Determinants of Economic Growth for Southern African Development Community Nations: A Panel Data Approach

Thomas Musora[1*] Florence Matarise[2]

[1]*Department of Mathematics and Statistics, Chinhoyi University of Technology, Private Bag 7724, Chinhoyi, Zimbabwe.*

[2]*Department of Mathematics and Computational Sciences, University of Zimbabwe P.O.Box MP167 Mt Pleasant Harare, Zimbabwe*

Abstract

It is critical to identify growth factors in order to effectively estimate economic growth. However, Africa and particularly the Southern African Development Community (SADC) region, have not identified any determinants of economic growth that are unique to the SADC region. In this study, the determinants of economic growth are gathered and assessed for sixteen SADC countries over a twenty-two-year period (2000-2021), requiring the use of panel data analysis, where we can have group effects, temporal effects or both. Data on different SADC countries contributing to the global economy is obtained from a variety of sources, but primarily the World Bank website. This article compared the ordinary least squares (OLS) model, fixed effects model (FEM) and random effects model (REM) for panel data from SADC countries. The F-test was employed as a specification test to choose between the OLS model and the FEM, the Breusch-Pagan test was used to choose between the OLS and the REM and the Hausman test to choose between the FEM and the REM. The fixed-effects model with an adjusted R^2 value of 98% was realised to be the best model to handle SADC community economic data. Imports, exports, external debt, international reserves, unemployment and labour force had positive impacts on the SADC community's economic growth. Foreign direct investment negatively influenced economic growth. Inflation, exchange rate and interest rate had no association with economic development for the SADC community. As for country effects, it was established that South Africa had a positive impact on GDP, whereas all other SADC nations' country effects negatively affected economic growth with the exception of Comoros and Seychelles, whose effects had no significant effects on economic growth.

Keywords: Economic Growth; SADC; Gross domestic product; Panel data analysis; Specification test; Adjusted R^2 value.

1. Introduction and Related Literature

1.1.0 Introduction

Determinants for economic growth for the Southern African Development Community (SADC) region have been under researched. There is limited empirical work that exclusively looked into factors that determine economic growth in SADC's developing economies. Currently most developing nations worldwide are benchmarking their economic prosperity against international trade and level of foreign direct investment (FDI) inflow (Moran et al. 2007). However the international trade mantra which promotes imports and exports ignores other key determinants of economic growth. The technological evolutions in the last few decades have changed the way nations and regions attempt to improve their economies. The model used in forecasting economic growth has a strong bearing on the impacts, moves and decisions to be made. Hence if a wrong model is used, it is likely that, impacts, moves and decisions made will be erroneous. Thus policy makers need to be equipped with the appropriate model to apply and when. Among others, this research will build models empirically in view of these challenges. The resulting model and recommendations will better equip planners of today and those of future generations with the most appropriate economic modelling methods when making decisions under uncertainty. Thus, this study has policy implications.

The ability to accurately forecast economic growth plays a crucial role in economic planning and economic policy formulation. For one to be able to correctly predict economic growth, it is key that growth factors are spelt out. A variety of researchers have identified; exports, exchange rate, imports external debt, labour force, international reserves, foreign direct investment and interest rate as determinants of economic growth as measured by gross domestic product (GDP). (Barro, 2003; Adams and Page, 2005; Samuel and Nurina, 2015; Basu, *et al*; 2000, Dobronogov and Iqbah, 2005; Sireesha, 2013; Phale, 2021; Mallick, 2016; Agalega & Antwi, 2013; Wajeetonggratana, 2020 and Yuliadi, 2020). However Africa and the SADC region principally have not singled out any determining factors of economic growth that are specific to the SADC community. Consequently this study intends to use the panel data approach to single out the determinants, fit a model and then propose fundamental areas to focus on in an attempt to realize and uphold economic prosperity in the SADC region. The SADC's community indicative strategic development plan (RISDP 2020–2030) which pulls its thrust from the administration's vision 2050, that seeks to attain "a peaceful, inclusive, competitive, middle to high-income industrialised region, where all citizens enjoy sustainable economic well-being, justice and freedom" (SADC RISDP 2020–2030). The SADC community is one of the epicentres of prospective economic development for the global economy that is at present experiencing immobility due to the COVID-19 pandemic which has affected nearly all nations globally.

Having the potential for commercial growth, abundant natural resources and human capital, it is very encouraging to invest in this strategic region (Adema, and Ladaique, 2009). Geographically, the SADC region is located in Africa and has boarders with two oceans, namely the Indian Ocean and the Atlantic Ocean, putting the SADC community as an indicator for political stability and security in the African continent (SADC RISDP 2020–2030).

The combination of natural resources richness, availability of labour, political stability and security and a healthy social culture makes SADC a region investors are looking foward to invest in different sectors of the economy. The SADC area is also a hub for commerce, financial activities and services to meet the growing demand for industrial goods and community requirements (Epaphra, 2018). In general, GDP increased in all SADC member countries. South Africa had the highest nominal GDP, followed by Angola. South Africa, however, received the most foreign direct investment followed by Eswatini. Looking at GDP growth from 2000 to 2021, the SADC community is a potential area in the global economy for developing the principal economic sector, specifically food and energy products as well as becoming an investment preference for information technology and manufacturing industries (SADC RISDP 2020-2030). Hence being able to identify determinants, model and forecast economic growth will be of prime importance and will assist in decision making, economic policy planning and implementation.

1.2.0 Theoretical Frameworks and Economic Models

Economic advancement is a lasting procedure to attain economic affluence for the whole society as a result of the interaction between economic and non-economic factors (Kei and Nakajima, 2015**)**. Economic growth to advance people's prosperity requires a boost in economic development over production factors to bring into being merchandises and facilities. Economic advancement is manifested through improved per capita income from year to year, resulting from GDP divided by entire population (Gray, and Bilsborrow, 2013). Panel data is a dual or multi-dimensional data set having realisations on multiple variables taken over multiple times (Baltagi, 2005; Gujarati, 2003 among many others). GDP is the most frequently used indicator of a state’s economic wellbeing. It is the result of appraising all productive activities in the country at a given year's pricing.

1.2.1 Fixed against Random Effects Model

Models for panel data looks at random or/and fixed effects of time or individuals. The function of dummy variables is where fixed effect and random effect models diverge most. According to Hun (2011), a parameter estimate of a dummy variable is a component of the intercept in a fixed effect model and of the error term in a random effect model. Slopes in either a fixed effect model or a random effect model are constant across groups or over time. One-way fixed and random effect models have the following functional forms:

Fixed effects model: $y_{it} = (\alpha + u_i) + X_{it}'\beta + v_{it}$ (1)

Random effect model: $y_{it} = \alpha + X_{it}'\beta + (u_i + v_{it})$, (2)

Where u_i is a random or fixed effect for a particular time to period or individual (group) which is not included within the regression, and the error terms are independently and identically distributed, $v_{it} \sim IID(0, \sigma^2{}_v)$.

The fixed group effects model looks at individual variances in the intercepts, supposing the constant variance and same slopes through individual (entity and group). Individual-specific effects are permitted to be associated with other regressors since they are time-invariant and regarded as part of the intercept. Thus, the ordinary least squares (OLS) assumption 2 is not violated. The least squares dummy variable (LSDV) regression (OLS with a set of dummies) and within effect, estimation methods are used to estimate this fixed effect model.

1.2.2 Differences between Pooled OLS, FEM and REM

According to Park (2011), the primary distinction between Pooled OLS, fixed effects model (FEM) and Random Effect Model (REM) is found in the role played by dummy variables. Park (2011) presented the basic differences between the three models as in table 1 below.

Table 1 Differences in Pooled OLS Model, Fixed Effects Model and Random Effects Model

	Ordinary Least Square (OLS)	Fixed Effect Model (FEM)	Random Effect Model (REM)
Functional Form	$y_{it} = \alpha + X_{it}'\beta + \varepsilon_{it}$ $(u_i = 0)$	$y_{it} = (\alpha + u_i) + X_{it}'\beta + v_{it}$	$y_{it} = \alpha + X_{it}'\beta + (u_i + v_{it})$,
Assumptions	Best Linear unbiased Estimator	No	Country effects would not be correlated with independent variables
Intercept	Fixed	Vary across group or time	Fixed
Error variances	Fixed	Fixed	Randomly distributed across groups or times
Slopes	Fixed	Fixed	Constant

Determination Method	OLS	LSDV	GLS, FGLS (EGLS)
Dummy variables	No	Yes	No
Time Invariants	No	Yes	Yes
Hypothesis Test	F test	F test	Breusch-Pagan LM test
Realisations	Nt	nT	nT

Source: Author's own classification

Random effects model undertakes that individual effect (heterogeneity) is unrelated to any regressor and then estimates error variance by time (or group). Consequently, a random effect model is also known as an error component model. Individuals have the same intercept and slope of regressors. The distinction between time periods (or nations) is based on their particular idiosyncratic errors, not their intercepts.

If the covariance structure of an individual ∑ (sigma) is known, generalized least squares (GLS) are used to estimate a random effect model. When ∑ is unknown, the feasible generalized least squares (FGLS) or estimated generalized least squares (EGLS) approach is used to estimate the full variance-covariance matrix V (∑ in all diagonal members and 0 in all off-diagonal elements). The maximum likelihood technique and simulation are two estimate methods for FGLS (Baltagi and Cheng, 1994). When individual particular random effects are linked with regressors, a random effect model decreases the number of parameters to be assessed but produces inconsistent results (Greene, 2008).

The F test examines fixed effects, while the Lagrange multiplier (LM) test examines random effects (Breusch and Pagan, 1980). If neither test rejects the null hypothesis, the pooled OLS regression is selected. Hausman (1978) compares a random effect model to its fixed equivalent in the Hausman specification test. A random effect model is favoured over its fixed counterpart if the null hypothesis that the individual effects are uncorrelated with the other regressors is not rejected. A one-way fixed or random effect model is used when just one cross-sectional or time-series variable is evaluated (for example, nation, company, and race). Two-way effect models entail certain challenges in interpretation and estimate since they feature two sets of dummy variables for individual and/or temporal variables (e.g., state and year).

1.2.3 Approximating Fixed Effects Models

There are several methods for estimating a fixed effects model. Dummy variables are used in the least squares dummy variable model (LSDV), but not in the "within" estimation. These methods yield parameter estimates of regressors (non-dummy independent variables) that are indistinguishable. The "between" estimate fits a model without dummies using individual or temporal means of dependent and independent variables.

Because it is relatively easy to estimate and interpret substantively, LSDV with a dummy dropped out of a set of dummies is commonly used. When there are many groups or individuals in panel data, this LSDV becomes difficult (Baltagi, 2001). If T is constant and $n \rightarrow \infty$ (n is the number of groups or businesses and T is the number of time periods), regressor parameter estimates are consistent but individual effect coefficients, $\alpha + u_i$, are not (Baltagi, 2001). LSDV contains a significant number of dummy variables in this short panel; the number of these parameters to be estimated grows as n grows (incidental parameter problem); consequently, LSDV loses n degrees of freedom yet provides less efficient estimators (Baltagi, 2001). In this case, LSDV is worthless, necessitating the employment of another method, within effect estimate.

The "within" estimation, unlike LSDV, does not require dummy variables and instead relies on departures from the group (or time period) averages. As a result, the "within" estimate employs variation within each individual or entity rather than a huge number of dummies. The "within" estimate is as follows:

$$(y_{it} - \bar{y}_{i.}) = (x_{it} - \bar{x}_{i.})'\beta + (\varepsilon_{it} - \bar{\varepsilon}_{i.}) \quad (3)$$

Where $\bar{y}_{i.}$ denotes the mean of dependent variable (DV) of a specific (group) i, $\bar{x}_{i.}$ represent the means of regressors of group i, and $\bar{\varepsilon}_{i.}$ is the mean of errors of group i.

The incidental parameter difficulty is no longer an issue in this "within" estimation. The regressor parameter estimates in the "within" estimation are the same as those in the LSDV. The "within" approximation reports correct the sum of squared errors (SSE). The "within" estimation, on the other hand, has significant backdrops. To begin with, the data transformation for "within" estimation removes any time-invariant variables that do not fluctuate within an entity (e.g., citizenship, ethnic group, and gender) (Kennedy, 2008). Because the deviations of time-invariant variables from their average are all zero, estimating coefficients of such variables in "within" estimation is impossible. As a result, when a model contains time-invariant independent variables, we must fit LSDV.

Secondly, the "within" estimation yields erroneous statistcs. Because there is no use of dummy, the within effects model has more degrees of freedom for errors, resulting in small mean squared errors (MSE), standard errors of the estimates (SEE) or the square root of mean squared errors (SRMSE) and incorrect (smaller) standard errors of parameter estimates. As a result, we must rectify inaccurate standard errors using the formula below.

$$\mathrm{se_k}^* = \mathrm{se_k}\sqrt{\frac{\mathrm{df}_{\mathrm{error}}^{\mathrm{within}}}{\mathrm{df}_{\mathrm{error}}^{\mathrm{LSDV}}}} = \mathrm{se_k}\sqrt{\frac{\mathrm{nT-k}}{\mathrm{nT-n-k}}} \quad (4)$$

Thirdly, because the intercept term is suppressed, the $R^2$of the "within" estimation is incorrect. Lastly, the "within" estimation does not include any dummy coefficients. If they are required, we must compute them using the formula.

$$d_i^* = \bar{y}_{i.} - \bar{x}_{i.}\,\beta. \quad (5)$$

Table 2 A Comparison of Three Approximation Approaches

	LSDV	Within Approximation	Between Approximation
Functional form	$y_i = i\alpha_i + X_i\beta + \varepsilon_i$	$y_{it} - \bar{y}_{i.} = x_{it} - \bar{x}_{i.} + \varepsilon_{it} - \bar{\varepsilon}_{i.}$	$\bar{y}_{i.} = \alpha + \bar{x}_{i.} + \varepsilon_i$
Time invariant variables	Present	Absent	Absent
Dummy variables	Used	Not used	Not used
Dummy coefficients	Computed	Have to be calculated	Not of concern
Transformations	Not done	Variance from group averages	Group averages
Intercept estimated	Done	Not done	Done
R^2	Accurate	Inaccurate	Not of concern
SSE	Right	Wrong	N/A
SEE/MSE (SRMSE)	Accurate	Wrong (often smaller)	N/A
Standard error terms	Accurate	Wrong(smaller)	
DFerror	$nT - n - k *$	$nT - k$(n lager)	$n - k - 1$
Realizations	nT	nT	n

Source: *Author's own classification*

The "between groups" estimate, also known as group mean regression, takes use of variation among individual groups (entities). This estimation, in particular, computes the group means of the dependent and independent variables, reducing the number of observations to n. Then, on these transformed, aggregated data, apply OLS: $\bar{y}_{i.} = \alpha + \bar{x}_{i.} + \varepsilon_i$. Table 2 contrasts LSDV, "within group" approximation and "between group" approximation.

1.2.4 Approximating Random Effects Models

The one-way random effects model includes a composite error term, $w_{it} = u_i + v_{it}$. Having u_i being assumed independent of usual error term v_{it} and independent variables X_{it}

being also independent to each other for all i and t. Note that this supposition is not essential in a fixed effects model. This model stands as:

$$y_{it} = \alpha + X_{it}'\beta + u_i + v_{it} \tag{6}$$

Where $u_i \sim IID(0,\sigma_u^2)$, and $v_{it} \sim IID(0,\sigma_v^2)$.

The covariance elements of $Cov(w_{it}, w_{js}) = E(w_{it}\, w'_{js})$ are $\sigma_u^2 + \sigma_v^2$ if $t = s$ and $i = j$ then σ_u^2 when $t \neq s$ and $i = j$. Therefore, the covariance construction of composite error terms; $\sum = E(w_i\, w_i')$ for specific i and the variance-covariance matrix for all errors (disturbances) V becomes;

$$\Sigma_{T\times T} = \begin{bmatrix} \sigma_u^2 + \sigma_v^2 \ldots & \ldots \sigma_u^2 \ldots & \ldots \sigma_u^2 \\ \vdots & \ldots \sigma_u^2 + \sigma_v^2 \ldots & \vdots \\ \sigma_u^2 \ldots & \ldots \sigma_u^2 \ldots & \ldots \sigma_u^2 + \sigma_v^2 \end{bmatrix} \tag{7}$$

and

$$V_{nT\times nT} = I_n \otimes \Sigma = \begin{bmatrix} \Sigma & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \Sigma \end{bmatrix} \tag{8}$$

When the covariance structure of composite errors is known, a random effect model is fitted using generalized least squares (GLS) and when it is unknown, it is fitted using feasible generalized least squares (FGLS) or estimated generalized least squares (EGLS). Because $\sum$ is frequently unknown, FGLS/EGLS is more commonly used than GLS. A random effect model is more difficult to assess than a fixed effects equivalent. In FGLS, you first need to approximate θ by means of $\hat{\sigma}_u^2$ and $\hat{\sigma}_v^2$. The $\hat{\sigma}_u^2$ arises from the between-effects approximation (group means regression) and $\hat{\sigma}_v^2$ is obtained from the SSE (error sum of squares) of the within-effects estimation or the deviations of error terms emanating from group means of the error terms.

$$\hat{\theta} = 1 - \sqrt{\frac{\hat{\sigma}_v^2}{T\hat{\sigma}_u^2 + \hat{\sigma}_v^2}} = 1 - \sqrt{\frac{\hat{\sigma}_v^2}{T\hat{\sigma}^2_{between}}}, \tag{9}$$

Where

$$\hat{\sigma}_u^2 = \hat{\sigma}^2_{between} - \frac{\hat{\sigma}_v^2}{T}, \text{ where } \hat{\sigma}^2_{between} = \frac{SSE_{between}}{n-k-1}, \hat{\sigma}_v^2 = \frac{SSE_{within}}{nT-n-k} = \frac{e'e_{within}}{nT-n-k}$$

$$= \frac{\sum_{i=1}^{n}\sum_{t=1}^{T}(v_{it} + \bar{v}_{i..})^2}{nT-n-k},$$

Where v_{it} denotes the error terms of the LSDV. Then, the dependent variable, regressors and the value of the intercept need to be converted as below;

$$y^*_{it} = y_{it} - \hat{\theta}\bar{y}_{i.} \tag{10}$$

$$x^*_{it} = x_{it} - \hat{\theta}\bar{x}_{i.} \text{ for all } x_k \tag{11}$$

$$\alpha^* = 1 - \hat{\theta} \tag{12}$$

Lastly, perform OLS on the resulting variables having the usual intercept suppressed.

$$y^*_{it} = \alpha^* + x^*_{it}{}'\beta^* + \varepsilon_{it}{}^* . \tag{13}$$

2.0 Methodology

2.1 Data

In this study determinants of economic growth are gathered and evaluated for the sixteen SADC countries for twenty two years (2000 to 2021), that dictates use of panel data analysis. Panel data may have group effects, time effects or both. Data is taken from various sources but mainly the World Bank website for different SADC countries contributing in the world economy. All monetary values are in million USDs and all rates are percentages.

2.2. Econometric Models

Among other things, this study will look at whether unemployment has an impact on the SADC countries' economic progress. In order to attain this goal, we first construct a production function framework that reflects production and is a good proxy for economic development. Assume variable factors of production only influence an economy's output level, and the model as presented by Tiwari and Mutascu in 2011 is as follows:

$$Y = f(L, K) \tag{14}$$

Where Y denotes output level (i.e. GDP), L represents labour amount (Labour force), and K designates capital (which is the Gross Capital Formation), it can be stated that increases in employed labour and capital are responsible for increasing any economy's output level. Following the preceding (equation (14)), the production function is expanded in accordance with growth theory (Barro and Sala-i-Martin, 1995; Tiwari and Mutascu 2011). We expanded the model for our investigation by incorporating the additional explanatory factors. The model would be expressed as:

$$GDPit = f\,(IMPit, EXPoit, INTRit, LFit, UNEMit, RIRit, INFit, FDIit, IRit, EXRit) \tag{15}$$

Where:

$IMPit$ = Imports, $EXPO\ it$ = Exports, $INTRit$ = International Reserves, $LFit$ = Labour Force,

$GDPit$ = Real GDP, $UNEMit$=Unemployment rate, $RIRit$ = Real interest rate,

$INFit$ = Inflation rate, $FDIit$ = Foreign direct investment, net inflows, $IRit$ = Interest rate and

$EXRit$ =Exchange Rate

The assumption of u_{it} is that $u_{it} \approx IID(0, \delta_u^2)$, i.e. errors are independently identically distributed with zero mean and constant variance δ_u^2. Where i stands for a specific country and t stands for a certain time period. Three approaches can be used to analyse empirical panel data. Ordinary least squares, random effects, and fixed effects models, as well as the least squares dummy variables (LSDV). In 2011, Akbar et al. employed OLS, FEM, and REM to estimate GDP per capita for nine (9) Asian nations. The empirical standard technique assumes that OLS is used to estimate regression equations, with the assumption that omitted variables are uniformly distributed and independent of repressors. As a result, this form of estimating may pose an interpretive issue when we wish to investigate country-specific features such as policy changes, political administrations, and good governance, which impact on economic growth rate but are not taken into account in the estimation process.

Thus we will conduct our methodology by way of FEM. The Hausman (1978) test answers this question of comparing the FEM and REM. The test examines if country specific effects are associated with other regressors, then REM violates the assumptions of Gauss-Markov and is now not considered as a best linear unbiased estimator (BLUE). This is so since country effects are only the part of the residuals in a REM. But if country effects were a part of intercept and correlation amongst regressors and intercept would not violate the assumptions of Gauss-Markov, then a FEM would be still BLUE.

2.3 Pooled OLS model

Of primary interest is to investigate how selected specific variables influence the economic growth in SADC countries. The standard model in order to assess the group effects, in which every coefficient is constant through time and states, would be presented as:

$$GDPit = \beta_0 + \beta_1 LFit + \beta_2 UNEMit + \beta_3 RIRit + \beta_4 INFit + \beta_5 FDIit + \beta_6 IRit + \beta_7 EXRit + \beta_8 IMPit + \beta_9 EXPOit + \beta_{10} INTRit + \mu_{it} \quad (16)$$

Where μ_{it} = is the error term.

In this situation, the fitted model assumes that the intercept values are the same for all nations or country entities. Furthermore, for all the sixteen countries, the slope coefficients of all independent variables are constant. As a result of the highly restrictive assumptions in the preceding equation (16), the real picture of the model may be distorted. As a result, we need to determine the country effects of various nations, as detailed in the next section.

2.4 Fixed effects model

Now, for estimating the fixed effect intercept of different countries, the method of least square dummy variables (LSDV) will be employed and the model is as follows:

$$GDPit = \beta_{0i} + \beta_1 LFit + \beta_2 UNEMit + \beta_3 RIRit + \beta_4 INFit + \beta_5 FDIit + \beta_6 IRit + \beta_7 EXRit + \beta_8 IMPit + \beta_9 EXPOit + \beta_{10} INTRit + \propto_i + \sum_{i=j=2}^{16} \propto_i C_{ij} + \mu_{it} \quad (17)$$

Where,

j = 2, 3… 16 denotes specific country dummies.

i = represent country effects in explanatory variables,

t = is the time effects in explanatory variables

In this case, $C_{i2} = 1$ if the study observation comes from country two, Botswana, and zero (0) otherwise. The same dummies would be used for the other nations (up to 16). Because we have sixteen countries, we must use only fifteen country dummies to avoid a dummy variable trap, which would be a situation of perfect multicollinearity. It is possible to state that there is no dummy for the first nation and reflects the intercept of the first country Angola. And $\propto_1 \propto_2 \propto_3 \dots\dots\dots \propto_{15}$ are intercepts for respective dummies for countries. $\beta_1, \beta_2, \beta_3 \dots\dots\dots \beta_{10}$, are slopes for explanatory variables such as unemployment, real interest rate, and FDI respectively.

We use dummies to estimate country-specific effects because we are interested in identifying the country effects that are due to distinct political frameworks, unique monetary and fiscal policies, and distinct managerial abilities. This method is also known as the LSDV (least-square dummy variables) method in the literature. As a result, the terms LSDV and fixed effect model are frequently used interchangeably, as are the terms LSDV model and covariance model.

2.5 Random Effects Model

The intercept is assumed to be a random ending variable in the random effects model, whereas the random outcome is a function of a mean value and a random error. The two way random effects model used for estimation purpose is:

$$GDPit = \beta_{0i} + \beta_1 LFit + \beta_2 UNEMit + \beta_3 RIRit + \beta_4 INFit + \beta_5 FDIit + \beta_6 IRit + \beta_7 EXRit + \beta_8 IMPit + \beta_9 EXPOit + \beta_{10} INTRit + \varepsilon_{it} \quad (18)$$

Instead of taking β_{0i} to be fixed, it is understood as a random variable having a mean value of β_0 while the intercept for a specific country can be written as;

$$\beta_{0i} = \beta_0 + \varepsilon_i, \quad i = 1,2,3,\ldots,N \quad (19)$$

Where ε_i denotes an error term having a mean zero and variance of $\sigma_\varepsilon{}^2$. Thus;

$$GDPit = \beta_0 + \beta_1 LFit + \beta_2 UNEMit + \beta_3 RIRit + \beta_4 INFit + \beta_5 FDIit + \beta_6 IRit + \beta_7 EXRit + \beta_8 IMPit + \beta_9 EXPOit + \beta_{10} INTRit + \varepsilon_{it} + \mu_{it} \quad (20)$$

Thus we have:

$$GDPit = \beta_0 + \beta_1 LFit + \beta_2 UNEMit + \beta_3 RIRit + \beta_4 INFit + \beta_5 FDIit + \beta_6 IRit + \beta_7 EXRit + \beta_8 IMPit + \beta_9 EXPOit + \beta_{10} INTRit + w_{it} \quad (21)$$

Here $w = \varepsilon_{it} + \mu_{it}$

In situations of this nature, the error term (v_i) is heterogeneity specific relative to a cross-sectional element. The v_i is constant across time. Consequently, $E[v_i{}^2/x\ ] = \sigma_i{}^2$ .The error term ε_{it} is particular to a specific observation. For $v_i$to be correctly quantified, it has to be orthogonal relative to specific effects. As a result of distinct cross-sectional random terms, these models often are occasionally entitled one-way random effects models. Due to this intra-panel variations, the random effects model possess distinctive benefit of permitting time-invariant variables to be integrated among the explanatory variables.

2.6 Putting Fixed and Random Effects to Test

How can we tell if the panel data have fixed and/or random effects? The F-test is used to analyse fixed effects whereas the Lagrange multiplier (LM) test is used to examine random effects. The former compares a fixed effect model to OLS to assess how much the fixed effect model improves goodness of fit whereas the latter compares a random effect model to OLS. A Hausman test is used to compare the similarity of fixed and random effect estimators.

2.6.1 Testing Fixed Effects Using the F-test

With the equation $y_{it} = \alpha + \mu_i + X_{it}'\beta + \varepsilon_{it}$, the null hypothesis states the following: All dummy variables with the exception of one are all zero, ie; $H_0 : \mu_0 = \ldots = \mu_{n-1} = 0$. While the alternative hypothesis says that at least one dummy variable is not zero. This proposition is evaluated by way of the F test that is hinged on the loss of goodness-of-fit. The test compares LSDV (robust model) and the pooled OLS (efficient model) and scrutinizes the degree that the goodness-of-fit as measured by SSE or R^2 has changed.

$$F_{(n-1,nT-n-k)} = \frac{(e'e_{pooled} - e'e_{LSDV})/(n-1)}{(e'e_{LSDV})/(nT-n-k)} = \frac{(R^2{}_{LSDV} - R^2{}_{pooled})/(n-1)}{(1-R^2{}_{LSDV})/(nT-n-k)} \quad (22)$$

Dismissing the null hypothesis says; at least one group/time specific intercept u_i is not zero, one may infer that the fixed effect model has a substantial fixed effect or a significant increase in goodness-of-fit; hence, the fixed effect model is superior to the pooled OLS.

2.6 2 Testing for Random Effects Using Breusch-Pagan LM Test

Breusch and Pagan's (1980) LM (Lagrange multiplier) test checks if time (or individual) specific variance components are zero, $H_0 : \sigma^2{}_u = 0$. The LM statistic has a chi-squared distribution having one degree of freedom.

$$LM_u = \frac{nT}{2(T-1)} = \left[\frac{T^2\bar{e}'\bar{e}}{e'e} - 1\right]^2 \sim \chi^2{}_{(1)} \quad (23)$$

Where $\bar{e}$ is the $n \times 1$ vector of the group means of pooled regression residuals, and $e'e$ is the SSE of the pooled OLS regression.

Baltagi (2001) expresses the equivalent LM test differently as follows:

$$LM_u = \frac{nT}{2(T-1)}\left[\frac{\sum(\sum e_{it})^2}{\sum\sum e_{it}{}^2} - 1\right]^2 = \frac{nT}{2(T-1)}\left[\frac{\sum(\sum e_{it})^2}{\sum\sum e_{it}{}^2} - 1\right]^2 \sim \chi^2{}_{(1)} \quad (24)$$

Rejecting the null hypothesis, one may infer that the panel data contains a substantial random effect and that the random effect model handles heterogeneity better than the pooled OLS.

2.6.3 Comparing Fixed and Random Effects; Use of Hausman Test

How can we tell which effect (fixed or random) is more significant and useful in panel data? Hausman test (1978) contrasts fixed and random effect models under the null hypothesis that individual effects are uncorrelated with any regressor in the model. LSDV and GLS are consistent if the null hypothesis of no association is not violated; otherwise, LSDV is consistent while GLS is inconsistent and biased. Greene, R. (2008). Under the null hypothesis, the estimates of LSDV and GLS should not differ systimatically. "The covariance of an efficient estimator with its difference from an inefficient estimator is zero," according to the Hausman test. Greene, R. (2008).

$$LM = (b_{LSDV} - b_{random})'\widehat{W}^{-1}(b_{LSDV} - b_{random}) \sim \chi^2_{(k)}, \qquad (25)$$

Here, $\widehat{W} = Var[b_{LSDV} - b_{random}] = Var(b_{LSDV}) - Var(b_{random})$ gives the difference in the projected covariance matrices of LSDV and GLS. Remember to leave out the intercept and dummy variables while computing. This test statistic has k degrees of freedom and follows the chi-squared distribution.

According to the formula, a Hausman test determines if "the random effects estimate is trivially different from the unbiased fixed effect estimate." Kennedy, E. (2008). If we reject the null hypothesis of no association, we may infer that individual effects u_i are highly linked with at least one regressor in the model, and hence the random effect model is problematic. As a result, we must choose a fixed effect model over a random effect model. The difference of covariance matrices W may not be positive definite; hence, we may argue that the null is not rejected assuming similarity of covariance matrices makes such a difficulty Greene (2008).

2.6.4 Testing for Poolability using Chow Test

Poolability inquires whether slopes are constant over groups or across time. Baltagi, (2001). The Chow test Chow, 1960 is an expansion of a simple form of the poolability test. The null hypothesis in the Chow test says that the slope of a regressor remain constant for all k regressors independent of the individual. $H_0 : \beta_{ik} = \beta_k$. Need is there to remember that gradiants remain fixed for random and fixed effects models; only error variances and intercepts matter.

$$F_{[(n-1)(k+1),n(T-k-1)]} = \frac{(e'e - \sum e'_i e_i)/(n-1)(k+1)}{(\sum e'e)/n(T-k-1)}, \qquad (26)$$

Where $e'e$ represents the SSE of the pooled OLS while $e_i'e_i$ is the SSE of the pooled OLS for group i. Rejecting the null hypothesis says that, the panel data cannot be poolable since each individual has their own slopes for all regressors. In this case, you may use the random coefficient model or the hierarchical regression model. The Chow test is based on the assumption that individual error variance components have a normal distribution, $\mu \sim N(0, s^2 I_{nT})$. If this assumption is not met, the Chow test may fail to appropriately assess the null hypothesis, according to Baltagi (2001). According to Kennedy (2008), "if there is reason to believe that errors in different equations have different variances, or that there is contemporaneous correlation between the equations' errors, such testing should be undertaken using the Stein's unbiased risk estimate (SURE) is an unbiased estimator of the mean-squared error of; a nearly arbitrary, nonlinear biased estimator, not OLS; … inference with OLS is unreliable if the variance-covariance matrix of the error is nonspherical" Baltagi (2001).

2.7 Selecting the Model: Fixed or Random Effect?

We obtain 12 potential panel data models when we combine fixed vs. random effects, time vs. group effects, and one-way vs. two-way effects, as shown in Table 3. In general, one-way models are frequently utilized due to their parsimony, and a fixed effect model is easier to estimate and explain than a random equivalent. It is, nevertheless, difficult to choose the finest model among the following 12.

Table 3 Grouping of Panel Data Analysis Approaches

	Type	Fixed Effects	Random Effects
One-way	Group	One-way fixed group effects	One-way random group effects
	Time	One-way fixed time effects	One-way random time effects
Two-way	Double groups*	Two-way fixed group effects	Two-way random group effect
	Double times*	Two-way fixed time effects	Two-way random time effects
	Hybrid	Two-way fixed group & time effects	Two-way random group & time effects
		Two-way fixed time and random group effect	
		Two-way fixed group and random time effects	

***Source**: Practical Guides to Panel Data Modelling and Author's classification*

3.0 Results and discussions

Table 4 Summary Results for Specific Models

Covariates	Estimate	Std.Error	t-value	P-value	Signif codes	
OLS Results for SADC Data						
(Intercept)	-1.036e+04	1.651e+03	-6.274	1.07e-09	***	
Inflaton	-2.759e-04	4.209e-04	-0.655	0.512659		
Imports	2.734e+00	1.491e-01	18.337	< 2e-16	***	
Exports	3.484e-01	1.047e-01	3.326	0.000976	***	
EDebt	5.342e-01	7.458e-02	7.162	4.92e-12	***	
ERate	2.742e-04	4.198e-04	0.653	0.514145		
IReserves	6.631e-02	2.445e-01	0.271	0.786360		
LForce	6.904e-01	1.148e-01	6.016	4.61e-09	***	
Unemployment	2.030e+02	5.233e+01	3.879	0.000126	***	
FDI	-1.232e+00	5.165e-01	-2.385	0.017641	*	
IRate	-2.688e+01	2.799e+01	-0.960	0.337489		
Total Sum of Squares:	**2.3377e+12**					
Residual Sum of Squares:	**5.3237e+10**					
R-Square Value:	**0.97723**					
Adjusted. R-Square Value:	**0.97656**					
F-value:	**1463.28 on**	**10 and 341**	DF			
p-statistic	**< 2.22e-16**					
Fixed Effects Model (FEWITHIN) for SADC Data						
Inflaton	-1.7634e-04	3.7515e-04	-0.4701	0.638625		
Imports	1.9377e+00	1.6422e-01	11.7998	< 2.2e-16	***	
Exports	2.9410e-01	1.1007e-01	2.6719	0.007920	**	
EDebt	2.4733e-01	7.7163e-02	3.2053	0.001483	**	
ERate	1.6558e-04	3.7598e-04	0.4404	0.659944		
IReserves	1.1309e+00	2.7618e-01	4.0949	5.333e-05	***	
LForce	1.5977e+00	3.6787e-01	4.3432	1.877e-05	***	
Unemployment	1.8080e+02	1.0585e+02	1.7080	0.088584	.	
FDI	-1.2494e+00	4.7780e-01	-2.6149	0.009341	**	

IRate	-3.1631e+01	2.5709e+01	-1.2304	0.219449		
Total Sum of Squares:	**2.5263e+11**					
Residual Sum of Squares:	**3.9218e+10**					
R-Square Value:	**0.84476**					
Adjusted. R-Square Value:	**0.83286**					
F-value:	**177.398 on**	**10 and 326**	DF			
p-statistic	**< 2.22e-16**					
Fixed Effects Model (BETWEEN) for SADC Data						
Intercept	-1699.48543	4537.27743	-0.3746	0.72335		
Inflaton	0.46130	1.76911	0.2608	0.80468		
Imports	2.74241	1.28630	2.1320	0.08618	.	
Exports	-0.38734	0.41669 -	0.9296	0.39526		
EDebt	1.54063	0.86147	1.7884	0.13374		
ERate	-0.40994	1.56944	-0.2612	0.80435		
IReserves	-0.16692	0.89035	-0.1875	0.85866		
LForce	0.15009	0.22451	0.6685	0.53341		
Unemployment	-23.15248	133.68740	-0.1732	0.86930		
FDI	-4.20909	2.66623	-1.5787	0.17525		
IRate	28.91778	209.28400	0.1382	0.89549		
Total Sum of Squares:	**9.4777e+10**					
Residual Sum of Squares:	**71069000**					
R-Square Value:	**0.99925**					
Adjusted. R-Square Value:	**0.99775**					
F-value:	**666.293 on**	**10 and 5**	DF			
p-statistic	**3.6046e-07**					
Fixed Effects (LSDV) Model for SADC Data						
Inflaton	-1.763e-04	3.751e-04	-0.470	0.638625		
Imports	1.938e+00	1.642e-01	11.800	< 2e-16	***	
Exports	2.941e-01	1.101e-01	2.672	0.007920	**	
EDebt	2.473e-01	7.716e-02	3.205	0.001483	**	

ERate	1.656e-04	3.760e-04	0.440	0.659944		
IReserves	1.131e+00	2.762e-01	4.095	5.33e-05	***	
LForce	1.598e+00	3.679e-01	4.343	1.88e-05	***	
Unemployment	1.808e+02	1.059e+02	1.708	0.088584	.	
FDI	-1.249e+00	4.778e-01	-2.615	0.009341	**	
IRate	-3.163e+01	2.571e+01	-1.230	0.219449		
Angola	-1.476e+04	4.546e+03	-3.246	0.001292	**	
Botswana	-1.501e+04	4.641e+03	-3.235	0.001340	**	
Comoros	-4.746e+03	2.902e+03	-1.635	0.102938		
DRC	-3.312e+04	8.990e+03	-3.683	0.000269	***	
Eswatini	-1.043e+04	5.711e+03	-1.827	0.068591	.	
Lesotho	-1.063e+04	4.663e+03	-2.280	0.023227	*	
Madagascar	-1.474e+04	4.578e+03	-3.219	0.001416	**	
Malawi	-9.334e+03	3.354e+03	-2.783	0.005704	**	
Mauritius	-9.439e+03	3.404e+03	-2.773	0.005868	**	
Mozambique	-1.872e+04	4.631e+03	-4.042	6.63e-05	***	
Namibia	-1.236e+04	5.089e+03	-2.429	0.015681	*	
Seychelles	-3.491e+03	2.693e+03	-1.296	0.195788		
South Africa	4.011e+04	1.087e+04	3.691	0.000262	***	
Tanzania	-2.186e+04	8.198e+03	-2.667	0.008041	**	
Zambia	-1.103e+04	3.845e+03	-2.869	0.004388	**	
Zimbabwe	-1.048e+04	3.560e+03	-2.944	0.003471	**	
Residual standard error:	**10970 on**	**326 DF**				
Multiple R-square value:	**0.9858**					
Adjusted R-Squared:	**0.9847**					
F-statistic:	**871 on 26**	**and 326**	**DF**			
p-value	**< 2.2e-16**					
Random Effects Model (REM) for SADC Data						
Intercept	-1.286e+04	2.170e+03	-5.9254	**3.115e-09**	***	
Inflaton	2.835e-04	4.041e-04	-0.7015	0.4829978		
Imports	2.513e+00	1.536e-01	16.3634	< 2.2e-16	***	
Exports	3.615e-01	1.096e-01	3.2979	0.000974	***	
EDebt	4.502e-01	7.628e-02	5.9020	3.591e-09	***	
ERate	2.843e-04	4.041e-04	0.7035	0.4817150		
IReserves	3.824e-01	2.624e-01	1.4572	0.1450722		

LForce	9.534e-01	1.556e-01	6.1265	8.983e-10	***	
Unemployment	3.000e+02	6.582e+01	4.5586	5.149e-06	***	
FDI	-1.210e+00	5.073e-01	-2.3849	0.0170831	*	
IRate	-3.137e+01	2.730e+01	-1.1491	0.2505199		
Total Sum of Squares:	**1.0548e+12**					
Residual Sum of Squares:	**4.8259e+10**					
R-Squared:	**0.95425**					
Adj. R-Squared:	**0.95291**					
Chi-square value:	**7112.23 on**	**10 DF**				
p-value:	**< 2.22e-16**					
Significance. codes :	**0 : '***'**	**0.001: '**'**	**0.01: '*'**	**0.05: '.'**	**0.1:' '**	**1**

Source: Author's own results.

Table 5 specification tests

Test	p-value	Tested	Selection
F-test	6.606e-15	OLS/Fixed	Fixed
Chow	2.2e-15	OLS/(Random or Fixed)	Random or Fixed
Breusch-Pagan	<2.2e-16	OLS/ Random	Random
Hausman	3.58e-14	Fixed/Random	Fixed

Source: *Author's own results.*

From Tables 4 and 5, the LSDV with an adjusted R^2-value of 98% is the superior model to handle the SADC data. Imports, exports, external debt, international reserves, unemployment, and labour force have positive impacts on the SADC community's economic growth. Foreign direct investment impacts negatively to economic growth. Inflation, exchange rate, and the interest rate have no association with economic development. To account for the effects of each country, the intercept is adjusted using a dummy variable for fixed effects. For all variables, the standard OLS approach is used. In the F test, a low p-value of 6.606e-15 counts against the null hypothesis that the pooled OLS model is acceptable, favouring fixed effects as a possible alternative. By allowing the intercept to vary across each nation, the individuality of each country is accounted for. The slope coefficients are also expected to be constant throughout the cross-section (Gujarati and Porter, 2003). Table 4 shows that the estimated coefficients dummy for South Africa has a positive impact on economic growth, whereas for all other SADC nations country effects negative relationships with economic growth, with the exception of Comoros and Seychelles, whose estimated dummy coefficients have no significant relationships with GDP as the SADC region's measure of economic growth. Differences in intercepts between nations may be attributable to the government's specific policies relative to imports and exports of commodities, pricing of goods in other countries, exchange rate, GDP compared to major economies, and/or other economic factors.

4. Conclusions and Recommendations

For over four decades, development economists have attempted to understand the role of international trade promotion (exports and imports), capital, and labour in economic growth. As a result, most SADC nations have enacted trade policies targeted at encouraging economic growth with the ultimate goal of improving citizens' livelihoods and exacerbating poverty. However, empirical studies conducted in a number of countries produced inconclusive results. As a result of these anomalies, doubts have been raised concerning the validity, robustness and universality of the export and import led growth theories. Several studies have been conducted to investigate the impact of various determinants on SADC countries' economic growth. This research, on the other hand, looked precisely at the influence of imports, exports, external debt, currency rate, international reserves, labour force, foreign direct investment and interest rate on economic development in the 16 SADC nations from 2000 to 2021. Exports, foreign debt, international reserves, employment level and labour force had positive impacts on economic growth for the SADC community, according to empirical research results. Foreign direct investment impacted negatively on the economic growth. Inflation, the exchange rate and the interest rate have no association with economic development in the SADC region.

Furthermore, the study found that estimated dummy coefficients for South Africa had a positive impact on GDP, whereas all other country effects of SADC nations have negative relationships with economic growth with the exception of Comoros and Seychelles, which had no significant relationships with GDP as a measure of economic growth in the SADC region. In order to boost economic growth, SADC nations should prioritize imports, exports, external debt, international reserves, employment levels and labour force. However, this will necessitate overcoming the regions' inconsistency in power supply (World Bank, 2012) as well as integrating the patchy intraregional trade regulations (Chea, 2012).

Nonetheless, it is critical for the SADC community to focus on strategic commodities, particularly highly developed technologies and key equipment that are unavailable within the region but are required for primary national economic growth by improving domestic production for local use and exports (Osei, 2012). After thoroughly examining the impact of imports, exports, external debt, exchange rate, international reserves, labour force, foreign direct investment and interest rate on economic growth in the SADC region, this study recognizes that it is essential to examine the direction of causation between the aforementioned variables in order to improve evidence-based policy-making and policy execution in relation to the trade-driven economic development agenda. Furthermore, the structure of this study captures some key growth determinants that may have a strong relationship with economic growth. Some of these factors include policy stability, education level (human capital) and other macroeconomic variables that were not included in the estimating procedure owing to a lack of data available throughout the research period. Including a broader set of socioeconomic indicators in the analysis may seem intuitive.

Acknowledgements

This paper is an output of PhD studies by Musora Thomas a student within Chinhoyi University of Technology, Department of Mathematics and Statistics. He is being supervised by Dr F. Matarise from the University of Zimbabwe Department of Mathematics and Computational Sciences. The authors would like to acknowledge Chinhoyi University of Technology in Zimbabwe for the invaluable support.

References

Adams, R. H & Page, J. (2005). *Do international migration and remittances reduce poverty in developing countries?* World Development, 33(10), 1645-1669. Available from: https://www.sciencedirect.com/science/article/abs/pii/S0305750X05001270.

Adema, W. & Ladaique, M. (2009). *How Expensive is the Welfare State?* Available from: https://doi.org/10.1787/1815199X .

Akbar, A., Muhammad, I.U., Muhammad, A.U., and Muhammad, A. (2011). *Determinants of Economic Growth in Asian Countries: A Panel Data Perspective.* Pakistan Journal ` of Social Sciences (PJSS) Vol. 31, No. 1 (June 2011), pp. 145-157.

Algalega, E and Antwi, S. (2013). *The Impact of Macroeconomic Variables on Gross Domestic Product: Empirical Evidence from Ghana*, Economics, International Business Research.

Baltagi, B.H. (2001). *Econometric Analysis of Panel Data*, Second Edition. Wiley, New York.

Baltagi, B. H. (2005). *Econometric Analysis of Panel Data.* 3rd ed. Cambridge University Press, New York.

Baltagi, Badi H., and Young-Jae Chang. (1994). *"Incomplete Panels: Comparative Stud of Alternative Estimators for the Unbalanced One- way Error Component Regression*

Model." Journal of Econometrics, 62(2): 67-89.

Barro, R. (2003). *Determinants of Economic Growth in a Panel of Countries*, CEMA Working Papers from China Economics and Management Academy, Central University of Finance and Economics. Available from: https://econpapers.repec.org/scripts/redir.

Barro, R.J. and X. Sala-i-Martin (1995). *Technological Diffusion, Convergence and Growth,* NBER Working Paper Series, No. 5151.

Basu, A., Calamitsis, E.A., and Ghura, D. (2000), *"Promoting Growth in Sub-Saharan Africa: Learning What Works,"* International Monetary Fund, 2000.

Breusch, T. and Pagan, A. (1980)re. *The Lagrange multiplier test and its application to model specification in econometrics.* Review of Economic Studies 47: 239–253.

Chea, A.C. (2012) *Sub-Saharan Africa and Global Trade: What Sub-Saharan Africa needs to do to maximize the Benefits from Global Trade Integration, Increase Economic Growth and Reduce Poverty?* International Journal of Academic Research in Business and Social Sciences, 2(4), 359-384

Chow, G. C. (1960). "Tests of Equality Between Sets of Coefficients in Two Linear Regressions." *Econometrica*, 28 (3): 591–605.

Dobronogov, *A and Iqbah, F, (2005). Economic Growth in Egypt: Constraints and Determinants,* Development and Comp Systems from University Library of Munich, Germany. Available from: https://econpapers.repec.org/RePEc:wpa:wuwpdc:0512024. [Accessed 17 February 2022].

Epaphra, M. (2018.). *An Econometric Analysis of The Determinants of Foreign Direct Investment in Africa,* International Journal of Development Economics. Available from: https://www.researchgate.net/publication/324517561.

Gray, C and Bilsborrow, R. (2013). *Environmental Influences on Human Migration in Rural Ecuador,*Demography (2013) 50 (4): 1217–1241. Available from: https://doi.org/ 10.1007/s 1 3524-012-0192-y.

Greene, W. H. (2008). *Econometric Analysis*, 6th ed. Upper Saddle River, NJ: Prentice Hall.

Gujarati, D. (2003). *Basic Econometrics.* 4th ed. New York: McGraw Hill, pp. 638-640

Hun, M.P. (2011). *Practical Guides to Panel DataModeling: A Step-by-step Analysis Using Stata*. Tutorial Working Paper. Graduate School of International Relations, University of Japan.

Hausman, J. A. (1978). "Specification Tests in Econometrics." *Econometrica*, 46(6):1251-1271.

Imakubo, K and Nakajima, J. 2015, *Estimating Inflation Risk Premia from Nominal* *and Real Yield Curves using a Shadow Rate Mode, Bank of Japan* Working Papers Series, Tokyo.

Kennedy, A. (2008*) A Guide to Econometrics*, Fourth Edition. The MIT Press Cambridge, Massachusett.

Mallick, L., Das, P.K. and Pradhan, K.C., (2016). *Impact of educational expenditure on economic growth in major Asian countries: Evidence from econometric analysis.* T heor. Appl. Econ., 2, pp.173–186.

Moran, T, Alfaro L, and Javorcik B. (2007). "*How to investigate the impact of Foreign Direct Investment on Development and Use the Results to Guide Policy|", Brookings Trade Forum: 1-60.*

Osei, V. (2012*). Import Demand and Economic Growth Analysis in Ghana.* Journal of Economics and Sustainable Development, 3 (14), 73-90.

Phale, K.; Li, F.; Adjei Mensah, I.; Omari-Sasu, A.Y.; Musah, M., 2021. *Knowledge-Based Economy Capacity Building for Developing Countries: A Panel Analysis in Southern African Development Community.* Sustainability, 13, 2890. Available from: https://www.mdpi.com/2071-1050/13/5/2890/pdf.

Semuel, H. & Nurina, S. (2015). *Analysis of the Effect of Inflation, Interest Rates, and Exchange Rates on Gross Domestic Product (GDP) in Indonesia.* Proceedings of the International Conference on Global Business, Economics, Finance and Social Sciences. Bangkok, Thailand, 20-22.

Sireesha, B.P. (2013). *Effect of Select Macro Economic Variables on Stock Returns in India* International Journal of Marketing, Financial Services & Management Research, 2(6).

Southern African Development Community (SADC) Regional Indicative Strategic Development Plan (RISDP) 2020–2030, Gaborone, Botswana, 2020.

Tiwari, A.K. and Mutascu, M. (2011) *Economic Growth and FDI in Asia: A Panel-Data Approach. Economic Analysis and Policy,* 41, 173-187. Available from: https://doi.org/10.1016/S0313-5926(11)50018-9.

Wajeetongratana, P. (2020), *Economic growth and its key factors: an alternative view on the factors stimulating agriculture growth,* FMS, Suan Sunandha Rajabhat University, 1 U-Thong Nok rd, 10200, Dusit, Bangkok, Thailand.

World Bank Open Data, Available from: https://data.worldbank.org/.

WTO, (2012). *Trade in Services. Publication of World Trade Organization*.

Yuliadi, I. (2020). *Determinants of Regional Economic Growth in Indonesia,* Jurnal Ekonomi dan Studi Pembangunan (JESP), Vol. 21, No. 1, p. 125-136.