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The Impact of Public Agricultural Spending on Foreign Direct Investment Inflows in Agriculture in South Africa: An ARDL Analysis

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ABSTRACT

Since the transformation of South African agriculture post-apartheid, public agricultural spending and foreign direct investment in agriculture were regarded as predominantly essential for the development of agriculture sector. However, many authors still argue whether public agriculture spending should be complemented by foreign direct investment inflows in agriculture or vice versa. Thus, the key focus of this paper is to investigate the impact of public agricultural spending on foreign direct investment inflows in agriculture in South Africa over the period 1991-2019. The Autoregressive distributed lag (ARDL) Bounds test and Granger causality were used to investigate both short run and long-run impact of public agricultural spending on foreign direct investment inflows in agriculture. The results of the long run model show that agriculture production has a positive and significant impact on foreign direct investment. However, public spending in agriculture has a negative and significant influence on the foreign direct investment inflows in agriculture. In addition, Granger causality results show causality flowing from public agriculture spending, net export and inflation to foreign direct investment inflows in agriculture. Hence, it is recommended that policymakers should take practical steps towards total eradication of misallocation and squandering of the available funds and redirected toward bridging infrastructural deficits, land restitution to promote foreign direct investment inflows the development of agriculture.

Keywords: Agriculture Production, Public Spending, FDI, ARDL Bound Test, Granger Causality, South Africa
JEL Classifications: C22, D24, Q14

1. INTRODUCTION

Government expenditure and Foreign Direct Investment (FDI) could be crucial macroeconomic factors for agriculture development. They are solid fuels for agriculture development through access to finance, research and technology (Lowder et al., 2012). Hence, the need to control and screen government spending and FDI to accomplish an unfaltering financial development in the agriculture sector is fundamental. Today in South Africa, the outlook for agriculture is positive and cases of robust production in the sector are more focused on field crops, horticulture and livestock production, which indirectly have a positive impact on other sectors of the economy (Fischer and Hajdu, 2015). South Africa is actually not only self-sufficient in practically every major agricultural product but is one of the largest exporters of agricultural products to the most lucrative markets in the developing world (Jambor and Babu, 2016). Since the first quarter of 2020, agricultural sector has been a positive contributor to the country's GDP growth with an increase of 28.6%, becoming the strongest performer (15.1%) in the second quarter of 2020 despite the unpleasant conditions of COVID-19 pandemic (Stat SA, 2020). The agricultural sector, however, will probably be the only shining star, in part because the sector was classified as essential and did not close down during the strict lockdown period, whose effect extended to the second quarter.

South Africa's population currently stands at 57.7 million and is expected to reach an average of 82 million by 2035 (Mateo-Sagasta et al., 2018). However, population increases at a high rate compared to agriculture production. This implies that the population of South Africa is not theoretically capable of increasing its nutritional quality or, at least, cannot meet its food requirements. In order to feed the people, the need for food production has to rise dramatically over time and indeed needs to double as the population grows fast. Nevertheless, South Africa needs to encourage the sustainability of natural resources and strengthen its environmental practices, which provide the vital products and services. The environmental practices underpins the country's agricultural practices and ensure continuing successful agricultural systems and food security. Therefore, innovation and development will ensure sustainability in food production in the future in South Africa with increasing investments in the sector through public-private partnerships such as public spending and foreign direct investment (Bruinsma, 2017). Poulton and Macartney (2012) argued that investment in South Africa's agriculture sector differs from other countries in Africa in that public spending is supplemented by the private investment such as Foreign Direct Investment (FDI) due to the high level of development in agro-processing sector.

However, there has been underinvestment from public spending and foreign direct investment inflows over agricultural sectors throughout the developing world (Fani et al., 2020). Most developing country policymakers are therefore trying to attract more foreign direct investment (FDI) in their agricultural sectors. In South Africa, between 1994 and 2005, the agricultural sector saw a growth in FDI after exchange rate adjustments. In 2005, FDI in agriculture dropped at an estimation of absolute capital of R 143.348 million (Vink and Rooyen, 2009). This information shows that FDI in South Africa's agriculture sector is not as solid as is regularly suspected. As per Nicholson (2014), it has been recorded that, FDI makes overflow impacts in the host nation. For example, the spread of new technologies and the executives rehearses, alongside upgrading the nation's development rate. However, FDI inflows in agriculture in South Africa agricultural production still remain relatively low ($US 2.5 billion) compared to developing countries (SARB, 2020).

The agriculture sector in South Africa gets the least FDI contrasted with others and albeit little, the significant investment in the area has been immediate ventures into agribusiness which are still growing in South Africa. Rodríguez-Pose and Cols (2017) asserted that FDI assumes a noteworthy role in supplementing agricultural export in South Africa, as foreign direct investment is more attractive in a sector that is competitive and can guaranty high return on investment. In addition, FDI is a significant wellspring of innovation, capital and abilities of creating financial development for nations that may eventually lead to poverty reduction, job creation and modernization (Masamba, 2017). However, because of a low level FDI needed to fill the capital gap to increase the supply of money, FDI inflows could be boosted by public investment to invigorate agricultural development (De Abreu, 2017).

The Comprehensive Africa Agriculture Development Programme (CAADP) is a good example of a framework that has inspired and energised African agricultural research institutions, farmers' associations, African governments and the private sector who believe that agriculture has a pivotal role in development. Regarding government spending in South Africa, the government's investment of 10% on farming is proportionate to R100 billion, and this has hugesuggestions for approach, prioritization and capacity to spend more than R800 billion (Pardey et al., 2016). Nonetheless, agricultural investment, rural development and agricultural reform are aimed at promoting rural development, food production and the aid of emerging farmers. According to National Treasury (2017), expenditure in agriculture, rural development and land reform (2018/2019) stands at R 30.2 billion (1.8% of total budget) compared to 26.5 billion for 2017/2018. In essence, CAADP is about boosting investment to stimulate growth in the agricultural sector and attract more FDI inflows. This means bringing together the public and private sectors and civil society at the continental, regional and national levels to increase investment, improve coordination, share knowledge, successes and failures, encourage one another and to promote joint and separate efforts (Kimenyi et al., 2013).

However, there is still a conflicting view on which between public agriculture spending and foreign direct investment improves faster agriculture production in developing countries. The contention is based on whether public agricultural spending crowds in foreign direct investment or vice versa. Hence there is a need to identify optimal policy and investment alternatives that will yield the highest payoffs. Therefore, the rationale of this study is to examine the effects of public agriculture spending on FDI inflows in agriculture in South Africa. This research presents the proverbial "chicken or the egg" dilemma in agricultural subsector output: Which comes first? This undertaking is aimed at adding to the body of literature by investigating how public agriculture spending in agriculture affect foreign direct investment inflows in South Africa. Moreover, the results obtained from the analysis will assist policymakers in finding an appropriate ways to stimulate FDI inflows in agriculture in South Africa. The remaining part of this paper are orginised as follows: Section 2 outlines both theoretical and empirical literature review, section 3 is the methodology employed, section 4 presents the results followed by section 5 which is the conclusion and policy recommendation.

2. LITERATURE REVIEW

The complicated and contentious topic of whether the components of investment are substitutes or complements has dominated the discussion over the relative impact of public investment on private investment. However, a substantial amount of empirical evidence has been recorded-albeit with diverse and sometimes contradictory outcomes (Bom and Ligthart, 2014). One argument to attain economic stability is the Keynesian theory that proposes deliberate government fiscal policy interventions. The use of fiscal policy stabilization tools such as government spending and taxation is usually the first line macro-economic tool rather than monetary policy (Ibi et al., 2016; Ogege and Boloupremo, 2020). The goal of Keynesian theorist towards economic stabilization is to increase spending in an economy, to stimulate employment, income and output aggregate spending is usually employed. The Keynesian model suggest that a positive nexus exist between deficit spending and investment. The implication following the Keynesian theory is that government can use its fiscal policy to control economic instability (Ibi et al., 2016; Ogege and Boloupremo, 2020).

Some economists argue that public investment can stimulate private investment (crowd-in effect), particularly when it is made in infrastructure development and public goods and services provision such as the state investment in research, health, education, water, transport and communication, because it offers a solid macro-environment for attracting capital and lowering private sector investment costs. Theoretically, the multiplier effect is sufficient enough to eventually produce an increase in the total Gross Domestic Product (GDP) that is greater than the amount of increased government spending. The result is an increased national income. From this theoretical point of view, the relevant question is whether an increase in public investment increases private investment. Fournier and Johansson (2016) found that public investment is more significant than private investment for economic growth. However, such findings might be justified in the context of high marginal productivity of public investment caused by key infrastructure shortages. Evans et al. (2022) assessed the impact of fiscal policy on foreign direct investment in Kenya. Using a time series secondary data from the period of 1987-2017. The findings show that government expenditure on infrastructure, tax and FDI are positively and significantly related, external debt and FDI are negatively and significantly related while Domestic debt and FDI are negatively and significantly related. Norashida et al. (2019) analyzed the impact of government fiscal policy on Foreign direct investment in seven countries which include Indonesia, Malaysia, Thailand, Singapore, Philippine, China and India using a panal data spanning from 1982 to 2016. Pooled Mean Group were employed to examine the association between variables adopting capital, market size, infrastructure and macroeconomic stability as control variables. Result showed that government expenditure significantly and positively contributed to the inflows of FDI in the long run. Sadibo and Adedeji (2020) examined the effect of fiscal policy on foreign direct investment as well as the impact of Foreign Direct Investment on economic growth in Nigeria over the period of 1981-2017. The study employed VECM estimation technique and the findings showed that corporate income tax as an indicator to fiscal policy has a positive effect on foreign direct investment and government expenditure has a negative effect on foreign direct investment.

Using a panel data set of seven countries ranging from 1982 to 2016, Othman, Yusop, Andaman, and Ismail (2018) analysed the influence of government expenditure on FDI inflows in the host nation. The research includes Malaysia, Indonesia, Singapore, Thailand, and the Philippines (ASEAN-5), as well as India and China. They use the Pooled Mean Group (PMG) approach devised by Pesaran et al. (2001) to investigate the influence of government expenditure on FDI, utilizing market size, capital, macroeconomic stability, and infrastructure as control variables. The findings of this study suggest that government expenditure has a long-term favorable impact on FDI inflows. Abille et al. (2020) explored the function of fiscal incentives in attracting foreign direct investment inflows into Ghana by using data from 1975 to 2017. This was done by applying the distributed lag (ARDL) bounds test technique, which showed that corporate tax rates have a significant negative impact on FDI inflows into the Ghanaian economy in the long run.

Ogege and Boloupremo, (2020) examined the influence of government fiscal policy on foreign direct investment in the Nigerian Economy, pre and post military rule. The Ordinary Least Square technique and correlation analysis were deployed to test the long-run association that exists among the variables. The result found that inflation has a significant positive influence on FDI in the military era in Nigeria; government expenditure is positively and significantly associated with FDI for both military and post military era; government domestic debt is adversely and insignificantly associated with FDI for both military and the post military era while foreign exchange rate is positively and significantly associated with FDI in the military and adversely associated with FDI in post-military era.

Furthermore, Adom et al. (2018) study the impacts of public R&D on Africa's agricultural productivity on FDI. This study uses an imbalanced panel fixed effect model to estimate data for 28 African nations from 1980 to 2014. Although FDIs have direct beneficial benefits on output, the results showed that public R&D enhances FDIs in the agriculture sector, which diminishes the productivity potential of public R&D indirectly owing to the putative dependence syndrome associated with FDIs.

In contrast, many opposing viewpoints claimed that public investment can drive out private investment. In theory, the crowding-out effect is a competing force for the multiplier effect. It refers to government "crowding out" private spending by using up part of the total available financial resources. In short, the crowding-out effect is the dampening effect on private-sector spending activity that results from public sector spending activity. The IS-LM theory illustrates the crowding-out effect of state investment on private investment. If monetary policy remains unchanged, an increase in government spending can cause a parallel shift in the IS curve, resulting in the phenomenon of rising prices and rising interest rates in the short run, reducing private investment (Ram, 1986; Brunnermeier and Sannikov, 2012). An increase in tax also leads to a fall in after-tax private investment, giving economic agents incentives to reduce investment decisions. Most economists and policymakers now believe that, based on their marginal contribution to growth, private investment is more efficient than governmental investment. This agreement is founded on recent research like Ponce and Navarro (2016), Yovo (2017), who found that private investment has a greater impact on economic growth than public investment. Djokoto et al. (2014) employed Auto Regressive Distributed Lag (ARDL) on time series data from 1976 to 2007 to analyse the relationship between domestic and foreign direct investment in Ghanaian agriculture. The results shows that a ratio of agricultural inward foreign direct investment is significantly affecting domestic capital flow. Similarly, Mitra and Hossain (2018), examines the direct link between total public spending and net FDI inflows (in proportion to GDP) for Benin Republic, one of the least researched West

African countries in this area. A structural VECM is estimated for the period 1971-2013. Results show that public spending is found to significantly complement FDI inflows in the long-run.

Some of the study show that there is no clear evidence that FDI crowd-in or crowd-out government spending into agriculture. From 1980 to 2018, Obekpa et al. (2021) looked at how agricultural development responded to foreign direct investment and public agricultural spending. Data was gathered from secondary sources and analyzed using the Johansen Co integration method and the Vector Error Correction Model. In the long term, foreign direct investment and state agricultural expenditure enhanced agricultural productivity, but in the short run, they diminished it.

3. DATA AND METHODOLOGY

3.1. Data

In achieving the specified empirical objectives, the study makes use of secondary data consisting of annual time series covering a period of 28 years from 1991 to 2019. The choice of using data that starts from 1991 was made deliberately to accommodate most of the study variables that lacked data of pre-1991. On the other hand, the closing data solely depended on the availability of the most recent data. Variable total agriculture production was sourced from the Department of Agriculture, Forestry and Fisheries(DAFF); variable FDI inflow was sourced from the Food and Agricultural Organization (FAO); variable real effective exchange rate and inflation rate were sourced from World Bank; variable net export was sourced from the Regional Strategic Analysis and Knowledge Support System (ReSAKSS) and public agricultural spending was sourced from QUANTEC.

3.2. Model Specification

To investigate the effect of public agricultural spending on foreign direct investment inflows, this paper tests the crowding-in or crowding-out effect of public investment on foreign direct investment following the lead of Makuyana and Odhiambo(2016). It estimates the following foreign direct investment equation as follow:

$$FDI_t = \alpha_0 + \alpha_1 PAS2_t + \alpha_2 TPROD_t + \alpha_3 REER_t + \alpha_4 NEXP_t + \alpha_5 INF_t + \varepsilon_t \quad (1)$$

We take the log of both sides based on the premise that the variables are linear except NEXP and INF which are measured in percentage. Because many economic time series data demonstrate a significant trend, logarithmic (L) transformations of variables are particularly popular in econometrics as it converts a large scale to small scale to reduce non-linearity. As a result, the model is presented as follows:

$$LFDI_t = \alpha_0 + \alpha_1 LPAS2_t + \alpha_2 LTPROD_t + \alpha_3 LREER_t + \alpha_4 NEXP_t + \alpha_5 INF_t + \varepsilon_t \quad (2)$$

Where α_0 is a constant parameter and ε_t is the white noise error term.
FDI is foreign direct investment in million US dollars,
TPROD is total agricultural production in tons
PAS2 is public agriculture spending which is Expenditure on intermediate goods and services in Million rand;
REER is the real effective exchange rate (2010=100);
NEXP is the net export in % of total merchandise exports
INF is the inflation rate in annual percentage (%)

3.3. Methodology

In this empirical investigation, we follow three main steps named unit root test, the Autoregressive distributed lag (ARDL) model and Granger causality test.

3.3.1. Unit root test

First, we examine the stionarity of variables foreign direct investment inflows, public agriculture spending, total agricultural production, real effective exchange rate, net export and inflation rate. For this reason, we use two of the most basic unit root tests named Augmented Dickey-Fuller (ADF) and Phillipd-Perron test (PP). ADF found an asymmetric distribution that used for the hypothesis testing of unit root. This distribution was used to separate between an AR(1) model from the integrated series. In other words to test for the existence of unit root, the ADF test constructs a parametric correction for the correlation of higher order if it is assumed that series follows an autoregressive procedure order k.

In addition, Phillips-Perron(PP) tests for serial correlation and heteroscedasticity on errors on regression tests modifying the statistical tests. PP is suitable for the analysis of time series where their differences can follow an ARMA (p,q) procedure with unknown rank. On the result of this test, they incorporate a non-parametric diagnostic test for serial correlation and heteroscedasticity on regression test. The null hypothesis of Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests is the existence of unit root (time series is non stationary). If a unit root is detected for more than one variable, we further conduct the test for cointegration through ARDL procedure to determine whether we should use Error Correction Model (ECM).

3.3.2. Autoregressive distributed lag (ARDL) model

In applied econometrics, ARDL model has been used to determine if cointegration exist between variables, that is to determine the long-run relationship between time series that are non-stationary. The cointegration methodology of ARDL was developed by Pesaran et al. (2001) for the examination of the long-run among variables on a VAR model and presents some advantages in relation to Johansen (1988) technique. The ARDL model has numerous advantages in comparison with other techniques. Firsly, irrespective of whether the underlying variables are I(0) or I(1) or a combination of both, ARDL technique can be applied. This helps to avoid the pretesting problems associated with standard cointegration analysis which requires the classification of the variables into I(0) and I(1). Secondly, the Autoregressive Distributed Lag (ARDL) approach helps in identifying the cointegrating vector(s) while other conventional cointegration techniques estimate the long run relationship using system equations, however the ARDL technique uses a single reduced form equation to simultaneously estimate the long and short run parameters of the model (Suharsono et al., 2017; Pesaran and Shin, 1999). Thirdly, ARDL is robust when there is a single long run relationship between the underlying variables in a small sample size. Lastly, the ARDL method provides unbiased estimates and valid t-statistics, irrespective of the endogeneity of some regressors. This is to say, the ARDL model is able to distinguish between the dependent and independent variable (Mobin and Masih, 2014; Adeleye et al., 2018).

Step 1: Choosing the appropriate lag length for the ARDL model

The ARDL procedure starts with the choice of the appropriate lag length for the ARDL model. The measurement of bounds on ARDL tests is sensitive in the selection of lag length. Thus, the inappropriate choice of lag length can cause biased results. So, it is necessary to obtain the exact information for series lags in order to avoid bias problem. Furthermore, the lag length for each variable in an ARDL model is important to avoid the non-normality, autocorrelation and heteroscedasticity on error terms. To determine the optimal lag in each variable for long run relationship, we use the Akaike Information Criteria (AIC), Schwarz Bayesian Criterion(SBC) or Hannan-Quinn Criterion(HQC) and sequential modified probability ratio test statistics (LR) are used (Nkoro and Uko, 2016). The values of AIC, SC, HQ and LR for model are given by:

$$AIC_P = n/2(1+\log 2\pi) - n/2log\delta^2 - p$$

$$SC_P = \log\left(\delta^2\right) + (logn/n)P$$

$$HP = \log\left(\delta\right) + (2loglogn/n)P$$

$$LR_{P,P} = n(\log[\sum P] - \log[\sum P]$$

Where δ^2 is Maximum Likelihood (ML) estimator of the variance of the regression disturbances, $\sum P$ is the estimated sum of squared residuals, and *n* is the number of estimated parameters, $p = 0,1,2,\ldots,P$ where *P* is the optimum order of the model selected. Among these four criteria, the AIC and SC are the most popular and most utilized as the model performs comparatively better with the smallest AIC, SC estimates (Nkoro and Uko, 2016).

Step 2: Determination of the existence of the long run relationship of the variables

In this second step, the existence of the long run relationship among variables is examined using as endogenous each variable of the model and exogenous the same variables. The empirical formulation of ARDL technique for cointegration is given below:

$$\begin{aligned}\Delta LFDI_t = {} & \alpha_0 + \sum_{i=1}^{n}\alpha_{1i}\Delta LFDI_{t-i} + \sum_{i=1}^{n}\alpha_{2i}\Delta LPAS2_{t-i} \\ & + \sum_{i=1}^{n}\alpha_{3i}\Delta LTPROD_{t-i} + \sum_{i=1}^{n}\alpha_{4i}\Delta LREER_{t-i} \\ & + \sum_{i=1}^{n}\alpha_{5i}\Delta LNEXP_{t-i} + \sum_{i=1}^{n}\alpha_{6i}\Delta INF_{t-i} \\ & + \gamma_1 LFDI_{t-1} + \gamma_2 LTPAS2_{t-1} + \gamma_3 LTPROD_{t-1} \\ & + \gamma_4 LREER_{t-1} + \gamma_5 NEXP_{t-1} + \gamma_6 INF_{t-1} + \theta_t\end{aligned}$$

$$\begin{aligned}\Delta LPAS2_t = {} & \alpha_0 + \sum_{i=1}^{n}\alpha_{1i}\Delta LPAS2_{t-i} + \sum_{i=1}^{n}\alpha_{2i}\Delta LFDI_{t-i} \\ & + \sum_{i=1}^{n}\alpha_{3i}\Delta LTPROD_{t-i} + \sum_{i=1}^{n}\alpha_{4i}\Delta LREER_{t-i} \\ & + \sum_{i=1}^{n}\alpha_{5i}\Delta NEXP_{t-i} + \sum_{i=1}^{n}\alpha_{6i}\Delta INF_{t-i} \\ & + \gamma_1 LPAS2_{t-1} + \gamma_2 LFDI_{t-1} + \gamma_3 LTPROD_{t-1} \\ & + \gamma_4 LREER_{t-1} + \gamma_5 NEXP_{t-1} + \gamma_6 INF_{t-1} + \theta_t\end{aligned}$$

$$\begin{aligned}\Delta LTPROD_t = {} & \alpha_0 + \sum_{i=1}^{n}\alpha_{1i}\Delta LTPROD_{t-i} + \sum_{i=1}^{n}\alpha_{2i}\Delta LPAS2_{t-i} \\ & + \sum_{i=1}^{n}\alpha_{3i}\Delta LFDI_{t-i} + \sum_{i=1}^{n}\alpha_{4i}\Delta LREER_{t-i} \\ & + \sum_{i=1}^{n}\alpha_{5i}\Delta NEXP_{t-i} + \sum_{i=1}^{n}\alpha_{6i}\Delta INF_{t-i} \\ & + \gamma_1 LTPROD_{t-1} + \gamma_2 LTPAS2_{t-1} + \gamma_3 LFDI_{t-1} \\ & + \gamma_4 LREER_{t-1} + \gamma_5 NEXP_{t-1} + \gamma_6 INF_{t-1} + \theta_t\end{aligned}$$

$$\begin{aligned}\Delta LREER_t = {} & \alpha_0 + \sum_{i=1}^{n}\alpha_{1i}\Delta LREER_{t-i} + \sum_{i=1}^{n}\alpha_{2i}\Delta LPAS2_{t-i} \\ & + \sum_{i=1}^{n}\alpha_{3i}\Delta LTPROD_{t-i} + \sum_{i=1}^{n}\alpha_{4i}\Delta LFDI_{t-i} \\ & + \sum_{i=1}^{n}\alpha_{5i}\Delta NEXP_{t-i} + \sum_{i=1}^{n}\alpha_{6i}\Delta INF_{t-i} \\ & + \gamma_1 LREER_{t-1} + \gamma_2 LTPAS2_{t-1} + \gamma_3 LTPROD_{t-1} \\ & + \gamma_4 LFDI_{t-1} + \gamma_5 NEXP_{t-1} + \gamma_6 INF_{t-1} + \theta_t\end{aligned}$$

$$\begin{aligned}\Delta NEXP_t = {} & \alpha_0 + \sum_{i=1}^{n}\alpha_{1i}\Delta NEXP_{t-i} + \sum_{i=1}^{n}\alpha_{2i}\Delta LPAS2_{t-i} \\ & + \sum_{i=1}^{n}\alpha_{3i}\Delta LTPROD_{t-i} + \sum_{i=1}^{n}\alpha_{4i}\Delta LREER_{t-i} \\ & + \sum_{i=1}^{n}\alpha_{5i}\Delta LFDI_{t-i} + \sum_{i=1}^{n}\alpha_{6i}\Delta INF_{t-i} + \gamma_1 NEXP_{t-1} \\ & + \gamma_2 LTPAS2_{t-1} + \gamma_3 LTPROD_{t-1} + \gamma_4 LREER_{t-1} \\ & + \gamma_5 LFDI_{t-1} + \gamma_6 INF_{t-1} + \theta_t\end{aligned}$$

$$\begin{aligned}\Delta INF_t = {} & \alpha_0 + \sum_{i=1}^{n}\alpha_{1i}\Delta INF_{t-i} + \sum_{i=1}^{n}\alpha_{2i}\Delta LPAS2_{t-i} \\ & + \sum_{i=1}^{n}\alpha_{3i}\Delta LTPROD_{t-i} + \sum_{i=1}^{n}\alpha_{4i}\Delta LREER_{t-i} \\ & + \sum_{i=1}^{n}\alpha_{5i}\Delta LNEXP_{t-i} + \sum_{i=1}^{n}\alpha_{6i} LFDI_{t-i} + \gamma_1 INF_{t-1} \\ & + \gamma_2 LTPAS2_{t-1} + \gamma_3 LTPROD_{t-1} + \gamma_4 LREER_{t-1} \\ & + \gamma_5 NEXP_{t-1} + \gamma_6 LFDI_{t-1} + \theta_t\end{aligned}$$

Where α_0 is the intercept; α_1–α_6 and γ_1–γ_6 are short run and long run elasticities, respectively. Of output with respect to above identified variables; θ_t is the error term; Δ is the difference operator; and *n* is the lag length.

After estimating the equations and obtaining the F-statistic, the next step is to compare the obtained F-statistic with the Upper and Lower Critical Bound (UCB, LCB) tabulated in Pesaran et al. (2001) in order to determine the existence of long run relationship among variables (cointegration). The bounds testing procedure is based on the joint F-statistics (Wald test) to determine existence of co-integration among the variables of interest. The ARDL bounds testing was done by estimating equations using the ARDL hypothesis test for model:

H_0: $\gamma_1 = \gamma_2 = \gamma_3 = \gamma_4 = \gamma_5 = \gamma_6$ (No cointegration)

H_1: $\gamma_1 \neq \gamma_2 \neq \gamma_3 \neq \gamma_4 \neq \gamma_5 \neq \gamma_6$ (Cointegration)

As such, in testing the two hypothesis, the ARDL model comprises an F-test and a set of two critical bounds (i.e. the lower and upper bound). Where I(0) denotes a lower bound whilst I(1) denotes an upper bound (Pesaran et al., 2001). The interpretation of the hypothesis states that if the calculated F-statistic is lower than the lower bound I(0) at the significance level of 5%, then the null hypothesis (H_0) is accepted and the alternative is rejected concluding that there is no existence cointegration (no long run relationship between variables). In contrast, if the calculated F-statistic is greater than the upper bound I(1) at the significance level of 5%, then the null hypothesis (H_0) of no cointegration is rejected and the alternative is accepted concluding the existence of cointegration(exixtence of long run relationship between the variables) (Habanabakize, 2016). However, if the calculated F-statistics is greater than the lower bound, but less than the upper bound at the significance level of 5%, a decision cannot be made as to the long run relationship in which case the decision is inconclusive (Pesaran et al., 2001).

Step 3: Reparameterization of ARDL model into error correction model (ECM)

In this section, we change the model's variables in initial differences to become stable in order to avoid false regression. Although the erroneous regression may be solved, the first order equation only offers a short-term link between variables. Because researchers care more about the long run relationship, cointegration and the error correction model were used to connect the short and long run relationships of the model's variables. The following is a description of an error correcting model:

$$\begin{aligned}\Delta LFDI_t = {} & \alpha_0 + \sum\nolimits_{i=1}^{n} \alpha_{1i}\Delta LFDI_{t-i} + \sum\nolimits_{i=1}^{n} \alpha_{2i}\Delta LPAS2_{t-i} \\ & + \sum\nolimits_{i=1}^{n} \alpha_{3i}\Delta LTPROD_{t-i} + \sum\nolimits_{i=1}^{n} \alpha_{4i}\Delta LREER_{t-i} \\ & + \sum\nolimits_{i=1}^{n} \alpha_{5i}\Delta NEXP_{t-i} + \sum\nolimits_{i=1}^{n} \alpha_{6i}\Delta INF_{t-i} \\ & + \omega ECT_{t-1} + \theta_t\end{aligned}$$

$$\begin{aligned}\Delta LPAS2_t = {} & \alpha_0 + \sum\nolimits_{i=1}^{n} \alpha_{1i}\Delta LPAS2_{t-i} + \sum\nolimits_{i=1}^{n} \alpha_{2i}\Delta LFDI_{t-i} \\ & + \sum\nolimits_{i=1}^{n} \alpha_{3i}\Delta LTPROD_{t-i} + \sum\nolimits_{i=1}^{n} \alpha_{4i}\Delta LREER_{t-i} \\ & + \sum\nolimits_{i=1}^{n} \alpha_{5i}\Delta NEXP_{t-i} + \sum\nolimits_{i=1}^{n} \alpha_{6i}\Delta INF_{t-i} \\ & + \omega ECT_{t-1} + \theta_t\end{aligned}$$

$$\begin{aligned}\Delta LTPROD_t = {} & \alpha_0 + \sum\nolimits_{i=1}^{n} \alpha_{1i}\Delta LTPROD_{t-i} + \sum\nolimits_{i=1}^{n} \alpha_{2i}\Delta LPAS2_{t-i} \\ & + \sum\nolimits_{i=1}^{n} \alpha_{3i}\Delta LFDI_{t-i} + \sum\nolimits_{i=1}^{n} \alpha_{4i}\Delta LREER_{t-i} \\ & + \sum\nolimits_{i=1}^{n} \alpha_{5i}\Delta NEXP_{t-i} + \sum\nolimits_{i=1}^{n} \alpha_{6i}\Delta INF_{t-i} \\ & + \omega ECT_{t-1} + \theta_t\end{aligned}$$

$$\begin{aligned}\Delta LREER_t = {} & \alpha_0 + \sum\nolimits_{i=1}^{n} \alpha_{1i}\Delta LREER_{t-i} + \sum\nolimits_{i=1}^{n} \alpha_{2i}\Delta LPAS2_{t-i} \\ & + \sum\nolimits_{i=1}^{n} \alpha_{3i}\Delta LTPROD_{t-i} + \sum\nolimits_{i=1}^{n} \alpha_{4i}\Delta LFDI_{t-i} \\ & + \sum\nolimits_{i=1}^{n} \alpha_{5i}\Delta NEXP_{t-i} + \sum\nolimits_{i=1}^{n} \alpha_{6i}\Delta INF_{t-i} \\ & + \omega ECT_{t-1} + \theta_t\end{aligned}$$

$$\begin{aligned}\Delta NEXP_t = {} & \alpha_0 + \sum\nolimits_{i=1}^{n} \alpha_{1i}\Delta NEXP_{t-i} + \sum\nolimits_{i=1}^{n} \alpha_{2i}\Delta LPAS2_{t-i} \\ & + \sum\nolimits_{i=1}^{n} \alpha_{3i}\Delta LTPROD_{t-i} + \sum\nolimits_{i=1}^{n} \alpha_{4i}\Delta LREER_{t-i} \\ & + \sum\nolimits_{i=1}^{n} \alpha_{5i}\Delta LFDI_{t-i} + \sum\nolimits_{i=1}^{n} \alpha_{6i}\Delta INF_{t-i} \\ & + \omega ECT_{t-1} + \theta_t\end{aligned}$$

$$\begin{aligned}\Delta INF_t = {} & \alpha_0 + \sum\nolimits_{i=1}^{n} \alpha_{1i}\Delta INF_{t-i} + \sum\nolimits_{i=1}^{n} \alpha_{2i}\Delta LPAS2_{t-i} \\ & + \sum\nolimits_{i=1}^{n} \alpha_{3i}\Delta LTPROD_{t-i} + \sum\nolimits_{i=1}^{n} \alpha_{4i}\Delta LREER_{t-i} \\ & + \sum\nolimits_{i=1}^{n} \alpha_{5i}\Delta NEXP_{t-i} + \sum\nolimits_{i=1}^{n} \alpha_{6i}\Delta LFDI_{t-i} \\ & + \omega ECT_{t-1} + \theta_t\end{aligned}$$

The ECM term derives from cointegration models and is referred to estimated equilibrium errors. The coefficient ω of ECM is the short run adjustment coefficient and presents the adjustment velocity from equilibrium or the correction of inequilibrium for each period. The sign of ω coefficient should be negative and statistical significant and it varies from 0 to 1. Finally, it should be mentioned that ARDL and ECM models are estimated with least squares methodology.

3.3.3. Granger causality test

The Granger Causality test was tested using the following equations:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \cdots + \alpha_l y_{t-1} + \beta_1 x_{t-1} + \cdots + \beta_l x_{-l} + \epsilon_t$$

$$x_t = a_0 + a_1 x_{t-1} + \cdots + a_l x_{t-1} + \lambda_1 y_{t-1} + \cdots + \lambda_l y_{-l} + \mu_t$$

Where it is assumed that ϵ_t and μ_t are uncorrelated White-noise error terms. α_1 to α_l and a_1 to a_l are coefficients for the lagged dependent variables and β_1 to β_l and λ_1 to λ_l are coefficients for the lagged independent variables. First for both time series, we take the maximum order of integration *(d)*; second, we select the maximum number of lags by applying the vector autoregression (VAR) lag selection technique; and third, we add the maximum order of integration (d) for both series to the lags selected by the VAR technique to obtain the total number of lags to be used while applying the Granger causality technique (Granger, 1969).

For every single equation. The null hypothesis is that *x* in the first regression does not Granger-cause y and that y in the second regression does not Granger-cause *x*. According to Ullrich (2009), the Granger causality test for two stationary variables can be performed to test for the following hypothesis:

H_0: $\beta_1 = \cdots \ldots\ldots = \beta_l$ and indicates x_t does not Granger cause y_t

H_0: $\lambda_1 = \cdots \ldots\ldots = \lambda_l$ and indicates y_t does not Granger cause x_t

When the probability value is <5% significant level, it is significant, then the null hypothesis" x_t does not Granger cause y_t " is rejected and it is concluded in the study that x_t does granger cause y_t. However, if the probability value above the 5% significant level is insignificant, implying that the null hypothesis" x_t does not Granger cause y_t " cannot be rejected and it is concluded that x_t does not Granger cause y_t.

3.3.4. Diagnostic and stability test

Both diagnostics tests and stability coefficients testing should be done to check that the estimated model is accurately stated and may be utilized for forecasting. Model specification, non-normality, autocorrelation, and heteroscedasticity are all examined using diagnostic tests. Brown et al. (1975) advised that stability tests be conducted using the cumulative sum of recursive residuals (CUSUM) and the cumulative sum of square recursive residuals (CUSUMSQ). The null hypothesis that all coefficients on the regression model are stable cannot be rejected if the plots of CUSUM and CUSUMSQ are within the critical boundaries at the 5% level of significance. Pesaran and Pesaran (1997) recommend using the cumulative sum of recursive residuals (CUSUM) and the cumulative sum of square recursive residuals (CUSUMSQ) to check for parameter stability while estimating the error correction model of ARDL limits.

4. EMPIRICAL RESULTS AND DISCUSSION

4.1. Unit Root Test

Before employing ARDL bounds testing, this paper examines variable stationarity in order to determine their integration order. The results of these unit root tests are presented on Table 1.

Results of unit root test in Table 1 show that foreign direct investment inflow in agriculture (LFDI) and inflation rate (INF) were stationary in level as reflected by the rejection of the null hypothesis with intercept for LFDI at 10% significance level, and with intercept for INF at 5% significance level. While series total agriculture (LTPROD), public agriculture spending (LPAS2), real effective exchange rate(LREER) and net export (NEXP) were not stationary at level as reflected by the non-rejection of the null hypothesis, but became stationary at I(1) after being differenced as reflected by the rejection of the null hypothesis. The conclusion of unit root test revealed that variables LFDI and INF are integrated in order zero I (0), while LTPROD, LPAS, LREER and NEXP are integrated in order one (I(1)). Because some variables are I(0) while others are I(1), the next step is to determine the optimal lag length criteria.

4.2. ARDL Results Process

4.2.1. Optimal lag length criteria

The selection of the optimal lag length criteria is very important in ARDL technique.

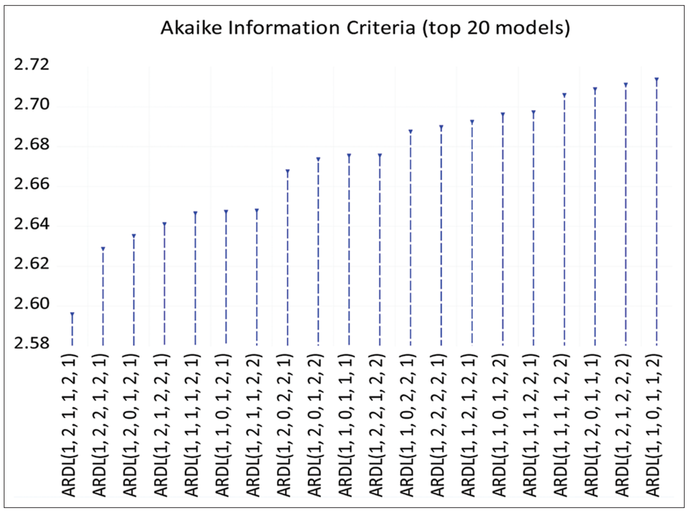
Pesaran and Shin (1999) suggested that the model with smaller estimates under criteria is the optimal model. For the purpose of this study, the automatic selection was used based on trend

Table 1: Unit root test results

Variables	Augmented Dickey-Fuller test (ADF)												Order of integration
	Level						1st difference						
	Intercept		Trend and intercept		None		Intercept		Trend and intercept		None		
	t-stat	P-value	t-stat	P-value	t-stat	P-value	t-stat	P-value	t-stat	P-value	t-stat	P-value	
LTPROD	−2.11	0.24	−2.25	0.211	0.98	0.90	−6.34***	0.000	−6.19***	0.000	−6.26***	0.00	I (1)
LPAS2	−1.10	0.16	−3.12	0.53	12.18	1.00	−5.94***	0.007	−4.67***	0.004	−0.82	0.34	I (1)
LFDI	−2.83*	0.064	−4.09**	0.016	0.40	0.79							I (0)
LREER	−1.54	0.498	−3.05	0.155	−1.124	0.230	−4.74**	0.000	−4.68***	0.000	−4.62***	0.00	I (1)
NEXP	−1.26	0.63	−1.14	0.90	−1.06	0.25	−6.80	0.000	−6.76	0.000	−6.83	0.000	I (1)
INF	−3.8***	0.00	−4.02**	0.02	−2.15**	0.03							I (0)
Phillip Perron test (PP)													
LTPROD	−1.97	0.29	−1.25	0.211	0.43	0.801	−13.56***	0.000	−13.31***	0.000	−8.69***	0.000	I (1)
LPAS2	−1.08	0.54	−2.51	0.96	1.45	0.75	−6.26***	0.002	−6.11***	0.001	−5.16***	0.000	I (1)
LFDI	−2.63*	0.097	−4.11**	0.016	0.07	0.69							I (0)
LREER	−1.283	0.623	−2.300	0.420	−1.28	0.219	−4.91***	0.000	−5.536***	0.000	−4.589***	0.000	I (1)
NEXP	−1.72	0.41	−2.41	0.36	−1.07	0.24	−6.41***	0.000	−8.51***	0.000	−5.46***	0.000	I (1)
INF	−3.4**	0.03	−3.87**	0.02	−2.28**	0.02							I (0)

(***) The rejection of the null hypothesis of not stationary at the 1% significance level. (**) The rejection of the null hypothesis of not stationary at the 5% significance level. (*) The rejection of the null hypothesis of not stationary at the 10% significance level specification constant and on AIC by alternating the lags of the variables. The model with the smallest AIC or SC estimated performd relatively better. For the ARDL model, AIC was found to be the best to minimizes information for all equations with lag 1 for the dependent variable and lag 2 for the independent variable as presented in Table 2. In conclusion, the AIC lags of (1,2,1,1,2,1) is selected for the ARDL model as specified in Figure 1 and will be applied to the following bounds test and its accompanying ECMs results.

Figure 1: ARDL model selection results



Source: Author's own calculations, data from the study data

The next step is to check if there is possibility to have a long run relationship between variables under conditions stated in chapter four using ARDL bound cointegration test.

4.2.2. Results of Bounds test for cointegration

The results for the ARDL bounds test are disclosed in Table 3 and report the results of the calculated F-statistics when each variable is considered as dependent variable in the ARDL model.

The results for the ARDL bounds test model are disclosed in Table 3 which show that there is only an existence of a long run relationship between foreign direct investment in agriculture, total production, public agricultural spending, real effective exchange rate, net export and inflation rate in South Africa when regression is normalised in foreign direct investment inflow as dependent variables. After confirming the existence of a long run relationship among the variables, the next step is to estimate the long run relationship between variables.

The results of the long run estimation is presented in Table 4, which determine the crowding-in or crowding-out effect between public agricultural spending and foreign direct investment inflows.

The results reported in Table 4 show that public agriculture spending in agriculture has an negative effect on foreign direct investment inflow in agriculture in the long run. This implies that there is a crowding out effect of public agricultural spending on foreign direct investment inflow. The coefficient

Table 2: ARDL model selection

Equation	Max lags	AIC*	SIC	HQC	R2	Best choice
LFDI	1,2	ARDL (1,2,1,1,2,1)	ARDL (1,1,0,1,1,1)	ARDL (1,2,1,1,2,1)	ARDL (1,0,1,2,0,0)	AIC
LPAS2	1,2	ARDL (1,2,1,2,2,2)	ARDL (1,1,1,0,2,0)	ARDL (1,1,1,0,2,0)	ARDL (1,2,1,2,2,2)	AIC
LTPROD	1,2	ARDL (1,0,0,0,0,2)	ARDL (1,0,0,0,0,0)	ARDL (1,0,0,0,0,0)	ARDL (1,0,0,0,0,2)	AIC
LREER	1,2	ARDL (1,0,0,1,1,1)	ARDL (1,1,0,0,0,1)	ARDL (1,0,0,1,1,1)	ARDL (1,0,0,1,1,1)	AIC
NEXP	1,2	ARDL (1,0,0,1,0,1)	ARDL (1,0,0,1,0,0)	ARDL (1,0,0,1,0,0)	ARDL (1,0,0,1,0,1)	AIC
INF	1,2	ARDL (1,2,0,2,2,1)	ARDL (1,0,0,0,2,0)	ARDL (1,2,0,0,2,0)	ARDL (1,2,0,2,2,1)	AIC

Note: *Denote the criteria that minimizes the information criteria

Table 3: ARDL bounds cointegration test results for model

Dependent variable	independent variables	lag	AIC/automatic selection with constant	F-statistic	Cointegration
LFDI	LPAS2 LTPROD LREER NEXP INF	(1,2)	(1,2,1,1,2,1)	F_{LFDI}=9.30	Yes
LPAS2	LFDI LTPROD LREER NEXP INF	(1,2)	(1,2,1,2,2,2)	F_{LPAS2}=2.35	No
LTPROD	LFDI LPAS2 LREER NEXP INF	(1,2)	(1,0,0,0,0,2)	F_{LTPROD}=3.40	No
LREER	LFDI LTPROD LPAS2 NEXP INF	(1,2)	(1,0,0,1,1,1)	F_{LREER}=3.19	No
NEXP	LFDI LTPROD LPAS2 LREER INF	(1,2)	(1,0,0,1,0,1)	F_{NEXP}=2.13	No
INF	LFDI LTPROD LPAS2 LREER NEXP	(1,2)	(1,2,0,2,2,1)	F_{INF}=1.85	No

Critical value bounds			
Significance	I (0) Bound	I (1) Bound	Null hypothesis: Decision
10%	2.26	3.35	Reject
5%	2.62	3.79	Reject
2.5%	2.96	4.18	Reject
1%	3.41	4.68	Reject

Source: Author's own calculations using E-views 10.1

of −2.119 of public agricultural spending suggests that 1% increase of public agricultural spending leads to a decrease on foreign direct investment inflow by 2.119%, other things held constant. This results are supported by Awunyo-Vitor and Sackey (2018) and Akinwale et al. (2018) who found a negative relationship between public investment and foreign direct investment inflow in agriculture in Ghana and Nigeria respectively.

Furthermore, results show that level of agriculture production has a positive and significant effect on foreign direct investment inflow. This implies that a 1% increase in agricultural production will lead to an increase in foreign direct investment inflow by approximately 5.63%, other things remain constant. Results revealed that net export is negatively associated with foreign direct investment inflow in agriculture in South Africa in the long run. The negative coefficient of 1.265 implies that 1% increase in net export will decrease foreign direct investment inflow by approximately 1.265%, other things remain constant. Results from the long run ARDL revealed that the coefficient of inflation rate is negatively significant to predict agricultural production. The negative coefficient of −0.155 implies that 1% increase in inflation will lead to a decrease foreign direct investment inflow by approximately 0.15%, other things remains constant. Based on the results, public agriculture spending crowding –out foreign direct investment inflow while agriculture production crowding-in foreign direct investment inflow.

4.2.3. Short run estimation result of ARDL model (ECM)

This section reports the short-run dynamic parameters obtained from ECM, after the long-run impacts have been determined by the bound test in the preceding section. The coefficient of adjustment that measures the speed of adjustment in foreign direct investment inflow (LFDI) following a shock is an important parameter in the estimation of ARDL model as shown in Table 5.

The ECT lagged by one period coefficient is −0.927 and is significant at 1% significance level, and therefore meets our expectation. This indicates a high speed of adjustment to equilibrium after a shock and indicates that that around 92.7% of any previous disequilibrium between the foreign direct investment inflow (LFDI) and independent variables is re-established back to long-run equilibrium within 1 year.

4.3. Granger Causality Results

The Granger causality test was performed to determine whether two variables cause changes in each other. The null hypothesis states that there was no causality. Table 6 indicates results of Granger causality test.

The Granger causality results revealed that unidirectional Granger causality exists from public agricultural spending to foreign direct investment inflows and supported by Azolibe (2021) who found that capital expenditure Granger caused FDI in Nigeria. In addition, results showed that net export Granger caused FDI in Ghana but not a reverse (Djokoto, 2012). Finally, there is unidirectional Granger causality from inflation to FDI inflows

Table 4: Long run estimates for ARDL model on LFDI

Dependent variable	LTFDI			
Variable	**Coefficient**	**Standard Error**	**t-Statistic**	**Probability**
LPAS2	−2.119	0.641	−3.304	0.0057
LTPROD	5.636	2.805	2.009	0.065
LREER	−2.052	1.613	−1.272	0.225
NEXP	−1.265	0.275	−4.601	0.0005
INF	−0.155	0.0635	−2.441	0.0297
C	−81.268	68.362	−1.761	0.2533

Source: Author's own calculations using E-views 10.1

Table 5: ECM and short run results for ARDL model on LFDI

Cointegrating form ARDL model (1,2,1,1,2,1)				
Dependent variable	**D (LFDI)**			
Variable	**Coefficient**	**Standard error**	**t-statistic**	**Probability**
D (LFDI(-1))	−0.471***	0.148	−3.171	0.0089
D (LPAS2)	−3.933*	1.858	−2.116	0.0579
D (LPAS2(−1))	0.694	0.883	0.786	0.4483
D (LPAS2(−2))	2.320**	0.917	2.529	0.0280
D (LTPROD)	3.543*	1.618	2.188	0.0511
D (LTPROD(−1))	4.320*	2.245	1.923	0.0807
D (LREER)	0.698	2.432	0.287	0.7793
D (LREER(−1))	−4.004	3.160	−1.266	0.2314
D (NEXP)	−0.099	0.329	−0.301	0.7686
D (NEXP(−1))	−0.720***	0.206	−3.495	0.005
D (NEXP(−2))	−0.300	0.285	−1.050	0.3159
D (INF)	0.0170	0.111	0.153	0.8811
D (INF(−1))	−0.2039	0.125	−1.622	0.1330
CointEq(−1)	−0.927***	0.338	−2.740	0.0019

Note: * Significant at 10%, (**) significant at 5% and (***) significant at 1%. Source: Author's own calculations using E-views 10.1

Table 6: Pairwise granger causality test results for ARDL model

Null hypothesis	Chi-square	Prob.	Conclusion
LPAS2 does not Granger cause LFDI	4.997	0.023*	Causality
LFDI does not Granger cause LPAS2	0.089	0.956	No causality
LTPROD does not Granger cause LFDI	2.730	0.255	No causality
LFDI does not Granger cause LTPROD	0.427	0.807	No causality
LREER does not Granger cause LFDI	3.235	0.198	No causality
LFDI does not Granger cause LREER	1.864	0.393	No causality
NEXP does not Granger cause LFDI	4.840	0.012*	Causality
LFDI does not Granger cause NEXP	0.381	0.826	No causality
INF does not Granger cause LFDI	5.520	0.043*	Causality
LFDI does not Granger cause INF	1.790	0.408	No causality

(**) denote statistical significance at 5% and (*) denote statistical significance at 10%. D stands for change in the variables of the study. Source: Own calculation using E-views 10.1

Table 7: Diagnostic test results

Test	Null hypothesis	Probability	Conclusion
Langrage Multiplier (LM)	No serial correlation	0.377	No serial correlation
Jarque –Bera (JB)	There is a normal distribution	0.754	Residual are normally distributed
White (Chi-sq)	There is no heteroscedasticity	0.957	No heteroscedasticity

Source: Own calculation using E-views 10.1

Figure 2: Stability diagnostic test results (CUSUM)

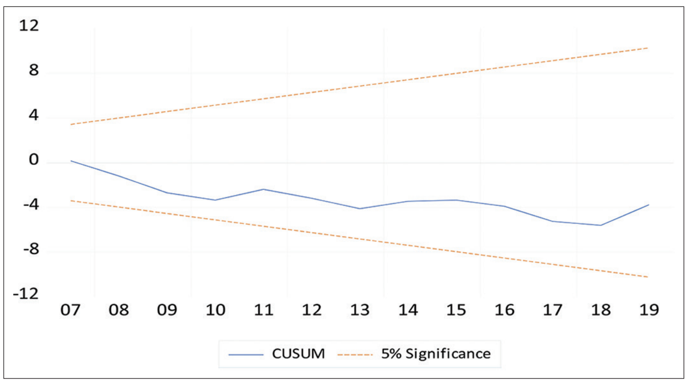
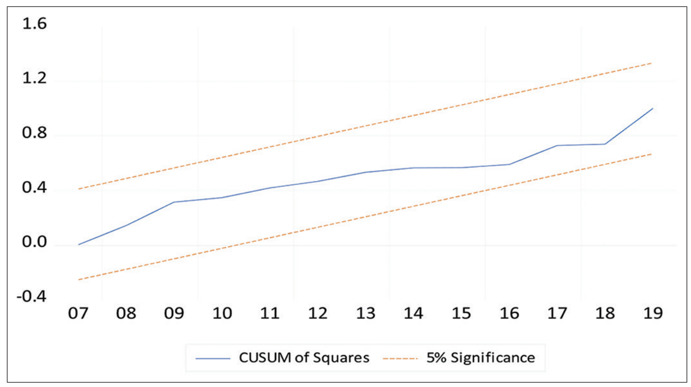


Figure 3: Stability diagnostic test results (CUSUMQ



as revealed also by Kwarbai et al. (2016) in selected African countries.

4.4. Diagnostic and Stability Test Results

4.4.1. Diagnostic test results

Table 7 presents results of the residual diagnostic to comply with the assumptions of the Classical Linear Regression Model (CLRM).

The null hypothesis for the Lagranger multiplier(LM) serial correlation test is no serial correlation, while the null hypothesis for the Jarque-Bera(JB) normality test is normal distribution. The null hypothesis of the White heteroscedasticity test is homoscedasticity. Thus, Table 7 shows that variables in the ARDL model are normally distributed, are unsusceptible to serial correlation and are homoscedastic. This means that none of the aforementioned null hypotheses are rejected, which implies that the bound test, the ECM results and the Granger causality results for the ARDL model are accurate and not misleading.

4.4.2. Stability test results

The results of the CUSUM and the cumulative sum of squared recursive residuals (CUSUMQ) on the ARDL model are shown in Figures 2 and 3. The outside crucial lines are shown at a 5% level of significance, whereas the blue (crooked) lines represent CUSUM and CUSUMQ statistics. Therefore, it can be deduced that there is no instability of residuals as the CUSUM and CUSUMQ statistics lines remain inside the lines of stability.

5. CONCLUSION AND POLICY RECOMMENDATIONS

This paper investigates the effect of public agriculture spending on foreign direct investment inflows in South Africa for the period 1991-2019. The study was motivated by the broad increasing disagreement in developing countries on whether public agriculture spending crowd-in foreign direct investment or vice-versa to increase agricultural production and preserve its competitiveness and sustainability. By doing this, South Africa government will understand how best public agricultural spending and foreign direct investment can be complemented or substituted and shift priorities and focus more on areas that increase agriculture production. The paper discussed the theoretical literature on the relative importance of public investment on private investment. Furthermore, the paper reviewed the empirical literature of public agricultural spending on foreign direct investment inflows in agriculture.

To investigate the effect of public agricultural spending on foreign direct investment inflows in agriculture, this paper applied time series data from the period of 1991 to 2019 using the ARDL model. In addition, Granger causality, diagnostic and stability test were carried on to confirm the quality and stability of the model. Results from the ARDL long run revealed that public agriculture spending, net export and inflation rate crowd-out (negative relationship) foreign direct investment inflow, while total production crowd-in (positive relationship) foreign direct investment inflow in agriculture. Furthermore, a Granger causality revealed that there is unidirectional relationship from public agricultural spending to FDI inflows, from net export to FDI inflows and from inflation rate to FDI inflows. This indicates that public agricultural spending cannot singularly be used to predictFDI inflow in agriculture.

Based on the results, the study recommended that in order to attract more foreign direct investment inflows in agriculture, the government of South Africa should start adopting a pragmatic approach toward reducing the huge recurrent expenditure and cost of governance in favour of capital expenditure for sustainable agriculture through an inter-ministerial collaboration and synchronization of spending in rural road (Department of transport), spending in health(Department of health), spending in training and education (Department of basic and high education) in order to expect better return in agriculture production. In addition, local government must be associated to the contribution formerly made by farmers (housing, infrastructure and services) in order to keep more permanent workers in the farm.

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