A New Approach to Monitoring Farmer Prices:
Method and an application to a low-income African country

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Abstract

This paper proposes a new approach to monitoring farmer prices for low-income developing countries, along with an account of its development and application in a low-income African country. This crowdsourcing method involves broadcasting radio jingles inviting farmers to report the prices and locations at which they sold their crops to a toll-free call center. To encourage participation, the telephone numbers of farmers who respond are entered into a weekly raffle to win farm input coupons. An application to Malawi is presented, which demonstrates the feasibility of this method in a low-income country where internet connectivity is limited but mobile phone coverage is reasonable. The vast majority of 2,313 farmers responding were found to sell to assemblers, small traders or retailers and to receive substantially less for their crops than official minimum farm gate prices. Non-parametric analysis shows that the prices that farmers receive vary according to bargaining power and the type of buyer but not by distance to the point of sale. These three stylized facts may be explained by dispersed, fragmented and monopolistic nature of food markets, and that farmers usually travel to the point on sale by bicycle or walking.

Keywords: monitoring farmer prices, crowdsourcing, conditional density estimates, bargaining power, time to market, Africa

Casual reading of various news outlets and social media suggests that it is common for farmers, civil society organizations, government officials and journalists to accuse traders and parastatal marketing organizations of ‘exploitative behavior’ and ‘price gouging’ in the post-harvest season (Baulch & Ochieng, 2020). Yet the evidence on which such accusations are made is largely anecdotal, as government efforts to collect and report farm gate prices are often patchy and inconsistent (Prieto et al., 2021). Whilst there have been developments in data-collection methodologies (Donmez et al., 2017; Solano-Hermosilla et al., 2022) there has been few applications, and with mixed results, of these methodologies within challenging data-collection environments such as the smallholder farming sector of a low-income African countries. In this paper, we seek to address this knowledge gap by introducing and testing a new, innovative and relatively inexpensive method for monitoring the price that farmers are actually paid together with an application to a low-income country in Africa. We then put this data to the test using non-parametric representations of the distributions of prices farmers receive using different measures of monopsonistic marketing power as the conditioning variable.

A recent review of new techniques in agricultural data collection concluded that:

> ‘Citizen generated data are attractive due to their potential to return data at high levels of spatial and temporal resolution with relatively limited costs. However, these data present significant challenges in their representativeness and the quality of the data generation process.’ (Carletto, 2021, p. 64)

Citizen generated data includes data generated via crowdsourcing, that is by enlisting a large ‘crowd’ of individuals (volunteers or for pay) or devices (e.g., sensors) to collect and share data. Crowdsourced data is increasingly common in industrialized and middle-income countries, where the widespread availability of smart phones and the internet of things makes it relatively easy to collect (Brabham, 2013). However, in low-income countries, where internet speeds are slow and ownership of smart phone is rare, a different method of crowdsourcing data is required.

One such method, which by the International Food Policy Research Institute (IFPRI) in collaboration with Farm Radio Trust (FRT), involves the crowdsourcing of the prices received by farmers via a competition. During the main marketing season, farmers who had recently sold their crops were invited to call a toll-free phone number to report the prices they had received, along with some other simple information about their sale. In return their phone numbers were entered into a weekly lottery to win vouchers that could be redeemed at any outlet of a major agro-input dealer.

Subsequently, given the inherent weaknesses in the available data, there remains a paucity of empirical studies within the extant academic literature on the numerous factors of farmer pricing within low-income African nations. Given the prevailing effects of farmgate prices, and the potential for exploitative behavior from buyers, it is unclear if the interface between these elements would result in a single steady state setting. In other words, there is the potential for price distributions to exhibit multi-modalities contingent on factors driven by monopsonistic power. Our contributions also pursue to address this gap and deigns to progress the existing academic knowledge on the dynamics of farmer prices through an innovative analysis of the data that we have collected via our crowdsourcing methodology. We put this data to the test with a novel non-parametric examination utilizing conditional density estimates (CDEs) of price against, *a priori*, representations of monopsonistic power, including measure for distribution of bargaining power between buyers and sellers, the types of buyers, and the time to market for sellers (Jaleta & Gardebroek, 2007; Nourani et al., 2021).

Utilizing our crowdsourced dataset of 2,313 unique observations of farmers prices over the 2020 harvest period (April – July 2020), we discover that the prices that farmers receive vary according to bargaining power and the type of buyer but not by distance to the point of sale. Our findings allow us to pose challenging but important questions about the geography of agricultural marketing in landlocked countries and how to ensure farmers receive better prices for their crops.

The remainder of the manuscript is organized as follows. In section 2, we illustrate the *a priori* developments in relation to farmers prices in low-income African nations. We also highlight in this section the methodological developments with regards to data-collection using crowdsourcing. We provide an explanation for the operationalization of our crowdsourcing methodology in Section 3 along with a description of the underlying empirical processes of our CDEs. We proceed to discuss our findings in Section 4 with subsequent concluding remarks in Section 5 where we offer both the academic and practical implications of our results.

1. Farmer Prices in Low-income African Nations

As noted in the introduction, it is common for traders and marketing parastatals in African countries to be accused of explotitative behavior and price gouging, particular in the immediate post-harvest season when quick sales to meet farmers' immediate cash needs are common. Most of the academic literature that has examined this issue quantitatively has concluded that traders operate in relatively competitive markets and that, after accounting for costs, their margins are relatively modest (*inter alia* Abbott (1967); Barrett and Dorosh (1996); Holtzman (1989); Sitko and Jayne, 2014; Dillon and Dambro, 2018)). However, there are also well-documented cases in which monopolistic power has been shown to have depressed the prices farmers receive (Crow, 1989; Harriss-White, 1996; Graubner *et al*., 2011; Saitone *et al*., 2008.)

A common response by developing country government to such accusations, whether grounded or not, is to implement prices (hereafter MFGP), often based loosely on the cost of production of the crop being sold. Often parastatal marketing boards are asked to support the prices that farmers receive for their food crops by buying at pre-determined 'above market' prices early on in the marketing season, only to sell at 'below market' prices to poor consumers later in in the agricultural seasons (Timmer, 1986). Of course, such buy high, sell low strategies are rather costly and parastatal agencies rarely have enough funding and storage capacity to be able to buy enough crops and sell enough food to stabilize prices effectively (Timmer, 1986). So, they resort to exhortation and enforcement to try to maintain minimum farmgate prices. In the worst cases, mistimed procurement and sales by parastatals, along with trade policy interventions, may even destabilize prices for farmers and consumers (Kherallah et al., 2002; Timmer, 1986)

As Bates (2014) argues in the immediate post-independence decades, many African countries pursued policies that undermined their rural economies by depressing prices for farmers in order to provide cheap food to politically more demanding urban consumers in addition to financial surpluses from exports of 'cash' crops. This was often coupled with the maintenance of overvalued exchange rates, which further depressed the prices paid to farmers, and restrictive tariffs intended to promote agricultural processing and value-added. (Kherallah *et al.*, 2002; Tsakok, 1985). While many African countries abandoned such policies in favor of freer agricultural markets in the 1980s and 1990s, elements of the old marketing arrangements such as parastatal marketing organizations still operate in many African countries to this day (Dillon and Danbro, 2017). Because of their high costs and inefficiencies, such parastatals often account for a significant share of government expenditures, particular when the government also try to regulate the prices paid to farmers (Kherallah et al., 2002; Timmer, 1986)

2. The Fundamentals of Crowdsourcing

The term "crowdsourcing" was first used in 2005 by Howe and Robinson, editors of *Wired* magazine, to describe how businesses were using the Internet to "outsource work to the crowd". Howe (2006) provided a definition for the term crowdsourcing in a follow-up article, "The Rise of Crowdsourcing", in June 2006, which stated that crowdsourcing represents the act of a company or institution taking a function once performed by employees and outsourcing it to an undefined (and generally large) network of people in the form of an open call.

Although the earliest examples of crowdfunding date back to ancient Greece and the Tang dynasty in China, the take-off of crowdsourcing was linked to the development of mobile phones and the internet in the late 20th and early 21st centuries. As the well-known examples of Pebble, Uber and Waze show, crowdsourced tasks are directly outsourced to individuals, who are not required to be employers or professionals to perform the outsourced work. In some, but not all cases, monetary rewards are offered to motivate individuals to supply the services or information that are outsourced but this is not always the case (Zeug et al., 2017). Prizes in competitions or the provision of airtime or text messages with reciprocal information are also frequently used as inducements in crowdsourcing exercises (Estelles-Arolas & Gonzalez-Ladron-de-Guevara, 2012).

It is important to recognize that "crowdsourcing" is a portmanteau term, which includes a variety of purpose and functions. It is possible to disentangle seventeen different types of crowdsourcing applications including crowd coding, crowd creating of content, crowd funding, crowd identification of pests and diseases (in agriculture), crowdsourcing of health care providers, crowd solving of problems, crowd shipping and even crowd voting (Brabham, 2013). For further information on the different activities comprising crowdsourcing, how it can be best implemented, plus its advantages and drawbacks see Brabham (2013).

In the current application to farm gate prices in Malawi, paid price collectors with notebooks or tablets are replaced by farmers with mobile phones, who are motivated to supply information on the prices they are paid for their crops by the opportunity to win agricultural input vouchers in a weekly raffle. It should be noted that internet connectivity in Malawi is currently too limited (and expensive) for internet based crowdsourcing methods to be feasible in rural areas of the country. The Economist Intelligence Unit's latest Inclusive Internet Index ranks Malawi as 114th out of 120 countries, with an affordability ranking of 116 and an accessibility ranking of 113.(EIU, 2021). However, mobile phone ownership is common with 43.6 percent of rural households and 82.4 percent of urban households owning at least one cellphone according to the 2019-20 Integrated Household Survey (National Statistical Office, 2020)

3. Data collection and empirical estimation

The following sections provide and explication of our adopted methodological practices in relation to the application of our novel data collection process and the subsequent analysis of the crowdsourced dataset. Section 4.1. details the processes involved with the crowdsourcing data-collection highlighting our on the ground, collaborative work with IFPRI from initiating the pilot programme to the running of the actual task. Our application of crowdsourcing is very much in line with the recent methodological literature especially within the context of crop prices and low-income African nations (Solano-Hermosilla et al., 2022). Section 4.2. indicates the empirical analysis utilizing non-parametric bivariate conditional density estimations (CDEs) of our collected data on farmers' prices against several measures of monopsonistic power.

3.1. Crowdsourcing Farmer Prices in Malawi

In mid-2019, IFPRI and Farm Radio Trust (FRT) undertook a pilot study in southern Malawi to access the feasibility of collecting data on the sales prices farmers receive using crowdsourcing (Ochieng, 2019). Due to limited ownership of smart phones, poor telecommunications infrastructure and high internet costs, the crowdsourcing method involved a competition in which pigeon pea and chickpea farmers were invited to call or text a toll-free telephone number operated by FRT to report the prices and locations of their most recent crop sale.[1] We discounted the use of SMS-based price reporting given its lack of success within prior trials in low-income African nations (Wyche & Steinfield, 2016). To address the issue of continual participation (Solano-Hermosilla et al., 2022), the telephone numbers all farmers who called-in were entered into a weekly raffle with a chance to win an agricultural input voucher redeemable at any outlet of a major agro-input dealer (Agora/Farmers World). Between August 15 and October 30, 2019, 637 farmers from fifteen districts called the toll-free telephone line operated by FRT to report the prices they had received for their legumes. Since the pilot study demonstrated the practicality of collecting data on the prices farmers receive using crowdsourcing methods, the study was upscaled to a nationwide exercise to collect the prices Malawian farmers receive for maize, the major food staple, and soybeans, a relatively new major cash crop, during the main marketing season of 2020.

In the next main marketing season, between April 15 and July 31, 2020, prices for maize and soybean were crowdsourced by broadcasting jingles in local languages on three leading radio stations (the Malawi Broadcasting Corporation, the Voice of Livingstonia, and Zodiak Radio). The jingles invited farmers to report the prices and locations at which they had sold their maize and soybeans to a toll-free call center operated by FRT. The telephone numbers of farmers who called-in were entered into a weekly raffle with a chance to win one of three vouchers each worth Malawi Kwacha (MWK) 25,000 (approximately US$ 33), redeemable at any outlet of a major agro-input dealer. In addition, to collecting data on the prices received, farmers were also asked about the

[1] The 2018 Population and Housing Census in Malawi found 51.7 percent of rural and urban households owned mobile phones, respectively. Less then one-tenth of one percent of households have landline connections, almost all of which are located in urban areas.

volume of maize or soybeans they had sold, the location of sale and to whom they had sold (see Annex 1 for the text of the radio jingles, the call-center checklist, and the questionnaire for the subsequent follow-up phone survey). In the four months of data collection between April and July 2020, a total of 1048 maize and 1265 soybean farmers called the FRT call center to report the prices at which they had sold these crops. This timing happened to coincide with the first wave of the COVID-19 pandemic in Malawi, so the IFPRI-FRT crowdsourcing exercise was able to provide valuable information on the crop prices paid to farmers during a period when the official system for monitoring maize and other agricultural prices, along with many other public services, were under considerable strain.[2]

A small number of duplicate calls (thirty for maize, and twenty for soybeans) were then eliminated from the transactions level data. The duplicate calls are believed to be farmers who called in to the FRT to report the same transaction more than once to increase their chances of winning the coupons. The number of such duplicate observations was minimized by the FRT call center by setting-up an automatic alert when the same phone number called back within the same week. At the end of the marketing season, the farmers who had reported their sales prices were called back by the Farm Radio Trust call center, and asked some additional questions about their age, education and farm, and their crop marketing experiences. The length of the follow-up calls was 10 to 12 minutes, and 1,775 (77 percent) of the farmers who had reported sales to the call center were re-contacted and interviewed. The total cost of the 2020 crowdsourcing exercise was approximately MWK 12.75 million (about US$ 17,250) of which 52 percent was for the broadcasting of the radio jingles, 37 percent for the operating costs of the call center, and 11 percent for coupons. This equates to a unit cost of approximately MWK 5,550 (US$7.44) per call. We provide a visualization of our crowdsourcing data-collection process in Figure 1.

[2] More generally, it should be noted that while the Ministry of Agriculture and Food Security, along with several other international organizations, collect information of the market prices of a number of food items on a weekly basis, the collection of data on 'farmgate' prices takes place more erratically and is usually restricted to major markets and trading centers when it does take place.

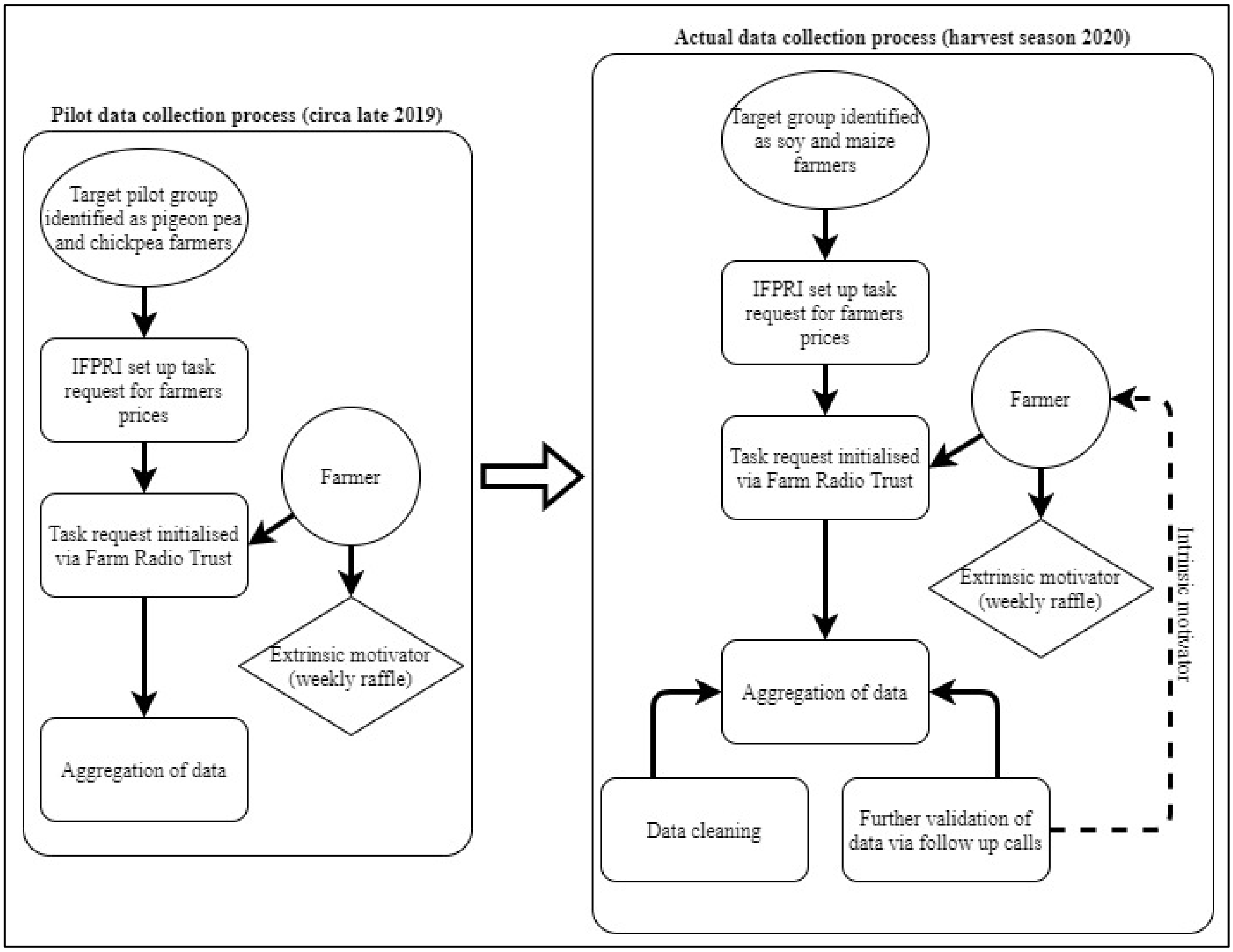


Figure 1: Breakdown of our crowdsourcing data-collection process

*Note: this figure indicates the application of our designed crowdsourcing data collection framework. The framework is operationalized in tandem with IFPRI via Farm Radio Trust. Pilot exercise was undertaken circa late 2019, and refined for the 2020 harvest season task initiation.

3.2. Conditional Density Estimation (CDE) of Farmer Prices

Much of the empirical examination of farmer price behavior adopts a β-convergence methodology whereby it is assumed that farmer prices converge along a single steady-state that can be measured by a simple catch all measure such as a beta coefficient(Li et al., 2019; Nguyen et al., 2021). However, the reality of the situation is more complicated given the potential impacts of monopsonistic buyer power and price manipulation within low-income African crop markets (Kherallah et al, 2002). Indeed, the usual notion of steady-state food price convergence becomes more complex, factoring in both dynamic and spatial characteristics of said prices. Given these limitations of traditional β-convergence methods, we elect to utilize a non-parametric distribution analysis, running kernel conditional density estimates (CDEs) on crowdsourced data set on farmers' crop sales. It should be noted as well that since the farmers who called in to report crop sales were self-selecting, they cannot be regarded as a random sample of farmers. In particular, farmers with mobile phones and radios are likely to be over-represented while farmers who did not sell any maize or soybeans are excluded.[3] As CDEs do not impose any assumptions on the underlying distribution of the data generating process, this allows us to capture the entire shape and dynamics of the crop price distribution including the presence of multi-modalities or equilibria within our crowdsourced farmer price data whilst also addressing the limitations of our unique dataset.

We utilize the Hyndman et al. (1996) modified form of the original Rosenblatt (1956) estimator, which can be represented as:

$$f(Y, X) = \frac{1}{Nh_y}\frac{1}{h_x}\sum_{i=1}^{N} K\left[\frac{y - y_i}{h_y}, \frac{x - x_i}{h_x}\right]$$

(eq. 1)

N is the number of farmers within our crowdsourced price dataset, and h_y and h_x are the optimal bandwidths for variables Y and X, computed using the reference rules in Bashtannyk and Hyndman (2001) and Hyndman and Yao (2002) to ensure minimization of the integrated asymptotic mean squared errors (IMSE). y_i and x_i are the realizations of variables Y and X, and K denotes the Epanechnikov kernel density function (Hyndman et al., 1996).

For our examination of farmer prices in Malawi, we treat the prices of maize and soybean as our response variable (Y), whilst we have our *a priori* representations of monopsonistic power as the conditioning variable (X). We utilize several measures for monopsonistic power, including bargaining power, type of buyer, and time to market. Each of these conditioning variables are outlined below. Following Jaleta and Gardenbroek (2007), bargaining power (α) is given as,

$$\alpha_{i,t} = \frac{P^* - p_{b,1}}{p_{s,1} - p_{b,1}}$$

(eq. 2)

where, P* is the final price of the transaction, $p_{s,1}$ and $p_{b,1}$ represent the seller's and buyer's initial offer, and that $\alpha \in [0, 1]$. A high α, i.e. closer to 1, represent greater bargaining power for the seller, whilst a low α, indicates bargaining power for the buyer. Type of buyer contains three categories of buyer – assemblers, ADMARC, and larger traders – rank-ordered by approximate transaction volumes. ADMARC is the Agricultural Development Marketing Corporation, Malawi's main agricultural marketing parastatal, which buys grain from farmers at fixed, pan-terriorial prices, which usually conform to the MFGPs set by the Ministry of Agricultural and Food Security.

[3] The 2019-20 Integrated Household Survey (IHS5) indicates that 43.6 percent of rural and 82.4 percent of urban households owned mobile phones. Less than one-tenth of one percent of households had MTL (fixed phone) connections, almost all of whom were located in urban areas.

Finally, time to market is expressed in terms of how long (in minutes) it takes the farmer to walk to the point of sale.

Additionally, to capture any temporal dynamics of prices, we choose to subdivide our data in to early and late harvest season with April and May 2020 described as the 'early harvest', and June and July 2020 are the 'late harvest' season.[4] We also engage in a longitudinal examination of our crowdsourced data using a within season, price-mapping exercise for the 2020 harvest. Using a proprietary mapping dashboard developed by IFPRI, we generate color-coded price maps of central Malawi over the period of May – July 2020. We present our findings in the following section.

4. Findings

Prices were reported from all districts in Malawi except for Likoma island, with most callers coming from the main maize and soybean producing districts in the center of the country (Figure 2).

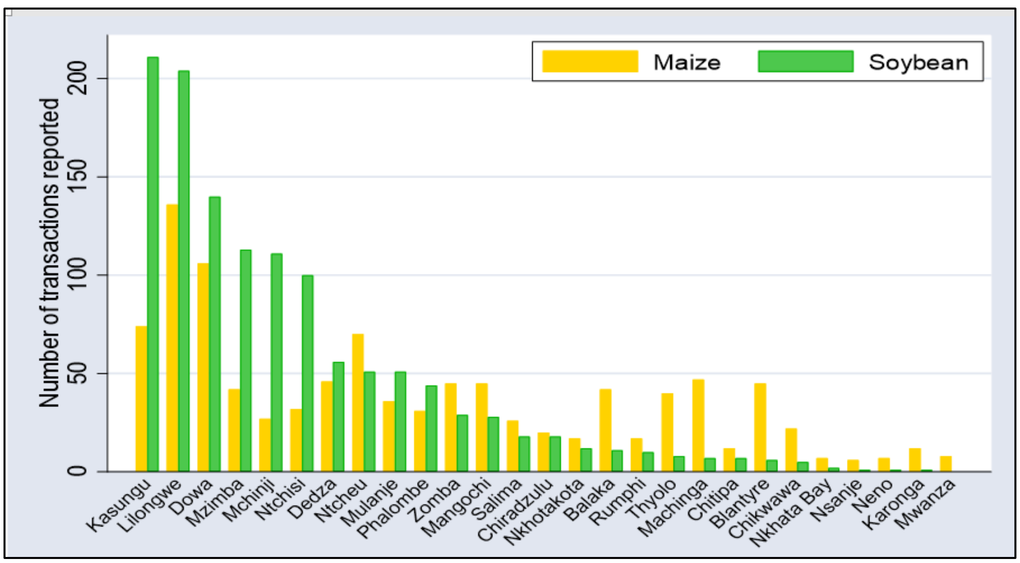


Figure 2: Number of sales reported by district (April – July 2020)

*Note: The figure indicates the number of transactions recorded within each district in Malawi over the period of data collection from April to July 2020. The bars in yellow and green indicate the total number of transactions reported to the Farm Radio Trust call center for maize and soybean, respectively.

The top panel of Table 1 shows that, in each transaction, maize farmers sold an average of 811 kg (16 bags) at MWK 151/kg, while soybean farmers sold 517 kg (10 bags) at MWK231/kg. Most of the farmers sold to assemblers, small traders and retailers (80 percent of maize and 90 percent of

[4] The maize and soybean harvest in central Malawi, where most of our crowdsourced data comes from, starts in late March/early April and runs through until late June/early July. In southern and northern Malawi, where little soybean is grown, the maize harvest starts about a month earlier and later than this, respectively.

soybean sales). Just 2 percent of maize farmers and 5 percent of soybean sellers reported sales to larger traders or processors. About 18 percent of maize farmers and 5 percent of soybean farmers reported sales to ADMARC (the Agricultural Development and Marketing Corporation), Malawi's agricultural marketing parastatal, which is expected to buy agricultural commodities from farmers at the official minimum farmgate price (MFGP). Less than one percent of farmers reported sales to other value chain actors, such as retailers and consumers. Most sales took place at local markets (41 percent for maize and 51 percent for soybeans) or on farm (around 40 percent for both crops).

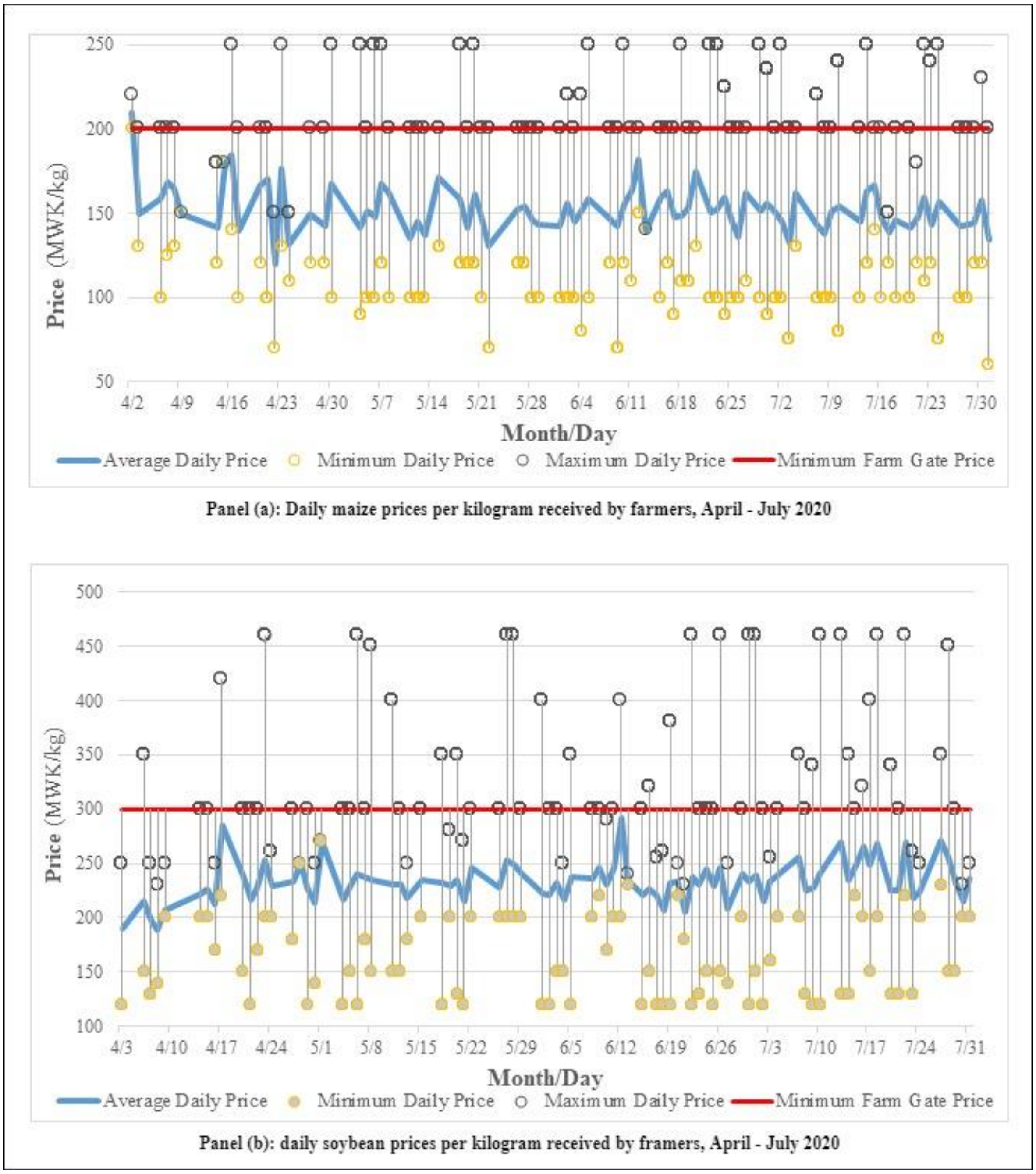
On average, farmers had about two previous transactions with the buyers and had been contacted by three potential buyers in the previous seven days. Around three-quarters of traders agreed with farmers on their assessment of crop quality. It should be noted that there are no commonly agreed quality standards set for crops in Malawi and traders mainly assess quality based on moisture content and visual appearance a common occurrence within rural markets (Prieto et al., 2021). Some 74 percent of maize farmers and 64 percent of soybean farmers were aware of the MFGP, which were MWK 200 for maize and MWK 300 for soybeans_ during the 2020 marketing season). However, when asked to state the MFGP, about 5 percent of farmers mentioned incorrect prices.

Table 1: Descriptive statistics for transactions and farmers

Variable	**Maize (n = 1018)**		**Soya (n = 1245)**	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**
Transaction and buyer characteristics				
Quantity sold (kg)	811.2	3081.6	517.5	930.7
Final sales price (MWK/kg)	151.1	36	231.6	48.1
Type of buyer				
Assembler/small trader	79.3		89.8	
ADMARC	18.2		4.5	
Large trader/processor	1.7		5.3	
Number of previous transactions with buyer	2.8	4.1	2.8	4.2
Did you agree on crop quality?	0.76	0.43	0.75	0.43
Aware of Minimum Farm Gate Price	0.74	0.42	0.64	0.38

*Note: this table presents the descriptive statistics for the crowdsourced data over the period April – July 2022. Quantity sold measured in kilograms; final sales price is Malawi Kwacha per kilogram; Yes/No questions are designated 1 = Yes, and 0 = No

Figure 2 illustrates the prices received by farmers who sold maize and soybeans during the main 2020 harvest season in panels (a) and (b) respectively. The blue line in each diagram shows the average price received by farmers (whether on their farm or in nearby assembly points and markets), while the red line shows the pan-territorial minimum farm gate price (MFG) announced by the Ministry of Agriculture and Food Security in April each year. As can be seen, with the exception of a few days, the average daily prices received by farmers for both maize and soybeans remained substantially below official MFG prices throughout the 2020 marketing season. This is confirmed in Table 2 in which it can be seen that average prices farmers received in 2020 were about 30 percent below the MFG price for maize and 23 percent below that for soybeans. The vertical lines in panels (a) and (b), Figure 2 shows the minimum and maximum price paid to farmers on each day that more than one sale was reported. On most days, the minimum price paid to farmers was much further below the MFG price than the maximum price received by farmers was above it.



Panel (a): Daily maize prices per kilogram received by farmers, April - July 2020

Panel (b): daily soybean prices per kilogram received by framers, April - July 2020

Figure 2: Daily maize and soybean prices per kilogram received by farmers, April–July 2020.

*Note: this figure presents the spread of our crowdsourced prices over the 2020 harvest season. Panel (a) indicates the prices for maize, whilst Panel (b) highlights the prices for soybean. For both panels, the blue line represents the average daily price, the red line is the 2020 harvest season's set minimum farmgate price, and the solid yellow and hallow black dots indicate minimum and maximum daily prices respectively.

The average farmer received 75 percent of the MFG price for maize and 77 percent of the MFG price for soybeans (Table 2). Almost a quarter (24.5 percent) of maize farmers received price equal to or greater than the MFG price, while a similar percentage of maize farmers received 60 percent or less of the MFG price. For soybeans, just under a tenth of farmers (9.8 percent) received prices equal to or greater than the MFG price, while the bottom tenth of farmers received 67% percent or less of the MFG price.

Table 2: Prices Received by Farmers Versus Minimum Farm Gate Price

	Mean	**Median**	**10th percentile**	**90th percentile**	**Number of Transactions**
Maize					
Price (MWK/kg)	151	140	120	200	1,018
% of MFGP	75%	70%	60%	100%	
Soybeans					
Price (MWK/kg)	231	230	200	290	1,245
% of MFGP	77%	77%	67%	97%	

*Note: this table breaks down the crowdsourced price relative to the minimum farmgate prices for the 2020 harvest season. Crowdsourced prices have been winsorized at the 99th percentile.

Table 3 further compares the characteristics of the farmers who participated in follow-up telephone survey to the crowdsourcing competition with farmers with cell phones who sold maize and soybeans in the nationally representative fifth Integrated Household Survey (IHS5) of the 2018-19. Our data shows that farmers who participated in the crowdsourcing exercise were more likely to be male, younger and have had some secondary school education than farmers who sold maize and soybeans in the IHS5. They also have farms that are almost one acre larger, cultivate larger acreages of maize and soybeans, and sold more than twice the amount of these crops during the main marketing season. The crowdsourcing survey means fall outside the 95 percent confidence intervals from the IHS5 for all variables. Nonetheless, from our crowdsourcing data-collection and subsequent data cleaning and checking, we discover no evidence that farmers of varying demographics are paid different prices for crops of the same quality sold in a particular location. As such, we do believe that the prices obtained in the crowdsourcing exercise were an accurate reflection of the prices paid to maize and soybean sellers in the main 2020 marketing season.

Table 3: Comparison of crowdsourced data with the fifth Integrated Household Survey (IHS5)

	Crowdsourced	**Survey**		**95% confidence interval**	
	Mean	**Mean**	**SE Error**	**Lower**	**Upper**
Maize Sellers					
Gender	0.9	0.81	0.17	0.78	0.84

Age (years)	36.4	42.5	0.63	41.22	43.68
Level of Education	1.66	1.46	0.02	1.42	1.5
Farm Size (acres)	3.47	2.65	0.25	2.15	3.14
Area of maize cultivated (acres)	2.04	1.54	0.05	1.45	1.64
Quantity of maize sold (kgs)	1000	419.59	47.82	325.58	513.6
Number of farmers	850	968			
Soybean Sellers					
Gender (1=Male)	0.9	0.86	0.02	0.82	0.89
Age (years)	36	42.43	0.65	41.14	43.71
Level of Education	1.62	1.39	0.2	1.35	1.44
Farm Size (acres)	3.97	2.94	0.11	2.73	3.14
Area of soybean cultivated (acres)	1.58	1.09	0.04	1	1.17
Quantity of soybeans sold (kgs)	680	305.02	27.6	250.77	359.27
Number of farmers	1080	452			

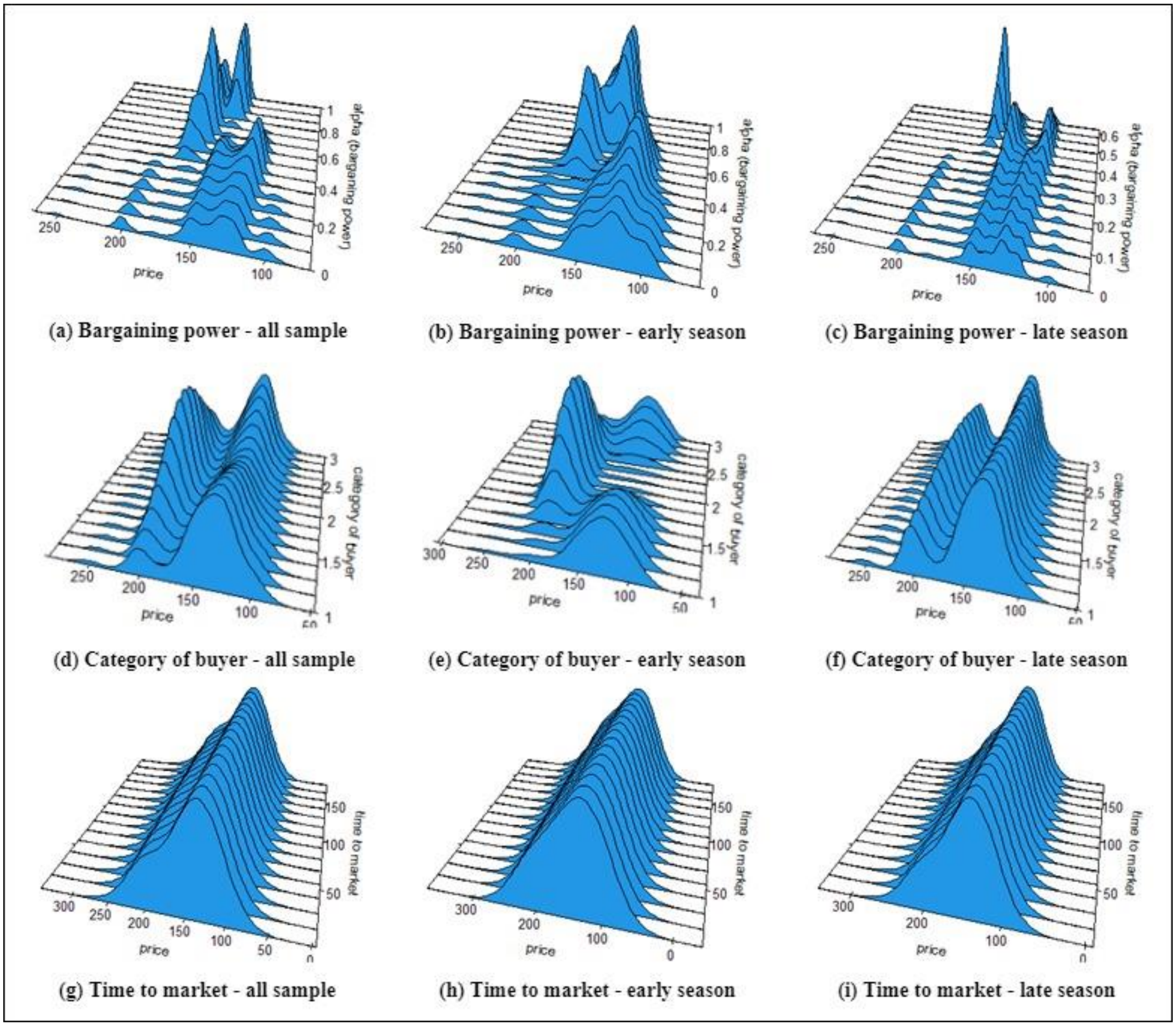
*Note: this table presents a comparison between our crowdsourced data and the average results of IHS5. Gender is measured as 1 = male, and 0 = female; age is measured in years; level of education is measured as 0 = no formal education, 1 = some primary schooling, and 2 = some secondary schooling; farm size given in acres; area of crop cultivated is measured in acres, and is for the wet season harvest; quantity of maize sold is measured in kilograms.

4.1. Maize Price Dynamics

We present estimated CDEs for maize in Figure 3, where panels (a) – (c) show the price of maize conditioned by our *alpha* measure of bargaining power, panels (d) – (f) show the price of maize conditioned against three categories of buyer, and panels (g) – (i) show the price of maize conditioned against the time to market. From panel (a) we observe that as bargaining power approaches 1, that is greater power for the buyer, the price of maize is higher. More specifically, we discern that values of *alpha* above 0.5, a potential cross-over point, there are more instances of maize being sold at higher prices. This result is relatively surprising given that the *a priori* conception would be that as bargaining power shifts to the buyer, prices would tend to be lower. This pattern of higher prices as the balance of bargaining power shifts to the buyer persists temporally as we observe this in both our early- and late-season estimations of the price and *alpha* – panels (b) and (c). Moreover, for both early- and late-season estimations, the *alpha* crossover for higher prices is still approximately 0.5. Beyond this unexpected relationship between price and bargaining power, we also are present with multimodalities within the distribution of prices of maize, especially at lower values of *alpha*. This indicates that sellers were just as likely to receive a higher price as a lower price with greater levels of seller bargaining power and vice versa. Moreover, these multimodalities in maize price and increased seller bargaining power are more persistent within late season trading.

Whilst we cannot be uncertain as to why this is the case, we do offer the following explanations. First, early season trading tends to be dominated assemblers and other small-scale traders, some of whom maybe operating as commission agents for—or financed—by larger trading companies, who do not start buying directly until later in the season. This is partly a consequence of the high moisture content of most of the maize being sold in the early season, which large traders and big institutional buyers (such as ADMARC and the National Food Reserve Agency(NFRA) are reluctant to buy directly.[5] Second, as explained below, the elongated geography with long porous borders with Mozambique and Zambia (and also Tanzania in the north) mean that conventional point space models of spatial price relations are very complicated and diverse. Furthermore, the episodic nature of government restrictions of the agricultural (in particular, maize) trade creates costs which, while not eliminating the informal cross-border maize trade, does create additional costs for small traders in the form of side-payments and trade facilitation fees which drive a wedge between Malawian, Mozambique and Zambian border prices (Edelman and Baulch, 2016). Third, the Malawian budget cycle, which until recently was based on a July-June financial year, is such that the National Budget (which includes subventions for ADMARC and the NFRA) is usually not approved by Parliament until June or July. So, in the crucial early season marketing period, the NFRA is usually unable to purchase grain while whatever grain ADMARC purchases has to be financed by short-term, costly commercial borrowing.

[5] Most maize and other crops in Malawi are sun-dried. In contrast to Eastern Africa and also South Africa, there are very few grain driers in Malawi. Use of moisture meters by all types of buyers, including the parastatal agencies, is also extremely rare.



(a) Bargaining power - all sample
(b) Bargaining power - early season
(c) Bargaining power - late season
(d) Category of buyer - all sample
(e) Category of buyer - early season
(f) Category of buyer - late season
(g) Time to market - all sample
(h) Time to market - early season
(i) Time to market - late season

Figure 3: Conditional density estimate for maize prices

*Note: this figure displays the bivariate conditional density estimates for maize using our crowdsourced data. It should be noted that in all panels, price is the response variable. Panels (a) – (c) estimate price of maize against a calculated alpha measure of bargaining power. Bargaining power is on a scale of 0 to 1 where values closer to zero indicate greater bargaining power for the seller and values closer to one indicating greater bargaining power for the buyer. Panels (d) – (f) estimate price of maize against the category of buyer where 1 = assembler, 2 = ADMARC, and 3 = large trader. Category of buyer is arranged by size in ascending order with 1 or assembler representing the smallest type of buyer, whilst 3 or large trade represents the largest type of buyer. Size is based upon the number of bags of maize bought. Panels (g) – (i) estimate price of maize against time to market, where time to market is the number of minutes taken to arrive at place of sale. Higher numbers indicate longer travel times. Panels (a), (d), and (g) are all-sample, that is data for the entire 2020 harvest period is included in the estimations. Panels (b), (e), and (h) are early harvest season estimations. We define early harvest as April – May 2020. Panels (c), (f), and (i) are late harvest season estimations. We define late harvest as June – July 2020.

Examining our CDEs for price of maize conditioned against the type of buyer we are presented once with some unexpected results. *A priori*, we would expect prices to be lower for larger-scale buyers, that is both the ADMARC and the large traders, since they possess more monopsonistic power than smaller scale assemblers. On the other hand, larger-scale buyers may possess greater economies of scale, particularly in transportation, allowing them to pay greater ability to negotiate more favorable prices. However, our estimated CDE – panel (d) – does indicate the presence of a clear bimodality of prices against the type of buyer, especially in the late marketing season., So, our results suggest that larger buyers are just as likely to pay a higher price as smaller buyers Furthermore, if we were to further detail the CDE in panel (d) we observe that smaller buyers – assemblers – are more likely to purchase at lower prices than their larger counterparts in the early season maize trade. This makes sense as ADMARC and the large commercial grain traders often wait until later in the season to start buying maize because (i) they do not want to buy 'wet' maize (i.e., with a high moisture content) and small farmers'; grain needs time to dry out after harvest, and (iii) ADMARC is not able to start purchasing grain until after the beginning of the financial year in July, and the National Budget (which include several line items for ADMARC) is approved. Indeed, in the 2020 season, ADMARC was not reported to have started buying maize from farmers until late June.

Furthermore, while ADMARC is usually mandated to buy from farmers at the minimum farmgate price set by the Ministry of Agriculture and Food Security, the divergence between market and MFGPs allows various rent-seeking activities to take place by ADMARC managers and employers, which Government has been unable to control.[6] And in years in which the substantial humanitarian relief operations are anticipated, the large commercial traders may enter the market earlier than normal in order to stockpile grain for resale to the Strategic Grain Reserve later in the season. Stockpiling of grain for later in the season was not, however, not a major motivation in the 2020 marketing season, which followed a relatively favorable rains in late 2019 and therefore a good harvest from March to May 2020. Given this, we do have to acknowledge that larger traders do pay the same price as small assemblers in early season maize trade. From panel (f) we notice that there are once again bimodalities in the price and type of buyer, whereby large buyers are just as likely to purchase maize at a higher price as small buyers are likely to purchase maize as a lower price.

Finally, our estimations of price against time to market, panel (g), we see a relatively stable relationship wherein we observe little to no change in price for any increase in distance travelled. This price pattern is fairly consistent over time, with similar CDE in both the early- and late-season, as shown in panels (h) and (i). This is confirmed by the lowess plots shown in Figure 4 – panel (a) is the plot for maize, and panel (b) the plot for soybean, from which it will be noticed that the prices paid are very similar for sales of maize on the farm/roadside, at local markets or in the larger trading centers.[7]

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[6] See, for example, the press statement made by the President of the Farmers Union of Malawi on 'The sidelining of ordinary farmers from accessing ADMARC markets' on 15th June 2020.

[7] The ADMARC price, which is meant to be pan territorial and corresponds to the official MFGP, is around a quarter to a third higher than farm/roadside, market and trading center prices. This line is shown as broken because ADMARC did not start purchasing maize from farmers until late June 2020.

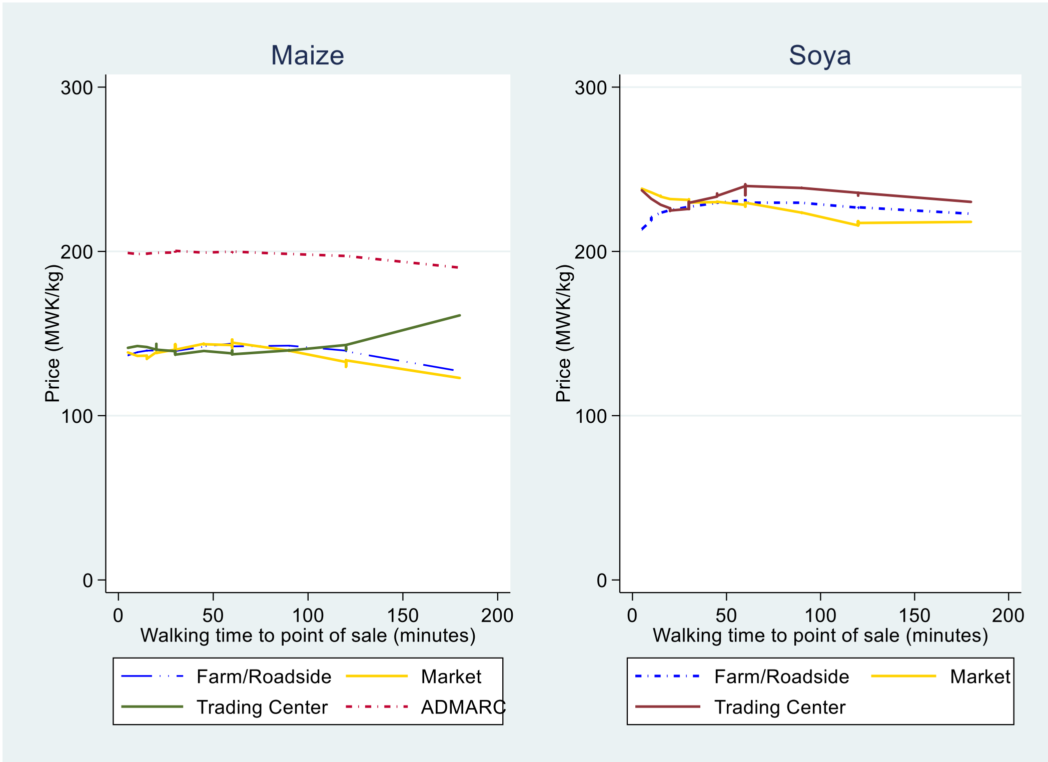

Figure 4: Non-parametric plots of price against time to point of sale

*Note: Panels (a) and (b) lowess plot for the price of maize, and soybean against time to point of sale respectively. We disaggregate the point of sale for each crop into farm/roadside, market, trading centre, and the ADMARC. It should be noted that ADMARC is not present in the panel (b) as very little soybean is bought by the Corporation. In both panels, a blue dashed line represents sales at the farm/roadside, the solid yellow line indicates market sales, solid green line is trading centra, and the broken red line is the ADMARC.

From a conventional point-space perspective, most agricultural economists would expect the prices to fall with distance to market as the buyers and sellers incorporate transportation and other transfer cost into their price. Tomek and Robinson, 2003), In addition, within season prices should rise over time in line with the cost of storage (Timmer et al.,1983; Tomek and Robinson, 2003). However, our results suggest otherwise. One explanation for this price pattern is that trading center exist in all districts of Malawi, and because it is the dominant food staple made is actively traded in all of them. Furthermore, despite the maize export ban that has been in force, almost continuously since December 2011, Malawi's borders are long and porous and there is an active informal trade in maize along most of Malawi's western border with Zambia, its northern land border with Tanzania, and also some informal trade with Mozambique in the south and east (Edelman and Baulch, 2016, Porteus, 2017). So, aside from the likely presence of monopsonistic power, the geographic dispersion and fragmentation of Malawian maize markets mitigates against conventional spatial and temporal price relationship.

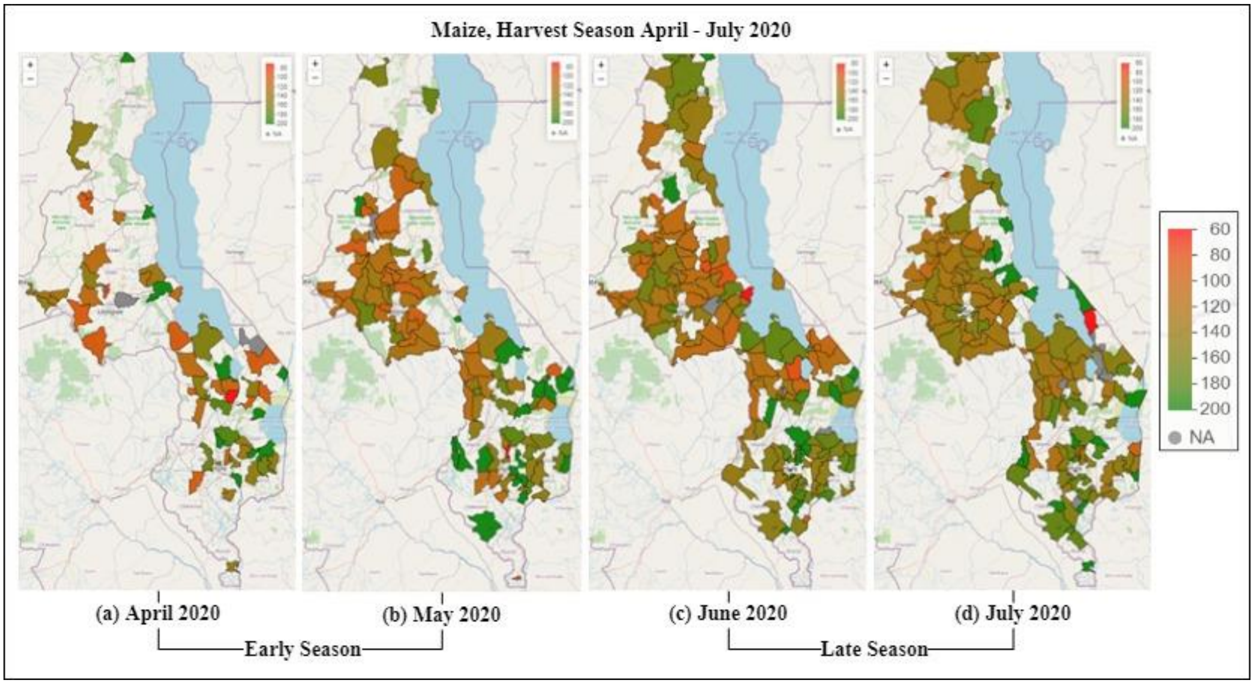

Figure 5: Spread of maize prices over the harvest period

*Note: this figure is a spatial representation of the changes in maize prices over the 2020 harvest season in Malawi. Panel (a) – (d) represent April 2020, May 2020, June 2020, and July 2020 respectively. Spatial mapping is done for all districts in Malawi except Likoma island. Regions transition from red where prices at 60MWK/kg to green where prices are 200MWK/kg

We further disaggregate our spatial and temporal argumentation in relation to geography by highlighting the price evolution of maize over the 2020 harvest season across Malawi in Figure 5, panels (a) and (b) represent the early season and panels (c) and (d) highlight late season price dynamics geographically at the traditional authority level (TA). We do observe from the mapping an increase not only in the number of buyers over the season but also progressions from red to green zones suggesting an increase in prices over time as well.

4.2. Soya Price Dynamics

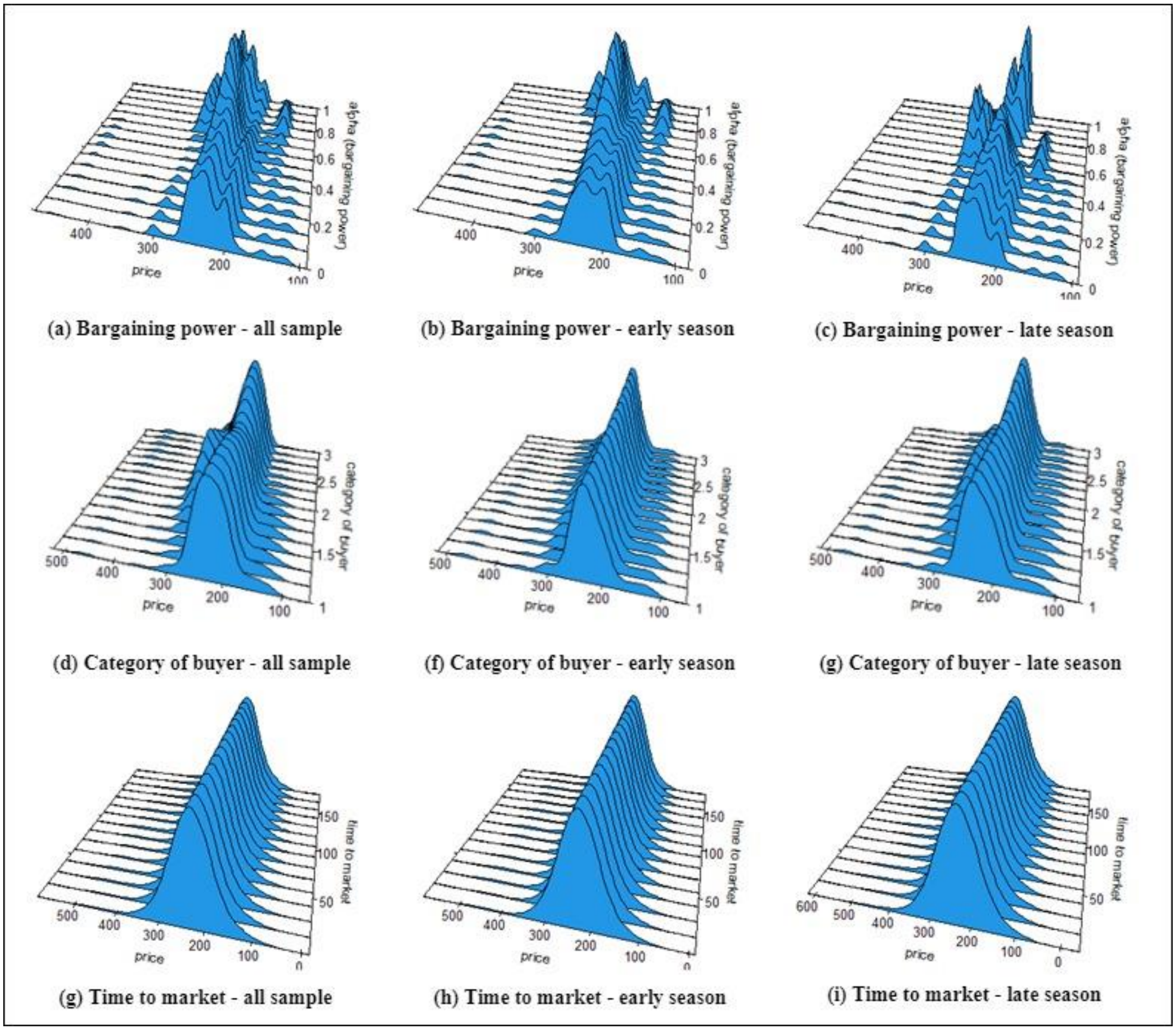

Figure 6: Conditional density estimates for soya

*Note: this figure displays the bivariate conditional density estimates for soybean using our crowdsourced data. Panels (a) – (c) estimate price of soybean against a calculated alpha measure of bargaining power. Bargaining power is on a scale of 0 to 1 where values closer to zero indicate greater bargaining power for the seller and values closer to one indicating greater bargaining power for the buyer. Panels (d) – (f) estimate price of soybean against the category of buyer where 1 = assembler, 2 = ADMARC, and 3 = large trader Category of buyer is arranged by size in ascending order with 1 or assembler representing the smallest type of buyer, whilst 3 or large trade represents the largest type of buyer. Size is based upon the number of bags of soya bought. Panels (g) – (i) estimate price of soybean against time to market, where time to market is the number of minutes taken to arrive at place of sale. Higher numbers indicate longer travel times. Panels (a), (d), and (g) are all-sample, that is data for the entire 2020 harvest period is included in the estimations. Panels (b), (e), and (h) are early harvest season estimations. We define early harvest as April – May 2020. Panels (c), (f), and (i) are late harvest season estimations. We define late harvest as June – July 2020.

The results of the CDEs for soya are presented in the Figure 6. Similarly, panels (a) – (c) is the price of soya conditioned by our *alpha* measure of bargaining power, panels (d) – (f) is the price of soya conditioned against the category of buyer, and panels (g) – (i) is the price of soya conditioned against the time to market. Examining price against bargaining power for soybeans, we observe marginally more conventional effects, in that as bargaining power move towards the buyers, we see slightly more transactions as a lower price. This is persistent for the all sample estimation in panel (a), as well as the early- and late-season estimations in panels (b) and (c). However, similar to maize, the CDEs still exhibit multimodalities, in that there is not a single steady state, point space relationship between prices and bargaining power for soybeans. regardless of respective bargaining power. This may be linked to there being four large buyers and processors of soyabeans in Malawi, two of whom are located a little north of Lilongwe, the capital, while the other two are located on the outskirts of Blantyre, Malawi second city and commercial hub, which is around five hours drive to the south. In addition, there is known to be an active cross border trade in soybean with Zambia and Zimbabwe, where there is high demand both for processed soybean and its byproduct soyacake, which is used in the manufacture of commercial animal feeds, although trade restrictions again soya exports from Malawi are frequently muted and periodically implemented (Edelman and Baulch, 2016).

Unlike maize, the CDEs – panels (d) to (g) – for soybean price against the type of buyer exhibit a relatively more unimodal distribution albeit still a relatively flat relationship in that there is not a lot of difference in price across the categories of buyers. *A priori*, we would expect prices paid to be lower for larger buyers but the results do suggest that prices remain relatively stable even when conditioned for buyer size. Once again, we cannot be certain as to why this is the case but suspect that farmers, who mostly travel to the point of sale on bicycle or by foot, are absorbing most of the transportation costs incurred in marketing their soybean.

Finally, we examine the CDEs for soybean price against time to market – panel (g) – and similar to the maize dynamics, we see do observe steady prices which do hardly vary with travel time to the point of sale. This characterization is also consistent across time with early- and late-season estimations of price against time to market demonstrating similar behavior as exhibited within panels (h) and (i). We offer a similar explanation for soybeans to that of maize above in that it is possible that farmers will absorb the cost of carry by charging a single price regardless of the distance travel. (The maps in Figure 7 show the evolution of soybean prices at the traditional authority (TA) level between April and July 2020. They show considerable spatial variation in average prices with prices generally lower in TAs far from the major trading and processing centers. As time progresses, there were also less TAs shaded in red and more TAs shaded in green, indicating a tendency for prices to rise with time, and the cost of carry, which we contend is usually absorbed by the seller given our unimodal CDE – see panels (g) to (i) Figures XXX and XXX. Interactive maps similar to these have been now made available to processors and large traders, and should prove useful in guiding their procurement decisions in the future.[8] If these larger buyers, then decide to source in the lower price TAs, this should help to drive up the prices that

[8] See: https://massp.ifpri.info/2021/06/14/interactive-heat-maps-on-crowdsourcing-exercise/.

farmers receive in these areas.[9] In the future, it may prove benefit to embed this in the National Agricultural Monitoring Information System or other web-based platforms including Facebook.[10]

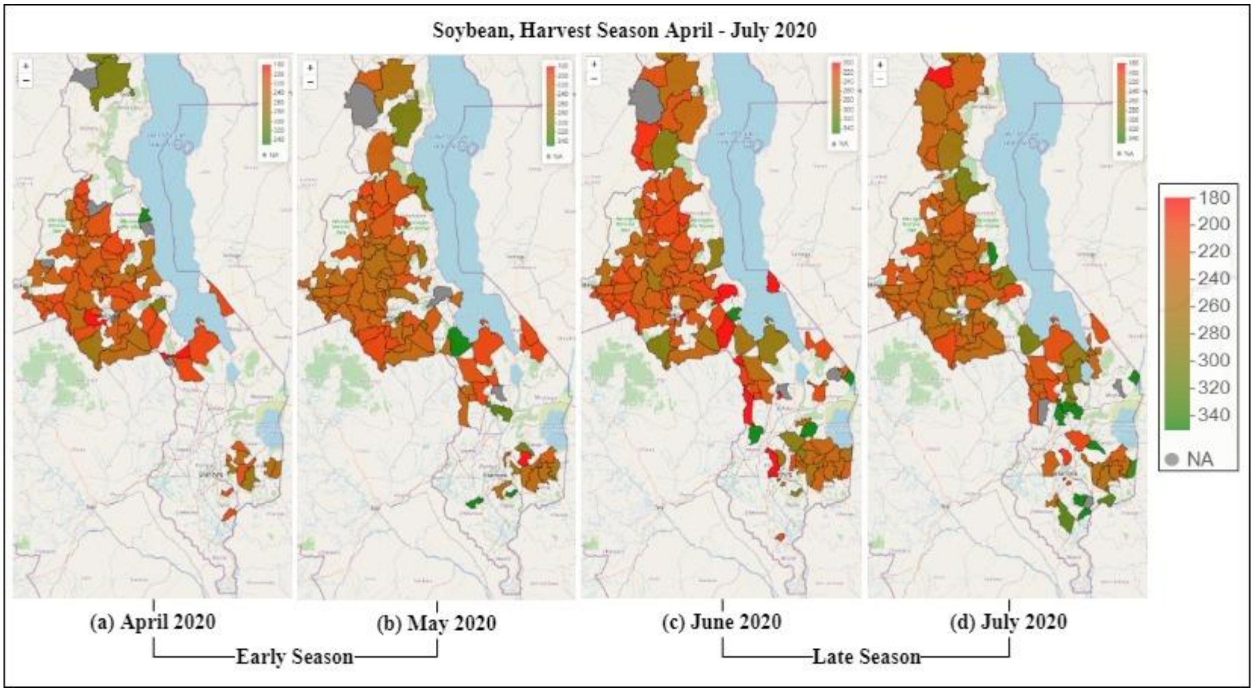

Figure 7: Spread of soybean prices over the harvest period

*Note: this figure is a spatial representation of the changes in soybean prices over the 2020 harvest season in Malawi. Panel (a) – (d) represent April 2020, May 2020, June 2020, and July 2020 respectively. Spatial mapping is done for the districts in Malawi. Regions transition from red where prices at 180MWK/kg to green where prices are 340MWK/kg

[9] In practice, processors and large traders would need to evaluate whether the lower prices in these TAs are sufficient to offset the additional costs of procuring from these locations.

[10] A Facebook platform for food prices was set-up by the World Food Programme in Malawi a few years ago but discontinued after it was discovered that most traders did not use smart phones but more basic cell phones. This may, however, be expected to change gradually over time,

Before concluding, the question of what should be done about the widespread non-observance of MFG prices should be discussed. Many commentators and policy makers instinctive reaction to these findings is that MFG prices should be enforced by the ministries of agriculture and trade, along with the Malawian Bureau of Standards and the police. IFPRI's perspective is, however, different. We would ask whether these organizations really have the capacity to enforce widespread adherence to MFG prices? We suspect not, and that the raising of penalties for non-payment of MFG prices might instead serve to deter assemblers and other small traders, while increasing rent-seeking behavior by those who are meant to be enforcing MFG prices. A better way to ensure that farmers receive higher prices for their crops is likely to be to encourage greater competition at all levels of the agricultural marketing chain.

Conclusion and Future Directions

This note has outlined a new, innovative, and relatively inexpensive method for monitoring the prices that farmers in a low-income economy are paid for their crops and the extent to which these conform to minimum farm gate prices. An application to a low-income country in southern Africa (Malawi) is presented which shows the feasibility of this crowdsourcing method in a setting in which internet connectivity is limited but mobile phone coverage is reasonable. As it does not rely on internet connectivity, our response rate in Malawi was much higher than other crowdsourcing experiments to collect food prices in Kenya, Sierra Leone and Uganda using the Knoema platform (Donmez et al., 2017). As our method only requires making payments to a small proportion of those who report prices, the cost of crowdsourcing at approximately MWK 5,550 (US$7.44) per reporting farmer is also less than the traditional system involving price collectors, while the resulting data is more complete. An additional unexpected advantage to the crowdsourcing method, its compliance with the regulations for social distancing required during the COVID-19 pandemic, become apparent during the 2020 harvest season. Put simply, the success of our data collection methodology of farmer prices via crowdsourcing does highlight the applicability of such processes in information curation over periods of exogenous shocks, especially within low-income, rural settings, wherein face-to-face processes are the norm.

Our results show that the majority of farmers in Malawi receive substantially less than the MFG prices announced each April by the Government. Only 25 percent of the farmers who reported selling maize between April and July 2020 received at least the MFG price. The corresponding figure for soybeans is just under 10 percent. Furthermore, the average farmer received just 75 percent of the MFG price for maize and 77 percent of the MFG price for soybeans. Our non-parametric conditional estimates further disaggregate the response of prices paid to farmers using several indicators of monopsonistic power. Specifically, we discover a pattern of declining prices for higher levels of buyer bargaining power that runs contrary to the *a priori* literature and suggest the presence of multiple market equilibria. Multimodalities in the conditional distribution of farmer prices is also present when estimated against types of buyers, especially for maize, where larger traders and processors are just as likely to pay a lower price as smaller assemblers.

Finally, distance to the point of sale exerts a weak effect on the prices received by farmers, suggesting that farmers- -who typically travel to the point of sale by bicycle or walking- -absorb the cost of transportation when making crop sales. The highly fragmented and diverse geography of food markets in Malawi, which is crucially conditioned by Malawi's long and porous borders with neighboring Mozambique and Zambia, must also be taken into account in understanding the spatial and temporal price patterns revealed by the crowdsourcing exercise.

Moving on to policy issues, the instinctive reaction of most farmers organizations, government officials and policy makers to our findings is that Malawi's minimum farmgate prices should be enforced more strictly, in order to protect farmers against unscrupulous traders, While public policy concerns are certainly raised by localized monopsonistic buying power that some traders have, we would argue that stricter enforcement of minimum farmgate prices, while well-intentioned, often 'backfire' by create opportunities for rent-seeking behavior by those who are meant to be enforcing these and other crop marketing regulations. Instead, we would argue that promoting competition is likely to do more in the medium to long term to raise the prices farmers receive than enforcing minimum price policies or imposing penalties on a minority traders who are observed not adhering to them.

Finally, the evolution of the prices actually paid to farmers during the main harvest season may be tracked and mapped relatively inexpensively using the crowdsourcing method proposed in theis paper. Such maps, especially if updated regularly, could prove useful to processors and larger traders in deciding where to source their supplies, and feed into Malawi's National Agricultural Monitoring Information System and market information platforms more generally. However, we are less optimistic about the use that farmers themselves would make of such information given the difficulties encountered with cell phone-based market information platforms in Kenya and other countries (Wyche & Steinfield, 2016). Weekly radio broadcasts may be a more effective way of dissemination farm gate and other crop prices in low-income countries with limited internet connectivity, such as Malawi.

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References

Abbott, J. C. (1967). Agricultural marketing boards in the developing countries. *American Journal of Agricultural Economics*, *49*(3), 705 - 722. https://doi.org/10.2307/1236903

Barrett, C. B., & Dorosh, P. A. (1996). Farmer's welfare and changing food prices: Nonparametric evidence from rice in Madagascar. *American Journal of Agricultural Economics*, *78*(3), 656 - 669. https://doi.org/10.2307/1243283

Bashtannyk, D. M., & Hyndman, R. J. (2001). Bandwidth selection for kernel conditional density estimation. *Computational Statistics & Data Analysis*, *36*(3), 279-298. https://doi.org/10.1016/S0167-9473(00)00046-3

Bates, R. H. (2014). *Markets and states in tropical Africa: The political basis of agricultural policies*. University of California Press.

Baulch, B., & Ochieng, D. O. (2020). Project note: Most Malawaian maize and soybean farmers sell below official minimum farmgate prices. https://massp.ifpri.info/2020/08/11/project-note-most-malawian-maize-and-soybean-farmers-sell-below-official-minimum-farmgate-prices/

Brabham, D. C. (2013). *Crowdsourcing*. The MIT Press.

Carletto, C. (2021). Better data, higher impact: Improving agricultural data systems for societal change. *European Review of Agricultural Economics*, *48*(4), 719 - 740. https://doi.org/10.1093/erae/jbab030

Crow, B. 1989. Plain tales from the rice trade: indications of vertical intergration in foodgrain markets in Bangladesh. *Journal of Peasant Studies*, 16(2): 198-229

Dillon, B. and Dambro, C. 2017. How competitive are crop markets in Sub-Saharan Africa. *American Journal of Agricultural Economics* 99(5): 1344-1361Donmez, A., Solano-

Hermosilla, G., Bougay, V., Subbaraman, B., M'barek, R., Santini, F., Adam, A., Bahemuka, S., Chinganya, O., Eskin, V., Kouakou, K. L., Leyeka, C., Mahjoubi, R., & Njosa, I. (2017). *Using web and mobile phone technologies to collect food market prices in Africa: Approaching real-time data and use of crowdsourcing, 2013-2016*.

EIU. (2021). *Inclusing internet index*. The Economist Intelligence Unit. Retrieved 5th November 2021 from https://theinclusiveinternet.eiu.com/explore/countries/performance

Estelles-Arolas, E., & Gonzalez-Ladron-de-Guevara, F. (2012). Towards an integrated crowdsourcing definition. *Journal of Information Science*, *38*(2), 189-200. https://doi.org/10.1177/0165551512437638

Edelman, B. and Baulch, B. 2016. Are Malawi's maize and soya trade restrictions causing more harm than good? A summary of the evidence and practical alternatives. *MaSSP Policy Note* 25, International Food Policy Research Institute, Lilongwe.

Fafchamps, M. and Hill, R. 2005. Selling at the farmgate or travelling to market. *American Journal of Agricultural Economics* 87(3): 717-734

Hariss-White, N. 1996. *A Political Economy of Agricultural Markets of South India*. New Delhi: Sage Publications.

Holtzman, J. S. (1989). Maddening myths of agricultural marketing in developing countries. *Journal of International Food & Agribusiness Marketing*, *1*(2), 55 - 62. https://doi.org/10.1300/J047v01n02_05

Howe, J. (2006). The rise of crowdsourcing. *Wired Magazine*, *14*(6), 1 - 4. https://www.wired.com/2006/06/crowds/

Hyndman, R. J., Bashtannyk, D. M., & Grunwald, G. K. (1996). Estimating and visualizing conditional densities. *Journal of Computational and Graphical Statistics*, *5*(4), 315-336. https://doi.org/10.2307/1390887

Hyndman, R. J., & Yao, Q. W. (2002). Nonparametric estimation and symmetry tests for conditional density functions. *Journal of Nonparametric Statistics*, *14*(3), 259-278. https://doi.org/10.1080/10485250212374

Jaleta, M., & Gardebroek, C. (2007). Farm-gate tomato price negotiations under asymmetric information. *Agricultural Economics*, *36*(2), 245-251. https://doi.org/10.1111/j.1574-0862.2007.00202.x

Kherallah, M., Delgado, C. L., Gabre-Madhin, E. Z., Minot, N., & Johnson, M. (2002). *Reforming agricultural markets in Africa*. John Hopkins University Press.

Li, Q., Vo, L. H., & Wu, Y. R. (2019). Intangible capital distribution in China. *Economic Systems*, *43*(2). https://doi.org/ARTN 10069810.1016/j.ecosys.2019.100698

NSO. (2020). *The Fifth Integrated Household Survey (IHS5) 2020 Report*. Zomba: National Statistical Office.

Nguyen, N. T., Nguyen, H. S., Ho, C. M., & Vo, D. H. (2021). The convergence of financial inclusion across provinces in Vietnam: A novel approach. *Plos One*, *16*(8). e025652410.1371

Nourani, V., Maertens, A., & Michelson, H. (2021). Public good provision and democracy: Evidence from an experiment with farmer groups in Malawi. *World Development*, *145*. https://doi.org/10.1016/j.worlddev.2021.105507

Ochieng, D. O. (2019). *Report on a pilot study to crowdsource farmgate prices for legumes in southern Malawi*.

Porteus, O. 2017. Empirical effects of short-term export bans: the case of African maize. *Food Policy* 71: 17-26

Prieto, S., Ricker-Gilbert, J., Bauchet, J., & Sall, M. (2021). Incomplete Information and Product Quality in Rural Markets: Evidence from an Experimental Auction for Maize in Senegal. *Economic Development and Cultural Change*. https://doi.org/10.1086/706816

Rosenblatt, M. (1956). Remarks on some nanparametric estimates of a density function. *The Annals of Mathematical Statistics*, *27*(3), 832-837. https://www.jstor.org/stable/2237390

Sitko, N . and Jayne, T. 2014. Exploitative briefcase businessmen, parasites, and other myths and legends: assembly raders and the perofmrance of maize markets in Eastern and Southern Africa. *World Development* 54: 56-67

Solano-Hermosilla, G., Barreiro-Hurle, J., Adewopo, J. B., & Gorrín-González, C. (2022). Increasing engagement in price crowdsourcing initiatives: Using nudges in Nigeria. *World Development*, *152*(105818), 1-12. https://doi.org/10.1016/j.worlddev.2022.105818

Timmer, C.P., Falcon, W., and Pearson, S. 1983. *Food Policy Analysis* Baltimore: John Hopkins University Press.

Timmer, P. (1986). *Getting Prices Right: The Scope and Limits of Agricultural Price Policy*. Cornell University Press.

Tomek, W. and Robinson K. 2003. *Agricultural Product Prices.* Fouth edition. Ithaca: Cornell University Press,

Tsakok, I. 1990. *Agricultural Price Policy: A Practioner's Guide to Particpal Equilibrium Analysis.* Ithaca: Cornell University Press.

Wyche, S., & Steinfield, C. (2016). Why don't farmers use cell phones to access market prices? Technology affordances and barriers to market information service adoption in rural

Kenya. *Information Technology for Development*, *22*(2), 320-333. https://doi.org/10.1080/02681102.2015.1048184

Zeug, H., Zeug, G., Bielski, C., Solano Hermosilla, G., & M'barek, R. 2017. *Innovative Food Price Collection in Developing Countries: Focus on Crowdsourcing in Africa*.