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How Global Value Chains Affect Economic Output and Unemployment: An Empirical Evidence from ASEAN Countries

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HOW GLOBAL VALUE CHAINS AFFECT ECONOMIC OUTPUT AND UNEMPLOYMENT: AN EMPIRICAL EVIDENCE FROM ASEAN COUNTRIES

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ABSTRACT

This paper examines the effects of Global Value Chains on economic output and unemployment in ten ASEAN countries from 1999 to 2018. This study provides estimation using the system GMM and panel causality test to determine the effect of GVC thoroughly. The results indicate a positive and significant effect of global value chains on economic output in ASEAN countries. However, the findings also show that global value chains increase unemployment during the observation period. Heterogenous panel non-causality findings suggest that economic output does not affect the level of participation of GVC, but unemployment affects the level of participation in ten members of ASEAN countries.

Keywords: Global value chain; Trade; Economic growth; Unemployment; System GMM.
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I. INTRODUCTION

The nexus between international trade and economic upgrading has always attracted interest from researchers. The classical idea of international trade is that a country would produce goods and provides services, then exports them as final products to consumers worldwide. During globalisation, traditional trade only accounts for 30% of total trade, and the rest are linked to Global Value Chains (GVCs) to produce a product (OECD, 2021). Motivated by globalisation and trade development, GVC trade has been highlighted as a potential solution for boosting industrialisation and revisiting the nexus between international trade and economic upgrading (Pahl and Timmer, 2020; Stolzenburg *et al.*, 2019).

Within GVCs, countries are involved together to construct a global economy, allow countries to leapfrog their development process, and promote economic growth by producing high-technology products (Antràs, 2020; Rodrik, 2021). However, there are always re-ignited debates about the supply chain risks associated with international production, highlighting the strengths and weaknesses of involving in GVCs. See Vidya and Prabheesh (2020) and Wuri *et al.* (2022).

Meanwhile, the empirical evidence for the effect of GVC trade on economic development, such as economic growth and the unemployment rate, needs more consensus. Some studies prove that GVCs will increase the efficiency of capital accumulation and improve productivity in developing countries, leading to significant economic growth (Jangam and Rath, 2021a, 2021b; Pahl and Timmer, 2020; Urata and Baek, 2020). Nevertheless, some studies argue that economic integration can create and elimate jobs simultaneously since international trade increases the demand for skilled labour but replaces unskilled labour with machines (Narayan *et al.*, 2021).

Jangam and Rath (2021) found that trade promoted economic growth in 58 countries from 2005 to 2015. Similarly, Urata and Baek (2020) also concludes that GVC participation is crucial in improving productivity, leading to increased economic growth. However, the literature also proves that participating in GVCs stimulates economic growth rather than employment growth. Banga (2016) shows that participating in GVC trade only displaced domestic labour and could not boost employment in India from 1995 until 2011. Pahl and Timmer (2020) argues that the massively growing trade activity in GVCs may not go *hand-in-hand* with employment availability. This hypothesis, known as the *mixed-blessing hypothesis*, suggests that GVC participation in developing countries will boost economic growth but create few opportunities for employment growth. Therefore, many studies doubt the benefit of GVC participation and have suggested a need to rethink GVCs since it only spurs economic growth without reducing unemployment.

Recently, studies analysing GVC participation are growing significantly. However, the limitation of the previous studies on understanding the effects of global value chains on economic growth and the unemployment rate is rarely focused on ASEAN countries. Some studies analyse the nexus between GVC participation and economic growth in ASEAN countries but forget to examine the effect together with the unemployment rate. Thus, the motivation of our study is to fill this research gap.

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Examining the GVC participation's effects on economic growth and unemployment rate for ASEAN is of foremost importance for ASEAN countries' governments. Based on ASEAN Economic Community Blueprint 2025, ASEAN countries have accepted the new opportunities by participating in more wide connection global value chains to create rapid economic growth and reduce unemployment (ASEAN-Japan Centre, 2019). However, the notion of the *mixed-blessing hypothesis* may incur a failure in achieving the primary goal of the ASEAN Economic Community Blueprint 2025.

The objective is to examine how GVC participation impacts economic growth and unemployment rate in ten members of ASEAN Countries. A study related to the effect of GVC participation can offer valuable information for policymakers about the gain and losses during involvement in global value chains.

This study related to the *mixed-blessing hypothesis* that GVC participation boosts economic growth but does not directly reduce unemployment. To examine the effect of GVC participation on economic growth and unemployment rate, this study links to the endogenous growth theories to present a theoretical framework linking international trade and economic growth. In addition, this study also relates to Sen (2008) to analyse the effect of GVC participation on employment. To thoroughly investigate the effect of GVC participation, this study includes two components of GVC: Forward Participation (FP) and Backward Participation (BP) (Hummels *et al.*, 2001).

To achieve our objective, this study uses panel data of ASEAN countries from 1999-2018 for GVC participation, backward participation, and forward participation, along with explanatory variables such as population, gross capital formation, human capital, and ICT export product. We obtain GVCs indicators data from the UNCTAD-Eora Global Value Chains (GVCs) database. The benefit of using the UNCTAD-Eora database is that GVC indicators can be decomposed based on value-added into three indicators: GVC participation, backward participation, and forward participation.

For econometrics analysis, this study employs three steps as follows. First, this study performs cross-sectional dependence and unit root tests. This step is crucial to investigate the cross-sectional dependence between countries and spurious regression due to non-stationary time series variables (Ajanaku and Collins, 2021). In the second step, this study uses the Blundell and Bond (1998) estimator—namely, the system-Generalized Method of Moments (GMM) to examine the effect of GVC participation on economic output and unemployment. The combination of the variability in cross-country, the time series data, and lagged variable dependent as the explanatory variables are exercised to improve our study's results. This study also provides robustness checks to ensure that the system GMM provides a more unbiased and consistent estimation. Lastly, we use panel causality analysis to examine short-run dynamic panel causality.

The contributions of our studies are as follows. First, in recent years, there have been many studies about global value chains in several countries (Dine, 2019; Foster-McGregor, 2019; Jangam and Rath, 2021a; Kummritz, 2016; Pahl and Timmer, 2020; Urata and Baek, 2020). However, as far as we are aware, studies that analyse the effect of global value chains on economic output and unemployment in ASEAN countries are still limited. Our results will contribute to extending the Global Value Chains literature in the ASEAN context and provide a valuable GVCs analysis for the future movement of ASEAN countries. Second, compared with previous studies, this study measured trade in value-added by decomposing it into three indicators: total GVCs participation, backward participation, and forward participation. In the literature, the backward and forward participation recorded different effects on economic growth and unemployment (Banga, 2016). A country with relatively strong backward participation tends to have weaker forward participation and vice versa. Third, this study uses a dynamic panel model regression with system GMM estimation and employs panel causality analysis. The advantage of using dynamic panel estimations is the ability to determine short-run coefficients and the dynamics of adjustment (Alan, 2014). Also, dynamic panel data estimation with the system GMM produces an efficient and consistent estimator that solves endogeneity problems and omitted variable bias (Ajanaku and Collins, 2021; Wuri *et al.*, 2022). Meanwhile, panel causality analysis provides the potential causal relationships between variables utilised in this study.

Foreshadowing the main results, this study finds global value chain has a positive effect on economic output in ASEAN countries. However, the result also indicates that the global value chain significantly increases unemployment in ASEAN countries. These findings confirm the *mixed-blessing hypothesis* proposed by Pahl and Timmer (2020), showing that in ASEAN countries, firms participating in GVCs may successfully adapt advanced technologies and boost productivity but less so in employing labour. The technologies associated with GVCs production increase the possibility of substituting unskilled labour for more advanced factors production. Manufacturing global market products requires precision and compliance with quality standards, requiring more automation and less manual work.

II. DATA AND METHODOLOGY

A. Data

This study uses panel data between 1999 to 2018 from ten countries of ASEAN members, namely the Philippines, Indonesia, Singapore, Cambodia, Brunei, Myanmar, Malaysia, Vietnam, Thailand, and Lao PDR. The selection of the period study and countries for this analysis is due to data availability and the level of GVCs participation. The source of our data is from the UNCTAD-Eora database, World Bank, the Penn-World table, and Asian Development Bank (ADB).

In the previous studies, GVCs are recognised with many terminologies, such as production fragmentation, intermediates trade, and vertical specialisation, that the traditional trade statistics do not portray (Hummels *et al.*, 2001). For instance, GVCs can portray imported goods that contain foreign value-added and domestic value-added returned to the origin country and exported goods that may contain foreign value-added.

This study divides the global value chain into three perspectives: GVCs participation, backward participation, and forward participation. GVC participation is the total of backward and forward participation. Backward participation is measured from Foreign Value Added (FVA), while forward participation is calculated from indirect value-added exports (DVX), indicating

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the domestic value-added in intermediate goods that are subsequently reexported by the partner country. It is important to examine the backward and forward participation separately since most developed and developing countries engage in both GVC activities. Forward Participation (FP) and backward participation (BP) are differed in how trading activity in terms of export (FP) and import (BP) embodied in the trade balance of a country can affect its GDP growth (Hummels *et al.*, 2001). For example, countries that primarily assemble products into final goods and exports tend to have high backward participation but low forward participation. Contrarily, a country that primarily provides intermediate goods typically shows highly developed forward participation but low backward participation

This study uses the UNCTAD-Eora Global Value Chains (GVCs) data for a series of global value chain indicators since this database provides data for many countries over a long period. We prefer this database to the OECD-WTO database since it provides many developing countries data. Besides, the scatterplots between UNCTAD-Eora and the OECD-WTO TiVA statistics showed that the two datasets are generally consistent (Casella *et al.*, 2019).

According to the UNCTAD-Eora database (2020), the derivation of value-added trade from the Multi-Regional Input Output (MRIO) table follows several steps. The standard Input-Output analysis is established for the MRIO table with *N* countries and *H* industries:

$$x = T + y = Ax + y \tag{1}$$

$$(I - A)x = y \tag{2}$$

$$x = (I - A)^{-1}y = Ly \tag{3}$$

where x is the squared gross outputs verctor by countries and by industries, T denotes the corresponding vector of intermediate uses, and y represents the final demand. The key matrices ($NH \times NH$) of the GVC construction contain the technological coefficient matrix A and the Leontief inverse L. The matrix ($NH \times NH$) is the matrix of embodied value-added flows F, as shown in equation 4

$$F = \begin{pmatrix} F^{11} & \cdots & F^{1N} \\ \vdots & \ddots & \vdots \\ F^{N1} & \cdots & F^{NN} \end{pmatrix} = \begin{pmatrix} V^1 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & V^N \end{pmatrix} \begin{pmatrix} L^{11} & \cdots & L^{1N} \\ \vdots & \ddots & \vdots \\ L^{N1} & \cdots & L^{NN} \end{pmatrix} \begin{pmatrix} E^1 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & E^N \end{pmatrix} \tag{4}$$

where F^{rs} is an ($H \times H$) matrix reporting inter-sector flows between country r and country s (domestic flows when r and s are the same country) with r, s = 1, 2, …, N. V and E are matrices showing value-added share and exports by countries and industries, respectively.

The matrix F explains how the value-added embodied in the exports of each country is created (by column) and distributed (by row) between countries.

By construction, the total exports of country 1 are determined by the sum (column) of domestic and foreign value-added. The latter terms are "indirect value-added exports" (DVX). DVX denotes the share of exports that another country in producing its export goods (Aslam *et al.*, 2017). The formula for GVCs participation is shown in equation 5.

$$GVC\ participation = FVA + DVX \tag{5}$$

This paper uses two dependent variables: economic output and unemployment. Economic output is measured using the Gross Domestic Product (GDP). Several control variables were used, such as human capital, population, gross capital formation, and the percentage of ICT export in total export. Table 1 describes the variables.

Table 1.
Data Description

This table provides data description in this study.

Variable	Description	Source
lnGDP	Gross Domestic Product: Real GDP per country, in US$, annual series	World Development Indicators (WFI)– World Bank
unemp	The unemployment rate	WDI – World Bank
lnGVC	Global Value Chains Participation, values are in current year (thousand US dollars)	UNCTAD-Eora
lnBP	Backward participation: Foreign value added (FVA) component of gross exports; Values are in current year (thousand US dollars)	UNCTAD-Eora
lnFP	Forward Participation: Indirect domestic value added (DVX), Values are in current year (thousand US dollars)	UNCTAD-Eora
hc	Human capital	Penn-World Table
pop	Total Annual Population (in million)	WDI – World Bank
ICT_exp	The percentage of ICT export on total export (%)	WDI – World Bank
GCF	Gross Capital Formation (US $)	WDI – World Bank; ADB database
T	Time year dummies; 1999 to 2018	Author created

B. Methodology

B.I Econometric models and estimation

This study's objectives lead us to estimate the following regression model:

$$\mathrm{lnGDP}_{c,t} = \alpha_0 + \beta_1 \mathrm{lnGDP}_{c,t-1} + \beta_2 \mathrm{lnGVC}_{c,t} + \beta_3 \mathrm{hc}_{c,t} + \beta_4 \mathrm{pop}_{c,t} + \beta_5 \mathrm{lnGCF}_{c,t} + \mathrm{T}_t + \varepsilon_{c,t} \tag{6}$$

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$$\ln GDP_{c,t} = \alpha_0 + \beta_1 \ln GDP_{c,t-1} + \beta_2 \ln FP_{c,t} + \beta_3 hc_{c,t} + \beta_4 pop_{c,t} + \beta_5 \ln GCF_{c,t} + T_t + \varepsilon_{c,t} \quad (7)$$

$$\ln GDP_{c,t} = \alpha_0 + \beta_1 \ln GDP_{c,t-1} + \beta_2 \ln BP_{c,t} + \beta_3 hc_{c,t} + \beta_4 pop_{c,t} + \beta_5 \ln GCF_{c,t} + T_t + \varepsilon_{c,t} \quad (8)$$

$$unemp_{ct} = \beta_0 + \beta_1 unemp_{ct-1} + \beta_2 \ln GVC_{c,t} + \beta_3 hc_{c,t} + \beta_4 gdp\_grow_{c,t} + \beta_5 ICT\_exp_{c,t} + T_t + \varepsilon_{c,t} \quad (9)$$

$$unemp_{ct} = \beta_0 + \beta_1 unemp_{ct-1} + \beta_2 \ln FP_{c,t} + \beta_3 hc_{c,t} + \beta_4 gdp\_grow_{c,t} + \beta_5 ICT\_exp_{c,t} + T_t + \varepsilon_{c,t} \quad (10)$$

$$unemp_{ct} = \beta_0 + \beta_1 unemp_{ct-1} + \beta_2 \ln BP_{c,t} + \beta_3 hc_{c,t} + \beta_4 gdp\_grow_{c,t} + \beta_5 ICT\_exp_{c,t} + T_t + \varepsilon_{c,t} \quad (11)$$

where $GDP_{c,t}$ indicates economic output measured by Gross Domestic Product (GDP) of country *c* in period *t*. Here, we assume that the lagged GDP affects current GDP. $unemp_{ct}$ is the unemployment rate. $GVC_{c,t}$, $FP_{c,t}$, and $BP_{c,t}$ indicate GVCs participation, forward participation, and backward participation, respectively. $hc_{c,t}$ indicates human capital. $pop_{c,t}$ is the number of populations in each country. $lnGCF_{c,t}$ represent gross capital formation (in natural logarithm). $gdp\_grow_{c,t}$ indicates change in Gross Domestic Product (GDP). $ICT\_export_{c,t}$ is the percentage of ICT goods export of total good export. T_t are time dummies, including to control time variation effect. $\varepsilon_{c,t}$ is the idiosyncratic error.

B.I.1 The dynamic panel data model

This study employs the system GMM estimation because our model contains the lagged dependent variable. The system GMM uses lagged differences as instruments, assuming that white noise errors are inconsistent when serially correlated. Thus, the Hansen test and Arellano and Bond (AB) tests are needed (Wuri *et al.*, 2022). The Hansen test is used to test the exogenous instrument's validity. The null hypothesis is that the error term is uncorrelated with the instrument. The Arellano and Bond test report AR (2) statistics to examine the null hypothesis of no second-order serial correlation.

For panel data estimation, at least four estimations can be applied to examine our models: pooled OLS, fixed effect, difference GMM, and system GMM. However, since our model contains a lagged dependent variable and the explanatory variables are not strictly exogenous, using OLS estimation or fixed effect would lead to bias, given that the strict exogeneity assumption is violated (Ullah *et al.*, 2018). Thus, for robustness check, this study compares the coefficient of estimation for Pooled Ordinary Least Square, fixed effect estimation, difference GMM, and system GMM. These comparisons are informative because they provide the lower and upper bound for the autoregressive coefficient for outcome variables. Bond (2002) proposes the following rules of thumb as follows. Pooled OLS provides the upper bound for the AR term, while fixed effects provide the lower bound. If the coefficient estimation of difference GMM estimation is less than the fixed effect, then system GMM provides a more consistent and unbiased estimation.

B.I.2. Cross-sectional dependence and unit root test

Cross-sectional dependence test is essential diagnostics before estimating panel data models to examine the cross-sectional dependence across countries (De Hoyos & Sarafidis, 2006). Several cross-sectional dependence tests can be used to detect the problem. This study uses the Pesaran (2004) CD test (which treats no cross-sectional dependence as the null). One advantage of Pesaran's CD test is that it is suited for both balanced and unbalanced panels.

Meanwhile, non-stationary is needed to be a concern because using non-stationary time series may provide spurious regression, stipulating a relationship between two variables where there is none (Lyócsa, 2009). Traditional unit root testing is inappropriate for data with a cross-sectional dependence (Paramati *et al.*, 2016). Therefore, the CIPS test is used.

B.I.3. Panel Causality Analysis

The two-step system GMM only tells how GVC participation impacts economic growth and unemployment but not the direction of causality. This study performs a panel causality test of Dumitrescu and Hurlin (2012) is employed. The DH test examines the causality between the variables used in the model. The dependent and independent variables also may be switched to examine causality in the opposite way, known as *bidirectional causality* (Ajanaku and Collins, 2021; Bilen *et al.*, 2017).

For the panel causality test, the lag length selection is based on the *Bayesian Information Criterion (BIC)* criteria commonly used for selecting the most appropriate-best fit model from a sum of estimated ones (Lopez and Weber, 2017).

B.II Variable selection

The theories related to models are described below. We also include several control variables appropriate for our models in this study. Some control variables in economic output and unemployment are the same, so this study explains the choice of variable in these two models as follows.

B.II.1. GVC Participation

In this study, the theoretical framework that links international trade and economic growth is adopted from the endogenous growth models by Rivera-Batiz and Romer (1991) and Grossman and Helpman (1991). These models argue that international trade promotes growth through various channels. First, international trade facilitates communication with worldwide partners to transfer technologies. Second, international trade avoids idea and technology duplications. Third, international trade provides access to global markets for domestically produced goods and quality intermediate inputs. Fourth, international trade allows Research

& Development to be more competitive. Lastly, international trade promotes country-specific products based on the comparative advantage that would drive economic growth. As one of the remarkable products made from international trade developments in the 21st century, Global Value Chains (GVCs) offer an opportunity for any country to partake in the production of high-technology products (Urata and Baek, 2020). In the recorded literature, GVC participation promotes economic growth by providing access to competitive markets, technological diffusion, and domestic innovation. GVCs also help countries increase capital accumulation efficiency and achieve a competitive market, leading to increase productivity (Constantinescu *et al*., 2019; Taglioni and Winkler, 2016).

Meanwhile, the link between international trade and unemployment comes through two main channels, namely the scale effect and the substitution effect. The scale effect is the increase in output and exports caused by using more affordable imported inputs in the production process. The increase in exports creates more job opportunities through the scale effect of trade (Sen, 2008). On the other side, trade liberalization can also boost importing cheaper inputs, raising the labour substitution elasticity. It would cause a diminishing in labour demand, which is called the substitution effect (Hasan *et al*., 2007; Banga, 2016).

On the extant literature, it is still being determined whether GVC participation has a positive or negative effect on employment in developing countries. In developing countries, jobs created by increased export capacity remain concentrated in low-skilled jobs, and through international trade, GVCs participation generates higher domestic employment, decreasing the unemployment rate (Caraballo and Jiang, 2016). Contrarily, Rodrik (2021) suggests that the technologies linked with GVC production demand increased precision and strict quality standards, requiring more automation. Therefore, GVC participation diminishes the possibility of substituting unskilled labour with other factors of production. The effect of GVCs participation on unemployment is suspected to be negative, indicating that participating in GVCs increases the demand for domestic employment more than foreign employment.

B.II.2. Human Capital

For unemployment, a highly skilled labour force may assert a comparative advantage in skill-intensive tasks. In emerging countries, this may indicate specialisation in manufacturing sectors and thus increase employment growth. Nevertheless, it also implies a transformation toward capital-intensive production when capital and skilled labour are complemented in the production stage. Therefore, we include human capital in our model.

B.II.3. Population

Population affects many phenomena, including age structure, inequality, international migration, and labour forces. Some studies provide theoretical arguments and empirical evidence to prove that robust population growth boosts economic growth. However, other studies argue the opposite conclusion (Peterson, 2017).

B.II.4. Gross Capital Formation

Studies have proven that capital formation is a key driver of economic development in many countries (Bal *et al.*, 2016; Meyer and Sanusi, 2019; Ntamwiza and Masengesho, 2022; Reddy and Ramaiah, 2020). The size of capital formation in a country is affected by domestic savings and investments, consisting of tangible and intangible goods. Capital formation spurs economic growth if savings are converted to investments in productive activities (Pasara and Garidzirai, 2020). Harrod–Domar argues that capital formation is the foundation of economic growth. Capital formation increases production productivity and generates more income through the multiplier effect, enhancing economic growth (Makris and Stavroyiannis, 2019).

B.II.5. Percentage of ICT Good Export

In developing countries, sustainable growth owes to productivity and higher value-added exports (Kouam and Foundation, 2020).

B.II.6. GDP Growth

Economic growth is one of the key determinants of unemployment. In most cases, the slowdown in economic growth has coincided with rising unemployment (Rath and Jangam, 2020). Theoretically, the negative correlation between unemployment and economic growth is hypothesized within Okun's law framework.

III. EMPIRICAL FINDINGS AND DISCUSSION

A. Preliminary Analysis

This section begins with providing the descriptive statistics for variables used in this study, as shown in Table 2. For ten members of ASEAN countries, Forward Participation (FP) has the highest mean, followed by GVCs participation, Backward Participation (BP), Gross Domestic Product (GDP), Gross Capital Formation (GCF), population (pop), the percentage of ICT good export (ICT_exp), unemployment (unemp), and human capital (hc). Comparing the three types of GVCs indicator, we note that forward participation has a higher mean but a lower standard deviation.

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Table 2.
Summary Statistics

Selected variable summary statistics is in this table. The variable descriptions are explained in Table 1. This table reports mean, maximum, minimum, and Standard Deviation (SD) of main variables used in the study.

Variables	Mean	Standard Deviation	Minimum	Maximum
Gross Domestic Product (*ln*)	25.08	1.59	21.94	27.77
Unemployment	2.95	2.16	0.13	9.32
Global Value Chain (*ln*)	30.04	2.38	25.25	33.31
Backward Participation (*ln*)	29.34	2.14	24.94	32.33
Forward Participation (*ln*)	30.39	2.01	26.02	33.15
Human Capital	2.35	0.51	1.50	4.15
Population (*ln*)	16.91	1.79	12.69	19.41
ICT export	14.21	16.45	0	54.97
Gross Capital Formation (*ln*)	23.75	1.87	9.26	28.54
GDP grow	5.75	3.18	-2.51	14.52

We also provide Pearson's correlation coefficient between each explanatory variable with respect to GDP and unemployment, as shown in Table 3. The results show a significant positive correlation between GDP and GVC participation; GDP and human capital; GDP and population; GDP and gross capital formation. The correlation between GDP and FP; and GDP and BP are also positive but insignificant. Meanwhile, the correlation between GVCs and unemployment; forward participation and unemployment; backward participation and unemployment; economic growth and unemployment are negatively significant. Human capital and unemployment and ICT export and unemployment are positive and significant.

Table 3.
Results of Pearson's Correlation

This table presents the pairwise Pearson's correlation with * (1%), ** (5%), and *** (10%) denoting statistical significance levels.

Variables	Pearson's Correlation Coefficient
GDP - GVC	0.17**
GDP – Forward Participation	0.09
GDP – Backward Participation	0.14
GDP – human capital	0.58***
GDP – Population	0.65***
GDP – Gross Capital Formation	0.81***
Unemployment - GVC	-0.37***
Unemployment – Forward Participation	-0.43***
Unemployment – Backward Participation	-0.29***
Unemployment – human capital	0.51***
Unemployment – economic growth	-0.53***
Unemployment – ICT export	0.54***

Figure 1 depicts the changes in GVC participation in ASEAN countries during the study period. This figure shows that GVCs participation has changed over the sample period, and there is a significant upward trend for Singapore and Myanmar. Malaysia, Lao PDR, and Indonesia also experienced an increasing trend, but relatively small compared to Singapore and Myanmar. Singapore had the highest level of GVCs participation in ASEAN countries over that period. Admittedly, for a country such as Singapore, which has limited natural resources, having a high level of GVC trade helps to focus on production processes or jobs with the strongest comparative advantage (Arbatli *et al.*, 2016). In 2021, the size of Singapore's trade (exports plus imports) amounted to 338.31% of the GDP.

Figure 1.
GVC Participation in ASEAN Countries, 1999-2018 (Million USD)

This figure shows time series plots of annual GVCs participation of ten countries.

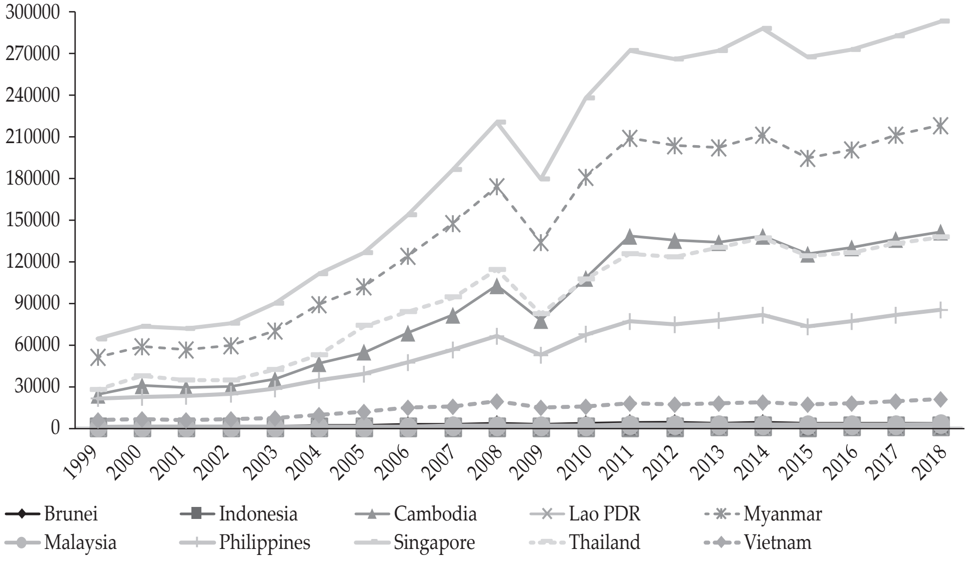

**Figure 2.
Forward and Backward Global Value Chains Participation, 1999–2018**

This figure demonstrates time series plots of Forward and Backward participation of ten countries.

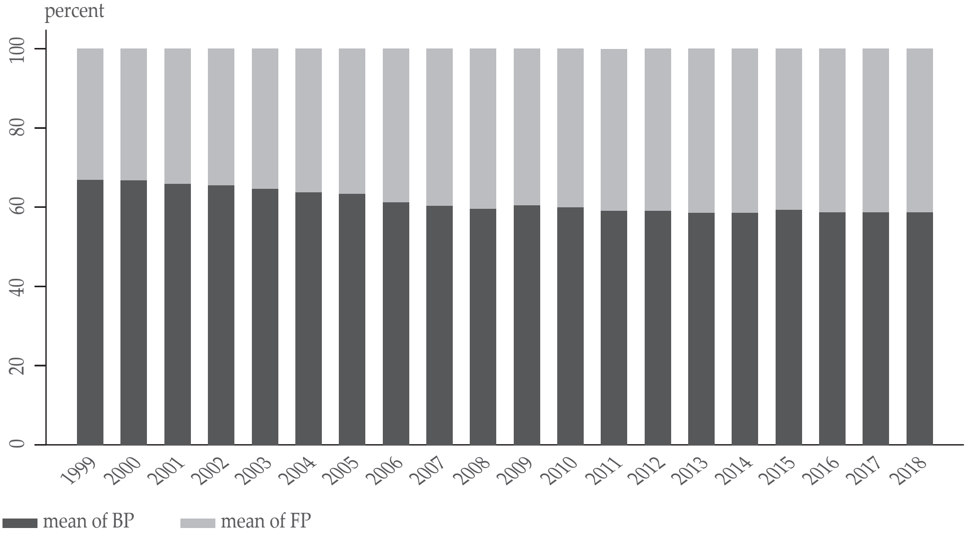

Figure 2 provides the proportion of backward participation and forward participation in ten ASEAN countries. It reveals that the global value chain in ten ASEAN countries is dominated by backward participation, indicating that during the period observation, most intermediate imports embodied domestic export (foreign value-added) of ten ASEAN countries. Singapore has the highest share of backward participation in the global value chain, and Malaysia has the lowest. These conditions remained during the period of observation.

B. Main Results

B.I. Cross-sectional Dependence and Panel Unit Root Testing Results

The main analysis begins by examining cross-sectional dependence using Pesaran's CD test. The results (see Table 4) suggest rejecting the null hypothesis of cross-sectional dependence.

Table 4.
Results of Cross-sectional

This table presents the cross-sectional dependence test based on Pesaran's CD test. And, * (1%), ** (5%), and *** (10%) denote statistical significance levels.

Variables	Pesaran CD Test
lnGVC	29.342***
lnDVX	28.998***
lnFVA	22.112***
lnGDP	28.098***
unemp	6.082***
hc	27.475***
gdp_grow	6.914***
pop	29.788***
lnGCF	21.434***
ICT_exp	6.401***

Results show that cross-sections significantly depend across countries; thus, this study used the cross-sectional augmented panel unit root test (CIPS) proposed by Pesaran (2004), which assumed cross-sectional dependence across the ASEAN countries. The results shown in Table 5 indicate that the variables are stationary at the first difference.

Table 5.
Unit Root Test Results

The Pesaran (2007) CIPS results are presented here with * (1%), ** (5%), and *** (10%) denoting statistical significance levels.

Variables	The Unit Root Test with Cross-sectional Dependence	
	CIPS (Level)	CIPS (First Difference)
lnGVC	-2.717	-4.735***
lnDVX	-2.730	-4.713***
lnFVA	-1.757	-4.098***
lnGDP	-0.986	-2.851*
unemp	-2.005	-4.225***
hc	-2.424	-3.674***
gdp_grow	-3.516	-5.458***
Pop	-2.205	-2.978**
lnGCF	-2.558	-4.636***
ICT_export	-3.619	-4.564***

B. II. Two-step System of GMM Estimation

This section discusses the empirical results of equations (6) – (11) based on the system GMM estimation, as shown in Tables (6) to (7). Heteroscedasticity is addressed via robust standard errors. The serial correlation AR (2) tests are insignificant in all estimations, indicating no autocorrelation in the first difference levels of AR (2). Instrument validity is tested using the Hansen test. The results show that the system's GMM results' is valid.

From Table 6, the coefficient of GVCs participation is positive (5% significance). The result indicates that a 1% rise in GVCs participation results in a 0.01% rise in GDP in the ASEAN countries (column 1). These results support the findings of Yanikkaya and Altun (2020) and Pahl and Timmer (2020), who documented a positive effect of GVCs participation on economic output. The coefficient of lagged GDP is also positive and significant, indicating that a 1% increase in GDP (*t-1*) increases GDP by approximately 0.978%. The results of the explanatory variables suggest that population (pop) and gross capital formation (*lnGCF*) positively and significantly affect GDP. A 1% increase in population and gross capital formation increases GDP by 0.0001% and 0.007%, respectively. Human capital (*hc*) is an insignificant effect on GDP.

Table 6.
Result of GVCs Indicator on GDP

This table reports results obtained by estimating Equation (6) – (8). We estimate these equations using the system GMM. Standard errors are in parentheses. And, * (1%), ** (5%), and *** (10%) denote statistical significance levels. p< 0.1, p-values are reported for AR(1), AR(2), and Hansen statistics. Global value chain, forward participation, backward participation, GDP, and gross capital formation are in their natural logarithms.1.lnGDP indicates lagged GDP (t-1)

Variables	Model 1	Model 2	Model 3
lnGVC	0.014** (0.006)		
lnFP		0.019* (0.007)	
lnBP			0.004** (0.002)
l.lnGDP	0.978*** (0.006)	0.981*** (0.030)	1.004*** (0.008)
hc	-0.012 (0.0114	-0.007 (0.013)	-0.052** (0.003)
pop	0.000** (0.000)	0.000*** (0.000)	0.000 (0.000)
lnGCF	0.007** (0.003)	0.006** (0.003)	0.012*** (0.003)
Constant	0.001 (0.171)	-0.187 (0.246)	-0.319** (0.156)
Time-year effect	Yes	Yes	Yes
Observation	190	179	179
Number of countries	10	10	10
AB - AR (1); *p*-value	-2.47; 0.013**	-2.51; 0.012**	-2.42; 0.015**
AB - AR (2); *p*-value	-1.58; 0.114	-1.63; 0.102	-1.62; 0.105
Hansen Test	1.000	1.000	1.000

Models (2) and (3) reveal the effect of Forward Participation (FP) and Backward Participation (BP) on GDP. The finding on the effect of forward participation is consistent with Jangam and Rath (2021) finding. This study finds that the effect of forward participation and backward participation on economic output is positive and statistically different from zero. In addition, based on the coefficient magnitude, forward participation generates more economic output than backward participation. In model (2), our finding suggests that a 1% improvement in forward participation spurs GDP by 0.019%. As for population and gross capital formation, a 1% increase in unemployment increases GDP by 0.0001% and 0.006%, respectively. Human capital is not significantly affecting GDP in model 2. Meanwhile, the model (3) result shows that gross capital formation also has a positive and statistically significant impact on GDP by 0.012%, suggesting that a 1% increase in unemployment decreases GDP by 0.012%.

Table 7 shows that GVC participation significantly affects increasing unemployment in ASEAN countries (column 1). A 1% increase in GVCs participation is related to a 0.056% increase in unemployment. It strongly contrasts our findings on Pearson's correlation and t-test results in Table 3. However, this result is similar to Banga (2016) and Pahl and Timmer (2020), who found that GVC participation is not positively affecting employment growth. Hasan *et al.* (2012) suggested that trade liberalisation might increase the unemployment rate in the short run. However, in the long run, trade liberalisation would eliminate unemployment. The complementary between skilled workers and capital has caused GVC participation may increase the unemployment rate. In developing countries, participation in GVCs requires companies to invest in improved technologies to satisfy productivity requirements and high-quality standards, leading to a significant increase in output growth from scale economies. However, GVCs participation will result in fewer jobs due to bias toward unskilled labour in digitalisation era caused by strict requirements from international firms. These results also prove the *mixed-blessing* hypothesis in ten ASEAN countries from 1998-2018.

For explanatory variables, human capital negatively and significantly affects unemployment by 0.274%. It shows that a 1% increase in human capital decreases unemployment by 0.274%. Similarly, the coefficient of economic growth was also significant at 0.068%. The results indicate that a 1% increase in economic growth decline unemployment by 0.068%.

The results from models (2) and (3) also reveal that forward participation and backward participation positively affect unemployment, but only forward participation is statistically significant. Similarly, Dine (2019) also found that higher forward linkages may be linked with massive job losses in Turkey. Model 2 shows that forward participation increases unemployment by 0.068%. In addition, a 1% increase in human capital and economic growth reduce unemployment by 0.261% and 0.067%, respectively. Additionally, in model (3), human capital is not significantly affecting unemployment. Meanwhile, economic growth also has significant effects on unemployment. The result shows that a 1% improvement in economic growth will lessen unemployment by 0.068%. The percentage of ICT goods exported is not significantly affecting unemployment for all models.

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Table 7.
Result of GVCs Indicator on Unemployment

This table reports results obtained by estimating Equation (9) – (11). We estimate these equations using system GMM. Standard errors are in parentheses. And, * (1%), ** (5%), and *** (10%) denote statistical significance levels. p< 0.1, p-values are reported for AR(1), AR(2), and Hansen statistics. Global value chain, forward participation, backward participation, and GDP are in their natural logarithms. 1.unemp indicates lagged unemployment (t-1).

Variables	Model 1	Model 2	Model 3
lnGVC	0.056** (0.025)		
lnFP		0.068* (0.041)	
lnBP			-0.017 (0.030)
l.unemp	0.955*** (0.036)	0.956*** (0.037)	0.920*** (0.025)
hc	-0.274*** (0.103)	-0.261** (0.123)	-0.043 (0.086)
gdp_grow	-0.068** (0.028)	-0.067** (0.028)	-0.068*** (0.026)
ICT_exp	-0.001 (0.003)	-0.000 (0.03)	-0.002 (0.003)
Constant	-0.593 (0.518)	-0.982 (0.854)	1.125 (0.600)
Time-year effects	Yes	Yes	Yes
Observation	190	190	190
Number of countries	10	10	10
AB-AR (1); *p*-value	-2.27; 0.022	-2.26; 0.024	-2.24; 0.025
AR (2)	-1.31; 0.189	1.30; 0.194	1.36; 0.174
Hansen Test	1.000	1.000	1.000

C. Robustness Check

There may be a reason to believe that regressors and errors are not orthogonal, but using IV estimation to solve this issue must be balanced with the inevitable loss of efficiency compared to other panel method estimation. Thus, it is essential to test whether the OLS estimator is inconsistent and whether system GMM is required (Baum *et al.*, 2003). To ensure our findings are valid, we compare the estimation of pooled OLS, fixed effect, difference GMM, and system GMM. This comparison ensures that system GMM results in an unbiased and consistent estimator. The coefficient estimation is shown in Table 8.

Table 8.
Robustness Check: Comparison Between Panel Estimation and Dynamic Panel Estimation

This table reports the estimates of the robustness check of our results. We estimate our equation model using four techniques: pooled OLS, fixed effect, difference GMM, and system GMM. Standard errors are in parentheses. And, * (1%), ** (5%), and *** (10%) denote statistical significance levels.

Variables	Model 1				Model 2				Model 3			
	Pooled OLS	*FE*	*Diff GMM*	*System GMM*	*Pooled OLS*	*FE*	*Diff GMM*	*System GMM*	*Pooled OLS*	*FE*	*Diff GMM*	*System GMM*
GDP												
l1.*lnGDP*	0.999***	0.986***	0.963***	0.978***	0.999**	0.985***	0.964***	0.981***	0.999***	0.988***	0.967***	1.004***
	(0.003)	(0.010)	(0.013)	(0.006)	(0.003)	(0.011)	(0.010)	(0.030)	(0.003)	(0.010)	(0.010)	(0.008)
Unemployment												
l1.*unemp*	0.977***	0.850***	0.807***	0.955***	0.977***	0.849***	0.806***	0.956***	0.975***	0.849***	0.809***	0.920***
	(0.019)	(0.042)	(0.046)	(0.036)	(0.019)	(0.042)	(0.046)	(0.037)	(0.018)	(0.042)	(0.046)	(0.025)

Based on the robustness check results, the system GMM produces more unbiased and consistent estimations than the other three estimators. The results show that the coefficient estimate OLS set as an upper bound and fixed effect estimation as a lower bound. The difference-GMM estimation is lower than fixed effect estimation, indicating that system GMM is the best approach.

D. Panel Causality Test Results

This section provides the results of panel causality tests using the Granger causality test, as shown in Table 9. There are three statistically significant bidirectional causalities related to economic output (GDP), which are between human capital and GDP, population and GDP, and gross capital formation and GDP. In addition, there are seven other statistically significant bidirectional causalities between population and GVC; population and forward participation; population and backward participation; population and human capital; gross capital formation and human capital; gross capital formation and population; forward participation and backward participation.

Meanwhile, three statistically significant unidirectional causal relationships to variable GDP exist: from variable GVC participation, forward participation, and backward participation. The unidirectional linkage between GVC participation and economic output (GDP) from the short-run heterogenous causality results shows that economic growth does not affect the level of GVC participation in ten ASEAN countries. In addition, the bidirectional linkage between backward and forward participation indicates that countries with higher backward participation would trigger higher forward participation and vice versa.

For the unemployment model, there are four statistically significant bidirectional causalities related to unemployment: between GVC and unemployment, forward participation and unemployment, backward participation and unemployment, human capital and unemployment, and between the percentage of ICT export goods and unemployment formation and GDP. A bidirectional causality from three GVC indicators to unemployment suggests that the unemployment rate has significantly affect the level of GVC participation in ten ASEAN countries. Besides, there are also three other statistically significant bidirectional causalities between economic growth and human capital, the percentage of ICT export goods and human capital, and between forward participation and backward participation. There is one statistically significant unidirectional causal relation to variable unemployment, and this is from variable economic growth.

Table 9.
Heterogenous Panel Causality Test Results of Variables in GDP Model

This table provides Dumitrescu & Hurlin (2012) Granger non-causality test results. The lag optimum is chosen based on BIC criteria. And, * (1%), ** (5%), and *** (10%) denote statistical significance levels.

Null Hypothesis	*Z*-bar Tilde
lnGVC ⇏ *lnGDP*	6.525***
lnFP ⇏ *lnGDP*	6.314***
lnBP ⇏ *lnGDP*	5.642***
hc ⇏ *lnGDP*	4.962***
Pop ⇏ *lnGDP*	18.97***
lnGCF ⇏ *lnGDP*	9.638***
lnGDP ⇏ *lnGVC*	0.736
hc ⇏ *lnGVC*	0.322
pop ⇏ *lnGVC*	16.389***
lnGCF ⇏ *lnGVC*	1.238
lnGDP ⇏ *lnFP*	1.319
hc ⇏ *lnFP*	-0.017
pop ⇏ *lnFP*	15.40***
lnGCF ⇏ *lnFP*	1.463
lnGDP ⇏ *lnBP*	1.319
hc ⇏ *lnBP*	-0.381
pop ⇏ *lnBP*	17.414***
lnGCF ⇏ *lnBP*	1.270
lnGDP ⇏ *hc*	32.361***
lnGCV ⇏ *hc*	7.116***
lnFP ⇏ *hc*	9.529***
lnBP ⇏ *hc*	12.160***
pop ⇏ *hc*	14.908***
lnGCF ⇏ *hc*	6.663***
lnGDP ⇏ *pop*	9.910***
lnGVC ⇏ *pop*	7.801***
lnFP ⇏ *pop*	7.967***
lnBP ⇏ *pop*	7.991***
hc ⇏ *pop*	17.04***
lnGCF ⇏ *pop*	4.302***
lnGDP ⇏ *lnGCF*	5.903***
lnGVC ⇏ *lnGCF*	3.255***
lnFP ⇏ *lnGCF*	3.635***
lnBP ⇏ *lnGCF*	3.916***
hc ⇏ *lnGCF*	5.997***
pop ⇏ *lnGCF*	25.992***
lnFP ⇏ *lnBP*	4.443***
lnBP ⇏ *lnFP*	1.816**

Table 10.
Heterogenous Panel Causality Test Results of Variables in Unemployment Model

This table provides Dumitrescu & Hurlin (2012) Granger non-causality test results. The lag optimum is chosen based on BIC criteria. And, * (1%), ** (5%), and *** (10%) denote statistical significance levels.

Null Hypothesis	*Z*-bar Tilde
lnGVC ⇏ unemp	7.962***
lnFP ⇏ unemp	6.750***
lnBP ⇏ unemp	9.000***
hc ⇏ unemp	10.630***
gdp_ ⇏ unemp	0.356
ICT_ ⇏ unemp	9.654***
unemp ⇏ lnGVC	3.884***
hc ⇏ lnGVC	0.071
gdp_ ⇏ lnGVC	-0.485
ICT_ ⇏ lnGVC	1.545
unemp ⇏ lnFP	4.862***
hc ⇏ lnFP	-0.017
gdp_ ⇏ lnFP	-0.381
ICT_ ⇏ lnFP	1.471
unemp ⇏ lnBP	3.674***
hc ⇏ lnBP	-0.381
gdp_ ⇏ lnBP	-0.554
ICT_ ⇏ lnBP	0.430
unemp ⇏ hc	13.173***
lnGCV ⇏ hc	7.116***
lnFP ⇏ hc	9.529***
lnBP ⇏ hc	12.160***
gdp_ ⇏ hc	10.934***
ICT_ ⇏ hc	13.209***
unemp ⇏ gdp_grow	5.227***
lnGVC ⇏ gdp_grow	4.762***
lnFP ⇏ gdp_grow	4.574***
lnBP ⇏ gdp_grow	4.603***
hc ⇏ gdp_grow	5.174***
ICT_export ⇏ gdp_grow	0.092
unemp ⇏ ICT_export	17.346***
lnGVC ⇏ ICT_export	44.946***
lnFP ⇏ ICT_export	42.052***
lnBP ⇏ ICT_export	38.706***
hc ⇏ ICT_export	51.512***
gdp_grow ⇏ ICT_export	5.491***
lnFP ⇏ lnBP	4.443***
lnBP ⇏ lnFP	1.816**

IV. CONCLUSION

This study analyses the effect of global value chains on economic output and unemployment in ten ASEAN countries using panel data between 1999 and 2018. Three perspectives of global value chains: GVCs participation, backward participation, and forward participation from the UNCTAD-Eora Global Value Chains (GVCs) database, are used in this study. We employ the system GMM model to examine our models..

This study has several important results. First, this study found that GVC participation positively and significantly affects economic output in the ASEAN countries. This result proves that trade linked to GVCs promotes the economy. Similarly, our results show that forward and backward participation significantly increase GDP. Second, we also document that GVCs participation significantly increases unemployment, indicating that the economic integration may create job losses, especially for unskilled workers. The other two indicators, forward and backward participation, also show similar results, but only forward participation is statistically significant. The results confirm the existence of the *mixed-blessing* hypothesis in ASEAN countries.

The results of the heterogeneous panel causality test showed unidirectional causality from three indicators of GVC to economic output. It suggests that economic output is not affecting the level of GVC participation. Meanwhile, for unemployment, the heterogeneous panel causality test detected a bidirectional causality from three indicators of GVC to unemployment, suggesting that the unemployment rate affects the level of GVC participation in ten ASEAN countries.

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