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Alert at Maradi: preventing food crises 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 markets which 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 at leading markets during crucial periods of the year can help in forecasting future crises.

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

JEL Code: Q18, C25, D40, O18

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1. 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.

However, in spite of the significant resources used at the national and international level to assess future food availability (e.g. yearly agricultural surveys, monitoring of the crop season, weather forecasting models and agro-climatic models based on satellite data, etc), the exercise remains difficult, politically sensitive, and prone to controversy. For example, marketing year 2004/05, initially considered as one of the best years ever known in the Sahel, finally proved to be a deficit year (Egg and al. 2006). Also regional dialogue within the framework of the food crisis prevention network in Sahel and West Africa regularly exhibits large inconsistencies between the forecasts established by bordering countries.

Furthermore, production forecasts provided in the Cereal Balance Sheet, which also integrates stocks and trade estimates are generally published in late October after the beginning of the harvest. These figures are then adjusted between January and March when yield data collected through the agricultural survey become available. As a consequence, production forecasts do not really provide early information about the state of future food availability. Assessing the level of stocks and trade flows constitutes another major difficulty when estimating food availability. Grain storage is handled by private agents who are reluctant to give such strategic information, while grain trade with neighboring countries usually takes place in the informal sector and is mostly unregistered. As a consequence the information on production forecasts, initial stocks and trade provided in the Cereal Balance Sheet, is generally considered to be of poor quality.

Paradoxically, little attention is paid to the information conveyed by market prices. In some countries such as Niger, occasional vulnerability analyses aimed at identifying the populations at risk, and targeting interventions, are conducted when production forecasts are alarming. 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.

But the information provided by market prices could also be used to forecast future crises. Indeed, if markets are efficient, prices at any given time fully reflect all available information not only on current food availability but also on agents' expectations about future scarcity (see for instance Ravallion 1985, Deaton and Laroque 1992). 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. Of course, if markets are not efficient due to agents' irrational behavior, or informational failures, market prices may not reflect the actual state of food availability. In that case the information provided by market prices will not be exploitable by an early warning system.

In this paper, it is argued that the information provided by market prices can usefully complement existing early warning systems which tend to privilege biophysical models. The objective is to use price data to consolidate food security forecasts, and build indicators to alert policymakers as to when a future crisis can be expected. In other words, the aim of this research is to exploit the statistical properties of grain price data to detect the warning signs of a looming crisis, early in the crop marketing year.

The analysis focuses on three countries – Mali, Niger and Burkina Faso – and a local crop – millet – which plays an essential role in the diets of Sahelian populations. Price data come from the national *Systèmes d'Information sur les Marchés* of each country. The paper is organized in the following manner. Section two stresses the important role of millet in food security and sets out the main characteristics of the sample markets. Section three is devoted to identifying the markets that play a leading role in influencing prices at the national and regional level. Section four 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. Section five is dedicated to the identification of warning indicators. 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 relevance of these indicators is tested in section six. The final section presents conclusions.

2. CONTEXT AND SAMPLE DESCRIPTION

Burkina Faso, Mali and Niger belong to the same regional integration area (ECOWAS) and to a common monetary union (UEMOA). These countries share many other common characteristics that call for a regional approach to food crisis prevention. We first stress the role of millet in food security, and then present the markets under study and the data set.

(a) The critical role of millet in food security

The Sahel is one of the poorest regions of the world and millet is the main grain crop. Nigeria is the largest producer, with 54% of West African millet production. Niger is the second producing country with 21% of West African production, ahead of Mali and Burkina Faso (Table 1). Northern Nigeria and South Niger belong to the same production basin, which is the largest in West Africa, while Burkina Faso and Mali belong to the second production basin of the region (Soulé and Gansari, 2010).

[Insert Table 1]

Burkina Faso, Mali and Niger are closely tied through millet trade flows. Niger is structurally an importer of millet. Its main source of imports is Nigeria, but imports from Burkina Faso and Mali have been expanding during the last decade. While millet is the subject of intensive cross-border trade in West Africa it is not traded internationally. As a consequence millet price variations in the sub-region mainly reflect changes in local supply conditions, demand being less volatile.

The millet growing season varies from year to year according to the start of the rains, but generally begins in April and ends in October. Usually, sowing takes place from May to August. Harvest starts in October and lasts until December. Part of millet production is sold at harvest by farmers to meet their financial needs. The other part, intended for family consumption and seed production, is stored on the farm until the next season or beyond; indeed millet can be stored without damage for more than a year. The wholesalers hold grain stocks for generally short periods, not more than two or three months (Aker, 2010). The public authorities also manage food stocks that are built up at the beginning of the year (February-March), and which are intended to be sold on the market in the following months.

Millet prices are characterized by large seasonal fluctuations especially in Niger, due to the seasonal pattern of the production cycle. 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.

Millet and sorghum are the staple diet, especially in rural areas. According to the latest available data, millet supply represents more than 20% of total food supply in Mali and Burkina Faso, and almost 40% in Niger (Table 1). In that context, a millet price increase may have dramatic consequences on food security by directly affecting the entitlement set of poor people (Sen, 1981).

Sharp rises in grain prices generally follow a crop failure due to bad weather conditions. Indeed, rain fed farming is the dominant production system and is highly vulnerable to climatic shocks, especially to drought. It should be stressed that the price increase does not necessarily reflect the severity of the food deficit. As shown by Sen (1981) the food price increase may be exacerbated by market failures – excessive hoarding or inadequate spatial arbitrage – so that a modest decline in food availability may generate large price variations.

The impact of a food price increase on food security is biggest when the exogenous shock also affects other sources of entitlement, such as wages, assets and transfers (Ravallion, 1997; O'Grada, 2007). This is typically the case during drought periods in Mali, Niger and Burkina Faso. The millet price is positively correlated with other local grain prices, and negatively correlated with the price of livestock, an asset which is typically held as a buffer stock in this region. As a consequence, the possibilities for substitution in consumption are limited, while livestock sales do not compensate for losses in income. More generally, the literature shows that insurance mechanisms against income shocks are weak, and only allow for partial consumption smoothing in African developing countries (see for instance, Kazianga and Udry, 2006).

(b) The sample markets

Burkina Faso, Mali and Niger share a harmonized system for collecting price information on grain markets. In each country a market information system (MIS) was started in the early 90s. The implementation of these devices was part of the measures accompanying the liberalization of the agricultural sector within the framework of structural adjustment programs. The aim was to increase market efficiency after the withdrawal of the State from the production and marketing of agricultural products.

MISs collect market prices for major agricultural products (but also livestock) and disseminate this information to producers, consumers and traders through the media. They 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.

[Insert map1]

We selected a sample of 44 millet markets from the markets covered by the MISs: l5 markets in Niger, 12 in Burkina Faso, and 17 in Mali (see Table A1 in the appendix). Market selection was based on the quality of available information: markets for which too much data is missing were dropped. As can be seen in table AI and map 1, the selected sample includes a variety of markets that differ according to their location: remote area, border proximity, production area or urban area. The observation period starts in January 1990 in Niger, January 1992 in Burkina Faso and February 1993 in Mali.[i]

3. THE LEADING MARKETS

The main objective of this part of the analysis is to identify markets whose prices can help in forecasting the future value of prices in other domestic and regional markets. These “leading markets” are identified using Granger causality tests that are conducted in a multivariate vector autoregressive (VAR) framework.

(a) The VAR model

The main advantage of the VAR model is that it takes 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:

$$\boldsymbol{P}_t = \gamma + \sum_{i=1}^{p} A_i P_{t-i} + \xi_t \qquad (1)$$

$\boldsymbol{P}_t$ is a k vector of real prices, A_i is a matrix of coefficients to be estimated and ξ_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.

$E(\xi_t) = 0$; $E(\xi_t \xi_t') = \boldsymbol{\Sigma}$ (an $m \times m$ positive semi definite matrix) ; $E(\xi_t \xi_{t'}') = 0$ for all $t \neq t'$.

t = 1, …, T. T = 201 for Burkina Faso, T = 226 for Niger and T = 191 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).

(b) The Granger causality test

The Granger causality tests indicate whether there is a statistically significant relationship between current prices on market i and lagged prices on market j. They consist of standard F-test, equation by equation, for the joint hypothesis of nullity of some of the coefficients of the VAR system. In the null hypothesis (P_j does not cause P_i), the coefficients of the lagged prices in market j in the P_i equation, are null.

The Granger causality tests do not reveal the true nature of the relationship between prices (the parameters are not readily interpretable), and do not provide information about the causal factors that lead to dynamic adjustments between prices. According to the Granger approach, P_i is said to be Granger caused by P_j if P_j helps in the prediction of P_i. The Granger causality test does not by itself indicate causality, but identifies precedence between two variables and measures the information content of lagged variables. This test can therefore be used to identify markets whose prices can help in forecasting future prices in other markets.

We consider as leading markets, those markets that *Granger cause* a large number of other markets, but are themselves *Granger caused* by only a few markets. In other words, 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 (i.e. they do not depend on the lagged prices of the other markets in the sample).

The Granger causality tests are first performed using a VAR model specific to each country, incorporating all the markets of that country. This approach allows identification of the leading markets in each country. Secondly, causality tests are performed on a regional VAR model limited to 25 markets of the sub-region.[ii]

(c) Results

To identify the leading markets, markets are ranked according to two criteria: the number of markets that are *Granger caused* by each market, and the number of markets that each market *Granger causes*. We consider as a leading market at the domestic level, a market that *causes* more than half of the sample markets (i.e. at least seven markets in Burkina Faso, nine markets in Mali, and eight markets in Niger). It appears that these markets are also caused by a small number of markets (less than 30%). As can be seen in figure 1, these criteria are highly discriminating. Only a few markets are classified as “leading markets” (Table 2): Gaya and Maradi in Niger; Dori, Tenkodogo and Banfora in Burkina Faso; Nara and Koulikoro in Mali. Nara and Dori are on the limit for consideration as leading markets; they could have been considered as non leading markets. Indeed, the subsequent analysis shows that the pertinence of alert indicators based on Nara prices is doubtful.

[Insert Figure 1]

These results are not surprising for Maradi and Gaya. Maradi is one of the most important markets of Southern Niger, the main producing region. Gaya is located on the border with Benin and is one of the main gateways for grain imports. In Mali, Koulikoro 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.

[Insert Table 2]

At the regional level, the analysis confirms the leading role of Maradi: prices in this market *Granger cause* those of 8 markets in Burkina Faso and Mali (Table 2). The leading role of Maradi probably reflects the influence of Nigeria on millet prices within the whole sub region. The markets of Dori and Tenkodogo also confirm their leading market status at the regional level. In contrast, Gaya (Niger), Nara (Mali) and Banfora (Burkina Faso) which appeared to be leading markets at the national level, do not play a significant role at the regional level.

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 to predict the prices of other markets, in the framework of an early warning system.

4. PRICE CRISIS CHARACTERISTICS

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

(a) Identifying price crises

The stationarity tests (Table A1 in the Appendix) reject the presence of a unit root, and lead to the consideration of all the price series as trend stationary. The price trend (2) is estimated for each market's price over the whole period. The seasonal dummies M_s, catch the monthly price fluctuations related to the production cycle, and the trend T, captures long term movements (e.g. related to population growth):

$$P_t = aT_t + \sum_{s=1}^{12} b_s M_{st} + \zeta_t \qquad (2)$$

with:

P_t the current millet price at time t and ζ_t an *iid* random variable with: $\zeta_t \sim N\left(0, \sigma_\zeta^2\right)$.

The coefficient's stability is tested using the Quandt-Andrews breakpoint test[iii] for 158 possible breakpoint dates in the period 1990-2008 in Niger, 131 for Mali and 139 for Burkina Faso[iv]. The tests fail to reject the null hypothesis of no structural breaks.

In the following we consider that there is a crisis at time t on the market under consideration if the spread between the observed price, P_t, and its trend value, $\hat{P}_t$, is greater than one standard deviation, i.e. if:

$$I_t = P_t - \hat{P}_t \geq \sigma_I \qquad (3)$$

[Insert Figure 2]

According to our definition of crisis, Burkina Faso, Mali and Niger experienced three common price crises in 1998, 2002 and 2005 (Figure 2). In addition to these shared major crises the three countries were affected by crises of smaller magnitude: 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 (Araujo and Brunelin, 2010). In 2008, a few episodes of short-term 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.

(b) Dating price 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 where crises erupt in April, and end in September. They are preceded by a period running from September/October to March during which prices are above their trend value. For example in Maradi, millet prices were above their trend value from September 1996 to March 1997, and the crisis broke out in April 1998 (Figure 3). At Gaya, prices were above their trend value from September 1996 to January 1997, and the crisis broke out in January 1997.

[Insert Figure 3]

In Mali, crises occur later in the year, erupting in May/June and ending 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 4 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.

[Insert Figure 4]

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, and Tenkodogo, and from January 1996 in Dori (Figure 5).

[Insert Figure 5]

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 their trend value during the harvest period.

5. 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. Different indicators are proposed, whose relevance is tested using nonlinear panel models.

These indicators aim at capturing as soon as possible the price movements which herald 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 price distortions during the alert phase.

First, for each leading market (l), we define a binary warning indicator (A_{lr}) equal to 1 if the market registers a positive shock during the month r of the harvest period that runs from October to March:

$$A_{lr} = 1 \text{ if } I_{lr} = P_{lr} - \hat{P}_{lr} > 0 \text{ ; } = 0 \text{ otherwise} \tag{4}$$

Second, vigilance should increase with the magnitude of the price disequilibrium that is captured by an indicator of the intensity of the alert (AI_{lr}):

$$AI_{lr} = I_{lr} / \sigma_I \tag{5}$$

This indicator is calculated for each leading market (l) and each month (r) of the alert period.

Third, the alert should go up if many markets are simultaneously on alert. An indicator of the spatial extent of the alert (AE_{nr}) is therefore given by the number of markets on alert during the month r in the country n:

$$AE_{nr} = \sum_{i=1}^{m} A_{ir} \; ; \qquad m = \text{number of markets in country } n. \tag{6}$$

Four limitations of these warning indicators must be underlined. First, while most of the crises are preceded by an alert phase, not all phases of alert lead to a crisis. Thus, in 1990, 1991 and 2003 in Niger, prices were above their trend value over the period September to December, but the bubble burst in March or April of the next year (Figure 3). In general, after an alert phase, it is observed that either the crisis occurs, or the bubble bursts in March or April. In the latter case, the alert can be lifted by the end of April.

Second, the alert phase can sometimes be short, and so the crisis not anticipated. This is the case for Niger in 2001 - the crisis occurred suddenly in Gaya and N'Guigmi in April 2001, without being preceded by an alert phase. In this case, however, the alert could have been given in September at Maradi. In Burkina Faso also, the 2001 crisis broke out suddenly in March/April 2001 without a generalized warning phase. We note however, that Dori, identified as a leading market in the above analysis, had been on alert since November 2001.

Third, after a crisis prices return to the normal level, but the process may take time so that predicting prices for the following year can be difficult. Prices tend to return slowly to their trend value after a crisis, so that the alert holds, sometimes unnecessarily, until May/June of the next year. This is the case, for example, in Mali after the 1996 crisis (Figure 4). Malian prices in all the markets of the sample were above their trend value until spring 1997, inferring that the warning indicators would have been activated until April/May 1997.

Finally, some markets, such as Kayes and N'Guimi, exhibit atypical behavior. In Kayes, crises tend to erupt a few months later (July/August) than in other Malian markets, and prices revert more slowly to their long-run equilibrium. This phenomenon can be explained by the relative isolation of these two markets, and delays in price shocks transmission.

6. PREDICTIVE POWER OF EARLY WARNING INDICATORS

The predictive power 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[v]. Each model allows for time specific random effects.[vi] The sample set consists of the three countries and a 19 year period of annual 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 (Table 3). Let:

$$\begin{cases} y_{nt} = 1 & \text{(with probability} \quad p) \\ y_{nt} = 0 & \text{(with probability} \quad 1-p) \end{cases}$$

A regression model is created by parametrizing the probability p to depend on a regressor vector of warning indicator (x), a parameter vector β and time-specific effects. The conditional probability is given by:

$$\Pr\left[y_{nt} = 1 \middle| x_{nt}, \beta, \alpha_t\right] = \Pr\left[y^*_{nt} > 0\right] = \Pr\left[x'_{nt}\beta + u_{nt} > 0\right] \qquad \text{with, } u_{nt} = \alpha_t + \varepsilon_{nt}$$

y^*: latent variable. n denotes the n-th country, t the t-th time period; α_t captures the time-specific unobserved effects assumed to be constant over individuals, $\alpha_t \sim iid\left(0, \sigma^2_\alpha\right)$; ε_{nt}, is an idiosyncratic error satisfying the usual assumptions: $\varepsilon_{nt} \sim iid\left(0, \sigma^2_\varepsilon\right)$, $E(x_{nt}, \varepsilon_{nt}) = 0$ and Cov

$(\varepsilon_{nt}, \varepsilon_{n't'}) = V(\varepsilon_{nt}) = 1$, if $n = n'$ and $t = t'$, or 0 otherwise. The unobservable time-specific effects are correlated neither with errors nor each explanatory variable.

The proportion of the total variance contributed by the time-level variance component is given by: $\rho = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + 1}$. When ρ is zero, the time-level variance component is unimportant and the panel estimator is not different from the pooled estimator.

[Insert Table 3]

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 (Table 3). y_{nt}, takes on non-negative integer values, including zero: {0, 1, 2, …}.

The basic Poisson probability specification is: $\text{Prob}(y\ |x) = f(y\ |x) = \frac{e^{-\lambda}\lambda^{y}}{y\ !}$, where $y!$ is y factorial ; $\lambda \equiv E(y|x) = V(y|x\ )$.

Following Hausman et al. (1984), we consider the random effects panel Poisson specification where the Poisson parameter is specified as: $\tilde{\lambda}_{nt} = \lambda_{nt}\alpha_t = e^{x_{nt}'\beta + \mu_t}$, $\tilde{\lambda}_{nt} > 0$; $\alpha_t = e^{\mu_t}$ are the time-specific effects (unobserved); x_{nt} is a vector of warning indicators. It is assumed that α_t is distributed as a gamma random variable: $\alpha_t \sim \Gamma(\eta,\eta)$, with $\mathrm{E}(\alpha_t) = 1, \mathrm{V}(\alpha_t) = \delta$. Note that when δ is zero the panel estimator is not different from the pooled estimator.

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 (Table 3) where $y_{nt} \in [0\ ; +\infty[$

The censored regression Tobit model expresses the observed response, y_{nt}, in terms of an underlying latent variable $y_{nt}^* = x_{nt}'\beta + u_{nt}$

with $\begin{cases} y_{nt} = y^*_{nt} & if \quad y^*_{nt} > 0 \\ y_{nt} = 0 & otherwise \end{cases}$; t = 1990, …, T ; n = 1, …, N .

x_{nt} is a vector of warning indicators; β is a vector of parameters to be estimated; u_{nt} is a random variable, $u_{nt} = \alpha_t + \varepsilon_{nt}$, defined as above.

The independent variables in the probit, Tobit and count models are the warning indicators defined above: a binary warning indicator for each leading market (A_{lr}), an indicator of the alert intensity for each leading market (AI_{lr}), and the number of markets on alert (AE_{nr}).

[Insert Table 4]

The test strategy consists in successively introducing 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 alert 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.

Table 4 gives the marginal effects of the exogenous variables derived from the probit model. The share of the specific component (ρ) 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 Maradi is significant from November; its marginal effect on the probability of crisis is 56% (Table 4, column 1). 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 are on alert in November. However, an alert at Nara cannot be considered as a significant harbinger of a crisis until December.

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 of the other leading markets considered. These results confirm the importance of monitoring price movements in Maradi.

The variable "number of markets on alert" is also significant from November (Table 4, 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 4). In other words, the higher the price increases in Maradi at the beginning of the season relatively to its trend value, the greater the likelihood of a widespread crisis.

[Insert Table 5]

Any early warning system (EWS) is confronted by two drawbacks: the number of false alarms (Type 2 errors), and the number of missing alarms (Type 1 errors). Table 5 presents some indicators of the predictive quality of the probit model based on the percentage of Type 1 and Type 2 errors, using a cut-off probability equal to 0.3[vii]. Choosing a low cut-off means considering that missing a crisis is more costly than a false alarm (i.e. an alarm not followed by a crisis). Given the potential cost of a food crisis this assumption seems reasonable, even if the cost of preventive measures should not be ignored in case of a false alarm. Table 5 highlights once again the higher performance of an EWS based on Maradi price signals. This model correctly predicts 86% of crises, with a probability of crisis given no alarm of only 7%, but at the expense of a 43% rate of false alarms.

The results from the count data model (Table 6) confirm the previous ones. They show that the warning indicator for Maradi significantly explains, from November onwards, the extent of the crisis to come, although only at the 10% significance level in November. The same applies for Dori's warning indicator from December onwards. Specifically, the incidence rate ratio (IRR)[viii] 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 (6.786). An alert in Gaya in February is a significant predictor of an impending and generalized crisis. We note that an alert in Nara or Tenkodogo does not significantly predict the extent of the future crisis.

[Insert Table 6]

The number of markets on alert (Table 6) 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 at Maradi is significant from December, and can be considered as a good predictor of the extent of the crisis (Table 6). The number of markets affected by the crisis increases sharply - by a factor of 13.2 - when the price shock in Maradi at the beginning of the season increases by one standard deviation. Lastly, for all regressions, the LR test confirms that the panel estimator is more relevant than the pooling estimator.

The results from the Tobit model (Table 7) corroborate these results. 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 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).

As in the probit model case, the marginal effect of the number of markets on alert increases with time (Table 7). 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.

[Insert Table 7]

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. 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 six or seven 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. Nevertheless, it may be useful to monitor the markets of Dori, Gaya and Tenkogogo in addition to Maradi. If these markets are also on alert during the last months of the year, the probability of crisis increases significantly.

7. 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.

Therefore 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, which is easy to collect, and quick to collate. These indicators could be calculated in each country and integrated into the national early warning system. The high inter-country 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.

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, on the other hand, the goodness of fit may be poor. The introduction of the consumer price index instead of the trend variable generally improves the accuracy of the estimates. However, the consumer price index is published with a delay of several months, so an early 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 good. However it is difficult to assess the ability of these indicators to prevent crises in advance. Out-of-sample 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 expense of an increase in the number of false alarms.

ENDNOTES

[i] The MIS of Niger also covers five markets located in northern Nigeria and one market in northern Benin. Unfortunately the observation period is quite short for these markets (2000-2008) so they cannot be incorporated in the following econometric analysis despite their importance in regional trade.

[ii] The regional sample includes: 8 markets in Niger, 7 in Burkina Faso, and 10 in Mali.

[iii] Test for one or more unknown structural breakpoints in the sample.

[iv] According to a 15% trimming procedure that excludes the first and last 7.5% of the observations.

[v] See Cameron and Trivedi (2005) and Wooldridge (2010) for a review of these models.

[vi] 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).

[vii] The cut-off is the threshold probability above which the predicted probability is interpreted as a signal of a coming crisis. The lower (higher) the threshold, the more (less) signals the model will send at the expense of raising the number of false alarms (missing crisis) (see for instance Berg and Patillo, 1999).

[viii] The incidence rate ratio is given by e^{β}. It measures the variation in the dependant variable for a one unit change in the independent variable, x_{nt}, with all other variables held constant.

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Table 1. Millet production and supply

	Burkina Faso	Mali	Niger
Millet production in 2008 (tons)	1 255 190	1 413 910	3 489 390
Millet production in % of West Africa production (2008)	8	8	21
Millet production in % of total cereal production (2008)	29	29	72
Millet supply (kg/capita/year) in 2007	70.3	65.8	137.8
Total food supply (kcal/capita/day) (2007)	2677	2614	2376
Millet supply in % total food supply (2007)	21	21	39

Source FAOSTAT. Millet supply = Production + Imports + ΔStocks – Exports – Seed – other utilizations

Table 2. Leading markets

		Number of markets that are Granger caused by market X		Number of markets that Granger cause market X	
	Market X	National level[a]	Regional level[b]	National level[a]	Regional level[b]
Niger	Gaya	10	3	1	3
	Maradi	9	8	2	3
Burkina Faso	Banfora	9	7	1	3
	Dori	7	9	3	2
	Tenkodogo	8	9	3	2
Mali	Koulikoro	10	3	3	5
	Nara	10	0	5	4

[a]: results from the VAR model estimated on a market sample restricted to domestic markets.
[b]: results from the VAR model estimated on the regional market sample (25 markets). Only markets belonging to foreign countries are accounted for in these calculations.

Table 3. Price crises in millet markets

	Country in crisis[a]			No. of markets affected by a crisis[b]			Crisis intensity[c]		
	Burkina Faso	Niger	Mali	Burkina Faso	Niger	Mali	Burkina Faso	Niger	Mali
1990	-	0	-	-	0	-	-	0	-
1991	-	0	-	-	1	-	-	0	-
1992	0	0		0	0	-	0	0	-
1993	0	0	0	0	0	0	0	0	0
1994	0	0	0	0	0	0	0	0	0
1995	0	0	0	0	0	0	0	0	0
1996	1	0	1	11	1	17	2	0,1	4
1997	0	1	0	2	14	0	0,1	1,5	0
1998	1	1	1	12	15	15	3,3	3.9	2,6
1999	0	0	0	0	0	0	0	0	0
2000	0	0	0	0	1	0	0	0	0
2001	1	1	0	11	14	6	1,6	1,8	0,5
2002	1	1	1	12	15	17	1,7	1,8	4,4
2003	0	0	0	0	0	13	0	0	0,9
2004	0	0	0	0	0	0	0	0	0
2005	1	1	1	12	15	17	4,3	3	4,6
2006	0	0	0	0	0	0	0	0	0
2007	0	0	0	0	0	0	0	0	0
2008	0	0	0	3	3	0	0,3	0,1	0

[a] Variable equal to one if the mean crisis indicator, E(I), calculated on the sample of the *m* markets of the country in question during the lean period (*S*) of year *t* is greater than one; = 0 otherwise, with :

$$E(I)=\frac{1}{m}\frac{1}{S}\sum_{i=1}^{m}\sum_{s=1}^{S}\frac{I_{is}}{\sigma_I} \text{ and } I_{is} = P_{is}-\hat{P}_{is}$$

[b] Number of markets that have experienced at least one episode of crisis during the lean season.
[c] Intensity of the crisis = E(I) if E(I) > 0; =0 otherwise
Number of markets in the sample: Burkina Faso 12; Niger 15; Mali 17.
Lean season in Mali and Burkina Faso: June to October. Lean season in Niger: May to August.

Table 4. Probit model. Marginal effects. Dependent variable = 1 if the country is in crisis; = 0 otherwise

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Alert at leading market	Maradi November (Niger)	0.558										
		[0.043]										
	Gaya November (Niger)		0.326									
			[0.077]									
	Dori November (Mali)			0.500								
				[0.043]								
	Tenkodogo Nov. (Burkina Faso)				0.340							
					[0.061]							
	Nara December (Mali)					0.498						
						[0.118]						
Number of markets on alert	November						0.067					
							[0.097]					
	December							0.104				
								[0.020]				
	January								0.106			
									[0.012]			
	February									0.128		
										[0.007]		
	March										0.172	
											[0.042]	
AI	Maradi November											0.736
												[0.060]
Log-likelihood		- 17.476	-19.446	- 17.677	- 18.439	- 18.479	- 19.340	- 17.474	- 17.505	- 15.382	- 12.885	- 15.954
ρ		0.80	0.89	0.85	0.87	0.88	0.90	0.89	0.89	0.86	0.80	0.78
LR ($\rho = 0$)		8.43	13.73	11.68	13.42	13.87	13.93	12.32	12.89	9.75	5.47	7.42
		[0.002]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.010]	[0.003]
Number of observations		51	51	48	48	45	49	49	52	52	52	51

Intercept not reported. AI: intensity of the alert on the leading market.

P-values are in brackets. Approximation method of the log-likelihood: adaptive Gauss-Hermite quadrature (Naylor – Smith, 1982).

Table 5. Probit model. Goodness-of-fit

	Alert at the leading market:					Number of markets on alert in:					Alert intensity
	Maradi Nov	Gaya Nov.	Dori Nov.	Tenkodogo Nov.	Nara Dec.	Nov	Dec.	Jan.	Feb	Mar.	at Maradi Nov
1. % of observations correctly predicted	0.78	0.71	0.71	0.65	0.69	0.71	0.71	0.73	0.73	0.92	0.76
2. % of crises correctly predicted	0.86	0.71	0.86	0.86	0.64	0.07	0.29	0.21	0.36	0.93	0.50
3. % of false alarms in total alarms	0.43	0.52	0.50	0.56	0.50	0.50	0.50	0.50	0.50	0.19	0.42
4. % prob. of crisis given no alarm	0.07	0.13	0.08	0.10	0.19	0.28	0.24	0.24	0.21	0.03	0.18

Cut-off probability of 30 %

1. (correct prediction of no crisis + correct prediction of crises) / total observations; 2. Correct prediction of crises / all true crises; 3. False alarms / total alarms; 4. Missing alarms / all predicted non-crises

Table 6. Estimation results for the count data model: Incidence rate ratio.

Dependent variable: Number of markets that have experienced at least one episode of crisis during the lean season

Alert at leading market		Obs	Number of markets on alert		Obs	Alert intensity in Maradi		Obs
Maradi November	6.725 [0.083]	51	November	n.s.	49	November	n.s.	51
Nara	n.s.	45	December	1.068 [0.030]	49	December	13.214 [0.086]	51
Dori December	6.786 [0.071]	48	January	1.091 [0.043]	52	January	4.807 [0.023]	52
Tenkodogo	n.s.	48	February	1.130 [0.001]	52	February	11.593 [0.027]	52
Gaya February	3.187 [0.082]	52	March	1.173 [0.002]	52	March	5.493 [0.056]	52

Cluster-robust standard errors obtained from a cluster bootstrap with 1000 replications. *P-values* are in brackets.
n.s.: non significant.
Approximation of the log-likelihood by adaptive Gauss-Hermite quadrature (Naylor – Smith, 1982).

Table 7. Estimation results for the Tobit model: Marginal effects.
Dependent variable: Crisis intensity

	Independent variables	Marginal effect	[illegible]	Log likelihood	Sample size
Alert at leading market	Maradi November (Niger)	2.812 [0.004]	0.72	- 52.87	51
	Gaya November (Niger)	1.792 [0.056]	0.78	- 55.18	51
	Dori December (Mali)	2.792 [0.008]	0.74	- 50.88	48
	Tenkodogo December (Burkina Faso)	3.151 [0.007]	0.74	- 50.45	48
Number of markets on alert	November	0.117 [0.030]	0.81	- 54.47	49
	December	0.170 [0.001]	0.82	- 52.06	49
	January	0.192 [0.000]	0.85	- 51.43	52
	February	0.214 [0.000]	0.85	- 48.10	52
	March	0.253 [0.000]	0.79	- 44.49	52
Alert intensity	Maradi November	3.096 [0.001]	0.68	- 52.05	51
	Maradi December	2.906 [0.003]	0.71	- 53.03	51
	Maradi January	2.812 [0.000]	0.64	- 51.80	52
	Maradi February	3.169 [0.000]	0.63	- 51.10	52

P-values are in brackets.
Approximation of the log-likelihood by adaptive Gauss-Hermite quadrature (Naylor – Smith, 1982).

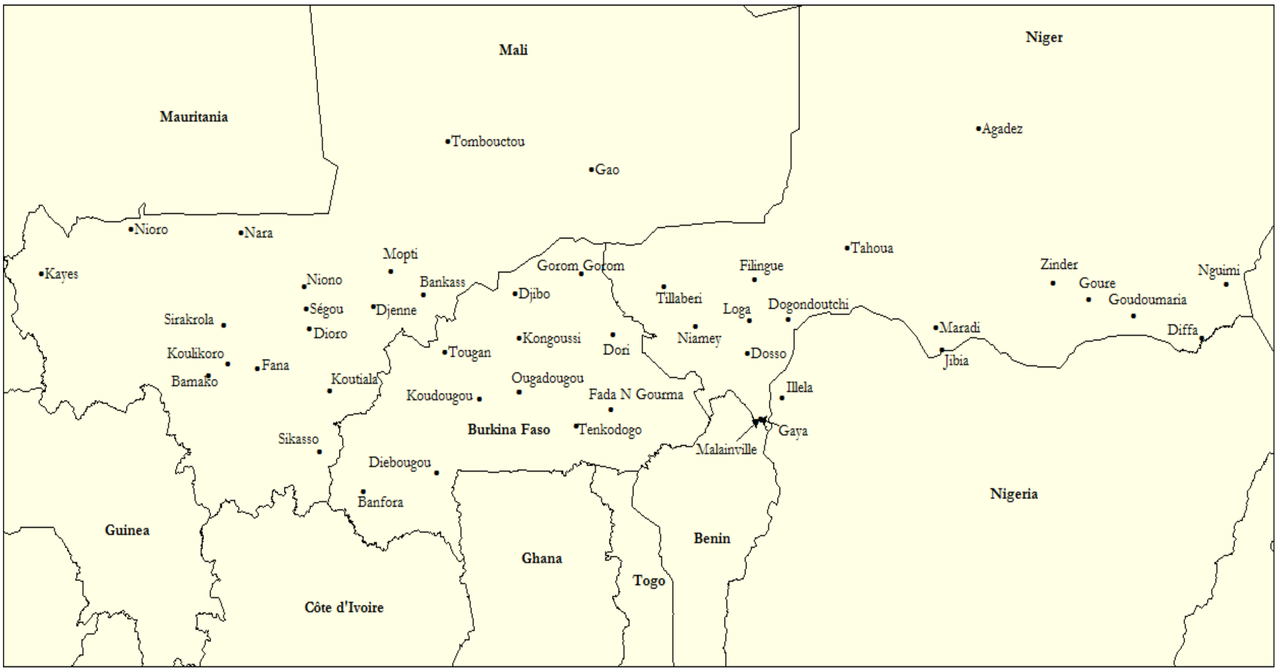
Table A1. Market characteristics and unit root tests.

Region	Market	Type of market	Millet production in the region: % of total	Min price	Max price	Mean price	No Obs.	ADF P.value	KPSS LM-Stat
NIGER	**Sample period: January 1990 – October 2008**								
Agadez	Agadez	bulk	0.04	52	337	134	226	0.00	0.12
Diffa	Diffa	bulk	1.6	41	328	138	221	0.00	0.09
Diffa	Goudoumaria	consumption		45	371	131	215	0.02	0.08
Diffa	Nguimi	consumption		55	333	148	218	0.01	0.06
Dosso	Dogondoutchi	collect	18.6	48	270	114	217	0.00	0.08
Dosso	Dosso	bulk		58	329	139	226	0.00	0.11
Dosso	Gaya	cross-border		42	315	124	226	0.00	0.10
Dosso	Loga	consumption		50	279	123	216	0.00	0.07
Maradi	Maradi	bulk	21.2	39	261	104	226	0.00	0.12
Tahoua	Tahoua	bulk	18.4	54	369	144	226	0.00	0.11
Tillaberi	Filingue	collect	20.9	51	326	129	210	0.00	0.09
Tillaberi	Tillaberi	collect		58	306	145	226	0.00	0.11
Zinder	Goure	consumption	18.4	52	319	118	226	0.00	0.08
Zinder	Zinder	bulk		40	312	109	226	0.00	0.12
Niamey	Katako	consumption	0.3	71	324	141	226	0.00	0.09
BURKINA FASO		**Sample period: January 1992–September 2008**							
Cascades	Banfora	retail	0.9	51	267	129	201	0.01	0.16
Centre est	Tenkodogo	retail	8.5	42	228	113	201	0.03	0.10
Centre nord	Kongoussi	retail	7.9	52	229	114	201	0.00	0.17
Centre ouest	Koudougou	retail	0.1	51	260	117	201	0.00	0.13
Est	Fada N'Gourma	retail	10.5	40	241	106	197	0.01	0.10
Mouhoun	Tougan	retail	18	33	220	105	194	0.01	0.12
Sahel	Djibo	retail	0.1	58	243	120	201	0.01	0.16
Sahel	Dori	retail		56	299	142	201	0.12	0.13
Sahel	Gorom-Gorom	retail		60	263	141	201	0.01	0.17
Sud Ouest	Diébougou	retail	5.4	36	265	120	201	0.02	0.14
Ouagadougou	Gounghin	consumption		69	236	126	201	0.04	0.08
Ouagadougou	Sankaryaré	consumption		70	271	137	201	0.05	0.10
MALI	**Sample period: February 1993 – December 2008**								
Kayes	Kayes	consumption	14	89	325	186	189	0.05	0.18
Kayes	Nioro			52	305	152	186	0.16	0.11
Koulikoro	Fana	production	16	45	227	112	185	0.02	0.09
Koulikoro	Koulikoro Gare	wholesale		55	249	127	190	0.01	0.10
Koulikoro	Nara			51	240	128	187	0.05	0.10
Sikasso	Sirakrola	production	18.2	34	212	100	188	0.00	0.13
Sikasso	Koutiala	bulk		46	218	118	188	0.02	0.15
Sikasso	Sikasso Centre	bulk		64	246	136	190	0.00	0.14
Segou	Dioro	production	17.1	35	205	89	192	0.02	0.07
Segou	Niono	bulk		46	228	111	192	0.01	0.06
Segou	Ségou centre	bulk		44	225	109	192	0.02	0.08
Mopti	Bankass	production	15.1	41	183	98	190	0.01	0.11
Mopti	Djenne	production		38	203	102	188	0.02	0.08
Mopti	Mopti Gangal	bulk		55	230	129	190	0.02	0.08
Tombouctou	Tombouctou	consumption	4.9	77	248	154	184	0.09	0.09
Gao	Gao	consumption	4	72	232	139	190	0.03	0.06
Bamako	Médine	consumption	10.3	69	263	142	191	0.05	0.09

Source: MISs and authors' calculations.

ADF test: H_0: I(1) ; KPSS : H_0: I(0). Tests administrated on current price values.
"Collect" markets are rural markets located in production areas. "Bulk" markets are markets where millet is assembled in bulk quantities before being transferred to other markets; they are located in rural or urban areas. "Consumption" markets are located in the main urban centres. "Cross-border" markets are gateways for regional trade flow.

Map 1: Millet markets studied



Source: the authors

Figure 1. Granger causality test results

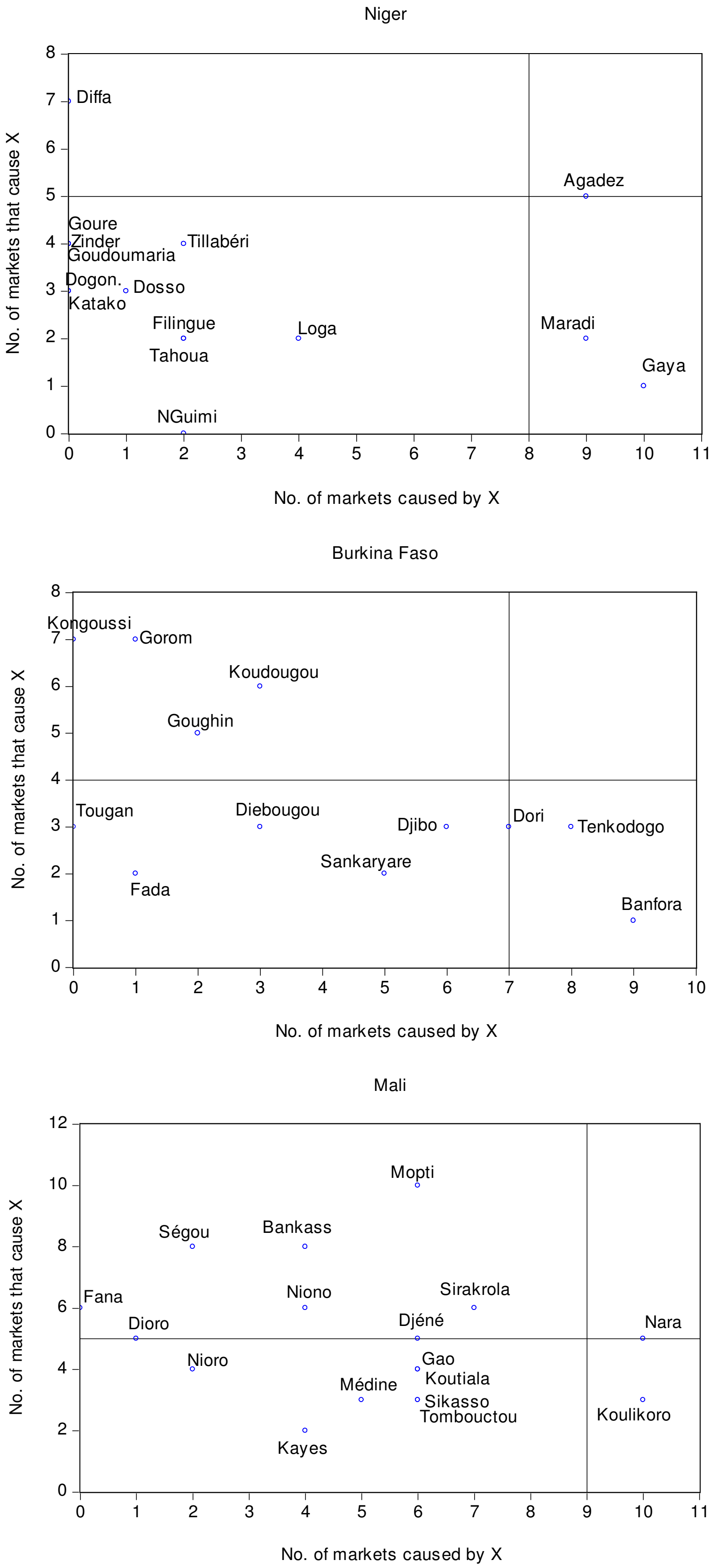
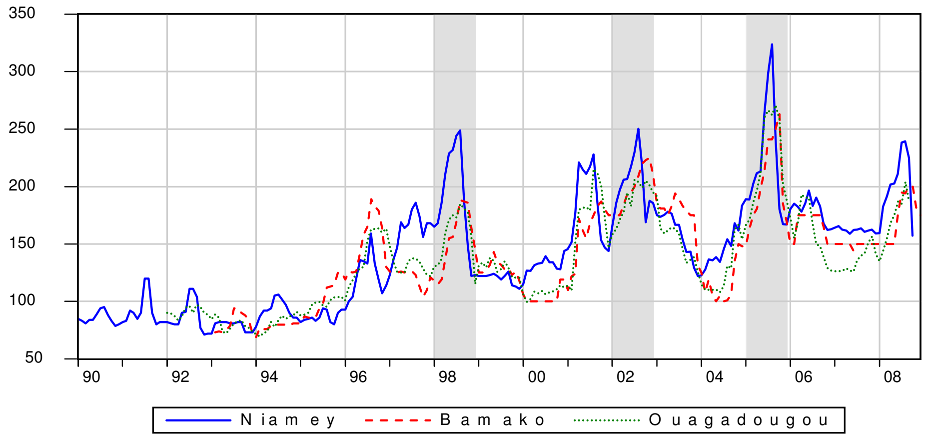
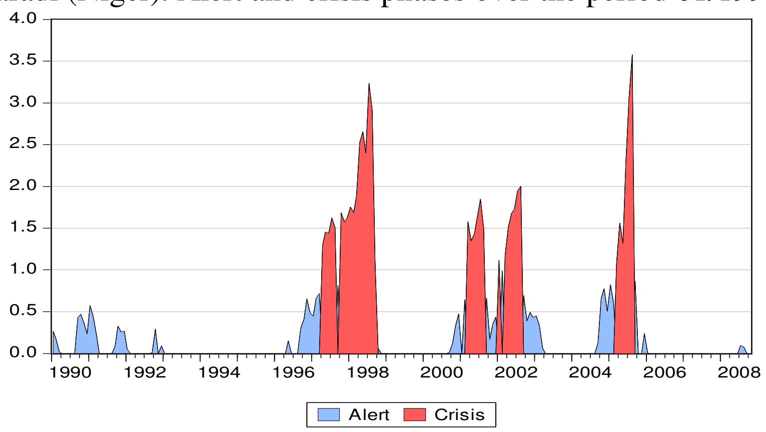


Figure 2. Millet prices in the capital cities (Fcfa/kg)



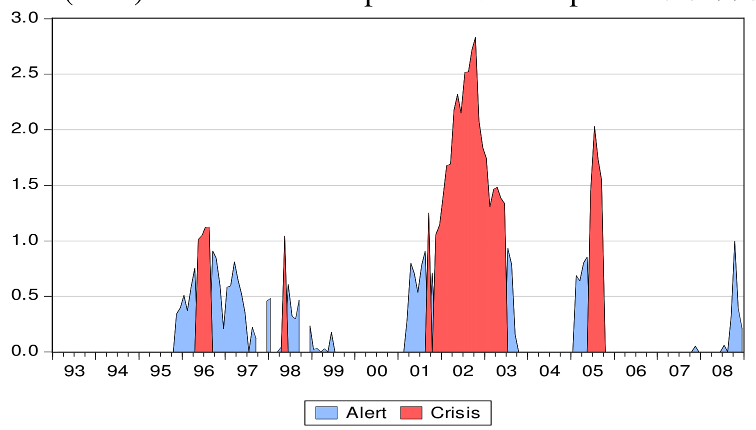
Gray: crises common to the three countries
Source: MIS's and authors' calculations

Figure 3. Maradi (Niger). Alert and crisis phases over the period 01/1990 to 10/2008



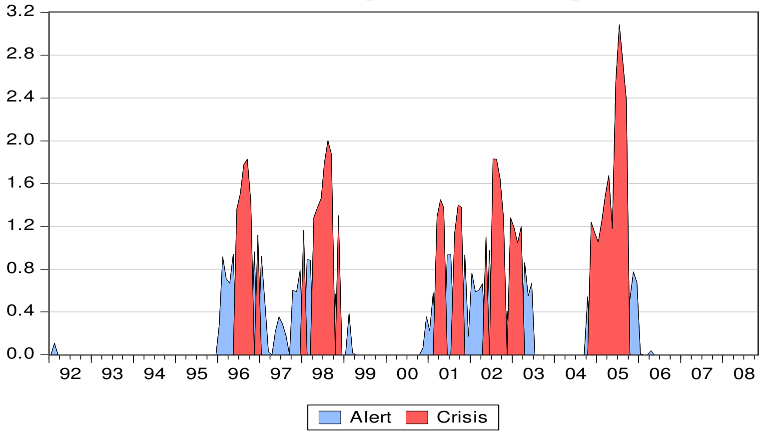
Crisis phase: $I_t/\sigma_I \geq 1$; alert phase: $I_t/\sigma_I > 0$

Figure 4. Nara (Mali). Alert and crisis phases over the period 02/1993 to 12/2008



Crisis phase: $I_t/\sigma_I \geq 1$; alert phase: $I_t/\sigma_I > 0$

Figure 5. Dori (Burkina Faso). Alert and crisis phases over the period 01/1992 to 10/2008



Crisis phase: $I_t / \sigma_I \geq 1$; alert phase: $I_t / \sigma_I > 0$

APPENDIX

[Insert Table A1]