

Faculty of Economics and Business

Role of Educational Attainment in Driving Productivity and Economic Growth in Malaysia

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Role of Educational Attainment in Driving Productivity and Economic Growth in Malaysia

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DECLARATION

I declare that the work in this thesis was carried out in accordance with the regulations of Universiti Malaysia Sarawak. Except where due acknowledgements have been made, the work is that of the author alone. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

……

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ABSTRACT

This research studies the influence of employed workers' educational attainment on sectoral labor productivity within the main sectors of the Malaysian economy, comprising agriculture, industry, and services—aiming to shed light on the role of educational quality in driving productivity and economic growth while addressing challenges posed by low-skilled labor and foreign worker employment. The study employs annual data from the World Bank and the Department of Statistics Malaysia, utilizing Vector Autoregressive (VAR), Autoregressive Distributed Lag (ARDL), and Nonlinear Autoregressive Distributed Lag (NARDL) models for an in-depth analysis of these relationships. The first objective is addressed via Model 1, which examines the impact of the educational quality of the employed workforce on Malaysian labor productivity from 1982 to 2023. The second objective involves Model 2—investigating the combined influence of educational quality and fixed capital on value-added agriculture during the same period—and Model 3, which investigates the impacts of both educational quality and the total foreign labor force on agricultural GDP spanning 1987–2023. The third objective, addressed by Model 4, explores the effect of workers' educational quality on the value-added industry during the period 1982–2023. The fourth objective digs deeper into sectoral labor productivity, with Models 5, 6, and 7 examining the influence of educational attainment across the agriculture, industry, and services sectors from 1991 to 2022 via ARDL estimations. Lastly, the fifth objective, utilizing Models 8, 9, and 10, studies the asymmetric effects of foreign worker employment and the impacts of low educational attainment on sectoral productivity for the same study period, using NARDL estimations. The findings reveal significant sectoral variations. Workers with secondary education consistently boost overall labor productivity, with significant positive impacts on the value-added industry for the period 1982–2023.

Tertiary education positively influences industrial productivity in the long run but shows no causal relationship with overall labor productivity. Conversely, workers lacking formal education negatively impact value-added agriculture and long-term service productivity. Primary education exhibits a mixed effect, being negative for the first nine years but followed by a sustained positive impact over 41 years. The analysis underscores that fixed capital positively affects service productivity in the long run. The NARDL estimations reveal that positive changes in foreign worker employment adversely affect industrial productivity in the short term and service productivity in the long term. Asymmetric effects are evident, with foreign workers significantly diminishing industrial productivity in the short run and workers with low educational attainment negatively impacting long-term agricultural productivity. Moving forward, Malaysia should prioritize transitioning its labor market toward higher-skilled employment to boost sectoral productivity. Policymakers ought to emphasize enhancing the access and quality of secondary and tertiary education, aligning educational outcomes with industry demands. The findings stress the urgency of reducing reliance on low-skilled foreign labor by fostering workforce upskilling, accelerating the adoption of Industry 4.0 technologies, and promoting innovation. These strategies are critical for Malaysia to achieve its aspirations of becoming a high-income nation while ensuring sustainable and inclusive economic growth.

Keywords: Educational attainment, foreign worker employment, labor productivity, economic growth, NARDL estimation

Peranan Pencapaian Pendidikan dalam Memacu Produktiviti dan Pertumbuhan Ekonomi di Malaysia

ABSTRAK

Kajian ini menyiasat pengaruh pencapaian pendidikan pekerja terhadap produktiviti buruh merentas sektor utama ekonomi Malaysia, termasuk pertanian, perindustrian, dan perkhidmatan. Kajian ini bertujuan untuk memberikan pandangan tentang peranan kualiti pendidikan dalam memacu produktiviti dan pertumbuhan ekonomi sambil menangani cabaran yang ditimbulkan oleh tenaga kerja berkemahiran rendah dan pekerjaan asing. Penyelidikan ini menggunakan data tahunan yang diperoleh daripada Bank Dunia dan Jabatan Perangkaan Malaysia, dengan menggunakan VAR, ARDL, dan NARDL untuk menganalisis hubungan ini secara menyeluruh. Objektif pertama ditangani melalui Model 1 untuk mengkaji impak kualiti pendidikan tenaga kerja yang bekerja terhadap produktiviti buruh Malaysia dari tahun 1982 hingga 2023. Objektif kedua melibatkan Model 2, menganalisis pengaruh kualiti pendidikan dan model tetap terhadap nilai ditambah sektor pertanian dalam tempoh yang sama. Model 3 yang menyiasat impak kualiti pendidikan dan tenaga buruh asing ke atas KDNK pertanian dari tahun 1987 hingga 2023. Objektif ketiga yang ditangani oleh Model 4, meneroka kesan kualiti pendidikan terhadap nilai ditambah sektor industri dari 1982 hingga 2023. Objektif keempat menyelidiki dengan lebih mendalam produktiviti buruh mengikut sektor, dengan Model 5, 6, dan 7 mengkaji pengaruh pencapaian pendidikan merentas sektor pertanian, perindustrian, dan perkhidmatan dari 1991 hingga 2022 dengan mengunakan anggaran ARDL. Akhirnya, objektif kelima, melalui Model 8, 9, and 10, menyiasat kesan asimetri pekerja asing dan impak pencapaian pendidikan yang rendah terhadap produktiviti sektor untuk tempoh kajian yang sama dengan menggunakan anggaran NARDL. Pekerja yang mempunyai

pendidikan menengah dapat meningkatkan produktiviti buruh secara keseluruhan, dengan impak positif yang ketara terhadap nilai ditambah sektor industri bagi tempoh 1982–2023. Pendidikan tinggi secara positif mempengaruhi produktiviti industri dalam jangka panjang tetapi tidak menunjukkan sebarang hubungan dengan produktiviti buruh secara keseluruhan. Sebaliknya, pekerja tanpa pendidikan formal memberi kesan negatif kepada nilah ditambah sektor pertanian dan produktiviti perkhidmatan dalam jangka panjang. Analisis ini juga menekankan bahawa modal tetap memberi kesan positif kepada produktiviti perkhidmatan dalam jangka panjang. Anggaran NARDL mendedahkan bahawa perubahan positif dalam pekerjaan pekerja asing memberi kesan negatif kepada produktiviti perindustrian dalam jangka pendek dan produktiviti perkhidmatan dalam jangka panjang. Bagi kesan asimetri yang ketara, pekerja asing mengurangkan produktiviti industri dalam jangka pendek dan pekerja dengan pencapaian pendidikan rendah memberi kesan negatif terhadap produktiviti pertanian dalam jangka panjang. Malaysia mesti mengutamakan peralihan pasaran buruh ke arah pekerjaan berkemahiran tinggi untuk meningkatkan produktiviti sektor. Pembuat dasar harus menumpukan pada peningkatan kualiti pendidikan menengah atau pendidikan tinggi, dan menyelaraskan hasil pendidikan dengan permintaan industri. Penemuan ini menekankan keperluan mendesak untuk mengurangkan pergantungan kepada tenaga kerja asing berkemahiran rendah dengan memupuk peningkatan kemahiran tenaga kerja, mempercepatkan penggunaan teknologi Industri 4.0, dan mempromosikan inovasi. Strategi ini adalah penting untuk Malaysia mencapai aspirasinya menjadi sebuah negara berpendapatan tinggi sambil memastikan pertumbuhan ekonomi yang mampan dan inklusif.

Kata kunci: *Pencapaian pendidikan pekerja, pekerja asing, produktiviti buruh, pertumbuhan ekonomi, anggaran NARDL*

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LIST OF ABBREVIATIONS

ADF	Augmented Dickey–Fuller
ARDL	Autoregressive Distributed Lag
DOSM	Department of Statistics Malaysia
GDP	Gross Domestic Product
MASCO	Malaysia Standard Classification of Occupations
MFP	Multi-Factor Productivity
MOE	Ministry of Education Malaysia
NARDL	Nonlinear Autoregressive Distributed Lag
OLS	Ordinary Least Squares
IRF	Impulse Response Function
KPSS	Kwiatkowski, Phillips, Schmidt, and Shin
PP	Phillips–Perron
SCORE	Sarawak Corridor of Renewable Energy
SDGs	Sustainable Development Goals
TFP	Total Factor Productivity
VAR	Vector Autoregressive

CHAPTER 1

INTRODUCTION

1.1 Introduction

Education plays a significant role in contributing to the economic development of a country because it enhances competitiveness, which sustains economic growth. In general, higher education creates more skilled and productive workers that promote growth and development in a country (Barro & Lee, 2001; Bartel & Lichtenberg, 1987; Sapovadia, 2015). Empirical studies indicate education enhances the quality of human capital, which is a significant contribution toward economic growth. Human capital refers to the knowledge, experience, and skills of labor that can create economic value and influence productivity. Higher skills and knowledge are needed by firms to fulfill all the conditions for employment to boost productivity in the industry. Therefore, human capital investment has been one of the main sources of modern economic growth. Heckman (2003) stated that a more skilled labor force would produce greater payoffs to capital and create greater national wealth. The effects of education on development outcomes differ based on the level of education, including primary education, secondary education, and tertiary education (Agiomirgianakis et al., 2002; Benos & Karagiannis, 2016; Gyimah-Brempong, 2011; Jalil & Idrees, 2013; Nowak & Dahal, 2016).

1.2 Background of the Study

1.2.1 Public Service–Education

Public service is a service that is mainly provided by the government to people living in the country, including health care, education, and transport—these services are

designed to benefit all citizens. Funds for public services are usually raised in various ways (i.e., taxes, fees, and financial transfers) from federal to provincial or state governments. The government uses its unique method of funding public services in different countries. Education is the systematic process of enhancing knowledge and skills through learning and understanding in school, college, university, or other educational institutions. Education is the most important factor that affects the development of individuals and countries. It has become an important factor in a bright future for the new generations in any society. Education enhances our knowledge, experience, skill, confidence level, and personality. In most developing countries, the government requires all children to receive education. In general, education is divided into three levels (i.e., primary education, secondary education, and tertiary education), which are mainly under the Ministry of Education of a country.

1.2.2 Education and its Importance

Education has become one of the fundamental factors for the development of the country. Sustainable investment in human capital is necessary to achieve sustainable economic development. Becker and Lewis (1993) stated that education plays a significant role in the economic health of the country. In addition, the relationship between education and economic growth is increasingly gaining attention from all over the world. Education enhances productivity and creativity, which promotes entrepreneurship and technological progress. Likewise, education plays a significant role in enhancing economic and social progress and income distribution. Many countries are now willing to invest more in their education systems to improve productivity levels and develop the national economy. Howe (1993) shows that more education always reduces the probability of unemployment, and it has become an increasingly important standard to weigh up the success of the job market

over time. Bartel and Lichtenberg (1987) suggest that highly educated people have higher levels of engagement in research and development activities and technological advancement. The demand for a highly educated workforce seems to change with economic growth and technological progress. The World Economic Forum 2016 recommended three ways education affects a country's productivity. First, it improves the work capacity of the labor force to finish the tasks more quickly. Second, secondary and tertiary education primarily promotes the transfer of knowledge regarding the latest information, products, and technologies created by others. Finally, a labor force's creativity enhances a country's ability to create more innovative products, technologies, and advanced knowledge. According to Woessmann (2015), education is one of the main factors that drive economic growth, income, and employment in modern knowledge-based economies. The Human Development Index includes the Education Index, an indicator that calculates the average years of schooling for adults and the expected years of schooling for children. Osathanunkul et al. (2023) found that government education expenditure significantly positively impacts productivity.

Table 1.1: Government Expenditure on Education for Selected Countries, 2013–2022

Country	**Government expenditure on education, total (% of GDP)**									
	Year									
	2013	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**
Argentina	5.4	5.4	5.8	5.5	5.5	4.9	4.8	5.3	4.6	4.8
Hong Kong	3.8	3.6	3.3	3.3	3.3	3.3	3.8	4.4	4.0	3.7
Indonesia	3.4	3.3	3.6	1.2	1.1	1.0	1.0	1.0	1.0	0.9
Malaysia	5.5	5.0	4.7	4.3	4.2	4.1	4.0	4.5	4.3	3.5

Table 1.1 continued

New Zealand	5.9	5.8	5.7	5.5	5.3	5.2	5.2	5.7	5.5	5.2
Pakistan	2.5	2.5	2.7	2.4	2.1	2.3	2.2	2.1	1.7	2.0
Sri Lanka	1.6	1.9	2.1	3.2	2.6	2.0	-	1.6	1.5	1.2
United States	6.2	6.1	4.9	4.8	5.1	4.9	5.0	5.4	5.4	-
United Kingdom	5.5	5.6	5.6	5.4	5.4	5.2	5.2	5.4	5.9	5.0

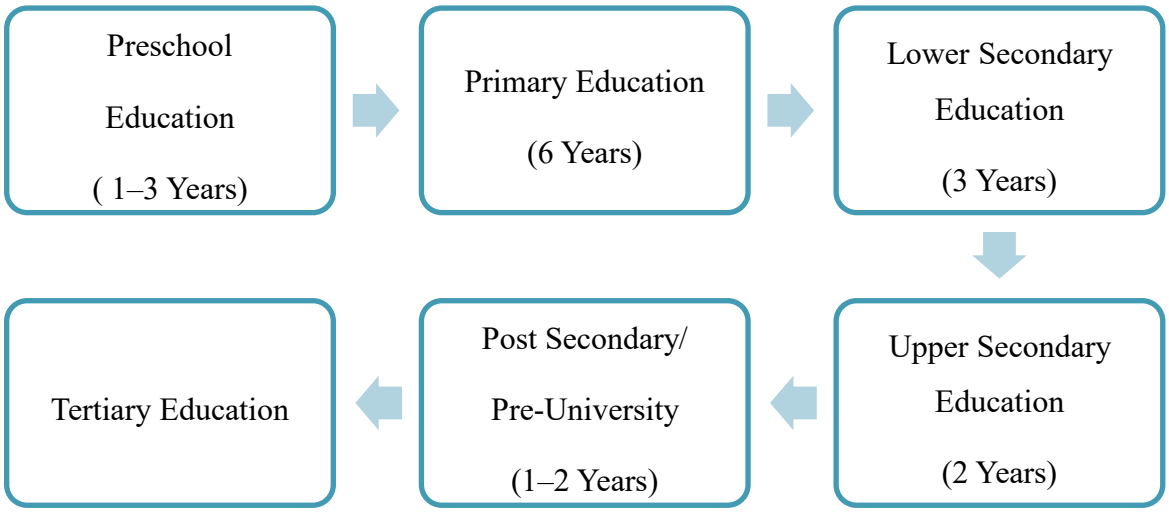
Source: World Bank (2023).

Table 1.1 presents the total percentage of GDP in government expenditure on education for selected countries, including Argentina, Hong Kong, Indonesia, Malaysia, New Zealand, Pakistan, Sri Lanka, the United States, and the United Kingdom, from 2013 to 2022. Based on the information, the United States had the highest percentage of GDP in government expenditure on education, which on average is between 6.2% and 4.8%, followed by New Zealand, which on average is between 5.9% and 5.2% from 2013 to 2022. Furthermore, the government of the United Kingdom also emphasized their national education, which expenditure contributed between 5.6% and 5.0% from 2013 to 2022. The total percentage of GDP in Malaysian government expenditure on education is, on average, between 5.5% and 3.5%. The total percentage of GDP in Malaysian government expenditure on education decreased from 5.5% in the year 2013 to only 3.5% in 2022. The Malaysian government invested more in education compared with Hong Kong, Indonesia, Pakistan, and Sri Lanka during the period of 2013–2022 (see Table 1.1).

1.2.3 Education in Malaysia

Education plays a significant role in building a country's resilience, encouraging a caring and just society, and sustaining economic growth in Malaysia. It also can help to

realize Malaysia's aspirations to become a developed country. Education is the responsibility of the federal government and state government of Malaysia. The government plays a leading role in funding education through the national education policy, consistently investing and spending on education. The Malaysian government has made remarkable progress in many aspects of education, including increased access to preschool and secondary education, as well as providing opportunities for further study in post-secondary and tertiary education. The education system of Malaysia is mainly divided into three levels (i.e., primary education, secondary education, and tertiary education). It consists of 6 years for primary education, 3 years for lower secondary education, 2 years for upper secondary education, 1 or 2 years for post-secondary or pre-university studies, and 3 to 5 years for a bachelor's degree in university education. The education industry is primarily divided into public and private education. In terms of the Malaysia Education Blueprint 2013–2025, the Malaysian education system focuses on reforming structural elements consistent with international best education system practices. In the process of preparing students for their future, the structure of education at each stage will be adjusted, and resources will be maximized for the purpose of offering the best education for Malaysians at all levels. Figure 1.1 displays the summary of the Malaysian education system.



Source: Ministry of Education Malaysia (2023).

Figure 1.1: The Education System in Malaysia

Under the Education Act 1996, preschool education is part of the education system in Malaysia. The purpose of preschool education is to cultivate students' development potential in all aspects of the study, including mastering basic knowledge and skills as well as developing a positive attitude in preparing to enter primary education. Children receive preschool education between the ages of four and six. Preschools are administered by several government agencies, private institutions, and voluntary organizations as well. The main government agencies responsible for preschool education are the Ministry of Education Malaysia, the Ministry of Rural and Regional Development, and the Department of National Unity and Integration, which began in the early 1970s. All preschool education centers are registered with the Ministry of Education Malaysia (MOE). Additionally, all preschool education centers must adhere to the curriculum guidelines established by the MOE. The curriculum emphasizes communication, social, and positive skills in preparing for primary education. Private preschools can offer additional courses upon approval by

the MOE. The main components of learning include social skills, language, moral education, physical development, spiritual growth, cognitive development, socio-emotional development, and aesthetic values.

Primary education is the first stage of formal education after preschool education, as it builds a strong foundation for formal education. This level of education aims to offer children solid basic skills (e.g., reading, writing, and arithmetic) with an emphasis on thinking skills and values throughout the curriculum. In primary school, children also learned a lot from other subjects, including moral education, Islamic education, science, and physical education. Formal schooling in Malaysia starts at the primary school, with a period of six years for students aged 7–12. In general, children begin their primary education at the age of seven. From 1988 to 2021, primary school students took the Primary School Achievement Test, also called *Ujian Pencapaian Sekolah Rendah* (UPSR), at the end of primary school education, but the test will be fully abolished in 2021. In 1962, primary school education fees were abolished by the Malaysian government and made available to all children regardless of ethnic group. Primary schooling, which lasts six years, has been compulsory in Malaysia since 2003.

After completing the primary level of education, students will continue their secondary education. The education system divides this level into lower and upper secondary levels, as well as a special year transition program, which is known as the Year-Long Transition Class for students from National-type Chinese and National-type Tamil schools. In general, the Year-Long Transition Class is a transition program that lasts for one year for students to prepare and enhance their national language competency. Between 1988 and 2021, students who performed well in their Primary School Achievement Test

(UPSR), especially in the national language, were allowed to proceed directly to Form 1 without going through the Year-Long Transition Class. Next, the lower secondary level of education lasts for three years, from Form 1 to Form 3. All subjects are core subjects and are required for all students at this level. The additional subjects are offered for students who want to learn the Arabic language, Chinese language, and Tamil language. Upon completion, students need to sit for an examination called *Pentaksiran Tingkatan Tiga* (PT3), but this PT3 exam will be abolished in 2022. The upper secondary level of education spans two years, from Form 4 to Form 5. Students at this level start to specialize in a particular field of study (i.e., science, arts, religious education, technical, and vocational). For each discipline, specific schools are designated, such as academic schools, technical schools, vocational schools, and religious schools. Upon completion, students need to sit for an examination called the Malaysian Certificate of Education (SPM) at the Form 5 level.

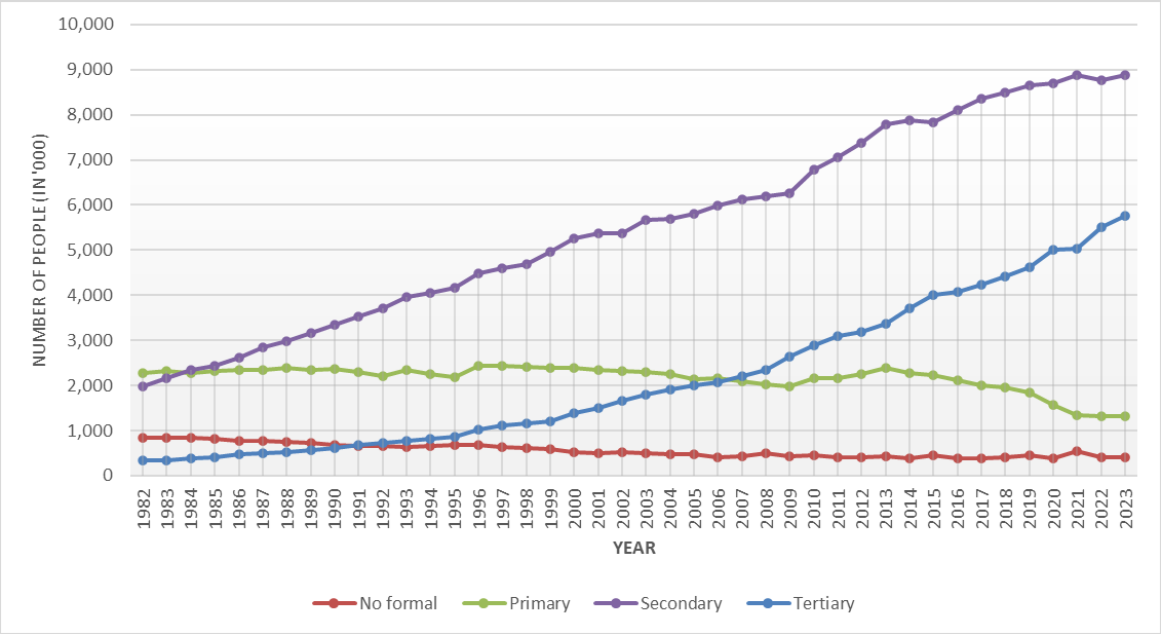
Tertiary education is also known as higher education—the educational level after completing secondary education. Higher education is seen as contributing to growth, poverty reduction, and promoting shared prosperity. For this education level, universities and university colleges offer programs such as bachelor's degrees, master's degrees, and Ph.D.s. The entrance requirements for universities and university colleges in Malaysia are the Matriculation Certificate, *Sijil Tinggi Persekolahan Malaysia* (STPM), *Sijil Tinggi Agama Malaysia* (STAM), Diploma, Foundation, etc. Bachelor's programs have a normal duration of approximately 3 to 4 years, but the programs in medicine and dentistry normally take around 5 years to complete the study. A master's degree is awarded to students who have finished their studies for about 2 to 3 years at this level and completed a

bachelor's program. Typically, a Ph.D. student needs to dedicate at least 3 or 4 years to completing their research.

Higher education is beneficial to individuals, society, and countries as well. Higher education graduates are more concerned about environmental awareness, healthy habits, and civic participation. Furthermore, higher education has the potential to increase tax revenues through higher incomes, enhance living standards, and promote health awareness. Consequently, higher education institutions offer the students sufficient and relevant job skills during the lectures. The World Bank Group report found that, on average, in Latin America and the Caribbean, a higher education graduate's income is more than twice as much as the income of those with high school diplomas. Governments are becoming more aware of the entire education system, from early childhood to higher education, to increase the number of well-trained, more skilled, and adaptable labor forces. According to Keller (2006), developed countries are growing faster, leading to enrollment rates in secondary and higher education that have increased.

1.3 Labor Market Educational Attainment

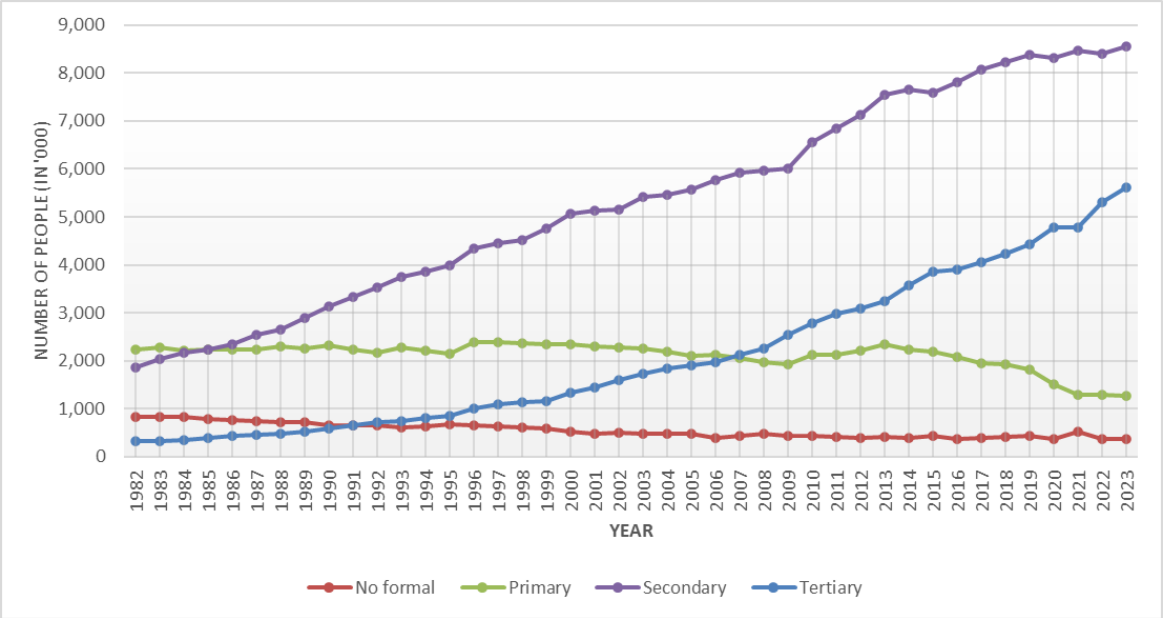
Labor market educational attainment means the highest level of education that someone has achieved. Figures 1.2 and 1.3 present the Malaysian labor force with educational attainment from 1982 to 2023, and there are three levels of education (i.e., primary education, secondary education, and tertiary education). The term "labor force" refers to the population within the working age group, which includes individuals aged 15 to 64 years who are either employed or unemployed in the labor market. Besides, the term "employed workers" refers to individuals who hold employment in the labor market.



Source: Department of Statistics Malaysia (2025).

Figure 1.2: Malaysian Labor Force with Educational Attainment, 1982–2023

Figure 1.2 illustrates the number of Malaysian workers classified according to primary, secondary, and tertiary education levels from 1982 to 2023. The number of people in the labor force with tertiary education has constantly increased, from 331.8 thousand to 5757.6 thousand. Additionally, the number of labor force members with secondary education increased from 1,983.4 thousand in 1982 to 8,885.3 thousand in 2023. As a result, the number of Malaysians with primary education dropped from 2,277.1 thousand in 1982 to 1,316.6 thousand in 2023, primarily due to an increase in those with secondary and tertiary education. Subsequently, the number of workers without formal education steadily decreased from 838.5 thousand to 407.3 thousand. The composition of the Malaysian labor force underlines that the labor force with secondary education remained the largest portion during 1984–2023. However, the labor force with no formal education remains the smallest portion between 1991 and 2023.



Source: Department of Statistics Malaysia (2025).

Figure 1.3: Employed Workers with Educational Attainment, 1982–2023

Figure 1.3 shows the number of employed workers in primary, secondary, and tertiary levels of education in Malaysia from 1982 to 2023. Based on the information, the number of employed workers with tertiary levels of education steadily increased from 318.2 thousand to 5609.1 thousand. In addition, the number of employed workers with secondary education also increased, from 1,861.9 thousand to 8,558.0 thousand. The number of employed workers in the primary level of education decreased from 2,237.5 thousand to 1,268.1 thousand because of the increases in the number of employed workers with secondary education and tertiary education, respectively. Likewise, the number of employed workers with no formal education constantly decreases, from 830.7 thousand in 1982 to 378.2 thousand in 2023. The composition of employed workers with educational attainment underlines that the labor force with secondary education remained the largest portion during 1986–2023.

1.4 Malaysian Sectoral Labor Productivity and Economic Growth

Productivity is the most important factor for long-term growth in a country. High-productivity countries can adapt quickly to changes in macroeconomic challenges and elementary shifts brought on by technological progress. Productivity growth is the main driver of Malaysian economic development as the country prepares to achieve its goal of having a high-income economy. The productivity growth rate accounts for 2.2%, from RM92,084 in 2018 to RM94,139 in the year 2019. Malaysia's productivity level per employee rose to RM96,692 in 2023, compared to RM95,858 in 2022. Despite the minimal rise, progress indicates productivity resilience against economic challenges. Higher growth in Total Factor Productivity (TFP), which sustains growth momentum for the national economy, results in Malaysians enjoying a higher standard of living. The projected benefits of productivity growth for the national economy stem from the estimated 4% to 5% growth in Malaysia's GDP in 2022. The improved global growth will increase the country's investment, trade, and income inflows and lead to strong growth in domestic demand (Central Bank of Malaysia, 2019). Labor productivity measures how much output is produced for every hour worked or every person employed. It measures the quality of skills, machines, and processes in production and service. Malaysian labor productivity rose by about 3.1%, from RM84,115 in 2015 to RM86,693 in 2016. Despite challenges from external factors such as a weaker ringgit, financial market volatility, declining business confidence, and the uncertainty of protectionist tendencies in some developed countries, Malaysia managed to maintain its labor productivity growth in 2016. Malaysian Gross Domestic Product (GDP) grew by about 4.2% to RM1.1 trillion, driven by labor productivity growth rather than employment. This trend indicates that economic growth is increasingly shifting from labor intensity toward digital and technology-driven factors. The

manufacturing sector still maintained its position as the biggest contributor to productivity, at RM106,647, with a growth rate of about 1.4%. The second biggest contributor was the service sector, which rose by 2.8% to a level of RM68,166. However, labor productivity growth in the agriculture sector increased by approximately 3.4% to RM55,485 in 2016, rebounding from a 2.3% decrease in 2015. Despite the relatively low productivity level of RM40,018, the construction sector's productivity grew by about 12.4% in 2016.

Table 1.2: Malaysian Productivity Performance, 2011–2023

Year	**Productivity** (RM Thousand)	**Labor Productivity Growth** (%)
2011	77.92	1.4
2012	79.18	1.6
2013	78.46	−0.9
2014	81.34	3.7
2015	84.12	3.4
2016	86.69	3.1
2017	89.96	3.8
2018	92.08	2.4
2019	94.14	2.2
2020	89.18	−5.3
2021	90.95	2.0
2022	95.86	5.4
2023	96.69	0.9

Source: Malaysia Productivity Corporation (2024).

Table 1.3: Malaysian Productivity Growth of the Main Economic Sectors, 2011–2022

Main Economic Sectors	**Average Productivity Growth** (%)
Agriculture	0.3
Construction	2.2
Manufacturing	2.7
Mining & Quarry	−1.9
Services	2.5

Source: Malaysia Productivity Corporation (2023).

Table 1.4: Productivity Growth in Malaysian Economic Sectors, 2013–2022

Main Economic Sectors	**Productivity Growth** (%)									
	2013	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**
Services	0.27	2.48	3.24	2.77	7.14	3.5	2.9	−5.7	0.8	6.6
Manufacturing	1.31	3.71	7.15	1.44	3.95	2.4	1.7	−2.7	6.7	4.1
Construction	1.41	12.52	5.50	12.41	0.56	3.4	3.3	−15.6	−4.2	5.3
Agriculture	−5.70	6.07	−2.27	3.37	−6.30	−0.2	0.4	−2.0	−0.7	1.9

Source: Malaysia Productivity Corporation (2023).

This highlights the low productivity levels in agriculture and construction when compared to manufacturing and services. Table 1.4 demonstrates that agricultural productivity experienced negative growth in most of the years (i.e., 2013, 2015, 2017, 2018, 2020, and 2021). The average productivity growth of agriculture and mining & quarry accounts for only 0.3% and −1.9%, respectively, between 2011 and 2022 (see Table 1.3). Malaysia's 2023 productivity performance reflected the country's normalized

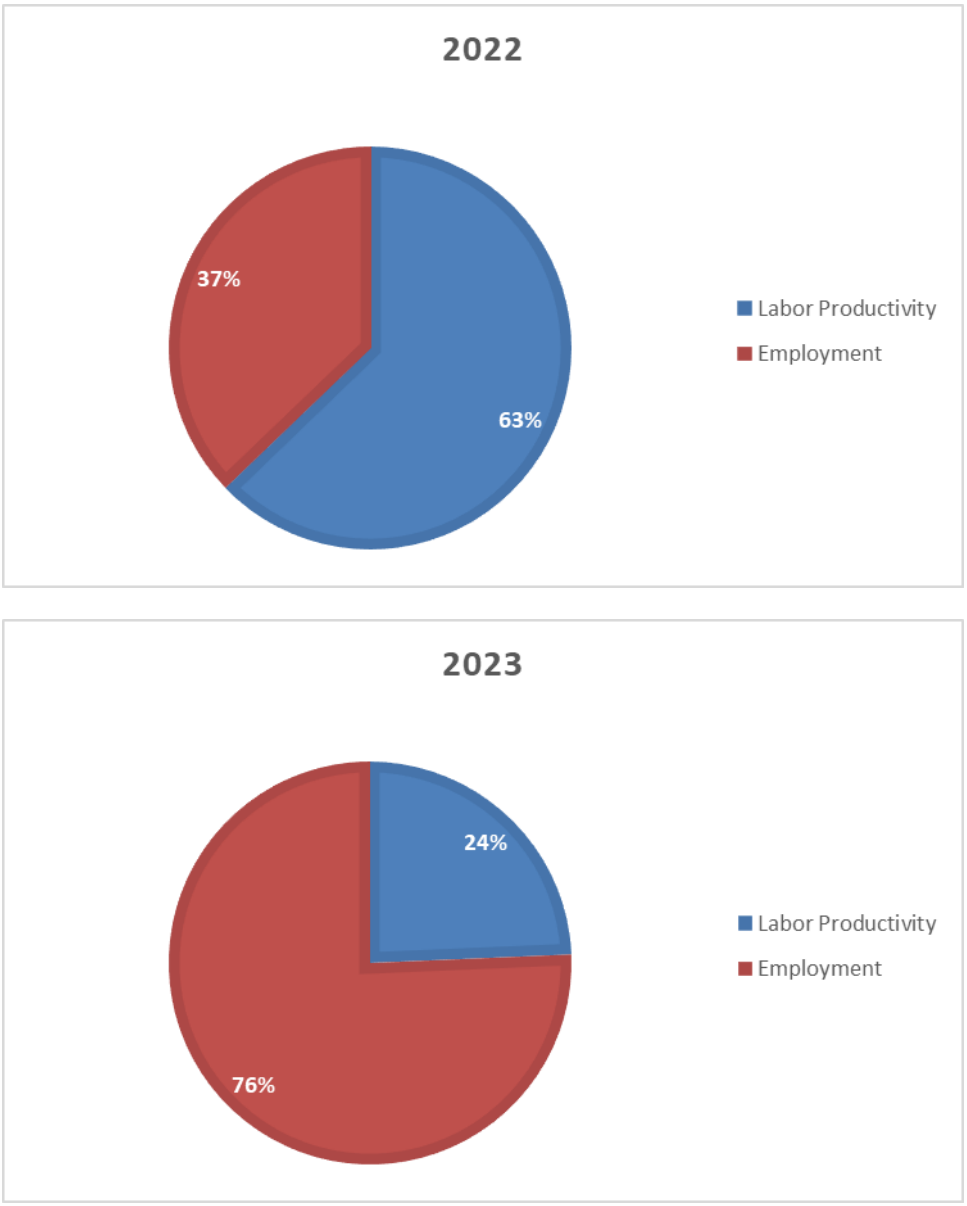
economic growth. The country's labor productivity per employee in 2023 showed a positive trend, moderated to 0.9 percent, compared to 2022's jump of 5.4 percent. Likewise, Malaysian productivity suffered negative growth only in 2013 and 2020 (see Table 1.2). The Twelfth Malaysia Plan (12MP) outlines a productivity growth target of 3.7 percent during the plan's duration. Productivity per employee grew only at an average annual growth rate of 2.8 percent during 2021 and 2023. Three sectors in Malaysia (i.e., manufacturing, construction, and services) performed above the national average productivity growth rate of 1.9 percent from 2011 to 2022. On the other hand, agriculture and mining and quarry sectors exhibited productivity growth below the national average. The Ekonomi MADANI framework has been pivotal in guiding the country's progress, facilitating higher value-added activities, and improving economic competitiveness.



	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
GDP	4.7	6.0	5.1	4.2	5.9	4.7	4.4	-5.5	3.3	8.7	3.7
Labor Productivity	-0.9	3.7	3.5	3.5	3.8	2.4	2.2	-5.3	2.0	5.4	0.9
Employment	5.7	2.3	1.6	0.7	2.0	2.3	2.1	-0.2	1.3	3.2	2.8

Source: Department of Statistics Malaysia (2025).

Figure 1.4: Growth Rate of GDP, Labor Productivity, and Employment, 2013–2023



Source: Department of Statistics Malaysia (2025).

Figure 1.5: Contribution of Labor Productivity and Employment to GDP, 2022 and 2023

Figure 1.4 shows the growth rate of Malaysian GDP, labor productivity, and employment from 2013 to 2023. Labor productivity, as measured by real added value per person employed, increased from −0.9% in 2013 to 0.9% in 2023. In addition, Malaysian Gross Domestic Product (GDP) growth decreased from 4.7% to 3.7% between 2013 and

2023. Likewise, the growth of employment decreased from 5.7% in 2013 to 2.8% in 2023. Figure 1.5 indicates the contribution of labor productivity and employment to Malaysian GDP in 2022 and 2023. Labor productivity was the largest contributor to GDP in 2022; however, its contribution fell from 63% to 24% between 2022 and 2023. In the meantime, the contribution of employment to GDP increased from 37% to 76% between 2022 and 2023. This trend underscores that the growth rate of employment is higher than the growth rate of labor productivity between 2022 and 2023. This indicates a decline in the growth rate of labor productivity, which is a less significant contributor to GDP growth.

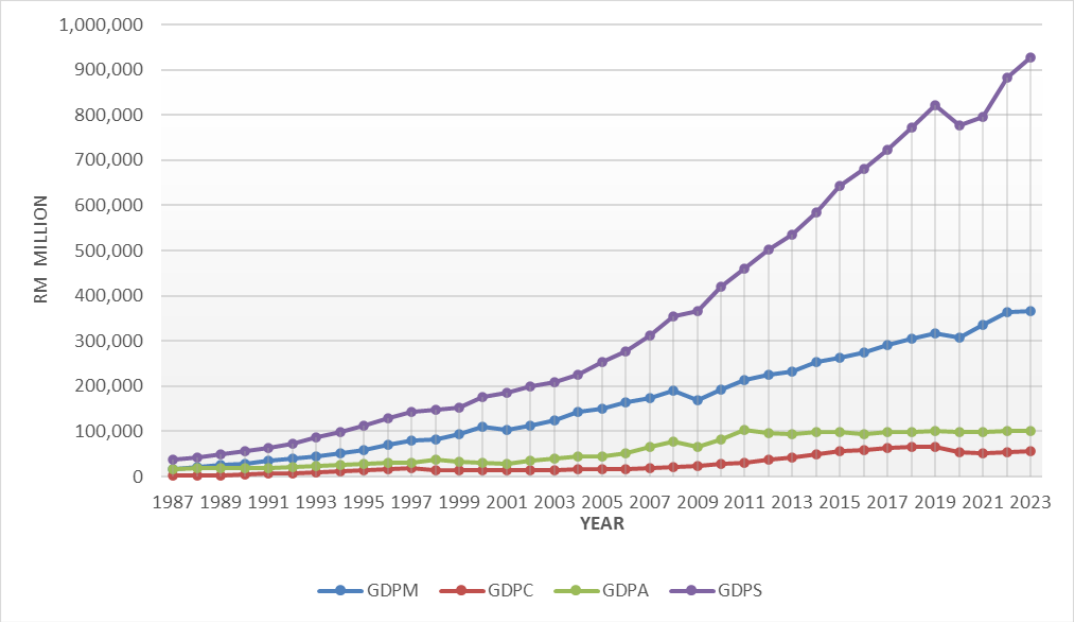
Table 1.5: Labor Productivity Growth of the Main Economic Sectors, 2021–2023

Main Economic Sectors	**Labor Productivity** Constant 2015 (RM)			**Labor Productivity** Average Growth (%)
	2021	**2022**	**2023**	
Services	85,089	90,636	92,251	3.0
Manufacturing	128,662	133,902	131,115	2.9
Construction	36,732	38,658	40,574	2.0
Agriculture	52,840	53,240	53,263	0.1

Source: Department of Statistics Malaysia (2025).

Table 1.5 describes the labor productivity growth of the main economic sectors (e.g., the services sector, manufacturing sector, construction sector, and agriculture sector) from 2021 to 2023. The agriculture sector recorded the slowest average productivity growth rate between 2021 and 2023, at 0.1 percent. The productivity level of agriculture remained below the national average, despite a slight increase between 2021 and 2023. The limited technological advancement and innovation, a greater reliance on traditional

farming methods, and climate change have contributed to slow growth. However, the services sector reported the highest average labor productivity growth at 3.0 percent. This is because consumer demand, digitalization, and the expansion of business and financial services drive robust post-pandemic economic activities. The productivity level in the construction sector was the lowest, at RM40,574 per employee in 2023, compared to other main economic sectors. Productivity is considered a key source of economic growth and competitiveness. This means higher productivity growth leads to higher economic growth in the long run. Economic growth can be defined as an increment in a country's gross domestic product (GDP). GDP was called the best single measure of socioeconomic well-being, which measures both the total income and total expenditure on goods and services in the economy. The Malaysian GDP for the main economic sectors (e.g., manufacturing, construction, agriculture, and services) is stated below:



Source: Department of Statistics Malaysia (2025).

Figure 1.6: Malaysian Gross Domestic Product (GDP) of the Main Economic Sectors, 1987–2023

Based on Figure 1.6, the Malaysian GDP is categorized into 4 main economic sectors (i.e., manufacturing, construction, agriculture, and services). The Malaysian GDP increased from RM 81,085 million in the year 1987 to RM 1,567,974 million in 2023. The 1997–1998 Asian financial crisis impacted Malaysian GDP, and the 2008 global financial crisis led to a decline from RM 769,949 million in 2008 to RM 712,857 million in 2009. Furthermore, the coronavirus disease (COVID-19) pandemic affected the Malaysian GDP, which decreased from RM 1,423,952 million in 2019 to RM 1,346,249 million in 2020. The Malaysian manufacturing GDP between 1987 and 2023 is shown in Figure 1.6. The manufacturing sector remains the main sector in the economy of Malaysia, which is the second largest contributor to Malaysian GDP. The GDP from manufacturing increased from RM 16,058 million in the year 1987 to RM 366,694 million in 2023. However, the Asian financial crisis in 1997–1998 had an impact on Malaysia's manufacturing GDP. The global financial crisis, also known as the 2008 financial crisis, affected the economic growth of Malaysia; the manufacturing GDP diminished from RM 189,105 million in the year 2008 to RM 169,661 million in 2009. The COVID-19 pandemic caused the manufacturing GDP to decrease from RM 316,283 million to RM 307,606 million between 2019 and 2020.

Additionally, from 1987 to 2019, the construction industry has been one of the important sectors contributing to the Malaysian economy. The construction GDP increased from RM 2,818 million in 1987 to RM 56,659 million in the year 2023. Malaysia was one of the countries affected by the Asian financial crisis in 1997–1998, the global financial crisis in 2008, and the COVID-19 pandemic in 2020–2023. The Asian financial crisis precipitated the collapse of the Malaysian economy, leading to a decline in the construction GDP from RM 18,474 million in 1997 to RM 13,971 million in 2000. In addition, the

global financial crisis that occurred in 2008 had a less significant impact on the growth of the construction GDP. The COVID-19 pandemic had impacted the construction GDP, which declined from RM 66,453 million in 2019 to RM 50,839 million in 2021.

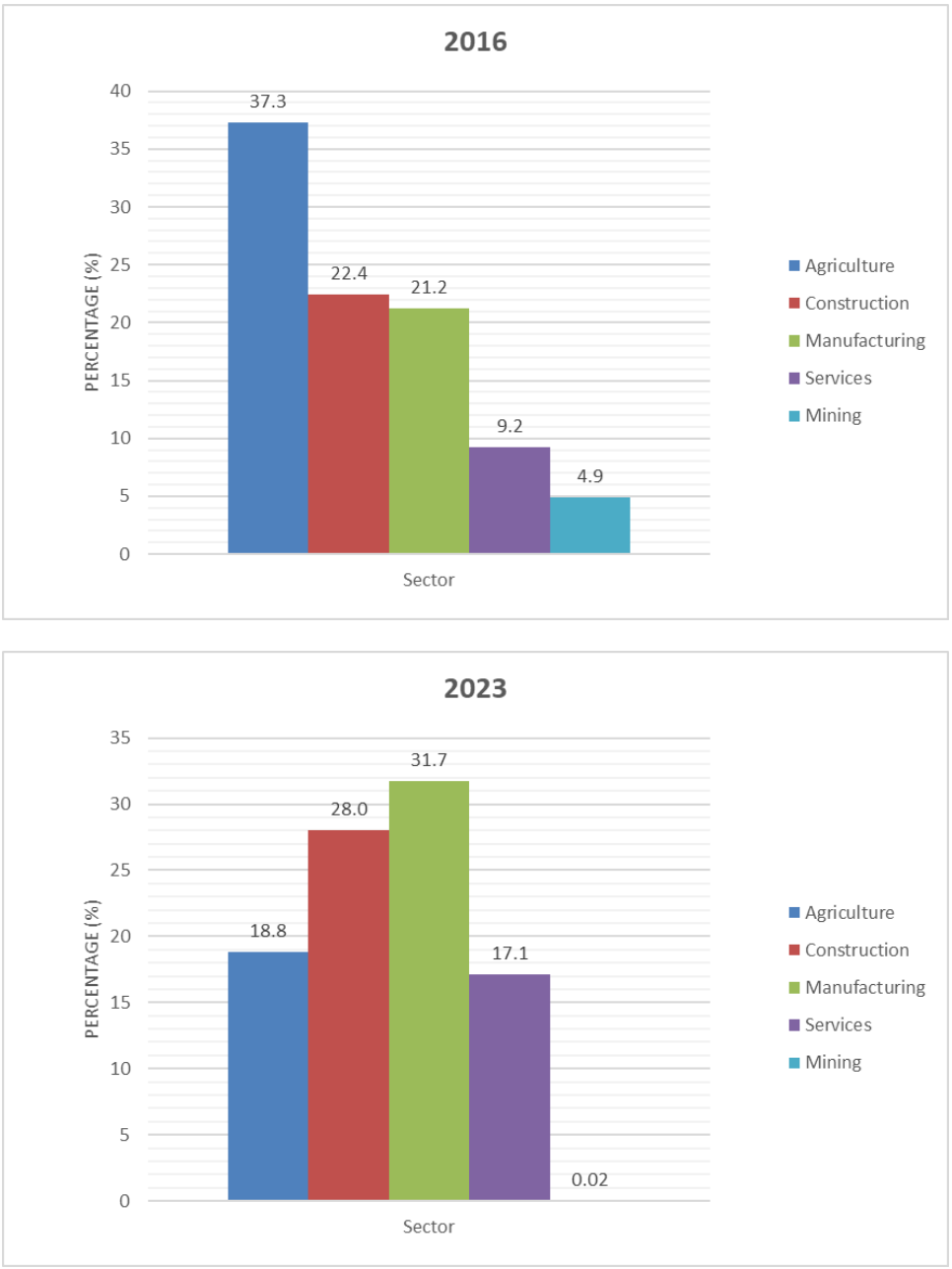
Figure 1.6 describes the Malaysian agricultural GDP between 1987 and 2023, showing an increase from RM 16,185 million in 1987 to RM 100,812 million in 2023. The growth of agriculture declined due to climate change, such as the lagged impact of El Niño on crude palm oil production; palm oil was the major agricultural contributor to the Malaysian GDP. The agricultural GDP declined during that period due to factors such as the Asian and global financial crises. The Asian financial crisis caused the agricultural GDP to decline from RM 37,706 million in 1998 to RM 28,245 million in 2001. The global financial crisis resulted in a decrease in agriculture's GDP from RM 76,753 million in 2008 to RM 65,719 million in 2009. Production constraints have affected the growth of agriculture in recent years. The European Union (EU) bans the use of palm oil for the production of biofuels in order to stop the deforestation of rainforests, especially in Malaysia and Indonesia. Moreover, the COVID-19 pandemic has negatively impacted Malaysia's agricultural GDP, which decreased from RM 101,573 million in 2019 to RM 98,843 million in 2021.

The services sector is the most significant contributor to Malaysia's economy, accounting for approximately 54% of the country's GDP. The contribution of services to GDP is on an increasing trend and reaches 58.9% of GDP in the year 2022. The GDP of services increased from RM 36,734 million in 1987 to RM 927,904 million in the year 2023. The growth in services slowed down because of the Asian financial crisis in 1997 and the global financial crisis in 2008. The services GDP experienced a slight increase

from RM 143,674 million in 1997 to RM 147,895 million in 1998, but the growth rate slowed to around 2.94% due to the effects of the Asian financial crisis. The global financial crisis led to a slowdown in the growth of the GDP of services, which increased from RM 355,233 million in 2008 to RM 365,983 million in 2009. The growth rate increased by around 3.03% during that period. The COVID-19 pandemic caused the services GDP to decline from RM 820,576 million to RM 777,693 million between 2019 and 2020.

1.5 Foreign Workers' Employment in Malaysia

Figure 1.7 illustrates the employment share of foreign workers per sector in both 2016 and 2023. Based on the figure below, the Central Bank of Malaysia reported that foreign workers held more than a fifth of the jobs in the main economic sectors (e.g., agriculture, construction, and manufacturing) in 2016. The agricultural sector had the highest employment share of foreign workers in 2016, while the manufacturing sector indicated the highest employment share in 2023. According to Ang et al. (2018), Malaysian employers primarily rely on low-skilled foreign laborers to keep wages low and maintain their profit margins. The local economic sectors that rely on foreign labor, such as the agriculture sector, construction sector, and manufacturing sector, also suffer from low productivity.



Source: Department of Statistics Malaysia (2025).

Figure 1.7: The Share of Foreign Workers in Employment by Sector, 2016 and 2023

1.6 Malaysian Skill Levels Classification

The Malaysia Standard Classification of Occupations (MASCO) serves as a national standard for the classification of occupations within the nation's employment

structure. MASCO categorizes four main skill levels based on education level and occupation, summarizing them as follows:

Table 1.6: Three Main Skilled Category based on Education and Occupation

Skilled Category	Qualification Level	Major Group
Low-Skilled	Primary education	▪ Elementary occupations
Semi-Skilled	Secondary or post-secondary education; Malaysian Skill Certificate (SKM) Level 1 and Level 2; or equivalent	▪ Clerical support workers ▪ Service and sales workers ▪ Skilled agricultural, forestry, livestock, and fishery workers ▪ Craft and related trades workers ▪ Plant and machine operators and assemblers
Skilled	Diploma; or Malaysian Skill Certificate (SKM) Level 3 or Malaysian Skill Diploma (DKM) Level 4; or equivalent	▪ Technicians and associate professionals
	Master/ Degree; or Malaysian Skill Advanced Diploma (DLKM) Level 5 and above; or equivalent	▪ Professionals
	PhD/ Master/ Degree; or Malaysian Skill Advanced Diploma (DLKM) Level 5 and above; or equivalent	▪ Managers

Source: Malaysia Standard Classification of Occupations (2020).

Table 1.7: Three Skill Levels of Workers in the Malaysian Industry

Skill levels	Occupations
Skilled workers	▪ Manager or legislator ▪ Professional and technicians
Semi-skilled workers	▪ Clerical, service, and sales occupations
Low-skilled workers	▪ Agricultural and fishery ▪ Craft and related trades ▪ Plant and machine operators ▪ Elementary occupations

Source: Malaysia Standard Classification of Occupations (2013).

Table 1.7 displays the three primary skill levels of workers in the Malaysian industry, which is based on MASCO 2013. Managers or legislators, professionals, and technicians are considered skilled workers. Semi-skilled workers are in clerical, service, and sales occupations, and low-skilled workers are involved in occupations (e.g., agricultural and fishery, craft and related trades, plant and machine operators, and elementary occupations). According to the World Bank (2011), the number of skilled workers in Malaysia who moved overseas was 121,662 who went to Singapore, 51,556 who went to Australia, 34,045 who went to the United States, and the rest who went to other countries like the United Kingdom, Canada, Brunei, New Zealand, India, China, Taiwan, etc. The statistics indicate that a growing number of Malaysians are choosing to work in Singapore due to its higher salaries, superior working conditions, and improved workplace environment. This issue leads to a shortage of skilled workers in Malaysian industries, particularly in the service, manufacturing, and construction sectors. Some

countries are willing to offer higher salaries to talented people such as doctors and engineers. Wong and Yip (1999) found that the educated worker shortage has an adverse impact on the wage rate of unskilled workers, but it increases the wage rate of skilled workers. The loss of skilled workers also tends to negatively affect the development of the country's resources.

1.7 Problem Statement

The Malaysian labor market has a shortage of skilled workers and a reliance on low-skilled workers in various sectors, particularly agriculture and industry. Along with economic development, Malaysian industries rely heavily on low-skilled domestic workers and low-wage migrant workers from other countries. Malaysian firms tend to rely mainly on low-cost production models that lead to the employment of low-skilled labor to sustain their profit margins (Ang et al., 2018). The share of low-skilled jobs in Malaysia increased markedly, and the Malaysian workforce now comprises mainly low-skilled workers. The share of low-skilled jobs in Malaysia increased markedly, and the Malaysian workforce now comprises mainly low-skilled workers. In addition, the Central Bank of Malaysia has reported that the share of highly skilled jobs created in Malaysia fell from approximately 51% to an average of 27% during the period 2010–2019. The poor creation of high-skilled jobs has lagged behind the supply of graduates in the Malaysian labor market. The Malaysian labor force was around 15.3 million, of which 27% were skilled workers and 73% were semi- and low-skilled workers in 2018. The Malaysian Industrial Development Finance Berhad (MIDF) mentioned that for every 100 jobs on offer, 89 were for low-skilled jobs, seven for medium-skilled jobs, and four for high-skilled jobs. Research by the Economics Department of the Central Bank of Malaysia shows that low-skilled foreign workers account for a large proportion of industries.

Additionally, their productivity is low, requiring longer working hours to produce the same output (Ang et al., 2018). The low creation of high-skilled jobs and over-reliance on low-skilled workers seem to affect the agricultural value added per worker in Malaysia. The World Bank report indicates that agricultural value added per worker in Malaysia was 45% of the average among high-income countries (World Bank Group, 2019). This underlines that Malaysian agricultural productivity is less than half that of high-income countries. Moreover, over the period 1980–2018, the ratio of agricultural employment to total employment diminished from 37% to 11.1%. According to the Malaysia Productivity Corporation (2024), the agriculture sector recorded the slowest average productivity growth rate between 2021 and 2023, at 0.1 percent. The productivity level of agriculture remained below the national average, despite a slight increase between 2021 and 2023. Agricultural productivity experienced negative growth in most of the years (i.e., 2013, 2015, 2017, 2018, 2020, and 2021). If agricultural industries continue to be over-reliant on low-skilled workers instead of high-skilled workers in the future, this seems to affect agricultural productivity. Therefore, this study investigates the issues of lower agricultural value added per worker and over-reliance on low-skilled labor. According to the World Bank Group (2019), agricultural transformation is crucial for supporting Malaysia's transition from upper middle-income to high-income nation status. If agricultural transformation continues to lag behind other countries, it will be challenging to emerge from upper middle-income status and to narrow the gap between rural and urban communities.

Local economic sectors heavily rely on foreign labor, accounting for more than a fifth of employment in the agriculture, construction, and manufacturing sectors, leading to low productivity (Ang et al., 2018). In Malaysia, the term foreign worker implies that a

foreigner is doing a low-skilled job (World Bank, 2021). If the Malaysian industry continues to depend on foreign workers in the future, these sectors may experience low productivity once more, potentially trapping Malaysia in the middle-income cycle. Over-reliance on low-skilled workers rather than pivoting toward high-skilled labor could significantly impede Malaysia's industrial growth. Such a trajectory might reduce production rates and overall output, making industrial transformation challenging. This stagnation poses the risk of Malaysia becoming entrenched in the middle-income trap. As emphasized by the World Bank Group (2019), a robust agricultural transformation is vital for Malaysia's progression from an upper-middle-income to a high-income nation. Failing to keep pace with global agricultural advancements not only hinders the nation's economic ascent but also perpetuates disparities between rural and urban communities.

From 2011 to 2017, the proportion of low-skilled jobs in Malaysia significantly increased to 16%, up from just 8% between 2002 and 2010. According to the Malaysian Productivity Corporation, labor productivity growth in the agriculture sector increased at a slower rate of 1.4%, and the construction sector registered labor productivity growth of 2.4% only in 2017. However, the services sector registered growth in labor productivity with a higher rate of 5.0% in the year 2017. World Bank Group (2019) reported that agricultural value added per worker in Malaysia was 45% of the average among high-income countries in the year 2017. Additionally, the ratio of agricultural employment to total employment declined from 37% to 11.1% during the period 1980–2018. The average productivity growth of agriculture indicates that Malaysians prefer to work in the urban cities, especially in the services industry, rather than in rural plantations. Predominantly low-skilled workers make up Malaysia's workforce, as evidenced by the comparatively lower proportion of skilled workers in the labor market. According to Ang et al. (2018), low-

skilled foreign workers account for a large proportion of industries with low productivity and rely more on longer working hours to produce output. A high reliance on low-skilled foreign workers has adversely affected Malaysia's reputation as a destination for low-skilled and labor-intensive investment. MASCO 2020 categorizes low-skilled workers as those with primary education (see Table 1.6).

The economy's excessive reliance on cheap foreign labor has resulted in reduced incentives to invest in labor-saving technologies (i.e., automation, robots, or new production methods). According to Loh et al. (2019), the Ministry of Home Affairs (MOHA) report, based on its enforcement and amnesty program operations, indicates that 4 out of 10 foreign workers are irregular, with an estimated number of 1.2–1.5 million irregular foreign workers and a total of about 3 million foreign workers in 2017. The unofficial data indicates that as many as 4 million irregular foreign workers are in Malaysia. Based on the latest estimation by the World Bank (2020b), irregular foreign workers account for over 40% of the total foreign worker population in Malaysia. This trend in favor of low-skilled foreign workers contributes to graduate unemployment, which affects Malaysian graduates. This trend favoring low-skilled foreign workers contributes to graduate unemployment, a problem that impacts Malaysian graduates.

Likewise, this trend weakens automation in industries, suppresses overall wages, and discourages the adoption of productivity-enhancing efforts. Undeniably, foreign workers contribute to the labor market and economic growth. Furthermore, the Hays Asia Salary Guide (2017) revealed that 97% of employers in Malaysia were still struggling to look for skilled workers. Malaysia's reliance on low-skilled foreign workers also exacerbates the migration of local talented workers to higher-paying employment countries.

Therefore, Malaysia's over-reliance on low-skilled foreign workers, particularly irregular migrant workers, led to a loss of educated and skilled individuals in its labor force. This resulted in a significant outflow to other countries, particularly Singapore, where the conditions and salaries are better. According to the World Bank (2011), a total of 276,558 skilled workers in Malaysia moved overseas, with 121,662 going to Singapore, 51,556 going to Australia, 34,045 going to the United States, and the rest going to other countries like the United Kingdom, Canada, Brunei, New Zealand, etc. For every ten Malaysians who are skillful, one of them decides to leave their country, which results in twice the world average. Sapovadia (2015) attributes the low productivity to the high proportion of unskilled labor, inadequate governance and management, and insufficient research and development.

Malaysia might be stuck in the middle-income trap if it remains constrained by low-skilled workers in its field of work—who lack experience, knowledge, and training. Low-skilled workers do not provide sufficiently skilled labor for industries. Additionally, it is crucial to address educational and skill mismatches and gaps, particularly for workers who possess post-secondary and tertiary education qualifications. These factors are the primary obstacle to achieving the targeted productivity needed to transition from an upper-middle-income country to a high-income country. World Bank (2020a) reported that Malaysia has lagged other countries in achieving high-income status and a developed economy recently, primarily due to a lower share of high-skilled employment and greater income inequality. According to the World Bank Group (2019), Malaysia requires high levels of productivity to achieve high-income status.

1.8 Research Questions

The research questions of this study include:

1. Does the employed workforce with a higher education level not represent high-skilled workers who can contribute more to Malaysian labor productivity?
2. What is the role of labor market education quality and the presence of a foreign workforce or fixed capital in driving value-added agriculture and economic growth?
3. How does the educational quality of Malaysian employed workers, as well as fixed capital, impact the value-added industry?
4. What is the impact of employed workers' educational attainment on labor productivity in the main economic sectors (i.e., agriculture, industry, and services)?
5. How do the asymmetric effects of foreign worker employment and the impact of workers with low educational attainment influence sectoral labor productivity (i.e., agriculture, industry, and services)?

1.9 Objectives of the Study

1.9.1 General Objective

The general objective of this study is to determine the role of labor market educational attainment in driving Malaysia's productivity and economic growth, drawing on annual data between 1982 and 2023. The goal of this research is to determine whether a higher education level correlates with increased labor productivity. The main objective of the study is to examine the educational quality of labor and the fixed capital as determinants that affect value-added and productivity—thereby impacting the Malaysian GDP. Additionally, the study delves into the asymmetric effect of foreign worker

employment and the influence of low educational attainment on sectoral labor productivity, specifically in agriculture, industry, and services. These factors can significantly impact the production output of these sectors—thus influencing the GDP of Malaysia. This study appears to identify low educational attainment as the primary cause of slow productivity growth.

1.9.2 Specific Objectives

The specific objectives of this study comprise:

1. To explore how the educational quality of the employed workforce influences Malaysian labor productivity by augmenting the Solow–Swan model**.**
2. To measure the role of labor market education quality and foreign workforce in driving Malaysia's economic growth and value-added agriculture by extending the Cobb–Douglas production function.
3. To analyze the impacts of Malaysian employed workers' educational quality and fixed capital on the value-added industry.
4. To examine the influence of employed workers' educational attainment on labor productivity in the main economic sectors (i.e., agriculture, industry, and services).
5. To investigate the asymmetric effects of foreign worker employment and the impacts of workers with low educational attainment on sectoral labor productivity (i.e., agriculture, industry, and services).

1.10 Significance of the Study

The contribution of the study is fourfold. First, previous studies offer a limited investigation of the educational quality of the labor market and how foreign workers affect

Malaysian productivity. The study adds to the body of knowledge by delving into the impacts of educational attainment on sectoral labor productivity, based on the estimation model results. The model (meso) looked at how the educational level of the labor market affected value-added agriculture between 1982 and 2023. In addition, the model (macro) looked at how these variables affected the agricultural GDP in Malaysia from 1987 to 2023. The existing literature concerning the impact of the educational quality of the labor market on value-added agriculture and agricultural GDP in Malaysia is currently rather limited. The study also provides a precise analysis of the relationship between lower value-added agriculture per worker and educational quality—how this relationship impacts Malaysian agricultural production. The current literature tends to emphasize the effect of education on overall economic growth (Agiomirgianakis et al., 2002; Anastasios et al., 2019; Gyimah-Brempong, 2011; Hanushek & Kimko, 2000; Jalil & Idrees, 2013; Self & Grabowski, 2004; Tsamadias & Prontzas, 2011). Second, most of the studies (e.g., Chan et al., 2020; Hussin et al., 2012; Ramli et al., 2016; Yun & Yusoff, 2018) have mainly explored the relationship between education expenditure and economic growth in Malaysia; however, only a few studies have investigated the impacts of educational attainment on Malaysian economic growth, especially in agriculture and industry. The study sheds new light on the impacts of not having a formal education as an independent variable that influences value-added, labor productivity, and economic growth. Previous studies (e.g., Agiomirgianakis et al., 2002; Anastasios et al., 2019; Benos & Karagiannis, 2016; Gyimah-Brempong, 2011; Jalil & Idrees, 2013) covered three main education levels (i.e., primary education, secondary education, and tertiary education) as independent variables. Similar studies fail to highlight the impact of the foreign labor force on economic growth, particularly in terms of sectoral labor productivity. This is since local economic sectors heavily rely on foreign labor,

accounting for more than a fifth of employment in sectors such as agriculture, construction, and manufacturing, which in turn leads to low productivity. Third, the study aims to further analyze the influence of employed workers' educational attainment on labor productivity in the three main economic sectors, including agriculture, industry, and services.

Lastly, the findings from Nonlinear Autoregressive Distributed Lag (NARDL) make three significant contributions to literature. First, by encompassing Model 1 (agriculture), Model 2 (industry), and Model 3 (services), NARDL bridges existing research gaps by providing fresh insights into the asymmetric effects of foreign worker employment on labor productivity across Malaysia's key sectors (i.e., agriculture, industry, and services), spanning the period from 1991 to 2022. Notably, current literature offers a limited exploration of how low educational attainment, which represents the educational quality of low-skilled labor, influences the Malaysian industrial landscape. This study shows these complex asymmetric effects in more detail by using the NARDL estimation method. Previous research has only focused on estimating using linear methods like OLS and ARDL (e.g., Jordaan, 2018; Kangasniemi et al., 2012). Second, while past research has primarily focused on how education levels drive overall economic growth, the NARDL model sheds new light on the asymmetric effects of foreign worker employment, and low-skilled labor can be principal contributors to the agricultural sector's reduced productivity. Furthermore, many studies have overlooked the impacts of not having a formal education, traditionally focusing on the primary, secondary, and tertiary education levels as pivotal indicators of educational quality. The study incorporated workers with no formal education, which has expanded the body of knowledge in the field. Third, the incorporation of a Nonlinear Autoregressive Distributed Lag (NARDL) model is to capture the potential nonlinear relationships between foreign worker employment and Malaysian sectoral labor

productivity. The existing literature rarely highlights the influence of foreign labor on labor productivity within Malaysia's economic sectors, especially regarding long-term and short-term asymmetric effects. Therefore, the study addresses these oversights, placing a magnified lens on the asymmetric repercussions of foreign labor across Malaysia's three dominant sectors.

1.11 Scope of the Study

The research studies primarily examine how the educational quality of the labor market influences productivity and Malaysian economic growth, utilizing annual data from 1982 to 2023 and employing the VAR estimation method. The labor market primarily comprises four main levels of educational attainment (i.e., no formal education, primary education, secondary education, and tertiary education). Likewise, another study aims to investigate the impacts of the educational attainment of employed workers on labor productivity in the main economic sectors, namely agriculture, industry, and services. To achieve this, it employs the ARDL estimation method, drawing on annual data from 1991 to 2022. Additionally, this study, covering the period 1991–2022, examines the asymmetric effect of foreign worker employment and the influence of workers with low educational attainment on sectoral labor productivity (i.e., agriculture, industry, and services) using the NARDL estimation method. The data used in this research is annual data that is obtained from the World Bank and the Department of Statistics Malaysia.

1.12 Organization of the Study

The study consists of five chapters. Chapter 1 presents an overview of the study, covering topics such as the importance of education, education in Malaysia, educational attainment, productivity in Malaysia, economic growth, employment of foreign workers,

the problem statement, the study's objectives, the significance of the study, and the study's scope. The remainder of the study is structured as follows: The next chapter reviews the literature on educational quality, productivity, and economic growth. This section also mainly discusses the effects of educational attainment (i.e., primary, secondary, or tertiary education) on productivity and economic growth. The following chapter presents the research method, and Chapter 4 analyzes the econometric findings. The last section covers the conclusion, a summary of the findings, and policy implications.

1.13 Chapter Summary

Malaysian firms' over-reliance on low-cost production models, particularly in agriculture and industry, is causing low productivity issues, according to a study by the Central Bank of Malaysia. The Malaysia Productivity Corporation reported a slow average productivity growth rate of 0.1% between 2021 and 2023, with negative growth in most years. The study investigates issues of lower agricultural value added per worker, low productivity in agriculture, construction, and manufacturing sectors, and over-reliance on low-skilled workers and foreign labor. This study defines low-skilled workers as those with primary education or no formal education and high-skilled workers as those with high educational attainment, in line with MASCO 2020. The NARDL model sheds new light on the asymmetric effects of foreign worker employment, and low-skilled labor can be principal contributors to the agricultural sector's reduced productivity. The incorporation of a Nonlinear Autoregressive Distributed Lag (NARDL) model is to capture the potential nonlinear relationships between foreign worker employment and Malaysian sectoral labor productivity. The study adds to the body of knowledge by delving into the impacts of educational attainment on sectoral labor productivity, based on the estimation model results.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter relates to the studies that explore the impacts of educational attainment on productivity and economic growth. The summary of empirical literature from several prior studies analyzes the variables used that can influence productivity and economic growth; the variables of similar studies (e.g., education levels, productivity, and GDP growth) had been discussed by researchers from other countries. The studies presented different methodologies, models, data, and empirical results in different ways by the researchers. The prior studies in this chapter presented the impacts of educational attainment on productivity and economic growth, offering a comprehensive understanding that facilitated in-depth research.

2.2 Educational Attainment

Educational attainment is defined as an individual who has successfully completed the highest level of education; it does not consider proficiency, quality, or grades. There is another term commonly used in literature, which is called educational qualification. The successful completion of an education level refers to an individual having completely achieved the learning objectives at that level; this is usually validated by the assessment of acquired knowledge, skills, and abilities learned from that education level. Educational attainment in secondary education refers to whether an individual has completed the highest level of education in secondary education or whether the individual has obtained a secondary school diploma or equivalent qualifications. An individual who has earned

higher education certificates, diplomas, or degrees from accredited educational institutions is considered to have reached the tertiary level of education. The federal authorities also can award educational certificates or diplomas to certified journeymen in the designated trades. Educational attainment is generally measured in terms of the successful completion of the highest education program, which is normally certified by a recognized qualification.

According to Jenkins and Sabates (2007), educational attainment significantly impacts young people's transition to employment and career progression and income levels. Moreover, strong relationships exist between education and factors such as entering partnerships, parenting behavior, and the timing and number of births. It is likely related to the other aspects of behavior (i.e., health in adulthood and citizen participation), the probability of committing crime, and various broad issues that concern social scientists. A qualification certificate can present a summary of an individual's formal educational experience. Additionally, it discloses the courses taken and the standards attained. Keller (2006) found that primary enrollment rates do not infer a direct benefit to capital growth, probably due to lesser variation. Nevertheless, they have shown an indirect impact by significantly reducing fertility rates, increasing secondary enrollment rates, and encouraging physical capital investment, all of which have improved due to capital growth. In general, secondary school enrollment rates appear to be the most critical factor for capital growth; if the coefficient for the larger Less Developed Countries (LDCs) were to increase globally, indicating an even faster growth rate—the annual growth rate would rise by 2.31 percent per one standard deviation (0.2682). Education indirectly influences other development objectives; for example, primary and secondary school enrollment rates, along with expenditures per primary school student, remarkably reduce fertility rates. Primary school enrollment rates have attracted investment, particularly in physical capital,

and secondary school enrollment rates have facilitated openness and reduced inflation. Likewise, college enrollment rates and expenditures are important to political rights. The effect of education on these development objectives suggests that including these variables as significant controls leads to indirect impacts.

As mentioned by Barro (2001a), data on internationally comparable examinations regarding students' test scores (i.e., science, mathematics, and reading) were utilized to measure educational quality, and the study found that science test scores have a positive relationship with growth. The educational quality is represented based on test scores, while the education's quantity is measured by average years of adult males' attainment at the secondary and tertiary education levels, which still has a positive relationship to subsequent growth. Kazmi and Quran (2005) analyze education as the main tool for human resource development in developed as well as developing countries of Asia. Elementary schooling is the most remunerative investment in educational programs in developing countries if opportunities for gainful employment for the educated are part of the strategy. Basic primary education, which provides the necessary foundation on which to develop the secondary and tertiary education systems, has not been given proper attention. Education sector development in Pakistan has been hampered by several problems (e.g., inadequate physical infrastructure and facilities, a shortage of trained and motivated teachers, and inadequacies related to the quality and relevance of curricula).

2.3 Productivity

Productivity is commonly described as a ratio of an output's volume measure to an input use's volume measure or measure of production efficiency. It measures how efficiently and effectively the production inputs are being utilized so as to produce a given

level of output. Productivity is a vital factor that affects the production performance of countries and enterprises (Yadav & Marwah, 2015). It is important to the economy because it is closely correlated with the standard of living. National productivity increase can improve the standard of living because of high income levels, which can enhance people's purchasing power to buy goods and services. According to Prokopenko (1987), higher productivity means that more work can be done with the same number of resources used, or higher output can be achieved with the same input of volume and quality. A worker's higher productivity indicates that the company can afford to pay a higher wage to attract them. In addition, productivity growth refers to the output produced that has increased for a given level of input over a specific period. Productivity growth is an important factor in modeling economic productive capacity (e.g., making it easy for analysts to determine capacity utilization, which in turn allows one to measure the position of economies in the business cycle and predict economic growth). Furthermore, production capacity is used to assess inflationary pressures and demand. Replication of established technologies can achieve economic growth without innovation. The investment increases the availability of these technologies, and the workforce expands as the population grows.

Productivity is primarily driven by four interrelated components (i.e., innovation, education, efficiency, and infrastructure). Innovation (e.g., creation and adoption of new technologies, products, and processes) can result in higher value-added economic activities. Such an outcome requires investment in research and development (R&D) and knowledgeable scientists and engineers to create the most advanced technologies. Innovation requires the strengthening of human capacities to be able to learn from existing technologies, products, and processes and apply them to new products and processes on the market. Education is a crucial factor because it enhances human capacity by promoting the

generation of new ideas, teaching skills and knowledge, and providing an environment conducive to research and development in both industries and schools. It is imperative to have an efficient education system that offers primary and secondary levels of education for everyone and also promotes tertiary levels of education in universities and continuous training programs in different industries. Studies indicate that the elasticity of total factor productivity (TFP) regarding years of schooling is significantly positive, especially for middle-income countries.

2.3.1 The Importance of Productivity Growth

According to Krugman (1997), productivity is not everything, but it is almost everything in the long term. A state's capacity to enhance its standard of living overtime depends almost entirely on its ability to raise its output per worker. Increasing productivity can lead to long-term growth in living standards. In general, countries with higher productivity can afford better living standards and have more options to improve people's well-being. Improved healthcare and education, better infrastructure, safer communities, and enhanced environmental quality all contribute to increased well-being. Productivity growth at an economy-wide level means that there are more aggregate outputs per aggregate inputs—which translates to greater returns on total inputs; as a result, more income is available to share around. At an industry level, productivity growth can be significant because it permits the industry to compete with other sectors of the economy for resources such as raw materials, labor, and capital to sustain international competitiveness. At a firm level, productivity growth is significant because it can permit the firm to remain competitive within the industry by paying higher salaries, returning to shareholders, and offering funds for investment.

2.3.2 The Measurement of Productivity

In general, productivity measures can be divided into single-factor productivity measures or multi-factor productivity measures. Single-factor productivity, also known as partial-factor productivity, relates a measure of output to a single measure of input. Additionally, multi-factor productivity (MFP), also called total factor productivity (TFP), is a measure that relates an output measure to a bundle of inputs. The following is an overview of the main productivity measures:

Table 2.1: An Overview of the Main Productivity Measures

Type of output measure	**Type of input measure**			
	Labor	**Capital**	**Capital and labor**	**Capital, labor, and intermediate inputs (energy, materials, and services)**
Gross output	Labor productivity (based on gross output)	Capital productivity (based on gross output)	Capital-labor MFP (based on gross output)	KLEMS multi-factor productivity
Value added	Labor productivity (based on value added)	Capital productivity (based on value added)	Capital-labor MFP (based on value added)	-
	Single-factor productivity measures		Multi-factor productivity (MFP) measures	

Source: OECD (2001).

Table 2.1 utilizes these criteria to define the key productivity measures, including labor and capital productivity measures and multi-factor productivity (MFP) measures. These productivity measures can take the form of capital-labor MFP, which is derived from the value-added concept of output, or in the form of capital-labor-energy-materials-services KLEMS MFP, based on a concept of gross output. Among these measures, value-added based labor productivity is the most frequently calculated productivity statistic, followed by capital-labor MFP and KLEMS MFP. The definition of labor productivity based on gross output can be found below:

$$\frac{Quantity\ index\ of\ gross\ output}{Quantity\ index\ of\ labor\ input} \qquad \text{Equation 2.1}$$

Next, the following is the definition of capital productivity based on value-added, followed by the KLEMS multi-factor productivity definition:

$$\frac{Quantity\ index\ of\ value\ added}{Quantity\ index\ of\ capital\ input} \qquad \text{Equation 2.2}$$

$$\frac{Quantity\ index\ of\ gross\ output}{Quantity\ index\ of\ combined\ inputs} \qquad \text{Equation 2.3}$$

The MFP measure is the ratio of gross output to the combined input factors. It gauges the efficiency of producing output by utilizing all available inputs. The growth accounting technique was utilized to measure MFP in the past, where inputs were limited to labor and capital. However, as a result of the influence of knowledge-based economic

factors in today's globalized economy, it is necessary to adopt a new method to measure MFP, which is known as KLEMS (Capital, Labor, Energy, Materials, and Services).

2.3.3 Production Function Theory

The production function is to describe the relationship between the quantity of inputs used in production and the quantity of output from production. Solow–Swan's exogenous growth model is an economic model of long-run economic growth set within a framework of neoclassical economics. It proposes that labor-augmenting knowledge, or effective labor, enhances economic growth in the long term (Solow, 1956; Swan, 1956). In the Solow–Swan model, the production function follows a Cobb–Douglas type. The Cobb–Douglas production function was proposed by Cobb and Douglas (1928). The model posits that the production function is structured due to the relationship between labor and knowledge (Becker, 1964; Romer, 1990), denoted by $A(t)L(t)$ as the measure of effective labor units (Mankiw et al., 1992). A refers to labor-augmenting knowledge or technology; thus, AL represents effective labor. A is knowledge that can increase productivity, and L denotes the number of workers (Ogunleye, 2015). To derive the educational quality of the labor equation, AL was applied. AL is effective labor (Harris, 2021; Shen et al., 2021).

2.4 Effects of Educational Quality on Productivity and Economic Growth

Relevant studies have examined how education affects productivity, and most of the prior studies have focused on the impact of education on economic development. The differences in the quality of the labor force are linked to schooling and have shown a consistent and robust association with economic development (Hanushek & Kimko, 2000). Prior studies indicate that education affects economic growth (Goumrhar, 2024; Gyimah-Brempong, 2011; Jalil & Idrees, 2013; Mussaiyib & Pradhan, 2024; Tamura, 2005;

Tsamadias & Prontzas, 2011; Yan, 2011). A study by Gyimah-Brempong (2011) found that education has significantly positive impacts on all development outcomes in Africa. The effects of education on developmental outcomes differ according to the levels of education (i.e., primary, secondary, or tertiary). Jalil and Idrees (2013) pointed out that education had a positive impact on economic growth in Pakistan over the period 1960–2010.

Education has been measured at three levels of education (i.e., primary, secondary, and tertiary education). Education positively influenced economic growth in Greece between 1960 and 2000 (see also Tsamadias & Prontzas, 2011). Prior studies (e.g., Agiomirgianakis et al., 2002; Gyimah-Brempong, 2011; Hanushek & Kimko, 2000; Self & Grabowski, 2004) found that low educational quality (i.e., primary education) influences economic development. Several other studies (Gyimah-Brempong, 2011; Jalil & Idrees, 2013; Tsamadias & Prontzas, 2011) have demonstrated that primary education positively affects economic growth (cf. Anastasios et al., 2019). Primary education also affects labor productivity (e.g., Benos & Karagiannis, 2016). Tsai et al. (2010) revealed that secondary education contributes significantly to the economic growth of developing countries. Secondary education shows a causal impact on economic growth (see also Self & Grabowski, 2004). Another finding by Tsai et al. (2010) demonstrated that tertiary education plays a significant role in the economic development of countries (i.e., developing countries and developed countries). A study by Ganegodage and Rambaldi (2011) using the ARDL method found that secondary education and tertiary education positively affected economic growth in Sri Lanka between 1959 and 2008. Physical capital is a key variable that affects the long-term growth of an economy. The allocation of resources into human capital development through educational attainment (i.e., secondary

and tertiary education) contributes positively to economic growth. The effect of secondary education is more significant than tertiary education (Anastasios et al., 2019; Tsai et al., 2010). The prior studies have examined the effect of education expenditure on Malaysian economic growth (e.g., Chan et al., 2020; Hussin et al., 2012; Ramli et al., 2016; Yun & Yusoff, 2018). Ramli et al. (2016) found that education expenditure has a positive relationship with Malaysian economic growth and that the labor force and capital also affect economic growth. Hussin et al. (2012) demonstrated that GDP has a positive relationship with government expenditure on education in the long term, which implies that educational quality affects Malaysia's economic growth. Additionally, Chan et al. (2020) demonstrated that education expenditure has a long-run relationship with national output. Government spending on education affects the growth rate of economic development (see also Islam & Alam, 2022). While upper secondary education and tertiary education have a positive relationship with labor productivity, primary education shows a negative relationship. Furthermore, lower secondary education does not show any relationship with productivity (Benos & Karagiannis, 2016). Higher educational attainment brings more skilled and productive workers into the labor force, which promotes the growth and development of a country (Barro & Lee, 2001).

A study by Agiomirgianakis et al. (2002) demonstrated that the effect of tertiary education is higher than secondary education (cf. Anastasios et al., 2019; Tsai et al., 2010). Education has a significant impact on economic growth in the short term and played a weighty role in the long term during 1990–2009 in China (Yan, 2011). Mkondiwa (2022) found that schooling has a positive impact on agricultural incomes. Another study by Lin (2003) demonstrated that schooling positively affects output in Taiwan. Each additional year of average schooling increases the growth of output by approximately 0.15%. Bashir

et al. (2012) reveal that the growth of education and income positively influenced each other between 2000 and 2010 in West Virginia, United States. Data covering 93 countries show that higher levels of educational quality are associated with higher economic growth and that the effect of tertiary education is larger than that of secondary education. However, secondary education has a greater effect on economic growth than primary education (Agiomirgianakis et al., 2002). Nevertheless, some studies (e.g., Tsai et al., 2010) have found that secondary education is a bigger contributor to economic growth, especially in developing countries. Lee (2005) observed that the lower productivity of service industries has affected productivity growth in Korea. The findings indicate that investment in human capital by education does not appear to exert an immediate influence on economic growth in Morocco; however, it is identified as a positive and important contributor to long-term economic growth (Goumrhar, 2024).

According to a study by Pudasaini (1983), higher education results in higher productivity, especially in modernizing agriculture compared to traditional agriculture in Nepal. The study also pointed out that higher education plays an important role in modernizing agriculture rather than retaining the traditional approach to it. Another study by Viswanath et al. (2009) demonstrated that investment in human capital has a positive relationship with economic growth. Basically, education is considered the most important component of human capital because higher education increases it, thereby augmenting productivity, which generally leads to greater added value. Shindo (2010) found that government educational subsidies influenced economic growth in Jiangsu and Liaoning. Government subsidies for education accelerate individual investment in human capital and economic growth. Some studies have found that secondary and tertiary education can positively affect economic growth (e.g., Tsai et al., 2010; Ganegodage & Rambaldi, 2011).

However, Agiomirgianakis et al. (2002) and Jalil and Idrees (2013) reaffirmed the outcomes by finding that higher levels of educational quality are associated with higher economic growth, which implies that the positive effect is based on the levels of education (cf. Anastasios et al., 2019; Tsai et al., 2010). The relationship between primary education and productivity is negative, while there is no significant relationship between lower secondary education and productivity (see also Benos & Karagiannis, 2016).

Jajri and Ismail (2010) suggested that the Malaysian education system must strengthen the quality of the workforce—through training programs to raise the output of human capital for economic growth. In the study, the capital-labor ratio significantly contributes to increasing labor productivity by utilizing more advanced technology. The study also revealed that tested variables, such as human capital, indirectly influence economic growth and labor productivity. Physical capital plays a dominant role in determining labor productivity and its contribution to economic growth. Utilizing more capital and seeking a labor force with higher education can also lead to technical innovation. Therefore, education plays an indirect role in supporting economic growth by enhancing labor productivity. Nevertheless, Howak and Dahal (2016) found that there is a direct and indirect benefit of primary, secondary, and tertiary education in Nepal over the period of 1975–2014.

Barro and Lee (2001) stated that education plays a significant role in contributing to the economic development of a country because it enhances competitiveness and helps sustain economic growth. Higher education attainment creates more skilled and productive workers—promoting development and growth in a country. Islam et al. (2016) found that education and human capital have a positive relationship with economic growth in

Malaysia. The worker with a high-level education is more skillful and productive in the workplace. The study involves 100 respondents who are employed within Bahau, Negeri Sembilan. The demographic factors, such as gender, age, ethnicity, education level, marital status, number of family members, career, and gross household income, are included in the research. According to Lin (2003), schooling has a positive and indispensable effect on increasing output in Taiwan, as evidenced by results from 1965 to 2000—the output growth is estimated to rise around 0.15% in an additional year of average schooling. Skilled labor increased physical capital by acquiring knowledge of new technologies. On the other hand, the results of the complementarity test indicate that physical capital and technical progress do not show remarkably significant relationships with schooling. Investing significantly in human capital or research and development (R&D) could enhance the complementarity between schooling and technology.

Bashir et al. (2012) pointed out that educational attainment increases productivity, increases income levels, reduces poverty risk, and enhances the standard of living. Thus, investment in education would be essential for income growth, especially in poor countries. First, empirical analysis shows that both the growth of education and the growth of income positively influence each other. Hence, more attempts to increase the income-generating opportunities or work would be advantageous. Second, empirical analysis shows the impact of tertiary education on the growth of population. Therefore, appropriate policy measures are required to manage immigration and create job opportunities inside the state of West Virginia. The empirical results and analysis suggest that West Virginia requires a comprehensive set of policies to maintain economic growth. These policies should sufficiently enhance facilities, increase income-earning opportunities, and improve basic infrastructure development. According to the Appalachian Regional Commission, the

Appalachian region lacks the infrastructure to take full advantage of emerging economic gains and make sustainable economic growth. A study by Yan (2011) found that education not only has a significant short-term impact on economic development but also plays an important role in the long run. The main driving force of China's economic growth is capital, and the importance of education is not reflected. The education spending in China remains very low; therefore, the government should heavily invest in education to ensure sustainable economic growth rather than focusing on highly promoted investments and efforts to change the industry and market's structure. Afzal et al. (2010) also pointed out that there is a direct relationship between education and economic growth in Pakistan, both in the short term and the long term.

Research by Gyimah-Brempong (2011) found that educational attainment has a significant positive impact on all development outcomes in Africa. Moreover, the impact of education on development outcomes varies in accordance with the level of education, such as primary education, secondary education, or tertiary education. In general, that means higher levels of education tend to have a greater impact on development than lower levels of education. Some exceptions to this generalization are such that for preventive health care, lower levels of education tend to be more important than higher levels of education, while higher levels of education are more essential for curative health and longer life expectancy. In addition, the various levels of education affect development in different ways—researchers must disaggregate education into its distinct levels. The findings indicate that raising the quantity and quality of education would improve the outcomes of development in Africa. As stated by Castelló-Climent and Hidalgo-Cabrillana (2012), the results further indicate that quality of education plays a crucial role in the human capital composition and in the long-term income level. Moreover, the quality of the

higher education system significantly impacts most economies. Conversely, the higher enrollment rates are statistically positive and significantly related to higher growth rates in per capita income. On the other hand, the effect is stronger in economies that were relatively poor than in countries with per capita incomes in the top 25th percentile of income distribution. Even though the coefficients of the interaction terms are both statistically significant, the quantitative effect of higher enrollment rates on growth is almost twice as high in lower-income countries as in the richest economies. Nowak and Dahal (2016) stated that the study indicates that education is crucial for Nepal's socio-economic development and economic growth. Primary, secondary, and tertiary levels of education provide both direct and indirect benefits related to job opportunities, participation in the labor market, household income, etc. The research suggests that the governments in developing countries should prioritize education and skill development programs, ensuring education remains a top priority in their public policies.

Growth at the secondary and tertiary levels shows a positive correlation with the average years of school attainment for adult males. These results indicate the diffusion of technology plays a crucial role, as workers with this level of education are likely to complement new technologies. In contrast, growth is insignificantly related to the years of school attainment for females at the secondary and tertiary levels. This result implies that many countries underutilize highly educated women in the labor markets. Furthermore, there is no significant correlation between growth and male schooling at the primary level. However, this schooling is a prerequisite for secondary schooling and hence would affect the growth through this channel. At the primary level, women's education stimulates growth indirectly by inducing a lower fertility rate (Barro, 2001b).

Secondary-level education is a bigger contributor to economic growth in most developing countries than it is in developed countries. However, tertiary-level education currently plays a significant role in economic growth for both developed and developing countries. The empirical results also demonstrate a significant positive correlation between high-tech human capital and economic growth. This finding suggests that a country should encourage higher enrollment in high-tech fields of study. Therefore, the percentage of tertiary graduates in engineering, mathematics, science, and computer science is a significant indicator of high quality of the labor force (Tsai et al., 2010). However, Benos and Karagiannis (2016) found that human capital has a strong positive relationship with labor productivity associated with upper secondary and tertiary education. In contrast, primary education demonstrates a negative relationship, while lower secondary education shows no relationship with productivity during the period 1971–2011.

According to Afzal et al. (2010), there is a direct relationship between education and economic growth in Pakistan in both the short term and the long term. This study utilizes annual time series data on real GDP, real physical capital, poverty, inflation, and general school enrollment ratio for the period 1970–71 to 2008–09 to study the short-term and long-term relationship between school education and economic growth in Pakistan. Moreover, macroeconomic instability because of inflation impedes economic growth both in the short term and the long term, while it impedes school education only in the long term. Furthermore, the results show a statistically significant and inverse relationship between school education and economic growth in the short term. Singh et al. (2018) found out that primary and tertiary education are the significant contributors to growth in the long term. In contrast, tertiary education has a positive and significant effect on economic growth in the short term. However, male education at primary and tertiary levels has a higher

contribution to economic growth in the long term. Secondary and tertiary education are also found to be significant and positive contributors to growth in the short term. On the other hand, secondary education of the female is seen to be more significant to growth than the male, while male education at the tertiary level contributed more to growth if compared to the female. Hence, the female's overall impact in the short term surpasses that of the male. Overall, male education has a higher effect on economic growth in the long term, while the impact of female education is found to be greater in the short term.

Wai et al. (2017) determined that all levels of education—primary, secondary, and tertiary—are crucial for economic growth, with tertiary education exerting the most substantial impact compared to primary and secondary education. Primary education has a positive relationship with economic growth, while secondary education exhibits a negative relationship with it. In contrast, tertiary education is significantly positively correlated with economic growth. The increased enrollment of international students in tertiary education in Malaysia has directly contributed to the economy through their spending. Hussin et al. (2012) found that the quality of education is crucial for enhancing a country's economic growth and human capital. The findings indicate a long-term relationship between education and economic growth, as higher educational standards improve the efficiency and productivity of the labor force, subsequently influencing economic development over time. Thus, the government should increase its expenditure on the education sector to enhance economic performance.

Babatunde and Adefabi (2005) assert that a long-term relationship exists between education and growth in Nigeria, as demonstrated by the Johansen cointegration technique and vector error correction methodology. The findings revealed that a highly educated

workforce exerted a positive and significant influence on economic growth via factor accumulation and on the advancement of total factor productivity. There is a long-term relationship between enrollments at the primary and tertiary levels, the average years of schooling, and output per worker. Seetanah and Teeroovengadum (2019) showed that tertiary education has a positive and significant relationship with economic growth based on a sample of 18 African economies over the period 1980–2015. The size of the tertiary education coefficient is reported to be relatively smaller than that obtained for developed country cases when compared to literature and primary and secondary enrollments, respectively. The analysis also revealed a bi-causal relationship in higher education growth modeling, highlighting that economic growth rates serve as a determinant of tertiary education, albeit with a lagged effect. Furthermore, this research found evidence linking tertiary education to both domestic and foreign direct investment—suggesting potential indirect effects of tertiary education on growth rates.

The results indicate that the estimated coefficients for primary and secondary school enrollment and average years of schooling used as measures of education have a positive and statistically significant effect on economic growth in Sub-Saharan Africa (SSA). Nevertheless, the estimates for both tertiary school enrollment and government expenditure on education are not statistically significant. Furthermore, the estimated parameters for health have a positive and statistically significant effect on economic growth in SSA. In comparing the estimated human capital elasticity of growth for the two forms, the health measure of human capital appears to make a larger contribution to economic growth in SSA than the education measure of human capital (Ogundari & Awokuse, 2018). Additionally, Adu and Denkyirah (2017) found that education is a driver for economic growth at different levels of education in the short term and long term.

Primary education was found to have a positive and significant impact on economic growth in the short term. Moreover, primary and secondary education had a positive impact on economic growth only in the long term. However, tertiary education had no significant effect on economic growth in the short term or long term. The finding also indicates that primary education is necessary for short-term economic development, while primary and secondary education are essential for long-term economic development. In addition, government expenditure on education has no statistically significant effect on economic growth, which could imply that the expenditure is not directly related to the quality of education but rather quantity (enrollment). Hence, the educational policies should focus not only on primary and secondary education but also on tertiary education—incorporating research and development into the curricula—and government expenditure should be directed towards the quality of education.

Adawo (2011) demonstrated that inputs from primary schools, physical capital formation, and health contribute to economic growth; however, inputs from secondary schools and tertiary institutions were found to hinder growth. Additionally, it noted that physical capital plays a vital role in promoting growth in the short term. The results suggest that primary school contributes to growth, as children help their parents, mostly in agriculture—reflecting traditional farming practices in rural areas. Likewise, paid employment is not readily available for products of both secondary schools and those of tertiary institutions; however, reducing their contributions to economic growth. Moreover, many students prefer to pursue admission into arts and social sciences rather than core sciences, engineering, and technical courses when applying to higher education institutions. Given the saturated labor market in Nigeria, many graduates struggle to discover self-employed opportunities. A significant amount of schooling occurs in Nigeria, but minimal

learning takes place during this time. According to Li and Huang (2008), the results confirm that both health and education investment have positive effects on economic growth. Especially, the education proxy variable, such as the percentage of secondary or above education in the population aged above 6 years old, is significant even when different estimation methods are used, and it has the highest significance level. The result means that education stock quality has a strong correlation with economic growth in China. The Chinese government's policy of implementing free education for twelve years and providing more chances for students to receive tertiary education is the right one to boost economic growth. However, the level of education stock is significantly higher than the level of health stock. It is important for policymakers to improve economic growth effectively by reinforcing either health or education development, with education investment being statistically more significant than health investment.

Brunello and Comi (2004) found evidence that employees with tertiary education have steeper experience profiles than employees with upper secondary or compulsory education. Hence, education provides not only an initial labor market advantage but also a permanent advantage that increases with time in the labor market. The differences in earnings growth based on education are smaller in countries with a higher level of corporatism. In contrast, these differences are larger in countries that have experienced relatively rapid labor productivity growth alongside low educational attainment. The educational system seems to play a significant role, as countries with a more stratified secondary education system exhibit smaller differences in earnings growth relative to education levels.

Primary and secondary education are most important for productivity growth based on micro studies for Guatemala. The results show a better-educated labor force having a positive and significant impact on economic growth. Human capital has a highly significant and positive impact on long-run growth. An increase of 1 percentage point in average years of schooling would raise output by about 0.33 percent. The effect is of similar magnitude to that in micro studies. A disaggregated analysis by level of education reveals that primary schooling is most important for productivity growth, followed by secondary schooling and tertiary education. It appears that general education and basic technical skills have been the main determinants for the diffusion of technological innovation, and people with primary education have particularly benefited from policies that promote competitiveness, such as trade openness. Such an exercise reveals that the increased skill level has been the main driving force behind productivity growth and that education explains more than 50 percent of output growth during the period of 1951–2002 (Loening, 2005). A study by Chatterji (1998) found that tertiary education did displace secondary education as a major driver of growth. The results suggest that tertiary education may well have an important role to play in the growth process. There is a clear interaction between secondary education and tertiary education. Secondary education forms the base from which tertiary education takes off. Narayan and Smyth (2006) point out that tertiary education and economic growth have been important in propelling investment, including foreign direct investment.

The results suggest that primary education significantly influences growth, whereas evidence for a similar impact from secondary education is more limited. Finally, the evidence is quite compelling that female education at all levels has the potential for generating economic growth; however, male education has a causal impact on growth only

at the primary level and perhaps weakly at the secondary level. The conclusion that primary education drives economic growth in India must be qualified since education's impact likely shows only after long time lags, and there may be important omitted variables (Self & Grabowski, 2004). Agasisti and Bertoletti (2020) found that an increase in the number of universities contributes to stronger economic growth in 284 European regions over an 18–year period, from 2000 to 2017. The quality of research and specialization in STEM subjects are the main factors by which universities positively influence the economic development of the region. Controlling the size of universities, the analysis showed a positive effect nearly twice as significant as that attributed solely to an increase in the number of universities. This finding indicates that growth in regional GDP per capita is primarily influenced by the overall expansion of the higher education system, rather than solely by the increase in the number of universities.

Afzal et al. (2011) found that there is a feedback causality relationship between education at all levels and economic growth. Among all levels of education, general higher education plays a significant role in driving economic growth. Additionally, there is a high confidence level in the impact of school education on economic growth. The study highlights that labor force, in contrast to physical capital, is a key factor in understanding the relationship between education and economic growth. It recommends increased investment in university education to further accelerate economic growth. According to Hassan and Cooray (2015), the externality effects of education are positive and robust for both males and females. These effects are relatively large and significant at primary, secondary, and tertiary levels. The findings indicate a gender productivity gap, characterized by the observation that the growth effects of male enrollment per worker are consistently estimated to be higher than those of female enrollment at all educational levels.

The greater the disparity in educational attainment between men and women, the larger the resulting productivity differential. By investing more in female education, Asian economies have the potential to achieve faster growth.

Bloom et al. (2014) found that tertiary education plays a significant role in promoting economic growth. The result finds evidence that tertiary education improves technological catch-up and helps maximize Africa's potential to achieve more rapid economic growth given current constraints. Investing in tertiary education in Africa may accelerate technological diffusion, which would decrease knowledge gaps and help reduce poverty in the region. Hussaini (2020) also found that there is positive long-run causality between the economic growth of the South Asian nations and the gross enrollment ratio of higher education. Pereira and Aubyn (2009) noted that increasing education at all levels, except for tertiary education, positively and significantly impacts economic growth. This finding indicates both primary and secondary education significantly contribute to Portuguese economic growth. Tertiary education, however, exerts a stronger influence on growth only when a country approaches technological leadership. Moreover, Papageorgiou (2003) noted that post-primary education primarily fosters innovation and imitation of technology, while primary education chiefly focuses on the production of final output. However, there is a significant relationship between regional growth and the intensity of research and development (R&D) as well as higher education in North European countries. Moreover, educational attainments have contributed to the growth of all the European regions (Sterlacchini, 2008). A study by Webber (2002) found that enrollment at the secondary level continues to have the most significant impact on economic growth. The results suggest that reducing undernutrition would only make a modest contribution to economic growth, whereas increasing enrollment ratios, especially in secondary education,

has a positive and more significant effect. Policies to increase economic growth should favor investments in education over health. Nevertheless, Brist and Caplan (1999) pointed out that enrollment at the secondary level had a positive relationship with real per capita GDP and life expectancy and a negative relationship with fertility.

Faridi et al. (2009) pointed out that educated males and females are successful in attaining employment, raising output, and growth. The results show that all the education levels, except the basic level, up to the middle level, have a positive and significant impact on the female labor force's participation. It is recommended that additional educational facilities be established throughout Pakistan, with a particular emphasis on providing technical, vocational, and job-oriented education in the specific study area. Other findings indicate that the influence of educated fathers and mothers is positive and insignificant on the female labor force's participation. It means that when the children grow up, they are independent decision-makers. Another important conclusion drawn in this study is that educated spouses (husbands) have a positive and significant effect on wives' employment.

The findings also indicated that changes in the completion rates of higher and secondary education have a significantly greater impact on economic growth in less developed countries compared to more developed ones. Furthermore, the influence of secondary education in those countries is even more substantial than that of higher education. This study has shown how changes in completion at different levels of education appear to be related to economic growth at various stages of economic development (Echevarria, 2009). Permani (2009) found that education is important for economic growth, but it is not sufficient. The complementarity between education and other factors in enhancing productivity and efficiency is commonly seen as the driving

force of economic growth. Statistical analysis suggests that education and economic growth in East Asia have two-way causality. Education consistently presents as a significant income determinant and, consequently, a growth factor, regardless of whether it can increase productivity.

The findings reveal that an increase in the share of people in the labor force having completed upper secondary education is not related to the rate of long-run growth, while tertiary education is positive and statistically significant both in the short-run and long-run growth. However, the study does not fully support the hypothesis that the higher average educational level fosters growth, taking into consideration the fact that the share of the active population having completed upper secondary education is twice as large as the share of people with tertiary education. Moreover, the upward trend of real output is attributed mainly to foreign direct investment, physical capital, and export (Neycheva, 2013). However, Khattak and Khan (2012) show that secondary education contributes significantly to the real GDP per capita in Pakistan. Elementary education also positively affects economic growth, but the result is statistically insignificant. Furthermore, the results confirmed the existence of long-term relationships in education and real GDP per capita. The study suggested keeping education a top priority in public policies. The government needs to make serious efforts for the universalization of primary education (UPE), as primary education provides input for secondary education, and UPE will accelerate the pace of school as well as college enrollment. The dropout rate at the elementary and secondary levels should be discouraged, and sources of dropout should be explored. Ali and Jabeen (2015) highlight the importance of education in enhancing economic conditions through the provision of quality education. Observations from developing countries indicate that education plays a crucial role in economic development.

The computable facts specify that a real GDP rise has a clear connection with primary school registration and workingmen's percentage. Primary education is instrumental in raising the economy. Therefore, the government must indiscriminately impart primary education at all levels to accelerate Pakistan's economic growth.

The results indicate that real GDP growth is positively related to the primary school enrollment-labor force ratio during the period 1980–2007. It implies that primary education is an important prerequisite for accelerating growth. Higher enrollment rates at primary and other educational levels have demonstrated a greater contribution to economic growth. Additionally, the study reveals that labor force participation is a significant predictor of economic growth and can contribute to the real GDP growth of the economy. Literacy significantly impacts economic growth, suggesting a positive outlook for sustainable economic development. It also enhances the return on education for the economy to a certain extent. The study suggests that the measures should be adopted to improve the primary education system in Pakistan so that a universal enrollment rate in primary education may be achieved soon—implementing measures to raise the country's literacy rate would also help economic growth in Pakistan (Kiani, 2010). Korkmaz and Kulunk (2016) pointed out that there is a relationship among the higher education schooling rate, life expectancy at birth, and economic growth in 10 selected OECD countries during the period of 2007–2013; the results indicated a unidirectional causality from economic growth to both the higher education schooling rate and life expectancy at birth. Therefore, investment in education should be increased to develop a higher-quality labor force. This enhancement in education can boost productivity and foster further economic growth, ultimately contributing to a more peaceful social environment.

The impact of education has been found to be positive and significant on total factor productivity (TFP), whereas the indicator of health also has a positive, robust, and significant impact on TFP for the period of 1990–2010 for thirty-seven developed and developing countries. Moreover, the study found that, in addition to factor accumulation, enhancing factor productivity through investment in human capital was a key factor in explaining the differences in development levels among countries. These findings reaffirm the necessity of improving education and health for the general population to promote sustainable growth and economic development worldwide (Alvi & Ahmed, 2014).

The study reveals the results of an empirical analysis examining the causality between education expenditure, health expenditure, and economic growth in eight selected developing countries: Argentina, Brazil, Chile, India, Indonesia, Mexico, South Africa, and Turkey during the period from 1995 to 2012. The findings reveal that in only two out of eight developing countries, specifically Brazil and Mexico, there exists a significant and positive causal relationship running from education and health expenditure to economic growth. In contrast, the results indicate a significant but negative causal relationship among education expenditure, health expenditure, and economic growth in Indonesia. Moreover, there are no causal and insignificant relationships between education and health expenditures and economic growth in the rest of the countries (Şen et al., 2018). Likewise, Hua (2005) pointed out that university education exerts a positive impact on efficiency change, technical progress, and productivity growth. However, primary education and secondary education have a negative impact on efficiency change. Additionally, university-educated workers positively impact efficiency improvement by moving to more efficient non-state sectors. These results completely justify the development of education, particularly university education, which is one priority objective of the Chinese

government. Wang and Liu (2016) found that higher education has a significantly positive impact on economic growth. However, primary education and secondary education do not have a significant positive impact on economic growth. Therefore, the study suggests that the government should pay more attention to higher education so that more people can receive it and avoid entering the labor market too early. The proportion of the labor force with higher education increased, thereby promoting the economic development of the country. Nevertheless, the government also needs to increase the investment in primary education and secondary education so that all people can enjoy the high quality of education and reduce illiteracy and semi-illiteracy rates at the same time. Secondary education is a key link in the connection between primary education and higher education.

The results suggest that in Uganda, the proportion of skilled workers and average education, as well as training, are positively associated with labor productivity. Similarly, in Tanzania, the proportion of skilled workers and the education level of the managers show a positive relationship with productivity. In addition, both average education and training in Kenya were positively associated with labor productivity. Tanzanian manufacturing firms showed a positive correlation between the manager's education and labor productivity. Additionally, firms that undertake training were shown to exhibit significantly higher levels of labor productivity than firms that do not train their workers in Kenyan manufacturing firms. These results have important policy implications for how to target policy prescriptions aimed at increasing manufacturing competitiveness (Aggrey et al., 2010). Nevertheless, Jones (2001) found strong evidence that education and productivity are positively correlated and that firms pay workers according to their productivity. The findings reveal that workers with tertiary education are more productive than those with secondary schooling, while workers with secondary schooling are more

efficient than those with primary schooling. Meanwhile, workers with primary schooling are more productive than those without formal education. Moreover, evidence suggests that workers who have received vocational training are more productive than workers with secondary schooling, although workers with secondary schooling typically possess more years of education than workers with vocational training.

The study findings indicate a positive correlation between managers with tertiary education and a 10% increase in productivity within the poultry industry—this suggests that investing in higher education could positively impact the commercial poultry industry in Ghana and predict an increase in productivity by 10 points on the margin. This finding is particularly important since improved performance of the commercial poultry industry is driven by advances in technology, effective organization of production, reduction of waste and long-term liabilities, efficient use of resources, lower operational costs, and increased competitive advantages, which are dependent on the level of a manager's education (Larbi-Apau & Sarpong, 2010). Meanwhile, Chansarn (2010) pointed out that only education and technological progress are the significant determinants of the growth rate of labor productivity. The mean years of schooling measure education, while the average annual growth rate of total factor productivity measures technological progress. Moreover, technological progress is considered the most important determinant of labor productivity growth, with a standardized coefficient of 0.975, whereas that of mean years of schooling, which represents education, is only 0.064.

Douangngeune et al. (2005) hypothesize that Thailand's slower economic progress has been due to its slower educational development induced by abundant land resources. The results reveal that the average schooling in Thailand had a positive effect on its

agricultural intensification and industrialization. However, land endowment had a negative effect on these variables as well as on educational investment. Thailand failed to mobilize resource rent effectively during the vent-for-surplus development stage, which hindered the ability to establish the necessary conditions for modern development. Significant population pressure on land compelled Japan and Korea to invest in education and other infrastructure to facilitate agricultural intensification and industrialization. Gherghina and Duca (2013) emphasize the significance of individuals' education levels, which contribute to enhanced economic development and an increase of GDP per capita. The study concluded that there is a direct relationship between increased spending on education at all three levels and GDP per capita. Moreover, the method of least squares pointed out that education-related costs influence both the level and evolution of the unemployment rate, as shown by the cross-correlation coefficients between the unemployment rate and education costs. The relationship between education, human development, and GDP per capita illustrates the interdependence of these three components, highlighting the significant role that education plays in a country's economic development.

The results indicate that tertiary education is positively and significantly related to national development. Additionally, tertiary education has a positive, strong, and significant relationship with human capital development. This study establishes that tertiary education is essential for developing human capital, which can positively transform an economy and help a state or country compete amid others. The study observed that tertiary education significantly influences the development of human capital. It concluded that the Nigerian government, specifically the Lagos State government, needs to establish a bridge that connects the crisis-saturated university system to the students who will drive the economy's development. Tertiary education must be adequately funded and equipped

with modern learning technologies so the students can compete in this globalizing world, and the government needs to take drastic measures to reduce the level of brain drain in the country (Mohammed et al., 2016).

The results reveal that there is cointegration between public expenditures on education, primary school enrollment, and economic growth. The findings also indicate that there is a bi-directional causality between public recurrent expenditures on education and economic growth. This result suggests that improvements in the quality and quantity of manpower in schools have a positive effect on economic growth. Likewise, the results revealed that public expenditure on education Granger-causes economic growth, whereas the reverse is not the case. This result reflects the inadequate funding of the education sector over time. Primary school enrollment does not Granger-cause economic growth, as revealed by the results. This conclusion is not surprising because primary school curricula have been found to be modeled after the Western education system with little or no relevance to the domestic environment. The curricula do not impart skills in agriculture and other vocations (Omojimite, 2010). However, Shaihani et al. (2011) reveal that all education levels have a significant impact on economic growth in the short run, while only tertiary education significantly affects economic growth in the long run for the period 1978–2007 in Malaysia. The study shows that primary education and tertiary education are negatively significant to explain the development of economic growth, but secondary education is positively significant to explain the development of economic growth in the short run. However, tertiary education shows a positive and significant impact on economic growth in the long run. Adopting new technology in the manufacturing and service sectors benefits higher education graduates by enabling them to produce higher-quality products. The results suggest that greater attention should be given to enrollment at

the tertiary education level, and the government should introduce policies that can induce innovation and promote economic growth. Furthermore, the government should provide more job opportunities to balance the increasing enrollment rate in tertiary education. Tertiary education is particularly important to generate workers' skills and achieve a high-income economy.

The empirical analysis reveals that there is a long-run cointegrating relationship between higher education, physical capital investments, and economic growth in Greece over the period of 1960–2009. The elasticity of economic growth with respect to higher education is 0.52%. The findings reveal a unidirectional Granger causality in both the long run and short run, indicating that higher education and physical capital investments lead to economic growth. The results suggest that economic growth should be considered endogenous to higher education and physical capital investments. The role of higher education in economic growth seems crucial and significantly explains it (Pegkas & Tsamadias, 2014). However, Siddiqui and Rehman (2017) found that primary education and secondary education were more prominent in explaining the fluctuations of economic growth in East Asia, whereas tertiary and vocational education showed positive effects on economic growth in South Asia. Government expenditure on education positively impacted economic growth in both East and South Asia. These findings provide new evidence that the variations in growth rates between these two regions are linked to differences in their educational progression. Saidi and Mongi (2018) pointed out that there exists a unidirectional causality from education and mobile cellular telephones to economic growth, from internet users and mobile cellular telephones to research and development (R&D), and from education to R&D. However, there is a bidirectional causal relationship between internet users and economic growth, between R&D and economic growth, and

between education, internet users, and mobile cellular telephones in the short run. The results suggest a bidirectional relationship exists between education, internet users, and mobile cellular telephones. Moreover, there is a unidirectional causality running from internet users to economic growth and R&D, as well as from mobile cellular telephones to economic growth and R&D in the long term.

The results of the analysis show that tertiary education has the strongest impact on labor productivity across the considered economies. Meanwhile, the breakdown of aggregate human capital by level of education leads to better clarification of the effects of human capital and physical capital on labor productivity. The findings confirm the trend of increasing returns to scale associated with human capital, primarily driven by tertiary education and secondary education. Therefore, it is crucial to disaggregate human capital to gain a clearer understanding of its role in the economy (Kocourek & Nedomlelová, 2017). Thinagar and Selvaratnam (2015) pointed out that there is a positive impact of pre-primary and primary education on economic growth, while there is a negative impact of secondary education and tertiary education on economic growth. Thus, the ministry of education must pay attention to the enrollment rate of students at secondary and tertiary education levels so that it can contribute to a positive relationship with Malaysian economic growth.

The study specifically examined the relationship between education and economic growth for South Africa using annual post-democratic data spanning from 1994 to 2014. The mode of empirical investigation is the ARDL model, which is applied to two empirical specifications, the first being a bivariate education growth model and the second being a multivariate model consisting of education, economic growth, and other control variables

like government size, inflation, investment, and terms of trade. The empirical results imply that education insignificantly impacts economic growth in both models, whereas government size and inflation are the only variables that produce significant and theoretically correct coefficient estimates. The insignificant link between education and economic growth implies that an increase in school enrollment numbers will not necessarily benefit the economy in terms of improved growth. Henceforth, the study implies that government should be rather concerned with deeper fundamental education issues, such as improved quality of education (Malangeni & Phiri, 2018). Additionally, Oancea et al. (2017) demonstrate that higher education significantly impacts economic growth, although the degree of its influence varies between the Czech Republic and Romania, based on data from 1980 to 2013. For the Czech Republic, an increase of 1% in the number of students leads to a 0.42% increase in GDP per capita, while in Romania it leads to a 0.2% increase. There is a causal relationship that goes from higher education to economic growth for both countries. EY and Safijllin (2019) found that school enrollment in primary and secondary has a positive and significant effect on real GDP per capita. However, tertiary school enrollment is not significant in terms of real GDP per capita. In addition, the public expenditure on education as a percentage adversely impacts real GDP per capita. The labor force participation is not significant; however, the unemployment rate is significant—which is negatively correlated with real GDP per capita. Likewise, the real final consumption expenditure is significant and strongly correlated with real GDP per capita, but real gross capital formation is not significant, which is a proxy for physical capital.

Tertiary education plays a more significant role than primary education and secondary education in economic growth in China. In addition, the composition of human

capital's role in regional economic growth is relevant to the level of development. The more developed provinces benefit more from tertiary education, while underdeveloped ones depend more on primary education and secondary education. The study also suggests that China should raise the percentage of workers with tertiary educational attainment to promote economic growth. Likewise, the government should be investing more in all educational levels of the poor provinces, especially to improve primary education and secondary education in western China so as to decrease regional disparities (Zhang & Zhuang, 2010).

2.5 Impacts of Foreign Workers and Educational Attainment on Productivity and Economic Growth

The previous studies have explored the effects of foreign workers on productivity. However, most of these studies have primarily focused on how human capital influences productivity, production output, and economic growth. Foreign workers are likely to affect labor productivity through their skills and various other factors. Kangasniemi et al. (2012) found that the foreign workers have a positive long-run impact on total factor productivity in the United Kingdom using the ARDL method, while a negative effect was observed in Spain. Then, the impact of foreign workers in the construction and personal services sectors has shown either a negative or neutral contribution to labor productivity growth in the United Kingdom. In Spain, the impact has been negative, especially in these sectors (i.e., agriculture and construction). The study by Jordaan (2018) found that both low-skilled and high-skilled foreign workers positively impact productivity in Malaysian manufacturing industries, based on data from 2005 to 2009 using OLS estimation.

Nonetheless, a recent study by Mamun et al. (2023) indicates that urban migration results in agricultural labor shortages, which ultimately reduce agricultural productivity in

Malaysia. Regarding the effect of educational attainment, previous studies have indicated that education influences productivity (Aljarallah & Angus, 2020; Benos & Karagiannis, 2016; Lin, 2003; Pudasaini, 1983; Viswanath et al., 2009) and also contributes to economic growth and development (Barro & Lee, 2001; Ganegodage & Rambaldi, 2011; Gyimah-Brempong, 2011; Hanushek & Kimko, 2000; Jalil & Idrees, 2013; Tsai et al., 2010; Yan, 2011). A study by Hanushek and Kimko (2000) revealed that the quality of labor force differences is related to schooling and has a stable, consistent, and strong relationship, which has a causal impact on economic growth. In addition, the results also exhibit strong evidence that the performance on international tests is associated with productivity differences. Differences in schooling appear to link these productivity differences, and this direct connection to productivity demonstrates a causal impact on international economic performance. A study by Aljarallah and Angus (2020) reported that productivity was positively impacted by education. The other findings reported by Chen et al. (2021) are that high-skilled foreign labor improves financial performance and innovation, particularly in VC-backed startups. Furthermore, human capital strengthens job performance in the Malaysian navy sector as well as its labor productivity (Shahiri et al., 2023). The result of a study by Tsai et al. (2010) confirms that secondary education is a bigger contributor to economic growth in developing countries than it is in developed countries. Likewise, tertiary education plays a critical role in economic growth for both developing and developed countries.

Ganegodage and Rambaldi (2011) indicated that physical capital is a crucial factor influencing long-term economic growth, while investment in human capital development via secondary education and tertiary education can contribute positively to economic growth. In addition, Gyimah-Brempong (2011) reveals that educational attainment has

significantly positively affected the development outcomes in Africa. The effects of education on development outcomes differ according to the levels of education, such as primary education, secondary education, or tertiary education. Nonetheless, Benos and Karagiannis (2016) assert that human capital has a strong positive relationship with labor productivity when considering upper secondary and tertiary education. In contrast, primary education shows a negative relationship, while lower secondary education does not exhibit any relationship with productivity. However, Jalil and Idrees (2013) pointed out that education has a positive impact on the economic growth of Pakistan over the period of 1960–2010; education was measured at three levels (i.e., primary education, secondary education, and tertiary education). Another study by Barro and Lee (2001) indicated that higher educational attainment leads to a workforce that is more skilled and productive, which can foster growth and development within a country. This finding suggests that education is vital for enhancing a nation's economic development, as it boosts the competitiveness required for sustaining economic growth. According to a study by Yan (2011), education not only has a significant effect on economic growth in the short term but also plays a weighty role in the long term during 1990–2009 in China. However, Lin (2003) reveals that schooling has a positive and indispensable effect on the increase of output in Taiwan—the output growth is estimated to rise about 0.15% in an additional year of average schooling.

Additionally, educational attainment not only can enhance productivity but also augment income earnings, reduce poverty risk, and improve living standards. Meanwhile, the findings reveal that both education growth and income growth can positively affect each other during 2000–2010 in West Virginia, United States (Bashir et al., 2012). The results are clear evidence that higher levels of educational quality are associated with

higher economic growth. With data covering 93 countries, the results underline that the effect of tertiary education is greater than secondary education, while the effect of secondary education is larger than primary education (Agiomirgianakis et al., 2002). Nevertheless, some studies, including Tsai et al. (2010), found that secondary education significantly contributes to economic growth, particularly in developing countries. Furthermore, Lee (2005) observed that the lower productivity performance of service industries influences overall productivity growth in Korea's economy. A study by Pudasaini (1983) indicates that education enhances productivity more significantly in modern agriculture than in traditional agriculture in Nepal. The study also reported that higher education significantly contributes to the modernization of agriculture rather than traditional agriculture. Another study conducted by Viswanath et al. (2009) showed that there is a strong positive relationship between investment in human capital and economic growth. Education is considered the most vital component of human capital, as higher levels of education enhance it. This enhancement in human capital leads to increased productivity and, generally, results in greater added value.

Subsequently, Shindo (2010) found that Jiangsu and Liaoning achieve greater economic growth due to greater government subsidies in education. The increase in government subsidies for education promotes individual investment in human capital, and economic growth is accelerated. Some of the studies (e.g., Ganegodage & Rambaldi, 2011; Tsai et al., 2010) underscore that secondary education and tertiary education can positively affect economic growth, while some studies (e.g., Agiomirgianakis et al., 2002; Jalil & Idrees, 2013) pointed out that higher levels of educational quality are associated with higher economic growth—implying that the positive effect is based on the levels of education. Nonetheless, Benos and Karagiannis (2016) demonstrate that primary education

shows a negative relationship, and lower secondary education does not indicate any relationship with productivity.

2.6 The Economic Indicators of Education

Ganegodage and Rambaldi (2011) identified physical capital as a primary variable influencing long-term economic growth. Investment in human capital development via secondary and tertiary levels of education contributes positively to economic growth. The secondary and tertiary levels of education demonstrate reasonable resource allocation toward human capital; however, the small magnitude of the estimated coefficient shows a need for a focused policy discussion on how to effectively utilize limited resources to improve the returns of human capital in Sri Lanka. The findings, which are important from the policy perspective, indicate that higher returns from physical capital investment are not likely to produce any sizable positive externalities under existing conditions, as would be the case in a more developed economy. Shindo (2010) found two main results regarding the relationship between economic development and the accumulation of human capital in the Chinese regions of Jiangsu and Liaoning. First, both regions achieve greater economic growth due to greater government subsidies in education. This is because greater government subsidies in education encourage individuals to invest more in human capital. Second, raising education subsidy rates uniformly widens the growth gap, highlighting the significant productivity disparities between the regions. The importance of education subsidies in the long term is that any reform that results in an increase in education subsidies will contribute to correspondingly higher economic growth—improving overall welfare at the same time. Nevertheless, both regions have different levels of productivity, resulting in any policy change that could effectively improve the regional disparities.

According to Hanushek and Kimko (2000), the labor-force quality differences are related to schooling, which has a causal impact on economic growth. Meanwhile, the simple estimates of cross-country growth relationships appear to overstate the causal impact of quality, but the precise cause or magnitude of this overstatement is unclear. The estimated impact of quality on growth shows that one standard deviation in science and mathematics skills translates into more than one percentage point in average annual real growth. There is no simple and agreed-upon way to translate the micro productivity differences from individual earnings into effects for economic growth, which makes it difficult to be precise. For example, quality significantly contributes to raising the steady-state income level, and conditional convergence links growth to this process. The results from the growth equation are substantially larger than those corresponding to individual earnings. Jalil and Idrees (2013) found that education has a positive impact on the economic growth of Pakistan over the period of 1960 to 2010. The study measured education at three levels: primary, secondary, and tertiary. Moreover, the coefficients for the various levels of education indicate that this study uses disaggregated education data to determine the factual effects of education on economic growth—using only the average level of education may lead to an aggregation bias in the aggregate education measure. This disaggregated analysis will provide better guidance to policymakers so as to mobilize public expenditure at a specific level of education. The study provides reasonable support for the policy of investing in educational activities along with the accumulation of physical capital. To achieve an industrial level of development, improve the investment in physical and human capital in the coming years.

Krueger and Lindahl (2001) stated that micro- and macro-literature emphasizes the role of education in income growth. Many studies using individual-level data on education

and income provide robust evidence of substantial payoff to investment in education, especially for those who traditionally complete low levels of schooling. In the aspect of micro evidence, it is unclear whether the social return to schooling exceeds the private return—although available evidence suggests that positive externalities in the form of reduced crime and reduced welfare participation are more likely to be reaped from investments in disadvantaged than advantaged groups. Likewise, the macroeconomic evidence of externalities in terms of technological progress from investments in higher education seems to us more fragile—resulting from imposing constant-coefficient and linearity restrictions that are rejected by the data. The findings may help resolve an important inconsistency between micro and macro literature on education. Sylwester (2000) found that higher levels of income inequality are associated with increased spending on public education. These expenditures negatively affect public education expenditures; the impact upon future growth is positive. These empirical findings differ from those of Easterly and Rebelo (1993), who report that income inequality raises public expenditures for education, but they found that these expenditures are positively linked with growth. Nevertheless, they treat education expenditures as an exogenous variable.

2.7 Educational Impacts Evaluation on Economic Growth

According to Frini and Muller (2012), multivariate cointegration analysis is implemented to explore the long-term relationship between education and economic growth. Vector Error Correction (VEC) is used to characterize the observed short-term fluctuations in a manner that aligns with long-term equilibrium. The investigation focuses on how quickly education influences fertility behavior, as the speed of demographic transition positively impacts economic growth. The results indicate that the error correction term derived from the long-term cointegration relationship is highly significant in the

fertility equation described by the Vector Error Correction (VEC). The findings reveal that education triggers the fertility transition both in the short and long term. Besides, education has somewhat contributed to economic growth, yet its influence on fertility has been minimal. Moreover, the variance decomposition and impulse response function indicate that the fertility transition has produced a feedback effect on both education and economic growth. Shindo (2010) proposed that a simulation of regional economic growth from education expenditure in Jiangsu and Liaoning. Two main results are found in the relationship between economic development and human capital accumulation in the long term in the six period Overlapping Generations (OLG) model. The first finding is that an increase in government subsidies for education promotes individual investment in human capital, and economic growth is expedited. The second finding is that differences in productivity exist between the regions over time; the growth gap widens with an increase in the education subsidy rate. When the subsidy rates are increased by the same 10% and 20% in both regions, the growth rate in Jiangsu becomes higher than that in Liaoning in every case. Raising the subsidy rates by 20% increases the disparities between the regions. More specifically, the net growth rates increase 1.4% and 3.2% with the rise in subsidies in Jiangsu, while the rates only increase 1.1% and 2.5% in Liaoning. According to Teixeira and Fortuna (2004), human capital had significant effects on economic growth in Portugal from 1960 to 2001. Human capital and indigenous innovation efforts are enormously important to the process of Portuguese economic growth during the period from 1960 to 2001, as demonstrated by Vector Autoregression (VAR) and Cointegration analyses. Nevertheless, the importance of human capital surpasses that of creating an internal framework for research and development. Moreover, the indirect impact of human capital

on innovation reveals that a sufficiently high level of human capital is crucial for a nation to benefit from its indigenous innovation efforts.

Agiomirgianakis et al. (2002) found that human capital has a direct positive effect on GDP growth. Further analysis of the Pooled Mean Group (PMG) estimation results revealed that the coefficients obtained for primary, secondary, and tertiary education are 0.05, 0.11, and 0.27, respectively. Hence, there is clear evidence that human capital positively affects growth, but it is also concluded that higher levels of educational quality are associated with higher economic growth. The effect of tertiary education is higher than that of secondary education, which in turn has a higher effect on growth than that of primary education. Therefore, the findings suggest that government measures taken to expand higher education might be a vital factor for economic development and sustained economic growth. Ahmad and French (2011) found that there is a long-run relationship between human capital stock and per capita real GDP in Bangladesh. Time series relationships between both aggregate and disaggregated human capital variables were analyzed by using Vector Autoregression (VAR) and Vector Error Correction (VEC) models in this research. The results indicate that, at the aggregate level, human capital is Granger-caused by per capita real GDP. Additionally, there was no evidence of causality running from the human capital stock to per capita real GDP. Disaggregating the human capital stock revealed that secondary and higher secondary levels of education contribute significantly to per capita real GDP. Furthermore, middle-level education has the greatest influence on the evolution of Bangladesh's GDP.

2.8 Human Capital and Productivity

According to Becker (1994), human capital is directly useful in the production process. Human capital increases a worker's productivity in all tasks, although the degree of this increase may vary depending on the specific task, organization, and situation. Human capital plays a complex role in the production process; however, there is a sense in which it is represented by a unidimensional object, such as the stock of knowledge or skills (*h)*, and this stock is directly part of the production function. Likewise, the study assumed that people would be hardheaded in calculating how much to invest in their own human capital. Barro (1998) stated that human capital accumulation is a significant part of the development process and is influenced in major ways by public programs for education and health.

Human capital has an essential role in determining the wealth of nations, and its quality varies systematically with the level of development. The model is successful in capturing the large variation in levels of education across countries and is also consistent with the cross-country evidence on Mincerian rates of return. The model suggests that a significant portion of the differences in output between countries can be attributed to variations in the quality of human capital. The typical individual in a poor country not only chooses to acquire fewer years of education but also acquires less human capital per year of education. From a policy perspective, the results indicate that even modest increases in productivity can result in large gains in output per worker in the long term. The model suggests that there are large payoffs to understanding what explains productivity differences (Manuelli & Seshadri, 2014). According to Lee and Lee (2016), the existing long-term data pointed out that the rate of income growth accelerated rapidly over the past two centuries. This increased growth was accompanied by rapid capital accumulation and

technological progress. Furthermore, it was also associated with decreases in fertility and mortality rates. Investment in human capital is also influenced by income growth, as well as changes in infant mortality rates. The interactions among income, human capital accumulation, and fertility rates must have played a significant role in many countries' transitions from low-income, uneducated societies to high-income, well-educated societies and their structural change from rural and agricultural to urban and industrial. Additionally, the level of educational attainment is considered to have a significant impact on social and political outcomes, such as democracy and the rule of law.

Benos and Karagiannis (2016) found a strong positive relationship between human capital and labor productivity via upper secondary and tertiary education. In contrast, primary education demonstrates a negative relationship, while lower secondary education shows no relationship with productivity during the period from 1971 to 2011, based on census data regarding educational human capital in Greek regions. Tertiary education spillovers, along with several education quality indicators, exhibit a significant positive relationship with productivity. Overall, the findings suggest that policymakers should account for education quality as well as spillovers and direct their efforts toward a more efficient and enhanced education system—with emphasis on high education levels to enhance labor productivity overall and reduce spatial productivity disparities. Based on the findings, Greece should improve its growth potential by focusing on the expansion of complementary types of education such as vocational training, in-job training, and lifelong learning along with upper-level traditional education. Lee (2005) noted that the total-factor productivity (TFP) growth of the Korean economy has been primarily driven by the manufacturing industry since the 1990s. Nevertheless, productivity in the service industries, such as finance, insurance, real estate, construction, and wholesale and retail trade,

demonstrated inadequate performance. The lower productivity performance of the service industries has affected the productivity growth of the aggregate economy. The Korean economy needs to promote investment in technologies and improve the human capital's quality to achieve sustainable productivity growth. Additionally, the Korean government also needs to promote capable small and medium-sized enterprises and be more aggressive in attracting investment from innovative foreign firms in the domestic market. Viswanath et al. (2009) observed that there is a strong positive relationship between human capital investment and economic growth. Human capital seems to be an essential factor in explaining the increase in India's production, even after controlling physical capital. However, education has been deemed the most significant component of human capital. The government must therefore concentrate on raising the quality of education at all levels.

Human capital exhibits a strong positive relationship with labor productivity when considering upper secondary and tertiary education. In contrast, primary education demonstrates a negative relationship, while lower secondary education shows no relationship with productivity during the period from 1971 to 2011 in Greece (Benos & Karagiannis, 2016). However, education has a positive impact on the economic growth of Pakistan, which was measured at three levels, including primary education, secondary education, and tertiary education, over the period of 1960–2010 in Pakistan (Jalil & Idrees, 2013). Meanwhile, Awad et al. (2013) reveal that human capital development, including secondary and tertiary education levels, has a significant impact on the economic growth of Arab countries during the period of 1990–2010.

Corvers (1997) demonstrates that both intermediate and highly skilled labor positively impact sectoral labor productivity levels; however, the significant effect is

primarily associated with highly skilled labor. Furthermore, there are indications of underinvestment in human capital across certain manufacturing sectors. Thus, these sectors could improve their competitive position by raising the employment shares of intermediate and highly skilled labor. Intermediate-skilled labor also has a significantly positive effect on the growth in sectoral labor productivity. Both capital intensity growth and the employment share of intermediate-skilled labor have a significant positive effect on the growth in labor productivity. The results imply that the employment share of intermediate-skilled workers has a diffusion effect on labor productivity. Chidoko (2014) pointed out that there is a positive relationship between labor and economic growth during the period 1980–2010. Moreover, the results also show a statistically significant positive relationship between capital and economic growth, and this indicates that capital is an important factor for boosting economic growth in Zimbabwe. The study recommends the government of Zimbabwe develop an education and training system geared toward employment creation—investing more money into the training of skilled personnel. The results conclude that labor, capital, and lagged gross domestic product have a positive impact on economic growth in Zimbabwe.

The empirical findings of the cross-country data sets suggest that the link between growth and education varies because of different levels of economic development. They also suggest that the role of primary and secondary education appears to be more important in less-developed countries (LDCs), while growth in OECD economies depends mainly on higher education (Petrakis & Stamatakis, 2002). However, Abbas and Nasir (2001) pointed out that there is a positive relationship between human capital measures, especially at secondary and higher levels of education, and economic growth. An increase in investment in human capital at the secondary and higher levels of education contributes to economic

growth. However, the low literacy rates in Pakistan negatively affect economic growth. The government of Pakistan should introduce policies to increase the investment in human capital for secondary and higher levels of education.

There is a positive correlation between the human capital measures, especially proxied by secondary and higher schooling enrollment rates, and economic growth. Additionally, human capital measures proxied by primary schooling enrollment rates have a negative impact on the growth of GDP; therefore, the government of Sri Lanka must implement policies to enhance the quality of education, particularly at the primary and secondary levels, so that the educated labor force can perform better compared to the uneducated labor force. Meanwhile, Sri Lanka has achieved a high literacy rate in South Asia but still needs to increase investment in technical education (Abbas & Nasir, 2001). Khan et al. (2005) reveal that countries that invest more in their human capital do better in terms of economic growth. Higher levels of education and better health care result in a more productive workforce, increasing total-factor productivity and pushing a country's production function outward. The results show that economic growth is influenced positively and significantly by indicators that reflect the quality of human capital, including average years of schooling, school enrollment, literacy rate, and life expectancy at birth. Thus, investing in human capital can help achieve higher growth and better economic prospects. The study suggests that primary and secondary education, basic healthcare, and social spending must be targeted to ensure that the poorer segments of society have adequate access to public education and healthcare.

The findings reveal that human capital is positively related to economic growth in Pakistan in the long run, from 1978 to 2007. The sensitivity analysis confirms the

robustness of the initial findings about the direction and significance of the effect of human capital on economic growth. The health-adjusted education indicator was found to be a highly significant determinant of economic growth, which indicates that both the health and education sectors should be given special attention to ensure long-run economic growth (Qadri & Waheed, 2011). A study by Asghar et al. (2012) pointed out the strong positive impact of human capital on economic growth—although Pakistan has been spending a smaller percentage of GDP on education and health facilities to create human capital. The study indicates that the government must develop and implement effective economic policies concerning the provision of education and healthcare facilities to the people so as to reap maximum benefits from human capital.

The main findings reveal that human capital is key to the short-run and long-run economic growth of Mauritius. In contrast to many of the previous studies investigating the above nexus, where human capital is typically treated as a homogeneous concept, this study uses an aggregate index of education, health, and nutrition to proxy human capital. The results show a bi-directional relationship between human capital and economic growth. The study evidenced that human capital formation was an important growth factor for the Mauritian economy over the period of 1970 to 2011. Meanwhile, the study found that output also positively affects human capital in the long run. A higher level of output would imply more tax revenue for the government, and as the inputs for human capital, including education and health, are essentially government-financed, more resources can be allocated to them (Neeliah & Seetanah, 2016). Furthermore, Abubakar et al. (2015) emphasized the prospective relationship among financial development, human capital accumulation, and real GDP growth. Consequently, the main findings of the study offer policymakers options to stimulate economic growth by promoting human capital accumulation—through proper

financial policy reforms aimed at easing credit constraints and thereby enhancing access to credit. The study suggested that developing more specific credit facilities targeted at both the private sector and households will ease credit constraints, encourage human capital accumulation, and subsequently lead to real GDP growth in the ECOWAS region. Afrooz et al. (2010) showed that educated workers and skilled workers have a significant effect on labor productivity. The measurements of this effect were 0.14 and 0.42 for educated and skilled workers, respectively. In other words, a one percent increase in the ratio of educated workers leads to a 0.14 percent increase in labor productivity, while a one percent increase in the ratio of skilled workers results in a 0.42 percent increase in labor productivity. The key aspect of this result is that the effect of human capital, which includes educated and skilled labor, exceeds the influence of the capital-to-labor ratio in Iran's food industries. Thus, augmented investments in human capital within the food industries may improve labor productivity. Education, skills, and capital per worker have a positive and significant effect on labor productivity in Iran's food industries.

The results reveal that the quality of human capital, including higher educational levels and better health status, is positively significant in improving the level of labor productivity in Malaysia. The contributions of secondary-educated workers have been the primary factor in explaining labor productivity in Malaysia. In contrast, the contributions of tertiary-qualified workers to labor productivity are significantly lower. The study suggests that adopting more advanced technology and addressing the issue of graduate incompetency, or the mismatch between skills needed by industry and those acquired by graduates, is essential for improving labor productivity in Malaysia. Our estimates also suggest that health has a greater impact on labor productivity than education. Improvements in the quality of health and education are crucial for Malaysia to achieve

higher productivity growth. Government expenditure on education should be utilized efficiently to ensure the education provided meets national requirements (Arshad & Ab Malik, 2015). However, Mat et al. (2015) highlighted that human capital investment positively impacts economic development in Sabah. Specifically, investment in education can lead to higher literacy rates due to the additional schooling attained for knowledge and skills. Human capital investment is crucial for improving the gross domestic product per capita by enhancing labor productivity through education, health, and migration. The study indicates that the necessity to hire unskilled immigrants generates gross domestic product per capita since there are no local workers willing to work on 3D (dirty, difficult, and dangerous) jobs. Hiring immigrant workers is less expensive and sufficient for employers to generate profit and boost productivity in Sabah compared to hiring local workers who have higher income demands.

The study suggests a hypothesis that cumulative investments in school education during the first half-century of modern economic growth have led Japan to a significant threshold of human capital accumulation. The growth of average schooling in Japan was significantly faster than in the United States from 1888 to 1995. By 1990, the major gap in educational attainment that existed between Japan and the United States in the early Meiji period was largely closed. The rate of reduction of this gap was especially rapid in earlier years, reflecting the Meiji government's determination to shoulder the extraordinarily heavy cost of education. The emphasis on education during the Meiji period indicates a consensus among leaders that educational progress was the most effective strategy to compete with Western economic and military dominance (Godo & Hayami, 1999).

The empirical results indicate a long-run relationship among the labor force, physical capital investment (as proxied by real gross domestic capital formation), human capital formation (as proxied by enrollment in educational institutions), and economic growth in Nigeria. The findings also reveal a feedback mechanism between human capital formation and economic growth in Nigeria. Therefore, the policy implication of the findings is that government should place a high priority on human capital development. Efforts should be intensified to increase investment in human capital to achieve the growth that would engender economic development. Education should be given prominence in Nigeria's developmental efforts. However, concentration should be on education, including both primary and secondary education, as well as higher education. Such an approach would propel the economy to higher levels of productivity (Dauda, 2010). However, Lawanson (2015) pointed out that coefficients of both education and health have positive and statistically significant effects on GDP per capita. The study affirms the strong relevance of human capital to the economic growth of West Africa. Policymakers should pursue increased resources and initiatives to motivate and enhance the population's access to both health and education. Hence, the results suggest that health has a slightly stronger impact than education on the economy. The results indicate that growth in educational capital, proxied by primary and secondary school enrollment rates, generally has a positive and statistically significant impact on per capita GDP growth. This study is a pointer to the fact that the level of technical progress and labor productivity, which positively affect economic growth, are enhanced by an increase in education.

The study found that human capital in various forms impacts the economic development of selected Central Asian countries, including Kazakhstan, Kyrgyzstan, and Tajikistan. Furthermore, it concluded that there is a long-run equilibrium among these

variables, indicating that they all influence economic development in Central Asia over time. The study emphasizes that investing in human capital is crucial for achieving a higher level of economic growth, which in turn leads to an increase in per capita income and an improved standard of living. Central Asian countries need to invest in both physical and human capital because both are important for one another, as well as for achieving a higher level of economic development (Rehman et al., 2018). Khan and Chaudhry (2019) highlighted that human capital variables, including life expectancy and education expenditures, are significant factors that contribute to growth and employment opportunities in developing countries. Governments of developing countries should increase education expenditures to boost human capital in these nations. To achieve this, the government should focus on improving education by developing and constructing schools in rural areas. The primary school education system should be strengthened. Moreover, basic health centers should provide free medicines to poor people to enhance life expectancy, as healthy individuals can contribute more efficiently to economic activities. In addition, Vinod and Kaushik (2007) pointed out that human capital has a statistically significant impact on economic growth in large developing countries.

The study found that human capital contributed to economic growth, as its indicators are positive and significant. The study also found that the relationship between human capital and economic growth depends on the level of economic development. In the study, there is a positive relationship between higher education and economic growth. Nevertheless, the primary level of education has a more robust and significant impact on economic growth than the secondary and tertiary levels. Our findings emphasized the importance of both educational and health measures of human capital. Policymakers must consider the level of economic development when formulating policies to enhance the

impact of human capital on economic growth in the Sub-Saharan Africa region (Akinlo & Oyeleke, 2020). Moreover, the findings suggest that the enrollment rate for higher education in Sub-Saharan Africa (SSA) has a very weak relationship with economic growth in those countries. This finding explains the weak relationship between economic growth and total factor productivity, which in turn leads to negative effects on overall total factor productivity. The main policy implication is that for SSA countries to maintain sustainable economic growth, home-based human capital must be given priority in the form of increased higher education budgets and financing (Akinola & Bokana, 2018).

The findings indicate a unidirectional causality from human capital to economic growth and agricultural added value. The results support hypotheses suggesting that high-level human capital development in Indonesia over time impacts economic growth and agricultural added value, which is increasing. The relationship between economic growth and agricultural added value shows bidirectional causality. In addition, the findings reveal that human capital variables, agricultural added value, population, lagged economic growth, government expenditures, foreign direct investment, non-agricultural added value, and technology jointly have a significant effect on economic growth. The implications of the model employed in this study are empirically consistent, suggesting that human capital serves as an exogenous variable influencing both economic growth and agricultural value-added (Bashir & Susetyo, 2018). Fleisher et al. (2010) found that human capital positively affects output per worker and productivity growth. Educated labor has a much higher marginal product based on its direct contribution to production. Workers with higher than primary school education have a significantly higher marginal product compared to those who labor with no higher than primary education. Additionally, there is a positive and direct relationship between human capital and Total Factor Productivity (TFP) growth—

human capital is measured by the proportion of workers who have more than a lower middle school education. The study concludes that investing in human capital will be an effective policy to reduce regional gaps in China as well as an efficient means to promote economic growth.

The results show that secondary education improves human capital development, while a satisfactory health system strengthens the quality of human capital. Moreover, human capital, including the interactive variables, has to a larger extent a positive and statistically significant effect on economic growth in the CEMAC subregion. However, knowledge acquired on the job increases the productivity of the workers, and the accumulated human capital significantly positively impacts the economic growth of the CEMAC region. The government should be emphasizing secondary education with increasing professionalization, and the youth should be educated and sensitized about the importance of technical, commercial, and vocational training (Emmanuel et al., 2014). Ada and Acaroglu (2014) demonstrate that improving educational quality would lead to an increase in GDP per capita, thereby enhancing growth significantly more effectively. Moreover, in both health and education, public spending on human capital has no significant effect on GDP per capita in MENA (Middle East and North Africa) countries. Analysis of the education variable suggests that the significant proxies are primary completion rate and pupil-teacher ratio. Moreover, an analysis of the health variable for human capital reveals that the statistically significant proxies are life expectancy at birth and fertility rate.

The empirical findings reveal that economic complexity and different levels of human capital have positive effects on long-term and short-term growth. A positive

interaction effect on economic growth exists between economic complexity and human capital. Additionally, the results indicate that both secondary education and higher education have positive impacts on a country's economic growth. When compared to higher education, secondary education serves as a proxy for human capital and has a relatively greater positive direct effect on economic growth, as well as a much stronger interactive effect with complexity. Nevertheless, the empirical results indicate that secondary education has a relatively strong positive effect on long-term and short-term growth. The development of human capital is conducive to the improvement of production capabilities in an economy (Zhu & Li, 2016).

The findings regarding the effect of skilled employment on economic growth align with theoretical literature, leading the study to conclude that human capital, specifically in the form of skilled labor, has a greater value-generating effect and positive influence on both economic output and growth in South Africa from 1993 to 2016. System GMM results largely indicate a positive and statistically significant relationship between the total output and skilled employment. However, semi-skilled and low-skilled employment are reported to have a negative impact on total output. The government is encouraged to provide training programs that will improve the labor force so as to equip people with critical skills that will render them ready to participate in innovative economic activities (Mabindisa, 2018).

Glawe and Wagner (2020) found that while growth in human capital fosters economic growth all over China, only coastal provinces record a positive effect of institutional improvements on the growth rate of per capita income. Moreover, the level of human capital has only a positive effect in the inland provinces. The results suggest that

policymakers should follow a nuanced reform strategy that considers the varying effects of institutional quality across regions. In general, fostering human capital accumulation might sustain economic growth over the following years in China and thus help the country escape the so-called middle-income trap. There is still large room for improvements regarding both secondary education and tertiary education in China, particularly in the inland provinces.

The better-educated and more productive workforce has contributed significantly to economic growth. The contribution of human capital to GDP growth has become more important than that of labor quantity. The study suggests that Korea needs to address the issue of declining labor quantity by focusing on improving labor quality. Given that the educational attainment levels are already very high, the future effectiveness of offering higher education may be limited. Improving the quality of higher education and providing lifelong training, especially after college graduation, can help improve the human capital of less productive workers and support aggregate human capital and economic growth (Han & Lee, 2020).

The study indicates that human capital, as a measure of human resources, can drive regional economic development. The findings confirm that human capital significantly contributes to encouraging regional micro- and macroeconomic growth. The accumulated effects of regional economic growth on human capital can positively influence further regional economic growth and enhance competitiveness. The study recommends that both current and future economic development in Indonesia prioritize enhancing the capacity of human resources and infrastructure to promote high-quality economic growth. This approach will support economic growth and sustainable development outcomes, as human

capital and infrastructure are essential for sustainable development (Prasetyo, 2020). Wusiman and Ndzembanteh (2020) found that in both countries, Malaysia and Turkey, over the period of 1988–2013, human capital, innovation output, and physical capital had a significant positive effect on economic growth. The findings reveal that there is a unidirectional causal relationship from human capital and innovation to economic growth; however, there is a bidirectional causality between physical capital and innovation in Malaysia. The effects of innovation output on economic growth are smaller compared to the effects of the other variables. Both human capital and innovation output positively impact growth in Malaysia and Turkey in the long term. Specifically, human capital has a greater positive effect on economic growth in Malaysia compared to its impact in Turkey. The study recommended that both Malaysia and Turkey maintain their support for education systems. Moreover, it suggested that the Malaysian and Turkish governments place greater emphasis on their innovation systems to enhance the effective utilization of their existing innovation output. Solarin and Eric (2015) pointed out that economic growth and foreign direct investment (FDI) positively influence human capital, while economic globalization negatively impacts human capital in Nigeria. The study suggests that the government should encourage diversification and enhance export activities to boost the country's GDP and positively impact human capital in Nigeria. Furthermore, favorable trade policies that would encourage a friendly business environment should be consistently embarked on by the government to attract more foreign investors to the country.

The study indicates that Nigeria's economic growth is sensitive to human capital shocks related to education; however, the long-term response to aid shocks is minimal. Human capital, when measured via education expenditure, seems more viable for explaining economic growth in Nigeria. The findings indicate that government expenditure

on education, along with enhanced support, can stimulate economic growth in Nigeria. Nevertheless, there is also an indication that attainment of economic growth might be challenging for this aid-dependent country (Fashina et al., 2018). Adelakun (2011) confirms that there is a strong positive relationship between human capital development and economic growth over the period of 1985–2009. A high level of human capital development is crucial for the nation's socio-economic development and serves as a significant catalyst for improving the population's standard of living. The study reveals that human capital development is beneficial and remains an essential tool of economic growth in Nigeria. Primary, secondary, and tertiary school enrollment, as well as total government expenditure on health and education, were significantly related to economic growth in Nigeria. The study recommended that efforts should be geared toward improving the standard of education in Nigeria. A substantial portion of the government budgetary allocation should be directed toward the educational sector. Additionally, special agencies should be established to improve the skills and capabilities of the workforce.

The empirical findings reveal that human capital development, which is in line with theoretical expectations, has a significant positive impact on output levels over the period of 1999–2012. The results indicate that enhancing human capital is essential for attaining sustainable economic growth in Nigeria—as economic performance escalates with each advancement in human capital development. The results indicate a relatively inelastic relationship between human capital development and output levels. The study suggests that governments and policymakers should make concerted and sincere efforts to build and enhance human capacity by ensuring sufficient educational funding across all levels. This approach is essential for achieving sustainable economic growth and development in any economy (Anaduaka, 2014). Likewise, Kanayo (2013) pointed out that investment in

human capital in the form of education and capacity building at the primary and secondary levels has a significant impact on economic growth, while capital expenditure on education was insignificant to the growth process. The study suggests that educational institutions in Nigeria should be restructured for quality schooling at the primary, secondary, and tertiary levels to make manpower relevant in the highly competitive and globalized economy.

The influence of trade openness on human capital is positive for both selected developed and developing countries; however, the results indicate that this is significant only to the developed countries, which have well-trained human capital. The benefits of trade openness, manifested as enhanced human capital productivity, have not been achieved in developing countries due to a workforce that is inadequately trained and less skilled. Investment in human capital is imperative for the developing countries to fully capitalize on trade liberalization (Jadoon et al., 2015). Arabi and Abdalla (2013) highlighted that quality of education plays a crucial role in economic growth, with highly educated individuals exerting a greater influence on economic output compared to those with only secondary education in Sudan during the period from 1982 to 2009. Additionally, the health quality factor positively impacts economic growth.

The study found that government expenditure on education maintained a positive long-run relationship with the index of industrial production, while government expenditure on health and gross capital formation exhibited a long-run negative relationship with dependent variables. Better infrastructural facilities should be provided for existing schools and hospitals, while new structured training institutions should be established to provide quality education and training to improve the skills of the Nigerian labor force. Consequently, it was recommended, among others, that more stock of physical

capital needed to be acquired to facilitate more investment in human capital and thereby enhance industrial productivity in Nigeria (Olayemi, 2012). Furthermore, Adeyemi and Ogunsola (2016) indicated that there is a positive long-run relationship among secondary school enrollment, public expenditure on education, life expectancy rate, gross capital formation, and economic growth, but it is statistically insignificant. The results reveal that there is a negative long-run relationship among primary school enrollment, tertiary school enrollment, public expenditure on health, and economic growth in Nigeria. The study concluded, based on the findings, that there is a long-run relationship between human capital development and economic growth over the period of 1980–2013. Moreover, it is concluded that there should be increased government financial commitment to education rather than to the health sector. The study recommended that the government implement an education and training policy designed to continuously upgrade a wide spectrum of human capital to a higher level and to reinvigorate innovation capacity that can ensure quality schooling for primary education and tertiary education. The government should allocate additional funds to the field of health to enhance human capital development since the life expectancy rate would boost economic growth.

2.9 Literature Gaps

Based on the reviews from previous studies, the results show that there is a relationship between educational attainment and productivity, but there is no study that has been published to show the impacts of educational attainment on labor productivity and economic growth in Malaysian industry during the period 1982–2023. First, the previous studies offer a limited investigation of the educational quality of the labor market and how foreign workers affect Malaysian productivity. The existing information pertinent to the impact of labor's educational quality on value-added agriculture and agricultural GDP is

limited. The prior studies tend to focus on the effects of education on overall economic growth (e.g., Agiomirgianakis et al., 2002; Anastasios et al., 2019; Gyimah-Brempong, 2011; Hanushek & Kimko, 2000; Jalil & Idrees, 2013; Mussaiyib & Pradhan, 2024; Self & Grabowski, 2004; Tsamadias & Prontzas, 2011).

Second, most of the studies (e.g., Chan et al., 2020; Hussin et al., 2012; Ramli et al., 2016; Yun & Yusoff, 2018) have mainly explored the relationship between education expenditure and economic growth in Malaysia; however, only a few studies have investigated the impact of educational attainment on Malaysian economic growth, especially in agriculture and industry. Previous studies (e.g., Agiomirgianakis et al., 2002; Anastasios et al., 2019; Benos & Karagiannis, 2016; Gyimah-Brempong, 2011; Jalil & Idrees, 2013) focused solely on three main education levels (i.e., primary education, secondary education, and tertiary education) as independent variables. Additionally, similar studies have not addressed the impacts of the total foreign labor force on value-added and GDP, particularly within Malaysian industry.

Lastly, current literature offers a limited exploration of how low educational attainment, defined as the highest level of education achieved and indicative of low-skilled labor quality, affects the Malaysian industrial landscape. The previous studies emphasize estimating by using linear approaches, including OLS and ARDL (e.g., Jordaan, 2018; Kangasniemi et al., 2012). Many studies have overlooked the impacts of having no formal education, traditionally concentrating on the primary, secondary, and tertiary education levels as pivotal indicators of educational quality. The existing literature rarely highlights the influence of foreign labor on labor productivity within Malaysia's economic sectors, especially regarding long-term and short-term asymmetric effects.

2.10 Chapter Summary

Previous studies have explored the impacts of foreign workers on productivity; however, most have primarily focused on how human capital affects productivity, production output, and economic growth. Similar studies suggested that foreign workers might affect labor productivity via their skills or other factors. Kangasniemi et al.'s (2012) study reveals that foreign workers exhibit a positive long-run effect on total factor productivity in the United Kingdom by employing the ARDL method, whereas a negative effect exists in Spain. Additionally, the impact of foreign workers in construction and personal services exhibits either a negative or neutral contribution to labor productivity growth in the United Kingdom, while the effect is distinctly negative in Spain (i.e., agriculture and construction). Furthermore, the literature is limited to the effects on foreign workers in Malaysia. For example, Jordaan (2018) reports that both low- and high-skilled foreign workers have a positive impact on productivity in Malaysian manufacturing industries, with data covering the 2005–2009 period using OLS estimation. A recent study by Mamun et al. (2023) reveals that urban migration leads to agricultural labor shortages, ultimately lowering agricultural productivity in Malaysia. Regarding the effect of educational attainment, previous studies have shown that education not only affects productivity (Aljarallah and Angus, 2020; Benos and Karagiannis, 2016; Lin, 2003; Pudasaini, 1983; Viswanath et al., 2009) but also enhances economic growth and development in relevant studies (Anastasios et al., 2019; Barro and Lee, 2001; Ganegodage and Rambaldi, 2011; Goumrhar, 2024; Gyimah-Brempong, 2011; Hanushek and Kimko, 2000; Jalil and Idrees, 2013; Tsai et al., 2010; Yan, 2011). The existing literature rarely highlights the influence of foreign labor on labor productivity within Malaysia's economic sectors, especially regarding long-term and short-term asymmetric effects.

CHAPTER 3

METHODOLOGY

3.1 Introduction

This chapter discusses the methodology that is applied in determining the economic impacts of labor market educational attainment on Malaysian productivity and economic growth. Time series analysis will be used to study the impacts of educational attainment, including no formal education, primary education, secondary education, and tertiary education, on Malaysian productivity and economic growth. The data range from 1982 to 2023 was used to find out the role of labor market educational attainment in driving Malaysian productivity and economic growth, particularly in the main targeted economic sectors (i.e., agriculture, industry, and services). The data are obtained from the Department of Statistics Malaysia and the World Bank. The methodology consists of several steps; the econometric methodology includes the various model specifications, and the estimation methods include unit root and stationary tests—the augmented Dickey-Fuller (ADF) test proposed by Dickey and Fuller (1979); the Phillips–Perron (PP) test proposed by Phillips and Perron (1988); and the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test proposed by Kwiatkowski et al. (1992). This study employs the unit root with break test, specifically the augmented Dickey-Fuller with structural breaks—following the outlined framework (e.g., Banerjee et al., 1992; Perron, 1989; Vogelsang & Perron, 1998; Zivot & Andrews, 1992). For VAR models, the other estimation methods consist of the robustness tests, the Johansen and Juselius (1990) cointegration test, and the Vector Autoregressive (VAR) Model Granger causality test. First, the unit root tests will be used to test the stationary properties of all tested variables. Second, the cointegration test is

applied to test the long-run equilibrium relationship among the tested variables. Next, the Granger (1988) causality test is used to determine the existence and direction of the causality between all the tested variables in the model. Finally, the study uses the variance decomposition and impulse response function to enhance the analysis and further support the results of the Granger causality test. The impulse response analysis is applied by utilizing the Cholesky decomposition and adjustment in the degree of freedom (Cholesky dof adjusted)—the evolution of a model's variables in reaction to a shock in one or more variables. In addition, the study employs the autoregressive distributed lag (ARDL) and nonlinear autoregressive distributed lag (NARDL) estimation approaches—comprising bounds tests, error correction models, long-run coefficients, diagnostic tests, dynamic multiplier graphs, and the Wald tests. The ARDL approach is applied in this study, which is more reliable due to the small samples and appropriate for a mixture of $I(0)$ and $I(1)$ variables if compared with the Johansen and Juselius (1990) cointegration test.

3.2 Theoretical Framework

Solow (1956) and Swan (1956) made a significant contribution with the Solow–Swan model, an exogenous growth model that sets long-term economic growth within the framework of neoclassical economics. This growth model serves as the foundation for the econometric models used in this research. In the Solow–Swan model, the production function is the Cobb–Douglas type. The Cobb–Douglas production function was proposed by Cobb and Douglas (1928). The model posits that the production function is structured due to the relationship between labor and knowledge (Becker, 1964; Romer, 1990), denoted by $A(t)L(t)$ as the measure of effective labor units (Mankiw et al., 1992). A refers to labor-augmenting knowledge or technology; thus, AL represents effective labor. A is knowledge that can increase productivity, and L denotes the number of workers (Ogunleye,

2015). To derive the educational quality of the labor equation, AL was applied. AL is effective labor (Harris, 2021; Shen et al., 2021).

$$Y = F(K, AL) \quad \text{Equation 3.1}$$

Where Y represents total production, K denotes capital, A refers to labor-augmenting knowledge or technology, and thus AL denotes effective labor. In this study, two kinds of labor are applied, which are domestic labor (LD) and foreign labor (LF).

$$Y_t = AK_t^{\alpha} LD_t^{\beta_1} LF_t^{\beta_2} \quad \text{Equation 3.2}$$

The concept of labor educational quality in Equation 3.2 can also be measured by levels of education as follows:

$$Y_t = AK_t^{\alpha} (LD_t^*)^{\beta_1} (LF_t)^{\beta 2} \quad \text{Equation 3.3}$$

Where $LD_t^* = LD_t \, {LD_{t1}}^{\theta 1} {LD_{t2}}^{\theta 2} {LD_{t3}}^{\theta 3} {LD_{t4}}^{\theta 4}$ denotes the domestic labor force with educational attainment, and LF indicates the foreign labor force. Equation 3.4

Substituting Equation 3.4 into Equation 3.3, I derive,

$$Y_t = AK_t^{\alpha} (LD_t \, {LD_{t1}}^{\theta 1} {LD_{t2}}^{\theta 2} {LD_{t3}}^{\theta 3} {LD_{t4}}^{\theta 4})^{\beta 1} (LF_t)^{\beta 2} \quad \text{Equation 3.5}$$

Where Y denotes real output, K represents physical capital stock, LD denotes domestic labor input, ${LD_i}^{\theta}$ is the number of the labor force with different levels of educational attainment (i.e., 1=no formal education, 2=primary level of education, 3=secondary level of education, and 4=tertiary level of education); θ_i represents the share of labor at different levels of educational attainment; A indicates an exogenous knowledge and technological factor; and α and β are the capital and labor shares, respectively. To derive the educational quality of the labor equation with physical capital for this study as follows:

$$Y_t = AK(LD_t^*)^{\beta_1}(LF_t)^{\beta 2} \quad \text{Equation 3.6}$$

Where $LD_t^* = LD_t\ {LD_{t1}}^{\theta 1}{LD_{t2}}^{\theta 2}{LD_{t3}}^{\theta 3}{LD_{t4}}^{\theta 4}$ denotes the domestic labor force with educational attainment, and LF represents the foreign labor force. Equation 3.7

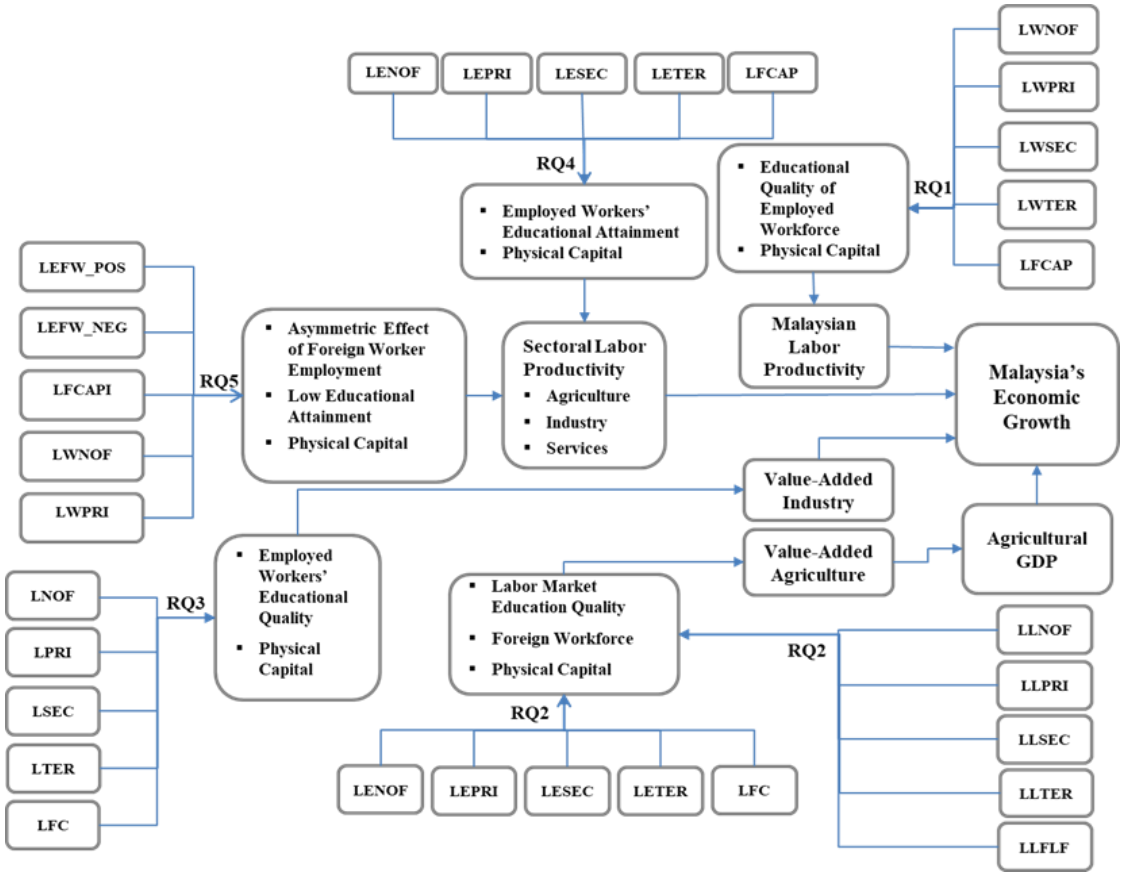


Figure 3.1: The Conceptual Framework of the Study

Figure 3.1 shows a conceptual framework for measuring the role of labor market educational attainment in driving Malaysia's productivity in the main targeted economic sectors (i.e., agriculture, industry, and services) and economic growth. The study's conceptual framework extends the body of knowledge on sectoral labor productivity by measuring the role of labor market educational attainment based on existing theories, such as the Solow–Swan model proposed by Solow and Swan (1956) and the Cobb–Douglas production function proposed by Cobb and Douglas (1928), to meet research objectives. The dependent variables of this study are labor productivity and economic growth, while the independent variables are no formal education, primary, secondary, and tertiary education, fixed capital, foreign worker employment, and foreign labor force.

Human capital, which includes educational attainment (i.e., no formal education, primary education, secondary education, and tertiary education), physical capital, and foreign workers, can affect Malaysia's productivity and economic growth in the main targeted economic sectors. Figure 3.1 describes the linkages between the variables in the study. For the effect of educational attainment, previous studies have shown that education not only affects productivity (Aljarallah & Angus, 2020; Benos & Karagiannis, 2016; Lin, 2003; Pudasaini, 1983; Viswanath et al., 2009) but also enhances economic growth and development in relevant studies (Anastasios et al., 2019; Barro & Lee, 2001; Ganegodage & Rambaldi, 2011; Goumrhar, 2024; Gyimah-Brempong, 2011; Hanushek & Kimko, 2000; Jalil & Idrees, 2013; Tsai et al., 2010; Yan, 2011).

3.3 Model Specifications and Data Descriptions

3.3.1 Vector Autoregressive Models

For the first objective of the study, the estimation of the labor-augmenting knowledge model is developed based on the Solow–Swan model, which the study covers the period between 1982 and 2023. Thus, the estimation of Model 1 for examining the impacts of the educational quality of the employed workforce on Malaysian labor productivity is expressed in terms of the following equation:

$$LPRODM_t = \alpha_0 + \beta_1 LWNOF_t + \beta_2 LWPRI_t + \beta_3 LWSEC_t + \beta_4 LWTER_t + \beta_5 LFCAP_t + \varepsilon_t \quad \text{Equation 3.8}$$

Where $LPRODM_t$ denotes the logarithm of Malaysian labor productivity—measured in constant 2015 US$, with the data obtained from the World Bank. Educational attainment

means the highest level of education that an individual has achieved; data are from the Department of Statistics Malaysia, measured in thousands of people (i.e., $LWNOF_t$ represents the logarithm of total employed workforce without formal education, $LWPRI_t$ indicates the total employed workforce with primary education in logarithm, $LWSEC_t$ denotes the logarithm of total employed workforce with secondary education, and $LWTER_t$ signifies total employed workforce with tertiary education in logarithm); $LFCAP_t$ is the fixed capital in logarithm, and ε_t denotes the error term.

To achieve the second objective, we extend the estimation of the labor market education quality model using the Cobb–Douglas production function, spanning the period from 1982 to 2023. The intermediary level between macroeconomics and microeconomics is known as mesoeconomics. The field of mesoeconomics is subdivided into the study of regional economics and that of sectoral developments, or industrial organization. Next, we base the estimation model 2 (meso) on the following equation to examine the impact of the educational quality of employed workers and fixed capital on value-added agriculture:

$$LVAA_t = \alpha_0 + \beta_1 LENOF_t + \beta_2 LEPRI_t + \beta_3 LESEC_t + \beta_4 LETER_t + \beta_5 LFC_t + \varepsilon_t \quad \text{Equation 3.9}$$

Where $LVAA_t$ denotes the logarithm of value-added agriculture (in constant 2015 US$), with data from the World Bank. Educational attainment refers to the highest level of education that an individual has achieved; data are from the Department of Statistics Malaysia, measured in thousands of people (i.e., $LENOF_t$ denotes the logarithm of total workers lacking formal education, $LEPRI_t$ represents the logarithm of total workers with primary education, $LESEC_t$ denotes the logarithm of total workers with secondary

education, and $LETER_t$ indicates the logarithm of total workers with tertiary education), LFC_t represents the logarithm of fixed capital, and ε_t denotes the error term.

Likewise, the estimation model 3 (macro) of the study examines the impacts of the educational quality of the labor force and the total foreign labor force on agricultural GDP during the period 1987–2023, in terms of the Cobb–Douglas production function. Therefore, the estimation model relies on the following equation:

$$LGDPA_t = \alpha_0 + \beta_1 LLNOF_t + \beta_2 LLPRI_t + \beta_3 LLSEC_t + \beta_4 LLTER_t + \beta_5 LLFLF_t + \varepsilon_t \quad \text{Equation 3.10}$$

Where $LGDPA_t$ represents the logarithm of Malaysian agricultural GDP (in RM million), educational attainment means the highest level of education that an individual has completed, and the labor force is measured in thousands of people (i.e., $LLNOF_t$ denotes the logarithm of the total labor force lacking formal education, $LLPRI_t$ is the total labor force with primary education in logarithm, $LLSEC_t$ signifies the logarithm of the total labor force with secondary education, $LLTER_t$ represents the logarithm of the total labor force with tertiary education); $LLFLF_t$ is the logarithm of the total foreign labor force, and ε_t represents the error term. Agricultural data are obtained from the Department of Statistics Malaysia. Equation 3.9 as Model 2 (meso) and Equation 3.10 as Model 3 (macro) are estimated by using the VAR Granger causality test. The research methodologies adopted in this study are the unit root and stationary test, the Johansen and Juselius (1990) cointegration test, the Granger (1988) causality test, and variance decomposition. This study also applied the impulse response function (IRF).

The third objective of the study involves developing an effective labor model by augmenting the Solow–Swan model, which includes annual data from 1982 to 2023. The following equation describes Model 4, the empirical model that investigates the impacts of worker educational quality on the value-added industry:

$$LVAI_t = \alpha_0 + \beta_1 LNOF_t + \beta_2 LPRI_t + \beta_3 LSEC_t + \beta_4 LTER_t + \beta_5 LFC_t + \varepsilon_t \quad \text{Equation 3.11}$$

Where $LVAI_t$ indicates the logarithm of value-added industry (in constant 2015 US$); the data was obtained from the World Bank. The term "educational attainment" refers to the highest level of education that an individual has achieved, as measured in thousands of people using data from the Department of Statistics Malaysia. (i.e., $LNOF_t$ represents the logarithm of workers lacking formal education, $LPRI_t$ is the logarithm of workers with primary education, $LSEC_t$ denotes the logarithm of workers with secondary education, and $LTER_t$ is the logarithm of workers with tertiary education), LFC_t signifies the logarithm of fixed capital, and ε_t represents the error term.

3.3.2 Autoregressive Distributed Lag Models

Based on the Cobb–Douglas production function, the labor educational quality model is established to answer the fourth research objective, which spans the years 1991–2022. The study aims to further analyze the influence of employed workers' educational attainment on labor productivity in the main economic sectors (i.e., agriculture, industry, and services); low productivity issues caused by over-reliance on low-skilled labor are under investigation. The ARDL approach is applied in this study, which is more reliable due to the small samples and appropriate for a mixture of *I*(0) and *I*(1) variables. MASCO

2020 categorizes low-skilled workers as those with primary education (see Table 1.7). Accordingly, the estimation models (i.e., Models 5, 6, and 7) are developed so as to study how the employed workers' educational attainment influences labor productivity in the main economic sectors, including agriculture, industry, and services, which three empirical models are described on the basis of the following equations:

$$LPROA_t = \alpha_0 + \beta_1 LENOF_t + \beta_2 LEPRI_t + \beta_3 LESEC_t + \beta_4 LETER_t + \beta_5 LFCAP_t + \varepsilon_t \quad \text{Equation 3.12}$$

$$LPROI_t = \alpha_0 + \gamma_1 LENOF_t + \gamma_2 LEPRI_t + \gamma_3 LESEC_t + \gamma_4 LETER_t + \gamma_5 LFCAP_t + \varepsilon_t \quad \text{Equation 3.13}$$

$$LPROS_t = \alpha_0 + \delta_1 LENOF_t + \delta_2 LEPRI_t + \delta_3 LESEC_t + \delta_4 LETER_t + \delta_5 LFCAP_t + \varepsilon_t \quad \text{Equation 3.14}$$

Where $LPROA_t$ denotes the logarithm of agricultural productivity, $LPROI_t$ refers to the logarithm of industrial productivity, $LPROS_t$ represents the logarithm of services productivity, $LENOF_t$ is the employed workers without formal education in logarithm, $LEPRI_t$ denotes the logarithm of employed workers with primary education, $LESEC_t$ represents the logarithm of employed workers with secondary education, $LETER_t$ is the employed workers with primary education in logarithm, $LFCAP_t$ is the logarithm of fixed capital, and ε_t denotes the error term. Labor productivity is measured as value added per worker; hence, data is obtained from the World Bank. For this study, industrial productivity refers to value added per worker, including mining and quarrying, manufacturing, construction, and public utilities. The objective of the study is to further analyze the influence of employed workers' educational attainment on labor productivity

in the main economic sectors (i.e., agricultural, industrial, and services) throughout the years 1991–2022. The labor educational quality models are developed based on the Cobb–Douglas production function. Following Pesaran et al. (2001), the autoregressive distributed lag (p, q) model can be written as follows:

$$y_t = \sum_{i=1}^{p} \emptyset_i \, y_{t-i} + \sum_{j=0}^{q} \theta_j \, x_{t-j} + \varepsilon_t \qquad \text{Equation 3.15}$$

Hence the ARDL proposed by Pesaran et al. (2001) is employed in this study based on the following equations:

$$\begin{aligned} \Delta LPROA_t = {} & \alpha + \rho LPROA_{t-1} + \beta_1 LENOF_{t-1} + \beta_2 LEPRI_{t-1} \\ & + \beta_3 LESEC_{t-1} + \beta_4 LETER_{t-1} + \beta_5 LFCAP_{t-1} \\ & + \sum_{i=1}^{p} \gamma_i \Delta \, LPROA_{t-i} + \sum_{j=0}^{q} \theta_j \, \Delta LENOF_{t-j} \\ & + \sum_{k=0}^{r} \sigma_k \Delta LEPRI_{t-k} + \sum_{l=0}^{s} \mu_l \Delta LESEC_{t-l} \\ & + \sum_{m=0}^{t} \omega_m \Delta LETER_{t-m} + \sum_{n=0}^{u} \chi_n \Delta LFCAP_{t-n} + \varepsilon_t \end{aligned} \qquad \text{Equation 3.16}$$

$$\Delta LPROI_t = \alpha + \eta LPROI_{t-1} + \gamma_1 LENOF_{t-1} + \gamma_2 LEPRI_{t-1} + \gamma_3 LESEC_{t-1} + \gamma_4 LETER_{t-1} + \gamma_5 LFCAP_{t-1} + \sum_{i=1}^{p} \zeta_i \Delta LPROI_{t-i} + \sum_{j=0}^{q} \iota_j \Delta LENOF_{t-j} + \sum_{k=0}^{r} \lambda_k \Delta LEPRI_{t-k} + \sum_{l=0}^{s} \kappa_l \Delta LESEC_{t-l} + \sum_{m=0}^{t} \xi_m \Delta LETER_{t-m} + \sum_{n=0}^{u} \nu_n \Delta LFCAP_{t-n} + \varepsilon_t$$

Equation 3.17

$$\Delta LPROS_t = \alpha + \tau LPROS_{t-1} + \delta_1 LENOF_{t-1} + \delta_2 LEPRI_{t-1} + \delta_3 LESEC_{t-1} + \delta_4 LETER_{t-1} + \delta_5 LFCAP_{t-1} + \sum_{i=1}^{p} \phi_i \Delta LPROS_{t-i} + \sum_{j=0}^{q} o_j \Delta LENOF_{t-j} + \sum_{k=0}^{r} \pi_k \Delta LEPRI_{t-k} + \sum_{l=0}^{s} \tau_l \Delta LESEC_{t-l} + \sum_{m=0}^{t} \sigma_m \Delta LETER_{t-m} + \sum_{n=0}^{u} \psi_n \Delta LFCAP_{t-n} + \varepsilon_t$$

Equation 3.18

The short-run dynamic parameters are estimated by error correction models associated with the long-run estimates. The short-run error correction model is specified as follows:

Equation 3.19

$$\Delta LPROA_t = \alpha + \sum_{i=1}^{p} \gamma_i \Delta\, LPROA_{t-i} + \sum_{j=0}^{q} \theta_j\, \Delta LENOF_{t-j} + \sum_{k=0}^{r} \sigma_k \Delta LEPRI_{t-k} + \sum_{l=0}^{s} \mu_l \Delta LESEC_{t-l} + \sum_{m=0}^{t} \omega_m \Delta LETER_{t-m} + \sum_{n=0}^{u} \chi_n \Delta LFCAP_{t-n} + \varphi_{1_o} ECT_{t-o} + \varepsilon_t$$

Equation 3.20

$$\Delta LPROI_t = \alpha + \sum_{i=1}^{p} \zeta_i \Delta\, LPROI_{t-i} + \sum_{j=0}^{q} \iota_j\, \Delta LENOF_{t-j} + \sum_{k=0}^{r} \lambda_k \Delta LEPRI_{t-k} + \sum_{l=0}^{s} \kappa_l \Delta LESEC_{t-l} + \sum_{m=0}^{t} \xi_m \Delta LETER_{t-m} + \sum_{n=0}^{u} \nu_n \Delta LFCAP_{t-n} + \varphi_{2_o} ECT_{t-o} + \varepsilon_t$$

Equation 3.21

$$\Delta LPROS_t = \alpha + \sum_{i=1}^{p} \phi_i \Delta\, LPROS_{t-i} + \sum_{j=0}^{q} o_j\, \Delta LENOF_{t-j} + \sum_{k=0}^{r} \pi_k \Delta LEPRI_{t-k} + \sum_{l=0}^{s} \tau_l \Delta LESEC_{t-l} + \sum_{m=0}^{t} \sigma_m \Delta LETER_{t-m} + \sum_{n=0}^{u} \psi_n \Delta LFCAP_{t-n} + \varphi_{3_o} ECT_{t-o} + \varepsilon_t$$

3.3.3 Nonlinear Autoregressive Distributed Lag Models

The estimation of the educational quality of the labor model is based on the Cobb–Douglas production function, which covers the period 1991–2022. For the fifth research objective, low productivity issues caused by over-reliance on foreign labor and low-skilled labor are under investigation. Thus, the estimation models (i.e., Models 8, 9, and 10) are developed to examine the asymmetric effects of foreign worker employment and the impacts of low educational attainment on sectoral labor productivity based on the equations as follows:

$$LPRODA_t = \alpha_0 + \beta_1 LEFW_t + \beta_2 LFCAPI_t + \beta_3 LWNOF_t + \beta_4 LWPRI_t + \varepsilon_t \quad \text{Equation 3.22}$$

$$LPRODI_t = \alpha_0 + \delta_1 LEFW_t + \delta_2 LFCAPI_t + \delta_3 LWNOF_t + \delta_4 LWPRI_t + \varepsilon_t \quad \text{Equation 3.23}$$

$$LPRODS_t = \alpha_0 + \theta_1 LEFW_t + \theta_2 LFCAPI_t + \theta_3 LWNOF_t + \theta_4 LWPRI_t + \varepsilon_t \quad \text{Equation 3.24}$$

Where $LPRODA_t$ denotes the logarithm of Malaysia's agricultural productivity, $LPRODI_t$ refers to the logarithm of Malaysian industrial productivity, $LPRODS_t$ is the logarithm of Malaysia's services productivity, $LEFW_t$ represents the logarithm of employed foreign workers, $LWNOF_t$ refers to the logarithm of employed workers without formal education, $LWPRI_t$ signifies the logarithm of employed workers with primary education, $LFCAPI_t$ represents the logarithm of fixed capital, and ε_t denotes the error term. Labor productivity is measured as value added per worker with World Bank data. For this study, industrial

productivity refers to value added per worker based on mining and quarrying, manufacturing, construction, and public utilities. This study aims to examine the asymmetric effects of foreign worker employment on Malaysian labor productivity (i.e., agriculture, industry, and services) as well as the impacts of workers with low educational attainment (i.e., no formal education attained, and primary education attained) over the 1991–2022 period in terms of the Cobb–Douglas production function. Accordingly, the NARDL model proposed by Shin et al. (2014) is employed in this study based on the following equations:

$$LPRODA_t = \alpha_0 + \beta_1^+ LEFW_t^+ + \beta_1^- LEFW_t^- + \beta_2 LFCAPI_t + \beta_3 LWNOF_t + \beta_4 LWPRI_t + \varepsilon_t \quad \text{Equation 3.25}$$

$$LPRODI_t = \alpha_0 + \delta_1^+ LEFW_t^+ + \delta_1^- LEFW_t^- + \delta_2 LFCAPI_t + \delta_3 LWNOF_t + \delta_4 LWPRI_t + \varepsilon_t \quad \text{Equation 3.26}$$

$$LPRODS_t = \alpha_0 + \theta_1^+ LEFW_t^+ + \theta_1^- LEFW_t^- + \theta_2 LFCAPI_t + \theta_3 LWNOF_t + \theta_4 LWPRI_t + \varepsilon_t \quad \text{Equation 3.27}$$

Equation (3.25) is Model 8, equation (3.26) is Model 9, and equation (3.27) is Model 10, which are estimated by using the NARDL model. As per asymmetry or nonlinear ARDL, employed foreign workers are composed of two components, which are positive and negative. The two variables are established—$LEFW_t^+$ denotes the partial sum processes of positive changes, and $LEFW_t^-$ denotes the partial sum processes of negative changes in $LEFW_t$:

$$LEFW_t^+ = \sum_{j=1}^{t} \Delta\, LEFW_j^+ = \sum_{j=1}^{t} \max\left(\Delta LEFW_j, 0\right) \quad \text{Equation 3.28}$$

$$LEFW_t^- = \sum_{j=1}^{t} \Delta\, LEFW_j^- = \sum_{j=1}^{t} \min\left(\Delta LEFW_j, 0\right) \quad \text{Equation 3.29}$$

Following Shin et al. (2014), the nonlinear autoregressive distributed lag (p, q) model derived from equations 3.25, 3.26, and 3.27 can be rewritten as follows:

$$LPRODA_t = \sum_{j=1}^{p} \lambda_j\, LPRODA_{t-j} + \sum_{j=0}^{q} (\beta_j^+\, LEFW_{t-j}^+ + \beta_j^-\, LEFW_{t-j}^-) + \varepsilon_t \quad \text{Equation 3.30}$$

$$LPRODI_t = \sum_{j=1}^{p} \gamma_j\, LPRODI_{t-j} + \sum_{j=0}^{q} (\delta_j^+\, LEFW_{t-j}^+ + \delta_j^-\, LEFW_{t-j}^-) + \varepsilon_t \quad \text{Equation 3.31}$$

$$LPRODS_t = \sum_{j=1}^{p} \varphi_j\, LPRODS_{t-j} + \sum_{j=0}^{q} (\theta_j^+\, LEFW_{t-j}^+ + \theta_j^-\, LEFW_{t-j}^-) + \varepsilon_t \quad \text{Equation 3.32}$$

Where λ_j, γ_j, and φ_j represent the autoregressive parameter and the parameters of asymmetric distributed lag (i.e., β_j^+ and β_j^-, δ_j^+ and δ_j^-, θ_j^+ and θ_j^-). $LEFW_t$ is decomposed into $LEFW_t^+$ and $LEFW_t^-$, formulating the nonlinear autoregressive

distributed lag proposed by Shin et al. (2014). The NARDL model includes the concept of partial asymmetry for this study as rewritten in the following equations:

$$\Delta LPRODA_t = \alpha + \rho LPRODA_{t-1} + \beta_1^+ LEFW_{t-1}^+ + \beta_1^- LEFW_{t-1}^- + \beta_2 LFCAPI_{t-1} + \beta_3 LWNOF_{t-1} + \beta_4 LWPRI_{t-1} + \sum_{j=1}^{p-1} \lambda_j \Delta LPRODA_{t-j} + \sum_{j=0}^{q-1} (\beta_j^+ \Delta LEFW_{t-j}^+ + \beta_j^- \Delta LEFW_{t-j}^- + \mu_j \Delta LFCAPI_{t-j} + \pi_j \Delta LWNOF_{t-j} + \sigma_j \Delta LWPRI_{t-j}) + \varepsilon_t \quad \text{Equation 3.33}$$

$$\Delta LPRODI_t = \alpha + \eta LPRODI_{t-1} + \delta_1^+ LEFW_{t-1}^+ + \delta_1^- LEFW_{t-1}^- + \delta_2 LFCAPI_{t-1} + \delta_3 LWNOF_{t-1} + \delta_4 LWPRI_{t-1} + \sum_{j=1}^{p-1} \gamma_j \Delta LPRODI_{t-j} + \sum_{j=0}^{q-1} (\delta_j^+ \Delta LEFW_{t-j}^+ + \delta_j^- \Delta LEFW_{t-j}^- + \xi_j \Delta LFCAPI_{t-j} + \omega_j \Delta LWNOF_{t-j} + \tau_j \Delta LWPRI_{t-j}) + \varepsilon_t \quad \text{Equation 3.34}$$

$$\Delta LPRODS_t = \alpha + \kappa LPRODS_{t-1} + \theta_1^+ LEFW_{t-1}^+ + \theta_1^- LEFW_{t-1}^- + \theta_2 LFCAPI_{t-1} + \theta_3 LWNOF_{t-1} + \theta_4 LWPRI_{t-1} + \sum_{j=1}^{p-1} \varphi_j \Delta LPRODS_{t-j} + \sum_{j=0}^{q-1} (\theta_j^+ \Delta LEFW_{t-j}^+ + \theta_j^- \Delta LEFW_{t-j}^- + \zeta_j \Delta LFCAPI_{t-j} + \iota_j \Delta LWNOF_{t-j} + \upsilon_j \Delta LWPRI_{t-j}) + \varepsilon_t \quad \text{Equation 3.35}$$

Where β_1^+, δ_1^+, and θ_1^+ denote the long-run coefficients of $LEFW_{t-1}^+$; β_1^-, δ_1^-, and θ_1^- represent the long-run coefficients of $LEFW_{t-1}^-$; however, the short-run coefficients (i.e., β_j^+ and β_j^-; δ_j^+ and δ_j^-; θ_j^+ and θ_j^-). Next, workers with low educational attainment are also one of the independent variables in this study, specifically focusing on two types of low educational attainment: no formal education ($LWNOF_t$) and primary education ($LWPRI_t$) (e.g., Conway et al., 2010; Fisher et al., 2015). Following Shin et al. (2014), the Wald statistics for the null hypothesis of long-run symmetry in this study are tested (i.e., $H_{LR}^s: \beta_1^+ = \beta_1^-; \delta_1^+ = \delta_1^-; \theta_1^+ = \theta_1^-$), whereas the short-run symmetry (i.e., $H_{SR}^s: \beta_j^+ = \beta_j^-; \delta_j^+ = \delta_j^-; \theta_j^+ = \theta_j^-$). The research methodologies adopted in this study are unit root and stationary tests and the nonlinear autoregressive distributed lag (NARDL) model, which are estimated by EViews. The NARDL estimation includes bounds tests, error correction models, long-run coefficients, diagnostic tests, and dynamic multiplier graphs, and the Wald tests are also applied in this study. The short-run dynamic parameters are estimated by the error correction models associated with the long-run estimates. The short-run error correction model is specified as follows:

Equation 3.36

$$\Delta LPRODA_t = \alpha + \sum_{j=1}^{p} \lambda_j \Delta\, LPRODA_{t-j} + \sum_{j=0}^{q1} \beta_j^{+}\, \Delta LEFW_{t-j}^{+} + \sum_{j=0}^{q2} \beta_j^{-}\, \Delta LEFW_{t-j}^{-} + \sum_{j=0}^{q3} \mu_j\, \Delta LFCAPI_{t-j} + \sum_{j=0}^{q4} \pi_j\, \Delta LWNOF_{t-j} + \sum_{j=0}^{q5} \sigma_j\, \Delta LWPRI_{t-j} + \chi_j ECT_{t-j} + \varepsilon_t$$

Equation 3.37

$$\Delta LPRODI_t = \alpha + \sum_{j=1}^{p} \gamma_j \Delta\, LPRODI_{t-j} + \sum_{j=0}^{q1} \delta_j^{+}\, \Delta LEFW_{t-j}^{+} + \sum_{j=0}^{q2} \delta_j^{-}\, \Delta LEFW_{t-j}^{-} + \sum_{j=0}^{q3} \xi_j\, \Delta LFCAPI_{t-j} + \sum_{j=0}^{q4} \omega_j\, \Delta LWNOF_{t-j} + \sum_{j=0}^{q5} \tau_j\, \Delta LWPRI_{t-j} + \psi_j ECT_{t-j} + \varepsilon_t$$

$$\Delta LPRODS_t = \alpha + \sum_{j=1}^{p} \varphi_j \Delta\, LPRODS_{t-j} + \sum_{j=0}^{q1} \theta_j^{+}\, \Delta LEFW_{t-j}^{+} + \sum_{j=0}^{q2} \theta_j^{-}\, \Delta LEFW_{t-j}^{-} + \sum_{j=0}^{q3} \zeta_j\, \Delta LFCAPI_{t-j} + \sum_{j=0}^{q4} \iota_j\, \Delta LWNOF_{t-j} + \sum_{j=0}^{q5} \upsilon_j\, \Delta LWPRI_{t-j} + o_j ECT_{t-j} + \varepsilon_t$$

Equation 3.38

3.4 Econometric Methods

The variables under investigation will be analyzed by using EViews software. There are few stages in time series analysis. Firstly, the data must be tested by unit root tests for the existence of the unit root problem in time series data. This is to examine the stationary and non-stationary properties of the data. Next, the test will proceed to the Johansen and Juselius cointegration test and the Granger causality test within vector autoregressive (VAR) models. The variance decomposition and impulse response function are used in the study to enhance the analysis to further support the results of the Granger causality test. The impulse response analysis is applied by utilizing the Cholesky decomposition and adjustment in the degree of freedom (Cholesky dof adjusted) to describe the evolution of a model's variables in reaction to a shock in one or more variables. The study also employs the autoregressive distributed lag (ARDL) and nonlinear autoregressive distributed lag (NARDL) estimation, including bounds tests, error correction models, long-run coefficients, diagnostic tests, dynamic multiplier graphs, and the Wald tests.

3.4.1 Unit Root and Stationary Tests

The three types of unit root tests applied in the study include the augmented Dickey–Fuller (ADF) test proposed by Dickey and Fuller (1979), the Phillips–Perron (PP) test proposed by Phillips and Perron (1988), and the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test proposed by Kwiatkowski et al. (1992). The null hypothesis of ADF is that the properties of the tested variable are non-stationary, while the alternative hypothesis of ADF is that the properties of the tested variable are stationary. The rejection rule for the null hypothesis is to reject it if the test statistic is greater than the critical value. If the null hypothesis is rejected, it means the tested variable has the problem of unit root.

The Phillips–Perron (PP) test was proposed by Phillips and Perron (1988), and it examined the properties of the tested variable based on the idea of controlling the serial correlation method. The null hypothesis of the Phillips–Perron test is that the tested variable contains a unit root problem, while the alternative hypothesis is that the tested variable does not contain a unit root problem. The rejection rule for the null hypothesis is the same as the augmented Dickey–Fuller test, which is to reject the null hypothesis when the test statistic is higher than the critical value. The PP test is based on the statistic as follows:

$$t_\alpha = t_\alpha \left(\frac{Y_0}{f_0}\right)^{\frac{1}{2}} - \frac{t\,(f_0 - Y_0)\big(SE(\propto)\big)}{2{f_0}^{1/2}s} \qquad \text{Equation 3.39}$$

Where t_α is the t-ratio of the α coefficient, Y_0 is a consistent estimation of the error variance, f_0 denotes an estimator of the residual spectrum at frequency zero, and $se(\alpha)$ refers to the coefficient standard error.

The Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test proposed by Kwiatkowski et al. (1992) is a unit root test different from ADF and PP tests because the null hypothesis of the KPSS is reversed from ADF and PP tests. The null hypothesis of the KPSS test is that the tested variable has no unit root problem, while the alternative hypothesis is that the tested variable contains the unit root problem. If the null hypothesis is rejected, then the tested variable may suffer from non-stationary properties. The following is the KPSS statistic based on the residuals from the OLS regression:

$$y_t = x_t\delta + \mu_t \qquad \text{Equation 3.40}$$

Where Y denotes the endogenous variable, while X represents the exogenous variable for the period of t.

3.4.2 Unit Root with Break Test

The unit root with break test applied in the study, which is the augmented Dickey–Fuller with structural breaks based on the basic framework outlined (e.g., Banerjee et al., 1992; Perron, 1989; Vogelsang & Perron, 1998; Zivot & Andrews, 1992), so as to establish stationarity properties of the series and can tackle the problem of structural breaks in the series. Perron (1989) shows two distinct approaches to modeling the break dynamics: the innovational outlier (IO) model and the additive outlier (AO) model. The IO model assumes that the break occurs steadily—with the breaks following the same dynamic path as the innovations; however, the AO model assumes the breaks occur immediately.

3.4.3 Johansen and Juselius Cointegration Test

The Johansen and Juselius cointegration test consists of the test statistics of the Max-Eigen statistic and Trace statistic—with each respective critical value at the 5% level of significance. This study applies the Johansen and Juselius (1990) cointegration test to test the long-run equilibrium relationship among the tested variables. The null hypothesis of the cointegration test is the number of cointegrating vectors, which is r. The number r starts at 0, while the alternative hypothesis is that the number of cointegrating vectors is r+1. The Johansen cointegration test is used to identify the relationship of cointegration among the variables. The Johansen multivariate cointegrating framework estimates the system as follows:

$$\Delta Z_t = \Pi_t \Delta Z_{t-1+\dots} + \Pi_{k-1} \Delta Z_{t-k-1} + \Delta Z_{t-1} + \mu + \varepsilon_t : \ t = 1, \dots, T \qquad \text{Equation 3.41}$$

Where Δ represents the first difference operator, Z indicates a vector of variables, μ refers to a drift parameter, ε denotes independently, normally distributed with mean zero, and Π is a (pxp) matrix of the form $\Pi = \alpha\beta'$. In this context, α and β are both $(p\ x\ r)$ matrices of full rank; β contains the r cointegrating relationships, while α carries the corresponding adjustment coefficients for each of the r vectors.

3.4.4 Granger Causality Test

The Granger (1988) causality test is used to determine the existence and direction of the causality between all the tested variables in the model. Granger causality is a method that is used in determining whether one time series is useful in forecasting another. This test is used to verify the causality between the tested variables. In this study, the empirical models will analyze the causality relationship between labor market educational attainment (i.e., no formal education, primary education, secondary education, and tertiary education levels) and Malaysian productivity. If the variables are cointegrated, the causality test will be tested in a vector error correction model (VECM) to avoid the misspecification problem. The Error Correction Term (ECT) in VECM is used to represent the long-run relationship found in the estimated model. On the other hand, if the variables are not cointegrated, the causality test will be tested in a vector autoregressive (VAR) model.

The VAR estimation method can be used to apply specific lagged endogenous multivariate models, called the vector autoregressive (VAR) models. To explain how a VAR is estimated, the Granger causality of the *X* and *Y* variables needs to be investigated:

$$X_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i X_{t-i} + \sum_{i=1}^{p} \beta_i Y_{t-i} + \varepsilon_{1t} \qquad \text{Equation 3.42}$$

$$Y_t = \delta_0 + \sum_{i=1}^{p} \delta_i X_{t-i} + \sum_{i=1}^{p} \gamma_i Y_{t-i} + \varepsilon_{2t} \qquad \text{Equation 3.43}$$

3.4.5 Autoregressive Distributed Lag

The ARDL approach is a cointegration technique for determining long-run and short-run relationships among variables. The ARDL approach is employed regardless of the order of integration, whether the variables in the study are purely *I*(0) or *I*(1). Following Pesaran et al. (2001), the autoregressive distributed lag (p, q) model can be written as:

$$y_t = \sum_{j=1}^{p} \emptyset_j \, y_{t-j} + \sum_{i=0}^{q} \theta_i \, x_{t-i} + \varepsilon_t \qquad \text{Equation 3.44}$$

3.4.6 Nonlinear Autoregressive Distributed Lag

The NARDL model is employed in the study so as to detect the asymmetric effects. Shin et al. (2014) propose a nonlinear ARDL (NARDL) framework in which short-run and long-run nonlinearities are modeled as positive and negative partial sum decompositions of the explanatory variables. The general form of the NARDL model is defined as follows:

$$y_t = \beta^+ x_t^+ + \beta^- x_t^- \qquad \text{Equation 3.45}$$

Where β^+ and β^- denote long-run parameters. As per asymmetry or nonlinear ARDL, consider the partial sum decomposition of a variable x_t; then x_t is composed of two components, which are positive and negative. The two variables are established—x_t^+ denotes the partial sum processes of positive changes, and x_t^- denotes the partial sum processes of negative changes in x_t:

$$x_t^+ = \sum_{j=1}^{t} \Delta x_j^+ = \sum_{j=1}^{t} \max(\Delta x_j, 0)$$ Equation 3.46

$$x_t^- = \sum_{j=1}^{t} \Delta x_j^- = \sum_{j=1}^{t} \min(\Delta x_j, 0)$$ Equation 3.47

Following Shin et al. (2014), the nonlinear autoregressive distributed lag (p, q) model can be rewritten as follows:

$$y_t = \sum_{j=1}^{p} \emptyset_j \, y_{t-j} + \sum_{j=0}^{q} (\theta_j^+ \, x_{t-j}^+ + \theta_j^- x_{t-j}^-) + \varepsilon_t$$ Equation 3.48

where $\emptyset_j$ is the autoregressive parameter, θ_j^+ and θ_j^- are the parameters of asymmetric distributed lag, and x_t is decomposed into x_t^+ and x_t^- —formulating the nonlinear autoregressive distributed lag proposed by Shin et al. (2014).

3.5 Chapter Summary

The study's conceptual framework extends the body of knowledge on sectoral labor productivity by measuring the role of labor market educational attainment based on existing theories, such as the Solow–Swan model proposed by Solow and Swan (1956) and the Cobb–Douglas production function proposed by Cobb and Douglas (1928), to meet research objectives. The study primarily examines how the educational quality of the labor market influences productivity and Malaysian economic growth, utilizing annual data from

1982 to 2023 and employing the VAR estimation method. Additionally, this study aims to investigate the impact of the educational attainment of employed workers on labor productivity in the main economic sectors, namely agriculture, industry, and services. To do this, it employs the ARDL estimation method, drawing on annual data from 1991 to 2022. Likewise, this study, covering the period 1991–2022, examines the asymmetric effect of foreign worker employment and the influence of workers with low educational attainment on sectoral labor productivity (i.e., agriculture, industry, and services) using the NARDL estimation method. The incorporation of a Nonlinear Autoregressive Distributed Lag (NARDL) model is to capture the potential nonlinear relationships between foreign worker employment and Malaysian sectoral labor productivity.

CHAPTER 4

EMPIRICAL RESULTS AND DISCUSSION

4.1 Introduction

This chapter discusses the results of the empirical analysis, which consists of all the test results examined in the study. The estimation models and research methodologies used in the study to answer the research objectives include unit root and stationary tests, the Vector Autoregressive (VAR) models (i.e., the first, second, and third research objectives), the Johansen and Juselius (1990) cointegration test, the Granger (1988) causality test, the Autoregressive Distributed Lag (ARDL) model proposed by Pesaran et al. (2001), the Nonlinear Autoregressive Distributed Lag (NARDL) model developed by Shin et al. (2014), the Wald test, etc. There are three types of unit root and stationary tests employed in this study, including the augmented Dickey–Fuller (ADF) test introduced by Dickey and Fuller (1979), the Phillips and Perron (PP) test proposed by Phillips and Perron (1988), and the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test introduced by Kwiatkowski et al. (1992). The study also applied the unit root with the break test; the augmented Dickey–Fuller test can address the problem of structural breaks in the data series. The purpose of unit root and stationary tests is to examine the stationarity of time series data for each tested variable, either stationary in level $I(0)$ or stationary in the first difference $I(1)$. For the fourth and fifth research objectives, the autoregressive distributed lag model and nonlinear autoregressive distributed lag model are applied to test the presence of cointegration among the tested variables, respectively. The NARDL estimation includes the bounds test, error correction model, long-run coefficient, diagnostic tests, and dynamic multiplier graph. In addition, the Wald test is applied in this study to find out the long-run

and short-run effect of education level in the ARDL model and the asymmetric effects of foreign workers in the NARDL model.

4.2 Educational Attainment, Employment, and Malaysian Labor Productivity

4.2.1 Unit Root and Stationary Tests

In order to answer the first research objective, there are three types of unit root tests employed for Model 1 to identify the stationary properties of the tested variables, which are the augmented Dickey–Fuller (ADF) test proposed by Dickey and Fuller (1979), the Phillips–Perron (PP) test proposed by Phillips and Perron (1988), and the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test proposed by Kwiatkowski et al. (1992). The unit root with the break test applied in the study is the augmented Dickey–Fuller with structural breaks based on the framework outlined in (e.g., Banerjee et al., 1992; Perron, 1989; Vogelsang & Perron, 1998; Zivot & Andrews, 1992), so as to establish the stationarity properties of the series and tackle the problem of structural breaks in the series. The unit root test for this study is to ensure that the variables tested in this study are not stationary at the second difference because the Johansen and Juselius (1990) cointegration test cannot estimate the variable that is stationary at the second difference.

Table 4.1: Descriptive Statistics for Model 1

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	JB
LPRODM	9.689	9.720	10.140	9.107	0.321	−0.468	1.979	3.358
LWNOF	6.267	6.208	6.722	5.881	0.266	0.249	1.676	3.504
LWPRI	7.637	7.701	7.779	7.013	0.181	−2.330	7.445	72.566
LWSEC	8.486	8.574	9.055	7.529	0.457	−0.531	2.142	3.267
LWTER	7.301	7.412	8.632	5.763	0.887	−0.198	1.770	2.921

Table 4.1 continued

LFCAP	14.364	14.408	15.407	13.040	0.735	−0.209	1.797	2.841

Notes: Std. Dev. denotes standard deviation, JB represents Jarque–Bera, LPRODM denotes the logarithm of Malaysia's productivity, measured in constant 2015 US$, and workers are measured in thousands of people.

Table 4.1 reports a summary of descriptive statistics for the variables investigated in this study. The mean for Malaysian productivity is 9.689%, with a median of 9.720%, a standard deviation of 0.321, and a maximum and minimum of 10.140 and 9.107, respectively. Fixed capital has the highest mean, followed by Malaysian productivity. The workers with tertiary education have the highest standard deviation, followed by the fixed capital. The standard deviation is a measure of dispersion in the series. The workers with no formal education have positive skewness, which indicates that the distribution has a long right tail. Then, the negative skewness emphasizes that the distribution has a long left tail. The kurtosis of the normal distribution is 3, and only the workers with primary education exceed 3 (i.e., the peakedness of the distribution).

Table 4.2: Results of Unit Root and Stationary Tests for Model 1

	ADF		**PP**		**KPSS**	
	Intercept	**Trend & Intercept**	**Intercept**	**Trend & Intercept**	**Intercept**	**Trend & Intercept**
			A: Level			
LPRODM	−1.388(0)	−1.400(0)	−1.360(1)	−1.561(2)	0.780(5)*	0.172(5)**
LWNOF	−1.690(2)	−2.042(1)	−1.318(1)	−4.299(4)*	0.770(5)*	0.171(4)**
LWPRI	0.406(0)	−1.659(1)	0.406(0)	−1.066(1)	0.532(4)**	0.159(4)**
LWSEC	−5.023(0)*	−1.260(0)	−5.023(0)*	−1.265(1)	0.788(5)*	0.200(5)**
LWTER	−1.800(0)	−0.748(0)	−4.856(35)*	0.667(32)	0.807(5)*	0.201(5)**
LFCAP	−1.324(0)	−3.312(4)***	−1.271(1)	−2.124(2)	0.797(5)*	0.099(4)

Table 4.2 continued

B: First Difference						
ΔLPRODM	−5.517(0)*	−5.621(0)*	−5.531(2)*	−5.621(0)*	0.178(2)	0.056(1)
ΔLWNOF	−12.217(0)*	−6.895(1)*	−12.841(1)*	−12.863(1)*	0.112(4)	0.077(6)
ΔLWPRI	−4.559(0)*	−5.168(1)*	−4.494(2)*	−4.493(5)*	0.284(1)	0.074(3)
ΔLWSEC	−4.572(0)*	−6.137(0)*	−4.693(4)*	−6.151(2)*	0.711(4)**	0.062(1)
ΔLWTER	−5.831(0)*	−5.982(2)*	−5.845(9)*	−10.577(21)*	0.349(9)**	0.343(30)*
ΔLFCAP	−4.923(0)*	−4.986(0)*	−4.949(1)*	−5.011(1)*	0.125(1)	0.046(1)

Notes: The types of unit root tests used are ADF, PP, and KPSS tests. The number in parentheses refers to the lag length or bandwidth used by the default setting in EViews. An asterisk (*) denotes the test statistic is significant at the 1% significance level, (**) indicates significant at the 5% significance level, and (***) indicates significant at the 10% significance level. Δ is the first difference operator.

The results of the unit root test reveal that all variables, including the dependent variable and independent variables, are Malaysia's labor productivity in logarithm (LPRODM), workers lacking formal education in logarithm (LWNOF), workers with primary education in logarithm (LWPRI), workers with secondary education in logarithm (LWSEC), workers with tertiary education in logarithm (LWTER), and fixed capital in logarithm (LFCAP). Table 4.2 shows the results of the unit root tests from the ADF, PP, and KPSS tests. The null hypothesis of the ADF and PP unit root tests is that the tested variable is non-stationary, while the null hypothesis of the KPSS unit root test is that the variable is stationary. The rejection rule is to reject the null hypothesis when the t-statistic is larger than the critical value.

Based on the results presented in Table 4.2, the statistical findings from the ADF unit root test at the level indicate that LPRODM is non-stationary in the intercept specification—as well as non-stationary in the trend and intercept specification. At the first difference, LPRODM is stationary in the intercept specification at the 1% significance

level—while stationary in the trend and intercept specification. Based on the results of the PP test, LPRODM is non-stationary in level, while stationary in both intercept and trend with intercept specifications in the first difference. Overall, the results from the ADF, PP, and KPSS tests suggest that LPRODM is an *I*(1) variable. LWNOF is considered an *I*(1) variable because all the test statistics from the ADF and PP tests failed to reject the null hypothesis in level except for the trend with intercept specification, but most of the test statistics rejected the null hypothesis in the first difference.

Likewise, the results of the PP unit root test at the level indicate that LWSEC and LWTER are stationary only in the intercept specification. In contrast, LFCAP is stationary only in the trend and intercept specification, according to the results of the KPSS test. The KPSS unit root test results at the first difference indicate that LWSEC is non-stationary under the intercept specification, while LWTER is non-stationary in both the intercept and the intercept with trend specifications. The variables LPRODM, LWNOF, LWPRI, and LFCAP are stationary in the intercept at the one percent significance level and are also stationary in the trend and intercept specification at the first difference. The KPSS test results reveal that LPRODM, LWNOF, and LWPRI are *I*(1) variables that are stationary in both the intercept and trend with intercept in the first difference while non-stationary at the stage of level. In conclusion, LPRODM, LWNOF, LWPRI, LWSEC, LWTER, and LFCAP are concluded to be stationary at the first difference—reflecting *I*(1) variables based on the results of the ADF, PP, and KPSS tests.

The results of the unit root with structural breaks portray that the test statistics of all the variables are statistically significant at the 1 percent level (see Table 4.3). This highlights that the combined results suggest that all the series are integrated of order one.

The estimated break date is mainly in the periods 1998–1999 and 2008–2009, which are associated mostly with the financial crisis period. The period 2019–2023 is related to the coronavirus disease (COVID-19) pandemic. Moreover, all inverse roots are smaller than 1, which infers that the VAR model is stationary (see Figure 4.1), based on the inverse roots of the characteristic AR polynomial (Lütkepohl, 1991). This underlines that VAR suffices the stability condition because all roots are situated inside the unit circle. In terms of robustness, the optimal lag length selected for the VAR model selects one lag based on the outcomes of the VAR lag order selection criteria (i.e., LR, FPE, AIC, SC, and HQ criterion) as described in Table 4.4. Next, the residual tests are employed (i.e., the VAR residual serial correlation LM tests and the VAR residual heteroskedasticity tests with cross terms), as portrayed in Table 4.5. There is no serial correlation and an absence of significant heteroskedasticity and specification bias problems.

Table 4.3: Results of the Unit Root with Structural Breaks for Model 1

	Level		**First Difference**	
	ADF_I	ADF_{TI}	ADF_I	ADF_{TI}
LPRODM	−3.854(9)	−3.517(0)	−6.198(0)*	−6.189(0)*
	[2021]	[1990]	[1995]	[1995]
LWNOF	−2.105(0)	−5.937(0)*	−12.856(0)*	−12.735(0)*
	[1989]	[1999]	[2021]	[2021]
LWPRI	−4.626(8)**	−3.530(3)	−6.819(1)*	−6.774(1)*
	[2011]	[2020]	[2018]	[2018]
LWSEC	−5.261(5)*	−2.982(7)	−5.748(0)*	−7.065(4)*
	[2009]	[2014]	[1993]	[2009]
LWTER	−3.467(3)	−1.970(0)	−6.538(0)*	−6.483(0)*
	[1995]	[1995]	[1996]	[1988]

Table 4.3 continued

LFCAP	−3.099(9)	−4.771(6)***	−5.153(0)*	−5.476(9)*
	[2011]	[1993]	[1997]	[2011]

Notes: The number in parentheses and square brackets denotes the lag length and break date, respectively. ADF_I and ADF_{TI} represent intercept and trend & intercept specification, respectively, with intercept break, selecting Dickey–Fuller min-t as the breakpoint selection with break type innovational outlier. An asterisk (*) denotes the test statistic is statistically significant at the 1 percent significance level, (**) indicates significant at the 5 percent significance level, and (***) indicates significant at the 10 percent significance level.

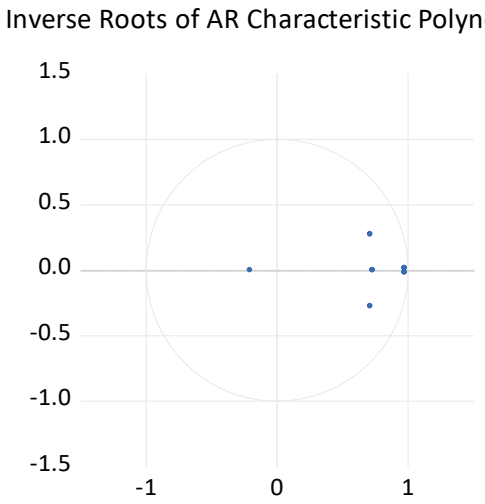


Figure 4.1: AR Roots Graph for Model 1

Table 4.4: VAR Lag Order Selection Criteria for Model 1

Lag	LR	FPE	AIC	SC	HQ
0	NA	4.01e−12	−9.215	–8.959	−9.124
1	416.401*	5.80e−17*	−20.382	−18.590*	−19.739*
2	34.110	1.13e−16	−19.848	−16.520	−18.654
3	50.667	8.37e−17	−20.535*	−15.672	−18.790

Notes: LR denotes sequential modified LR test statistic (each test at the 5 percent level), FPE refers to final prediction error, AIC represents Akaike information criterion, SC indicates Schwarz information criterion, and HQ represents Hannan–Quinn information criterion. An asterisk (*) denotes the lag order selected by the criterion.

Table 4.5: Diagnostic Tests for Model 1

VAR Residual Serial Correlation LM Tests			
H_0 : No serial correlation at lag h			
	LRE* stat	df	Prob.
Model 1	Lag 1= 33.675	36	0.580
	Lag 2= 51.952	36	0.042
H_0 : No serial correlation at lags 1 to h			
	LRE* stat	df	Prob.
Model 1	Lag 1= 33.675	36	0.580
	Lag 2= 90.731	72	0.067
VAR Residual Heteroskedasticity Tests			
	Joint test:		
	Chi-sq	df	Prob.
Model 1	611.782	567	0.094

Notes: An asterisk denotes the Edgeworth expansion corrected likelihood ratio statistic, using the LR version of the Breusch–Godfrey Lagrange Multiplier (LM) test for autocorrelation with the Edgeworth expansion correction proposed by Edgerton and Shukur (1999). VAR residual heteroskedasticity tests are the system equation extension of White's (1980) test.

4.2.2 Johansen and Juselius Cointegration Test

The Johansen and Juselius (1990) cointegration test is used for detecting the long-run equilibrium relationship among the tested variables in Model 1. The cointegration test consists of two types of test statistics, which are the trace statistic and the max-eigen statistic. The two test statistics may yield different results, leading to potential conflicts in the results. Johansen and Juselius (1990) stated that the Max-Eigen test statistic should be considered because it is more powerful than the Trace test statistic.

Table 4.6: Results of the Johansen and Juselius Cointegration Test for Model 1

		k=1 r=0			
		Max-Eigen		Trace	
Null	**Alternative**	**Unadjusted**	**95% C.V.**	**Unadjusted**	**95% C.V.**
r = 0	**r = 1**	33.425	40.078	91.868	95.754
r ≤ 1	**r = 2**	22.026	33.877	58.443	69.819
r ≤ 2	**r = 3**	14.768	27.584	36.417	47.856
r ≤ 3	**r = 4**	10.340	21.132	21.649	29.797
r ≤ 4	**r = 5**	9.749	14.265	11.309	15.495
r ≤ 5	**r = 6**	1.560	3.841	1.560	3.841

Notes: k denotes the number of lag lengths, and r indicates the number of cointegrating vectors detected. Asterisks (**) indicate statistical significance at the 5 percent level.

Table 4.6 indicates the results of the Johansen and Juselius (1990) cointegration test, which includes the Max-Eigen statistic and Trace statistic along with the respective critical values at the 5% level of significance. The null hypothesis of the cointegration test is that the number of cointegrating vectors is r, and the number of r starts from the number 0, while the alternative hypothesis is that the number of cointegrating vectors is r+1. The rejection rule is to reject the null hypothesis when the test statistic value is bigger than the critical value at the 5% significance level. The results concluded that there is no cointegrating vector detected from Model 1 based on the suggested results of the Max-Eigen statistic with 1 lag length—implying that there is no long-run equilibrium relationship between the tested variables. Because no long-run equilibrium relationship is being detected, the results suggest proceeding to test the causality direction using the VAR modeling for the variables.

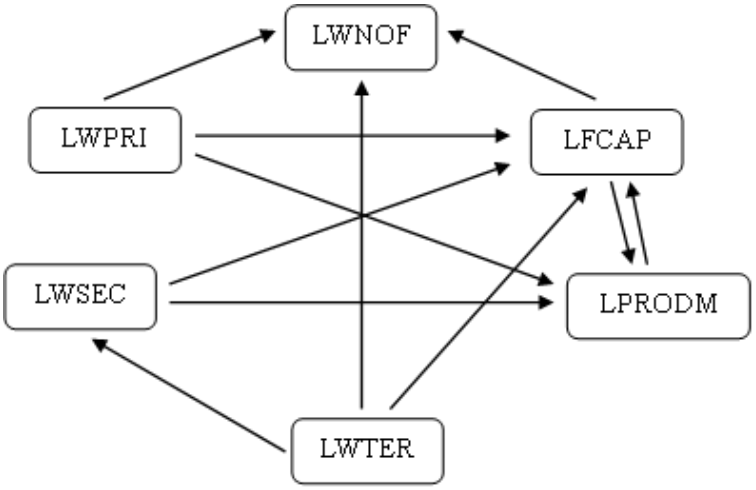
4.2.3 Vector Autoregressive Granger Causality Test

The VAR Granger causality test is conducted in the study because the Johansen and Juselius (1990) cointegration test result suggested that there is no long-run equilibrium relationship among the tested variables. Therefore, the Vector Error Correction Model is not suitable to proceed with due to no long-run equilibrium relationship being detected. The Error Correction Term (ECT) in VECM is used to represent the long-run relationship found in the estimated model. ECT provides information about the adjustment speed and the time required to achieve equilibrium, as well as identifies the most endogenous variable.

Table 4.7: Results of the VAR Granger Causality Test for Model 1

Dependent Variable	ΔLPRODM	ΔLWNOF	ΔLWPRI	ΔLWSEC	ΔLWTER	ΔLFCAP
	χ^2 Statistic (p- value)					
ΔLPRODM	-	0.239 (0.625)	3.618 (0.057)***	14.357 (0.000)**	0.123 (0.726)	3.595 (0.058)***
ΔLWNOF	0.098 (0.754)	-	6.134 (0.013)**	0.002 (0.969)	9.864 (0.002)**	4.691 (0.030)**
ΔLWPRI	0.181 (0.670)	0.020 (0.885)	-	0.021 (0.884)	0.449 (0.503)	0.091 (0.764)
ΔLWSEC	0.012 (0.914)	1.171 (0.279)	0.000 (0.984)	-	0.255 (0.613)	1.670 (0.196)
ΔLWTER	0.246 (0.620)	0.281 (0.596)	0.882 (0.348)	2.347 (0.126)	-	0.315 (0.575)
ΔLFCAP	8.230 (0.004)**	1.983 (0.159)	3.685 (0.055)***	2.886 (0.089)***	3.110 (0.078)***	-

Notes: The chi-square statistic is represented by the symbol χ^2. Asterisks (** and ***) denote statistical significance at the 5 percent level and 10 percent level, respectively. Δ denotes the first different operator.



Notes: Figure 4.2 shows the unidirectional and bidirectional causality among the tested variables (i.e., LPRODM, LWNOF, LWPRI, LWSEC, LWTER, and LFCAP) based on the results of the VAR Granger causality test in Table 4.7.

Figure 4.2: Results of the Vector Autoregressive (VAR) Granger Causality Flow

Table 4.7 indicates that the results of the Granger causality test are estimated using a Vector Autoregressive (VAR) Model. The causality relationship between the selected independent variables and the dependent variable has been identified based on the results of the study. The Granger (1988) causality test is used to determine the existence and direction of the causality between all the tested variables in the model. Based on Table 4.7, the results illustrate that only LWPRI, LWSEC, and LFCAP can Granger-cause LPRODM at the 5% level of significance, respectively. The results of the study show that workers with primary education and workers with secondary education can affect Malaysian labor productivity respectively between 1982 and 2023. Moreover, the Granger causality flow indicates that LWPRI, LWSEC, and LFCAP have a unidirectional causal relationship with LPRODM, respectively (see Figure 4.2). This finding underscores that the existence of unidirectional causality runs from workers with primary education (LWPRI) to Malaysian labor productivity (LPRODM), based on the results of the Granger causality test. The results also indicate the unidirectional causality from workers with secondary education

(LWSEC) to Malaysia's labor productivity (LPRODM). Likewise, there is a unidirectional causality running from fixed capital (LFCAP) to Malaysian labor productivity (LPRODM) during the period 1982–2023.

Workers with secondary education can Granger-cause Malaysian labor productivity at the 5 percent level of significance. However, workers with primary education and fixed capital Granger-cause Malaysian labor productivity at the 10 percent significance level, respectively. On the other hand, workers with no formal education and workers with tertiary education do not Granger-cause Malaysia's labor productivity based on the results of the VAR Granger causality test. This result proves that neither workers lacking formal education nor tertiary education affect labor productivity, which is only affected by workers in the labor market who have primary education or secondary education during the study period. The results indicate that the workers with different education levels (i.e., primary, secondary, and tertiary education) can Granger-cause fixed capital at the 10% level of significance. Additionally, Malaysian labor productivity can Granger-cause fixed capital during the study period. The VAR Granger causality flow illustrates that there is a unidirectional causal relationship running from LPRODM to LFCAP, LWPRI to LFCAP, LWSEC to LFCAP, and LWTER to LFCAP. The VAR Granger causality flow reveals a unidirectional causal relationship running from LWPRI to LWNOF, LWTER to LWNOF, and LFCAP to LWNOF. Based on Figure 4.2, which illustrates the Granger causality flow, LFCAP is the most endogenous variable among the tested variables, as it is influenced by four variables at the same time. Likewise, the Granger causality flow indicates that there is the existence of bidirectional causality between LFCAP and LPRODM during 1982–2023.

The summary of the results proves that workers with education levels (i.e., secondary education) Granger-cause Malaysian labor productivity at the 5 percent level of significance. Primary education does Granger-cause labor productivity at the 10% significance level during the study period. In addition, fixed capital can Granger-cause Malaysian labor productivity between 1982 and 2023. Fixed capital has a bidirectional causal relationship with Malaysian labor productivity. However, workers with no formal education and workers with tertiary education do not Granger-cause Malaysia's labor productivity based on the results of the VAR Granger causality test (see Table 4.7). The results of the study reveal that education levels (i.e., primary, secondary, and tertiary) can affect fixed capital between 1982 and 2023.

4.2.4 Variance Decomposition

The Granger causality results indicate the direction of causality but are unable to provide the strength of the Granger causality. Therefore, variance decomposition is used to examine the strength of the causal relationship between the tested variables. Table 4.8 displays the decomposition of the forecast error variable throughout 50 years. It can improve Granger causality results by presenting the percentage of variance in each variable caused by others. This test can identify the most endogenous and exogenous variables in the model and provide information about the most influential variable. The results of variance decomposition provide additional support for the VAR Granger causality findings regarding the impacts of educational attainment on labor productivity in Malaysia.

Table 4.8: Variance Decomposition Results

Percentage of Variations in	Horizon (Years)	Due to Innovation in:						
		ΔLPRODM	ΔLWNOF	ΔLWPRI	ΔLWSEC	ΔLWTER	ΔLFCAP	ΔCU
Years Relative Variance in: ΔLPRODM								
	1	**100**	0	0	0	0	0	0
	4	**64.028**	4.969	2.010	25.204	0.003	3.786	35.972
	8	**45.833**	5.279	2.755	42.817	0.013	3.303	54.167
	12	**42.794**	4.919	2.651	45.715	0.161	3.760	57.206
	20	**39.876**	4.657	3.175	47.692	0.521	4.079	60.124
	30	**37.330**	4.574	4.132	49.215	0.649	4.100	62.670
	40	**35.795**	4.576	5.252	49.636	0.658	4.082	64.205
	50	**34.833**	4.610	6.281	49.589	0.641	4.046	65.167
Years Relative Variance in: ΔLWNOF								
	1	1.112	**98.888**	0	0	0	0	1.112
	4	1.142	**76.570**	10.785	1.355	7.220	2.929	23.430
	8	1.138	**71.948**	14.449	2.183	7.459	2.822	28.052
	12	1.379	**69.225**	16.499	2.808	7.233	2.857	30.775
	20	1.749	**65.595**	18.504	4.554	6.813	2.785	34.405
	30	1.955	**62.926**	20.156	5.709	6.520	2.734	37.074
	40	2.075	**61.405**	21.283	6.176	6.370	2.691	38.595
	50	2.139	**60.541**	22.021	6.339	6.300	2.660	39.459
Years Relative Variance in: ΔLWPRI								
	1	1.034	9.228	**89.738**	0	0	0	10.262
	4	2.476	8.508	**88.293**	0.010	0.650	0.063	11.707
	8	3.674	8.346	**85.955**	0.164	1.815	0.045	14.045
	12	3.928	8.380	**84.523**	0.311	2.821	0.037	15.477
	20	3.922	8.229	**83.378**	0.293	4.144	0.035	16.622

30	3.828	8.057	**82.629**	0.344	5.085	0.057	17.371
40	3.724	7.922	**81.972**	0.637	5.649	0.097	18.028
50	3.644	7.815	**81.331**	1.080	5.987	0.143	18.669
Years	Relative Variance in: ΔLWSEC						
1	1.526	1.664	12.674	**84.136**	0	0	15.864
4	0.866	4.189	16.885	**76.090**	0.147	1.823	23.910
8	2.227	4.005	25.321	**65.252**	0.091	3.104	34.748
12	3.568	4.371	29.932	**58.951**	0.069	3.108	41.049
20	4.447	5.014	34.694	**52.956**	0.063	2.826	47.044
30	4.832	5.401	38.396	**48.639**	0.117	2.615	51.361
40	4.994	5.625	40.787	**45.919**	0.210	2.465	54.081
50	5.062	5.758	42.352	**44.150**	0.313	2.365	55.850
Years	Relative Variance in: ΔLWTER						
1	1.285	12.053	2.358	0.960	**83.344**	0	16.656
4	0.622	5.998	1.300	7.975	**83.111**	0.994	16.889
8	0.684	3.829	2.484	21.745	**68.902**	2.356	31.098
12	0.783	2.839	3.278	33.320	**56.777**	3.002	43.223
20	0.965	2.020	2.921	46.255	**44.039**	3.801	55.961
30	1.339	1.748	2.443	53.531	**36.690**	4.249	63.310
40	1.701	1.778	2.938	56.606	**32.577**	4.399	67.423
50	1.997	1.911	4.038	57.641	**29.996**	4.418	70.004
Years	Relative Variance in: ΔLFCAP						
1	8.517	23.516	0.101	3.332	2.708	**61.826**	38.174
4	11.824	27.830	2.846	5.837	1.507	**50.156**	49.844
8	19.156	23.471	3.075	10.377	1.919	**42.001**	57.999
12	17.310	21.274	2.829	19.740	1.951	**36.894**	63.106
20	15.539	18.945	3.720	26.687	2.061	**33.048**	66.952
30	14.563	17.444	5.405	30.395	2.023	**30.170**	69.830

Table 4.8 continued

40	14.003	16.630	7.066	31.956	1.924	**28.421**	71.579
50	13.675	16.173	8.482	32.502	1.844	**27.325**	72.675

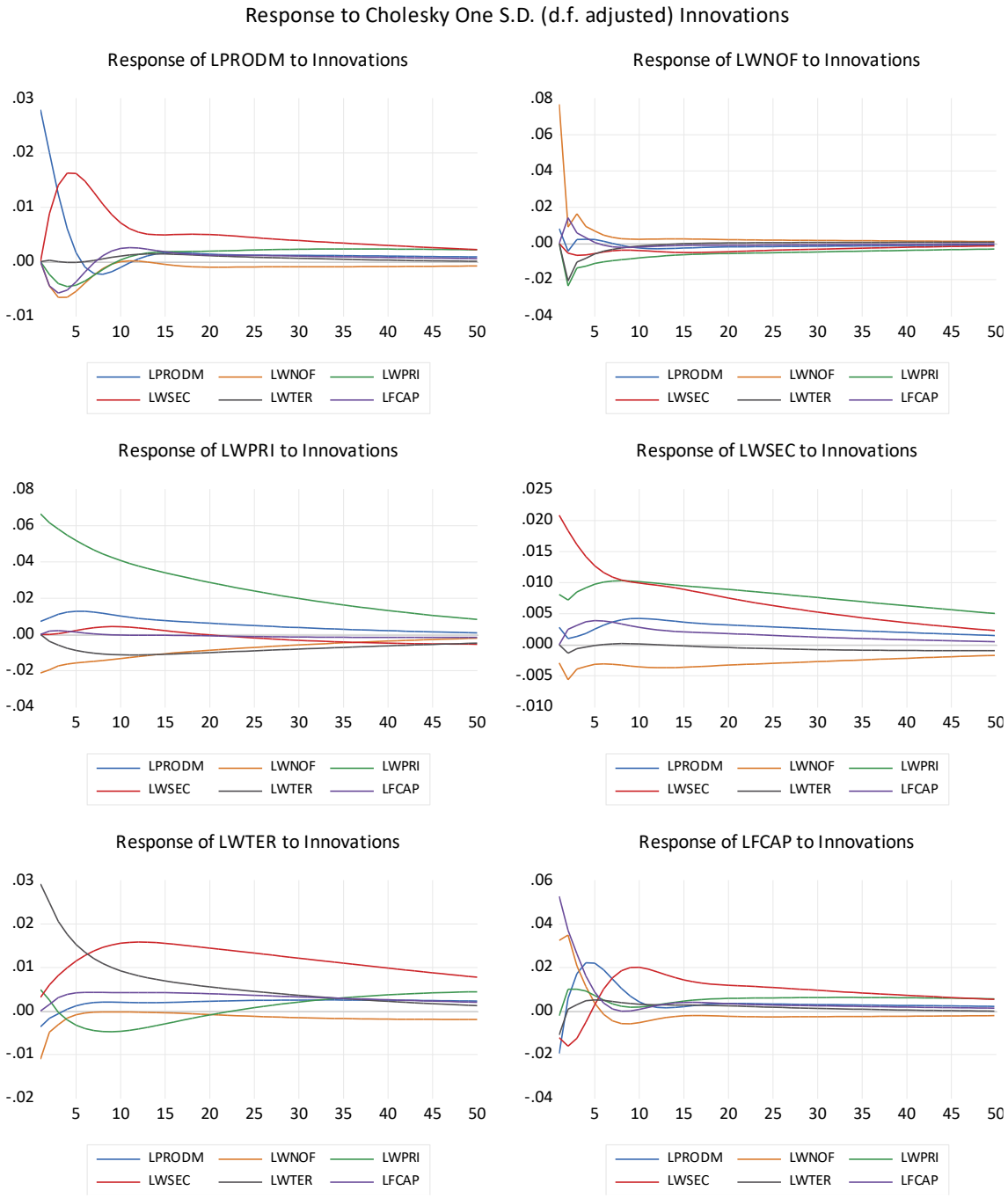
Notes: The last column provides the percentage of forecast error variances for each variable explained collectively by the other variables. The bold column represents the impact of one's own shock.

There is around 65.17% of the forecast error variance in LPRODM that can be explained by the shock of other variables, which are 4.61% by LWNOF, 6.28% by LWPRI, 49.59% by LWSEC, 0.64% by LWTER, and 4.05% by LFCAP at the end of 50 years. This underlines that the workers with secondary education shocks account for more than 49 percent of Malaysian labor productivity. The variance decomposition shows that workers with primary education are able to explain more than 6 percent of forecast error variance in labor productivity at the end of 50 years. It is also affirmed by variance decomposition that the workers with tertiary education do not significantly explain the forecast error variance in labor productivity. Furthermore, around 39.46% of forecast error variance in LWNOF was explained by LPRODM (2.14%), LWPRI (22.02%), LWSEC (6.34%), LWTER (6.30%), and LFCAP (2.66%) at the end of 50 years. There is about 18.67% of the forecast error variance in LWPRI that was caused by the shock in other variables, with 3.64% by LPRODM, 7.82% by LWNOF, 1.08% by LWSEC, 5.99% by LWTER, and 0.14% by LFCAP at the end of 50 years. Based on the results of variance decomposition, LFCAP is the most endogenous variable, highly absorbing the shocks from other variables, and only 27.33% of the variation can be explained by itself after 50 years. The result indicates that among the 72.68% of forecast error variance, about 13.68%, 16.17%, 8.48%, 32.50%, and 1.84% of variation can be caused by LPRODM, LWNOF, LWPRI, LWSEC, and LWTER, respectively. This percentage value indicates that LWSEC is the most influential variable, and LPRODM is the second most influential variable. However, LPRODM is a dependent

variable, and around 34.83% of the variation can be explained by itself, but the result indicates it is the second most endogenous variable. The outcome indicates that among the 65.17% of forecast error variance, about 4.61%, 6.28%, 49.59%, 0.64%, and 4.05% of variation can be caused by LWNOF, LWPRI, LWSEC, LWTER, and LFCAP, respectively. This percentage value suggests that LWSEC is the most influential variable affecting LPRODM, as variations from this variable consistently account for a large portion over a 50-year period. This result further explains that workers with secondary education can significantly influence Malaysian labor productivity compared to those with other levels of education. However, the workers with tertiary education only affect a small percentage of Malaysian labor productivity. The result is consistent with the findings of the Granger causality test, where LWSEC does Granger-cause LPRODM, while LWTER does not Granger-cause LPRODM during the study period. LWPRI is indicated to be the most exogenous variable in the result because the percentage of variation caused by LWPRI itself is greater than variations caused by other variables every year. Compared to the changes in CU of other variables, LWPRI exhibits the lowest CU value at the end of the 50-year period. This suggests that LWPRI is less affected by other variables, with most of the impact deriving from itself. This is supported by the results of the Granger causality test, which indicate that no other variables can Granger-cause LWPRI.

4.2.5 Impulse Response Function

Figure 4.3 shows the results of the Impulse Response Function (IRF) for a 50-year horizon. The impulse response analysis is employed by utilizing the Cholesky decomposition and adjustment in the degree of freedom (Cholesky dof adjusted)—the evolution of a model's variables in reaction to a shock in one or more variables.



Notes: Figure 4.3 was developed by using EViews and the Cholesky decomposition method (dof) for impulse response throughout 50 years. Each variable (i.e., LPRODM, LWNOF, LWPRI, LWSEC, LWTER, and LFCAP) is characterized by the different colors of lines as stated above.

Figure 4.3: Results of the Impulse Response Function for Model 1

Based on the graph in Figure 4.3, the response of LPRODM to a shock in the LWSEC is positive and significant, which underscores that workers with secondary

education positively affect labor productivity in Malaysia throughout 50 years, especially in the fifth year. The positive response intensely increases and reaches its maximum in the 4th–5th year. It shows a significant decline from the 6th year until the 13th year and then a gradual decline from the 14th year until the 50th year. This result further supports the results of the Granger causality test, which confirms that workers with secondary education can positively affect Malaysia's labor productivity during the study period, and there is a significant effect over the fourth and fifth years. Likewise, the response of LPRODM to LWTER indicates that workers with tertiary education have a negative impact on Malaysia's labor productivity but only in the 3rd–6th year, which reaches its maximum in the fifth year. A significant positive effect begins in the 7th year and continues until the 14th year, reaching its peak during this period. Following this maximum, the positive response gradually declines from the 15th year to the 50th year. This infers that workers with tertiary education negatively affect Malaysia's labor productivity, but only in the beginning period, whereas workers with tertiary education positively influence labor productivity over 46 years, especially from the 7th year until the 50th year. However, the results of the VAR Granger causality test reveal that tertiary education does not Granger-cause Malaysian labor productivity during the study period. The response of LPRODM to a shock in the LWPRI is negative, but this effect is observed only during the first 9 years; it reaches its peak in the fourth year. There is a positive effect of primary education on Malaysian labor productivity over a 40-year span. This positive effect shows a dramatic increase from the 10th to the 13th year. However, after the 13th year, the impulse response analysis graph indicates a slight decline in labor productivity, starting in the 36th year and continuing until the 50th year. The result confirms that primary education can positively affect Malaysian labor productivity from the 10th year to the 50th year. The results of the VAR Granger

causality test indicate that LWPRI can Granger-cause LPRODM during the study period. Furthermore, the response of LPRODM to LWNOF reveals that workers with no formal education have a negative impact on Malaysia's labor productivity in the first 10 years and reach a maximum in the third year. The negative effect on labor productivity is evident only during the initial period. However, there is a positive response only in the 11th year, and then the negative effect remarkably increases to its maximum in the 19th year; after that, this negative effect shows a slight decline from the 37th year until the 50th year.

In addition, the response of LPRODM to a shock in the LFCAP indicates that fixed capital positively impacts workers with secondary education over a period of 43 years, as shown in the graph of impulse response analysis. The positive effect of fixed capital on Malaysian labor productivity happens from the 8th year to the 50th year; this positive response intensely increases from the 8th year to the 11th year and then gradually decreases from the 12th to the 50th year. However, there is only a negative effect in the first six years; the negative response increases sharply and reaches its peak in the third year. After that, it shows a significant decline from the fourth year until the seventh year. This result of impulse response analysis further supports the findings of the VAR Granger causality test, which indicates that fixed capital can positively impact Malaysian labor productivity during the study period. The response of LFCAP to a shock in LPRODM indicates that Malaysian labor productivity positively impacts fixed capital over a span of 49 years. However, there is a negative effect observed only in the first year, according to the results of impulse response analysis. The positive response exhibits a dramatic increase, reaching its peak in the fourth year, followed by a notable decline to a minimum from the fifth to the thirteenth year. Subsequently, the positive effect shows slight increases from the 14th to the 20th year. It then experiences a gradual decline and maintains a consistent impact level

from the 20th year to the 50th year. The VAR Granger causality results demonstrate that Malaysian labor productivity can Granger-cause fixed capital during the study period (see Table 4.7).

The impulse response analysis indicates that LFCAP's response to a shock in the LWPRI is both positive and significant. This finding underscores that workers with primary education positively influence fixed capital over a span of 50 years. It suggests that primary education can positively affect fixed capital during the study period. The positive effects are particularly pronounced in the first two years, after which the response effect begins to decrease significantly from the fourth year until the ninth year. The positive response increases significantly until the 18th year, followed by a gradual increase from the 19th to the 40th year. After that, this positive effect diminishes gradually from the 41st to the 50th year. The response of LFCAP to LWSEC indicates a positive effect over a span of 45 years; however, a negative effect occurs during the first four years, as shown in the graph of impulse response analysis. This negative effect persists from the first year to the fourth, peaking in the second year. In contrast, the positive response experiences a significant increase from the sixth to the tenth year, followed by a decline from the eleventh year to the fiftieth year. Additionally, the response of LFCAP to a shock in the LWTER indicates that workers with tertiary education positively influence fixed capital for 48 years, with negative effects occurring only in the initial two years. The positive response rises intensely from the third to the fifth year, then gradually decreases over the subsequent years. This finding is consistent with LFCAP's response to LWSEC, where negative responses are also limited to the initial period.

The response of LWNOF to LWPRI indicates workers with primary education negatively influence those with no formal education over a span of 50 years. Specifically, this negative effect is most pronounced in the first two years; however, it significantly declines starting from the third year to the fifth year and continues to gradually decrease from the sixth year to the fiftieth year. The response of LWNOF to a shock in the LWTER indicates that workers with tertiary education negatively impact those with no formal education, but this effect is observed only during the initial 15 years. Conversely, the response of LWNOF to LFCAP shows that fixed capital positively affects workers with no formal education, but only within the first five years.

4.3 Labor Market Education Quality, Agricultural Growth, and Value-Added Agriculture

4.3.1 Unit Root and Stationary Tests

The study employs three types of unit root tests to identify the stationary properties of the tested variables, including the augmented Dickey–Fuller (ADF) test proposed by Dickey and Fuller (1979), the Phillips–Perron (PP) test proposed by Phillips and Perron (1988), and the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test proposed by Kwiatkowski et al. (1992). Likewise, the unit root with the break test applied in the study aims to establish the stationarity properties of the series and tackle the problem of structural breaks in the series. Specifically, the augmented Dickey–Fuller with structural breaks is used in the study and follows on the basic framework outlined (e.g., Banerjee et al., 1992; Perron, 1989; Vogelsang & Perron, 1998; Zivot & Andrews, 1992).

Table 4.9: Descriptive Statistics for Models 2 and 3

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	JB
Model 2								
LVAA	23.636	23.578	23.982	23.223	0.247	0.020	1.628	3.295
LENOF	6.275	6.233	6.721	5.880	0.263	0.218	1.674	3.330
LEPRI	7.649	7.702	7.779	7.013	0.166	−0.927	3.384	5.687
LESEC	8.472	8.549	9.044	7.529	0.454	−0.513	2.130	3.099
LETER	7.268	7.370	8.578	5.763	0.873	−0.190	1.764	2.856
LFC	14.339	14.381	15.407	13.040	0.726	−0.191	1.801	2.705
Model 3								
	Mean	**Median**	**Maximum**	**Minimum**	**Std. Dev.**	**Skewness**	**Kurtosis**	**JB**
LGDPA	10.840	10.712	11.986	9.692	0.712	−0.005	1.586	3.084
LLNOF	6.241	6.191	6.655	5.946	0.219	0.351	1.711	3.320
LLPRI	7.658	7.716	7.797	7.183	0.165	−1.940	5.821	35.476
LLSEC	8.643	8.665	9.092	7.952	0.346	−0.377	2.025	2.345
LLTER	7.532	7.598	8.658	6.216	0.758	−0.199	1.769	2.581
LLFLF	6.898	6.942	7.733	5.399	0.737	−0.712	2.376	3.730

Notes: Std. Dev. denotes standard deviation, JB represents Jarque–Bera, LVAA denotes the logarithm of value-added agriculture—measured in constant 2015 US$, LGDPA indicates the logarithm of agricultural GDP (in RM million), and labor force is measured in thousands of people.

Table 4.10: Results of Unit Root and Stationary Tests for Models 2 and 3

	ADF		PP		KPSS	
	Intercept	**Trend & Intercept**	**Intercept**	**Trend & Intercept**	**Intercept**	**Trend & Intercept**
Model 2						
A: Level						
LVAA	−1.002(0)	−2.302(0)	−1.007(6)	−2.383(1)	0.788(5)*	0.084(4)

Table 4.10 continued

LENOF	−1.645(1)	−0.867(1)	−1.270(1)	−4.290(4)*	0.750(5)*	0.166(4)**
LEPRI	1.004(0)	−1.425(1)	0.746(1)	−0.399(1)	0.520(4)**	0.152(4)**
LESEC	−4.881(0)*	−1.174(0)	−4.881(0)*	−1.181(1)	0.774(5)*	0.196(5)**
LETER	−1.709(0)	−0.791(0)	−4.669(36)*	0.141(25)	0.791(5)*	0.198(5)**
LFC	−1.418(0)	−1.709(0)	−1.351(1)	−2.026(2)	0.781(5)*	0.090(4)
			B: First Difference			
ΔLVAA	−6.067(1)*	−6.099(1)*	−6.577(5)*	−6.594(5)*	0.114(6)	0.092(6)
ΔLENOF	−12.359 (0)*	−12.591(0)*	−12.957(2)*	−13.118(1)*	0.102(4)	0.086(5)
ΔLEPRI	−4.475(0)*	−5.093(1)*	−4.475(0)*	−4.601(2)*	0.366(2)***	0.096(1)
ΔLESEC	−4.391(0)*	−5.973(0)*	−4.541(4)*	−5.976(2)*	0.704(4)**	0.063(1)
ΔLETER	−5.609(0)*	−5.850(2)*	−5.605(10)*	−9.620(21)*	0.338(9)	0.353(30)*
ΔLFC	−4.434(0)*	−4.537(0)*	−4.384(2)*	−4.495(2)*	0.142(1)	0.062(0)
			Model 3			
			A: Level			
LGDPA	−0.768(0)	−2.582(0)	−0.791(14)	−2.588(2)	0.720(5)**	0.075(4)
LLNOF	−1.880(2)	−0.836(2)	−1.791(2)	−3.770(4)**	0.661(5)**	0.177(4)**
LLPRI	−1.421(0)	−0.103(0)	−1.199(2)	−0.428(3)	0.559(4)**	0.145(4)***
LLSEC	−3.828(0)*	−1.221(0)	−4.270(2)*	−1.130(2)	0.721(5)**	0.189(4)**
LLTER	−1.840(0)	−0.820(0)	−4.939(29)*	0.629(28)	0.727(5)**	0.207(4)**
LLFLF	−2.062(0)	−1.450(0)	−2.076(2)	−1.491(2)	0.661(5)**	0.145(4)***
			B: First Difference			
ΔLGDPA	−5.928(1)*	−5.814(1)*	−6.427(14)*	−6.267(14)*	0.267(17)	0.233(17)*
ΔLLNOF	−10.732(0)*	−6.413(1)*	−11.196(1)*	−11.324(1)*	0.132(2)	0.064(4)
ΔLLPRI	−4.373(0)*	−4.723(0)*	−4.412(3)*	−4.685(2)*	0.343(3)	0.104(2)
ΔLLSEC	−4.461(0)*	−5.868(0)*	−4.470(3)*	−5.888(2)*	0.549(4)**	0.079(2)
ΔLLTER	−5.445(0)*	−6.006(0)*	−5.447(8)*	−9.795(21)*	0.339(12)	0.322(25)*
ΔLLFLF	−5.341(0)*	−5.621(0)*	−5.371(3)*	−5.621(1)*	0.255(3)	0.053(1)

Table 4.10 continued

Notes: The types of unit root tests used are ADF, PP, and KPSS tests. The number in parentheses denotes the lag length or bandwidth used by the default settings in EViews. An asterisk (*) denotes the test statistic is statistically significant at the 1 percent significance level, (**) indicates significant at the 5 percent significance level, and (***) indicates significant at the 10 percent significance level. Δ refers to the first difference operator.

Table 4.9 provides a summary of descriptive statistics for the variables investigated in this study. Value-added agriculture has the highest mean, followed by fixed capital, if compared with other variables in Model 2 (meso), while agricultural GDP also has the highest mean in Model 3 (macro). Positive skewness infers that the distribution has a long right tail; skewness is an asymmetry of the distribution measurement around its mean. Model 2 (meso) and Model 3 (macro) are examined in the study so as to answer the second research objective. Table 4.10 shows the suggested results of the unit root and stationary tests from the ADF, PP, and KPSS tests. The null hypothesis of the ADF and PP tests is that the variable has a unit root, while the null hypothesis of the KPSS test is that the variable is stationary. All the variables, including LVAA, LENOF, LEPRI, LESEC, LETER, and LFC, are concluded to be stationary at the first difference, which is an $I(1)$ variable based on the results of the ADF, PP, and KPSS unit root tests. The test statistics for all variables are statistically significant at the 1 percent significance level, according to the results from the ADF and PP unit root tests at the first difference.

Additionally, the results of the unit root tests with structural breaks at the first difference, as presented in Table 4.11, indicate that the test statistics for all variables tested are also statistically significant at the 1 percent level. This underscores that the combined results suggest that all the series are integrated of order one. The estimated break date is primarily in the periods 1998–1999 and 2008–2009, which are associated mostly with the financial crisis period. Subsequently, the COVID-19 pandemic is associated with the

period 2019–2023. Likewise, all inverse roots are smaller than 1, which implies that the VAR model is stationary, as portrayed in Figure 4.4, based on the inverse roots of the characteristic AR polynomial (Lütkepohl, 1991). This points out that VAR meets stability conditions due to all roots being situated inside the unit circle. In terms of robustness, Table 4.12 shows the optimal lag length selected for the VAR model, which selects one lag based on the outcomes of the VAR lag order selection criteria (i.e., LR, FPE, AIC, SC, and HQ criterion). Subsequently, the residual tests are performed, and the results are shown in Table 4.13 (i.e., the VAR residual serial correlation LM tests and the VAR residual heteroskedasticity tests with cross terms). There is no serial correlation and an absence of significant heteroskedasticity and specification bias problems in Model 2 (meso).

For Model 3 (macro), the findings indicate that LGDPA, LLNOF, LLPRI, LLSEC, LLTER, and LLFLF are identified as stationary at the first difference, classified as *I*(1) variables, according to the outcomes of the ADF, PP, and KPSS unit root tests. The ADF and PP unit root tests reveal that the test statistics for all the variables are significant at the 1% significance level. The results of the unit root test with structural breaks are presented in Table 4.11. The test statistics of all the variables are statistically significant at the 1 percent level. Consequently, these findings suggest that all the series are integrated of order one. The estimated break date is mainly in the periods 1998–1999 and 2008–2009, which are associated mostly with the financial crisis period. However, the other estimated break date is the period 2019–2023, which is connected to the COVID-19 pandemic. Likewise, all inverse roots are smaller than 1, which specifies that the VAR model is stationary, as depicted in Figure 4.5. This highlights that VAR satisfies the stability condition because all roots are situated inside the unit circle based on the inverse roots of the characteristic AR polynomial (Lütkepohl, 1991). In terms of robustness, the optimal

lag length selected for the VAR model selects one lag based on the outcomes of the VAR lag order selection criteria (i.e., LR, FPE, AIC, SC, and HQ criterion) as described in Table 4.12. Afterward, the residual tests are employed (i.e., the VAR residual serial correlation LM tests and the VAR residual heteroskedasticity tests with cross terms) as represented in Table 4.13. The results of residual tests reveal that there is no serial correlation and an absence of significant heteroskedasticity and specification bias problems in Model 3 (macro).

Table 4.11: Results of the Unit Root with Structural Breaks for Models 2 and 3

	Model 2			
	Level		**First Difference**	
	ADF_I	ADF_{TI}	ADF_I	ADF_{TI}
LVAA	−3.614(2)	−5.803(7)*	−7.895(0)*	−7.734(0)*
	[2002]	[2009]	[2009]	[2009]
LENOF	−4.330(5)**	−4.396(0)	−14.184(0)*	−13.996(0)*
	[2000]	[2002]	[2008]	[2008]
LEPRI	−3.732(5)	−3.664(3)	−4.939(1)**	−5.608(0)*
	[2008]	[2019]	[2009]	[2021]
LESEC	−3.296(9)	−2.936(7)	−6.070(0)*	−6.654(1)*
	[2000]	[2015]	[2000]	[2012]
LETER	−3.332(3)	−2.868(0)	−6.287(0)*	−6.345(0)*
	[1995]	[2015]	[1996]	[1996]
LFC	−3.014(9)	−5.110(4)**	−4.820(9)**	−5.242(9)**
	[2011]	[1993]	[1999]	[2011]
	Model 3			
LGDPA	−2.708(2)	−4.752(1)**	−6.045(1)*	−6.497(1)*
	[2003]	[2006]	[2004]	[2004]

Table 4.11 continued

LLNOF	−3.884(2)	−5.591(0)*	−11.826(0)*	−10.722(0)*
	[1999]	[2018]	[2021]	[1995]
LLPRI	−3.368(1)	−4.782(3)	−5.835(0)*	−5.671(0)*
	[2019]	[2019]	[2013]	[2013]
LLSEC	−5.123(5)*	2.691(7)	−5.322(0)*	−6.733(4)*
	[2009]	[2019]	[1993]	[2009]
LLTER	−2.661(3)	−2.776(0)	−6.092(0)*	−6.246(0)*
	[1998]	[2015]	[2011]	[1999]
LLFLF	−2.828(0)	−4.055(9)	−7.234(0)*	−6.882(0)*
	[1990]	[2001]	[1996]	[1996]

Notes: The number in parentheses and square brackets denotes the lag length and break date, respectively. ADF_I and ADF_{TI} represent intercept and trend & intercept specification, respectively, with intercept break, selecting Dickey–Fuller min-t as the breakpoint selection with break type innovational outlier. An asterisk (*) denotes that the test statistic is statistically significant at the 1 percent level of significance, (**) indicates statistical significance at the 5 percent level, and (***) indicates statistical significance at the 10 percent level.

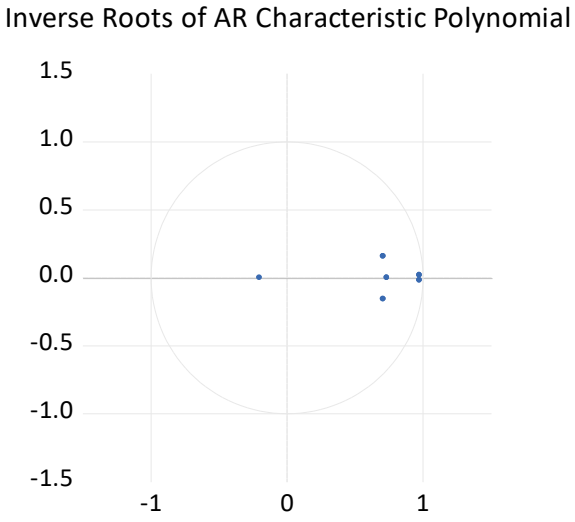


Figure 4.4: AR Roots Graph for Model 2

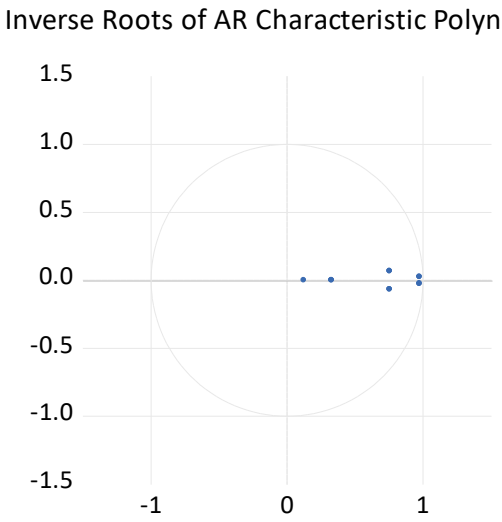


Figure 4.5: AR Roots Graph for Model 3

Table 4.12: VAR Lag Order Selection Criteria for Models 2 and 3

Model 2					
Lag	**LR**	**FPE**	**AIC**	**SC**	**HQ**
0	NA	7.63e−12	−8.571	−8.316	−8.480
1	395.881*	2.10e−16*	−19.097*	−17.305*	−18.454*
2	47.772	2.42e−16	−19.088	−15.761	−17.894
3	32.534	4.43e−16	−18.868	−14.006	−17.124
Model 3					
Lag	**LR**	**FPE**	**AIC**	**SC**	**HQ**
0	NA	9.37e−12	−8.367	−8.100	−8.275
1	329.352*	5.90e−16*	−18.072*	−16.206*	−17.428*
2	39.078	9.46e−16	−17.791	−14.325	−16.595

Notes: LR denotes sequential modified LR test statistic (each test at the 5 percent level), FPE indicates final prediction error, AIC represents Akaike information criterion, SC denotes Schwarz information criterion, and HQ represents Hannan–Quinn information criterion. An asterisk (*) denotes the lag order selected by the criterion.

Table 4.13: Diagnostic Tests

VAR Residual Serial Correlation LM Tests			
H_0 : No serial correlation at lag h			
	LRE* stat	df	Prob.
Model 2	Lag 1= 41.920	36	0.230
	Lag 2= 47.367	36	0.097
Model 3	Lag 1= 32.345	36	0.643
	Lag 2= 39.849	36	0.303
H_0 : No serial correlation at lags 1 to h			
	LRE* stat	df	Prob.
Model 2	Lag 1= 41.920	36	0.230
	Lag 2= 86.224	72	0.121
Model 3	Lag 1= 32.345	36	0.643
	Lag 2= 81.874	72	0.199
VAR Residual Heteroskedasticity Tests			
Joint test:			
	Chi-sq	df	Prob.
Model 2	604.201	567	0.135
Model 3	611.905	567	0.094

Notes: An asterisk denotes the Edgeworth expansion corrected likelihood ratio statistic, using the LR version of the Breusch–Godfrey Lagrange Multiplier (LM) test for autocorrelation with the Edgeworth expansion correction proposed by Edgerton and Shukur (1999). VAR residual heteroskedasticity tests are the system equation extension of White's (1980) test.

4.3.2 Johansen and Juselius Cointegration Test

This study uses the Johansen and Juselius (1990) cointegration test to test the long-run equilibrium relationship among the tested variables. The null hypothesis of the cointegration test is the number of cointegrating vectors, which is r. The number of r starts at 0, while the alternative hypothesis is that the number of cointegrating vectors is r+1.

Table 4.14 shows the results of the Johansen and Juselius (1990) cointegration test, which consists of the test statistics of the Max-Eigen statistic and Trace statistic with each respective critical value at the 5% level of significance.

Table 4.14: Results of the Johansen and Juselius Cointegration Test for Models 2 and 3

Model 2					
		k=1 r=0			
		Max-Eigen		**Trace**	
Null	**Alternative**	**Unadjusted**	**95% C.V.**	**Unadjusted**	**95% C.V.**
r = 0	**r = 1**	31.920	40.078	94.231	95.754
r ≤ 1	**r = 2**	28.349	33.877	62.311	69.819
r ≤ 2	**r = 3**	14.440	27.584	33.962	47.856
r ≤ 3	**r = 4**	11.511	21.132	19.522	29.797
r ≤ 4	**r = 5**	7.549	14.265	8.011	15.495
r ≤ 5	**r = 6**	0.462	3.841	0.462	3.841
Model 3					
		k=1 r=1			
		Max-Eigen		**Trace**	
Null	**Alternative**	**Unadjusted**	**95% C.V.**	**Unadjusted**	**95% C.V.**
r = 0	**r = 1**	39.586	40.078	107.962**	95.754
r ≤ 1	**r = 2**	28.867	33.877	68.376	69.819
r ≤ 2	**r = 3**	22.565	27.584	39.509	47.856
r ≤ 3	**r = 4**	11.673	21.132	16.944	29.797
r ≤ 4	**r = 5**	4.486	14.265	5.272	15.495
r ≤ 5	**r = 6**	0.786	3.841	0.786	3.841

Notes: k denotes the number of lag lengths, and r represents the number of cointegrating vectors detected. Asterisks (**) indicate statistical significance at the 5 percent level.

The results of Model 2 indicate that both the Max-Eigen and Trace Statistics suggest that no cointegrating vector was found. This result concluded that no cointegrating vector was detected from Model 2, as evidenced by the Max-Eigen statistic with 1 lag length. This finding implies that there is an absence of a long-run equilibrium relationship between the tested variables. For Model 2 (meso), the results suggest that the analysis should proceed to test the direction of causality using VAR modeling for the variables. Additionally, the findings indicate that the Trace Statistic from Model 3 reveals the presence of one cointegrating vector, which contradicts the outcome suggested by the Max-Eigen statistic. Johansen and Juselius (1990) stated that the Max-Eigen test statistic should be considered because this is more powerful than the Trace test statistic. The results indicate that no cointegrating vector was detected in Model 3, as suggested by the Max-Eigen statistic with 1 lag length. This result implies the absence of a long-run equilibrium relationship among the tested variables. Afterward, the results recommend proceeding to test the causality direction by using the VAR modeling for the variables in Model 3 (macro).

4.3.3 Vector Autoregressive Granger Causality Test

Table 4.15 indicates the Granger causality test results, which are estimated through a vector autoregressive (VAR) model. The Granger (1988) causality test is used to determine the existence and direction of the causality between all the tested variables in the model. A summary of the results for Model 2 indicates that a high education level does not Granger-cause value-added agriculture, especially for employed workers who have secondary and tertiary education (see Table 4.15). The results demonstrate that only LENOF does Granger-cause LVAA at the 5 percent level of significance.

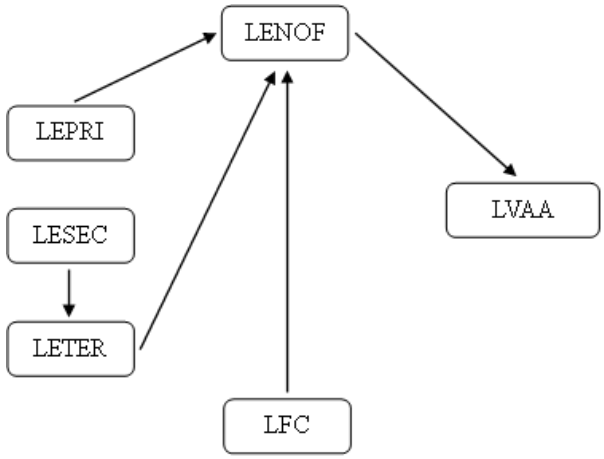
Table 4.15: Results of the VAR Granger Causality Test for Models 2 and 3

Model 2						
Dependent Variable	**ΔLVAA**	**ΔLENOF**	**ΔLEPRI**	**ΔLESEC**	**ΔLETER**	**ΔLFC**
	χ^2 Statistic (p- value)					
ΔLVAA	-	4.172 (0.041)**	0.002 (0.969)	2.639 (0.104)	0.781 (0.377)	0.173 (0.677)
ΔLENOF	0.603 (0.438)	-	6.903 (0.009)**	0.137 (0.711)	9.151 (0.003)**	5.265 (0.022)**
ΔLEPRI	1.091 (0.296)	0.001 (0.978)	-	0.040 (0.842)	0.010 (0.921)	0.015 (0.903)
ΔLESEC	0.006 (0.939)	1.177 (0.278)	0.002 (0.966)	-	0.151 (0.697)	1.506 (0.220)
ΔLETER	0.004 (0.948)	0.329 (0.566)	0.988 (0.320)	4.540 (0.033)**	-	0.190 (0.663)
ΔLFC	0.137 (0.712)	2.093 (0.148)	1.841 (0.175)	0.003 (0.955)	2.109 (0.147)	-
Model 3						
Dependent Variable	**ΔLGDPA**	**ΔLLNOF**	**ΔLLPRI**	**ΔLLSEC**	**ΔLLTER**	**ΔLLFLF**
	χ^2 Statistic (p- value)					
ΔLGDPA	-	0.330 (0.566)	0.029 (0.865)	0.583 (0.445)	2.908 (0.088)***	0.080 (0.777)
ΔLLNOF	0.472 (0.492)	-	3.927 (0.048)**	0.033 (0.855)	3.137 (0.077)***	0.386 (0.535)
ΔLLPRI	1.423 (0.233)	0.686 (0.407)	-	0.571 (0.450)	0.192 (0.662)	0.892 (0.345)
ΔLLSEC	0.825 (0.364)	0.518 (0.472)	0.001 (0.977)	-	0.552 (0.458)	0.720 (0.396)

Table 4.15 continued

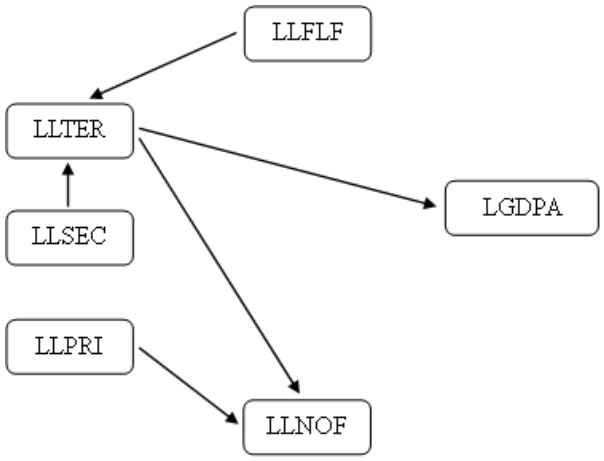
ΔLLTER	0.213	2.136	0.712	7.634	-	2.977
	(0.645)	(0.144)	(0.399)	(0.006)**		(0.085)***
ΔLLFLF	0.569	0.010	0.007	0.078	0.130	-
	(0.451)	(0.921)	(0.935)	(0.781)	(0.719)	

Notes: The chi-square statistic is represented by the symbol χ^2. Asterisks (** and ***) indicate statistical significance at the 5 percent and 10 percent levels, respectively. Δ is the first difference operator.



Notes: Figure 4.6 displays the unidirectional causality between tested variables (i.e., LVAA, LENOF, LEPRI, LESEC, LETER, and LFC) based on the results of the VAR Granger causality test in Table 4.15.

Figure 4.6: Results of the VAR Granger Causality Flow for Model 2



Notes: Figure 4.7 illustrates the unidirectional causality between tested variables (i.e., LGDPA, LLNOF, LLPRI, LLSEC, LLTER, and LLFLF), in accordance with the results of the VAR Granger causality test in Table 4.15.

Figure 4.7: Results of the VAR Granger Causality Flow for Model 3

The Granger causality flow shows that there is a unidirectional causality running from LENOF to LVAA, as illustrated in Figure 4.6. The results of the Granger causality test reveal that only employed workers lacking formal education can affect the value-added agriculture between 1982 and 2023. This result implies that employed workers with primary education (LEPRI), employed workers with secondary education (LESEC), employed workers with tertiary education (LETER), and fixed capital (LFC) do not Granger-cause value-added agriculture during the study period; however, only employed workers with no formal education can Granger-cause value-added agriculture based on the results of the VAR Granger causality test (see Table 4.15). The findings suggest that employed workers with tertiary education can Granger-cause individuals with no formal education at the 5 percent level of significance. Additionally, the VAR Granger causality test indicates that employed workers with primary education can also Granger-cause those with no formal education.

Employed workers with no formal education (LENOF) are much affected by the other variables (i.e., independent variables). The results reveal that LEPRI, LETER, and LFC Granger-cause LENOF, respectively, at the same time. This finding indicates that workers with primary education, workers with tertiary education, and fixed capital are the independent variables in the study—where can Granger-cause workers with no formal education, respectively, at the 5 percent level of significance. Additionally, the employed workers with secondary education can Granger-cause those with tertiary education at the 5% significance level (see Table 4.15). Likewise, the VAR Granger causality flow (see Figure 4.6) illustrates that LESEC has a unidirectional causal relationship with LETER. Specifically, there is a unidirectional causality running from LESEC to LETER—indicating that the employed workers with secondary education can Granger-cause

employed workers with tertiary education at the 5% level of significance. Based on the VAR Granger causality flow, LENOF is the most endogenous variable among the tested variables, as it is influenced by three variables simultaneously between 1982 and 2023.

The summary of the results demonstrates that value-added agriculture in this study from 1982 to 2023 was not affected by high education levels, particularly among employed workers with secondary education and employed workers with tertiary education. This means that only employed workers with no formal education can Granger-cause value-added agriculture during the study period. Based on the results of the VAR Granger causality flow, there is unidirectional causality running from LENOF to LVAA between 1982 and 2023. The results also reveal that fixed capital does not Granger-cause value-added agriculture at the same time. Employed workers lacking formal education are considered an endogenous variable in this study due to being much affected by other variables (i.e., employed workers with primary education, employed workers with tertiary education, and fixed capital), based on the results of the VAR Granger causality test (see Table 4.15). The results show that LEPRI, LETER, and LFC can Granger-cause LENOF at the 5% significance level, respectively. The VAR Granger causality results demonstrate that, during the study period, only employed workers without a formal education impacted value-added agriculture, while the other independent variables had no such effect.

For Model 3 (macro), the results of the VAR Granger causality test are portrayed in Table 4.15, while Figure 4.7 shows the VAR Granger causality flow results for Model 3. The Granger (1988) causality test is used to determine the existence and direction of the causality between all the tested variables in the model. The results of Model 3 indicate that LLTER does Granger-cause LGDPA, respectively, at the 10 percent level of significance

(see Table 4.15). The Granger causality flow illustrates that there is a unidirectional causal relationship running from LLTER to LGDPA (see Figure 4.7). The summary of the results for Model 3 confirms that tertiary education does Granger-cause agricultural GDP. This underscores that the labor force with tertiary education can affect the agricultural GDP during the study period.

The results of the VAR Granger causality test (see Table 4.15) show that the Malaysian labor force lacking formal education, as well as those with primary and secondary education, do not Granger-cause agricultural GDP. Additionally, the results also indicate that the foreign labor force does not Granger-cause agricultural GDP between 1987 and 2023. This result proves that the foreign labor force does not affect the agricultural GDP in Malaysia—since only a small percentage of the foreign labor force has a tertiary education level. Moreover, the results indicate that LLSEC Granger causes LLTER at the 5% level of significance. The finding underlines that the Malaysian labor force with secondary education can impact the labor force with tertiary education during the study period. Afterward, the Granger causality flow illustrates that LLSEC has a unidirectional causal relationship with LLTER in the study (see Figure 4.7). The foreign labor force does Granger-cause tertiary education at the 10 percent level of significance during the study period. The Granger causality flow illustrates that there is a unidirectional causal relationship from LLFLF to LLTER in the study. Likewise, the results demonstrate that LLTER can Granger-cause LLNOF at the 10 percent level of significance, while LLPRI does Granger-cause LLNOF at the 5 percent significance level. In other words, the Malaysian labor force with tertiary education affected the labor force with no formal education between 1987 and 2023, while the labor force with primary education affected the labor force with no formal education. The Granger causality flow illustrates that there

is unidirectional causality running from LLTER to LLNOF and from LLPRI to LLNOF. Based on the Granger causality flow (see Figure 4.7), LLTER and LLNOF are the most endogenous variables among the tested variables due to being influenced by two variables at the same time.

The summary of the results indicates that higher education—specifically, the labor force with tertiary education Granger-cause agricultural GDP from 1987 to 2023. The Malaysian labor force with secondary education influenced those with tertiary education during the study period. The Malaysian labor force with tertiary education can influence those with no formal education, while primary education also impacts the labor force lacking formal education. The results reveal that the labor force with education levels (i.e., no formal education, primary education, and secondary education) does not Granger-cause agricultural GDP, according to the findings of the VAR Granger causality test. Furthermore, the results also reveal that the foreign labor force did not affect the agricultural GDP in Malaysia between 1987 and 2023.

4.3.4 Variance Decomposition

Table 4.16: Variance Decomposition Results for Models 2 and 3

Model 2								
Percentage of Variations in	Horizon (Years)	Due to Innovation in:						
		ΔLVAA	ΔLENOF	ΔLEPRI	ΔLESEC	ΔLETER	ΔLFC	ΔCU
Years Relative Variance in: ΔLVAA								
	1	**100**	0	0	0	0	0	0
	4	**79.414**	11.763	0.686	2.061	5.747	0.330	20.586
	8	**70.476**	11.899	0.926	2.461	13.708	0.530	29.524
	12	**68.121**	11.465	1.096	2.581	16.136	0.602	31.879

Table 4.16 continued

20	**65.433**	10.872	1.434	3.728	17.277	1.256	34.567
30	**63.334**	10.383	1.406	5.108	17.806	1.963	36.666
40	**61.744**	10.041	1.635	6.260	17.871	2.449	38.256
50	**60.466**	9.790	2.157	7.116	17.714	2.756	39.534
Years Relative Variance in: ΔLENOF							
1	3.985	**96.015**	0	0	0	0	3.985
4	4.933	**72.599**	8.756	0.429	7.634	5.650	27.401
8	4.785	**69.235**	10.024	2.542	7.894	5.521	30.765
12	4.742	**67.044**	10.700	4.273	7.664	5.576	32.956
20	4.710	**63.770**	12.522	5.926	7.322	5.751	36.230
30	4.608	**61.128**	14.558	6.866	7.035	5.804	38.872
40	4.515	**59.546**	15.976	7.318	6.854	5.792	40.454
50	4.450	**58.622**	16.898	7.516	6.753	5.760	41.378
Years Relative Variance in: ΔLEPRI							
1	6.143	5.043	**88.813**	0	0	0	11.187
4	2.534	4.677	**92.574**	0.163	0.012	0.039	7.426
8	1.936	3.496	**92.927**	1.035	0.575	0.031	7.073
12	1.946	2.891	**91.598**	1.793	1.738	0.035	8.402
20	2.090	2.375	**89.662**	2.164	3.677	0.032	10.338
30	2.422	2.145	**88.114**	2.014	5.223	0.083	11.886
40	2.780	2.054	**86.756**	1.944	6.256	0.210	13.244
50	3.079	2.011	**85.556**	2.056	6.923	0.376	14.444
Years Relative Variance in: ΔLESEC							
1	20.275	0.067	8.387	**71.271**	0	0	28.729
4	16.562	1.396	12.819	**66.914**	0.079	2.230	33.086
8	13.452	1.026	21.393	**59.424**	0.393	4.312	40.576
12	11.396	0.820	27.893	**53.832**	0.657	5.402	46.168

Table 4.16 continued

20	9.054	0.628	35.981	**47.416**	0.759	6.162	52.584
30	7.599	0.536	41.602	**43.375**	0.653	6.234	56.625
40	6.832	0.499	44.915	**41.088**	0.587	6.079	58.912
50	6.412	0.482	46.921	**39.683**	0.594	5.907	60.317
Years Relative Variance in: ΔLETER							
1	9.583	8.800	1.186	0.004	**80.426**	0	19.574
4	9.848	3.824	0.848	4.592	**79.313**	1.575	20.687
8	11.417	2.425	1.638	13.235	**65.575**	5.709	34.425
12	13.040	1.855	1.430	18.572	**56.570**	8.534	43.430
20	14.471	1.313	1.483	24.207	**47.356**	11.168	52.644
30	14.379	1.016	3.698	27.913	**40.645**	12.348	59.355
40	13.702	0.867	7.003	29.734	**36.069**	12.626	63.931
50	12.974	0.785	10.304	30.482	**32.919**	12.535	67.081
Years Relative Variance in: ΔLFC							
1	16.303	12.309	0.132	0.818	0.023	**70.415**	29.585
4	10.064	19.055	4.814	0.572	2.199	**63.295**	36.705
8	8.668	16.282	9.959	1.062	5.261	**58.768**	41.232
12	8.384	14.549	13.021	2.893	6.747	**54.406**	45.594
20	8.133	12.463	16.468	7.290	7.134	**48.512**	51.488
30	7.798	10.976	19.837	10.657	6.737	**43.994**	56.006
40	7.451	10.127	22.583	12.291	6.321	**41.227**	58.773
50	7.173	9.632	24.623	13.044	6.020	**39.508**	60.492

Model 3

Percentage of Variations in	Horizon (Years)	Due to Innovation in:						
		ΔLGDPA	ΔLLNOF	ΔLLPRI	ΔLLSEC	ΔLLTER	ΔLLFLF	ΔCU
Years Relative Variance in: ΔLGDPA								
	1	**100**	0	0	0	0	0	0

Table 4.16 continued

4	**85.766**	2.301	1.615	1.264	7.329	1.726	14.234
8	**72.810**	2.783	2.945	1.681	12.760	7.020	27.190
12	**65.651**	4.046	3.267	3.315	14.752	8.968	34.349
20	**52.618**	6.811	12.598	4.644	15.410	7.919	47.382
30	**40.865**	8.894	26.512	3.929	13.890	5.911	59.135
40	**34.430**	9.899	35.393	3.178	12.341	4.758	65.570
50	**30.975**	10.357	40.499	2.787	11.222	4.159	69.025
Years Relative Variance in: ΔLLNOF							
1	5.098	**94.902**	0	0	0	0	5.098
4	5.906	**77.674**	12.760	0.148	2.860	0.653	22.326
8	5.456	**62.707**	28.274	0.129	2.904	0.530	37.293
12	5.976	**52.642**	37.803	0.202	2.843	0.535	47.358
20	6.740	**42.871**	46.599	0.498	2.683	0.609	14.258
30	7.128	**38.018**	50.792	0.885	2.484	0.693	61.982
40	7.286	**35.983**	52.397	1.223	2.344	0.767	64.017
50	7.346	**35.117**	52.956	1.487	2.270	0.824	64.883
Years Relative Variance in: ΔLLPRI							
1	0.366	7.381	**92.252**	0	0	0	7.748
4	2.864	11.187	**83.728**	0.806	0.017	1.397	16.272
8	5.737	10.119	**79.396**	2.365	0.035	2.348	20.604
12	6.866	9.648	**77.222**	3.582	0.039	2.643	22.778
20	7.479	9.273	**75.078**	5.285	0.037	2.848	24.922
30	7.571	8.990	**73.628**	6.668	0.118	3.025	26.372
40	7.528	8.821	**72.699**	7.510	0.291	3.151	27.301
50	7.472	8.770	**72.130**	7.926	0.496	3.205	27.870
Years Relative Variance in: ΔLLSEC							
1	0.114	0.177	23.254	**76.455**	0	0	23.545

Table 4.16 continued

4	2.396	3.308	36.287	**54.840**	2.209	0.960	45.160
8	4.993	4.304	42.151	**41.905**	5.770	0.877	58.095
12	5.833	5.520	44.413	**35.410**	8.147	0.678	64.590
20	6.213	7.890	48.411	**26.804**	10.126	0.556	73.196
30	6.563	9.798	53.606	**19.597**	10.022	0.414	80.403
40	6.916	10.711	57.400	**15.417**	9.220	0.336	84.583
50	7.175	11.101	59.728	**13.188**	8.482	0.327	86.812
Years Relative Variance in: ΔLLTER							
1	0.454	9.335	10.783	0.546	**78.882**	0	21.118
4	0.252	4.815	9.524	18.267	**62.337**	4.805	37.663
8	0.678	7.353	13.903	25.451	**46.829**	5.785	53.171
12	1.520	9.464	22.244	23.686	**38.208**	4.878	61.792
20	3.372	11.837	37.591	16.599	**27.576**	3.025	72.424
30	4.951	12.930	49.173	10.726	**20.376**	1.844	79.624
40	5.848	13.226	55.256	7.829	**16.486**	1.355	83.514
50	6.357	13.247	58.481	6.473	**14.277**	1.164	85.723
Years Relative Variance in: ΔLLFLF							
1	3.693	0.154	68.121	5.332	0.425	**22.277**	77.723
4	9.269	0.084	63.161	6.180	0.205	**21.101**	78.899
8	11.892	0.092	61.096	6.236	0.418	**20.266**	79.734
12	12.406	0.131	60.458	6.526	0.779	**19.701**	80.299
20	12.335	0.351	59.768	7.024	1.431	**19.090**	80.910
30	12.088	0.859	59.513	7.138	2.003	**18.399**	81.601
40	11.886	1.434	59.790	6.927	2.332	**17.631**	82.369
50	11.745	1.917	60.228	6.669	2.484	**16.957**	83.043

Notes: The last column provides the percentage of forecast error variances for each variable explained collectively by the other variables. The bold column represents the impact of one's own shock.

As VAR Granger causality results indicate the direction of causality, variance decomposition is applied to examine the strength of the causal relationship between the tested variables. Table 4.16 shows the decomposition of the forecast error variable up to 50 years for Models 1 and 2. It can strengthen the VAR Granger causality results by presenting the percentage of variance in each variable that is caused by other variables. This test can identify the most endogenous and exogenous variables in the model, as well as provide information about the most influential variable. For Model 2 (meso), the results of variance decomposition provide additional support for the Granger causality findings regarding the effect of the educational quality of employed workers on value-added agriculture in Malaysia.

There is approximately 39.53% of the forecast error variance in LVAA that can be explained by the shock of other variables, which are 9.79% by LENOF, 2.16% by LEPRI, 7.12% by LESEC, 17.71% by LETER, and 2.76% by LFC at the end of 50 years. This result underlines that the employed workers with no formal education shocks account for more than 9 percent of value-added agriculture. This percentage value infers that LENOF is the second most influential variable to LVAA, as the variations from this variable keep taking the second major portion throughout these 50 years. This result indicates that employed workers without formal education can significantly impact value-added agriculture when compared to those with formal education. Variance decomposition shows that employed workers with tertiary education are able to explain more than 17 percent of forecast error variance in value-added agriculture throughout 50 years. Meanwhile, employed workers with tertiary education affect a large portion of value-added agriculture in Malaysia; however, the VAR Granger causality results indicate that LETER does not Granger-cause LVAA during the study period. It is also affirmed by variance

decomposition that the employed workers with primary education do not significantly explain the forecast error variance in value-added agriculture. Therefore, variance decomposition results indicate that LENOF has a significant impact on LVAA if compared with other variables, while this result is consistent with the findings of the VAR Granger causality test, where only LENOF can Granger-cause LVAA between 1987 and 2023. Furthermore, around 41.38% of forecast error variance in LENOF was explained by LVAA (4.45%), LEPRI (16.90%), LESEC (7.52%), LETER (6.75%), and LFC (5.76%) at the end of 50 years.

According to the variance decomposition results, LETER is the most endogenous variable in this study instead of LVAA as a dependent variable—since LETER highly absorbs the shocks from the other variables, and only around 32.92% of the variation can be explained by itself at the end of 50 years if compared with the other variables. LETER indicates that among the 67.08% forecast error variance, approximately 12.97%, 0.79%, 10.30%, 30.48%, and 12.54% of variation can be caused by LVAA, LENOF, LEPRI, LESEC, and LFC, respectively. These percentage values indicate that LESEC is the most influential variable to LETER, as its variations account for the major portion throughout these 50 years. This result suggests that employed workers with secondary education can significantly impact those with tertiary education compared to others. In the meantime, employed workers with no formal education can only affect a small percentage of the employed workers with tertiary education in Malaysia. Thus, the results indicate that LESEC has a significant impact on LETER; this result is consistent with the findings of the VAR Granger causality test (see Table 4.15), where LESEC does Granger-cause LETER during the study period. There is approximately 60.49% of the forecast error variance in LFC that can be explained by the shock of other variables, which are 7.17% by LVAA,

9.63% by LENOF, 24.62% by LEPRI, 13.04% by LESEC, and 6.02% by LETER at the end of 50 years. This variance decomposition result indicates that primary education occupies the most significant portion, which means that it can affect a large part of the fixed capital in 50 years. Furthermore, around 60.32% of forecast error variance in LESEC was explained by LVAA (6.41%), LENOF (0.48%), LEPRI (46.92%), LETER (0.59%), and LFC (5.91%) at the end of 50 years.

LEPRI is indicated to be the most exogenous variable, according to the results of variance decomposition, because the percentage of variation is approximately 85.56%—which is caused by LEPRI itself and is greater than the variations caused by other variables at the end of 50 years. LEPRI reveals that among the 14.44% of forecast error variance, about 3.08%, 2.01%, 2.06%, 6.92%, and 0.38% of variation can be caused by LVAA, LENOF, LESEC, LETER, and LFC, respectively. Compared to the changes in CU of the other variables, LEPRI has the lowest value of CU at the end of the 50 years, which implies that LEPRI is less affected by the other variables and most of the impact is coming from itself. Thus, the variance decomposition results are consistent with the results of the VAR Granger causality test, in which LEPRI is not Granger caused by any variables. Surprisingly, LVAA is the second most exogenous variable based on the variance decomposition results in this study. LVAA indicates that among the 39.53% of forecast error variance, 9.79%, 2.16%, 7.12%, 17.71%, and 2.76% of variation can be caused by LENOF, LEPRI, LESEC, LETER, and LFC, respectively. These percentage values specify that LVAA is the most influenced by LETER throughout these 50 years.

For Model 3 (macro), the variance decomposition results corroborate the Granger causality results for the effect of educational quality on agricultural GDP. 69.03% of the

forecast error variance in LGDPA can be explained by the shock of other variables, which are 10.36% by LLNOF, 40.50% by LLPRI, 2.79% by LLSEC, 11.22% by LLTER, and 4.16% by LLFLF at the end of 50 years. This result specifies that the labor force with tertiary education shocks accounts for more than 11 percent of agricultural GDP. This percentage value suggests that the labor force with tertiary education is the second most influential variable to agricultural GDP, as its variations have accounted for the second largest portion in 50 years. In other words, the result explains that the labor force with tertiary education affects the second largest part of agricultural GDP. This result is consistent with the findings of the VAR Granger causality test, where LETER does Granger-cause LGDPA between 1987 and 2023. Furthermore, variance decomposition reveals that the labor force with primary education can explain more than 40 percent of forecast error variance in agricultural GDP at the end of 50 years. This finding underscores that the effect of the labor force with primary education is greater than the labor force with tertiary education on agricultural GDP. However, this result is inconsistent with the findings of the VAR Granger causality test—where LEPRI does not Granger-cause LGDPA during the study period. Variance decomposition also affirms that the labor force with secondary education and the foreign labor force do not significantly explain the forecast error variance in agricultural GDP. Additionally, approximately 64.88% of forecast error variance in LLNOF was explained by LGDPA (7.35%), LLPRI (52.96%), LLSEC (1.49%), LLTER (2.27%), and LLFLF (0.82%) at the end of 50 years.

Based on the results of variance decomposition, LLSEC stands out as the most endogenous variable—since it is highly absorbing the shocks from the other variables, and only around 13.19% of variation can be explained by itself at the end of the 50 years. LLSEC indicates that among the 86.81% of forecast error variance, about 7.18%, 11.10%,

59.73%, 8.48%, and 0.33% of variation can be caused by LGDPA, LLNOF, LLPRI, LLTER, and LLFLF, respectively. These percentage values indicate that LLPRI is the most influential variable affecting LLSEC, as its variations consistently account for the largest portion over the span of 50 years. However, the VAR Granger causality results reveal that secondary education is not Granger-caused by primary education between 1987 and 2023.

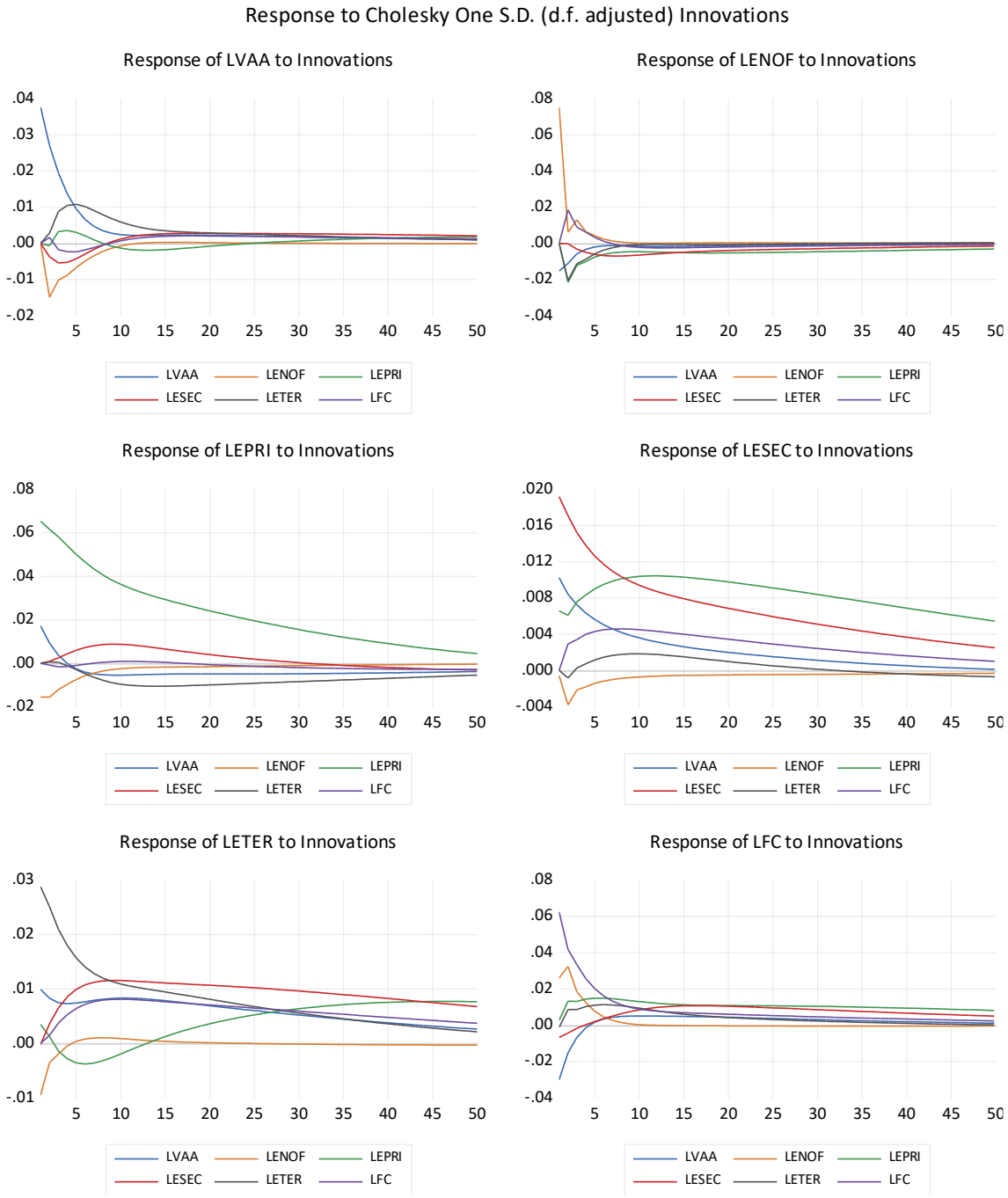
LLFLF shows that among the 83.04% of forecast error variance, about 11.75%, 1.92%, 60.23%, 6.67%, and 2.48% of variation can be caused by LGDPA, LLNOF, LLPRI, LLSEC, and LLTER, respectively—this percentage value infers that LLPRI is the most influential variable for LLFLF, as its variations keep taking up the largest portion throughout these 50 years. Meanwhile, this result reveals primary education affects a large part of the foreign labor force; however, no formal education and tertiary education affect a small part of the foreign labor force, respectively. Nevertheless, the result is consistent with a study by the Central Bank of Malaysia, which indicates that a significant proportion of migrants in Malaysia have low educational attainment, with only 5.2% possessing tertiary education (Ang et al., 2018).

There is about 27.87% of the forecast error variance in LLPRI that was caused by the shock of the other variables, which are 7.47% by LGDPA, 8.77% by LLNOF, 7.93% by LLSEC, 0.50% by LLTER, and 3.21% by LLFLF at the end of 50 years. LLPRI is the most exogenous variable, as the percentage of variation caused by it is greater than that caused by other variables each year. Compared to the changes in CU of the other variables, LLPRI has the lowest value of CU at the end of the 50 years, which implies that LLPRI is less affected by other variables and most of the impact comes from itself. The results of the

VAR Granger causality test also attest that all other variables do not Granger-cause LLPRI (see Table 4.15).

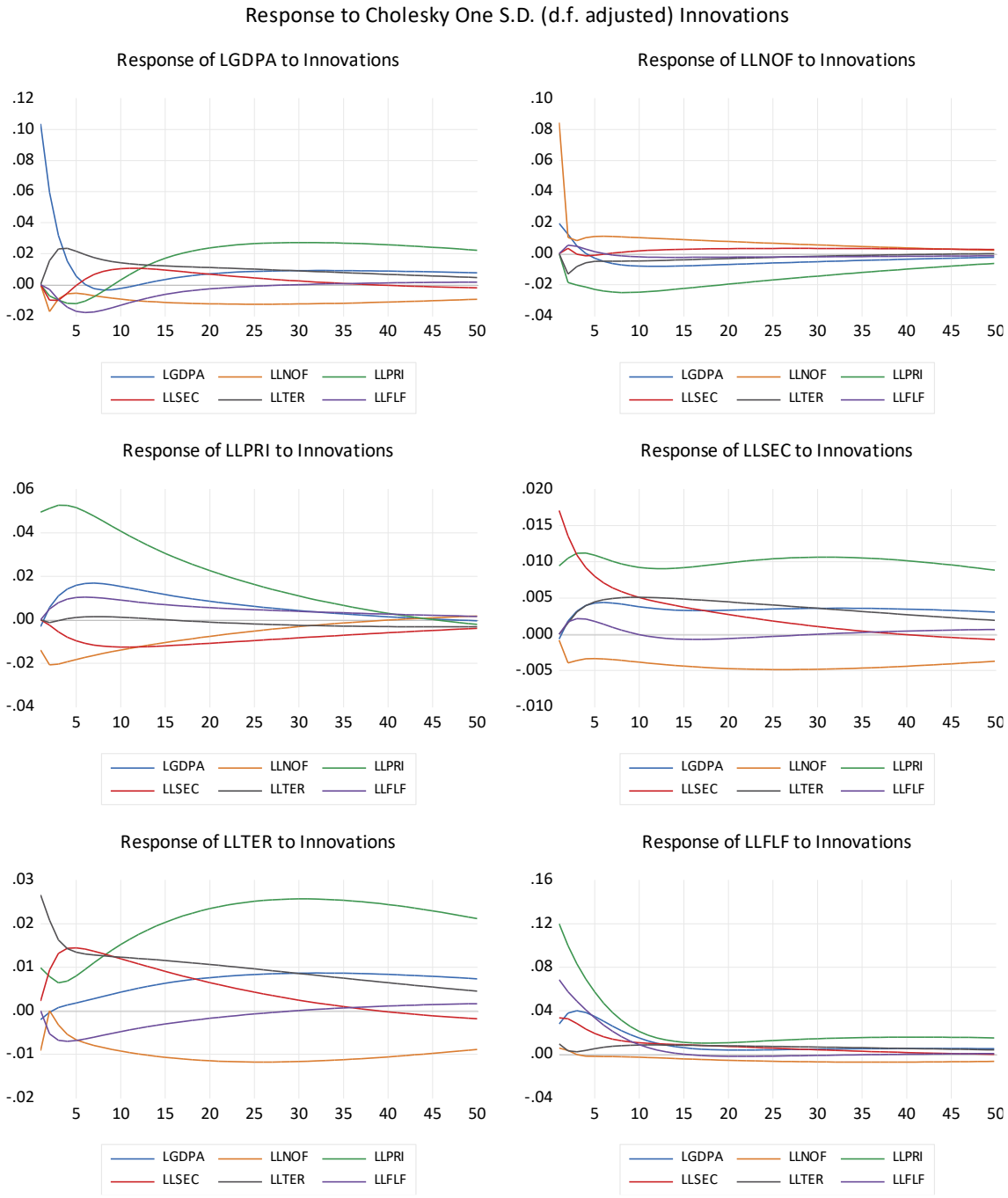
4.3.5 Impulse Response Function

Figure 4.8 displays the results of the Impulse Response Function (IRF) over a 50-year horizon. The impulse response analysis is applied by utilizing the Cholesky decomposition and adjustment in the degree of freedom (Cholesky dof adjusted) to describe the evolution of a model's variables in reaction to a shock in one or more variables. This study illustrates the effect of education-level shocks on value-added agriculture over a 50-year period. In accordance with the graph in Figure 4.8, LVAA's response to a shock in the LENOF is both negative and significant, but this effect lasts only for the first 12 years. This finding suggests that employed workers lacking formal education have a negative impact on value-added agriculture, especially in the second year.



Notes: Figure 4.8 was developed by using EViews and the Cholesky decomposition method (dof) for impulse response over 50 years. Each variable (i.e., LVAA, LENOF, LEPRI, LESEC, LETER, and LFC) is represented by the different colors of lines as stated above.

Figure 4.8: Results of the Impulse Response Function for Model 2



Notes: Figure 4.9 was developed by using EViews and the Cholesky decomposition method (dof) for impulse response throughout 50 years. Each variable (i.e., LGDPA, LLNOF, LLPRI, LLSEC, LLTER, and LLFLF) is characterized by the different colors of lines as stated above.

Figure 4.9: Results of the Impulse Response Function for Model 3

The negative response dramatically increases and reaches its peak in the second year, while it shows a significant decline from the third year until the 12th year. Then there

is a light positive effect that starts from the 13th until the 30th year; after that, there remains a negative impact from the 31st until the 50th year. This impulse response result further supports the results of the VAR Granger causality test (see Table 4.15)—it demonstrates that employed workers with no formal education negatively affect value-added agriculture between 1982 and 2023, especially having a significant negative effect in the second year. According to the impulse response results, only LETER as an independent variable has a positive impact on LVAA in 50 years, but LVAA does not Granger-cause LETER during the study period. The response of LVAA to LLTER indicates that employed workers with tertiary education positively impact value-added agriculture, particularly reaching its peak in the fifth year. This positive effect increases dramatically during the first five years and achieves its peak in the fifth year. Subsequently, this positive effect declines dramatically from the sixth year until the 15th year and then decreases slightly from the 16th until the 50th year. This finding indicates that tertiary education has a significant positive impact on value-added agriculture, especially in the beginning period.

Additionally, the response of LVAA to LESEC indicates that employed workers with secondary education have a negative impact on value-added agriculture only in the first 8 years; there is a dramatic increase in the first 3 years, which reaches its peak in the 3rd year, and then this negative effect decreases dramatically from the 4th year until the 9th year, while the significant positive effect happens from the 10th until the 15th year and then reaches its maximum in the 15th–20th year. Afterward, the positive effect declines slightly from the 20th year to the 50th year, as shown in the graph of the impulse response analysis (see Figure 4.8). The response of LVAA to LEPRI shows that employed workers with primary education adversely affect value-added agriculture in the beginning period and reach its peak in the second year. The positive response happens in the third year and then

increases remarkably to its peak in the fourth year. Then, this positive effect shows a significant decline from the 5th year until the 8th year. Later, the negative response happens again from the 9th year until the 24th year; this negative effect dramatically increases from the 9th year until the 13th year, and then it declines from the 14th year until the 25th year. The positive effect occurs again from the 26th year until the 50th year. Likewise, the response of LVAA to LFC indicates that fixed capital positively impacts value-added agriculture during the first two years. Following that, a negative effect occurs from the third year to the eighth year. However, the positive response remarkably increases from the ninth year to the seventeenth year. Afterward, the positive effect gradually decreases from the 18th year until the 50th year, as illustrated by the graph in the impulse response analysis (see Figure 4.8).

The response of LENOF to LFC suggests that fixed capital positively influences employed workers without formal education in the 7th year. However, a negative effect emerges from the 8th year and continues until the 50th year, as illustrated in the impulse response analysis graph. The positive response shows a significant increase from the 1st year to the 2nd year, peaking in the 2nd year. However, the positive response declines sharply from the third year to the sixth year. A negative effect emerges and significantly increases from the seventh year to the twelfth year, after which it decreases slightly from the twelfth year to the fiftieth year. This result reinforces the findings of the VAR Granger causality test, which indicates that fixed capital can positively affect the employed workers with no formal education but only in the first 7 years during the study period. In addition, the response of LENOF to LEPRI reveals that employed workers with only primary education have a negative impact on those without formal education over a span of 50 years. This effect is particularly pronounced in the early years, especially in the second

year, where a significant negative effect is observed. The negative response increases dramatically from the first year to the second year, reaches its peak, and then significantly declines from the third year until the ninth year. Thereafter, it gradually increases from the 10th year to the 19th year. There is a slight decline while maintaining a certain level of impact from the 20th to the 50th year. This result further reinforces the Granger causality findings, indicating that employed workers with primary education negatively impact the employed workers without formal education during the study period. This effect is particularly significant in the second year.

The results of impulse response analysis reveal that LFC's response to a shock in the LESEC is positive and significant, but only after the fourth year. This implies that employed workers with secondary education have a negative impact on fixed capital only in the first 3 years, while the positive effect occurs over 47 years. This result is inconsistent with the results of the VAR Granger causality test, which indicates that secondary education did not Granger-cause fixed capital during the study period (see Table 4.15). The positive effects occur dramatically after the initial three years, peaking in the sixteenth year. Following this peak, the positive response gradually diminishes starting in the 17th year and continuing until the 50th year. The response of LFC to a shock in the LETER is positive and significant, indicating a notable positive effect during the first six years. This response increases dramatically, reaching its peak in the sixth year. However, it then declines significantly from the seventh year until the twentieth year. The positive effect then gradually diminishes from the 20th year to the 50th year, as illustrated in the graph of the impulse response analysis (see Figure 4.8). Hence, this result indicates that the employed workers with tertiary education positively influence fixed capital over a 50-year

period. However, the findings from the Granger causality test reveal that tertiary education did not Granger-cause fixed capital during the study period.

Additionally, LENOF's response to a shock in the LETER is negative and significant, but this effect lasts only for the first two years. The result indicates that employed workers with tertiary education have a negative impact on employed workers without formal education over a 50-year period. The negative response remarkably increases in the first two years, reaches its peak in the second year, and then dramatically declines from the third year until the 10th year. Subsequently, the negative response gradually declines again from the 11th year until the 36th year, and then small positive effects happen from the 37th year until the 50th year. This finding further supports the VAR Granger causality results, which reveal that the employed workers with tertiary education have a significant negative impact on the employed workers with no formal education at the beginning of the study period; this impact increases significantly over the second year. The response of LETER to a shock in the LESEC is positive and significant. Employed workers with secondary education significantly and positively affect employed workers with tertiary education during the initial period, particularly over the first nine years. This positive response begins dramatically in the first year and peaks in the ninth year, after which the effect gradually diminishes from the tenth year to the fiftieth year. The graph of impulse response analysis supports the Granger causality findings, indicating that employed workers with secondary education have a positive effect on employed workers with tertiary education from 1982 to 2023. This positive effect is particularly significant in the ninth year.

Figure 4.9 shows the results of the Impulse Response Function (IRF) in Model 3 over a 50-year horizon. According to the graph in Figure 4.9, the response of LGDPA to a shock in the LLTER is both positive and significant. This suggests that the labor force with tertiary education has a positive impact on agricultural GDP throughout the 50 years, especially in the fourth year. The positive response increases dramatically, peaking in the fourth year. However, it significantly declines from the fifth year to the tenth year. It then declines gradually from the 11th year to the 50th year. This result further supports the Granger causality test, which shows that the labor force with tertiary education can positively affect the agricultural GDP during the study period, with a significant effect over the fourth year. In addition, the response of LGDPA to a shock in the LLSEC indicates that the labor force with secondary education negatively impacts agricultural GDP during the initial five years, reaching its peak in the third year. Then, a positive effect emerges and intensifies from the 6th year to the 11th year. Thereafter, this positive effect gradually declines from the 12th year until the 38th year, but the negative response occurs again from the 39th year until the 50th year. However, the results of the VAR Granger causality test, which concludes that the labor force with secondary education did not Granger-cause agricultural GDP between 1987 and 2023. The IRF results underscore that only the labor force with tertiary education positively affects the agricultural GDP over 50 years. Moreover, the response of LGDPA to LLPRI indicates that the negative effect of the labor force with primary education on agricultural GDP in the first 9 years, specifically the 5th year, reaches its peak. The positive effect begins on the 10th, continues until the 50th year, and reaches its maximum in the 30th year, as shown in the graph of the impulse response analysis (see Figure 4.9).

Additionally, the response of LGDPA to a shock in the LLNOF is both negative and significant, indicating that the labor force lacking formal education negatively impacts agricultural GDP over a span of 50 years. The findings indicate that the labor force lacking formal education has a negative impact on agricultural GDP; however, there is no evidence of causality between 1987 and 2023, according to the VAR Granger causality test results. The negative response increases dramatically and reaches its peak in the second year, followed by a significant decline from the third year until the fifth year, and then a gradual increase from the fifth year to the 26th year. Subsequently, this negative effect slightly decreases from the 27th year until the 50th year. The response of LGDPA to LLFLF shows that the foreign labor force has a negative impact on agricultural GDP only during the first 30 years, with a peak in the 6th year. Then, the graph of the impulse response analysis illustrates that the noticeable negative effect declines intensely from the 7th year to the 30th year. Afterward, the positive response occurs from the 31st year until the 50th year.

The response of LLTER to a shock in the LLSEC is both positive and significant; however, there is a negative response only in 12 years. The results suggest that the labor force with secondary education positively impacts the labor force with tertiary education during the initial 38 years, as illustrated by the graph in the impulse response analysis (see Figure 4.9). The positive response dramatically increases and reaches its maximum in the fifth year while showing a significant decline from the sixth year until the 38th year. Then, the result indicates that the negative effect starts from the 39th year until the 50th year. This result from the impulse response analysis further corroborates the findings of the VAR Granger causality test. It confirms that the labor force with secondary education had a positive impact on the labor force with tertiary education from 1987 to 2023, especially in the fifth year. The response of LLTER to a shock in LLFLF is negative—the foreign labor

force has a negative impact on the labor force with tertiary education in the first 30 years. There is a positive response from the 31st year until the 50th year, as indicated by the graph in Figure 4.9. This result reinforces the findings of the VAR Granger causality test, which demonstrated that the foreign labor force had a significant negative impact on the labor force with tertiary education, especially during the fourth year.

Moreover, the response of LLNOF to a shock in the LLTER is negative—the labor force with tertiary education negatively impacts the labor force lacking formal education over a period of 50 years. The negative response increases significantly, reaching its peak in the second year. Following this peak, there is a notable decline from the third year to the sixth year. Subsequently, a gradual decline occurs, maintaining a consistent level of impact from the seventh year to the fiftieth year. This result further supports the VAR Granger causality findings, concluding that the labor force with tertiary education had a negative impact on the labor force with no formal education between 1987 and 2023. This effect is particularly significant in the second year, as indicated by the graph of the impulse response analysis (see Figure 4.9). The response of LLNOF to a shock in LLPRI is both negative and significant. The labor force with primary education exerts a negative impact on the labor force without formal education over a period of 50 years. This negative response increases sharply, peaking in the 9th year, and then gradually diminishes from the 10th year to the 50th year. The findings underscore that the labor force with primary education has negatively impacted the labor force lacking formal education from 1987 to 2023, with a significant effect observed in the ninth year.

4.4 Labor Force Employment, Educational Quality, and Value-Added Industry

4.4.1 Unit Root and Stationary Tests

The study applies the unit root tests, such as the augmented Dickey–Fuller (ADF) test proposed by Dickey and Fuller (1979), the Phillips–Perron (PP) test proposed by Phillips and Perron (1988), and the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test proposed by Kwiatkowski et al. (1992) to identify the stationary properties of the tested variables in Model 4. Likewise, the unit root with break test is used in the study—the augmented Dickey–Fuller with structural breaks, based on the framework outlined (e.g., Banerjee et al., 1992; Perron, 1989; Vogelsang & Perron, 1998; Zivot & Andrews, 1992). This study performs a unit root test to determine that the variable under investigation is not stationary in the second difference. The Johansen and Juselius (1990) cointegration test cannot estimate the variables that are stationary in the second difference. Table 4.17 presents a summary of the descriptive statistics for the tested variables examined in the study. The value-added industry has the highest mean compared to other variables, followed by fixed capital. Only workers without formal education exhibit positive skewness, indicating a long right tail in the distribution. The workers with tertiary education exhibit the highest standard deviation, with fixed capital following closely behind. The Jarque–Bera is a test statistic for testing whether the series has a normal distribution in the study.

Table 4.17: Descriptive Statistics for Model 4

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	JB
LVAI	24.952	25.106	25.692	23.808	0.564	−0.565	2.036	3.864
LNOF	6.256	6.183	6.720	5.881	0.259	0.269	1.696	3.399
LPRI	7.635	7.701	7.779	7.014	0.183	−0.889	3.158	4.383

Table 4.17 continued

LSEC	8.509	8.599	9.055	7.621	0.437	−0.521	2.142	3.116
LTER	7.338	7.453	8.632	5.793	0.864	−0.209	1.788	2.810
LFC	14.396	14.434	15.407	13.081	0.714	−0.211	1.799	2.767

Notes: Std. Dev. denotes standard deviation, JB represents Jarque–Bera, LVAI refers to the logarithm of value-added industry measured in constant 2015 US dollars, and labor force employment is quantified in thousands of people.

Table 4.18: Results of Unit Root and Stationary Tests for Model 4

	ADF		**PP**		**KPSS**	
	Intercept	**Trend & Intercept**	**Intercept**	**Trend & Intercept**	**Intercept**	**Trend & Intercept**
			A: Level			
LVAI	−2.598(0)	−1.435(0)	−2.735(4)	−1.446(2)	0.777(5)*	0.196(5)**
LNOF	−1.780(2)	−2.090(1)	−1.603(0)	−4.256(4)*	0.754(5)*	0.172(4)**
LPRI	−0.377(0)	−1.743(1)	0.377(0)	−1.064(1)	0.530(4)**	0.157(4)**
LSEC	−4.437(0)*	−0.873(0)	−4.716(2)*	−0.826(2)	0.773(5)*	0.193(5)**
LTER	−2.294(0)	−1.001(0)	−6.016(23)*	0.385(39)	0.792(5)*	0.202(5)**
LFC	−1.434(0)	−3.313(4)***	−1.372(1)	−2.218(2)	0.779(5)*	0.093(4)
			B: First Difference			
ΔLVAI	−5.423(0)*	−5.816(0)*	−5.423(0)*	−5.799(4)*	0.497(1)**	0.070(5)
ΔLNOF	−12.086(0)*	−6.825(1)*	−12.704(1)*	−12.797(1)*	0.117(4)	0.077(6)
ΔLPRI	−4.471(0)*	−5.063(1)*	−4.406(2)*	−4.457(6)*	0.269(1)	0.075(3)
ΔLSEC	−4.385(0)*	−5.394(1)*	−4.568(4)*	−5.930(2)*	0.627(4)**	0.069(2)
ΔLTER	−5.572(0)*	−5.781(2)*	−5.579(10)*	−9.806(21)*	0.448(7)***	0.233(21)*
ΔLFC	−4.869(0)*	−4.873(0)*	−4.879(1)*	−4.887(1)*	0.136(1)	0.047(1)

Notes: The types of unit root tests used are the ADF, PP, and KPSS tests. The number in parentheses indicates the lag length or bandwidth utilized by the default settings in EViews. An asterisk (*) indicates the test statistic is statistically significant at the 1 percent significance level, (**) denotes statistical significance at the 5 percent level, and (***) indicates statistical significance at the 10 percent level. Δ refers to the first difference operator.

The dependent variable includes the logarithm of value-added industry (LVAI), and the independent variables consist of the logarithm of workers with no formal education (LNOF), the logarithm of workers with primary education (LPRI), the logarithm of workers with secondary education (LSEC), the logarithm of workers with tertiary education (LTER), and the logarithm of fixed capital (LFC). Table 4.18 portrays the results of unit root tests from ADF, PP, and KPSS tests in EViews. The null hypothesis of the ADF and PP tests is the variable that is non-stationary, while the null hypothesis of the KPSS test is the variable that is stationary. The rejection rule is to reject the null hypothesis when the t-statistic is higher than the critical value.

The results of the ADF unit root test at the level indicate that LVAI is non-stationary when only the intercept specification is considered and remains non-stationary when both the trend and intercept specifications are included. However, LVAI is stationary at the 1 percent significance level when only the intercept specification is considered. It is also stationary when both trend and intercept specifications are included in the first difference. The results of the PP unit root test indicate that LVAI is non-stationary at the level. However, when assessing the first difference, LVAI is found to be stationary at the 1 percent significance level for both the intercept and the trend with intercept specifications. The results of the KPSS unit root test at the level indicate that LVAI is non-stationary when considering both the intercept and trend with intercept specifications; however, it is found to be stationary only under the trend with intercept specification in the first difference. Based on the results from the ADF, PP, and KPSS unit root tests, the dependent variable LVAI is determined as an $I(1)$ variable.

Likewise, the statistical results of the ADF unit root test at the level suggest that independent variables (i.e., LNOF, LPRI, and LTER) are non-stationary at both the intercept and trend with intercept specifications. In contrast, LSEC is stationary at the 1 percent significance level at the intercept specification, while LFC is stationary at the 10 percent significance level at both the trend and intercept specifications. The ADF unit root test results for the first difference indicate that LNOF, LPRI, LSEC, LTER, and LFC are stationary at the 1 percent significance level for both the intercept and the trend with intercept specifications. Moreover, the results of the PP unit root test demonstrate that LNOF, LPRI, LSEC, LTER, and LFC are categorized as *I*(1) variables—most test statistics fail to reject the null hypothesis at the level stage, whereas all the test statistics reject the null hypothesis at the first difference. The KPSS unit root test results for the first difference indicate that only LTER is non-stationary in both the intercept and trend with intercept specifications. The independent variables LNOF, LPRI, LSEC, and LTER are identified as non-stationary at the intercept specification; however, at the level, these variables are also non-stationary at both the trend and intercept specifications. This infers that the KPSS unit root test results suggest that LNOF, LPRI, LSEC, LTER, and LFC are *I*(1) variables, as most test statistics in the KPSS unit root test reject the null hypothesis at the stage level. In conclusion, all the independent variables (i.e., LNOF, LPRI, LSEC, LTER, and LFC) are concluded to be stationary in the first difference, which is the *I*(1) variable, in accordance with the results of the ADF, PP, and KPSS unit root tests.

The results of the unit root test with structural breaks reveal that all the variables are statistically significant at the 1 percent significance level (see Table 4.19). This emphasizes that the combined results suggest that all the series are integrated of order one. The estimated break date is primarily in the periods 1998–1999 and 2008–2009, which are

related mostly to the financial crisis period. The period 2019–2023 is related to the COVID-19 pandemic. Then, all inverse roots are smaller than 1, indicating that the VAR model is stationary (see Figure 4.10). This means that VAR satisfies the stability condition because all roots are situated inside the unit circle, which is based on the inverse roots of the characteristic AR polynomial (Lütkepohl, 1991). For robustness analysis, the optimal lag length selected for the VAR model selects one lag based on the outcomes of the VAR lag order selection criteria (i.e., LR, FPE, AIC, SC, and HQ criterion), as shown in Table 4.20. Next, the residual tests are applied, which are the VAR residual serial correlation LM tests and the VAR residual heteroskedasticity tests with cross terms, as described in Table 4.21. Based on the results of residual tests, there is no serial correlation and an absence of significant heteroskedasticity and specification bias problems.

Table 4.19: Results of the Unit Root with Structural Breaks for Model 4

	Level		**First Difference**	
	ADF_I	ADF_{TI}	ADF_I	ADF_{TI}
LVAI	−2.984(0)	−3.276(0)	−6.806(0)*	−6.644(0)*
	[1987]	[1993]	[1998]	[1998]
LNOF	−3.011(0)	−5.996(0)*	−12.574(0)*	−12.738(0)*
	[2002]	[1999]	[2001]	[2023]
LPRI	−3.861(6)	−3.623(3)	−5.088(0)*	−5.791(0)*
	[2010]	[2020]	[2021]	[2021]
LSEC	−2.775(0)	−2.905(7)	−6.057(0)*	−6.712(1)*
	[1986]	[2015]	[2000]	[2010]
LTER	−3.421(3)	−2.318(0)	−6.215(0)*	−6.381(0)*
	[1995]	[1995]	[1996]	[1999]
LFC	−3.502(9)	−4.300(4)	−6.254(9)*	−6.859(9)*
	[2011]	[1996]	[1999]	[2011]

Table 4.19 continued

Notes: The number in parentheses and square brackets represents the lag length and break date, respectively. ADF_I and ADF_{TI} denote intercept and trend & intercept specification, respectively, with intercept break, selecting Dickey–Fuller min-t as the breakpoint selection with break type innovational outlier. An asterisk (*) denotes the test statistic is statistically significant at the 1 percent significance level, (**) indicates statistical significance at the 5 percent level, and (***) denotes statistical significance at the 10 percent level.

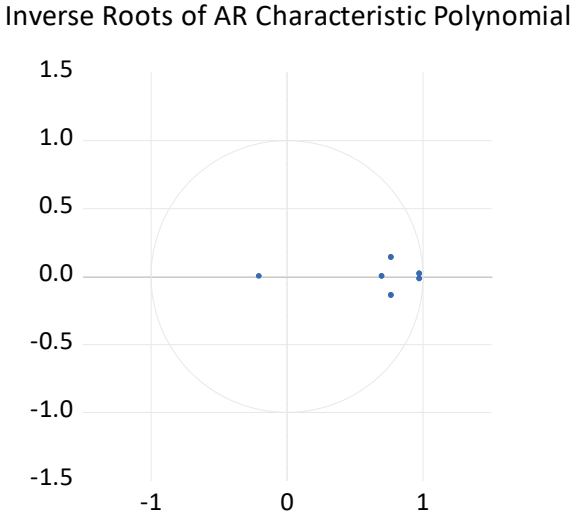


Figure 4.10: AR Roots Graph for Model 4

Table 4.20: VAR Lag Order Selection Criteria for Model 4

Lag	LR	FPE	AIC	SC	HQ
0	NA	1.36e−11	−7.996	−7.740	−7.904
1	399.857*	3.29e−16*	−18.646*	−16.854*	−18.003*
2	30.690	7.34e−16	−17.980	−14.653	−16.786
3	45.053	7.17e−16	−18.386	−13.524	−16.642

Notes: LR indicates the sequential modified LR test statistic (each test at the 5 percent level), FPE denotes the final prediction error, AIC represents the Akaike information criterion, SC refers to the Schwarz information criterion, and HQ signifies the Hannan–Quinn information criterion. An asterisk (*) denotes the lag order selected by the criterion.

Table 4.21: Diagnostic Tests

VAR Residual Serial Correlation LM Tests			
H_0 : No serial correlation at lag h			
	LRE* stat	df	Prob.
Model 4	Lag 1= 29.490	36	0.770
	Lag 2= 50.095	36	0.059
H_0 : No serial correlation at lags 1 to h			
	LRE* stat	df	Prob.
Model 4	Lag 1= 29.490	36	0.770
	Lag 2= 73.828	72	0.418
VAR Residual Heteroskedasticity Tests			
	Joint test:		
	Chi-sq	df	Prob.
Model 4	599.865	567	0.164

Notes: An asterisk denotes the Edgeworth expansion corrected likelihood ratio statistic, using the LR version of the Breusch–Godfrey Lagrange Multiplier (LM) test for autocorrelation with the Edgeworth expansion correction proposed by Edgerton and Shukur (1999). VAR residual heteroskedasticity tests are the system equation extension of White's (1980) test.

4.4.2 Johansen and Juselius Cointegration Test

The Johansen and Juselius (1990) cointegration test is utilized to identify the long-run equilibrium relationship among the tested variables in the model. The Johansen and Juselius (1990) cointegration test includes two types of test statistics: the Trace statistic and the Max-Eigen statistic; however, these two test statistics may yield different results, leading to potential conflicts in interpretation. Johansen and Juselius (1990) stressed the importance of prioritizing the Max-Eigen test statistic due to its perceived superiority over the Trace test statistic.

Table 4.22: Results of the Johansen and Juselius Cointegration Test

		k=1 r=0			
		Max-Eigen		Trace	
Null	**Alternative**	**Unadjusted**	**95% C.V.**	**Unadjusted**	**95% C.V.**
r = 0	**r = 1**	36.049	40.078	87.765	95.754
r ≤ 1	**r = 2**	20.146	33.877	51.716	69.819
r ≤ 2	**r = 3**	13.615	27.584	31.570	47.856
r ≤ 3	**r = 4**	8.778	21.132	17.955	29.797
r ≤ 4	**r = 5**	8.280	14.265	9.177	15.495
r ≤ 5	**r = 6**	0.897	3.841	0.897	3.841

Notes: k denotes the number of lag lengths, and r indicates the number of cointegrating vectors that are detected based on the test statistic. Asterisks (**) indicate statistical significance at the 5 percent level.

The results of the Johansen and Juselius (1990) cointegration test are shown in Table 4.22—the test statistics of the Max-Eigen statistic and the Trace statistic with each respective critical value at the 5 percent level of significance. The null hypothesis of the Johansen and Juselius (1990) cointegration test is that the number of cointegrating vectors is r, and the number of r starts from the number 0, while the alternative hypothesis is that the number of the cointegrating vectors is r+1. The rejection rule states that the null hypothesis should be rejected if the test statistic exceeds the critical value at the 5 percent significance level. The results indicate that no cointegrating vector was detected from Model 4, based on the findings from the Max-Eigen statistic and the Trace statistic with one lag length. This confirms the absence of a long-run equilibrium relationship among the tested variables. Consequently, it is recommended to proceed with a Vector Autoregressive (VAR) Model, as no long-run equilibrium relationship has been identified. In contrast, the Vector Error Correction Model (VECM) is not suitable in this context since it is designed to identify long-run equilibrium relationships between the tested variables. Then, the

Vector Autoregressive (VAR) Model should proceed to test the causality direction as a result of the absence of a long-run equilibrium relationship between the tested variables in the model, which is suggested by the Johansen and Juselius (1990) cointegration test.

4.4.3 Vector Autoregressive Granger Causality Test

The VAR Granger causality test is conducted in this study because the results of the Johansen and Juselius (1990) cointegration test affirmed that there is no long-run equilibrium relationship among the tested variables. Therefore, the Vector Error Correction Model (VECM) is not suitable to be applied due to no long-run equilibrium relationship detected. The Error Correction Term (ECT) in VECM is applied to denote the long-run equilibrium relationship found in the estimated model. ECT provides information on the adjustment speed and time required to achieve equilibrium and can also detect the presence of the most endogenous variable.

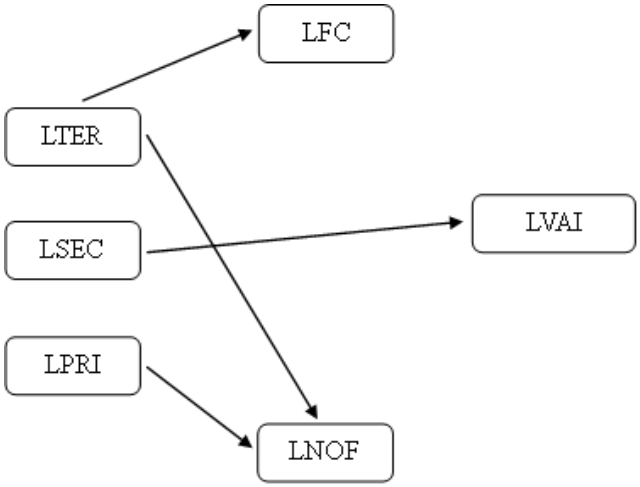
Table 4.23: Results of the VAR Granger Causality Test for Model 4

Dependent Variable	ΔLVAI	ΔLNOF	ΔLPRI	ΔLSEC	ΔLTER	ΔLFC
	χ^2 Statistic (p- value)					
ΔLVAI	-	0.376 (0.540)	1.493 (0.221)	7.637 (0.005)**	1.830 (0.176)	0.265 (0.606)
ΔLNOF	0.585 (0.444)	-	6.633 (0.010)**	0.437 (0.508)	9.989 (0.002)**	4.606 (0.032)
ΔLPRI	0.012 (0.913)	0.013 (0.911)	-	0.070 (0.791)	0.367 (0.545)	0.055 (0.814)
ΔLSEC	2.305 (0.129)	1.212 (0.271)	2.247 (0.996)	-	0.315 (0.575)	1.815 (0.178)
ΔLTER	0.001 (0.978)	0.326 (0.568)	1.016 (0.314)	2.573 (0.109)	-	0.235 (0.628)

Table 4.23 continued

ΔLFC	1.044	2.192	2.110	0.557	4.303	
	(0.307)	(0.139)	(0.146)	(0.456)	(0.038)**	-

Notes: The chi-square statistic is represented by the symbol of χ^2. Asterisks (** and ***) denote statistical significance at the 5 percent and 10 percent levels, respectively. Δ is the first different operator.



Notes: Figure 4.11 illustrates the unidirectional causality between tested variables (i.e., LVAI, LNOF, LPRI, LSEC, LTER, and LFC), based on the results of the VAR Granger causality test in Table 4.23.

Figure 4.11: Results of the Vector Autoregressive (VAR) Granger Causality Flow

The Granger (1988) causality test is conducted to determine the existence and direction of the causality between all the tested variables in the model. The results of the VAR Granger causality test are portrayed in Table 4.23, which is estimated by the Vector Autoregressive (VAR) Model, and Figure 4.11 displays the results of the VAR Granger causality flow. The causal relationship between the independent variables and the dependent variable has been identified based on the results of the VAR Granger causality test. Based on Table 4.23, the results of the VAR Granger causality test demonstrate that only LSEC does Granger-cause LVAI at the 5 percent significance level. The VAR Granger causality flow indicates a unidirectional causal relationship running from LSEC to LVAI. Therefore, the results of the VAR Granger causality test suggest that only workers

with secondary education can affect value-added industry during the study period. The results confirm that workers with no formal education, workers with primary education, workers with tertiary education, and the fixed capital do not Granger-cause value-added industry, respectively; however, only workers with secondary education (LSEC) did Granger-cause value-added industry (VAI) between 1982 and 2023, based on the results of the VAR Granger causality test. Moreover, the results indicate that LTER Granger causes LFC at the 5 percent significance level. The VAR Granger causality flow illustrates a unidirectional causal relationship running from tertiary education to fixed capital, according to the findings of the VAR Granger causality test.

In addition, the results of the VAR Granger causality test indicate that the workers with no formal education (LNOF) are affected by the two independent variables (i.e., LPRI and LTER) during the study period (see Table 4.23). The results confirm that LPRI does Granger-cause LNOF at the 5 percent significance level. The VAR Granger causality flow reveals that there is a unidirectional causal relationship running from workers with primary education (LPRI) to workers with no formal education (LNOF). Then, the results indicate a unidirectional causal relationship from workers with tertiary education (LTER) to workers lacking formal education (LNOF), as illustrated by the VAR Granger causality flow in Figure 4.11. The VAR Granger causality test proves that LTER does Granger-cause LNOF at the 5 percent level of significance between 1982 and 2023. The VAR Granger causality results attest that the independent variable (i.e., workers with secondary education) can affect value-added industry, while it is not affected by the other independent variables during the study period. Based on Figure 4.11 VAR Granger causality flow, LNOF is the most endogenous variable among the tested variables in the model because it gets influenced by two variables, which are LTER and LPRI, at the same time. However, LTER

is considered the most exogenous variable because it influences two variables in the study. The results of the VAR Granger causality test confirm that a high education level (i.e., secondary education) affected the value-added industry, while a tertiary education level did not influence the value-added industry during the study period.

4.4.4 Variance Decomposition

The study performs variance decomposition to assess the strength of the causal relationships among the tested variables. However, the results of the VAR Granger causality test only indicate the direction of causality in the model and do not provide insights into the strength of this Granger causality. Hence, Table 4.24 indicates the decomposition of the forecast error variable up to 50 years. This analysis can be used to strengthen the results of the VAR Granger causality test by presenting the percentages of variance in each variable that are caused by other variables in the model. This test can identify the most endogenous and exogenous variables in the model and provides information on the most influential variable. Additionally, the results of variance decomposition reinforce the Granger causality findings regarding the effect of the educational quality of workers on value-added industry in the study.

Table 4.24: Results of Variance Decomposition for Model 4

Percentage of Variations in	Horizon (Years)	Due to Innovation in:						
		ΔLVAI	ΔLNOF	ΔLPRI	ΔLSEC	ΔLTER	ΔLFC	ΔCU
Years Relative Variance in: ΔLVAI								
	1	**100**	0	0	0	0	0	0
	4	**83.605**	0.346	0.312	13.229	1.942	0.566	16.395
	8	**62.535**	0.787	1.884	30.766	2.229	1.798	37.465
	12	**50.596**	1.288	8.147	35.270	1.865	2.835	49.404

Table 4.24 continued

20	**37.954**	2.008	21.491	32.901	1.838	3.808	62.046
30	**31.016**	2.522	31.054	29.656	1.652	4.100	68.984
40	**27.698**	2.835	36.389	27.521	1.467	4.090	72.302
50	**25.972**	3.031	39.549	26.074	1.374	4.001	74.028
Years Relative Variance in: ΔLNOF							
1	0.834	**99.166**	0	0	0	0	0.834
4	5.254	**77.169**	7.420	0.421	6.144	3.591	22.831
8	5.171	**73.218**	9.707	2.266	6.238	3.400	26.782
12	4.934	**70.101**	11.787	3.676	6.084	3.418	29.899
20	4.613	**65.346**	15.683	4.982	5.785	3.591	34.654
30	4.433	**61.525**	19.276	5.623	5.460	3.684	38.475
40	4.368	**59.170**	21.707	5.835	5.233	3.688	40.830
50	4.358	**57.734**	23.285	5.862	5.099	3.661	42.266
Years Relative Variance in: ΔLPRI							
1	6.500	9.665	**83.835**	0	0	0	16.165
4	7.203	8.802	**83.328**	0.056	0.524	0.087	16.672
8	7.688	7.963	**82.555**	0.126	1.499	0.170	17.445
12	7.898	7.534	**81.927**	0.132	2.320	0.190	18.073
20	8.181	7.128	**80.895**	0.114	3.516	0.166	19.105
30	8.503	6.894	**79.563**	0.270	4.620	0.151	20.437
40	8.736	6.751	**78.226**	0.626	5.469	0.192	21.774
50	8.865	6.648	**77.037**	1.087	6.088	0.274	22.963
Years Relative Variance in: ΔLSEC							
1	12.645	3.548	7.767	**76.040**	0	0	23.960
4	3.946	6.474	13.659	**73.816**	0.101	2.004	26.184
8	2.205	5.724	26.449	**61.243**	0.590	3.788	38.757
12	1.573	5.318	36.129	**51.233**	1.128	4.619	48.767

Table 4.24 continued

20	1.333	5.037	46.587	**40.634**	1.327	5.082	59.366
30	1.495	5.007	52.792	**34.563**	1.121	5.023	65.437
40	1.712	5.052	56.239	**31.201**	0.972	4.824	68.799
50	1.919	5.100	58.261	**29.164**	0.924	4.632	70.836
Years Relative Variance in: ΔLTER							
1	0.047	12.530	2.328	0.763	**84.332**	0	15.668
4	0.270	6.097	1.118	9.552	**81.743**	1.220	18.257
8	1.421	3.653	0.893	23.199	**66.848**	3.985	33.152
12	2.403	2.638	0.708	31.356	**56.929**	5.966	43.071
20	2.869	1.851	2.336	38.064	**46.765**	8.115	53.235
30	2.452	1.666	7.209	40.039	**39.479**	9.155	60.521
40	2.042	1.785	12.920	39.516	**34.359**	9.378	65.641
50	1.816	1.987	18.099	38.133	**30.708**	9.258	69.292
Years Relative Variance in: ΔLFC							
1	10.652	24.333	0.720	0.197	0.808	**63.290**	36.710
4	5.425	31.361	5.395	0.441	1.948	**55.430**	44.570
8	5.561	28.165	7.899	1.743	3.407	**53.225**	46.775
12	5.267	25.426	9.718	5.699	3.985	**49.905**	50.095
20	4.374	21.409	14.579	11.914	4.464	**43.260**	56.740
30	3.707	18.538	20.964	14.615	4.481	**37.696**	62.304
40	3.401	16.964	25.875	15.297	4.201	**34.262**	65.738
50	3.288	16.058	29.375	15.279	3.924	**32.075**	67.925

Notes: The last column provides the percentage of forecast error variances for each variable explained collectively by the other variables. The bold column represents the impact of one's own shock.

LVAI accounts for 74.03% of the forecast error variance; approximately 3.03%, 39.55%, 26.07%, 1.37%, and 4.00% of the variation can be caused by LNOF, LPRI, LSEC, LTER, and LFC, respectively. These percentage values reveal that LVAI is the most

influenced by LPRI over a span of 50 years, consistently accounting for the largest portion compared to the other independent variables. This indicates that workers with primary education have the potential to influence a significant portion of the value-added industry. However, this finding is at odds with the results of the VAR Granger causality test, which indicated that workers with primary education did not Granger-cause the value-added industry during the study period. The variance decomposition shows that workers with secondary education are able to explain more than 26 percent of forecast error variance in the value-added industry at the end of 50 years. The analysis highlights that workers with secondary education are the second most influential variable in the value-added industry (VAI), contributing to the second largest portion of shocks, as illustrated by the variance decomposition results. Additionally, the results from the VAR Granger causality test indicate that workers with secondary education can Granger-cause the value-added industry during the study period.

There is about 42.27% of the forecast error variance in LNOF that can be explained by the shock of other variables, which are 4.36% by LVAI, 23.29% by LPRI, 5.86% by LSEC, 5.10% by LTER, and 3.66% by LFC at the end of the 50 years. LNOF is the second most exogenous variable based on the variance decomposition results in the study. The results indicate that shocks to workers with primary education account for over 23 percent of those with no formal education. This percentage value suggests that LPRI is the most influential variable affecting LNOF, as variations from this variable consistently represent a larger portion throughout the 50-year period. The findings indicate that workers with primary education significantly impact those with no formal education in Malaysia compared to other variables. This finding aligns with the results of the VAR Granger causality test, which demonstrates that LPRI can Granger-cause LNOF during the study

period. The variance decomposition results confirm that LPRI has a greater influence on LNOF compared to LTER, which contributes to just over 5 percent of LNOF.

However, fixed capital only influences a small percentage of workers with no formal education, and the VAR Granger causality test also does not show any causal relationship between LFC and LNOF. Variance decomposition also confirms that the fixed capital does not significantly explain the forecast error variance in workers without formal education. LSEC is the second most endogenous variable in the study, absorbing shocks from other variables, and only 29.16% of the variation can be explained by itself at the end of 50 years. There is around 70.84% of forecast error variance in LSEC that is explained by LVAI (1.92%), LNOF (5.10%), LPRI (58.26%), LTER (0.92%), and LFC (4.63%) at the end of 50 years. The variance decomposition indicates that workers with primary education can explain more than 58 percent of forecast error variance in the workers with secondary education at the end of 50 years. This percentage value indicates that LPRI is the most influential variable affecting LSEC compared to other variables.

Based on the results of variance decomposition, LVAI is the most endogenous variable in this study as a dependent variable, since LVAI is highly absorbing the shocks from other variables, and only around 25.97% of the variation can be explained by itself at the end of 50 years. The analysis of LFC reveals that, within the 67.93% of forecast error variance, approximately 3.29%, 16.06%, 29.38%, 15.28%, and 3.92% of the variation can be attributed to LVAI, LNOF, LPRI, LSEC, and LTER, respectively. This percentage value indicates that LPRI is the most influential variable affecting LFC, as it accounts for the largest portion of variation over the span of 50 years. This result shows that workers with primary education can influence the largest part of fixed capital in Malaysia compared

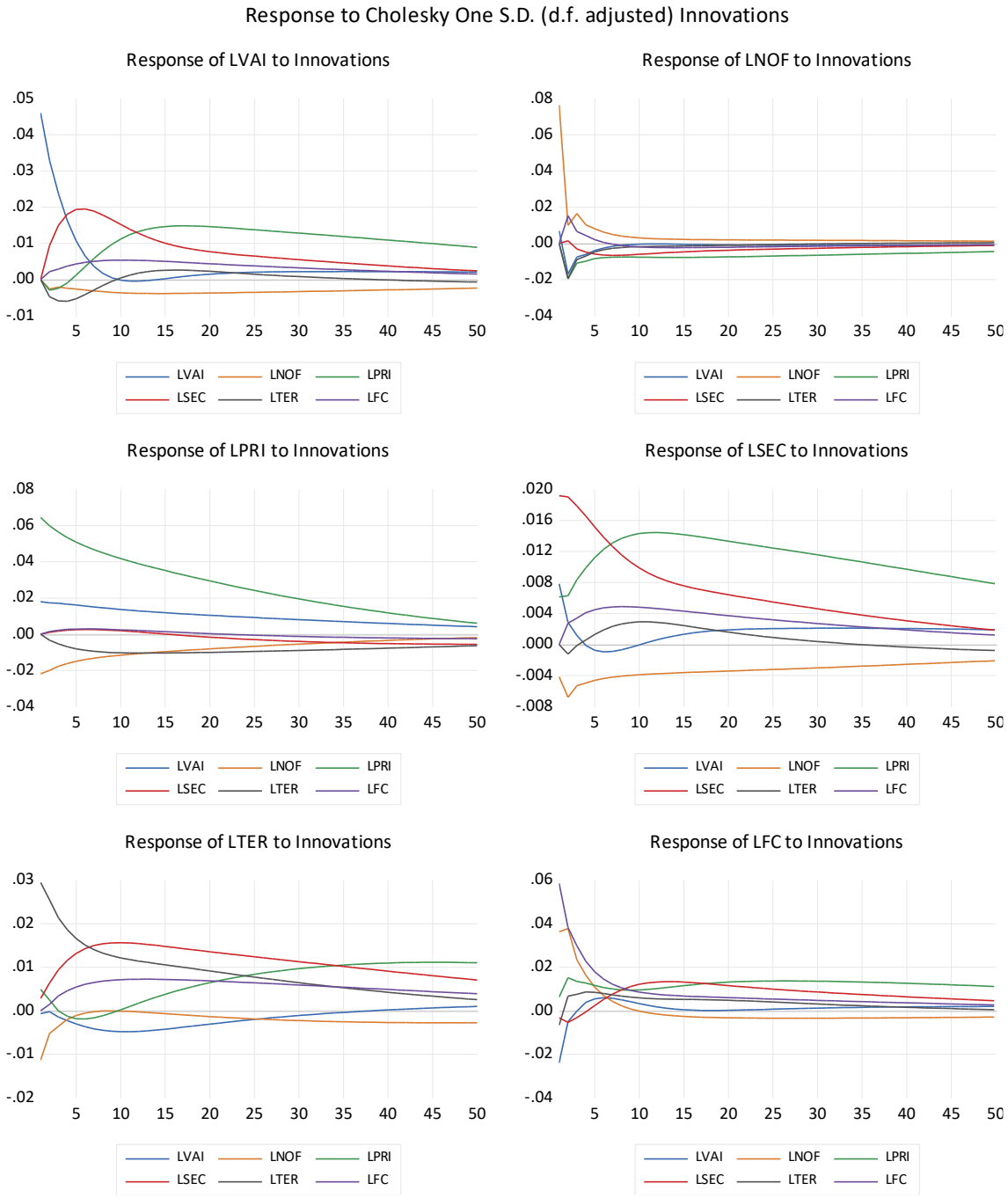
to other variables, while workers with no formal education can impact the second largest portion. The workers with tertiary education only affect a small percentage of the fixed capital in Malaysia. However, the results of the VAR Granger causality test reveal that only LTER can Granger-cause LFC between 1982 and 2023. The variance decomposition results indicate that LPRI is the most exogenous variable, accounting for 77.04% of the variation, which is greater than the variations caused by other variables over the 50-year period. LPRI indicates that among the 22.96% of forecast error variance, approximately 8.87%, 6.65%, 1.09%, 6.09%, and 0.27% of variation can be caused by LVAI, LNOF, LSEC, LTER, and LFC, respectively. At the end of the 50-year period, LPRI exhibits the lowest CU value compared to the changes in other variables. This suggests that LPRI is less influenced by other variables, with most of the impact coming from itself. Hence, this variance decomposition result is consistent with the results of the VAR Granger causality test, which indicates that there are no variables that can Granger-cause LPRI.

4.4.5 Impulse Response Function

Figure 4.12 illustrates the results of the Impulse Response Function (IRF) over a 50-year horizon. The impulse response analysis is applied by utilizing the Cholesky decomposition and adjustment in degree of freedom (Cholesky dof adjusted)—the evolution of a model's variables in reaction to a shock in one or more variables. Based on the graph, as shown in Figure 4.12, the response of the LVAI to a shock in the LSEC is positive and significant. The graph of the IRF illustrates that workers with secondary education have a positive impact on the value-added industry in 50 years. The graph of the IRF indicates that there are dramatic increases, reaching the maximum in the 6th year, then the positive response decreases significantly from the 7th until the 19th year, and after that, it gradually decreases from the 20th year until the 50th year. The IRF found that there was a

significant positive effect of secondary education on the value-added industry in the sixth year. The IRF results further support the VAR Granger causality test results, which prove that workers with secondary education positively affected the value-added industry between 1982 and 2023.

The response of LVAI to LNOF shows that workers with no formal education have a negative impact on the value-added industry in 50 years. The negative response increases dramatically from the first year to the second year and then declines from the second year to the third year. The negative response intensifies, reaching its peak in the 15th year. Thereafter, the negative effect gradually diminishes from the 17th until the 50th year. However, the results of the VAR Granger causality test demonstrate that workers lacking formal education do not Granger-cause the value-added industry during the study period. This finding implies that the IRF results indicate that no formal education has a negative impact on value-added industry, but the results of the VAR Granger causality test show no causal relationship between 1982 and 2023.



Notes: Figure 4.12 was developed by using EViews and the Cholesky decomposition method (dof) for impulse response over 50 years. Each variable (i.e., LVAI, LNOF, LPRI, LSEC, LTER, and LFC) is represented by the different colors of lines as stated above.

Figure 4.12: Results of the Impulse Response Function for Model 4

Moreover, the response of LVAI to a shock in LPRI indicates that workers with primary education have a negative impact on the value-added industry in the first 4 years only. Then, the positive effect increases intensely from the fifth year until reaching its peak in the 17th year, but this positive response decreases slightly from the 18th year until the 50th year. The impulse response function reveals that LTER has a negative impact on the value-added industry in the first 9 years, while the positive effect exists from the 9th year until the 39th year and reaches its maximum in the 16th year. The graph indicates that a negative effect arises, gradually intensifying from the 40th to the 50th year. This suggests that tertiary education positively impacts the value-added industry over a span of 30 years. However, the findings from the VAR Granger causality test show that the workers with tertiary education do not Granger-cause the value-added industry (see Table 4.23).

Furthermore, the response of LNOF to a shock in the LPRI is both negative and significant. The IRF graph indicates that workers with primary education negatively impact workers with no formal education over a 50-year period. Notably, there is a dramatic increase in this negative effect during the initial period, particularly in the second year, when it reaches its peak. Following this, the negative effect intensely declines from the third year to the seventh year. Afterward, it slightly decreases from the fifteenth year to the fiftieth year. This underlines that a significant negative effect is only present in the second year. This finding further corroborates the results of the VAR Granger causality test, which confirms that between 1982 and 2023, workers with primary education negatively affected those with no formal education. The LNOF's response to a shock in the LTER reveals that workers with tertiary education negatively impact those without formal education over a span of 40 years, peaking in the second year. The positive response begins in the 41st year and demonstrates a consistent increase in this effect from the 41st year to the 50th year. In

contrast, workers with tertiary education persist in negatively impacting those without formal education throughout the 40-year period. This outcome further corroborates the findings of the VAR Granger causality test, revealing that tertiary education has negatively affected no formal education during the study period. LFC's response to a shock in the LTER is positive. The positive response dramatically increases during the first four years, peaks in the fourth year, and then significantly decreases from the fourth year until the eleventh year. Thereafter, this positive effect continues to decline consistently from the twelfth year to the fiftieth year. This result indicates that workers with tertiary education have a positive impact on fixed capital over a period of 50 years, as indicated by the graph of impulse response analysis. This infers that workers with tertiary education positively impacted the fixed capital between 1982 and 2023.

4.5 Employed Workers' Educational Attainment and Malaysian Sectoral Labor Productivity

4.5.1 Autoregressive Distributed Lag

The Autoregressive Distributed Lag (ARDL) model is applied to test the presence of cointegration among the tested variables. The ARDL estimation includes the bounds test, error correction model, long-run coefficient, and diagnostic tests. Additionally, the Wald test is performed in this study to measure the long-run and short-run effect of educational attainment on sectoral labor productivity (i.e., agriculture, industry, and services) in the ARDL model.

4.5.2 Unit Root and Stationary Tests

This study employs three types of unit root tests to identify the stationary properties of the variables under investigation—the augmented Dickey–Fuller (ADF) test proposed by Dickey and Fuller (1979); the Phillips–Perron (PP) test proposed by Phillips and Perron

(1988); and the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test proposed by Kwiatkowski et al. (1992). The purpose of performing unit root and stationary tests in this study is to determine whether the variables are non-stationary at the second difference.

Table 4.25: Results of Unit Root and Stationary Tests for Models 5, 6, and 7

	ADF		**PP**		**KPSS**	
	Intercept	**Trend & Intercept**	**Intercept**	**Trend & Intercept**	**Intercept**	**Trend & Intercept**
			A: Level			
LPROA	−0.244(2)	−3.127(0)	−0.847(0)	−3.096(1)	0.666(4)**	0.137(3)***
LPROI	−2.634(0)	−2.382(0)	−4.111(9)*	−2.381(7)	0.627(4)**	0.164(4)**
LPROS	−2.176(0)	−4.692(1)*	−2.176(0)	−3.837(1)**	0.757(4)*	0.084(1)
LENOF	−1.536(1)	−0.893(1)	−1.508(2)	−3.919(3)**	0.651(4)**	0.165(4)**
LEPRI	1.531(0)	−0.778(1)	1.380(2)	−0.055(2)	0.491(4)**	0.138(3)***
LESEC	−2.804(0)***	−1.481(0)	−2.804(0)***	−1.521(1)	0.744(4)*	0.141(4)***
LETER	−1.706(0)	−1.503(0)	−4.843(20)*	−0.975(14)	0.748(4)*	0.182(4)**
LFCAP	−2.013(0)	−2.479(0)	−1.952(1)	−2.554(1)	0.741(4)*	0.067(3)
			B: First Difference			
ΔLPROA	−6.349(1)*	−6.570(0)*	−6.564(1)*	−7.237(3)*	0.141(5)	0.116(7)
ΔLPROI	−4.360(0)*	−4.528(0)*	−4.274(4)*	−4.412(6)*	0.242(1)	0.089(5)
ΔLPROS	−4.666(1)*	−4.377(1)*	−4.167(5)*	−4.054(4)**	0.228(0)	0.083(1)
ΔLENOF	−10.976(0)*	−3.933(4)**	−11.313(1)*	−12.197(2)*	0.104(4)	0.110(5)
ΔLEPRI	−3.860(0)*	−4.516(0)*	−3.831(2)*	−4.536(1)*	0.351(3)***	0.119(2)
ΔLESEC	−4.513(0)*	−5.231(0)*	−4.438(2)*	−5.231(0)*	0.475(3)**	0.067(0)
ΔLETER	−5.061(0)*	−5.307(0)*	−5.049(10)*	−9.163(23)*	0.338(9)	0.298(20)*
ΔLFCAP	−4.374(0)*	−4.526(0)*	−4.379(1)*	−4.539(1)*	0.208(1)	0.083(1)

Notes: The types of unit root tests used are ADF, PP, and KPSS tests. The number in parentheses refers to the lag length or bandwidth used by the default settings in EViews. An asterisk (*) denotes the test statistic is significant at the 1% significance level, (**) indicates statistical significance at the 5 percent level, and (***) indicates statistical significance at the 10 percent level. Δ denotes the first difference operator.

The results of the unit root test reveal that all variables include dependent variables and independent variables. The dependent variable includes the logarithm of agricultural productivity (LPROA), the logarithm of industrial productivity (LPROI), and the logarithm of services productivity (LPROS), while the independent variables include the logarithm of employed workers with no formal education (LENOF), the logarithm of employed workers with primary education (LEPRI), the logarithm of employed workers with secondary education (LESEC), the logarithm of employed workers with tertiary education (LETER), and the logarithm of fixed capital (LFCAP). Table 4.25 shows the results of unit root and stationary tests from the ADF, PP, and KPSS tests in EViews. The null hypothesis of the ADF and PP unit root tests is the variable that is non-stationary, while the null hypothesis of the KPSS unit root test is the variable that is stationary. The decision rule is to reject the null hypothesis when the test statistic value is greater than the critical value at the 10% significance level.

Based on the results presented in Table 4.25, the results of the ADF unit root test at level indicate that LPROA, as the dependent variable, is non-stationary under both the intercept specification and the trend and intercept specification. The KPSS unit root test results at level demonstrate that LPROA is non-stationary in both the trend and intercept specification, as well as in the intercept specification alone. Additionally, the results of the PP unit root test reveal that LPROA is non-stationary at the level under the intercept specification; it is also non-stationary under the trend and intercept specification. The outcomes of the ADF and PP unit root tests at the first difference demonstrate that LPROA is stationary at the 1% significance level for both intercept and trend with intercept specifications. The KPSS unit root test results further indicate that LPROA is stationary in the first difference under both intercept and trend with intercept specifications. The results

from the ADF and PP unit root tests in the first difference reveal that LPROI and LPROS are stationary when assessed under both intercept and trend with intercept specifications. The KPSS unit root test suggests that LPROI and LPROS are classified as *I*(1) variables; these variables are stationary in the first difference under both intercept and trend with intercept specifications. However, the results of the ADF, PP, and KPSS unit root tests at the level reveal that LPRODS is stationary under the trend and intercept specification—underscoring that LPRODS is an *I*(0) variable in this study. In conclusion, the dependent variables LPROA and LPROI are *I*(1) variables; however, LPRODS is an *I*(0) variable, based on the results from the ADF, PP, and KPSS unit root tests.

The statistical results of the ADF unit root test indicate that independent variables (i.e., LENOF, LEPRI, LESEC, LETER, and LFCAP) are non-stationary in level under both intercept and trend with intercept specifications. However, LESEC is stationary in the intercept specification at the 10 percent significance level. The ADF unit root test results for the first difference show that LENOF, LEPRI, LESEC, LETER, and LFCAP are stationary at the 1% significance level under both intercept and trend with intercept specifications. However, only LENOF is stationary at the 5% significance level under the trend and intercept specification. Moreover, the statistical results of the PP unit root test reveal that LENOF, LEPRI, LESEC, LETER, and LFCAP are *I*(1) variables. This conclusion is drawn from the fact that the majority of the test statistics fail to reject the null hypothesis at the level, while all test statistics reject the null hypothesis in the first difference. Additionally, the results at the level indicate that LETER and LESEC are stationary under the intercept specification, whereas LENOF is stationary under the trend and intercept specification.

The KPSS unit root test results for the first difference reveal that only LETER is non-stationary under the trend and intercept specification, while LEPRI and LESEC are non-stationary under the intercept specification. Simultaneously, LFCAP remains stationary under the trend with intercept specification—indicated by the results of the KPSS unit root test at the level. The independent variables LENOF and LFCAP are stationary under the intercept specification; however, these variables are also stationary at the trend and intercept specification, as demonstrated by the suggested results in the first difference given by the KPSS unit root test. This emphasizes that the results of the KPSS unit root test reveal that LENOF, LEPRI, LESEC, and LETER are *I*(1) variables because the majority of the test statistics of the KPSS unit root test reject the null hypothesis at the level. In conclusion, all the independent variables (i.e., LENOF, LEPRI, LESEC, LETER, and LFCAP) are determined to be stationary in the first difference, classified as *I*(1) variables, according to the statistical results of the ADF, PP, and KPSS unit root tests.

The unit root with break test is employed in the study to determine the stationarity properties of the series and to address the issue of structural breaks—the augmented Dickey–Fuller with structural breaks is based on the framework outlined (e.g., Banerjee et al., 1992; Perron, 1989; Vogelsang & Perron, 1998; Zivot & Andrews, 1992). The unit root with structural breaks in the first difference is described in Table 4.26, which reveals that the test statistics of all the variables are statistically significant at the 1 percent level, except for LPROS and LEPRI, which are stationary at the 5 percent significance level in trend and intercept specification—underscoring that the combined results reveal that all the series are integrated in order one except LENOF. The results reveal that the LENOF is stationary at the intercept specification and stationary at the trend with intercept specification in the level. The estimated break date is mainly in the periods 1997–1999 and

2007–2009, which are related mostly to the financial crisis periods. The other estimated break date is the period 2019–2022, which is connected to the COVID-19 pandemic.

Table 4.26: Results of the Unit Root with Structural Breaks for Models 5, 6, and 7

	Level		**First Difference**	
	ADF_I	ADF_{TI}	ADF_I	ADF_{TI}
LPROA	−1.976(0)	−4.588(0)	−7.126(0)*	−7.536(1)*
	[2010]	[1994]	[2000]	[2019]
LPROI	−2.967(0)	−4.767(3)***	−5.654(5)*	−5.495(5)*
	[1994]	[2004]	[2006]	[2006]
LPROS	−2.832(0)	−5.955(1)*	−5.304(0)*	−5.188(0)**
	[2003]	[2006]	[1998]	[1998]
LENOF	−4.314(0)***	−5.915(0)*	−12.476(0)*	−11.806(0)*
	[1999]	[1999]	[2008]	[1997]
LEPRI	−3.124(6)	−4.375(3)	5.306(0)*	−5.342(0)**
	[2014]	[2019]	[2013]	[2019]
LESEC	−5.060(5)*	−3.716(7)	−5.459(0)*	−6.386(4)*
	[2009]	[2019]	[2013]	[2009]
LETER	−3.134(3)	−3.173(0)	−5.568(0)*	−5.674(2)*
	[2008]	[2015]	[1996]	[2008]
LFCAP	−3.312(2)	−6.081(4)*	−5.903(0)*	−5.737(0)*
	[2006]	[2010]	[1999]	[1999]

Notes: The number in parentheses and square brackets denotes the lag length and break date, respectively. ADF_I and ADF_{TI} represent intercept and trend & intercept specification, respectively, with intercept break, selecting Dickey–Fuller min-t as the breakpoint selection with break type innovational outlier. An asterisk (*) indicates that the test statistic is statistically significant at the 1 percent level, (**) denotes statistical significance at the 5 percent level, and (***) signifies statistical significance at the 10 percent level.

4.5.3 ARDL Bounds Test for Cointegration

The Autoregressive Distributed Lag (ARDL) bounds test is adopted to estimate the long-run and short-run relationship among the tested variables in the model for the sample period 1991–2022. The cointegration test was proposed by Pesaran et al. (2001) and is robust to whether variables of interest are *I*(0), *I*(1), or mutually cointegrated. The ARDL approach is applied in this study, which is more reliable due to the small samples and appropriate for a mixture of *I*(0) and *I*(1) variables if compared with the Johansen and Juselius (1990) cointegration test. The ARDL bounds test in the study is to determine the existence of cointegration among the tested variables and then estimate the long-run coefficient for the models. The null hypothesis for the bounds test is that no long-run relationship exists among the variables, whereas the alternative hypothesis holds the presence of a long-run relationship among the variables. Thus, if the calculated value of the F-statistic is larger than the critical value of the upper bound, there is a long-run relationship that exists among the variables.

Table 4.27: Results of the Bounds Testing Approach for Cointegration

Model	**F-statistic**	**ARDL Order**
Model 5: LPROA, LENOF, LEPRI, LESEC, LETER, LFCAP	4.370***	(1, 3, 0, 3, 0, 2)
Model 6: LPROI, LENOF, LEPRI, LESEC, LETER, LFCAP	13.225***	(1, 0, 0, 3, 2, 4)
Model 7: LPROS, LENOF, LEPRI, LESEC, LETER, LFCAP	4.780***	(1, 2, 3, 0, 0, 0)

Critical value bounds of the F-statistic: restricted intercept and no trend (*k*=5)

Significance level	**Pesaran Critical Values**		**Narayan Critical Values**	
	k=5		*k*=5	
	I(0)	*I*(1)	*I*(0)	*I*(1)
10%	2.08	3.00	2.407	3.517
5%	2.39	3.38	2.910	4.193

Table 4.27 continued

1%	3.06	4.15	4.134	5.761

Notes: Critical values of Models 5, 6, and 7 are obtained from Pesaran et al. (2001), Table Case II: restricted intercept and no trend, while another critical value is obtained from Narayan (2005), Table Case II: restricted intercept and no trend. The lag length selection is based on the Schwarz information criterion (SIC). The asterisks (***) and (**) denote statistical significance at the 1 percent and 5 percent levels, respectively.

Table 4.27 displays the results of the bounds testing approach for cointegration, where k denotes the number of independent variables used in the study. The F-statistic value of Model 5 is indicated as 4.370 in Table 4.27, which is greater than the critical value of the upper bound proposed by Pesaran et al. (2001) at the 1% significance level and Narayan (2005) at the 5% significance level. The results of Model 5 reveal that there is a long-run relationship between the dependent variable and independent variables over the period of study. The optimal lag length selection is the ARDL (1, 3, 0, 3, 0, 2) model, which is selected based on the Schwarz information criterion (SIC). Likewise, the F-statistic value for Model 6 is 13.225, which is higher than the critical value of the upper bound proposed by Pesaran et al. (2001) and Narayan (2005) at the 1% significance level. This highlights that the results indicate a long-run relationship between the dependent variable and independent variables throughout the study period. The optimal lag length selection is the ARDL (1, 0, 0, 3, 2, 4) model, which is selected based on the Schwarz information criterion (SIC). The F-statistic value of Model 7 is presented as 4.780, which is larger than the critical value of the upper bound proposed by Pesaran et al. (2001) at the 1% significance level and Narayan (2005) at the 5% significance level. This means the results reveal that there is a long-run relationship between the dependent variable and independent variables between 1992 and 2022. The Schwarz information criterion (SIC) determines the optimal lag length selection, which is the ARDL (1, 2, 3, 0, 0, 0) model.

4.5.4 ARDL Long-Run Estimates

Table 4.28 portrays the results of the long-run estimation of Model 5 over the period of 1991–2022 in the study. The bound testing approach results of Model 5 presented in Table 4.28 indicate that there is a long-run relationship between the dependent variable and independent variables during the study period. Then, the bound testing approach results of Models 6 and 7 also indicate that there is a long-run relationship between the dependent variable and independent variables.

Table 4.28: Results of ARDL Long-Run Estimates

Model 5				
Variable	**Coefficient**	**SE**	**t-statistic**	**p-value**
LENOF	0.621	0.370	1.678	0.116
LEPRI	0.025	0.146	0.169	0.868
LESEC	1.641***	0.510	3.216	0.006
LETER	−0.022	0.245	−0.089	0.931
LFCAP	−0.407	0.195	−2.087	0.056
C	−2.642	4.590	−0.576	0.574
Model 6				
Variable	**Coefficient**	**SE**	**t-statistic**	**p-value**
LENOF	0.528**	0.183	2.890	0.014
LEPRI	0.392***	0.120	3.254	0.007
LESEC	−0.468	0.642	−0.730	0.480
LETER	0.842**	0.309	2.724	0.019
LFCAP	−0.500**	0.167	−2.991	0.011
C	−9.137***	2.481	3.682	0.003
Model 7				
Variable	**Coefficient**	**SE**	**t-statistic**	**p-value**

Table 4.28 continued

LENOF	−0.660**	0.243	−2.712	0.015
LEPRI	−0.139	0.174	−0.796	0.437
LESEC	0.095	0.406	0.235	0.817
LETER	−0.330	0.254	−1.300	0.211
LFCAP	0.534***	0.133	4.027	0.001
C	8.571***	2.221	3.859	0.001

Notes: The lag length selection is based on the Schwarz information criterion (SIC). The asterisks (**) and (***) indicate statistical significance at the 5 percent and 1 percent levels, respectively.

The long-run estimation results of Model 5, shown in Table 4.28, indicate that LESEC has a positive impact on LPROA at the 1% significance level in the long term. This result reported that employed workers with secondary education positively affect agricultural productivity, with a coefficient of 1.641. For Model 6, the employed workers lacking formal education have a positive and statistically significant impact on industrial productivity at the 5 percent level. The result reveals that the employed workers without formal education have a positive impact on industrial productivity with a coefficient of 0.528. Likewise, the employed workers with primary education positively impact industrial productivity with a coefficient of 0.392. The employed workers with tertiary education have a positive and statistically significant impact on industrial productivity at the 5 percent level. This highlights that the long-run estimation results reveal that the employed workers with tertiary education have a positive impact on industrial productivity, with a coefficient of 0.842.

However, the result reveals that fixed capital has a negative impact on industrial productivity with a coefficient of −0.500. This underscores the fact that a 1 percent increase in fixed capital results in a 0.500 percent decrease in industrial productivity. Then,

the result indicates secondary education has a negative impact on industrial productivity, but this result is not statistically significant because the p-value exceeds 0.05. For Model 7, the employed workers with no formal education have a negative and statistically significant impact on services productivity at the 5 percent level. This result reveals that the employed workers with no formal education negatively affect services productivity with a coefficient of −0.660. Afterward, the fixed capital has a positive impact on services productivity with a coefficient of 0.534, and this result is statistically significant at the 1 percent level. However, these results are statistically insignificant; the results reveal that employed workers with secondary education have a positive impact on services productivity, while those with tertiary education have a negative impact.

4.5.5 Error Correction Representation and Diagnostic Tests

The ARDL estimation results of Models 5, 6, and 7 are shown in Table 4.29. The results of Model 5 indicate that LENOF has a positive impact on LPROA at the 5% significance level in the short run. This demonstrates that the employed workers with no formal education have a short-run positive impact on agricultural productivity with a coefficient of 0.123. This implies a 1 percent increase in employed workers without formal education, resulting in a 0.123 percent increment in agricultural productivity. Furthermore, the employed workers with secondary education positively affect agricultural productivity with a coefficient of 1.163; the result is statistically significant at the 1 percent level. The error correction term (ECT) measures the speed of adjustment, which consists of a negative sign and is statistically significant at the 1 percent level. The coefficient of ECT is −0.655, indicating that the adjustment speed for the variable to reach the long-run equilibrium is approximately 65.5% annually.

Table 4.29: ARDL Estimation Results

Variable	Coefficient	SE	t-statistic	p-value
Model 5: LPROA, LENOF, LEPRI, LESEC, LETER, LFCAP (1, 3, 0, 3, 0, 2)				
ΔLENOF	0.123*	0.053	2.306	0.037
ΔLENOF_{t-1}	−0.306**	0.074	−4.124	0.001
ΔLENOF_{t-2}	−0.264**	0.066	−3.989	0.001
ΔLESEC	1.163**	0.133	8.719	0.000
ΔLESEC_{t-1}	−0.453	0.226	−2.006	0.065
ΔLESEC_{t-2}	−1.175**	0.210	−5.603	0.000
ΔLFCAP	0.140	0.067	2.089	0.056
ΔLFCAP_{t-1}	0.352**	0.090	3.901	0.002
ECT_{t-1}	−0.655**	0.099	−6.611	0.000
Diagnostic Tests:				
JB	0.387 (0.824)			
AR [2]	2.468 (0.291)			
ARCH [1]	0.008 (0.928)			
RESET [1]	3.596 (0.080)			
CUSUM	Stable			
CUSUM^2	Stable			
Model 6: LPROI, LENOF, LEPRI, LESEC, LETER, LFCAP (1, 0, 0, 3, 2, 4)				
ΔLESEC	−0.665**	0.175	−3.807	0.003
ΔLESEC_{t-1}	−0.221	0.195	−1.136	0.278
ΔLESEC_{t-2}	−1.148**	0.212	−5.427	0.000
ΔLETER	0.197	0.103	1.912	0.080
ΔLETER_{t-1}	−0.937**	0.130	−7.219	0.000
ΔLFCAP	−0.091	0.060	−1.511	0.157
ΔLFCAP_{t-1}	0.273**	0.075	3.623	0.003
ΔLFCAP_{t-2}	−0.181**	0.050	−3.580	0.004

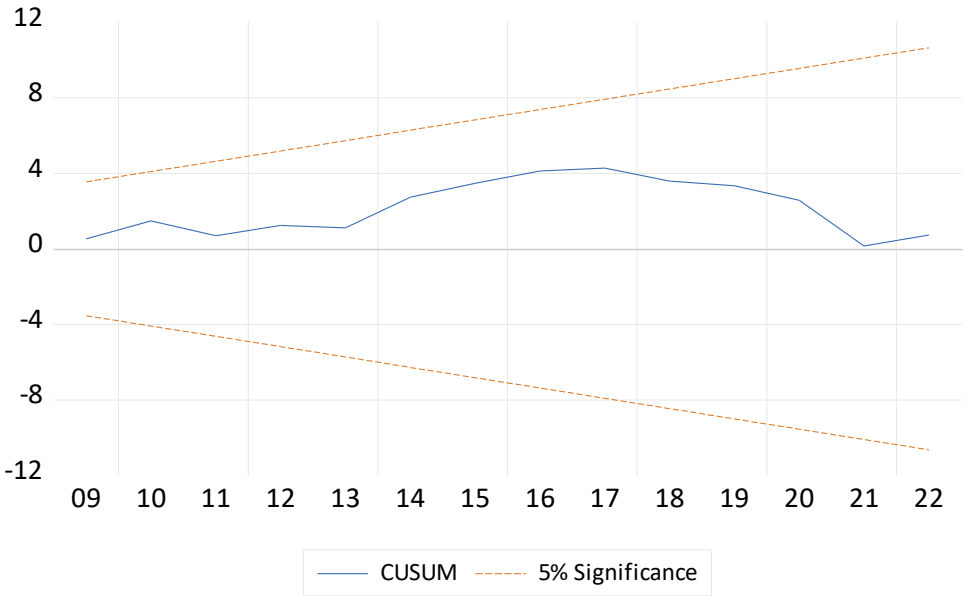
Table 4.29 continued

$\Delta LFCAP_{t-3}$	0.179**	0.051	3.545	0.004
ECT_{t-1}	−0.639**	0.054	−11.784	0.000
Diagnostic Tests:				
JB	0.978 (0.613)			
AR [2]	3.180 (0.204)			
ARCH [1]	2.087 (0.149)			
RESET [1]	0.216 (0.651)			
CUSUM	Stable			
$CUSUM^2$	Stable			
Model 7: LPROS, LENOF, LEPRI, LESEC, LETER, LFCAP (1, 2, 3, 0, 0, 0)				
ΔLENOF	−0.047	0.053	−0.890	0.386
$\Delta LENOF_{t-1}$	0.183*	0.078	2.351	0.031
ΔLEPRI	0.001	0.084	0.010	0.992
$\Delta LEPRI_{t-1}$	−0.032	0.097	−0.333	0.744
$\Delta LEPRI_{t-2}$	−0.578**	0.103	−5.591	0.000
ECT_{t-1}	−0.740**	0.110	−6.728	0.000
Diagnostic Tests:				
JB	0.181 (0.914)			
AR [2]	2.811 (0.245)			
ARCH [1]	0.056 (0.813)			
RESET [1]	0.824 (0.378)			
CUSUM	Stable			
$CUSUM^2$	Stable			

Notes: The lag length selection is based on the Schwarz information criterion (SIC). JB is the Jarque–Bera statistic for the residuals normality test. AR is the Lagrange Multiplier test for serial correlation. ARCH and RESET represent the ARCH heteroskedasticity test and Ramsey RESET specification test, respectively. Figures in parentheses are the p-values. The asterisks (* and **) indicate statistical significance at the 5 percent and 1 percent levels, respectively.

The ARDL estimation results of Model 6 reveal that the employed workers with secondary education have a negative and statistically significant impact on industrial productivity at the 1 percent level. This result shows that secondary education negatively influences industrial productivity with a coefficient of −0.665 in the short run. However, the employed workers with tertiary education have a positive impact on industrial productivity, but the result is statistically insignificant. The error correction term (ECT) measures the speed of adjustment, which consists of a negative sign and is statistically significant at the 1 percent level. The coefficient of ECT is −0.639, revealing that the adjustment speed for the variable to reach the long-run equilibrium is about 63.9% annually.

For Model 7, the results indicate that employed workers with no formal education negatively affect services productivity with a coefficient of −0.047, and primary education has a positive impact on services productivity with a coefficient of 0.001; however, these results are statistically insignificant. The coefficient of ECT is −0.740, which shows that the adjustment speed for the variable to reach the long-run equilibrium is approximately 74% annually. Table 4.29 displays the results of diagnostic tests, indicating that all the probabilities exceed 0.05—fail to reject the null hypothesis. The results reveal that Models 5, 6, and 7 pass all the diagnostic tests with normal residual distribution, no serial correlation problem, variances that are homoscedastic, and no misspecification. In addition, the results of the cumulative sum of recursive residuals (CUSUM) and the cumulative sum of squares of recursive residuals (CUSUM^2) reveal that all the equations for Model 5, Model 6, and Model 7 are stable, as shown in Figure 4.13, Figure 4.14, and Figure 4.15, respectively.



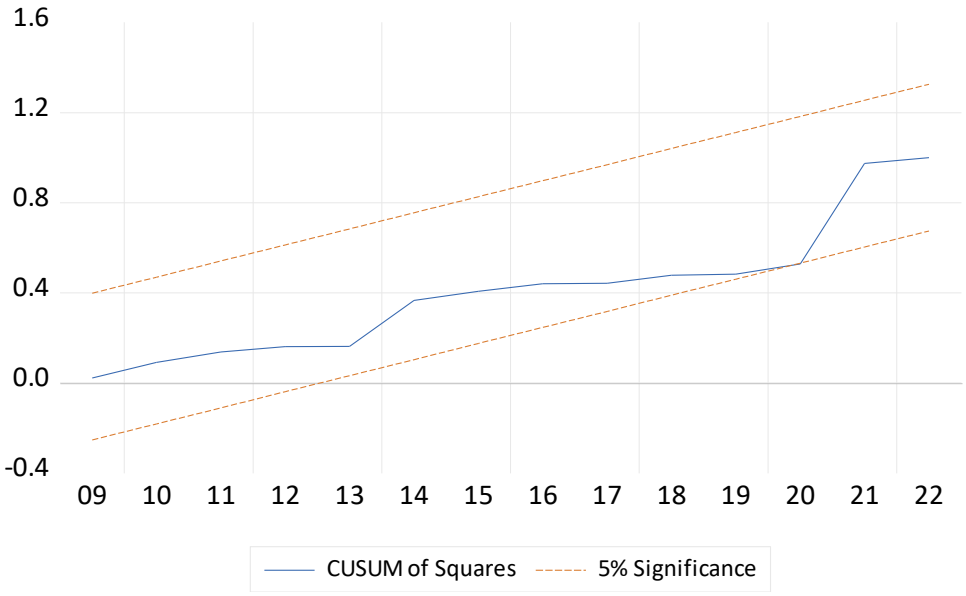
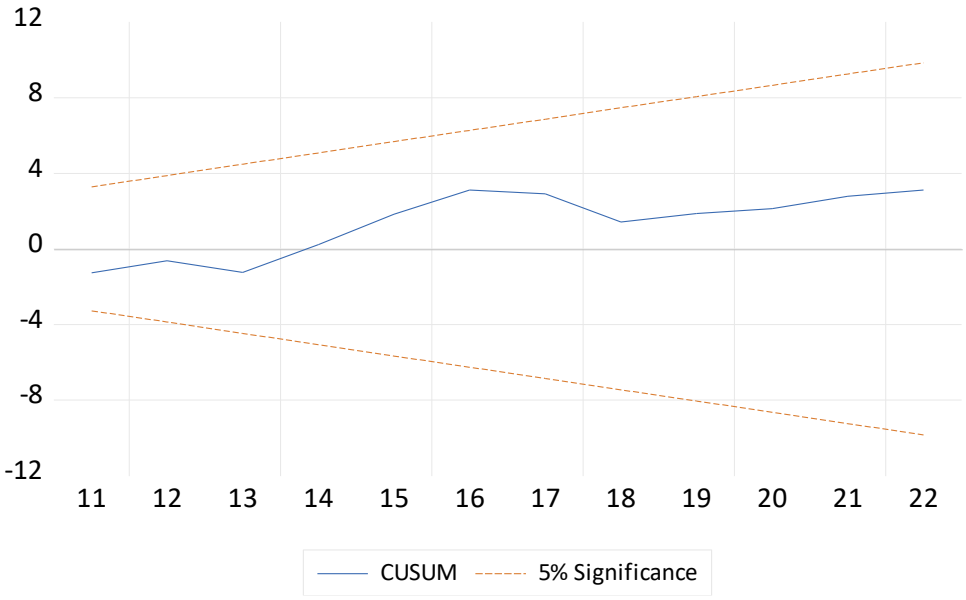


Figure 4.13: CUSUM and CUSUM of Squares for Model 5



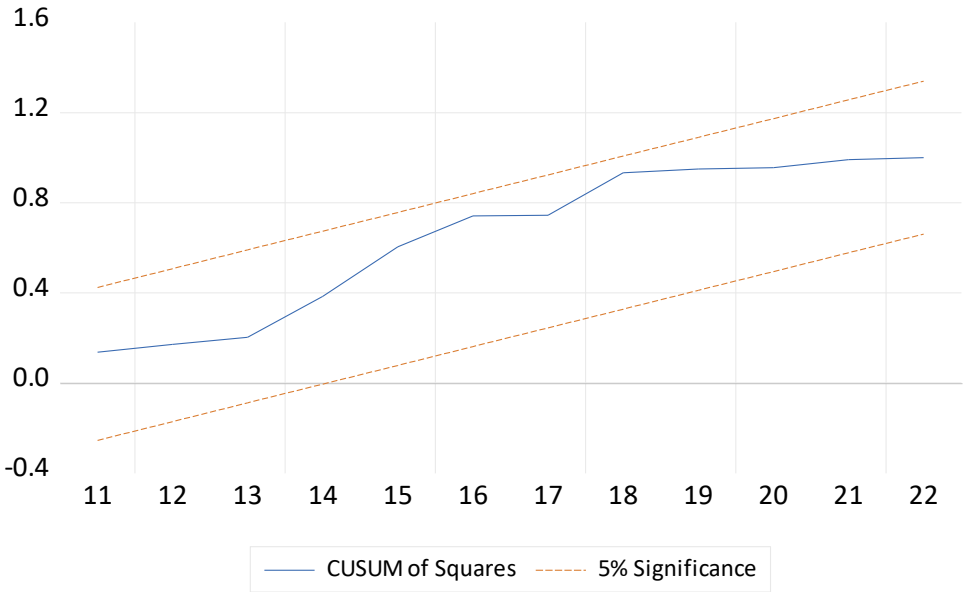
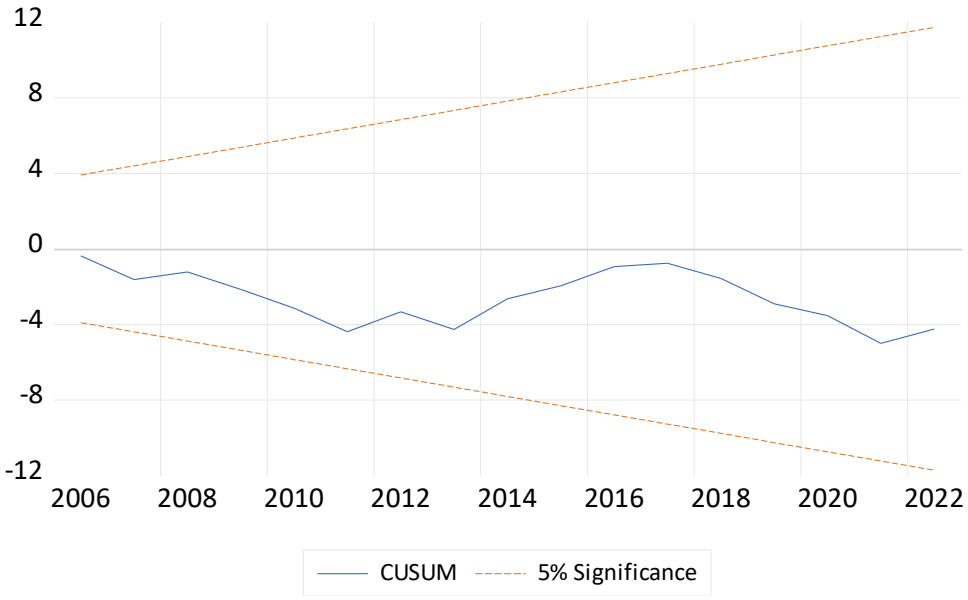


Figure 4.14: CUSUM and CUSUM of Squares for Model 6



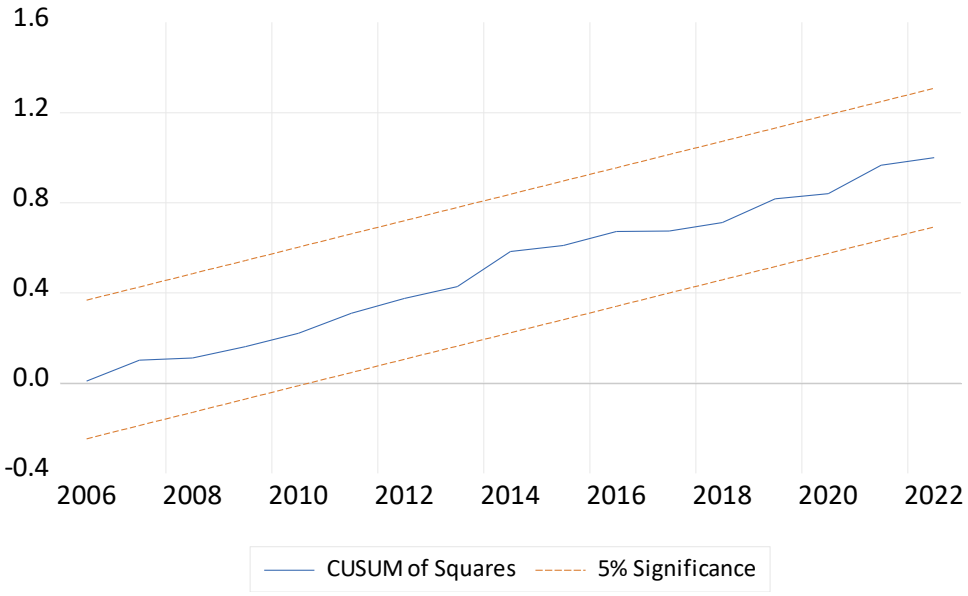


Figure 4.15: CUSUM and CUSUM of Squares for Model 7

Table 4.30: Results of the Long-Run and Short-Run Effects of Employed Workers with Educational Attainment in Wald Tests

Wald Tests				
	Low Educational Attainment		**High Educational Attainment**	
	F-statistic	**p-value**	**F-statistic**	**p-value**
		Model 5		
Long-run	4.880*	0.025	9.567**	0.002
Short-run	3.241	0.054	12.012**	0.000
		Model 6		
Long-run	8.296**	0.006	13.696**	0.001
Short-run	-	-	7.175**	0.003
		Model 7		
Long-run	5.223*	0.017	1.946	0.173
Short-run	4.158*	0.012	-	-

Notes: The lag length selection is based on the Schwarz information criterion (SIC). The asterisks (* and **) denote statistical significance at the 5 percent and 1 percent levels, respectively.

The results of the Wald test shown in Table 4.30 reveal the long-run and short-run effects of employed workers with educational attainment (i.e., high educational attainment and low educational attainment) on agricultural productivity, industrial productivity, and services productivity, respectively. For Model 5, the results reveal that low educational attainment has a statistically significant impact on agricultural productivity only in the long run; however, low educational attainment has a statistically insignificant impact on agricultural productivity in the short run because the p-value exceeds 0.05. Based on the results of the Wald test, the employed workers who have high education levels have a statistically significant impact on agricultural productivity both in the long term and short term. The result is statistically significant at the 1 percent level. Additionally, the findings of Model 6 demonstrate that the result is statistically significant at the 1 percent level for

the long-run effect of employed workers who have low education levels on industrial productivity. In the meantime, employed workers with high educational attainment have a statistically significant impact on industrial productivity in both the long term and short term. The result is statistically significant at the 1 percent level, which is based on the results of the Wald test shown in Table 4.30. Additionally, the employed workers with low educational attainment have a statistically significant impact on services productivity, both in the long term and short term. The result is statistically significant at the 5 percent level, according to the Wald test results of Model 7. However, the results of the Wald test indicate that high educational attainment has a statistically insignificant impact on service productivity in the long run.

4.6 Foreign Workers' Employment, Low Educational Attainment, and Malaysian Sectoral Labor Productivity

4.6.1 Nonlinear Autoregressive Distributed Lag

The purpose of NARDL is mainly to examine the asymmetric effects of employed foreign workers on labor productivity (i.e., agriculture, industry, and services). The nonlinear ADRL is applied to trace hidden cointegration and asymmetric relationships between employed foreign workers and labor productivity. As per asymmetry or nonlinear ARDL, employed foreign workers are composed of two components, which are positive and negative. It enables the use of a nonlinear or asymmetric autoregressive distributed lag (NARDL) model to estimate long-run and short-run relationships, as well as cointegrating relationships among the variables using a bound test approach. The study includes employed workers with low educational attainment as one of the independent variables—encompassing two education levels (i.e., no formal education and primary education). Additionally, the study also includes fixed capital as an independent variable. The study

uses the Nonlinear Autoregressive Distributed Lag (NARDL) model to examine the asymmetric effects of employed foreign workers on labor productivity and to measure the impacts of low educational attainment and fixed capital on labor productivity, particularly in the Malaysian sectoral industries (i.e., agriculture, industry, and services) between 1991 and 2022.

4.6.2 Unit Root and Stationary Tests

This study employs three types of unit root tests, including the Augmented Dickey–Fuller (ADF) test proposed by Dickey and Fuller (1979), the Phillips–Perron (PP) test proposed by Phillips and Perron (1988), and the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test proposed by Kwiatkowski et al. (1992). Table 4.32 presents the suggested results of unit root and stationary tests for Model 8, Model 9, and Model 10, based on the ADF, PP, and KPSS unit root tests, while the descriptive statistics of variables are presented in Table 4.31. Fixed capital has the highest mean, followed by industrial productivity. However, when compared to other variables, employed workers without formal education have the lowest mean. The standard deviation is a dispersion or spread measurement in the series, which underscores that the employed foreign workers have the highest standard deviation, followed by fixed capital, whereas agricultural productivity has the lowest standard deviation.

Table 4.31: Descriptive Statistics for Models 8, 9, and 10

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	JB
LPRODA	9.475	9.459	9.681	9.305	0.106	0.274	2.018	1.686
LPRODI	10.181	10.228	10.327	9.829	0.141	−1.159	3.453	7.442
LPRODS	9.571	9.596	9.956	8.987	0.252	−0.369	2.346	1.296
LEFW	7.042	6.952	7.716	5.689	0.578	−0.668	2.679	2.517

Table 4.31 continued

LFCAPI	14.679	14.601	15.407	13.584	0.524	−0.273	2.103	1.471
LWNOF	6.174	6.152	6.501	5.881	0.199	0.375	1.766	2.780
LWPRI	7.639	7.687	7.780	7.162	0.156	−2.034	6.537	38.745

Notes: Std. Dev. denotes standard deviation; JB represents Jarque–Bera; LPRODA, LPRODI, and LPRODS are the logarithms of agricultural productivity, industrial productivity, and services productivity, respectively, which are measured in constant 2015 US dollars; and employed workers are measured in thousands of people.

Table 4.32: Results of Unit Root and Stationary Tests for Models 8, 9, and 10

	ADF		**PP**		**KPSS**	
	Intercept	**Trend & Intercept**	**Intercept**	**Trend & Intercept**	**Intercept**	**Trend & Intercept**
			A: Level			
LPRODA	−0.244(2)	−3.127(0)	−0.847(0)	−3.096(1)	0.666(4)**	0.137(3)***
LPRODI	−2.634(0)	−2.382(0)	−4.111(9)*	−2.381(7)	0.627(4)**	0.164(4)**
LPRODS	−2.176(0)	−4.692(1)*	−2.176(0)	−3.837(1)**	0.757(4)*	0.084(1)
LEFW	−2.737(0)***	−1.927(0)	−2.775(2)***	−1.949(2)	0.686(4)**	0.102(3)
LFCAPI	−2.013(0)	−2.479(0)	−1.952(1)	−2.554(1)	0.741(4)*	0.067(3)
LWNOF	−1.536(1)	−0.893(1)	−1.508(2)	−3.919(3)**	0.651(4)**	0.165(4)**
LWPRI	1.531(0)	−0.778(1)	−1.380(2)	−0.055(2)	0.491(4)**	0.138(3)***
			B: First Difference			
ΔLPRODA	−6.349(1)*	−6.570(1)*	−6.564(1)*	−7.237(3)*	0.141(5)	0.116(7)
ΔLPRODI	−4.360(0)*	−4.528(0)*	−4.274(4)*	−4.412(6)*	0.242(1)	0.089(5)
ΔLPRODS	−4.666(1)*	−4.377(1)*	−4.167(5)*	−4.054(4)**	0.228(0)	0.083(1)
ΔLEFW	−4.836(0)*	−5.342(0)*	−4.863(3)*	−5.340(2)*	0.320(3)	0.089(2)
ΔLFCAPI	−4.374(0)*	−4.526(0)*	−4.379(1)*	−4.539(1)*	0.208(1)	0.083(1)
ΔLWNOF	−10.976(0)*	−3.933(4)**	−11.313(1)*	−12.197(2)*	0.104(4)	0.110(5)
ΔLWPRI	−3.860(0)*	−4.516(0)*	−3.831(2)*	−4.536(1)*	0.351(3)***	0.119(2)

Table 4.32 continued

Notes: The types of unit root tests used are ADF, PP, and KPSS tests. The number in parentheses denotes the lag length or bandwidth used by the default settings in EViews. An asterisk (*) denotes the test statistic is statistically significant at the 1 percent level, (**) indicates statistical significance at the 5 percent level, and (***) signifies statistical significance at the 10 percent level. Δ denotes the first difference operator.

Based on the results of the ADF, PP, and KPSS tests, the unit root tests confirm that the variables, including LPRODA, LPRODI, LEFW, LFCAPI, LWNOF, and LWPRI, are stationary in the first difference—which are *I*(1) variables. The results reveal that LPRODS is stationary at the trend and intercept specification in the level—LPRODS is an *I*(0) variable. This study applied unit root tests with a breakpoint, which is the augmented Dickey–Fuller with structural breaks, based on the framework outlined (e.g., Banerjee et al., 1992; Perron, 1989; Vogelsang & Perron, 1998; Zivot & Andrews, 1992). The results of the unit root with structural breaks are described in Table 4.33, which reveals that all the variables are stationary in the first difference at the 1 percent significance level; however, LWNOF is stationary at the 10 percent level of significance under the intercept specification while stationary at the 5 percent significance level under the trend and intercept specification, based on the results of the unit root with structural breaks in the level. This underscores that the combined results suggest that all the series are integrated in order one, except for LWNOF, which is stationary in the level. The estimated break date is mainly in the periods 1997–1999 and 2007–2009, which are primarily associated with the financial crisis period. The other estimated break date is 2019–2022, which is connected to the COVID-19 pandemic.

Table 4.33: Results of the Unit Root with Structural Breaks for Models 8, 9, and 10

	Level		First Difference	
	ADF_I	ADF_{TI}	ADF_I	ADF_{TI}
LPRODA	−1.976(0)	−4.588 (0)	−7.126(0)*	−7.536(1)*
	[2010]	[1994]	[2000]	[2019]
LPRODI	−2.967(0)	−4.767(3)***	−5.654(5)*	−5.495(5)*
	[1994]	[2004]	[2006]	[2006]
LPRODS	−2.832(0)	−5.955(1)*	−5.304(0)*	−5.188(0)**
	[2003]	[2006]	[1998]	[1998]
LEFW	−4.065(0)	−2.780(0)	−6.922(0)*	−7.229(7)*
	[2009]	[1995]	[1996]	[2009]
LFCAPI	−3.312(2)	−6.081(4)*	−5.903(0)*	−5.737(0)*
	[2006]	[2010]	[1999]	[1999]
LWNOF	−4.314(0)***	−5.915(0)*	−12.476(0)*	−11.806(0)*
	[1999]	[1999]	[2008]	[1997]
LWPRI	−3.124(6)	−4.375(3)	−5.306(0)*	−5.342(0)**
	[2014]	[2019]	[2013]	[2019]

Notes: The number in parentheses and square brackets denotes the lag length and break date, respectively. ADF_I and ADF_{TI} denote the intercept and trend & intercept specification, respectively, with intercept break, selecting Dickey–Fuller min-t as the breakpoint selection with break type innovational outlier. An asterisk (*) indicates that the test statistic is statistically significant at the 1 percent significance level, (**) denotes statistical significance at the 5 percent level, and (***) signifies statistical significance at the 10 percent level.

4.6.3 Nonlinear ARDL Bounds Test for Cointegration

Table 4.34: Results of the NARDL Bounds Testing Approach

Model	F-statistic	NARDL Order
Model 8: LPRODA, LEFW_POS, LEFW_NEG, LFCAPI, LWNOF, LWPRI	4.277**	(1, 0, 0, 1, 2, 0)
Model 9: LPRODI, LEFW_POS, LEFW_NEG, LFCAPI, LWNOF, LWPRI	4.973**	(2, 1, 2, 3, 2, 0)
Model 10: LPRODS, LEFW_POS, LEFW_NEG, LFCAPI, LWNOF, LWPRI	6.380**	(1, 0, 0, 0, 1, 3)

Table 4.34 continued

Critical value bounds of the F-statistic: restricted intercept and no trend (k=5)		
Significance level	$I(0)$	$I(1)$
10%	2.08	3.00
5%	2.39	3.38
2.5%	2.70	3.73
1%	3.06	4.15

Notes: Critical values of Models 8 (agriculture), 9 (industry), and 10 (services) are obtained from Pesaran et al. (2001), Table Case II: restricted intercept and no trend. The lag length selection is based on the Schwarz information criterion (SIC). Asterisks (* and **) indicate statistical significance at the 5 percent and 1 percent levels, respectively.

Table 4.34 reveals the results of the NARDL bounds testing approach for Model 8 (agriculture), Model 9 (industry), and Model 10 (services) throughout 1991–2022. The results of the NARDL bounds testing approach for cointegration are displayed in Table 4.34, which indicates that k is the number of independent variables used in this study. The F-statistic value for Model 8 is 4.277, as shown in Table 4.34. This F-value is greater than the critical value of the upper bound proposed by Pesaran et al. (2001) at the 1% significance level, which implies that the null hypothesis of no cointegration is rejected. The results of Model 8 confirm that there is the existence of an asymmetric (cointegrating) long-run relationship between agricultural productivity and independent variables over the period of 1991–2022. The optimal lag length selection is the NARDL (1, 0, 0, 1, 2, 0) model, which is selected based on the Schwarz information criterion (SIC). Moreover, the calculated F-statistic value of Model 9 is presented as 4.973, which is higher than the critical value of the upper bound proposed by Pesaran et al. (2001) at the 1% significance level. This implies that the results of Model 9 also indicate the existence of an asymmetric long-run relationship between industrial productivity and independent variables during the

period 1991–2022. The optimal lag length selection is the NARDL (2, 1, 2, 3, 2, 0) model, which is also designated based on the Schwarz information criterion (SIC). Next, the F-statistic value of Model 10 is shown as 6.380, which is larger than the critical value of the upper bound proposed by Pesaran et al. (2001) at the 1% significance level. The results of Model 10 demonstrate that there is the presence of an asymmetric cointegration between the dependent variable (i.e., services productivity) and independent variables throughout the study period based on the NARDL bounds test. The optimal lag length selection for Model 10 is the NARDL (1, 0, 0, 0, 1, 3) model, which is nominated based on the Schwarz information criterion (SIC).

4.6.4 Nonlinear ARDL Long-Run Estimates

Table 4.35: Results of NARDL Long-Run Estimates

Model 8				
Variable	**Coefficient**	**SE**	**t-statistic**	**p-value**
LEFW_POS	0.494	0.275	1.796	0.088
LEFW_NEG	0.751	0.465	1.614	0.122
LFCAPI	−0.527	0.342	−1.539	0.140
LWNOF	−0.461**	0.197	−2.343	0.030
LWPRI	−0.634**	0.256	−2.476	0.022
C	24.244***	7.050	3.439	0.003
Model 9				
Variable	**Coefficient**	**SE**	**t-statistic**	**p-value**
LEFW_POS	−0.550	0.487	−1.130	0.279
LEFW_NEG	−1.996	1.446	−1.380	0.191
LFCAPI	0.753	0.649	1.161	0.266
LWNOF	0.705	0.691	1.021	0.326
LWPRI	0.128	0.434	0.294	0.773

Table 4.35 continued

C	−5.396	15.435	−0.350	0.732
		Model 10		
Variable	**Coefficient**	**SE**	**t-statistic**	**p-value**
LEFW_POS	−0.148**	0.070	−2.125	0.048
LEFW_NEG	0.175	0.224	0.780	0.446
LFCAPI	0.510***	0.086	5.916	0.000
LWNOF	−0.342***	0.094	−3.653	0.002
LWPRI	−0.038	0.185	−0.207	0.838
C	4.742	2.721	1.743	0.098

Notes: The lag length selection is based on the Schwarz information criterion (SIC). The asterisks (** and ***) indicate statistical significance at the 5 percent and 1 percent levels, respectively.

The results of long-run estimation of Models 8, 9, and 10 over the period of 1991–2022 are shown in Table 4.35. The results confirm that both positive and negative components of employed foreign workers are obtained by the nonlinear ARDL for Models 8, 9, and 10. The NARDL bounds testing approach results of Model 8 are exhibited in Table 4.34, which indicates that there is an asymmetric long-run relationship between the dependent variable and independent variables because the calculated value of the F-statistic is greater than the critical value of the upper bound at the 1% significance level during 1991–2022. Likewise, the results of the bound testing approach for Models 9 and 10 also indicate the presence of an asymmetric cointegration between the dependent variable and independent variables, as the calculated F-value is higher than the critical value of the upper bound at the 1% significance level. The long-run estimation results of Model 8 based on NARDL, as exhibited in Table 4.35, reveal that only LWNOF has a negative and statistically significant impact on LPRODA at the 5 percent level. This result reported that

the workers with no formal education negatively affect agricultural productivity with a coefficient of −0.461. Moreover, workers with primary education have a negative impact on agricultural productivity with a coefficient of −0.634. This indicates that a 1% increase in workers with primary education results in a decrease of approximately 0.634 percent in agricultural productivity. The long-run estimation results of Model 8 affirm that LEFW_POS has a positive and statistically insignificant impact on LPRODA, with a coefficient of 0.494. In addition, LEFW_NEG has a positive impact on LPRODA with a coefficient of 0.751, but the result is statistically insignificant. However, the fixed capital has a negative impact on agricultural productivity with a coefficient of −0.527, but the result is statistically insignificant.

Additionally, the bounds test results of Model 9, based on NARDL, reveal that there is an asymmetric long-run relationship detected between the dependent variable and independent variables. The result also specifies that LEFW_POS has an adverse impact on LPRODI, with a coefficient of −0.550; the estimated coefficient on LEFW_POS is statistically insignificant at the 5 percent level. However, LEFW_NEG has a negative and statistically insignificant long-run impact on LPRODI, with a coefficient of −1.996, because the p-value is greater than the 5% significance level. This result is inconsistent with the findings from Jordaan (2018) that foreign labor positively impacts productivity in Malaysian manufacturing industries. Likewise, the long-run estimation results of Model 9 indicate that the variables LFCAPI, LWNOF, and LWPRI positively impact LPRODI, respectively; however, these results are statistically insignificant at the 5 percent level. This means that fixed capital, workers lacking formal education, and workers with primary education have a positive and statistically insignificant impact on industrial productivity, with coefficients of 0.753, 0.705, and 0.128, respectively. Furthermore, the long-run

estimation of Model 10, as exhibited in Table 4.35, highlights that only LEFW_POS has a negative and statistically significant long-run impact on LPRODS at the 5 percent level. The positive changes in employed foreign workers negatively affect services productivity, indicated by a coefficient of −0.148. This finding indicates that positive changes in employed foreign workers by 1 percent led to a decrease in services productivity of 0.148. The results of long-run estimation reveal that LWNOF has a negative and statistically significant impact on LPRODS at the 1 percent level, with a coefficient of −0.342. This highlights that an increase in employed workers with no formal education by 1 percent leads to a decrease in services productivity by approximately 0.342 percent in the long term. However, the results underline that LFCAPI has a positive impact on LPRODS, evidenced by a coefficient of 0.510; this result is statistically significant at the 1 percent level. This result indicates that an increase in fixed capital by 1 percent leads to an increase in services productivity by 0.510 percent. Afterward, LWPRI has a negative and statistically insignificant long-run impact on LPRODS, with a coefficient of −0.038, as it failed to reject the null hypothesis on account of the p-value being greater than 0.05.

4.6.5 NARDL Error Correction Representation and Diagnostic Tests

Table 4.36: NARDL Estimation Results

Variable	Coefficient	SE	t-statistic	p-value
Model 8: LPRODA, LEFW_POS, LEFW_NEG, LFCAPI, LWNOF, LWPRI (1, 0, 0, 1, 2, 0)				
ΔLFCAPI	0.012	0.055	0.226	0.824
ΔLWNOF	−0.003	0.062	−0.044	0.965
ΔLWNOF_{t-1}	0.146	0.078	1.872	0.076
ECT_{t-1}	−0.530***	0.085	−6.239	0.000
Diagnostic Tests:				

Table 4.36 continued

JB	1.213 (0.545)			
AR [2]	2.582 (0.275)			
ARCH [1]	0.072 (0.788)			
RESET [1]	4.031 (0.059)			
CUSUM	Stable			
$CUSUM^2$	Stable			
Model 9: LPRODI, LEFW_POS, LEFW_NEG, LFCAPI, LWNOF, LWPRI (2, 1, 2, 3, 2, 0)				
$\Delta LPRODI_{t-1}$	0.273	0.132	2.069	0.059
ΔLEFW_POS	−0.121**	0.047	−2.555	0.024
ΔLEFW_NEG	0.313	0.192	1.634	0.126
$\Delta LEFW\_NEG_{t-1}$	1.445***	0.260	5.546	0.000
ΔLFCAPI	−0.003	0.069	−0.049	0.962
$\Delta LFCAPI_{t-1}$	−0.440***	0.075	−5.883	0.000
$\Delta LFCAPI_{t-2}$	−0.242**	0.091	−2.663	0.020
ΔLWNOF	0.144**	0.058	2.504	0.026
$\Delta LWNOF_{t-1}$	−0.142	0.067	−2.111	0.055
ECT_{t-1}	−0.377***	0.053	−7.133	0.000
Diagnostic Tests:				
JB	0.743 (0.690)			
AR [2]	3.254 (0.197)			
ARCH [1]	0.053 (0.818)			
RESET [1]	1.824 (0.202)			
CUSUM	Stable			
$CUSUM^2$	Stable			
Model 10: LPRODS, LEFW_POS, LEFW_NEG, LFCAPI, LWNOF, LWPRI (1, 0, 0, 0, 1, 3)				
ΔLWNOF	−0.049	0.042	−1.161	0.261
ΔLWPRI	0.126	0.080	1.583	0.131

Table 4.36 continued

$\Delta LWPRI_{t-1}$	−0.063	0.092	−0.686	0.502
$\Delta LWPRI_{t-2}$	−0.617***	0.093	−6.637	0.000
ECT_{t-1}	−0.824***	0.107	−7.171	0.000
Diagnostic Tests:				
JB	1.381 (0.501)			
AR [2]	4.352 (0.114)			
ARCH [1]	0.338 (0.561)			
RESET [1]	0.395 (0.538)			
CUSUM	Stable			
$CUSUM^2$	Stable			

Notes: The lag length selection is based on the Schwarz information criterion (SIC). JB denotes the Jarque–Bera statistic for the residuals normality test. AR is the Lagrange Multiplier test for serial correlation. ARCH and RESET refer to the ARCH heteroskedasticity test and Ramsey RESET specification test, respectively. Figures in parentheses are the p-values. The asterisks (** and ***) indicate statistical significance at the 5 percent and 1 percent levels, respectively.

The short-run results of nonlinear ARDL, as exhibited in Table 4.36, were obtained by using the NARDL model proposed by Shin et al. (2014). The results of Model 8 highlight that LFCAPI has a positive impact on LPRODA with a coefficient of 0.012; the estimated coefficient on LFCAPI is statistically insignificant at the 5 percent level. Likewise, workers with no formal education have a negative and statistically insignificant impact on agricultural productivity, with a coefficient of −0.003. The error correction term (ECT) measures the speed of adjustment, which consists of a negative sign and is statistically significant at the 1 percent level. The coefficient of ECT is −0.530, indicating that the adjustment speed for the variables to reach the long-run equilibrium is approximately 53% annually.

The results of Model 9 reveal that LEFW_POS has a negative impact on LPRODI in the short run; the result is statistically significant at the 5 percent level. More specifically, positive changes in employed foreign workers negatively impact industrial productivity, with a coefficient of −0.121 percent. This indicates that a 1 percent positive change in employed foreign workers results in a diminution in industrial productivity by approximately 0.121 percent. However, the estimated coefficient on LEFW_NEG is positive, but the result is not statistically significant. The result indicates that the estimated coefficient on LWNOF is positive and statistically significant at the 5 percent level. Based on the short-run results of the nonlinear ARDL, workers without formal education have a positive impact on LPRODI, with a coefficient of 0.144. This implies that a 1 percent increase in workers lacking formal education leads to an increment in industrial productivity by 0.144 percent in the short run. The results reveal the estimated coefficient on LFCAPI is negative and statistically insignificant. The coefficient of ECT is −0.377, which points out that the adjustment speed for the variables to reach the long-run equilibrium is about 37.7% annually.

Likewise, the results of Model 10 indicate that LWNOF has a negative impact on LPRODS in the short run, but the result is statistically insignificant at the 5 percent level. This underlines that workers without formal education negatively impact services productivity with a coefficient of −0.049, but the coefficient is not statistically significant. The short-run results of NARDL for Model 10 indicate that LWPRI has a positive short-term impact on LPRODS, with a coefficient of 0.126. This result reveals that a 1 percent increase in workers with primary education results in an increment in services productivity of about 0.126 percent, but the estimated coefficient on LWPRI is statistically insignificant at the 5 percent level. The coefficient of ECT for Model 10 is −0.824, which portrays the

adjustment speed for the variables to reach the long-run equilibrium as approximately 82.4% annually. Subsequently, Table 4.36 reports the results of diagnostic tests—demonstrating that all the probabilities of diagnostic tests are greater than 0.05, thereby failing to reject the null hypothesis. The findings underscore that Models 8, 9, and 10 pass all the diagnostic tests, indicating the residuals are normally distributed, there is no serial correlation issue, the variances are homoscedastic, and there is no misspecification. In addition, the results of the cumulative sum of recursive residuals (CUSUM) and cumulative sum of squares of recursive residuals (CUSUM^2) reveal that all the equations for Models 8, 9, and 10 are stable (see Figures 4.16 to 4.20).

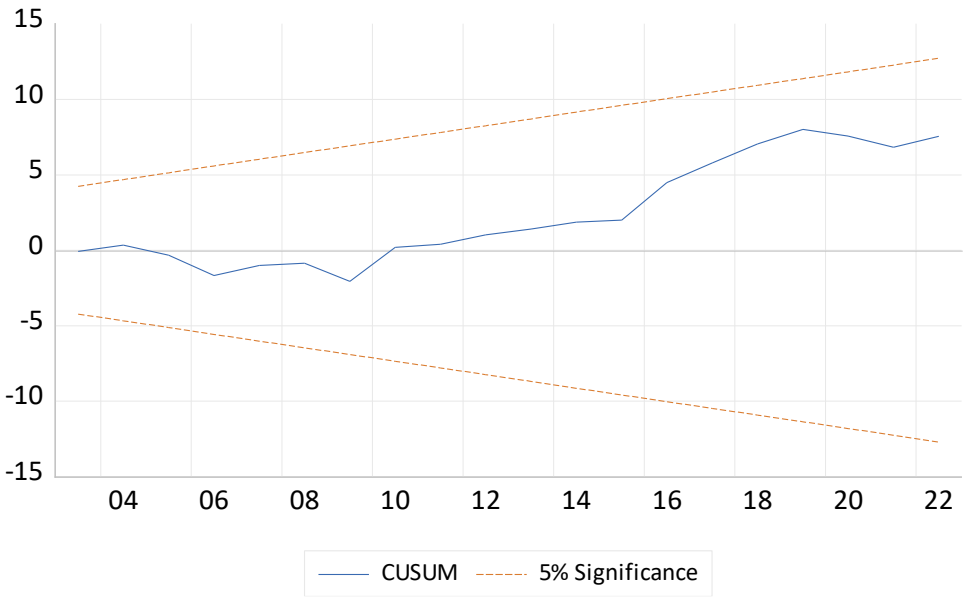


Figure 4.16: NARDL CUSUM for Model 8

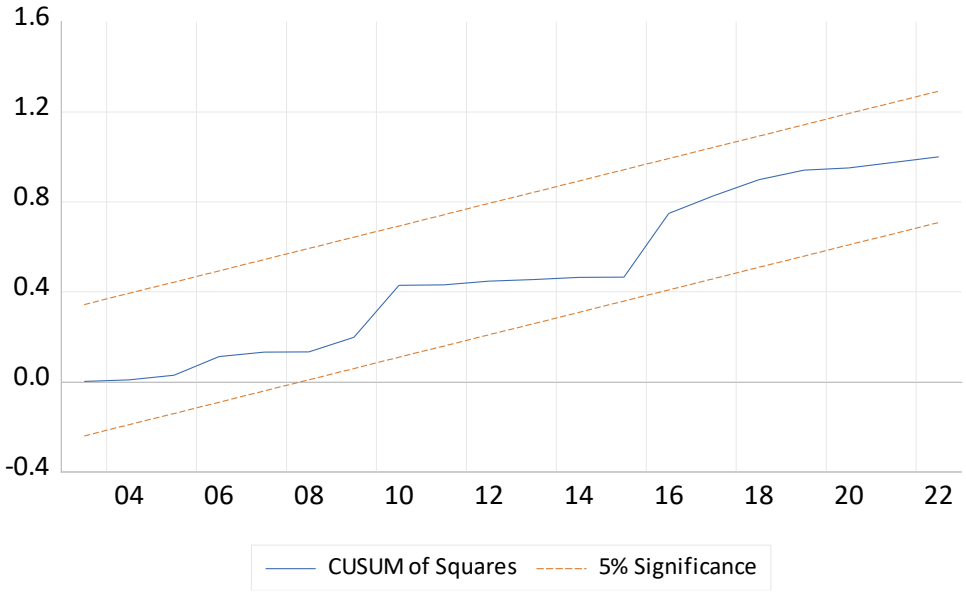


Figure 4.17: NARDL CUSUM of Squares for Model 8

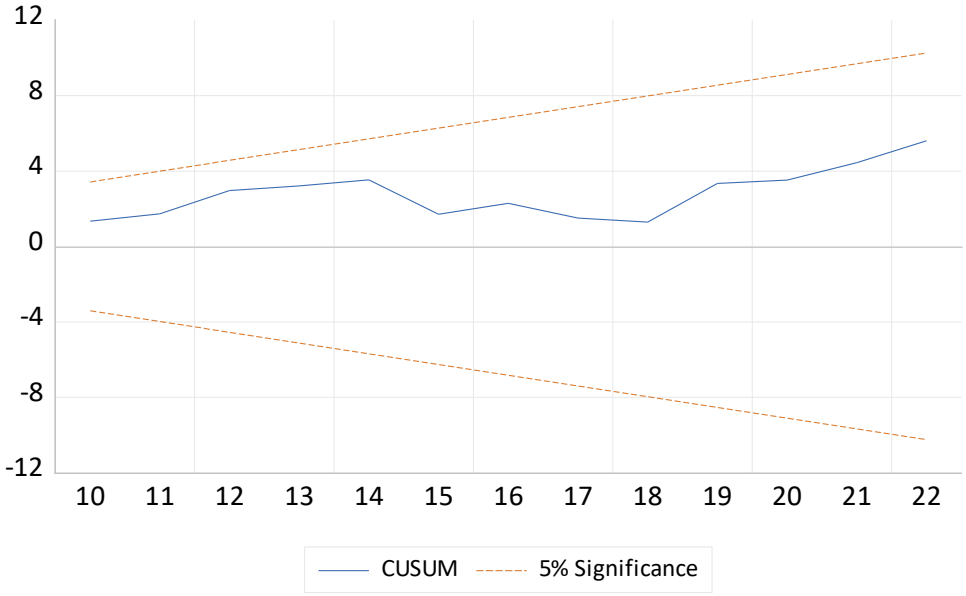


Figure 4.18: NARDL CUSUM for Model 9

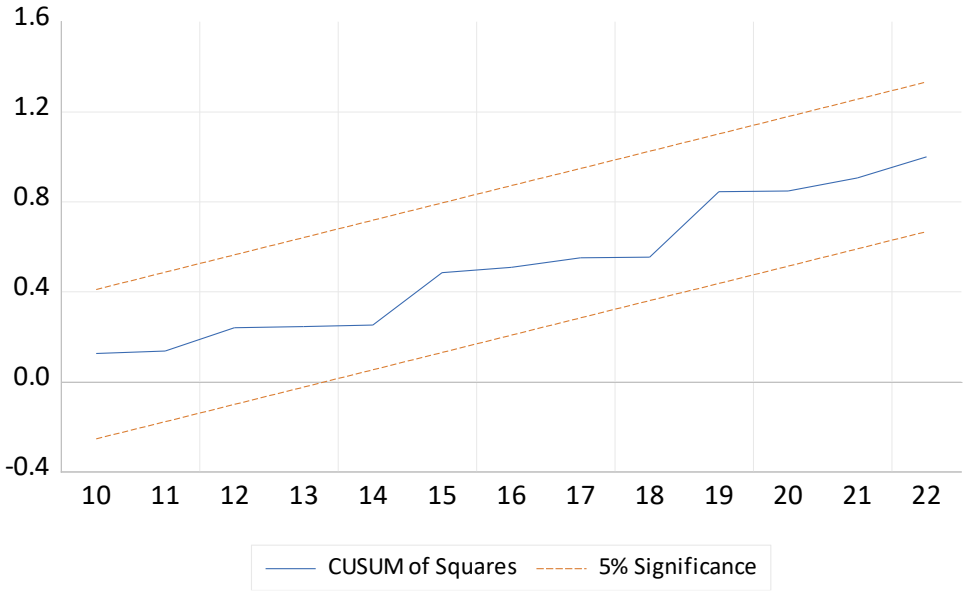


Figure 4.19: NARDL CUSUM of Squares for Model 9

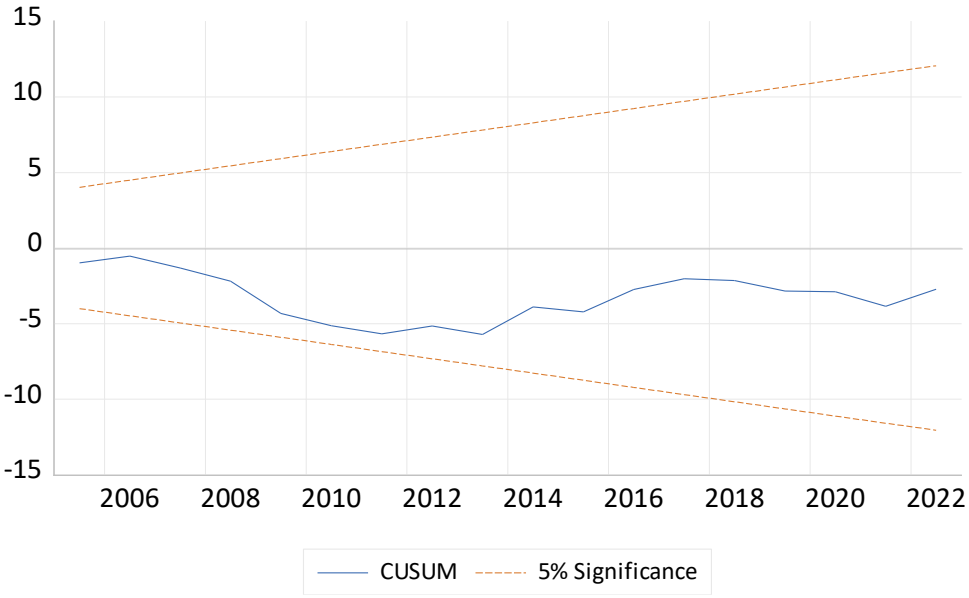


Figure 4.20: NARDL CUSUM for Model 10

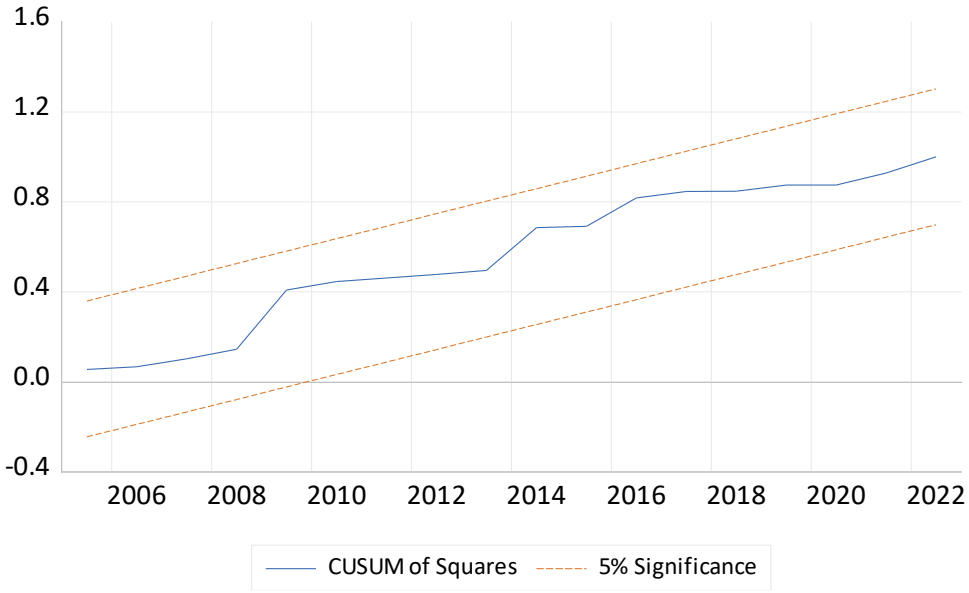


Figure 4.21: NARDL CUSUM of Squares for Model 10

Table 4.37: The Results of the Long-Run and Short-Run Asymmetric Effects of Employed Foreign Workers in Wald Tests

	Wald Tests	
	t-statistic	**F-statistic**
	Model 8	
Long-run	−0.615 (0.546)	0.378 (0.546)
Short-run	-	-
	Model 9	
Long-run	1.569 (0.141)	2.461 (0.141)
Short-run	−3.109 (0.008)***	9.664 (0.008)***
	Model 10	
Long-run	−1.465 (0.160)	2.145 (0.160)
Short-run	-	-

Notes: The lag length selection is based on the Schwarz information criterion (SIC). The asterisks (** and ***) denote statistical significance at the 5 percent and 1 percent levels, respectively. Figures in parentheses are the p-values.

The results of the Wald test are presented in Table 4.37, which specifies the long-run and short-run asymmetric effects of employed foreign workers on agricultural productivity, industrial productivity, and services productivity, respectively. The results of Model 8 demonstrate that employed foreign workers have asymmetric effects on agricultural productivity in the long run, but the result is statistically insignificant at the 5 percent level. In addition, the results of Model 9 reveal that there are not statistically significant long-run asymmetric effects of employed foreign workers on industrial productivity because the p-value exceeds 0.05. In the short run, the employed foreign workers have statistically significant asymmetric effects on industrial productivity, which is based on the results of the Wald test (see Table 4.37). Likewise, the employed foreign workers have statistically insignificant long-run asymmetric effects on services productivity at the 5 percent level, based on the Wald test results of Model 10.

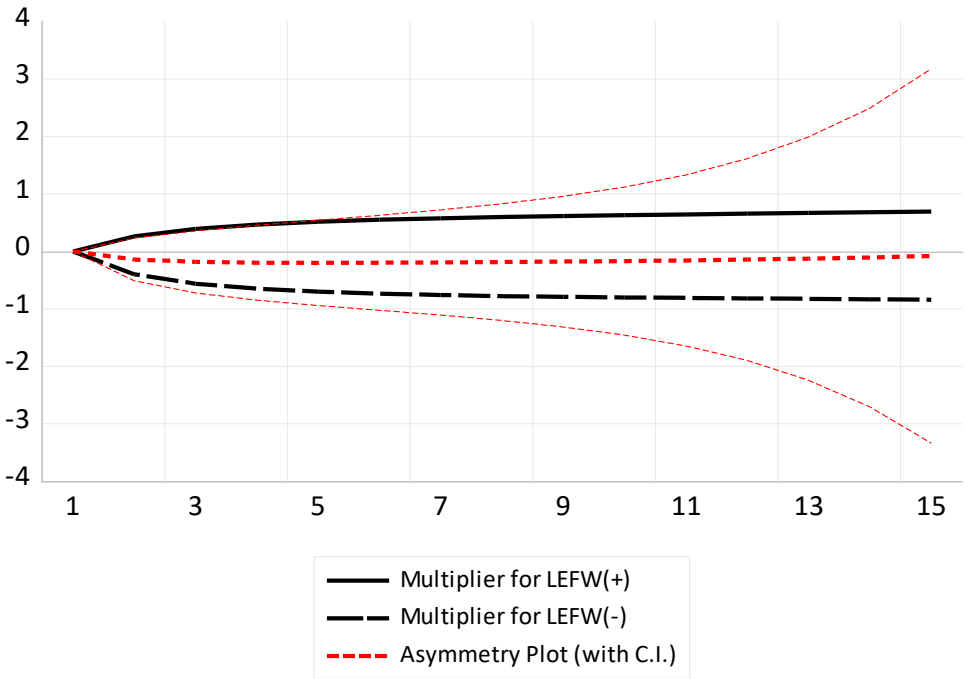


Figure 4.19: NARDL Multiplier Graph for Model 8

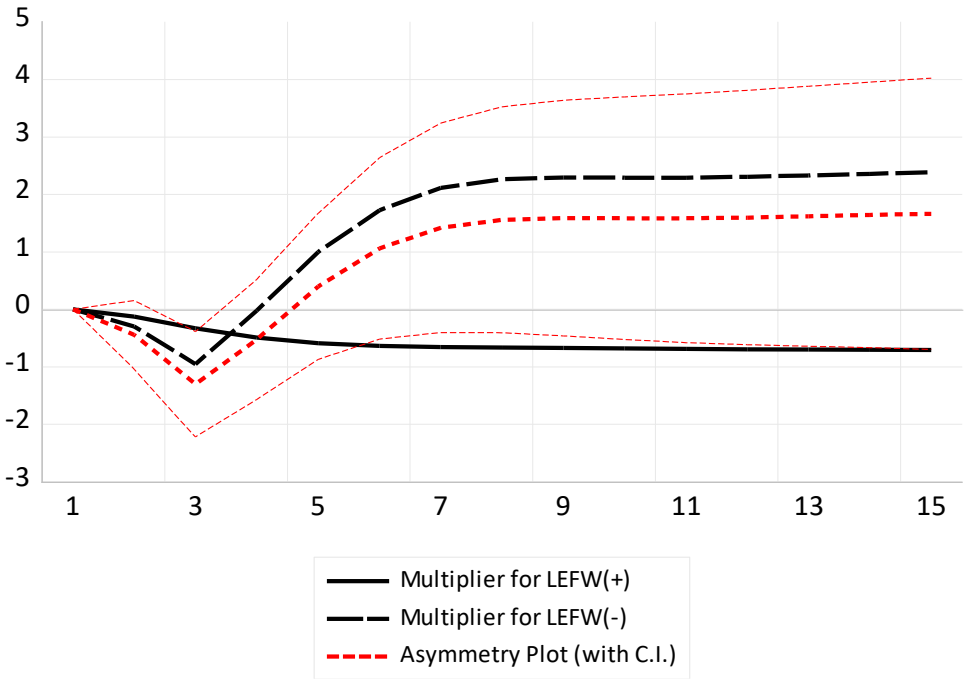


Figure 4.20: NARDL Multiplier Graph for Model 9

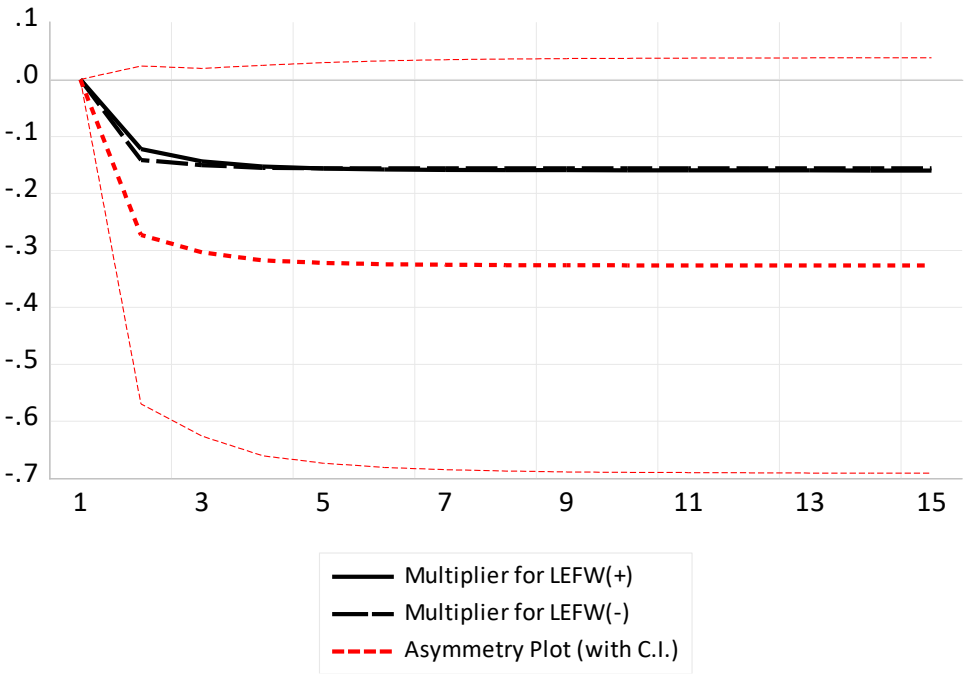


Figure 4.21: NARDL Multiplier Graph for Model 10

The dynamic multiplier graph describes the adjustment of non-linear effects in the long-run equilibrium due to the positive and negative shocks in employed foreign workers,

as shown in the graphs (see Figures 4.19 to 4.21). The positive and negative change curves are plotted on the dynamic multiplier graph for NARDL, which depicts the evidence regarding asymmetric adjustment at a given period. The asymmetry plot presents the linear combination of dynamic multipliers related to positive and negative shocks. Figure 4.19 illustrates the results of dynamic multiplier changes for Model 8. The graph indicates that LPRODA's response to a shock in LEFW_POS is positive. This positive response gradually increases and sustains a certain level of impact until the 15th year. The response of LPRODA to a shock in LEFW_NEG is negative; this negative effect exhibits a slight increase from the beginning until the 15th year. Likewise, Figure 4.20 illustrates the dynamic multiplier changes for LEFW and LPRODI over a 15-year period; the response of LPRODI to LEFW_POS indicates a slight negative response from the first year to the fifteenth year. In contrast, the LPRODI's response to LEFW_NEG indicates a negative effect from the first year to the third year, followed by a decline in the negative response from the third year to the fourth year. Thereafter, the positive response dramatically increases from the 4th year until the 7th year and gradually increases from the 8th year until the 15th year. Figure 4.21 portrays the results of dynamic multiplier changes for LEF and LRPODS. The response of LPRODS to LEFW_POS indicates a negative response in 15 years; this negative effect intensely increases from the 1st year to the 2nd year, gradually rises from the 2nd year to the 3rd year, and then remains a consistent impact from the 5th to the 15th year. The response of LPRODS to a shock in LEFW_NEG remains negative throughout 15 years. This negative response shows a significant increase from the first year to the second year, with a slight increase continuing from the second year to the third year. Additionally, the negative response persists at a certain impact level from the fifth year to the fifteenth year.

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

This chapter presents the key findings from the empirical results of the analysis, which include all the test results employed in the study. The conclusion comprises four main sections: a summary of the findings, policy implications, limitations and recommendations for future studies, and concluding remarks. The summary of the findings provides a review of the overall study.

5.2 Summary of the Findings

5.2.1 Educational Attainment, Employment, and Malaysian Labor Productivity

Based on the unit root and stationary tests, the results reveal that the variables (i.e., Malaysia's labor productivity, workers with no formal education, workers with primary education, workers with secondary education, workers with tertiary education, and fixed capital) are stationary in the first difference—underscoring that all variables are integrated at order one. The results of the unit root test with structural breaks reveal that all the series are integrated in order one. The VAR model is stationary; this model demonstrates a stability condition because all inverse roots are smaller than 1. There is no long-run equilibrium relationship between the variables in the model based on the results of the Johansen and Juselius (1990) cointegration test. The findings demonstrate that the workers with primary education can Granger-cause Malaysian labor productivity during the study period (i.e., 1982–2023). Surprisingly, the IRF found that workers with primary education negatively affect Malaysian labor productivity but only in the first 9 years; there is a

positive effect from the 10th year until the 50th year. The results of the VAR Granger causality test indicate that workers with secondary education can Granger-cause Malaysian labor productivity between 1982 and 2023. The VAR Granger causality flow results illustrate the existence of a unidirectional causal relationship running from LWSEC to LPRODM. The impulse response function (IRF) results indicate that workers with secondary education positively influence Malaysian labor productivity during the study period, particularly the significant positive effect in the 4th–5th year. The findings reveal a significant decline from the 6th year to the 13th year, followed by a gradual decline from the 14th year to the 50th year. The variance decomposition proves that the effect of the workers with secondary education has more influence on Malaysian labor productivity if compared with the workers with primary education. The results indicate that LWSEC is the most influential variable affecting LPRODM, consistently accounting for the largest portion over the 50-year period. The workers with no formal education and those with tertiary education did not Granger-cause Malaysian labor productivity during the period from 1982 to 2023, respectively. The findings indicate that fixed capital does Granger-cause Malaysian labor productivity during the period from 1982 to 2023. This suggests a unidirectional causal relationship between fixed capital and Malaysian labor productivity. The IRF proves that fixed capital positively influences Malaysian labor productivity from the 8th year to the 50th year, but the negative effect happens only in the first 6 years. However, the findings reveal that Malaysian labor productivity can Granger-cause fixed capital during the study period, according to the results of the VAR Granger causality test. The Malaysian labor productivity has a positive impact on fixed capital in 49 years, whereas there is a negative effect only in the first year. This underlines that fixed capital has a bidirectional causal relationship with Malaysian labor productivity. The variance

decomposition results prove fixed capital is the most endogenous variable since it is highly absorbing shocks from other variables. This result explains that workers with secondary education are the most influential variable for fixed capital, followed by Malaysian labor productivity.

Additionally, the findings demonstrate that education levels—namely, primary, secondary, and tertiary education—Granger-cause fixed capital, respectively, at the 10% significance level. The Granger causality flow illustrates that there is a unidirectional causal relationship running from LWPRI to LFCAP, LWSEC to LFCAP, and LWTER to LFCAP. The impulse response function results reveal that workers with primary education positively impact fixed capital over a 50-year period, specifically a significant effect in the first two years. The variance decomposition results demonstrate that workers with primary education are the most exogenous variable in the study. However, workers with secondary education contribute positively to fixed capital only in 45 years, while having a negative effect in the first 4 years. The workers with tertiary education have a positive impact on fixed capital for a duration of 48 years. However, there is a negative effect on fixed capital during the initial period (i.e., in the first two years). In addition, the VAR Granger causality analysis reveals a unidirectional causal relationship running from LWPRI to LWNOF, LWTER to LWNOF, and LFCAP to LWNOF.

The summary of the findings demonstrates that high educational attainment, particularly among workers with secondary education, can positively increase labor productivity in Malaysia, while workers with tertiary education do not affect Malaysian labor productivity in the study. The results reveal that hiring workers with secondary education positively increases Malaysian labor productivity, particularly the significant

positive effect in the 4th–5th year. The results found that employees who have secondary education can increase Malaysian labor productivity between 1982 and 2023. However, workers with primary education only have a negative impact on Malaysian labor productivity for the first 9 years, while positive effects last for 41 years. In line with the findings of Benos and Karagiannis (2016), primary education indicates a negative relationship with productivity. This finding is contrary to a study by Gyimah-Brempong (2011), which states that primary education positively impacts development outcomes. Then, the findings reveal that fixed capital affects Malaysian labor productivity during the period of 1982 to 2023. The fixed capital can positively influence Malaysian labor productivity from the 8th year to the 50th year, but the negative effect happens only in the first 6 years. The study found that the Malaysian labor productivity positively impacts fixed capital in 49 years, but there is a negative effect only in the first year. Additionally, the findings indicate that the education levels (i.e., primary, secondary, and tertiary education) affect the fixed capital from 1982 to 2023, respectively. The findings attest that high educational attainment (i.e., secondary education) is the main determinant boosting labor productivity growth, which in turn drives continuous growth in the gross domestic product (GDP). In line with the previous studies (e.g., Barro & Lee, 2001; Bashir et al., 2012; Gyimah-Brempong, 2011; Islam et al., 2016; Tsai et al., 2010), higher education attainment was found to positively affect productivity and promote growth and development. Malaysia should rely on secondary education to educate the labor market, enhance labor productivity, accelerate the transformation of labor-intensive industries, and transition towards Industry 4.0, with the aim of achieving a high-income nation.

5.2.2 Labor Market Education Quality, Agricultural Growth, and Value-Added Agriculture

The main findings of the study demonstrate that the results of Model 3 (macro) further corroborate the results of Model 2 (meso)—higher education among employees in the agricultural industry, especially those with tertiary education, positively affects agricultural GDP in Malaysia, based on the results of the VAR Granger causality test and the impulse response function (IRF). The findings reveal that there is a unidirectional causal relationship from tertiary education to agricultural GDP for the period 1987–2023. The labor force with tertiary education can positively affect the agricultural GDP during the study period, with a significant effect over the fourth year. The variance decomposition result further explains that the labor force with tertiary education is the second most influential variable for agricultural GDP in 50 years. Next, there is unidirectional causality running from the labor force with secondary education (LLSEC) to the labor force with tertiary education (LLTER) during the period 1987–2022. The study demonstrated that the labor force with secondary education positively influenced the labor force with tertiary education from 1987 to 2023, particularly in the fifth year. This underscores that increasing the numbers in the labor force with secondary education leads to an increase in the labor force with tertiary education. The labor force with tertiary education suffered a significant negative impact from the foreign labor force during the initial 30 years, particularly in the fourth year. A positive effect was observed from the 31st year until the 50th year. The results indicate that the foreign labor force does not Granger-cause Malaysian agricultural GDP. Additionally, the findings demonstrate that the foreign labor force does not impact agricultural GDP, as only a small percentage of this workforce possesses a high level of education. The variance decomposition results further corroborate that LLPRI is the most influential variable affecting LLFLF, with variations from this variable consistently

representing the largest portion over the 50-year period. Consequently, this result indicates primary education significantly impacts a large portion of the foreign labor force; however, those with no formal education and those with tertiary education only influence a minor portion. The result is consistent with a study by the Central Bank of Malaysia, which indicates that a significant proportion of migrants in Malaysia have low educational attainment, with only 5.2% possessing tertiary education (Ang et al., 2018). The IRF results illustrate that the labor force with no formal education has a negative impact on agricultural GDP throughout 50 years. However, the labor force with no formal education does not Granger-cause Malaysian agricultural GDP during the study period.

For this study, the findings are consistent with the prior studies (e.g., Ganegodage & Rambaldi, 2011; Tsai et al., 2010), where tertiary education can positively affect economic growth. The Malaysian government should encourage the hiring of more employees with higher education levels in agricultural industries, especially those with tertiary education. The findings suggest that a labor force with tertiary education can positively influence agricultural GDP. This is because the labor force with tertiary education can assist the local agricultural industry, especially traditional agriculture, in expediting the agricultural transformation. Simultaneously, the government should provide more free training courses to employees or employers, equipping them with advanced technologies (e.g., robotics, drones, artificial intelligence, or virtual reality)—along with the necessary skills and techniques to enhance agricultural transformation and ultimately boost production, aligning with the MADANI Economy Framework and Sustainable Development Goals. Second, the Ministry of Education should collaborate with the Ministry of Agriculture and Food Security to provide complimentary training courses—these courses should offer certificates issued by local universities to motivate employees to

participate. The Malaysian Education Blueprint 2015–2025 (Higher Education) underlines the importance of improving collaboration between universities and companies. Finally, the findings confirm that employees with a high level of education could expedite the transformation process in the agricultural industry, thereby boosting value-added agriculture and driving the continuous growth of gross domestic product (GDP). It is imperative for Malaysia to transform itself at an accelerated pace and move towards Industry 4.0 to achieve a high-income nation. Therefore, this study may result in less reliance on low-skilled labor and strengthen the skills of agricultural workers, especially in the agricultural industry.

The summary of the empirical results of Model 2 (meso) indicates that a high education level does not Granger-cause value-added agriculture, especially for employed workers who have secondary education or tertiary education. Also, employed workers with primary education do not Granger cause value-added agriculture during the study period 1982–2023. However, employed workers without formal education can Granger-cause value-added agriculture, based on the findings of the VAR Granger causality test. There is a unidirectional causal relationship from those with no formal education to value-added agriculture over the period 1982–2023. The findings indicate that a heavy reliance on employees without formal education in agricultural industries will negatively impact value-added agriculture between 1982 and 2023—with a particularly significant negative impact in the second year, as indicated by the IRF graph. Afterward, the variance decomposition further clarifies that employed workers lacking formal education are the second most influential variable affecting value-added agriculture, consistently accounting for the second largest portion throughout the 50-year period. Among the tested variables, employed workers with no formal education (LENOF) are the most endogenous variable,

as it was influenced simultaneously by three others from 1982 to 2023. The results indicate that LEPRI, LETER, and LFC can Granger-cause LENOF at the 5% significance level, respectively. Additionally, this study found that fixed capital (LFC) did not Granger-cause value-added agriculture during the study period. There is a unidirectional causality running from LESEC to LETER—as findings indicate that employed workers with secondary education can Granger-cause employed workers with tertiary education at the 5 percent significance level. The findings indicate that employed workers with secondary education positively influenced those with tertiary education from 1982 to 2023, particularly illustrating a significant positive effect in the ninth year. First, the government and agricultural industries should reduce their reliance on workers who lack formal education, as the findings indicate no formal education can negatively impact value-added agriculture during the study period. Second, an increase in high school graduates will lead to an increase in university graduates in the labor market—where the findings indicate that employed workers with secondary education can Granger-cause those with tertiary education. The IRF results further corroborate that employees with tertiary education positively affect value-added agriculture over the span of 50 years; however, there is no evidence of causality between 1982 and 2023. Furthermore, there is a unidirectional causality running from tertiary education to no formal education during the study period. The IRF reveals that there is a negative effect of tertiary education on those without formal education over a 50-year period. This implies that an increase in the number of employees with tertiary education would diminish the number of employed workers with no formal education, thereby aiding in addressing the flagging output of the agricultural industry.

The findings are consistent with Pudasaini's (1983) study, which emphasizes that enhancing agriculture via higher education results in greater productivity than traditional

agriculture. Additionally, these findings align with previous studies (e.g., Bawazir et al., 2021; Ganegodage & Rambaldi, 2011; Tsai et al., 2010) that demonstrate the positive impact of tertiary education on economic growth. Accordingly, the Malaysian government should promote the employment of workers with high educational attainment, particularly those with tertiary education, in the agricultural industries to aid its transformation. Simultaneously, the government must present additional complimentary training courses for employees or employers to equip them with skills and practices in sophisticated technologies (e.g., robotics, drones, artificial intelligence, or virtual reality) to facilitate agricultural transformation and improve production. The Ministry of Education ought to partner with the Ministry of Agriculture and Food Security to offer complimentary training programs and confer certificates from local universities, thus enhancing employee engagement. Consequently, technical and vocational education and training (TVET) are essential for cultivating skilled labor, as they equip individuals with the requisite skills to foster economic growth and development. The research emphasizes the need to expedite agriculture transformation via enhanced educational attainment to boost production, aligning with the MADANI Economy Framework and Sustainable Development Goals.

5.2.3 Labor Force Employment, Educational Quality, and Value-Added Industry

The summary of the empirical results affirms that secondary education positively impacts the value-added industry over a span of 50 years, as evidenced by the results of the IRF. This suggests that hiring more employees with secondary education will lead to an increase in the value-added industry during this 50-year period. The results of the VAR Granger causality test reveal that the workers with secondary education can Granger-cause the value-added industry over the period 1982–2023. There is a unidirectional causal relationship running from secondary education to the value-added industry. The study

found that employed workers with secondary education positively impact the value-added industry, especially since there is a significant positive effect in the sixth year. Next, the results demonstrate that tertiary education has a positive impact on value-added industry throughout 30 years, but there is a negative effect in the first 9 years and last 10 years. However, the findings show that there was no causal relationship between tertiary education and value-added industry during 1982–2023, as per the results of the VAR Granger causality test. This infers that employees who have tertiary education did not affect the value-added industry between 1982 and 2023. The findings attest that only secondary education can positively affect the value-added industry during the period 1982–2023. The VAR Granger causality test proves that employees who have a low education level (i.e., no formal education or primary education) do not have a causal relationship with the value-added industry during the period 1982–2023.

LVAI is the most endogenous variable among the tested variables; the results also explain that primary education and secondary education can affect a large part of the value-added industry if compared with others. This highlights that workers with secondary education are the second most influential variable in the value-added industry (VAI). Meanwhile, workers with tertiary education only affect a small percentage of the value-added industry in Malaysia. Additionally, the results indicate that the employed workers with tertiary education positively impacted fixed capital during the study period of 1982–2023. The IRF results confirm that workers with tertiary education have a positive impact on fixed capital over a period of 50 years. This underscores that an increase in workers with tertiary education results in an increment in fixed capital. Likewise, the findings indicate there is a unidirectional causal relationship running from LTER to LNOF and LPRI to LNOF between 1982 and 2023. The results indicate that tertiary education has

negatively impacted workers with no formal education over a span of 40 years. This suggests that an increase in employees with tertiary education results in a diminution in employed workers lacking formal education in the labor market. This is a solution to a situation where the IRF indicates that employed workers with no formal education have a negative impact on the value-added industry over 50 years. However, the study found no causal relationship running from LNOF to LVAI during the observed period. Next, the results confirm that workers with primary education negatively affect those with no formal education during the study period.

The findings suggest that industries reliant on workers with secondary education will positively influence the value-added industry. First, the Malaysian industries should hire more employees with secondary education—as the impulse response function demonstrates a significant positive impact on value-added industry over a 50-year period. Second, the government can provide complimentary training programs to employers and employees across various industries to augment workers' skills. Acquiring new competencies and innovative techniques can achieve this, ultimately enhancing productivity and elevating the value-added industry. Finally, the findings confirm that secondary education can transform the low-skilled industries, enhancing the value-added industry, promoting sustained growth, and advancing towards Industry 4.0. This contribution can help move closer to achieving the MADANI Economy Goals.

5.2.4 Employed Workers' Educational Attainment and Malaysian Sectoral Labor Productivity

The results of unit root tests demonstrate that all the series, with the exception of the LPRODS—$I(0)$ variable in the study, are integrated in order one. Likewise, the results of the unit root test with structural breaks reveal that all the series are integrated in order

one, except for LENOF. This study applied the ARDL approach, which is more reliable due to the small samples and appropriate for a mixture of *I*(0) and *I*(1) variables. There is a long-run relationship between the dependent variable and independent variables during the study period in Model 5. Additionally, the bound testing approach results of Model 6 and Model 7 indicate that each model shows a long-run relationship between the dependent variable and independent variables. The long-run estimation results of Model 5 reveal that LESEC has a positive impact on LPROA in the long term; the result is statistically significant at the 1 percent level. This result reported that employed workers with secondary education positively impacted agricultural productivity, with a coefficient of 1.641. This underlines that if the number of employed workers with secondary education rises by 1 percent, this will lead to an increase in agricultural productivity of 1.641 percent. The employed workers lacking formal education have a short-run positive impact on agricultural productivity with a coefficient of 0.123. This implies a 1 percent rise in employed workers without formal education, resulting in a 0.123 percent increase in agricultural productivity. Likewise, the employed workers with secondary education positively influence agricultural productivity in the short run, with a coefficient of 1.163; the result is statistically significant at the 1 percent level. The error correction term indicates that the adjustment speed for the variable to reach the long-run equilibrium is approximately 65.5% annually.

Next, the findings of Model 6 indicate the employed workers with no formal education positively influence industrial productivity with a coefficient of 0.528. The results also reveal that primary education has a positive impact on industrial productivity in the long term, with a coefficient of 0.392. Likewise, the long-run estimation results reveal that tertiary education has a significant positive impact on industrial productivity with a

coefficient of 0.842 when compared to the effects of no formal education and primary education, respectively. This underscores that hiring more employees with tertiary education can significantly boost industrial productivity, followed by employees with no formal education and employees with primary education. In line with the findings of Mussaiyib and Pradhan (2024, p. 8), higher education enhances productivity and hence contributes to economic growth. Surprisingly, the study found that fixed capital negatively impacts industrial productivity between 1991 and 2022, with a coefficient of −0.500. This underscores the fact that a 1 percent increase in fixed capital results in a 0.500 percent decline in industrial productivity. Additionally, the findings reveal that secondary education negatively impacts industrial productivity with a coefficient of −0.665 in the short run. The error correction term reveals that the adjustment speed for the variable to reach the long-run equilibrium is about 63.9% annually.

Furthermore, the findings of Model 7 indicate that the employed workers without formal education have a negative impact on services productivity at the 5% significance level in the long run. This emphasizes that employed workers without formal education have a long-run negative impact on services productivity with a coefficient of −0.660. However, the results indicate that employed workers lacking formal education negatively impact services productivity in the short run, with a coefficient of −0.047; the result is statistically insignificant. Afterward, the fixed capital has a positive impact on services productivity with a coefficient of 0.534, and this result is statistically significant at the 1 percent level. This implies a 1 percent increase in fixed capital, resulting in an increment in service productivity of 0.534 percent. For the Wald test, the results confirm that low educational attainment has a statistically significant impact on agricultural productivity only in the long run. However, the employed workers with high education levels have a

statistically significant impact on agricultural productivity in both the long term and short term; the result is statistically significant at the 1 percent level. Moreover, low educational attainment has a statistically significant impact on industrial productivity only in the long run. The employed workers with high educational attainment have a statistically significant impact on industrial productivity in both the long run and short run. Additionally, the employed workers with low educational attainment have a statistically significant impact on services productivity, both in the long term and short term.

The Malaysian industry needs to increase its investment in research and development to enhance productivity. Hiring employees with high educational attainment can facilitate the transformation because the study found that secondary education positively impacts agricultural productivity in both the long and short run. Tertiary education significantly enhances industrial productivity in the long term compared to the effects of no formal education and primary education. However, the study found that workers without formal education can only positively influence agricultural productivity in the short run. Surprisingly, secondary education negatively affects industrial productivity in the short run, while fixed capital negatively impacts industrial productivity in the long term. Therefore, the Malaysian government should prioritize addressing skills mismatches and skill-related underemployment to improve overall labor productivity.

5.2.5 Foreign Workers' Employment, Low Educational Attainment, and Malaysian Sectoral Labor Productivity

The asymmetric effects of foreign workers on Malaysian sectoral labor productivity were analyzed by the NARDL model for the annual period during 1991–2022. First, the empirical evidence of Model 8 affirms that workers with no formal education negatively affect agricultural productivity in the long run, with a coefficient of −0.461. This implies

that an increase in workers without formal education by 1 percent results in a decline in agricultural productivity by 0.461 percent. Likewise, workers with primary education negatively impact agricultural productivity in the long term, with a coefficient of −0.634; the result is statistically significant at the 5 percent level. However, the findings indicate that positive changes in employed foreign workers have a positive impact on agricultural productivity in the long run, with a coefficient of 0.494, although the result is statistically insignificant. The result also reveals that negative changes in employed foreign workers have a negative impact on agricultural productivity, with a coefficient of 0.751; the estimated coefficient on LEFW_NEG is statistically insignificant at the 5 percent level. Moreover, the findings indicate that the fixed capital negatively affects agricultural productivity in the long run, while there is a positive impact in the short run; the result is statistically insignificant. Based on the findings, both the agricultural sectors and the Ministry of Agriculture and Food Security should consider implementing advanced training programs for employees with low educational attainment—these programs aim to enhance their skills and knowledge in planting and harvesting, which is essential for ensuring sustainable productivity growth.

Second, the findings of Model 9 demonstrate that positive and negative changes in employed foreign workers have a negative and statistically insignificant impact on industrial productivity in the long run, respectively. However, the short-run result indicates that positive changes in employed foreign workers have a negative and statistically significant impact on industrial productivity, with a coefficient of −0.121. This implies that a one percent positive change in employed foreign workers results in a diminution in industrial productivity of approximately 0.121 percent in the short term. Likewise, the study found that workers without formal education positively influence industrial

productivity in the short term, with a coefficient of 0.144. This indicates that a 1 percent increase in workers lacking formal education leads to an increment in industrial productivity by 0.144 percent in the short run. Moreover, fixed capital has a positive and statistically insignificant impact on industrial productivity in the long run. Afterward, employees with primary education and no formal education positively impact industrial productivity, respectively, although the results are statistically insignificant. The findings of this study do not align with a study by Jordaan (2018), which found that low-skilled foreign workers positively impacted productivity in Malaysian manufacturing industries from 2005 to 2009. Given these findings, the government should collaborate with local industries to provide courses and free industrial training designed to strengthen the skills of employed foreign workers, ultimately boosting their labor productivity.

Third, the results of Model 10 reveal that positive changes in foreign worker employment have a negative and statistically significant long-run impact on services productivity at the 5 percent level, with a coefficient of −0.148. More specifically, this result reveals that a one percent positive change in employed foreign workers corresponds to a 0.148 decline in services productivity. However, the negative changes in employed foreign workers have a positive and statistically insignificant impact on service productivity in the long run. Likewise, the study found that workers without formal education have a negative and statistically significant impact on services productivity at the 1 percent level, with a coefficient of −0.342. This emphasizes that an increase in workers lacking formal education by 1 percent leads to a decrease in services productivity by approximately 0.342 percent in the long run. However, the results reveal that workers with no formal education negatively impact services productivity in the short run, although the estimated coefficient on LWNOF is not statistically significant at the 5 percent level. The

findings indicate that fixed capital positively impacts services productivity, with a coefficient of 0.510; this result is statistically significant at the 1 percent level. More explicitly, this result indicates that an increase in fixed capital by one percent leads to an increase in services productivity by 0.510 percent. Interestingly, the employed foreign workers have statistically significant short-run asymmetric effects on industrial productivity at the 1 percent level, based on the results of the Wald test. However, the results underline that employed foreign workers have statistically insignificant long-run asymmetric effects on industrial productivity. Moreover, foreign worker employment has long-run asymmetric effects on agricultural productivity, but the result is statistically insignificant at the 5 percent level. Likewise, the employed foreign workers have statistically insignificant long-run asymmetric effects on service productivity at the 5 percent level, according to the Wald test results. Based on the study's findings, the government should continue to support agricultural industries to reduce their reliance on workers with low educational attainment. The study found that workers with primary education and workers without formal education negatively impacted agricultural productivity in the long run, respectively.

A practical solution to enhancing labor productivity in Malaysian sectoral industries is to prioritize hiring highly educated local employees rather than those with lower educational attainment—this shift in workforce composition can reduce the dependence on low-skilled workers, which often leads to lower productivity. The study's findings demonstrate the asymmetric effects of foreign worker employment on labor productivity, particularly in the agriculture and services sectors, which are limited according to the Wald test results. The study found that positive changes in foreign workers negatively impacted services productivity in the long run, while positive changes

in foreign worker employment had a negative impact on industrial productivity in the short run—since only a small percentage of foreign labor in the Malaysian market possesses high educational qualifications. According to the Central Bank of Malaysia, just 5.2% of migrant workers have attained tertiary education levels (Ang et al., 2018). While foreign workers have played a weighty role in Malaysia's economic growth, this study suggests that local industries should focus on hiring more skilled workers to enhance labor productivity. Aljarallah and Angus (2020) reported that education positively influenced productivity. Higher education enhances the productivity and efficiency of human capital, hence contributing to the economic growth of a country (Mussaiyib & Pradhan, 2024, p. 8).

As a policy recommendation, the Malaysian government should promote the employment of highly educated employees in local industries or enhance the quality of low-skilled labor via training programs. Concurrently, the government ought to provide complimentary training programs to equip employees and employers with advanced skills and techniques—thus facilitating industry transformation. This training program aims to improve labor productivity, increase production output, and facilitate Malaysia's progress towards achieving high-income nation status. Meanwhile, higher labor productivity is able to attract and enhance foreign direct investment (FDI). Strong associations exist between foreign direct investment and labor productivity (Boghean & State, 2015). Likewise, collaboration between the Ministry of Education and the Ministry of Human Resources is crucial in offering free training courses, certified by local universities, to uplift the skills of low-skilled workers. For this study, the findings confirm that low educational attainment has a negative impact on labor productivity, particularly agricultural productivity and services productivity in the long run, whereas it has a positive impact on industrial productivity in the short term. Finally, Malaysia must accelerate its industrial

transformation toward Industry 4.0 while simultaneously decreasing its reliance on low-skilled labor to tackle low productivity challenges. Enhancing the educational quality of the labor market is crucial for boosting labor productivity and fostering GDP growth—moving closer to its MADANI Economy Goals and the Sustainable Development Goals.

5.3 Policy Implications

Regarding the effects of educational attainment, previous studies have shown that education not only affects productivity (Aljarallah & Angus, 2020; Benos & Karagiannis, 2016; Lin, 2003; Pudasaini, 1983; Tamura, 2005; Viswanath et al., 2009) but also enhances economic growth and development in relevant studies (Anastasios et al., 2019; Barro & Lee, 2001; Ganegodage & Rambaldi, 2011; Gyimah-Brempong, 2011; Hanushek & Kimko, 2000; Jalil & Idrees, 2013; Tsai et al., 2010; Yan, 2011). However, the findings of the study can be used as a guideline for the Malaysian government to understand the role of educational attainment in driving labor productivity, particularly in agriculture and industry, because these sectors suffer from low productivity. The findings could offer the Malaysian government a more comprehensive understanding of the impacts of educational attainment on labor productivity and economic growth in the main targeted economic sectors—a more profound understanding of the main causes of low productivity experienced by Malaysian industries (e.g., agriculture and industry). The empirical results of the study are potentially important for policymakers to make precise decisions that enhance labor productivity in the main targeted economic sectors of the Malaysian economy. This study seeks to identify the effects of low-skilled workers on labor productivity within Malaysian industry and to explore strategies for mitigating any negative impacts.

The Malaysian government can refer to the empirical results from the study to improve the educational quality of the labor market, which can boost labor productivity and ultimately enhance economic growth. First, Malaysia's government should encourage local industries to hire more employees who have a high education level, especially secondary education or tertiary education—investing more in the research and development (R&D) in small and medium enterprises (SMEs) to enhance their production, in line with the Twelfth Malaysia Plan (12MP). This can be one step closer to realizing the vision of the MADANI Economy as guiding the country's progress, facilitating higher value-added activities, and improving economic competitiveness. Meanwhile, free training courses by the Ministry of Human Resources provide information on advanced technologies with skills and techniques (e.g., robotics, drones, artificial intelligence, or virtual reality) to expedite the transformation process, thereby improving production efficiency in labor-intensive industries (i.e., agriculture and industry). Second, the Ministry of Education and the Ministry of Higher Education must collaborate with other related departments (e.g., the Ministry of Science, Technology, and Innovation; the Ministry of Agriculture and Food Security; the Ministry of Human Resources; the Ministry of Investment, Trade, and Industry; and the Malaysian Productivity Corporation, etc.)—providing complimentary training courses (i.e., advanced technologies and skills courses) with the certificates that are issued by local universities to encourage more employees or employers to get involved. Third, the local industries (i.e., agriculture, industry, and services) should try to rely less on low-skilled workers, especially labor-intensive industries. The government needs to provide subsidies to assist the labor-intensive industries, particularly SMEs, to accelerate their transformation and transition toward Industry 4.0. Malaysia should work to lessen its dependence on labor-intensive industries

and implement new policy designed to attract foreign skilled workers. This initiative aims to accelerate the transformation of these industries. The main strategy is to foster industrial transformation, move toward Industry 4.0, and emerge from labor-intensive industries by offering training courses and hiring employees with high educational attainment. This is because the main findings of the study indicate that secondary education positively impacts Malaysian labor productivity during the study period 1982–2023. Malaysia needs to create an education system that combines formal education, non-formal education, and technical and vocational education and training (TVET) to prepare its labor force to become skilled workers and boost labor productivity, thereby enhancing economic growth and aligning with its goal of becoming a high-income nation.

5.4 Limitations and Recommendations for Future Studies

There are limitations to the study that need to be considered. The study lacks comprehensive data regarding workforce, value-added, or labor productivity across the targeted economic subsectors (e.g., crops, livestock, fisheries, forestry, and logging) for the study period (i.e., 1982–2023). This data is unavailable from the World Bank or the Department of Statistics Malaysia. This limitation is due to the fact that the labor productivity data from subsectors (e.g., agriculture and industry) are more reliable and accurate in determining the causal relationship between labor market educational attainment and low subsector productivity during the study period. Accordingly, the data limitation may hinder the analyses from revealing the causal relationship between educational attainment and the variables tested across the subsector industries (i.e., agriculture, industry, and services). A future study is suggested to investigate the economic impacts of labor market educational attainment on subsectors of agriculture and industry. If

the study can analyze data from subsectors and obtain meaningful results, it could propose more suitable policy recommendations.

5.5 Concluding Remarks

This research provides the deepest analysis and clear evidence to determine the role of the educational quality of the labor market in driving Malaysian productivity and economic growth. Based on the findings of the study, the results demonstrate that high educational attainment, which equips the labor market with skills, knowledge, and a mindset, can transform labor-intensive industries to higher value-added and productivity levels—thereby driving continuous growth in the economy. The World Bank (2021) pointed out that upskilling the labor force via more market-responsive academics and creating high-skilled jobs is a facilitator of inclusive development. Malaysia must transform itself at an accelerated pace and move towards Industry 4.0 to achieve a high-income nation. Therefore, this study may also result in less reliance on low-skilled labor and strengthen the skills of local workers, especially in agriculture and industry. The findings of the study are consistent with those of the study by Sapovadia (2015), which found that the low level of productivity is caused by the high level of unskilled labor, the low level of governance and management, and the lack of research and development. Then, higher educational attainment means more skilled and productive workers can be produced—the remarkable improvements in education have resulted in a relative shortage of low-skilled workers needed in low-skill sectors (i.e., agriculture, construction, and low-tech manufacturing sectors). Thus, low-skill sectors (e.g., SMEs) must transition their production processes and move toward Industry 4.0 to reduce dependence on low-skilled labor for output expansion. The findings reveal that positive changes in foreign worker employment negatively affected services productivity in the long run. In the short term,

positive changes in employed foreign workers negatively impacted industrial productivity. However, the study's findings contradict the study of Del Carpio et al. (2013)—where foreign workers positively impact the productivity of the manufacturing and construction sector in medium- and large-sized enterprises but negatively impact the productivity of the plantation and construction sector in small-scale enterprises.

The government is advised to enhance the labor market by providing subsidies and attracting new investments to retain skilled workers, which would increase production. For example, the Sarawak government initiated the Regional Corridor Development Authority to promote the SCORE. This initiative offers additional benefits to investors, with the goal of creating new markets and fostering innovation in manufactured products. Ultimately, this effort aims to generate high-skilled job opportunities. Consequently, an increase in Foreign Direct Investment (FDI) leads to skilled foreign workers contributing their intellectual abilities, thereby improving productivity, inducing technological upgrades, and increasing knowledge transfer to local workers. Likewise, the Malaysian government can implement minimum wage policies that discourage local industries (e.g., SMEs) from hiring low-skilled foreigners because of no wage differences between domestic labor and foreign labor. This could lead employers to prefer hiring skilled domestic labor over unskilled foreign labor due to no wage differences. In the meantime, the government must construct new training institutes that offer allowances to equip workers with advanced knowledge and technologies, thereby potentially increasing production in the future. Enhancing productivity is accomplished by bolstering local industries via investments in fixed capital, leveraging technology, automation, innovation, and R&D, and fostering a highly educated workforce to satisfy industry demands. This makes sure that Malaysia is moving closer to its MADANI Economy goals.

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APPENDICES

Appendix A: Summary of Literature Review

Table 2.1: Review Summary of the Economic Impacts of Education on Productivity

Authors (Year)	Countries (Time Horizon)	Variables	Methodology	Major findings
Jajri and Ismail (2010)	Malaysia (1981–2007)	• Real Gross Domestic Product • Real physical capital stock • Quantity of labor • Quantity of effective labor • Number of employments with primary education, secondary education, and tertiary education • Real government-private capital stock ratio • Money stock-real GDP ratio • (Export + import)-GDP ratio • Gross domestic product-labor ratio • Capital-labor ratio	• Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) test • Error Correction Model (ECM)	• Education is important, as it indirectly supports economic growth through increasing labor productivity in this study.

Barro and Lee (2001)	Multiple Countries (1960–2000)	• Enrollment ratio for primary schooling • Enrollment ratio for secondary schooling • Enrollment ratio for higher schooling • Mortality rate	• Perpetual inventory method	• Higher education attainment creates more skilled and productive workers, which can promote growth and development in a country. • The level and distribution of educational attainment have a strong impact on social outcomes, including fertility, child mortality, income distribution, and education of children.
Islam et al. (2016)	Malaysia	• Economy growth • Education • Human capital	• Pearson correlation test • Regression test	• The workers with high-level education are more skillful and productive in the workplace.
Lin (2003)	Taiwan (1964–2000)	• Economic output • Physical capital input • Labor input • Human capital or educational stock	• Dickey–Fuller test • Durbin–Watson test	• Schooling has a positive and indispensable effect on increasing output in Taiwan. The output growth is estimated to rise around 0.15% in an additional year of

				average schooling. • The growing investment in human capital and R&D could lead to the complementarity between schooling and technology being more significant.
Bashir et al. (2012)	West Virginia, United States (2000–2010)	• Change in per capita income from 2000 to 2010 • Change in higher education from 2000 to 2010 • Change in population density from 2000 to 2010 • Per capita income in 2000 • Higher education in 2000 • Population density in 2000 • Percentage of all age population below poverty • Serious crime rate • Per capita government expenditures on	• Three-stage least squares (3SLS)	• Educational attainment raises productivity, increases income earnings, reduces poverty risk, and improves living standards. • Empirical analysis reveals that both education growth and income growth positively affect each other.

		education • Unemployment rate • Dummy variable		
Yan (2011)	China (1990–2009)	• Gross Domestic Product (GDP) • Fixed asset investment • Year-end number of employees • Yearly above junior high school graduates	• Vector Autoregression (VAR) • Impulse response • Variance decomposition	• Education not only has a significant effect on economic growth in the short term but also plays a significant role in the long term.
Gyimah-Brempong (2011)	Africa (1960–2010)	• Growth rate of per capita income • Political stability • The participation of women in national politics • Life expectancy at birth • Under five mortality rates • The proportion of adult tuberculosis cured using dots • The prevalence of HIV/AIDS • Immunization against measles • The proportion of children inoculated	• DPD estimator • GMM-IV estimator • Hausman–Taylor estimator • SUR estimator	• Educational attainment has significantly positive impacts on all development outcomes in Africa. • The effects of education on development outcomes differ according to the level of education, such as primary, secondary, or tertiary. • Higher levels of education tend to have larger development

		against tetanus and DPT • Per capita income • Investment • Government consumption • Population growth rate • Foreign aid • Post-conflict situation • Health expenditure/GDP ratio • Rule of law • The government effectiveness • The proportion of the country's population that lives in urban areas • Post-conflict as a dummy variable • Primary education • Secondary education • Tertiary education		impacts than lower levels of education. • For preventive health, lower levels of education tend to be more important than higher levels of education. • Higher levels of education are more significant for curative health and longer life expectancy.
Castelló-Climent and Hidalgo-Cabrillana (2012)	Multiple Countries (1960–2008)	• Primary education • Secondary education • Tertiary education • Public spending on education as a	• Ordinary Least Squares (OLS) estimator • Robustness	• The result further suggests that educational quality plays a vital role in the composition of human capital and

		share of GDP • The share of total population living in urban areas • Real per capita GDP • Physical capital investment rate • The government share of real GDP • Exports plus imports divided by real GDP • Inflation rate		the level of income in the long run.
Nowak and Dahal (2016)	Nepal (1975–2014)	• Gross Domestic Product (GDP) • Gross enrollment ratio in primary level education • Gross enrollment ratio in secondary level education • Gross enrollment ratio in tertiary level education	• Augmented Dickey–Fuller (ADF) Test • Johansen Cointegration • Ordinary Least Squares (OLS) estimator	• There are direct and indirect benefits of primary, secondary, and tertiary.
Tsai et al. (2010)	60 Countries (1999–2006)	• Real GDP per capita growth rate • Real GDP per capita • Openness • Inflation • Fertility rate	• Ordinary Least Squares (OLS) estimator • Generalized Method of Moments (GMM) estimator	• Secondary education is a bigger contributor to economic growth in developing countries than it is in developed

		• Secondary enrollment rate • Tertiary enrollment rate • Percentage of tertiary graduates in - Agriculture human capital - High-tech human capital - Business and service human capital - The humanities' human capital - Health and welfare human capital		countries. • Tertiary education plays a significant role in economic growth for both developing and developed countries. • High-tech human capital is significantly positively correlated with economic growth.
Afzal et al. (2010)	Pakistan (1970–71 to 2008–09)	• Real GDP • Real physical capital • Poverty • Inflation rate • General school enrollment ratio	• Augmented Dickey–Fuller (ADF), Phillips–Perron (PP), and Ng–Perron tests • Autoregressive Distributed Lag (ARDL) • CUSUM Square tests • Error Correction Model (ECM)	• The existence of a direct relationship between school education and economic growth in Pakistan, which is in the short term and the long term. • Macroeconomic instability due to inflation impedes economic growth in the short term and long term, while it

				impedes school education only in the long term. • The results show a statistically significant and inverse relationship between school education and economic growth in the short term.
Barro (2001)	Multiple Countries (1960–1995)	• Growth rate of real per capita GDP • The log of real per capita GDP • Average years of school attainment for males at the upper level (secondary and higher) • The rule of law index • Government consumption ratio • The openness ratio • The openness ratio multiplied by the log of per capita GDP at the start of the period • The ratio of real investment to GDP	• Three-stage least squares	• Growth is positively related to the starting level of average years of school attainment of adult males at the secondary and higher levels. • These results suggest an important role for the diffusion of technology in the development process. • Growth is insignificantly related to years of school attainment for females at the secondary and higher levels. • This result suggests

	• The inflation rate • The total fertility rate • The growth rate of the terms of trade	that highly educated women are not well utilized in the labor markets of many countries. • Growth is insignificantly related to male schooling at the primary level. • Education for women at the primary level stimulates economic growth indirectly by inducing a lower fertility rate. • Scores on science tests have a particularly strong positive relation with economic growth. However, the effect of school quality is quantitatively much more important.

Table 2.2: Review Summary of the Economic Indicators of Education

Authors (Year)	Countries (Time Horizon)	Variables	Methodology	Major findings
Ganegodage and Rambaldi (2011)	Sri Lanka (1959–2008)	• Economic output • Physical capital • Human capital - Secondary level of education - University levels of education • Labor • Measures of openness and war	• Autoregressive Distributed Lag (ARDL) • Error Correction Model (ECM)	• The resource allocation into human capital development through secondary and tertiary education contributes positively to economic growth.
Shindo (2010)	China (1998–2007)	• GDP per capita • Human capital • Education subsidy rate • Consumption tax rate • Technology transfer • The asset per effective labor unit • Debt issues per effective labor unit • Capital per effective labor unit	• Overlapping Generations (OLG) model	• The productivity of Jiangsu is potentially higher than that of Liaoning because both parameters for human capital productivity and education investment are higher in Jiangsu despite the lower subsidy rate. • The increase in government subsidies for education promotes

				individual investment in human capital, and economic growth is accelerated. • Jiangsu and Liaoning achieved greater economic growth due to greater government subsidies in education. • The growth gap widens with evenly raised education subsidy rates due to large differences in productivity between the regions.
Hanushek and Kimko (2000)	Multiple Countries (1960–1990)	• Ratio of real government consumption expenditure net of spending on defense and on education to real GDP • Average of total gross enrollment rate for primary education • Average ratio of nominal	• Ordinary Least Squares (OLS) estimator	• The labor force quality differences are related to schooling and have a stable, consistent, and strong relationship, which has a causal impact on economic growth. • Clear evidence shows that international test performance relates

		government expenditure on education to nominal GDP • Average of population growth rate • Annual average growth rate of per capita real GDP for the period of 1960–1990 • Per pupil current public expenditure • Average ratio of private investment relative to GDP • Average pupil/teacher ratio in primary schools • Average pupil/teacher ratio in secondary schools • Measures of schooling quality • Ratio of recurring nominal government expenditure on education to nominal GDP	to productivity differences. • These productivity differences appear related to schooling differences and not family support, attitudes, cultural factors, etc. This direct linkage to productivity suggests a causal impact on international economic performance. • Simple estimates of cross-country growth relationships appear to overstate the causal impact of quality. The precise cause or magnitude of this overstatement is unclear. • There is also a distinct policy dilemma because standard school resource policies do not relate to the variations in quality that have been identified.

		• Arithmetic average years of schooling for 1960, 1965, 1970, 1975, 1980, and 1985 • Dummy for participants in international comparison studies of student achievement • Ratio of total trade to GDP • Initial income, 1960 [$1,000]		
Jalil and Idrees (2013)	Pakistan (1960–2010)	• Real GDP • Average level of education • Primary level of education • Secondary level of education • Tertiary level of education	• Augmented Dickey–Fuller (ADF) test • Ericsson and Mackinnon (2002) test • NLTSLS-IV estimators	• Education has a positive impact on the economic growth of Pakistan over the period of 1960 to 2010. Education was measured at three levels, which are primary, secondary, and tertiary.
Sylwester (2000)	Multiple Countries (1970–1985)	• Growth rate of GDP from 1970 to 1985 • Average of the ratio of public education	• Three-stage least squares	• A higher level of income inequality is related to more spending on public education. • There is a negative

		expenditures to output from 1970 to 1985 • Average measure of political instability from 1970 to 1984 • Average of public investment as a fraction of GDP • Average of government defense expenditures as a fraction of GDP • Average of investment share of GDP • Average of government purchases as share of GDP • Initial real GDP per capita • Initial level of human capital • Income inequality • Natural logarithm of the population density in 1970	impact upon simultaneous growth with these public education expenditures; the impact upon future growth is positive. • These empirical findings differ from those of Easterly and Rebelo (1993), who report that income inequality raises public expenditures for education, but they found that these expenditures are positively linked with growth. They treat education expenditures as an exogenous variable.

Table 2.3: Review Summary of the Educational Impacts Evaluation on Economic Growth

Authors (Year)	Countries (Time Horizon)	Variables	Methodology	Major findings
Frini and Muller (2012)	Tunisia (1963–2007)	• Real GDP per capita • Total fertility rate • The infant mortality rate • The contraceptive prevalence rate • Gross enrollment rate of primary schooling • Gross enrollment rate of secondary schooling • Gross enrollment rate of higher education	• Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) test • Johansen and Jesulius trace test • Vector Error Correction Model (VECM) • Variance decomposition • Impulse response	• The results indicate that the error correction term derived from the long-term cointegration relationship is highly significant in the fertility equation described by the VEC. • Education is found to trigger fertility transition in the short run and long run. It has relatively fostered economic growth but hardly boosted it through its dynamic interaction with fertility. • The variance decomposition and impulse function show that fertility transition has produced a feedback effect on both education and economic growth.

Teixeira and Fortuna (2004)	Portugal (1960–2001)	• GDP • Labor • Physical capital stock • TFP index • R&D stock or internal stock of knowledge • Human capital stock	• Dickey–Fuller (DF), Augmented Dickey–Fuller (ADF), and Phillips–Perron (PP) tests • Johansen Cointegration • Vector Autoregression (VAR)	• Human capital and indigenous innovation efforts are enormously important to the process of Portuguese economic growth during the period 1960–2001 by using cointegration and VAR analyses. • The indirect effect of innovation on human capital indicates that a reasonably higher level of human capital is important for a country to fully benefit from its indigenous innovation efforts.
Agiomirgianakis et al. (2002)	93 Countries	• GDP per capita • Enrollments in primary education • Enrollments in secondary education • Enrollments in tertiary education	• Augmented Dickey–Fuller (ADF) test • Pooled Mean Group (PMG) estimator	• PMG estimation results showed that the obtained coefficients for the primary, secondary, and tertiary education are 0.05, 0.11, and 0.27, respectively. • There is clear evidence that human capital positively affects growth, but it

				is also concluded that higher levels of educational quality are associated with higher economic growth. • The effect of tertiary education is higher than that of secondary education, which in turn has a higher effect on growth than that of primary education.
Ahmad and French (2011)	Bangladesh (1973–2004)	• Real GDP per capita • Primary level of education • Secondary level of education • Higher secondary level of education • Tertiary level of education • Average years of schooling attained by the adult population	• Augmented Dickey–Fuller (ADF) test • Johansen (1991) rank test • Vector Error Correction (VEC) and Vector Autoregression (VAR) • Variance decomposition	• The results show that on the aggregate level per capita real GDP Granger-causes human capital, and no causality running from human capital stock to per capita real GDP was found. • When human capital stock was disaggregated, secondary and higher secondary levels of education were found to Granger-cause per capita real GDP. • The evolution of Bangladesh's GDP is

				most influenced by middle-level education.

Table 2.4: Review Summary of the Human Capital and Productivity

Authors (Year)	Countries (Time Horizon)	Variables	Methodology	Major findings
Benos and Karagiannis (2016)	Greece	• GDP per worker • Public capital per worker • Primary education graduates • Secondary education graduates • Tertiary education graduates • Student-teacher ratio • Dropout ratio • Tertiary success rate • University success rate • Patents • Spillovers	• Generalized Method of Moments (GMM) estimator	• Human capital has a strong positive relationship with labor productivity through upper secondary and tertiary education. • Primary education shows a negative relationship, and lower secondary education does not show any relationship with productivity. • Tertiary education spillovers, along with a number of education quality indicators, exhibit a significant positive relationship with productivity.

Lee (2005)	Korea	• Output per worker • Human capital per worker		• Total factor productivity (TFP) growth of the Korean economy, which is mainly in the manufacturing industry since the 1990s. • The lower productivity performance of the service industries influences the productivity growth of the aggregate economy.
Viswanath et al. (2009)	India 26 Indian states and union territories (1995–96) and (1998–99)	• Net State Domestic Product per capita (NSDP) • Per capita productive capital 1997 (PC97) • Mean years of schooling 1998 (MYS98)	• Ordinary Least Squares (OLS) estimator	• There is a strong positive relationship between investments in human capital and economic growth. • Education has been deemed the most important component of human capital.