

## Maize price volatility and on-farm storage in Burkina Faso

Maître d'Hôtel Elodie, CIRAD

Le Cotty Tristan, CIRAD

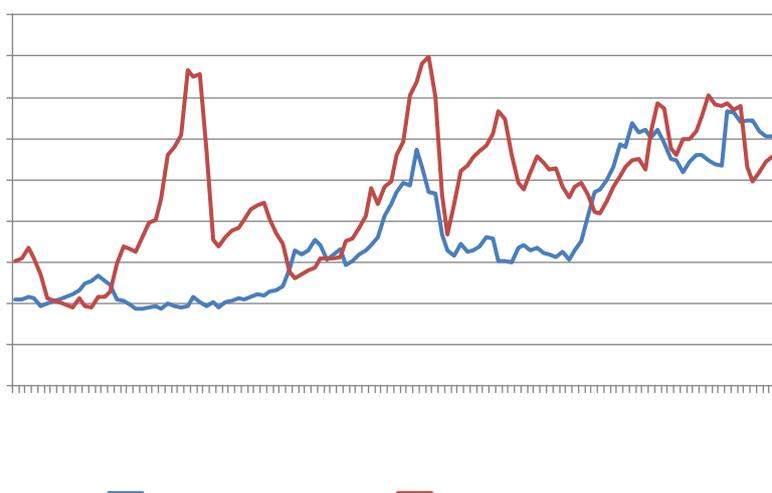
### Abstract

The role of grain storage by inventory holders or government agencies in managing price volatility has received a great deal of attention. But the role of on-farm storage on price volatility is not so richly documented, in spite of its importance in rural areas in Africa. In this paper, we merge historical price and household data on maize markets in Burkina Faso to measure the influence of on-farm storage on price volatility. We show how the seasonal management of on-farm storage is responsible for price volatility. We focus in particular on the analysis of carry-over and its impact on price pattern. In an inter-temporal analysis, an unexpected price drop is followed by a decrease in production and tends to stabilize price to its original level. But in a seasonal pattern, an unexpected price drop occurring during the planting season simply delays the sale of existing stocks, without decreasing the production, which generates further price drops later in the year, generally right before the harvest or during the harvest time. We establish that on-farm carryover increases the occurrence of unexpected price drops after harvest.

### Introduction

The 2007-2008 sharp rises in food prices in developing countries recalled that price volatility had not been fully understood. In the recent years, much attention has been devoted to explain volatility on international markets by exogenous supply shocks (drought) and sharp changes in demand (Asia) and supply (biofuels, gas prices), etc. (FAO, IFAD et al. 2011; Prakash 2011). If most of the studies focused on international price volatility, some studies focused on domestic price volatility in developing countries and its determinants (Hazell, Shields et al. 2005; Demeke, Pangrazio et al. 2008; Tschirley and Jayne 2010). Among those determinants, price transmission has been widely used as a key concept to explain how volatile international food prices can create domestic volatile food price (Daviron, Aubert et al. 2009; Torero 2009). However, several studies demonstrated that domestic price volatility can be weakly correlated with international price volatility, notably in the cases of landlocked countries that do not depend on international trade (Hazell, Shields et al. 2005; David-Benz, Diallo et al. 2010). This is the case in Burkina Faso, where maize prices are weakly integrated with international maize prices (Figure1). For instance, the sharp increase in burkinabè maize prices by mid 2005 was attributable to a poor harvest in 2004 (production devastated by locust invasion) and has not been mitigated by steady international price. The same occurred by mid 2009 where previous maize harvest in Burkina was affected by drought. However, they may have been at least a case of price transmission from international markets to burkinabè markets in 2008 that corresponds to a low harvest in 2007 in Burkina so the country had to import high price maize from international markets to meet its domestic demand. All this suggests that price volatility in Burkina Faso does not find its main origin in international markets.

Figure 1. International and Burkinabe maize nominal prices (USD/ton)  
(from FAO and SONAGESS data)



Several authors have shown that domestic factors play a major role in explaining price volatility, including domestic production shocks, stock levels and policy interventions (Hazell, Shields et al. 2005; Byerlee, Jayne et al. 2006; Tschirley and Jayne 2010). There is also an important literature on the role of inventory on price dynamics (Williams and Wright 1991; Deaton and Laroque 1992), and even on price volatility specifically (Serra and Gil 2013). This literature does not look at the role that on-farm stocks themselves could play on farm volatility. A key feature of this literature rests on the optimal inventory theory, based on the “buy low, sell high” principle (Gustafson 1958). This is the key reason why inventory holders behavior tend to compensate for price moves, except when they have sold their whole inventory and price still increase (Deaton and Laroque, 1992). For these authors, this is the root of a price asymmetric dynamics (“sharper increases than decreases”).

Farmers’ behavior regarding stocks and prices completely departs from optimal inventory theory. First, they hardly ever buy grains but for their own consumption in the lean season if they lack grains and can afford them. But this is not a strong difference, because it can simply be explained by different constraints. The main difference relies in the fact that their selling dynamic throughout the year is cyclical, creating (i) a price seasonality (ii) a risk of unexpected sharp price decrease toward the end of the lean season, due to carryover. Contrary to the inventory holder indeed, farmers have a cyclical pattern in mind in which “everything has to be sold by the end of the cropping season”. Although this is not rigorously true for every farmer, it is true for many, leading many of them to sell too early, far before the end of the cropping year. We show how this behavior, combined with price anticipation errors, explains why on-farm stocks do not mitigate prices drop as they can mitigate prices increase (contrary to the optimal inventory theory). According to us, the role of on-farm storage management on domestic price volatility might have been underestimated, and is probably not fully understood yet, at least in rural Africa.

We model a cyclical pattern of sales, in which the farmer makes his trading plan after harvest for the all coming year. His preference for the present typically favors early sales which, combined with a stable demand, produces increasing prices. If these prices are as expected by the farmer, no volatility episode occurs. If these prices increase more than he expected, he reevaluates his selling plan, sells a bit earlier than expected, which tends to smoothen the price increase. But if the price increases less than he thought, he reevaluates his selling plan and sells less than expected, waiting for better prices. If this type of anticipation error happens just before the new harvest, he fails to sell his whole resource on time, generating a carry-over, which further feed the excess supply of the new harvest, and finally generates unexpected price drops.

To empirically test this in Burkina Faso, we use an ARCH model to build two series of positive and negative volatility in 16 local markets and we build upon a panel approach to find that carryover has a significant effect on increasing negative volatility.

The paper is structured as follows. In section 1, we review the economic literature on the influence of storage on price volatility. In section 2, we model the dynamics of stocks on a one-year schedule and we illustrate the impact of a late price-anticipation error on price negative volatility, defined by unexpected price drops. In section 3, we present the ARCH model used to measure positive and negative price volatility and describe the panel used to establish the relationship between on-farm storage and . In section 4, we introduce the Burkina Faso case by describing the data we used on price and storage behavior. Lastly, in section 5, we estimate the panel where price volatility is regressed over carry-outs, and provide empirical evidence that carry-outs increase unexpected price drops.

## 1. The effect of storage on price volatility in the literature

### ***Food price volatility***

There are several definitions of food price volatility in the economic literature (Huchet-Bourdon 2011; Piot-Lepetit and M'Barek 2011; Prakash 2011). They tend to differentiate price variation from price volatility, because of the damages to economic agents related to volatility and/or the inability of those agents to anticipate price volatility. International institutional authorities define volatility as follows: *"Variations in prices become problematic when they are large and cannot be anticipated and, as a result, create a level of uncertainty which increases risks for producers, traders, consumers and governments and may lead to sub-optimal decisions"* (FAO, IFAD et al. 2011). This definition assumes that price variations may be detrimental to agents when they are not predictable. Unpredictable price variations are not necessarily problematic indeed: a consumer can take advantage of unexpected prices decreases for instance; and predictable price shifts can be problematic for some agents: the post harvest price drop is predictable, but still harmful for farmers with liquidity constraints. But when a price shift is detrimental to an agent, it is all the more harmful as it is unexpected by this agent. Indeed, *"as households and planning agencies are able to cope better with predictable variation, unpredictable changes are of primary concern"* (Prakash 2011).

In this paper, we focus on the unpredictable character of price variation. The measurement of unpredictable price variability requires to make assumptions on agents' ability to anticipate price. It implies that a same price series is less volatile for well-informed agents than for poorly informed agents. We have to choose a level of information supposed to reflect information available to agents, and a particular price forecast model supposed to represent agents' ability to anticipate price.

Indicators of aggregate price variability like the standard deviation of prices have been used widely in the economic literature (Balcombe 2009; Gilbert and Morgan 2010; Huchet-Bourdon 2011), but they encompass both the predictable (for example, seasonal price variations) and unpredictable components of price variations. To measure price volatility, i.e. isolate the unpredictable component of price variations from the predictable one, we need a price forecast model. The series of differences between actual prices and modeled prices can be interpreted as volatility. The variance of the residuals of a price formation model typically measures the unpredictable price shifts, and this variance can be called volatility. After the seminal work of Engle (Engle 1982), several authors have used the conditional variance of price as an indicator of price volatility through the use of Auto-Regressive Conditional Heteroskedastic models (Shively 1996; Barrett 1997; Yang, Haigh et al. 2001; Karanja, Kuyvenhoven et al. 2003; Nyange and Wobst 2005; Maïtred'Hôtel, Le Cotty et al. 2013). The use of ARCH-family models is adapted to the measurement of volatility, because the variance of

residual does not need to be constant, and as a consequence the volatility does not need to be a single figure, it can be a serie, and the different levels of this series can be interpreted.

### ***Storage as a determinant of food price volatility***

Theoretical models have been developed, notably the competitive storage model that accounts for products that are storable for one year to another and that are subject to random production shocks (Gustafson 1958; Cafiero, Bobenrieth et al. 2011). In this model, the demand for storage depends on consumption, yields, storage costs and interest rates. It is very clear that in general, competitive storage decrease price variations. Nevertheless, competitive storage is more efficient for handling price drops than price spikes. Indeed, a key assumption made is that storage cannot be negative, as stocks “cannot be borrowed from the future” (Wright 2011). The implication is that, in the event of shortfall, stocks cannot decrease lower than zero and are inefficient in mitigating price rises. To our knowledge, there is no direct (with storage data) empirical estimation of this storage model effect on price volatility. A main reason seems to be the scarcity of data series on stocks, which strongly constraints empirical estimations of the competitive storage model (Bobenrieth, Bobenrieth et al. 2013; Serra and Gil 2013). Indeed, most of the studies on competitive storage either skip the use of storage data or use data that are not direct observations but that are derived from observations of production, consumption and trade (Abbott 2010). Furthermore, the indirect estimation procedure (through price series only) is not fully satisfactory (Deaton and Laroque 1992).

In the empirical litterature on the relation between storage and price dynamics, many authors have emphasized that periods with low stocks correspond to price spikes (Wiggings and Keat 2009; Wright 2011).

At the international level, it is generally acknowledged that periods of low stock levels correspond to periods of price spikes. This has been true for each of the last three episodes of low grain stock: early 1970S, mid 1990s and late 2000s. When stocks are low, a small production or consumption shock can have large price impacts because of more inelastic adjustments (Williams and Wright 1991; Gilbert and Morgan 2010).

At the national level, a majority of empirical studies also come to the conclusion that price volatility increases as public inventory decline (Barrett 1997; Nyange and Wobst 2005; Jayne, Myers et al. 2008; Serra and Gil 2013). In Kenya, Jayne, Myers and Nyoro adapted a VAR model to assess the effect of storage policy on maize prices dynamic : they revealed that stocks held by the National Cereal Producers Board significantly reduced price variability (Jayne, Myers et al. 2008). Working on nine commodities at the international level, Balcombe estimated both a panel model with annual data and an ARCH model with monthly data and established that the use of stock levels consequently reduced price volatility (Balcombe 2009). Kim and Chavas studied the US dry milk market and found that an increase of public and private stocks will reduce price volatility (Kim and Chavas 2002). Simulation approaches have been used to compare a no-storage regime to a storage regime and, applied to the soybean prices in USA, it is shown that storage greatly reduces the variance of annual prices (Helmberger and Akinyosoye 1984). A particular case occur in situations of shortage leading to price peaks, public authorities may decide to “buy high” in order to “sell low” to poor consumers, subsidizing food prices and increasing stock levels beyond competitive levels (Gouel 2013) .

But many other empirical studies question this systematic effect of storage on volatility. In Madagascar, Barrett used an ARCH model to analyze rice price volatility and establishes that storage had not significant effect on price volatility (Barrett 1997). The application of another ARCH model, applied to maize price in Tanzania revealed that storage policies had no effect on price volatility while trade policies could contain price volatility (Nyange and Wobst 2005). At the world level, Roache came to the result that storage are not found to have a significant impact on price variability (Roache 2010).

The logics ruling storage on-farm differs from the one ruling private inventory. Prices are cyclical. They are at their lowest level just after harvest, and then increase until the lean season, when they fall again during the new harvest. This price dynamics creates a proper incentives to store (Abbott 2010). The “buy low, sell high” principle ruling the competitive storage model may not apply to farmers because they have a strong liquidity constraint at harvest time (when prices are low), and have a hard time to sell at the lean season when prices are high, because they have a resource constraint together with high preference for present. Many poor farmers in Burkina Faso sell low and buy high for their own consumption. In the same way, producers may have an incentive to sell when prices are high (Fackler and Livingston 2002) but at the same time may need to keep their grain stock to smooth family consumption until next harvest, especially in developing countries where production and consumption decisions are closely linked. Thus, the competitive storage literature singles out price arbitrages, but those price arbitrage may only constitute a partial reason for producers to store as they have to meet the needs of their household’s consumption (Saha and Stroud 1994). Producers are jointly maximizing profits and minimizing consumption risks and storage prevent them from buying food when prices are high (Park 2009). That means that on-farm storage can be considered as an insurance for producers against starvation until next harvest (Saha and Stroud 1994). If the later models better describe farmers’ storage behavior, they do not go to the point of explaining price volatility.

The ambition of the present paper is to finely describe farmers’ storage behavior in Burkina Faso, including the cyclical aspect of production, price and storage on farm, and its consequences in terms of positive and negative volatility. To do so, we first develop a conceptual framework that models the dynamics of stocks on a one-year schedule and we illustrate the impact of a late price-anticipation error on price negative volatility, defined by unexpected price drops. Then, we measure empirically some elements of these features, building upon historical price and household data in Burkina .

## 2. Conceptual framework : a yearly dynamics of optimal stock outs

### *Modelling the dynamics of stocks in a seasonal pattern*

We formalize the selling decision of a farmer after harvest. Right after harvest, the farmer has a trading plan in mind for the coming year. He sets aside the grain amount that he keeps for autoconsumption and establishes a sales plan for his net production,  $y$ , that he wants to sell throughout the year. During the first month after harvest he sells a certain amount of grain  $x_1$  and stores the rest. To calculate this amount, he has to have a sale plan for each of the 11 next months,  $\tilde{x}_2, \dots, \tilde{x}_{12}$ , which depends on his prices expectation for the 11 months  $\tilde{P}_2, \dots, \tilde{P}_{12}$ . The reason why he does not sell out the whole crop after harvest is that prices are expected to grow (see figure 2). The second month, he takes note of the actual price in month 2, and eventually re-evaluates his sales plan. If his price prediction was correct, the plan does not change. If the actual price in month 2 is higher than expected, he sells more than he expected one month yearlier, which reduces the amount of grain available for sale on the tenth next month. So he establishes a new sales plan. If the actual price is below his prediction, he sells less than in his first plan. We recognise that it is possible that some farmers maximize their utility over a longer time horizon, which gives a case for resource accumulation from one year to another. But in our context, capital accumulation is so small that everything happens as if the time horizon of farmers maximisation was the next harvest.

Furthermore, it is not uncommon that in a particular month, a farmer does not sell at all. We integrate this through a reservation price assumption. If the actual price at month  $t$ ,  $P_t$ , drops below the reservation price,  $\bar{P}_t$ , the farmer does not sell at all,  $x_t=0$ , and the sales plan is re-evaluated. Note

that if this zero-sale-month occur in month twelve (the month right before harvest), the corresponding amount of grain is the carry-over. Without this reservation price mechanism, there would be no carry-over as long as the time horizon of the farmer is the next harvest. So the carry-over is the amount of crop that the farmer intended in month 11 to sell in month 12 and that he finally did not sell. We find it more likely that in the absence of unexpected compulsory expenses (like medical tablets) the reservation price is close to the expected price. Literally, farmers do not want to sell below their expected price. For this reason, we will mainly study the case where the reservation price is equal to the expected price  $\bar{P}_t = \tilde{P}_t$ . Because of this reservation price, price overestimation and price underestimation have asymmetric consequences on sales, thus on prices, but this is not necessary to our conclusion that anticipation errors generate volatility. It is necessary for having carryover, and for our conclusion on the impact of carry-over on negative volatility.

The first trading plan of the farmer is established right after harvest, upon the observed price  $P_1$ , and a series of future expected sales, that depends on the series of future expected prices  $\{\tilde{P}_2, \dots, \tilde{P}_{12}\}$ . The trading plan established in month 1 is a series of hypothetical sales  $\{\tilde{x}_2, \dots, \tilde{x}_{12}\}$ , established through the following maximisation program (a discounted CRRA utility function):

$$EU = \max_{x_1, \tilde{x}_2, \dots, \tilde{x}_{12}} \frac{(P_1 x_1)^{1-r^p}}{1-r^p} + \frac{1}{1+\delta} \frac{(\tilde{p}_2 \tilde{x}_2)^{1-r^p}}{1-r^p} + \dots + \frac{1}{(1+\delta)^{t-1}} \frac{(\tilde{p}_t \tilde{x}_t)^{1-r^p}}{1-r^p} + \dots + \frac{1}{(1+\delta)^{11}} \frac{(\tilde{p}_{12} \tilde{x}_{12})^{1-r^p}}{1-r^p} \quad (1)$$

$$\text{s.t. } x_1 + \tilde{x}_2 + \dots + \tilde{x}_{12} \leq y \quad (2)$$

$$\forall t > 1, \tilde{x}_t (\tilde{P}_t - \bar{P}_t) \geq 0 \quad (3)$$

Subscript  $t$  stands for month,  $t=1$  corresponds to the harvest month ( $t=12$  corresponds to the last month before harvest),  $\tilde{P}_t$  is expected price for month  $t$  as it is planned in month 1. More rigorously, this expected price should be given two different time indexes, like  $\tilde{P}_t^1$  but we decided to keep it more readable with one time index. Keep in mind that  $\tilde{P}_t$  potentially takes a different value at each period. Furthermore,  $r^p$  is the producer's risk aversion,  $\delta$  is monthly discount rate. Constraint (2) is the physical constraint on the total sales. At the end of the year, when the sale sequence is known, the carryover is  $y - x_1 - \dots - x_{12}$ . Constraint (3) is the price reservation constraint. It means that at each month, the planned sale is nil if the expected price is below the reservation price. The first order conditions for his problem lead to :

$$\left\{ x_1 = \mu_1 \frac{1}{r^p} P_1 \frac{1-r^p}{r^p}; \quad \forall t, \tilde{x}_t = \mu_1 \frac{1}{r^p} (1+\delta)^{\frac{1-t}{r^p}} \tilde{P}_t \frac{1-r^p}{r^p} \right\} \quad (4)$$

where  $\mu_1$  is the Lagrange multiplier associated to constraint (2) as it applies in month 1; and  $\tilde{x}_t$  is the amount of crop that the farmer intends (in month 1) to sell in month  $t$ . If expected prices are constant, this monthly sale clearly decreases with time throughout the year.

This program is revised at each period, after information on actual price is made available to the farmer:

$$EU = \max_{x_t, \tilde{x}_{t+1}, \dots, \tilde{x}_{12}} \frac{(P_t x_t)^{1-r^p}}{1-r^p} + \frac{1}{1+\delta} \frac{(\tilde{p}_{t+1} \tilde{x}_{t+1})^{1-r^p}}{1-r^p} + \dots + \frac{1}{(1+\delta)^{12-t}} \frac{(\tilde{p}_{12} \tilde{x}_{12})^{1-r^p}}{1-r^p} \quad (5)$$

$$\text{s.t. } x_1 + x_2 + x_t + \tilde{x}_{t+1} \dots + \tilde{x}_{12} \leq y \quad (6)$$

$$x_t (P_t - \tilde{P}_t) \geq 0 \quad (7)$$

From now, we consider the case where the reservation price is equal to the expected price, as explained above, so that constraints (7) turns out to a single inequality, for the present time only. The result is as follows:

$$\left\{ \begin{array}{l} x_t^* = \mu_t \frac{1}{r^p} P_t \frac{1-r^p}{r^p} \quad \text{if } P_t - \tilde{P}_t \geq 0 \\ x_t^* = 0 \quad \text{if } P_t - \tilde{P}_t < 0 \end{array} \right\} \quad (8)$$

Where  $\mu_t$  is the Lagrange multiplier for constraint (6). If no anticipation error was made since now, we can see that  $\mu_t = \mu_1(1 + \delta)^{t-1}$ .

If  $P_t - \tilde{P}_t \geq 0$ , Lagrange multiplier of constraint (7) is nil and Lagrange multiplier of constraint (6) is not affected by this prediction error, so that,  $x_t^* > \tilde{x}_t$ . Because of this, the constraint (6) at the t+1 period and following periods will be stiffer than in the farmer's prediction :  $\mu_{t+1} > \mu_1(1 + \delta)^t$ .

If  $P_t - \tilde{P}_t < 0$ ,  $x_t^*=0$ . For  $t < 12$ ,  $x_t^*=0$  does not imply carryover because a later maximization will increase  $x_{12}$ . The fact that  $x_t^* = 0$  contributes to alleviate the constraint (6) for future periods, and  $\mu_{t+1} < \mu_1(1 + \delta)^t$ .

The demand side is supposedly generated by a monthly income –whereas supply is generated by a yearly income (the harvest) – so that we do not monthly discount utility function of food consumption.

The CRRA utility function of the consumer then writes:

$$U_t = \max_{d_t} \frac{d_t^{1-r^c}}{1-r^c} + \gamma(I_t - P_t d_t) \quad (9)$$

Where  $I_t$  stands for consumer's monthly budget,  $d_t$  is food demand at month  $t$ ,  $r^c$  is the consumer risk aversion, and  $\gamma$  is the Lagrange multiplier associated to budget constraint.

The derivation of this utility function gives the demand for food:

$$d_t = \gamma^{-1/r^c} P_t^{-\frac{1}{r^c}} \quad (10)$$

The market clearing results from the above demand function and two types of supply: the supply from the imperfectly anticipating farmer described above,  $x_t^*$ , and the supply from a perfectly anticipating farmer with similar characteristics,  $v_t$ . This second source of supply has no consequences but stabilizes the market price in case of error anticipation.

The market price is the solution of market clearing :

$$x_t^*(P_t, \tilde{P}_t, \tilde{P}_{t+1}, \dots, \tilde{P}_{12}) + v_t^*(P_t) = d_t^*(P_t) \quad (12)$$

This produces two price regimes, depending on price expectation errors.

$$P_t = \begin{cases} \gamma^{-\frac{r^p+r^c-r^p r^c}{r^p}} \left[ \mu_1^{-\frac{1}{r^p}} (1 + \delta^b)^{\frac{1-t}{r^p}} + v_1^{-\frac{1}{r^p}} (1 + \delta^g)^{\frac{1-t}{r^p}} \right]^{-\frac{r^p+r^c-r^p r^c}{r^p r^c}} & ; \text{if } \forall t P_t \geq \tilde{P}_t \quad (13) \\ \gamma^{-\frac{r^p+r^c-r^p r^c}{r^p}} \left[ 0 + v_1^{-\frac{1}{r^p}} (1 + \delta^g)^{-\frac{t}{r^p}} \right]^{-\frac{r^p+r^c-r^p r^c}{r^p r^c}} & ; \text{if } P_t < \tilde{P}_t \quad (14) \end{cases}$$

This produces a price re-adjustment at the next period:

$$P_{t+1} = \begin{cases} \gamma^{-\frac{r^p+r^c-r^p r^c}{r^p}} \left[ \mu_{t+1}^{-\frac{1}{r^p}} + v_1^{-\frac{1}{r^p}} (1 + \delta^g)^{-\frac{t}{r^p}} \right]^{-\frac{r^p+r^c-r^p r^c}{r^p r^c}} ; \text{ if } \forall t P_t \geq \tilde{P}_t & (15) \\ \mu_{t+1} > \mu_1 (1 + \delta)^t \\ \gamma^{-\frac{r^p+r^c-r^p r^c}{r^p}} \left[ \mu_{t+1}^{-\frac{1}{r^p}} (1 + \delta^b)^{-\frac{t}{r^p}} + v_1^{-\frac{1}{r^p}} (1 + \delta^g)^{-\frac{t}{r^p}} \right]^{-\frac{r^p+r^c-r^p r^c}{r^p r^c}} ; \text{ if } P_t < \tilde{P}_t & (16) \\ \mu_{t+1} < \mu_1 (1 + \delta)^t \end{cases}$$

Where  $\delta^b$ , and  $\delta^g$  stand for the discount rate of the bad and the good anticipating farmers respectively.

At any time of the year  $t$ , an overestimation of the next period price,  $P_{t+1} < \tilde{P}_{t+2}$ , produces a price increase in the next period (equation 14). But it also increases the total amount of available resource, which induces a greater sale in the following periods, which produces a price decrease in the following period at a level below the level that was expected in period  $t$  (equation 15). This can be seen in the simulations below (figure 3).

When such an overestimation happens in the lean season, for instance in period 11 the farmer overestimates period 12 prices, this produces a carryover at the end of period 12, which amplifies the price drop in the first period of following year, and simulated (figure 5).

### **Simulating the effect of price anticipation errors**

Simulations below illustrate above result. Any succession of anticipation errors produces volatility. But when errors of price overestimation occur before the end of the new harvest, they also produce carry-over that amplifies prices unexpected drops for the new campaign.

Simulation parameters	
$\gamma$	1200 kg
$r^p$	0,9
$r^c$	0,8
$\gamma$	0,8
$\mu_1$ ( $\mu_1 = x_1^{-r^p} P_t^{1-r^p}$ )	0,02
$\mu_8$ (if overestimation at $t=7$ )	0,015
$\mu_{1, \text{year } 2}$ (overestimation at $t=12$ )	0,015
$v_1$	0,01
$\delta^b$	0,05
$\delta^g$	0,01

Figure 2. Supply after price overestimation in month 7

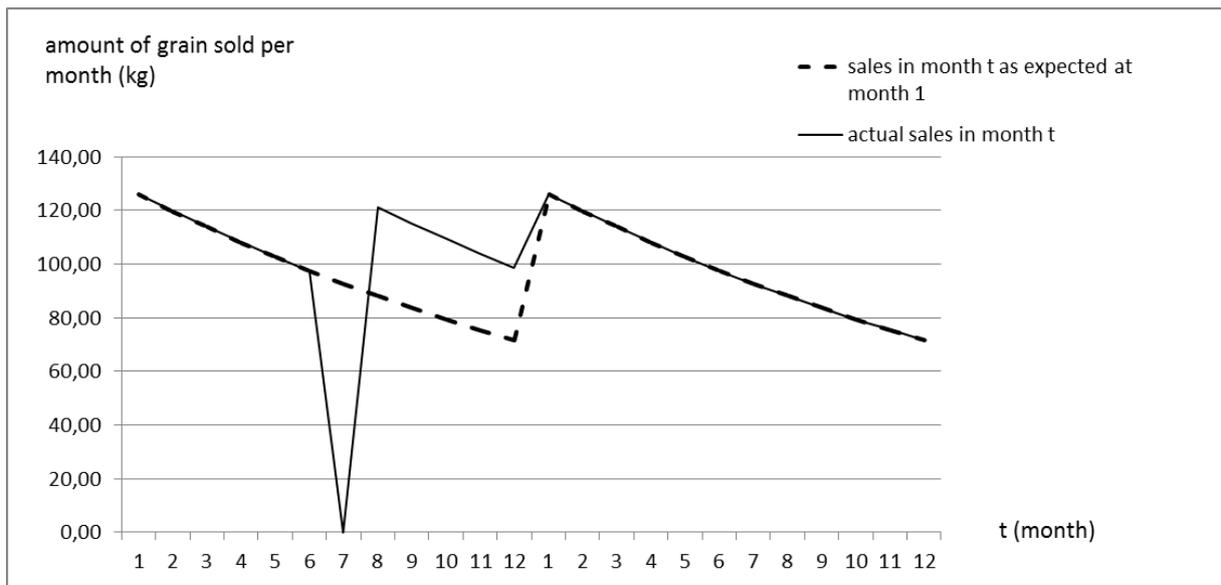


Figure 3. Market price after price overestimation in month 7

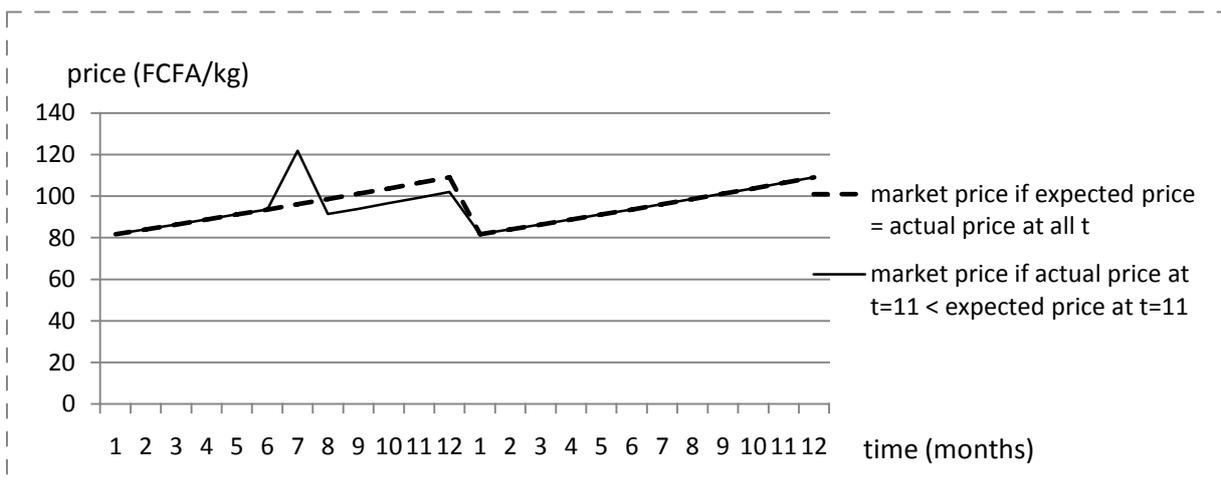


Figure 4. Supply after price overestimation at month 12 (carryover)

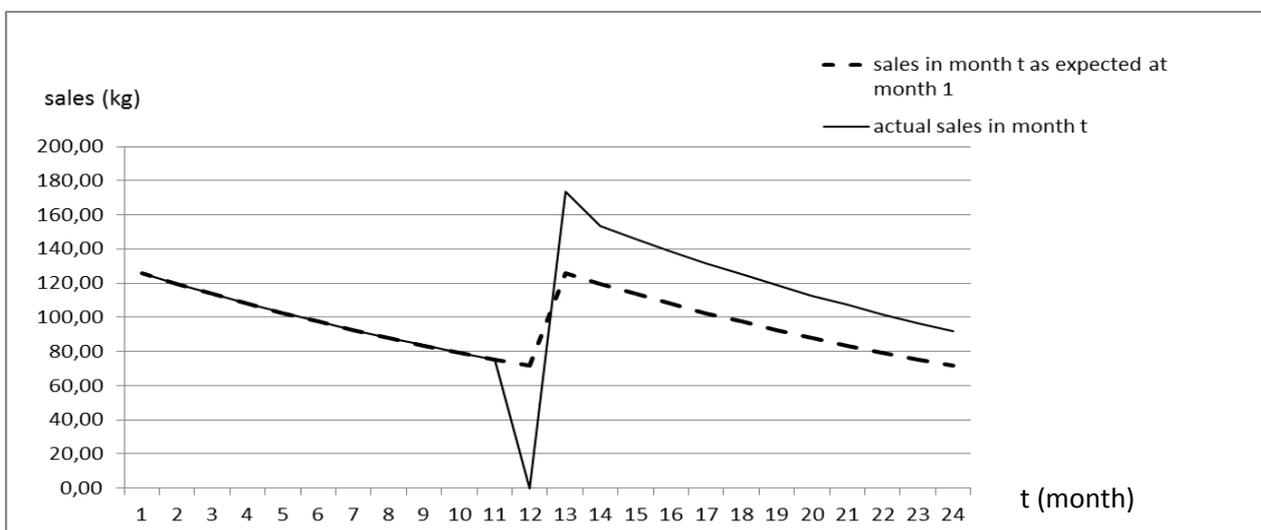
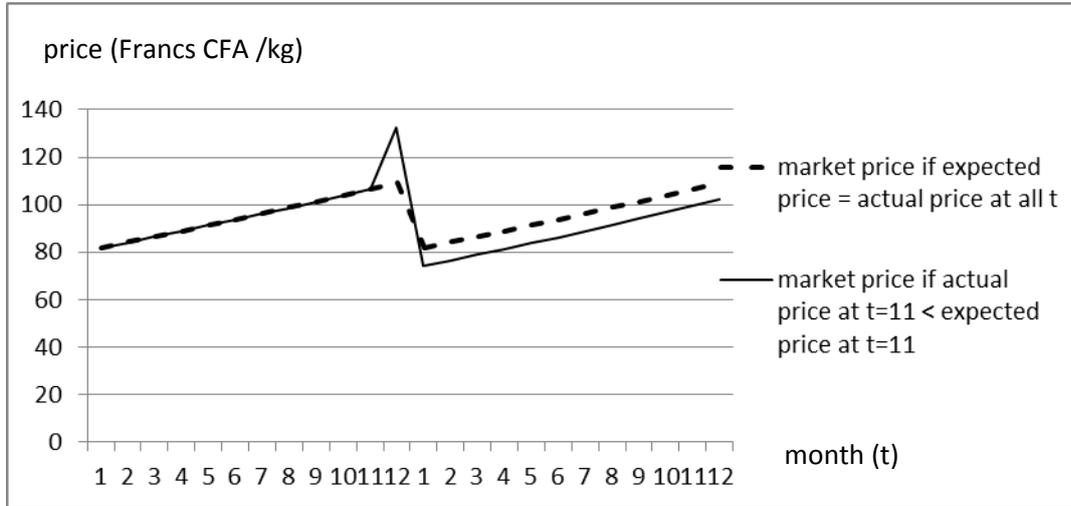


Figure 5. Market price after price overestimation at month 12



### 3. Empirical strategy : method

Our procedure to test the asymmetric effect of carry-out on price volatility uses two stages. First for each village, we build a series of positive volatility made of positive unexpected shocks of price and a series of negative volatility made of negative unexpected price shocks. The definition of unexpected shocks is derived from the ARCH- model (see Engle, Shiveley, Barrett). An autoregressive model of price is estimated to model what is expected in prices movements, through information of past levels of price, seasonality, trend, and geographical dummies. The residuals form the series of unexpected shocks, but the variance of these is generally – as in our case – heteroscedastic , ie correlated with past shocks. This variance is a good measure of volatility, defined as the variance of unpredictably price shifts, which takes a different value at each period (month).

Second, we build a panel of these monthly time series of volatility for each village, merged with the yearly carry-over in each village at the end of campaign. The effect of the latter on the next campaign negative volatility gives the effect of carryout on volatility.

#### ***Estimating positive and negative maize price volatility***

ARCH models are used to characterize and model observed time series (Engle 1982). ARCH modeling allows simultaneous estimation of temporal variation in the conditional mean and variance of a dependent variable, in this paper namely the deflated maize producer price. The analysis of the error term of the mean equation at any time  $t$  provides useful information to interpret price volatility. In particular, when the variance of the error term of the mean equation is not homoscedastic, this variance can increase with the lagged values of the error term of the mean price equation, and the –conditional – variance is interpreted as a measure of price volatility. This is basically what is done in this paper. The ARCH model general structure is as follows.

$$p_{it} = \beta_0 + \beta_1 p_{i,t-1} + \gamma_1 S_{it} + \gamma_1 A_{it} + \varepsilon_{it} \quad \varepsilon_{it} \quad iidN(0, h_{it}) \quad (1)$$

$$h_{it} = \alpha_0 + \alpha_1 \varepsilon_{i,t-1}^2 + v_{it} \quad v_{it} \quad iidN(0, \sigma) \quad (2)$$

where the subscripts  $i$  and  $t$  stand for region and monthly period respectively.

Equation (1) is the mean equation that determines the maize producer price  $p_{it}$  process as an autoregressive process of 1 period, and depending from seasonal dummies and geographical dummies.  $S_{it}$  is the dummy for Shortage season, going from June to August,  $A_{it}$  is the Abundance season, going from October to December, and  $G_k$  is a geographical dummy for village  $k$ . Seasons have been selected after testing monthly dummies on each of the 16 price series. The one period lag for price autoregression has been selected after testing the number of significant periods on each individual market. Trend variable has been removed because of very low significance. Equation (2) determines the conditional variance of the error term of equation (1), as a function of recent past shocks (namely last period shock) and confirms the significant ARCH nature of the price process in 9 out of the 16 villages (see results). In the 7 remaining villages, the price process proves autoregressive with homoscedastic variance. Many other specifications could have been tested for each village, but our aim here was mainly to get series of variance for each village, and to compare the behaviour of these series, which supposes to keep a common basic specification for each price series.

Above estimations have been led for the 16 markets so as to get 16 series of volatilities  $h_{it}$ . Next, these series have been segregated in two groups of series, ones with positive volatility, one with negative volatility. The segregation is processed as follows:

The estimated conditional variance  $\hat{h}_i$  is a panel of  $i$  time series providing  $i$  series of volatility. If it is clear that the level of carry-over is likely to influence these series of measures volatility, it is likely that carryovers do not affect positive price shocks in the same way as negative price shocks. Contrarily to the speculators' stocks which can increase or decrease, farmers do not buy cereals when the cereals prices drop. They simply sell cereals when prices increase. This makes an important difference because whereas speculators' stocks can smoothen positive price shocks (buy selling) and negative price shocks (by buying), farmers' stocks are not expected to smoothen negative prices shocks.

To check this, we segregate our volatility time series in two series for each market: one for positive price shocks and one for negative price shocks.

We denote  $h_{ij}^+$  the sub-series extracted from  $h_{it}$  where  $\varepsilon_{it} \geq 0$  and  $h_{ij}^-$  the sub-series where  $\varepsilon_{it} \leq 0$ . And because carry-over is a yearly data, we build a yearly variable of positive volatility and a yearly variable of negative volatility, for each market  $i$  and each year  $j$ , i.e.

$$\hat{h}_{ij}^+ = \sum_{\substack{t=1 \\ \text{year}=j}}^{t=12} \frac{\hat{h}_{it}^+}{n_{ij}^p} = \hat{\alpha}_0 + \frac{1}{n_{ij}^p} \sum_{\substack{t=1 \\ \text{year}=j \\ \varepsilon_{it} \geq 0}}^{t=12} \hat{\alpha}_1 \varepsilon_{it-1}^2$$

Where  $n_{ij}^p$  is the number of observations in year  $j$  and in area  $i$  where  $\varepsilon_{it} \geq 0$

$$\hat{h}_{ij}^- = \sum_{\substack{t=1 \\ \text{year}=j}}^{t=12} \frac{\hat{h}_{it}^-}{n_{ij}^n} = \hat{\alpha}_0 + \frac{1}{n_{ij}^n} \sum_{\substack{t=1 \\ \text{year}=j \\ \varepsilon_{it} \leq 0}}^{t=12} \hat{\alpha}_1 \varepsilon_{it-1}^2$$

Where  $n_{ij}^n$  is the number of observations in year  $j$  and in area  $i$  where  $\varepsilon_{it} \leq 0$

### **Measuring the effect of anticipation errors on carryover**

The empirical estimation of equation (7) gives the effect of the two types of volatility on carryover.

$$c_{i,j} = a_0 + a_1.c_{i,j-1} + a_2.y_{i,j-1} + a_3.\hat{h}_{ij}^+$$
$$c_{i,j} = b_0 + b_1.c_{i,j-1} + b_2.y_{i,j-1} + b_3.\hat{h}_{ij}^-$$

Where  $c_{i,j}$  is the amount of carryover at the end of year  $j$  and  $y_{i,j-1}$  is the production in year  $j-1$ .

Equation (7) predicts  $b_3 > 0$  (negative volatility increases carryover) and  $a_3 = 0$  (positive volatility does not impact carryover).

### **Measuring the effect of carry-over on prices shocks**

We then estimate the effect of storage on these two kinds of volatility, after Balcombe. We consider here the effect of carryover of year  $j-1$  on volatility in year  $j$ ; The associate coefficient  $e_3$  and  $f_3$  supposes that the effect of the stock is proportional to the amount of this stock. Prices are all the more stable as the total stock is large.

The following panel is estimated with an Arellano and Bond GMM estimation.

$$\hat{h}_{ij}^+ = e_0 + e_1.\hat{h}_{i,j-1}^+ + e_2.y_{i,j-1} + e_3.\pi_{i,j-1}$$
$$\hat{h}_{ij}^- = f_0 + f_1.\hat{h}_{i,j-1}^- + f_2.y_{i,j-1} + f_3.\pi_{i,j-1}$$

Where  $i$  index stands for the market,  $j$  index stands for the year,  $y_{i,j-1}$  is the lagged production in village  $i$ ,  $\pi_{i,j-1}$  is the proportion of farmers with nil carryover at the end of year  $j-1$ . We have chosen this measure of carryover instead of the amount of carryover because a carryover in one farm is unpredictable for another farm. The average amount of carryover is less unpredictable because those farmers who keep carryover know that the price in next period is likely to drop.

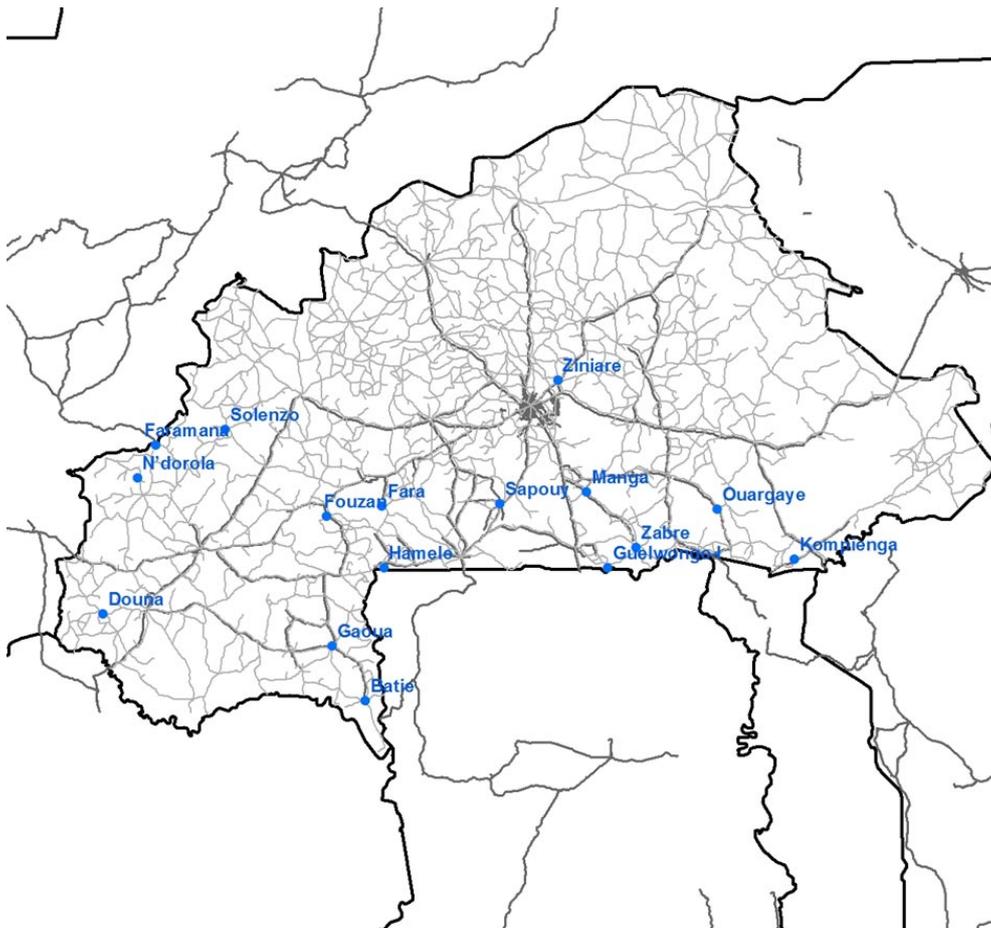
Equation (9) predicts  $f_3 < 0$  (the proportion of farmers with nil carryover decreases negative volatility) and  $e_3 = 0$  (the proportion of farmers with carryover does not increase positive volatility).

## **4. Empirical strategy: Data**

### **Historical maize price data**

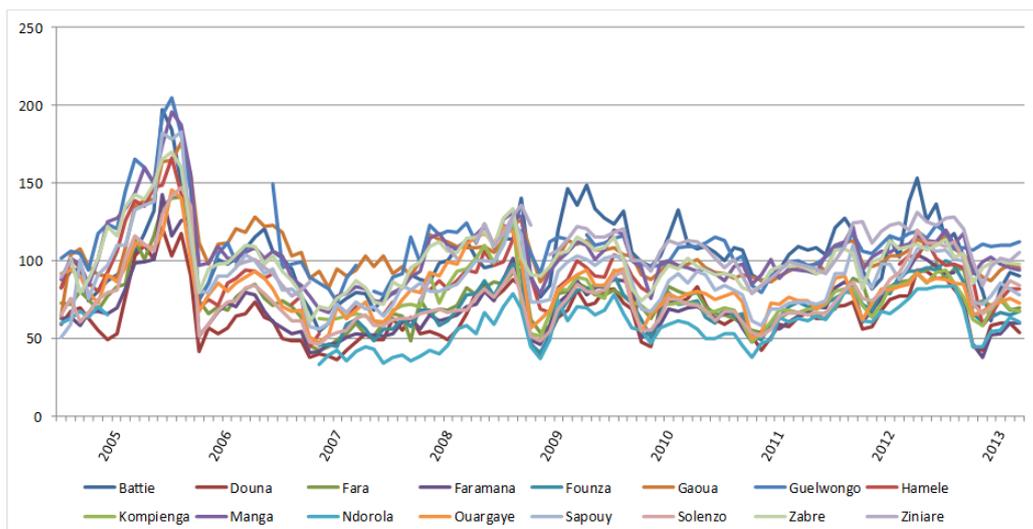
In Burkina Faso, SONAGESS (Société Nationale de Gestion du Stock de Sécurité) is collecting data on consumer, retail and producer prices on 48 markets, and communicating those data on a monthly basis. We used a subset of 16 temporal series where maize producer prices are available for the period mid 2004-mid 2013. Those markets are located in the southern regions of the country, less affected by drought, where maize production is quite an important activity for producers (in the northern regions, millet and sorghum are the main crop produced). Those 16 markets are represented in Figure 6. Each one of those markets corresponds to a different administrative level named province. There are 45 provinces in Burkina Faso.

Figure 6. Localization of the 16 markets studied in Burkina Faso (from the authors)



Monthly price data have then been deflated by the use of burkinabè Consumer Price Index, obtained from INSD (Institut National des Statistiques Démographiques). The evolution of maize producer real prices on the 16 markets is represented in Figure 7.

Figure7. Evolution of maize real prices (Data sources: SONAGESS AND INSD)



What we can learn from Figure 2 is that :

- Prices are affected by seasonal patterns : they are at their highest points around july-september, before harvest, which correspond in Burkina to what is called the “soudure” period and after harvest, around october-december they are at their lower points.
- Beyond those seasonal variations, price rises followed by price falls were quite pronounced in 2005, 2008, 2009 and 2012. Those phenomenons are mainly linked to poor harvest periods, related to the event of acridian invasions (2005) or drought (2009 and 2012) and probably combined to international price spikes (2008, 2012). The 2005 price spike is more pronounced than the other ones.
- Prices follow quite a similar dynamics from one market to one another, even if prices seem to present slightly higher or lower levels for some markets, as it appears in Table 1 representing basic descriptive statistics obtained from the 16 time series we used.

Table 1. Descriptive statistics of the prices observed on the 16 markets studied (from SONAGESS and INSD data)

	Number of observations	Mean	Standard deviation	Min	Max
Battie	105	103,520517	23,8905005	54,3568359	197,295223
Douna	105	65,5695045	17,4782981	36,1708631	121,234597
Fara	105	75,8888256	18,0049969	42,5653664	140,972345
Faramana	104	70,3150479	19,1369529	37,8342021	142,205264
Founza	77	70,4319972	14,3278841	40,4455339	99,7089441
Gaoua	105	104,977494	17,1856137	64,6690139	175,840989
Guelwongo	101	110,554732	21,7612417	73,282273	204,695252
Hamele	73	92,8393789	22,7648739	44,8269687	166,225442
Kompienga	77	75,3655603	14,3747573	47,9464131	126,501945
Manga	105	104,600166	22,0939336	66,7406107	195,575586
Ndorola	83	58,1559524	13,4756142	33,5959222	83,8978136
Ouargaye	105	82,4515923	17,8870714	47,3618116	145,482477
Sapouy	105	90,0946762	23,1543589	50,9567356	182,526671
Solenzo	105	76,2479912	20,3845846	46,3828587	146,833894
Zabre	104	101,137333	19,2095734	60,911938	169,443407
Ziniare	78	104,876839	14,943425	73,8579508	135,80676

### ***Household surveys and on farm-storage data***

The burkinabè Ministry of Agriculture is collecting data on agricultural production since 1992, through the implementation of the EPA (Enquête Permanente Agricole), which consists of a detailed survey where once a year an average number of 4500 rural households are interviewed and their agricultural production is measured. The EPA relies upon a stratification method by administrative levels and inside those administrative levels upon randomized methods thus interviewed households

are expected to be representative from burkinabè rural households. To combine household survey data with price data, we used a subset of EPA data available that corresponds to the 16 different provinces for which we observed maize producer price data. From this subset, we have been working on two main variables of interest: the annual maize production, and the amount of stock that households still have before the new harvest comes. Individual data have been aggregated at the level of the provinces.

The final panel database we have been working on was made of 16 markets observed through 8 years. The two panels are estimated through the generalized moments method, using the Arellano and Bond procedure. The instruments used for the estimation are the lagged production and the lagged prices as predetermined variables, and the dummy variables of fixed market-effects for the exogenous variables. Table 2 describes the variables we have been working on.

Table 2. Descriptive statistics of the variables used in the panel estimations (from EPA, SONAGESS and INSD data)

Variable	N	Moyenne	Ecart-type	Minimum	Maximum
positive volatility	105,00	109,97	11,34	93,68	130,11
negative volatility	105,00	114,62	18,48	94,68	149,71
lagged production	93,00	1439,51	1932,82	23,00	12960,00
lagged proportion of farms with carry-over	90,00	0,70	0,45	0	1,00
real price	97,00	84,52	19,36	42,16	122,92
lagged stock share	75,00	49,13	204,18	0,00	1620,75

## 5. Empirical strategy : Results

### *Characterization of maize price volatility in Burkina Faso*

The mean equation shows that the maize price follows an autoregressive process with a highly significant and strong monthly autocorrelation. Pre-harvest price (shortage season) is significantly higher and post harvest price (abundance season) is significantly lower than the rest of the year. These results are consistent with the ones of Shively (1996) and Barrett (1997) and Karanja et al (2003) and all farmers talks in Burkina Faso. For a deflated price index which means is around 100 (depending on the markets) the seasonal average difference between high and low season is only ten. This unique definition of seasonality for each village underestimates price seasonality. A specific work on this issue where we use monthly dummies instead of trimestriels dummies exhibits higher difference between low season and high season.

The ARCH1 term confirms that the price process is correctly described by an ARCH model. The variance of the residuals is increased by high recent values of the residuals.

One example of ARCH result is given for the Battie market in Table 3. The second row of Table 3 corresponds to the results of the estimation of the mean equation (price level is the dependent variable) while the third row gives us the results of the estimation of the conditional variance equation (price volatility is the dependent variable).

**Table 3. ARCH estimation results for the Battie market**

ARCH family regression

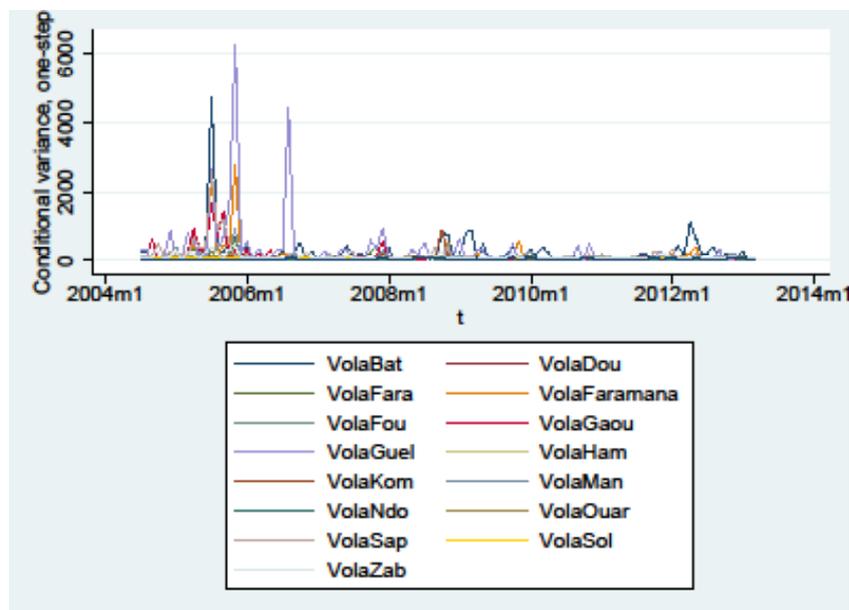
Sample: 2004m8 - 2013m3  
 Distribution: Gaussian  
 Log likelihood = -413.1054

Number of obs = 104  
 Wald chi2(3) = 173.22  
 Prob > chi2 = 0.0000

Battie	OPG					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
<b>Battie</b>						
Battie						
L1.	.6739954	.0751341	8.97	0.000	.5267352	.8212556
Recolte	-13.17909	2.729671	-4.83	0.000	-18.52915	-7.829037
Soudure	2.899477	2.514275	1.15	0.249	-2.028411	7.827366
_cons	35.65672	8.168469	4.37	0.000	19.64682	51.66663
<b>ARCH</b>						
arch						
L1.	.9511485	.2197542	4.33	0.000	.5204382	1.381859
_cons	73.5973	19.00031	3.87	0.000	36.35737	110.8372

Figure 8 gives a representation of the evolution of maize price volatility in the 16 markets studied.

**Figure 8. Evolution of maize price volatility in Burkina Faso ( being the indicator)**



It appears that maize price volatility differs from one market to one other and from one period to one another. The sharp rise of prices observed by mid 2005 on the majority of markets (see Figure 2) corresponds to an episode of high volatility in a restricted number of markets. Compared to 2005, volatility is then quite narrow, even if episodes in 2008, 2009 and 2012 can be identified.

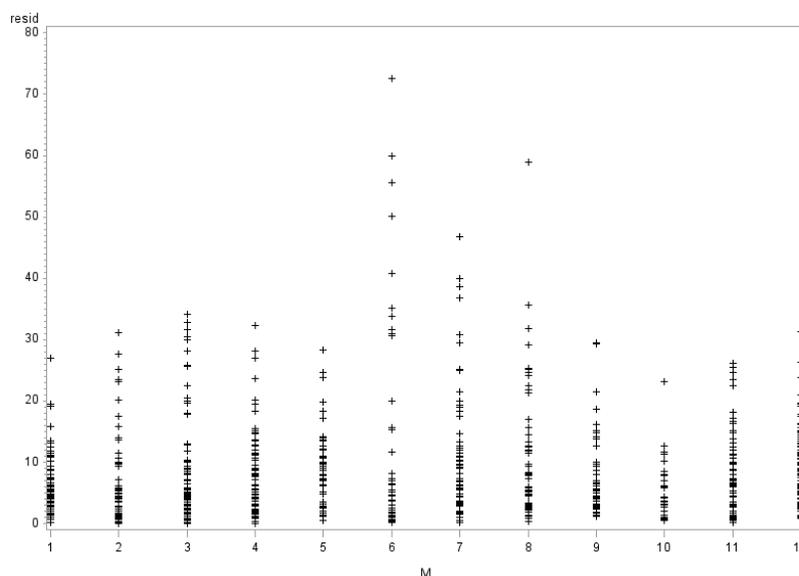
**Table 4. Descriptive statistics on maize price volatility ( )**

Variable	Obs	Mean	Std. Err.	[95% Conf. Interval]	
VolaBat	105	257.638	47.17805	164.0821	351.1938
VolaDou	105	97.49661	2.229655	93.07513	101.9181
VolaFara	105	97.08561	8.454306	80.32041	113.8508
VolaFaramana	105	163.9583	34.2769	95.98594	231.9307
VolaFou	105	62.6017	.340933	61.92561	63.27778
VolaGaou	105	126.0601	23.99984	78.46749	173.6527
VolaGuel	105	322.1565	77.49906	168.4729	475.84
VolaHam	105	116.9342	.4195357	116.1023	117.7662
VolaKom	105	86.10438	8.977762	68.30114	103.9076
VolaMan	105	139.0367	10.45249	118.309	159.7644
VolaNdo	105	56.92118	2.044931	52.866	60.97635
VolaOuar	105	104.5493	4.324214	95.97417	113.1243
VolaSap	105	181.6782	28.17667	125.8028	237.5536
VolaSol	105	112.6529	.3198998	112.0185	113.2872
VolaZab	105	113.8488	7.773605	98.43344	129.2641
VolaZin	105	58.70742	1.22166	56.28482	61.13001

**Distinction between positive and negative prices shocks**

From the results obtained through ARCH models, we then splitted volatility into positive and negative dynamics. Figure 9 presents the distribution of positive residuals across the year for the different markets and different years, and Figure 10 gives us the distribution of negative residuals across the year for the different markets and different years.

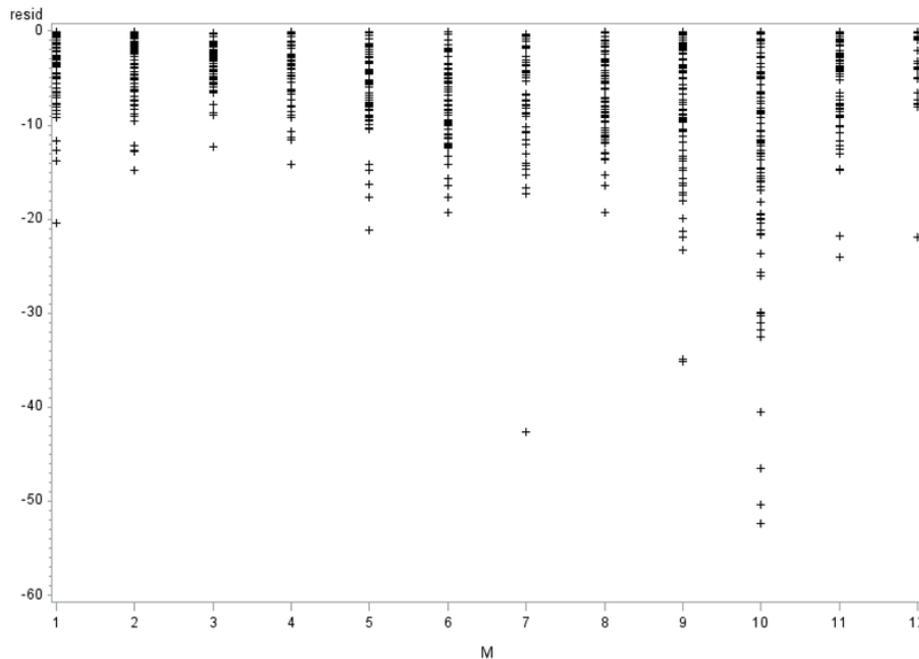
**Figure 9. Positive price shocks around the year (1 for January, 12 for December)**



This graph illustrates that the probability of large positive price shocks is not equal around the year (this is also an illustration of the heteroskedasticity of those residuals justifying the ARCH model). Note that this uneven distribution remains after prices series have been de-seasonalized (see the first equation of the ARCH model = mean equation). It is clear that prices are in average higher in June but in addition to that, unexpected prices shocks also happen most frequently in June and July.

By contrast the similar graph below of negative volatility illustrates that negative prices shocks occur mainly in October, when prices drop.

Figure 10. Negative price shocks around the year(1 for January, 12 for December)



These graphs are to show that the carry-over (measured in September, before harvest) have no reason to impact positive volatility and negative volatility in the same way. Whereas the peak of volatility in June-July will probably be smoothen for the years or the villages where carry-over remain (thus increasing sales and reducing the peak), it is not clear why remaining carry-over in September would reduce the price drop in October. In fact, the opposite is expected.

***The effect of anticipation errors on carryover***

Our model predicts that carry-over at the end of farming year  $j$  should be nil if volatility is low in year  $j$  and the amount of carry-over should be large if in case of unpredictable price drops. This is confirmed by results below.

Estimation results			
Variable	estimates	t-test	Pr >  t
Intercept	15.37582	0.17	0.8699
Lagged price overestimation	1.952934	2.44	0.0246
Lagged production	0.094342	1.89	0.0748
Lagged carryover	0.382589	4.65	0.0002

Sargan test confirms the improvement of estimation with chosen instruments.

Thus negative volatility increases the amount of carry-over, which is as predicted by equation (7). Equation (7) has been set as a function of errors of anticipation of  $p_{12}$  only, but it can be shown that anticipation errors occurring at earlier periods produce the same result.

By contrast, the effect of positive volatility on carry-over as predicted by the model is nil, which is an interesting support to the theoretical framework: carryover is not planned by farmers. If it were, positive price shocks would modify this plan into selling more, hence reducing the amount of carryover, which is not what we observe here. In terms of equation (7), positive shocks simply maintain the planned sales schedule where carryover=0.

Variable	estimate	t-test	Pr >  t
Intercept	129.3986	1.44	0.1665
Lagged price underestimation	0.162853	0.23	0.8243
Lagged production	0.099777	1.96	0.0643
Lagged carryover	0.39421	4.70	0.0002

### ***The effect of carryover on volatility in Burkina Faso***

The positive effect of carryover on next year negative volatility is small. However, if we replace the amount of carryover by the proportion of farmers who have strictly positive carryover, this proxy of carryover has a positive effect on negative volatility at the 1% level.

Estimation results			
Variable	Valeur estimée	Valeur du test t	Pr >  t
Intercept	29.52	4.96	<.0001
Lagged negative volatility	0.114	3.06	0.006
Lagged production	-0.00371	-1,54	0.1398
Lagged proportion of carryover	90,14	7,64	<0.001

The effect of carryover on positive volatility does not appear significant, or, in some trials, appears positive, as if carryover at the end of year  $j$  could contribute to increase positive volatility of prices in year  $j+1$ . Although not impossible, this is not explained by the model at this stage.

## Conclusion

Most of the research on agricultural prices volatility has focused on international markets, and most of the research on stocks as a determinant of volatility has focused on stocks held by public authorities or private traders. The influence of stocks held by agricultural producers themselves on domestic price volatility has received little attention in the economic literature. In this paper, we focus on maize price volatility in a developing country, Burkina Faso, and we analyze the relationship between the levels of stocks held by farmers and volatility levels observed on different local markets, differentiating between negative and positive prices shocks.

Our results are twofold. First, we show that unanticipated price movements during the crop season can be responsible for the existence of on farm stocks at the end of the crop season. Carryover is explained by volatility more than by price level. Unexpected price drops tend to decrease instant supply and delay global supply. When this occurs at the end of the cropping season, and if farmers actually have an implicit minimal price to accept selling, this generates carryover. On the contrary, unexpected price increase does not seem to impact carryover because, as is already mentioned in the literature on inventory, agents cannot sell more than they have, whatever the increase in price. Second, we show that the existence at the end of the crop season of stocks held by farmers was a potentially determinant factor in the collapse of post-harvest prices. Carryover tends to increase the negative volatility of the next year, because it brings more commodity on the market that other agents (farmers with no carryover for instance) can forecast, creating an over sale.

If we want to avoid massive price drops after harvest, our results appeal for the implementation of policy measures to ensure that on-farm stocks will be nil at the end of the year or to ensure that farmers would be able to hold their production just after harvest. Two objectives can be followed :

- Enable farmers a better access to market information and notably markets prices, through more available MIS and better infrastructures. This better access should result in lowering anticipation errors on prices and then avoid situations where farmers have consistent carry-over at the end of the year.
- Promote on-farm storage just after harvest, in order to smooth both price drops after harvests and extreme price increases at the end of the season. This is quite a challenge in the context of developing countries because at the harvest period, farmers need liquidity so they tend to sell a major part of their production, even if the prices are at their lowest point. Thus, encourage storage through subsidization of storage infrastructures in the villages must be accompanied by measures to facilitate farmers access to credit, in order to meet the liquidity needs of farmers. Warehouse receipt systems are expanding among developing countries, precisely because those systems allow farmers both access to liquidity after harvests and a better remuneration for their activity because they can store their products and sell later in the year, when prices are higher. Those systems are of great interest to consumers as well, because they tend to stabilize food prices.

## Bibliographic references

Abbott, P. (2010). Stabilisation policies in developing countries after the 2007-2008 food crisis. Working Party on Agricultural Policies and Markets, Organisation for Economic Cooperation and Development.

Balcombe, K. (2009). The nature and determinants of volatility in agricultural prices: An empirical study from 1962-2008. M. P. n°24819, Reading University.

Barrett, C. (1997). "Liberalization and food price distributions : ARCH-M evidence from Madagascar." Food Policy **22**(2): 155-173.

Bobenrieth, E., J. Bobenrieth, et al. (2013). Bubble Troubles? Rational Storage, Mean Reversion and Runs in Commodity Prices. The Economics of Food Price Volatility. J. Chavas, D. Hummel and B. Wright, University of Chicago Press.

Byerlee, D., T. Jayne, et al. (2006). "Managing food price risks and instability in a liberalizing market environment : Overview and policy options." Food Policy **31**: 275-287.

Cafiero, C., E. Bobenrieth, et al. (2011). "The empirical relevance of the competitive storage model." Journal of Econometrics **162**: 44-54.

David-Benz, H., A. Diallo, et al. (2010). L'imparfaite transmission des prix mondiaux aux marchés agricoles d'Afrique subsaharienne, FARM.

Daviron, B., M. Aubert, et al. (2009). Les mécanismes de transmission de la hausse des prix internationaux des produits agricoles dans les pays africains Paris FARM Foundation.

Deaton, A. and G. Laroque (1992). "On the behaviour of commodity prices." Review of Economic Studies **59**: 1-23.

Demeke, M., G. Pangrazio, et al. (2008). Country responses to the food security crisis: Nature and preliminary implications of the policies pursued. Food and Agriculture Organization.

Engle, R. (1982). "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation." Econometrica **50**(4): 987-1007.

Fackler, P. L. and M. J. Livingston (2002). "Optimal Storage by Crop Producers." American Journal of Agricultural Economics **84**(3): 645-659.

FAO, IFAD, et al. (2011). Price Volatility in Food and Agricultural Markets: Policy Responses. Rome, FAO.

Gilbert, C. and W. Morgan (2010). "Food price volatility." Philosophical Transactions of the Royal Society **365**: 3023-3034.

Gouel, C. (2013). Food price volatility and domestic stabilization policies in developing countries. The economics of food price volatility J. Chavas, D. Hummels and B. Wright. Chicago, Chicago University Press.

Gustafson, R. (1958). Carryover levels for grains: A method for determining amounts that are optimal under specified conditions. Technical Bulletin No. 1178. Washington USDA.

Hazell, P., G. Shields, et al. (2005). The nature and extent of domestic sources of food price instability and risk. World Bank Workshop on Food Price Risk Management in Low Income Countries, Washington DC.

Helmberger, P. and V. Akinyosoye (1984). "Competitive pricing and storage under uncertainty with an application to the US Soybean market." American Journal of Agricultural Economics **66**(2): 119-130.

Huchet-Bourdon, M. (2011). Is agricultural commodity price volatility increasing? A historical review. Working Party on Agricultural Policies and Markets. Paris Organisation for Economic Development and Cooperation.

Jayne, T., R. Myers, et al. (2008). "The effects of NCPB marketing policies on maize market prices in Kenya." Agricultural Economics **38**: 313-325.

Karanja, A., A. Kuyvenhoven, et al. (2003). "Economic Reforms and Evolution of Producer Prices in Kenya: An ARCH-M Approach." African Development Review 271-296.

Kim, K. and J. Chavas (2002). "A Dynamic Analysis Of The Effects Of A Price Support Program On Price Dynamics And Price Volatility." Journal of Agricultural and Resource Economics **27**(02): 495-514.

Maître d'Hôtel, E., T. Le Cotty, et al. (2013). "Trade Policy Inconsistency and Maize Price Volatility: An ARCH Approach in Kenya." African Development Review **25**(4): 607-620.

Nyange, D. and P. Wobst (2005). Effects of Strategic Grain Reserve, Trade and Regional Production on Maize Price Volatility in Tanzania: An ARCH Model Analysis.

Park, A. (2009). "Risk and household grain management in developing countries." The Economic Journal **116**(514): 1088-1115.

Piot-Lepetit, I. and R. M'Barek (2011). Methods to analyze agricultural commodity price volatility. Methods to analyze agricultural commodity price volatility. P.-L. a. M'barek. New York, Springer-Verlag: 1-11.

Prakash, A. (2011). Why volatility matters. Safeguarding food security in volatile global markets. Prakash. Rome, FAO.

Roache, S. (2010). What explains the rise in food price volatility? . I. W. P. WP/10/129, International Monetary Fund.

Saha, A. and J. Stroud (1994). "A household model of on-farm storage under price risk." American Journal of Agricultural Economics **76**(3): 522-534.

Serra, T. and J. M. Gil (2013). "Price volatility in food markets: can stock building mitigate price fluctuations?" European Review of Agricultural Economics **40**(3): 507-528.

Shively, G. (1996). "Food price variability and economic reform: An ARCH approach for Ghana." American Journal of Agricultural Economics **78**: 126-136.

Torero, M. (2009). A system of virtual global reserves. Workshop on Institutions and Policies to Manage Global Market Risks and Price Spikes in Basic Food Commodities. Rome FAO.

Tschirley, D. and T. Jayne (2010). "Exploring the logic behind Southern Africa's Food Crises." World Development **38**(1): 76-87.

Wiggings, S. and S. Keat (2009). Grain stocks and price pikes. O. D. Institute: 61.

Williams, J. and B. Wright (1991). Storage and commodity markets, Cambridge University Press.

Wright, B. (2011). "The Economics of Grain Price Volatility." Applied Economic Perspectives and Policy **33**(1): 32-58.

Yang, J., M. Haigh, et al. (2001). "Agricultural liberalization policy and commodity price volatility: a GARCH application." Applied Economics Letters **8**: 593-598.