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MODELLING AND FORECASTING THE FOREIGN AID-POVERTY NEXUS IN ZIMBABWE: EMPIRICAL EVIDENCE FROM A BOX-JENKINS ARIMA APPROACH

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Abstract

This study delves into the impact of foreign aid on economic development and poverty reduction in Zimbabwe, exploring their causal relationship. Despite extensive research on foreign aid's potential to drive development, there is a lack of comprehensive understanding of its impact on economic growth in developing countries. This knowledge gap necessitates a rigorous examination of the relationship between foreign aid and expansion in developing nations. The study hypothesizes that foreign aid has no significant impact on economic development and poverty reduction in Zimbabwe. Using Box-Jenkins ARIMA methodology, the study models and forecasts the foreign aid-economic development nexus and poverty reduction in Zimbabwe. The research covers a period of 1961-2021 and provides forecasts till 2031, offering a long-term perspective on the dynamics of aid, economic development, and poverty reduction. The findings suggest that foreign aid has a minimal effect on poverty reduction, which in turn hinders economic development. Adjusting for macroeconomic factors like inflation, the study reveals aid's inefficiency in reducing poverty. The study identifies long-term negative links between economic progress, foreign assistance inflows, and poverty alleviation. Forecasting foreign aid inflows from 2022 to 2031 using ARIMA indicates a modest increase. The results remain consistent across poverty indicators. The study concludes that increased foreign aid does not guarantee improved economic development or poverty reduction in Zimbabwe. It stresses the importance of effective macroeconomic policies and institutional functioning for sustained poverty alleviation. The study contributes to the body of knowledge by providing nuanced insights into the complex relationships between foreign aid, economic development, and poverty reduction in Zimbabwe. It highlights the need for context-specific solutions and effective policy interventions. The findings of this study are crucial for policymakers and stakeholders in Zimbabwe and other developing countries to reassess their approach to foreign aid and its role in achieving economic development and poverty reduction.

Keywords

Foreign aid, Poverty Reduction and Economic Development

1.0 Introduction and Background

Despite the growing amount of foreign aid provided to developing countries, poverty levels continue to rise, raising questions about the efficacy of aid in promoting economic development (Kim and Lekhe, 2019). The impact of Official Development Assistance (ODA) on economic growth remains a highly debated topic among economists and policymakers, with no clear consensus. While foreign aid has the potential to reduce poverty and improve health outcomes, its effectiveness is hindered by various factors, including inadequate institutional frameworks, political instability, and dependence on external resources. This study aims to contribute to the ongoing discussion by examining the relationship between foreign aid, economic development, and poverty reduction in developing countries.

According to the 2019 World Development Indicators (WDI), health wealth in emerging nations is seen by short life expectancy, subpar child health and maternal, and extraordinary rates of mortality and illness. This has not, in any way, called into question the efficacy of medical assistance in underdeveloped areas (Jemiluyi, Bank-

Ola and Alao-Owunna, 2021). Thus, the efficacy of the objectives of Foreign aid to alleviate poverty and achieve sound economic development in developing countries is contentious.

The exodus of human capital rate out of developing countries has become quite alarming. At the same time the foreign aid into the developing countries has been exponentially growing over the years. However, the poverty levels in most developing countries are on a rise despite the increase in foreign financial aid and foreign and these are a no new phenomenon. As financial markets have become more globalized, their economic and political significance has expanded.

1.1.1 Dynamics of foreign aid flows, economic development and poverty level trends in Zimbabwe (1961-2022)

The poverty headcount ratio in Zimbabwe, defined as the fraction of the population living on less than $5.50 a day at international prices, stood at 85.0% in 2019, marking a 0.9% increase from the previous year. From 2011 to 2017, the poverty rate surged by 6.2%, reaching 84.10%. In 2011, the poverty rate was 77.90%, a 77.9% increase from 2010 (World Bank, 2022). The food poverty rate, starting at 23% in 2011, rose steadily to 30% in 2017, reaching 38% in 2019, and peaking at 49% in July 2020, amidst the COVID-19 pandemic. However, with an economic rebound and improved maize harvests, the food poverty rate declined by 6 percentage points to 43% in 2021, still far from the goal of reducing it to 10% by 2025.

Official development aid (ODA), comprising multilateral and bilateral grants, low-interest loans, and technical assistance, increased from approximately $5 billion per year in 1960 to over $128 billion in 2008 (Todaro, 2012). However, despite efforts to bridge the human development gap in Sub-Saharan Africa, the proportion of developed-country GNP allocated to ODA declined from 0.51% in 1960 to 0.23% in 2002, before rising to 0.33% in 2005 and 0.45% in 2008 (Todaro, 2012). Figure 1.1 illustrates the trajectory of foreign aid in Zimbabwe from 1961 to 2021.

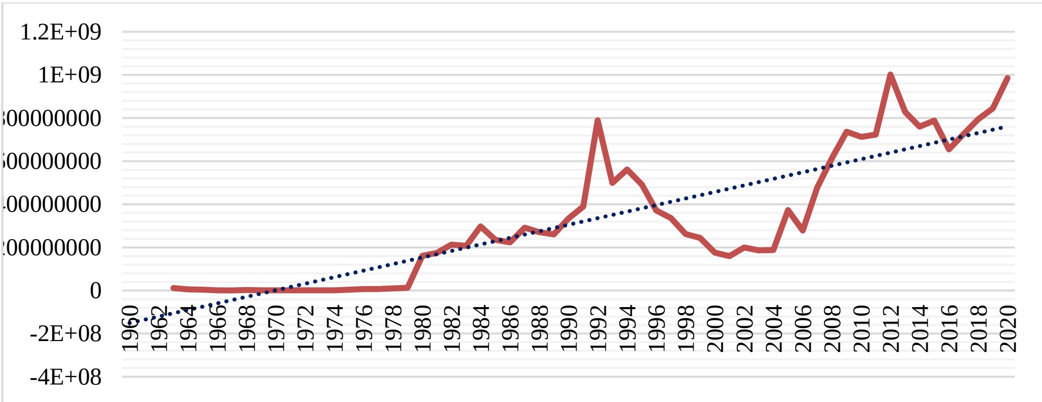


Figure 1.1: Foreign Aid in Zimbabwe Trend 1961-2021
Source: Author's compilations from world development indicators (World Bank, 2023)

Zimbabwe's economy enjoyed stability upon independence, bolstered by strong economic ties globally. In the 1980s, outward-oriented trade, financial, and investment policies replaced previous inward-focused strategies due

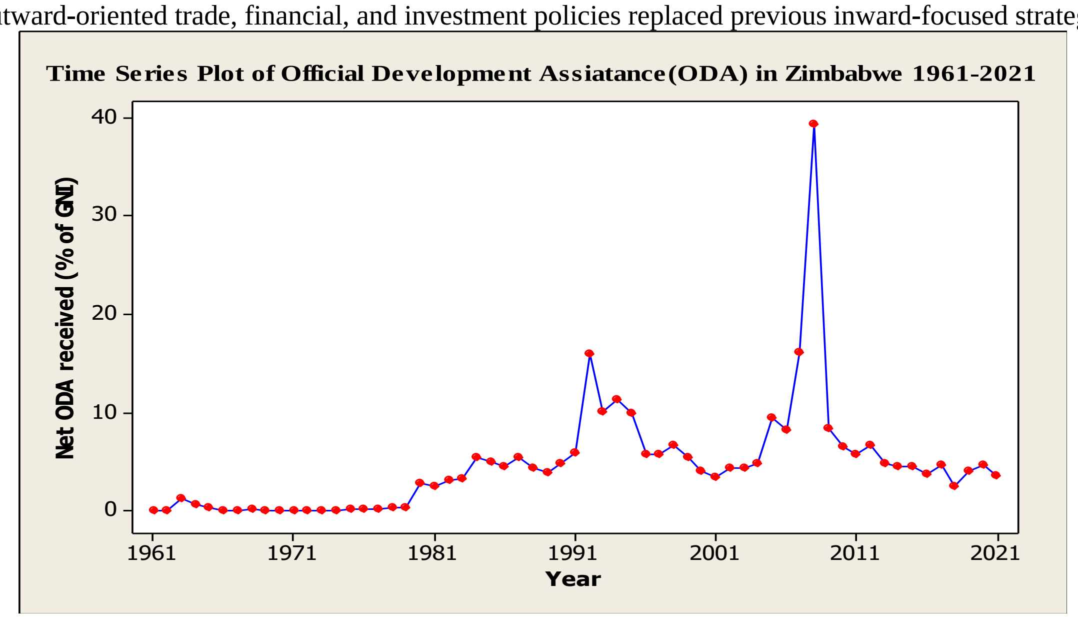


Figure 1.2 Official Development Assistance as a % of GNI 1961-2021
Source: Author's compilations from Minitab using World Bank data (WDI) 1961-2021

to sanctions during the Smith government era (Jones, 2011). Joining the IMF and WB in 1980 marked Zimbabwe's integration into the global economy, attracting foreign financial and technical resources (Jones, 2011). Despite these efforts, Zimbabwe struggled with low to negative economic growth and high poverty rates. Despite substantial aid, the nation's development remained stagnant, failing to achieve self-sustainability. Figure 1.2 highlights the peak foreign aid inflows during the 2001-2010 period.

Figure 1.3 below shows Gross Domestic Product Per Capita Trends in Zimbabwe (1961-2021). The GDP per capita was at its highest in 2019 despite the low ODA as shown in figure 1.2 above.

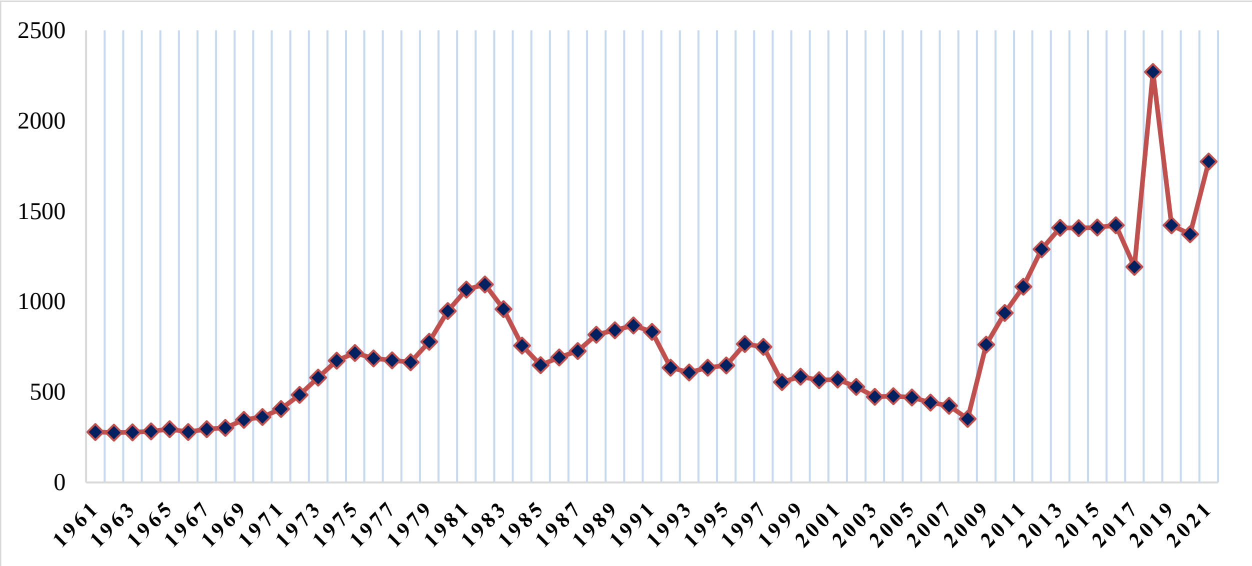


Figure 1.3: Gross Domestic Product Per Capita Trends in Zimbabwe (1961-2021)
Source: Author's compilations from world development indicators (World Bank, 2023)

Zimbabwe implemented three strategic plans between 1980 and 1990 to attract foreign financial aid, emphasizing investments in productive industries. Notable plans include the Growth with Equity of 1980, Transitional National Development Plan of 1981, and First Five Year and Second Five Year Plans covering 1982 to 1990 (Besada, 2011). These initiatives led to increased external financial inflows, trade expansion, and assistance from multilateral financial institutions for balance of payments (BOP) (Mupunga and Le Roux, 2014; IMF, 2001).

However, Zimbabwe's engagement in consumptive activities, regional wars like in the Democratic Republic of the Congo in 1997, and lavish spending on war veteran payments and land redistribution programs in 1999 and 2000 strained international relations (Moyo and Mafuso, 2017; Kabonga, 2020). Consequently, trade, economic, political, and financial sanctions were imposed starting in 1999 (Moyo and Mafuso, 2017; Kabonga, 2020; Jones, 2011).

These sanctions, coupled with hyperinflation from 2003 to 2008, led to negative economic growth, high unemployment, and decreased agricultural and industrial output (IMF, 2014). As relations with Europe improved, aid priorities shifted towards emerging creditors, primarily China, and from development to humanitarian aid (IMF, 2014). Consequently, foreign assistance transitioned from fiscal routes to specialized grants, primarily focused on poverty reduction programs (Jones, 2011; GoZ, 2009).

In light of the above, this study investigates the impact of foreign aid on economic development and poverty reduction in Zimbabwe, challenging the conventional wisdom that aid is essential for development. The findings provide new insights into the limitations of foreign aid in reducing poverty and promoting economic development, highlighting the need for effective macroeconomic policies and institutional functioning for sustained poverty alleviation. It also highlights the importance of effective macroeconomic policies and institutional functioning for sustained poverty alleviation in developing nations.

2.0 Research design

The researcher employed a quantitative research design, utilizing both Box-Jenkins ARIMA methodology and the ARDL technique. Quantitative techniques were chosen due to the availability of data on financial aid in Zimbabwe and related variables like economic development, inflation, and proxies for economic growth and poverty levels over the past four decades. The research design is a detailed strategy or blueprint developed to address the study topic and control for variance. In this study, a descriptive correlational research design was utilized. According to Atmowardoyo (2018), a descriptive correlational study design accurately represents current events. The correlational research approach was employed to ascertain the relationship between foreign aid and economic growth.

2.1 Empirical Model Specifications

The variables in the model were estimated and analyzed using the Autoregressive Distributed Lags (ARDL) method, while the foreign aid data was modeled and projected using the Box Jenkins ARIMA approach.

2.1.1 Foreign aid, Economic Development and poverty models

The models assessed the influence of foreign aid and economic development on poverty. Foreign aid was proxied through official development assistance to Zimbabwe, and economic development was assessed by GDP per capita. Finally, the poverty reduction was proxied by the infant mortality rate.

2.1.2 Foreign aid-Economic development nexus and Foreign aid-poverty nexus models

The boundary testing approach (ARDL) was employed to explore the link between Foreign aid and economic development, as well as foreign aid and poverty in Zimbabwe. Compared to other co-integration techniques, ARDL offers several advantages. It can be utilized for any order of integration (e.g., I(1), I(0), or fractionally integrated), and has been demonstrated to perform better in small samples (Narayan, 2004). Additionally, when appropriate lags are employed, ARDL mitigates issues of serial correlation and endogeneity (Jalil & Ma, 2008). The ARDL technique allows for the joint approximation of long-run and short-run parameters (Khan et al., 2005). Based on the presumption of a special relationship between FAID, economic development, and poverty, the ARDL model was selected.

The two models are generally specified as follows;

$POV = \alpha + \beta_1 FAID + \varepsilon_t$ …………………………………………………………………….. **(1)**

$EDEV = \alpha + \beta_1 FAID + \varepsilon_t$ ……………………………………………………………….... **(1.1)**

The logarithmic forms will be as follows

$lnPOV = \alpha + \beta_1 lnFAID + \varepsilon_t$ ………………………………………….………………… **(2)**

$lnEDEV = \alpha + \beta_1 lnFAID + \varepsilon_t$ …………………………………………..…………… **(2.1)**

Where α denotes constant

β_1 Denotes coefficients

$\boldsymbol{\varepsilon_t}$ Denotes the disturbance term

POV Denotes the Poverty captured by the infant mortality rate.

EDEV denotes Economic Development proxied by GDP per Capita

FAID is Foreign Aid captured by the Official development assistance (ODA).

Empirically, the ARDL models specification will be as follows:

$$\Delta POV = \alpha_0 + \sum_{i=1}^{n} \alpha_{1i}\ \Delta POV_{t-1} + \sum_{i=0}^{n} \alpha_{2i}\ \Delta FAID_{t-1} + \beta_1 POV_{t-1} + \beta_2 FAID_{t-1} + \varepsilon_{1t} \ldots\ldots (\mathbf{3})$$

$$\Delta \mathrm{EDEV} = \alpha_0 + \sum_{i=1}^{n} \alpha_{1i}\ \Delta \mathrm{EDEV}_{t-1} + \sum_{i=0}^{n} \alpha_{2i}\ \Delta \mathrm{FAID}_{t-1} + \beta_1 \mathrm{EDEV}_{t-1} + \beta_2 \mathrm{FAID}_{t-1} + \varepsilon_{1t} (\mathbf{3.1})$$

Where, α_0 is constant, α_{1i} and α_{2i} are short-run coefficients and ε_{1t} is the white noise error term.

In equations (3) and (3.1), the bound F-statistics for both the total and the combined significance of the coefficients of the lagged levels are utilized to assess the existence of a long-run link between the variables under inquiry so that H_0: α_1= α_2 = 0 and t-test for the null hypothesisH_0: α_1= 0

Moreover, if the independent variables are I(d) (where 0≤d≤1), critical value constraints provide a test for co-integration: a lower value for I (0) regressors and a higher value for I (1) regressors. If the test statistics exceed the associated upper critical values, we are able to deduce that a long-term causal connection exists. We fail to reject the null hypothesis of lack of co integration if the test statistics fall below the lower critical values. If the numbers are within their respective bounds, inference would be inconclusive. Moreover, for long-run relationship analysis, we used the following general form of the conditional ARDL (p, q) models 4 and 4.1:

$$POV = \alpha_0 + \sum_{i=1}^{p} \alpha_{1i}\ POV_{t-1} + \sum_{i=0}^{p} \alpha_{2i}\ FAID_{t-1} + \beta_1 POV_{t-1} + \beta_2 FAID_{t-1} + \varepsilon_{1t} \ldots\ldots\ldots (\mathbf{4})$$

$$EDEV = \alpha_0 + \sum_{i=1}^{p} \alpha_{1i}\ EDEV_{t-1} + \sum_{i=0}^{p} \alpha_{2i}\ FAID_{t-1} + \beta_1 EDEV_{t-1} + \beta_2 FAID_{t-1} + \varepsilon_{1t} \ldots (\mathbf{4.1})$$

Following the establishment of the long-run co-integration relationship between financial assistance and poverty, and financial aid and economic development, the next step is to investigate the causal relationship using the ECM based on ARDL. By employing this approach, POV_t, EDEV_t and FAID_t are stationary variables I (0) equation (5) and (5.1) without error correction term can be estimated using OLS method. Nonetheless, if POV_t, EDEV_t and FAID_t are non-stationary variables, I (1) and are not co-integrated, the ECM model such as equation (5) and (5.1) without error correction term in the first difference form can be used. The equation (5) and (5.1) are in the context of ECM-ARDL as follows which will apply to both model 2 and 2.1:

$$\partial y_t = \alpha_0 + \sum_{i=1}^{n} \alpha_{1i}\ \partial y_{t_{t-1}} + \sum_{j=0}^{n} \alpha_{2j}\ \partial x_{t_{t-j}} + \alpha_3 \varepsilon_{t-1} + \mu_t \ldots\ldots\ldots\ldots\ldots \mathbf{(5)}$$

$$\partial x_t = b_0 + \sum_{i=1}^{n} b_{1i}\ \partial x_{t_{t-1}} + \sum_{j=0}^{n} b_{2j}\ \partial x_{t_{t-j}} + b_3 \varepsilon_{t-1} + v_t \ldots\ldots\ldots\ldots\ldots (\mathbf{5.1})$$

Where, ε_{t-1} is the error correction term, x_t is Granger cause to y_t and similarly y_t would be Granger cause to x_t. A bilateral causal link occurs between y_t and x_t if all α_{2j} and b_{2j} are significant. The α_3 and b_3 are coefficients of error correction. A bilateral causal association exists among y_t and, x_t if all α_{2j} and $b_{2j}$are significant.

After establishing that economic development and poverty have a long-run link with foreign aid, the next step is to investigate the short- and long-run causality between these variables. In this case, an error correction-based ARDL Causality model is applied, with the significance of the coefficient of the lagged error-correction term and the F-statistic being used to determine causality. The significance of the F-statistic shows short-run causality, whereas the t-statistic on the coefficient of the lagged error-correction factor determines long-run causality.

2.1.3 Modelling and Forecasting Foreign aid using ARIMA Methodology

To model and predict the Foreign aid inflows in Zimbabwe the next 10 years (2022-2031), the ARIMA Model was utilized by employing data from the set of 60 observations.

ARIMA model

The Box-Jenkins technique is accredited to Box & Jenkins (1970); and in this study, it was used for analyzing annual foreign aid inflows in Zimbabwe (1961-2021). A generalized Box-Jenkins ARIMA model may, thus, be specified as shown in equation [1] below:

$$\boldsymbol{\emptyset_p(\beta)\emptyset_p(\beta^s)N_t = \theta_q(\beta)\theta_q(\beta^s)\varepsilon_t} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (\mathbf{6})$$

Where B is the backshift operator, ϕ, $\emptyset$, θq *and* Θq are polynomials of order p, P, q and Q respectively. εt is a white noise process and $Nt = \nabla d \Delta s\ DYt$ is the differenced N series.

For univariate time series forecasting, large time series data is necessary (Wabomba et al, 2016). In fact, Chatfield (1996) and Meyler et al (1998) advise using more than 50 observations to develop a solid ARIMA model. To that purpose, estimating Zimbabwean foreign aid inflows in this study was based on 60 observations of annual time series data from 1961 to 2021. The IMF, World Bank and ZimStats provided all of the data for this study.

For the time series study of foreign aid inflows in Zimbabwe, an ARIMA model will be used. To satisfy the requirements for ARIMA modeling, the stationarity of time series data was assessed using upgraded and applied differencing methods. The accuracy of the level of differencing variable (d) was determined concurrently. The auto-correlation function (ACF) and partial auto-correlation function (PACF) were then examined to determine a range for the lag order (p) and order of MA (q) components in ARIMA (p, d, q) models.

The time series with ACF exhibiting a gradually falling or geometric pattern, and PACF indicating a sudden cutoff after big spikes, were tested for a probable AR (p, d, 0) model. The prospective MA (p, d, q) model was tested for time series with opposing characteristics, whereas the ARMA model was tested for time series with geometric or progressively falling patterns in both the ACF and PACF.

2.1.4 Empirical Model Building and Estimation

2.1.4.1The Moving Average Process

Given that μ_t is a completely random process with mean zero and varianceσ^2, equation one below defines a process $FAID_t$

$$\boldsymbol{FAID_t = \mu + \mu_t + \theta_1\mu_{t-1} + \theta_2\mu_{t-2} + \cdots + \theta_q\ \mu_{t-q}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (\mathbf{7})$$

is functionally known as a Moving Average (MA) process of order q and is technically denoted by MA(q), where $FAID_t$ represents Foreign aid inflows inflows at time t, $\theta_1 \ldots \theta_q$ are estimating parameters, μ_t is the current disturbance and $\mu_{t-1} \ldots \mu_{t-q}$ are past disturbances. The above equation 1 represents a q th order moving average mode, abbreviated MA (q). This can be expressed using sigma notation as:

$$\boldsymbol{FAID_t = \mu + \sum_{i-1}^{q} \theta_i \ \mu_{t-i} + \mu_t} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. (\mathbf{8})$$

An MA model is basically a linear arrangement of white noise processes, where $FAID_t$ is established by the current and previous values of a white noise disturbance term. With the Introduction of the lag operator notation, this might be written as $LFAID_t = FAID_{t-1}$ to signify that $FAID_t$ is lagged once. Showing ith will be shown by the following notation expressed as:

$$\boldsymbol{L^i FAID_t = FAID_{t-i}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. (\mathbf{9})$$

The lag operator is called the backshift operator B, this can be denoted by the following definition,

$$\boldsymbol{FAID_t = \mu + \sum_{i-1}^{q} \theta_i L^i \mu_t + \mu_t} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. (\mathbf{10})$$

Alternatively, it can be written as $FAID_t = \mu + \theta(L)\mu_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (10.1)$

Where $\theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_q L^q$

The differentiating characteristics of the MA process of order q given above are: since $\mathrm{E}(\mu_t) = 0$, for all time it then imply that $\mathrm{E}\ (FAID_t) = 0$ and var $(FAID_t) \approx FAID_0 = (1 + {\theta_1}^2 + {\theta_2}^2 + \cdots + {\theta_q}^2)\sigma^2$

In general, an MA process has a constant mean, a constant variance, and autocovariances that are non-zero until latency q and then always zero.

2.1.4.2 Autoregressive processes

An autoregressive model is one in which the present value of a variable, $FAID_t$, is determined only the values that the variable's prior values plus an error term. AR (p), an autoregressive model of order p, can be written as:

$$\boldsymbol{FAID_t = \mu + \emptyset_1 FAID_{t-1} + \emptyset_2 FAID_{t-2} + \cdots + \emptyset_P \ FAID_{t-P} + \mu_t} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (\mathbf{11})$$

Where μ_t is a white noise disturbance term. To demonstrate the attributes of an autoregressive model, expression (3) must be manipulated. This expression can be represented more concisely in sigma notation as follows:

$$\boldsymbol{FAID_t = \mu + \sum_{i-1}^{p} \emptyset_i \ FAID_{t-i} + \mu_t} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (\mathbf{12})$$

Introducing a lag operator, this can also be expressed as:

$$\boldsymbol{FAID_t = \mu + \sum_{i-1}^{p} \emptyset_i L^i \ FAID_t + \mu_t} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. (\mathbf{13})$$

OR $\emptyset(L)FAID_t = \mu + \mu_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (13.1)$

Where $\emptyset(L) = (1 + \emptyset_1 L + \emptyset_2 L^2 + \cdots + \emptyset_p L^p)$.

2.1.4.3 The ARMA process

Box and Jenkins (1976) developed an ARMA model by combining the AR and MA elements. According to this model, the present value of a series $FAID_t$is linearly related to its preceding values plus a mixture of current and previous values of a white noise error component. Rather than depending just on MA (q) or AR (p) models, a more advanced model dubbed an ARMA (p, q) process, which is a combination of AR (p) and MA (q) processes, is developed in this study. As a result of combining equations (10) and (13), the following ARMA (p, q) process can be expressed:

$$\boldsymbol{\emptyset(L)FAID_t = \mu + \theta(L)\mu_t} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (\mathbf{14})$$

Where$\emptyset(L) = (1 + \emptyset_1 L + \emptyset_2 L^2 + \cdots + \emptyset_p L^p)$ and $\theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_q L^q$
and $\emptyset(L)$ and $\theta(L)$ are polynomials of orders p and q respectively, With $\mathrm{E}\ (\mu_t) = 0; E(\mu_t^2) = \sigma^2$; $\mathrm{E}\ (\mu_t \ \mu_s) = 0, t \neq s$

Because the ARMA (p, q) solely can be applied to stationary time series data, numerous time series are actually non-stationary due to the presence of trends and/or seasonal patterns. As a result, from an application standpoint, ARMA models are ineffective for characterizing non-stationary time series. As a result, this research presents an ARIMA model, which is just a generalization of an ARMA model that accounts for non-stationarity. The three steps for ARMA modeling are as follows:

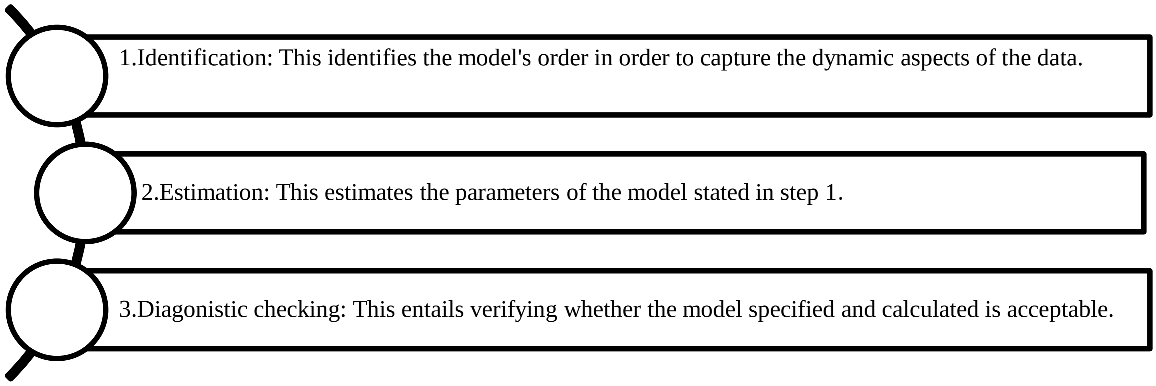


Figure 2.1 Steps in Building ARMA Models

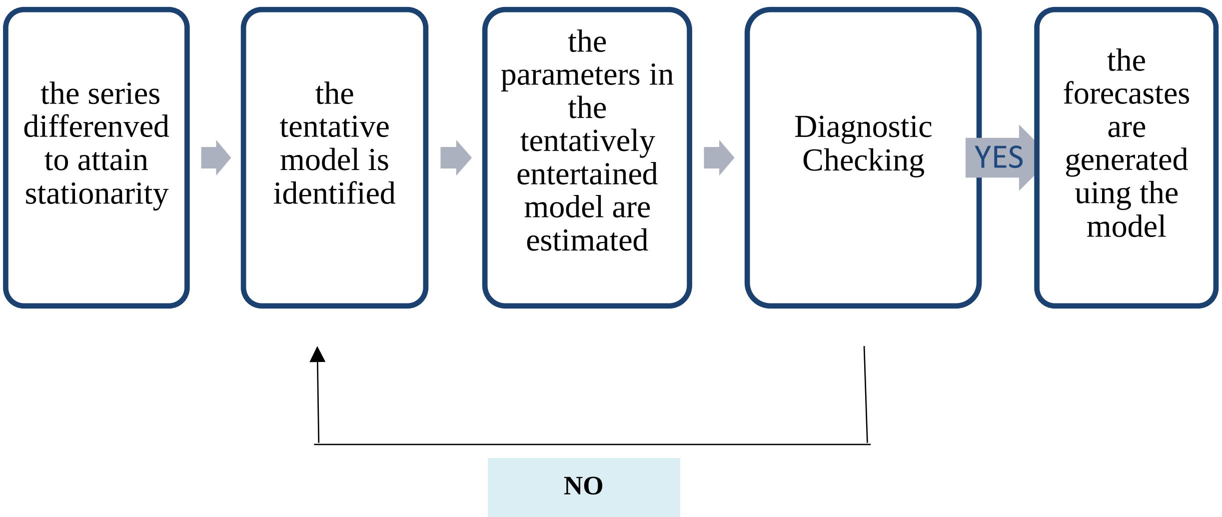
2.1.4.4 The ARIMA Modelling

The ARIMA models are the most effective for forecasting in time series using a univariate technique (Alnaa & Ahiakpor, 2011). An ARIMA [p, d, q] process is formed when a stochastic process is I (d) and the d times differenced process has an ARMA (p, q) representation. Box & Jenkins (1974) defined ARIMA models as a class of models that characterize the process (such as $FAID_t$) as a function of its own lags and white noise process. The series of $FAID_t$ also satisfies the ARIMA (p, d, q) process if the sequence, $\Delta^d FAID_t$, satisfies an ARMA (p, q) process, meaning that**:**

> The additional letter "I" in the abbreviation for ARIMA modeling, as opposed to ARMA modeling, stands for "integrated." The unit circle is the root of the characteristic equation of an integrated autoregressive process. Usually, researchers will alter the variable as needed before creating an ARMA model using those variables. An ARIMA (p, d, q) model on the original data is equivalent to an ARMA (p, q) model in the variable differenced d times.

2.1.4.5 The Box-Jenkins Methodology

Box and Jenkins (1970) introduced a method for constructing an Autoregressive Integrated Moving Average (ARIMA) model that best fits a given time series while adhering to the principle of parsimony. This approach, fundamental in time series analysis and forecasting, involves a three-step iterative process: model identification, parameter estimation, and diagnostic verification (Box & Jenkins, 1970; Lombardo & Flaherty, 2000; Zhang, 2003). Importantly, this method doesn't presuppose any particular pattern in the historical data of the series to be forecasted. The Box-Jenkins technique selects the most parsimonious model from a general class of ARIMA models. A diagrammatic representation of the Box-Jenkins method is presented below.



2.2 Data type and source.

Quantitative time series data spanning 1961–2021 were compiled from secondary sources, including Zimbabwe National Statistics Agency publications, IMF websites, and World Bank data. Secondary data was chosen for cost-effectiveness. Foreign aid, GDP, and inflation statistics were utilized. Diagnostic tests and statistical analyses enhanced the reliability of findings.

3.1 Empirical Results presentation and analysis

3.1.1 Descriptive Statistics

Prior to applying time series techniques, statistical properties of variables were tested. Descriptive statistics for Foreign Aid (FAID) in Zimbabwe from 1961-2022 were examined. The poverty variable (POV), proxied by infant mortality rate, ranged from 36.60 to 92.80 with a mean of 60.47541. Economic development (EDEV) varied from 275.96631 to 2269.177 with a mean of 756.4956. FAID, the independent variable, ranged from 0.001161 to 39.28212 with a mean of 4.617255.

Description	**Statistic**
Mean	4.617255
Median	4.309531
Minimum	0.001161
Maximum	39.28212
Standard Deviation	5.814617
Skewness	3.741540
Excess Kurtosis	22.09124
p-value	0.0000

Table 3.1 Descriptive statistics for Foreign Aid inflows in Zimbabwe (1961-2021)

In the table above, the mean of 4.617255 indicates that, on average, 4.62% of net official development aid (foreign aid) as a percentage of gross national income was received during the study period. The median is 4.31%, with a maximum of 39.28% in 2008, reflecting a peak amidst Zimbabwe's economic and political turmoil. The minimum, 0.001161 in 1961, represents the lowest foreign aid percentage. A positive skewness of 3.741540 suggests right-leaning distribution. Kurtosis of 22.09124, exceeding 3, indicates a non-normal distribution. A significant p-value (0.000) confirms the non-normality of the series.

3.1.2 Unit Root Test

To conduct the empirical study, various econometric instruments are employed. The non-stationarity issue is addressed through the Augmented Dickey Fuller (ADF) unit root test, considering the annual data spanning 1961-2021. The ADF test is crucial for investigating the long-run association between the variables. Non-stationary datasets are transformed into stationary forms using the first difference method. Although the ARDL method doesn't mandate preliminary stationarity tests, such tests help determine its suitability, as it's appropriate only for first-order variables [I(1)]. Before analysis, stationarity of variables is confirmed via ADF unit root tests, with outcomes detailed in Table 3.2.

Variable	**ADF Statistics**	**Test Critical Value**	**P-Value**	**Order of integration**	**conclusion**
POV	-3.809761***	1% -3.550396 5% -2.913549 10% -2.594521	0.0048	I(1)	Stationary Stationary Stationary
EDEV	-10.81629***	1% -3.546099 5% -2.911730 10% -2.593551	0.0000	I(1)	Stationary Stationary Stationary
FAID	-10.355220***	1% -3.886751 5% -3.052169 10% -2.666593	0.0000	I(1)	Stationary Stationary Stationary
RESID	-9.177229***	1% -3.548208 5% -3.912631 10% -2.594027	0.0000	I(1)	Stationary Stationary Stationary

The *, ** and *** means significant at 10%, 5% and 1% levels of significance; respectively and I(1) means integrated at order 1

Table 3.2 Augmented Dickey Fuller test for Stationarity at First difference

Source: Author's computations from EViews 12

Variable	Level		First difference		Conclusion	
	Intercept	Intercept and trend	Intercept	Intercept and trend	Intercept	Intercept and trend
POV	0.593	0.3829	0.0048	0.0217	Non stationary at level, stationary at 1st difference	Non stationary at level, stationary at 1st difference
EDEV	0.8317	0.2587	0	0	Non stationary at level, stationary at 1st difference	Non stationary at level, stationary at 1st difference
FAID	0.002	0.0024	0	0	Both stationary at level and 1st difference	Both stationary at level and 1st difference
RESID			0	0	stationary at 1st difference	stationary at 1st difference

Table 3.3: Unit Root test Results

Source: Author's computations from EViews 12

The Augmented Dickey Fuller (ADF) test assessed the stationarity levels of each variable in the model, testing the null hypothesis of a unit root problem against the alternative hypothesis of variable stationarity. Results indicate that all variables, except FAID, are non-stationary at the level, but become stationary after first differencing. All variables exhibit integration order one, I(1), with p-values less than 0.05. Tables 3.2 and 3.3 demonstrate consistent stationarity in first differences for all parameters. Consequently, an ARDL approach to data analysis is appropriate. Cointegration tests were conducted to determine if components in each model are cointegrated, as shown in the respective tables.

Dependent variable: Poverty Reduction (Pov)

ECM Regression Case 1: No Constant and No Trend				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(POV1(-1))	0.794168	0.091404	8.688525	0.0000
D(POV1(-2))	0.477840	0.118636	4.027773	0.0002
D(POV1(-3))	-0.514348	0.089149	-5.769560	0.0000
D(ODA)	0.027325	0.012076	2.262757	0.0284
D(INF)	0.000480	0.001164	0.412377	0.6820
D(INF(-1))	0.017551	0.005686	3.745330	0.0005
D(INF(-2))	0.016901	0.004518	3.740805	0.0005
D(INF(-3))	0.023097	0.003865	5.976607	0.0000
CointEq(-1)*	-0.002047	0.000449	-4.561157	0.0000
R-squared	0.885856			
Adjusted R-squared	0.866832			
S.E. of regression	0.489455			
Sum squared resid	11.49919			
Log likelihood	-35.25742			
Durbin-Watson stat	1.594205			

Table 3.4 Model 1 ARDL Error correction Regression results

However, the ARDL short-run form and F-bound test results for Model 2, as depicted in Table 3.4, show inconclusive findings regarding the relationship between economic development and foreign aid. Although the calculated F-bound test statistic falls within the lower and upper bounds, the cointegration error term is significant. Meanwhile, the short-run ARDL ECM results reveal a significant negative impact and relationship between current foreign aid and economic development. Additionally, inflation at lag 1, and economic development at lags 2 and 3, also influence current-year development.

Dependent variable: Economic Development (EDEV)

The table 3.5 above shows the ARDL error correction regression results. Generally, there is a consensus between the short run form and long form and bound test that there an inconclusive findings on the relationship between the foreign aid and economic development if a control variable is included. However, economic development's long run behavior reconciles to its short run behavior significantly by -0.045563 as indicated by a significant error correction term with p value of 0.0049

ECM Regression
Case 1: No Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(EDEV(-1))	-0.102175	0.161604	-0.632259	0.5303
D(EDEV(-2))	-1.045309	0.294653	-3.547595	0.0009
D(EDEV(-3))	0.806071	0.234085	3.443500	0.0012
D(FAID)	-9.911831	4.474159	-2.215351	0.0316
D(FAID(-1))	-16.22196	5.270517	-3.077869	0.0035
D(INF)	2.049151	0.672946	3.045046	0.0038
D(INF(-1))	-6.657555	2.022272	-3.292117	0.0019
CointEq(-1)*	-0.045563	0.015436	-2.951837	0.0049

R-squared	0.445035	Mean dependent var	26.16743
Adjusted R-squared	0.365754	S.D. dependent var	215.9694
S.E. of regression	171.9971	Akaike info criterion	13.26230
Sum squared resid	1449567.	Schwarz criterion	13.54905
Log likelihood	-369.9756	Hannan-Quinn criter.	13.37374
Durbin-Watson stat	1.894262		

* p-value incompatible with t-Bounds distribution.

Table 3.5 Model 2 ARDL Error correction Regression results

3.2 Results presentation

The researcher conducted time series regressions analyzing the impact of foreign aid (FAID), measured by Official Development Assistance (ODA), on economic development (EDEV), assessed by GDP per capita, and on Poverty Reduction (POV), represented by infant mortality rate in Zimbabwe from 1961 to 2021. The results of these regressions are presented in Tables 3.6 and 3.7.

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
POV(-1)	1.648737	0.120744	13.65484	0.0000
POV(-2)	-0.076221	0.221164	-0.344634	0.7318
POV(-3)	-1.099922	0.218358	-5.037241	0.0000
POV(-4)	0.482352	0.114410	4.216005	0.0001
FAID	0.018690	0.017084	1.094008	0.2793
FAID(-1)	-0.045098	0.017230	-2.617454	0.0118
C	3.487393	1.533957	2.273461	0.0274
@TREND	-0.025410	0.014104	-1.801656	0.0778

Table 3.6: ARDL Regression long run results estimation Model 1

Source: Author's computations from Eviews 12

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
EDEV(-1)	0.427237	0.135929	3.143077	0.0028
EDEV(-2)	0.269381	0.157037	1.715391	0.0925
EDEV(-3)	0.323749	0.162108	1.997119	0.0513
EDEV(-4)	-0.303063	0.189617	-1.598292	0.1163
FAID	-12.41508	5.182997	-2.395348	0.0204
C	98.03148	64.71457	1.514829	0.1361
@TREND	6.263135	2.387224	2.623606	0.0115

Table 3.7: ARDL Regression long run results estimation Model

The ARDL regression results for Model 1 reveal that current-year FAID has a very insignificant positive relationship with Poverty reduction (POV), with a coefficient of 0.018690, while prior-year FAID is significant at 10% and negatively related to POV, with a coefficient of -0.045098. Additionally, previous-year POV lagged at 1 exhibits a significant positive impact on current POV, with a coefficient of 1.648767. However, POV at lag -2 indicates an insignificant negative coefficient of -0.076221, with a p-value of 0.7318.

In Model 2, the ARDL results show that current-year FAID has a significant negative impact on economic development at 5%, with a coefficient of -12.41508 and a p-value of 0.0204, while prior-year FAID is also significant at 10% but positively impacts Economic Development, with a coefficient of 11.99298, a t-statistic of 2.314801, and a p-value of 0.0245. Moreover, Economic Development at lags 1, 2, and 3 indicates a significant positive impact on current economic development at 5% significant levels.

The ARDL models is generally specified as follows

$$POV = \alpha_0 + \sum_{i=1}^{p} \alpha_{1i}\ POV_{t-1} + \sum_{i=0}^{p} \alpha_{2i}\ FAID_{t-1} + \beta_1 POV_{t-1} + \beta_2 FAID_{t-1} + \varepsilon_{1t} \ldots\ldots\ldots \mathbf{(4)}$$

$$EDEV = \alpha_0 + \sum_{i=1}^{p} \alpha_{1i}\ EDEV_{t-1} + \sum_{i=0}^{p} \alpha_{2i}\ FAID_{t-1} + \beta_1 EDEV_{t-1} + \beta_2 FAID_{t-1} + \varepsilon_{1t} \ldots \mathbf{(4.1)}$$

Implications

A unit increase in current-year foreign aid leads to approximately a 0.006 unit increase in poverty levels, while a prior-year unit increase in foreign aid results in approximately a -0.041 unit change in poverty. Poverty levels and a lag of 2 units in poverty correspond to approximately 1.85 and -0.86 unit changes in current-year poverty levels, respectively. Similarly, a unit increase in current-year foreign aid leads to approximately a -11.63 unit change in economic development, while a prior-year unit increase in foreign aid results in approximately a 11.99 unit change in economic development. Prior-year economic development and a lag of 2 units in economic development correspond to approximately 0.62 and 0.33 unit changes in current-year economic development, respectively.

3.2.1 The Error Correction Mechanism (ECM)

Engle and Granger's error correction mechanism (ECM) was utilized to reconcile short-run and long-run characteristics of the dependent variable. The significant error correction term, as indicated by the probability value being less than 0.05 in Table 4.10, highlights the importance of this correction mechanism.

Results suggest that the reduction in poverty, measured by infant mortality, reconciles its short-term behavior to its long-term behavior by approximately -0.046809. Economic development's short-run behavior also adjusts to its long-run behavior with a statistically zero equilibrium error term, indicating immediate adaptation to changes in foreign aid. However, foreign aid negatively influences economic development while minimally impacting poverty alleviation.

Engle and Granger's error correction mechanism (ECM) was used to reconcile the dependent variable's short-run and long-run characteristics. As a result, the word error correction was employed to denote the short run dynamics. The results of the mistake correction are shown in Table 4.10. Because the probability value is less than 0.05, the results in table 4.10 above show that the Error correcting term is significant.

The results of this study suggest that for a year, the reduction in poverty that is measured by infant mortality reconciles its short-term behavior to its long-term behavior by a factor of roughly -0.046809, whereas economic development's short run behavior reconciliation factor with its long run behavior shows an equilibrium error term that is statistically zero, implying that economic development adjusts to changes in foreign aid during the same time period. However, Foreign aid has a negative influence on economic development while having a negligible beneficial impact on poverty alleviation.

Model 1(Dependent variable:POV)				
Variable	**Coefficient**	**Std Error**	**t-statistic**	**Prob**
C	0.991195***	0.553752	1.789963	0.00791
D(POV(-1))	0.864201***	0.072120	11.98281	0.0000
D(FAID)	0.006528	0.0019031	0.343041	0.7329
CointEqtn(-1)*	-0.015406**	0.0.007392	-2.084083	0.0419
Model 2(Dependent variable:EDEV)				
C	65.49225	52.99823	1.235744	0.2219
D(EDEV(-1))	-0.332420	0.127030	-2.616870	0.0115
D(FAID)	-11.62545	4.538587	-2.561468	0.0132
CointEqtn(-1)*	-0.046809	0.066845	-0.700257	0.4868

*Note: *, ** and *** denotes stationarity at 10%, 5% and 1% significance levels, respectively.*

Table 3.8 : Estimated short run coefficients Results

Source: Author's computations from EViews 12

3.3 Modelling and Forecasting foreign aid Results Presentation, interpretation and analysis

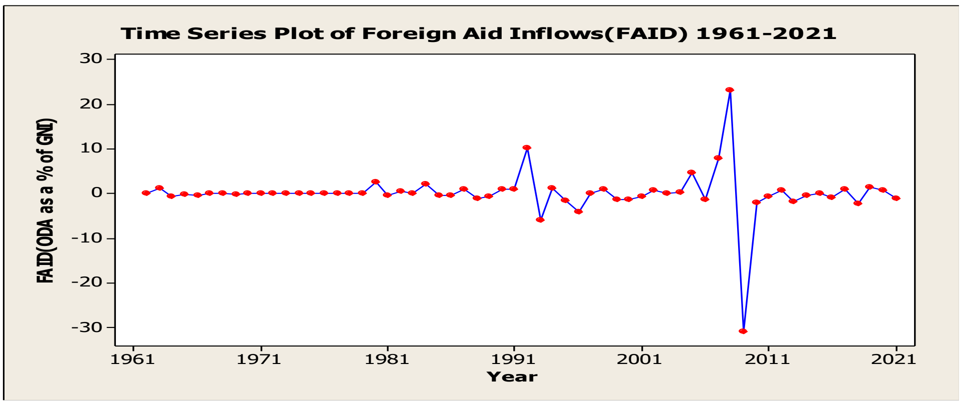


Figure 3. 1: Stationarity test-Graphical Analysis

Source: Author's computations from Mintab

Figure 3.1 above indicates that the N series does not follow any particular trend. However, in as much as it is reasonable to suspect stationarity, it is quite imperative to formally test the series for stationarity.

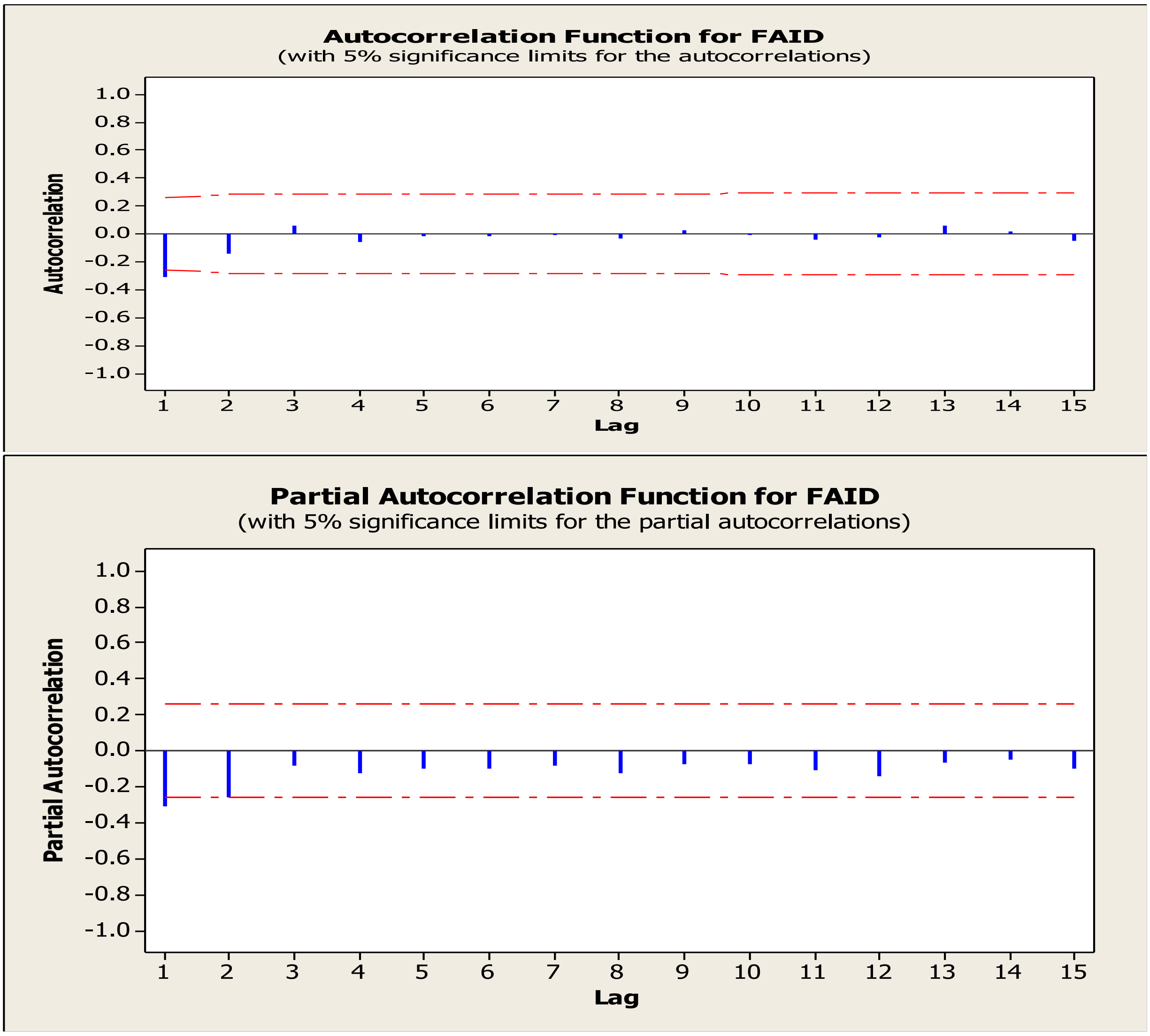
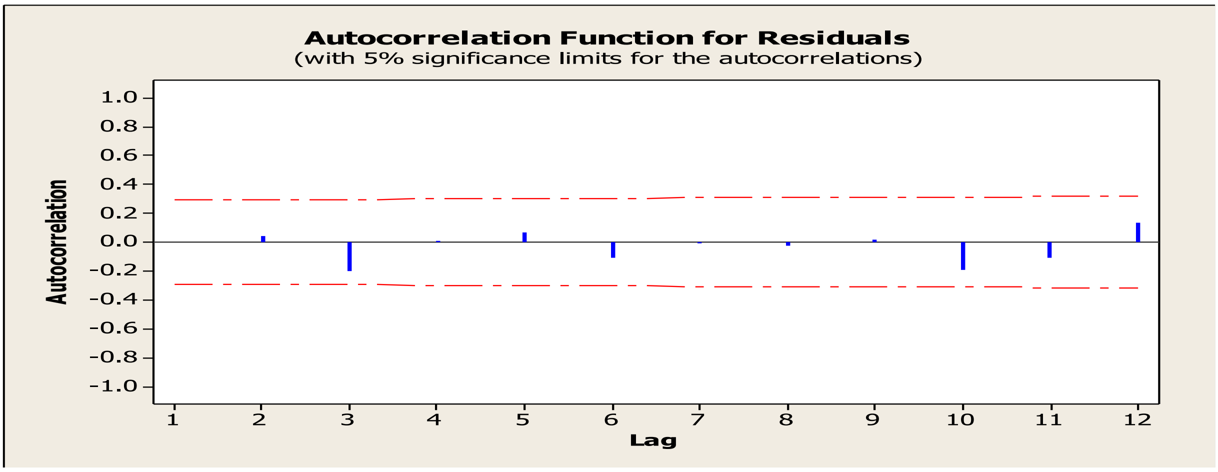


Figure 3.2: Autocorrelation function and Partial Autocorrelation function for differenced $FAID_t$

Source: Author's computations from Mintab

Figure 3.2 above shows that the first difference of the Foreign aid data are stationary since the ACFs and PACFs at various lags, generally, lie within the bands. This also implies that the data can be used to choose a suitable model which is parsimonious, stable and acceptable for forecasting annual foreign aid inflows in Zimbabwe.



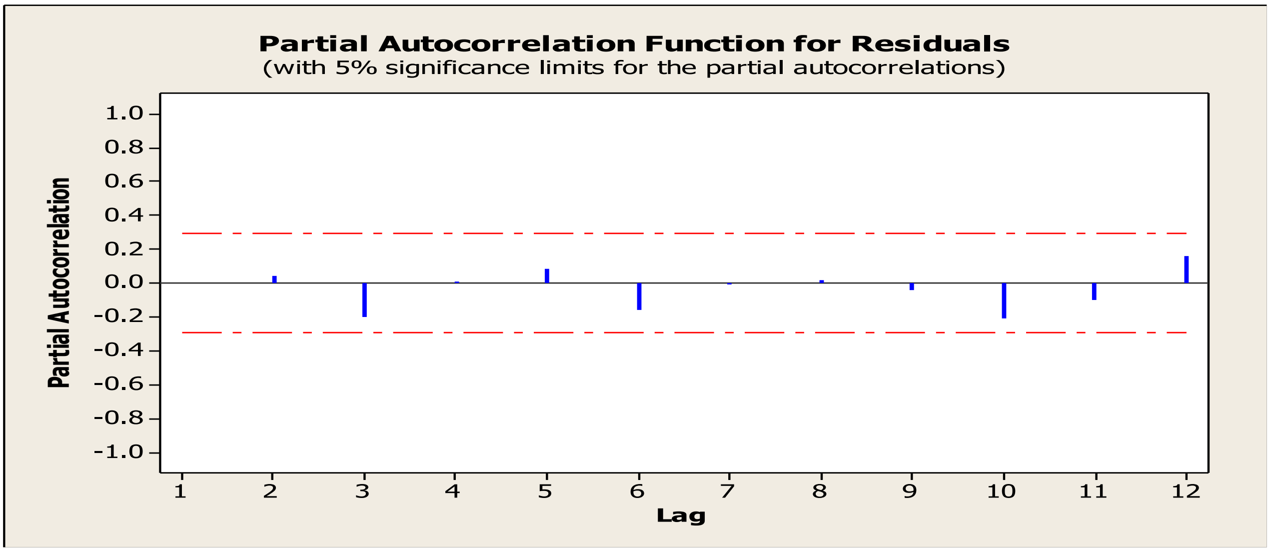


Figure 3. 3: Autocorrelation function and Partial Autocorrelation function for the Residuals

Source: Author's computations from mintab

Figure 3.3 above shows that the residuals of the Foreign aid data are stationary and a white noise since the ACFs and PACFs at various lags, generally, lie within the bands. This also implies that the data can be used to choose a suitable model which is parsimonious, stable and acceptable for forecasting annual foreign aid inflows in Zimbabwe.

3.4 The ADF Test

Variable	Level		First difference		Conclusion	
	Intercept	Intercept and trend	Intercept	Intercept and trend	Intercept	Intercept and trend
$FAID_t$	0.002	0.0024	0	0	Both stationary at level and 1st difference	Both stationary at level and 1st difference

Table 3.9: Unit Root test Results.

Source: Author's computations from Eviews 12

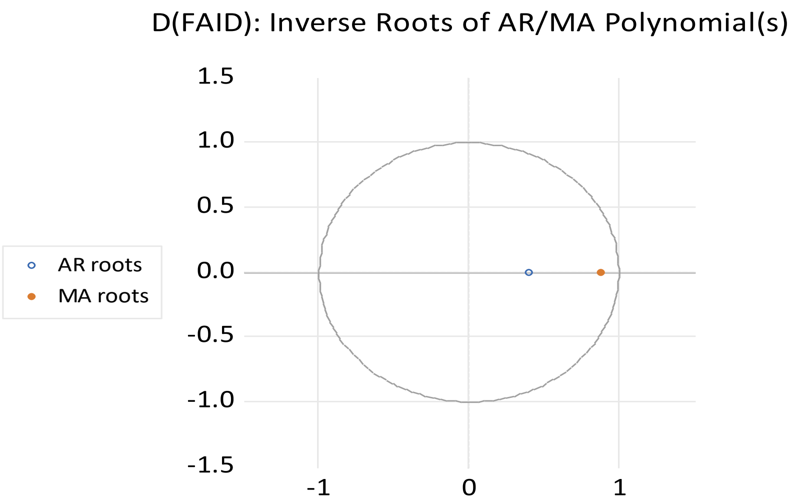


Figure 3.4: Test for Stationarity and invertability

Table 3.9 indicate that the N series of is an $FAID_t$ I (1) variable. Therefore, the null hypothesis that there is unit root is rejected.

The figure above shows that both the AR roots and MA roots are less than 1 and lie inside the circle. The ARMA processes roots lie inside the circle, the ARMA processes are stationary and invertible. The above conditions are satisfied, we there continue to forecasting as the ARMA (1,1) model meet the minimum standards of a better model. The fitted model is adequate, it can be used to obtain forecasts

Model	Variable	Coef	SE Coef	t-Statistic	P-Value	AIC	Adj R^2
ARIMA(1 1 2)	AR(1)	-0.479071	0.05866	-8.16678	0.0000***	6.12467	0.162688
	MA(2)	-0.442155	0.10334	-4.27869	0.0001***		
	SIGMASQ	24.01704	1.57239	15.2742	0.0000***		
ARIMA(111)	AR(1)	0.40731	0.2155	1.89007	0.0638*	6.093087	0.193231
	MA(1)	-0.885013	0.1659	-5.33466	0.0000***		
	SIGMASQ	23.14095	1.41152	16.3944	0.0000***		

The *, ** and *** means significant at 10%, 5% and 1% levels of significance; respec tively. The ARIMA (1, 1, 1) (1, 1, 1) model is the best model in terms of the AIC, simple parsimony, Adjusted R squared and Significance thus it is chosen.

Table 3.10: Evaluation of ARIMA Models (without a constant)

3.5 Interpretation of Results

The F-statistic assesses the overall model's relevance and fitness, while theR^2 indicates the explanatory power of independent variables. In Model 1, the independent variables explain approximately 99% of the variation in the dependent variable, with an F statistic value (4853.846) far exceeding the conventional threshold of 5, supporting rejection of the null hypothesis. The ARDL also yields a significant p-value (<0.05), confirming model significance and fitness.

Similarly, in Model 2, the F-statistic (34.39523) significantly exceeds 5, and independent variable (FAID) explains around 80.05% of the variation in the dependent variable (EDEV). Again, the ARDL provides a p-value (<0.05), indicating model significance and fitness. These results underscore the importance and validity of both models in explaining the relationship between foreign aid and economic development.**4.4.3.2 The extent at which the Poverty reduction measured by Infant mortality rate is influenced by foreign aid inflows measured by official development assistance as a percentage of GNI**

According to the results in table 4.8 above, the observed R^2 is 0.998101, indicating that the significant features in the model explain the variations in poverty reduction by roughly 99 percent. The remaining percentage can be attributed to other stochastic components. Following rectification, the effects of extra poor explanatory factors in the model reduced R^2 to 0.997829.

3.5.1 The extent at which the Economic development measured by GDP per capita is influenced by foreign aid inflows measured by official development assistance as a percentage of GNI

According to the findings in table 4.9 above, the observed R^2 is 0.804970, indicating that the significant elements in the model explain the swings in economic development by roughly 80.5 percent. The remaining 25% can be attributed to other stochastic components. After rectification, the influence of extra unworthy explanatory factors in the model led $R^2$to fall to 0.781567.

Research Hypothesis

H_0 : Foreign aid has no impact on economic development and poverty reduction in Zimbabwe

Regression results show significant negative impact of official development assistance (ODA) on economic development (EDEV), rejecting null hypothesis, implying foreign aid influences economic development (R^2 = 0.804970, coefficient: -12.41508). Yet, recent FAID has no significant effect on poverty alleviation, rejecting null hypothesis. However, prior year's FAID significantly and negatively affects poverty reduction in the long run, rejecting null hypothesis.

H_0 : Foreign Aid will increase in Zimbabwe in the next decade (2022-2031)

Type	Coef	SE Coef	T Statistic	P value
AR1	0.6611	0.2582	2.56	0.014**
SAR12	-1.0012	0.0491	-20.38	0.000***
MA1	0.8526	0.1784	4.78	0.000***
SMA12	-0.8629	0.1708	-5.05	0.000***

The *, ** and *** means significant at 10%, 5% and 1% levels of significance; respectively. The ARIMA $(1,1,1)^{12}(1,1,1)^{12}$ model is the best forecast model with seasonality of 12.

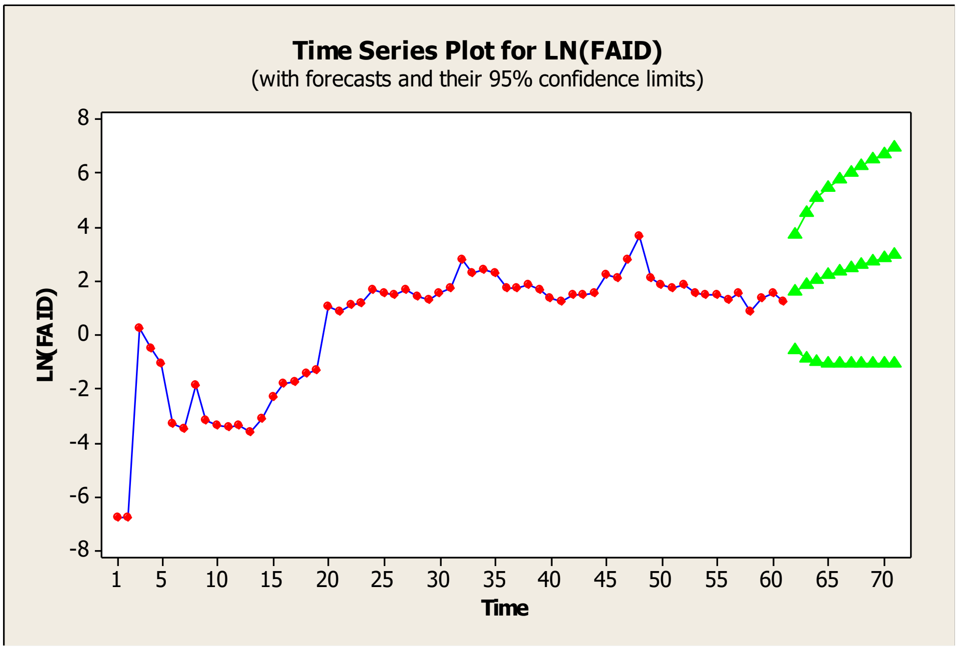
Table 3.11 Final Estimates of Parameters

The final estimates of the forecast model show that the model is suitable and stable. The coefficients of the parameters are all statistically significant with p values less than 0.05 and t statistic is greater than 1.96 at 5% level of significance.

Period	Forecast	Lower	Upper Actual
2022	1.37950	-0.67228	3.43128
2023	0.20054	-2.43800	2.83909
2024	0.41957	-2.56703	3.40617
2025	0.29333	-2.93569	3.52235
2026	0.78370	-2.63209	4.19949
2027	0.78716	-2.78314	4.35747
2028	0.88108	-2.82376	4.58593
2029	1.77240	-2.05394	4.59875
2030	1.35582	-2.58307	5.29471
2031	2.07583	-1.96919	6.12086

Table 3.12 Out of sample Forecasts at 95% Limits

The forecast indicates a modest increase in net foreign aid inflows over the next decade, from 2022 to 2031. However, the projected growth is relatively low and unimpressive. Figure 3.4 illustrates the graphical representation of the forecast sample.



4.1 Summary of findings

This research aimed to investigate the relationship between foreign aid inflows and economic progress, as well as poverty reduction in Zimbabwe. GDP per capita represented economic progress. While official development assistance (ODA) stood for foreign aid (FAID), and infant mortality rate served as an indicator of poverty reduction. The findings reveal a detrimental impact of foreign aid on Zimbabwe's economic progress and poverty alleviation. The empirical results confirm a negative relationship between FAID and EDEV, signifying a significant negative connection between foreign aid inflows and economic progress at a 5% significance level. Moreover, foreign aid dependency may hinder the nation's economic growth. It's imperative for policymakers and governments to reduce reliance on donor aid, which could impede economic development and exacerbate poverty cycles. Additionally, Zimbabwe's economic progress demonstrates a highly negative association with controllable factors, including inflation.

Foreign aid-Poverty reduction nexus

According to the analysis, Zimbabwe's economic development is significantly negatively correlated with foreign aid at lag one in both short and long terms, as indicated by the ARDL long-run form and bound test, as well as the ARDL error correction regression results. The findings demonstrate a consistent negative impact of foreign aid on economic development in both short and long terms.

Regarding poverty reduction, both short and long-term associations with foreign aid exist when controlling for other variables. In the short term, foreign aid positively and significantly affects poverty reduction. However, overall, there's inconclusive evidence regarding the connection between foreign aid and economic development when controlling for variables.

Granger causality results suggest no significant association between foreign aid and economic development or poverty reduction. Current year foreign aid shows an insignificant positive relationship with poverty reduction, while prior year foreign aid is negatively related to poverty reduction.

These findings align with previous studies by authors such as Kang, Prati, and Rebucci (2013), Saungweme (2021), Batana (2009), Gebregergis and Mekuria (2016), Bawatneh (2020), Kim and Lekhe (2019), and Makwalila (2019), indicating that financial aid inflows hinder economic development and have minimal or negative impact on poverty reduction. Results from Mahembe and Odhiambo (2019) similarly suggest that foreign aid increases poverty levels.

4.1.1 Forecasting Foreign aid inflows

The forecasted foreign aid inflows for Zimbabwe from 2022 to 2031 indicate limited evidence of substantial aid that could sustainably foster economic development and poverty reduction. Despite projected increases, mainly in humanitarian aid due to political instability, an unstable macroeconomic environment, and El Niño-induced droughts from climate change, economic development and poverty reduction are expected to remain inhibited during the review period.

4.2 Recommendations

The study recommends the Zimbabwean government to implement policies aligning with National Development Strategy 1 (NDS1), Sustainable Development Goals (SDGs), and Africa Agenda 2063 to reduce aid dependency and foster domestic solutions for economic development and poverty reduction. Public sector expenditure reforms are advised to ensure disciplined spending and create an environment conducive to internal solutions. The findings indicate foreign aid's ineffectiveness in poverty reduction and economic development, suggesting a need for aid allocation to pro-poor government spending in sectors like agriculture, education, and health. Addressing bureaucratic obstacles and corruption is crucial for economic development. To stimulate domestic investment, the Reserve Bank of Zimbabwe must manage economic volatility. Getting prices, policies, and institutions right is recommended to alleviate poverty and foster meaningful participation in economic opportunities. Overall, the study emphasizes domestic solutions over foreign aid for sustainable economic development and poverty reduction in Zimbabwe.

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