role of digital spillovers in boosting productivity lies in the transfer of information and knowledge. Paunov and Rollo (2016) explained that the knowledge spillover via the digital platform is significant to small and medium firms because they are the groups who face difficulty in accessing advanced technology and the latest knowledge due to the problem of funding and compatible human resources. Through digital spillover, these less advantageous firms are able to absorb external knowledge and improve their productivity. When they can catch up with the large firms, the industry productivity could be lifted as a whole subsequently. Similarly, Pilat and Criscuolo (2018) mentioned that ICT externalities help to lower the price of resources in an industry when other firms follow the ICT applications used by leading firms.

Similar to the literature on digital spillover-innovation nexus, the study on the relationship between external digital spillover effects and productivity is limited. The effect of external digital spillovers on productivity is ambiguous at the firm level in different countries. By studying the Canadian firm, Moshiri (2016) discovered that digital spillover from the digital investment made by its major trading partner, the United States, is significant. On the contrary, Moshiri and Simpson (2011) could not detect the presence of digital spillovers among Canadian firms that come from Canadian digital investment. Looking at the US firms, Tambe and Hitt (2014) confirmed the ICT spillovers transmitted from the IT worker's flows in the labour markets; meanwhile, Marsh et al. (2017) discovered positive vertical digital spillovers and negative horizontal digital spillovers. Moreover, Van Leeuwen (2003) found that digital spillovers in Dutch services companies boost labour productivity.

On the other hand, the association of these two variables at the industry level are weak due to the aggregation bias that appeared in the industry-level data (Cardona et al.,2013; Haskel & Wallis,2010). Few studies are unable to find evidence of digital spillover in developed countries, whether in the study of individual or group countries, for example, Haskel and Wallis (2010) in the UK, Stiroh (2002) in the US, Acharya (2016) in OECD countries and Inklaar et al.(2008) in European countries. However, by examining the country-level panel data, Shahnazi (2021) found a positive association between spatial ICT spillover and labour productivity in 28 OECD countries. Likewise, Kim et al. (2021) also revealed a positive digital spillover in improving the output growth of the industries that are involved in international trade.

Generally, the external knowledge created by the digital technologies that are used by the firm's stakeholders is significant to the firm productivity, especially the small and medium firms. The flow of this external knowledge enables the firm to know its stakeholders better and allows it to respond quickly to market changes. The SMEs are the less advantageous groups because they face difficulty in accessing advanced technology and the latest knowledge due to the problem of funding and compatible human resources. These limitations that constrained them to grow further can be lesser by the utilization of external digital spillover effects. In addition, firms can minimize the wastage of resources during the production process when they have a better understanding of their suppliers and customers. Nonetheless, the significant positive relationship between external knowledge spillovers and firm productivity has not been discovered by some researchers.

In response to the mixed results of the effect of digital spillover on productivity, Paunov and Rollo (2016) enlightened that the possible reason for this phenomenon lies in the knowledge network, i.e. from whom the firm gets the knowledge and information. A firm could get the knowledge from offline networks and/or online networks. For instance, a firm that collaborates with advanced countries relies more on offline networks because it would communicate with experts from advanced countries to clarify the information instead of looking for solutions from publicly available sources (online networks). As a result, the ICT spillover on an exporter is limited compared to a non-exporter. Paunov and Rollo (2016) mentioned that the firm types that are exposed relatively more to offline knowledge networks are multinational corporations (MNC), exporters and conglomerates; meanwhile, small and medium firms and informal businesses benefited from the digital spillover.

Even though the literature on the digital spillover-innovation-productivity nexus is limited, most of the literature has pointed out another critical perspective – the importance of the absorptive capacity for a firm to benefit from digital spillover effects (Marsh et al., 2017; Paunov & Rollo, 2016). Absorptive capacity is defined as the ability of a firm to recognise and assimilate new information, which subsequently transforms external ideas and commercialises them to achieve a dynamic organisational capacity (Zahra & George, 2002).

The recent study done by Li et al. (2023) has confirmed the role of high-skilled labour in assimilating novel online knowledge and facilitating innovation activities via the integration of this new information. Moreover, Todorava and Durisin (2007) advocated that compatible intellectual ability is required in the process of integrating external knowledge and converting this knowledge into new ideas and products. It implies that the level of employees' capability in internalising and managing external knowledge influences the absorptive capacity, affecting innovation activities and productivity. Thus, based on this explanation, it is believed that the degree of digital spillover effects enjoyed by the firm largely depends on its capacity to assimilate and transform the knowledge gained from the external environment. This capacity is often proxied by R&D investment and labour quality (Griffith et al., 2006; Cohen & Levinthal, 1989; Todorava & Durisin, 2007).

By studying the impact of Internet adoption on firm productivity from 117 developing countries, Paunov and Rollo (2016) have discovered that firms equipped with sufficient absorptive capacity can benefit from Internet-enabled knowledge access and use of Internet adoption. A similar conclusion has been made by Bresnahan et al. (2002) and Black and Lynch (2001). Bresnahan et al. (2002) pointed out that information technology increases the demand for skilled labour. These skilled labourers are essential input for innovative firms that innovate products and services. Likewise, Black and Lynch (2001) highlighted that both highly educated labourers and non-managerial labourers who broadly apply computer usage contribute positively to the firm productivity. In short, the firm needs to leverage the quality of human capital to fully utilize the digital spillover effects, including both internal and external.

2.8 Research Gap

There are a few puzzles that remain unsolved by the researchers in applying the CDM model. First, the complex interactions and complementariness between the technological (product and process) and non-technological (marketing and organisational) have raised the interest of researchers, yet they are tricky to observe due to the limitation of data. Second, as the firm characteristics can be proxied by many variables, thus, it is challenging to reach a consensus on a vector of firm-relevant variables that affect the innovation input and innovation output of a firm. Lastly, there is limited research that has integrated the digital spillover effects into the CDM model even though digital is found to be an essential component that stimulates innovation activities and firm productivity.

The research scope of this study focuses on the manufacturing sector in Malaysia. In the context of Malaysia, the application of the CDM model in the innovation study is relatively scarce. Other relevant past literature has studied the relationship between firm characteristics, innovation and productivity individually rather than in a recursive system like the CDM model (see Yap et al.,2020; Teoh et al.,2018; Liew et al., 2012). Moreover, there are also limited studies that have integrated digital spillover effects into the CDM model in developing countries, including Malaysia (see Zhu et al.,2021; Marsh et al., 2017; Hall et al.,2013; Polder et al.,2009). In terms of the significance of the ICT spillover effect, Marsh et al.(2017) commented that there is still less empirical evidence proving the presence of ICT spillover. Lastly, the results on the effect of innovation on productivity in Malaysia are somewhat mixed, as shown by Hegde and Shapira (2007) and Lee (2011).

As a result, this study intends to provide empirical evidence as a little contribution to fill the existing literature gaps in the study of innovation and productivity in the context of the Malaysian manufacturing sector by applying the CDM model. This study has incorporated digital spillover effects in the CDM model to determine the importance of these variables in stimulating innovation and productivity.

2.9 Concluding Remark

The research domain on innovation and productivity has evolved over time. Different data types, definitions and measurements of innovation and productivity have been applied in the analyses. The CDM model was founded by Crépon et al. (1998) to study the relationship between innovation and productivity using firm-level data. This model has been used widely in the past literature because it can show the interactions between the innovation input, innovation output and productivity sequentially and it allows the researchers to add their interested variables into the CDM model as the extension, to fulfil different research objectives.

This study aims to contribute to the literature of the CDM model by incorporating the digital spillover effects as the model extension. The digital spillover effects happened during the implementation of digital technologies. It is a type of externalities, in the form of information sharing and knowledge transfer to another firm and even to the whole industry. Although the digital spillover effects are essential in the era of Industrial Revolution 4.0. limited studies have focused on their role in affecting innovation and firm productivity.

As innovation and productivity are the central themes of this research, this chapter starts with the theoretical reviews on the Endogenous Growth Theory and Schumpeter's Theory of Innovation. After that, the explanation of the conceptual framework, i.e. the extended CDM model, is elaborated to show hypotheses that tally with the research objectives. Finally, the literature reviews on the relationships that are derived from the conceptual framework (the three stages of the CDM model) are carried out.

In short, the CDM model has experienced continuous modifications and extensions in past studies. This situation not only indicates various interests and concerns of the researchers but also implies that a united consensus on the relationships between innovation and productivity is not achieved. In addition, the results of the empirical studies on internal and external digital spillover effects are somewhat mixed. By comparing the literature on these two variables, studies on the external digital spillover effects are relatively scarce because they involve complex calculations and require the integration of different data. In contrast, the internal digital spillover is proxy by digital expenditure spent by a firm and more empirical studies have been carried out in examining the relationship between digital spending, innovation and productivity. The details of proxy selection for the variables, methodologies applied and calculation of external digital spillover effects are elaborated in the next chapter.

CHAPTER 3

METHODOLOGY

3.1 Introduction

This chapter starts with the definition of the variables used in this study. Then, the design of the conceptual CDM model is elaborated, together with the explanation of the proxy selection. The CDM model is a recursive system and different equations are treated with varying techniques of estimation. The discussion on the estimation techniques is carried out after that, followed by the explanation of data sources and data description.

3.2 Definition of Terms

This research aims to study the associations between firm characteristics, digital spillover effects, innovation activities and firm productivity in Malaysian manufacturing firms in the context of the Crépon-Duguet-Mairesse (CDM) model. As there is jargon used in this research, the definitions of these firms are described before the elaboration of the subsequent sections.

3.2.1 Definition of Firm Productivity

Firm productivity measures the efficiency of a firm in turning its resources into production. It can be measured in terms of the relation of output to input. The Cobb-Douglas function describes that the firm production is affected by the number of labourers, capital and total factor productivity (Cobb & Douglas, 1928). In other words, the firm productivity can be calculated by dividing the total production made by a firm by the amount of resources used.

In this study, firm productivity is proxied by labour productivity. It is calculated by dividing the total amount of output by the number of people employed. Labour productivity is chosen because the CDM model is applied for firm-level study and labour productivity is more appropriate for the comparison across the firms (Carvalho & Aveallar, 2017; Crépon et al.,1998)

3.2.2 Definition of Innovation Activity

The Organization for Economic Cooperation and Development (OECD) first published the international reference guideline for researchers in collecting and applying innovation-related data in 1992 (OECD, 2018). The guideline, named the Oslo Manual, has undergone several revisions to align with the latest developments in innovation, reaching its latest version in 2018.

OCED (2018) defines innovation activity as the action or event that creates the intention for a firm to implement or has implemented the innovation. The innovation activity is considered carried out by a firm when (i) the innovation has been implemented successfully, (ii) in the progress of implementation, or (iii) has been abandoned before implementation. In short, innovation activities mean all actions that encompass the beginning stage of research and development, the intermediate stage of operational activities and the final stage of innovation implementation. In this research, the innovation activities refer to the stages of innovation input and innovation output, following the context of the CDM model (Crépon et al.,1998).

OECD (2018) interprets innovation input as the resources and capabilities owned by a company in conducting innovation activities. It is normally proxy by innovation expenditure. Innovation expenditures are the costs incurred during innovation activities and they can be categorised into seven areas:

(i) Research and development (R&D),

(ii) Creative work development,

(iii) Human capital development,

(iv) Information and communication technology (ICT) development,

(v) Marketing relevant expenditures

(vi) Intellectual property relevant expenditures

(vii) Capital accumulation

On the other hand, innovation output is the outcome of innovation input. OCED (2018) mentions that innovation is the implementation of a novel or upgraded product, service, process or business operation method in a company which is beneficial to the stakeholders of the organisation. Product innovation is considered when the firm introduces newly created or improved goods and services, meanwhile process innovation is done when the firm implements a novel or enhanced method in the production and delivery process. Meanwhile, organisational and marketing innovation is carried out when new methods are implemented in business operations and the 4Ps marketing mix (OCED, 2018).

Nonetheless, the innovation output in this study is not proxy by the four types of innovation outlined by OCED (2018), but by the “patent issuance”. This is because “patent” is the proxy used by Crépon et al. (1998), the founder of the CDM model. In addition, this is also the data provided by the Department of Statistics Malaysia (DOSM) that represents innovation output reported by the manufacturing firms (see Appendix 1). A patent is one of the intellectual properties and it is an exclusive right granted by the government to help a firm enjoy the dividend bought by its novel product or/and process invention for a period of 20 years (DOSM, 2017). The table below shows the summary of the innovation-related terms used in this study.

Table 3.1: Innovation-related Terms Used in the Study

Term	Interchangeable term in this study	Meaning in this study
Innovation Activities	-	All actions or events happened during the stages of innovation input and innovation output.
Innovation Input	R&D Expenditure	All investment costs incurred during R&D and innovation activities.
Innovation Output	Patent or patent issuance	The outcome of innovation investment, in the form of patent issuance reported by a manufacturing firm.

3.2.3 Definition of Firm Characteristics

In the CDM model, firm characteristics are a vector of variables representing the attributes of a company that affect the innovation activities (Crépon et al.,1998). In the original work of Crépon et al. (1998), the firm characteristics refer to a firm's R&D determinants that can be measured, such as firm size, market share, number of industry segments, diversification index etc. By referring to the work of Crépon et al. (1998) as well as Shafi'l and Ismail (2015) who studied Malaysian innovation activities in the context of CDM. The chosen variables in the vector of firm characteristics in this study are firm size, industry group, market share, and export volume.

The definition of "firm size" refers to the scale or magnitude of a firm, typically assessed using various quantitative metrics (Crépon et al., 1998).

According to SME Corporation Malaysia (2013), the size of a manufacturing firm in Malaysia can be defined from the perspective of volume of sales volume and number of employees, as follows.

Table 3.2: Definition of Firm Size in the Malaysian manufacturing sector

Firm Size	Volume of Sales Turnover	Number of employees
Micro Firm	Less than RM300,000	Less than 5
Small Firm	RM300,000 to less than RM 15 million	5 to 74
Medium Firm	RM 15 million to less than RM50 million	75 to 200
Large Firm	More than RM50 million	More than 200

Pertaining to the industry group, the OECD has categorized manufacturing industries, based on the intensity of R&D investment, into low-, medium- and high technological groups (Kirner et al., 2009). High technological manufacturing industries are those industries which require the latest technical knowledge, and thus, heavy R&D investment is needed. Whereas, even low-tech and medium-tech manufacturing industries tend not to carry out innovation by themselves, but they usually fully utilise the knowledge diffused from high-tech industries or adapt their innovation (Santamaría et al.,2009).

In Malaysia, the manufacturing sector is classified into 24 divisions and 72 groups following the classification of Malaysia Standard Industrial Classifications 2008 Version 1.0 (MSIC) (DOSM, 2015). These groups are then divided into low-productive groups and high-productive groups. The high-productive groups are those groups which recorded a gross output of RM10 billion and above, according to the Economic Census of Manufacturing 2016 (DOSM,2017). Meanwhile, the market share is calculated by dividing the firm sales amount by the industry sales amount, following the calculation of Shafi'l and Ismail (2015). Finally, the export volume is the amount of goods and services that a firm sells to a foreign country, if any.

3.2.4 Definition of Digital Spillover Effects

The digital economy has flourished in recent eras. This development has made digital technologies no longer explicitly applied in certain areas, such as information processing and sharing, but become the general-purpose tools that are applied to a broader scope and spectrum (Marsh et al, 2017). The application of digital technologies is different from conventional capital because it is not constrained by geographical mobility. With digitalisation, businesses can initiate business collaboration with internal and external parties. Thus, the impact of digital technologies on firms, society and the country can be more significant than the conventional capital (Marsh et al., 2017; Xu & Cooper, 2017).

The digital spillover effect refers to the external knowledge created via the application of digital technologies. Xu and Cooper (2017) defined digital spillover effects as the information flows that are transferred via digital platforms that can be enjoyed by any economic agents, aside from the investors of digital technologies. Meanwhile, Marsh et al. (2017) described digital spillover as the measurement of the creation of external knowledge via digital channels. Mun and Nadiri (2002) and Lane et al. (2006) viewed that the external knowledge created by digital technology applications allows information and knowledge transmission to go beyond boundaries, whether inside or outside firms and industries.

Xu and Cooper (2017) have separated the digital spillover effect into two areas, namely internal and external digital spillovers. The internal digital spillover effect refers to the information flow within the firm and it is normally proxy by the digital expenditure spent by a firm. Xu and Cooper (2017) believe that when more investment is injected into digitalisation, the firm could make use of digital platforms, especially the intranet, email and company website, to encourage knowledge and information sharing among the staff of that particular firm.

Meanwhile, the external digital spillover means the information flows beyond the firm (Xu & Cooper, 2017). A firm can know more about its stakeholders via the digital platform, such as the Google search engine and social media. For instance, when a firm's suppliers share about their latest products and technology used in the production process, the firm can learn the products and technology at the fastest pace. Besides, the firm may find a way to improve itself and make sure it has the compatible capability to apply these products and technology in its production process.

The external digital spillovers can be categorised into two directions, which are horizontal spillovers and vertical spillovers. Horizontal spillover is also named intra-industry spillover because it happens inside the industry itself. There is horizontal digital spillover when a firm absorbs the external knowledge created by its competitors via any digital technology. The intra-industry spillover also implies that the firm is acquiring knowledge that is close to their business operation and experience, especially those technical-type of industry-specific knowledge (Kogut & Zander, 1993; Cohen & Levinthal, 1990).

On the other hand, vertical spillovers, i.e. inter-industry spillovers, refer to the knowledge diffusion across industries. The firm can grasp the externalities of adopting digital technologies by its suppliers or customers (Schmidt, 2010; Cohen & Levinthal, 1990). By looking at the direction of their relationship, vertical spillover can be divided into two types:

(i) forward digital spillover involving the firm's direction to its downstream customers and

(ii) backward digital spillover involving the firm's direction to its upstream supplier.

The direction of the digital spillover effects is illustrated as below.

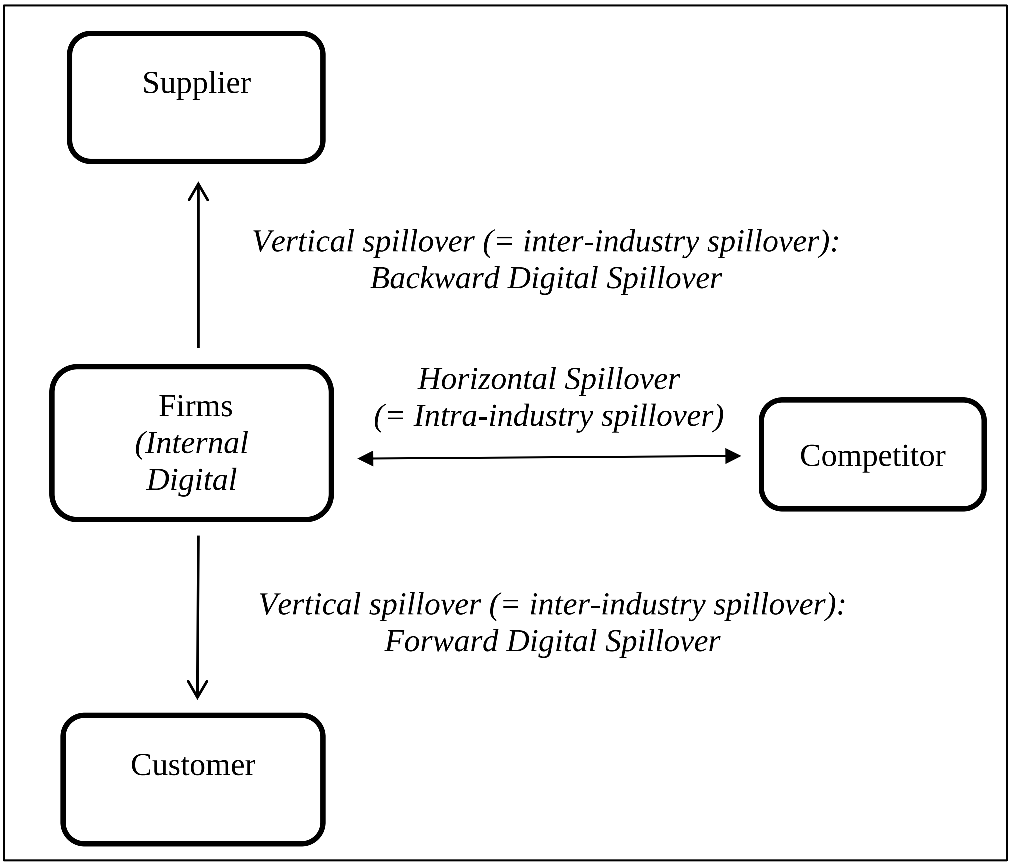


Figure 3.1: Directions of Digital Spillover Effects (Xu & Cooper, 2017)

3.3 Specification of the CDM Model

The CDM model created by Crépon et al.(1998) describes the process from the propensity of a firm to carry out innovation to the effect of innovation on productivity. Based on the conceptual framework illustrated in Chapter 2, the CDM model used in this study is extended by the integration of digital spillover effects to study the impact of digitalisation on innovation activities and firm productivity in Malaysian manufacturing firms.

The CDM model is generally estimated in a recursive system, which consists of three blocks of equations, starting from the innovation input function until the production function. A recursive system means that the endogenous variables of the equations are determined sequentially. In addition, the endogenous variable in the first equation will be forecasted and used as the independent variables of the second equation, and the same procedure is applied until the last equation of the system (Crépon et al.,1998; Crespi & Zuniga, 2012).

3.3.1 Development of Innovation Input Function

The first stage of the CDM model follows the specification of Heckman's (1979) two-step model in modelling the innovation input. It first examines the propensity of a firm to invest in innovation by a selection equation. The propensity of investing in innovation activities is measured by binary dependent variables. The r_{ijt}* is the binary dependent variable of R&D expenditure. If the firm reports the formal R&D expenditure, then a value of 1 is denoted, representing the R&D activities is observed. Otherwise, a value of 0 is given.

$r_{ijt}{}^{*} = \{1\ if\ RD_{ijt} > 0\ \ 0\ if\ RD_{ijt} \leq 0$ -----------------------------(Equation 3.1)

The selection function is estimated based on the following model:

$r_{it}* = \alpha\, x_{1it} + \upsilon_{it}$ --(Equation 3.2)

where

$r_{it}*$ = propensity of investing in innovation activities firm i at year t

x = vector of firm characteristics; α = coefficient of the vector

υ = error term

i,j,t = individual firm, industry and time respectively

After that, the level of the innovation input is estimated by the response equation to identify the intensity of innovation input investment made by the firm. The R&D intensity function is designed as:

$r_{ijt} = \alpha\, x_{1ijt} + \upsilon_{it}$ --(Equation 3.3)

where

r_{it} = annual investment expenditure on innovation invested by firm i at year t

x = same vector of firm characteristics as selection equation; α = coefficient of the vector

υ = error term

i,j,t = individual firm, industry and time respectively

Proxy selection

As mentioned in section 3.2.2, OECD (2018) has included seven areas of costs in the calculation of innovation input, including research and development (R&D), human capital development, ICT development etc. Even though these seven areas of expenditure need to be recorded separately when calculating the innovation expenditure, most of the firms in the market treat innovation expenditure and R&D expenditure as interchangeable terms (OECD, 2018). This is because the current accounting practice does not differentiate the innovation expenditure from the R&D expenditure but records all costs incurred during the innovation activities under the R&D expenditure account (OECD, 2018). As a result, R&D expenditure is sometimes treated as the innovation expenditure.

Numerous studies have used research and development (R&D) expenditure as the proxy of innovation input, for example, Zhu et al. (2021), Griffith et al. (2006) and Crépon et al. (1998). Griffith et al. (2006) viewed R&D investment as an appropriate measure of innovation input because R&D expenditure reflects the monetary investment injected by the firm for the innovation activities. In terms of innovation input intensity, some researchers calculate the ratio of total R&D expenditure to the total firm's sales (Eurostat Statistics Explained,2022; Audretsch & Belitski, 2020; OECD, 2018; Khachoo et al., 2018) or the total R&D expenditure per worker (Zhu et al., 2021; Garcia-Pozo et al., 2018; Hall et al., 2013). Meanwhile, the creators of the CDM model, Crépon et al. (1998), used the research capital per employee as the proxy of innovation input.

The proxies used to represent the chosen variables in this study are based on the data extracted from the Economic Census 2016. The innovation input intensity in this study is measured by the R&D expenditure per labour. According to DOSM (2017), R&D expenditure incurred by manufacturing firms in Malaysia is defined as the expenses incurred in the R&D activities, including both internal and outsourced R&D expenditures.

In terms of the vector of firm characteristics, Crépon et al. (1998) mentioned that the same variables can be used in the innovation input selection and response equations unless there is a good theoretical reason for saying different sets of variables need to be applied to both equations. The chosen variables are firm size, industry group, market share, and export volume, as suggested by the work of Crépon et al. (1998) as well as Shafi'l and Ismail (2015) who studied Malaysian innovation activities in the context of CDM model. Due to the data availability, the firm size is identified based on the number of employees, as follows.

i) Small firm: Firm that employs 1- 74 workers

ii) Medium firm: Firm that employs 75 – 200 workers

iii) Large firm: Firm that employs more than 200 workers

Even though the vector of the firm characteristics in the selection equation and response equation can be identical, the firm size is included only in the R&D selection equation but not the R&D response equation in this study. It is because firm size is used to serve as the exclusion restriction, i.e., at least one variable in the R&D intensity equation is not included in the R&D selection equation for identification purposes (Fu et al.,2018; Kachoo et al., 2018). Firm size is chosen as the exclusion restriction because the scale of R&D investment is implied by the firm size, according to Morris (2018), Griffith et al. (2006) and Zhang and Islam (2022).

Meanwhile, the industry groups of the manufacturing sector covered in this study are limited to only 67 groups, as per Appendix 2. There are 24 out of these 67 groups are categorized under high-productive groups. The market share is calculated by dividing the firm sales amount by the industry sales amount following the calculation of Shafi'l and Ismail (2015). The export volume is taken as per given by the data.

In terms of the digital spillover effects, the internal digital spillover effect is proxied by ICT expenditure per worker spent in manufacturing firms, by referring to the proxy used by Xu and Cooper (2017). The ICT expenditure used by Malaysian manufacturing firms is defined as the expenditure incurred on the usage of computers, internet and web presence (DOSM, 2017).On the other hand, the external digital spillover effects are derived based on a calculation based on the procedure of Marsh et al. (2017) and Mun and Nadiri (2002)., as illustrated in section 3.5.4.

Nonetheless, there is a need to check the multicollinearity between digital expenditure and R&D expenditure to decide the inclusion of digital expenditure in the innovation input equation. The OECD (2018) mentioned that the digital expenditure used for R&D activities is included in the R&D expenditure, but not all organisations separate the items of R&D activities clearly in the accounting practice. Based on the definition of DOSM (2017), R&D expenditure is defined as the expenses incurred in the R&D activities that are carried out both inside the firm as well as the outsources to external parties while ICT expenditure is the expenditure incurred on the usage of computers, the Internet and web presence. Thus, it is not clear whether the digital expenditure related to the R&D activities is counted in the R&D expenditure. If the cost is included in the R&D expenditure, then the issue of model misspecification would arise in the model.

By incorporating all elements mentioned above, the R&D selection equation is structured as:

$$r_{ij}^* = \alpha_1 + \alpha_2 dbig_{ij} + \alpha_3 dmed_{ij} + \alpha_4 dind_{ij} + \alpha_5 log(ex_{ij}) + \alpha_6 log(rms_i) + \alpha_7 log(it_{ij}) + \alpha_8 log(soi_{ij}) + \alpha_9 log(sob_{ij}) + \alpha_{10} log(sof_{ij}) + \upsilon_{ij} \text{--------------------(Equation 3.4)}$$

Whereas the R&D response function is structured as:

$$log(rd_{ij}) = \beta_1 + + \beta_2 dind_{ij} + \beta_3 log(ex_{ij}) + \beta_4 log(rms_i) + \beta_5 log(it_{ij}) + \beta_6 \, log(soi_{ij}) + \beta_7 log(sob_{ij}) + \beta_8 \, log(sof_{ij}) + \mathcal{E}_{ij} \text{-------------------------------(Equation 3.5)}$$

where,

r^* = dummy for investing innovation input of firm [1=yes]

log(rd) = R&D expenditure per labour invested by the firm [in log form]

dbig = dummy for large firm [1=large firm]

dmed = dummy for medium firm [1=medium firm]

dind = dummy for industry group [1=high productive industry]

log(ex)= export volume [in log form]

log(rms)= market share, as measured by the ratio of firm output to industry output [in log form]

log(itw) digital expenditure [in log form]

log(soi) = intra-industry digital spillover effect [in log form]

log(sob) = backward digital spillover effect [in log form]

log(sof) = forward digital spillover effect [in log form]

α_i = coefficient of the variables

υ_{ij} = error term

i,j = individual firm and firm's industry respectively

3.3.2 Development of Innovation Output Function

The second stage of the CDM model is used to estimate the innovation output, i.e. the realization of innovation input. The innovation output function takes the general form as follows,

$p_{ijt} = \chi_1 r_{ijt}^* + \chi_2 x_{ijt} + \omega_{ijt}$ ---------------------------------------(Equation 3.6)

where

p_{it} = innovation output produced by firm *i* at year *t*
r = investment expenditure on innovation (derived from Equation 3.13); χ_1 = coefficient of the vector
x = vector of firm characteristics; χ2 = coefficient of the vector
ω = error term
i,j,t = individual firm, industry and time respectively

Proxy selection

Past researchers have studied the innovation output in the form of product innovation and process innovation, such as Zhu et al. (2021), Garcia-Pozo et al. (2018), Griffith et al. (2006), Hall et al. (2011) etc. Nonetheless, due to the availability of data, the innovation output in this study is not proxy by product innovation and process innovation but by the report of patent ownership. This proxy is used by the researchers, such as the founder of the CDM model, Crépon et al. (1998) and Khachoo et al. (2018). Crépon et al. (1998) measured the innovation output in the form of patents per employee while Khachoo et al. (2018) used the number of patent grants.

Based on the DOSM (2017), a patent is one of the intellectual properties and it is an exclusive right granted by the government to help a firm enjoy the dividend bought by its novel product or/and process invention for a period of 20 years. By following the practice of Shafi'l and Ismail (2015) who studied the innovation activities in Malaysia, the report of patent ownership used in this report is measured by a binary variable whereby a value of 1 is assigned if the firm reports patent ownership, zero otherwise.

The forecasted R&D intensity is added as one of the factors that affect the innovation output. To alleviate the problem of endogeneity, the R&D intensity included in this equation is the estimated value that is derived from the first stage, equation 3.13. A similar practice has been applied by Khachoo et al. (2018) and Shafi'l and Ismail (2015) in including the R&D intensity into the innovation output function.

Furthermore, the vector of firm characteristics used in the innovation output function is similar to the innovation input function because the firm characteristics which are believed to have an effect on the R&D intensity are proposed to have an effect on creating the innovation output (Crépon et al.,1998). Thus, the firm characteristics that are used in the innovation output function include firm size, industry group, market share, export volume and digital spillover effects.

The innovation output equation is structured as follows.

$$p_{ij} = \chi_1 + \chi_2 1og(\mathrm{rd}_{ij}^*) + \chi_3\ dbig_{\ ij} + \chi_4\ dmed_{\ ij} + \chi_5\ dind_{\ ij} + + \chi_6\ log(ex_{\ ij}) + \chi_7\ log(rms_{ij}) + \chi_8\ log(lhs_{\ ij}) + \chi_9\ log(it_{ij}) + \chi_{10}\ log(soi_{ij}) + \chi_{11} log(sob_{ij}) + \chi_{12} log(sof_{ij}) + \omega_{\ ij} \text{ ---(Equation 3.7)}$$

where

p_{ij} = innovation output produced by firm i

log(rd*) = estimated R&D intensity derived from the first stage [in log form]

dbig = dummy for large firm [1=large firm]

dmed = dummy for medium firm [1=medium firm]

dind = dummy for industry group [1=high productive industry]

log(ex) = export volume [in log form]

log(rms)= market share, as measured by the ratio of firm output to industry output [in log form]

log(lhs)= high-skilled labour [in log form]

log(it)= digital expenditure [in log form]

log(soi) = intra-industry digital spillover effect [in log form]

log(sob) = backward digital spillover effect [in log form]

log(sof) = forward digital spillover effect [in log form]

χ_i = coefficient of the variables

ω, ε = error term

i,j = individual firm and firm's industry respectively

Aside from the digital spillover effects, this study also aims to examine the impact of absorptive capacity in grasping the digital spillover effects, which in turn affect the innovation output. Marsh et al. (2017), Paunov and Rollo (2016), Bresnahan et al. (2002) and Black and Lynch (2001) have proven the importance of absorptive capacity in grasping the digital externalities. The absorptive capacity is defined as the ability of a firm to absorb, assimilate and transform the knowledge, no matter external or internal, on improving the production process or organisational activities (Cohen & Levinthal, 1990). It is believed that the high absorptive capacity owned by a firm significantly contributes to innovation activities.

The absorptive capacity could be proxied by the number of high-skilled labourers, as suggested by Cohen and Levinthal (1989) and Griffith et al. (2006) because high-skilled labour can assimilate external knowledge at a faster pace as compared to low-skilled labour. In this study, the absorptive capacity is proxy by the number of high-skilled labour in a firm. According to the definition of Annual Economic Statistics Manufacturing released by the DOSM (2015), skilled labourers in the manufacturing sector refer to the managers, technicians, professionals and associate professionals.

The number of skilled labourers, instead of the labour's education level, is used in this study because the education level could not reflect the quantity of skilled labour in the Malaysian manufacturing sector. As summarised in the National Industry 4.0 Policy Framework (Ministry of International Trade and Industry, 2018), only 18% of the total employed in the manufacturing sector are high-skilled labourers, and the rest are semi-skilled labourers (75%) and low-skilled labourers (7%). However, only 7.5% of the total employed obtained the qualification of a university degree and above, 12% achieved a diploma or STPM level and the majority (80.5%) gained a SPM level or below. As a result, the number of skilled labourers is a better indicator of human capital and absorptive capacity as compared to labour's education level in the Malaysian manufacturing sector.

To examine the leverage of absorptive capacity in utilizing digital spillover effects, the digital spillover effects in the innovation output function are then replaced by the interaction term between the ratio of high-skilled labour and digital spillover effects to examine the complementariness of these two variables, by referring to the procedure of Marsh et al. (2017)[6]. The interaction term is used to identify the conditional effect and/or synergistic effect of two independent variables (Gujarati, 2021).

Some researchers applied the interaction term in their study of the CDM model to know the interaction between two independent variables. For instance, Audretsch and Belitski (2020) applied the interaction term between R&D intensity and size of knowledge spillover while Khachoo et al. (2018) interacted the R&D intensity with the FDI spillover instead. Similarly, Howell (2019) included the interaction terms to identify the effect of industry relatedness to the innovation activities as well as the impact on firm productivity pre- and post-FDI liberation. Likewise, to know the additional effect between innovation and the formal nature of a firm, Fu et al. (2018) compare the equations with and without the interaction terms of these two variables.

[6] Marsh et al. (2017) included the interaction term between the R&D expenses and ICT spillover effects to capture the absorptive capacity of a firm.

The extended innovation output function takes the following form. The coefficients, χ_8 , χ_{10}, χ_{11} *and* χ_{12} reflect the digital externalities captured by the firm through the firm's high-skilled labour.

$$p_{ij} = \chi_1 + \chi_2 1og(\mathrm{rd}_{ij}^*) + \chi_3 dbig_{ij} + \chi_4 dmed_{ij} + \chi_5 dind_{ij} + \chi_6 log(ex_{ij}) + \chi_7 \, log(rms)_{ij} + \chi_8(log(lhs_{ij})*log(it_{ij})) + \chi_9(log(lhs_{ij})*log(soi_{ij})) + \chi_{10}(log(lhs_{ij})*log(sof_{ij}) + \chi_{11}(log(lhs_{ij})*logsob_{ij})) + \varepsilon_{ij} \text{ --------------------------------------(Equation 3.8)}$$

where

p_{ij} = innovation output produced by firm i

log(rd*) = estimated R&D intensity derived from the first stage [in log form]

dbig = dummy for large firm [1=large firm]

dmed = dummy for medium firm [1=medium firm]

dind = dummy for industry group [1=high productive industry]

log(ex) = export volume [in log form]

log(rms)= market share, as measured by the ratio of firm output to industry output [in log form]

log(lhs)= high-skilled labour [in log form]

log(itw)= digital expenditure per labour [in log form]

log(soi) = intra-industry digital spillover effect [in log form]

log(sob) = backward digital spillover effect [in log form]

log(sof) = forward digital spillover effect [in log form]

χ_i = coefficient of the variables

ω, ε = error term

i,j = individual firm and firm's industry respectively

3.3.3 Development of Production Function

In the last stage of the CDM model, the production function is regressed to show the effect of firm characteristics and innovation output on firm productivity. The last stage of the CDM model investigates the effect of firm characteristics and innovation output on firm productivity. The general form of the production function is structured as follows.

$$y_{ijt} = \eta_1 p_{ijt^*} + \eta_2 x_{3ijt} + \rho z_j + \varepsilon_{it} \text{ --------------------------------------(Equation 3.9)}$$

where
y_{it} = production of firm *i* at year *t;*
p = innovation output (derived from Equation 3.8); η_1= coefficient of the vector
x = vector of firm characteristics; η2 = coefficient of the vector
z = vector of other relevant variables; ρ = coefficient of the vector
ε = error term
i, t = individual firm, industry and time respectively

In this study, the production function is structured based on the framework of an augmented Schumpeterian endogenous growth model. Schumpeter (1942) believed that the long-run growth rate of an economy is driven by innovation activities through the investment in R&D, the development of a firm's competency as well as the exploration of new markets. As mentioned by Udeogu et al. (2021), most of the empirical studies which applied the endogenous growth model have formed the production function based on the Cobb-Douglas general form:

$$Y = AK^{\alpha}L^{\beta} \text{ --(Equation 3.10)}$$

where the output (Y) is determined by the capital (K), labour (L) and technological progress (A). Hall (2011) commented that the level of technological advancement (A) owned by different firms makes the variation in the output level across the firms even though a similar level of capital (K) and labour (L) were employed.

Meanwhile, the α and β are the elasticities of output for capital and labour respectively. The Schumpeterian endogenous growth model assumes that there are constant returns to scale to the production and thus $\alpha + \beta = 1$ (Aghion et al.,1998).

Assume that the original production function is $Y = f(K, L) = AK^{\alpha}L^{\beta}$

To check the magnitude of returns to scale, the scale multiple (t) is added to the new production function as follows,

$$
\begin{aligned}
f(tK, tL) &= A \times (tK)^{\alpha} \times (tL)^{\beta} \\
&= A \times t^{\alpha}K^{\alpha} \times t^{\beta} \times L^{\beta} \\
&= A \times t^{(\alpha+\beta)} \times K^{\alpha} \times L^{\beta} \\
&= t^{(\alpha+\beta)} \times A \times K^{\alpha} \times L^{\beta} \\
&= t^{(\alpha+\beta)} \times f(K, L) \\
&= t^{(\alpha+\beta-1)} \times tf(K, L)
\end{aligned}
$$

$$
\begin{aligned}
\text{As } t^{(\alpha+\beta)} &= t^{(\alpha+\beta)} \\
&= t^{(\alpha+\beta)} \times \frac{t}{t} \\
&= t^{(\alpha+\beta-1)} \times t
\end{aligned}
$$

If $\alpha + \beta = 1$, then $f(tK, tL) = tf(K, L)$, showing constant returns to scale because the value of new production is equal to the old production function;

If $\alpha + \beta > 1$, then $f(tK, tL) > tf(K, L)$, showing increasing returns to scale because the value of new production function is higher than the old production function;

If $\alpha + \beta < 1$, then $f(tK, tL) < tf(K, L)$, showing decreasing returns to scale because the value of the new production function is lower than the old production function.

To examine the effect of innovation on production, Hall (2011) has augmented the production function by including IN, the proxy of innovation effort. The innovation effort (IN) can be proxy by a firm's innovation capability, innovation input or innovation output.

$Y = AK^{\alpha}L^{\beta}IN^{\gamma}$---(Equation 3.11)

Following Zhu et al. (2021) and Garcia-Pazo et al. (2018) who applied the assumption of constant returns to scale, the logarithmic per-worker form of production function is then represented by:

$log\ y\ = log\ (A)\ + \alpha log\ (k)\ + \beta + \gamma log\ (in)\ + \varepsilon$-----(Equation 3.12)

Proxy selection

In past studies, labour productivity has been commonly used as the proxy of the productivity in the Cobb-Douglas production function due to its simplicity in measurement and the availability of data (Crépon, 1998; Shafi'i and Ismail, 2015; Carvalho & Aveallar, 2017). Besides, labour productivity is applied because it can capture the net value that is created by the employees without taking into consideration the cost of material input as well as the services in the measurement. The labour productivity is usually measured by output per worker or the value added per worker. In this study, the production of firms is proxy by the labour productivity which is measured by the output per labour.

The firm productivity is expected to be affected by the accumulation of capital and labour, as well as the innovation output and digital spillover effects. The capital intensity is added to the production function, following the practice of Griffith et al. (2006) and Shafi'I and Ismail (2015). Meanwhile, the human capital of the firm is proxy by the ratio of high-skilled labour to total labour, by referring to Goedhuys (2007) and Leiva et al. (2017).

To avoid the endogeneity issue, the innovation output that is included in the production function is the forecasted value of innovation output derived from Equation 3.8. Similar to the other stages of the model, the internal digital spillover effect is proxied by the ICT expenditure spent by a manufacturing firm, meanwhile the external digital spillover effects are derived based on the procedure of Marsh et al. (2017) and Mun and Nadiri (2002).

By combining all elements, the production function is structured as follows.

$$logy_{ij} = \eta_1 + \eta_2\ dpt_{ij}* + \eta_3\ log(k_{ij}) + \eta_4 log(rlhs_{ij}) + \eta_5 log(itw_{ij}) + \eta_6 log(soi_{ij}) + \eta_7 log(sob_{ij}) + \eta_8 log(sof_{ij}) + \omega_{it} \text{-------------------------------(Equation 3.13)}$$

where

$log(y)$ = labour productivity [in log form]

$dpt*$ = estimated innovation output (derived from 2nd equation);

$log(k)$ = capital intensity of firm (per labour) [in log form]

$log(rlhs)$= ratio of high-skilled labour to total firm labour [in log form]

$log(itw)$= digital expenditure per labour [in log form]

$log(soi)$ = intra-industry digital spillover effect [in log form]

$log(sob)$ = backward digital spillover effect [in log form]

$log(sof)$ = forward digital spillover effect [in log form]

η_i= coefficient of the variable

ω = error term

Similar to the practice of innovation output, the interaction term between high-skilled labour and digital spillover effects are then included in the extended production function (Equation 3.14) to examine the extent of internal and external knowledge that is captured by the human capital of the firm. The extended production function takes the following form.

$$logy_{ij} = \eta_1 + \eta_2\ dpt_{ij}^* + \eta_3\ log(k_{ij}) + \eta_4 log(rlhs_{ij}) + \eta_5(log(lhs_{ij}) * log(it_{ij})) + \eta_6(log(lhs_{ij})*log(soi_{ij})) + \eta_7(log(lhs_{ij})*log(sob_{ij})) + \eta_8(log(lhs_{ij})*log(sof_{ij})) + \omega_{it.} \text{ ---------------------------------(Equation 3.14)}$$

where

$log(y)$ = labour productivity [in log form]

dpt^* = estimated innovation output (derived from 2nd equation);

$log(k)$ = capital intensity of firm (per labour) [in log form]

$log(rlhs)$= ratio of high-skilled labour to total firm labour [in log form]

$log(itw)$= digital expenditure per labour [in log form]

$log(soi)$ = intra-industry digital spillover effect [in log form]

$log(sob)$ = backward digital spillover effect [in log form]

$log(sof)$ = forward digital spillover effect [in log form]

η_i= coefficient of the variable

ω = error term

3.4 Endogeneity Issue in the CDM model

In the study of the CDM model, the endogeneity problem occurs when examining the association between innovation input and innovation output, as well as the relationship between innovation output and production. For the first association, an innovative firm is believed to have higher intention and intensity in investing innovation input. In turn, the higher innovation investment leads to higher innovation output. Meanwhile, for the second association, the innovation output is assumed to have an effect on enhancing productivity and the productive firm tends to carry out more innovation to improve its productivity further.

An endogeneity problem arises when the independent variable is correlated with the error term (Antonakis et al., 2010; 2014). The possible reasons which caused the endogeneity problem are (i) wrong specification of the model, i.e., measurement error and omitted variable, as well as (ii) the bilateral relationship between the independent variable and dependent variable, i.e. the simultaneity problem. The endogeneity problem can lead to biased estimates, i.e., overestimating or underestimating the estimates as well as the inconsistency of expected signs that are supported by theory. Sometimes, the results even show a reverse direction, i.e., the dependent variable causes the independent variable (Antonakis et al., 2010; Hughes et al., 2018). The endogeneity problem implies that the causal effects between the variables are hard to explain or potentially uninterpretable.

The endogeneity problem can be alleviated by introducing the instrument variables (IV) in the model as the remedial (Antonakis et al., 2010). The instrument variable is the variable that is exogenously determined, meaning that the variable is predetermined outside the model and it has an effect on the endogenous variable. However, the usage of the appropriate instrument variable is another issue for researchers because the instrument variable needs to have a high correlation with the independent variable and has the prediction power on the endogenous variable (Larcker & Rusticus, 2010).

To alleviate the problem of endogeneity bias, past researchers have used different IVs in the CDM model. As it is a sequential model, the popular IV is the estimated dependent variable of the first equation and is included in the subsequent equation as the explanatory variable. For example, Hall et al. (2013), Mohan et al. (2018), Audrestch and Belitski (2020), Edeh and Acedo (2021), and Zhu et al. (2021) have used this method in their innovation equation and production equation. Likewise, some researchers have used the lagged value of variables in the CDM model (Kachoo et al.,2018; Ramirez et al.,2019). Kachoo et al. (2018) have used the lagged R&D in the innovation output equation and the lagged value of some exogenous variable in three stages; meanwhile Ramirez et al. (2019) used the lagged value of exogenous and endogenous human capital as the proxy of high-skilled labour in three stages of CDM model.

On the other hand, controlling for the fixed effect of individual samples and time is another way of solving the endogeneity problem. Kachoo et al. (2018) have also applied the interaction term that captures the differences in trends across industries and time. Furthermore, Audrestch and Belitski (2020) have included the control variables in the model to control the heterogeneity in the firms, such as the number of subsidiaries, firm internationalisation, industry competition and knowledge transfer.

In this study, the endogeneity problem is alleviated by employing the estimated dependent variable of the first equation in the second equation as the explanatory variable, as the practice used by Hall et al. (2013), Mohan et al. (2018), Zhu et al. (2021) and other. To be specific, the estimated R&D intensity gained in the 1st stage estimation will be included in the innovation output in the 2nd stage as one of the explanatory variables, and then the estimated innovation output in the 2nd stage will be included in the production output function in the 3rd stage.

3.5 Estimation Techniques

Due to the variation in the nature of dependent variables and data applied in each of the equations in the CDM model, different econometric methods are needed for the estimation purpose. In this study, the econometric software--Eviews Version 12 is used for the data analysis. This section discusses the econometric methods as well as the remedies which deal with the problem that arose from the econometric issues. Figure 3.2 portrays the overall idea of the methodologies required for this study.

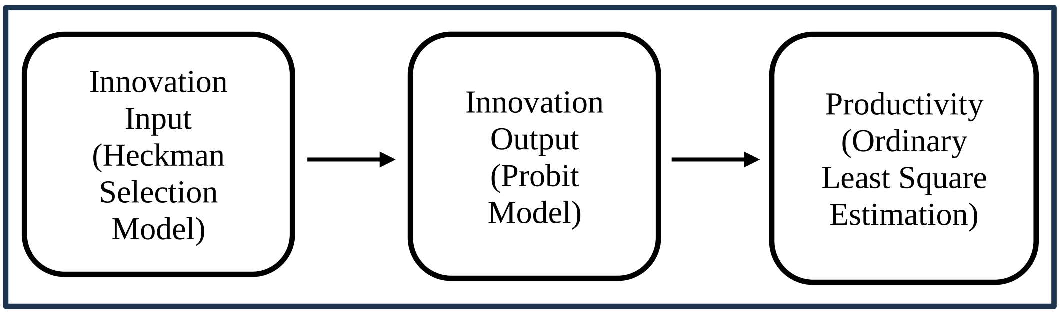


Figure 3.2: Econometric methods required for respective equations and variables (Developed by author)

3.5.1 Heckman Selection Model

Following the studies of Shafi'i and Ismail (2015) and Khachoo et al. (2018), the first equation in the CDM model, which is the innovation input function, is examined by the Heckman selection model. The Heckman selection model, which is also known as the Heckit model, is mainly dealing with the issue of sample selection bias (Heckman, 1976). Crépon (1998) mentioned that the issue of sample selection bias has to be handled meticulously in the field of innovation studies, especially for those using survey data for data analysis due to the nature of innovation survey data.

The sample selection bias arose when the sample selected from the population did not follow a random selection but was based on specific criteria or factors related to the research objective (Heckman, 1976). As a result, the data analysis based on this non-random selection might lead to misleading outcomes as the results are not representative enough to reflect the condition of the population. In this study, the Heckman selection model is essential because it helps the researcher to identify whether to include the Malaysian manufacturing firm that does not formally report R&D expenditure in the data analysis.

Based on Shafi'i & Ismail (2015), they mentioned that not all Malaysian manufacturing firms, including large firms, which are involved in innovation activities have formally reported their involvement in R&D. Even though a firm does not formally report any R&D expenditure in the innovation survey, it doesn't mean that the firm does not have the intention in carrying out R&D activities in the future or did not involve in some R&D activities in prior time. If these firms are essential but excluded in the data analysis, it makes the estimation process suffer from the issue of sample selection bias and generated misrepresentative estimators.

In addition, the structure of the manufacturing sector in Malaysia is unique because the small and medium enterprises (SMEs) have accounted for more than 97% of the market structure (Economic Planning Unit, 2021). They are the significant players in the sector but a majority of them are not involved in innovation activities due to the difficulties in recruiting high-performing talents and securing funding (Ministry of International Trade and Industry,2018). Based on the conventional method, the majority of the SMEs are excluded from the research. Thus, there is a possibility that selectivity bias arose and caused the total impact of digitalisation and innovation on the manufacturing firm's productivity to be underestimated.

For applying Heckman's two-step model, two equations are needed, namely the selection equation and the response equation. The selection equation is used to identify if the dependent variable is observable or not. Meanwhile, the response equation is used to estimate the variable of interest. In other words, the selection equation is used to identify whether the manufacturing firm in Malaysia has the intention to invest in R&D activities while the response equation shows the degree of R&D investment injected by that particular manufacturing firm.

For the selection equation, the dependent variable which fulfils the predetermined criteria is only observable. For instance, in the case of innovation, a firm’s innovation is only observed if the firm has made the innovation investment. Otherwise, the firm is unobservable. If the firm is observable, the response equation is estimated subsequently.

The selection equation and response equation are regressed as follows:

Selection equation: $z_i = W_i\alpha + u_i$ -------------------------------(Equation 3.15)

Response equation : $y_i = x_i \beta + \varepsilon_i$ --------------------------------(Equation 3.16)

where z_i is a binary variable and y_i is observed when z_i is equal to one. Both u_i and ε_i are disturbances which are bound to a bivariate normal distribution.

With the conditional z_i is equal to one on y_i :

$E(y_i \mid z_i = 1) = x_i \beta + \rho\sigma\lambda_i W_i\alpha$

$y_i = x_i \beta + \rho\sigma\lambda_i W_i\alpha + \nu_i$

$y_i = x_i \beta + \rho\sigma\lambda_i + \nu_i$, if $W_i\alpha > 0$, then $z_i = 1$ --------------------(Equation 3.17)

where λ (X) is the Inverse Mills Ratio (IMR). Greene (2008) explained that the IMR is used to examine the relationship between the error terms in the selection and response equation. Then, the IMR is included in the response equation and acts as a correction factor to adjust the estimates if the estimator suffers from the selection bias problem. As a result, the estimation outcomes are free from the selection bias.

The selection equation is first estimated by the Probit equation while the response equation is regressed by the least square method, based on the estimation of Eviews 12 (IHS Markit, 2020). Meanwhile, the result of IMR can be referred to as the p-value of rho generated by Eviews 12. If the p-value of rho is significant, it means that it is appropriate to apply the Heckman Selection Model in the innovation input estimation to deal with the selectivity problem.

3.5.2 Binary Dependent Variable Model: Probit Model

The Probit model is a binary dependent variable model which is used to identify the choice behaviour of an economic agent. In other words, it is used to estimate the probability of the occurrence of an event which is carried out by an individual or firm. For instance, this study aims to identify whether the firm chooses to innovate or not innovate in the first equation of the CDM model. By applying a binary dependent variable model, it can quantify the relationship between the firm characteristics and the probability of investing in innovation activities. In addition, this model is also applied in the second stage of the CDM model, which is to find out whether a manufacturing firm reports a patent issuance.

The conventional binary dependent variable model is a linear probability model (LPM) in which the dependent variable is assigned the value of 1 if the outcome is chosen and 0 if the outcome is not chosen. As the LPM is a linear model, the increase in the value of the independent variable causes an increase in the dependent variable proportionally. Thus, the estimated value of the dependent variable can be more than 1 or less than zero if the value of the independent variable is big or small enough respectively. However, this result does not make sense as the value of probability must lie between 0 and 1. Besides, the linear probability model follows the binomial distribution; thus, the error term is not normally distributed (Amemiya, 1981). Due to the limitations of LPM, a non-linear model, such as the probit model, is required as the slope of the non-linear regression diminishes when it closes to one. Hence, it can ensure that the dependent variable fulfils the 0 and 1 conditions of probability.

The probit model starts with the estimation of an unobservable latent variable y_i* with the setting of a specific threshold value (McFadden, 1973). For instance, if the threshold value is set to zero and the latent variable is linearly regressed to x.

$y_i{}^* = x_i{}'\beta + u_i$ --(Equation 3.18)

If the latent variable exceeds the threshold value, y_i is given the value of one; otherwise, zero $y_i = \{1\ if\ y_i{}^* > 1 \quad 0\ if y_i{}^* \leq 0$

Thus, Pr (y_i=1 | x_i β)

= Pr (y_i *>0)

= Pr (x_i' β + u_i >0)

= 1- F_u(-x_i' β) --(Equation 3.19)

where F_u is the cumulative distribution of error terms. The probit model follows the standard normal distribution with the assumption that the disturbance is normally distributed, as shown by

$\varepsilon_i \sim N(0, \sigma^2)$

Prob (y_i = 1) =F($\frac{\beta_0 + \beta_1 x_i}{\sigma}$)

where F is the standard normal cumulative density function. For the empirical analysis, the steps of estimating the probit model are as follows:

1) Set a threshold value on the examined independent variable.
2) Estimate the dependent variable the regression (y_i) by substituting the relevant threshold values of independent variables into the model. The result of y_i is the probit value, which is also called the Z-value.
3) Refer the Z-value to the normal table and obtain the normal density value.
4) Multiply the normal density value with the estimated coefficient of the independent variable to identify the unit change in the probability.

The Probit model is estimated by the maximum likelihood estimator because this estimator is efficient when the distributional assumptions are held (Gujarati, 2021). In Eviews, the estimation output of the Probit Model is shown in Z-statistic but Gujarati (2021) mentioned that the sign of the Z-statistic is meaningful but the interpretation of the coefficient of Z-statistic is meaningless. The positive sign of the Z-statistic indicates that the independent variable would increase the probability of realising the dependent variable, and vice versa. Meanwhile, if the researcher needs to interpret the coefficient of the Probit model, all Z-statistics have to be transformed into marginal effect.

Marginal Effect of the Independent Variables

In Eviews 12, the marginal effects of the independent variable are not provided in the estimation output of the Probit model and they need to be calculated manually. Before calculating the marginal effect, the Probit model needs to be evaluated to know its prediction power in matching the estimated outcomes with the actual binary data. In Eviews 12, the prediction power of the Probit model is measured by the percent correctly predicted measures, which is named the "Expectation-Prediction Evaluation for Binary Specification" (IHS-Markit,2020). The outcome of the "% correct" shown on the expectation-prediction classification table shows the percentage of the observations that are correctly predicted by the model.

Then, the marginal effect of the independent variables can be calculated using the "Forecast" method under the procedures of binary equations.

Initially, the binary variable model is illustrated as follows:

$Y_i^* = \beta_0 + \beta_i X_i + u_i$ where $[u_i \sim N\ (0, \sigma_u^2)]$ ------------(Equation 3.20)

indicating the error term is usually distributed and homoscedasticity

Then, the fitted value of the dependent variables is estimated based on:

$$\begin{aligned} Prob\ (y_i = 1|x_i) &= Prob\ (y_i > 0|x_i) \\ &= Prob\ (u_i > -\beta_0 - \beta_i X_i|x_i) \\ &= 1 - Prob\ (u_i < -\beta_0 - \beta_i X_i|x_i) \\ &= 1 - F\ (-\beta_0 - \beta_i X_i|x_i) \end{aligned}$$

where $F\ (-\beta_0 - \beta_i X_i|x_i)$ is the cumulative standard distribution function

The marginal effect of the Probit model is calculated based on :

$$Prob\ (y_i = 1|x_i) = \theta\ (\widehat{\beta_0} + \widehat{\beta_\iota}\, X_i)$$

$$\frac{\partial Prob\ (y_i = 1|x_i)}{\partial x_\iota} = \emptyset\ (\widehat{\beta_0} + \widehat{\beta_\iota}\, X_i)\widehat{\beta_\iota} \text{-----------------------(Equation 3.21)}$$

where = $\emptyset\left(\widehat{\beta_0} + \widehat{\beta_\iota}\, X_i\right)$ is known as the probability distribution function (pdf)

With this function, the individual marginal effect and mean marginal effect can be calculated for the model that has a number of independent variables, which are measured in terms of continuous variables. If there are binary independent variables in the model, then the marginal effect is calculated based on:

Marginal effect = $Prob\ (y_i = 1|x = 1) - Prob\ (y_i = 1|x = 0)$

$$= \theta\ (\widehat{\beta_0} + \widehat{\beta_\iota}\, X_i) - \theta\ (\widehat{\beta_0}) \text{ ---------------(Equation 3.22)}$$

Practically, the steps of calculating marginal effects using Eviews 12 in this study are illustrated below:

For continuous variable

Step 1: Forecast the probability of the dependent variable, i.e. the probability distribution function, and save the estimated series as pdf

Step 2: Multiply the auto-series @dnorm(-pdf) with the coefficients of the interested variable and extract the mean value.

For binary variable

Step 1: Multiply the auto-series @cnorm with all variables and extract the mean value.

Step 2: Multiply the auto-series @cnorm with all variables, except the interested binary variable. Then, extract the mean value from the series.

Step 3: Minus the mean value of step 3 from the mean value of step 2.

3.5.3 Ordinary Least Square (OLS) Estimator

As mentioned in section 3.3.4, the CDM model tends to encounter the endogeneity problem because innovation and productivity are always interrelated and determined simultaneously (Crépon et al., 1998). The remedy for the endogeneity problem is the application of instrument variables (IV) which are highly correlated with the dependent variable and orthogonal to the error term of the dependent variable. The common estimation methods for IV are Two-stage Least Squares (2SLS) and Generalized Method of Moments (GMM) (Stock and Watson, 2018).

Due to the data availability, the 2SLS estimator is employed in this study to estimate the production function. The estimation of 2SLS involves two stages. The first stage is the identification of the appropriate instrument variables by estimating the candidate variable on a set of instrument variables. Subsequently, the fitted values derived from the first step are then included in the original equation and the original regression using the Ordinary Least Square (OLS) estimator (Stock and Watson, 2018).

However, as the CDM model is a sequential model, the first stage of the 2SLS is actually carried out at the innovation output equation (the second stage of the CDM model), and the second stage of the 2SLS remains at the production equation (the last stage of the CDM model). In other words, after estimating the innovation output equation with the Probit model, the series of predicted innovation output can be generated and it will be included in the production function as an additional independent variable. Then, the production function can be run using the OLS estimator.

The inclusion of the predicted innovation output in the production function solves the possible problem of endogeneity because the predicted series of innovation output has become the continuous data (the probability of issuing a patent) instead of the binary variable (whether a manufacturing issue is a patent) that used in the innovation output equation. As a result, it is assumed that the predicted innovation output is uncorrected with the error term and correct for the possible endogeneity. A similar argument has been made by Baumann and Kritikos (2016) when running their innovation and production equation in the context of the CDM model. In addition, a similar practice has been applied by

García-Pozo et al. (2018), Khachoo et al. (2018), Audrestch and Belitski (2020), Edeh and Acedo (2021), Zhu et al. (2021) in their CDM study.

The OLS is still the best estimator if the regression is free from the endogeneity problem as it demonstrates unbiased and consistent properties when the estimated model fulfils the assumptions of the classical linear regression model (Gujarati, 2021; Stock and Watson, 2018). Nonetheless, when the OLS estimation is working with cross-sectional data, the assumption of homoskedasticity is usually violated which then leads to invalid estimation outcomes. Thus, White (1980) and Wooldridge (2001) suggested that the OLS equation diagnosed with heteroskedasticity needs to be adjusted with the Huber-White covariance method to obtain a valid estimation result. The same approach has been applied by Kleis et al. (2012) and Véganzonès-Varoudakis and Plane (2019) in their empirical studies.

3.5.4 Digital Spillovers Measure

The external digital spillover effects measurement used in this study follows the procedure of Marsh et al. (2017) and Mun and Nadiri (2002). The procedure of Xu and Cooper (2017) is not applied in this study because their study focused on panel data but this research employs cross-sectional data. In addition, Xu and Cooper (2017) calculated the digital spillover effects to be fitted into the productivity function that incorporates technology investment, knowledge diffusion and time effect, following the model of Mankiw et al. (1992). However, this study focuses on the interdependency of the industries during the calculation of digital spillover effects. As a result, the procedure of Marsh et al. (2017) and Mun and Nadiri (2002) who calculated the ICT spillover effects is more appropriate to be applied in this study.

In this section, the measurement of horizontal spillover digital spillover, i.e., intra-industry spillover is first explained, followed by vertical digital spillovers, including the backward spillover and forward spillover. The horizontal digital spillover is measured by the total ICT expenditure per labour at the industry level. In other words, total industry ICT expenditure is divided by the total number of labourers involved in that particular industry. As mentioned by Marsh et al. (2017), the horizontal digital spillover effect mainly captures the digital-related external knowledge that a firm learns from its competitors in the areas that are close to their practices and experience.

Horizontal Spillover: $SOI = \frac{\sum_{i\epsilon j} ICT_{ij}}{\sum_{i\epsilon j} L_{ij}}$ -----------------------(Equation 3.23)

where ICT_{ij} represent the ICT expenditure spent/invested in industry j meanwhile the L_{ij} is the total employment in industry *j*.

On the other hand, the measurement of vertical spillovers, including backward spillovers and forward spillovers, is relatively complicated as compared to horizontal spillovers. According to Marsh et al. (2017), the vertical spillover effects can be measured based on the aspect of transaction intensity or technological proximity. The information of the intermediate transactions is needed for the former measurement while the patent citation flows are necessary for the latter. In this study, the backward and forward spillover are measured following the procedure of Mun and Nadiri (2002) which incorporates the transaction intensity, as shown below:

Backward spillover: $SOB = \sum_{j \neq i} \frac{\alpha_{ij}}{x_i} ICT_j$ --------------------(Equation 3.24)

Forward spillover: $SOF = \sum_{j \neq i} \frac{\beta_{ij}}{x_i} ICT_j$ ----------------------(Equation 3.25)

where

$\propto_{ij}$ = total amount of intermediate input that industry *i* bought from their suppliers (industry *j*)

β_{ij} = total amount of intermediate output that industry *i* sold to their customers (industry *j*)

x_i = total amount of inter-industry transaction of industry *i*

ICT_j = total amount of ICT expenditure spent or invested by industry *j*

In short, the digital spillover is the weighted amount of ICT expenditure of all industries other than the firm's industry. Based on the measurement above, it shows that digital spillover happens provided there is an inter-industry intermediate transaction, i.e., upstream buying and downstream selling transactions, carried out between industries *i* and *j*. If there is no transaction between two industries, the weightage of $\frac{\alpha_{ij}}{x_i}$ and $\frac{\beta_{ij}}{x_i}$ become zero, and the digital spillover will be zero as well no matter the intensity of ICT expenditure spent by industry *j*. Furthermore, the digital spillover is more apparent if there are heavy inter-industry intermediate transactions taking place between the industries as the value of the weightage is higher.

The information on the mentioned industry output that is produced and purchased by foreign firms is extracted from the input-output (IO) table. The IO table is a matrix-form quantitative model developed by Wassily Leontief to depict the interlinkages between different sectors in a country or different economies in a region (Thijs, 2010). The input-output table, the essential tool of IO analysis, describes the interaction of producing (the row entries) and consuming (the column entries) along the supply chain. In other words, the path of the output of one industry which is later used as an input by another industry (-ies) can be traced.

Again, by adopting the procedure of Mun and Nadiri (2002), the weights used in the vertical spillovers are extracted by following steps:

Step 1:

Referring to the use table in the IO dataset that depicts the purchase of commodities of each industry and their respective production.

Step 2:

Compose Matrix A by adding up each column and row in the use table.

Step 3:

Modify the value of the diagonal of Matrix A to zero to exclude the transactions happening within the industry.

Step 4:

Transpose Matrix A and obtain Matrix B

Step 5:

Add up Matrix A and B to get Matrix C. The aggregate amount of the inter-industry intermediate transaction of each industry is represented by the total value of each column in Matrix C.

Step 6:

Dividing each column in Matrix A by the respective column in Matrix C and obtaining the weightage for backward spillovers.

Step 7:

Dividing each column in Matrix B by respective columns in Matrix C and obtaining the weightage for forward spillovers.

3.6 Data Sources

In this study, multiple data sources are used because there are a number of variables that are applied in this study. CDM model is a sequential model that applies a large number of firm-level data for analysis. Thus, the first data used in this study is the firm-level data provided by DOSM in March 2020 upon official request via the DOSM portal as the firm-level data was not published publicly. The evidence of the data handover can be referred to Appendix 1.

There are a total of 14,723 firms in the sample provided by DOSM. This sample accounts for 30% of microdata in Malaysia's manufacturing sector based on the Economic Census 2016 (reference year 2015). The Economic Census published by DOSM is a survey conducted at a five-year interval and entails a thorough enumeration of all business entities and non-profit organisations in Malaysia. Based on the official portal of DOSM, the latest available publication on the economic census is the Fifth Economic Census, Economic Census 2023 (the reference year of 2022) (DOSM, 2024). Meanwhile, the Economic Census 2016 (the reference year of 2015) is the Fourth Economic Census.

It is acknowledged the data in 2015 is nine years away from the year 2024, yet this is the latest data that could be obtained by the author. During the data analysis that was conducted in the year 2022, the author did ask about the availability of firm-level data in the year 2021 beyond the Economic Census 2016, yet the reply from the DOSM officer mentioned that the latest unpublished firm-level data of the manufacturing sector was up to the Economic Census 2016. The response of the DOSM officer has been attached to Appendix 3.

When data collection for Economic Census 2023 ended on 31 December 2023, the author submitted the second request for the firm-level data in 2023 on 23 July 2024. However, the DOSM officer replied that the firm-level data could not be supplied as the data is yet to be published. As a result, the data provided by the DOSM officer in 2020 is the best sample that couldn't be used by the author. The reply of the DOSM officer can be referred to Appendix 4.

The issue of data availability in studying firm-level innovation has been faced by past researchers as well, see Table 3.3. Generally, there is a gap of more than 5 years between the date of publication and the data set used in the research. The study done by Zhu et al. (2021) and Ramirez et al. (2019) has even reached a gap of 10 years. Even though the data used by Xu and Cooper (2017) is just one year gap from the publication, the Total Economy Database (TED) has done its innovation in 2016 by including the contribution of technological assets to the economy. If this innovation had not been carried out by TED, Xu and Cooper (2017) might not have been able to validate the concept of "digital spillover effect".

Table 3.3: Past Studies on CDM Model and Data Set Applied

Author	Country	Data used in the research
Zhu et al. (2021)	China	Firm-level data which consists of 2700 firms, was extracted from the World Bank Survey 2012.
Audrestch & Belitski (2020)	United Kingdom	Panel data that consists of 9213 firms, covering the period from 2002 to 2014.
Ramirez et al. (2019)	Colombia	Firm-level data which consists of 6326 firms, was extracted from the Survey of Development and Technological Innovation 2007 to 2010.
Khachoo et al. (2018)	India	Panel data that consists of 753 firms, covering the period from 2000 to 2013.
Xu & Cooper (2017)	Global	Employ the Total Economy Database (TED) 2016 because it is the **first time** that TED calculating the contribution of technologies assets, e.g. the productivity improvements in cloud computing.
Shafi'I & Ismail (2015)	Malaysia	Firm-level data which consists of 7222 firms, was extracted from the Annual Survey of Manufacturing 2008.

Meanwhile, the second type of data used in this study is the cross-sectional data at the industry level, extracted from the Annual Economic

Statistics Manufacturing 2015, Report on Annual Survey of Manufacturing Industries 2015 and Economic Census 2016 (cater for data of the year 2015). All these reports were released by the DOSM in 2019, 2016, and 2017 respectively. The Annual Economic Statistics Manufacturing and Economic Census mainly provides information on the input, output, and value-added along the production process as well as the employment in manufacturing sectors (DOSM 2017, 2019) meanwhile the Report on Annual Survey of Manufacturing Industries provides insights on the performance of manufacturing industries and other relevant statistics pertaining to this sector (DOSM, 2016).

On the other hand, in order to measure the intermediate transaction weights used in digital spillover effects, the data is extracted from the Input-Output Tables (the year 2015) which was published by the DOSM in 2018. The preparation of the IO table is labour and computer-intensive because it requires enormous amounts of data to comprehend the expenditures and revenues of all industries in Malaysia. Similar to other countries, it takes a long time (on average four years) to complete the IO table in Malaysia.

3.7 Data Description

Based on these unpublished and published data, the data description of the chosen variables used in this study is illustrated as below.

Table 3.4: Data Description for Variables Chosen

Variable		Measurement
Firm Characteristics		
Firm size	dbig	Dummy variable 1= large sized firm (more than 200 employees)
	dmed	Dummy variable 1= medium-sized firm (75 to 200 employees)
Export activity	ex	Level variable Export Volume (in log form)
Industry group	dind	Dummy variable 1 = High productive industry (Gross industry output of RM10 billion and above)
Market share	rms	Ratio variable Ratio of firm output to total industry output
High-skilled labour	lhs	Level variable Number of high-skilled labour
	rlhs	Ratio variable Ratio of high-skilled labour to total labour
Capital Intensity	k	Level variable Fixed asset amount (exclude ICT expenditure) per worker
Labour productivity	y	Level variable Total firm output per worker
Innovation Activities		
R&D decision / R&D propensity	r*	Dummy variable 1 = R&D expenditure is reported by the firm
R&D intensity	rd	Level variable R&D expenditure per worker
Innovation output	dpt	Dummy variable 1 = Patent issuance is reported by firm

Table 3.4 (Continued): Data Description for Variables Chosen

Variable		Measurement
Digital Spillover Effects		
Internal digital spillover	it	Level variable Digital expenditure, i.e. ICT expenditure (Internal digital spillover)
	itw	Ratio variable Digital expenditure per worker
Horizontal digital spillover	soi	Level variable Horizontal digital spillover (Intra-Industry)
Backward digital spillover	sob	Level variable Backward digital spillover (Inter-Industry)
Forward digital spillover	sof	Level variable Forward digital spillover (Inter-Industry)

3.8 Concluding Remark

The Crépon, Duguet, and Mairesse (CDM) model, created by Crépon et al. (1998), is applied in this study to examine the impact of firm characteristics and digital spillover effects on innovation and productivity of manufacturing firms in Malaysia. The CDM model is a recursive system that applies firm-level data, consisting of three equations to reflect the interactions between innovation performance and firm productivity. As the data used in this study carries a different nature, different estimation techniques are applied in the CDM model.

The first stage in the CDM model is estimated using Heckman's two-step model, starting with the selection equation and followed by the response equation. The selection equation is estimated to deal with the selectivity problem attributed to the nature of innovation survey data. Otherwise, severe selectivity bias could produce inaccurate estimates, which lead to biased analysis. The second stage of the CDM model estimates the innovation output function. As the dependent variable of this function is a binary variable, the Probit model is applied in the data estimation. The last equation, the production function, examines the labour productivity of a firm by applying the Ordinary Least Square (OLS) estimator.

As the impact of digitalisation is the main research axis of this study, both internal and external digital spillover effects are included in three stages of the CDM model. The internal digital spillover effect is proxy by digital expenditure spent by a manufacturing firm while the external digital spillover effects are calculated based on the input-output table. Multiple data sources are used in this study but the major cross-sectional data applied is the unpublished firm-level data that was provided by the Department of Statistics Malaysia. This unpublished firm-level data was extracted from the Economic Census 2016, carrying a total of 14,723 Malaysian manufacturing firms in the sample size.

CHAPTER 4

DATA ANALYSIS

4.1 Introduction

Chapter 4 is the keystone chapter of this research as the data analysis provides insights in answering the research questions. This chapter starts with a descriptive analysis, describing the distribution and characteristics of Malaysian manufacturing firms in the sample. Next, the empirical analyses are performed to reveal the underlying relationships between the variables, associated with the interpretation of the results of analyses. Finally, the robustness checking is carried out to validate the findings in the empirical analyses.

4.2 Descriptive Analysis

In this study, the unpublished firm-level data provided by the Department of Statistics Malaysia [DOSM] is used for the data analyses. There are a total of 14,723 manufacturing firms included in the sample, and this sample size accounted for 30% of the Malaysian manufacturing sector based on the Economic Census 2015. Table 4.1 shows the distribution of these 14,723 manufacturing firms.

In the sample, the SMEs accounted for 96.28% of the total sample size, which is close to the actual situation in the Malaysian manufacturing sector. In Malaysia, SMEs have formed 97% of the manufacturing sector (Economics Planning Unit, 2021). Among the manufacturing firms in the sample, only 20% were exporting firms; surprisingly, most were SMEs. Nevertheless, by looking at the firm size, almost 88% of the large firms were exporters, and this percentage has lowered to 69% for medium firms and 14% for small firms.

Table 4.1: Distribution of Firms in the Sample Size

	Large Firm	**Medium Firm**	**Small firm**	**Total**
Weightage	3.72% (548)	6.35% (935)	89.93% (13,240)	100% (14,723)
Firm characteristics				
Exporter	3.27% (481)	4.40% (648)	12.93% (1,903)	20.59% (3,032)
Non-exporter	0.46% (67)	1.95% (287)	77.00% (11,337)	79.41% (11,691)
				100.00%
High productive industry	2.97% (437)	4.97% (731)	47.07% (6,930)	55.00% (8,098)
Low productive industry	0.75% (111)	1.39% (204)	42.86% (6,310)	45.00% (6,625)
				100.00%

Source: Author’s calculation for research

On the other hand, almost half of the firms in the sample belonged to high-productive industries. The high-productive industry refers to those industrial groups which recorded a gross output of RM10 billion and above, according to the DOSM (2017). By looking at the firm size, approximately 80% of the large and medium firms were located in the high-productive industries but this percentage was recorded at 50% only for the small manufacturing firms.

Meanwhile, Table 4.2 presents the resources held by the firms based on the firm size. The situation of human capital owned by the firm is similar to the distribution of industry groups shown in the table above. All larger firms and 99.7% of medium firms hired high-skilled labour but only half of the small firms own high-skilled labour. This circumstance implied that high-skilled labour is an indispensable resource for firms operating in highly productive industries.

Nevertheless, a different scene was captured on the digital expenditure spent by the firms. In this study, the digital expenditure refers to the ICT expenditure spent on computers, internet and web presence usage. Table 4.2 depicts that large firms tend to spend digital expenditure compared to SMEs as almost three-quarters of the large firms invested in ICT spending. However, the gap between the medium firms with and without digital expenditure was 62.78% and this gap was even widened among the small firms, which was 90.8%. This result has shown the slow adoption among SMEs and the existence of technology gaps between large firms and SMEs.

Table 4.2: Resources Held by Firms Based on Firm Size

	Large Firm	**Medium Firm**	**Small firm**
Total number of firms	548	935	13,240
Human Capital			
Have high-skilled labour	100%	99.68%	53.24%
	(548)	(932)	(7,049)
Do not have high-skilled labour.	0.00%	0.32%	46.76%
	(0)	(3)	(6,191)
	100%	100%	100%
Effort on Digitalisation			
Report digital expenditure	73.72%	18.61%	3.10%
	(404)	(174)	(410)
Did not report digital expenditure	26.28%	81.39%	93.90%
	(144)	(761)	(12,830)
	100%	100%	100%

Source: Author's calculation for research

Table 4.3 shows the innovation activities, including the innovation input and output, of the manufacturing firms based on firm size. Similar to digital expenditure, large firms in the sample tend to invest in R&D activities compared to SMEs. However, the number of large firms that invested in R&D expenditure was lower than in digital expenditure, shown by weightage of 73.72% and 56.39% respectively. Meanwhile, the gap between the medium firms that were investing and those not investing in R&D expenditure was 41.6% and this gap was widened among the small firms, which was 91.68%.

Table 4.3: Innovation Activities Based on Firm Size

	Large Firm	Medium Firm	Small firm
Total number of firms	548	935	13,240
<u>Innovation Input</u>			
Have R&D expenditure	56.39%	29.20%	4.16%
	(309)	(273)	(551)
Did not have R&D expenditure	43.61%	70.80%	95.84%
	(239)	(662)	(12,689)
	100%	100%	100%
<u>Innovation Output</u>			
Have patent	51.64%	15.61%	1.44%
	(283)	(146)	(191)
Did not have patent	48.36%	84.39%	98.56%
	(265)	(789)	(13,049)
	100%	100%	100%

Source: Author's calculation for research

For the report of patent ownership, most of the large firms which spent on R&D realised their innovation output as 52% reported patent ownership. Nonetheless, the percentage of SMEs which reported patent ownership was much lower than the percentage of reporting R&D expenditure. Almost 47% of medium firms and 65% of small firms failed to turn their R&D investment into patents. This result implies that SMEs faced more obstacles in realising their innovation investment.

Table 4.4 presents the descriptive statistics of the significant variables used in this study. Among 14723 firms, the average output per worker in 2015 amounted to RM 231,328.40 while the value added per worker accounted for

29.58% of output per worker. The average R&D expenditure per worker was recorded at RM830.40 and the maximum amount invested by the sample firm was RM2,925,310. From another perspective, there was no big difference between physical capital per worker and physical capital (excluding capital in digitalisation) per worker. It implies that the accumulation of ICT capital is limited, which is also reflected by the low value of ICT capital per worker.

Table 4.4: Descriptive Statistics of Major Variables

	Mean	SD	Min	Max
Firm-level				
Value added per worker (RM'000)	68.4500	753.7781	0.00500	64837.20
Output per worker (RM'000)	231.3284	2177.55	0.2000	170246.0
Physical capital per worker (RM'000)	52.5864	404.2974	0.0000	44284.40
Physical capital (excluding capital in digitalisation) per worker (RM'000)	52.5098	404.2433	0.0000	44284.40
Digital expenditure per worker (RM'000)	0.07666	1.6515	0.0000	150.7200
R&D expenditure per worker (RM'000)	0.8304	27.6024	0.0000	2925.31
Industry level				
Intra-industry digital spillover (RM'000)	216.6614	310.0484	21.81902	4685.454
Backward digital spillover (RM'000)	113.2010	109.1098	10.54547	555.1905
Forward digital spillover (RM'000)	103.4604	251.9274	0.0000	4130.263

Source: Author's calculation for research

At the industry level, the intra-industry digital spillover recorded the highest mean value followed by backward digital spillover and forward digital spillover. The intra-industry spillover is measured by digital expenditure per worker at the firm's industry level; meanwhile the backward and forward digital spillovers are interindustry-weighted amounts of digital expenditure of all industries other than the firm's industry. The detailed information of digital spillovers among manufacturing divisions is illustrated in Table 4.5.

Among all manufacturing industries, there were six industries having increasing trends in three types of digital spillovers, namely (i) manufacture of paper and paper products; (2) manufacture of rubber and plastic products; (iii) manufacture of basic metals; (iv) manufacture of electrical equipment ; (v) manufacture of machinery and equipment N.E.C. and (vi) manufacture of other transport equipment. Most interestingly, the manufacture of furniture industry had the largest value in three types of digital spillovers, both in 2010 and 2015.

Generally, the digital spillover distribution shows that the intra-industry digital spillover scored the highest value in all industries, both in the year 2010 and 2015. It means that a firm mainly benefitted from the external knowledge created by the investment in digital expenditure spent by its competitors compared to its suppliers and customers. Meanwhile, there were a total of 13 divisions, out of 24 divisions, having larger backward digital spillover than forward digital spillover in the year 2010 and this trend was higher in 2015. It

Table 4.5: Digital Spillover Effects among Manufacturing Divisions

Division	Intra-Industry spillover			Backward spillover			Forward spillover		
	soi15	**soi10**		**sob15**	**sob10**		**sof15**	**sof10**	
Manufacture of Food Products	242.72	208.23	▲	216.82	81.54	▲	25.90	126.69	▼
Manufacture of Beverages	126.41	229.39	▼	124.12	228.74	▼	2.29	0.65	▲
Manufacture of Tobacco Products	184.26	268.97	▼	184.26	268.93	▼	0.00	0.05	▼
Manufacture of Textiles	57.48	77.19	▼	20.35	39.50	▼	37.13	37.68	▼
Manufacture of Wearing Apparel	23.15	8.29	▲	22.30	5.82	▲	0.85	2.47	▼
Manufacture of Leather and Related Products	21.82	77.47	▼	15.96	27.13	▼	5.86	50.34	▼
Manufacture of Wood and Products of Wood and Cork, except Furniture, Manufacture of Articles of Straw and Plaiting Materials	32.13	61.56	▼	12.67	13.48	▼	19.46	48.08	▼
Manufacture of Paper and Paper Products	197.84	147.68	▲	160.92	135.47	▲	36.92	12.21	▲
Printing and Reproduction of Recorded Media	152.75	188.88	▼	111.57	132.81	▼	41.18	56.07	▼
Manufacture of Furniture	4685.45	5094.79	▼	617.25	3816.83	▼	4068.21	1277.96	▲
Manufacture of Coke and Refined Petroleum Products	1002.49	964.81	▲	419.39	270.35	▲	583.10	694.45	▼
Manufacture of Chemicals and Chemical Products	95.85	296.46	▼	52.44	134.96	▼	43.41	161.50	▼
Manufacture of Rubber and Plastic Products	389.71	186.87	▲	272.15	76.63	▲	117.56	110.24	▲

Table 4.5 (Continued): Digital Spillover Effects among Manufacturing Divisions

Division	**Intra-Industry spillover**			**Backward spillover**			**Forward spillover**		
	soi15	**soi10**		**sob15**	**sob10**		**sof15**	**sof10**	
Manufacture of Basic Pharmaceutical Product and Pharmaceutical Preparations	105.13	115.17	▼	69.19	57.45	▲	35.95	57.72	▼
Manufacture of Other Non-Metallic Mineral Products	125.15	285.59	▼	49.67	96.87	▼	75.48	188.72	▼
Manufacture of Basic Metals	260.74	124.98	▲	89.08	37.49	▲	171.66	87.50	▲
Manufacture of Fabricated Metal Products, except Machinery and Equipment	875.37	2674.45	▼	576.70	1426.99	▼	298.66	1247.46	▼
Manufacture of Computer, Electronic and Optical Products	116.46	231.19	▼	95.47	212.74	▼	20.98	18.45	▲
Manufacture of Electrical Equipment	295.39	195.61	▲	203.13	164.21	▲	92.25	31.40	▲
Manufacture of Machinery and Equipment N.E.C.	888.12	317.89	▲	430.17	303.68	▲	457.95	14.22	▲
Manufacture of Motor Vehicles, Trailers and Semi-Trailers	268.15	127.73	▲	268.15	122.16	▲	0.00	5.57	▼
Manufacture of Other Transport Equipment	47.39	23.67	▲	41.57	20.74	▲	7.78	2.92	▲
Other Manufacturing	114.69	120.28	▼	83.86	39.26	▲	35.04	81.02	▼
Repair and Installation of Machinery and Equipment	72.52	36.74	▲	14.28	15.76	▼	61.98	20.98	▲

Source: Author’s calculation for research indicates that the digital spillover effect brought by the firm's intermediate suppliers was getting more relevant to the firm. This phenomenon is consistent with Mun and Nadiri (2002) who studied the digital spillover effect in the US.

4.3 Empirical Analysis

For the empirical analysis, the CDM model developed by Crépon et al. (1998) is applied to examine the relationships among firm characteristics, innovation, digital spillovers and productivity in the Malaysian manufacturing sector. By referring to Xu and Cooper (2017) who first introduced the term "digital spillover", the variable of digital spillovers in this study is proxy by the spillovers of ICT expenditure. The data analyses of the CDM model are illustrated in the respective sections below.

4.3.1 Innovation Input Function

The estimation of the CDM model starts with the prediction of innovation input functions, which consist of (i) the R&D selection equation （Equation 3.8） and (ii) the R&D response equation (Equation 3.13). The R&D selection equation is used to estimate the probability of a firm to invest firm to invest in R&D expenditure meanwhile the response equation is used to estimate the level of R&D expenditure invested by the firm. As mentioned in Chapter 3, the innovation input functions are estimated by Heckman's (1979) selection model to overcome the concern of selectivity bias, as proposed by Thornhill (2006) and Fonseca et al. (2019).

Before the estimation of the Heckman Selection Model, it is vital to check the correlation between R&D expenditure and digital expenditure to avoid the multicollinearity issue. Digital expenditure is proxied by ICT expenditure spent by a firm. As mentioned in Chapter 3, the OECD (2018) said that the ICT expenditure used for R&D activities is included in the R&D expenditure. However, based on the definition given by DOSM, it is not clear whether the ICT expenditure related to the R&D activities is counted in the R&D expenditure[7]. If the correlation between ICT expenditure and R&D expenditure is low, excluding ICT expenditure would create another econometric issue, i.e., a variable omission problem. Based on the result in Table 4.6, shows that there is a low correlation between R&D expenditure and digital expenditure. Thus, digital expenditure is included in the estimation of the innovation input equation.

Table 4.6: Correlation between R&D Expenditure and Digital Expenditure

	R&D expenditure	**Digital expenditure**
R&D expenditure	1	0.14756
Digital expenditure	0.14756	1

[7] Based on the definition of DOSM, the R&D expenditure is defined as the expenses incurred in the R&D activities that carried out both inside in the firm as well as the outsources to external parties (DOSM,2017). Meanwhile, ICT expenditure is defined as the expenditure incurred on the usages of computers, internet and web presence (DOSM, 2017).

The result of the Heckman Selection Model is illustrated in Table 4.7. The p-value of rho is 0.0000 (significant at 1%), proving the appropriateness of applying the Heckman Selection Model to the estimation of innovation input functions to deal with the selectivity problem. In other words, the firms which do not report R&D expenditure should not be excluded in the data analysis, or else the result of the response equation is misleading (Garcia-Pozo et al, 2018).

Table 4.7: Estimation Result of Innovation Input Equation

	(1)-Original		(2)-Adjusted		
	Selection Equation (Eq 3.4)	Response Equation (Eq 3.4)	Selection Equation		Response Equation
	Coefficient (z-statistic)	Coefficient (t-statistic)	Coefficient (z-statistic)	Marginal Effect	Coefficient (t-statistic)
DBIG	0.5562***		0.5577***	0.68%	
DMED	0.2978***		0.2981***	0.49%	
DIND	0.2869***	0.9084***	0.2781***	1.65%	0.8877***
LOG (EX)	0.0499***	0.0867***	0.0498***	0.54%	0.0861***
LOG(RMS)	0.2001***	0.6304***	0.1988***	1.96%	0.6285***
LOG(IT)	0.08132***	0.1950***	0.08195***	0.90%	0.1965***
LOG(SOI15)	0.3380***	0.8467**	0.2346***	2.14%	0.5893**
LOG(SOB15)	-0.0702	-0.1767	-	-	-
LOG(SOF15)	-0.1295***	-0.2239**	-0.0979***	-0.86%	-0.1454**
c	-1.0044***	-2.755***	-0.9232***	-9.37%	-2.5497***
rho	0.8906***		0.8904***		

*The denotation of ***/**/* represents the 1%, 5% and 10% significance level respectively.*

The result of the Heckman Selection Model is significant because there were 13590 out of 14723 firms, and almost 92.3% of the firms in the sample did not report any R&D expenditure. Although these firms did not report any R&D expenditure in the year 2015, it does not mean that these firms were not involved in any innovation activities before 2015 or plan to be involved in any innovation activities after 2015. In addition, Shafi'I and Ismail (2015) mentioned that not all Malaysian manufacturing firms that carry out innovation activities have formally reported their involvement in R&D.

By looking at the results of the selection equation (Equation 3.8), all variables are significant at 1%, except the backward digital spillover (SOB15). Similar results are obtained on the response equation (Equation 3.13), but the digital spillovers (both horizontal and forward) are significant at 5% instead. When the SOB15 is excluded, the significance of the variables is the same as in the panel 1. Thus, the selection and response equations are modified as follows and reported in panel 2.

Modified R&D selection equation:

$$r^*_{ij} = \alpha_1 + \alpha_2 dbig_{ij} + \alpha_3 dmed_{ij} + \alpha_4 dind_{ij} + \alpha_5 log(ex_{ij}) + \alpha_6 log(rms_i) + \alpha_7 log(it_{ij}) + \alpha_8 log(soi_{ij}) + \alpha_9 log(sof_{ij}) + \upsilon_{ij} \quad \text{(Equation 4.1)}$$

Modified R&D response equation:

$$log(rd_{ij}) = \beta_1 + + \beta_2 dind_{ij} + \beta_3 log(ex_{ij}) + \beta_4 log(rms_i) + \beta_5 log(it_{ij}) + \beta_6 \, log(soi_{ij}) + \beta_7 \, log(sof_{ij}) + \mathcal{E}_{ij} \quad \text{(Equation 4.2)}$$

Overall, almost all variables on the modified equations have positive signs, i.e., they have a positive impact on the intention of a firm to invest in R&D expenditure as well as the intensity of the R&D expenditure. However, the forward digital spillover shows the opposite result, which has a negative impact on the innovation input.

In order to interpret the coefficient of the selection equation, the marginal effect needs to be calculated because the interpretation of the Z-statistic produced by the Probit model is meaningless (Gujarati, 2021). Before calculating the marginal effect, the prediction power of the Probit model needs to be evaluated. Based on the result in Table 4.8, it shows that the estimated selection equation has correctly predicted 93.27% of the observations. The model prediction power is accepted and could proceed with the marginal effect calculation.

Table 4.8: Expectation-Prediction Evaluation for Selection Equation

Expectation-Prediction Evaluation for Binary Specification
Equation: PROBIT
Date: 10/21/22 Time: 13:21
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	13334	840	14174	13477	1122	14599
P(Dep=1)>C	143	282	425	0	0	0
Total	13477	1122	14599	13477	1122	14599
Correct	13334	282	13616	13477	0	13477
% Correct	98.94	25.13	**93.27**	100.00	0.00	92.31
% Incorrect	1.06	74.87	6.73	0.00	100.00	7.69
Total Gain*	-1.06	25.13	0.95			
Percent Gain**	NA	25.13	12.39			

Impact of firm characteristics

The results of the selection equation model show that the probability of a large firm investing in R&D expenditure increases by 0.68%, on average, holding other factors constant. Nonetheless, the probability is lowered to 0.49%

if the firm is medium-sized. This result is consistent with Giotopoulos et al. (2023), Ma et al. (2022), Ong et al.(2019) and Ouyang et al. (2022), who found that the firm size positively affects the decision to carry out R&D investment. These researchers argued that large firms have higher accessibility to finance and innovation resources, thus they have a high intention to invest in R&D expenditure. In addition, they are more likely to absorb the irrecoverable sunk cost, compared to less advantageous firms. Furthermore, this result ties in with the conditions in the Malaysian manufacturing sector. As mentioned by the Ministry of International Trade and Industry (2018), large manufacturing firms find it relatively easy to recruit high-performing talents and obtain sufficient funding to conduct innovation activities. Thus, they have a higher intention to invest in R&D investment.

The industry group carries the second highest influential power in affecting the probability of a firm in R&D investment. The result shows that the firms which belong to the highly productive industry groups, i.e., the industry groups which recorded a gross output of RM10 billion and above (DOSM,2017), their probability of investing in R&D expenditure is higher by 1.65%. At the same time, the R&D expenditure invested by these firms is 88.77% higher than the firms in low-productive industries. Shafi'I and Ismail (2015) who studied the innovation activities in the Malaysian manufacturing sector obtained the same result. The high productive industries are normally associated with higher technological requirements, thus higher R&D investment is needed for the firms which belong to these industries to keep them up to par on the level of technological advancement (Audretsch & Belitski, 2020; Mariev et al.,2022).

From another perspective, the results of innovation input equations have also fulfilled Schumpeter's Theory of Innovation (Schumpeter,1934; 1939). It can be viewed from the point of market share and exporting activities. Schumpeter's Theory of Innovation advocates that a firm with a high market share tends to carry out innovation to keep its competitiveness and thus sustain its market power and position (Jitsutthiphakorn, 2021; Montégu et al., 2022). A similar reason applied to the exporter, as revealed by Jitsutthiphakorn (2021), Fedyunina and Radosevic (2022), and Younas and ul-Husnain (2022). For the firms with high market share, the intention for them to invest in R&D is 1.96% higher and their R&D investment would increase by 0.6285% if their market share increases by 1%. Meanwhile, the probability of an exporter investing in R&D expenditure is 0.54% higher and its R&D expenditure would increase by 0.0861% when its export volume increases by 1%, on average.

Impact of internal and external digital spillovers

Based on the estimation results, the firm digital expenditure increases the probability of a firm carrying out R&D expenditure by 0.90% and the R&D expenditure would increase by 0.1965% when the firm spends an additional 1%

of digital expenditure. This phenomenon confirms the existence of internal digital spillover.

OCED (2018) has stressed the importance of digitalisation in strengthening information transmission within a firm and this information flow is vital in affecting a firm's decision to carry out innovation activities. In addition, Xu and Cooper (2017) mentioned that the digital application used in a company helps the action of information sharing among employees, especially for firms that have subsidiaries in different locations and countries. These companies tend to have their own intranet collaborative platform for the staff to have discussions and brainstorming which encourages innovation inputs and R&D activities.

Among the three types of external digital spillover effects, horizontal digital spillover has the highest influential power in affecting the intention of a firm in carrying out R&D expenditure as well as the intensity of R&D expenditure. The horizontal digital spillover would increase the probability of a firm carrying out R&D expenditure by 2.14% and the R&D expenditure would increase by 0.59% proportionally.

This positive impact of intra-industry digital spillover reflects that if a firm in the industry invests in R&D activities, this action is likely to be emulated by the competitors when the R&D-related information of the first company is transmitted to the competitors through digital platforms or channels. (Xu & Cooper, 2017). This imitative behaviour is even stronger when the first firm demonstrated the effectiveness of innovation in reducing cost and sustaining profit. This result further supports the significance of the industry group as the second-highest influential power in stimulating both intention and intensity of R&D investment.

Interestingly, only the forward digital spillover is found to be significant for the vertical digital spillovers, but the impact is in the negative direction. The forward digital spillover would decrease the probability of a firm carrying out R&D expenditure by 0.86% and the R&D expenditure would decrease by 0.15% proportionally. This result contradicts past studies because past researchers revealed that the forward digital spillover helps in promoting innovation activities. This is because the firms could understand the customers' demands better when they receive more information from the customers (Hioki & Ding, 2023; Karhade & Dong, 2021; Niebel et al., 2019, Vo et al., 2023). The information from the customers could help them to save the innovation investment and increase the possibility of realising the innovation output.

The possible explanation for the negative relationship between forward digital spillover and innovation investment is the competition effect. When manufacturing firms are able to receive messages from their customers quickly, these firms tend to carry out innovation activities to meet their customers' demands because the chance of failure is reduced. However, this phenomenon creates competition for the resources, such as machinery, talent and technology in the market and ultimately pushes up the price of these resources (Yang & Wang, 2022). Subsequently, the high cost of acquiring resources discourages the firms from carrying out innovation activities.

The National Survey of Innovation of 2015 and 2018 conducted by the Ministry of Science, Technology and Innovation (MOSTI) and the Malaysian Science and Technology Information Centre (MASTIC) supported this argument as they found that cost factor is the main factor that discourages innovation activities in the Malaysian manufacturing sector (MOSTI & MASTIC, 2015, 2020). In addition, Tay et al. (2021) who did interview research on Malaysian manufacturing firms have mentioned that the issue of capital adequacy remains an obstacle that drives Malaysian manufacturing firms to embrace Industry 4.0, especially to those SMEs. The pecuniary capital involved in innovation is not only limited to creating and improving goods and services, but money needs to be spent on human resources and organisational transformation.

Furthermore, the National Survey of Innovation also explained another perspective that relates to the high cost of innovation (MOSTI & MASTIC, 2015). When there are changes in consumer demand, SMEs tend to acquire products from large firms or even foreign firms because their purchasing price is much lower than the benefit bought by innovation. If the SMEs conduct innovation activities, they are unable to achieve economies of scale as the large firms, their selling price would be much higher than the large firms in the end. This reason has further demotivated their intention to carry out innovation activities.

Lastly, the possible reason that the forward digital spillover reduces the R&D investment is that the manufacturing firms do not have the urge for innovation activities. The manufacturing firms have also expressed their perceived risk in the innovation activities in the National Survey of Innovation because some of the innovation is easily imitated by competitors (MOSTI & MASTIC, 2015). As a result, manufacturing firms, especially SMEs, tend to take up the role of middleman to look for other suppliers who can provide products that meet customers' needs instead of being innovators.

In addition, when manufacturing firms get more information from the customer via the ICT platform, they can directly modify goods and services according to the consumers' demand. As a result, the manufacturing firms do not need to invest additional funds in research and development activities to create new products that could attract consumers. This reason is also revealed by MOSTI and MASTIC (2015, 2020) when they studied the reasons that hamper the innovation activities in the Malaysian manufacturing sector.

4.3.2 Innovation Output Function

In the second stage of the CDM model, the estimation of the innovation output equation is carried out. The base innovation output equation (Equation 3.7) is first estimated, followed by the extended equation (Equation 3.8) which includes the interaction term between highly skilled labourers and digital spillovers. The interaction term is added to examine the absorptive capacity of the manufacturing firms in learning and utilising the external knowledge transmitted by different parties via digital platforms, and then transform this external knowledge in realising the innovation output, i.e., patent issuance in this study. Finally, a best-fitted innovation output function (Equation 4.3) is derived based on the outcome of Equations 3.3 and 3.4. The dependent variables of these equations are binary variables in which the value of 1 denotes the existence of a patent reported by the firm.

The result of the base innovation output equation (Equation 3.7) is presented in Table 4.9. Panel 1 shows that the binary variable of the medium firm (dmed) and the number of high-skilled labour are insignificant in realising the innovation output. Meanwhile, the export volume and forward digital spillovers are found to be significantly affecting patent issuance at 10% and 5% significance levels respectively. All other variables score a significance level of 1% in affecting the issuance of patents. After removing the insignificant variables, the significance level of export volume is improved while the sign and size of other coefficients are consistent.

Table 4.9: Estimation Result of Baseline Innovation Output Equation

	Baseline Equation (Equation 3.7)	
	(1) Before Adjustment	**(2) After Adjustment**
	Coefficient (z-statistic)	Coefficient (z-statistic)
LOG(RDF)	0.1578***	0.1561***
DBIG	0.7774***	0.7206***
DMED	0.1420	-
LOG(EX)	0.0171*	0.0216**
DIND	0.4384***	0.4961***
LOG(RMS)	0.2819***	0.3169***
LOG(LHS)	0.0555	-
LOG(IT)	0.1393***	0.1462***
LOG(SOI15)	0.8122***	0.8440***
LOG(SOB15)	-0.3448***	-0.3598***
LOG(SOF15)	-0.2771**	-0.2856**
c	-1.4035	-1.1069

*The denotation of ***/**/* represents the 1%, 5% and 10% significance level respectively.*

Then, the extended innovation output equation (Equation 3.8) is estimated to examine the effect of the absorptive capacity of a firm in grasping the digital spillover effects. In the extended innovation output equation, the variable of high-skilled labour is taken out. All digital spillover effects are replaced with the interaction term between high-skilled labourers and digital spillovers. The results are shown in Table 4.10. Similar to Equation 3.7, the binary variable of medium-sized firms is found to be insignificant in affecting patent issuance. Interestingly, the export volume and forward digital spillover effects that carry a significance level of 5% in Equation 3.7 have turned out to be insignificant in Equation 3.8.

Table 4.10: Estimation Result of Extended Innovation Output Equation

	Extended Equation (Equation 3.8)	
	(1) Before Adjustment	**(2) After Adjustment**
	Coefficient (z-statistic)	Coefficient (z-statistic)
LOG(RDF)	0.1325***	0.1291***
DBIG	0.7053***	0.6132***
DMED	0.1293	-
LOG(EX)	0.0097	-
DIND	0.3347***	0.3644***
LOG(RMS)	0.2244***	0.2421***
LOG(IT)*LOG(LHS)	0.0414***	0.0424***
LOG(SOI15)*LOG(LHS)	-0.1292**	-0.1229***
LOG(SOB15)*LOG(LHS)	0.1721***	0.1715***
LOG(SOF15)*LOG(LHS)	0.0029	-
c	-0.3835	-0.2228

*The denotation of ***/**/* represents the 1%, 5% and 10% significance level respectively.*

Based on the result of Equation 3.7 and Equation 3.8, the “best-fitted” line of innovation output (Equation 4.3) is derived. The binary value of the medium-sized firm, export volume and number of high-skilled labour are excluded from the modified equation. Meanwhile, the forward digital spillover effect has remained in the equation without any interaction terms. Since the internal, horizontal and backward digital spillovers showed significant impact in both baseline and extended equations, a few rounds of trial and error are conducted to find the “best combination” of these variables. Finally, the modified innovation output equation is derived as follows:

Modified innovation output equation:

$$p_{ij} = \chi_1 + \chi_2 log(\mathrm{rd}^*_{ij}) + \chi_3\, dbig_{ij} + \chi_4\, dind_{ij} + \chi_5\, log(rms)_{ij} + \chi_6\, log(it_{ij}) + \chi_7\, log(soi_{ij}) + \chi_8 log(sob_{ij})*log(lhs_{ij}) + \chi_9 log(sof_{ij}) + e_{ij} \text{ ----------(Equation 4.3)}$$

All variables in the modified equation carry a 1% significance level in realising the patent issuance, as exhibited in Table 4.11. Similar to the practice in the innovation input equation, the marginal effects of the coefficients in the innovation output equation are calculated because Gujarati (2021) explained that the interpretation of the Z-statistic is meaningless.

Before the calculation of the marginal effect, the prediction power of the innovation output equation has to be first evaluated using the expectation-prediction evaluation provided in Eviews. Based on the result in Table 4.12, shows that the estimated selection equation has correctly predicted 96.54% of the observations. The model prediction power is accepted and could proceed to the marginal effect calculation.

Table 4.11: Estimation Result of Modified Innovation Output Equation

	Modified Equation	
	Coefficient (z-statistic)	**Marginal Effect**
LOG(RDF)	0.1490***	0.69%
DBIG	0.6236***	0.50%
DIND	0.4153***	1.02%
LOG(RMS)	0.2750***	1.27%
LOG(IT)	0.1401***	0.65%
LOG(SOI15)	0.3261***	1.50%
LOG(SOB15)*LOG(LHS)	0.0302***	0.14%
LOG(SOF15)	-0.2088***	-0.96%
C	-0.8057***	-3.72%

*The denotation of ***/**/* represents the 1%, 5% and 10% significance level respectively.*

Impact of firm characteristics

The estimation outcomes in Table 4.11 have validated the existence of Schumpeter's Theory of Innovation in the Malaysian manufacturing sector because the market share owned by a firm is the most influential factor in realising the innovation output. When there is a 1% increase in the market share of a manufacturing firm, the probability of the firm issuing a patent would increase by 1.27%.

Table 4.12: Expectation-Prediction Evaluation for Innovation Output Equation

Expectation-Prediction Evaluation for Binary Specification
Equation: BEST1
Date: 09/27/23 Time: 15:40
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	13041	270	13311	13078	469	13547
P(Dep=1)>C	37	199	236	0	0	0
Total	13078	469	13547	13078	469	13547
Correct	13041	199	13240	13078	0	13078
% Correct	99.72	42.43	97.73	100.00	0.00	**96.54**
% Incorrect	0.28	57.57	2.27	0.00	100.00	3.46
Total Gain*	-0.28	42.43	1.20			
Percent Gain**	NA	42.43	34.54			

Schumpeter's Theory of Innovation and the arguments made by Aghion et al. (1998) and Grossman and Helpman (1994) advocated that a firm with a high market share tends to issue a patent to grant the firm a certain level of monopoly power, as well as the firm competitiveness and market power. This result is also in line with Ong et al. (2019) and Lee (2004) who studied Malaysian manufacturing firms. They both discovered that firms under highly competitive market structures are likely to conduct innovation activities to secure their market position. Likewise, Ugur (2024) who studied the case of OECD countries confirmed that there is a positive bidirectional relationship between market power and innovation.

The second most influential factor in issuing a patent is the industry group that the manufacturing firm belongs to. If a firm belongs to a high-productive industry, the tendency for the firm to issue a patent is 1.02% higher as compared to those which stay in the low-productive industries. This is because high-productive industries are usually abundant with resources and talents which allow them to carry out innovation activities. Similar conclusions have been reached by Ong et al. (2019) and Na and Kang (2019). In addition, Mariev et al.(2022) also mentioned that the R&D investment carried by the large firms located in these industries is the highest, in turn, motivates them to conduct even more innovation activities.

Thirdly, the forecasted R&D expenditure derived from equation 4.2 has imposed its significant power in realising the patent issuance as expected because the R&D expenditure is the direct input for the innovation activities. The result exhibits that if there is a 1% increase in the R&D expenditure, the probability that a firm will own a patent would increase by 0.69%. This result is justifiable because the R&D expenditure is the innovation input, which is the significant funding for a firm to carry out the innovation activities and realise the output. Undeniably, this result is consistent with past research, such as

Audretsch and Belitski (2020), Jitsutthiphakorn (2021), Giotopoulos et al.,2023, Younas & ul-Husnain, 2022 and Zhu et al. (2021).

Lastly, the result shows that if the manufacturing firm is considered a large firm, the probability of the firm issuing a patent is 0.69% higher. This result is related to the first two influential factors mentioned above because a large firm is usually the firm that is able to fund and invest in R&D expenditure as well as the firm that holds a high market share. Similar results have been discovered by Ong et al. (2019) and Shafi'I and Ismail (2015) in Malaysia, Giotopoulos et al. (2023) in Greece and Zhu et al. (2021) in China.

Impact of internal and external digital spillovers

The impact of the digital spillover effects on the innovation output equation is similar to innovation input equations. All variables are found to be significant at 1% except for the backward digital spillover effect. The backward digital spillover only shows its significance when the interaction term associated with the absorptive capacity is added to the equation.

The digital expenditure is the proxy of the internal digital spillover. The result shows that the probability of realising a patent increases by 0.65% when there is a 1% increase in the digital expenditure spent within the firm. The increase in digital expenditure boosts digitalisation in a firm, which speeds up information sharing within the firm and encourages idea formation. This reaction chain helps actualise patent issuance (Karhade & Dong, 2021; Khalifa, 2023; Zhu et al., 2021).

The horizontal digital spillover is the most influential spillover channel in increasing the chances of patent issuance. The probability of a firm issuing a patent could increase by 1.50% when the firm is able to enjoy the external knowledge shared by its competitors via any digital platform. This result is consistent with Paunov and Rollo (2016) and Conley and Udry (2010). Paunov and Rollo (2016) revealed that the Internet has reduced the cost of disseminating knowledge and allows firms in the same industry to share new technology. This could reduce the uncertainty and possible error during the innovation process and thus increase the possibility of realising the innovation output. In addition, Yang and Wang (2022) mentioned that the innovation information flow within the industry via digital channels helps form an effective innovation system that benefits the firms in the same industry when conducting innovation activities.

Similar to the result of the innovation input functions, the forward digital spillover is found to have a negative impact on the innovation output, which is opposite to the finding of Gong and Wang (2022) and Vo et al. (2023). The probability of a firm issuing a patent could decrease by 0.96% when the firms absorb more external knowledge transmitted from the downstream firms via digital platforms. The decrease in the probability of issuing a patent means (i) reducing the success rate of realising the innovation output and (ii) lowering the intention of possessing a patent.

The forward digital spillover causes a decrease in the success rate of realising the patent issuance because this spillover channel has also reduced the innovation input, as shown in the first stage of the CDM model. When there is a reduction in the investment in R&D, it decreases funding for innovation activities. Thus, the process of patent issuance might be ceased halfway or discontinued totally.

From another perspective, Tay et al. (2021) mentioned that the failure to realise innovation output comes with the challenges of managing and integrating the data from the consumers. Through interviews with some Malaysian manufacturing firms, Tay et al. (2021) discovered that Malaysian manufacturing firm has difficulty managing and analysing large volumes of data collected internally and externally. When the firms spend sufficient time analysing the data and try to integrate the data into the production process or innovation activities, the data collected might be outdated and not fit the consumers' demand anymore. As a result, the high-volume information that flew from the downstream firms was not able to help in realising the innovation output because the speed of integrating the data was not faster than the changes required in the application of Industry 4.0.

Another possible reason that caused this negative relationship lies in the competition effect as happens on the stage of innovation input. Yang and Wang (2022) and Spencer (2008) explained that when more firms decide to carry out innovation activities, it could form intense competition for the resources needed for the innovation in the market and thus push up the price of the resources and cost of production. This scenario makes it hard for leading innovative firms to earn the required innovation profits. As a result, some firms would decrease their investment intensity or the reinvestment amount while some firms would discontinue R&D activities. These two consequences definitely lower the probability of realising the patent issuance.

The backward digital spillover effect is found to be significant in affecting the dependent variable, where the probability of patent issuance increases by 0.14% when there is absorptive capacity in benefitting the digital externalities generated by the suppliers. The result shows that a manufacturing firm needs high-skilled labourers to assimilate and transform the knowledge shared by suppliers into innovation output, as verified by Li et al. (2023), Marsh et al. (2017), and Sun et al. (2020). The recent research done by Vo et al. (2023) also proved that an MNC firm which has a better understanding of its local suppliers has a higher chance of actualizing the innovation in the destination country.

With sufficient absorptive capacity and compatible intellectual ability, the labourers are able to benefit from ICT-enabled knowledge access and respond quickly to the structural changes in the production process, especially the transformation in the process of automation and digitalisation. Thus, Tay et al. (2021) mentioned that it is vital for Malaysian manufacturing firms to ensure that their human capital is able to keep up with the breakneck-paced development in Industry 4.0 to maintain their firm competitiveness.

4.3.3 Production Function

The last stage of the CDM model caters for the estimation of the production function. The production function is formed on the Cobb-Douglas general form and modified based on the augmented Schumpeterian endogenous growth model proposed by Udeogu et al. (2021). In order to examine the impact of innovation and digital spillovers on firm productivity, these variables are included in the baseline estimation (Equation 3.13) together with the capital intensity and ratio of high-skilled labour of the firm. Then, the baseline equation is extended by including the interaction term between high-skilled labourers and digital spillovers to capture the impact of the absorptive capacity in assimilating the external knowledge.

The productivity function (Equation 3.13) is first estimated using the OLS estimator and the result is shown on the first panel in Table 4.13. However, the model is found to suffer from the heteroskedasticity problem and the result of the estimation is invalid. As suggested by White (1980) and Wooldridge (2001), the OLS equation which is diagnosed with heteroskedasticity can be adjusted with the Huber-White covariance method to obtain a valid estimation result. The same approach has been applied by Kleis et al. (2012) and Véganzonès-Varoudakis and Plane (2019) in their studies. In addition, the sample of this study is considered a large sample as it consists of 14,723 cross-sectional data. Gujarati (2021) mentioned that the OLS estimator is asymptotically unbiased. In other words, the estimates generated by the OLS estimator will be more precise when the sample size is getting larger. This is because the standard error of the coefficient is smaller and the sample estimates will converge to the true population parameter.

The result of the adjusted OLS estimation is presented on the second panel in Table 4.13. The p-value of the conventional F-statistics and Wald F-statistics for the adjusted OLS estimation statistics is less than 0.01, indicating that all coefficients are jointly statistically significant. By comparing the pre-adjusted (panel 1) and post-adjusted (panel 2) OLS estimation, the significance and coefficient of the variables yield the same result, i.e., all variables are found to be important at a 1% significance level.

The same procedure is then applied to the extended productivity equation (Equation 3.14) and the results are presented in Table 4.14. Equation

3.14 also suffers from the problem of heteroskedasticity and the estimator is adjusted with the Huber-White covariance method. All variables have shown significance at a 99% confidence interval except for the horizontal digital spillover effect.

Table 4.13: Estimation Result of Baseline Production Equation

	Baseline Production Function (Equation 3.13)	
	OLS estimator	Adjusted with Huber-White covariance method
	(1) Coefficient	**(2)** Coefficient
LOG(DPT)	0.3609***	0.36092***
LOG(K)	0.3510***	0.35098***
LOG(LHSW)	0.0105***	0.01046***
LOG(ITW)	-0.0186***	-0.0186***
LOG(SOI15)	0.4377***	0.43773***
LOG(SOB15)	-0.5042***	-0.5042***
LOG(SOF15)	0.0654***	0.06538***
c	3.1971***	3.19714***
R-Squared	0.56994	0.56994
F-statistic	2563.22	-
Prob (F-statistic)	0.0000	-
Wald F-statistics	-	1851.650
Prob (Wald F-statistics)	-	0.0000

*The denotation of ***/**/* represents the 1%, 5% and 10% significance level respectively.*

In order to derive the “best-fitted” productivity function (Equation 4.4), Equation 3.13 and 3.6 are integrated. It is obvious that the forecasted probability of patent issuance derived from Equation 4.3, capital per worker, the ratio of high-skilled labour to firm labour and the horizontal digital spillover effect are included in the modified equation. However, the internal, backwards and forward digital spillover effects show their significance both with and without the interaction term of absorptive capacity. Thus, different combinations of these variables are tried, as shown in Table 4.15. The last combination with the highest R-squared is selected as the modified production equation.

Modified production function:

$logy_{ij} = \eta_1 + \eta_2\ dpt_{ij}{*} + \eta_3\ log(k_{ij}) + \eta_4 log(rlhs_{ij}) + \eta_5(log(lhs_{ij})\ {*}log(it_{ij})) + \eta_6 log(soi_{ij}) + \eta_7 log(sob_{ij}) + \eta_8(log(lhs_{ij}){*}log(sof_{ij})) + \omega_{it.}$-----(Equation 4.4)

Table 4.14: Estimation Result of Extended Productivity Equation

	Extended Production Function (Equation 3.14)	
	OLS estimator	Adjusted with Huber-White covariance method
	(1) Coefficient	**(2)** Coefficient
LOG(DPT)	0.44843***	0.44843***
LOG(K)	0.42524***	0.42524***
LOG(LHSW)	0.08414***	0.08414***
LOG(ITW) * LOG(LHS)	0.01705***	0.01705***
LOG(SOI15) * LOG(LHS)	-0.0318	-0.0318
LOG(SOB15) * LOG(LHS)	-0.1044***	-0.1044***
LOG(SOF15) * LOG(LHS)	0.11265***	0.11265***
c	4.09199***	4.09199***
R-Squared	0.52973	0.52973
F-statistic	2178.675	-
Prob (F-statistic)	0.0000	-
Wald F-statistics	-	1482.104
Prob (Wald F-statistics)	-	0.0000

*The denotation of ***/**/* represents the 1%, 5% and 10% significance level respectively.*

Table 4.15: Selection of “Best-fitted” Production Function

	Modified Production Function (OLS estimator adjusted with Huber-White covariance method)						
Other four variables	✓	✓	✓	✓	✓	✓	✓
LOG(ITW) * LOG(LHS)	✓	✓	✓	✗	✗	✗	✓
LOG(SOB) * LOG(LHS)	✗	✓	✓	✓	✓	✗	✗
LOG(SOF) * LOG(LHS)	✗	✗	✓	✗	✓	✓	✓
R-squared	0.5941	0.5850	0.5345	0.5770	0.5320	0.5915	0.6013

Note: ✓ means the variable is included in the equation while ✗ shows the opposite.

Table 4.16 presents the estimation outcome of the modified productivity function. The patient issuance is found to have a positive impact on labour productivity, as expected. The labour productivity of a firm which owns a patent is 46.95% higher than those firms which do not issue any patent. This result is consistent with the idea of Hall (2011) who mentioned that the innovation output could create sustainable competitive advantages for a company that enables the improvement of firm productivity. In addition, a similar result has been found in ASEAN countries (Zhang & Islam, 2022) and other individual developing countries such as China (Dai & Sun, 2021), Columbia (Ramírez et al., 2020) and Greece (Giotopoulos et al., 2023).

Table 4.16: Estimation Result of Modified Productivity Equation

	Modified Production Function (Equation 4.4)
	Adjusted with Huber-White covariance method
	Coefficient
LOG(DPT)	0.4695***
LOG(K)	0.3759***
LOG(RLHS)	0.0530***
LOG(ITW) * LOG(LHS)	0.0262***
LOG(SOI15)	0.7194***
LOG(SOB15)	-0.7021***
LOG(SOF15) * LOG(LHS)	-0.0344***
c	3.8572***
R-Squared	0.6013
Wald F-statistics	2162.068
Prob (Wald F-statistics)	0.0000

*The denotation of ***/**/* represents the 1%, 5% and 10% significance level respectively.*

By looking at the conventional factors of production, the results of capital and labour elasticities that are measured in the “per-worker” form are also consistent with past studies, for instance, Dai and Sun (2021), Howell (2020) and Zhu et al,(2021). The labour productivity could be increased by 0.3759% when there is a 1% increase in capital intensity. Meanwhile, labour productivity can go up by 0.0530% when there is a 1% increase in the proportion of high-skilled labour.

Impact of internal and external digital spillover

The result shows that the horizontal and backward digital spillover effects are significant in affecting labour productivity, but one in a positive way and another in an opposite way. Meanwhile, the internal and forward digital spillover effects need the inclusion of absorptive capacity to show its significance on labour productivity.

The data analysis indicates that labour productivity could increase by 0.0262% when there is a 1% increase in the internal digital spillover effect associated with the absorptive capacity. This finding opposed the "Solow Paradox" and proves that the internal digital spillover takes effect in improving labour production. This result is consistent with the finding of Gal et al. (2019) who mentioned the importance of digital adoption in improving the productivity of firms with heavily routine activities, such as manufacturing firms. Moreover, similar findings have been detected in Malaysia, as revealed by Yap et al. (2020) and Liew et al. (2012).

In terms of the horizontal spillover effect, the result shows that labour productivity could increase by 0.7194% when there is a 1% increase in the intra-industry spillover. This finding is consistent with Paunov and Rollo (2016), Todorava and Durisin (2007) and Black and Lynch (2001) who have stressed the importance of absorptive capacity in grasping the digital spillover. This scenario is explainable as high-skilled labourers are needed to unlock the tacit knowledge transmitted by the firm's competitors. Even though there is information sharing via digital platforms, firm's competitors tend to keep a certain level of confidentiality to preserve their competitiveness in the market. As a result, the staff of the firm needs to possess specialised skills and relevant experience to absorb the external knowledge provided by their competitors.

Nonetheless, the positive impact of internal and horizontal digital spillover effects is offset by the negative impact of backward and forward digital spillover effects. The labour productivity decreased by 0.7021% when there was a 1% increase in the backward spillover effects. In other words, the manufacturing firms in Malaysia could not benefit from the external knowledge transferred by their suppliers through digital channels.

Paunov and Rollo (2016) have explained this scenario based on the idea of "knowledge network". They explained that a manufacturing firm could get knowledge and information from online and offline networks, and the communication between firms and suppliers might rely more on offline networks. This is because the manufacturing firm in Malaysia might directly communicate with their suppliers if they need any clarification or assistance on the supplied product and service instead of looking for solutions from publicly available sources, i.e., the online network. Thus, the backward digital spillover exerts a negative effect on labour productivity.

Aside from the "knowledge network" explanation, Marsh et al. (2017) enlightened that the information flow from the upstream industries might set up a barrier for the manufacturing firm to utilise this external knowledge in business operation and production. For instance, even though the supplier has provided the manual of a machine or technology online, the staff of the firms still need to have the pre-requisite knowledge to understand the underlying concept and mechanism before applying the machine or technology. In other words, there might be a technology or knowledge gap between the manufacturing firms and their suppliers. In addition, if the integration of external knowledge transmitted by the suppliers requests more adjustments and a substantial pecuniary amount, it would also slow down the integration process and negatively affect the firm productivity.

Another possible explanation of the negative relationship between backward digital spillover and labour productivity is inspired by Dai and Sun (2021) and Ping et al. (2018) who stress the idea of resource adjustment and resource reallocation. These authors justified that, even though the firm is able to absorb the external knowledge transferred from the suppliers via the digital platforms, it needs time and effort to make adjustments for utilising and integrating the knowledge in the production process. For instance, when a portion of high-skilled labourers who were initially assigned for the production process have been reassigned to study these knowledge externalities might cause insufficient human resources to reach the optimal production point and thus reduce the firm productivity. As a result, within this transition period, the firm might experience a temporary decrease in labour productivity to build the firm's compatibility that meets the supplier's requirements.

For the forward digital spillover, even though the absorptive capacity is employed to absorb the external knowledge that is transferred from the downstream industries, the labour productivity of the firm could be reduced by 0.0344% proportionately. Again, a possible explanation lies in the "knowledge network" that is mentioned on the backward digital spillover effects. The Malaysian manufacturing firm might directly communicate with their customers if they want to understand their customers' needs more thoroughly rather than searching for information via an online network. It might take longer time and more effort to unlock and reveal the customers' demand from the internet, social media or other digital channels.

Furthermore, this result might also be caused by the issue of resource reallocation mentioned by Dai & Sun (2021) and Ping et al. (2018). Even though understanding more about the customers' information helps boost the firm production, the assignment of high-skilled labour in assimilating the external knowledge has taken the human resources that are responsible for the production process. As a result, it slows down labour productivity in the short term.

In conclusion, internal and horizontal digital spillovers exert positive effects on labour productivity, in which the impact of horizontal digital spillovers is much stronger than internal digital spillovers. It means that manufacturing firms benefit more from the external knowledge that their competitors transfer via digital channels. It also implies that information sharing via digitalisation within the industry is essential to the growth of manufacturing firms. Nonetheless, these positive impacts have been offset by the vertical digital spillover effects and the net digital spillover effects left only 0.0091%.

4.4 Robustness Checking

The robustness checking is carried out by replacing the patent issuance with other types of innovation output in Equation 4.3 and Equation 4.4. The Intellectual Property Corporation of Malaysia (MyIPO) (2023) has categorised patent, trademark, copyright, industrial design, geographical indication and layout designs of integrated circuits as intellectual property, i.e., the innovation output that is possessed by a firm. Thus, the replacement variable used in the robustness checking is a binary variable, the "dioxp", in which the value of one denotes the manufacturing firm issuing the non-patent intellectual property.

The robustness checking starts with the estimation of the robust innovation output equation and then forecasting the probability of a manufacturing firm issuing a non-patent intellectual property. Then, the forecasted probability is included in the estimation of the productivity function.

The independent variables in the robust innovation output and productivity functions remain the same as the Equations 4.3 and 4.4.

Robust innovation output equation:

$$\text{dioxp}_{ij} = \chi_1 + \chi_2 1og(\text{rd*}_{ij}) + \chi_3\, dbig_{ij} + \chi_4\, dind_{ij} + + \chi_5\, log(rms)_{ij} + \chi_6\, log(it_{ij}) + \chi_7\, log(soi_{ij}) + \chi_8 log(sob_{ij}) * log(lhs_{ij}) + \chi_9 log(sof_{ij}) + e_{ij} \text{ --------(Equation 4.5)}$$

Robust production function:

$$logy_{ij} = \eta_1 + \eta_2\, dioxp_{ij}* + \eta_3\, log(k_{ij}) + \eta_4 log(rlhs_{ij}) + \eta_5(log(lhs_{ij}) * log(it_{ij})) + \eta_6 log(soi_{ij}) + \eta_7 log(sob_{ij}) + \eta_8(log(lhs_{ij}) * log(sof_{ij})) + \omega_{it.} \text{ ---(Equation 4.6)}$$

Equation 4.5 is first estimated and the model prediction power is evaluated. Table 4.17 shows that the robust innovation output equation has correctly predicted 95.08% of the observations and it is accepted to proceed with the marginal effect calculation. Then, the results of Equation 4.3 and 4.5 are compared in Table 4.18.

Table 4.17: Expectation-Prediction Evaluation for Robust Innovation Output Equation

Expectation-Prediction Evaluation for Binary Specification
Equation: PBEST1
Date: 09/30/23 Time: 12:37
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	12828	436	13264	12880	667	13547
P(Dep=1)>C	52	231	283	0	0	0
Total	12880	667	13547	12880	667	13547
Correct	12828	231	13059	12880	0	12880
% Correct	99.60	34.63	96.40	100.00	0.00	**95.08**
% Incorrect	0.40	65.37	3.60	0.00	100.00	4.92
Total Gain*	-0.40	34.63	1.32			
Percent Gain**	NA	34.63	26.84			

All variables presented in Table 4.18 show a significance level of 1% in affecting the issuance of non-patent intellectual property. In other words, it is validated that all selected independent variables are significantly affecting the realisation of innovation output, whether it is patent or other types of intellectual property. By comparing the impact of the independent variables on the innovation outputs, the forecasted R&D expenditure, digital expenditure spent by a firm and the backward digital spillover effect do not show a big difference in the magnitude of the marginal effects.

Table 4.18: Estimation Result of Robustness Checking on Innovation Output Equation

	Innovation Output Equation				
	Estimated Equation (Equation 4.3)		**Robustness Checking (Equation 4.5)**		**Difference - in the marginal effect**
	Coefficient (z-statistic)	**Marginal Effect**	**Coefficient (z-statistic)**	**Marginal Effect**	
LOG(RDF)	0.1490***	0.69%	0.0950***	0.61%	
DBIG	0.6236***	0.50%	0.2564***	0.20%	0.30%
DIND	0.4153***	1.02%	0.4733***	1.63%	-0.61%
LOG(RMS)	0.2750***	1.27%	0.3011***	1.94%	-0.67%
LOG(IT)	0.1401***	0.65%	0.1153***	0.74%	-0.09%
LOG(SOI15)	0.3261***	1.50%	0.5956***	3.84%	-2.34%
LOG(SOB15)* LOG(LHS)	0.0302***	0.14%	0.0336***	0.22%	-0.08%
LOG(SOF15)	-0.2088***	-0.96%	-0.3578***	-2.30%	-1.34%
C	-0.8057***	-3.72%	-1.2315***	-7.93%	

*The denotation of ***/**/* represents the 1%, 5% and 10% significance level respectively.*

Among the variables, the forecasted R&D expenditure and binary variable of large-sized firms are more important to the issuance of patents as compared to other types of intellectual property as the magnitude of marginal effects on the estimation of patent issuance are larger. This outcome is explainable because the patent is an exclusive right given to a firm to control the use of its product invention and process invention (DOSM,2023). Thus, the issuance of a patent needs the achievement of inventions to be in place beforehand and a considerable amount is required in order to make the invention successful. The National Innovation Survey 2015 also revealed that the cost of innovation is the primary concern for the manufacturing sector in applying for patents compared to other types of intellectual property (MOSTI & MASTIC, 2015).

On the other hand, other independent variables carry higher explanatory power on the issuance of non-patent intellectual property. Coincidently, the marginal effects of the industry group and market share on the robust equation are approximately 60% higher than the modified equation. It means that Malaysian manufacturing firms which belong to the highly productive industry or positioned themselves as the market leader have higher intentions in issuing non-patent intellectual property, as compared to patents. This situation is consistent with the statistics published in the National Survey of Innovation 2015 (MOSTI & MASTIC, 2015), as presented in the table below.

For the digital spillover effects, there is a small difference in the magnitude of marginal effects of internal and backward digital spillover between the modified and robust innovation output functions. Nevertheless, the marginal effect of the horizontal digital spillover effect on the robust equation is 2.34% higher than the modified equation. It means that the more external knowledge the firm absorbs from its competitors via digital channels, the greater its intention to issue a non-patent intellectual property.

Table 4.19: Percentage of Intellectual Properties Applied and Granted in the Manufacturing Sector

Types	Applied (%)	Granted (%)
Patents	24.82%	24.10%
Non-patent Intellectual Properties		
Trademark	38.65%	42.56%
Copyright	17.73%	18.47%
Industrial Design	18.80%	14.87%
Total	**100%**	**100%**

This situation might happen because the non-patent intellectual property makes the firm different from its competitors at a lower cost and it can be done at faster processing time (MOSTI & MASTIC,2015). For instance, the trademark owned by a firm makes its customers recognise the shop quickly. In contrast, the industrial design makes the appearance of the product sold by the firm more outstanding than its competitors. In the report of the National Survey of Innovation, MOSTI and MASTIC (2015) emphasised that a trademark is the most essential protection method for the manufacturing sector, followed by patents and other types of Intellectual Property.

Meanwhile, the marginal effect of the forward digital spillover effect on the robust equation is 1.34% higher than the modified equation but in a negative direction. It means that when the manufacturing firm receives more information from its retailers or customers via digital channels, its intention in realising a non-patent intellectual property is even lower than the patent issuance.

It is understandable that when a firm knows its customers well, it can produce products that suit the customers' needs. In such cases, the firm may prioritise patent protection to safeguard its inventions compared to other types of intellectual property. This situation is even more likely to occur when the firm's competitors can quickly gain information on the customers via digital channels. MOSTI and MASTIC (2015) mentioned that the easiness of intimating a firm's innovation would discourage the manufacturing firm from carrying out innovation activities. On the contrary, patent protection can grant the manufacturer a higher market share.

Then, Equation 4.5 is used to forecast the value of the probability of a manufacturing firm issuing the non-patent intellectual property. The forecasted value is included as one of the independent variables, "dioxp*", in Equation 4.6 to solve the endogeneity problem. Meanwhile, other independent variables remained the same as the Equation 4.4. The results of the estimation of the productivity functions are presented in Table 4.20.

All independent variables in Equation 4.6 have the same sign and significance level as those in Equation 4.4. In addition, the R-square of these two equations is very close as well. This outcome proves that the patent and non-patent intellectual property, associated with all selected independent variables are significantly affecting the labour productivity in Malaysian manufacturing firms.

Table 4.20: Estimation Result of Robustness Checking on Productivity Equation

	Productivity Function	
	Estimated Function (Equation 4.4) Adjusted with Huber-White covariance method **(1)**	**Robustness Checking (Equation 4.6)** Adjusted with Huber-White covariance method **(2)**
	Coefficient	Coefficient
LOG(DIOXP*)	0.4695***	0.4212***
LOG(K)	0.3759***	0.3807***
LOG(LHSW)	0.0530***	0.0490***
LOG(ITW)*	0.0262***	
LOG(LHS)		0.0285***
LOG(SOI15)	0.7194***	0.8180***
LOG(SOB15)	-0.7021***	-0.9088***
LOG(SOF15)*	-0.0344***	
LOG(LHS)		-0.0204***
c	3.8572***	3.8551***
R-Squared	0.6013	0.6000
Wald F-statistics	2162.068	2142.164
Prob (Wald F-statistics)	0.0000	0.0000

*The denotation of ***/**/* represents the 1%, 5% and 10% significance level respectively.*

The purpose of estimating Equation 4.6 is to find out the impact of non-patent intellectual property on labour productivity, as only this variable was replaced in the equation. The result showed that the impact of the non-patent intellectual property on labour productivity is slightly lower, approximately

0.05%, than the impact of the patent issuance. This finding is interesting and corresponds to the research of Bei (2019) and Sweet and Eterovic (2019). Bei (2019) discovered that manufacturing firms which hold a valuable trademark have less tendency to carry out innovation activities and patent their inventions. Meanwhile, Sweet and Eterovic (2019) viewed that patenting activities do not improve productivity growth significantly. Instead, the ability to utilise the innovation spillover effect via the leverage of absorptive capacity served as the key to productivity growth.

4.5 Concluding Remark

This chapter presents the results of descriptive and empirical data analyses. Based on the unpublished firm-level data provided by the Department of Statistics Malaysia, the sample distribution is in line with the market structure of the manufacturing sector in Malaysia. In terms of innovation investment, innovation output and digital expenditure, large firms were leading the market. The medium-sized firms and small firms did participate in the innovation activities and digital technologies adoption, but the participation and adoption rates were much lower than the large firms. This phenomenon has revealed the vulnerability of SMEs in getting sufficient resource allocation to make them more competitive. At the same, it also explained the widening gap in digitalisation and productivity between large and SME manufacturing firms in Malaysia.

By referring to the results of the empirical analyses, the effects of the firm characteristics on the innovation input and innovation output are coherent with the past studies. The firm's market share becomes the main driving engine for a manufacturing firm to invest in R&D investment and issue a patent. It implies that innovation is an unavoidable pathway for firms, especially the market leaders, to uphold their market position and surpass their peers. Similarly, the exporters in the manufacturing sector are keen to conduct innovation activities to sustain their international competitiveness.

In addition, firm size and industry group are found to affect innovation activities positively. These results show the importance of possessing relevant resources in innovation activities. Those large firms and the firms that belong to the high-productive industries have an advantageous position in recruiting high-performing talents and obtaining sufficient funding from investors to pursue innovation activities as compared to other types of firms.

Nonetheless, the effect of the digital spillovers on the innovation input, innovation output and productivity are somewhat mixed. In general, the internal and horizontal digital spillover effects are found to have positive impacts on three stages but the forward digital spillover effect exerts a negative impact on three stages. The consistent positive effects of the horizontal digital spillover show that there is a mimic effect happening within the industry. In contrast, the negative impact of the forward digital spillover effect might be caused by the competition for resources for innovation.

On the other hand, the backward digital spillover effect has a positive influence on innovation activities, both innovation expenditure and issuance of a patent. However, it turns out to be negatively affecting the firm productivity. The results show that the innovation that is driven by the backward spillover effect is not significant enough to translate into the firm efficiency. It implies that there might be a need for resource adjustment and reallocation to fully utilize the innovation in boosting the firm productivity. Lastly, by examining the interaction term between the digital spillover effect and high-skilled labour, it is found that absorptive capacity is essential to assimilate the external knowledge transmitted via different spillover effects, except the horizontal spillover effect.

CHAPTER 5

CONCLUSION

5.1 Introduction

This chapter is the last chapter of this research. It starts with the summary of this study, together with the conclusion drawn from the description and empirical analyses. With the insights gained from the analyses, the research implications to academia, government bodies, and the manufacturing sector are then discussed. Finally, the chapter ends with an explanation of the limitations of this study, associated with respective recommendations for future researchers.

5.2 Summary and Conclusion

In the 21^{st} century, the world has entered into the era of Industrial Revolution 4.0 (IR4.0). The concept of "Industry 4.0" has been introduced under IR 4.0 and this concept is even extended to tertiary concepts, such as smart manufacturing, smart factories and IoT for the manufacturing sector (World Economic Forum, 2019). The manufacturing sector is always the first sector that experiences technological transformation whenever there is an industrial revolution. This round of the Industrial Revolution required manufacturing firms to undergo technological transformation by heavily applying disruptive technologies, such as the Internet of Things (IoT), robotics, artificial intelligence (AI) and cloud computing.

This study starts with the illustration of the importance of the manufacturing sector in driving Malaysian economic growth. Numerous policies have been implemented to develop the manufacturing sector as a sector that holds international competitiveness (MITI, 2019; Ministry of Economy, 2024). The policies encouraged export-led industrialisation as well as high-value-added and high-tech manufactured exports. Currently, the policies focus on digitalisation and innovation in the manufacturing sector to keep up with the development of the idea of Industry 4.0 (MITI,2018).

Nonetheless, the low adoption rate of digital technologies and the inadequacy of innovation capabilities have prolonged the embracement of Industry 4.0 in Malaysia. It is observed that the situations of digitalisation and innovation vary from firm to firm due to different firm characteristics which ultimately drive different performance in the firm productivity. Most importantly, Xu and Cooper (2017) mentioned that the exclusion of indirect effects of digitalisation makes the study on the total impact of digital investment show a biased estimation. In view of the importance of these variables, this study explores the roles of firm characteristics and the digital spillover effects in stimulating innovation activities and firm productivity in the Malaysian manufacturing sector.

Chapter Two presents the theoretical review of Endogenous Growth Theory and Schumpeter's Theory of Innovation in response to the research objectives. Endogenous Growth Theory has mentioned that the firm productivity is not only affected by the accumulation of capital and labour but also the unknown residual, such as innovation. Meanwhile, Schumpeter's Theory of Innovation explains that the innovation activities of a firm are motivated by the firm's intention to enhance the firm's competitiveness and sustain the firm's market share. After that, the conceptual framework structured under the CDM model is presented, together with illustrations of the relationships between the interested variables.

Chapter Three starts with a description of the definitions of the key terms in this study, followed by an explanation of the development of the functions and proxy selection. The CDM model is a recursive system that applies firm-level data, consisting of three equations, namely innovation input function, innovation output function and production function. Different estimation techniques are applied in different stages to the unique nature of the data applied. Heckman's two-step model is applied to the innovation input function, meanwhile the Probit model is used to estimate the innovation output function. Finally, the production function is estimated by the Ordinary Least Square Estimator.

The firm-level data applied in this study is the unpublished data provided by the Department of Statistics Malaysia in March 2020. The data was extracted from the Economic Census 2016 (the reference year of 2015), consisting of a total of 14723 manufacturing firms and accounted for 30% of microdata in the Malaysian manufacturing sector. This sample could portray the market structure of the manufacturing sector in Malaysia because 96% of the sample are small and medium firms, which was very close to the actual situation --- 97% of SMEs in the Malaysian manufacturing sector (Economics Planning Unit, 2021).

Chapter Four shows the description analysis on the unpublished firm-level date as well as the estimation results of the CDM model. In the sample, the large firm reported the highest R&D investment and patent issuance, as expected based on the actual situation of the Malaysian manufacturing sector. In addition, the realisation rate of the innovation output from the R&D investment is the highest among the large firms. The successful rate of turning the R&D expenditure into patent issuance was 91.59% in the large firms, 53.48% in the medium-sized firms and 34.66% in the small firms that were able to realise the patent issuance by investing in R&D expenditure. This result implied that the R&D activities were not the only reason that SMEs failed in creating the innovation output but there might be some unrevealed factors that caused this phenomenon.

In addition, the spending on digitalisation shows a big difference between large firms and SMEs. There was a total of 73.72% of large manufacturing firms spending on information and communication technology (ICT) expenditure but only 18.61% of the medium-sized firms and 3.10% of the small firms have done so. This statistic implied that large firms focused more on digitalisation as they were more willing to spend on computers, internet and web presence usage, at the same time, leading to the wide gap in digital adoption between the large firms and SMEs. In terms of the external digital spillover effects, it shows that the horizontal spillover effect scored the highest mean value, meaning that the manufacturing firms could benefit the most from the external knowledge shared by their competitors via digital channels.

For the empirical analysis of the CDM model, the results of the Heckman Selection Model show that the manufacturing firm which does not report R&D expenditure in the sample should not be excluded in the data analysis, or else the result of the response equation is misleading. All firm characteristics variables (firm size, industry group, export volume and market share) are found to be significant in affecting the probability of a manufacturing firm investing in R&D expenditure and the intensity of the R&D expenditure. Furthermore, the firm's market share and industry group are the most influential factors in affecting the innovation input.

In terms of the digital spillover effects, the internal and horizontal spillover effects are confirmed as the significant variables that positively affect the firm's probability of investing in R&D investment. When the information flow in a company is getting faster via digital platforms, it lowers the costs of communication and increases the effectiveness of communication. With that, it motivates the innovation activities among the staff. On the other hand, the highest influential power of the horizontal spillover effect indicates that there is a mimic effect happening in the manufacturing sector in Malaysia. When there is a manufacturing firm successfully carrying out R&D activities and is able to translate the benefits gained to the production process, other industry players are likely to imitate the behaviour of the first mover (Xu & Cooper,2017).

Nonetheless, the backward spillover effect is found insignificant in motivating manufacturing firms to invest in R&D activities. The manufacturing firms in Malaysia might focus more on the offline knowledge that is transferred by their suppliers instead of the online knowledge. This is the "knowledge network" mentioned by Paunov and Rollo (2016). In other words, the manufacturing firms in Malaysia prefer approaching their suppliers directly whenever facing problems using the products. Thus, the external knowledge created by the suppliers is not essential enough to motivate the manufacturing firms to carry out R&D activities.

At the same time, the forward spillover effect exerts a negative effect on the investment in innovation input. It means the externalities that are generated by the customers do not provide an incentive for the firm to create new products or to change their existing production process and operation methods. When manufacturing firms can learn more about their customers' needs via digital platforms at almost zero cost or low cost, they can directly customise the needed products without trial and error to get the customers' preferences (MOSTI & MASTIC, 2020). In addition, manufacturing firms can look for alternative suppliers which are able to provide the products needed by their customers without any innovation activities needed in between.

The results on the innovation output function have revealed similar results with the innovation input function. All firm characteristics were found to significantly and positively affect the probability of a manufacturing firm realising a patent issuance. Similarly, the market share and industry group are the most influential factors in this function, followed by the R&D investment. The importance of market share and industry group in both innovation input and output function has validated the existence of Schumpeter's Theory of Innovation in the manufacturing sector in Malaysia because the firm's competitiveness is the main driving engine for the firm in engaging in innovation activities.

In terms of the impact of digital spillover effects, similar results with the innovation input function have been yielded except for the backward spillover effect. It shows that high-skilled labour plays a vital role in assimilating the backward digital spillover effect. As mentioned in the section on innovation input, manufacturing firms in Malaysia tend to approach suppliers for offline knowledge when they need support on the products and services. Thus, this spillover channel shows minimal intention to conduct an innovation activity. If a manufacturing firm wants to issue a patent, it needs to hire high-skilled labourers to absorb the external knowledge transferred by the suppliers instead.

The last stage of the CDM model estimates the production function. The estimation outcomes show that patent issuance, capital and labour significantly and positively affect the labour productivity of manufacturing firms. Furthermore, internal and horizontal effects improve labour productivity, but the backward and forward spillover effects impose the opposite impact. The horizontal spillover effect has the highest influential power in improving firm labour productivity but the internal digital spillover effect is the lowest. Once again, the importance of the horizontal spillover effect confirmed the existence of the mimic effect in the manufacturing sector because the manufacturing firm can study the behaviours of the competitors via digital platforms easily and alter its strategies in responding to the competitors' actions, in turn, improve the firm productivity.

To explain the negative impacts of backward and forward digital spillover effects, the possible explanations lie in the matter of resource adjustment and reallocation, which could cause a temporary reduction in the firm productivity. For the supplier side, if the external knowledge transferred from the suppliers is very technical and complicated, the firm needs time and effort to adjust their capital, such as the equipment and machinery, to be able to transform and apply the external knowledge in their production process and business operation. As a result, there is a temporary decrease in firm productivity to ensure the compatibility of the firm's resources with the supplier's requirements.

At the same time, the reallocation of high-skilled labour to utilize the forward digital spillover effect might cause the inadequacy of high-skilled labour in the production line which leads to a decrease in firm productivity. Nonetheless, the negative impact of the forward digital spillover is much smaller than the backward digital spillover. This phenomenon might be caused by the higher complexity of technical knowledge transferred by the suppliers that need to be unlocked compared to the retailers.

5.3 Research Implications

The empirical analyses have drawn the conclusion on the relationships between the firm characteristics, innovation, digital spillovers and firm productivity in the Malaysian manufacturing sector. These findings hold valuable contributions to the body of knowledge and practical implications for real-world applications. In this section, the research implications for the academic and respective stakeholders are discussed.

5.3.1 Implication to Academia

The CDM model has become a popular model in studying the relationship between innovation and productivity after its introduction by Crépon et al. (1998). The popularity of the CDM model was caused by its ability to apply firm-level data in the research as well as its discovery power on the interrelationships between innovation input, innovation output and firm productivity via sequential equations. Over time, researchers have incorporated various interesting variables into the CDM model for their research objectives.

The emergence of Industrial Revolution 4.0 and advanced internet infrastructure has grown researchers' interest in adding ICT-related variables in the CDM model as the extension and modification variable, for instance, Hall et al. (2013), Kijek and Kijek (2018) and Zhu et al.(2021). Nonetheless, Xu and Cooper (2017) who studied the impact of digital spillover on firm productivity claimed that studying the direct effect of digital expenditure alone is insufficient to reflect the true impact of digital expenditure. They have stressed that the indirect effects, i.e., the digital spillover effects, have to be included.

Past research has recognised the influence of ICT-related variables, including digital expenditure, on innovation and firm productivity. However, to the author's best knowledge, there are limited studies that stress the relevance of digital spillover effects in the context of the CDM model. By integrating the digital spillover effect in each stage of the CDM model, this study contributes significantly to the existing body of knowledge on the emergence of the digital spillover concept.

Moreover, the application of inter-industry intermediate transactions in calculating the digital spillover effect is another distinctive aspect of this study. Even though this method is not novel in the spillover analysis, such as FDI spillovers and knowledge spillovers, it is underutilised in constructing ICT spillovers or digital spillovers (Mun & Nadiri, 2002; Marsh et al.,2017). The method used by Mun and Nadiri (2002) in measuring the ICT spillover is chosen over the method used by Xu and Cooper (2017) because the inter-industry intermediate method is able to observe the interdependency of various industries in the manufacturing sector. Meanwhile, the method of Xu and Cooper (2017) is used to examine the extra marginal product of digital investment technology, i.e., the rate of knowledge diffusion, via the growth accounting approach.

In this study, the digital expenditure spent by a manufacturing firm is viewed as the internal digital spillover effect. Meanwhile, the horizontal and vertical digital spillover effects are categorised as the external digital spillover effect. The data analyses of three stages of the CDM model have shown the significant impact of the internal digital spillover effect, in which the most significant effect is shown on the innovation input equation, followed by the innovation output and production equation respectively. This outcome has validated the argument made by the OECD (2018) which stressed the importance of digitalisation in promoting the information flow inside the firm that can stimulate the need for innovation.

Nonetheless, the impact of external digital spillover effects exerts ambiguous results on three stages of the CDM model. In past studies, it is hard to detect the external digital spillover, especially the vertical digital spillover. In this study, the outcomes of the data analysis have concluded the positive effects of the horizontal spillover effect on both innovation input and innovation output. Nevertheless, the absorptive capacity is needed to unlock the knowledge shared by the competitors in improving the firm productivity in the manufacturing sector.

Meanwhile, the results of the vertical spillover effect are relatively mixed. The backward digital spillover is found to have no relationship with innovation unless the high-skilled labourers are utilised to absorb the external knowledge, and it even has a negative relationship with productivity. On the other hand, the forward spillover effect is found to have a negative impact on innovation and firm productivity. The study of the interaction term between the digital spillover effect and absorptive capacity in the CDM model is another novelty of this study, which differs from previous research.

In short, the results of the data analyses have confirmed the significance of both direct and indirect effects of digitalization on innovation activities and firm productivity. The researchers are suggested to take into consideration the role of indirect effects when conducting the study on digitalisation because the exclusion of indirect effects may lead to misleading conclusions and ineffective policy recommendations. This is especially relevant in the context of developing countries where investment in digitalisation may be limited. Focusing solely on the direct effect of digitalisation risks underestimating the true influence of digitalisation, even though its broader contributions could be substantial.

Furthermore, this study presents significant implications for theoretical development, particularly regarding the incorporation of digitalization and digital spillovers in the production function. There may be an opportunity for research to examine the inclusion of these variables in the endogenous growth model as control variables, which could enhance the theoretical frameworks of firm productivity and economic growth while remaining relevant to today's digital economy. This suggestion responds to Fu et al. (2021), who proposed that future researchers emphasize the multiplier effects of digital platforms on economic development in developing countries.

Aside from the digital spillover effects, the interrelationships between firm characteristics, innovation and productivity are found in accordance with past studies, which fulfil the Endogenous Growth Theory. The conventional factors of production (both capital and labour), as well as innovation, are found to be significant in boosting the firm productivity. Another interesting insight is the validation of Schumpeter's Theory of Innovation in the Malaysian manufacturing sector. The positive impacts of horizontal spillover effects on innovation input and output imply the mimic effect within an industry. In addition, the industry group and market share are found to be the most influential firm-related variables that promote innovation investment and innovation output in a manufacturing firm. These results are particularly important to the manufacturing sector firms in setting their strategies, which will be discussed in section 5.3.3.

5.3.2 Implication to Policymakers

This study has validated the importance of digitalisation and innovation in enhancing the productivity of manufacturing firms in Malaysia. In Malaysia, the government has implemented the National Industry 4.0 Policy Framework (Industry 4WRD) to help the manufacturing sector embrace the idea of Industry 4.0, yet various policy reinforcements have to be initiated to accelerate the adoption rate of digital technologies and boost the innovation capabilities of manufacturing firms. In addition to Malaysia, this study also serves as a reference for countries with manufacturing sectors at a developmental stage akin to Malaysia's, aiding in the formulation of their industrial policies.

First of all, the results of the analyses show that industry groups and intra-industry digital spillover play the most significant roles in stimulating the manufacturing firms to invest in research and development activities and realising the innovation output. Since the government has identified the industry of electronic and electrical (E&E), pharmaceuticals, aerospace, and chemicals as the focused industry under the New Investment Policy and 12th Malaysia Plan, the government should provide funding opportunities and tax incentives to the manufacturing firms, especially the market leader in these industries. When the market leader in the industry initiates innovation activities proactively, other firms in the industry will follow the action taken by the market leader, as implied by the results of analyses. In addition, the government should increase state-led investments in R&D and efforts to acquire international tech assets for fostering innovation and digital transformation in the sector, alike the "Made in China 2025[8]" industrial policy taken by the Chinese government in 2015

Moreover, the government should attract more foreign direct investment to these focused industries because the results of the study also reveal that the manufacturing firms in Malaysia rely on offline knowledge networks rather than

[8] Made in China 2025 (MIC25) is a national strategic plan and industrial policy initiated by the China government in upgrading China's manufacturing sector from a labour-intensive sector that focused on low-tech goods to a technology-intensive powerhouse that produces high-tech products (Wübbeke et al., 2016).

online knowledge networks. In other words, if the foreign investor can set up their factory and office in Malaysia, it eases the knowledge transfer because Malaysian manufacturing firms prefer to have physical discussions and meetings with the suppliers and retailers to get the relevant information, rather than studying the information flows on the digital platforms. As a result, the government should increase its development investment in building necessary infrastructures, such as high-speed internet and data centres, to attract foreign direct investment to the manufacturing sector. Likewise, the government can learn from Thailand on setting up Special Economic Zones (SEZs)[9] or promoting new investment corridors that focus on the growth of the focused industries.

Thirdly, the government can provide financial assistance and subsidies to the low-productive industries in adopting digital technologies and hiring digital talents. The government can leverage digital tools to optimize the supply chain of these industries, for example, by utilizing real-time tracking and IoT technologies in the production process. When the supply chain is enhanced and comprehended, the production process of these industries could speed up and adapt to the market changes quickly. Slowly, the manufacturing firms in these industries can strengthen their agility and resilience and, in turn be able to transform themselves to be the manufactured exporter.

[9] Special Economic Zones (SEZs) are the zones in Thailand that designed to attract foreign investment and enhance industrial development by providing tax breaks, streamlined regulations, and infrastructure support (NESDC, 2023).

In addition, the government should foster public-private partnerships with small and medium firms and increase the investment in the facilities that are needed by the SMEs. By lifting the firm size, the SMEs have higher confidence in sustaining their business survival in the market, encouraging them to be more active in innovation activities. The government should increase the number of Higher Institution Centres of Excellence (HICoE) among the universities to encourage collaboration between academicians and SMEs in carrying out R&D projects. This channel can solve the problem of shortage of talent faced by SMEs because there are experts in tertiary education institutions who can support them in certain disciplines. Participation in innovation activities is particularly important in SMEs because patent issuance indeed increases the firm productivity, as shown by the data analysis.

Regardless of the industry group and firm size, human capital is the main driver that promotes digitalisation and innovation activities. The government is recommended to promote workforce transformation and cultivate more talent in the manufacturing sector because the integration of digital technologies necessitates a skilled workforce. The upskilling and reskilling of the workforce are important to both focused industries and low-productive industries to keep up with the latest developments in digital manufacturing technologies, especially the Internet of Things, artificial intelligence, and robotics. More educational programs and training initiatives in these digital areas should be promoted to the universities and manufacturing firms. As a result, a dynamic workforce which is capable of navigating the complexities of modern manufacturing environments could be created, leading the manufacturing sector to achieve self-reliance and reduce its dependence on external technological support.

Last but not least, the government should promote the importance of intellectual property (IP) and cultivate the innovation ecosystem among manufacturing firms. By having more seminars and courses on IP and innovation, manufacturing firms can have a better understanding of the importance of improved product quality and process innovation. The government can require the manufacturing firms to fulfil a certain number of Continuing Professional Development (CPD) hours that are relevant to the innovation. Thus, the manufacturing firm can have more inspiration on carrying out the innovation via the training, and be able to ensure higher precision and quality control, contributing to the production of superior products.

5.3.3 Implication to Manufacturing Sector Firms

As the firm characteristics are another interesting variable in this study, this research has significant implications for manufacturing firms. The firm size is a critical factor in determining the firm's participation in innovation activities. The data analyses discover that both medium and large firms have higher intention in investing in R&D activities as compared to small firms, but only the large firms have a higher possibility of issuing the patent. This result implies that the firm size is the determinant that links to the resource acquisition which makes the innovation activities succeed. In addition, the result of the productivity equation stresses again the importance of firm resources because the patent, capital and high-skilled labour exert a positive effect on the firm productivity.

The management team of the manufacturing firms should strategise on expanding the business to improve its competitiveness, so it has higher bargaining power in recruiting relevant talents and technology in the industry. The management team may join international conferences or exhibitions to expand its business opportunities and market share. When the firm size expands, the manufacturing firm has more resources to finance the innovation activities. Thus, it can maintain its competitive edge via innovation and increase further the market share. The cycle of innovation and firm expansion would ensure the firm's sustainability in the long term.

From another perspective, the management team of the manufacturing firms can consider allocating more funding to the digital expenditure spent in the firm. The ICT expenditure spent by the manufacturing firm stimulates the intention of a manufacturing firm in carrying out research and development activities, increases the successful rate of issuing a patent, as well as enhances the firm productivity, as shown by the data analysis. The manufacturing firm should encourage the application of an intranet for communication and an internal portal for data management. In addition, the manufacturing firm should focus on the area of cybersecurity to ensure that digitalisation in the computer is immunized from external cyber attracts.

In terms of external digital spillover effects, the outcomes of the data analysis imply that there is a mimic effect happening in the Malaysian manufacturing sector. The manufacturing firm can consider exploring the possibility of partnering with its rivals to establish a networked cluster. By doing so, the company shifts from competing against its competitors to cooperating with them, particularly in the sharing of innovative resources. This approach has the potential to cultivate an innovation ecosystem within the industry and enhance the success rate of innovation investments by minimizing competitive pressures.

Furthermore, manufacturing firms should be proactive in innovation and “create the demand” for the retailers. The result has reflected that the manufacturing firm is discouraged from carrying out innovation when they get more information flow from their customers via digital channels. Even though receiving clear customer feedback during transactions enables the firm to bypass some steps in innovation, this approach does not enhance the firm's productivity. As a result, the firm should shift from a passive to an active role, creating new products that stimulate consumer demand instead of merely awaiting customer feedback to modify the products.

Similarly, Malaysian manufacturing firms should reduce their reliance on suppliers. Similar to the forward digital spillover effect, the result shows a lower intention for manufacturing firms to invest in R&D activities when there is a backward digital spillover effect. Nonetheless, the manufacturing firms can actually utilise the knowledge shared by the supplier and transform it into patent issuance if there is participation of the high-skilled labourers in the innovation activities. Thus, the manufacturing sector should absorb more STEM (Science, Technology, Engineering, and Mathematics) talents and tech-savvy innovators. Likewise, the manufacturing sector can collaborate with the universities in nurturing high-skilled labourers who meet the sector’s requirements. This collaboration could include providing internship opportunities, revising curricula to align with the latest developments in the sector, and initiating industrial projects that involve both academicians and university students.

Finally, resource allocation in the manufacturing sector is the critical element in driving innovation activities and firm productivity among manufacturing firms. Obviously, SMEs face challenges in securing resources, especially high-skilled labour, because they often lack the financial capacity to offer competitive salaries that can attract talented individuals. Thus, SMEs should consider leveraging the internal digital spillover effect because the ICT expenditure exerts a positive impact on innovation and firm productivity. The SMEs are suggested to prioritise the digital technology adoption in the production process, especially the internet and intranet usage. They can opt for process innovation, marketing innovation or operation innovation using digital platforms and channels instead of focusing on product innovation, which requires vast amounts of funding and expensive equipment and machinery. Thus, the barrier to conducting the innovation activities can be lowered, leading to a significantly higher success rate in transforming the innovation output into firm productivity.

5.4 Limitations of Study

There are a few limitations in this study. The first limitation is related to the availability of the latest firm-level data in the Malaysian manufacturing sector, as the CDM model is applied in this study. The published data on the portal of the DOSM shows that most of the data related to the manufacturing sector are industry-level data, such as the “Monthly Manufacturing Statistics, Malaysia”, “Annual Economic Statistics Manufacturing” and “Report on Annual Survey of Manufacturing Industries, Malaysia”. As a result, the firm-level data which was unpublished can only be obtained by applying data requests to DOSM.

Nonetheless, the data provided by DOSM was extracted from the Economic Census 2016 (the reference year of 2015), which is nine years away from the year 2024. Authors have submitted two rounds of official requests to get the latest firm-level data but the data is not available, as replied by the DOSM officer (see details in section 3.6). A similar issue has been faced by past researchers as well, for instance, Zhu et al. (2021), Ramirez et al. (2019), as well as Shafi'I & Ismail (2015) who studied the case of the Malaysian manufacturing sector.

The second limitation of this study is that this study is limited only to static research, i.e., it is unable to study the dynamic changes, but only the contemporaneous impacts on the interested variables in this research. It may need time for some variables to observe their impact on another variable. For example, the research and development invested this year may not realise any innovation output in the same year. Instead, it may only happen next year or an extended period. As a result, static research has restraints the observation of the full impact of certain variables.

The third limitation of this study is related to the data on innovation and digital expenditure. The data request on the "innovation output" variable was sent to the DOSM, but the data obtained was the binary data that showed if a particular manufacturing firm issued a patent, a trademark, copyright or other intellectual property (IP) protection on industrial design, geographical indication or layout designs of integrated circuits. As a result, it is unable to differentiate the innovation from the perspectives of product innovation, process innovation and business operation innovation, as recommended by OECD (2018). In addition, this research used only patent issuance as the proxy of innovation output due to the recognition of patents as the proxy of innovation output in past studies, such as Dai and Sun (2021), Khachoo et al. (2018), and Paunov and Rollo (2056), and Ramírez et al. (2020).

On the other hand, the ICT expenditure is used as the proxy of digitalisation in this study. The digital expenditure and digital spillover effects are the principal axes of this research. However, the ICT expenditure for each firm that was given by the DOSM was an aggregate amount. The ICT expenditure is the total amount spent on computer hardware, computer software and telecommunications equation, based on the definition in the "*Panduan Mengisi Soal Selidik Banci Ekonomi 2016"* (DOSM, 2017). It included (i) ICT-related expenses, such as the fees on data processing, data tabulation and data transfer from/to different platforms and channels, and (ii) telecommunication fees, which cover telephone, telegram, email, internet, etc. As this is a lump sum fee, it is unable to identify the channel that diffuses the digital spillover effect most effectively.

5.5 Recommendations for Future Research

For the first limitation, future researchers are recommended to keep track of the latest issue of the Economic Census, i.e. the Economic Census 2023, and rerun the model when the latest firm-level data is available. Otherwise, researchers can use other methodologies to study the relationships between firm characteristics, innovation and productivity at the industry and national levels to avoid the limitation of firm-level data.

Meanwhile, in order to break through the second limitation, future researchers can consider applying panel data at the firm level for analysis if the data is available. By adding in the element of time, future researchers are able to observe the dynamic changes in the interrelationships between the variables. This situation arises because of the time lag in converting innovation investment into actual innovation outcomes. In addition, the particular manufacturing firm might need an adjustment period to integrate the innovation output into the production process and business operation. As a result, the time effect might play an essential role in studying the process of realising innovation and its impact on the firm productivity.

In response to the third limitation on the innovation-related data, future researchers are suggested to look into the impact of product innovation, process innovation, operational innovation and marketing innovation on the productivity of Malaysian manufacturing firms. If the differences in these impacts can be identified, it helps the policy design which drives the innovation activities that favour the growth of manufacturing firms. Furthermore, manufacturing firms can better understand and set effective resource allocation strategies to reach the optimal production point.

Finally, future research could dive into the identification of the channels of digital spillover effects. In other words, future researchers could study the impact of different types of ICT and disruptive technologies, such as big data analysis and cloud computing, that are used by the stakeholders of the manufacturing firm in creating and transferring knowledge and information. This is because the adoption of disruptive technologies is unavoidable for the Malaysian manufacturing sector in embracing Industry 4.0 (Ministry of International Trade and Industry, 2018). In addition, the penetration and influence of digitalisation across all spectrums of the economy are running at an unprecedented rate (Xu & Cooper, 2017). As a result, it is believed that the identification of the channels of digital spillover effects contributes significantly to academia, society and the country.

As a concluding remark, the availability of firm-level data is the main issue to handle when applying the CDM model in studying the relationship between innovation and productivity. As mentioned in section 5.2, the CDM model is an appropriate model to study the impact of innovation on the productivity of Malaysian manufacturing firms because the majority of the manufacturing firms in Malaysia are SMEs. All recommendations on future research are feasible in the near future because DOSM has started to collect data on different types of innovation as well as the disaggregate usage of related technology in the Annual Economic Survey 2022 (DOSM, 2023b). Thus, getting the relevant data for academic research is just a matter of time.

5.6 Concluding Remark

This chapter has marked the end of this study. The research objectives of this study revolved around exploring the interrelationships between firm characteristics, digital spillovers, innovation activities and firm productivity in the Malaysian manufacturing sector. Each research objective is fulfilled by the respective stage of the CDM model, using the unpublished firm-level data provided by the Department of Statistics Malaysia.

The most significant contribution of the study is the inclusion of the digital spillover effects, both internal and external, in the CDM model. The idea of the digital spillover effect is relatively new, as it was first introduced by Xu and Cooper (2017). Thus, the empirical study of the digital spillover effect contributes significantly to the body of knowledge. The researchers should focus on the digital spillover effects because the digital expenditure spent in the era of Industrial Revolution 4.0 is much higher than in other eras of Industrial Revolution. Thus, including the indirect effect of digitalisation is appropriate in figuring out the total return of digital expenditure. In addition, the era of IR4.0 heavily relies on ICT and digital technologies, making it inevitable for researchers to recognise and consider the profound impact of these technologies fully.

Nonetheless, this research is still constrained by a common limitation faced by the CDM model users, which is data availability. The published and unpublished innovation and digital data available in Malaysia are the aggregate data which prevent the researchers from gaining a holistic understanding of the interactions between the interested variables in this study. Remarkably, the disaggregate channels of the digital spillover effects are unable to be recognised even though the significance of digital spillover effects is proven. Thus, the stakeholders of the manufacturing firms are unable to fully benefit from the digital expenditure as they do not know whether the significance of the indirect effect is coming from the internet, big data analysis, web presence, artificial intelligence or any other digital platforms. Nevertheless, the DOSM is collecting the disaggregate digitalisation data and innovation data in the coming Economic Census and the publication of these data is believed to reveal more insights to the study in the field of digitalisation and innovation.

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APPENDICES

Appendix 1: Letter from Department of Statistics Malaysia – The Unpublished Firm Level Data

JABATAN PERANGKAAN MALAYSIA
(DEPARTMENT OF STATISTICS, MALAYSIA)
BLOK C6, KOMPLEKS C
PUSAT PENTADBIRAN KERAJAAN PERSEKUTUAN
62514 PUTRAJAYA
MALAYSIA

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Faks : 03-8888 9248
Portal : https://www.dosm.gov.my

Ruj. Kami : JP/BIPD/S/174 ( )
Tarikh : 16 Mac 2020

Liew Feng Mei
Universiti Tunku Abdul Rahman Kampar Campus,
Jalan Universiti, Bandar Barat,
31900 Kampar, Perak

Puan,

PERMOHONAN DATA MIKRO SEKTOR PEMBUATAN DI MALAYSIA.

Dengan segala hormatnya merujuk kepada perkara di atas.

2. Sukacita bersama ini disertakan CD-ROM yang mengandungi 30 % data mikro sektor pembuatan di Malaysia berdasarkan Banci Ekonomi 2015. Untuk makluman, data yang dibekalkan ini adalah mengikut garis panduan Dasar Penyebaran Data Mikro, Jabatan Perangkaan Malaysia (Pindaan 2015). Bilangan pertubuhan dan senarai pemboleh ubah adalah seperti di **Lampiran 1.**

3. Mohon perhatian pihak puan berhubung perkara berikut:

Data yang dibekalkan ini adalah sulit dan terhad untuk kegunaan dalaman kajian puan sahaja serta tidak boleh disebarkan kepada pihak lain.

Sekian, terima kasih.

"BERKHIDMAT UNTUK NEGARA"

Saya yang menjalankan amanah,

(SITI HASLINDA BINTI MOHD DIN)
b.p. Ketua Perangkawan Malaysia
Jabatan Perangkaan Malaysia

Lampiran 1

Bilangan Data Bagi Permohonan Data Mikro Sektor Pembuatan Di Malaysia.

Bil.	Tahun Banci Ekonomi	Bil. Pertubuhan
1	2015	14273

Pemboleh ubah bagi data mikro Sektor Pembuatan Di Malaysia.

Bil.	Pemboleh ubah
1	Dummy ID
2	MSIC 3D
3	Research and Development Expenditure (RM'000)
4	Information Technology Expenditure (RM'000)
5	Innovation Output Patent
6	Innovation Output Trademark
7	Innovation Output Copyright
8	Innovation Output Others
9	Innovation Output None
10	Number of High skilled labour
11	Number of Semi-skilled labour
12	Number of Low-Skilled labour
13	Number of Labour (Malaysian)
14	Number of Labour (Non-Malaysian)
15	Value of Fixed Asset (RM'000)
16	Export (RM'000)
17	Value of Gross Output (RM'000)
18	Value of intermedia Input (RM'000)
19	Value added (RM'000)
20	Firm Sales (RM'000)

Appendix 2: Description on Manufacturing Industry Groups Covered in This Study

No	Group code	Description
1	101	Processing and preserving of meat
2	102	Processing and preserving of fish, crustaceans and molluscs
3	103	Processing and preserving of fruit and vegetables
4	104	Manufacture of vegetable and animal oils and fats
5	105	Manufacture of dairy products
6	106	Manufacture of grain mill products, starches and starch products
7	107	Manufacture of other food products
8	108	Manufacture of prepared animal feeds
9	110	Manufacture of beverages
10	120	Manufacture of tobacco products
11	131	Spinning, weaving and finishing of textiles
12	139	Manufacture of other textiles
13	141	Manufacture of wearing apparel, except fur apparel
14	142	Manufacture of articles of fur
15	143	Manufacture of knitted and crocheted apparel
16	151	Tanning and dressing of leather; manufacture of luggage, handbags, saddlery and harness; dressing and dyeing of fur
17	152	Manufacture of footwear
18	161	Sawmilling and planing of wood
19	162	Manufacture of products of wood, cork, straw and plaiting materials
20	170	Manufacture of paper and paper products
21	181	Printing and service activities related to printing
22	182	Reproduction of recorded media
23	192	Manufacture of refined petroleum products
24	201	Manufacture of basic chemicals, fertiliser and nitrogen compounds, plastic and synthetic rubber in primary forms
25	202	Manufacture of other chemical products
26	203	Manufacture of man-made fibres
27	210	Manufacture of pharmaceuticals, medicinal chemicals and botanical products
28	221	Manufacture of rubber products
29	222	Manufacture of plastics products
30	231	Manufacture of glass and glass products
31	239	Manufacture of non-metallic mineral products n.e.c.
32	241	Manufacture of basic iron and steel
33	242	Manufacture of basic precious and other non-ferrous metals
34	243	Casting of metals

35	251	Manufacture of structural metal products, tanks, reservoirs and steam generators
36	259	Manufacture of other fabricated metal products; metalworking service activities
37	261	Manufacture of electronic components and boards
38	262	Manufacture of computers and peripheral equipment
39	263	Manufacture of communication equipment
40	264	Manufacture of consumer electronics
41	265	Manufacture of measuring, testing, navigating and control equipment; watches and clocks
42	266	Manufacture of irradiation, electromedical and electrotherapeutic equipment
43	267	Manufacture of optical instruments and photographic equipment
44	268	Manufacture of magnetic and optical media
45	271	Manufacture of electric motors, generators, transformers and electricity distribution and control apparatus
46	272	Manufacture of batteries and accumulators
47	273	Manufacture of wiring and wiring devices
48	274	Manufacture of electric lighting equipment
49	275	Manufacture of domestic appliances
50	279	Manufacture of other electrical equipment
51	281	Manufacture of general-purpose machinery
52	282	Manufacture of weapons and ammunition; Manufacture of special-purpose machinery
53	291	Manufacture of motor vehicles
54	292	Manufacture of bodies (coachwork) for motor vehicles; manufacture of trailers and semi-trailers
55	293	Manufacture of parts and accessories for motor vehicles
56	301	Building of ships and boats
57	303	Manufacture of railway locomotives and rolling stock; Manufacture of air and spacecraft and related machinery
58	309	Manufacture of transport equipment n.e.c.
59	310	Manufacture of furniture
60	321	Manufacture of jewellery, bijouterie and related articles
61	322	Manufacture of musical instruments
62	323	Manufacture of sports goods
63	324	Manufacture of games and toys
64	325	Manufacture of medical and dental instruments and supplies
65	329	Other manufacturing n.e.c.
66	331	Repair of fabricated metal products, machinery and equipment
67	332	Installation of industrial machinery and equipment

Appendix 3: Reply from Department of Statistics Malaysia – Limitation on The Availability of Firm-Level Data (19 April 2022)

JABATAN PERANGKAAN MALAYSIA
(DEPARTMENT OF STATISTICS, MALAYSIA)
BLOK C6, KOMPLEKS C
PUSAT PENTADBIRAN KERAJAAN PERSEKUTUAN
62514 PUTRAJAYA
MALAYSIA

Talian Am : 03-8885 7000
Faks : 03-8888 9248
Portal : https://www.dosm.gov.my

Salam Sejahtera
Tuan/Puan,

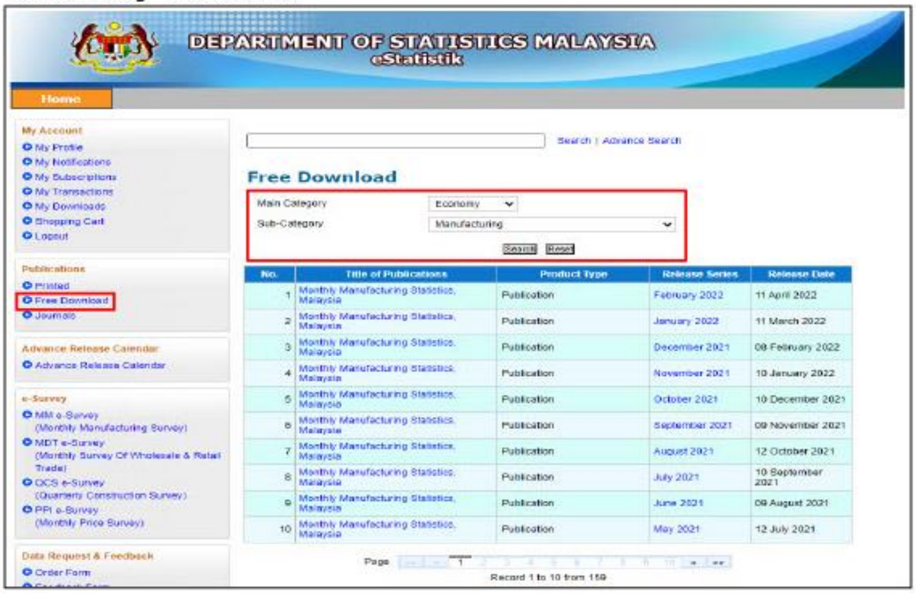
Merujuk kepada no. rujukan permintaan data : **20220419-53250**
Data of Manufacturing Sector in 2021

Subjek *	Data of Manufacturing Sector in 2021
Kategori Utama *	Ekonomi
Sub-Kategori *	Pembuatan
Tarikh Permintaan Data *	19/04/2022
Deskripsi Permintaan Data *	I would like to request the following data: 1) Firm-level data of manufacturing sector in the year 2021 2) Industry-level data of manufacturing sector in the year 2021 3) Input-output table for 2021 I have attached the dummy table in the attachment for your perusal.
Catatan	I am a Ph.D. student from Universiti Tunku Abdul Rahman (UTAR), currently doing a study on the firms' innovation in the Malaysian manufacturing sector. I am writing to request the firm-level data in the manufacturing sector that relates to firms' innovation activities. I have gone through the statistic and publications posted on the DOSM portal, however, the data for the year 2021 is not available.

2. Terima kasih kerana mendaftar di eStatistik.

3. Dimaklumkan bahawa data ***Firm-level and Industry-level data of manufacturing sector in the year 2021*** adalah tidak tersedia di jabatan kami. Sila rujuk ketersediaan data kami di dalam penerbitan yang boleh dimuat turun secara percuma melalui pautan:

- eStatistik
  Klik "Free Download" > "Main Category" pilih "Economy" > "Sub-Category" pilih "Manufacturing" > Klik "Search"



4. Untuk makluman jua, Jadual *Input-Output* yang terkini adalah pada tahun **2015** dan penerbitan berkenaan boleh dimuat turun secara percuma melalui pautan seperti berikut.

- eStatistik
  Klik "Free Download" > Taip kata kunci seperti "input" > Klik "Search"

5. Sebarang pertanyaan boleh diajukan kepada kami melalui e-mel ke data@dosm.gov.my. Kami memohon maaf atas kesulitan yang dialami.

Sekian, terima kasih.

Bahagian Integrasi & Pengurusan Data
Jabatan Perangkaan Malaysia.

"PENJANA STATISTIK NEGARA"
"Producer of National Statistics"

Appendix 4: Reply from Department of Statistics Malaysia – Limitation on The Availability of Firm-Level Data (23 July 2024)

JABATAN PERANGKAAN MALAYSIA
(DEPARTMENT OF STATISTICS, MALAYSIA)
BLOK C6, KOMPLEKS C
PUSAT PENTADBIRAN KERAJAAN PERSEKUTUAN
62514 PUTRAJAYA
MALAYSIA

Talian Am : 03-8885 7000
Faks : 03-8888 9248
Portal : https://www.dosm.gov.my

Dear Sir/Madam,

Refer to order no **61593 - Data of Manufacturing Sector (Year 2022 or 2023) Data for Retail sale of sports goods and equipments 2023**

No. Rujukan Permintaan Data	2024/07/18 61593
Bahagian	Bahagian Perangkaan Komunikasi Strategik dan Antarabangsa
Permintaan Data *	Ya
Kategori Permintaan Data	
Sumber Permintaan Data*	Online
Subjek *	Data of Manufacturing Sector (Year 2022 or 2023)
Kategori Utama *	Ekonomi
Sub-Kategori *	Pembuatan
Tarikh Permintaan Data *	18/07/2024
Deskripsi Permintaan Data *	I would like to request the latest data as following: 1) Firm-level data of manufacturing sector, 2) Industry-level data of manufacturing sector. I have attached the dummy table in the attachment for your perusal
Catatan	I am a Ph.D. student from Universiti Tunku Abdul Rahman (UTAR), currently doing a study on the firms' innovation in the Malaysian manufacturing sector. I am writing to request the firm-level data in the manufacturing sector that relates to firms' innovation activities. I have gone through the statistic and publications posted on the DOSM portal, however, the firm level data is not available

2. Thank you for your request through eStatistik.

3. Attached herewith is a description of the data request for your attention. Kindly be informed that **data cannot be supplied because data has not been published for the requested year period.**

4. Anything inquiries,can be submitted to us via email data@dosm.gov.my.

Thank you and regards.

Integration & Data Management Division
Department of Statistics Malaysia

"PENJANA STATISTIK NEGARA"
"Producer of National Statistics"

Appendix 5 : EViews Output-Innovation Input Equation using Heckman Selection Model (Before Adjustment)

Dependent Variable: LOG(RD)
Method: ML Heckman Selection (Newton-Raphson / Marquardt steps)
Date: 09/23/22 Time: 17:01
Sample: 1 14723
Included observations: 14599
Selection Variable: DRD
Convergence achieved after 12 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Response Equation -LOG(RD)				
DIND	0.908393	0.158351	5.736586	0.0000
LOG(EX)	0.086716	0.016872	5.139604	0.0000
LOG(RMS)	0.630404	0.039173	16.09299	0.0000
LOG(IT)	0.194972	0.039294	4.961826	0.0000
LOG(SOI15)	0.846735	0.392687	2.156257	0.0311
LOG(SOB15)	-0.176666	0.276179	-0.639679	0.5224
LOG(SOF15)	-0.223856	0.124976	-1.791184	0.0733
C	-2.755398	0.547034	-5.036978	0.0000
Selection Equation - DRD				
DBIG	0.556216	0.062056	8.963073	0.0000
DMED	0.297816	0.046230	6.442090	0.0000
DIND	0.286918	0.049833	5.757557	0.0000
LOG(EX)	0.049902	0.005668	8.804075	0.0000
LOG(RMS)	0.200084	0.013611	14.70057	0.0000
LOG(IT)	0.081319	0.017039	4.772379	0.0000
LOG(SOI15)	0.338036	0.126399	2.674359	0.0075
LOG(SOB15)	-0.070231	0.083308	-0.843027	0.3992
LOG(SOF15)	-0.129486	0.043140	-3.001500	0.0027
C	-1.004392	0.186418	-5.387858	0.0000
Interaction terms				
@LOG(SIGMA)	0.912820	0.040209	22.70185	0.0000
TFORM(RHO)	5.759615	0.921568	6.249798	0.0000
SIGMA	2.491338	0.100174	24.87002	0.0000
RHO	0.890559	0.017168	51.87289	0.0000

Root MSE	1.020823	Mean dependent var	-0.071820
S.D. dependent var	1.825098	S.E. of regression	1.021523
Akaike info criterion	0.676070	Sum squared resid	15213.31
Schwarz criterion	0.686466	Log likelihood	-4914.971
Hannan-Quinn criter.	0.679524		

Appendix 6 : EViews Output-Innovation Input Equation using Heckman Selection Model (After Adjustment)

Dependent Variable: LOG(RD)
Method: ML Heckman Selection (Newton-Raphson / Marquardt steps)
Date: 09/23/22 Time: 17:05
Sample: 1 14723
Included observations: 14599
Selection Variable: DRD
Convergence achieved after 14 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Response Equation - LOG(RD)				
DIND	0.887740	0.154653	5.740210	0.0000
LOG(EX)	0.086107	0.016797	5.126436	0.0000
LOG(RMS)	0.628526	0.039060	16.09132	0.0000
LOG(IT)	0.196527	0.039046	5.033274	0.0000
LOG(SOI15)	0.589271	0.100567	5.859470	0.0000
LOG(SOF15)	-0.145434	0.068641	-2.118751	0.0341
C	-2.549671	0.473495	-5.384784	0.0000
Selection Equation - DRD				
DBIG	0.557668	0.062043	8.988387	0.0000
DMED	0.298138	0.046060	6.472861	0.0000
DIND	0.278136	0.048329	5.755059	0.0000
LOG(EX)	0.049776	0.005662	8.790767	0.0000
LOG(RMS)	0.198801	0.013560	14.66033	0.0000
LOG(IT)	0.081947	0.016920	4.843152	0.0000
LOG(SOI15)	0.234555	0.032776	7.156227	0.0000
LOG(SOF15)	-0.097924	0.022342	-4.382977	0.0000
C	-0.923208	0.157747	-5.852454	0.0000
Interaction terms				
@LOG(SIGMA)	0.912836	0.040200	22.70741	0.0000
TFORM(RHO)	5.752532	0.919264	6.257761	0.0000
SIGMA	2.491377	0.100153	24.87568	0.0000
RHO	0.890427	0.017166	51.87115	0.0000

Root MSE	1.020730	Mean dependent var	-0.071820
S.D. dependent var	1.825098	S.E. of regression	1.021360
Akaike info criterion	0.675846	Sum squared resid	15210.56
Schwarz criterion	0.685202	Log likelihood	-4915.337
Hannan-Quinn criter.	0.678954		

Appendix 7 : EViews Output-Marginal Effect of Innovation Input Equation

Binary Variable

	Series that include all variables	Series that include all variables except firm size (large firm =1)	Series that include all variables except firm size (medium firm =1)	Series that include all variables except industry group
	mhd1	**md0big**	**mhd0Med**	**mhd0ind**
Mean	0.077159	0.070406	0.072235	0.060664
Median	0.028565	0.028565	0.028553	0.01977
Maximum	0.987024	0.955902	0.987024	0.975267
Minimum	0.000375	0.000375	0.000375	0.000375
Std. Dev.	0.133888	0.112056	0.126038	0.116747
Skewness	3.299657	3.157165	3.631242	3.754891
Kurtosis	15.10607	14.88188	18.08313	19.21179
Jarque-Bera	115641	110131.1	170470.4	194178.2
Probability	0	0	0	0
Sum	1126.445	1027.861	1054.554	885.6269
Sum Sq. Dev.	261.6856	183.3002	231.8976	198.9679
Observations	14599	14599	14599	14599

Continuous Variable

	MEX	MRMS	MIT	MSOI	MSOF	MC
Mean	0.54%	1.96%	0.90%	2.14%	-0.86%	-9.37%
Median	0.003383	0.012379	0.005715	0.013537	-0.00546	-0.059
Maximum	0.020671	0.075637	0.034916	0.082708	-0.00011	-0.001
Minimum	7.06E-05	0.000258	0.000119	0.000283	-0.03337	-0.362
Std. Dev.	0.005267	0.019272	0.008897	0.021074	0.008504	0.092
Skewness	1.52583	1.52583	1.52583	1.52583	-1.52583	-1.526
Kurtosis	4.390293	4.39029	4.39029	4.39029	4.39029	4.390
Jarque-Bera	6840.567	6840.567	6840.567	6840.567	6840.567	6840.567
Probability	0	0	0	0	0	0.000
Sum	78.18629	286.0866	132.0652	312.8317	-126.233	-1368.092
Sum Sq. Dev.	0.404979	5.422084	1.155441	6.483251	1.055639	123.994
Observations	14599	14599	14599	14599	14599	14599.000

Appendix 8 : EViews Output-Innovation Output Equation (Baseline Equation) using Probit Model (Before Adjustment)

Dependent Variable: DPT
Method: ML - Binary Probit (Newton-Raphson / Marquardt steps)
Date: 09/27/23 Time: 14:39
Sample: 1 14723
Included observations: 13547
Convergence achieved after 8 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
LOG(RDF)	0.157778	0.029448	5.357799	0.0000
DBIG	0.777427	0.131369	5.917873	0.0000
DMED	0.142023	0.097330	1.459194	0.1445
LOG(EX)	0.017110	0.008942	1.913316	0.0557
DIND	0.438350	0.078023	5.618184	0.0000
LOG(RMS)	0.281856	0.026462	10.65120	0.0000
LOG(LHS)	0.055489	0.041178	1.347541	0.1778
LOG(IT)	0.139298	0.023526	5.921108	0.0000
LOG(SOI15)	0.812192	0.192915	4.210098	0.0000
LOG(SOF15)	-0.344758	0.062476	-5.518240	0.0000
LOG(SOB15)	-0.277073	0.128917	-2.149244	0.0316
C	-1.403521	0.310865	-4.514883	0.0000

McFadden R-squared	0.419904	Mean dependent var	0.034620
S.D. dependent var	0.182823	S.E. of regression	0.138926
Akaike info criterion	0.176325	Sum squared resid	261.2326
Schwarz criterion	0.182981	Log likelihood	-1182.341
Hannan-Quinn criter.	0.178545	Deviance	2364.681
Restr. deviance	4076.364	Restr. log likelihood	-2038.182
LR statistic	1711.683	Avg. log likelihood	-0.087277
Prob(LR statistic)	0.000000		

Obs with Dep=0	13078	Total obs	13547
Obs with Dep=1	469		

Appendix 9 : EViews Output-Innovation Output Equation (Baseline Equation) using Probit Model (After Adjustment)

Dependent Variable: DPT
Method: ML - Binary Probit (Newton-Raphson / Marquardt steps)
Date: 09/27/23 Time: 14:40
Sample: 1 14723
Included observations: 13547
Convergence achieved after 7 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
LOG(RDF)	0.156091	0.029455	5.299289	0.0000
DBIG	0.720555	0.097143	7.417429	0.0000
LOG(EX)	0.021558	0.008727	2.470175	0.0135
DIND	0.496079	0.074144	6.690788	0.0000
LOG(RMS)	0.316887	0.021968	14.42513	0.0000
LOG(IT)	0.146203	0.023454	6.233518	0.0000
LOG(SOI15)	0.843960	0.192142	4.392388	0.0000
LOG(SOF15)	-0.359779	0.062060	-5.797270	0.0000
LOG(SOB15)	-0.285592	0.128804	-2.217254	0.0266
C	-1.106915	0.279792	-3.956203	0.0001

McFadden R-squared	0.418552	Mean dependent var	0.034620
S.D. dependent var	0.182823	S.E. of regression	0.138766
Akaike info criterion	0.176437	Sum squared resid	260.6672
Schwarz criterion	0.181984	Log likelihood	-1185.096
Hannan-Quinn criter.	0.178287	Deviance	2370.193
Restr. deviance	4076.364	Restr. log likelihood	-2038.182
LR statistic	1706.171	Avg. log likelihood	-0.087480
Prob(LR statistic)	0.000000		
Obs with Dep=0	13078	Total obs	13547
Obs with Dep=1	469		

Appendix 10 : EViews Output-Innovation Output Equation (Extended Equation) using Probit Model (Before Adjustment)

Dependent Variable: DPT
Method: ML - Binary Probit (Newton-Raphson / Marquardt steps)
Date: 09/27/23 Time: 14:40
Sample: 1 14723
Included observations: 13547
Convergence achieved after 8 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
LOG(RDF)	0.132452	0.028845	4.591796	0.0000
DBIG	0.705283	0.129761	5.435247	0.0000
DMED	0.129260	0.095733	1.350215	0.1769
LOG(EX)	0.009675	0.008824	1.096459	0.2729
DIND	0.334656	0.070545	4.743884	0.0000
LOG(RMS)	0.224420	0.025205	8.903670	0.0000
LOG(IT)*LOG(LHS)	0.041374	0.006829	6.058417	0.0000
LOG(SOI15)*LOG(LHS)	-0.129230	0.065059	-1.986346	0.0470
LOG(SOB15)*LOG(LHS)	0.172071	0.051533	3.339055	0.0008
LOG(SOF15)*LOG(LHS)	0.002897	0.025103	0.115388	0.9081
C	-0.383492	0.241942	-1.585058	0.1130

McFadden R-squared	0.415216	Mean dependent var	0.034620
S.D. dependent var	0.182823	S.E. of regression	0.140547
Akaike info criterion	0.177589	Sum squared resid	267.3837
Schwarz criterion	0.183690	Log likelihood	-1191.896
Hannan-Quinn criter.	0.179623	Deviance	2383.792
Restr. deviance	4076.364	Restr. log likelihood	-2038.182
LR statistic	1692.573	Avg. log likelihood	-0.087982
Prob(LR statistic)	0.000000		

Obs with Dep=0	13078	Total obs	13547
Obs with Dep=1	469		

Appendix 11 : EViews Output-Innovation Output Equation (Extended Equation) using Probit Model (After Adjustment)

Dependent Variable: DPT
Method: ML - Binary Probit (Newton-Raphson / Marquardt steps)
Date: 09/27/23 Time: 14:50
Sample: 1 14723
Included observations: 13547
Convergence achieved after 7 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
LOG(RDF)	0.129080	0.028635	4.507719	0.0000
DBIG	0.613213	0.102133	6.004031	0.0000
DIND	0.364449	0.068865	5.292187	0.0000
LOG(RMS)	0.242134	0.022384	10.81741	0.0000
LOG(IT)*LOG(LHS)	0.042350	0.006858	6.175734	0.0000
LOG(SOI15)*LOG(LHS)	-0.122858	0.031368	-3.916726	0.0001
LOG(SOB15)*LOG(LHS)	0.171453	0.033420	5.130328	0.0000
C	-0.222795	0.209154	-1.065221	0.2868

McFadden R-squared	0.414375	Mean dependent var	0.034620
S.D. dependent var	0.182823	S.E. of regression	0.140278
Akaike info criterion	0.177399	Sum squared resid	266.4193
Schwarz criterion	0.181836	Log likelihood	-1193.611
Hannan-Quinn criter.	0.178878	Deviance	2387.221
Restr. deviance	4076.364	Restr. log likelihood	-2038.182
LR statistic	1689.143	Avg. log likelihood	-0.088109
Prob(LR statistic)	0.000000		

Obs with Dep=0	13078	Total obs	13547
Obs with Dep=1	469		

Appendix 12 : EViews Output-Innovation Output Equation (Modified Equation) using Probit Model

Dependent Variable: DPT
Method: ML - Binary Probit (Newton-Raphson / Marquardt steps)
Date: 09/27/23 Time: 14:51
Sample: 1 14723
Included observations: 13547
Convergence achieved after 8 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
LOG(RDF)	0.149022	0.029286	5.088503	0.0000
DBIG	0.623591	0.102087	6.108437	0.0000
DIND	0.415281	0.071935	5.773036	0.0000
LOG(RMS)	0.275037	0.024350	11.29504	0.0000
LOG(IT)	0.140072	0.023580	5.940205	0.0000
LOG(SOI15)	0.326095	0.057132	5.707738	0.0000
LOG(SOB15)*LOG(LHS)	0.030222	0.007463	4.049592	0.0001
LOG(SOF15)	-0.208778	0.034132	-6.116805	0.0000
C	-0.805688	0.227550	-3.540699	0.0004

McFadden R-squared	0.420046	Mean dependent var	0.034620
S.D. dependent var	0.182823	S.E. of regression	0.138881
Akaike info criterion	0.175840	Sum squared resid	261.1183
Schwarz criterion	0.180832	Log likelihood	-1182.052
Hannan-Quinn criter.	0.177505	Deviance	2364.105
Restr. deviance	4076.364	Restr. log likelihood	-2038.182
LR statistic	1712.260	Avg. log likelihood	-0.087256
Prob(LR statistic)	0.000000		

Obs with Dep=0	13078	Total obs	13547
Obs with Dep=1	469		

Appendix 13 : EViews Output-Marginal Effect of Modified Innovation Output Equation

Binary Variable

	Series that include all variables	Series that include all variables except firm size (large firm =1)	Series that include all variables except industry group
	Mb1	Mb0big	Mb0Ind
Mean	0.0350	0.0300	0.0248
Median	0.0087	0.0087	0.0044
Maximum	0.9999	0.9994	0.9997
Minimum	0.0000	0.0000	0.0000
Std. Dev.	0.1103	0.0907	0.0965
Skewness	6.2217	7.0512	7.1991
Kurtosis	45.0880	59.3841	59.3521
Jarque-Bera	1087280	1906765	1909489
Probability	0	0	0
Sum	474.0968	407.0225	336.5406
Sum Sq. Dev.	164.7298	111.4642	126.0133
Observations	13547	13547	13547

Continuous Variable

	mprdf	**mprms**	**mpit**	**mpsoi15**	**mpsoblhs**	**mpsof15**	**mpc**
Mean	0.0069	0.0127	0.0065	0.0150	0.0014	-0.0096	-0.0372
Median	0.0035	0.0065	0.0033	0.0077	0.0007	-0.0049	-0.0190
Maximum	0.0595	0.1097	0.0559	0.1301	0.0121	0.0000	0.0000
Minimum	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0833	-0.3214
Std. Dev.	0.0099	0.0183	0.0093	0.0217	0.0020	0.0139	0.0536
Skewness	3.1484	3.1484	3.1484	3.1484	3.1484	-3.1484	-3.1484
Kurtosis	14.0384	14.0384	14.0384	14.0384	14.0384	14.0384	14.0384
Jarque-Bera	91158	91158	91158	91158	91158	91158	91158
Probability	0	0	0.00	0	0	0	0
Sum	93.139	171.899	87.545	203.81	18.888	-130.487	-503.558
Sum Sq. Dev.	1.3329	4.5401	1.1776	6.3822	0.0548	2.6161	38.9597
Observation	13547	13547	13547	13547	13547	13547	13547

Appendix 14 : EViews Output-Productivity Equation (Baseline Equation) using OLS Estimator

Dependent Variable: LOG(YW)
Method: Least Squares
Date: 09/29/23 Time: 15:21
Sample: 1 14723
Included observations: 13547

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(DPTF)	0.360918	0.005459	66.11096	0.0000
LOG(KW)	0.350976	0.013017	26.96242	0.0000
LOG(LHSW)	0.010460	0.002774	3.770032	0.0002
LOG(ITW)	-0.018621	0.005115	-3.640812	0.0003
LOG(SOI15)	0.437732	0.038078	11.49567	0.0000
LOG(SOB15)	-0.504167	0.024296	-20.75141	0.0000
LOG(SOF15)	0.065383	0.011977	5.459066	0.0000
C	3.197138	0.090774	35.22102	0.0000

R-squared	0.569938	Mean dependent var	3.247124
Adjusted R-squared	0.569716	S.D. dependent var	0.951226
S.E. of regression	0.623967	Akaike info criterion	1.895151
Sum squared resid	5271.200	Schwarz criterion	1.899588
Log likelihood	-12828.81	Hannan-Quinn criter.	1.896631
F-statistic	2563.216	Durbin-Watson stat	1.716325
Prob(F-statistic)	0.000000		

Appendix 15 : EViews Output-Heteroskedasticity Test

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

F-statistic	11.40074	Prob. F(7,13539)	0.0000
Obs*R-squared	79.38443	Prob. Chi-Square(7)	0.0000
Scaled explained SS	244.7743	Prob. Chi-Square(7)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 09/29/23 Time: 15:22
Sample: 1 14723
Included observations: 13547

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.036616	0.140282	-0.261016	0.7941
LOG(DPTF)	-0.011620	0.008437	-1.377290	0.1684
LOG(KW)	0.135373	0.020117	6.729317	0.0000
LOG(LHSW)	-0.003230	0.004288	-0.753419	0.4512
LOG(ITW)	0.028751	0.007904	3.637448	0.0003
LOG(SOI15)	-0.104023	0.058846	-1.767710	0.0771
LOG(SOB15)	0.089558	0.037547	2.385258	0.0171
LOG(SOF15)	0.021349	0.018509	1.153402	0.2488

R-squared	0.005860	Mean dependent var	0.389105
Adjusted R-squared	0.005346	S.D. dependent var	0.966872
S.E. of regression	0.964285	Akaike info criterion	2.765730
Sum squared resid	12589.17	Schwarz criterion	2.770167
Log likelihood	-18725.67	Hannan-Quinn criter.	2.767209
F-statistic	11.40074	Durbin-Watson stat	1.869055
Prob(F-statistic)	0.000000		

Appendix 16 : EViews Output-Productivity Equation (Baseline Equation) using OLS Adjusted with Huber-White Covariance Method

Dependent Variable: LOG(YW)
Method: Least Squares
Date: 09/29/23 Time: 15:23
Sample: 1 14723
Included observations: 13547
Huber-White-Hinkley (HC1) heteroskedasticity consistent standard errors and covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(DPTF)	0.360918	0.007424	48.61348	0.0000
LOG(KW)	0.350976	0.021206	16.55069	0.0000
LOG(LHSW)	0.010460	0.002940	3.557579	0.0004
LOG(ITW)	-0.018621	0.007069	-2.634276	0.0084
LOG(SOI15)	0.437732	0.038027	11.51117	0.0000
LOG(SOB15)	-0.504167	0.024282	-20.76327	0.0000
LOG(SOF15)	0.065383	0.011976	5.459322	0.0000
C	3.197138	0.143311	22.30903	0.0000

R-squared	0.569938	Mean dependent var	3.247124
Adjusted R-squared	0.569716	S.D. dependent var	0.951226
S.E. of regression	0.623967	Akaike info criterion	1.895151
Sum squared resid	5271.200	Schwarz criterion	1.899588
Log likelihood	-12828.81	Hannan-Quinn criter.	1.896631
F-statistic	2563.216	Durbin-Watson stat	1.716325
Prob(F-statistic)	0.000000	Wald F-statistic	1851.650
Prob(Wald F-statistic)	0.000000		

Appendix 17 : EViews Output-Productivity Equation (Extended Equation) using OLS Estimator

Dependent Variable: LOG(YW)
Method: Least Squares
Date: 09/29/23 Time: 15:25
Sample: 1 14723
Included observations: 13547

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(DPTF)	0.448428	0.006889	65.09455	0.0000
LOG(KW)	0.425237	0.013701	31.03695	0.0000
LOG(LHSW)	0.084144	0.003209	26.21965	0.0000
LOG(ITW)*LOG(LHS)	0.017047	0.001693	10.07101	0.0000
LOG(SOI15)*LOG(LHS)	-0.031804	0.020023	-1.588369	0.1122
LOG(SOB15)*LOG(LHS)	-0.104409	0.015100	-6.914396	0.0000
LOG(SOF15)*LOG(LHS)	0.112650	0.008453	13.32731	0.0000
C	4.091991	0.077871	52.54818	0.0000

R-squared	0.529728	Mean dependent var	3.247124
Adjusted R-squared	0.529485	S.D. dependent var	0.951226
S.E. of regression	0.652485	Akaike info criterion	1.984533
Sum squared resid	5764.046	Schwarz criterion	1.988970
Log likelihood	-13434.23	Hannan-Quinn criter.	1.986012
F-statistic	2178.675	Durbin-Watson stat	1.485521
Prob(F-statistic)	0.000000		

Appendix 18 : EViews Output- Heteroskedasticity Test

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

F-statistic	27.97347	Prob. F(7,13539)	0.0000
Obs*R-squared	193.1367	Prob. Chi-Square(7)	0.0000
Scaled explained SS	464.9183	Prob. Chi-Square(7)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 09/29/23 Time: 15:25
Sample: 1 14723
Included observations: 13547

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.899650	0.110721	-8.125410	0.0000
LOG(DPTF)	-0.069456	0.009795	-7.091045	0.0000
LOG(KW)	0.169910	0.019481	8.722004	0.0000
LOG(LHSW)	-0.038081	0.004563	-8.345668	0.0000
LOG(ITW)*LOG(LHS)	-0.001031	0.002407	-0.428212	0.6685
LOG(SOI15)*LOG(LHS)	0.059186	0.028469	2.078938	0.0376
LOG(SOB15)*LOG(LHS)	-0.003875	0.021470	-0.180499	0.8568
LOG(SOF15)*LOG(LHS)	-0.044139	0.012018	-3.672654	0.0002

R-squared	0.014257	Mean dependent var	0.425485
Adjusted R-squared	0.013747	S.D. dependent var	0.934174
S.E. of regression	0.927731	Akaike info criterion	2.688440
Sum squared resid	11652.81	Schwarz criterion	2.692878
Log likelihood	-18202.15	Hannan-Quinn criter.	2.689920
F-statistic	27.97347	Durbin-Watson stat	1.888685
Prob(F-statistic)	0.000000		

Appendix 19 : EViews Output-Productivity Equation (Extended Equation) using OLS Adjusted with Huber-White Covariance Method

Dependent Variable: LOG(YW)
Method: Least Squares
Date: 09/29/23 Time: 15:26
Sample: 1 14723
Included observations: 13547
Huber-White-Hinkley (HC1) heteroskedasticity consistent standard errors and covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(DPTF)	0.448428	0.009470	47.35398	0.0000
LOG(KW)	0.425237	0.020161	21.09165	0.0000
LOG(LHSW)	0.084144	0.003419	24.61157	0.0000
LOG(ITW)*LOG(LHS)	0.017047	0.001967	8.665309	0.0000
LOG(SOI15)*LOG(LHS)	-0.031804	0.024287	-1.309508	0.1904
LOG(SOB15)*LOG(LHS)	-0.104409	0.017749	-5.882603	0.0000
LOG(SOF15)*LOG(LHS)	0.112650	0.010654	10.57368	0.0000
C	4.091991	0.116655	35.07781	0.0000

R-squared	0.529728	Mean dependent var	3.247124
Adjusted R-squared	0.529485	S.D. dependent var	0.951226
S.E. of regression	0.652485	Akaike info criterion	1.984533
Sum squared resid	5764.046	Schwarz criterion	1.988970
Log likelihood	-13434.23	Hannan-Quinn criter.	1.986012
F-statistic	2178.675	Durbin-Watson stat	1.485521
Prob(F-statistic)	0.000000	Wald F-statistic	
Prob(Wald F-statistic)	0.000000		

Appendix 20 : EViews Output-Productivity Equation (Modified Equation) using OLS Adjusted with Huber-White Covariance Method

Dependent Variable: LOG(YW)
Method: Least Squares
Date: 09/29/23 Time: 12:16
Sample: 1 14723
Included observations: 13547
Huber-White-Hinkley (HC1) heteroskedasticity consistent standard errors and covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(DPTF)	0.469543	0.008600	54.59865	0.0000
LOG(KW)	0.375883	0.019883	18.90495	0.0000
LOG(LHSW)	0.053033	0.003288	16.13101	0.0000
LOG(ITW)*LOG(LHS)	0.026208	0.001864	14.06194	0.0000
LOG(SOI15)	0.719352	0.012204	58.94425	0.0000
LOG(SOB15)	-0.702103	0.012794	-54.87827	0.0000
LOG(SOF15)*LOG(LHS)	-0.034371	0.002746	-12.51878	0.0000
C	3.857187	0.122379	31.51833	0.0000

R-squared	0.601281	Mean dependent var	3.247124
Adjusted R-squared	0.601075	S.D. dependent var	0.951226
S.E. of regression	0.600799	Akaike info criterion	1.819478
Sum squared resid	4887.032	Schwarz criterion	1.823916
Log likelihood	-12316.24	Hannan-Quinn criter.	1.820958
F-statistic	2916.751	Durbin-Watson stat	1.692723
Prob(F-statistic)	0.000000	Wald F-statistic	2162.068
Prob(Wald F-statistic)	0.000000		

Appendix 21 : EViews Output-Robustness Check : Innovation Output Equation

Dependent Variable: DIOXP
Method: ML - Binary Probit (Newton-Raphson / Marquardt steps)
Date: 09/29/23 Time: 19:18
Sample: 1 14723
Included observations: 13547
Convergence achieved after 8 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
LOG(RDF)	0.094960	0.026444	3.591023	0.0003
DBIG	0.256434	0.098263	2.609664	0.0091
DIND	0.473275	0.064704	7.314489	0.0000
LOG(RMS)	0.301071	0.022899	13.14761	0.0000
LOG(IT)	0.115262	0.022970	5.017990	0.0000
LOG(SOI15)	0.595624	0.051184	11.63697	0.0000
LOG(SOB15)*LOG(LHS)	0.033584	0.006747	4.977339	0.0000
LOG(SOF15)	-0.357770	0.030475	-11.73995	0.0000
C	-1.231467	0.205808	-5.983575	0.0000

McFadden R-squared	0.385648	Mean dependent var	0.049236
S.D. dependent var	0.216368	S.E. of regression	0.172545
Akaike info criterion	0.242473	Sum squared resid	403.0481
Schwarz criterion	0.247465	Log likelihood	-1633.394
Hannan-Quinn criter.	0.244138	Deviance	3266.787
Restr. deviance	5317.455	Restr. log likelihood	-2658.727
LR statistic	2050.668	Avg. log likelihood	-0.120572
Prob(LR statistic)	0.000000		

Obs with Dep=0	12880	Total obs	13547
Obs with Dep=1	667		

Appendix 22 : EViews Output-Robustness Checking: Marginal Effect of Innovation Output Equation

Binary Variable

	Series that include all variables	Series that include all variables except firm size (large firm =1)	Series that include all variables except industry group
	Mrb1	Mrb0big	Mrb0Ind
Mean	0.0496	0.0476	0.0333
Median	0.0123	0.0123	0.0058
Maximum	0.9999	0.9998	0.9996
Minimum	0.0000	0.0000	0.0000
Std. Dev.	0.1243	0.1169	0.1056
Skewness	5.0595	5.1775	6.1715
Kurtosis	31.6934	33.6779	45.3918
Jarque-Bera	522522	591756	1100361
Probability	0	0	0
Sum	672.4485	644.7217	451.5204
Sum Sq. Dev.	209.1289	185.1513	151.073
Observations	13547	13547	13547

Continuous Variable

	mrrdf	mrrms	mrit	mrsoi15	mrsoblhs	mrsof15	mrc
Mean	0.0061	0.0194	0.0074	0.0384	0.0022	-0.0230	-0.0793
Median	0.0030	0.0096	0.0037	0.0189	0.0011	-0.0114	-0.0391
Maximum	0.0379	0.1201	0.0460	0.2376	0.0134	0.0000	0.0000
Minimum	0.0000	0.0000	0.0000	0.0000	0.0000	-0.1427	-0.4913
Std. Dev.	0.0078	0.0249	0.0095	0.0492	0.0028	0.0296	0.1018
Skewness	2.1154	2.1154	2.1154	2.1154	2.1154	-2.1154	-2.1154
Kurtosis	7.3366	7.3366	7.3366	7.3366	7.3366	7.3366	7.3366
Jarque-Bera	20719	20719	20719	20719	20719	20719	20719
Probability	0	0	0.00	0	0	0	0
Sum	82.857	262.697	100.571	519.708	29.3037	-312.170	-1074.51
Sum Sq. Dev.	0.8344	8.3877	1.2294	32.8285	0.1044	11.8444	140.3307
Observation	13547	13547	13547	13547	13547	13547	13547

Appendix 23 : EViews Output-Robustness Check : Productivity Equation

Dependent Variable: LOG(YW)
Method: Least Squares
Date: 09/30/23 Time: 12:10
Sample: 1 14723
Included observations: 13547
Huber-White-Hinkley (HC1) heteroskedasticity consistent standard errors and covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(DIOXPF)	0.421209	0.007681	54.84018	0.0000
LOG(KW)	0.380690	0.020408	18.65416	0.0000
LOG(LHSW)	0.048955	0.003330	14.69961	0.0000
LOG(ITW)*LOG(LHS)	0.028548	0.001880	15.18427	0.0000
LOG(SOI15)	0.818045	0.013209	61.93241	0.0000
LOG(SOB15)	-0.908829	0.015417	-58.95107	0.0000
LOG(SOF15)*LOG(LHS)	-0.020420	0.002631	-7.762171	0.0000
C	3.855086	0.125590	30.69590	0.0000

R-squared	0.600042	Mean dependent var	3.247124
Adjusted R-squared	0.599835	S.D. dependent var	0.951226
S.E. of regression	0.601732	Akaike info criterion	1.822582
Sum squared resid	4902.225	Schwarz criterion	1.827020
Log likelihood	-12337.26	Hannan-Quinn criter.	1.824062
F-statistic	2901.717	Durbin-Watson stat	1.660702
Prob(F-statistic)	0.000000	Wald F-statistic	2142.164
Prob(Wald F-statistic)	0.000000		