American Journal of Economics 2023, 13(1): 25-33
DOI: 10.5923/j.economics.20231301.03

Effects of Population Growth on the Availability of Agricultural Products in Burundi

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Abstract Food availability and population growth have long been of concern to researchers. Using ARDL model and bounds co-integration test for estimating the impact of population growth in both short and long run in Burundi, the findings showed that ECT is negatively significant for both items at 1% level and therefore the long run equilibrium can be reached. Annually, the coefficient of ECT for maize production is equal to -0,394 meanwhile this for rice production is equal to -0,813. Population growth (PGR) is a major factor in food availability because when this variable increases by one unit, in the short term, rice production increases by 0.524%. But the increase of one percent of rural population (RPR) in the first instance implies a decrease of 0.407% of rice in the short term. However, in the long term, increasing this variable by one percent implies a reduction in production of 0.122% for maize and 1.337% for rice annually. For the long run, the contribution of the population growth (PGR) is not significant for the two items and sign is different from one to another.

Keywords Population growth, Food availability, Lags, ARDL

1. Introduction

The availability of sufficient food for a growing population is a major concern in both developed and developing countries. In his Essay -*Principle of Population*- Malthus (1798) indicates that food scarcity is an important problem for the growing population of the globe. Thus, he developed a theoretical framework between the productive capacity of the earth and population growth. He concludes by saying that the power of population is infinitely greater than the power of the earth to produce the sustenance of man. The environmental reality testifies that the availability of drinking water and arable land is becoming scarce while the population is growing at a constant rate. This alarming increase in population places human beings in a universal famine as Malthus asserts in his Essay; which is also the current case according to FAO et al. (2015) the cause of the increase in the number of undernourished people in the world.

Moderate population growth has positive effects on long-term living standards in both developed and developing countries compared to steady or rapid population growth. This seems obvious from the fact that each additional person exerts a pressure of needs on their parents, society and the environment (Simon, 2012). Some authors such as Simon (2014) point out that the empirical data does not support this single a priori view of Malthus using concrete historical examples; population growth can be an asset for developing countries. But the most important phenomenon in the study of population is the change in population size because it affects the resources available to people. The wealth of a group of people or their offspring (in food, manufactured goods, space and other resources) is strongly correlated with the size of the population. Resources are the main reason why the study of population is important, and resources are the subject of economics.

On a global scale, the African continent is experiencing galloping population growth and more particularly sub-Saharan Africa. The countries of the EAC bloc come in the closest ranks of countries with strong growth, including Uganda in the first place with its 5th place followed by Burundi (9th place) with a rate of 2.94% in 2020. In This region, experiencing accelerated population growth, is also experiencing a very pronounced rate of undernourishment as in four people one person suffers from undernourishment (Rabin, 2011; Hall et al., 2017).

While the population increases with exponential growth, the resources do not keep peace. This effect has multiple repercussions on this same population and on the environment since the increase in population implies an increase in the demand for goods and services, which implies

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Received: Jan. 9, 2023; Accepted: Jan. 30, 2023; Published: Feb. 25, 2023
Published online at http://journal.sapub.org/economics

additional pressure on the environment (Guillebaud & Hayes, 2008). As production does not keep pace with the population, an unprecedented increase in different forms of malnutrition is observed in different age groups of the social fabric. Aware of this phenomenon, man seeks to terminate this deficit by intensification and industrialization, which leads to the erosion of biodiversity and the environment in general either by pollution (emission of GHGs and soil pollution) or by extension of arable land (implication on deforestation), etc. (UNDP, 2012). This phenomenon places us right in the face of a snowball effect that the human race will no longer be able to stretch except by becoming aware. This paper shows the (non-exhaustive) effects of population growth in Burundi on the availability of rice and maize.

2. Literature Review

A vast literature exists on the relationship between food security and population growth. According to Ahmad & Ali (2016) agricultural production depends mainly on natural resources, the performance of the agricultural sector, public investments and incentives for private farmers in the provision of rural health care and R&D plan funded by the private sector (NGOs) and spillovers from intervention products to significantly strengthen the agricultural productivity sector. Where some researchers have given more importance to agricultural inputs to explain agricultural productivity, other economic research has gone so far as to include the contribution of human capital in their analyzes (Antholt, 1994; Beal, 1994; Evenson and McKinsey, 1991; Jamison and Lau, 1982; Nehru and Dhareshwar, 1994; Pardey et al., 1992; Pray and Evenson, 1991; Rosegrant and Evenson, 1992 cited by Zepeda (1995) et Ahmad & Ali (2016)).

Sub-Saharan African countries such as Burundi face a series of constraints that increase their vulnerability to the causes and consequences of food insecurity (UNDP, 2012). This region of Africa is well within reach of the SDGs which are the eradication of hunger ("Zero Hunger" in 2030) and the achievement of food security, as is the case for the achievement of food security on a global scale, especially in the era of the Anthropocene and more accelerated population growth. A very simple and striking fact, it is estimated that in 2050 the African population will be multiplied more than twice between 2015 and 2050 (it will increase from 1.1 to 2.4 billion), and even more for some of the poorest countries, including Angola, Burundi, Democratic Republic of Congo (DRC), Malawi, Mali, Niger, Somalia, Uganda, Tanzania and Zambia, a five-fold increase is expected between 2015 and 2100 (UN, 2015), which leads to urbanization and parceling, thus reducing cultivable land such as the constructions observed today in the rice-growing region of the Imbo plain and will continue, which does not exclude effects on production, food demand and directly on food security (Christiansen, 2009). According to Hall et al. (2017) such a dramatic population increase in these countries will make it even more difficult to eradicate poverty, social inequality, hunger and malnutrition.

However, faced with this state of affairs of loss of production, man seeks to compensate for this deficit by conquering new, more productive virgin lands such as forests to relaunch the growth of the agricultural sector (Degand & Lefebre, 1980; Tachibana et al., 2001) by extension of arable land, which is the case for African countries (NEPAD, 2013; OCDE, 2016). This deforestation and overexploitation of the soil have the main consequences of pollution and impoverishment (of the soil) as well as climate change. To this, let us add that urbanization supports food availability and increases the share of GDP through the development of the secondary sector, which is synonymous with pollution.

3. Research Methodology

Definition of variables

The data we used come from the sites of the FAO, the World Bank (World Bank Indicator) as well as the climate change knowledge portal (CCP). The period of analysis extends from 1966 to 2018. For the case of our paper, we analyzed the effect of population growth (PGR) on the availability of main food products (FP)[1] in Burundi such as corn and rice. The choice of these two commodities is not the result of chance. These two cereals are staples of human nutrition in East Africa (Macauley & Ramadjita, 2015). PGR being the variable of interest, we used other determinants of food availability as control variables.

Table 1. Description of model variables

Var.	Description	Expectation.
F_P	It represents the volume of agricultural products in tones of crops considered.	
P_{GR}	It represents the growing of population	-
P	It represent the price of item in short and long term	+ -
U_{PR}	It represented the rate of the population living in urban areas.	
G_{HG}	It represents the greenhouse gas (GHG) emissions in CO2 equivalent at national level.	-
H_A	It represents the agricultural land allocated to cultivation	+
R_{PR}	It represents the population affected	-
R_F	It represents average of annual rainfall by year	+
T	It represents average of temperature by year	-
F	It represents the average amount of manure applied per hectare	+
GDP_{PC}	It represents the GDP per capita	

[1] Data is logarithmically transformed.

ARDL Model

According to (Kuma, 2018) the ARDL (Autoregressive Distributed Lag) model are dynamic models whose particularity is to include in the explanation of the dependent variable the introduction in the equation of the model the temporal dynamics which improves the forecasts and the decision-making by the political decision-makers which is not the case for the instantaneous models (non-dynamic).

However, these dynamic models generally suffer from problems of autocorrelation of errors, with the presence of the lagged endogenous variable as an explanatory (AR and DL models), and of multi-collinearity (for the step lag (DL) and autoregressive distributed lag models (ARDL), which complicates parameter estimation by Ordinary Least Squares/OLS. To overcome these challenges, robust estimation techniques must be used. Also, it should be noted that the variables considered in these models must be stationary to avoid spurious regressions. In its (explicit) form, an ARDL model is written as follows:

$$y_t = \alpha + \beta_1 y_{t-1} + \beta_2 y_{t-2} + ... + \beta_p y_{t-p} + \gamma_0 x_t + \gamma_1 x_{t-1} + \gamma_2 x_{t-2} + ... + \gamma_q x_{t-q} + \varepsilon_t$$

$$\Leftrightarrow y_t = \alpha + \sum_{i=1}^{p} \beta_i \, y_{t-i} + \gamma_0 x_t + \sum_{j=1}^{q-1} \gamma_j \, \Delta x_{t-j} + \varepsilon_t \quad (1)$$

With

$$\Delta x_t = P_1 \Delta x_{t-1} + P_2 \Delta x_{t-2} + ... + P_m \Delta x_{t-m} + \eta_t$$

Where x_t is a matrix of integrated order $I(0)$ and $I(1)$ k dimension variables that are not cointegrated with each other, ε_t and η_t are series of uncorrelated errors with zero means and constant variance-covariance matrices and P_i is the dimension matrix of the coefficients such that the vector $k \times k$ of the autoregressive process in Δx_t is stable.

Or implicitly:

$$y_t = \alpha + \sum_{i=1}^{p} \beta_i y_{t-i} + \sum_{j=0}^{q} \gamma_j x_{t-j} + \varepsilon_t \quad (2)$$

In this equation, two types of parameters are distinguished: short run and long run parameters.

Note that $\alpha, \beta_i, \gamma_j$, represents the short run effect of x_t on y_t while the long run effect of de x_t on y_t (φ) is obtained by making a computation from the following relationship:

$$y_t = c + \varphi x_t + u$$

And then we get:

$$\varphi = \sum \gamma_j \Big/ (1 - \sum \beta_i)$$

The estimating equation is then given by:

$$\begin{aligned} FP_t = {} & \alpha + \sum_{i=1}^{p} \beta_i \, FP_{t-i} + \gamma_1 PGR_t + \gamma_2 UPR_t + \gamma_3 GDPC_t + \gamma_4 GH_t + \gamma_5 P_t + \gamma_6 HA_t + \gamma_7 F_t + \gamma_8 RF_t + \gamma_9 T_t + \gamma_{10} RPR_t + \\ & \sum_{j=1}^{q} \gamma_{1j} PGR_{t-j} + \sum_{j=1}^{q-1} \gamma_{2j} \Delta UPR_{t-j} + \sum_{j=1}^{q-1} \gamma_{3j} \Delta GDPC_{t-j} + \sum_{j=1}^{q-1} \gamma_{4j} \Delta GH_{t-j} + \sum_{j=1}^{q-1} \gamma_{5j} \Delta P_{t-j} + \sum_{j=1}^{q-1} \gamma_{6j} \Delta HA_{t-j} \\ & + \sum_{j=1}^{q-1} \gamma_{7j} \Delta F_{t-j} + \sum_{j=1}^{q-1} \gamma_{8j} \Delta RF_{t-j} + \sum_{j=1}^{q-1} \gamma_{9j} \Delta T_{t-j} + \sum_{j=1}^{q-1} \gamma_{10j} \Delta RPR_{t-j} + \varepsilon_t \end{aligned} \quad (3)$$

However, before starting to estimate the equation of the ARDL (p, q) model, as for any dynamic model, it is first mandatory to determine the optimal shifts (p,q) of the model parsimony by using a criterion either Akaike Information Criterion (AIC) or Schwarz Bayesian Criterion (SBC) or Hannan-Quinn Criterion (HQC) (Pesaran & Shin, 1998; Nkoro & Uko, 2016; Kuma, 2018).

Diagnostic tests and model validation

The information criteria allow us to find the optimal lags of the variables to include in the regression equation but do not specify anything about the error term of the estimated equation. The latter has many of the assumptions of classical multiple regressions that it must meet so that we can ensure that we have a well-specified model equation that term must be such that:

(IIA) $E(\varepsilon_i) = 0 \quad \forall i$

(IIB) $Var(\varepsilon_i) = E\left[(\varepsilon_i - E(\varepsilon_i)^2 \right] = \sigma^2 \quad \forall i$

(IIC) $Cov(\varepsilon_i, \varepsilon_j) = E(\varepsilon_i - E(\varepsilon_i))(\varepsilon_j - E(\varepsilon_j)) = 0 \quad \forall i \neq j$

(IID) $\varepsilon_i \sim iid(0, \sigma^2)$

The first hypothesis implies a good distribution of the point cloud of the sample on either side of the regression. The second assumption implies that the error terms are homoscedastic (i.e. the variance remains constant) and the third states that they are non-auto correlated (i.e. the covariance is zero). In the opposite case of the last two hypotheses, the terms are said to be heteroscedastic for IIB while they are said to be auto correlated for IIC. The IID hypothesis translates that the error terms have a normal distribution with zero mean and constant variance σ^2. In order to validate our model, we performed tests on the residuals of the estimated model. These include tests for normality (Jarque-Bera statistic), autocorrelation (Breusch-Godfrey), heteroscedasticity (Breusch-Pagan-Godfrey and the ARCH test) and specification (Ramsey).

Bounds cointegration test

This test aims to examine the existence or not of a long run relationship between the variables. The approval of the cointegration hypothesis implies the existence of a long run equilibrium relationship between the variables. The classic cointegration tests as presented by Engle & Granger (1987) and Johansen (1988) are not up to serving for our case since they assume that the variables are integrated of the same order. This is how Pesaran et al. (2001) presented a test that is suitable for mixing the embedded variables of different order I(0) and I(1).

It is a test based on the Fisher test which, in its null hypothesis, assumes the joint equality of the coefficients. The cointegration test at the bounds (I(0) and I(1)) is performed in order to establish a long run relationship between the variables. Each sample variable is taken as a dependent variable in the calculation of this test (Narayan, 2005; Nkoro & Uko, 2016). The cointegration testing approach of our ARDL model is given by the following equation:

$$\Delta FP_t = \alpha + \beta_i FP_{t-1} + \gamma_j X_{t-1} + \sum_{j=0}^{q} \phi_j \Delta X_{t-j} + \sum_{i=1}^{p} \varpi_i \Delta FP_{t-i} + \varepsilon_t \quad (4)$$

Where Δ is the difference operator, β_i and γ_j are the coefficients of long run while ϖ_i and ϕ_j are the parameters of short run.

This specification presents the ARDL model as either an error correction model (ECM) or a vector error correction model (VECM). This then assumes the existence of cointegrating relationships between the variables. Indeed, the test is done in two stages, namely:

- Determine the optimal shift first and foremost using an information criterion of choice;
- Use Fisher's test to test the hypotheses: $H_0 : \beta_i = \gamma_j = 0$.
- The test procedure is that one must compare the Fisher values calculated with the critical values (limits) tabulated at the different thresholds by Pesaran et al. (2001).

It should be specified that the lower limit takes the critical values of the variables integrated in level I(0) while the upper limit takes the values of the variables integrated in first difference I (1). Thereby:

- If the calculated Fisher statistic > upper bound: existence of cointegration;
- If the calculated Fisher statistic < lower bound: cointegration does not exist;
- If upper bound < calculated Fisher statistic < lower bound: no conclusion.

Short run and long run relationship

The concept of cointegration between variables leads to a representation of an ARDL model in the form of an ECM or a VECM. The ECM is a representation of the dynamics of a linear time series in terms of its level and a shift polynomial in the differences. Its coefficient represents the restoring force or speed of adjustment to long-term equilibrium. Following (Pesaran, 2016) and starting from our model equation, the ECM can be represented as follows:

$$FP_t = \alpha + \sum_{i=1}^{p} \beta_i FP_{t-i} + \sum_{j=0}^{q} \gamma_j X_{t-j} + \varepsilon_t \quad (5)$$

With X representing the matrix of all the explanatory variables of the model, we then have this equation which can be rewritten as follows:

$$\Delta FP_t = \alpha + \sum_{j=0}^{q} \gamma_j \Delta X_{t-j} + \sum_{i=1}^{k} \lambda_i \Delta FP_{t-i} - (1 - \sum_{i=1}^{p} \beta_i)(FP_{t-i} - \frac{\sum_{j=1}^{q} \gamma_j}{(1 - \sum_{i=1}^{p} \beta_i)} X_{t-j}) + \varepsilon_t$$

$$\Leftrightarrow \Delta FP_t = \alpha + \sum_{j=0}^{q} \gamma_j \Delta X_{t-j} + \sum_{i=1}^{k} \lambda_i \Delta FP_{t-i} - (1 - \sum_{i=1}^{p} \beta_i)(FP_{t-i} - \varphi X_{t-j}) + \varepsilon_t \quad (6)$$

Where $\lambda = 1$ at the moment $i = 0$, φ is the coefficient of the slope of the relationship of long run X on agricultural production (FP). The preceding relation is known as the error correction representation of the ARDL (p, q) model.

The term ΔX_t is called derivative effect while $(FP_{t-i} - \varphi X_{t-j})$ is error correction term (ECT). Its coefficient shows how much the imbalance is corrected, that is, the extent to which any imbalance from the previous period is adjusted in the dependent variable. A positive coefficient indicates divergence, while a negative and significant coefficient indicates convergence.

4. Results Presentation

Stationarity of model variables

In time series analyses, several problems have been identified including the problem of "stationarity" which results in spurious regressions (Granger & Newbold, 1974) if not given more attention. To do this, Dickey & Fuller, (1979; 1981) recommended performing stationarity tests before any study on time series. Thus, the following table shows the level of stationarity of each variable of the model.

Table 2. Unit Root Test Results

Variables	FP	GDPC	GH	HA	F	PGR	P	RF	T	RPR	UPR
I(d)	I (1)	I (1)	I (1)	I (1)	I (1)	I (1)	I(1)	I (0)	I (1)	I (1)	I (1)

Source: Author's computation

Table 3. Model estimation with lags

Rice		Maize	
Dependent variable: FP (Rice production) Selected model: ARDL (3, 1, 2, 2, 2, 2, 2, 2, 2, 2, 1, 1)		Dependent variable: FP (Maize production) Selected model: ARDL (3, 2, 0, 2, 0, 0, 1, 1, 2, 2, 2, 0)	
Explanatory variables	Coefficient	Explanatory variables	Coefficient
FP (-1)	0.755**	FP (-1)	0.089
FP (-2)	0.192	FP (-2)	0.168*
FP (-3)	-0.761**	FP (-3)	0.347**
RPR	-0.407	P	0.0157
RPR (-1)	-0.680***	P (-1)	-0.075
T	10.151	P (-2)	-0.171**
T (-1)	13.081**	PGR	-0.066
T (-2)	17.651**	RF	-0.075
UPR	45.393	RF (-1)	-0.228*
UPR (-1)	101.900	RF (-2)	-0.291**
UPR (-2)	-150.874***	RPR	-0.048**
RF	-0.142	T	-0.340
RF (-1)	-1.273**	UPR	2.691**
RF (-2)	0.769	UPR(-1)	-2.628**
PGR	0.524	HA	1.275***
PGR(-1)	-1.538	HA(-1)	-0.204
PGR(-2)	1.030	F	-0.030
P	0.441*	F(-1)	0.014
P(-1)	0.106	F(-2)	-0.031
P(-2)	0.140	GDPC	-0.091
GH	-0.023	GDPC(-1)	-0.231
GH(-1)	-1.999	GDPC(-2)	0.344**
GH(-2)	0.784	GDPGR	0.006***
GDPGR	-0.007	GDPGR(-1)	0.006**
GDPGR(-1)	-7.71E-05	GDPGR(-2)	0.006***
GDPGR(-2)	0.006	GH	0.016
GDPC	0.056	C	3.315
GDPC(-1)	-0.956		
GDPC(-2)	1.497**		
F	-0.261**		
F(-1)	0.054		
HA	0.478*		
HA(-1)	-0.416		
C	-15.638		
R^2	0.999		0.970
F-statistic	254.062		28.139
Prob (F-statistic)	0.000		0.000

Note: ***, ** and * indicate significance at 1%, 5% and 10% respectively.
Source: Author's computation in Eviews 10

The results of the unit root tests (Table 2) show that all the explanatory variables of the model do not have the same order of integration, which can cause a spurious regression problem. To fix this kind of problem which goes beyond classical cointegration tests Engle & Granger (1987), Pesaran & Shin (1998) and (Pesaran et al., 2001) presented a cointegration test procedure suitable for this problem, and is called "bounds test to cointegration" or even more "cointegration test by distributed lags". Said test is applied on the basis of a model which serves as its basis, which is none other than the cointegrated ARDL (Autoregressive Distributed Lags) specification which takes the form of an error correction model (ECM).

Model estimation with determination of lags

The determination of the optimal shifts followed the AIC under the software Eviews 10. To avoid the problem of singularity of the matrix which arises when one is in the presence of a small sample and several explanatory variables; we fixed the number delays which gives access to the software to automatically choose a better combination by following the criterion chosen above. The results are presented in *the Table 3.*

5. Results of Diagnostic Tests of Estimated Models

The estimated models are statistically significant and the explanatory variables taken into the models contribute more than 90% in determining the production of the two crops considered. The residuals of the models are then tested and the results show that no test is significant at the 5% level. The following table shows the results of the diagnostic tests of our models estimated above.

Table 4. Model diagnostic tests

		Maize	Rice
Test hypothesis	Tests	Value (prob.)	Value (prob.)
Autocorrelation	Breusch-Godfrey	0.4786 (0.787)	74.298 (0.086)
Heteroscedasticity	Breusch-Pagan -Godfrey	28.214 (0.348)	34.593 (0.391)
	ARCH	0.356 (0.550)	0.576 (0.447)
Normality	Jarque-Bera	1,291 (0.524)	0.52 (0.76)
Specification	Ramsey	0.951 (0.352)	1.622 (0.180)

Note: (.) denotes probability
Source: Author's computation

As shown by the results in Table 4, our models do not suffer from any anomaly; they are well specified.

COINTEGRATION TEST

The test applies to ARDL models that have already been estimated and the principle stipulates that the calculated test statistic (Fisher's value) is compared to the critical values tabulated by (Pesaran et al., 2001). Indeed, the calculated Fisher statistical values (10.731 and 5.987) are above the tabulated upper critical bound at all the different thresholds. The following table shows the results of the cointegration test.

Table 5. Bounds cointegration test

Maize					Rice			
Fisher's bound test		H0: no relationship between levels			H0: no relationship between levels			
Test stat.	Value	Signif.	I(0)	I(1)	Value	Signif.	I(0)	I(1)
F-statistic	10.731	10%	1.76	2.77	5.987	10%	1.76	2.77
K	10	5%	1.98	3.04	11	5%	1.98	3.04
		1%	2.41	3.61		1%	2.41	3.61

Source: Author's calculation using Eviews 10

Thus, as the values of the Fisher test calculated exceed the upper bound, this means that there is a cointegration between the variables for the two models (for maize and rice). This then allows us to define or estimate the long run and short run effects.

LONG RUN EFFECTS AND SHORT RUN DYNAMICS

Since we performed the cointegration test at the bounds (Bound F-statistic) and found that the value of the calculated Fisher test is greater than the value of the upper bound (i.e. the variables are cointegrated), this gives us the right to be able to estimate the coefficients of short run and long run.

Dynamics of short run

The results in Table 6 show that with respect to maize production in short run, price, rainfall, urban population, fertilizers and harvested areas contribute positively and significantly to production.

Contrary to what one might expect, economic growth per capita contributes negatively to maize production; this may be due to the fact that in developing countries agriculture is left to people with low capital who produce for the self-consumption. Even farmers who manage to have more income tend to abandon agriculture in favor of trade. The coefficient of the Error Correction Term (ECT) is negative and significant at 1% indicating that long run equilibrium can be reached. It is equal to -0.394 in the short run model, which means that the imbalance between production and its determining factors is corrected by 39.4% each year.

Table 6. Error Correction Model (Short Run)

Maize		Rice	
Explanatory variables	Coefficient	Explanatory variables	Coefficient
D(FP(-1))	-0.5160***	D(FP(-1))	0.569***
D(FP(-2))	-0.347***	D(FP(-2))	0.761***
D(P)	0.015	D(RPR)	-0.407***
D(P(-1))	0.171***	D(T)	10.151***
D(RF)	-0.075	D(T(-1))	-17.651***
D(RF(-1))	0.291***	D(UPR)	45.393***
D(UPR)	2.691***	D(UPR(-1))	150.87***
D(HA)	1.275***	D(RF)	-0.142*
D(F)	-0.030**	D(RF(-1))	-0.769***
D(F(-1))	0.031***	D(PGR)	0.524***
D(GDPC)	-0.091	D(PGR(-1))	-1.030***
D(GDPC(-1))	-0.344***	D(P)	0.441***
D(GDPGR)	0.006***	D(P(-1))	-0.140***
D(GDPGR(-1))	-0.006***	D(GH)	-0.023
ECT(-1)*	**-0.394*** **	D(GH(-1))	-0.784**
		D(GDPGR)	-0.007***
		D(GDPGR(-1))	-0.006***
		D(GDPC)	0.056
		D(GDPC(-1))	-1.497***
		D(F)	-0.261***
		D(HA)	0.478***
		ECT(-1)*	**-0.813*** **

*Note: ***, ** and * indicate significance at 1%, 5% and 10% respectively.*

With regard to rice production, population growth positively affects production. These results (Table 6) corroborate with those of Gobin (1980) saying that more births this year (in other words in the short run) means more dependents rather than more workers per unit area, and although it is conceivable that more dependents could stimulate economic activity. In addition, young people participate a lot in the work of rice cultivation in most times, which is also confirmed by Gahiro (2013). When the GDP/capita contributes negatively for the production of maize, it is the opposite for the production of rice. This could be explained by the fact that this crop is mainly practiced for the market. This is also justified by looking at the contribution of the price for the production of this positive crop; which means that producers are reactive to market signals. With regard to CO2 emission, contrary to what Molyneux et al. (2012) found, the fertilizing effect of atmospheric CO2 is negative for rice. The variables responsible for climate change (precipitation, temperature and gas emissions) taken together have a negative impact on production, which corroborates with the results of the latter. It might be surprising to see that the high rate of rural population does not positively explain food availability, but this is easy to understand since it is in this part of the country where we observe the population highest growth rate. This leads to the atomization or fragmentation of land which has a strong chance of reducing production. The urban population contributes positively to the food availability because for example for rice, most of the rice is produced in the rice fields of the Imbo plain, the people of the city invest there for the production of rice. Another point is associated with the assistance that city dwellers give to their relatives who have remained in the countryside and these gifts are invested in the agricultural field. It is also to be considered that urbanization stimulates agricultural production seen in the angle of the proliferation of processing units, the city is a flow market par excellence. In the short run, the price is an incentive to production for both crops during the first period.

Long Run Coefficients

In long term (LT), the effects of population growth (insignificant though they are) diverge for the two crops. For rice, the results found (Table 7) corroborate those of Simon (1977) who says that positive population growth produces considerably better economic performance in the long term. He also agrees with Christiansen (2009) who points out that the impressive growth of agricultural production in China has been facilitated by strong population growth, while for maize the results corroborate those of Ahmad & Ali (2016) saying that population growth leads to a decrease in production in the long run. For both crops, the rate of affected population in agriculture contributes negatively to production. Annually, an increase in the rural population leads to a decrease of 0.122% for maize and 1.337% for rice. As is the case for the short run, with the faster growth of the population in the rural world, there is an atomization of the population, hence the growing land pressure, which means that the land is exploited relentlessly, which causes a loss of soil fertility (the land is never at rest).

Table 7. Long Run Coefficients

Maize		Rice	
Explanatory variables	Coefficient	Explanatory variables	Coefficient
P	-0.587	RPR	-1.337**
PGR	-0.168	T	50.235*
RF	-1.509	UPR	-4.399
RPR	-0.122**	RF	-0.794
T	-0.863	PGR	0.019
UPR	0.160	P	0.846*
HA	2.719*	GH	-1.522
F	-0.119	GDPGR	-0.001
GDPC	0.052	GDPC	0.733
GDPGR	0.049	F	-0.254**
GH	0.041	HA	0.076
C	8.411	C	-19.215

Source: Author's calculation

Thus, as in all other developing countries, the increases in food production were mainly due to the cultivation of more land where the area harvested positively influences production. An increase in cultivable land by 1% leads to an increase in maize production of 2.719%. The quantity of fertilizers applied per hectare for the cultivation of rice acts negatively because at long run the land ends up being impoverished which causes production to fall. The effect of temperature on rice cultivation demonstrates the extent to which rice is more of a crop of hot regions than cold regions in Burundi (yields are higher in the plain compared to other regions). The contribution of price to the increase in long run production is more noticeable in rice. This further reinforces the idea of the entrenchment of rice as a cash crop.

6. Conclusions and Recommendations

In Burundi, the growth of production generated by population growth is not effective knowing that high population growth is observed in rural areas while this large part of the population negatively affects agricultural production due to of the highest dependency ratio but also it decreases the share of production per inhabitant which is the source of capital as well as a good proxy for food accessibility. The fragmentation of land caused by higher population growth leads to excessive exploitation and the use of more mineral fertilizers depleting the soil more and more in the long term, which causes a drop in production. The higher population growth is therefore not good news for the maintenance of food security, rather the urbanization accompanied by the development of the secondary sector even if it is still at an embryonic stage in Burundi.

The government should therefore put in place a new land use planning policy by creating villages in order to remedy the problem of land fragmentation and a birth control policy in order to end the food deficit. It should also make a price stabilization policy, guarantee a remunerative producer price; especially for corn. Since overall economic growth is not positively correlated with the growth of agricultural production, we should see how to increase the budget allocated to the agricultural sector and increase initiatives in Research and Development oriented in the agricultural sector.

With regard to the mainly rural population, change mentalities on the old sayings around the child (the child is a wealth "Umwana ni itunga" or the child is a blessing "Umwana ni umugisha") which illustrate that a high number of children brings more happiness while ignoring that they are also a burden for them as well as for society in general. Producers should also feel the need to use organic or organo-mineral manure to boost production and restore the fertility of poor soils.

For the scientific community, I recommend that such a study be conducted using short frequency data as soon as it becomes available and also expand the study area to confirm the authenticity of the results of this study.

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