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Market Information and Access to Structured Markets by Small Farmers and Traders

Evidence from an action research experiment in central Malawi

Dennis O. Ochieng, Rosemary Botha, and Bob Baulch

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ABBREVIATIONS

ACE	Agricultural Commodity Exchange for Africa
ADMARC	Agricultural Development and Marketing Corporation
AHL	Auctions Holdings Limited
APES	Agricultural Production Estimates
DiD	Difference in differences
FA	Farmers Association
FE	Fixed effects
GDP	Gross Domestic Product
ITT	Intention to Treat
Kg	Kilogram
Km	Kilometer
LR	Likelihood ratio
MoAIWD	Ministry of Agriculture, Irrigation and Water Development
MWK	Malawi Kwacha
MN	Mean differences
MT	Metric ton
PSM	Propensity Score Matching
RE	Random effects

ABSTRACT

Small farmers and traders often lack the market information they need to earn the most from their crop sales. This paper analyzes the effects of an action research experiment in central Malawi, in which four groups of smallholder farmers were provided with maize and soybean price information from a local commodity exchange during the 2019 marketing season, while another four groups of smallholder farmers did not receive this information. Using data from a panel survey of 399 farmers and 78 traders conducted before and after the main marketing season, and using kernel propensity score matching approach to account for possible differences between the treated and non-treated farmers, we estimate the effects of the intervention on the outcome indicators.

We find that the share of sales through structured markets, the volume of maize sold by traders, and maize and soybean prices increased significantly after the intervention. We also find positive, though insignificant, effects on maize and soybean sales prices, sales through structured markets and levels of commercialization. However, we find negative and significant effects on the quantities of maize farmers sold, suggesting paradoxically that providing farmers with price information reduces their sales volumes.

The study concludes that provision of price information alone is not enough to facilitate small farmers' and traders' use of structured markets. Greater effort is needed to sensitize farmers and traders on the quality and quantity requirements, as well as the operations of structured markets.

Key words: price information, action research, farmers, traders, maize and soybean, structured markets, Malawi

1. INTRODUCTION

The fundamental theorem of welfare economics states that markets are Pareto efficient and competitive with free flow of information among economic agents (Makowski and Ostroy 1995). This perfect information is central to increasing market efficiency. However, there are hardly any perfect markets especially in low-income countries where cost of information search is high, and information is usually incomplete (Stigler 1961; Tack and Aker 2014). Yet improved information flow is beneficial for four reasons. First, it facilitates spatial market integration that reduces price differences across markets and increases competitiveness of buyers particularly in rural markets (Goyal 2010; Aker 2010; Shimamoto et al. 2015). Second, increased efficiency in allocating agricultural commodities across markets improves food security in low income countries (Jensen 2007; Jensen 2010; Acker 2011). Third, improved price information increases sales at higher prices which in the longer-term increases land allocation towards crops that fetch higher prices (Svensson and Yanagizawa 2009; Goyal 2010). Lastly, given that most of small farmers and traders heavily depend on agriculture for their livelihoods, increased sales increase incomes while simultaneously reducing consumer prices (Roller and Waverman 2001; Svensson and Drott 2010). Hence, improving access to information by small farmers and traders is central to improving food production and marketing.

In Malawi, small farmers and traders dominate production and marketing of food crops, such as maize and soybean (Ochieng et al. 2019). Maize and soybean are mainly marketed locally with occasional informal exports to neighboring countries. However, there has been a policy push towards the development of trading for the two commodities through structured markets. Structured markets are organized platforms where economic agents such as farmers, traders, processors and financial institutions enter transparent and legal trading and financial arrangements (East Africa Grain Council 2013). Notable structured markets in Malawi are the commodity exchanges and warehouse receipt systems (WRS). Malawi has two commodity exchanges: Agricultural Commodity Exchange for Africa (ACE) and Auction Holdings Limited Commodity Exchange (AHL), established in 2006 and 2013, respectively. In addition, two warehouse receipt systems (WRS) plus a parallel system of direct collateral financing by the commercial banks exist (Baulch et a. 2018). Maize and soybean contribute a substantial share to volumes traded at the two exchanges. As of 2016, maize and soybean contributed about 70 percent and 12 percent of volumes traded by ACE, respectively. Maize contributed 96 percent and soybean 2 percent of volumes traded by AHL during the same period (Baulch and Gondwe 2017). The volumes of soybean traded by both the exchanges have increased significantly in 2017, accounting for about 57 percent of volumes traded (Baulch et al. 2018).

Other structured markets in Malawi include auctions for tobacco and tea and direct contracts with exporters. In this study, we consider structured markets to include sales arrangements with millers, brewers, warehouse operator/food suppliers, ADMARC, institutions (schools, hospitals, etc.), international development agencies, and non-governmental organizations.

Structured markets are important for the stabilization of commodity volumes and prices in an economy (Rashid 2014). Such markets can help diversify foreign exchange earnings from maize and soybean as well as other cereals and legumes in a country, but so far only Malawi's tobacco industry has a thriving structured market supported through export mandates (Edelman et al. 2014). Supported by export mandates, structured markets for cereals and legumes could also limit informal cross-border trade and increase agricultural exports thereby increasing the gross domestic product (GDP) of the agriculture sector (Government of Malawi 2016). Structured markets could potentially also provide better statistics on volumes traded to aid in the planning, production, and marketing of staples in Malawi (Baulch and Gondwe 2017).

Despite the existence of such structured markets in Malawi, use of them by small farmers and traders remains limited. Previous studies document that low volumes traded by small farmers and traders as well as low levels of awareness among them of the existence of commodity exchanges are the main reasons for limited access (Baulch et al. 2018; Ochieng et al. 2019). It is paradoxical that small farmers and traders often cite lack of markets as a major problem in marketing maize and soybean in Malawi while the existing commodity exchanges operate at suboptimal levels due to lack of enough volumes of these commodities. The exchanges are mainly used by large traders and processors to procure grains for export, storage and processing, and only few small farmers access the exchanges through their farmers associations (Baulch et al. 2018).

Small farmers and traders often lack the market information they need to earn the most from their crop sales. The question is whether improving access to price information increases small farmers' and traders' access to structured markets. Further, it is not known whether providing price information increases volumes sold through structured markets, sales prices, and farmers' levels of commercialization of the marketed commodities.

In this paper, we address these questions through an action research experiment in which four groups of small farmers and traders were provided with information on maize and soybean prices on the ACE trading platform, while another four groups of farmers did not receive the price information. Our expectation was that better price information would trigger increased sales through commodity exchanges and other structured markets, sales at higher prices and levels of commercialization of maize and soybean by farmers in the intervention group.

The rest of the paper is organized as follows: The next section details the methodology used, the study area, data collection, and empirical strategy. Section 3 discusses the study findings while section 4 concludes.

2. METHODOLOGY

2.1. Approach

The underpinnings of this study lie in the action research agenda, pioneered by Lewin (1946) in the mid-1940s, and subsequently built upon by Heron (1971), Freire (1973), and Chambers (1997).[1] An action research experiment occupies the middle-ground between an observation study and a randomized control trial (Argyris and Schön 1997). An action research experiment is not a pure observation study because some units of observations (farmers, people, households, communities, etc.) are assigned to an intervention group while others are not. At the same time, it is not a pure, or even a clustered randomized control trial, because sample selection is not random as the intervention group was purposively selected. In addition, action research experiments usually have an insufficient number of observations to conduct formal statistical tests of the differences in outcomes between the intervention and control groups, although comparisons between groups are both possible and informative. Nonetheless, for some action research studies including this one, comparisons between the intervention and control

[1] Some people would also include 'action science' (Argyris 1970), living educational theory (Barry 2012) and rational social management (Lewin 1946) in the category of action research.

groups based on households with similar initial characteristics are possible using the matching procedures first proposed by Rosenbaum and Rubin (1983).

The intervention considered here was in the form providing better information to farmers. This was done via mobile phone text messages of maize and soybean prices on the ACE trading platform. Our expectation was that this information would lead to increased sales, better selling prices and more use of structured markets. We first conducted a baseline survey to assess the status quo of farmers and traders before rolling out the intervention, and then an endline survey to assess any changes that had occurred after the intervention.

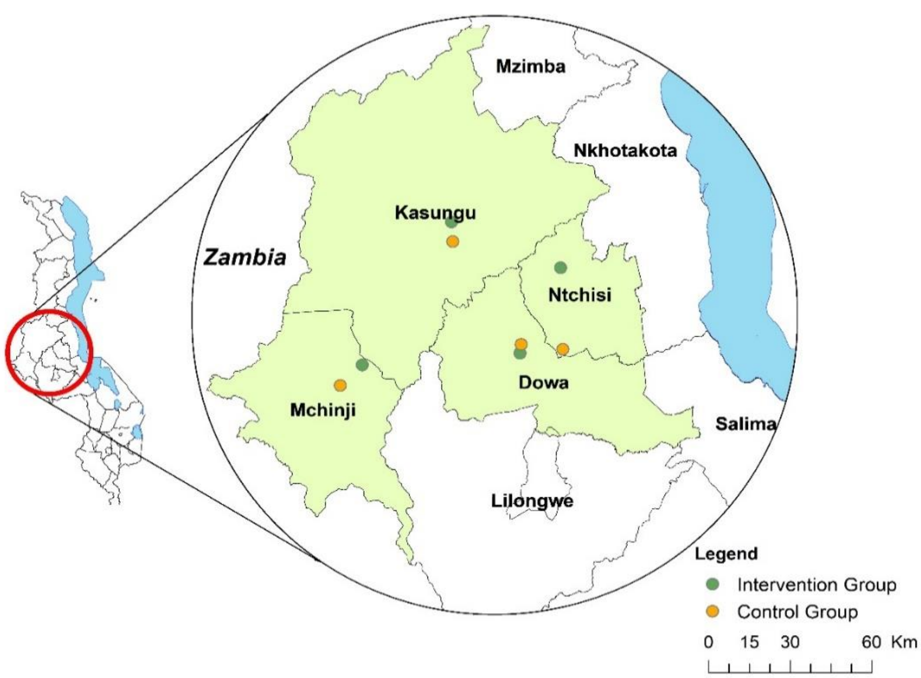
Both traders and treated farmers received price information throughout the main harvest marketing season (April – September) with subsequent bi-monthly follow-up surveys on their sales activities. This was done to reduce the recall period and increase the level of accuracy of sales data captured.

2.2. Study area

Malawi is a land-locked country in southeastern Africa, bordering Zambia, Tanzania, and Mozambique. Malawi's economy largely depends on agriculture, which contributes 30 percent of the GDP and about 80 percent of national export earnings (World Bank 2019). More than 84 percent of Malawi's population lives in rural areas and largely relies on agriculture as the main source of livelihood (Dabalen et al. 2017). About 88 percent of the population is employed in agriculture (World Bank 2019).

This study was conducted in Mchinji, Ntchisi, Dowa, and Kasungu districts in central Malawi (Figure 1). The selected districts are similar in terms of socio-economic settings, agroecology, farming systems and infrastructure. Therefore, comparisons of household welfare indicators are possible. All the four districts are accessible from the capital within two hours by road.

Figure 1. Sampled districts



Source: Authors' construction (2019).

2.3. Sampling procedure

We employed a multistage sampling procedure to sample the study areas, smallholder farmers and traders. The four districts were purposively chosen because of their contribution to the national maize and soybean output, as compared to other districts according to the agricultural production estimates (APES) by the Ministry of Agriculture, Irrigation and Water Development (MoAIWD 2019). In each district, we purposively selected two farmers associations (FA), and assigned one FA that was closer to an ACE warehouse to the intervention group and another that was farther away from the ACE warehouse to the non-intervention (control) group.

All FAs were aggregating maize and soybean but had not yet sold any agricultural commodity through ACE or AHL. Small farmers were randomly sampled from a list of FA members. Small farmers referred to those who cultivated an average of 5 acres and below. At least 100 farmers were interviewed from each district, with 50 farmers receiving the intervention (the treated group) and 50 not receiving it (the non-treated group). The study also aimed to randomly sample 20 traders from each district and the same localities as the farmers. This number was too small to assign traders to treatment and control groups. Hence, all 78 traders were treated. Besides, the trader interviews aimed to validate the findings from farm household surveys and not to analyze the causal effects of providing traders with price information.

The baseline sample for the study surveyed a total of 416 (204 treated and 212 non-treated) farmers and 78 traders in March 2019 while the endline sample in September 2019 included 399 (204 treated and 195 non-treated) farmers and 68 traders. Attrition was therefore small.

2.4. Data

The study uses data from two rounds of farm household and trader surveys. Using semi-structured questionnaires, a baseline survey was conducted between March and April 2019 and retrospectively collected data on the 2017/18 agricultural season. Afterwards, the study team conducted fortnightly follow-up visits with farmers and traders to collect data on sales of the two commodities throughout the 2019 main harvest marketing season (April to September 2019). An endline survey was conducted to triangulate the data collected and for an *ex post* assessment of the impact of the intervention and the marketing environment of maize and soybean in general.

The questionnaires consisted of several modules that captured: (1) household socio-economic characteristics; (2) general farm production (crop and livestock) and marketing activities; (3) geospatial profiles; and (4) food security and nutrition characteristics. The trader questionnaire captured traders' socio-economic characteristics and trading activities. A separate section in both questionnaires captured data on: (1) access to market and price information for maize and soybean; (2) long term storage facilities; and (3) structured markets such as WRS, commodity exchanges and e-auctions.

2.5. Empirical strategy

We are interested in estimating the impact of access to price information on sales of farmers and traders by comparing the three outcomes (indicators) of interest for the treated group with potential outcomes without treatment. We hypothesize that providing price information to farmers and traders translates to: (1) increased awareness of the commodity exchanges operations; (2) greater shares of output sold (commercialization level); and (3) greater sales through structured markets.

Since we observed the respondents both before and after the intervention, we estimate the Intention-to-Treat (ITT) effects (δ) using mean differences (MN) and a pooled difference-in-differences estimator (DiD) using both baseline and endline data. A tobit model is used in the case of censored dependent variables and linear probability models for binary dependent variables.

We begin with the mean differences to estimate the ITT effect for farmer ***i*** from district ***d***

$$y_{id} = \alpha + \delta_{MN} H_i + \beta \boldsymbol{X}_{id} + \mu_d + \varepsilon_{id} \tag{1}$$

Where y_{id} refers to the observed outcomes of interest; δ_{MN} is the coefficient of the treatment assignment H_i (=1 if farmer receives market information, 0 otherwise) which is of interest; β is a vector of parameters related to farmer characteristics; $\boldsymbol{X}_{id}$ is a matrix of farmer characteristics**;** μ_d is the district fixed-effects that controls for any differences across the four districts; and ε_{id} is the error term.

The pooled DiD estimator for farmers in time *t* is:

$$y_{id} = \alpha + \omega H_i + \varphi P_t + \delta_{DiD} P_t * H_i + \beta \boldsymbol{X}_{id} + \mu_d + \varepsilon_{idt} \tag{2}$$

where P_t is the time fixed-effect (1=follow up; 0=Baseline); $P_t * H_i$ is the interaction of treatment and time whose coefficient δ_{DiD} is the ITT. The estimation eliminates the time-invariant unobserved heterogeneity of the farmers (Wooldridge 2010).

Considering the panel structure of the data and the time invariant nature of some variables of interest, a fixed effects (FE) estimator could not be used. For household data, balance tests indicated imperfect balance for some of the covariates of interest, such as farm size (as highlighted in Table 1 in the next section). Hence, we estimated the models using a kernel propensity score matching (PSM) approach with repeated cross-sections to reduce possible sample selection biases while also clustering the standard errors (Papke and Wooldridge 1996).

For the traders' survey, all traders were provided with price information and there was no control group. Hence, the analysis simply involved comparing the indicators of interest before and after the intervention along with mean differences between the two time periods.

We checked if the treatment effects remained significant if we assumed a perfect balance between the covariates of the intervention and control group. Based on likelihood ratio (LR) tests, we established that a pooled logit was more appropriate than a random effects (RE) model as a DiD estimator of the treatment effects on the awareness level of farmers. However, a RE estimator was more appropriate to estimate the effects on sales and sales price. A RE Tobit was therefore used to estimate the treatment effects on quantities sold and sales price because these outcome variables are censored and cannot be negative. Level of commercialization was captured as a bounded fraction between 0 and 1. Hence, a fractional logit was the most appropriate method for estimating the treatment effects on commercialization. As a robustness check, we also estimate the ITT effects using mean difference estimator. The results are shown in the appendix (Table A 1. and A 2.).

3. RESULTS AND DISCUSSION

3.1. Farm household survey findings

3.1.1. Descriptive statistic of farmers

Table 1 presents the descriptive statistics of the farm households interviewed in the baseline survey. The first column shows the statistics for the full sample, while columns 2 and 3 show the statistics for the treated and non-treated farmers. The last column shows the test results for the differences between the two groups. About 80 percent of the farm household heads were men. The mean age of household heads was 47 years with about 6.5 years of formal schooling. Even though the average household comprised five members, the dependency ratio was generally high (32 percent) for both the treated and control households. The average farm size was about 3.8 acres but the level of crop diversity among sampled farmers was minimal as sampled farmers grew only about three crops on their farms.

In terms of market access, the average distance from dwelling place to the nearest market was about 4.8 kilometers (km) while the average distance to the nearest warehouse that stores agricultural commodities was about 1.7 km. The average level of commercialization, defined as the ratio of sales to harvest, was 16 percent for maize and 77 percent for soybean. About 64 percent of the farmers were able to sell whenever they wanted to, indicating that markets for both maize and soybean were not readily available to approximately one-third of all farmers. About 55 percent of farmers were aware about the existence of commodity exchanges in Malawi. The average quantities of maize and soybeans sold at baseline were 285 kg and 899 kg while average selling prices were MWK127/kg and MWK210/kg, respectively. The average annual household income was about Malawi Kwachas (MWK) 413,000 and about 41 percent of the households had off-farm incomes.

Notably, the group mean differences in most of the important indicators of market access, such as distance to markets and warehouses plus availability of markets for the two commodities, were not statistically significant from zero. Hence, in terms of market access the two groups are comparable, which facilitates estimation of the effects of the intervention. However, farm size and the quantity and price of soybeans sold were significantly higher in the intervention group.

Table 1. Baseline profile of farmers and balance tests

Variable	Description	Full sample	Treated	Control	Mean difference (Control-Treated)
Age of head	Years of age	47.38 (13.79)	46.68 (13.90)	48.08 (13.67)	1.39
Gender of head	Dummy variable: 0 = female, 1 = male	0.80 (0.01)	0.79 (0.40)	0.81 (0.39)	0.01
Education of head	Years of schooling	6.50 (3.60)	6.82 (3.51)	6.18 (3.66)	-0.64**
Family size	Number of household members	5.37 (1.95)	5.49 (1.92)	5.25 (1.98)	-0.24*
Dependency ratio	Number of household members aged <=14 and > 64 /number aged 15–64 years old	0.32 (0.21)	0.33 (0.19)	0.31 (0.22)	-0.02
Farm size	Size of farms (acres)	3.76 (4.01)	4.29 (4.99)	3.22 (2.55)	-1.07***
Number of crops	Number of crops grown	2.92 (0.03)	2.97 (0.05)	2.87 (0.04)	-0.09
Distance_market	Distance to the nearest market (kilometers)	4.83 (5.30)	4.57 (4.57)	5.10 (5.92)	0.53
Distance_whse	Distance to the nearest warehouse (kilometers)	1.68 (3.12)	1.85 (3.59)	1.50 (2.57)	-0.35
Off-farm income (dummy)	Dummy variable: 1 = household had off-farm income; 0 = otherwise	0.41 (0.49)	0.39 (0.49)	0.44 (0.49)	0.05
Household income	Annual household income ('000'MWK)	413.14 (926.78)	448.81 (941.87)	377.04 (910.98)	-71.76
Market availability	=1 if farmers can sell all the maize and soybean, they wish to sell	0.64 (0.02)	0.64 (0.02)	0.64 (0.02)	-0.00
Maize sold	Quantity of maize sold (kg)	284.63 (25.38)	291.87 (41.81)	277.29 (28.60)	-14.58
Soybean sold	Quantity of soybean sold (kg)	897.92 (23.16)	530.03 (41.86)	256.14 (13.59)	-273.90***
Maize selling price	Average selling price for maize (MWK/kg)	126.83 (1.89)	128.47 (2.75)	125.11 (2.58)	-3.37
Soybean selling price	Average selling price for soybean (MWK/kg)	209.51 (2.28)	217.89 (3.21)	200.32 (3.15)	-17.57***
Commercialization level	Ratio of quantity of maize sold to quantities harvested	0.16 (0.20)	0.16 (0.20)	0.16 (0.20)	-0.00
	Ratio of quantity of soybean sold to quantities harvested	0.77 (0.23)	0.80 (0.21)	0.74 (0.24)	-0.06***

Source: IFPRI baseline survey (2019.) **Note:** Observations from all two survey rounds were pooled; MWK = Malawi Kwacha; Kg = Kilogram; Mean values are shown with standard deviations in (parentheses); *p<0.1, **p<0.05, ***p<0.01.

Table 2 presents a summary of ratios of farmers who accessed market information and the type of market information they lacked. Column 1 presents the overall sample statistic that combines both treated and control farmers while columns 2 and 3 provide summaries for individual groups. Columns 4 and 5 present pooled summaries for baseline and endline surveys while column 6 presents the differences between endline and baseline values at 1 percent level. Overall, about 60 percent of the farmers accessed market information. The proportion of treated farmers who accessed market information was 13 percent higher than the one for control farmers. Of the three types of market information farmers lacked, information on market opportunities was the most cited (76 percent), followed by information on prices (66 percent) and quality standards (38 percent). Access to these types of information seemed to have improved between baseline and endline periods, as indicated by the significant differences in the proportion of farmers that reported lacking information across the two periods.

Table 2. Farmer's access to market information

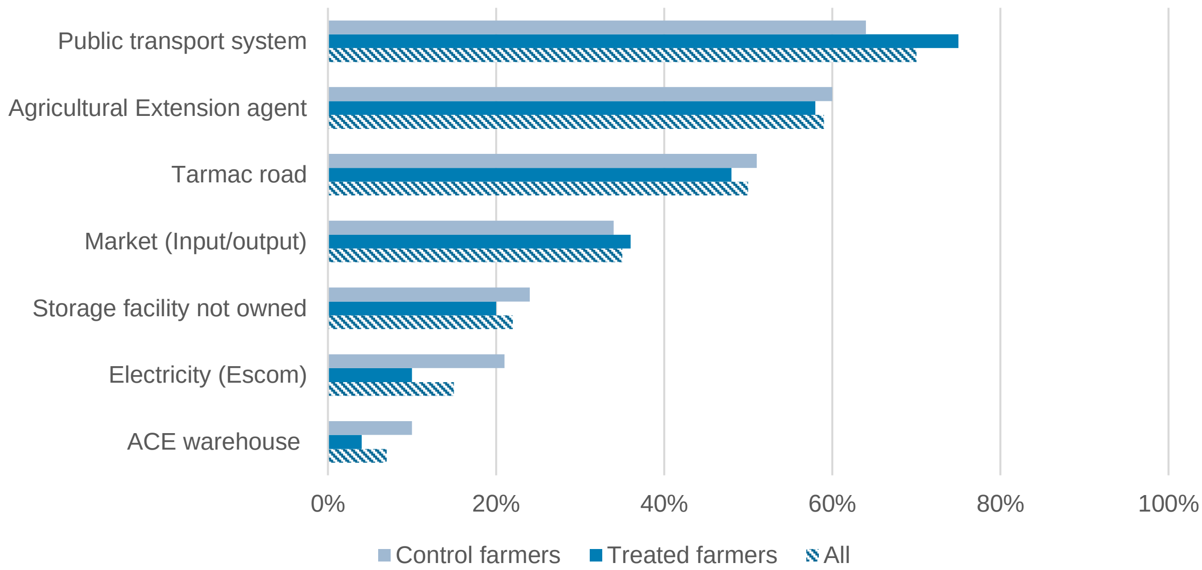
Type of information	All (1)	Treated farmers (2)	Control farmers (3)	Baseline (4)	Endline (5)	Difference (6)
Access to market information	60%	67%	54%			
Lacking information on…						
Market opportunities	76%	70%	82%	93%	46%	-47***
Market prices	66%	59%	73%	84%	34%	-50***
Quality standards	38%	38%	38%	57%	19%	-38***

Source: IFPRI baseline survey (2019).

Note: *** mean differences between endline and baseline are statistically significant at the 1% level.

Figure 2 provides an overview of the enabling environment in terms of access to infrastructure. Farmers were asked about availability of various infrastructure in the village. Public transport was available to most farmers (70 percent). About 60 percent of the farmers could access the local agricultural extension agent. Even though one half of the farmers had access to tarmac roads, access to markets was limited for both treated and control farmers with only about 30 percent having markets within their localities. Other infrastructure such as electricity and long-term storage facilities were also not available to many farmers.

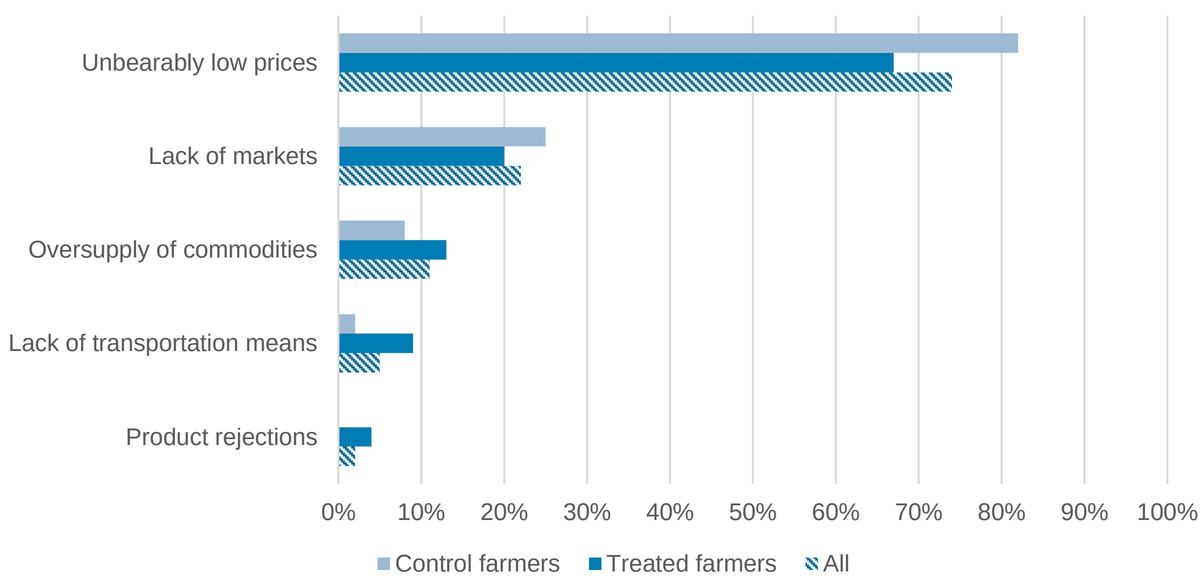
Figure 2: Access to infrastructure in the village (% yes)



Source: IFPRI baseline survey (2019).

Figure 3 presents the maize and soybean marketing challenges listed by farmers. The most cited challenge was 'unbearably low' prices (74 percent), which did not cover the production costs. This was followed by lack of markets mentioned by at least 20 percent of both treated and control farmers. Other cited challenges included oversupply of the two commodities in the market that led to price falls, lack of transportation means and product rejection by buyers due to quality concerns.

Figure 3. Marketing challenges (% yes)



Source: IFPRI baseline survey (2019).

3.1.2. Empirical results for farmers

This section presents the kernel propensity score matching estimates of the treatment effects of providing price information on: (1) maize and soybean sales; (2) sales price; (3) level of commercialization; and (4) sales through structured markets. For each of the tables, the first four rows are for maize while the rest are for soybean. All discussions are based on the kernel PSM estimates. We find significant treatment effects on maize sales but not maize sales price, levels of commercialization and sales through structured markets. All the kernel PSM estimates for soybean were statistically insignificant. Other insignificant kernel PSM estimates of the treatment effects on sales through structured markets and level of commercialization are presented in the appendix together with the MN and other ITT estimates.

Effects of the intervention on farmers

Table 3 presents the results on effects of the intervention on maize and soybean sales and sales prices received by farmers, while Table 4 shows its effects on their access to structured markets and level of commercialization. In general, the coefficients in these tables are not statistically significant from zero at the 5 or 10 percent levels. This is largely a function of the relatively small number of farmers associations in the intervention and control groups.[2] This is a common issue with action research experiments, as by their very nature it is difficult to implement such experiments at scale. However, we found a negative and significant treatment effect on the quantity of maize sold at the percent level, suggesting, paradoxically, that providing farmers with better price information reduced volumes sold by 156.3 kg. The coefficient on the soybean sales prices is also statistically different from zero after the intervention, suggesting that prices that intervention farmers received may have been around MWK 16.5 per kg higher than the control group although the treatment effect is not itself statistically significant from zero at the 10 percent level.

The negative and statistically significant effect of the intervention on farmers' sales of maize deserves further comment. At first sight, these results seem counter-intuitive, as it suggests that farmers who received the treatment (better price information) sold less maize than those who did not. However, this is predicated on the assumption that members of farmers' associations aim to maximize their sales of maize, which may not be correct, if the farmers also have food security or safety-first objectives. The agricultural economics literature states that farmers allocate endowments according to neo-classical profit maximization rules where producers have perfect information (knowledge) of market conditions and the only constraint they face are fixed resources (Schultz 1964; Hopper 1965). However, this is normally not the case because smallholder farmers are risk averse, and may desire to ensure that their families are fed before they maximize their net incomes (Ghatak and Ingersent 1995). Small farmers therefore maximize utility by trading-off lower risk against higher profits (Lipton 1968; Wolgin 1975; Ellis 1993). This literature is relevant in our case, as maize and soybean marketing risks are high in Malawi due to numerous market, price and production uncertainties (Edelman and Baulch 2016; Ochieng et al. 2019). Hence, the paradoxical negative impact of the intervention on maize sales is not surprising for the two main reasons. First, even though the treated farmers could have become allocatively (price) efficient from the intervention, their risk aversion combined with other production constraints (unaffordability of commercial fertilizer, unavailability of quality seeds, etc.) behavior could have led to lower maize sales and retention of surpluses for household food security reasons. Second, a positive

[2] Note that the original design of the action research experiment was for 16 clusters (farmers associations), eight of which would receive the intervention and eight of which would be controls. However, for both logistical and budget considerations, ACE was unable to locate the requisite number of farmers associations in the four districts considered here.

(though statistically insignificant impact) of the intervention on sales prices could have triggered a wait-and-see attitude among farmers hoping for better prices in the future, which reduced sales volumes.[3]

Table 3. Treatment effects on volumes sold and sales price of maize and soybean

	Sales			Sales price		
	Before	**After**	**DiD**	**Before**	**After**	**DiD**
Maize						
Coefficient	87.80	-68.5	-156.3**	2.86	9.32	6.46
Standard error	95.89	81.97	50.10	6.78	9.25	13.53
Observations	391	407	797	214	220	434
Soybean						
Coefficient	281.80	226.8	-55.02	9.78	26.33*	16.54
Standard error	183.94	200.5	59.76	16.21	13.14	11.05
Observations	380	371	751	357	353	710

Source: IFPRI surveys (2019).

Note: DiD = difference-in-differences estimates; Before = before the intervention; After = after the intervention; Means and standard errors are estimated by linear regressions.

On reflection, the positive but insignificant effects of the intervention on sales through structured markets and the level of commercial are also not surprising. Several existing empirical studies in other developing countries show insignificant or mixed effects of improving market information on farmers or traders market participation in Malawi (Chikuni and Kilima 2019); Ethiopia (Tadesse and Bahiigwa 2015), Niger (Aker and Ksoll 2017); and even India (Fafchamps and Minten 2012).[4] It has also been argued that provision of market or price information may only have significant effect on prices of perishable commodities, such as bananas in the case of Uganda. (Muto and Yamano 2009).

[3] Robustness tests showed that the treatment effects remain significant for the RE Tobit model even though the magnitude of the effects was higher than for the main model (Kernel PSM) as shown in Table A 1. in the appendix.

[4] See Nakasone et al. (2014) for a review of the mixed impacts of mobile phone on agricultural performance at the macro and micro-levels.

Table 4. Treatment effects on sales through structured markets and levels of commercialization

	Sales through structured markets			Commercialization rate		
	Before	After	DiD	Before	After	DiD
Maize						
Coefficient	0.04	0.03	-0.02	0.03	-0.01	-0.04
Standard error	0.04	0.03	0.01	0.05	0.03	0.04
Observations	408	389	797	406	389	795
Soybean						
Coefficient	0.07	0.18	0.11	0.07	0.04	-0.03
Standard error	0.04	0.16	0.17	0.04	0.07	0.06
Observations	408	389	797	370	368	738

Source: IFPRI surveys (2019).

Notes: DiD = difference-in-difference estimates; Before = before the intervention; after = After the intervention; Means and standard errors are estimated by linear regressions.

3.2. Trader survey findings

3.2.1. Descriptive statistics of traders

Table 5 presents a summary of traders' profiles and trade characteristics. On average, traders were 37 years old and the majority were men (95 percent). The sampled traders had about 11 years of formal schooling and at least 7 years of experience in trading maize or soybean, which was the main source of income for 68 percent of traders. Collective marketing by traders was minimal as only 4 percent of the traders were members of any organization marketing either of the commodities. In terms of resources, traders employed about five paid and two unpaid employees on average. At least 60 percent of the traders were close (about 2.6 km away) to an agricultural commodities warehouse where they could store maize or soybean. The average capacity of warehouses owned by traders was 19.6 metric tons (MT).

Traders seemed to have limited access to structured markets, given that only 1 percent sold maize through commodity exchange and none of the traders sold soybean through this channel. About 23 percent and 21 percent of traders sold maize and soybean under contracts, respectively. Only 15 percent and 4 percent of maize and soybean sales were made through competitive tenders, respectively. Further, only 4 percent of t traders used a warehouse receipt system. The average trader traded in maize and soybean for about 10 and 6 months in a year, respectively. The volume of maize sold during the 2019 main harvest marketing season was 7 percent higher than in 2018 and 63 percent lower for soybean in the same period.

Table 5. Profile of traders and trade characteristics (N=78)

Variable	Mean
Age of trader (years)	36.54 (7.75)
Male trader (% yes)	0.95 (0.22)
Years of schooling of trader	10.46 (2.65)
Years of experience in maize trade	7.26 (3.70)
Years of experience in soybean trade	7.00 (3.73)
Maize or soybean trade as primary source of income (% yes)	0.68 (0.47)
Member of a maize/soybean marketing organization (%yes)	0.04 (0.20)
Number of paid employees	4.53 (8.78)
Number of unpaid employees	1.56 (2.69)
Availability of warehouse (% yes)	0.60 (0.49)
Distance to warehouse (km)	2.56 (2.54)
Capacity of long-term storage facility owned (MT)	19.63 (131.21)
Maize sales through commodity exchanges (% yes)	0.01 (0.02)
Soybean sales through commodity exchanges (% yes)	0.00 (0.00)
Experience with maize contracts (%yes)	0.23 (0.42)
Experience with soybean contracts (%yes)	0.21 (0.41)
Experience with maize competitive tenders (%yes)	0.15 (0.36)
Experience with soybean competitive tenders (%yes)	0.04 (0.20)
Experience with warehouse receipt system (%yes)	0.04 (0.20)
Maize purchases (# of months)	10.03 (2.71)
Soybean purchases (# of months)	6.03 (3.87)
Average quantity of maize sold in Kilograms (April - September 2019)	215.47 (520.04)
Average quantity of soybean sold in kilograms (April - September 2019)	90.89 (300.35)
Average quantity of maize sold in kilograms (April - September 2018)	200.34 (300.35)
Average quantity of soybean sold in kilograms (April - September 2018)	246.96 (905.59)

Source: IFPRI baseline survey (2019).

Note: MT = metric ton; Km = kilometer; Standard deviation in (parentheses).

Traders were asked about their sources of price information for maize and soybean. The majority of traders appeared to rely on personal knowledge of the market (87 percent). 40 percent of the sampled traders relied on public sources and buyers of the commodities as a source of price information. 35 percent of traders reported sourcing price information from the ACE platform. Surprisingly, ADMARC was the least reported source of price information, although it is a major player in Malawi's maize market.

Table 6. Sources of price information

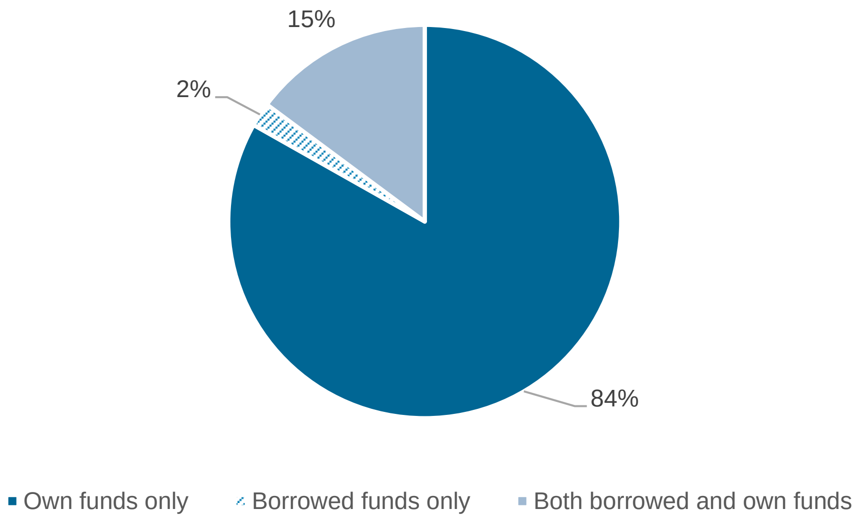
Source of price information	Maize	Soybean
Personal knowledge of the market	0.87 (0.34)	0.86 (0.35)
Public sources (radio/TV, Commodity exchanges, SMS, Newspaper, Information boards at agricultural offices)	0.45 (0.50)	0.47 (0.50)
Buyer of commodity	0.41 (0.49)	0.40 (0.49)
ACE	0.36 (0.48)	0.38 (0.49)
ADMARC	0.07 (0.26)	0.04 (0.19)

Source: IFPRI baseline survey (2019).

Note: Standard deviation in (parentheses).

Figure 4 shows the source of capital for traders. Most traders used own capital to finance trading activities (84 percent) and only 2 percent financed their activities using borrowed funds. About 15 percent used both own and borrowed funds. This is plausible given the high cost of collateralized financing with bank interest rates as high as 30 percent. Besides, collateral requirements are punitive for small traders. This limits their capacity to access structured markets with higher quantity requirements and delayed payments on deliveries.

Figure 4. Source of capital (%)



Source: IFPRI baseline survey (2019).

Note: N=78.

3.2.2. Mean comparisons between baseline and endline surveys

Table 7 presents a summary of the effects of providing price information to traders on selected welfare indicators by comparing means between the baseline and endline surveys. There were significant differences in level of awareness of ACE among traders and use of ACE services between baseline and endline periods. Unsurprisingly, the proportion of traders who were aware of ACE increased by about

25 percent after the intervention, while the proportion that used ACE services increased by 62 percent. There was also a positive and significant change in average volume of maize sold by traders between the two periods of 15 MT. However, soybean sales reduced from 246 MT at baseline to 91 MT at endline. Strikingly, the average maize and soybean prices per kg increased significantly between the two periods by MWK62/kg and MWK68/kg, respectively, although this likely reflects strong demand by processors for soybean during the period rather than the effect of the intervention itself. The share of maize and soybean sales through structured markets increased between baseline and endline periods, but the increments were not statistically significant.

Table 7. Differences between baseline and endline periods

Variables	Baseline (n=78)	Endline (n=68)	Difference (Endline-Baseline)
Proportion of traders aware of ACE	71.79	97.06	25.27***
Proportion of traders that used ACE services	21.43	83.33	61.9***
Maize Sales (MT)	200.34	215.47	15.13*
Soybean Sales (MT)	246.96	90.89	-156.07
Maize price	139.10	201.43	62.33***
Soybean price	205.14	293.04	87.9***
Sales share of maize through structured markets (%)	17.94	23.40	5.46
Sales share of soybean through structured markets (%)	22.37	23.89	1.52

Source: IFPRI surveys (2019).

Note: MT = metric ton; Standard deviations in (parentheses). *p<0.1, **p<0.05, ***p<0.01.

4. CONCLUSION

The study analyzed the impact of providing price information on small farmers' and traders' sales of maize and soybean, sales through structured markets, sales price, and levels of commercialization of the two commodities by small farmers. The study was conducted in four districts (Mchinji, Ntchisi, Dowa, and Kasungu), which contribute significantly to national maize and soybean output. Two FAs were randomly selected from each district, with one assigned to the treatment group who received better price information and the other to the control group, who did not. At least fifty members (farmers) from each FA and at least twenty traders from each district were randomly selected for interviews. Semi-structured interviews were conducted with 416 farmers and 78 traders during baseline (April 2019), and 399 farmers and 68 traders during the endline survey (September 2019). ACE provided information on maize and soybean prices from its platform via mobile phone text messages to the treated farmers during the duration of the study. Treatment effects were estimated using a kernel PSM approach with repeated cross-section data. We analyzed the ex post and ex ante mean differences for indicators of interest in the case of traders where we only had the treatment group.

For farmers, difference-in-difference regressions with covariate matching show that providing price information had a positive impact on sales through structured markets, sales price and levels of commercialization but this difference was not statistically significant. For maize sales, the price information had a significant but negative impact on maize sales, indicating that receipt of price information reduced the volume of maize sold by farmers in general.

For traders, we find positive and statistically significant differences between the baseline and end-line periods for maize sales but not soybean sales. We also find positive and significant differences in sales prices for maize and soybean. However, the difference in shares of maize and soybean sales through structured markets was positive but not significant.

Thus, providing small farmers and traders with price information alone is not enough to facilitate their access to structured markets. Development measures should also make small farmers and traders aware of existing structured market opportunities, the quantity and quality requirements of the exchanges and on the benefits of trading through such platforms.

ABOUT THE AUTHORS

Dennis O. Ochieng is an Associate Research Fellow at IFPRI Malawi and leads the Strengthening Agricultural Markets and Institutions theme within the Malawi Strategy Support Program (MaSSP).

Rosemary Botha is Research Analyst within the Strengthening Agricultural Markets and Institutions Theme of the program.

Bob Baulch is a Senior Research Fellow and IFPRI Malawi's Program Leader.

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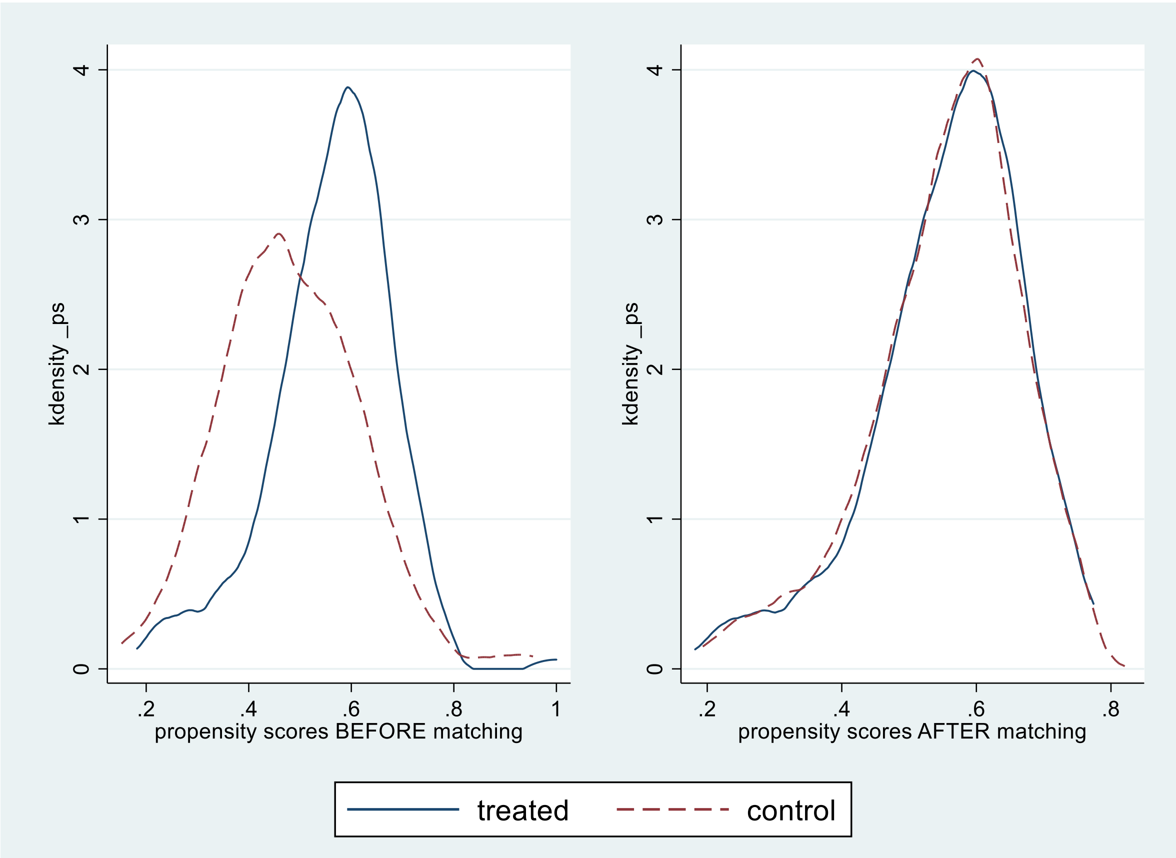
APPENDIX

Figure A 1. Kernel density functions before and after matching



Source: IFPRI survey data (2019).

Table A 1. Treatment effects on maize - Robustness test

	Commercialization		Sales through structured markets		Quantity sold		Selling price	
	MN	**DiD**	**MN**	**DiD**	**MN**	**DiD**	**MN**	**DiD**
DID		-0.022 (0.029)		0.007 (0.018)		.-265.565* (140.593)		8.040 (14.828)
Treatment	-0.005 (0.011)	0.015 (0.025)	0.095*** (0.019)	0.038*** (0.010)	-92.195 (72.642)	173.490 (110.554)	7.265 (5.619)	-0.481 (7.463)
Time (dummy)		-0.017 (0.024)	-0.002	-0.013 (0.016)		102.596 (101.810)		47.439*** 5.816
Age of head	-0.001 (0.001)	-0.002*** (0.001)	-0.013* (0.001)	-0.001 (0.000)	-5.292* (2.865)	-5.410 (3.422)	-0.294 (0.228)	-0.168 (0.142)
Gender of head	-0.027 (0.018)	-0.015 (0.015)	0.005 (0.011)	-0.011 (0.007)	-98.960 (93.562)	-17.743 (114.053)	1.007 (5.751)	0.529 (3.854)
Education of head	0.001 (0.003)	0.001 (0.004)	0.013*** (0.002)	0.003 (0.003)	13.784 (10.806)	17.939 (13.005)	-0.347 (0.273)	-0.082 (0.379)
Family size	-0.004 (0.001)	-0.008** (0.002)	0.004 (0.008)	0.002*** (0.004)	-14.238 (19.292)	-50.923** (23.443)	-1.238 (0.674)	1.346*** (0.298)
Farm size (acres)	-0.003 (0.001)	0.000 (0.002)	0.004 (0.008)	0.006* (0.003)	-5.343 (13.820)	15.125 (12.657)	2.961 (1.096)	2.123 (0.936)
Distance_market (km)	0.001 (0.001)	-0.001 (0.002)	0.005 (0.003)	0.002* (0.001)	-6.640 (6.951)	-12.851 (8.624)	-0.142 (0.209)	-0.081 (0.282)
ACE Warehouse (dummy)	0.004 (0.001)	0.025 (0.016)	0.060 (0.021)	0.021*** (0.007)	24.170 (161.236)	185.265 (189.754)	11.089 (8.367)	8.484 (3.538)
Higher producer (dummy)	0.073 (0.017)	0.123*** (0.019)	0.061 (0.015)	0.047*** (0.005)	540.054*** (74.670)	837.247*** (86.729)	11.900 (4.002)	8.377** (3.872)
District dummies [a]								
Kasungu	0.046*** (0.010)	0.041* (0.024)	0.101*** (0.037)	0.086*** (0.025)	-258.565** (114.865)	-288.939** (137.463)	12.149 (6.936)	5.347 (2.903)
Mchinji	-0.068*** 0.014	-0.082 (0.027)		0.005 (0.012)	.-286.251*** (109.730)	.-482.681*** (135.000)	31.281 (6.879)	13.732*** (3.265)
Ntchisi	0.004 (0.005)	-0.018* (0.028)		0.008* (0.004)	92.714 (100.939)	4.525 (121.732)	9.081 (8.831)	-3.820 (3.606)
Constant					232.708 (197.364)	-45.342 (246.715)	141.795***	
Observations	397	808	201	812	398	812	223	447
Wald χ^2	4.82*	145.58***	32.34***	92.18***	87.94***	152.49***	6.55***	26.15***

Source: IFPRI survey data (2019).

Note: MNs are mean difference estimates; DiD = difference-in-difference estimates with robust standard errors in (parentheses) clustered at Farmers Association level; Km = Kilometers; [a] Base category is Dowa district; Estimators: Quantity sold = Random effects Tobit; Price = Random effects Tobit. *p<0.1, **p<0.05, ***p<0.01.

Table A 2. Treatment effects on soybean - Robustness test

	Commercialization		Sales through structured markets		Quantity sold		Selling price	
	MN	DiD	MN	DiD	MN	DiD	MN	DiD
DID		-0.012 (0.033)		0.001 (0.054)		-66.714 (53.056)		16.307** (7.829)
Treatment	0.029 (0.026)	0.033 (0.023)	0.162*** (0.049)	0.091** (0.046)	123.442** (59.479)	209.454*** (61.145)	18.404*** (6.149)	4.423 (6.262)
Time (dummy)		-0.026 (0.025)		0.118*** (0.045)		7.294 (39.517)		19.733*** (5.776)
Age of head	0.001 (0.001)	-0.000 (0.001)	0.002 (0.002)	0.000 (0.001)	-0.192 (1.910)	0.460 (2.152)	-0.493** (0.237)	-0.339* (0.190)
Gender of head	0.024 (0.034)	0.024 (0.023)	-0.034 (0.062)	-0.013 (0.034)	52.306 (41.420)	11.067 (71.198)	9.046 (8.589)	15.479** (6.341)
Education of head	0.010** (0.004)	0.005* (0.003)	0.006 (0.006)	0.001 (0.003)	22.745* (12.286)	16.129** (8.185)	0.250 (0.797)	0.900 (0.728)
Family size	-0.005 (0.002)	-0.002 (0.004)	0.009 (0.013)	-0.001 (0.006)	-12.531 (19.765)	-13.231 (14.616)	-3.063* (1.684)	-3.293** (1.288)
Farm size (acres)	-0.001 (0.002)	0.004 (0.003)	0.019** (0.008)	0.001 (0.002)	18.400 (20.224)	21.417*** (7.020)	0.850 (0.576)	0.561 (0.595)
Distance_market (km)	-0.000 (0.002)	-0.001 (0.002)	0.006 (0.006)	0.000 (0.003)	2.480 (3.672)	1.152 (5.465)	0.147 (0.537)	0.050 (0.474)
ACE Warehouse (dummy)	0.021 (0.050)	-0.027 (0.039)	0.029 (0.097)	-0.056 (0.055)	141.103** (67.247)	62.901 (119.3556)	7.941 (14.286)	14.024 (10.560)
Higher producer (dummy)	0.047* (0.028)	0.105*** (0.017)	0.121** (0.056)	0.094*** (0.032)	418.474*** (39.393)	389.130*** (44.075)	20.231*** (6.970)	17.358*** (5.085)
District dummies[a]								
Kasungu	-0.037 (0.047)	-0.017 (0.030)	0.100 (0.078)	0.128*** (0.048)	-25.456 (51.147)	-66.420 (87.989)	10.833 (9.380)	8.109 (7.783)
Mchinji	0.057 (0.038)	0.015 (0.026)	-	-0.048* (0.025)	54.903 (52.237)	-10.325 (83.008)	29.126*** (8.472)	33.131*** (7.330)
Ntchisi	0.155*** (0.033)	0.083*** (0.023)	0.248*** (0.067)	0.131*** (0.032)	397.756*** (117.508)	280.358*** (79.832)	26.759*** (8.670)	33.708*** (7.012)
Constant	0.543*** (0.088)	0.654*** (0.061)			-220.638 (174.734)	-199.405 (154.771)	212.876*** (15.858)	176.890*** (13.752)
Observations	348	699	270	716	352	716	333	674
Wald χ^2	4.48***	80.62***	49.14***	73.56***	11.78***	210.08***	6.01***	143.34***

Source: IFPRI survey data (2019)

Note: MN = mean difference estimates; DiD = difference-in-difference estimates with robust standard errors in (parentheses) clustered at Farmers Association level; Km = Kilometers; [a] Base category is Dowa district; Estimators: Quantity sold = Random effects Tobit; Price = Random effects Tobit; *p<0.1, **p<0.05, ***p<0.01.

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IFPRI Malawi, Area 14 Office, Plot 14/205, Lilongwe, Malawi | Mailing Address: PO Box 31666, Lilongwe 3, Malawi

T +265-1-771-780 | Email: IFPRI-Lilongwe@cgiar.org | http://massp.ifpri.info