Combining Machine Learning and Market Integration to Improve Maize Price Predictions in Sub-Saharan Africa

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Abstract

In the context of developing countries, there is an urgent need to refine systematic food price prediction models. Yield forecasting has received considerable attention, in comparison, food price forecasting has received considerably less attention; yet food prices provide one of the most accurate estimations of household food access and they provide a more accurate and timely characterization of local food security. A key deterrent to building skillful price prediction models is the difficulty and cost of obtaining complete subnational price data. Here we use a novel method that combines traditional econometric techniques of price transmission and new machine learn methods to predict maize prices one, three, and six months into the future for 59 maize markets in Zambia. We find that we can predict monthly prices with a high degree of predictive accuracy and price data that only relies on a few central markets rather than using 59 individual price series.

Keywords: Food security, food prices, price prediction, price transmission

Introduction

Food prices are the most common measure of food access because they capture two main components correlated with food security – the ability of households to purchase and consume food and the capacity of farmers to plan for future food production. Several governments, NGOs, and international organizations such as World Food Program (WFP), Food and Agriculture Organization (FAO), and FEWSNET have been collecting subnational food price data for years across several countries to inform their in-country operations and monitor subnational levels of food security. Because of the high correlation between food price movements and food security, this data is often used to predict food insecurity crises before they occur. However, in developing countries, food price data can be difficult and costly to obtain. The cost of collecting price data often increases when it is collected from smaller, remotely located, tertiary areas that are more prone to food insecurity crises. In addition to being more costly, rural, and isolated markets tend to display starkly different price dynamics than their urban counterparts making them more difficult to predict. Despite these difficulties, accurate records of food price dynamics in both urban and rural areas are vital to measuring and monitoring the significant spatial heterogeneity that exists in food insecurity crises (Maxwell et al., 2020).

In this paper we combine traditional econometric time series techniques and machine learning algorithms to construct skillful monthly maize price prediction models for Zambia Theoretical models of price transmission commonly assume that shocks are transmitted from an external market (typically modeled as the world market) to the largest domestic city or port within a country and then, depending on the degree of market integration within the country, these shocks are transmitted to local markets. However recent evidence suggests that internal shocks have a larger impact on prices than external shocks. In an analysis of 554 local commodity markets across 51 countries during the period between 2008-2012, Brown & Kshirsagar (2015) find that 20% of local market prices were affected by domestic weather disturbances in the short-run in comparison to 9% by international price changes. This finding has prompted recent literature to relax assumptions about international price transmission to investigate how shocks are transmitted through local and regional markets.

In their estimation of price determinants Baffes et al. (2019) identify that local wholesale market prices in Tanzania responded three to four times faster to the main regional market, Nairobi, than to the international benchmark (US Golf). An extension of this work incorporates network analysis and identifies that the largest city and port in Tanzania is not a significant influencing market (Baffes & Kshirsagar, 2020), rather isolated markets located in maize surplus areas bear more influence on price transmission. The findings in Baffes & Kshirsagar (2020) highlight the need to properly identify a market (or markets) that serve as a reference or benchmark when studying price dynamics and transmission in developing countries. Furthermore, they show that the benchmark market can change depending on the season, local factors, and the relative importance of surrounding domestic and regional markets.

While markets in developing countries have historically exhibited low levels of integration, empirical evidence suggests that they display some level of efficiency during climate related shocks. Empirically, Aker (2010) shows in Niger drought occurring in two markets has a negative statistically significant impact on grain price dispersion occurring between those two markets. She also finds that as the number of markets experiencing drought increases the average effect of drought on price dispersion increases. Similarly, Salazar et al. (2019) expands on Aker (2010) and finds that grain price dispersion in Mozambique also decreases during droughts but increases during flood periods, an effect that they attribute to increasing transport costs. Both papers suggest that markets show some degree of efficiency during supply shocks in developing countries. More recent empirical evidence from Chile also supports this claim. Salazar et al. (2023) find that drought shocks in Chile reduce market price differentials for potatoes around harvesting and commercialization periods

This paper incorporates the results of supply shocks on market performance/integration to build skillful price prediction models that use limited price data and other readily accessible secondary data to predict monthly grain prices three, six, and nine months ahead in Zambia. The goal of this paper is to systematically construct subnational price forecasting models that minimize the use of large quantities of spatial price data, a major limitation faced by other proposed estimation approaches. We limit the amount of data used by first determining if monthly price series in each country co-move. We then use bivariate vector error correction models (VECM) to both assess whether price movements in each country follow well-defined paths and identify influencing and influenced markets. From this analysis we utilize the Least Absolute Shrinkage and Selection Operator (LASSO) to construct a network of markets that identify regional price anchors. Because local climate conditions have been found to both affect and accurately predict agricultural prices, price dispersion, and yields in developing countries we also incorporate climate conditions at both the market location and anchor market location.

1. Maize markets in Zambia

Zambia is a landlocked, lower-to-middle income country in southern Africa. Maize in Zambia is the most commonly grown crop by smallholders. Approximately Ninety percent of maize in Zambia is produced by smallholders who are supported through two primary government programs the Farmer Input Support Program (FISP) which promote maize production through the distribution of subsidized inputs and the Food Reserve Agency (FRA) which is the larger buyer of maize in the country and often purchases maize directly from farmers at pan-territorial pricing which often exceeds market prices. The marketing channel for maize smallholders includes a variety of market outlets, namely, assembly traders who buy grain in villages, informal and large-scale grain wholesalers, the FRA, and direct sales to processors. Timing of sales plays a significant role in the price received for maize. Farmers who have significant surplus and can delay trades to later on in the season can often demand higher prices from formal buyers (Chamberlin et al., 2014). On the other hand, farmers who produce smaller quantities and need access to income sell shortly after harvest within the farmgate. Using representative data Chapoto and Jayne (2011) show that over 60% of smallholders who sold maize sold to assembly traders within the village and that competition at the village level is high.

Zambia produces maize in all ten of its provinces. However, Central, Eastern, and Southern provinces contribute more than 50% of total production. Eastern province is the major producer as its climate is most favorable, followed by Southern province which is more prone to drought conditions (Esterhuizen & Caldwell, 2021). Less than 5% of cropped land in Zambia is under irrigation; Zambian maize is primarily rainfed and dependent on volatile rainfall. As a result, the country frequently experiences food price spikes and volatile food supply (Chamberlin et al., 2014). Price spikes have typically occurred in drought years such as 1992, 1995, 1998, 2001, 2002, and 2005 when maize production fell drastically.

Government intervention in the maize market of Zambia is, and always has been, high. In addition to actively subsidizing both maize inputs and outputs the government also tightly regulates formal imports and exports of maize. Price responses to supply deficits are often worsened by the large wedge between import and export parity prices, resulting from high transport costs and poor market infrastructure (Sitko & Kuteya, 2013). Additionally, ad hoc trading restrictions are often implemented, making it difficult for Zambia to emerge as a significant trading region (World Bank, 2022).The unreliability and unpredictability in government policy have increased the reluctance of traders to engage in cross border trade. However, when trade does occur Zimbabwe is the primary destination for formally exported maize from Zambia (Sitko & Kuteya, 2013) and Zambia's maize imports come primarily from South Africa.

2. Modeling Framework

2.1. Spatial price transmission

Conceptually, this paper builds on the spatial market integration literature which emphasizes the importance of space and transaction costs associated with trading an identical good between markets. Markets are said to be spatially integrated if there is some degree of price transmission occurring between them. The foundational regression framework to evaluate the degree of price transmission occurring between two markets for an identical commodity relies on examining the following relationship:

$$P_{it} = \alpha_0 + \alpha_1 P_{jt} + \epsilon_{it} \qquad \text{(Eq. 1)}$$

where P_{it} denotes the price of a homogenous good in market *i* (domestic market) at time *t*, and P_{jt} denotes the price of homogenous good in market *j* (external market), ϵ_t is a random error term. This regression is often used to test for perfect market integration in the short run; if $\alpha_0 = 0$, $\alpha_1 = 1$, then markets *i* and *j* are integrated in the short run (Isard, 1977; Richardson, 1978; Mundlak & Larson, 1992).

A fundamental shortcoming of estimating Eq. 1 through regression analysis is nonstationarity of prices invalidates most standard econometric results and thus can give misleading results regarding the degree of integration. It is therefore necessary to employ a model that accounts for nonstationarity (Baffes & Gardner, 2003). If prices, P_{it} and P_{jt}, are nonstationary and ϵ_t is stationary then co-movement between the two prices occurs (Ardeni, 1989). To account for the non-unity slope coefficient, we can assume $\alpha_1 = 1$ and test the following:

$$\left(P_{it} - P_{jt}\right) \sim I(0) \qquad \text{(Eq. 2)}$$

Which is equivalent to testing for a unit root in the price differential. If Eq. 2 is confirmed (i.e. the price differential is stationary) then we can assume that market *i* follows price movements occurring in market *j* in the long-run. However, we cannot make inferences about the degree of integration in the short run or other economic implications about the degree of integration from Eq. 2.

To test for short-run integration we can impose lags into the structure of Eq.1:

$$P_{it} = \alpha_0 + \alpha_1 P_{jt} + \alpha_2 P_{jt-1} + \alpha_3 P_{it-1} + \epsilon_{it} \qquad \text{(Eq. 3)}$$

And following Hendry et al. (1984) we can impose the homogeneity restriction to Eq.3. which will allow us to test if prices in market *j* will eventually be transmitted to market *i*. If $\sum_i \alpha_i = 1$ Eq. 3 will become:

$$(P_{it} - P_{it-1}) = \alpha_0 + (1 - \alpha_3)(P_{jt-1} - P_{it-1}) + \alpha_1(P_{jt} - P_{jt-1}) + \epsilon_{it} \qquad \text{(Eq. 4)}$$

The coefficients in Eq. 4 are interpreted as follows:

1. α_1 indicates how much of a given change in the external price will be transmitted to domestic markets within the first period. This is referred to as the error correction term or speed of adjustment.
2. α_1 indicates how much of a given change market *j's* price will be transmitted to market *i* within the first period. This is referred to as the error correction term or speed of adjustment.
3. $(1 - \alpha_3)$ indicates how much of the external-domestic price spread will be eliminated in each subsequent period.

Following Baffes & Kshirsagar (2020), we relax the assumption that market *j* is an external market. Rather we let *i* and *j* represent separate domestic markets and estimate Eq. 4 using an error correction model to determine which domestic markets in Zambia are price influencers. We include seasonal dummy variables and domestic weather disturbances occurring in both markets our preferred specification takes the following form:

$$P_{it} - P_{it-1} = \alpha_0 + (1 - \alpha_3)(P_{jt-1} - P_{it-1}) + \alpha_1(P_{jt} - P_{jt-1}) + \beta_1 W_{it} + \beta_2 W_{jt} + \delta_t + \epsilon_{it} \qquad \text{(Eq. 5)}$$

Where P_{it} and P_{jt} are the log real prices of maize in market pairs *i* and *j* at time *t, W* denotes the domestic weather disturbance estimated using the z-scores of rainfall, and δ denotes a vector of dummy variables to capture seasonality.

To estimate Eq. 5, price series *i* and *j* must satisfy the following:

1. Integrated to the same order.
2. Cointegrated.

To test for the order of integration we use the Augmented Dickey Fuller (ADF) test and the KPSS test. To test the series for cointegration we use the Johansen test (details explained in section 4).

3.2. Price prediction

The goal of this paper is to improve the predictive accuracy of price prediction models while minimizing the use of subnational price data. Recently, concepts from market integration have been merged with machine learning techniques to improve the predictive accuracy of electricity price prediction models. Lago et al. (2018) use deep neural networks to understand the temporal structure and impact of neighboring and connected markets on forecast accuracy. They show that the inclusion of neighboring market features significantly improves the predictive accuracy of local market predictions. In a similar paper, Ziel et al. (2015) utilize an autoregressive model to analyze the relationship between the day-ahead electricity price of the Energy Exchange Austria (EXAA) and other day-ahead electricity prices in European markets. They find that the inclusion of EXAA prices improves predictive accuracy in the prediction of local electricity market prices. Also, Panapakidis & Dagoumas (2016) apply a clustering algorithm to create homogenous groups of electricity market clearing prices from different competitive markets. Forecasts are then made within these groups. This framework allows the prices in similar markets to inform the predictive capacity of the neural network used to predict prices in local market

We use the price transmission framework to identify a set of markets which are responsible for influencing surrounding maize markets. We then use these markets as predictors in a random forest model to predict prices one, three, and six months ahead. We also use other readily available data to control for transaction costs such as CPI, fuel prices, and travel distance between markets. Finally, we compare the differences in predictive accuracy between the baseline model that uses its own lagged prices as predictors and the model that uses price anchors as predictors.

3. Data

Our primary data source, the World Food Program (WFP) Vulnerability Analysis and Mapping (VAM), provides monthly price data for 71 markets across both urban and rural areas in Zambia from 2003 to 2022. Data from 2003-2012 covers 40 markets that are primarily located in more urbanized and denser areas. In 2012 the market coverage was expanded to 71 markets and included markets in more remote and rural areas. Because rural markets often display price dynamics that starkly contrast those in urban areas, we focus our analysis on the sample from 2012-2022 and provide further analysis on markets that span the 2003 to 2022 time period in the Appendix. Table 1 summarizes the sample of WFP price data used for analysis.

Table 1

Summary statics of maize prices in Zambia (2012-2022)

Province	N. Markets	Average	Min	Max	Volatility
Central	7	2.26	0.62	6.21	0.23
Copperbelt	6	2.33	0.67	6.67	0.19
Eastern	5	1.98	0.53	6.67	0.20
Luapula	6	2.03	0.73	5.36	0.21
Lusaka	3	2.38	0.71	5.67	0.16
Muchinga	4	2.07	0.67	6.11	0.22
North-Western	7	2.18	0.32	7.78	0.26
Northern	8	2.12	0.73	6.67	0.23
Southern	7	2.15	0.50	6.67	0.21
Western	6	2.50	0.50	7.78	0.23
Overall	59	2.20	0.32	7.78	0.22

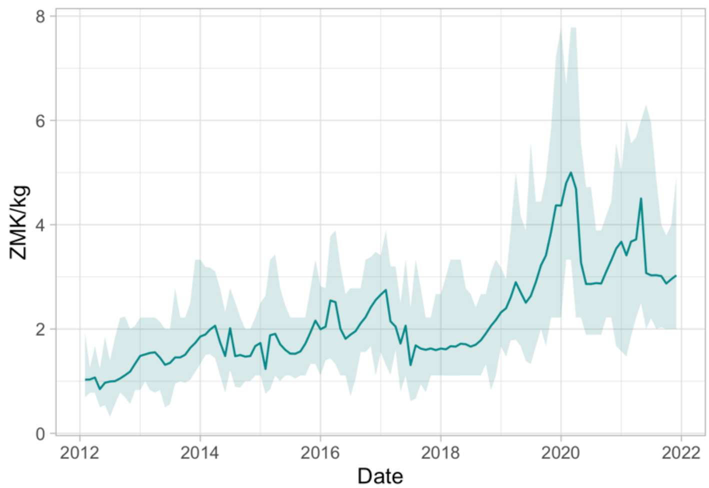
Note. All prices are displayed in real prices ZMK/kg

In common with most price data from developing countries, WFP VAM suffers from missing observations. To ensure we do not rely on an abundance of imputed data we retain markets for analysis that have at least 70% of the data present. We impute missing observations using cubic spline interpolation[1]. The resulting sample is 59 retail markets, consisting of 120 monthly observations each. Figure 1 plots the average maize prices for the respective time period.

Figure 1

Average maize price in Zambia (2012-2022)

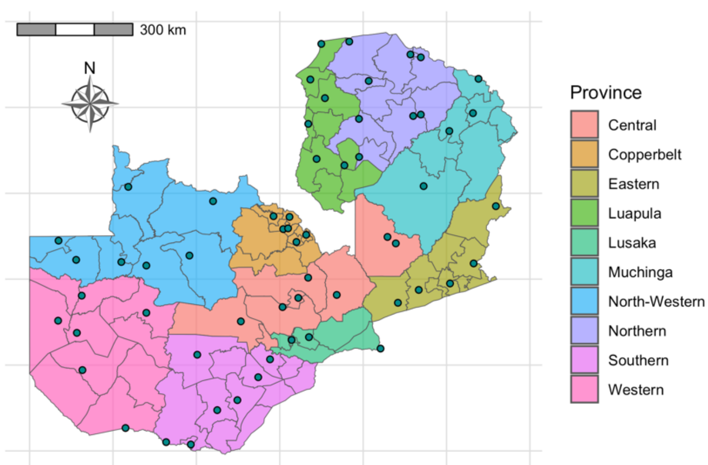
[1] To compute the imputed values we use the R function *spline* from the "Stats" package.



Note. All prices are displayed in real prices ZMK/kg

Figure 2

Distribution of maize markets across provinces in Zambia



Note. Circles represent market locations.

Zambia is divided into 10 provinces and 116 districts. The primary maize growing regions are in Eastern and Southern province. Markets are located throughout the country, with at least one market in each province. Figure 2 displays the location of each market.

Weather disturbances are estimated using Climate Hazards Center Infrared Precipitation with Stations (CHIRPS) dataset which provides gridded (0.1◦ latitude × 0.1◦ longitude) monthly precipitation data spanning our time period of interest – 1982 to 2022 (Chamberlin et al., n.d.). CHIRPS and products have been used for modelling and forecasting maize yields in Southern

Saharan Africa and to support custom FEWS NET agroclimatic historical drought analyses in Eastern and Southern Africa (Davenport et al., 2018; Davenport et al., 2021; Guimarães Nobre et al., 2019; Lee et al., 2022). We use the long-term deviation from the mean precipitation, captured by z-scores, for a given market area and month as our measure of local weather disturbances.

In the following sections, we analyze the data using the empirical framework discussed above. We employ a market integration analysis to analyze maize price dynamics for each of the 59 markets and identify markets that act as price anchors. We then use incorporate these results in into a random forest model to make one, three, and six months ahead price predictions. We compare the predictive accuracy of the price predictions that utilize information from the market integration analysis.

4. Results

4.1. Selecting the appropriate price anchors

We begin by applying unit root tests to log real prices using the Augmented Dickey-Fuller (ADF) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) procedures. Results from the ADF test indicate stationarity in log levels with a without a trend is rejected in all cases, stationarity with a trend is rejected in all but two cases at the five percent level. Results from the KPSS test indicate stationarity is not rejected in all case both with and without a trend. Both tests confirm that when first differences are applied all series are stationary under both KPSS and ADF procedures. See Table 2 for summary of results. These results indicate long-term relationships exists between markets and they should be examined using co-integration statistics and short-run relationships should be examined using an error correction model.

Table 2

Stationary properties

	Augmented Dickey-Fuller			Kwiatkowski-Phillips-Schmidt-Shin		
	With trend	No trend	Differences	With trend	No trend	Differences
$p < 0.10$	0	0	0	0	0	0
$p < 0.05$	2	0	8	0	0	0
$p < 0.01$	0	0	51	59	59	0

Note.

As an intermediate step to determining the long run relationships between markets we use Eq. 1 and Eq. 2. First, we use the ADF procedure to test for a unit root in the price differential of each market pair[2]. If the price differential is I(0) and the we can assume that market *i* follows market *j* price movements in the long-run. To determine the validity of the model presented in Eq. 1 we test the order of integration of the error term. If prices are nonstationary and the residuals of Eq.1 are stationary this implies movement between prices in market *i* and market *j* and we can conclude that market *i* prices follow price signals from market *j*. We use the ADF procedure to check that the residuals are stationary. A summary of results are displayed in Table 3[3].

All markets, except for one (Chingola), display a long-term co-moving relationship with at least one other market in the sample. Based on the summary of indicators of long term relationships we determine that Lukulu, Kaputa, Mongu, Choma, Kaoma have the most long-term co-moving relationships with the other markets within Zambia. The specified error correction model will quantify the relationships between these markets in the short-run.

Table 3

Summary indicators of long-term relationships between 59 markets in Zambia

Province	Market	(1) Price differential	(2) Average R-squared	(3) Average Coefficient	(4) Residuals
Western	Lukulu	50	0.69	0.94	50
Northern	Kaputa	45	0.56	0.73	45
Western	Mongu	43	0.69	1.10	43
Southern	Choma	38	0.76	1.04	38
Western	Kaoma	38	0.72	1.00	38
Northern	Luwingu	37	0.65	0.80	37
Western	Senanga	35	0.71	0.92	35
Southern	Kazungula	35	0.71	0.84	35
Muchinga	Nakonde	35	0.60	0.77	35
Central	Mkushi	32	0.77	0.94	32
Overall	Mean	19.72	0.70	0.82	18.72
Overall	Min	0	0.45	0.57	0
Overall	Max	50	0.82	1.10	50

Note. Table provides summary statistics for the markets with the most co-moving relationships between markets. (1) indicates the number of markets that reject null of non-stationarity of the price difference in the market pair by the ADF procedure at the 5% level. (2) indicates the average R-squared of the model estimated from Eq. 1 for each market pair. (3) indicates the average of the coefficient, α_1, estimated from Eq. 1 for each market pair. (4) indicates the number

[2] 59 markets result in 3422 unique market pairs
[3] A table of complete results can be provided upon request from the corresponding author.

of markets that reject the null of non-stationarity in the residuals resulting from the estimated model of Eq. 1 for each market pair by the ADF procedure at the 5% level.

4.2. *Using price anchors for prediction models*

For now, we use the first five markets in table 3 as as price anchors in the prediction models. Later, these models will be better specified using information from the error correction models to better define the price anchors. Currently, we specify the prediction models using a regression based random forest in which the predictors in each model are lagged prices and the outcome is the log real price in time period *t.*

To predict prices in each market we do the following

1. Split the data into training and test sets sequentially such that 70% of the for each market is in the training set and the remaining 30% is in the test set.
2. Due to the random shuffling, k-fold cross validation does not respect the nature of time series data. To remedy this, we tune the parameters in the random forest using methods from financial time series forecasting (Hyndman & Athanasopoulos, 2013). Specifically, we perform a grid-search of optimal parameter values using a moving window time series cross validation approach.
3. Using the tuning parameter from (2) we specify a regression based random forest that uses lags of price prices as predictors for each market.
4. To measure the predictive accuracy of each model we use the root mean squared error (RMSE). Because prices are logged, we compute the RMSE in the following way:

$$RMSE = \sqrt{\frac{1}{N \times T} \sum_{i=1}^{N} \sum_{t=1}^{T} \left(e^{y_{it}} - e^{\hat{y}_{it}} \right)^2}$$

Results using each price anchor are provided in Table 4. Currently, this is a very sparsely specified model future plans will incorporate results from short-term price transmission integration and weather disturbances.

Table 4

RMSE across models using price anchors

Price anchor	Mean	Min	Max	Median
Choma	0.29	0.19	0.56	0.27
Kaoma	0.31	0.15	0.63	0.31

Kaputa	0.43	0.26	0.73	0.41
Lukulu	0.35	0.20	0.62	0.34
Mongu	0.37	0.23	0.65	0.36
Own prices	0.24	0.11	0.47	0.22

5. Discussion

The prediction models presented in this paper provide intuition on how price transmission can be incorporated into price prediction models to minimize the use of costly price data. Current price prediction models utilized by FEWS NET and other aid organizations are labor intensive and require large swaths of data on production, market conditions, and other external market forces. Additionally, many aspects of current price forecasting models are qualitative in nature and scenario based. Our goal in this paper is not to construct the perfect prediction model, but to determine when and where weather disturbances (forthcoming) and markets linked through price transmission can contribute most to improving predictive accuracy across different time horizons (forthcoming). The results presented in this paper can be utilized to build more quantitatively rigorous models that are less labor intensive and more reliant on frequently updated and accessible data.

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