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Assessing the Impact of Cereal Prices on Consumer Price Index in Mali

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Abstract This study examines the relationships between cereal prices and consumer price index (CPI) in Mali. Using monthly series of consumer price indexes from 1993 to 2014, Vector Error-Correction Model (VECM) was estimated in a co-integration analysis. This was in order to investigate the short and long-term dynamics and mechanisms of cereal prices. Results indicated that, a statistically significant long-run equilibrium relationship exists between consumer price index and those of the main variable inputs consumed, such as rice, corn and wheat. It also showed that, there existed a negative long-run relationship between CPI and the variables except for millet-sorghum prices. Furthermore, all the error correction terms were negative and significant. Despite these, there was no short run causality between them except for the millet-sorghum equation. There was short run causality from millet-sorghum to those variables such as CPI, rice, corn and wheat prices. The parsimonious VEC model suggests that, the dynamics of cereal prices market systems are linked to the process of changing CPI.

Keywords: *consumer prices index, cereal prices, inflation, co integrations and VEC model*

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1. Introduction

Agricultural and food market products are an integral part of monetary and financial economics, accounting for a share of the wealth produced in Mali [5]. Consumer Price Index (CPI) is an instrument used in measuring price inflation. It also allows an estimation between two given periods as well as the average variation in prices of products consumed by households [1,16]. An analysis of the evolution in Consumer Price Index (CPI) determines a general tendency to measure the change in inflation [17,31].

Grain products are known to account for a large part of consumer spending in developing countries [30]. Nonetheless, this consumer spending of households is often influenced by price elasticity [6]. This leads to a cause and effect relationship between the Consumer Price Index (CPI) and prices of cereal products. This is because; prices of cereal products are intrinsically related to the price elasticity [13]. For instance, global prices for cereal products such as wheat, rice and oilseeds have risen since 2005 and continue to do so [13]. This price escalation has played a key role in raising global awareness towards issues relating to food and nutritional insecurity especially in less developed countries [27,30].

Cereals make up over 80% of cultivated lands with almost 75% of the population depending on these cereal products. In Mali as in many other Sub-Saharan African countries, most of these are imported despite these enormous human and natural potentials [6,12,22,26]. These shortcomings are often attributed to a reduction in agricultural production, climate changes, absence of appropriate storage facilities, and increase in the use of agricultural products for bio-fuels as well as increase in transportation costs.

Since independence, food security issues have remained a major objective of development policies in Mali as the world continues to experience a surge in food prices. These soaring prices cause immense unavailability of and inaccessibility to food with a consequence for almost a billion people [2,11]. Soaring food prices have been accompanied by an unprecedented volatility, especially in the cereals, highlighting the prevalence of greater market uncertainty [2]. The major challenge faced by the grain market operation, lies on how to reconcile and guarantee remunerative prices to producers. It also does not take into account, consumer access to food insurance at prices consistent with the purchasing power of the majority. Hence, raising the thorny issue of targeting the category of actors to support and use such as to improve on market performance.

Technically, monitoring price evolution (usually by survey and permanent sampling) is tedious therefore statistical research builds on a basket of representative goods and final services, weighted by their share in consumption. This study aims at analyzing the impact of household consumption of cereal products on Consumer Price Index (CPI) in Mali, West Africa.

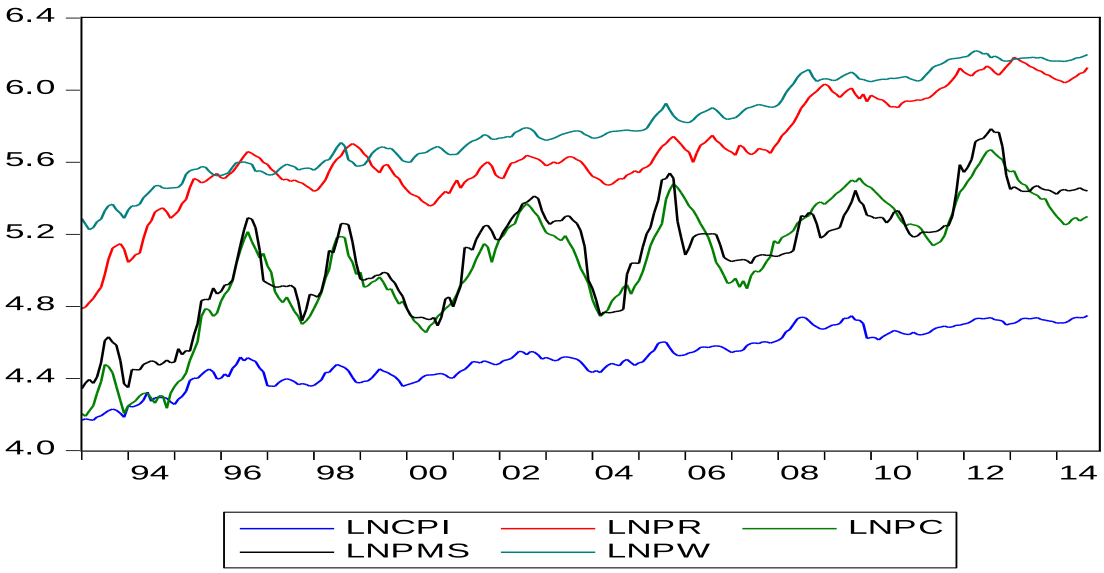

Figure 1. Consumer Price Indexand different cereal prices (CFAF) at different periods (years) in Mali.The prices have been calculated in the local currency CFA Francs whereas at time of writing this manuscript, 1US$ was equivalent to 570CFA Francs

2. Methodology and Data Analysis

The data were obtained during field studies from the Malian National Institute of Statistics (INSTAT) for Consumer Prices Index (CPI) logarithmic variables which is one of the main indicators to reflect inflation and its logarithm is represented by LNCPI. Data was also obtained from the Organization of Agricultural Market (OMA) for different cereal logarithmic prices for rice, corn, millet-sorghum and wheat variables represented by LNPR, LNPC,LNPMS and LNPW respectively from 1993 to 2014.The idea behind this is to eliminate the influence of heteroskedasticity, all variables are taken on the number of treatment.

The first step of the analysis focuses on the stochastic properties of the series by testing for the presence of unit roots. This allows for the identification of stationary and non-stationary time series, which in turn permits the specification of a model that should not produce spurious results. Provided that the variables are non-stationary, as is usually the case with time series of prices, the existence of long run equilibrium among variables is then tested by applying the Granger Causality and Johansen approach. This test starts with the specification of a Vector Auto Regression (VAR) model of order k [9,20].

$$Y_t = \mu + A_1 Y_{t-1} + \ldots + A_k Y_{t-k} + \varepsilon_t \qquad (1)$$

In Eq. (1),Y_t denotes the (5×1) vector of Consumer Price Index and prices for rice, corn, millet-sorghum as well as wheat, whileε_t denotesthe white-noise error term. A key feature of the VAR model is that, it does not impose any a priori restriction on the exogeneity of variables. This is attractive in the present context because of the possibility of bidirectional causality. The idea behind the approach proposed by Johansen [20] is, to reformulate the VAR model so as to impose and test the validity of co integrating constraints in the following equation:

$$\Delta Y_t = \mu + \Gamma_1 Y_{t-1} + \ldots + \Gamma_{k-1} Y_{t-k+1} + \prod \Delta Y_{t-k} + \varepsilon_t \qquad (2)$$

The (5×5) matrices Γi (i=1, 2…k-1) guide the short-run dynamics of the model, while any long term relationships are captured by the (5×5) matrix Π. The full dynamics of the system are better understood by rewriting model(2) in vector error-correction (VEC) form. This come into play, when possible, decomposing matrix Π into the product αβ′. Each vector of the (5×r) matrix β describes a stationary co-integration linear relationship that holds among the variables in the long-run equilibrium, while the (5×r) matrix α gathers the coefficients that dictate the speed of adjustment ofY_t to the long-run equilibrium. The method proposed by Johansen [20] and Johansen [9] to establish whether this decomposition is possible relies on a test of the rank $r \leq 5$ of matrix Π. If r=0, no co-integration relationship exists, while if r=5 all the variables inY_t are stationary. Most often, matrix Π has reduced rank r corresponding to the number of co-integration relationships.

2.1. Ethical Aspects of this Study

All procedures performed in this study involving human participants were in accordance with ethical standards. These include the ethical research committee of the Beijing Forestry University, China. Beijing Forestry University, bases its foundations on the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Given that informed consent is crucial for human subject's protection, it was clearly explained to the participants that it was an educational research study. The participants were informed of the nature and purpose of the research, procedures and expected benefits to Mali. The participants were offered the choice to participate or not in case were they expressed risks, stresses and discomforts stemming from the research. Participants were given the opportunity to ask questions to which complete and simplified answers were provided. In places or instances were potential participants were unable to read and understand the French language; the local

Bambara dialect was used to ensure proper understanding. The participant's consent to participate in the research was voluntary, free of any coercion or promise of benefits from participation.

The survey data was confidential, anonymous and was strictly collected for research purpose only not to be passed on to third parties. The questionnaires and semi structured interviews were done by the researchers and not by someone who had authority over the participants. In other cases, the potential participants were able to discuss their participation in the study with family and trusted friends.

3. Results

Before implementing the model, it was necessary to check in advance if the stationary variables were retained. This was in order to have an idea on the possible analysis to perform or correct the model (co-integration, differentiation and VECM modeling). For this, it was necessary to use the tests KPSS, Phillips-Perron and Dickey-Fuller Augmented (ADF). These tests are based on the Dickey Fuller Simple and take into account, differentiated and lagged values of order greater than or equal to the tested variable.

3.1. Unit Root Test

The empirical analysis starts with the unit root tests for the logarithm of all five time series included in the model. The results of the Augmented Dickey–Fuller (ADF) test are reported, due to their simplicity and generality. This is similar to the Phillips–Perron (PP) and Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test. Therefore, the guidelines of the ADF test use the null hypothesis: the variables of different series have unit root (non-stationary), meaning that the variables of time series are not stationary, but whether they have low power (i.e. if the probability of serial values is greater than 5%, they reject the null hypothesis).Nevertheless, the series are stationary, it is thus necessary to report the results of the Augmented Dickey Fuller ADF since this relies on the opposite null hypothesis of series' stationary, Table 1.

Table 1. Results of Unit Root of ADF test of CPI and different Cereal Prices

Variable	Exogenous	ADF test					
		t-statlevel	Cv 5%	p-value level	t-stat 1st diff	Cv 5%	p-value 1st dif
ln CPI	Cst	-1.6904	-2.8727	0.4349	-9.7339	-2.8727	0.0000
ln Pr	Cst	-2.5533	-2.8725	0.1042	-9.5141	-2.8725	**0.0000**
ln Pc	Cst	-2.7539	-2.8725	0.0665	-6.2541	-2.8725	**0.0000**
ln Pms	Cst	-2.7522	-2.8725	0.0668	-9.6608	-2.8725	**0.0000**
ln Pw	Cst	-1.3024	-2.8727	0.6290	-9.9863	-2.8727	**0.0000**

3.2. Cointegration Test

The Johansen procedure was used to test for the existence of co-integration relationships among the five variables after establishing the length of the lag in Eq. (2). This was achieved by optimising the value of an information criterion in the unrestricted VAR model (1). On the basis of four different criteria (Akaike, Schwarz, Hannan–Quinn and Final Prediction Error), the lag length of two months is found to be optimal. The optimum chosen lagis 2 lag, as described by Johansen [19]. This was used in the co-integration relationships among the five variables of the model to test the hypothesis the rank of matrix Π in Eq. (2) Table 2.

Table 2. Results of Co-integration tests

Hypothesized No. of CE(s)	Rank Test (Trace)			Rank Test (Maximum Eigen-value)		
	Tr -Stat	CV 5%	P-value	Max-Eigen Stat	CV 5%	P-value
None *	82.6758	69.8189	**0.0033**	36.0808	33.8769	**0.0268**
At most 1	46.5950	47.85613	0.0654	23.0175	27.5843	0.1727
At most 2	23.5776	29.7971	0.2189	11.8237	21.1316	0.5652
At most 3	11.7539	15.4947	0.1691	9.8940	14.2646	0.2190
At most 4	1.8597	3.8415	0.1726	1.8599	3.84147	0.1726

3.3. Granger Causality Test

According to AIC criterion to determine the lag, and on the interaction between cereal prices and the CPI Granger causality test based on VAR model; the results showed that at 5% significance level, between cereal prices and the CPI by bidirectional causal relationship, which changes in cereal prices, is the Granger cause CPI to rise and vice versa. Analysis of causality test allows us to know the statistically significant influence of different variables presented between them. We proceed to Granger causality test from the presentation of VEC model estimated previously. Granger causality considers that a variable is `a cause another if predictability is improved when the first information is relative to the second and it is incorporated into the analysis, the test results are shown in the Table 3. This leads to Granger causality test before to VEC model.

Table 3. Result of Granger causality test:

Null Hypothesis:	Obs	F-Statistic	Prob
$\ln(P_r)$ does not Granger Cause $\ln(CPI)$	259	0.60095	0.5491
$\ln(CPI)$ does not Granger Cause $\ln(P_r)$		16.8127	0.0000
$\ln(P_c)$ does not Granger Cause $\ln(CPI)$		3.49706	0.0318
$\ln(CPI)$ does not Granger Cause $\ln(P_c)$		5.46503	0.0047
$\ln(P_{ms})$ does not Granger Cause $\ln(CPI)$		3.45172	0.0332
$\ln(CPI)$ does not Granger Cause $\ln(P_w)$		26.8636	0.0000
$\ln(P_w)$ does not Granger Cause $\ln(CPI)$		29.3693	0.0000
$\ln(CPI)$ does not Granger Cause $\ln(P_w)$		3.10110	0.0467
$\ln(P_c)$ does not Granger Cause $\ln(P_r)$		20.5775	0.0000
$\ln(P_r)$ does not Granger Cause $\ln(P_c)$		1.89795	0.1520
$\ln(P_{ms})$ does not Granger Cause $\ln(P_r)$		5.95737	0.0030
$\ln(P_r)$ does not Granger Cause $\ln(P_{ms})$		4.18426	0.0163
$\ln(P_w)$ does not Granger Cause $\ln(P_r)$		21.0484	0.0000
$\ln(P_r)$ does not Granger Cause $\ln(P_w)$		0.49326	0.6112
$\ln(P_{ms})$ does not Granger Cause $\ln(P_c)$		4.87502	0.0084
$\ln(P_c)$ does not Granger Cause $\ln(P_{ms})$		36.4319	0.0000
$\ln(P_w)$ does not Granger Cause $\ln(P_c)$		4.56012	0.0113
$\ln(P_c)$ does not Granger Cause $\ln(P_w)$		1.30709	0.2724
$\ln(P_w)$ does not Granger Cause $\ln(P_{ms})$		27.4825	0.0000
$\ln(P_{ms})$ does not Granger Cause $\ln(P_w)$		3.14902	0.0446

3.4. Vector Error Correction Model

Based on the VECM model, we specify a conditional VEC showing CPI and different cereal prices as endogenous variables. So the model equations are as follows:

$$\begin{aligned}\Delta \ln CPI_t &= \mu_{cp} + \sum_{i=0}^{2}\gamma_{cpcp,i}\Delta \ln P_{cp,t-1}\sum_{i=0}^{2}\gamma_{cpr,i}\Delta \ln P_{r,t-1}\\ &+\sum_{i=0}^{2}\gamma_{cpc,i}\Delta \ln P_{c,t-1}+\sum_{i=0}^{2}\gamma_{cpms,i}\Delta \ln P_{ms,t-1}\\ &+\sum_{i=0}^{2}\gamma_{cpw,i}\Delta \ln P_{w,t-1}+\delta_{cp}EC_t\end{aligned} \tag{3}$$

$$\begin{aligned}\Delta \ln P_{r,t} &= \mu_r + \sum_{i=0}^{2}\gamma_{rcp,i}\Delta \ln P_{cp,t-1}\sum_{i=0}^{2}\gamma_{rr,i}\Delta \ln P_{r,t-1}\\ &+\sum_{i=0}^{2}\gamma_{rc,i}\Delta \ln P_{c,t-1}+\sum_{i=0}^{2}\gamma_{rms,i}\Delta \ln P_{ms,t-1}\\ &+\sum_{i=0}^{2}\gamma_{rw,i}\Delta \ln P_{w,t-1}+\delta_r EC_t\end{aligned} \tag{4}$$

$$\begin{aligned}\Delta \ln P_{c,t} &= \mu_c + \sum_{i=0}^{2}\gamma_{ccp,i}\Delta \ln P_{cp,t-1}\sum_{i=0}^{2}\gamma_{cr,i}\Delta \ln P_{r,t-1}\\ &+\sum_{i=0}^{2}\gamma_{cc,i}\Delta \ln P_{c,t-1}+\sum_{i=0}^{2}\gamma_{cms,i}\Delta \ln P_{ms,t-1}\\ &+\sum_{i=0}^{2}\gamma_{cw,i}\Delta \ln P_{w,t-1}+\delta_c EC_t\end{aligned} \tag{5}$$

$$\begin{aligned}\Delta \ln P_{ms,t} &= \mu_{ms} + \sum_{i=0}^{2}\gamma_{mscp,i}\Delta \ln P_{cp,t-1}\\ &+\sum_{i=0}^{2}\gamma_{msr,i}\Delta \ln P_{r,t-1}+\sum_{i=0}^{2}\gamma_{msc,i}\Delta \ln P_{c,t-1}\\ &+\sum_{i=0}^{2}\gamma_{msms,i}\Delta \ln P_{ms,t-1}+\sum_{i=0}^{2}\gamma_{msw,i}\Delta \ln P_{w,t-1}+\delta_{ms}EC_t\end{aligned} \tag{6}$$

$$\begin{aligned}\mathrm{EC_t EC_t} &= \ln CPI_{t-1} - 0.167\ln \mathrm{Pr}_{t-1} - 0.347\ln Pc_{t-1}\\ &+0.306\ln Pms_{,t-1} - 0.305\ln Pw_{t-1} - 1.603\end{aligned} \tag{7}$$

After converting all the variables into first differenced, they then become stationary and integrated in the same order. When the variables are co-integrated or have long run relationship, we can run restricted VAR (VECM model). After choosing the order of VECM model and optimum lag number, the coefficients of VECM are estimated. This can be done by Ordinary Least Squares (OLS) and when performed, each equation of the model gives the Table 4.

Table 4. Estimated VEC model

Error Correction	$\Delta \ln CPI$	$\Delta \ln P_r$	$\Delta lnPc$	ΔlnPms	ΔlnPw
EC	-0.100298 (0.02836) [-3.53666]	-0.051687 (0.03581) [-1.44352]	- 0.130388 (0.06167) [- 2.11419]	-0.190394 (0.07181) [-2.65133]	-0.029277 (0.02548) [-1.14912
$\Delta(\ln CPI(-1))$	0.038038 (0.07094) [0.53622]	0.005996 (0.08957) [0.06694]	-0.037986 (0.15427) [-0.24624]	0.678764 (0.17963) [3.77876]	0.185495 (0.06373) [2.91065]
$\Delta(\ln CPI(-2))$	0.044366 (0.07229) [0.61374]	0.037448 (0.09127) [0.41029]	0.204784 (0.15721) [1.30265]	0.297141 (0.18305) [1.62330]	0.086665 (0.06494) [1.33446]
$\Delta(\ln P_r(-1))$	-0.044845 (0.04993) [-0.89808]	0.252284 (0.06305) [4.00150]	-0.198308 (0.10859) [-1.82617]	-0.338967 (0.12644) [-2.68078]	-0.007525 (0.04486) [-0.16773]
$\Delta(\ln P_r(-2))$	0.003359 (0.04663) [0.07204]	0.022832 (0.05888) [0.38777]	0.110121 (0.10141) [1.08586]	0.234958 (0.11808) [1.98977]	0.036863 (0.04190) [0.87990]
$\Delta(\ln P_{cor}(-1))$	0.021223 (0.03044) [0.69729]	0.128623 (0.03843) [3.34704]	0.364700 (0.06619) [5.50994]	0.356281 (0.07707) [4.62282]	-0.003992 (0.02734) [-0.14601]
$\Delta(\ln P_{cor}(-2))$	0.014217 (0.03242) [0.43857]	0.092888 (0.04093) [2.26951]	0.206940 (0.07049) [2.93554]	0.155773 (0.08208) [1.89775]	-0.001535 (0.02912) [-0.05271]
$\Delta \ln P_{ms}(-1)$	0.012532 (0.02492) [0.50287]	-0.033633 (0.03147) [-1.06887]	0.056231 (0.05420) [1.03753]	0.235647 (0.06311) [3.73415]	0.021099 (0.02239) [0.94234]
$\Delta \ln P_{ms}(-2)$	0.017423 (0.02317) [0.75188]	0.000488 (0.02926) [0.01667]	-0.020837 (0.05039) [-0.41348]	-0.138541 (0.05868) [-2.36111]	-0.022228 (0.02082) [-1.06772]
$\Delta \ln P_w(-1)$	0.416755 (0.08037) [5.18523]	0.298531 (0.10148) [2.94180]	0.427464 (0.17479) [2.44562]	0.683415 (0.20352) [3.35798]	0.447284 (0.07221) [6.19445]
$\Delta \ln P_w(-2)$	0.012748 (0.08243) [0.15464]	0.089326 (0.10408) [0.85823]	-0.322496 (0.17927) [-1.79894]	0.015634 (0.20874) [0.07490]	-0.192289 (0.07406) [-2.59643]
C	0.000442 (0.00102) [0.43285]	0.001388 (0.00129) [1.07693]	0.001274 (0.00222) [0.57381]	-0.002621 (0.00259) [-1.01387]	0.002105 (0.00092) [2.29483]
R-squared	0.250513	0.401695	0.370824	0.504761	0.296974
Adj. R-squared	0.217000	0.374942	0.342690	0.482616	0.265538

This leads to a short run causality test before to the test of validation Table 5

Table 5. (Wald statistics for short run causality) Specification tests of the short term structure of the VEC. Statistics in bold and with a star indicate rejection of the null hypothesis at 5% level of significant

Null hypothesis	Chi-square statistics	p-value
$\gamma_{cpcp,1} = \gamma_{cpcp,2}$=0	0.597757	0.7416
$\gamma_{cpr,1}$=$\gamma_{cpr,2}$=0	0.882519	0.6432
$\gamma_{cpc,1}$=$\gamma_{cpc,2}$=0	1.036688	0.5955
$\gamma_{cpms,1}$=$\gamma_{cpms,2}$=0	0.966320	0.6168
$\gamma_{cpw,1}$=$\gamma_{cpw,2}$=0	28.94054	0.0000
$\gamma_{rcp,1}$=$\gamma_{rcp,2}$=0	0.168777	0.9191
$\gamma_{rr,1}$=$\gamma_{rr,2}$=0	19.97047	0.0000
$\gamma_{rc,1}$=$\gamma_{rc,2}$=0	25.17326	0.0000
$\gamma_{rms,1}$=$\gamma_{rms,2}$=0	1.167721	0.5577
$\gamma_{rw,1}$=$\gamma_{rw,2}$=0	11.23498	0.0036
$\gamma_{ccp,1}$=$\gamma_{ccp,2}$=0	1.853082	0.3959
$\gamma_{cr,1}$=$\gamma_{cr,2}$=0	3.536394	0.1706
$\gamma_{cc,1}$=$\gamma_{cc,2}$=0	58.38628	0.0000
$\gamma_{cms,1}$=$\gamma_{cms,2} = 0$	1.138190	0.5660
$\gamma_{cw,1}$=$\gamma_{cw,2}$=0	7.547571	0.0230
$\gamma_{mscp,1}$=$\gamma_{mscp,2}$=0	15.73360	0.0004
$\gamma_{msr,1}$=$\gamma_{msr,2}$=0	8.362073	0.0153
$\gamma_{msc,1}$=$\gamma_{msc,2}$=0	36.07968	0.0000
$\gamma_{msms,1}$=$\gamma_{msms,2}$=0	17.10808	0.0002
$\gamma_{msw,1}$=$\gamma_{msw,2}$=0	12.08986	0.0024
$\gamma_{wcp,1}$=$\gamma_{wcp,2}$=0	9.499245	0.0087
$\gamma_{wr,1}$=$\gamma_{wr,2}$=0	0.801661	0.6698
$\gamma_{wc,1}$=$\gamma_{wc,2}$=0	0.034171	0.9831
$\gamma_{wms,1}$=$\gamma_{wms,2}$=0	1.747552	0.4174
$\gamma_{ww,1}$=$\gamma_{ww,2}$=0	39.69788	0.0000

This leads to a validation test before to the impulse response (Table 6).

Table 6. Test of validation

Exogeneity variables	**LM Test**		**H-Skedasticity test**		**Normality test**	
	Chi-squared	**p-value**	**Chi-squared**	**p-value**	**Jarque-bera**	**p-value**
ln cpi	6.064682	0.0482	26.60317	0.0321	587.3976	0.0000
ln Pr	0.764680	0.6823	27.65563	0.0238	29.92115	0.0000
ln Pc	2.460780	0.2922	44.79169	0.0001	4.842642	0.0888
ln Pms	0.965047	0.6172	25.92052	0.0389	146.1408	0.0000
ln Pw	7.829909	0.0199	29.44178	0.0141	113.7339	0.0000

4. Discussion

The paper has used time series econometrics to investigate the dynamics of cereal prices formation on CPI in Mali as described by [18].

The lag length in the auto-regression forming the basis of the ADF test is chosen by maximizing the Akaike information criterion, with a maximum lag of 13 as described by. The Bartlett kernel spectral estimation method was used as described by. The results indicate that, all of the series variables are integrated of order one (e.g. I (1). However, the null hypothesis of non-stationary of wheat price at level is strongly rejected followed by CPI, rice and corn prices because its p-value is more than 5% and also greater than p-valuesof all other variables, Table 1. This strong observation non-stationary at level is constant for CPI and wheat prices, is also seen at level constant and trend deterministic. But in all ways, the series are stationary at first differenced in constant because they do not have unit root all their absolute value of t-statistics are more than their absolute critical value at 5%.

Analysing the co-integration for Johansen test shows that, there are at most one co-integration relationships between the time series variables at the threshold of 5 percent, Table 2. Indeed to the rank 0, the trace statistic and the maximum Eigen-value statistic are greater than their critical value at the threshold of 5 percent. But to the rank1, the trace statistic and Eigen-value statistics are less than their critical value at the threshold of 5 percent.

This can be concluded that, at critical value, a threshold of 5 percent has at least one co integration equation among the time series variables as indicated by VAR Johansen test. This means that, variables such as CPI, rice prices, corn prices, millet-sorghum prices and wheat prices are co-integrated or have long run relationships and when moved together [25]. As the five variables are co-integrated, the VECM model is run. This leads to the long run co integration relationship among the different variables.

The normalized long run co-integration relationships among the five variables estimated by Johansen technique is as follow:

$$\ln CPI = -0.167 \ln \mathbf{P_r} - 0.347 \ln \mathbf{P_c} + 0.306 \ln \mathbf{P_{ms}} - 0.305 \ln \mathbf{P_w} \quad (8)$$
$$\qquad (\mathbf{0.0742}) \qquad (\mathbf{0.0673}) \qquad (\mathbf{0.0712}) \qquad (\mathbf{0.0748})$$

As shown in **Eq. (8)** above, standard errors of the estimated coefficient are reported below in parentheses. But in this case, there is no constant without econometric meaning. And the estimated coefficients are all negative sign except for millet-sorghum prices coefficients. This implies that, there is a negative long-run relationship between CPI and the variables except that for millet-sorghum prices. When the respective prices of rice, corn and wheat go down, CPI goes up. And when these prices go up, CPI goes down implying an unset of inflation because the coefficients signs are negatives. Almost these cereals prices such as rice and wheat prices are depending the general world prices despite their productivity in Mali [28] and so, this lies is those cereal prices have negative long term impact on CPI [22]. Furthermore, when millet-sorghum prices go up CPI also goes up. And whether millet-sorghum prices go down CPI goes down confirming that, millet-sorghum prices and CPI move positively together. This is because cereals field are dominated by millet-sorghum in Mali [21]. According to Li [23], confirming those entire different cereal prices and CPI positively move each other in China.

In the Table 3 Granger sense, Causality test between $\ln CPI$ and ln (Pr), shows that, rice price does not affect CPI, instead CPI affect rice price because the probability of causality test between them is less than 5%.According to the causality test between ln(Pc) and ln(CPI), it can be said that corn price does cause CPI because critical p-values is less than 5 percent and reciprocally CPI does also cause corn prices. The resulting causality test between ln(Pms) and ln(CPI), shows and accepts the two null hypotheses of millet-sorghum price does cause CPI. This means that, its p-value is smaller than 5 percent and vice versa CPI does cause millet-sorghum prices. This is normal to understand the interaction between them becausemillet-sorghum are the most cereal products and most consumed but more expensive in the cities of Mali [8]. For causality test between ln(Pw) and ln(CPI), it was found that, wheat price does cause CPI and CPI does also cause wheat prices. This is because their p-values are also less than 5 percent. Causality test between ln(Pc) and ln(Pr), the test decision is that, rice prices do not cause corn prices. This infers that, the null hypothesis is accepted but reciprocally corn prices do cause rice prices because its p-value is less than 5 percent. For Causality test between ln(Pms) and ln(Pr), it is found that, millet-sorghum prices can affect rice prices. It implies that, the null hypothesis of Granger is not accepted and rice price do cause millet-sorghum prices. According to causality test between ln(Pw) and ln(Pr), the test decision finding is that rice prices do not influence wheat prices. But reciprocally, wheat prices affected rice prices in Granger causality sense. In the same way, causality test between ln(Pms) and ln(Pc), millet sorghum prices do cause corn prices. This means the null hypothesis of Granger test is rejected and that corn prices have influence on millet-sorghum prices. This is because critical p-value is less than 5 percent. And for Causality test between ln(Pw) and ln(Pc), it is found that, wheat prices do cause corn prices but rice prices do not cause corn prices i.e. its p-value is greater than 5 percent.

For the causality test for ln(Pw) and ln(Pms), the test decisions of Granger have been wheat price do cause millet-sorghum price. That means all null hypotheses for Granger Causality are rejected. Meanwhile, millet-sorghum prices do also cause wheat prices implying that its critical p-value is less than 5 percent.

From the Table 4, $\Delta \ln CPI$, $\Delta \ln P_r$, $\Delta \ln P_c$, $\Delta \ln P_{ms}$ and $\Delta \ln P_w$ denote respectively at first difference of Consumer Price Index, rice prices, corn prices, millet-sorghum prices and wheat prices logarithm. The first difference here is the difference between the current value of price and the last value of the period. Adjusted coefficient of determination analysis shows that, the CPI inflation rate is explained by 21.70% explanatory values, Table 4.

Other prices such as rice, corn, millet-sorghum and wheat, these are respectively explained by 37.49%, 34.26%, 48.26% and 26.55%. Almost all adjusted coefficients are greater than CPI adjusted coefficient, probably instigating inflation can come up. The greater adjustment coefficient is millet-sorghum prices. This due to the fact that, this cereal is widely cultivated in Mali and the higher adjustment of rice in Mali, is because it is state subsidized [28]. Thus the estimated VECM model, VECM is globally good adjusted. However, the low adjustment of wheat confirms that, little of it is grown or farmed in Maliand which is also confirming by [21,24].

Otherwise we notice that many of the coefficients associated with the delayed terms are not significantly different (zero), because the p-values of all those coefficients are almost not significant. Thus the Eq. (3)

inflation equation (target model equation), shows that, the past rice price increased by 4.48% of CPI and the past corn price has increased by 2.12% in the CPI or inflation rate. And the rate of inflation also depends positively on the price of one month late millet-sorghum (1.25%), wheat (41.16%) whereas the inflation of the past period of one month delay is 3.80 %, Table 4. Furthermore those three variables alone can explain approximately the half of changes the food prices in Mali as well as other countries in West Africa [11,12,24].

For the price of wheat and rice these are explained respectively by -0.39% and 12.86% in the past one month delay of corn since corn price depends on the price of the past period. Past prices of wheat, rice, corn and millet-sorghum positively explain the current price of millet and sorghum, Table 4. And also, the past prices of wheat and rice have a positive influence on the present price of corn in Mali because their coefficient are positive, Table 4.

So it is noted that rice, corn and millet-sorghum are perfectly substitutable products. Corn occupies 20% of cereal production in Mali after millet and sorghum but it emerges that its production covers only 25% of needs in a normal year [8,29]. Therefore, the deficit is made by exports implying that Mali still remains very dependent on imports to ensure food security [7,15,31].

So from Eq.3 (target model) the coefficient of CPI error correction term or speed of adjustment towards equilibrium is negative. This is caused by two issues; there long run causality and the short run causality.

Long run causality: The error correction term is negative and significant, and speed of adjustment is 10.03% meaning that system corrects its previous period disequilibrium at a speed of 10.03% monthly [32]. So there is a long run causality running from different cereal prices such as rice and wheat to CPI. This means that, the different cereal prices variables have influence on dependent variables such as CPI in the long run. In other words, there is long run causality running from different cereal prices to CPI and this is confirmed by Zhu and Lu [33].

Moreover, in the long-term equilibrium equation, all the coefficients are reflecting the long-term effect size of the cereal prices fluctuation on Mali`s CPI index and measuring the elastic influences between them because all of their coefficient are less than 1% elasticity [6]. When the rice price varies 1%, the CPI will fluctuate 0.16%in the meantime and when millet-sorghum and wheat prices change 1%, the CPI fluctuates 0.30%, Table 4.

Short run causality: The null hypothesis (p-value of chi-square is more than 5 percent), Table 5. This infers that, all the coefficients of variable are equal to zero, hence there is no short run causality running from different cereal price variables to CPI. And since p-value in CPI or inflation equation model is almost greater than 5 percent. There exists no short run causality running from these variables such as rice and corn prices to CPI except to wheat prices. It can thus be concluded that, there is a long run causality running from these different cereal price variables but no short run between CPI and different cereal prices variables except to wheat prices. Moreover, the respective effects of the variation of CPI and Mali`s wheat market price of last month on CPI in the current month are 0.038 and 0.416, Table 5. Whereas the respective effects of the variation of the CPI and Mali wheat price in phase 2 on CPI in the current month are0.044 and 0.017, Table 5. So the model of wheat prices and CPI will be adjusted from des-equilibrium status to equilibrium with the adjustment of 10%.InEq.6millet-sorghum equation, the short run causality from millet-sorghum prices to other variables (CPI, wheat prices), all the p-value chi-square are less than 5 percent. The error correction term coefficient is significant and negative (-0.1903). It therefore be concluded that, there is long run and short run causalities from millet-sorghum to those variables such as CPI, and wheat prices. Furthermore, all the error corrections terms are negatives and significant. This means that, there is long run causality between them but no short run causality [14]. This leads to the validation test before to the impulse response function.

In Eq.3 the consumer price index or inflation equation R-square is 0.25 less than 60 % and adjusted R-square is 0.21.Also, the p-value of serial correlation is more than 5 percent. There is therefore no serial correlation in the residual that is desirable, the model is good. This means that, the different cereal prices can affect Consumer Price Index (CPI) [18]. But the p-value of heteroskedasticity is less than 5 percent, so that is not desirable for the model. Further, the numbers of Jarque-bera are all very high except for millet-sorghum jarque-bera number`s. Therefore, different cereal prices variables such as rice, corn, millet-sorghum and CPI are not normal distributed because its LM-test p-value is less than 5 percent, Table 6. It was then necessary to see how the variables will be react one standard deviation shock or innovation by cholesky impulse response functions [25].

According to the analyses, impulse response function to cholesky one standard deviation shock shows future of ten period or ten months and the five variables such as CPI and different prices (rice, corn, millet-sorghum and wheat) react towards each other, Figure 2. The response of CPI to other variables means that, CPI affects different future cereal price variables in ten months. When there is shock CPI, rice, corn and wheat are always positive. But from zero to ten months, millet-sorghum is negative, Figure 2. For the response of wheat to other variables when CPI has positive shock, its curve is under wheat curve. This shows a positive nature whereas millet-sorghum is always negative. If one standard deviation shock is given to corn, the reaction of those variables such as CPI, rice, millet-sorghum and wheat are always positive because their curves are still above zero, Figure 2.The millet-sorghum prices play a significant and quantitatively more limited role the impact the equilibrium level on consumer prices index in Mali indicated by the results of the impulse response function [4].

With regard to the logarithmic nature of the model, all variables are influenced by CPI in the long run though millet-sorghum and rice prices have higher impact on CPI. Indeed when CPI increases 1%, millet-sorghum and wheat prices reduce around 3%, Table 4.

Furthermore in Granger sense, Table 3 found the variables presented in this study have significant statistical influences between them. But the longest causality chain is that the rice causes millet-sorghum, millet-sorghum cause corn, corn causes wheat and wheat causes CPI. This is therefore obvious that, inflation causes all these variables [4]. Moreover, it is necessary to know that, these products such as rice, corn and the millet-sorghum constitute Mali's staple foods as well as for many regional countries [17,21]. These cereals are consumed as porridge and couscous providing household nutritional and calorific needs. But some food products are subsidized by the government due to soaring prices [5,11]. Adjusted coefficient of determination analysis shows that, the CPI inflation rate is explained by 21.70% explanatory values. Meanwhile, almost all adjusted coefficients are greater than CPI adjusted coefficient, thus instigating inflation. The greater adjustment coefficient is millet-sorghum prices and it is explained by the fact that, this cereal is cultivated throughout Mali [21]. The error correction term is negative and significant, and then there is a long run causality running from different cereal prices to CPI. This implies that, the different cereal price variables have influence on dependent variable such as CPI in the long run [22]. Furthermore, all the error correction terms are negatives and significant. This also means that, there is long run causality between them and no short run causality.

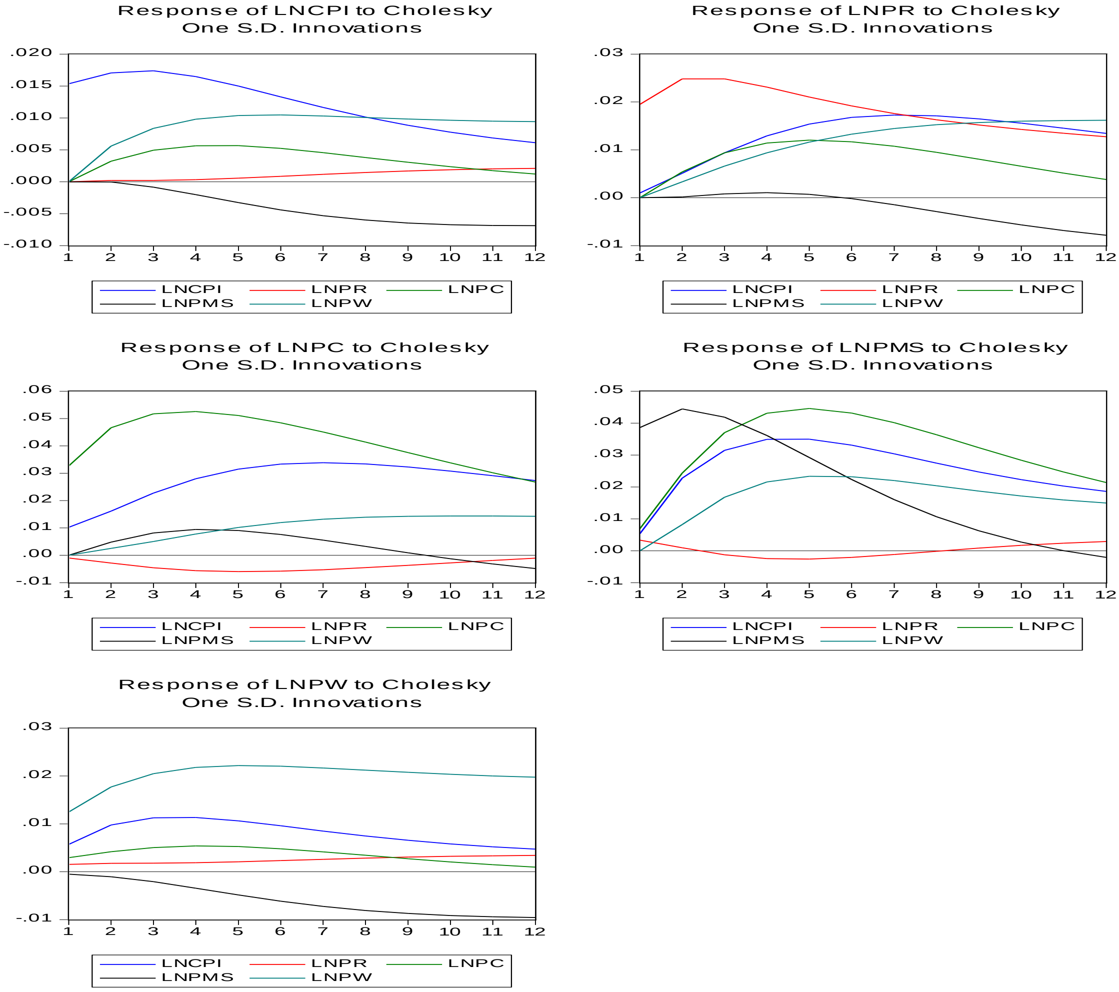

Figure 2. Impulse response functions

So regardless of long-term and short-term, the increase in cereal prices is susceptible likely to cause some negative impacts on CPI in Mali`s economics. Thus, in the development of rural agriculture, an increase in farmers' income would go a long way to avoid food price volatility. This impact on the general price level, will thus have a negative impact on the economy, therefore, the government could take important and necessary economic measures (both legislative and administrative) such as to regulate, and stabilize cereal market. This will enable the staple food prices fluctuations, to remain within an affordable range, and coordinated with the overall price level, in order to avoid large fluctuations.

5. Conclusion

The variables presented in this study have significant statistical influences between them. But the longest causality chains are rice, corn, millet-sorghum and wheat which all cause CPI, hence, the inflation causes all these variables. Moreover, it is necessary to understand that, these products such as rice, corn and the millet-sorghum constitute Mali's staple foods consumed as porridge, or couscous.

Using multi-variate analysis (VEC model) to analyze our data, this showed an interrelationship between CPI and cereal prices. This thus explains the variations in consumer price indices (CPI) as a result of changes in cereal prices (correlation between rice prices and CPI).

Our analysis was derived by a VEC model but after looking at the different graphs, a unit root test was necessary in order to make our series stationary. The results of these tests showed all variables to be stationary in the first differences. These differences explained 20.08% of the inflation rate hence confirming an interrelationship between the different cereal prices.

Granger causality analysis was further used to ensure that, the variables had significant statistical influence after the estimate. It is preferable to predict inflation in Mali through prices of different cereal products such as millet, sorghum, corn and rice. It is thus imperative for Malian authorities to put in place strategies that will curtail these price hikes.

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