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BIOFUELS TO FOOD INSECURITY: ARE WE RESPONSIBLE ?

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ABSTRACT

Our study analyzes the impact of biofuel production on food security in Africa for a period of 11 years (2000-2010). The estimated after verification tests (Fisher specification, Hausman specification test, test and test heteroscedasticity autocorrelation) model is the fixed effects model. Our results highlight the influence significantly positive biofuel production and purchasing power on food security in Africa. While food trade openness exacerbates the situation of malnutrition in this region as it has a positive effect on our dependent variable. By cons, population growth has no effect on food insecurity.

KEYWORDS: Africa, Biofuels, Food Insecurity, Fixed Effects Model, Panel Data

INTRODUCTION

Faced with soaring global oil prices, the industrialized countries are used in the production of biofuels to replace fossil fuels. However, this economic and environmental solution does not seem quite appropriate for developing countries. In Africa, especially in sub-Saharan Africa, a question may arise and must "eat or roll ? ". It is in this framework that will fit our problem. We try to provide some answers to this question: what is the impact of biofuels on food security in Africa?

METHODOLOGY

Description of the database and presentation variables

In this article, we try to identify challenges between biofuel development and food security. To do this, we have a database on panel 7 African countries (Algeria, Egypt, Ethiopia, Mozambique, Tanzania, Zambia and South Africa) throughout a period from 2000 to 2010, therefore 77 observations.

The dependent variable is food insecurity (IA). The explanatory variables are population growth (CROISS_DEMOG) purchasing power (PA), the food trade balance (XM) and biofuels (BIOCARB).

Table 1: Description of Variables

Acronym	Variable	Measure
IA	Food Insecurity	Prevalence of undernourishment as a percentage of the total population (% annual)
CROISS-DEMOG	Population growth	Rate of population growth (annual%)
PA	Purchasing Power	PPP GNI (in current international $)
XM	Trade Balance food	Trade Balance food = Exports food – Imports food (calculated by the author)
BIOCARB	Biofuel	Wheat consumption kt for the production of biofuels in million liters

Source: The author, 2013

Descriptive Analysis

We conducted a descriptive analysis of our variables for preliminary results on them. To do this, we calculated under the STATA software, averages, standard deviations, minimums and maximums.

Table 2: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
ia	77	26.57273	19.91151	4	55.3
crois_demog	77	2.091713	.5535547	.9620562	2.979847
pa	77	3350.909	3147.215	420	10330
xm	77	11.06745	27.50945	-28.00338	68.08166
biocarb	77	2002.525	2454.699	1	8523

Source: The author, 2013

According to the table above, we see that the number of observations for the different variables is the same. The absence of missing data in this database confirms that our model is cylinder capacity.

We also note that the prevalence of malnutrition varies between 4 percent and 55 percent, while the average is around 26%, that is to say, about one in four people suffer from undernourishment. We try in this paper to determine the impact of biofuel production on food security of these seven African countries with a relatively high percentage of undernourishment.

The coefficients of variation for each variable allows us to conclude the existence of heterogeneity of the sample with respect to these variables because most of them have a coefficient of variation greater than 33.3 percent, this confirms that the change is very high and the average is more reliable (Gendron and Martin, 2004).

ESTIMATION TECHNIQUES IN PANEL

The Fisher Test

We can not perform linear regressions longitudinal data after performing a test specification Fisher, which allows us to ascertain whether we can estimate our model estimation techniques in panel. In other words, if there are specific effects for each country or other otherwise the theoretical model is the same for all countries. Indeed, Christophe HURLIN (2004) confirms that the verification test, noting that " the test specification phase amounts to determining whether the data generating process can be considered homogeneous, that is to say the same for all individuals, or whether it is completely heterogeneous, in which case the use of panel techniques can not be justified."

The results of this test are:

Table 3: Results of the Fisher Test

```
( 1)  crois_demog = 0
( 2)  pa = 0
( 3)  xm = 0
( 4)  biocarb = 0

       F(  4,    72) =  209.60
            Prob > F =    0.0000
```

Source: The author, 2013

The p- value is less than 5%, then we reject the null hypothesis of homogeneity.

This allows us to retain the structure panel and a second step in determining whether specific and specific effects for each country are fixed or random effects. The Hausman test is the best referee who can judge between these two models.

The Hausman Test

This test can be interpreted as a specification test. Under H0, the model can be specified with individual random effects and we must remember the estimator MCG. Under the alternative hypothesis H1, the model must be specified with individual fixed effects and we must remember the estimator Within (Christophe HURLIN, 2004). Then we use the Hausman test to choose whether we will estimate our model by a fixed-effects model or the random effects.

To implement it, we need to estimate the fixed effects model, store the results, estimate the random effects model and testing (Nicolas Couderc, 2012).

The Fixed Effects Model

The fixed effects model can be written as follows :

$$Y_{i,t} = \alpha_i + \sum_{k=1}^{K} \beta_k \, x_{kit} + \varepsilon_{i,t} \; \forall \; i \; \in \; [1, N] \text{ et } \forall \; t \; \in \; [1, T]$$

For the fixed effects model, the individual effects α_i are represented by constants, hence the terminology used fixed effects model. This is confirmed by GOAIED Mohamed et al (2012) as they state that "the fixed effects model assumes that the relationship between the dependent variable and the explanatory variables are the same for all individuals," the individual specificity is therefore assumed constant.

The Random Effects Model

One of the essential interests of panel data is that their double dimension allows 'isolate' the influence of unobservable factors. Since they are stable over time, they can be represented by specific individual effects. This is the assumption made about the specific effects that fundamentally differentiates the error model consisted of fixed effects model (Patrick SEVESTRE, 2002).

Indeed, the latest model addresses the issue of heterogeneity of individuals differently because it interprets the error term as a combination of two components (hence the name of the model error component). This model is written as follows:

$$y_{it} = \alpha + \sum_{k=1}^{K} \beta_k \, x_{kit} + \mu_i + \varepsilon_{it} \; \forall \; i \; \in \; [1, N] \text{ et } \forall \; t \; \in \; [1, T]$$

with

εit : the first is similar to that existing in the fixed effects model component

μi : is the second component, it requests that each individual differs from the others by the realization of a random variable.

It is important to realize that contrary to what happens in the fixed effects model in which individuals stand out from each other by a constant factor, the μi component that appears here is not a constant but the realization of a random variable (Philippe ROUS, 2013), hence the terminology used random effects model.

The Results of the Hausman Test

The application of the Hausman test gives us the following results:

Table 4: Results of the Hausman Test

	Coefficients (b) fixed	(B) .	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
crois_demog	2.743601	3.701148	-.9575473	.
pa	.0000455	-.0008112	.0008567	.
xm	.0725	.1568145	-.0843145	.
biocarb	-.0021652	-.0027214	.0005562	.

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

chi2(4) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 52.12
Prob>chi2 = 0.0000
(V_b-V_B is not positive definite)

Source: The author, 2013

The p-value is below the threshold of 5 percent, we reject the null hypothesis and accept the alternative hypothesis of the presence of fixed effects. The estimate by the fixed effects model is more appropriate than the random effects model.

Test of Heteroscedasticity

The fixed effects model is a multiple regression model "almost" like any other, nothing prohibits the use of conventional tests of no heteroscedasticity tests such as Breusch -Pagan and White (Patrick SEVESTRE 2002). For this, we apply the first test:

Table 5: Result of Heteroscedasticity Test

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: fitted values of residus

chi2(1) = 1.78
Prob > chi2 = 0.1825

Source: The author, 2013

This test provides a greater than 5 percent p- value, this allows us to accept the null hypothesis and infer that there is no problem of heteroscedasticity.

Test Autocorrelation

We obtain a p- value below the threshold of 5 percent, this result leads us to conclude that the errors are autocorrelated. We must correct this autocorrelation.

Table 6: Results of Autocorrelation Test

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
F(1, 6) = 287.218
Prob > F = 0.0000

Source: The author, 2013

RESULTS

After verification tests (Fisher's exact test, the Hausman test, the test Breush -Pagan test and Wooldridge) and the correction of the error autocorrelation, we use the following model:

Table 7: Estimation Results of the Fixed Effects Model after Verification Tests

```
Cross-sectional time-series FGLS regression

Coefficients:  generalized least squares
Panels:        homoskedastic
Correlation:   common AR(1) coefficient for all panels  (0.8423)

Estimated covariances      =         1          Number of obs      =        77
Estimated autocorrelations =         1          Number of groups   =         7
Estimated coefficients     =         5          Time periods       =        11
                                                Wald chi2(4)       =    331.30
                                                Prob > chi2        =    0.0000
```

ia	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
crois_demog	.2010175	1.163443	0.17	0.863	-2.079288	2.481323
pa	-.0042494	.0003752	-11.33	0.000	-.0049848	-.003514
xm	.1050995	.0285346	3.68	0.000	.0491728	.1610262
biocarb	-.0015899	.0003474	-4.58	0.000	-.0022708	-.0009089
_cons	42.3837	3.377545	12.55	0.000	35.76383	49.00357

Source: The author, 2013

Finally, after checking the specification tests and other tests, we use the following fixed effects model :

$$IA_{i,t} = \alpha_i + \beta_1 . CROIS\_DEMOG_{i,t} + \beta_2 . PA_{i,t} + \beta_3 . XM_{i,t} + \beta_4 . \mathbf{BIOCARB}_{i,t} + \varepsilon_{i,t}$$

and

IA represents the dependent variable : food insecurity;

CROIS_DEMOG, PA, XM and BIOCARB are the independent variables 4;

αi represents individual specificity, assumed constant ;

β1, β2, β3 and β4 are the model parameters, which are also constants;

εit are the residuals.

DISCUSSIONS

The results show that population growth has no impact on food security. Tans said that other explanatory variables act in a very significant way (at 1 percent) on the dependent variable. The coefficient of the food trade openness is positive, this aggravates the situation of food insecurity in our sample of African countries. When purchasing power and the variable of interest (wheat consumption for the production of biofuels), they negatively influence food insecurity. In other words, our variable of interest significantly reduces undernourishment in these African countries.

These results show that biofuel production does not act negatively on food security in Africa, but rather it is "a source of cleaner energy and cheap" (CMA / COA, 2007) for agricultural development, which is itself one of the most important food safety factors.

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