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Effects of Agricultural Investments on Poverty in Rural Areas of Congo

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Abstract

This paper analyzes the effects of agricultural investment on poverty in rural areas Congo over the period 1989 to 2019, focusing on a monetary approach (income or consumption expenditure). The results obtained from this study through the Autoregressive Lagged Model (ARDL) showed that agricultural investment has a positive and significant influence on poverty in the short and long term in Congo. As in most developing countries, the majority of the population lives in rural areas, and derives its income from agricultural activities. For this reason, the development of agricultural investment could be one of the essential ways of eradicating poverty in rural areas.

Keywords

Investment, Agriculture, Poverty and Congo

1. Introduction

According to the context of poverty reduction in rural areas, many initiatives are regularly implemented by international organizations. Poverty in rural areas accounts for 63% of global poverty, reaching 90% in countries such as Bangladesh, 65% in Africa, and in the Congo, extreme poverty has risen from 51.9% of the population in 2020 to 53.9% (WB, 2021).

Thus, developing countries are still the places with the highest rates of poverty and income inequality. Extreme poverty remains the lot of around 767 million people, approximately two-thirds of whom live in rural areas, mainly in sub-Saharan Africa and South Asia (FAO, 2018). Schultz observed: "The majority of the world's poor derive their income from agriculture, so studying the agricultural economy would provide us with a great deal of information about the economics of poverty".

Today, poverty has a multidimensional character, highlighted in particular by the work of Sen (1998). Poverty is no longer linked solely to the insufficiency of resources (natural, financial, immaterial, etc.) or to the unsatisfaction of basic needs experienced by individuals, but also covers sociological, political, psychological and cultural aspects.

It is manifested essentially by the monetary and non-monetary approaches.

The monetary approach denotes the weakness or absence of an income (Dubois, 1999). The non-monetary approach, on the other hand, manifests itself in precarious housing, poor health, under-education, undernourishment or a degraded environment (Sen 1998).

The eradication of extreme poverty worldwide is one of the major thrusts of the Sustainable Development Goals (SDGs). There are several channels through which we can support the improvement of living conditions for rural populations, such as investment in farm tracks, in agriculture, in the provision of fertilizers and so on.

In the context of this work, we are going to focus specifically on agricultural investments, because we believe that poverty reduction in rural areas of the Congo starts with agriculture, given the high percentage of people facing food insecurity. Indeed, according to a detailed 2017 World Bank report on poverty in the Congo in rural areas, this rose from 64.8% to 69.4% between 2014 and 2016.

In 2013, 14.2% of Congolese households were recorded as being food insecure. Poverty affects around 46% of the population, mainly in rural areas (57.4%). (Source: PNIASAN 2017-2021). Congolese agricultural production, characterized by low productivity and insufficient income for producers, cannot meet the needs of a growing rural population.

However, the relationship between agricultural investment and poverty reduction in rural areas has always been the subject of attention by researchers, both theoretically and empirically. On the one hand, there are researchers who believe that agricultural investment has a positive influence on poverty in rural areas, and on the other, those who believe that it has a negative influence.

Indeed, the idea that agricultural investment positively impacts poverty in rural areas defended by Lawrence & Thirtle (2001); Ravallion et al. (2004); Ma, Abdulai, & Ma, 2018; Twumasi, Jiang, & Acheampong, (2018); Twumasi, Jiang, & Danquah, 2019 is beaten to the punch by other authors such as Adams & Von Pischke, (1992); (Annim, Dasmani, & Armah, 2011). The latter believe that there is a negative relationship between agricultural investment and poverty reduction in rural areas. These two approaches also find empirical support through the work of Akinkunmi (2017); Diamoutene (2018); Henry et al. (2018) who establish a positive link between agricultural investment and poverty reduction in rural areas. In contrast, the work of Grootaert (1996, 2018); Kanbur (1990); Kouako et al. (2017); Saliga & Alinsato, (2021) establish a negative link between the two variables.

Rural living conditions imply appropriate financing needs as savings are scarce or even non-existent in these areas. Agriculture is also seen as an effective means of reducing poverty, as it enables many farmers to ensure their food security.

Our study therefore sets out to analyze the effects of agricultural investment on poverty in rural Congo.

This leads us to support the hypothesis that agricultural investments improve the living conditions of populations in rural Congo.

This paper is structured in five sections: introduction; literature review, methodology, results and discussion; conclusion and economic policy implications.

2. Literature Review

The debate of agriculture is very old and still occupies a crucial place in economic literature. However, the question of agricultural investment on poverty remains a subject for reflection. Our work attempts to identify the various theories and empirical studies carried out on the relationship between agricultural investment and poverty

2.1. Theoretical Review

This sub-section presents the approach supporting a positive relationship between agricultural investment and poverty reduction in rural areas, and that supporting a negative relationship between these two variables of interest.

2.1.1. Positive Relationship between Agricultural Investment and Rural Poverty Reduction

Lawrence & Thirtle (2001) theorizes that growth in the agricultural sector, particularly productivity growth, plays an important role in achieving pro-poor growth. Improved agricultural yields lead to higher incomes. Higher income levels, in turn, reduce poverty levels and improve well-being in rural farming households.

In the same vein, Ravallion et al. (2004) defend the point of view outlined above, indicating that income growth is one of the most effective strategies for reducing poverty.

Indeed, Agriculture remains a strategic sector due to its importance linked to poverty reduction, the fight against social inequalities, income redistribution and food security (Badouin, 1971; Mellor 1976, Griffith 1999; Thirtle et al. 2003; Thiam 2020).

Twumasi, Jiang, & Danquah, 2019 have also shown that access to credit improves investment in production activities by liquidity-constrained households by giving them several alternative means of meeting planned expenditure. Credit availability improves productivity (Ma, Abdulai, & Ma, 2018; Twumasi, Jiang, & Acheampong, 2018).

Access to credit improves agricultural productivity (Twumasi, Jiang, & Acheampong, 2018). In this way, farmers can improve their purchasing power, enabling them to optimize the use of inputs and the financing of operating expenses. By providing farmers with additional funds, they free up financing capacity.

Henry et al. (2018), analyzes the effect of access to input credit on the performance of beneficiary farms located in the Banza-Ngungu territory in the DRC The results further argue that access to input credit improves the production, profitability and productivity of beneficiary farms.

However, this issue is still being addressed in the study by Lilala et al. (2019), which assesses the impact of agricultural projects co-financed by development aid partners on the poverty of beneficiary households in the DRC's Isangi territory (Tshopo province). While these investments improved the income of households in the Isangi territory, they had very little impact on the socio-economic and human conditions of households.

There are other channels through which road infrastructure contributes to agricultural productivity (Fan et al., 2000; Lilala 2019). Investment in rural roads leads to the expansion and improvement of the rural road network (density), which reduces transport and transaction costs and facilitates market access for inputs and production. This reduces input prices and improves producer prices, and therefore rural incomes.

2.1.2. Negative Relationship between Agricultural Investment and Poverty Reduction in Rural Areas

Taking the opposite view, other authors insist on the negative impact of agricultural investment on poverty reduction in rural areas. The reality of agricultural investment manifests itself negatively in the fact that there is constant soil degradation, often correlated with low levels of employment and income, as can be seen in the work that follows.

For Kouako et al. (2017), agricultural growth in Congo is not yet solving the problem of poverty, as agriculture's share of GDP is so low that the poverty rate is high. In a study carried out in Ethiopia, Abebaw & Haile (2013) found that the investment that promoted the adoption of improved maize seed had a positive but insignificant impact on farmers' incomes.

Despite the benefits of agricultural credit for rural households and the efforts of national governments and policymakers, many researchers have argued that access to credit adds no value to household welfare or agricultural productivity (Adams & Von Pischke, 1992; Annim, Dasmani, & Armah, 2011).

The same conclusions emerge from studies by Cuong et al. (2007), Mahjabeen (2008) and Aziz & Lilti (2017) on Vietnam and Bangladesh respectively. At the end of their work, these authors conclude that credit access measures in favor of the rural poor had induced a negligible drop in the poverty rate.

Similarly, Ulrich Kamdem, (2019) work on Cameroon shows that credit does not significantly combat monetary poverty and that the liquidity of the system does not benefit everyone, especially the poor.

2.2. Empirical Review

Empirical work on the relationship between agricultural investment and poverty reduction in rural areas is structured around two axes. On the first axis, we note the work of authors who support a positive link between agricultural investment and the second axis, the work of those who support a negative relationship between these two variables of interest.

2.2.1. Positive Relationship between Agricultural Investment and Poverty Reduction in Rural Areas

Without constraint on the method used to measure productivity, several empirical works have shown that increasing agricultural productivity is a sine qua non condition for poverty reduction (Griffith, 1999; Thirtle et al., 2003, Jayne et al., 2017).

Diamoutene (2018) uses the Endogeneity Switching Regression (ESR) method and adopted the one-step Maximum Likelihood Method (MLM) estimation method. The results reveal, on the one hand, that credit has a positive effect on rice productivity, obtaining an elasticity of 0.16. On the other hand, they also highlight that, compared with informal credit, formal credit increases rice productivity by 10%. The positive effect of credit is justified by the fact that it is mainly intended for the purchase of agricultural fertilizer, and therefore contributes in some small way to increasing household income. In the same vein, Henry et al. (2018) analyze the average effect of access to input credit on the agricultural performance of treated beneficiaries in the DRC (Average Treatment Effect on Treated - ATT). ATT is calculated by comparing the variables of interest (gross margin, total production, land productivity and labor productivity) of two groups conditionally on propensity scores. To ensure that the conditional independence hypothesis is verified, four matching methods are applied: Nearest Neighbor Matching, Kernel Matching, Radius Matching and Stratification Matching.

The results show that access to input credit has a positive impact on all the performance indicators of the market garden farms under study. Indeed, the results reveal that the average effect of access to input credit on the gross margin of beneficiary farms is of the order of $661.25 (1% threshold) under the nearest neighbor method, $661.25 (1 percent threshold) under the radius function matching method and $586.07 (1% threshold), under the method based on the Kernel function. It can be seen that this impact lies in the interval between $586.07 and $661.25. As the ATT values obtained are close, we can confirm the hypothesis of conditional independence. Overall, these results suggest that access to input credit improves the profitability of market gardeners, and are in line with some empirical studies that have demonstrated the positive effect of credit on agricultural profitability.

These results are in line with studies that have shown that participation in the credit market has a positive and statistically significant effect on agricultural production, efficiency, productivity and profitability.

However, according to Lilala (2019), the evaluation of the impact of agricultural projects co-financed by development aid partners on the poverty of beneficiary households in Isangi territory in the DRC (Tshopo province) using the two-phase simple sampling method the sample size was the same for the different survey periods, *i.e.* 470 each including 235 beneficiary and 235 non-beneficiary households. The following analyses were carried out: univariate analysis of qualitative variables (frequency distribution, median, mean and standard deviation), bivariate analysis (Chi-square). At the end of the survey, the results showed that the agricultural projects carried out in the Isangi territory had contributed to a 22.9% increase in household income in the Isangi territory, and had slightly and partially improved the socio-economic and human conditions of beneficiary households.

Akinkunmi (2017) examined the influence of access to credit on agricultural production in Sub-Saharan Africa. The nature and availability of the panel data set forced the study to analyze its objective using a Panel Co-integration approach. The analysis was carried out for 21 African countries, over the period 2000-2014. The results showed evidence of a long-term relationship between agricultural production and total credit. Estimation results significantly underlined the positive influence of total credit on agricultural production and household income levels in the sub-region.

A number of studies on poverty highlight the role of investment.

The inability of agricultural investment to reduce poverty and improve living standards has often been well documented in theory and tends to become a slogan. However, empirical evidence generally remains scarce or non-existent.

2.2.2. Negative Relationship between Agricultural Investment and Poverty Reduction in Rural Areas

Grootaert (1996, 2018), following the example of Kanbur (1990), used a decomposed index to examine the effect of economic policy measures on poverty variation. Using data from the Cote d'Ivoire Living Standard Study, he shows that the incidence of poverty did not change over the 1985-86 period, but increased sharply in rural areas over the 1987-88 period. A more recent study has attempted to delineate the profile of poverty in Côte d'Ivoire. Based on the results of household surveys carried out in 1985-88, 1993-95 and 1998, it shows that poverty in rural Côte d'Ivoire has worsened considerably, despite the agricultural investments made.

In the same vein, empirical work, in particular that of Kouako et al. (2017) After analysis of the results using the Error Correction Model, the data for the study period runs from 1982 to 2015. The results show that agricultural policy in Congo has a negative impact on poverty. Indeed, the elasticity of agricultural productivity is significant and negative. However, despite these significant investments in rural agriculture, poverty is still persistent.

Saliga & Alinsato (2021) obtained the estimation results of the Logit regression model performed using EMICOV 2015 data revealed that poverty and food insecurity remains a reality that compromises farming households in the Borgou department of Benin Despite several programs have been designed by institutions to ensure food security living conditions of populations.

2.3. Lessons from the Literature Review

At the end of these debates on poverty, we note quasi-divergent results on the theoretical and empirical levels. On the theoretical level, several works have been developed, but for the purposes of our study, we rely on the approach of Thirtle et al. (2003), who emphasize that agriculture is a strategic sector in terms of its importance in reducing poverty, combating social inequalities and redistributing income.

Empirically speaking, a large number of studies have been carried out using a wide variety of methods to verify the effect of agricultural investment on poverty, and the results are far-reaching. These results vary from study to study. As such, our review draws on Akinkunmi's (2017) empirical approach to the influence of access to credit on agricultural production in Sub-Saharan Africa.

3. Methodology

In order to achieve the objective pursued in this work, we will use an econometric approach inspired by the poverty equation of Gomane (2003), which will be carried out in an autoregressive staggered lag model (ARDL). Given that not all the variables used in this work are integrated of the same order, the use of the autoregressive staggered lag model (ARDL) as an estimation technique is therefore econometrically validated.

3.1. Theoretical Model

The endogenous growth model takes into account the fact that public action can increase the economy's productivity.

Endogenous growth economists believe that there is a causal relationship between agricultural productivity and food insecurity, as a rise in productivity can, in theory, increase both producers' income and consumers' purchasing power (Barro, 1990), thanks to the unitary control of production costs. We believe that public investment in agriculture has an effect on poverty.

3.2. Empirical Model

The poverty equation used is inspired by that of Gomane et al. (2003), whose poverty level is a functional model of the form:

$$\mathrm{NP} = \mathrm{f}\left(\mathrm{Y};\mathrm{G};\mathrm{A}\right) \tag{1}$$

with: Y: GDP per capita; G: government expenditure; A: foreign aid.

This equation was also specified by Dazoué et al. (2015) in their work on official development assistance (ODA), through which they introduce into the model the variable public investment (INVpu), which is none other than government spending, whose equation is as follows:

$$\mathrm{NP} = \mathrm{f}\left(\mathrm{ODA}, \mathrm{GDP/capita}, \mathrm{INVpu}\right) \tag{2}$$

The work of Arndt et al. (2015) uses the same model, introducing the infant mortality rate variable as an important indicator of health-related poverty, from which they arrive at the following specification:

$$\mathrm{NP} = \mathrm{f}\left(\mathrm{ODA}, \mathrm{GDP/capita}, \mathrm{INVpu}, \mathrm{Tmi}\right) \tag{3}$$

This equation has also been re-specified by Lee Tobin (2015), who addresses the same question by introducing government effectiveness and corruption as indicators of governance, and presented as follows:

$$\mathrm{NP} = \mathrm{f}\left(\mathrm{ODA}, \mathrm{GDP/capita}, \mathrm{INVpu}, \mathrm{Tmi}, \mathrm{Gou}\right) \tag{4}$$

Furthermore, Mahembe (2019) resorts to this specification by introducing the poverty rate variable (Poor_t) to assess the level of poverty through the following equation:

$$\mathrm{NP} = \mathrm{Poor}_t = \mathrm{f}\left(\mathrm{ODA}, \mathrm{GDP/capita}, \mathrm{INVpu}, \mathrm{Tmi}, \mathrm{Gou}\right) \tag{5}$$

Similarly, this associated poverty equation used to address the issue of governance through the political regime (Gouv) while taking into account public investment (INVpu) explained by final government consumption (Cpu) gives us the following equation in the remainder of the study:

$$\mathrm{Poor}_t = \mathrm{f}\left(\mathrm{APD}_t, \mathrm{PIB/hab}_t, \mathrm{Cpu}_t, \mathrm{Tmi}_t, \mathrm{Gouv}_t\right) \tag{6}$$

This equation , adding the variable unemployment rate (Tch) gives as:

$$\mathrm{Poor}_t = \mathrm{f}\left(\mathrm{APD}_t, \mathrm{PIB/hab}_t, \mathrm{Cpu}_t, \mathrm{Tmi}_t, \mathrm{Gouv}_t, \mathrm{Tch}_t\right) \tag{7}$$

Similarly, Adebayo (2020), Elakkad & Hussein (2021) use internal savings (Epa), a key variable in Big Push theory (Rosenstein-Rodan, 1943), as a variable to assess the influence of ODA in an economy via the following equation:

$$\mathrm{Poor}_t = \mathrm{f}\left(\mathrm{APD}_t, \mathrm{PIB/hab}_t, \mathrm{Cpu}_t, \mathrm{Epa}_t, \mathrm{Tmi}_t, \mathrm{Tch}_t, \mathrm{Gouv}_t\right) \tag{8}$$

Assuming a linear relationship between the dependent variable and the independent variables in the model, we can write this model in the following form:

$$\begin{aligned}\mathrm{Poor}_t = {} & \beta_0 + \beta_1 \mathrm{ADP}_t + \beta_2 \mathrm{GDP/capita}_t + \beta_3 \mathrm{cpu}_t + \beta_4 \mathrm{Epa}_t + \beta_5 \mathrm{Tmi}_t \\ & + \beta_6 \mathrm{Tch}_t + \beta_7 \mathrm{Gouv}_t + \mu_t\end{aligned} \tag{9}$$

Thus, in the context of our work, this model can be re-specified as follows:

$$\mathrm{TP}_t = \beta_0 + \beta_1 \mathrm{FBCA}_t + \beta_2 \mathrm{PIBH}_t + \beta_3 \mathrm{ADP}_t + \beta_4 \mathrm{IPC}_t + \mu_t \tag{10}$$

where β_0 is the constant term or intercept; β_1, β_2, β_3, β_4 represent the coefficients of the exogenous variables; μ_t represents the random disturbances. It is possible that there are other variables that could explain poverty reduction. But in the context of explaining poverty in the Republic of Congo, these variables may have negligible effects.

What's more, based on this linear equation and stationarity test, the model chosen for estimation purposes is the autoregressive staggered lag model (ARDL). This is a dynamic model, which has the particularity of taking into account temporal dynamics (adjustment lag, expectations, etc.) in the explanation of a given situation.) In the explanation of a variable (time series), thus improving forecasts and the effectiveness of policies (decisions, actions, etc.), unlike the simple (non-dynamic) model, whose instantaneous explanation captures only part of the variation in the variable to be explained.

In other words, it's a model that allows us to estimate short-term dynamics and long-term effects for cointegrated or even integrated series of different orders, enabling us to estimate an error-correction/MCE model. The equation for this model can be represented as follows:

$$\Delta y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_{1i} \Delta y_{t-i} + \sum_{i=0}^{q} \alpha_{2i} \Delta x_{t-i} + \beta_1 y_{t-1} + \beta_2 x_{t-1} + \varepsilon_t \tag{11}$$

where y_t is the variable to be explained; x_{t-1} is the vector of explanatory variables α_{1i} and α_{2i} are the short-term effects; β_1 and β_2 are the long-term effects, Δ is the first difference; ε_t is the error term. Thus our model can be written in the following form:

$$\mathrm{TP}_t = \mathrm{f}\left(\mathrm{FBCA}_t, \mathrm{PIBH}_t, \mathrm{ADP}_t, \mathrm{IPC}_t\right) \tag{12}$$

Applying the general form of the ARDL model on the variables retained in this work, the specified model translates as follows:

$$\begin{aligned} \Delta \ln \mathrm{TP}_t = {} & \alpha_0 + \sum\nolimits_{i=1}^{p} \alpha_{1i} \Delta \ln \mathrm{TP}_{t-i} + \sum\nolimits_{i=0}^{q} \alpha_{2i} \Delta \ln \mathrm{FBCA}_{t-i} \\ & + \sum\nolimits_{i=0}^{q} \alpha_{3i} \Delta \ln \mathrm{PIBH}_{t-i} + \sum\nolimits_{i=0}^{q} \alpha_{4i} \Delta \ln \mathrm{ADP}_{t-i} + \sum\nolimits_{i=0}^{q} \alpha_{5i} \Delta \ln \mathrm{IPC}_{t-i} \\ & + \beta_1 \ln \mathrm{TP}_{t-1} + \beta_2 \ln \mathrm{FBCA}_{t-1} + \beta_3 \ln \mathrm{PIBH}_{t-1} + \beta_4 \ln \mathrm{ADP}_{t-1} \\ & + \beta_5 \ln \mathrm{IPC}_{t-1} + \mu_t \end{aligned} \tag{13}$$

with Δ: the first difference operator; α_0: a constant; α_1, …, α_5: short-term effects; β_1, …, β_5 are the long-term dynamics of the model; $\varepsilon \sim (0,1)$: error term (white noise), optimum (p, q) shifts.

3.3. Description of Variables and Data Sources

Our study is based on 360 annual observations, covering the period from 1989 to 2019, and the data required for the empirical assessments and the development of the methodology described above are drawn from two key sources: the World Bank's data on "World Development Indicators" (2022) (Table 1).

Table 1. Description of variables and data source.

Variables	Data source	Expected signs
TP: Poverty rate	World Bank (WDI)	−
FBCA: Agricultural investment	World Bank (WDI)	+
PIBH: GDP per capita	World Bank (WDI)	+/−
APD: Development aid	World Bank (WDI)	+
IPC: Consumer price index	World Bank (WDI)	−

Source: Author based on documentary analysis.

4. Results and Discussion

In this section, we present the results of the various tests carried out, including descriptive statistics, the unit root test and the cointegration test, before presenting and discussing the results of the estimation of the estimated model.

4.1. Descriptive Statistics

The aim of descriptive statistics is to structure and represent the information contained in data. Table 2 below shows the characteristics of the variables, using the mean and standard deviation to assess the distribution of the series.

The table shows that in Congo, the maximum poverty value is −1.47, while the minimum is −2.28. Among the variables used, agricultural investment and per capita income (PIBH) have the highest mean values, while official development assistance and inflation (IPC) have the lowest. In terms of standard deviation (Std. Dev.), only the GDP per capita variable has a low value compared with the other variables. This implies that all these series are closely distributed around their central mean and therefore show less variability than GDP per capita. This implies that our different series are not too dispersed around their central mean.

Moreover, the probability associated with the Jarque-Bera value is above the 5% threshold for all series, with the exception of the agricultural investment variable (FBCA), which seems to be more volatile than the others. Given the probability law governing this variable, it therefore follows a normal distribution. As a result, our various series are normally distributed. This allows us to accept the H0 hypothesis of variable normality.

4.2. Stationarity Tests

In this section, we will first test for the presence of random walks in our various series under study, by performing unit root tests. Indeed, these tests are important, as the presence of random walks in the series will lead to biased results. We

Table 2. Descriptive statistics.

	lnTP	*lnFBCA*	*lnPIBH*	*lnAPD*	*lnIPC*
Mean	−1.726008	17.98349	7.882176	3.804790	4.346326
Median	−1.651936	18.07078	7.879630	3.675637	4.389656
Maximum	−1.465697	18.39456	8.010538	5.975073	4.826236
Minimum	−2.282973	15.77058	7.756134	2.330207	3.576768
Std, Dev,	0.235285	0.457989	0.069480	0.859773	0.395018
Skewness	−0.989572	−3.728204	0.160438	0.777887	−0.774003
Sum	−53.50626	557.4883	244.3474	117.9485	134.7361
Observations	31	31	31	31	31

Source: Author, using Eviews 9 software, estimated on the basis of World Bank and FAO-2020 data.

then use two commonly used unit root tests: 1) Augmented Dickey Fuller; 2) Phillips Perron. In effect, ADF and PP test the null hypothesis of series non-stationarity against stationarity under the alternative hypothesis.

4.2.1. Test Dickey Fuller Augmenté (ADF)

Hypotheses of the Augmented Dickey Fuller test are:

- H_0: $\rho = (\Phi - 1)(1 - \theta_1 - \cdots - \theta_{p?1}) = 0$ $\Phi = 1$ (the serie is non-stationary)
- H_1: $|\phi| < 1$ (the serie is stationary)

If the absolute value of the ADF statistic is greater than the critical value (or if the probability is less than 5%), then we accept hypothesis H1: the X series is stationary.

If the absolute value of the Augmented Dickey Fuller (ADF) statistic is less than the critical value (or if the probability is greater than or equal to 5%), then we accept the hypothesis H0: the X series is non-stationary. Tests are performed at the 5% threshold.

4.2.2. Phillips-Perron (PP) Test

Phillips-Perron (1988) proposes a non-parametric method for correcting the presence of autocorrelation, based on the verification of the hypothesis posed by Dickey Fuller, in the following models:

$$\Delta Y_t = \rho Y_{t-1} + \alpha + \beta_t + \varepsilon_t$$

- $\Delta Y_t = \rho Y_{t-1} + \alpha + \varepsilon_t$
- $\Delta Y_t = \rho Y_{t-1} + \varepsilon_t$

The Phillips-Perron (1988) test statistic is a Student statistic corrected for the presence of autocorrelation by taking into account an estimate of the long-term variance of εt (calculated by the spectral density εt, at zero frequency). The table below shows the results of these tests:

The test results mentioned in **Table 3** above reveal that some series, such as lnFBCA and lnAPD, are stationary at level I (0) at the 5% statistical threshold for the ADF and PP tests, while the others are stationary at first difference I (I). This leads to the conclusion that not all the series retained in this work are integrated of the same order, which confirms the existence of a long-term relationship and therefore the use of an ARDL model.

4.3. Cointegration Test by Pesaran et al. (2001)

For this test, it is important that the calculated test statistic (Fisher's F-statistic) is compared with critical values that form bounds, allowing the detection of a cointegrating relationship as stated by the following hypotheses:

If Fisher > upper bound: Cointegration exists

If Fisher < lower bound: Cointegration does not exist

If lower bound < Fisher < upper bound: No conclusion

The results of the cointegration test at the bounds confirm the existence of a cointegrating relationship between the variables in the model, as the value of the Fisher statistic (F-stat = 5.800241) is greater than that of the upper bound and less than the thresholds of 1%, 2.5%, 5% and 10%. (**Table 4**)

Table 3. Stationarity test.

Variable	Degree of tests	Type of test	No constant and no trend	With constant and without trend	With constant and trend	Critical value at 5% threshold	Stat of test	Decision
lnTP	In level	ADF	No	No	No	−2.963972	−1.380907	I (1)
		PP	No	No	No	−2.963972	−1.481806	
	In difference	ADF	Yes	Yes	Yes	−2.967767	−4.272366	
		PP	Yes	Yes	Yes	−2.967767	−4.273005	
lnFBCA	En niveau	ADF	Yes	Yes	Yes	−2.963972	−4.590814	I (0)
		PP	Yes	Yes	Yes	−2.963972	−4.581936	
	In difference	ADF	Yes	Yes	Yes	−2.967767	−9.063324	
		PP	Yes	Yes	Yes	−2.967767	−19.74902	
lnPIBH	In level	ADF	No	No	No	−2.963972	−1.570191	I (1)
		PP	No	No	No	−2.963972	−1.658189	
	In difference	ADF	Oui	Oui	Oui	−2.967767	−4.439811	
		PP	Oui	Oui	Oui	−2.967767	−4.426677	
lnAPD	En niveau	ADF	Oui	Oui	Oui	−2.963972	−3.644617	I (0)
		PP	Oui	Oui	Oui	−2.963972	−3.662852	
	In difference	ADF	Oui	Oui	Oui	−2.967767	−8.258161	
		PP	Oui	Oui	Oui	−2.967767	−9.357489	
lnIPC	In level	ADF	Non	Non	Non	−2.991878	−1.353113	I (1)
		PP	Non	Non	Non	−2.963972	−2.484830	
	In difference	ADF	Oui	Oui	Oui	−2.986225	−3.952360	
		PP	Oui	Oui	Oui	−2.967767	−4.247175	

Source: Author, using Eviews 9 software, estimated on the basis of World Bank and FAO-2020 data.

Table 4. Pesaran et al. (2001) cointegration test.

Test Statistic	Valeur	K
F-statistic	5.800241	4
	Valeur critique aux bornes	
Significativité	Borne<	Borne>
10%	2.2	3.09
5%	2.56	3.49
2.5%	2.88	3.87
1%	3.29	4.37

Source: Author, using Eviews 9 software, estimated on the basis of World Bank and FAO-2020 data.

4.4. Coefficient Stability Test (Cusum Test)

The model's stability hypothesis is validated if the Cusum curve does not fall outside the corridor (confidence interval).

The below graph (Figure 1) shows that the curve does not leave the dotted corridor. This means that the model used is structurally stable.

4.5. Model Diagnostic Tests

This Table 5 shows that the probability associated with the various tests that help diagnose the estimated ARDL model is above the statistical threshold of 5%. The null hypothesis of absence of autocorrelation and heterocedasticity of errors is therefore accepted for all these tests. There is therefore the presence of error normality. The model used in this work is therefore statistically validated.

5. Discussion of the Results

In this section, we present the main estimation results obtained, *i.e.* the short- and long-term relationship.

Table 6 shows that:

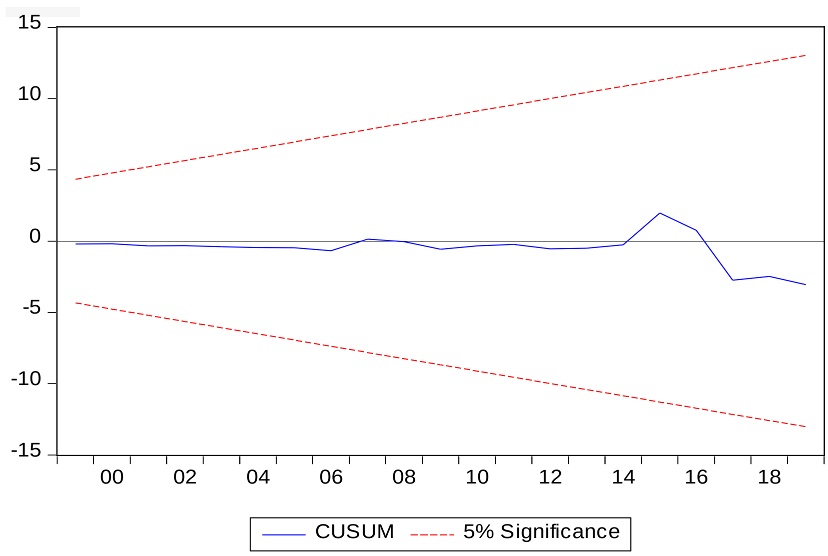

Figure 1. Stability test or cusum test. Source: Author, using Eviews 9 software, estimated on the basis of World Bank and FAO-2020 data.

Table 5. Results of diagnostic tests.

Test hypothesis	Tests	Statistics	Probabilities
Autocorrélation	Breusch-Godfrey	1.337961	(0.2610)
Heterocedasticity	Ljung Box	16	(0.841)
Normality	Jarque- Bera	4.741287	(0.093420)
Spécification	Ramsey	0.825797	(0.4187)

Source: Author based on World Bank 2021 database, obtained from Eviews10.

Table 6. Results of the short-term relationship.

Variable	Coefficient	Std, Error	t-Statistic	Prob
D (lnFBCA)	0.129256	0.020801	6.213801	0.0000
D (lnPIBH)	−1.793960	0.328974	−5.453203	0.0000
D (lnAPD)	−0.019154	0.010916	−1.754674	0.0939
D (lnIPC)	−0.100804	0.140246	−0.718768	0.4802
CointEq (−1)	−0.566673	0.088758	−6.384446	0.0000

Source: Author, using Eviews 9 software, estimated on the basis of World Bank and FAO-2020 data.

The coefficient of adjustment is statistically significant and negative, and lies between zero and one. This guarantees an error correction mechanism, and therefore the existence of a long-term relationship (cointegration) between the variables in the model.

Agricultural investment has a positive and significant influence, at the 5% threshold, on short- and long-term poverty reduction. This implies that a 1% increase in agricultural investment leads, all other things being equal, to a 0.12% reduction in poverty in Congo in the short term. This result corroborates those of (Fan et al., 2000; Fan & Zhang, 2004), who point out that agricultural investment reduces transport and transaction costs and facilitates access to the input and output markets. This reduces input prices and improves producer prices and therefore rural incomes. This in turn reduces poverty. This result also demonstrates that in Congo, agricultural investment is an important tool in the fight against poverty. The expected sign of this variable is in line with our expectations.

GDP per capita has a significant negative effect on short-term poverty at the statistical threshold of 5%, implying that a 1% drop in GDP results in a short-term poverty reduction of −1.79%. This confirms the hypothesis that economic growth has a limited effect on poverty reduction. This result is similar to the trickle-down or inverted-U theory developed by Kuznets (1955), which states that economic growth is always and everywhere accompanied by a simultaneous and systematic evolution in poverty and inequality.

These results suggest that the fight against poverty in the Congo should be based on policies that essentially require major investment in the agricultural sector.

The effects of official development assistance on poverty are negative and insignificant. This implies that official development assistance does not contribute to poverty reduction in the Congo. This result confirms the view of liberal theory, which emphasizes that official development assistance serves to distort markets and disempower governments and civil societies, even imprisoning recipient states to live in dependency.

The results from **Table 7** below indicate that: The effects of agricultural investment on poverty reduction in Congo are positive and significant in the long

Table 7. Long-term relationship results.

Variable	Coefficient	Std, Error	t-Statistic	Prob
LnFBCA	0.373053	0.073155	5.099521	0.0000
LnPIBH	−1.266528	0.354756	−3.570134	0.0018
LnAPD	−0.067277	0.033339	−2.017975	0.0566
LnIPC	−0.251845	0.063100	−3.991216	0.0007
C	2.887574	3.337788	0.865116	0.3968

Source: Author, using Eviews 9 software, estimated on the basis of World Bank and FAO-2020 data.

term, and are more than proportional, since a 1% increase in agricultural investment results in a 0.37% reduction in poverty in the long term. This result is similar to that obtained by Lilala (2019), who emphasize that agricultural investment has a positive impact on poverty reduction.

GDP per capita negatively and significantly influences poverty at the statistical threshold of 5%, in the long term. This implies that a 1% reduction in GDP per capita in the Congo results in a −1.26% reduction in poverty over the long term. This result is in line with structural poverty theories, which evoke the limited nature of the effects of growth on poverty reduction.

Official development assistance has a negative and significant influence at the 10% threshold on long-term poverty reduction in the Congo. This implies that official development assistance does not contribute to poverty reduction in the Congo. This result is similar to those of Boone (1994), who reveals the absence of development aid effects on poverty reduction.

The effect of inflation (CPI) on poverty is negative in the long term. This implies that in Congo, a 1% drop in inflation leads to a −0.25% drop in poverty in the long term. This result confirms the classic hypothesis that any increase in inflation leads to an increase in unemployment and hence poverty.

6. Conclusion and Policy Implications

The results of the ARDL model used to evaluate agricultural investment clearly demonstrate the positive effect of public investment on rural poverty in the Congo. These effects, measured over the period 1989-2019, imply that every 1% increase in agricultural investment leads to a 0.12% reduction in poverty in the Congo in the short term, and a 0.37% reduction in the long term.

In this respect, it can be argued that the measures implemented as part of Congo's agricultural policy have timidly catalyzed growth in the agricultural sector in the short term. It should be noted, however, that the Congolese government has focused on the construction of works and infrastructure to benefit the rural sector, and if the objectives identified and set out in the NDPs are achieved, there is no doubt that poverty will decline in the long term.

We must, however, take up the challenge of investment (credit, microcredit and the government budget) and avoid remaining dependent on official development assistance, which has a negative impact on the economies of developing countries, trapping them in a vicious circle.

Indeed, given the importance of the sector, we need to make agricultural financing an instrument of monetary policy through the principle of credit selectivity, which limits the threshold and ceiling of financing and will undoubtedly make it possible to control inflation on agricultural markets, through the mechanism of surplus agricultural financing (State budget and subsidy) creates an overproduction of agricultural products in the face of insufficient demand, leading to a fall in prices.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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Annexes

Test de stationnarité

Null Hypothesis: TP has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic - based on SIC, maxlag = 7)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		−1.384212	0.5766
	1% level	−3.670170	
Test critical values:	5% level	−2.963972	
	10% level	−2.621007	

*MacKinnon (1996) one-sided *p*-values.

Null Hypothesis: D (TP) has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic - based on SIC, maxlag = 7)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		−4.557611	0.0011
	1% level	−3.679322	
Test critical values:	5% level	−2.967767	
	10% level	−2.622989	

*MacKinnon (1996) one-sided *p*-values.

Null Hypothesis: TP has a unit root			
Exogenous: Constant			
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel			
		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		−1.471855	0.5338
	1% level	−3.670170	
Test critical values:	5% level	−2.963972	
	10% level	−2.621007	

*MacKinnon (1996) one-sided *p*-values.

Null Hypothesis: D (TP) has a unit root			
Exogenous: Constant			
Bandwidth: 0 (Newey-West automatic) using Bartlett kernel			
		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		−4.557611	0.0011

Continued

Test critical values:	1% level	−3.679322	
	5% level	−2.967767	
	10% level	−2.622989	

*MacKinnon (1996) one-sided *p*-values.

Null Hypothesis: PIBH has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic - based on SIC, maxlag = 7)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		−1.554275	0.4929
Test critical values:	1% level	−3.670170	
	5% level	−2.963972	
	10% level	−2.621007	

*MacKinnon (1996) one-sided *p*-values.

Null Hypothesis: D (PIBH) has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic - based on SIC, maxlag = 7)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		−4.261330	0.0024
Test critical values:	1% level	−3.679322	
	5% level	−2.967767	
	10% level	−2.622989	

*MacKinnon (1996) one-sided *p*-values.

Null Hypothesis: D (PIBH) has a unit root			
Exogenous: Constant			
Bandwidth: 3 (Newey-West automatic) using Bartlett kernel			
		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		−4.214482	0.0027
Test critical values:	1% level	−3.679322	
	5% level	−2.967767	
	10% level	−2.622989	

*MacKinnon (1996) one-sided *p*-values.

Null Hypothesis: FBCA has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic - based on SIC, maxlag = 7)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		−2.780043	0.0731
	1% level	−3.670170	
Test critical values:	5% level	−2.963972	
	10% level	−2.621007	

*MacKinnon (1996) one-sided *p*-values.

Null Hypothesis: D (FBCA) has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic - based on SIC, maxlag = 7)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		−8.516773	0.0000
	1% level	−3.679322	
Test critical values:	5% level	−2.967767	
	10% level	−2.622989	

*MacKinnon (1996) one-sided *p*-values.

Null Hypothesis: FBCA has a unit root			
Exogenous: Constant			
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel			
		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		−2.719267	0.0826
	1% level	−3.670170	
Test critical values:	5% level	−2.963972	
	10% level	−2.621007	

*MacKinnon (1996) one-sided *p*-values.

Null Hypothesis: D (FBCA) has a unit root			
Exogenous: Constant			
Bandwidth: 6 (Newey-West automatic) using Bartlett kernel			
		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		−9.358855	0.0000
	1% level	−3.679322	
Test critical values:	5% level	−2.967767	
	10% level	−2.622989	

*MacKinnon (1996) one-sided *p*-values.

Null Hypothesis: APD has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic - based on SIC, maxlag = 7)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		−5.131255	0.0002
Test critical values:	1% level	−3.670170	
	5% level	−2.963972	
	10% level	−2.621007	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D (APD) has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic - based on SIC, maxlag = 7)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		−8.824503	0.0000
Test critical values:	1% level	−3.679322	
	5% level	−2.967767	
	10% level	−2.622989	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: APD has a unit root			
Exogenous: Constant			
Bandwidth: 0 (Newey-West automatic) using Bartlett kernel			
		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		−5.131255	0.0002
Test critical values:	1% level	−3.670170	
	5% level	−2.963972	
	10% level	−2.621007	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D (APD) has a unit root			
Exogenous: Constant			
Bandwidth: 28 (Newey-West automatic) using Bartlett kernel			
		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		−26.28016	0.0001
Test critical values:	1% level	−3.679322	
	5% level	−2.967767	
	10% level	−2.622989	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: IPC has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic - based on SIC, maxlag = 7)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		−0.659703	0.8420
	1% level	−3.670170	
Test critical values:	5% level	−2.963972	
	10% level	−2.621007	

*MacKinnon (1996) one-sided *p*-values.

Null Hypothesis: D (IPC) has a unit root			
Exogenous: Constant			
Lag Length: 4 (Automatic - based on SIC, maxlag = 7)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		−2.830783	0.0683
	1% level	−3.724070	
Test critical values:	5% level	−2.986225	
	10% level	−2.632604	

*MacKinnon (1996) one-sided *p*-values.

Null Hypothesis: IPC has a unit root			
Exogenous: Constant			
Bandwidth: 7 (Newey-West automatic) using Bartlett kernel			
		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		−0.688132	0.8349
	1% level	−3.670170	
Test critical values:	5% level	−2.963972	
	10% level	−2.621007	

*MacKinnon (1996) one-sided *p*-values.

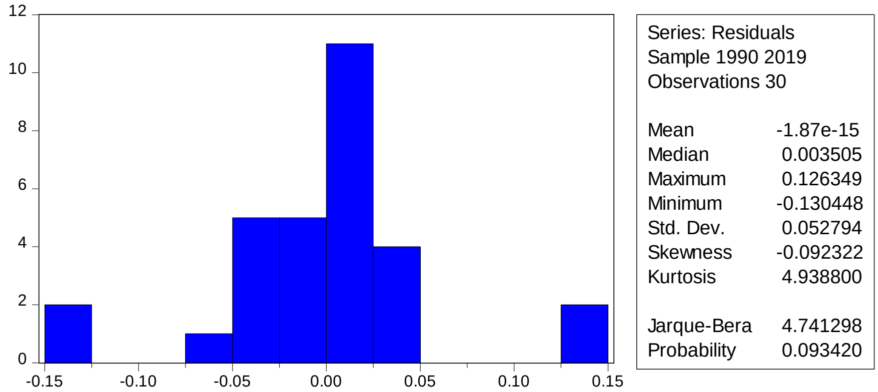
Null Hypothesis: D (IPC) has a unit root			
Exogenous: Constant			
Bandwidth: 11 (Newey-West automatic) using Bartlett kernel			
		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		−5.371290	0.0001

Continued

	1% level	−3.679322
Test critical values:	5% level	−2.967767
	10% level	−2.622989

*MacKinnon (1996) one-sided *p*-values.

Test de normalité des variables



Test d'autocorrélation de Breusch Godfrey

Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	1.337961	Prob. F (1.20)	0.2610
Obs * R-squared	1.881099	Prob. Chi-Square (1)	0.1702

Les résultats de ce test indiquent que la probabilité critique associée à la statistique du Fisher (Pr = 0.2610) est supérieur à 5%. Donc, on peut dire qu'il y a absence d'autocorrélation des erreurs.

Test de Ramsey ou test de la bonté global du modèle

Table A1. Test de Ramsey.

	Value	Df	Probability
t-statistic	0.825797	20	0.4187
F-statistic	0.681941	(1, 20)	0.4187
F-test summary:			
	Sum of Sq.	df	Mean Squares
Test SSR	0.002665	1	0.002665
Restricted SSR	0.080830	21	0.003849
Unrestricted SSR	0.078165	20	0.003908

Test de stabilité des Coefficient ou test Cusum