Maize price volatility: does market remoteness matter?

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Abstract

This paper addresses the role of market remoteness in explaining maize price volatility in Burkina Faso. A model of price formation is introduced to demonstrate formally that transport costs between urban and rural markets exacerbate maize price volatility. Empirical support is provided to the proposition by exploring an unusually rich data set of monthly maize price series across 28 markets over 2004–13. The methodology relies on an autoregressive conditional heteroskedasticity model to investigate the statistical effect of road quality and distance from urban consumption centers on maize price volatility. The analysis finds that maize price volatility is greatest in remote markets. The results also show that maize-surplus markets and markets bordering Côte d'Ivoire, Ghana and Togo have experienced more volatile prices than maize-deficit and non-bordering markets. The findings suggest that enhancing road infrastructure would strengthen the links between rural markets and major consumption centers, thereby also stabilizing maize prices.

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1. Introduction

High transport costs in Sub-Saharan Africa directly stem from distance and lack of quality infrastructure, which hampers farmers' participation in markets (**Kisamba, 2005**), while traders from urban areas are discouraged from purchasing food items directly from rural farmers in remote areas. A relevant concern arises from the subsequent mismatch between supply and demand, namely the probable influence of transport costs on price volatility. Against this background, this paper contributes to the literature on the determinants of food price volatility in Sub-Saharan Africa by focusing on market remoteness. Previous empirical studies emphasized the relationship between price variations (and not necessarily price volatility[1]) and a number of market characteristics including road quality (**Minten and Kyle, 1999**), the market region's development level (**Kilima et al., 2008 ; Minot, 2013**) [2], market location in a maize-surplus or deficit region (**Kilima et al., 2008**), border contiguity with a maize-producing country (**Kilima et al., 2008**), and traders' margins (**Fafchamps, 1992; Minten and Kyle, 1999**). Yet, only a few studies have formally explored theoretically and/or empirically the relationship between price volatility across markets and transport costs. Thus, our contribution lies in the development of a conceptual model that relates price volatility to transport costs and to assess its empirical relevance in explaining spatial volatility differences across markets in Burkina Faso. We assume that market remoteness implies higher transport costs, which fuel maize price volatility.

Focusing on transport costs, there is a specific literature on market integration that seeks to analyze the interconnectedness between price dynamics prevailing in different markets. Volatility occurring in local markets may be related to price changes occurring in central markets (**Abdulai, 2000; Badiane and Shively, 1998**). The underlying intuition is that food prices can differ greatly from one local market to another because of differences in transport costs, these costs being themselves related to different levels of spatial integration with the central market. When analyzing the effect of a price-shock originating from the central market on local markets in Ghana, **Badiane and Shively (1998)** find that the maize price level and

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[1] It is important to differentiate between the terms "price variability" and "price volatility": price variability gives an overall description of price variation i.e. the deviation from an average or a trend while price volatility is defined in the economic literature as the unpredictable part of price variations (**Piot-Lepetit and Mbarek, 2011**).

[2] **Kilima et al., 2008** established that the level of economic development of regions has a decreasing effect on maize price volatility in Tanzania. This result indicates that developed regions tend to show lower price volatility than undeveloped regions. Relying on a sample of 11 African countries, **Minot (2013)** established that food prices were less volatile in capital cities than in other cities and this result holds for six commodities (beans, cooking oil, maize, rice, sorghum, and teff).

volatility prevailing in one local market are very much correlated with the "central market price history", while prices observed in the other local market are more related to "local price history", the difference being explained by different transport costs. However, their analysis is based on two local markets (one that is integrated and close to the central market and one that is less integrated and further located) and does not allow to gauge the statistical effect of the degree of interdependence between local markets and the central market on price volatility. Furthermore, in their study, transport costs are not directly used as explanatory variables of price volatility in local markets, but are rather suggested through spatial price spreads between central and local markets.

Our study borrows from **Badiane and Shively (1998)**, but departs from their work in the sense that it measures interdependence between markets by using distance to major cities [3] (expressed in kilometers and hours) and road quality, both variables being proxies for transport costs. We explain spatial volatility differences across markets through the inclusion of explanatory variables that are directly related to transport costs.

The paper is organized as follows. In section two, we introduce a simple price-modeling framework that allows us to establish that high price volatility stems from changes in transport costs between rural and urban markets. In section three, we present the context of maize price and production in Burkina Faso. Maize is widely consumed throughout the country and maize production has significantly increased recently: it is the second source of income for farmers, after cotton. As volatility may hinder investments in agricultural production, understanding and analyzing maize price volatility is of strategic in Burkina Faso, for food security as well as for rural development more broadly. In section four, we present our empirical strategy to analyze the effect of market remoteness on price volatility, based on the estimation of an autoregressive conditional heteroskedasticity model adapted from **Shively, 1996** and **Maître d'Hôtel et al., 2013**. In section five, we finally deliver our empirical results by exploring a database of maize prices in Burkina Faso on 28 markets[4] over 2004-2013. We find robust evidence that maize price volatility is greater in remote markets. This result validates the empirical relevance of our conceptual model.

[3] 'central market', 'main cities', 'major cities', 'major consumption centers', 'urban consumption centers' and 'urban market are used synonymously in this paper, all referring to the leader market i.e. the capital city (Ouagadougou) and largest cities with a population of more than 100, 000 (Bobo-Dioulasso and Koudougou).

[4] A market is defined as the meeting place between local farmers and traders, including intermediaries, wholesalers and semi-wholesalers who transport and deliver maize at consumption centers. It is worth noting that there also exist consumer and wholesaler markets where traders and consumers meet. Among traders, wholesalers are usually those who are responsible for inter- and intra-regional trade, by selling commodities to other wholesalers, retailers and consumers.

2. Spatial price modelling, market remoteness and price volatility: Theoretical premises

2.1 A spatial model of agricultural price

Different models have been used to study spatial price behavior. The most common approach was introduced by **Enke (1951)** and **Samuelson (1952)**, where price differences between two markets equal the cost of moving the good from the low-price market to the high-price market, i.e. transport costs. We develop a simple model of spatial price based on this transport cost assumption. Let's consider two markets, a rural one and an urban one, the transport cost between those two markets being significant. We denote the rural and urban markets by the superscripts r and u, respectively.

If effective product flows exist between the rural market and the urban market, prices are expected to follow the relationship[5]:

$$P^u = P^r + c \qquad (1)$$

Where P^u represents the urban price, P^r the rural market price and c the unit transport cost.

2.2 Modeling spatial price volatility

To link market integration and transport costs to local price volatility, **Badiane and Shively (1998)** rely on the theory of price formation presented in **Deaton and Laroque (1992)**[6]. In a scenario of positive storage and connectedness between local and central markets, they assume that the current-period price volatility in a local market depends on previous prices in that market, harvests, and supply-shock induced price changes in the central market. The authors investigate price volatility based on supply shifts in the central market where the price-shock originates. In our analysis, we conversely consider the case of a supply shock occurring in the rural market. It creates price volatility whose size is determined by the proximity of the rural market to the urban market. The price volatility we strive to explain results from the fact that excess supply in rural markets fails to meet and satisfy excess

[5] In a non-competitive framework, the difference between prices in rural and urban markets will include transaction costs (T) and traders' rents (R) in addition to transport costs. Rents originate from each trader's monopoly or oligopoly position related to their ability to choose between different farmers to buy grains. In urban areas, it translates to their ability to speculate by storing these grains and selling them when prices are high. In a competitive market, R=0. Due to data availability considerations, we keep our theoretical model simple and assume T=R=0. Our price-modelling framework relies on a supply and demand model. Despite its simplicity, we believe it reasonably manages to explain price volatility without the inclusion of complex strategic interactions between agents.

[6] In their model, the authors demonstrate that there is a relationship between current-period price volatility and past inventories after stockholding.

demand in the urban market. By analogy to international trade theory, we call “excess supply” the difference between local supply and local demand in the rural market (equation (2)). Reversely, excess demand reflects the difference between local demand and local supply (possibly nil) in the urban market (equation (3)).

Monthly excess supply from rural market

The monthly rural market ‘excess supply’ x_t is the share of rural production that has not been matched with rural demand[7]. It is a function of the month[8] t considered, the harvest of the year h, the local price p_t^r prevailing in the rural market at month t, and a stochastic shock ε_t aggregating all shocks affecting rural market supply:

$$x_t = f(h, p_t^r, \varepsilon_t, t) \qquad (2)$$

Monthly excess demand from urban market

In a similar way, we define an “excess demand” from the urban market as the part of urban market demand that is not satisfied by the rest of other potential suppliers, for each price level. The monthly excess demand from the urban market can be written as:

$$m_t(p_t^u) = m_t(p_t^r + c) \qquad (3)$$

The excess demand $m_t(p_t^u)$ is decreasing and convex in price, m_t'*<0,* m_t''*>0.*

Therefore, we note that m'_t, increases with transport cost c. The consequence of this is that the demand function from the urban market toward the rural market is more inelastic ($m_t' \rightarrow 0$) if the transport cost between this rural market and the urban market is high.

Market clearing conditions suppose equality between an excess supply from the rural market and excess demand from the urban market.

$$x_t(h, p_t^r, \varepsilon_t, t) = m_t(p_t^r + c) \qquad (4)$$

This equilibrium implicitly defines a market price $p^*(h, \varepsilon_t, t, c)$

Totally differentiating equation (4) leads to:

$$\frac{\partial x_t}{\partial h} dh + \frac{\partial x_t}{\partial p_t} dp_t + \frac{\partial x_t}{\partial \varepsilon_t} d\varepsilon_t + \frac{\partial x_t}{\partial t} dt = m_t' dp_t + m_t' dc \ ,$$

[7] It is worth noting that rural production is corrected for on-farm consumption.
[8] The month of the year in itself also matters in farmers selling behaviours that is not due to prices or shocks. There is seasonality in sales due in particular to high time preferences: farmers tend to sell immediately most of their production on post-harvest time; this has been due to their lack of storage capacity and liquidity constraints.

$$\frac{\partial x_t}{\partial p_t}dp_t - m_t' dp_t = -\frac{\partial x_t}{\partial h}dh - \frac{\partial x_t}{\partial \varepsilon_t}d\varepsilon_t - \frac{\partial x_t}{\partial t}dt + m_t'dc$$

Or,

$$dp_t = -\frac{\frac{\partial x_t}{\partial h}dh}{(\frac{\partial x_t}{\partial \partial p_t} - m_t')} - \frac{\frac{\partial x_t}{\partial \varepsilon_t}d\varepsilon_t}{\left(\frac{\partial x_t}{\partial p_t} - m_t'\right)} - \frac{\frac{\partial x_t}{\partial t}dt}{\left(\frac{\partial x_t}{\partial p_t} - m_t'\right)} + \frac{m_t'dc}{\left(\frac{\partial x_t}{\partial p_t} - m_t'\right)} \quad (5)$$

Equation (5) can be used to investigate the effect of a variation in *harvest, shocks, seasonality* and *transport cost* variables on price behavior.

$$\frac{\partial p_t}{\partial h} = -\frac{\frac{\partial x_t}{\partial h}}{\left(\frac{\partial x_t}{\partial p_t} - m_t'\right)} \quad (6)$$

$$\frac{\partial p_t}{\partial \varepsilon_t} = -\frac{\frac{\partial x_t}{\partial \varepsilon_t}}{\left(\frac{\partial x_t}{\partial p_t} - m_t'\right)} \quad (7)$$

$$\frac{\partial p_t}{\partial t} = -\frac{\frac{\partial x_t}{\partial t}}{\left(\frac{\partial x_t}{\partial p_t} - m_t'\right)} \quad (8)$$

$$\frac{\partial p_t}{\partial c} = \frac{m_t'}{\left(\frac{\partial x_t}{\partial p_t} - m_t'\right)} \quad (9)$$

With $m_t' < 0$ and $\frac{\partial x_t}{\partial p_t} > 0$, we have $\left(\frac{\partial x_t}{\partial p_t} - m_t'\right) > 0$

Equation (6) gives the marginal effect of a change in grain production on price. Since $\frac{\partial x_t}{\partial p_t} > 0$, we have $\frac{\partial p_t}{\partial h} < 0$. This confirms that an increase in production reduces the grain price.

Equation (7) provides a theoretical estimation of the effect of shocks on price behavior. It is useful to recall at this point that in this study price volatility is defined as the unpredictable component of price variations. Thus, we consider that the effect of a shock on price behavior can be seen as an expression of price volatility. Accordingly, the instantaneous measure of price volatility is given by equation (7). We assume two types of supply shocks: positive ones and negative ones. We consider asymmetric shocks, which mean that the effects of positive and negative shocks on excess supply may differ in magnitude or size. Let ε_t^+, be a positive shock, such as an increase in monthly grain supply resulting from a sudden stock release by an important trader. This positive shock raises the rural market's monthly excess supply and this translates into downward price variations (i.e. negative volatility).

Let ε_t^-, be a negative shock, such as a drop in the monthly supply of grain, following a sudden and massive purchase of grain by traders or idiosyncratic damage to grain by insects.

This negative shock reduces the monthly excess supply in the rural market and raises upward price fluctuations (i.e. positive volatility).

So $\frac{\partial x_t}{\partial \varepsilon_t} > 0$ implies that $\frac{\partial p_t}{\partial \varepsilon_t} < 0$, and $\frac{\partial x_t}{\partial \varepsilon_t} < 0$ implies that $\frac{\partial p_t}{\partial \varepsilon_t} > 0$

Equation (8) describes the effect of seasonality on price behavior. In general, it is observed (and can be shown theoretically) that after harvest, the monthly supply tends to decrease throughout the year, and the local price tends to increase until the lean season (or pre-harvest season), which is a shortage period. Equation (8) predicts how a decrease in monthly supply $\frac{\partial x_t}{\partial t} < 0$ turns into a price increase $\frac{\partial p_t}{\partial t} > 0$.

Seasonality corresponds here to the existence of two seasons: (i) the harvest season, characterized by the abundance of products on markets, high excess supply and low prices and (ii) the lean season, featuring product scarcity, low monthly excess supply and high grain prices[9].

Equation (9) describes the price effect of the transport cost between rural and urban markets. It comes out that $\frac{\partial p_t}{\partial c} < 0$, since $m_t' < 0$. It indicates that rural price decreases with the remoteness of markets from an urban market. The higher the transport cost between the rural market and the urban market, the lower the price in the rural market. This means that prices tend to be higher in areas close to the urban market than in remote areas.

We use **equation (7)** to investigate the effect of transport costs on price volatility. We derive equation (7) with respect to transport cost.

$$\frac{\partial p_t}{\partial \varepsilon_t} = -\frac{\frac{\partial x_t}{\partial \varepsilon_t}}{\left(\frac{\partial x_t}{\partial p_t} - m_t'\right)} \quad (7)$$

$$\frac{\partial^2 p_t}{\partial \varepsilon_t \partial c} = -\frac{\partial\left(\frac{\frac{\partial x_t}{\partial \varepsilon_t}}{\left(\frac{\partial x_t}{\partial p_t} - m_t'\right)}\right)}{\partial c}$$

$$\frac{\partial^2 p_t}{\partial \varepsilon_t \partial c} = -\frac{\partial x_t}{\partial \varepsilon_t}\left(-\frac{-m_t''}{\left(\frac{\partial x_t}{\partial p_t} - m_t'\right)^2}\right), \text{ ie } \frac{\partial^2 p_t}{\partial \varepsilon_t \partial c} = -\frac{\partial x_t}{\partial \varepsilon_t}\ \frac{m_t''}{\left(\frac{\partial x_t}{\partial p_t} - m_t'\right)^2}$$

With m_t''>0 and $\left(\frac{\partial x_t}{\partial h} - m_t'\right)^2 > 0$, thus

[9] The economic literature also shows that seasonality may be captured by post-harvest losses and the opportunity cost of capital across markets **(Kaminski et al., 2014)**.

$$Sign\ \left(\frac{\partial^2 p_t}{\partial \varepsilon_t \partial c}\right) = -Sign(\frac{\partial x_t}{\partial \varepsilon_t}) \qquad (10)$$

By (10), a positive supply shock, $\frac{\partial x_t}{\partial \varepsilon_t} > 0$, implies $\frac{\partial^2 p_t}{\partial \varepsilon_t \partial c} < 0$, and by (7) implies that $\frac{\partial p_t}{\partial \varepsilon_t} < 0$. In case of a positive supply shock, the price decrease is all the more important as transport cost is high.

By (10), a negative supply shock, $\frac{\partial x_t}{\partial \varepsilon_t} < 0$, implies $\frac{\partial^2 p_t}{\partial \varepsilon_t \partial c} > 0$, and by (7) implies that $\frac{\partial p_t}{\partial \varepsilon_t} > 0$. In case of a negative supply shock, the price increase is all the more important as transport cost is high.

To summarize, in both cases, transport costs increase the magnitude of the price shock, be it positive or negative: $\left|\frac{\partial^2 p_t}{\partial \varepsilon_t \partial c}\right| \propto \left|\frac{\partial x_t}{\partial \varepsilon_t}\right|$.

A positive supply shock generates a local price decrease all the more as transport cost is high, and negative supply shocks increase local price all the more as transport cost is high. In both cases, the expected effect is that price volatility is higher in remote than in urban markets.

2.3 Graphical analysis of price volatility

Figure 1 illustrates an exogenous shift in monthly local supply y in a rural market in two cases (i) when there are no transportation costs between the rural market (net supplier) and the urban market (net demander) and (ii) when there are transportation costs c between the two markets (dashed lines). To illustrate the case that rural markets are characterized by volatility and that this is exacerbated in the case of remote rural markets, we assume that price changes are due to shifts in excess supply.

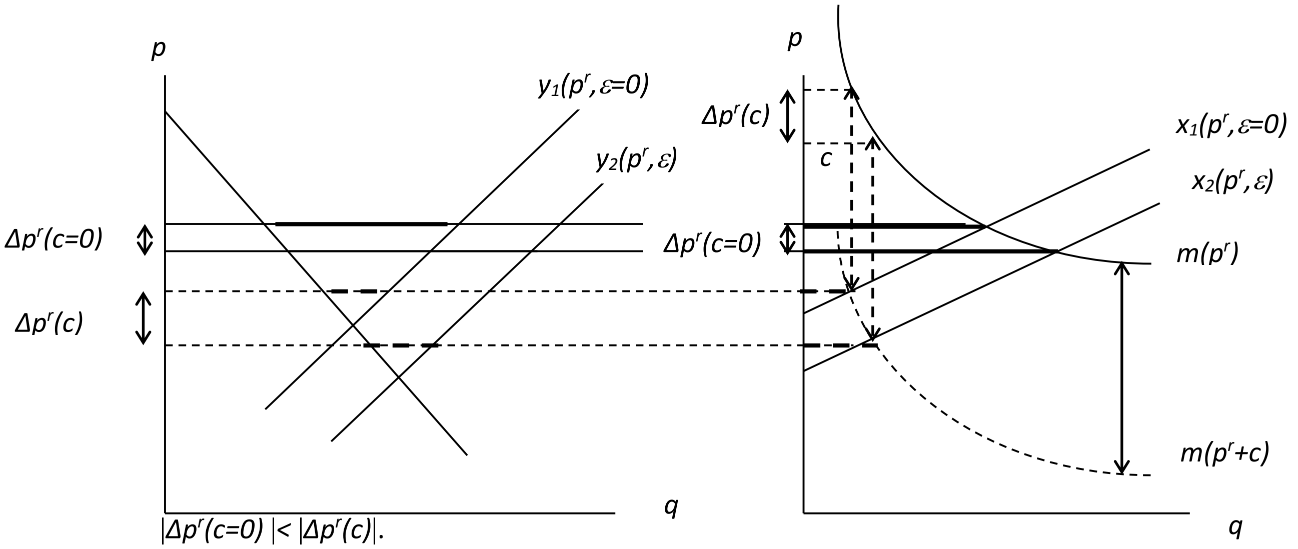
Whereas the local demand can be linear, the excess demand from the urban center has to be strictly convex for the transportation cost to impact volatility (see demonstration of equation (10)).

(i) If the rural market is connected to the urban market with no transport costs, excess supply x_1 and excess demand meet in the upper part of the right-hand-side diagram (plain line). The shift in the rural supply, for example due to a stock release, produces a shift in the excess supply from *x1* to *x2*. Prices in both rural and urban markets are identical and decrease by $\Delta pr(c=0)$.

(ii) If we introduce transport costs between the two markets (say the road is interrupted at some point so that traders have to take a long and tedious itinerary), *y1* is much lower and the rural market price differs from the price in the urban center by *c*. The trader bears this cost and his willingness to pay for the grain decreases by c. This leads to a marginal decrease in excess demand in the urban market by *c*. Because the supply toward the urban center decreases, the urban price increases. This assumes of course that the rural market is an important one, or in other words, that the excess demand from the urban center is not perfectly horizontal. The same supply shift from y_1 *to* y_2 as above produces a greater price drop *Δpr(c>0)*, both in the rural and urban markets because the introduction of transport costs moves the market equilibrium to the left side of the excess demand of the urban center, i.e. the stiffer part of the curve.

The introduction of transport costs between a production area and a consumption area increases price shifts in both markets due to supply or demand shifts in the rural market. A corollary is that in the absence of any intermediary bargaining power, transport costs have no impact on volatility if the urban market excess demand is linear.

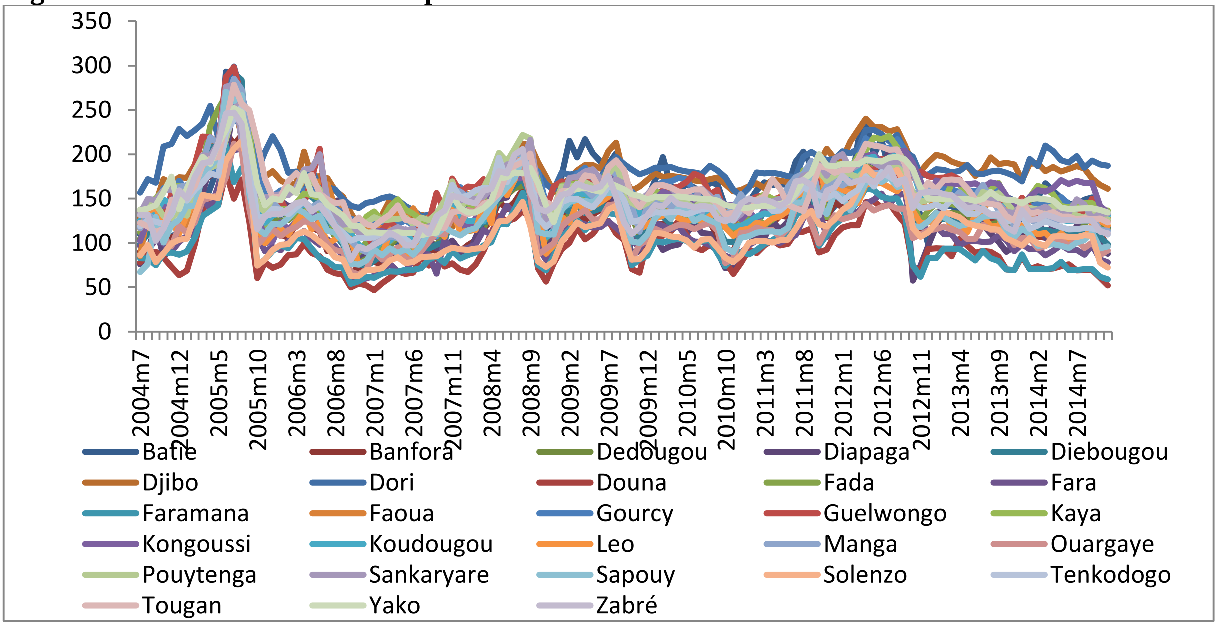
Figure 1: market equilibria and price shift in rural markets



3. Maize price and production in Burkina Faso: Data and trends

Agricultural development is strategic for Burkina Faso and maize production is strategic for agricultural development in Burkina Faso. Agriculture employs around 85 percent of the population and contributes to 34 percent of gross domestic product. Maize is one of the main sources of agricultural income in Burkina Faso, ranking second after cotton. As depicted by **Figure A1** in the Appendix, maize production has significantly increased in the last decade, rising at a faster pace than millet and sorghum. Production growth was most remarkable in Hauts-Bassins, Boucle du Mouhon and Cascades regions in western Burkina Faso (**Appendix A2 and A3**). In addition to these spatial disparities, maize is mainly traded within the country, flowing from maize-surplus to maize-deficit regions, but is also exported to Niger and Mali while imports originate from Côte d'Ivoire and Ghana. Our analysis relies on historical price data collected by the ***Société Nationale de Gestion du Stock Alimentaire (SONAGESS)***. SONAGESS manages its own market information system since 1992. Prices of main agricultural commodities are collected weekly on 48 markets, and price averages are computed monthly. In this study, we analyze 28 markets with available data over July 2004-November 2013. We deliberately set aside markets for which price series present discontinuities. For each market, monthly maize price series are expressed in FCFA per kilogram and then deflated[10] by the Burkinabe Consumer Price Index (2008 base 100) calculated monthly by the Institut National des Statistiques et de la Démographie. Descriptive. Statistics of deflated maize price series in each market are presented in **table A4**.

Figure 2: Evolution of maize real price



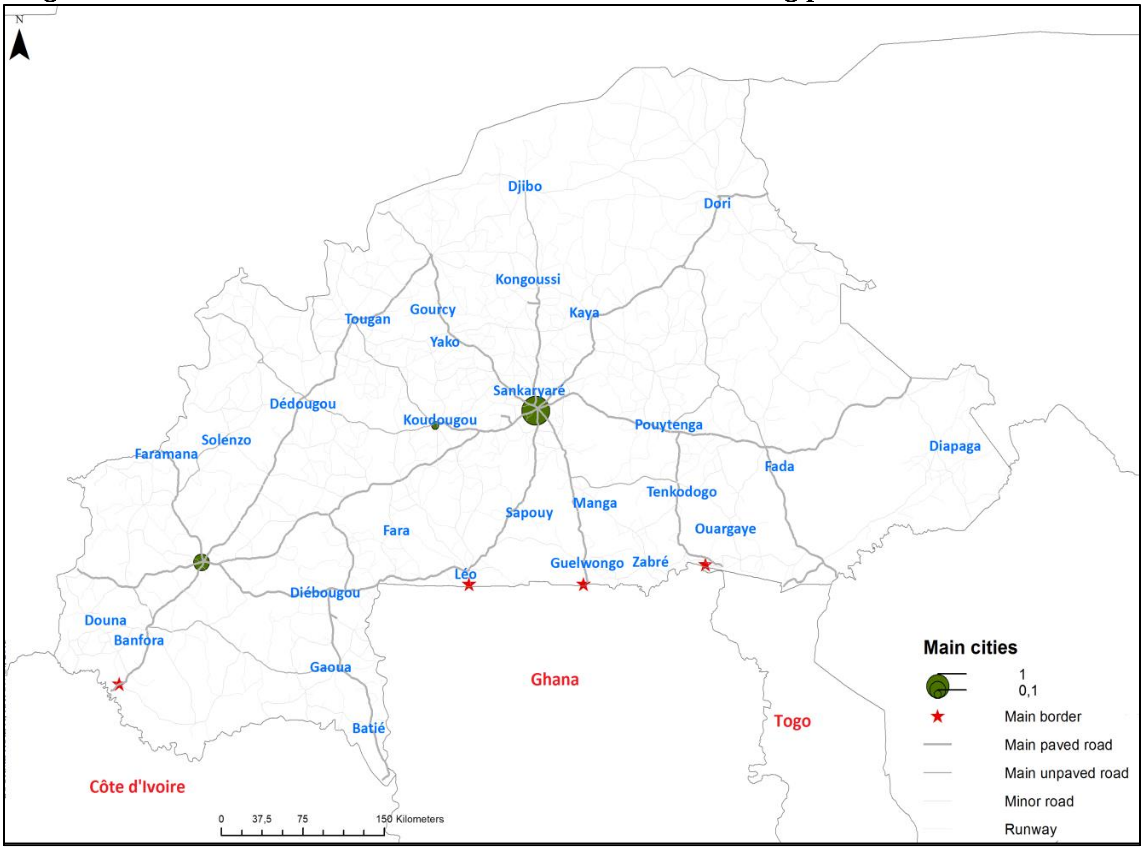
<u>Source: SONAGESS and INSD</u>

Figure 2 displays the evolution of real prices on the 28 maize markets. The price series present similarities between markets, and notably important price spikes followed by price

[10] Section 5.3 will make use of nominal price series in robustness checks.

drops in 2004/2005 (grasshopper invasion), 2007/2008 (drought and international crisis) and 2010/2011 (drought). Prices are affected by seasonal patterns: they are lower in the harvest season around October-December and higher in the lean period (June to September).

Figure 3: Localization of maize markets, main border crossing points[11] and main cities



Source: Author calculation

The localization of each selected maize market is shown in **Figure 3**. Market remoteness is defined as market distance to main cities, namely Ouagadougou, Bobo-Dioulasso and Koudougou. Statistics pertaining to these three main cities are given in **Table 1**.

Table 1: Statistics related to main cities

	Ouagadougou	Bobo-Dioulasso	Koudougou
Region	Center	Hauts-Bassins	Centre-Ouest
Population	1.5 million	0.5 million	0.1 million
Population growth rate	7.6%	7.23%	3.4%

Source: Author calculation

[11] Relying on the volume of maize trade, we identified four major maize border-crossing points (in red in **Figure 3**) among eighteen: Bittou (Togo), Dakola (Ghana), Léo (Ghana) and Niangoloko (Côte d'Ivoire). Figure 3 also plots the three main consumption centers in green.

4. Empirical strategy

We test the effect of market remoteness on price volatility. To do so, we use a pooling regression of 28 markets that permits an estimation of the average effect of market remoteness on maize price volatility. Our work focuses on the empirical analysis of price volatility, which is defined as the unpredictable component of price fluctuations (**Prakash, 2011**). Appropriate models for this measure of volatility are ARCH family models, in which the variance of residuals is allowed to depend on the most recent residuals and other variables.

Drawing on **Shively (1996)**, **Barrett (1997)** and **Maître d'Hôtel et al. (2013)**, we build upon an ARCH model that displays mean and variance equations of maize prices to investigate maize price volatility in Burkina Faso. To measure this volatility, we isolate the unpredictable component of price variations from the predictable one, relying on price forecast models. To identify predictable price moves, several authors have used the conditional variance of price as an indicator of price volatility. The variance of the residuals of a price formation model typically measures the unpredictable price shifts. Thus, we use an ARCH model for two reasons. First, many storable commodity prices such as maize have an ARCH process (**Beck, 1993**). Second, ARCH models are particularly adaptable to the study of price volatility defined as the unpredictable part of price variations, as they enable the variance of the residual not to be constant over time, thus depicting an unpredictable dimension. The ARCH model assumes that the conditional variance depends on the lagged squared residuals of a price series over time. By including variables as regressors, the model can be used to identify potential determinants of price volatility. The ARCH model was introduced by **Engle (1982)** and generalized by **Bollerslev (1986)**[12].

The ARCH structure is given by equations **(12)** and **(13)**:

$$Y_t = X'_t\beta + \varepsilon_t \qquad \textbf{(11)}$$

With $$\varepsilon_t|\Omega_{t-1} \approx N(0,h_t) \qquad \textbf{(12)}$$

[12] A General Autoregressive Conditional Heteroskedasticity (GARCH) process can also model price volatility. Some studies have used a GARCH model to analyse price volatility for different commodities (**Yang et al., 2001** ; **Gilbert and Morgan, 2010**). We choose ARCH model instead of GARCH, because monthly data usually do not exhibit GARCH effects (**Baillie and Bollerslev, 1990**). GARCH model is more appropriate for high frequency data. A robustness check is conducted in section 5.3, which relies on GARCH model. By using ARCH and GARCH processes, we assume that a quadratic relationship between the error term and the conditional variance (i.e. volatility). Series are assumed to feature high and low volatility, whatever the sign of the shock causing the volatility. Other specifications called asymmetric models exist such as Exponential-ARCH (EGARCH) model, which has been used whether the price volatility depends on the information of past shock in a non-linear fashion. The asymmetric models assumes that volatility can be spotted with clusters of amplitudes that significantly vary over time and volatility can increase or decrease depending on the information on past error terms.

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon^2_{t-i} \qquad \textbf{(13)}$$

where Y_t is the dependent variable, X'_t denotes the vector of explanatory variables (column vector), ε_t is the error component, h_t is the time-varying variance of the error; Ω_{t-1} is the information set available at $t-1$, ω, α_i for i = 1,2,. . ., β are parameters. **Equation (11)** gives the conditional mean while **equation (13)** describes the evolution of the conditional variance. We adapt **equations (11)** and **(13)** to our study so as to investigate the determinants of maize price volatility in Burkina Faso.

We proceed in a two-step approach. Firstly, we pool 28 maize markets in order to estimate the average effect of market remoteness (i.e. transport cost, time distance between market i from Ouagadougou, Bobo-Dioulasso and Koudougou: the major consumption centers) on price level (**equation 14**), and secondly, on price volatility (**equation 15**):

$$ln\, P_{it} = \theta_0 + \theta_1 ln\, P_{it-1} + \theta_2 Trend_t + \theta_3 ln\, RER_t + \theta_4 lnIP_t + \sum_i \mu_i S_{it} + \sum_j \upsilon_j M_{jh} + \rho lnTC + \delta_1 lnBorder + \delta_2 Surplus + \varepsilon_{it} \qquad \textbf{(14)}$$

$$h_{it} = \lambda_0 + \lambda_1 \varepsilon^2_{t-i} + \Omega_1 ln\, P_{it-1} + \Omega_2 Trend_t + \Omega_3 ln\, RER_t + \Omega_4 lnIP_t + \sum_i \pi_i S_{ht} + \varphi lnTC + \omega_1 lnBorder + \omega_2 Surplus + v_{it} \qquad \textbf{(15)}$$

The specifications retained indicate that explanatory variables have been introduced in both mean and variance equations. $\boldsymbol{Ln\, P_{it}}$ and $\boldsymbol{Ln\, P_{it-1}}$ are the natural logarithms of real maize price in market $\boldsymbol{i}$ at months $\boldsymbol{t}$ and $\boldsymbol{t-1}$ respectively. $\boldsymbol{Trend}$, $\boldsymbol{RER}$ and $\boldsymbol{IP}$ represent the monthly trend, the real exchange rate[13] and the international maize price respectively. $\boldsymbol{S}$ refers to seasonal[14] dummy variables (lean and harvest seasons) while $\boldsymbol{M}$ denotes maize market dummy variables. $\boldsymbol{\varepsilon_{it}}$ is the error term. $\boldsymbol{Border}$ is a continuous variable that measures the distance between market i and the nearest cross-border maize point with Ghana, Côte d'Ivoire, or Togo, four border points being considered because of their importance in terms of maize trade volumes. $\boldsymbol{Surplus}$ is a dummy variable which indicates whether the market is in surplus production area. $\boldsymbol{Surplus}$ equals 1 for maize-surplus regions and 0 for maize-deficit regions. In this study, we capture ***(TC) Transport Cost*** through three measures: time distance,

[13] The real exchange rate and the real international price are computed as the ratio of the FCFA to the US dollar and then deflated using the Burkinabe Consumer Price Index. We also use the natural logarithm to smooth the series.
[14] In Burkina Faso, seasonal variability is characterized by differences in prices between the lean (June to September) and the harvest (October to December) seasons.

kilometric distance and road quality[15]. ***Transport Cost*** or ***Market remoteness*** can be defined in various ways. The kilometric distance and travel time to a main urban center or a major market are the most commonly used measures (**Barrett, 1996; Minten and Kyle, 1999; Stifel and Minten, 2008; Minot, 2013**). The quality of road infrastructure can be alternatively used (**Minten and Randrianarison, 2003)** to have a more accurate measure of travel costs (time, gasoline).

In **equations (14)** and **(15)**, ρ tests whether the mean prices are different between remote markets and markets close to the main urban centers, whereas $\boldsymbol{\varphi}$ tests to which extent maize price series in remote markets are volatile. In accordance with the theoretical model in **equation 7**, we expect maize prices to be lower in remote markets than in markets located close to main consumption centers ($\boldsymbol{\rho} < 0$). Based on **equation 10**, we expect $\boldsymbol{\varphi} > \mathbf{0}$, i.e. remote markets exhibit greater maize price volatility than markets located close to main consumption centers. The coefficient μ_i tests the effect of seasonality on maize price level. In accordance with **equation 8**, we expect low price levels in the harvest season ($\mu > 0$) and high price levels in the lean season ($\mu < 0$). In the case of maize-surplus markets, we should have δ_2 <0 based on **equation 6**. Data source and descriptive statistics of all the variables used in our study are presented in **Appendix 5 and 6**. The model is estimated in a system framework (with mean and variance equations) with Eviews 7 software. Our procedure is based on the maximum likelihood estimation method. Before starting the estimations, maize price series, the dependent variable, was tested for stationarity. The Augmented Dickey Fuller (ADF) for panel data was applied to test the null hypothesis of the presence of unit roots, following (**Im et al., 2003**). The panel unit root test leads to reject the null hypothesis of non-stationarity at the 5% level. The order of the ARCH model is determined through an assessment of the statistical significance generated from the Lagrange multiplier test. Results suggest that the price process is correctly described by an autoregressive order of one. The asymmetric (leverage) effect is investigated by examining whether the lagged values of standardized residuals influenced the price volatility. Results indicate that the price volatility is uncorrelated with the level of standardized residual, suggesting that there are no asymmetric effects; therefore, we do not need to apply an asymmetric model such as an EGARCH. Market dummy variables are omitted in the variance equation because dummy variables such as ***Surplus*** capture market characteristics.

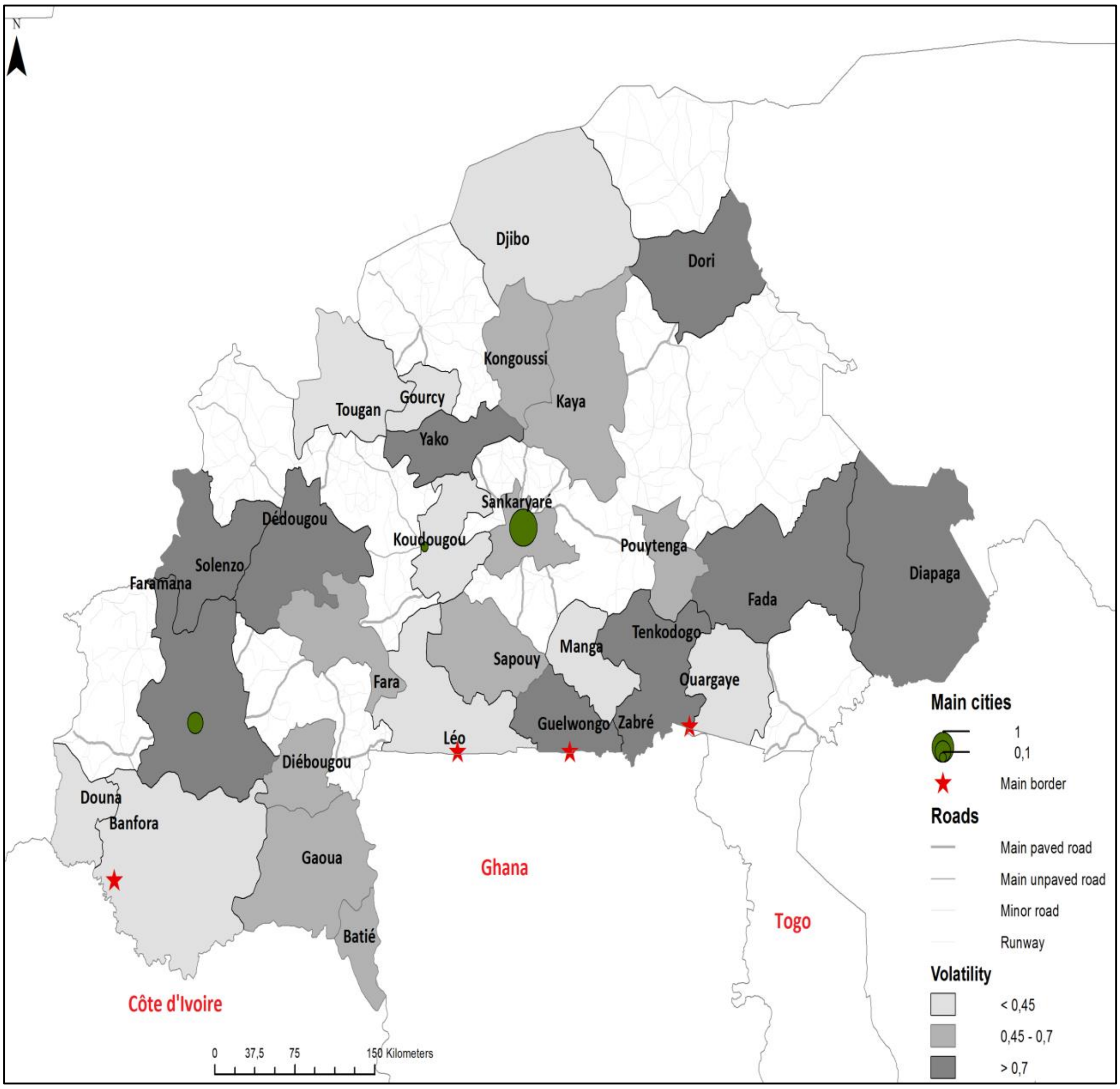
[15] Kilometric distance between a selected market and the nearest urban center and the road quality dummy variable indicating whether the road leading to a market is paved or not are exclusively used in robustness checks (section 5.3) as alternatives measures of remoteness.

5. Empirical estimations

5.1 Spatial disparities in maize price volatility

Figure 4 presents the level of maize price volatility in each of the 28 Burkinabe markets over 2004-2013. It clearly suggests spatial differences in maize price volatility across markets. It appears that markets located far from the major consumption centers – Ouagadougou, Bobo-Dioulasso or Koudougou - register the highest levels of price volatility, thereby justifying our research question.

Figure 4: Differences spatial volatility of maize in Burkina Faso over 2004-2013



Source: Author calculation

5.2 Market remoteness as an explaining factor

We analyze the effect of time distance between a market and the nearest urban center on the volatility of the maize price prevailing in this market.

Table 2: The impact of market remoteness on price volatility

Variables	Mean Equation	Variance Equation
Constant	4.0838*** (12.25)	0.0522*** (3.16)
Ln P_{t-1}	0.9098*** (119.12)	-0.0002 (0.00)
ARCH(1) term		0.1095*** (5.87)
Lean	0.0156*** (3.12)	0.0009*** (3.16)
Harvest	-0.0625*** (13.30)	0.0139*** (26.68)
Trend	-0.0003 (1.13)	-0.0000*** (5.76)
Exchange Rate	0.0744 (1.61)	-0.0034 (1.65)
International Price	0.0041 (0.18)	-0.0017 (1.82)
Time distance	-0.0586*** (6.46)	0.0001*** (4.05)
Border	0.0601** (2.57)	-0.0004*** (3.28)
Surplus	-0.0890*** (3.19)	0.0016*** (5.60)
Markets Dummy	YES	NO
N	3163	
R^2	0.8285	

Notes: Values in parentheses are t-statistics
*** and ** denote significance at 1% and 5% levels, respectively.

Results from the ARCH model estimates from maximum likelihood estimation are found in **table 2**. This table presents the results of the model fitted to 28 pooled maize markets. Estimates of the mean equation indicate that price series follow an autoregressive process with a strong monthly autocorrelation. Results establish a seasonal pattern characterized by low prices during the harvest time and high prices during the lean season[16]. These results are

[16] Because of the existence of natural agricultural production cycles, agricultural prices are affected by seasonality: indeed, there is an intra-annual price variation that tends to repeat regularly (**Schnepf, 2005**). Intra-annual agricultural price variations imply that prices are at their lower level in harvest time because of the abundance of products on markets but they progressively go up and are at their highest level just before the next harvest season.

consistent with our theoretical model and findings from many studies in the literature (**Shively, 1996; Barrett, 1996; Jordaan et al., 2007; Kilima et al., 2008** and **(Maître d'Hôtel et al., 2013**). On average, the level of maize price does not particularly increase over time. We find that there is no significant effect of the exchange rate and international maize prices on price levels in Burkina Faso, suggesting that such external factors do not seem to influence price levels: maize prices are rather driven by domestic factors.

Coefficients on the spatial variables suggest that geographic location has an impact on the domestic price level with a 5% level of statistical significance. The results show that maize prices are lower in maize-surplus markets; this finding being consistent with **Kilima et al. (2008)**. Prices in maize-surplus markets are on average 8.9% lower than those prevailing in maize-deficit markets. In these markets, supply exceeds demand, which drives the price down. The price of maize is also lower in markets close to the main maize border-crossing points. However, it is not easy to interpret this result. The price of maize in remote markets is 5,8% smaller than that observed in markets close to the main urban centers. It is worth noting that remote markets are not all net suppliers; those located in the north (Dori and Djibo) are typically net deficit markets. However, the majority of remote markets in our data appear to be net suppliers, implying on average lower maize prices. Furthermore, maize is the second-preferred crop (after rice) in main consumption centers. As these urban markets are located in low maize-production areas, demand exceeds supply, leading prices to be higher than in remote markets. This finding is consistent with the theoretical model that we have developed in **equation 7**, presented in section 2, which suggests that the price of food increases, as one gets closer to urban areas.

Estimates from the variance equation confirm that our model is correctly described by an ARCH model. The significance of the ARCH term indicates that price volatility depends on the past values of the residuals; this result is statistically significant at the 1% level. In addition, seasonality[17], trend and spatial position across markets have a significant effect on price volatility: The effect of international prices and exchange rate on price volatility is non-significant. We also find that price volatility in Burkinabe maize markets has decreased over time. Spatial price volatility across markets is examined through time distance, maize border-crossing points and maize-surplus variables. Results indicate that coefficients on these

[17] Results from the variance equation suggest that seasonality is an important component of maize price volatility. Seasonality seems to be a good predictor of maize price volatility.

variables are statistically significant at the 1% level. The positive parameter on *Surplus* suggests that prices in maize-surplus markets are more volatile than prices in maize-deficit markets. Previous findings also indicate that price volatility tends to be higher in maize-surplus markets than in maize-deficit markets (**Kilima et al., 2008**). The intuition is that a local supply shock arising on a maize-surplus market does not necessarily lead to a reduction in maize supply on this market through a transfer of quantities to maize-deficit regions, essentially because of the lack of sufficient market integration. This results in price volatility in maize-surplus markets. We also find that the coefficient on time distance to urban centers is significant. For example, results from the ARCH model indicate that on average remoteness from main consumption centers led to an increase of maize price volatility to 0,01%. The positive sign shows that remote markets tend to exhibit higher price volatility. Indeed, the urban center draws food production over the year, which ensures an adequate equilibrium between supply and local demand, thus stabilizing prices. This confirms the theoretical model we have been drawing in section 2, and the expected effects derived from equation (10). The negative and significant impact of *border* on price volatility indicates that prices in markets close to the main maize border-crossing points are more volatile than in other markets. The statistical significance of the coefficient on *border* - independently from the coefficient on remoteness - suggests that *border* captures additional information: market isolation should not only be comprehended as simple geographic remoteness from domestic urban centers. Remoteness is also expressed through high transport costs, export prohibitions and non-tariff barriers to crossing the border, which all hamper maize marketing abroad. Tackling remoteness by reducing or eliminating non-tariff barriers is essential to promoting regional integration and maize marketing in neighboring countries **(Kaminski et al., 2013)**. Opening of borders is indeed crucial in reducing spatial price volatility and ultimately fostering food security in Burkina Faso (**World Bank, 2012**).

5.3 Robustness checks

The robustness of the previous results is tested in three ways. First, alternative measures of market remoteness are used; second, we carry out the same analysis with nominal price and lastly, we allow a change in the estimator used (GARCH model).

Alternative measure of market remoteness

Table 3: The impact of market remoteness on price volatility: Alternative measures of market remoteness

	(1)		(2)	
Variables	Mean Equation	Variance Equation	Mean Equation	Variance Equation
Constant	4.1408***	0.0521***	3.8022***	0.0275
	(12.41)	(3.15)	(11.73)	(1.78)
Ln P_{t-1}	0.9103***	-0.0003	0.9014***	0.0002
	(119.85)	(0.56)	(114.56)	(0.51)
ARCH(1) term		0.1101***		0.0805***
		(5.94)		(4.02)
Lean	0.0157***	0.0009***	0.0152***	0.0010***
	(3.14)	(3.20)	(3.06)	(3.55)
Harvest	-0.0625***	0.0139***	-0.0638***	0.0135***
	(13.28)	(26.81)	(13.51)	(22.93)
Trend	-0.0003	0.0000***	-0.0004	0.0000***
	(1.15)	(5.80)	(1.47)	(6.24)
Exchange Rate	0.0746	-0.0035	0.0687	-0.0022
	(1.62)	(1.66)	(1.48)	(1.12)
International Price	0.0044	-0.0017	0.0067	-0.0003
	(0.20)	(1.78)	(0.30)	(0.34)
Kilometric distance	-0.0603***	0.0001***		
	(6.25)	(3.84)		
Road quality			-0.1448***	0.0021***
			(4.82)	(6.57)
Border	0.0527**	-0.0004***	0.0742***	-0.0006***
	(2.28)	(3.29)	(2.79)	(4.01)
Surplus	-0.0835***	0.0016***	-0.0433	0.0012***
	(2.97)	(5.62)	(1.28)	(4.46)
Markets Dummy	YES	NO	YES	NO
N	3163		3163	
R^2	0.8284		0.8286	

Note: (1) Market remoteness measure is the natural logarithm of the kilometric distance in minutes.
(2) Market remoteness measure is the dummy road quality
Values in parentheses are t-statistics
*** and ** denote significance at 1% and 5% levels, respectively.

Two alternative measures of market remoteness are tested. The first measure is the distance in kilometers[18] between a selected market and the nearest main consumption center, the second one is the quality of the road[19] connecting the market with its main consumption center. **Table 3** reports the results obtained. Columns (1) and (2) present the results obtained with the kilometric distance and road quality, respectively.

In column (1), the finding that remote markets exhibit greater maize price volatility than markets located close to main consumption centers is confirmed again through the strongly positive coefficient on distance in kilometers. The same result holds in column (2) of **table 3**. Market remoteness proxied by unpaved road connected to the markets is positively and significantly associated with maize price volatility. The coefficient on the road quality is positive and statistically significant at the 1% level. The positive effect of market remoteness on maize price volatility in Burkina Faso holds for each of the three empirical specifications used.

Estimation with nominal price

We analyze our initial results with nominal price**.** We test whether our results are sensitive to price specification. **Table 4** reports the results obtained. It indicates that even with nominal price series, the positive and significant impact of time distance on maize price volatility still holds and appears identical with the results obtained in **table 2**. Therefore, we show that the results are not sensitive to the functional form retained.

[18] To compute information about kilometric distance, we relied on data from the Ministry of Agriculture, specifically from the DGESS (Direction Générale des Etudes et des Statistiques Sectorielles) and data from google maps. We used DGESS data and resort to google maps to fill in for missing data due to the fact that information about some markets are not communicated by DGESS. However, it is reassuring to note that the DGESS data are comparable to data from google maps.

[19] Road quality is equal to 1 if the national road connected to the selected market is unpaved, 0 otherwise. Road conditions are taken into consideration by using the 2009 map of the **"Institut Géographique du Burkina Fas"**.

Table 4: The impact of market remoteness on price volatility: estimation with nominal price

Variables	Mean Equation	Variance Equation
Constant	0.4863 (0.82)	0.0037 (0.55)
Ln P_{t-1}	0.8988*** (100.49)	-0.0003 (0.71)
ARCH(1) term		0.0986*** (9.53)
CPI	0.8958 (16.23)	0.0032*** (6.28)
Lean	0.0147*** (2.60)	0.0012*** (5.81)
Harvest	-0.0621*** (12.83)	0.0158*** (25.66)
Trend	-0.0005 (1.65)	-0.0000*** (16.57)
Exchange Rate	-0.0470 (0.56)	-0.0008 (0.58)
International Price	0.0008 (0.03)	-0.0004 (0.83)
Time distance	-0.0388*** (4.15)	0.0001*** (3.08)
Border	0.1015** (4.46)	-0.0004*** (4.00)
Production	-0.1228*** (4.73)	0.0017*** (7.28)
Markets Dummy	YES	NO
N	3163	
R^2	0.8740	

Notes: Values in parentheses are t-statistics
*** and ** denote significance at 1% and 5% levels, respectively.

Estimation with GARCH model

An alternative specification to test the sensitivity of our results is implemented with the GARCH model. A number of studies have used a GARCH model to analyze maize price volatility (**Gilbert and Morgan, 2010** ; **Minot, 2013**). In a GARCH model (**Bollerslev, 1986**), an autoregressive moving average (ARMA) model is assumed for the error variance. A GARCH (p,q) model may be presented in the same manner as the ARCH model except that the variance equation is now as follows:

$$h_t = \omega + \sum_{i=1}^{q} \lambda_i \varepsilon^2_{t-i} + \sum_{j=1}^{p} \beta_j б^2_{t-j} \qquad \textbf{(16)}$$

Non-negativity of the conditional variances requires $\omega, \lambda_i, \beta_i > 0$.

$$ln\, P_{it} = \theta_0 + \theta_1 ln\, P_{it-1} + \theta_2 Trend_t + \theta_3 ln\, RER_t + \theta_4 lnIP_t + \sum_i \mu_i S_{it} + \sum_j \upsilon_j M_{jh} + \rho lnRemote + \delta_1 lnBorder + \delta_2 Production + \varepsilon_{it} \qquad \textbf{(17)}$$

$$h_{it} = \lambda_0 + \lambda_1 \varepsilon^2_{t-i} + \beta_1 б^2_{t-i} + \Omega_1 ln\, P_{it-1} + \Omega_2 Trend_t + \Omega_3 ln\, RER_t + \Omega_4 lnIP_t + \sum_i \pi_i S_{ht} + \varphi lnRemote + \omega_1 lnBorder + \omega_2 Production + v_{it} \qquad \textbf{(18)}$$

The corresponding estimation is shown in **table 5** which reports a significant and positive impact of market remoteness on maize price volatility, with similar findings for other variables. However, the coefficient associated with the GARCH model is non-significant. It is not easy to explain the non-significance of the GARCH term. One possibility is that monthly data usually do not exhibit GARCH effects (**Baillie and Bollerslev, 1990)**. Even if a GARCH process exists, it will be due to the structural break of unconditional variance. Furthermore, GARCH application is more appropriate for high frequency data; however, in our application we use monthly data. Both ARCH and GARCH processes usually generate persistence in price volatility, i.e. high volatility is followed by high volatility, and the same holds for low volatility. The ARCH process features high persistence of price volatility but with short memory in that only the most recent residuals (shocks) have an impact on the current volatility. The GARCH model gives a much more smoothed volatility profile with long duration, in which past residuals and lagged volatility terms affect the current price volatility. This means that price volatility in Burkina Faso's maize market is mainly due to recent shocks and the geographic situation within the country.

Table 5: The impact of market remoteness on price volatility: GARCH model

Variables	Mean Equation	Variance Equation
Constant	4.0883***	0.0526***
	(12.28)	(3.20)
Ln P_{t-1}	0.9101***	-0.0002
	(118.36)	(0.42)
ARCH(1) term		0.1115***
		(5.92)
GARCH(1) term		**0.0059**
		(0.25)
Lean	0.01558***	0.0009***
	(3.10)	(3.21)
Harvest	-0.0628***	0.0139***
	(13.11)	(26.71)
Trend	-0.0003	-0.0000***
	(1.14)	(5.65)
Exchange Rate	0.0742	-0.0035
	(1.61)	(1.67)
International Price	0.0039	-0.0018
	(0.17)	(1.88)
Time distance	-0.0585***	0.0001***
	(6.42)	(3.97)
Border	0.0600**	-0.0004***
	(2.57)	(3.31)
Production	-0.0893***	0.0016***
	(3.21)	(5.60)
Markets Dummy	YES	NO
N	3163	
R^2	0.8285	

Notes: Values in parentheses are t-statistics

*** and ** denote significance at 1% and 5% levels, respectively.

6. Conclusion

The aim of this study was to examine the role of market remoteness in explaining maize price volatility in Burkina Faso over the period July 2004-November 2013. To reach this objective, we develop a model of price formation and transport costs between rural and urban markets and also captures the implications for price volatility in rural market. We explore the empirical implications of our conceptual model by using the autoregressive conditional heteroskedasticity (ARCH) model introduced by Engle (1982). The empirical estimations with data on 28 markets established that markets that are close to the main cities, where quality road infrastructure is available, display less volatile price series. The results also show that maize-surplus markets and markets bordering Côte d'Ivoire, Ghana and Togo have experienced more volatile prices than maize-deficit and non-bordering markets. Furthermore, we find strong evidence of a seasonal pattern in maize price volatility across Burkinabe markets.

These findings suggest that policies targeted towards infrastructure development and better regional integration and economic development within the ECOWAS area would reduce maize price volatility. For instance, authorities could support remote markets by linking them through better roads with major consumption centers across the country as well as in neighboring countries. This will be key to improve the commercialization of agricultural products in remote areas and reduce price volatility across markets in Burkina Faso.

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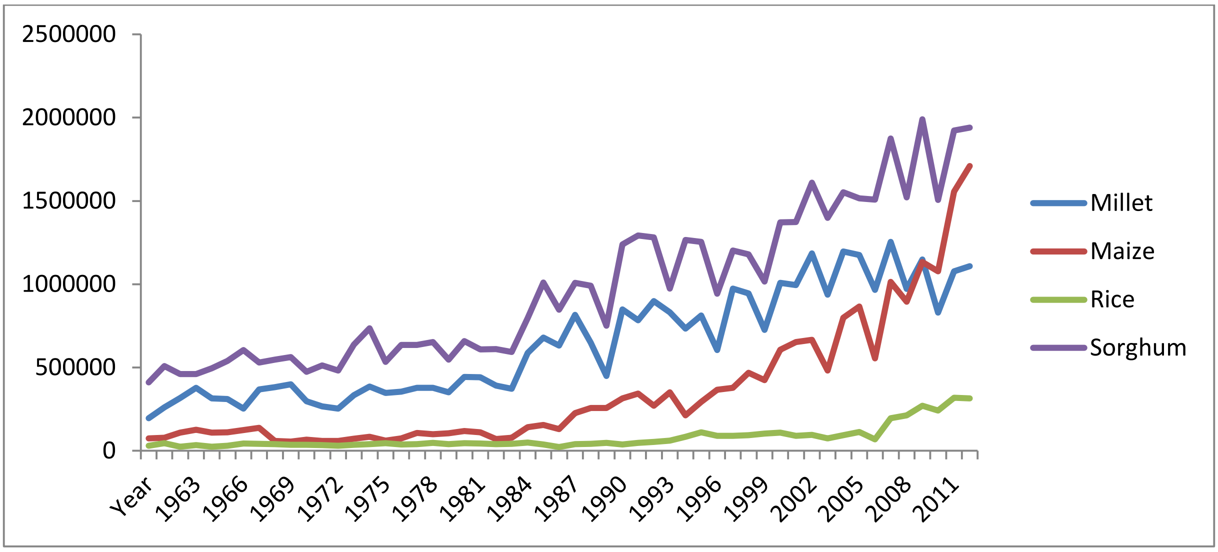
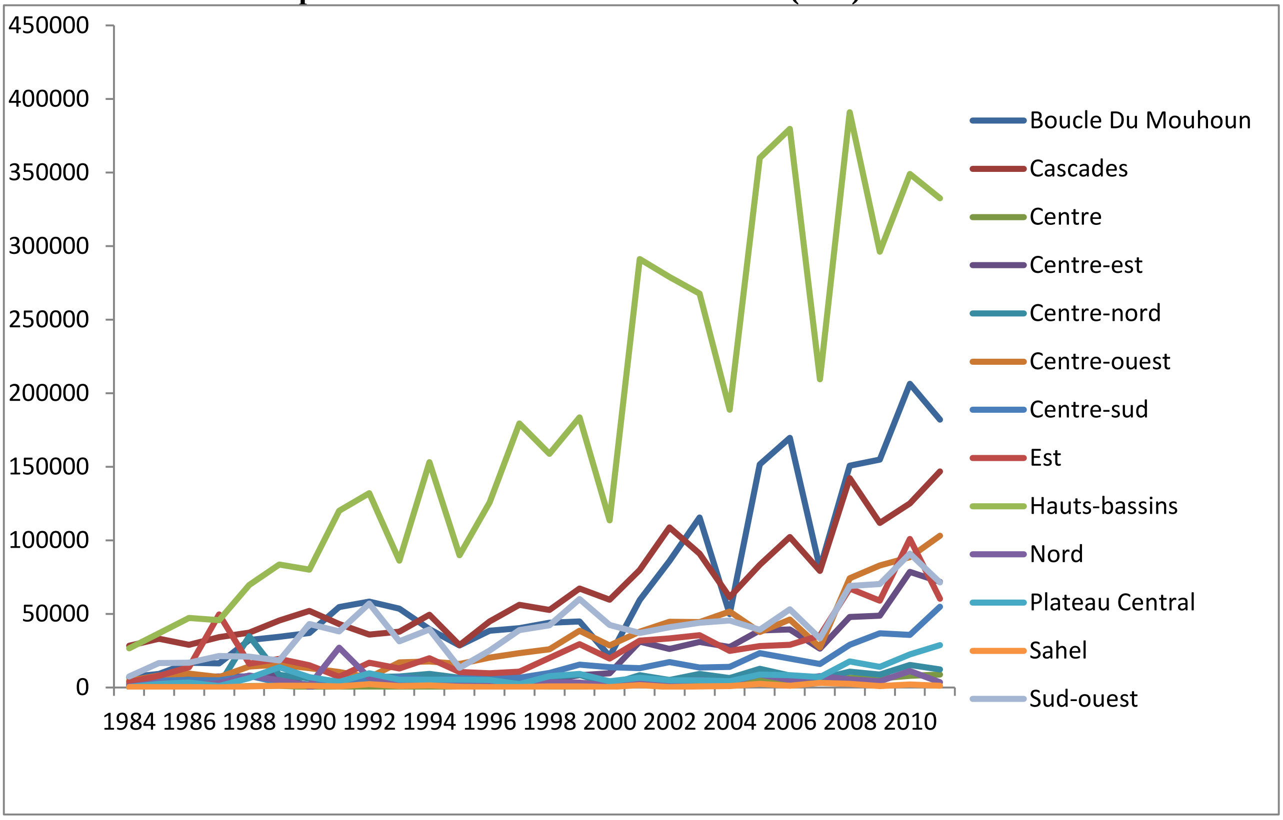
A1: Evolution of millet, maize, rice and sorghum production in Burkina Faso since 1961



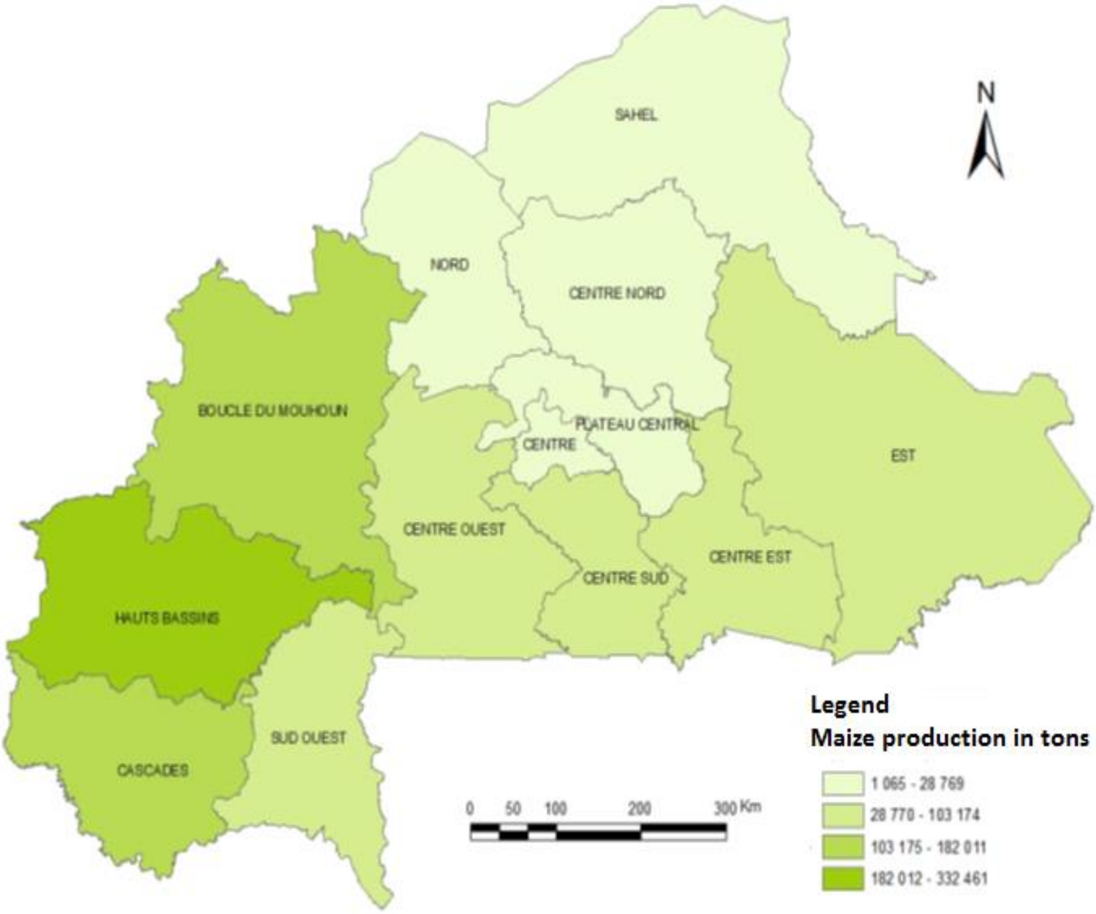
<u>Source: FAO, Data viewed on January 06, 2015</u>

A2: Evolution of maize production in Burkina Faso since 1984 (tons)



<u>Source: COUNTRYSTAT data downloaded on July 05, 2013</u>

A3: Map of maize production in 2011



Source: MAFAP/SPAAA 2012

A4: Descriptive statistics of the prices observed in each market

	Number of Observations	Mean	Standard deviation	Min	Max
Banfora	113	83.86	19.27	49.99	151.42
Batié	113	102.33	23.45	54.35	197.29
Dédougou	113	92.29	21.75	58.74	178.68
Diapaga	113	87.30	25.40	35.46	178.61
Diébougou	113	89.99	24.13	55.02	199.76
Djibo	113	119.57	17.21	83.81	176.88
Dori	113	123.79	21.26	95.81	205.08
Douna	113	64.65	17.28	36.17	121.23
Fada	113	99.56	22.96	60.28	184.23
Fara	113	74.83	17.78	42.56	140.97
Faramana	113	68.81	19.17	37.83	142.20
Gaoua	113	103.55	17.39	64.66	175.84
Gourcy	113	109.64	16.58	85.49	166.19
Guelwongo	113	109.20	21.47	73.28	204.69
Kaya	113	107.86	18.40	81.14	174.82
Kongoussi	113	102.54	18.45	72.12	178.26
Koudougou	113	100.12	19.53	68.26	173.39
Léo	113	91.21	20.75	56.47	175.48
Manga	113	103.41	21.86	66.74	195.57
Ouargaye	113	81.32	17.75	47.36	145.48
Pouytenga	113	106.17	16.23	80.34	169.71
Sankaryaré	113	108.39	20.06	78.40	191.04
Sapouy	113	88.927	22.75	50.95	182.52
Solenzo	113	75.80	19.76	46.38	146.83
Tenkodogo	113	98.27	17.41	72.22	173.60
Tougan	113	108.82	20.14	74.62	190.86
Yako	113	106.49	17.93	80.19	172.77
Zabré	113	99.61	19.31	60.91	169.44

Source: SONAGESS and INSD

A5: Explanatory variables used

	Variable name	Type of variable	Unit	Source
P_{it}	Real price	Continuous	FCFA/kg	SONAGESS
P_{it-1}	Lagged real price	Continuous	FCFA/kg	SONAGESS
RER_t	Real exchange rate	Continuous	FCFA/USD	IMF database
IP_t	Real international Price of Maize	Continuous	FCFA/kg	IMF database
TC	Time and kilometer distance between local market and main consumption center	Continuous	Minutes	Google maps
Border	Time distance between local market and main border crossing points	Continuous	Minutes	countrystat
Surplus	Surplus of production	Dummy	1(Surplus of production)/0	Countrystat

All prices are deflated by Consumer Price index.

A6: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Real Price	3164	96.73006	24.50788	35.46873	205.46873
Trend	3164	57	32.62417	1	113
Real exchange Rate	3164	353.4873	69.90379	253.5087	513.5203
Real international price of maize	3164	64838.47	16633.54	39751.56	100274.8
TC	3164	141.8214	81.19211	0	374
Border	3164	164.5357	89.76841	0	346