A Model of West African Millet Prices in Rural Markets

Molly Brown, NASA Goddard, Biospheric Sciences Branch
molly.e.brown@nasa.gov
Nathaniel Higgins, Economic Research Service, USDA
nhiggins@ers.usda.gov
Beat Hintermann, University of Basel, Dept. of Business and Economics
b.hintermann@unibas.ch

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Abstract

In this article we specify a model of millet prices in the three West African countries of Burkina Faso, Mali, and Niger. Using data obtained from USAID's Famine Early Warning Systems Network (FEWS NET) we present a unique regional cereal price forecasting model that takes advantage of the panel nature of our data, and accounts for the flow of millet across markets. Another novel aspect of our analysis is our use of the Normalized Difference Vegetation Index (NDVI) to detect and control for variation in conditions for productivity. The average absolute out-of-sample prediction error for 4-month-ahead millet prices is about 20 %.

Keywords: Millet, cereal, West Africa, price forecasting, remote sensing, NDVI, regional panel data

JEL codes: O13, O18, Q11, Q13, Q17, R32

1. Introduction

Predicting prices for food staples in poor regions is crucial for combating food insecurity, defined as the ability to purchase enough food to lead an active and healthy life. Food insecurity is most frequently caused by insufficient access to food instead of absolute lack of food availability. In West Africa, with its large population of poor who spend over half their income on food, the local price of food can be a significant source of food insecurity (Barrett and Maxwell, 2005). Improved estimates of harvests mid-season are an indispensible tool in predicting and combating food insecurity, but the physical presence of food may not avert a crisis if large parts of the population are unable to afford it. Price prediction models therefore should be an important complement to food quantity forecasts. Until now, there have been no usable commodity forecasting models for the small, informal farmer's markets that dominate much of the Sahel.

In this article we specify a model of millet prices in the three West African countries of Burkina Faso, Mali, and Niger. We construct two econometric panel data models that are capable of predicting prices at the rural-market-level across the region while controlling for unobserved heterogeneity. Using monthly millet price data from 1994 to 2006 obtained from USAID's Famine Early Warning Systems Network (FEWS NET) we estimate a price model for 234 rural markets over time. We control for intra-annual price variation caused by imperfect storage and asymmetric integration into world markets, and for the influx of caloric substitutes such as wheat and rice. Ours is the only article we're aware of that builds a price forecasting model usable at the market-level and over such a large region, answering the need expressed by various development and early warning institutions (Beekhuis and Laouali, 2007).

Another novel aspect of our analysis is our use of satellite-based remote sensing data, specifically of satellite-derived Normalized Difference Vegetation Index (NDVI), to detect and control for variation in local agricultural conditions. We include NDVI as a proxy for local millet supply in our model, for which no appropriate market-level data is available. Previous research has shown that NDVI is directly related to yield (Tucker et al., 1981). This is because many of the conditions that adversely affect plant development such as drought, fertilization, precipitation events and pests also result in a corresponding reduction in the crop’s photosynthetically active biomass which can be captured with NDVI (Tucker, 1979).

The inclusion of NDVI improves the model in a statistically significant way, although the economic magnitude of the effect is rather small. We think that this is due to the fact that NDVI measures all vegetation in a region, not just crop growth. Because our price dataset begins in the 1980s, we are compelled to use a relatively low-resolution dataset that combines much non-crop vegetation information in with crop information. Linking NDVI with information about planted area would likely increase the predictive power of NDVI, but unfortunately comprehensive information about the area in cultivation is not readily available on the local level in West Africa.

Price forecasting models used for the analysis of food security should consider conditions of agricultural productivity as well as the role of markets on the distribution of food, a comparatively neglected research topic (Beekhuis and Laouali, 2007). In our model we account for the transmission of prices throughout a region, as local farmers and traders move their product to the markets that offer the best prices. We find that after controlling for local growing conditions, prices across the region are correlated and that the strength of this correlation decreases with distance. This is consistent with arbitrage across markets on behalf of medium to long-distance traders (Terpend, 2006).

A major challenge for the development of local grain price forecasts in Africa is the scarcity of available data. All of our included price drivers are significantly related to millet prices. However, the most highly correlated determinants of millet prices in our model are lagged millet prices, which we interpret as evidence of a range of unobserved price determinants on the local level. These determinants likely include income, planted area, population, government policies and price expectations. Lagged prices on the right-hand-side of a price regression serve as proxies for slowly-changing unobserved determinants, while our fixed-effects approach accounts for time-invariant unobserved characteristics. Considering this, our model is not particularly useful in identifying the major millet price drivers because these remain "hidden" behind the price lags and fixed effects. However, because we implicitly account for these unobserved price drivers, the predictive power of the model is very high. The model accounts for 85% to 90% of the observed price variation, and the error of the 4-month-ahead forecast is in the range of 13.4% (Niger) to 19.5% (Burkina Faso) on average using in-sample observations, or 18.8% (Burkina Faso) to 21.9% (Mali) on average using out-of-sample observations.

2. Food markets in West Africa

In the following we will briefly describe agricultural conditions in West Africa and introduce the main price drivers for local millet prices that we use in our model.

Agricultural conditions

Technological change has transformed agriculture in the US, Europe and large parts of Asia and South America, but it has largely bypassed West Africa. In this region, most farms are small, primarily cultivated with hand tools, planted with seeds with a low yield potential, using little or no chemical or organic fertilizer. The climate is arid or semi-arid, and there is inadequate infrastructure to provide water for irrigation. Consequently, most small farms are only able to attain yields which are less than one seventh of those regularly achieved in industrialized systems (Breman, 2003; Taylor et al., 2002).

In our article we focus on food markets in Burkina Faso, Mali and Niger, all of which are landlocked in the West African Sahel. Despite high rainfall variability, rain-fed agriculture remains one of the main sources of income for the population. Table 1 provides basic descriptive statistics for the three countries. According to a "typology of food security" by Yu et al. (2009), all of these West African countries are "trade insecure", meaning that they are net food importers and that they spend more than 10% of export revenue on food imports. Furthermore, their climate is considered to be unfavorable to agriculture and they are classified as countries with low food production, most of which is consumed locally. Because of the difficult growing conditions and the risk inherent in agricultural activity, most farmers have diversified their income sources by raising livestock and working in wage labor markets (Abdulai and CroleRees, 2001), some to the extent of becoming net purchasers of food (Bryceson, 2002).

Although each country is food insecure, they do regularly produce 70% or more of their cereal needs (Kelly, Dembele and Staatz, 2008). Domestic coarse grains make up a significant portion of total food consumption, especially for the rural poor (Breman, 2003). The most widely available grain, and the grain most frequently purchased when farmers' own production is exhausted, is millet (Jayne et. al. 1996 and Brown 2008). We focus exclusively on millet in our analysis. Millet can be grown even in semi-arid zones where most other crops require irrigation. Planting time varies between April and July depending on local growing conditions, and the seeds take about 60-70 days to mature (Baker, 2003). In Burkina Faso and Mali, most areas harvest in October, whereas the predominant harvest time in Niger is in September (Terpend 2006).

Observed millet price determinants

There are a series of millet price drivers for which there exists no data on the market or sometimes even the country level. We control for this unobserved heterogeneity by including fixed effects (to control for time-invariant unobserved heterogeneity), and in our first model also by including lagged prices on the right hand side (to control for time-varying unobserved variables). In this subsection we present the observable variables that feature in our model.

Global wheat and rice prices

Although millet is a West African food staple in the sense that it is the most cultivated and most consumed cereal, there is practically no global market for it. The vast majority of millet consumed in West Africa is also produced there, with very little imports and even less exports recorded by the FAO. Although regional trade does occur, it is not usually observed by authorities nor captured by trade statistics (Allen, 1998). Because of this, millet is considered to be an imperfectly traded commodity (Dorosh and Subran, 2009). The three countries in our study are linked to international food markets via other grains that serve as caloric substitutes for millet and which we therefore expect to be correlated with the millet price. We don't expect this correlation to be perfect, as market integration seems to be asymmetric in the sense that international prices act as a ceiling but not a floor to millet prices (Brown, Hintermann and Higgins, 2009). Due to costly export procedures, poor transportation infrastructure and overall low volumes potentially available for export, selling millet on the world market is not a practical option for most farmers. Thus, when domestic millet prices are sufficiently high we expect the importation of substitute grains to mitigate continued millet price increases, but we do not expect periods of low domestic millet prices to be mitigated by the export of millet to international markets.

Cereal imports combined for 14.24 million tons in the period between 1982 and 2006, compared with 0.84 million tons of exports.[1] An additional 3 million tons of cereals entered the region in the form of food aid over the same time frame. Millet constitutes only a minor fraction of this trade. As can be seen in figure 1, the main import cereals are wheat and rice, and to a lesser extent corn. We will therefore include global wheat and rice prices in our analysis.

Inter-annual variation of production: NDVI

Because of imperfect integration into international markets, important millet price drivers include regional and local output variations. For example, weather-related harvest reductions cause significant increases in local food prices (Brown, Pinzon and Prince, 2006). In contrast, globally traded commodities are largely unaffected by local growing conditions because prices are determined by world output. In such a setting, the ideal variable to include would be actual harvest amounts from the area surrounding the markets, but this information is not available on the market level.

Dorosh & Subran (2009) control for the impact of varying local production by using price ratios of two regions, with the underlying assumption that production shocks are multiplicative and affect both regions equally. In contrast, we will avoid such a stringent assumption and proxy local crop output by means of the Normalized Differenced Vegetation Index (NDVI), which is an index of "greenness" and measures the fraction of the incoming visible light absorbed by plant photosynthesis on a scale between 0 (no absorption) and 1 (complete absorption).

We use NDVI based on the assumption that an increase of photosynthetic activity is correlated with an increase in millet output, as opposed to a mere increase in non-crop

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[1] FAO trade statistics, http://faostat.fao.org/site/535/default.aspx#ancor, last accessed in September 2009. We chose this time frame in order to match it with our local millet price dataset.

vegetation. NDVI is a closer proxy for yield than for output, and if we had local data about area planted, we could use the product of area planted and NDVI to proxy for output. Unfortunately, no such information is available, and we therefore assume that the area planted is constant and use NDVI to proxy directly for output.

NDVI data have been used extensively in the Sahel to detect variations in vegetation production, and have been shown by a number of authors to be correlated to both NPP, crop yields (Tucker, 1985; Prince, 1991; Fuller, 1998), and precipitation (Nicholson, 1994). However, since this research was not done using data from Burkina Faso, Mali, and Niger during our study period, it makes sense to attempt to verify the NDVI-to-output connection for our particular application, using the best available data. At the country-level, the link between NDVI and output seems to hold. Figures 2a-c show the relationship between NDVI during the millet growing season and annual output for each of the three countries, and there is clearly a positive correlation. Low accuracy of millet production statistics, contamination of the NDVI signal by non-crop vegetation at the country level and variations in area planted are all sources of the scatter in the plots. Lastly, we capture output changes over time due to technological change and population growth by introducing a time trend.

Intra-annual price fluctuations

Unlike cereal prices in industrialized countries, prices for non-traded local food staples in West Africa such as millet and sorghum exhibit strong intra-annual variation. Figure 3 shows average deflated monthly millet prices by country. The average relative intra-annual variation ranges from 25% of post-harvest prices in Burkina Faso to more than 50% in Niger.

The reasons for this variability are twofold: First and foremost, there is a widespread lack of storage facilities (Dembele and Staatz, 1999). Because they cannot store grains for an entire year, small farmers sell more than their surplus (defined by total output minus annual consumption) on the market after harvest and buy some grain back later in the year, often at higher prices. Because of the simultaneous influx of grain, prices drop to their base levels after harvest. As producers draw down their stocks, supply on the market decreases, whereas consumer demand remains unchanged, leading to a gradual increase of millet prices during spring. During the "hungry season" in summer, many farmers become net millet buyers because their own stocks are depleted, further boosting prices (Cekan, 1992). Presumably, it is during this period that international cereal imports and aid shipments enter the region, provided that prices surpass import parity. Annual prices peak just before harvest, the time of which differs across climate zones, which is the reason for the different price peaks in Niger on the one hand (July) and Burkina Faso and Mali on the other (August).

The second reason for the observed intra-annual price pattern is asymmetric integration into global markets in general and the lack of a sufficiently liquid international market for millet in particular, as discussed above. Perfect integration into an international millet market would act as a partial substitute for storage in the sense that farmers could export after harvest instead of driving down local prices and import when their own stocks are low during summer.

The intra-annual price variation makes it possible for small farmers to be net food buyers by value (in the sense that they spend more money buying than selling millet on the market), even if they are net producers by volume (in the sense that they sell more than what they buy in terms of quantity). We control for the cyclical behavior of prices by introducing monthly dummy variables.

Domestic trade

Although there is very little international trade in millet, there exists domestic trade between local markets and to some extent also regional trade across neighboring countries. Traders buy millet from farmers in surplus areas and sell it to city markets for purchase by consumers as well as other traders that transport millet to rural areas with a millet shortage (Terpend, 2006). Imports from overseas arrive in the capital and port cities and are distributed to rural markets via the same distribution channels.

In theory, arbitrage between markets ensures that prices do not diverge beyond transaction costs. Thus, prices are determined jointly but they are never fully equalized across markets. If transportation costs are high, for instance, it is not worthwhile for the owners of supply to travel to distant markets, even though the prices in those distant markets are higher than in their home market. In our first model, we include prices in other markets as price determinants for the price at any given market. In the restricted model version, we assume that no neighboring price information is available, and exclusively rely on millet prices in the capitals instead. This allows for arbitrage between local and capital markets, but not among local markets.

3. Millet price forecasting model

In the following we present our millet price forecasting model. We start with a discussion of our general approach, followed by the econometric specification of our two models and corresponding price predictions, and a description of our data.

General approach

We specify two different models. In the first, we use lagged local and neighboring millet price information, along with the price drivers mentioned above. Our second model is a constrained version of the first, where we assume that local millet price information is not available. We restrict the explanatory variables to those that we believe are always available, such as world prices for wheat and rice, millet capital prices, and NDVI. There are two reasons to assume that local price information is not available. For one, this information is not collected routinely, so if not impossible it would be at least costly to obtain. Second, even if local data were collected regularly, this will generally not be the case during a political crisis, as we are witnessing in Mali at the time of writing (June 2012). In such a setting, using information that can be obtained from abroad may be the only safe alternative. In particular, NDVI data gathered from space is presumably especially valuable in such a context, because it is likely the only local information available during a crisis.

We specify both models as fixed effect regressions. The first model additionally includes a function of lagged millet prices in neighboring markets and lagged own-prices. The latter control for important price drivers are unobserved such as income, distribution bottlenecks, local price-related policies, the area planted with millet[2], price expectations by farmers and consumers, and the quality of agricultural land. Some of these unobserved price determinants tend to move slowly over time. If complete information about all price determinants were available, there would be no need to include lagged dependent variables on the right hand side of the equation when using monthly data nor to use fixed effects.[3] In our second model, we omit lagged local millet prices under the assumption that this information would not exist for a forecast.

Our objective is to project millet price variations four months into the future. We focus here on the four month projection because 1) knowing that rising food prices will persist or worsen over a period of several months can significantly improve the likely response of humanitarian agencies (Buchanan-Smith and Davies, 1995), 2) vegetation information can be estimated with a high degree of accuracy estimated four months ahead using observed humidity and rainfall (Funk and Brown, 2006), and 3) being able to identify high prices can help aid organizations target areas where food availability might be low. Although we do not use estimated NDVI but actual NDVI in this analysis, considering the high persistence of plant biomass, coupled with fairly mature research, we anticipate that NDVI projected four months into the future will be available soon.

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[2] NDVI is measured using the Advanced Very High Resolution Radiometer (AVHRR) and represents overall greenness, but is of too low a resolution to measure photosynthetic activity of a particular field.

[3] With annual agricultural data, last year's price could influence this year's planting decisions and thus this year's price. For daily data, there could be a dynamic price dependency due to inertia in information flows, transportation delays etc. The point is that two subsequent prices may be similar because the underlying price drivers move slowly, not because this month actually influences

In order to compute out-of-sample predictions along with in-sample predictions, we use only 80% of our data to estimate the coefficients of the included determinants. Using these coefficient estimates, we then predict millet prices on the market level for up to four months ahead for the entire period. This results in 80 % in-sample predictions and 20% out-of-sample predictions. Producing the millet forecasts requires also producing predicted values for all explanatory variables four periods ahead. For rice and wheat prices we fit an autoregressive equation with monthly dummies and a time trend and construct predictions using the estimated coefficients.

Econometric model

For each country *c*, we estimate two fixed effects (FE) panel models, where $i \in (1,...,N_c)$ and $t \in (1,...,T_c)$ index the market and time period that includes 80% of the data, respectively. Suppressing the subscript *c* for exposition purposes we estimate the following regression for our first model:

$$A(L)y_{it} = \mu_i + t\lambda + B_w(L)w_t + B_r(L)r_t + M_t\,\gamma + \frac{y_{jt-1}/D_{ij}}{\sum 1/D_{ij}}\phi_1 + \left(\frac{y_{jt-1}/D_{ij}}{\sum 1/D_{ij}}\right)^2 \phi_2 + V_{it}\,\delta + \varepsilon_{it} \quad (1)$$

$$\varepsilon_{it} \sim N(0,\sigma_i^2)$$

The dependent variable y_{it} refers to the natural logarithm of deflated millet price in market *i* at time *t*. We decided in favor of logs and against real prices based on a test originally derived by Sargan (1964) and discussed by Godfrey and Wickens (1981).

$A(L)$ is a p^{th}-order lag polynomial defined by $A(L) \equiv 1 - \sum_{k=1}^{p} \alpha_k L^k$, with L being the lag operator. Similarly, $B_w(L) \equiv \sum_{k=0}^{q} \beta_k^w L^k$ and $B_r(L) \equiv \sum_{k=0}^{q} \beta_k^r L^k$ are lag polynomials of order q associated with the logarithm of deflated world prices for wheat w_t and rice r_t. We include monthly dummies in the (1 x 11) vector M_t to account for the cyclical nature of millet prices, as well as a linear trend $t\lambda$.

The $\mathbb{R}^{i-1} \rightarrow \mathbb{R}^{r}$ function $F(y_{it-1}^{-i})$ aggregates lagged log millet prices in markets other than *i* and all countries based on their distance from market *i* into an array of r values. In theory, variables that are determined jointly have to be estimated as a system in order to avoid a bias from endogeneity, but considering that we have 234 markets this is clearly impractical. We therefore make the assumption that for a particular market, lagged average prices in all other markets (differentiated by distance) are weakly exogenous.[4]

We chose a relatively simple functional form for $F(y_{it-1}^{-i})$ that is different for Burkina Faso on the one hand and Mali and Niger on the other. For the latter two, we define $F(y_{it-1}^{-i})$ as

$$F^{ML,NI}(y_{it-1}^{-i}) = \left(\frac{\sum_{j \in R_1} y_{jt-1}}{N_{R_1}}, \frac{\sum_{j \in R_2} y_{jt-1}}{N_{R_2}}, \frac{\sum_{j \in R_3} y_{jt-1}}{N_{R_3}} \right) \quad for \quad j \neq i \tag{2}$$

[4] Using lagged other prices also reduces the amount of bias introduced by endogeneity. With an autocorrelation parameter of less than unity (for stationary series), the bias decreases with the lag order.

Region R_1 includes all markets that are at a Euclidean distance of less than 300 km; R_2 includes the markets located in a range of 300-600 km, and region R_3 contains the remainder of the markets that are located at a distance of more than 600 km. Because prices may influence each other across national borders, these distance bins include price information from all three countries, not just the country for which the regression is fit. Naturally, we expect prices in closer markets to have a stronger impact on local prices than markets located at a greater distance. For Burkina Faso, we combined bins 1 and 2, such that $F^{BF}(y_{it-1}^{-i})$ contains r=2 variables that contain the average lagged millet price in markets located up to 600 km from market i and of those located at a distance of greater than 600 km.[5]

The elements of the (1 x v) vector V_{it} contain information about photosynthesis as measured by NDVI. There is no consensus in the literature as to how exactly NDVI is best used to proxy for crop output, and the choice may well depend on the region and the crop in question. We tried a number of different specifications in our model and our results suggest that NDVI at the end of the growing season is the best proxy for local millet output. Alongside NDVI from the preceding growing season we also include current and lagged NDVI in order to account for the possibility that high photosynthetic activity in any month leads to increased availability of food even outside the millet

Note that with a lag of *p+1*, there would be no endogeneity problem, but it is unclear why prices in other markets that are lagged by 13 months would drive a local market's current price.

[5] We chose to vary the bin structures because when predicting prices, any bin that does not contain an entry (i.e. there are no predicted prices for that set of markets) will cause the prediction to be missing. Because Burkina Faso has fewer observations than Mali and Niger, the closest or second-closest bin tended to become unpopulated such that we were not able to make any predictions for Burkina Faso based on a finer bin structure. Combining the two closest bins mitigated this problem significantly.

growing season (for example, more milk and meat from livestock). If there is substitution between millet and these other agricultural outputs, an increase in photosynthetic activity outside of the millet growing season would result in a decreased demand for millet and therefore a decreased millet price.

We specify all elements of V_{it} to be differences between actual NDVI realizations and their long-term monthly mean[6]. We chose to include deviations from means rather than actual realizations because the cyclical (deterministic) nature of photosynthesis is already accounted for in the monthly dummies. For example, what matters is not the photosynthesis level in September, but whether photosynthesis in that month was especially high or low relative to "normal" September levels, which are captured by the September monthly dummy.

The introduction of fixed effects is necessary to remove unobserved time-invariant heterogeneity across markets, such as the quality of the surrounding agricultural land, connectedness to other markets and local institutions like marketing boards. These unobserved characteristics could well be correlated with the price in neighboring markets contained in $F(y_{it-1}^{-i})$, in which case estimating the regression by generalized least squares (GLS) in random effects specification (assigning a constant error component to each market in addition to the idiosyncratic error) could lead to severely biased coefficient estimates.

[6] For example, the expected NDVI value for January is the average NDVI value for all 25 January entries in the period 1982-2006.

There is an econometric issue with including fixed effects in a dynamic panel model. The transformation of the data necessary to estimate the model involves the subtraction of the average value from each observation, which means that the lagged dependent variable contains the entire history of the error term. As a result, the lagged dependent variable is correlated with the error term by construction. However, in long panels (T>30), the bias introduced from the introduction of fixed effects procedure is more than outweighed by the increased efficiency of the FE estimator compared to Instrumental Variable (IV) or Generalized Method of Moments (GMM) estimation (Attanasio, Picci and Scorcu, 2000).

Finally, ε_{it} is a normally distributed, but potentially heteroskedastic error term with variance σ_i^2, with $E[\varepsilon_{it}]=0$, $E[\varepsilon_{it} * \varepsilon_{jt}] = \sigma_{ij}^2$ for $i \neq j$ and $E[\varepsilon_{it} * \varepsilon_{js}] = 0 \; \forall i, j$ for $t \neq s$. We estimate the parameters $\alpha_1, ..., \alpha_p, \beta_0^1, ..., \beta_q^2, \lambda$, the elements of the parameter vectors γ (dimension 12 x 1), ϕ (r x 1) and δ (v x 1) and the fixed effects μ_i from the data by maximum likelihood.

In our restricted model, we remove local millet price information from the RHS of (1) and replace (2) by lagged capital millet prices, weighted by inverse distance and inverse distance squared, such that we estimate the following regression:

$$y_{it} = \mu_i + t\lambda + B_w(L)w_t + B_r(L)r_t + M_t\gamma + \frac{y_{t-1}^c}{D_i}\psi_1 + \frac{y_{t-1}^c}{D_i^2}\psi_2 + V_{it}\delta + \varepsilon_{it} \qquad (3)$$

where y^c_{t-1} refers to lagged millet prices in the capital, and D_i is the distance (in km) between market *i* and the capital. We exclude capital markets from this regression as LHS variables.[7]

Price predictions

To compute predictions for millet prices, we first need to predict wheat and rice prices. We fit the following equations:

$$x_t = \varphi_1^x x_{t-1} + \varphi_2^x x_{t-2} + \ldots + \varphi_q^x x_{t-q} + \lambda^x t + M_t \kappa^x + v_t^x \tag{4}$$

$$v_t^x = \rho^x v_t^x + u_t^x; \qquad u_t^x \sim N(0, \sigma_x^2) \tag{5}$$

for $x_t = (w_t, r_t)$ and M_t as defined in (1). These are a pair of standard dynamic regressions with autoregressive residuals of order one (AR1), supplemented by monthly dummies and a deterministic trend. We estimate (4) and (5) by maximum likelihood and use the coefficient estimates (denoted by a hat) to compute wheat and rice price predictions up to a time horizon of *h* periods ahead by successive substitution:

$$\begin{aligned} \hat{x}_{t+1} &= \varphi_1^x x_t \quad + \varphi_2^x x_{t-1} + \varphi_3^x x_{t-2} + \ldots + \varphi_q^x x_{t-q+1} + (t+1)\hat{\lambda}^x + M_{t+1}\hat{\kappa}^x \\ \vdots \;\; &= \;\; \vdots \\ \hat{x}_{t+h} &= \varphi_1^x \hat{x}_{t+h-1} + \varphi_2^x \hat{x}_{t+h-2} + \ldots + \varphi_h^x x_t + \ldots + \varphi_q^x x_{t-q+h} + (t+h)\hat{\lambda}^x + M_{t+h}\hat{\kappa}^x \end{aligned} \tag{6}$$

[7] The problem of dividing by zero could be avoided by adding 1 to each denominator. However, the focus of this second model is on price predictions in local markets, and how they depend on capital prices. Including capital prices in this regression would not be meaningful.

For the restricted model, (6) can be used directly to predict any period ahead. For the model that includes local data we compute price predictions out to horizon *h* by

$$
\begin{aligned}
\hat{y}_{it+1} &= \hat{\alpha}_1 y_{it} + \hat{\alpha}_2 y_{it-1} + \ldots + \hat{\alpha}_p y_{it-p+1} \\
&\quad + \hat{\mu}_i + (t+1)\hat{\lambda} + \hat{B}_1(L)\hat{w}_t + \hat{B}_2(L)\hat{r}_t + M_{t+1}\hat{\gamma} + F(y_{it}^{-i})\hat{\phi} + V_{it+1}\hat{\delta} \\
\vdots \quad &= \quad \vdots \\
\hat{y}_{it+h} &= \hat{\alpha}_1 \hat{y}_{it+h-1} + \hat{\alpha}_2 \hat{y}_{it+h-2} + \ldots + \hat{\alpha}_h y_{it} + \ldots + \hat{\alpha}_p y_{it-p+h} \\
&\quad + \hat{\mu}_i + (t+h)\hat{\lambda} + \hat{B}_1(L)\hat{w}_t + \hat{B}_2(L)\hat{r}_t + M_{t+h}\hat{\gamma} + F(\hat{y}_{it+h-1}^{-i})\hat{\phi} + V_{it+h}\hat{\delta}
\end{aligned}
\tag{7}
$$

where $\hat{B}_x(L)\hat{x}_t$, *x=(w,r)* refer to lag polynomials employing a mix of observed and predicted values for wheat and rice prices. For a prediction horizon of *h* periods, the first *h* elements of $\hat{B}_x(L)\hat{x}_t$ are based on predictions computed with (6), followed by actually observed prices. Starting with prediction horizon =2 we first have to compute $F(\hat{y}_{it+h-1}^{-i})$ using predictions for *h*-1, substitute and compute $\hat{y}_{it+h}$. We compute 4-months predictions because this is the time frame for which FEWS NET is able to make reliable predictions for NDVI, but naturally the model can be used to predict to any time horizon.

We compute in-sample predictions for the time periods that include the first 80% of the millet price data per country and compare these in-sample predictions them to the actually observed prices using mean squared errors. Likewise, we compute out-of-sample predictions for the remainder of the data.

Data

We obtained average monthly millet prices from local market price monitoring organizations through the USAID's FEWS NET (Chopak, 1999; May, 1991). The data have been kept in the local currency CFA, deflated by the consumer price index[8]. The data covers the time span 1982 through December 2006, but because there were a series of policy changes affecting grain markets in the 1980's and early 1990's, as well as a devaluation of the CFA in 1994, we restrict the analysis to the period 1995-2006. There are 162 markets in our dataset during this period.

The panel is highly unbalanced and many markets were not sampled in a given month. The total number of price entries is 10,929 or about 47 % of all possible (162 markets x 144 months) 23,328 market/month combinations. The last month of the period that covers 80% of the data per country is February 1998 for Burkina Faso, April 1996 for Mali and August 2002 for Niger. Average millet prices for each country from January 1985 to December 2006 are presented in figure 4.

Using geographic location we are able to match prices with Normalized Difference Vegetation Index (NDVI) data, which also exists at the monthly level. NDVI data were obtained from the NOAA Advanced Very High Resolution Radiometer (AVHRR) archive, which has 8 x 8 km spatial and monthly temporal resolutions. The data were processed by the Global Inventory Monitoring and Mapping Systems (GIMMS) group at the NASA Goddard Space Flight Center (Tucker et al., 2005). The AVHRR sensor has appropriate spatial, spectral and temporal resolutions to monitor the entire Earth, hence it is adequate to cover all West Africa (Townshend, 1994; Justice et al., 1991). We computed the mean of a five by five-pixel box (40 x 40km) centered on each market

[8] The CFA (franc de la Communauté Financière d'Afrique) is fixed for all three countries at the same exchange rate with the French franc, and with the Euro since 2002.

from monthly maximum value NDVI composites (Holben, 1986) and used it as a proxy for agricultural production.

Table 2 presents summary statistics for price and NDVI data, computed for each country for the period that covers the first 80% of the millet price data.

4. Results

To test for stationarity of the data, we employed a panel unit root test developed by Maddala and Wu (1999) and refined by Choi (2001) (also known as the ADF-Fisher test)[9], which involves carrying out a unit root test for all individual groups and using the p-values from these tests to build an aggregate measure of stationarity. We were able to reject the null of all markets being nonstationary at $p<0.001$, irrespective of the lag order chosen for the ADF tests. Individual tests on the 160 markets that have at least 24 consecutive months of price information[10] lead to the rejection of the null hypothesis of a unit root for 85 markets at $p<0.05$ and for 104 markets at $p<0.1$.[11] We therefore proceed under the assumption of stationarity.

This result is most likely due to farmers' inability to store grain efficiently. With perfect storage, discounted millet prices would have to follow a martingale, i.e. the

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[9] There exists a range of panel unit root tests, but the ADF-Fisher test is the only one that does not require the panel to be balanced.

[10] Unit root tests involving only a few months of data on variables that exhibit clear seasonality would not be meaningful.

[11] In principle, rather than testing for integration one would have to test for cointegration across the markets if individual price series are found to be nonstationary. Estimation of a full cointegration model among the 234 markets is econometrically impossible and economically not meaningful. Testing for

expectation of next months' price is this months' price times (1+r), where r is the monthly interest rate (plus storage costs). A martingale is a nonstationary process, meaning that the mean and variance changes over time. If prices were expected to rise faster than the rate of interest, it would be profitable to buy today and sell at a later point in time at a profit. Likewise, if prices were to rise slower than the interest rate, it would be profitable to sell short and purchase later. Because of the opportunity for arbitrage, most commodities and stocks follow martingales, and the martingale property is the underlying assumption of most asset pricing models. Millet prices in West Africa are different (i.e. stationary) because arbitrage within a year is limited, and across years practically impossible since storage is so costly.

Based on the Akaike Information Criterion (AIC)[12] we chose p=q=12 lags for all prices. The left panel of table 3 presents the results from estimating (1) by country, with some of the parameter estimates suppressed for ease of exposition (the complete results are provided in the Appendix). The overall fit of the model is high, with 90 % (Burkina Faso), 85 % (Mali) and 90 % (Niger) of the price variation explained by the model parameters. The set of monthly dummies is highly significant for all countries, confirming the strongly cyclical pattern of millet prices shown in Figs. 3-4. There is a small but significant positive time trend for Burkina Faso and Niger and none for Mali.

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cointegration among a subset of markets (e. g. capital cities) would be possible, but because this article focuses on local rather than national markets, we leave this for future research.

[12] Defined as $AIC=2k-2\ln(L)$, where k is the number of parameters in the model and L refers to the maximized value of the likelihood function. Using the Bayesian Information Criterion (BIC) instead would have led to an almost identical choice of lag order for the three countries.

The assumption of overall stationarity is confirmed by $A(1) = 1 - \alpha_1 - ... - \alpha_{12}$, which is not close to zero in any regression.[13]

Global cereal prices are significantly correlated with millet prices in all countries. The precise relationship is not straightforward to assess because we included a total of 13 prices for wheat and rice (current prices plus 12 lags). Overall, however, wheat and rice prices are jointly significant for all countries.

Millet prices are positively correlated with prices in neighboring markets, and this correlation is generally stronger for the nearest markets and weaker or insignificant for the markets that are >600 km away. Not all distance "bins" are significant for all countries, but millet prices in the closest markets are positively and significantly associated with millet prices in market *i* for all countries. This is an indication that neighboring markets are indeed connected by trade, and that transportation costs matter. The lack of differentiation of neighboring markets' impact by distance for Burkina Faso is likely due to the very coarse binning structure we employed for this country in order to be able to make 4-period-out predictions (see above).

We tried a range of specifications for NDVI, as the literature suggests several ways in which NDVI might be related to production. Of course, we are only interested in millet prices, so we tailored our specification to the growing season of millet. We used the set of current and lagged mean NDVI deviations, NDVI deviations during the

[13] That the t-statistic on A(1) is not appropriate because under the null hypothesis of A(1)=0, the limiting distribution is not defined. However, because A(1) is not close to zero (i.e. the sum of the lag coefficients are far from one), this should not be a problem.

growing season months June through September,[14] the summation of NDVI deviations over the growing season as suggested by Jiang et al. (2004) and Rasmussen (1998), and maximum deviation during the growing season as suggested by Fuller (1998). The regression results from estimating (1) as well as regressing country-level output on a measure of country-level NDVI deviations indicates that NDVI deviations at the end of the growing season matter most, whereas the summation and the maximum value are not meaningfully related with millet output and prices in these three countries. We therefore select the model that includes deviations in current NDVI as well as NDVI during the months July, August and September, in order to cover most of the growing season in all markets.

The coefficients estimates indicate that an increase in “greenness” during the last month of the previous growing season (September in Burkina Faso and Mali and August in Niger) significantly decreases prices, which is consistent with the hypothesis that NDVI proxies for local millet production (a greater supply decreases the price). NDVI deviations during earlier months of the growing season are either insignificant or positively correlated with prices. The results imply that increased photosynthetic activity is a better proxy for actual harvest at the end of the growing period than in the beginning, when weather has not yet had time to influence crop yield substantially.

[14] Previous research has shown a high level of correlation between yields and NDVI (Tucker et al., 1980). Basnyat et al. (2004) showed that correlations between grain yield and NDVI obtained one month prior to harvest when biomass was at its height were significant and were larger than NDVI obtained at other times during the growing period.

Current NDVI deviation is negatively and significantly associated with current millet prices in Mali and Niger (for Burkina Faso, the coefficient is negative but not statistically significant). Since NDVI deviations in specific growing season months are already accounted for, this means that overall greenness leads to a decrease in millet prices regardless of the time of year. As hypothesized above, the pathway responsible for this result could be an increased production of crops or feedstuffs other than millet, which, directly or indirectly, serve as caloric substitutes.

We carried out a series of specification tests. First, we tested whether it would be appropriate to combine all three countries into one large panel dataset and estimate a joint model. This is equivalent to assuming that the impact of the included regressors on millet prices is the same across countries, while controlling for market-specific heterogeneity using the fixed effects. Using LR tests and country interaction dummies on various subsets of the included variables we arrived at a strong rejection of this hypothesis. This is probably due to the fact that in spite of being located in the Sahel, the actual climates and soil qualities of these countries are quite different (Yu, You and Fan, 2009). Also, the countries differ in size and income levels (table 1).

Next, we tested whether all fixed effects are equal, which would be the implicit assumption of a regression by OLS, but we had to reject this hypothesis in favor of individual intercepts. Accordingly, the fraction of the total error variance ($\sigma_i^2 + Var[\mu_i]$) due to the variance of the fixed effects $Var[\mu_i]$ is high: 26% in Burkina Faso, 45% in Mali and 22% in Niger.

Third, we re-estimated all models using a random effects specification and used Hausman tests to check whether the unobserved heterogeneity is correlated with the error term, which we found to be the case for all countries. Based on these tests, we selected the fixed effects specification. We further tested the residuals for the presence of spatial correlation. Moran's I-tests rejected the presence of spatial correlation across all markets and all time periods based on inverse Euclidean distance and inverse Euclidean distance squared.

Lastly, we carried out LR test to check whether each group of included price determinants (millet price lags, wheat prices, rice prices, monthly dummies and NDVI) is jointly significant, which we found to be the case for all countries. Thus, the variables included in our model are indeed millet price determinants and/or serve as proxies for such determinants.

Figures 5-7 show average observed market prices by country, along with average in-sample predictions to the left of the vertical line and average out-of-sample predictions to the right. The predictions are clearly not perfect, but they are quite close to the actual prices both for in-sample and out-of-sample. The gaps in predictions are due to missing values in some of the neighbor-price bins in certain time periods (note that in order to get an average price per period, all that is required is a single price, whereas at least 3 prices (2 for Burkina Faso) at different distances are required in order to avoid missing variables in $F(\hat{y}_{it+h-1}^{-i})$). The average absolute error is 19.5% (in-sample) and 18.8% (out-of-sample) for Burkina Faso. The corresponding numbers are 14.5% and 21.9% for Mali and 13.4 % and 20.5% for Niger.

5. Conclusions

In this article we construct a millet price prediction model for 234 small, informal markets located in Burkina Faso, Mali and Niger. We control for intra-annual price variation due to imperfect storage and asymmetric integration into world markets, prices of imported cereals, prices in neighboring markets and local supply levels as proxied by NDVI and find that the model fits the data well. Using coefficient estimates from the first 80% of the data we then construct in-sample as well as out-of-sample price predictions. The average predictions are within 25% of the average actual price in nearly 75 % of the out-of-sample months, which makes them an acceptable tool in forecasting millet prices for purpose of increasing food security in West Africa.

The importance of lagged prices in the model, along with our specification tests (FE vs. OLS, pooled vs. country-by-country, FE vs. RE) imply that there exists a series of unobserved millet price drivers such as local income levels and planted crop area. Collecting these data would increase our understanding of food markets in Africa and likely lead to better price predictions.

We find that NDVI is a valid proxy for local millet supply in the sense that the coefficient estimates have the correct sign and are statistically significant, but that its impact is relatively small compared to that of lagged own prices and prices in other markets. This is most likely due to the fact that NDVI, without combining it with information about planted crop area, aggregates the signal from trees, weeds and crops together into one number. It also cannot capture non-weather related production deficits, such as inadequate planting for food needs, damage due to wind, and other nonbiophysical problems. This results in a measuring error of true cereal supply, and it is well known that measuring errors lead to a downward bias of the coefficient estimates. We find that it is NDVI at the end of growing season, rather than maximum NDVI or the integral over the entire growing season that proxies best for millet output. This result is similar to that found by Basnyat et al (2004) in their study estimating yields using NDVI in Canada.

With this research, we have developed a price prediction model that can be of use in early warning of food insecurity as well as in planning and implementing an appropriate response. Because most food security crises in West Africa are caused by an inability to purchase food instead of an overall food availability problem, monitoring and forecasting food prices should contribute to improved response. The global price fluctuations in 2008 have shown that even West Africa, one of the most isolated regions of the world, can be negatively affected by increases in global commodity prices (Brown, Hintermann and Higgins, 2009). Implementing a local price projection model for these food insecure regions could reduce their exposure and vulnerability to such variations by providing the possibility for appropriate policy response.

Tables

Table 1: Background Information for Burkina Faso, Mali and Niger

	Burkina Faso	Mali	Niger
Population	15.7 mio	12.7 mio	15.3 mio
Surface area	274,000 km^2	1,240,000 km^2	1,267,000 km^2
Arable land (% of total)	17.60%	3.76%	11.43%
Permanent crop land (%)	0.22%	0.03%	0.01%
GDP (PPP), mio 2008 US$	17,820	14,590	10,040
GDP per capita, 2008 US$	1,132	1,152	656
Agriculture, % of GDP	29%	45%	39%
Agricultural workforce	90%	80%	90%
Currency	CFA	CFA	CFA
Capital City	Ouagadougou	Bamako	Niamey

Source: CIA World Fact Book

Table 2: Summary Statistics for the Period with the First 80% of Data

	Burkina Faso		Mali		Niger	
	mean	std. dev	mean	std. dev	mean	std. dev
log millet price	4.72	0.32	4.80	0.37	4.70	0.37
log wheat price	5.05	0.18	5.00	0.19	4.95	0.20
log rice price	5.76	0.15	5.78	0.15	5.66	0.24
NDVI	0.318	0.127	0.286	0.140	0.190	0.071
NDVI deviation	0.0003	0.039	-0.004	0.037	0.003	0.026
NDVI dev. Jul	0.002	0.044	0.007	0.045	0.002	0.036
NDVI dev. Aug	-0.001	0.050	0.004	0.046	0.002	0.039
NDVI dev. Sep	-0.004	0.046	0.002	0.035	0.005	0.039
Data through:	Aug 1998		Oct 1996		Feb 2003	

Table 3: Results from Estimating eq. (1)

	Burkina Faso			Mali			Niger		
	coeff	t[a]		coeff	t[a]		coeff	t[a]	
millet A(1)[b]	0.4035	13.14	d	0.5335	14.96	d	0.4216	16.80	d
L.millet	0.6981	14.80	***	0.5851	17.06	***	0.6390	27.36	***
L2.millet	-0.0641	-1.72		-0.0652	-2.08	*	-0.0631	-2.78	**
L3.millet	-0.0022	-0.09		0.0255	0.97		0.0624	3.22	**
L4.millet	0.0204	0.94		-0.0030	-0.14		0.0465	2.40	*
L5.millet	-0.0056	-0.15		0.0030	0.17		-0.0363	-1.61	
L6.millet	0.0050	0.15		0.0375	1.74		0.0124	0.71	
L7-L12.millet	included[c]		***	included[c]		***	included[c]		***
L.millet_R1	0.1025	2.32	*	0.2886	6.94	***	0.2751	9.00	***
L.millet_R2	0.1285	2.56	*	0.0025	0.06		0.0602	2.38	*
L.millet_R3				0.1537	3.87	***	-0.0189	-1.90	
Wheat	-0.1610	-3.21	**	-0.0333	-0.72		-0.1440	-3.70	***
L.wheat	-0.0241	-0.35		0.0312	0.50		0.1009	2.14	*
L2.wheat	0.2207	2.32	*	-0.0340	-0.42		0.0034	0.08	
L3.wheat	0.0124	0.13		0.0831	1.33		-0.0414	-0.79	
L4.wheat	-0.1542	-1.40		-0.1231	-1.46		0.0683	1.21	
L5.wheat	0.1292	1.36		-0.2062	-2.19	*	-0.0037	-0.07	
L6.wheat	-0.1242	-1.27		0.3301	3.23	**	0.1313	2.91	**
L7-L12.wheat	included[c]		***	included[c]		***	included[c]		***
Rice	0.1437	2.76	**	0.0273	0.83		0.0093	0.40	
L.rice	-0.0686	-0.90		0.0067	0.18		-0.0088	-0.24	
L2.rice	-0.2217	-3.43	***	-0.2031	-4.75	***	-0.0456	-1.00	
L3.rice	0.2009	3.72	***	0.1640	4.73	***	0.1521	3.79	***
L4.rice	0.0229	0.29		0.0136	0.39		-0.0582	-1.29	
L5.rice	0.0621	0.69		0.0991	2.37	*	-0.1414	-2.91	**
L6.rice	0.0314	0.36		0.0276	0.81		0.1314	2.46	*
L7-L12.rice	included[c]		***	included[c]		***	included[c]		***
Period	0.0023	9.60	***	0.0002	0.73		0.0003	3.48	***
month dummies	included[c]		***	included[c]		***	included[c]		***
NDVIdev	-0.0147	-0.21		-0.1197	-2.05	*	-0.3659	-3.91	***
NDVIdev Jul	-0.0494	-0.61		0.0039	0.07		0.4400	5.13	***
NDVIdev Aug	0.2245	1.64		-0.1872	-2.35	*	-0.3538	-3.37	***
NDVIdev Sep	-0.5057	-4.80	***	-0.3141	-3.70	***	-0.0709	-0.80	
N	1'213			4'664			3'834		
Markets	23			155			54		
Rsq within	0.910			0.851			0.882		
Rsq between	0.887			0.921			0.968		
Rsq overall	0.900			0.851			0.899		
Ll	1'196			3'542			3'042		
$Var_u/(Var_u+Var_e)$	0.241			0.447			0.208		

*: p<0.05; **: p<0.01; ***: p<0.001

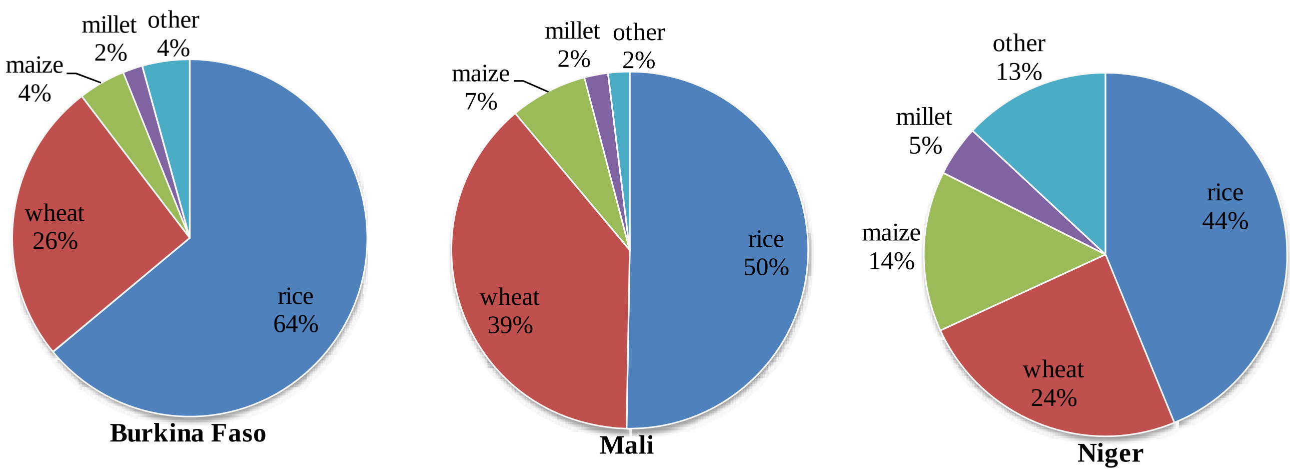
a: SE computed using robust standard errors; b: $A(1)=1-a_1....-a_{12}$

c: not presented for space but jointly significant; full results in Appendix

d: Statistic does not follow t-distribution

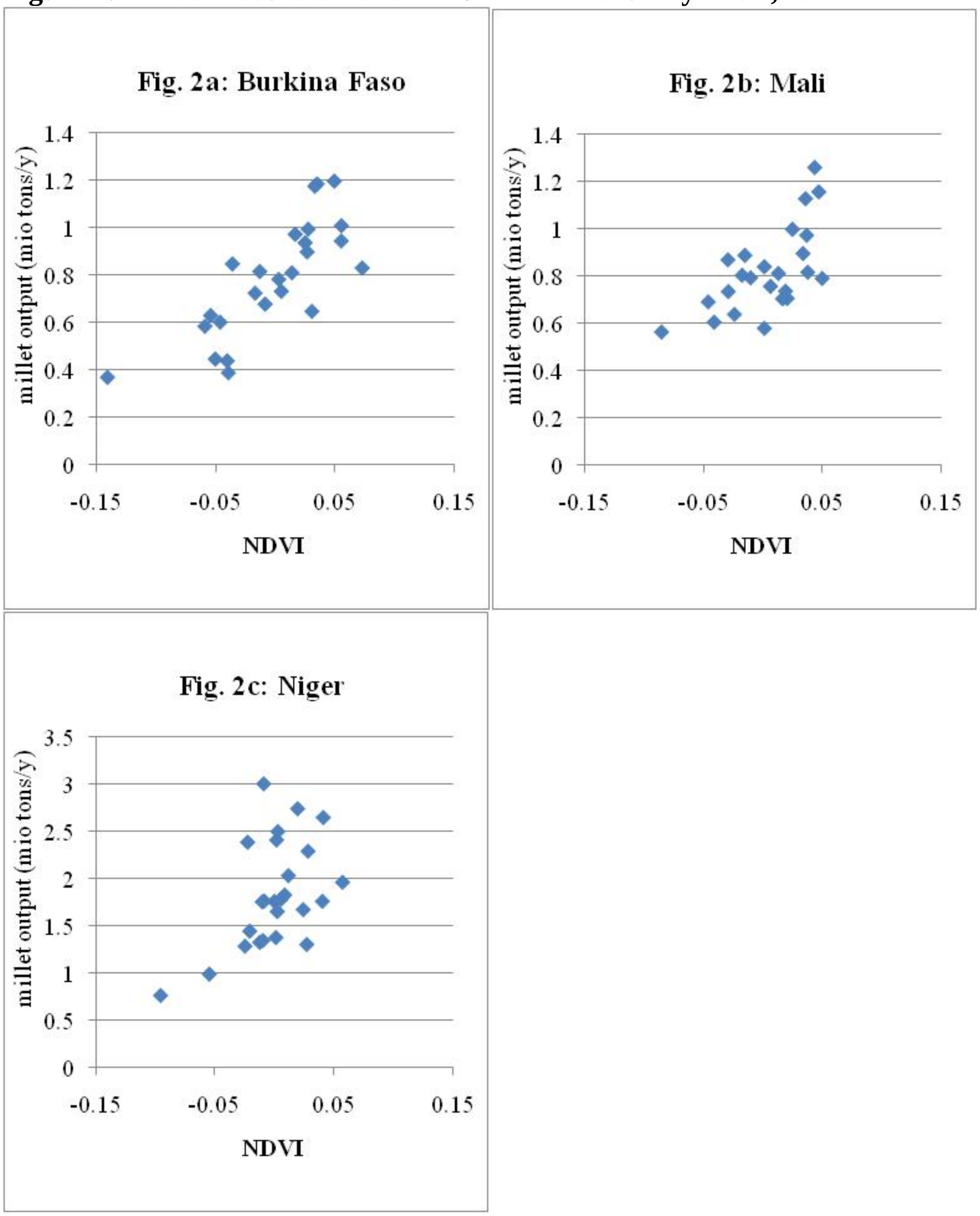
Figures

Figure 1: Cereal Imports[a] 1982-2006 into Burkina Faso, Mali and Niger



a: Data from FAO

Figure 2: Millet Production[a] and NDVI[b] on the Country Level, 1982-2006



a: Data from FAO; b: NDVI represents deviations from 25-year means during the last month of the growing season (September in BF and ML, August in NI)

Figure 3: Average Monthly Millet Prices by Country, 1982-2006

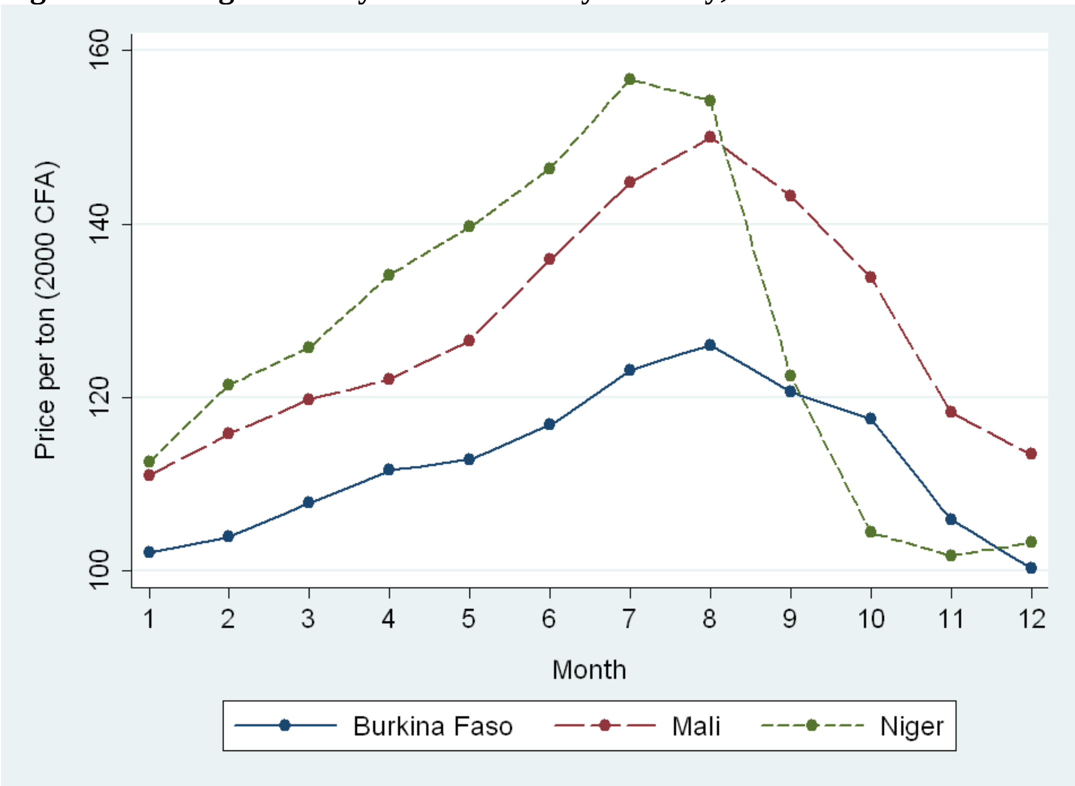


Figure 4: Average millet Prices in 1985-2006 in Burkina Faso, Mali and Niger

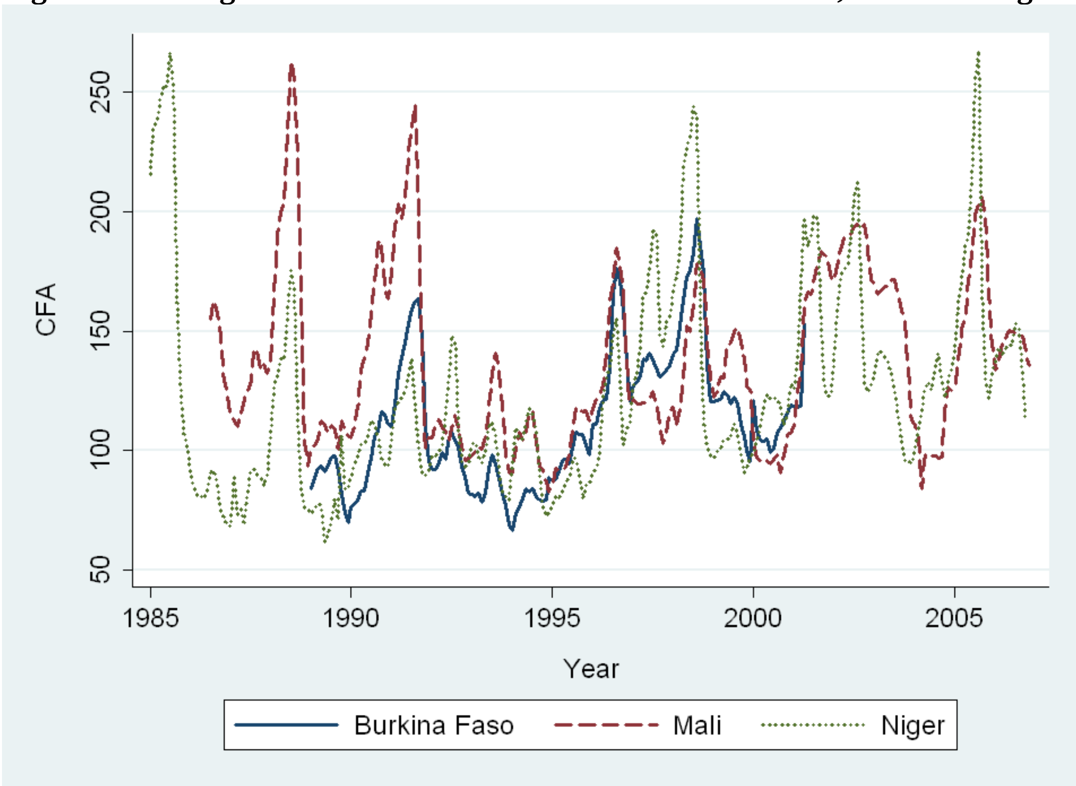
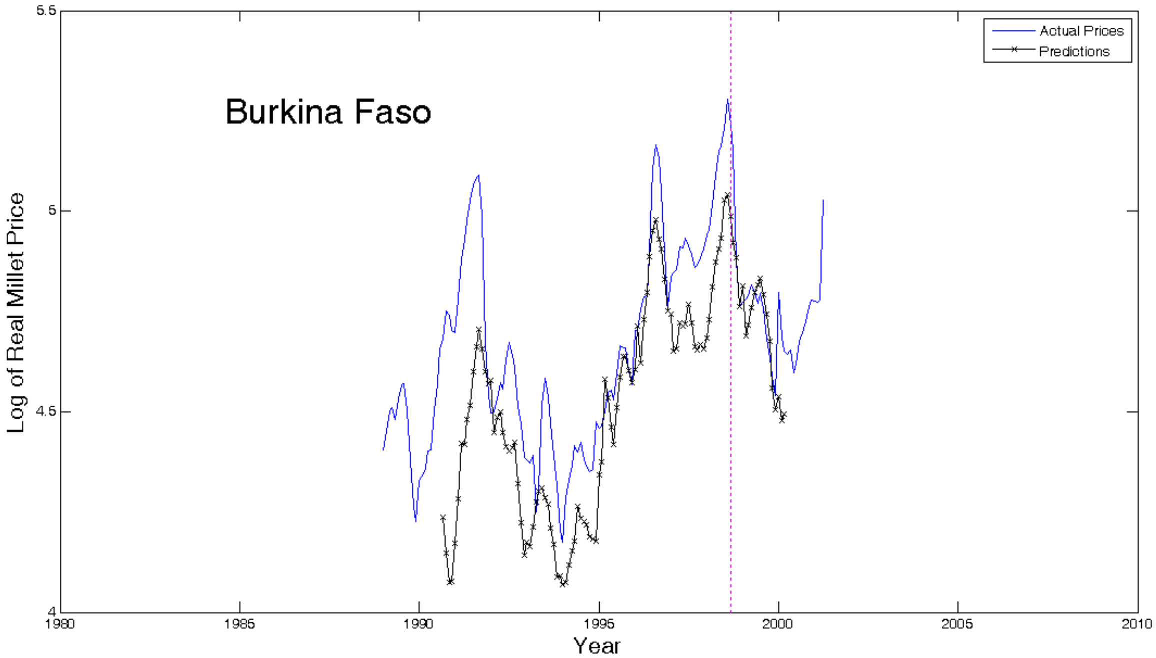
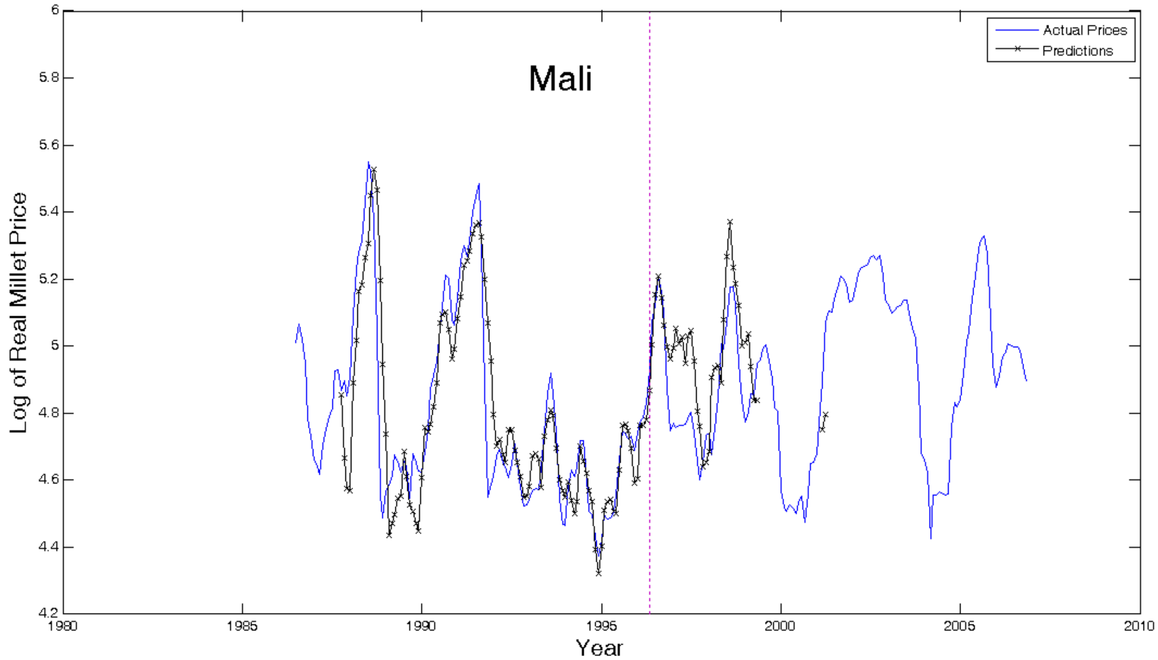


Figure 5: Average Prices and 4-month Predictions for Burkina Faso.



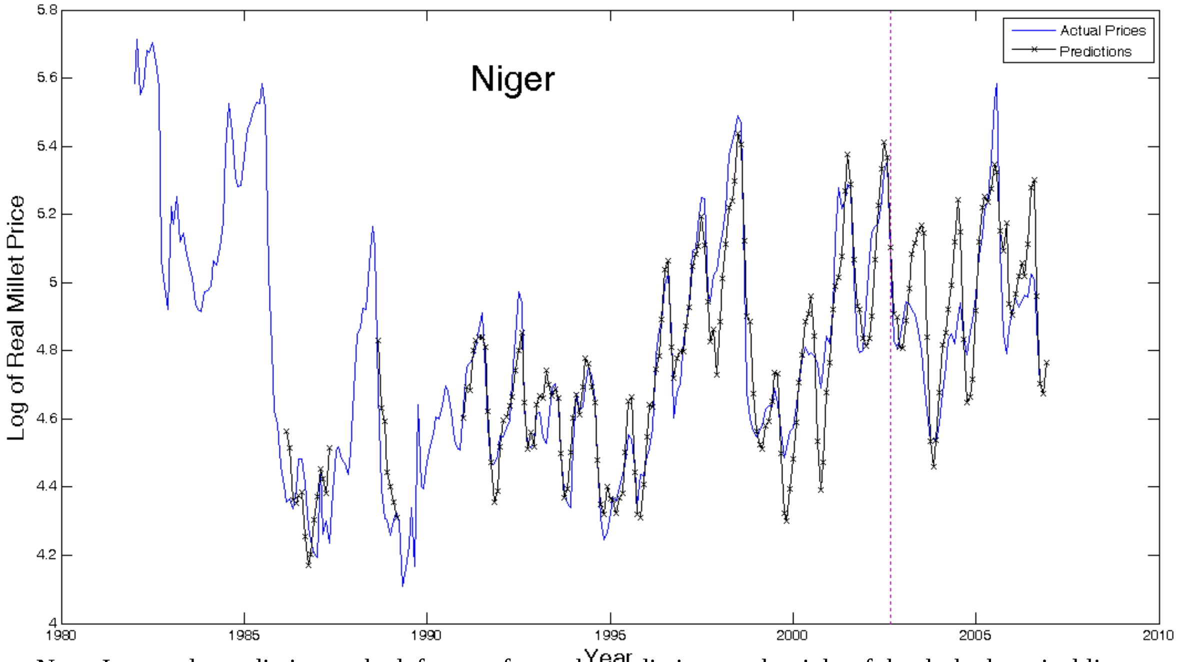
Note: In-sample prediction to the left, out-of-sample predictions to the right of the dashed vertical line. 80% of the available price data lies to the left of this line.

Figure 6: Average Prices and 4-month Predictions for Mali.



Note: In-sample prediction to the left, out-of-sample predictions to the right of the dashed vertical line. 80% of the available price data lies to the left of this line.

Figure 7: Average Prices and 4-month Predictions for Niger.



Note: In-sample prediction to the left, out-of-sample predictions to the right of the dashed vertical line. 80% of the available price data lies to the left of this line.

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Notes

Description and discussion of regression series for the new paper:

We start by showing that 1.) NDVI is a useful predictor for millet supply on the country level, 2.) millet supply is a useful predictor for capital millet prices, and 3.) NDVI is a useful predictor for capital millet prices. The next step is then to 4.) investigate how good a predictor NDVI is for local millet prices.

1.) Relationship between NDVI and annual millet harvest

We regress country-level harvest amounts on total area harvested and the average NDVI for cropland (whether this is indeed the average we should check). As it turns out, the maximum NDVI during the growing season (June-Sept) has the most explanatory power, for all three countries. We also tried individual growing-season months, as well as the average of August and September, and cumulative NDVI. September NDVI was also significantly correlated with millet output, but the corresponding model Rsq was lower. Cumulative (or average, same thing) NDVI was not significant. So we work with maximum NDVI during the growing season. This is consistent with at least part of the literature. Unit root tests for millet harvest were inconclusive (DF test does not reject null of unit root, KPSS test does not reject null of stationarity), but there is no good economic reason to assume that millet supply is nonstationary. Also, the residuals from levels-regressions were stationary, indicating that if there's a unit root problem, it would also be in harvest area (those tests are inconclusive as well), and the two are cointegrated. In any case, since the residuals are stationary, a levels regression is ok.

For BF and ML, the residuals from simple OLS are white (Portmanteau test for 24 months, limit p=0.1). For NI, we had to include one AR term to whiten the residuals, but the results again indicate that maximum NDVI is the best measure to predict millet output (rather than highest Rsq, this is implied by the lowest BIC). Results in paper or appendix.

2.) Relationship between millet supply and monthly millet prices in capital cities

Tests indicate that monthly millet prices in BF and ML have a unit root, but that first differences are stationary. However, rice and wheat prices have unit roots too. I first ran all regressions on first differences, which is the safe version. But then NDVI turned out not to be significant. This is the problem when going to differences, we lose precision. So I re-did the regressions in levels, and the results are cleaner. Since the residuals are stationary, the levels-regressions are ok (millet, rice and wheat prices appear to be cointegrated, making the linear combination stationary).

Note that these regressions can be done in many different ways. I chose to include monthly dummies, total of most recent millet harvest, total import of cereals (net import plus aid), and (log of) wheat and rice prices. I also include two lags of millet prices and month-production interaction terms, but the latter were never jointly significant. I then choose the minimum combination of ARMA terms that renders white residuals, and test for blocks of variables. I also tried including lags of wheat and rice prices, but this led to conversion problems without improving the model quality. So all regressions are based on current wheat and rice prices only.

Results: For all countries, the most recent harvest is highly significant in explaining prices throughout the year (negative sign). For BF, total imports of cereals are highly significant, but not for ML and NI (for NI, imports are significant but have the wrong, i.e. positive, sign). Results in paper or appendix.

3.) Relationship between NDVI and capital millet prices

This next analysis starts with the regression specification in 2.) but replaces output with the maximum NDVI during the most recent growing season. For BF and NI, NDVI "replaces" output in the sense that it is also statistically significant, whereas for ML, the corresponding p-value is 0.135. This may still be ok for a prediction model.

To summarize: NDVI is a valid predictor of output, output helps in predicting prices, and output can be replaced by NDVI when predicting prices, at least for BF and NI, and possibly also for ML.

Next, we try to predict local millet prices. We estimate three sets of models, always with and without NDVI, and separately per country. In the first (local) model we build a price model for local millet prices that incorporates distance-weighted capital millet prices, as well as wheat and rice prices. In addition, we include local NDVI information (growing season max). Note that this makes only sense for markets that are located in livelihood zones that produce millet. For BF, the veg-model outperformed the noveg version, but not so for ML and NI.

Next, I built a model under the assumption that no capital millet prices are available. I simply replaced distance-weighted millet prices by distance-weighted country-level NDVI information. So this model has two types of NDVI info, local and country. Here, the veg-model outperforms the nonveg model for all three countries.

Last, I run OLS without own-price lags. This means that there is no previous price information on which to base forecasts, and no fixed effect to take into account. This makes the model much cruder, but on the other hand it allows us to estimate a local millet prices for markets that have not recently been sampled, or markets that never have been sampled. (Note that if a market was sampled last in October 2010, we could only make a four-out predict ion for February 2011, but we could never get a number for March 2013, using the first two models). Again, the veg-models outperform the nonveg versions for all three countries.