

# **Alert at Maradi: preventing food crises in West Africa by using price signals**

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## Abstract

The aim of this paper is to exploit grain price data to detect the warning signs of looming food crises in Mali, Burkina Faso and Niger. Firstly we identify which markets play a leading role at the national and regional level. The second step consists of identifying crisis periods and characterizing price movements during the period preceding a crisis. This analysis leads to the identification of early warning indicators whose relevance is tested using panel data qualitative choice models. The results show that monitoring price movements on “leading markets” during crucial periods of the year can help in forecasting future crises.

Key words: Food security – Africa – Niger – early warning systems – discrete choice panel model

Code JEL: Q18, C25, D40, O18

## Introduction

Countries located in the Sahel region of Africa are repeatedly confronted by episodes of rapid increase in grain prices resulting in food crises, sometimes acute, as in Niger in 2005. This crisis highlighted the weaknesses of the early warning system which failed to anticipate the crisis, and under-estimated its extent. In Niger, as in the other countries of the Sahel region, the food crisis prevention systems remain primarily oriented towards the detection of food production deficits. In these countries, food insecurity is above all the consequence of insufficient food production, which results from adverse weather conditions. As a consequence, the present early warning systems focus on monitoring the conditions of food crops and estimating food availability.

Information on the state of food availability, summarized in the Cereal Balance Sheet, is, in some countries such as Niger, complemented by vulnerability analyses for the populations exposed to food insecurity. These analyses aim at evaluating the households’ ability to ensure access to food, identifying the populations at risk, and targeting the interventions. In these analyses, food price information is considered as an indicator of the ability of the households to ensure access to markets to compensate for food deficit.

The information provided by market prices could also be used to forecast the state of future food supply. Indeed, if markets are efficient, prices at any given time fully reflect all available information, not only on the current food availability but also on agents’ expectations about future scarcity (Ravallion 1985, Deaton and Laroque 1992). In other words, price changes are driven by the arrival of new information in the market, and any new information on future market conditions is immediately reflected in prices. Thus, it is expected that prices reflect the available information on the future harvest very early in the crop season, even as early as during the period of crop maturation.

The aim of this paper is to show that the information provided by market prices can usefully complement existing early warning systems which tend to privilege biophysical models. Using market price data we build indicators to alert policymakers to when a future shortage can be expected. In other words, we exploit the statistical properties of grain price data series to detect the warning signs of a looming crisis.

The analysis focuses on three countries – Mali, Niger and Burkina Faso – and a local crop – millet – which plays an essential part in the diets of Sahelian populations. Price data come from the national *Systèmes d’Information sur les Marchés* (SIM) of each country. The paper is organized in the following manner. Section one presents the data set. Section two is devoted to identifying the markets that play a leading role in influencing price at the national and regional levels. Section three presents an analysis of millet price dynamics aimed at identifying the price crises during the sample period, and characterizing the price behavior

during the period preceding a crisis. This analysis leads to the identification of warning indicators detailed in the fourth section. The relevance of these indicators is tested in the fifth section of the paper. These indicators are based on the difference between the current price and its long run value measured at the beginning of the harvest season. The final section presents conclusions.

## 1. The sample markets

Millet is a non-tradable cereal *i.e.* a good for which there is no international market but which is the subject of intensive cross-border trade in West Africa. Our analysis covers the markets of three countries Mali, Niger, and Burkina Faso, which belong to the same regional integration area (ECOWAS), and to a common monetary union (UEMOA). These three countries also share a harmonized system for collecting market price information on agricultural products: the SIMs.

In each country a market information system (SIM) was started in the early 90s. SIMs collect market prices for major agricultural products (inc. livestock) and disseminate this information to producers, consumers and traders through the media. SIMs have now accumulated a large amount of information and can trace the evolution of food prices in a wide geographical area and for a wide range of commodities.

We selected a sample of 50 millet markets from the markets covered by the SIMs: 15 markets in Niger, 12 in Burkina Faso, and 17 in Mali. Market selection was based primarily on the quality of available information: markets for which too much data is missing were not selected. Also markets were selected according to their importance in terms of trade, production, consumption, and to their location (e.g. vulnerable area, border proximity, etc) to capture the diversity of situations. The observation period starts in January 1990 in Niger, January 1992 in Burkina Faso and February 1993 in Mali.<sup>1</sup>

Millet prices are characterized by large seasonal fluctuations especially in Niger, due to the seasonal pattern of the production cycle. Millet prices are lowest during the harvest and post-harvest period (October to February). Then they gradually rise to reach their maximum level at the end of the lean season (May to August in Niger; June to October in Mali and Burkina Faso) which precedes the new harvest and during which farmers' stocks are depleted.

## 2. The leading markets

We consider a leading market to be a market whose past prices significantly contribute to influencing current prices in other domestic and/or regional markets. These "leading markets" are identified using Granger causality tests on a vector autoregressive (VAR) model estimated at the national or regional level.

### ***The VAR model and the Granger causality test***

The main advantage of the VAR model is to take into account the fact that prices are determined simultaneously on a set of markets, as well as the dynamic nature of price adjustments. Each price is considered as endogenous and is expressed as a function of the lagged values of all of the endogenous variables in the system. The estimated model is given by:

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<sup>1</sup> Five markets in northern Nigeria and one market in northern Benin, covered by the SIM of Niger, are also part of the sample. Unfortunately the observation period is quite short for these markets (2000-2008), so these markets cannot be incorporated in most of the following econometric analysis, despite their importance in regional trade.

$$P_t = \gamma + \sum_{i=1}^p A_i P_{t-i} + DX_t + \xi_t \quad (1)$$

$P_t$  is a  $k$  vector of prices,  $X_t$  is a  $d$  vector of exogenous variables,  $A_i$  and  $D$  are matrices of coefficients to be estimated and  $\xi_t$  is a vector of innovations that may be contemporaneously correlated but are uncorrelated with their own lagged values and uncorrelated with all of the right-hand side variables.

$E(\xi_t) = 0$ ;  $E(\xi_t \xi_t') = \Sigma$  (an  $m \times m$  positive semi definite matrix);  $E(\xi_t \xi_{t'}) = 0$  for all  $t \neq t'$ .  $t = 1, \dots, T$ .  $T = 201$  for Burkina Faso,  $T = 226$  for Niger and  $T = 187$  for Mali.

The lag order  $p$  is selected using the Schwarz information criterion. Prices are deflated by the domestic consumer price index (base 2000 = 100).

The system is estimated using OLS and then Granger causality tests are computed to evidence the interdependencies between markets.

The Granger causality test indicates whether there is a statistically significant relationship between current prices on market  $i$  and lagged prices on market  $j$ . It does not by itself indicate causality, but identifies precedence between two variables and measures the information content of lagged variables. The purpose of this analysis is thus to identify markets whose prices can help in forecasting future prices in other markets.

These tests allow us to distinguish four categories of markets:

- Leading markets – these markets *Granger cause* a large number of other markets, but are themselves *Granger caused* by only a few markets. Lagged prices in leading markets play a significant role in influencing current prices in other markets and can help to predict the latter. In addition, prices in leading markets are weakly exogenous – they do not depend on the lagged prices of the other markets in the sample.
- Markets that are isolated from trade or information flows - these are markets for which prices do not *Granger cause* those of other markets (or only a small number) and are not *Granger caused* by prices of other markets in the sample (or only a small number).
- Markets that are integrated at the regional or national level, linked by grain trade and information flows to other markets in the sample - prices in these markets *Granger cause* a large number of prices in domestic and/or foreign markets and are themselves *Granger caused* by the prices of many other markets.
- Between these last two types of markets, can be distinguished a fourth category, with blurred contours, of "poorly integrated" markets - prices in these markets *Granger cause* only a few other prices and are *Granger caused* by the price of a small number of other markets.

## Results

The Granger causality tests are first performed using a VAR model specific to each country, incorporating all the selected markets of the country in question. This approach allows us to identify the leading markets in each country. In a second step, causality tests are performed on a regional VAR model limited to 25 markets of the sub-region.<sup>2,3</sup>

The analyses conducted at the country level lead to consider as leading markets: Gaya and Maradi in Niger; Dori, Tenkodogo and Banfora in Burkina Faso, Nara and Koulikoro in Mali. These results are not surprising for Maradi and Gaya, which being close to the borders with Nigeria and Benin respectively, are two main gateways for grain imports. In Mali, Koulikoro

<sup>2</sup> Including all the domestic markets in the regional sample was not feasible due to computer processing limitation.

<sup>3</sup> The regional sample includes: 8 markets in Niger, 7 in Burkina Faso, and 10 in Mali.

is an important wholesale market located in the same region as Nara. In Burkina Faso, Dori is an important wholesale market for millet in the Sahel region and is close to the border with Niger. Banfora is located at the intersection of major roads, close to the borders of both Mali and Ivory Coast, and is also close to Bobo Dioulasso the second city in Burkina Faso. Tenkodogo is located in a major production area.

In contrast some markets appear isolated or poorly integrated. In Niger, the markets of Diffa, Goudoumaria and N'Guimi (Region of Diffa), Dosso and Dogondoutchi (Region of Dosso) and Gouré (Region of Zinder) can be classified as isolated. In Burkina Faso, Tougan and Fada N'Gourma are poorly integrated. This is also the case in Mali for Fana (Koulikoro Region), Dioro (Segou Region) and Nioro (Kayes Region). Some of these markets are located in regions classified by the World Food Program as highly vulnerable to food risks (Diffa). Others are located in production areas (Tougan, Fada N'Gourma, Dioro) and were expected to be more integrated to other markets. These results may be due to high transaction costs and low effective demand in poor regions.

Table 1. Market integration: summary

	Leader	Isolated	Poorly integrated	Integrated
Niger	Gaya, <b>Maradi</b>	N'Guimi	Goudoumaria, Dosso, Dogondoutchi, Katakou, Gouré, Filingue, Tahoua	Agadez, Tillabéri
Burkina	<b>Dori, Tenkodogo</b> , Banfora	Tougan, Fada		Djibo, Koudougou, Banfora
Mali	Koulikoro, Nara		Kayes, Nioro	Bankass, Mopti, Djénne, Sirakrola

In bold, the leading regional markets (identified from the regional VAR model).

At the regional level, the analysis confirms the leading role of Maradi: prices in this market *Granger cause* those of a large number of markets in Niger, Burkina Faso and Mali. The leading role of Maradi probably reflects the influence of Nigeria on millet prices within the whole sub region. Gaya, which is also a border market close to Benin, has no well-defined regional role.

The markets of Dori and Tenkodogo also confirm their leadership at the regional level, while Nara (Mali) which appeared to be a leading market at the national level does not play a significant role at the regional level. Banfora (Burkina Faso) also, cannot be considered as a regional leader, but is well integrated with other regional markets.

In summary, the causality tests highlight the important role of a small number of markets at the national and regional level, namely: Maradi, Dori and Tenkodogo and to a lesser extent, Gaya, Nara and Koulikoro. Priority should be given to the monitoring of these markets whose lagged prices can help predicting the prices of other markets, in the framework of an early warning system.

### 3. Price crisis characteristics

The approach consists of firstly identifying price crises, and then characterizing the price behavior during periods that precede crises.

#### **Identifying price crises**

The stationarity tests (ADF and KPSS) reject the presence of a unit root and lead to consider all the price series as trend stationary.

The price trend is derived from equation (2). The seasonal dummies,  $M_s$ , catch the monthly price fluctuations related to the production cycle and the trend,  $T$ , captures long term movements related, for example, to population growth:

$$P_{it} = aT_t + \sum_{s=1}^{12} b_s M_{st} + \zeta_{it} \quad (2)$$

with:  $P_{it}$ : current millet price on  $i$  market at time  $t$ ;  $\zeta_{it}$ : *iid* random variable with:  $\zeta_{it} \sim N(0, \sigma_\zeta^2)$ .

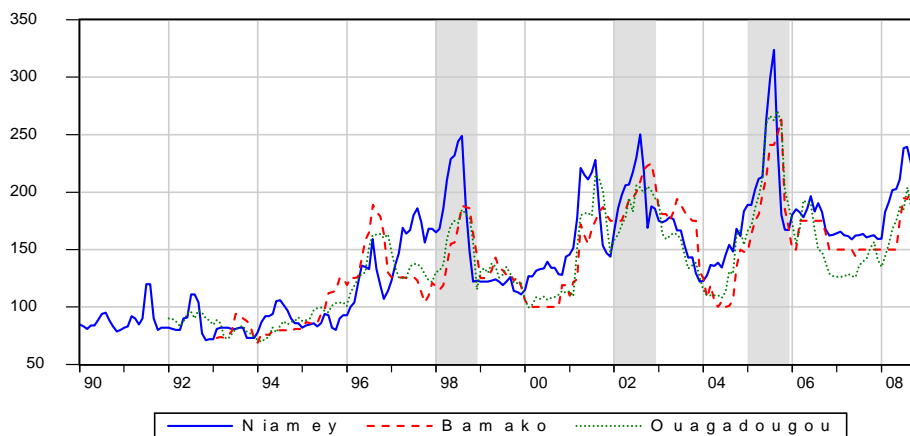
In the following we consider that there is a crisis at time  $t$  if the price spread between the observed price and its trend value is greater than one standard deviation, *i.e.* if :

$$I_{it} = \frac{P_{it} - \hat{P}_{it}}{\sigma_\zeta} \geq 1. \quad (3)$$

with  $\hat{P}_{it}$ : the trend value of  $P_{it}$ .

The trend equation (1) is estimated for each market price over the whole period. The coefficient's stability is tested using the Quandt-Andrews breakpoint test<sup>4</sup> for 158 possible breakpoint dates in the period 1990-2008 in Niger, 131 for Mali and 139 for Burkina Faso<sup>5</sup>. The tests fail to reject the null hypothesis of no structural breaks.

Figure 1. Millet prices in the capitals of the three countries (Fcfa/kg)



Gray: crises common to the three countries

Source: SIMs and authors' calculations

According to our definition of crisis, Niger, Mali and Burkina Faso experienced three common crises during this period - 1998, 2002 and 2005 (Figure 1). In addition to these shared major crises the three countries were affected by crises of smaller magnitude, limited to one or two countries - 1997 in Niger, 1996 in Mali and Burkina Faso, 2001 in Niger and Burkina Faso, 2003 in Mali. Most of these crises resulted from a drop in production, but the correlation between price and supply shocks is fairly weak. In 2008, a few episodes of transitory crises were recorded, limited to a small number of millet markets in Niger and Burkina Faso. These crises were of lesser importance, and 2008 cannot be considered as a crisis year in the millet markets.

### **Origination and ending dates of crises**

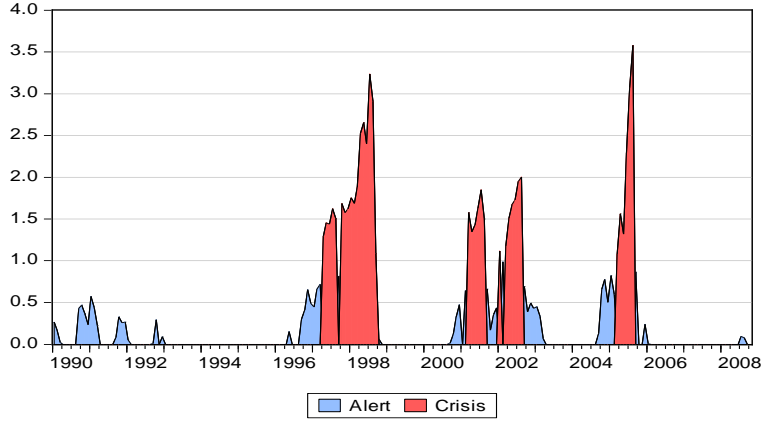
A deeper analysis shows that crises break out during the lean period and are preceded by a period of high prices that can be regarded as an alert phase. This phenomenon is most obvious in Niger - crises erupt in April, and end in September. They are preceded by a period during which prices are above their trend value. This period runs from September/October to March. Thus, for example in Maradi, millet prices were above their trend value from September 1996

<sup>4</sup> Test for one or more unknown structural breakpoints in the sample.

<sup>5</sup> According to a 15% trimming procedure that excludes the first and last 7.5% of the observations.

to March 1997, while the crisis broke out in April 1998 (Figure 2). At Gaya, prices were above their trend value from September 1996 to January 1997, and the crisis broke out in January 1997.

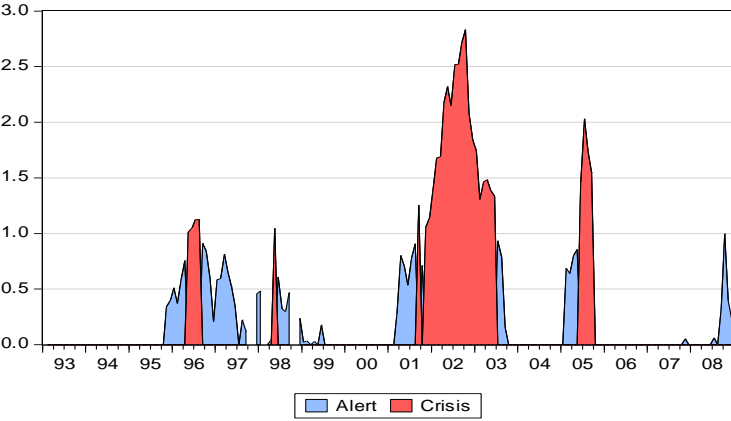
Figure 2. Maradi (Niger). Alert and crisis phases over the period 01/1990 to 10/2008



Crisis phase:  $I_{it} \geq 1$  ; alert phase:  $I_{it} > 0$

In Mali, crises occur later in the year, during May/June and end in October/November. This lag follows the harvest calendar that starts later in Mali. These crises are preceded by a period of high prices running from October to May. Thus, for example, the 1996 crisis that broke out in May/June on the 17 markets of the sample was preceded by a period running from October 1995 to April 1996 during which prices in almost all the markets were above their trend value (see Figure 3 as an illustration). The 1999 crisis was preceded in all markets, except Koulikoro, by a phase of high prices that began in December 1998. The 2002 crisis, the most severe, was preceded by particularly high prices starting in September 2001. In contrast, the 2002 crisis started very early in the year, in October or November for most markets.

Figure 3. Nara (Mali). Alert and crisis phases over the period 02/1993 to 12/2008



Crisis phase:  $I_{it} \geq 1$  ; alert phase:  $I_{it} > 0$

In Burkina Faso, as in Mali, crises occur, generally in May or June and are preceded by positive shocks, but of lower magnitude, from November or December. For instance, the 1996 crisis was preceded by a period of high prices starting from November 1995 in Banfora, Koudougou, Tenkodogo and Tougan, and from January 1996 in Dori, February in Sankaryare.

In short, over the period studied, crises break out at the beginning of the lean season and reach their climax at the end of the lean season. They are usually preceded by a warning phase, characterized by prices higher than normal during the harvest period.

## 4. Early warning indicators

The above observations lead to the proposition of warning indicators based on the gap between prices and their trend value during the harvest and post-harvest period running from October to March. Different indicators are proposed and their relevance is tested using nonlinear panel models.

### **Definition**

These indicators aim at capturing as soon as possible the price movements heralding a crisis. Special attention is paid to the markets previously identified as leading markets. Three types of indicators are proposed being designed to capture the intensity and the spatial extent of the shocks during the alert phase.

First, for each leading market ( $l$ ), we define a binary warning indicator ( $IA_{lr}$ ) equal to 1 if the market registers a positive shock during the month  $r$ , and equal to 0 otherwise.  $r = 1$  to 6, represents the six months of the harvest period running from October to March.

$$IA_{lr} = 1 \text{ if } I_{lr} = P_{lr} - \hat{P}_{lr} > 0 ; = 0 \text{ otherwise} \quad (4)$$

$I_{lr}$  is the price shock on the leading market  $l$  during month  $r$

Second, vigilance should increase with the magnitude of the price disequilibrium that is captured by an indicator of the intensity of the alert:

$$II_{lr} = I_{lr} / \sigma_l \quad (5)$$

This indicator is calculated for each leading market and each month ( $r$ ) of the alert period (October to March).

Third, the alert should go up if many markets are simultaneously in a crisis situation. An indicator of the spatial extent of the alert is given by the number of markets on alert during the month  $r$  in the country  $n$ :

$$IE_{nr} = \sum_{i=1}^m IA_{ir} \quad ; \quad m = \text{number of markets in country } n. \quad (6)$$

### **Predictive power of early warning indicators**

The predictive value of the early warning indicators defined above is tested econometrically using three types of nonlinear panel models: a probit model, a count data model and a Tobit model<sup>6</sup>. Each model allows for time specific random effects.<sup>7</sup> The sample set consists of the three countries and 19 years of time series observations (1990 – 2008).

1. The first model (probit) seeks to explain the likelihood of a price crisis in country  $n$  at year  $t$ . The outcome,  $y_{nt}$ , is a binary variable that takes 1 if the country is in crisis at year  $t$ , and 0 otherwise. We consider that the country  $n$  is in crisis at year  $t$  if the mean crisis indicator,  $E(I)$ , calculated on the sample of the  $m$  markets of the country during the lean period ( $s$ ) of year  $t$ , is

greater than one. Let: 
$$\begin{cases} y_{nt} = 1 & \text{(with probability } p) \\ y_{nt} = 0 & \text{(with probability } 1 - p) \end{cases}$$

A regression model is formed by parametrizing the probability  $p$  to depend on a regressor vector of warning indicator ( $x$ ), a parameter vector  $\beta$  and time-specific effects.

<sup>6</sup> See Cameron and Trivedi (2005) and Wooldridge (2001) for a review of these models.

<sup>7</sup> A qualitative response model with fixed effects is confronted by the incidental parameters problem. In a fixed effects model the specific effects may be correlated with the regressors, generally leading to inconsistent estimation of all parameters (Lancaster, 2000).



Table 2. Probit model. Dependent variable = 1 if the country is in crisis; = 0 otherwise

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Constante	-3.497 (1.575)**	-3.414 (1.173)**	-3.606 (1.467)**	-3.668 (1.46)**	-2.855 (1.235)**	-3.308 (1.239)**	-4.030 (1.342)**	-4.255 (1.271)**	-4.524 (1.527)**	-5.505 (2.824)**	-3.232 (1.489)**
Alert at leading market	Maradi November (Niger)	3.643 (1.797)**									
	Gaya November (Niger)		2.965 (1.678)*								
	Dori November (Mali)			3.606 (1.780)**							
	Tenkodogo November (Burkina Faso)				3.257 (1.739)*						
	Nara December (Mali)					2.855 (1.827)*					
	Number of markets on alert	November					0.168 (0.101)*				
December							0.261 (0.112)**				
January								0.265 (0.106)**			
February									0.322 (0.119)**		
March										0.430 (0.211)**	
Iaml	Maradi November										6.257 (3.327)*
Log-likelihood	-17.476	-19.446	-17.677	-18.439	-18.479	-19.340	-17.474	-17.505	-15.382	-12.885	-15.954
$\sigma_\alpha$	2.029 (1.017)	2.779 (1.154)	2.352 (1.061)	2.565 (1.136)	2.714 (1.255)	2.977 (1.384)	2.853 (1.290)	2.900 (1.226)	2.481 (1.122)	2.005 (1.340)	1.885 (0.980)
$\rho$	0.805 (0.158)	0.885 (0.084)	0.847 (0.117)	0.868 (0.101)	0.880 (0.097)	0.899 (0.085)	0.891 (0.088)	0.894 (0.080)	0.860 (0.109)	0.801 (0.213)	0.780 (0.178)
LR ( $\rho = 0$ )	8.43 [0.002]	13.73 [0.000]	11.68 [0.000]	13.42 [0.000]	13.87 [0.000]	13.93 [0.000]	12.32 [0.000]	12.89 [0.000]	9.75 [0.001]	5.47 [0.010]	7.42 [0.003]
Nb of observations	51	51	48	48	45	49	49	52	52	52	51

Significance level: \* 10%, \*\* 5%, \*\*\* 1%. Standard errors are in parenthesis; *p-value* are in brackets. Iaml : intensity of the alert on the leading markets. Approximation method of the log-likelihood: adaptive Gauss-Hermite quadrature (Naylor – Smith, 1982).

2. The second estimated model is a count data model that seeks to explain the extent of the crisis. The dependent variable,  $y_{nt}$ , is a count of the number of markets across country  $n$  which experienced at least one episode of crisis during the lean season of the year  $t$ .  $y_{nt}$ , takes on non-negative integer values, including zero:  $\{0, 1, 2, \dots\}$ .

3. The third model to be estimated is a limited dependent variable model (standard censored Tobit) that seeks to explain the intensity of the crisis  $y_{nt} \in [0 ; +\infty[$ . The censored regression Tobit model expresses the observed response,  $y_{nt}$ , in terms of an underlying latent variable.

The independent variables in the probit, Tobit and count models are the warning indicators defined above - a binary warning indicator for each leading market ( $IA_{lr}$ ), an indicator of the alert intensity for each leading market ( $II_{lr}$ ), and the number of markets on alert ( $IE_{nr}$ ). These three types of indicator are calculated monthly for the harvest and post-harvest period from October to March.

The test strategy consists in introducing successively the monthly warning indicators into the regressions, starting with the earliest indicator (October) and ending with the last one (March). The testing procedure stops when the indicator enters significantly in the regression. This procedure allows both for testing the adequacy of warning indicators, and identifying those which detect a looming crisis earliest.

The estimation results for the probit model are given in Table 2; Table 3 gives the marginal effects of the exogenous variables. The share of the specific component ( $\rho$ ) is quite high and significant, which means that the panel estimation is more relevant than the pooling estimation (see the likelihood ratio test).

The warning indicator for the leading market Maradi is significant from November (Table 2, column 1), and its marginal effect on the probability of crisis is 56% (Table 3). According to these results, if the millet price in Maradi is above its trend value during November, the likelihood of a widespread crisis arising six to seven months later is 56%. The probability of crisis also increases by, respectively, 33%, 50% and 34%, if the markets of Gaya, Dori, and Tenkodogo (three leading markets) are on alert in November. However, an alert at Nara may not be considered as a significant harbinger of a crisis until December.

Table 3. Marginal effects: probability of a price crisis (probit model)

	Maradi	Gaya	Dori	Tenkodogo	Nara
Market on alert ( $IA_{ls}$ )	November	November	November	November	December
	0.558	0.326	0.500	0.340	0.498
Number of markets on alert ( $IE_{ns}$ )	November	December	January	February	March
	0.067	0.104	0.106	0.128	0.172
Alert intensity at Maradi ( $II_{ls}$ )	November				
	0.736				

Source: the authors.

Therefore, the marginal effect of an alert in Maradi during the month of November is high, both in absolute terms, and relative to the marginal effect of an alert in any other of the leading markets considered. These results confirm the importance of monitoring the price movements in Maradi.

The variable "number of markets on alert" is also significant from November (Table 2, columns 6-10). The marginal effect of the number of markets on alert in November on the probability of crisis is 7%, and this effect increases over time - it increases to 10% in December, 11% in January, 13% in February, and 17% in March.

The alert intensity, which is measured as the price deviation from its trend value relative to its standard deviation, appears to be a good indicator of the occurrence of a crisis. This indicator

is more relevant than the scope of the alert, which is caught by the number of markets on alert. Indeed, the marginal effect of the alert intensity at Maradi on the probability of crisis is as high as 74% for the month of November (Table 3). In other words, the higher the price increases in Maradi at the beginning of the season, the greater the likelihood of a widespread crisis.

In the count data model, the incidence rate ratio (IRR) is given by  $e^{\beta}$ . It measures the variation in the dependant variable for a one unit change in the independent variable,  $x_{nt}$ , with all other variables in the model held constant.

The results from this model (Table 4) confirm the previous ones. The warning indicator for Maradi significantly explains, from November onwards, the extent of the crisis to come. The same applies for Dori's warning indicator from December onwards. Specifically, the IRR shows that when Maradi (Dori) goes on alert in November (December) the predicted number of markets in crisis increases by a factor of 6.725 (Equations 1 and 3, Table 4). We note that an alert in Gaya or Tenkodogo in November or December does not significantly predict the extent of the crisis (Equations 2 and 4, Table 4).

The number of markets on alert (Equations 5-9, Table 4) enters significantly in the Poisson regression model, but its ability to predict the extent of the crisis is fairly low, with an IRR close to one in November. However the IRR for the number of markets on alert in March is slightly higher - the expected number of markets in crisis increases by 17% when one more market is on alert during March.

The intensity of the alert on the leading markets, especially Maradi, is only significant from February, and cannot be considered as a good predictor of the extent of the crisis (equations 10-13, Table 4). In other words, the number of markets affected by the crisis is not directly related to the magnitude of price increases in Maradi at the beginning of the season.

The results from the Tobit model (Table 4) corroborate the previous ones - the warning indicator for Maradi in November is positively related to the intensity of the coming crisis. The same applies for the Gaya warning indicator in November, as well as Dori and Tenkodogo in December. The marginal effects<sup>8</sup> show that when Maradi goes on alert in November, the crisis intensity rises by 2.8. The marginal effect of Dori's warning indicator (November) and Tenkodogo (December) is of the same order of magnitude, it is lower for Gaya (November) (Equations 14-17, Table 4).

As in the probit model case, the marginal effect of the number of markets on alert increases with time (Equations 18 to 22, Table 4). Finally, the intensity of the alert at Maradi at the beginning of the season (November) significantly explains the intensity of the future crises. However, the marginal effect of this variable on the intensity of the crisis is not higher than the effect of the binary warning indicator.

In summary, the results show that the three types of warning indicators identified above, are relevant as they significantly explain the scope and the intensity of future crises. Our analysis shows that it is of most importance to monitor millet price movements in Maradi during the harvest period. Indeed, the probability of a widespread crisis breaking out five or six months later sharply increases when prices in Maradi are above their trend value in November. The results also show that monitoring all markets during the harvest period does not add significant extra information. However, it may be useful to monitor the markets of Gaya, Nara

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<sup>8</sup> Marginal effect on the expected value for  $y$  is given by:  $\frac{\partial E[y]}{\partial x} = \Phi\left(\frac{X_i\beta}{\sigma}\right)$ . This indicates how a one unit change in an independent variable  $x$  affects censored observation ( $y$ ).

and Tenkogogo as well as Maradi. If these markets are also on alert during the last months of the year, the probability of crisis increases significantly.

## 5. Conclusion

Whatever the explanatory factors of the price crisis, our analysis shows that it is possible to anticipate crises from the observation of past price movements. The crises that erupt usually during April or May, may in fact be anticipated as early as November by monitoring the price movements in some key markets – most importantly Maradi, but also Dori, and to a lesser extent Gaya and Tenkodogo.

The warning indicators defined in this paper should usefully complement the early warning systems currently focused on crop monitoring. They have the advantage of being based on objective information, easy to collect, and rapid to collate. These indicators could be calculated in each country and integrated into the national warning system. However, the high correlation of crises should encourage the construction of a regional warning system, incorporating indicators from all the three countries. Irregularities detected early, at the beginning of the harvest, on the border markets of Nigeria and Benin must lead to alerts for not only the authorities of Niger, but also of Burkina Faso and Mali, about the possible occurrence of a crisis.

Of course, our calculations face a number of limitations. The main one is the quality of the estimated price trend value. We used a very simple form for the trend equation. The advantage of this specification is ease of calculation and updating of indicators. In return, the goodness of fit is sometimes poor. The introduction of the consumer prices index instead of the trend variable generally improves the accuracy of the estimates. However the consumer prices index is published with a delay of several months, so a warning system based on this index would be ineffective.

With hindsight, the adequacy of the warning indicators, based on the deviation of prices from their trend value seems to be satisfactory. However it is difficult to assess the ability of these indicators to prevent crises in advance. Simulations were made for the period 2000-2008 which were satisfactory. They show, however, the need to periodically update the price trend. In that regard, we suggest a “conservative” approach that consists in updating the trend estimates only if the predicted trend values are lower than previous forecasts. This method, which tends to underestimate the trend value, is expected to lead to better detection of coming crises, although at the cost of an increase in the number of false alarms.

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Table 4. Estimation results for the count data model and the censored data Tobit model

Dependent variable		Count data model (Poisson)						Censored data model (Tobit)						
		Number of markets that have experienced at least one episode of crisis during the lean season						Crisis intensity						
Independent variables		$\beta$	IRR	$\delta$	LR ( $\delta=0$ )	Log-V	Eq.	$\beta$	marginal effect	$\sigma_\alpha$	$\rho$	Log-V	Eq.	obs
Alert at leading market	Maradi November (Niger)	1.906 (0.875)**	6.725 (5.884)**	3.255 (1.380)	152.13 [0.000]	- 113.56	<b>(1)</b>	3.187 (1.106)***	2.812	1.822 (0.505)	0.719 (0.130)	- 52.87	<b>(14)</b>	51
	Gaya November (Niger)	1.109 (0.962)	3.032 (2.917)	4.018 (1.612)	248.58 [0.000]	- 117.84	<b>(2)</b>	2.285 (1.196)**	1.792	2.135 (0.580)	0.781 (0.106)	- 55.18	<b>(15)</b>	51
	Dori December (Mali)	1.915 (0.913)**	6.786 (6.195)**	3.152 (1.408)	154.80 [0.000]	- 110.64	<b>(3)</b>	3.182 (1.197)***	2.792	1.922 (0.553)	0.739 (0.126)	- 50.88	<b>(16)</b>	48
	Tenkodogo december (Burkina Faso)	1.420 (0.976)	4.136 (4.037)	3.697 (1.593)	219.95 [0.000]	- 111.49	<b>(4)</b>	3.453 (1.273)***	3.151	1.932 (0.551)	0.739 (.126)	- 50.45	<b>(17)</b>	48
Number of markets on alert	November	0.034 (0.019)*	1.035 (0.019)*	4.053 (1.625)	241.75 [0.000]	- 113.50	<b>(5)</b>	0.117 (0.054)**	0.117	2.131 (0.566)	0.806 (0.098)	- 54.47	<b>(18)</b>	49
	December	0.066 (0.020)***	1.068 (0.022)***	3.747 (1.535)	206.46 [0.000]	- 109.95	<b>(6)</b>	0.170 (0.051)***	0.170	1.975 (0.513)	0.815 (0.095)	- 52.06	<b>(19)</b>	49
	January	0.087 (0.022)***	1.091 (0.025)***	4.042 (1.650)	218.95 [0.000]	- 108.28	<b>(7)</b>	0.192 (0.049)***	0.192	2.061 (0.528)	0.848 (0.081)	- 51.43	<b>(20)</b>	52
	February	0.122 (0.024)***	1.129 (0.027)***	3.442 (1.473)	162.84 [0.000]	- 101.74	<b>(8)</b>	0.214 (0.043)***	0.214	1.831 (0.462)	0.847 (0.082)	- 48.10	<b>(21)</b>	52
	March	0.159 (0.028)***	1.173 (0.033)***	2.321 (1.164)	78.03 [0.000]	- 97.43	<b>(9)</b>	0.253 (0.044)***	0.253	1.460 (0.369)	0.789 (0.106)	- 44.49	<b>(22)</b>	52
Alert intensity	Maradi November	2.367 (1.557)	10.670 (16.611)	3.473 (1.443)	204.93 [0.000]	- 113.93	<b>(10)</b>	3.793 (1.123)***	3.096	1.885 (0.980)	0.676 (0.140)	- 52.05	<b>(23)</b>	51
	Maradi December	2.581 (1.741)	13.214 (23.011)	3.516 (1.455)	218.59 [0.000]	- 113.99	<b>(11)</b>	3.691 (1.230)***	2.906	1.732 (0.486)	0.706 (0.132)	- 53.03	<b>(24)</b>	51
	Maradi January	1.569 (1.023)	4.807 (4.920)	3.786 (1.567)	186.30 [0.000]	- 114.69	<b>(12)</b>	3.269 (0.872)***	2.812	1.485 (0.435)	0.640 (0.151)	- 51.80	<b>(25)</b>	52
	Maradi February	2.450 (1.191)**	11.592 (13.81)**	3.233 (1.393)	168.85 [0.000]	- 113.75	<b>(13)</b>	3.640 (0.935)***	3.169	1.448 (0.419)	0.626 (0.154)	- 51.10	<b>(26)</b>	52

Significance level: \* 10%, \*\* 5%, \*\*\* 1%. Standard errors are in parenthesis; *p-value* are in brackets. IRR : Incidence rate ratio.

The constant value is not reproduced. Approximation of the log-likelihood by adaptive Gauss-Hermite quadrature (Naylor – Smith, 1982)