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# Role of Labor Market Education Quality in Driving Economic Growth and Value-Added Agriculture: A Malaysian Perspective

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## Abstract

This paper examines the impacts of the labor market's educational quality on value-added agriculture and economic growth in Malaysia during the period 1982-2019, using the VAR Granger causality test, variance decomposition, and impulse response function (IRF). The paper explores how educational attainment, and foreign workers affect value-added agriculture and economic growth. The empirical results of Model 1 (meso) reveal the existence of unidirectional causality running from no formal education to value-added agriculture. The IRF further underscores that no formal education negatively affects value-added agriculture in 50 years, whereas attaining a tertiary education positively impacts value-added agriculture, but no causality exists during the study period. The IRF also underlines the fact that employing foreign workers had an adverse impact on value-added agriculture over 50 years, although no causality existed between 1982-2019. Additionally, Model 2 (macro) shows there is a unidirectional causality running from secondary education to agricultural GDP and from tertiary education to agricultural GDP. The IRF affirms that tertiary education will positively impact agricultural GDP in 50 years. Surprisingly, the graph exhibits that the significantly positive effect of tertiary education diminished the negative effect of secondary education on agricultural GDP in the first five years. The findings demonstrate that there is a need to hasten the transformation of agriculture towards high-skilled labor to expand its production output.

**Keywords:** Education quality, Labor market, Value-added agriculture, Economic growth, VAR Granger causality
**JEL Classifications**: I25, J08, J24, Q18

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# 1. Introduction

The Malaysian labor market faces a shortage of skilled workers and over-reliance on low-skilled workers in various industries, particularly the agriculture sector. 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 in order to sustain their profit margins (Ang et al., 2018). Recently, the share of low-skilled jobs in Malaysia increased markedly, and the Malaysian workforce now comprises mainly low-skilled workers. This is reflected in the relatively lower proportion of workers with tertiary education in the labor market. Besides, the Central Bank of Malaysia has reported that the share of highly skilled job creation fell from approximately 51% to an average of 27% in Malaysia during the period 2010-2019. Moreover, 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% semi- and low-skilled workers in 2018. At the same time, 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. Furthermore, their productivity is low, and the working hours are longer for producing output (Ang et al., 2018). The low creation of high-skilled jobs and overreliance 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%.

If agricultural industries continue to be overly reliant on low-skilled workers instead of high-skilled workers in the future, this seems to affect agricultural productivity. Accordingly, this study focuses on the issues of lower agricultural value added per worker and over-reliance on low-skilled labor, which are under investigation in this study. 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 hard to emerge from upper middle-income status and to narrow the gap between rural and urban communities.

With the issue, motivation, and challenges at hand, the main objective of this study is to examine the educational quality of labor and also the total number of foreign workers as determinants that affect value-added agriculture and agricultural productivity, which has a knock-on effect on the Malaysian agricultural GDP. We used Model 1 and Model 2 to investigate the educational quality of the labor market as a vital factor to help boost agricultural transformation in order to enhance agricultural productivity, which will enable Malaysia to emerge from upper-middle income status.

The contribution of this paper is fourfold. First, previous studies offer a limited investigation of the educational quality of the labor market and how foreign workers affect Malaysian agricultural production. Model 1 is defined as a meso model, and Model 2 is referred to as a macro model. Both models contribute to the literature, which fills the research gaps by presenting new evidence to the Malaysian agricultural industry from the findings of the study by investigating the impact of the educational quality of the labor market on value-added agriculture between 1987 and 2019 and how this impacted agricultural GDP in Malaysia between 1982 and 2019. The current information pertinent to the impact of the educational quality of the labor market on value-added agriculture and agricultural GDP is currently rather limited in Malaysia. Second, Model 1 (meso) also shows a precise analysis of how educational quality is the main cause of lower value-added agriculture per worker and how this affects 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, 2012). Third, 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, and only a few studies have investigated the impact of educational attainment on Malaysian economic growth, especially in the agricultural industry. This study reveals new insights into the impacts of no formal education as one of the independent variables that influence value-added agriculture and agricultural 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 level of education, secondary level of education, and tertiary level of education) as independent variables. Lastly, other similar studies also do not point out the impacts of the total foreign labor force on value-added and GDP, particularly in the Malaysian agricultural industry.

The remainder of this study is structured as follows: Section 2 reviews the literature on educational quality, productivity (i.e., value-added per worker), and economic growth. Section 2 also discusses the effect of educational attainment (i.e., primary, secondary, or tertiary education) on productivity and economic growth. Section 3 presents the research method, and Section 4 analyzes the econometric findings. Section 5 covers the conclusion and policy implications.

# 2. Literature Review

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 clearly show that education affects economic growth (Gyimah-Brempong, 2011; Jalil & Idrees, 2013; Tsamadias & Prontzas, 2012; 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 development 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, 2012). 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, 2012) 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 that of tertiary education (Anastasios et al., 2019; Tsai et al., 2010).

For the effect of education expenditure on Malaysian economic growth (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. Also, 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 (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 (2023) 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 showed that higher levels of educational quality are associated with higher economic growth, and that the effect of tertiary education is greater than that of secondary education. However, secondary education has a greater effect on economic growth than primary education (Agiomirgianakis et al., 2002).

Nevertheless, Tsai et al. (2010) 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. 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 agriculture. 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 human capital, 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 this 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). Primary education has a negative relationship, and lower secondary education does not exert any relationship with productivity (see also Benos & Karagiannis, 2016).

# 3. Methodology

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 technology, or effective labor, enhances economic growth in the long term (Solow, 1956; Swan, 1956). In this study, the growth model is the starting point of the econometric models. We then term the production function the Cobb-Douglas production function. The growth model assumes that the production function takes the following form as a result of the association between labor and knowledge. A(t)L(t) denote the number of effective units of labor (Mankiw et al., 1992):

$$Y = F(K, AL) \tag{1}$$

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 (i.e., domestic labor (LD) and foreign labor (LF))

$$Y_t = AK_t^{\alpha} LD_t^{\beta_1} LF_t^{\beta_2} \tag{2}$$

The concept of labor educational quality in Equation (2) can also be measured by levels of education as follows:

$$Y_t = AK_t^{\alpha} (LD_t^*)^{\beta_1} (LF_t)^{\beta 2} \tag{3}$$

where

$$LD_t^* = LD_t \, {LD_{t1}}^{\theta 1} {LD_{t2}}^{\theta 2} {LD_{t3}}^{\theta 3} {LD_{t4}}^{\theta 4} \tag{4}$$

denotes the domestic labor force with educational attainment. $LF$ indicates foreign labor force.

Substituting Equation (4) into Equation (3), we derive,

$$Y_t = AK_t^{\alpha} (LD_t \, {LD_{t1}}^{\theta 1} {LD_{t2}}^{\theta 2} {LD_{t3}}^{\theta 3} {LD_{t4}}^{\theta 4})^{\beta 1} (LF_t)^{\beta 2} \tag{5}$$

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), $\theta_i$ represents the share of labor at different levels of educational attainment, $A$ indicates an exogenous knowledge and technological factor, $\alpha$ and $\beta$ are the capital and labor shares, respectively. In order to derive the educational quality of the labor equation without physical capital for this study, only $AL$ applied:

$$Y_t = A(LD_t^*)^{\beta_1}(LF_t)^{\beta 2} \tag{6}$$

where

$$LD_t^* = LD_t \, LD_{t1}{}^{\theta 1} LD_{t2}{}^{\theta 2} LD_{t3}{}^{\theta 3} LD_{t4}{}^{\theta 4} \tag{7}$$

denotes the domestic labor force with educational attainment. LF represents the foreign labor force.

The estimation of the educational quality of the labor model is based on the Cobb-Douglas production function, which covers the period 1982-2019. Thus, the estimation of Model 1 (meso) for examining the impacts of educational quality of employed workers and total employed foreign workers on value-added agriculture is based on the following equation:

$$LVAA_t = \alpha_0 + \beta_1 LENOF_t + \beta_2 LEPRI_t + \beta_3 LESEC_t + \beta_4 LETER_t + \beta_5 LEF_t + \varepsilon_t \tag{8}$$

where $LVAA_t$ denotes the logarithm of value-added agriculture (in constant 2010 US$), with data from the World Bank. Educational attainment means their highest level of education; data are from the Department of Statistics Malaysia (i.e., $LENOF_t$ denotes the logarithm of total employed workers with no formal education (in '000), $LEPRI_t$ represents the logarithm of total employed workers with primary education, $LESEC_t$ denotes the logarithm of total employed workers with secondary education, and $LETER_t$ indicates the logarithm of total employed workers with tertiary education), $LEF_t$ represents the logarithm of total employed foreign workers, and $\varepsilon_t$ denotes the error term.

Moreover, the estimation Model 2 (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 1987-2019 in terms of the Cobb-Douglas production function. Thus, the second estimation model is based on the equation as follows:

$$\begin{aligned} LGDPA_t = \alpha_0 &+ \beta_1 LLNOF_t + \beta_2 LLPRI_t + \beta_3 LLSEC_t + \beta_4 LLTER_t \\ &+ \beta_5 LLFLF_t + \varepsilon_t \end{aligned} \tag{9}$$

where $LGDPA_t$ represents the logarithm of Malaysian agricultural GDP (in RM million), educational attainment means the highest level of education (i.e., $LLNOF_t$ represents the logarithm of the total labor force with no formal education (in '000), $LLPRI_t$ is the logarithm of the total labor force with primary education, $LLSEC_t$ denotes 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 $\varepsilon_t$ represents the error term. Agricultural data are obtained from the Department of Statistics Malaysia. Equation (8) as Model 1 (meso) and Equation (9) as Model 2 (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 cointegration test, the Granger causality test, and variance decomposition. This study also applies the impulse response function (IRF).

# 4. Results and Discussion

### *4.1 Results of Unit Root and Stationary Tests*

Table 1 reports a summary of the descriptive statistics of the variables investigated in this study. 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). Also, the unit root with break test was applied in the study, which is the augmented Dickey-Fuller with structural breaks based on framework outliners (e.g., Perron, 1989; Vogelsang & Perron, 1998; Zivot & Andrews, 1992; Banerjee et al., 1992).

Table 1: Descriptive Statistics

| | **Mean** | **Median** | **Maximum** | **Minimum** | **Std. Dev.** | **Skewness** | **Kurtosis** | **JB** |
|---|---|---|---|---|---|---|---|---|
| | | | | **Model 1** | | | | |
| **LVAA** | 23.762 | 23.681 | 24.141 | 23.383 | 0.234 | 0.185 | 1.796 | 2.511 |
| **LENOF** | 6.295 | 6.245 | 6.722 | 5.933 | 0.260 | 0.167 | 1.611 | 3.232 |
| **LEPRI** | 7.692 | 7.711 | 7.780 | 7.507 | 0.064 | –1.073 | 3.703 | 8.079 |
| **LESEC** | 8.428 | 8.538 | 9.033 | 7.529 | 0.442 | –0.467 | 2.102 | 2.662 |
| **LETER** | 7.171 | 7.237 | 8.397 | 5.763 | 0.830 | –0.154 | 1.759 | 2.590 |
| **LEF** | 6.590 | 6.868 | 7.716 | 4.915 | 0.886 | –0.383 | 1.811 | 3.169 |
| | | | | **Model 2** | | | | |
| **LGDPA** | 10.717 | 10.571 | 11.678 | 9.692 | 0.652 | 0.077 | 1.575 | 2.824 |
| **LLNOF** | 6.261 | 6.192 | 6.655 | 5.959 | 0.218 | 0.261 | 1.632 | 2.947 |
| **LLPRI** | 7.710 | 7.724 | 7.797 | 7.525 | 0.069 | –0.904 | 3.087 | 4.503 |
| **LLSEC** | 8.590 | 8.642 | 9.066 | 7.952 | 0.328 | –0.307 | 2.047 | 1.766 |
| **LLTER** | 7.405 | 7.492 | 8.437 | 6.216 | 0.702 | –0.151 | 1.754 | 2.258 |
| **LLFLF** | 6.820 | 6.922 | 7.733 | 5.399 | 0.743 | –0.547 | 2.215 | 2.493 |

*Notes: Std. Dev. denotes standard deviation, JB represents Jarque-Bera, LVAA denotes the logarithm of value-added agriculture measured in constant 2010 US$, LGDPA indicates the logarithm of agricultural GDP (in RM million), employed workers and labor force are measured in thousand people.*

Source: Authors' estimation from EVIEWS

Table 2 shows the suggested results of the unit root and stationary tests for Models 1 and 2 from the ADF, PP, and KPSS tests. The null hypothesis of the ADF and PP tests is the variable, which is non-stationary, while the null hypothesis of KPSS is the variable, which is stationary. For Model 1, all the variables, including LVAA, LENOF, LEPRI, LESEC, LETER, and LEF, are concluded to be stationary at the first difference, which are $I(1)$ variables based on the results of ADF, PP, and KPSS tests. For Model 2, the results indicate that LGDPA, LLNOF, LLPRI, LLSEC, LLTER, and LLFLF are determined to be stationary at the first difference, which is the $I(1)$ variables.

Table 2: Results of Unit Root and Stationary Tests

| | ADF | | PP | | KPSS | |
|---|---|---|---|---|---|---|
| | **Intercept** | **Trend & Intercept** | **Intercept** | **Trend & Intercept** | **Intercept** | **Trend & Intercept** |
| | | | **Model 1** | | | |
| | | | **A: Level** | | | |
| **LVAA** | –0.520(0) | –2.509(0) | –0.359(6) | –2.574(1) | 0.727(5)** | 0.114(4) |
| **LENOF** | –1.481(0) | –2.275(0) | –1.481(0) | –2.112(2) | 0.714(5)** | 0.132(4)*** |
| **LEPRI** | –0.793(0) | –3.185(3) | –1.143(4) | –2.050(3) | 0.480(4)** | 0.103(3) |
| **LESEC** | –4.047(0)* | –1.758(0) | –4.047(0)* | –1.757(1) | 0.731(5)** | 0.185(5)** |
| **LETER** | –1.672(0) | –0.572(0) | –3.659(31)* | 1.853(36) | 0.742(5)* | 0.213(4)** |
| **LEF** | –1.598(0) | –1.727(0) | –1.600(2) | –1.924(3) | 0.708(5)** | 0.139(4)*** |
| | | | **B: First Difference** | | | |
| **ΔLVAA** | –6.108(1)* | –6.012(1)* | –6.600(6)* | –6.475(6)* | 0.085(7) | 0.083(7) |
| **ΔLENOF** | –7.498(0)* | –7.626(0)* | –7.685(2)* | –7.997(3)* | 0.134(0) | 0.074(1) |
| **ΔLEPRI** | –5.864(0)* | –5.987(0)* | –5.892(3)* | –5.998(3)* | 0.168(3) | 0.057(3) |
| **ΔLESEC** | –1.724(2) | –5.422(1)* | –4.770(4)* | –5.706(2)* | 0.599(4)** | 0.079(1) |
| **ΔLETER** | –5.018(0)* | –5.703(2)* | –5.007(18)* | –8.073(17)* | 0.321(13) | 0.273(26)* |
| **ΔLEF** | –5.675(0)* | –5.711(0)* | –5.677(3)* | –5.706(2)* | 0.189(2) | 0.056(2) |
| | | | **Model 2** | | | |
| | | | **A: Level** | | | |
| **LGDPA** | –0.816(0) | –2.236(0) | –0.806(6) | –2.236(0) | 0.646(5)** | 0.080(4) |
| **LLNOF** | –1.760(0) | –2.349(0) | –1.782(1) | –2.208(2) | 0.628(5)** | 0.161(3)** |
| **LLPRI** | –0.707(0) | –3.323(3)*** | –0.956(3) | –2.147(3) | 0.520(4)** | 0.069(3) |
| **LLSEC** | 2.813(0)*** | –2.115(0) | –2.861(1)*** | –2.111(1) | 0.765(4)* | 0.168(4)** |
| **LLTER** | –1.642(0) | –0.744(0) | –4.023(29)* | 0.888(24) | 0.662(5)** | 0.189(4)** |
| **LLFLF** | –1.631(0) | –6.238(8)* | –1.651(2) | –1.729(2) | 0.710(4)** | 0.120(4)*** |
| | | | **B: First Difference** | | | |
| **ΔLGDPA** | –5.408(0)* | –5.320(0)* | –5.459(6)* | –5.356(6)* | 0.114(7) | 0.102(7) |
| **ΔLLNOF** | –7.199(0)* | –7.387(0)* | –7.414(2)* | –7.812(3)* | 0.147(0) | 0.062(1) |
| **ΔLLPRI** | –5.548(0)* | –5.594(0)* | –5.566(3)* | –5.604(3)* | 0.144(3) | 0.064(3) |
| **ΔLLSEC** | –4.631(0)* | –5.412(0)* | –4.616(3)* | –5.428(2)* | 0.461(3)*** | 0.094(2) |
| **ΔLLTER** | –4.512(0)* | –4.918(0)* | –4.418(21)* | –6.628(17)* | 0.339(12) | 0.349(25)* |
| **ΔLLFLF** | –5.267(0)* | –5.385(0)* | –5.280(3)* | –5.382(2)* | 0.177(3) | 0.067(2) |

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

Source: Authors' estimation from EVIEWS

In addition, the results of the unit root with structural breaks, as shown in Table 3, portray that all the variables are statistically significant at the 1 percent level (i.e., all variables are I(1) in Models 1 and 2). Then, this underscores that the combined results suggest that all the series are integrated into 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. Likewise, all inverse roots are smaller than 1, which specifies that our VAR for Models 1 and 2 is stationary, as portrayed in Figures 1 and 2, respectively. This underlines that VAR meets the stability condition due to all roots situated inside the unit circle. In terms of robustness, the optimal lag length selected for both VAR models (i.e., Models 1 and 2) 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. Subsequently, the residual tests are performed (i.e., the VAR residual serial correlation LM tests and the VAR residual heteroskedasticity tests with cross terms) portrayed in Table 5. There is no serial correlation and an absence of significant heteroskedasticity and specification bias problems in Models 1 and 2.

Table 3: Results of Unit Root with Structural Breaks

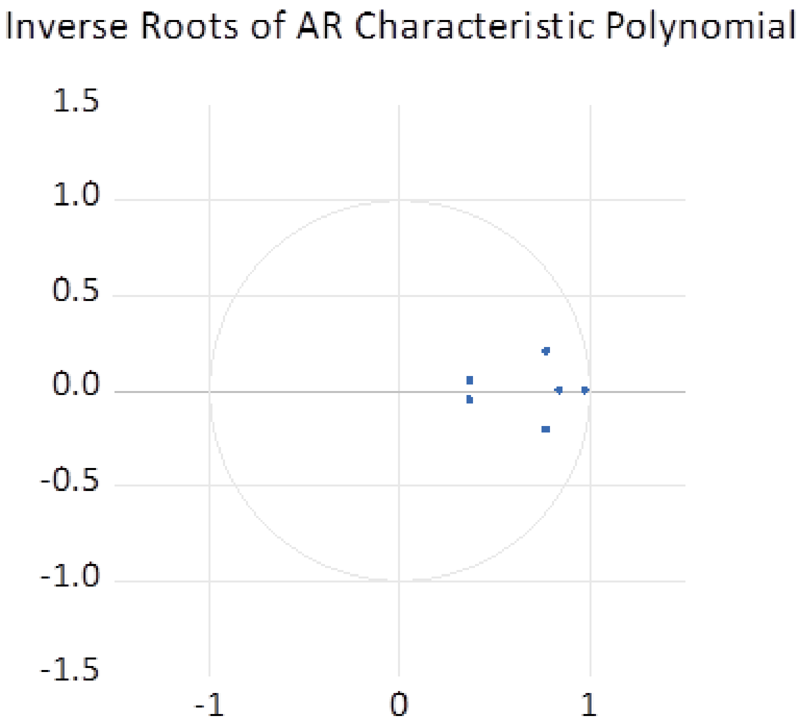
| | Level | | First Difference | |
|---|---|---|---|---|
| | $ADF_I$ | $ADF_{TI}$ | $ADF_I$ | $ADF_{TI}$ |
| **Model 1** | | | | |
| **LVAA** | –2.852(2) [2002] | –4.989(7)** [2009] | –7.870(0)* [2009] | –6.920(1)* [2002] |
| **LENOF** | –4.519(4)** [1999] | –3.479(0) [2017] | –8.879(0)* [2008] | –8.660(0)* [2008] |
| **LEPRI** | –3.860(3) [2004] | –4.301(3) [1995] | –7.288(0)* [2013] | –7.150(0)* [2013] |
| **LESEC** | –6.035(5)* [2009] | –3.733(8) [1995] | –5.900(1)* [1997] | –7.169(4)* [2009] |
| **LETER** | –3.228(3) [1995] | –2.379(0) [2015] | –5.954(2)* [2015] | –6.034(2)* [1995] |
| **LEF** | –2.717(0) [1990] | –5.004(7)** [1995] | –6.119(0)* [2010] | –6.247(0)* [2010] |
| **Model 2** | | | | |
| **LGDPA** | –2.985(2) [2003] | –4.927(6)** [1998] | –5.372(0)* [2008] | –6.336(1)* [2003] |
| **LLNOF** | –4.247(4)*** [1999] | –3.600(0) [1998] | –8.660(0)* [2008] | –8.415(0)* [2008] |
| **LLPRI** | –3.793(4) [2007] | –4.022(8) [2001] | –6.880(0)* [2013] | –6.746(0)* [2013] |
| **LLSEC** | –5.455(5)* [2009] | –3.101(7) [1998] | –5.507(0)* [1993] | –6.746(4)* [2009] |
| **LLTER** | –2.620(0) [1995] | –2.516(0) [2015] | –5.108(1)* [2002] | –5.579(2)* [2015] |
| **LLFLF** | –3.717(3) [2009] | –6.059(8)* [2016] | –7.292(0)* [1996] | –6.998(0)* [1996] |

*Notes: The number in parentheses and square brackets denote 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. Asterisk (*) denotes the test statistic is significant at 1% significance level, (**) indicates significant at 5% significance level and (***) denotes significant at 10% significance level.*

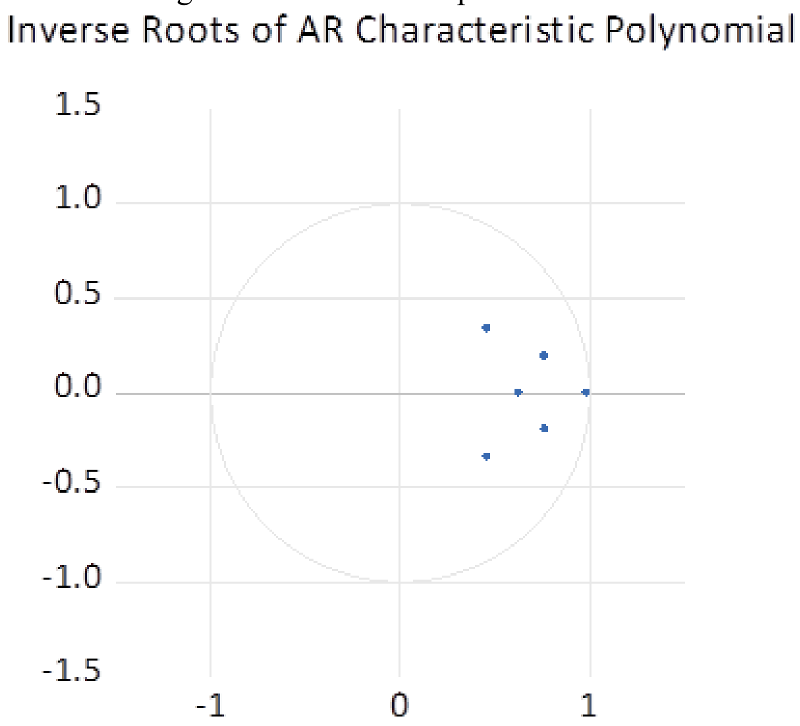
Source: Authors' estimation from EVIEWS

Figure 1: AR Roots Graph for Model 1




Source: Authors’ estimation from EVIEWS

Figure 2: AR Roots Graph for Model 2




Source: Authors’ estimation from EVIEWS

Table 4: VAR Lag Order Selection Criteria

| Model 1 | | | | | |
|---|---|---|---|---|---|
| **Lag** | **LR** | **FPE** | **AIC** | **SC** | **HQ** |
| 0 | NA | 6.30e-13 | -11.067 | -10.800 | -10.975 |
| 1 | 346.169* | 2.17e-17* | -21.373* | -19.506* | -20.728* |
| 2 | 35.495 | 4.10e-17 | -20.929 | -17.463 | -19.732 |
| 3 | 31.377 | 7.91e-17 | -20.833 | -15.767 | -19.084 |
| **Model 2** | | | | | |
| **Lag** | **LR** | **FPE** | **AIC** | **SC** | **HQ** |
| 0 | NA | 1.01e-12 | -10.592 | -10.314 | -10.501 |
| 1 | 261.227* | 2.03e-16* | -19.153* | -17.211* | -18.520* |
| 2 | 34.273 | 4.10e-16 | -18.735 | -15.127 | -17.559 |

*Notes: LR denotes sequential modified LR test statistic (each test at 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. Asterisk (*) denotes lag order selected by the criterion.*

Source: Authors' estimation from EVIEWS

Table 5: Diagnostic Tests

| VAR Residual Serial Correlation LM Tests | | | |
|---|---|---|---|
| $H_0$ : No serial correlation at lag h | | | |
| | LRE* stat | df | Prob. |
| Model 1 | Lag 1= 28.222 | 36 | 0.819 |
| | Lag 2= 32.130 | 36 | 0.653 |
| Model 2 | Lag 1= 34.097 | 36 | 0.559 |
| | Lag 2= 28.362 | 36 | 0.814 |
| $H_0$ : No serial correlation at lags 1 to h | | | |
| | LRE* stat | df | Prob. |
| Model 1 | Lag 1= 28.222 | 36 | 0.819 |
| | Lag 2= 69.067 | 72 | 0.576 |
| Model 2 | Lag 1= 34.097 | 36 | 0.559 |
| | Lag 2= 89.837 | 72 | 0.076 |
| VAR Residual Heteroskedasticity Tests | | | |
| Joint test: | | | |
| | Chi-sq | df | Prob. |
| Model 1 | 579.674 | 567 | 0.347 |
| Model 2 | 594.334 | 567 | 0.207 |

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

Source: Authors' estimation from EVIEWS

### *4.2 Results of the Johansen and Juselius Cointegration Test*

Table 6: Results of Johansen and Juselius Cointegration Test

| Model 1 | | | | | |
|---|---|---|---|---|---|
| | | k=1 r=0 | | | |
| | | Max-Eigen | | Trace | |
| **Null** | **Alternative** | **Unadjusted** | **95% C.V.** | **Unadjusted** | **95% C.V.** |
| **r = 0** | **r = 1** | 37.535 | 40.078 | 89.389 | 95.754 |
| **r ≤ 1** | **r = 2** | 21.743 | 33.877 | 51.854 | 69.819 |
| **r ≤ 2** | **r = 3** | 11.004 | 27.584 | 30.111 | 47.856 |
| **r ≤ 3** | **r = 4** | 9.313 | 21.132 | 19.107 | 29.797 |
| **r ≤ 4** | **r = 5** | 6.064 | 14.265 | 9.794 | 15.495 |
| **r ≤ 5** | **r = 6** | 3.731 | 3.841 | 3.731 | 3.841 |
| **Model 2** | | | | | |
| | | k=1 r=1 | | | |
| | | Max-Eigen | | Trace | |
| **Null** | **Alternative** | **Unadjusted** | **95% C.V.** | **Unadjusted** | **95% C.V.** |
| **r = 0** | **r = 1** | 38.908 | 40.078 | 102.086** | 95.754 |
| **r ≤ 1** | **r = 2** | 23.415 | 33.877 | 63.178 | 69.819 |
| **r ≤ 2** | **r = 3** | 19.339 | 27.584 | 39.763 | 47.856 |
| **r ≤ 3** | **r = 4** | 15.279 | 21.132 | 20.423 | 29.797 |
| **r ≤ 4** | **r = 5** | 4.020 | 14.265 | 5.145 | 15.495 |
| **r ≤ 5** | **r = 6** | 1.124 | 3.841 | 1.124 | 3.841 |

*Notes: k denotes the number of used lag length and r represents the number of cointegrating vector that detected based on the test statistic. Asterisks (**) indicate statistically significant at 5 % significance level.*

Source: Authors' estimation from EVIEWS

Table 6 shows the results of the Johansen and Juselius cointegration test, which consists of the test statistics of the Max-Eigen statistic and the Trace Statistic with each respective critical value at the 5% level of significance. The Johansen and Juselius (1990) cointegration test is applied to test the long-run equilibrium relationship among the tested variables in this study. 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. The results of Models 1 and 2 show that only the suggested result of the Trace Statistic from Model 2 indicates that one cointegrating vector was detected, which implies that the result is not consistent with the suggested result of the Max-Eigen statistic. Johansen and Juselius (1990) stated that the Max-Eigen test statistic should be considered due to that fact that the Max-Eigen test statistic is more powerful than the Trace test statistic, so we concluded that there is no cointegrating vector detected from both models (i.e., Model 1 and Model 2) based on the suggested result of the Max-Eigen statistic with 1 lag length, which means the absence of a long-run equilibrium relationship between the tested variables. Subsequently, we proceed to test the causality direction using VAR modeling for the variables in both models.

### *4.3 Vector Autoregressive (VAR) Model Granger Causality Test*

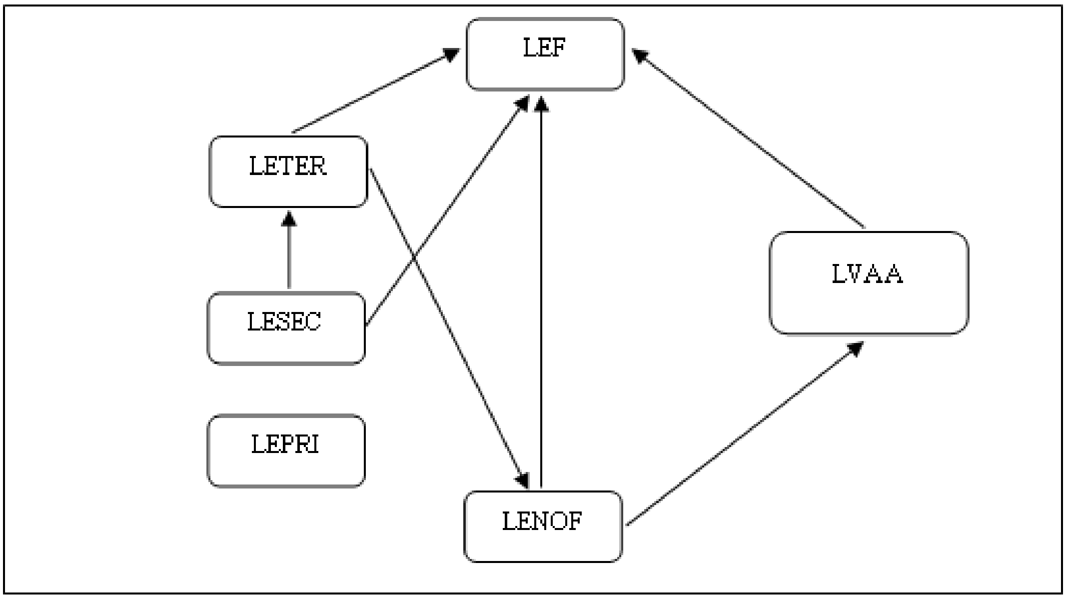
Table 7: Result of VAR Granger Causality Test

| Model 1 | | | | | | |
|---|---|---|---|---|---|---|
| **Dependent Variable** | **ΔLVAA** | **ΔLENOF** | **ΔLEPRI** | **ΔLESEC** | **ΔLETER** | **ΔLEF** |
| | **$\chi^2$ Statistic (p- value)** | | | | | |
| **ΔLVAA** | - | 3.509 (0.061)*** | 0.022 (0.881) | 2.287 (0.130) | 1.729 (0.189) | 0.142 (0.706) |
| **ΔLENOF** | 1.219 (0.270) | - | 2.401 (0.121) | 0.022 (0.883) | 4.280 (0.039)** | 0.145 (0.228) |
| **ΔLEPRI** | 1.449 (0.229) | 0.182 (0.669) | - | 0.224 (0.636) | 0.022 (0.883) | 0.021 (0.885) |
| **ΔLESEC** | 1.135 (0.287) | 1.485 (0.223) | 0.0124 (0.911) | - | 2.112 (0.146) | 1.859 (0.173) |
| **ΔLETER** | 1.030 (0.310) | 0.344 (0.557) | 0.346 (0.556) | 6.220 (0.013)** | - | 0.970 (0.325) |
| **ΔLEF** | 5.227 (0.022)** | 4.198 (0.041)** | 0.370 (0.543) | 2.726 (0.099)*** | 3.302 (0.069)*** | - |
| **Model 2** | | | | | | |
| **Dependent Variable** | **ΔLGDPA** | **ΔLLNOF** | **ΔLLPRI** | **ΔLLSEC** | **ΔLLTER** | **ΔLLFLF** |
| | **$\chi^2$ Statistic (p- value)** | | | | | |
| **ΔLGDPA** | - | 1.984 (0.159) | 0.283 (0.595) | 2.709 (0.099)*** | 3.322 (0.068)*** | 0.532 (0.466) |
| **ΔLLNOF** | 1.949 (0.163) | - | 0.788 (0.375) | 0.762 (0.383) | 5.332 (0.021)** | 0.0003 (0.985) |
| **ΔLLPRI** | 0.028 (0.868) | 0.035 (0.851) | - | 0.651 (0.420) | 0.010 (0.922) | 1.453 (0.228) |
| **ΔLLSEC** | 0.220 (0.639) | 0.252 (0.616) | 1.403 (0.236) | - | 0.605 (0.437) | 0.543 (0.461) |
| **ΔLLTER** | 0.004 (0.953) | 0.920 (0.337) | 0.118 (0.731) | 6.026 (0.014)** | - | 1.653 (0.199) |
| **ΔLLFLF** | 0.015 (0.902) | 1.410 (0.235) | 2.337 (0.126) | 0.433 (0.511) | 0.009 (0.922) | - |

*Notes: The chi-square statistic is represented by the symbol of $\chi^2$. Asterisk (**) and (***) denotes the result is significant at 5 % significance level and 10 % significance level respectively. Δ represents the variable is in the first difference.*

Source: Authors' estimation from EVIEWS

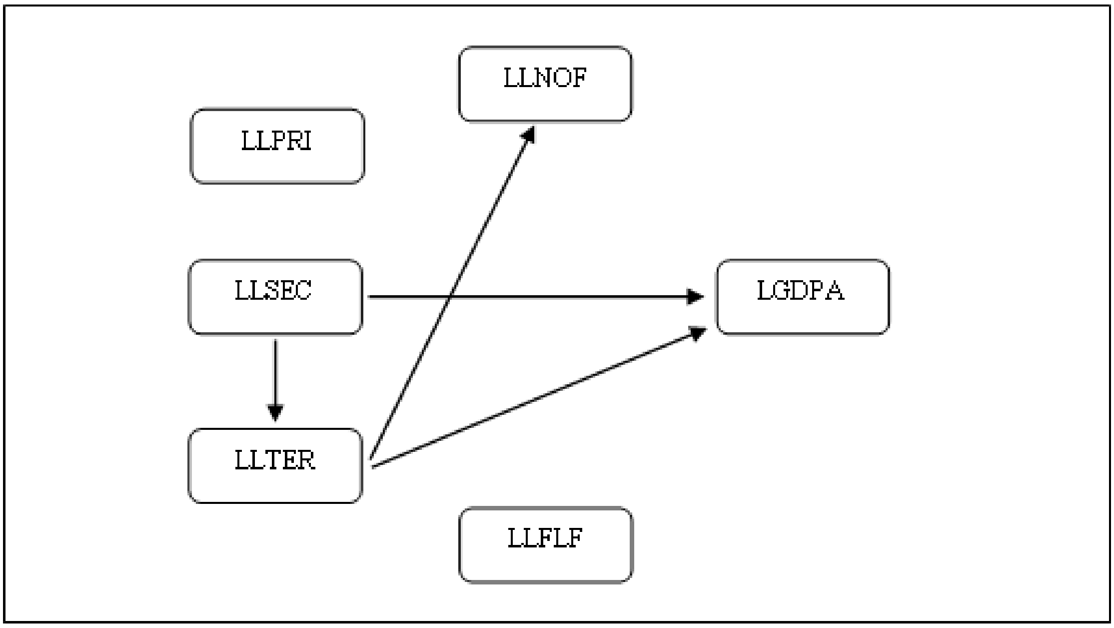
Figure 3: Result of Vector Autoregressive (VAR) Granger Causality Flow for Model 1




*Notes: Figure 3 display the unidirectional causality between tested variables (i.e., LVAA, LENOF, LEPRI, LESEC, LETER, and LEF), grounded on the results of the VAR Granger causality test in Table 7.*

Source: Authors' estimation from EVIEWS

Figure 4: Result of Vector Autoregressive (VAR) Granger Causality Flow for Model 2




*Notes: Figure 4 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 7.*

Source: Authors' estimation from EVIEWS

The results of the VAR Granger causality test are portrayed in Table 7, and the VAR Granger causality flow for Models 1 and 2 is shown in Figure 3 and Figure 4, respectively. The Granger (1988) causality test is used to determine the existence and direction of causality between all the tested variables in the model. A summary of the results for Model 1 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). The results show that only employed workers with no formal education Granger cause value-added agriculture during the period of the study. This means there is a unidirectional causality running from LENOF to LVAA, as shown in Figure 3. The results also indicate that employed foreign workers do not Granger cause value-added agriculture. The value-added agriculture and employed workers with no formal education Granger cause employed foreign workers, respectively. We find that the result is statistically significant at the 5% significance level. The employed workers with secondary education and the employed workers with tertiary education Granger cause employed foreign workers, respectively, at the 10% level of significance. Likewise, the result of Model 2 indicates that only LLTER and LLSEC Granger cause LGDPA, respectively, at the 10 % level of significance. The Granger causality flow illustrates that there is a unidirectional causal relationship running from LLTER to LGDPA and LLSEC to LGDPA. The summary of the results for Model 2 affirms that higher education level does Granger cause agricultural GDP. Meanwhile, the Malaysian labor force with secondary education does Granger cause labor force with tertiary education level during the study period. Then, the Malaysian labor force with tertiary education does Granger cause labor force with no formal education. The result specifies that unidirectional causality runs from LLTER to LLNOF, as shown in Figure 4. However, the labor force with no formal education and labor force with primary education does not Granger cause agricultural GDP, respectively. The results also affirm that the foreign labor force does not Granger cause agricultural GDP in Malaysia.

### *4.4 Variance Decomposition*

Table 8: Variance Decomposition Results

| Model 1 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Percentage of variations in | Horizon (years) | Due to Innovation in: | | | | | | |
| | | ΔLVAA | ΔLENOF | ΔLEPRI | ΔLESEC | ΔLETER | ΔLEF | ΔCU |
| Years Relative Variance in: ΔLVAA | | | | | | | | |
| | 1 | **100** | 0 | 0 | 0 | 0 | 0 | 0 |
| | 4 | **61.859** | 26.873 | 0.283 | 2.619 | 7.123 | 1.243 | 38.141 |
| | 8 | **45.911** | 29.391 | 2.092 | 3.290 | 16.624 | 2.693 | 54.089 |
| | 12 | **43.257** | 28.095 | 2.425 | 3.394 | 19.645 | 3.185 | 56.743 |
| | 20 | **41.555** | 26.538 | 2.357 | 5.434 | 20.308 | 3.808 | 58.445 |
| | 30 | **40.243** | 25.626 | 2.236 | 7.004 | 20.409 | 4.483 | 59.757 |
| | 40 | **39.480** | 25.082 | 2.151 | 7.949 | 20.452 | 4.885 | 60.520 |
| | 50 | **39.030** | 24.757 | 2.101 | 8.523 | 20.464 | 5.125 | 60.970 |
| Years Relative Variance in: ΔLENOF | | | | | | | | |
| | 1 | 0.028 | **99.972** | 0 | 0 | 0 | 0 | 0.028 |
| | 4 | 0.485 | **82.998** | 6.066 | 0.147 | 6.916 | 3.388 | 17.002 |
| | 8 | 0.636 | **76.623** | 8.379 | 1.408 | 8.754 | 4.200 | 23.377 |
| | 12 | 1.276 | **73.862** | 8.127 | 3.493 | 8.806 | 4.435 | 26.138 |
| | 20 | 2.507 | **70.332** | 7.745 | 5.563 | 8.953 | 4.900 | 29.668 |
| | 30 | 3.250 | **68.018** | 7.435 | 6.593 | 9.395 | 5.310 | 31.982 |
| | 40 | 3.672 | **66.664** | 7.258 | 7.205 | 9.664 | 5.538 | 33.336 |
| | 50 | 3.927 | **65.845** | 7.151 | 7.572 | 9.829 | 5.676 | 34.155 |
| Years Relative Variance in: ΔLEPRI | | | | | | | | |
| | 1 | 7.300 | 0.536 | **92.163** | 0 | 0 | 0 | 7.837 |
| | 4 | 4.210 | 2.364 | **92.650** | 0.597 | 0.157 | 0.023 | 7.350 |
| | 8 | 3.748 | 7.490 | **83.445** | 2.657 | 2.462 | 0.199 | 16.555 |
| | 12 | 3.612 | 8.312 | **80.087** | 3.255 | 4.412 | 0.322 | 19.913 |
| | 20 | 3.609 | 8.260 | **79.197** | 3.321 | 5.218 | 0.394 | 20.803 |
| | 30 | 3.746 | 8.272 | **78.541** | 3.543 | 5.396 | 0.503 | 21.459 |

**Model 1**

| Percentage of variations in | Horizon (years) | Due to Innovation in: | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | ΔLVAA | ΔLENOF | ΔLEPRI | ΔLESEC | ΔLETER | ΔLEF | ΔCU |
| | 40 | 3.844 | 8.295 | **78.071** | 3.700 | 5.501 | 0.588 | 21.929 |
| | 50 | 3.909 | 8.307 | **77.772** | 3.807 | 5.562 | 0.643 | 22.228 |
| Years Relative Variance in: ΔLESEC | | | | | | | | |
| | 1 | 28.263 | 2.000 | 15.736 | **54.001** | 0 | 0 | 45.999 |
| | 4 | 21.976 | 0.892 | 7.121 | **63.719** | 2.219 | 4.074 | 36.281 |
| | 8 | 22.994 | 1.359 | 4.834 | **61.046** | 3.150 | 6.617 | 38.954 |
| | 12 | 23.502 | 3.665 | 3.862 | **55.670** | 4.957 | 8.344 | 44.330 |
| | 20 | 22.999 | 6.214 | 2.874 | **49.397** | 8.409 | 10.106 | 50.603 |
| | 30 | 22.641 | 7.089 | 2.401 | **46.542** | 10.419 | 10.907 | 53.458 |
| | 40 | 22.476 | 7.513 | 2.180 | **45.164** | 11.388 | 11.279 | 54.836 |
| | 50 | 22.384 | 7.743 | 2.061 | **44.414** | 11.919 | 11.479 | 55.586 |
| Years Relative Variance in: ΔLETER | | | | | | | | |
| | 1 | 6.490 | 0.836 | 1.586 | 0.248 | **90.840** | 0 | 9.160 |
| | 4 | 4.271 | 0.360 | 2.446 | 3.549 | **86.875** | 2.499 | 13.125 |
| | 8 | 8.099 | 1.459 | 5.076 | 11.971 | **67.960** | 5.434 | 32.040 |
| | 12 | 11.431 | 3.996 | 4.726 | 16.428 | **55.793** | 7.626 | 44.207 |
| | 20 | 14.297 | 7.040 | 3.282 | 20.184 | **45.199** | 9.998 | 54.801 |
| | 30 | 15.710 | 8.124 | 2.539 | 22.625 | **39.887** | 11.115 | 60.113 |
| | 40 | 16.372 | 8.577 | 2.217 | 23.806 | **37.429** | 11.599 | 62.571 |
| | 50 | 16.713 | 8.809 | 2.052 | 24.418 | **36.161** | 11.847 | 63.839 |
| Years Relative Variance in: ΔLEF | | | | | | | | |
| | 1 | 5.444 | 9.264 | 46.071 | 1.093 | 0.021 | **38.107** | 61.893 |
| | 4 | 3.397 | 42.920 | 24.071 | 5.784 | 2.088 | **21.741** | 78.259 |
| | 8 | 3.507 | 40.055 | 26.608 | 12.570 | 1.504 | **15.756** | 84.244 |
| | 12 | 5.306 | 36.538 | 27.446 | 14.298 | 1.794 | **14.618** | 85.382 |
| | 20 | 6.751 | 34.973 | 24.798 | 14.695 | 4.203 | **14.581** | 85.419 |
| | 30 | 7.654 | 33.297 | 23.039 | 15.765 | 5.642 | **14.603** | 85.397 |
| | 40 | 8.239 | 32.330 | 22.020 | 16.475 | 6.326 | **14.610** | 85.390 |
| | 50 | 8.584 | 31.761 | 21.418 | 16.893 | 6.728 | **14.616** | 85.384 |

**Model 2**

| 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 |
| | 4 | **75.125** | 7.050 | 0.426 | 5.105 | 11.770 | 0.524 | 24.875 |
| | 8 | **64.053** | 7.863 | 0.670 | 4.903 | 20.145 | 2.366 | 35.947 |
| | 12 | **59.015** | 8.660 | 1.594 | 5.378 | 22.122 | 3.230 | 40.985 |
| | 20 | **54.339** | 8.754 | 1.771 | 7.849 | 23.657 | 3.631 | 45.661 |
| | 30 | **50.754** | 8.837 | 1.655 | 10.219 | 24.525 | 4.011 | 49.246 |
| | 40 | **48.417** | 8.915 | 1.579 | 11.699 | 25.119 | 4.271 | 51.583 |
| | 50 | **46.856** | 8.965 | 1.528 | 12.692 | 25.516 | 4.444 | 53.144 |
| Years Relative Variance in: ΔLLNOF | | | | | | | | |
| | 1 | 3.461 | **96.539** | 0 | 0 | 0 | 0 | 3.461 |
| | 4 | 11.252 | **72.045** | 8.266 | 0.942 | 7.188 | 0.306 | 27.955 |
| | 8 | 11.120 | **67.844** | 10.563 | 2.473 | 7.477 | 0.522 | 32.156 |
| | 12 | 11.061 | **66.735** | 10.444 | 3.589 | 7.648 | 0.524 | 33.265 |
| | 20 | 10.808 | **65.187** | 10.289 | 4.828 | 8.174 | 0.714 | 34.813 |
| | 30 | 10.557 | **63.921** | 10.049 | 5.677 | 8.862 | 0.934 | 36.079 |
| | 40 | 10.387 | **63.039** | 9.883 | 6.282 | 9.332 | 1.077 | 36.961 |
| | 50 | 10.266 | **62.418** | 9.766 | 6.709 | 9.663 | 1.177 | 37.582 |
| Years Relative Variance in: ΔLLPRI | | | | | | | | |
| | 1 | 0.012 | 0.586 | **99.402** | 0 | 0 | 0 | 0.598 |
| | 4 | 2.453 | 1.499 | **91.295** | 0.190 | 0.009 | 4.555 | 8.705 |
| | 8 | 3.960 | 5.219 | **83.093** | 0.358 | 0.775 | 6.595 | 16.907 |
| | 12 | 4.086 | 5.549 | **81.961** | 0.421 | 1.419 | 6.564 | 18.039 |
| | 20 | 4.069 | 5.524 | **81.750** | 0.533 | 1.598 | 6.526 | 18.250 |
| | 30 | 4.060 | 5.533 | **81.519** | 0.671 | 1.686 | 6.532 | 18.481 |
| | 40 | 4.052 | 5.544 | **81.348** | 0.757 | 1.761 | 6.539 | 18.652 |
| | 50 | 4.046 | 5.551 | **81.225** | 0.820 | 1.815 | 6.543 | 18.775 |

| Model 2 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Percentage of variations in | Horizon (years) | Due to Innovation in: | | | | | | |
| | | ΔLGDPA | ΔLLNOF | ΔLLPRI | ΔLLSEC | ΔLLTER | ΔLLFLF | ΔCU |
| Years Relative Variance in: ΔLLSEC | | | | | | | | |
| | 1 | 0.086 | 5.405 | 34.798 | **59.711** | 0 | 0 | 40.289 |
| | 4 | 3.562 | 2.909 | 21.580 | **69.584** | 1.459 | 0.906 | 30.416 |
| | 8 | 5.047 | 2.187 | 19.094 | **69.570** | 3.221 | 0.880 | 30.430 |
| | 12 | 4.335 | 2.929 | 17.950 | **66.090** | 6.543 | 2.153 | 33.910 |
| | 20 | 3.351 | 5.036 | 14.013 | **60.182** | 13.242 | 4.176 | 39.818 |
| | 30 | 2.804 | 5.993 | 11.605 | **57.013** | 17.472 | 5.113 | 42.987 |
| | 40 | 2.516 | 6.485 | 10.321 | **55.401** | 19.668 | 5.609 | 44.599 |
| | 50 | 2.344 | 6.782 | 9.554 | **54.431** | 20.982 | 5.907 | 45.569 |
| Years Relative Variance in: ΔLLTER | | | | | | | | |
| | 1 | 0.011 | 2.656 | 13.634 | 0.003 | **83.695** | 0 | 16.305 |
| | 4 | 0.128 | 1.813 | 7.617 | 15.051 | **70.609** | 4.782 | 29.391 |
| | 8 | 0.230 | 4.918 | 4.557 | 26.870 | **56.639** | 6.786 | 43.361 |
| | 12 | 0.240 | 6.313 | 3.365 | 30.999 | **51.639** | 7.444 | 48.361 |
| | 20 | 0.228 | 7.568 | 2.345 | 34.471 | **47.281** | 8.106 | 52.719 |
| | 30 | 0.221 | 8.214 | 1.825 | 36.211 | **45.087** | 8.441 | 54.913 |
| | 40 | 0.218 | 8.526 | 1.573 | 37.062 | **44.019** | 8.602 | 55.981 |
| | 50 | 0.216 | 8.704 | 1.430 | 37.544 | **43.412** | 8.694 | 56.588 |
| Years Relative Variance in: ΔLLFLF | | | | | | | | |
| | 1 | 10.088 | 1.197 | 58.516 | 4.499 | 0.262 | **25.437** | 74.563 |
| | 4 | 13.221 | 18.435 | 30.988 | 13.679 | 0.545 | **23.133** | 76.867 |
| | 8 | 12.567 | 16.108 | 34.278 | 19.054 | 1.137 | **16.856** | 83.144 |
| | 12 | 11.807 | 15.145 | 35.893 | 19.954 | 1.269 | **15.931** | 84.069 |
| | 20 | 11.268 | 15.225 | 34.427 | 20.448 | 2.784 | **15.847** | 84.153 |
| | 30 | 10.881 | 15.060 | 33.238 | 21.164 | 4.035 | **15.622** | 84.378 |
| | 40 | 10.620 | 14.946 | 32.423 | 21.689 | 4.848 | **15.474** | 84.526 |
| | 50 | 10.438 | 14.868 | 31.857 | 22.050 | 5.416 | **15.372** | 84.628 |

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

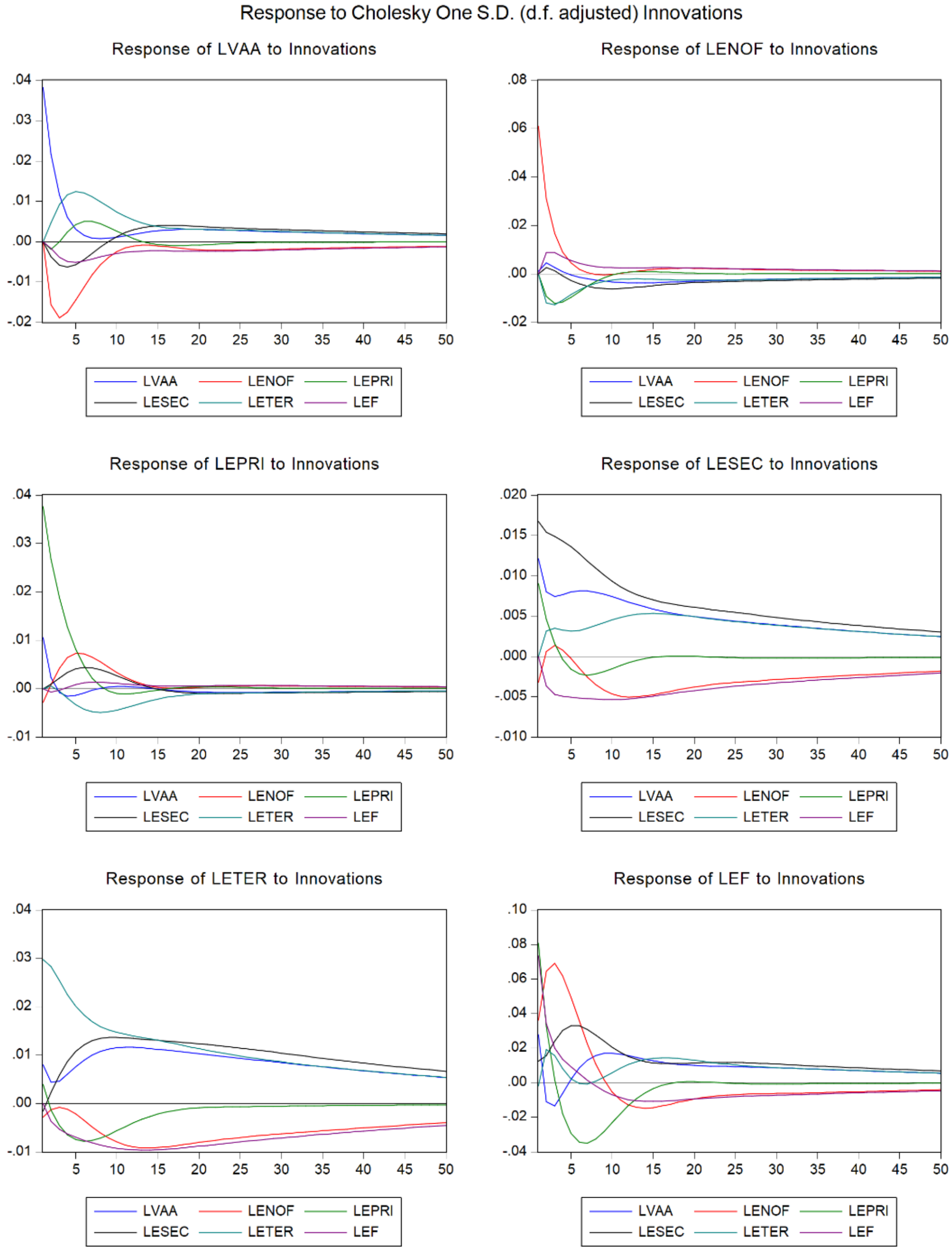
Source: Authors' estimation from EVIEWS

Based on the results of variance decomposition for Model 1, LEF is the most endogenous variable in this study instead of LVAA as a dependent variable since LEF highly absorbs the shocks from the other variables, and only around 14.62% of the variation can be explained by itself at the end of the 50 years. LEF indicates that among the 85.38% of forecast error variance, about 8.58%, 31.76%, 21.42%, 16.89%, and 6.73% of variation can be caused by LVAA, LENOF, LEPRI, LESEC, and LETER, respectively. LENOF is the most influential variable for LEF, as the variations in this variable keep taking up the biggest portion throughout these 50 years. Thus, this indicates LENOF has causality toward LEF, a result consistent with the findings of the Granger causality test, where LENOF can Granger cause LEF. The variance decomposition result also reveals that the proportion of employed foreign workers is based on their various levels of education. This means most employed foreign workers do not have a high education level because the results indicate that no formal education and primary education occupy the biggest portion, which means that this can affect a large part of employed foreign workers throughout 50 years. LEPRI is indicated to be the most exogenous variable based on the result of variance decomposition because among the 22.23% of forecast error variance, about 3.91%, 8.31%, 3.81%, 5.56%, and 0.64% of variation can be caused by LVAA, LENOF, LESEC, LETER, and LEF, 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 Granger causality test, in which LEPRI is not Granger caused by any variables. LENOF is the second most exogenous variable based on the variance decomposition results in the study. The results explain that employed workers with tertiary education can affect more employed workers with no formal education in Malaysia compared with others. This result is consistent with the finding of the Granger causality test, where LETER can Granger cause LENOF.

The results of variance decomposition for Model 2 further support the significant effect of various levels of education on agricultural GDP. The 53.14% of the forecast error variance in LGDPA can be explained by the shock of the other variables, which are 8.97% by LLNOF, 1.53% by LLPRI, 12.69% by LLSEC, 25.52% by LLTER, and 4.44% by LLFLF at the end of 50 years. The results indicate that the labor force with tertiary education shocks accounts for more than 25 percent of agricultural GDP. This percentage value implies that the labor force with tertiary education is the most influential variable with regard to agricultural GDP, as the variations in this variable have taken up the biggest portion throughout these 50 years. This result is consistent with the findings of the Granger causality test, where LETER does Granger cause LGDPA. Besides, variance decomposition shows that the labor force with secondary education can account for more than 12 percent of the forecast error variance in agricultural GDP at the end of 50 years. This result is consistent with the findings of the Granger causality test, where LESEC does Granger cause LGDPA. This underlines that the impact of the labor force with tertiary education is greater than the labor force with secondary education on agricultural GDP. Variance decomposition also affirms that the labor force with no formal education and the labor force with primary education do not significantly explain the forecast error variance in agricultural GDP. Next, LLFLF is the most endogenous variable since it highly absorbs the shocks from the other variables, and only around 15.37% of the variation can be explained by itself at the end of the 50 years. LLFLF indicates that among the 84.63% of forecast error variance, about 10.44%, 14.87%, 31.86%, 22.05%, and 5.42% of variation can be caused by LGDPA, LLNOF, LLPRI, LLSEC, and LLTER, respectively. These percentage values show that LLPRI is the most influential variable with regard to LLFLF, as the variations from this variable keep taking the biggest portion throughout these 50 years. This result can imply that most of the foreign labor force only has a primary and secondary level of education in Malaysia. Meanwhile, only a small percentage of the foreign labor force in Malaysia has a tertiary education. This result is consistent with a study by the Central Bank of Malaysia, which shows that a large number of migrants in Malaysia have a low educational level; only 5.2% of them have tertiary education (Ang et al., 2018). LLPRI is indicated to be the most exogenous variable in the result because the percentage of variation caused by LLPRI is greater than variations caused by other variables every 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 result of the VAR Granger causality test (see Table 7) also attests that all other variables do not Granger cause LLPRI.

### *4.5 Impulse Response Function (IRF)*

Figure 5: Results of Impulse Response Function for Model 1



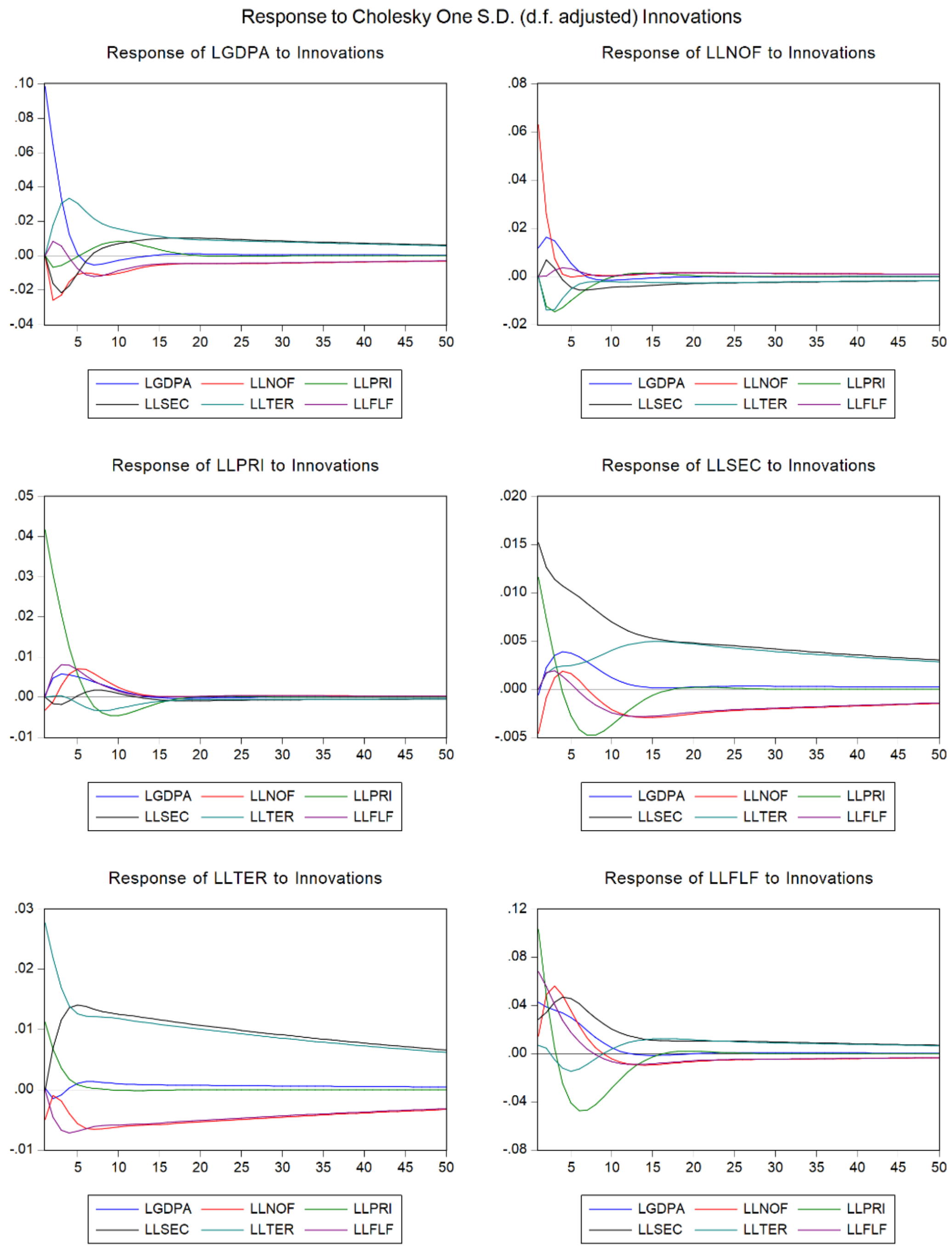

*Notes: Figure 5 was developed by using EViews and the Cholesky decomposition method (dof) for impulse response over 50 years. Each variable (i.e., LVAA, LENOF, LEPRI, LESEC, LETER, and LEF) is represented by the different colors of lines as stated above.*

Source: Authors' estimation from EVIEWS

Figure 5 displays the results of the Impulse Response Function (IRF) for Model 1 over a period of 50 years. The impulse response analysis is applied by utilizing the Cholesky decomposition and adjustment in the degree of freedom (Cholesky dof adjusted), so as to describe the evolution of a model's variables in reaction to a shock in one or more variables. In this case, the effect of education levels on value-added agriculture over 50 years. Based on the graph in Figure 5, the response of LVAA to a shock in the LENOF is negative and significant, which indicates that employed workers with no formal education have a negative impact on value-added agriculture over 50 years. The negative response significantly increases and reaches its maximum in the third year, while it shows a significant decline from the 4$^{th}$ until the 14$^{th}$ year, then gradually increases from the 15$^{th}$ until the 24$^{th}$ year. It subsequently decreases slightly from the 25$^{th}$ until the 50$^{th}$ year. This result further supports the result of the Granger causality test (see Table 7), which shows that employed workers with no formal education Granger cause value-added agriculture. Besides, the response of LVAA to LEF also reveals that employed foreign workers have a negative impact on value-added agriculture over 50 years, reaching its maximum in the 5$^{th}$ year. However, the impulse response function affirms that only LETER has a positive impact on value-added agriculture over 50 years compared with other variables. The positive effect starts increasing dramatically in the first five years and reaches its maximum in the 5$^{th}$ year. The positive effect declines dramatically from the 6$^{th}$ until the 18$^{th}$ year and then decreases slightly from 19$^{th}$ until the 50$^{th}$ year. This implies that employed workers with tertiary education have a positive impact on value-added agriculture, especially in the early period, although employed workers with tertiary education do not Ganger cause value-added agriculture over the study period based on the results of the Granger causality test (see Table 7).

For Model 2, the effect of education level shock on agricultural GDP over 50 years is shown in the graph in Figure 6. The response of LGDPA to a shock in the LLTER is positive and significant, which indicates that labor force with tertiary education had a positive impact on agricultural GDP throughout the past 50 years. The positive response increases dramatically and reaches its maximum in the 4$^{th}$ year but declines significantly from the 5$^{th}$ to the 9$^{th}$ year. It then declines gradually from the 10$^{th}$ to the 50$^{th}$ year. This result further supports the result of the Granger causality test that the labor force with tertiary education does Granger cause agricultural GDP. Besides, the response of LGDPA to LLSEC shows that the labor force with secondary education has a negative impact on agricultural GDP only during the first six years and reaches its maximum during the 3$^{rd}$ year, while there is a slightly positive effect starting from the 7$^{th}$ year until the 50$^{th}$ year. On the other hand, the response of LGDPA to LLFLF confirms that the foreign labor force has a positive impact on gross domestic product (GDP) from agriculture over the first four years, particularly during the 2$^{nd}$ year when it reaches its maximum effect. In the meantime, the graph of the IRF illustrates that there is a noticeable negative effect starting from the 4$^{th}$ year until the 13$^{th}$ year, whereas a slightly negative effect happens from the 13$^{th}$ until the 50$^{th}$ year. The results of impulse response analysis are consistent with the results of the Granger causality test (see Table 7) and show that a labor force with secondary education does Granger cause labor force with tertiary education. Moreover, the response of LLNOF to LLTER displays that labor force with tertiary education has a negative impact on labor force with no formal education in 50 years. The negative response dramatically increases and reaches its maximum during the 2$^{nd}$ year, while it declines significantly from the 3$^{rd}$ until the 8$^{th}$ year, and then continues to remain at a certain impact level from the 8$^{th}$ to the 50$^{th}$ year.

Figure 6: Results of Impulse Response Function for Model 2




*Notes: Figure 6 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.*

Source: Authors' estimation from EVIEWS

# 5. Conclusion

The summary of the empirical results of Model 1 (meso) specifies that employees who have had no formal education Granger cause value-added agriculture based on the results of the VAR Granger causality test (see Table 7). There is a unidirectional Granger causality running from no formal education to value-added agriculture over the period 1982-2019 (see Figure 3). The findings reveal that if agricultural industries rely too much on employees who have no formal education, this will negatively affect value-added agriculture based on the graph of IRF (see Figure 5). The IRF result also displays that employed workers with no formal education have had a negative impact on value-added agriculture throughout 50 years, with the negative response reaching its maximum in the third year. Subsequently, variance decomposition (see Table 8) further explains that most employed foreign workers do not have a high education level because they have no formal education, and primary education level keeps taking the biggest portion, respectively, which means that it can affects a large part of employed foreign workers throughout 50 years. First, the government and agricultural industries should try to rely less on low-skilled foreign workers. The results affirm that most foreign workers only have a low educational level in our labor market because the findings reveal no formal education can adversely impact the value-added agriculture. Second, the agricultural industries should hire more high school graduates because we find that employed workers with secondary education do Granger cause them to attain a tertiary education. The IRF results also support that employees with secondary and tertiary education positively affect value-added agriculture throughout the 50 years, but there is no causality between 1982 and 2019. Also, there is a unidirectional causality from tertiary education to no formal education. The IRF reveals that tertiary education has had adverse effects on no formal education throughout 50 years. This means that if agricultural industries hire more employees who have had a tertiary education, it would diminish the number of employed workers with no formal education, which would help solve the flagging output of the agricultural industry.

The results of Model 2 (macro) further support the results of Model 1 (meso), which show that 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 (see Table 7) and the impulse response function (IRF) (see Figure 6). Meanwhile, the findings reveal that there is a unidirectional causality from tertiary education to agricultural GDP for the period 1987-2019 (see Figure 4). The IRF illustrates that tertiary education has a significantly positive effect during the third, fourth, and fifth years throughout the 50 years. Next, there is a unidirectional causality from secondary education to agriculture GDP during 1987-2019 (see Figure 4). The graph of IRF (see Figure 6) also shows that secondary education has a negative impact on agricultural GDP in the early period only, then a positive effect for the remaining 43 years. This underlines that increasing the numbers of those in the labor force who have a secondary education led to a slight reduction in the early period only and gradually increased agricultural GDP from the $7^{th}$ to the 50th year. The graph of IRF in Figure 6 also proves that the significant positive effect of tertiary education does reduce the short-run negative impacts of secondary education on agricultural GDP. The variance decomposition results (see Table 8) also further support that the effect of tertiary education is greater than that of secondary education on agricultural GDP. The results also confirm that the foreign labor force does not Granger cause agricultural GDP in Malaysia. This finding also proves that the foreign labor force does not affect agricultural

GDP much due to the small percentage of the foreign labor force in the local labor market having a high education level. The variance decomposition reveals that most of the foreign labor force has only a primary and secondary level of education. This result is consistent with the study of the Central Bank of Malaysia, which found that few migrants in Malaysia have a high education level only 5.2% of them have a tertiary education level (Ang et al., 2018). Next, the IRF results (see Figure 6) illustrate that a labor force with no formal education has a negative impact on gross domestic product (GDP) from the agriculture sector throughout 50 years.

For this study, the findings are consistent with a study by Pudasaini (1983), who found that higher education creates more productivity in modernizing agriculture than traditional agriculture. Also, our findings are similar to those studies (e.g., Tsai et al., 2010; Ganegodage & Rambaldi, 2011); secondary and tertiary education can positively affect economic growth. Accordingly, the Malaysian government should encourage agricultural industries to hire more employees who have a high education level, especially those with a tertiary or secondary education. At the same time, the government needs to offer more free training courses to employees or employers to provide advanced technologies (e.g., robotics, drones, artificial intelligence, or virtual reality) with skills and techniques to boost agricultural transformation, thereby enhancing production output. Second, the Ministry of Education must work together with the Ministry of Agriculture and Food Industries to offer free training courses with certificates issued by local universities in order to encourage employees to get involved. Finally, we can confirm that employees with a high level of education are able to bring skill, knowledge, and the right mindset to labor markets that will enable them to transform local industry, boost value-added agriculture, and drive 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 improve the skills of local workers, especially in the agricultural industry.

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