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Agricultural extension in times of crisis and emergent threats: Effectiveness of a fall armyworm information intervention in Myanmar

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ABSTRACT

Agricultural extension can have important impacts on vulnerable populations by increasing food production, which improves both rural incomes and urban food security. Yet, crises induced by violent conflict or disease outbreaks can sever the connections between extension agents and farmers. Understanding how agricultural extension systems can safely and effectively reach farmers in times of crisis could help stabilize agri-food systems in fragile states. In the context of COVID-19, a military coup, and an emergent threat of fall armyworm in Myanmar, this paper uses a randomized controlled trial to test the effectiveness of two cellphone-based extension interventions – a direct-to-farmer and a lead-farmer intervention – for fall armyworm control in maize. Despite low compliance, both interventions caused knowledge improvements. However, damage control estimates show that the lead-farmer group used pesticides most effectively. Similar cellphone-based lead-farmer programs could be an effective tool in fragile states and when faced with emergent threats to agriculture.

1. INTRODUCTION

Agricultural extension can have direct and important impacts on vulnerable populations, affecting both rural livelihoods and urban food security through technology adoption (Yitayew et al., 2021) and increased agricultural production (Evenson, 2001). But in fragile states, attention and funding are justifiably diverted away from extension services towards more immediate concerns. At the same time, crises induced by violent conflict or disease outbreaks can sever the connection between farmers and extension agents, preventing safe delivery of information (Kimenyi et al., 2014). Though not the central concern in a crisis, the lost benefits from extension services may exacerbate or prolong the negative impacts of conflict as farming and the broader agri-food system are especially important in such situations (Uwishema et al., 2022). Understanding how agricultural extension systems can safely and effectively deliver information within restricted budgets in times of crisis could help mitigate losses and help stabilize agri-food systems in fragile states.

This paper tests the effectiveness of two remote agricultural extension programs implemented during the dual crises of COVID-19 and a military coup, and an emergent threat of fall armyworm on maize production in Myanmar. We use a randomized controlled trial (RCT) to identify the causal impacts of the extension campaign on farmer knowledge, behaviors, and farm technical efficiency during the 2021 monsoon season. The extension programs delivered information to maize farmers on the identification and management of fall armyworm. A recent arrival in Myanmar, fall armyworm (FAW) came to Southeast Asia in 2019 after migrating from Africa, where it became widespread and a major production threat just three years prior (De Groot et al., 2020; Rijal, 2019). Fall armyworm can cause large yield declines especially when effective control measures are not taken (Day et al., 2017). Similar instances of migrating pests and other new or emergent threats to agricultural production may become more common as the climates change (Skendžić et al., 2021). Agricultural extension is especially urgent and significant in these contexts as farmers are unable to rely on individual or collective experience: new information must be distributed quickly to mitigate the losses from the new threats.

At the time of the study, COVID-19 and the military coup presented immense obstacles to agricultural extension. In-person delivery of information was infeasible for three reasons; (i) agricultural extension agents (along with most other government employees) were on strike and not actively serving their rural communities, (ii) movement into and within the study region was disrupted by COVID-19 travel restrictions and lockdowns, and (iii) there were risks of violence or arrests following the military coup. On top of these obstacles to in-person information delivery, the military blocked mobile (cellphone) internet for several months thereby preventing the use of mobile phone applications for information delivery.

However, cellular networks for direct messaging or phone calls (i.e., not through internet applications) were largely uninterrupted allowing us to use two short message service (SMS) based extension interventions for our study. The first – direct SMS messages to farmers – has been used in multiple contexts, while the second – a lead-farmer SMS program where SMS messages are sent to lead farmers who are then tasked with distributing that information to other farmers in their villages – is an innovation attempting to combine benefits of rapid SMS information delivery with the documented benefits of a lead-farmer program. By randomly assigning villages into either one of these treatment arms or a control group, this paper avoids selection problems and identifies the causal impacts of the information intervention on FAW knowledge, control behaviors, and input efficiency.

There is very little evidence on extension program efficacy or impact during a coup, but in general the use of information and communication technologies (ICT) – e.g., radio, videos, SMS, and application-based phone programs – have been found to be effective in reaching farmers when face-to-face agricultural extension visits are not an option (Larochelle et al., 2016; Fu and Akter, 2016; van Campenhout et al., 2017) or as a complement to face-to-face extension service (Maredia et al., 2017). These methods are cost-effective, and can reach farmers with information more frequently and with tailored information specific to a timeframe in the agricultural production calendar (Aker, 2011; Fafchamps and Minten, 2012; Deichmann et al., 2016). Sharing timely information with farmers is especially important in response to a new disease or pest outbreak, such as FAW. In Uganda, Tambo et al. (2019) found that utilizing a mix of radio, video, and SMS to reach farmers led to improved knowledge of FAW identification management. Similar results were found when radio was used to disseminate FAW knowledge and management practices to farmers in Zambia (Rware et al., 2021).

ICT extension programs typically substitute the depth and detail of in-person information for rapid dissemination and scalability to reach a wide audience quickly. Conversely, lead-farmer extension programs effectively do the opposite by providing detailed information to lead-farmers and then tasking them with distributing or sharing that information with farmers in their communities. RCTs of lead-farmer programs show that they can effectively change farmer knowledge and behaviors, though knowledge gains can be uneven across information topics (Goeb and Lupi, 2021). Benyishay and Mobarak (2019) show that incentivizing farmer trainers to distribute information can increase impact.

This paper makes three principal literature contributions. First, we provide, to our knowledge, the first controlled test of extension programs during severe insecurity induced by a coup. In such contexts when traditional extension lines are broken, it is important to understand how to effectively reach farmers with information. Second, this paper adds to the lead-farmer extension literature by testing the efficacy of a remote information transfer to farmers through lead farmers contacted by SMS. While this adapted lead-farmer method is not well-suited for some contexts, it may combine the in-person depth of information from conventional lead-farmer programs with the rapid scalability and cost-efficacy of ICT extension programs, reaching farmers with information from a credible source at a time when outsiders are not trusted. Third, we provide, to our knowledge, the first causal test of extension interventions on the efficacy of pest control practices using a damage control specification. We apply a two-stage semi-parametric approach that allows us to identify differences in the impacts of pesticide use on technical efficiency across treatment group assignments.

As a preview of our results, our analysis shows significant improvements in farmer knowledge attributable to both extension programs. Yet, there are differences across the two extension groups in the areas of knowledge improvement, and in practices and outcomes. The lead-farmer group demonstrated greater knowledge of pesticide action thresholds than both the control group and the SMS group. Putting the knowledge to practice, the lead-farmer group used pesticides more effectively than both the SMS and control groups. Our results demonstrate that remote lead-farmer information dissemination mechanisms can be effective – and more effective than direct SMS campaigns – in a time of high distrust and crisis, and in the context of an emergent threat to crop production.

Lastly, extension information may be a relatively fast and low-cost way to improve farmer welfare in the face of a new production threat and in fragile states, but future research should compare the impacts and cost effectiveness of other farm interventions such as cash transfers.

This paper proceeds as follows. In the next section, we provide background details on COVID-19 and the military coup in Myanmar, as well as on maize production and FAW. Section 3 describes our data, the experimental design, and the information intervention. We then lay out our empirical methods including our application of the Simar and Wilson (2007) estimation procedure incorporating damage control and technical efficiency. Section 5 then presents our estimates of the causal impacts of the information intervention on farmer knowledge, pest control practices, and maize production. In the conclusion, we discuss the implications of this work for future extension programs in fragile states characterized by violence and instability.

2. BACKGROUND

2.1 Crises in Myanmar

In early 2020, Myanmar began experiencing COVID-19-related disruptions and the government was quick to respond with policies to both curb the potential spread of the disease and to mitigate its impact on the local economy. Throughout the ongoing pandemic, localized lockdowns and movement restrictions have been implemented intermittently including stay-at-home orders, closing public transportation and limiting the number of people gathering (Diao et al, 2020). These policies have been enforced at very localized levels (Goeb et al. 2022a) that often overlap and compound transport disruptions. To support the economy, the democratically elected government developed a Comprehensive Economic Recovery Plan (CERP) in 2020 with several policies designed at supporting agri-food system (Maredia et al., 2022). The economic impacts of COVID-19 were widespread, but throughout 2020 the agri-food system demonstrated resilience (Boughton et al. 2021; Goeb et al. 2022b).

Hopes of a fast recovery from COVID-19 were halted by the military coup on February 1, 2021. The military junta seized full control of the government and civilians responded with protests and a general strike against the military regime known as the Civil Disobedience Movement (CDM). The CDM affected most public services including many hospitals and schools that closed as staff participated in peaceful and non-violent protests against the military takeover (Han et al., 2021). After a period of allowing peaceful protests, the military violently cracked down on dissidents. The economy subsequently collapsed, and GDP contracted by 18 percent (World Bank, 2022). The once resilient agri-food system began showing signs of cracking as consumer food prices increased (MAPSA, 2022). One of the main coping mechanisms households cited to manage income loss during this time was the reduction of food consumption (Heady et al. 2020; Lambrecht et al. 2020). Unsurprisingly, food insecurity rose with as many as 30 percent of women reporting not having eaten enough healthy food in the past month and 8 percent reporting having run out of food in urban areas; these numbers were roughly half for rural households (Headey et al., 2020).

Following the coup, obstacles to extension were multiple and severe. First, many agricultural extension agents were participating in the CDM and thus were not serving rural communities in their usual capacities. Second, movement around Myanmar was impeded by lockdowns and transportation restrictions related to COVID-19 as well as security and safety risks following the coup. Third, extensive disruptions to cellphone internet services, including a continuous nationwide blockage for several months ordered by the military, inhibited the digital sharing of information.

The end result was a complete severing of information flows to farmers at a crucial time: when farmers were preparing to plant their monsoon crops, and during just the second full season of FAW's presence in the country.

2.2 Maize production and fall armyworm

Maize is Myanmar's second most important crop with more than one million acres planted annually and accounting for 8-9 percent of annual crop value between 2015 and 2019. The maize sector grew rapidly under the democratic government, and the number of maize growing households in Shan state – which accounts for about 60 percent of national maize production – tripled in the ten years to 2017 (Fang & Belton, 2020). Maize is grown as a cash crop supplying the domestic feed industry and sold as exports via land to China and, more recently, Thailand.

Fall armyworm arrived in Myanmar and broader Southeast Asia in late 2018 (Rijal et al., 2019). Native to the Americas, FAW migrated to Asia from Africa where it arrived in force in 2016 (Goergen et al., 2016; De Groot et al., 2020). Literature shows extensive FAW prevalence spanning both continents and impacting over half of maize plots in some areas (Lamsal et al., 2020; Hailu, et al., 2018). Estimated yield losses from FAW range widely from 11 percent to 54 percent (Baudron et al., 2019; DeGroot et al., 2020). A review of 12 African maize-producing countries estimated that in the absence of control methods, FAW has the potential to decrease annual maize production by 21-53 percent, which equates to economic damages of between US$2.5-6.2 billion (Abrahams et al., 2017). In some cases, yield loss and costs of controlling FAW led to farmers ceasing to produce maize altogether.

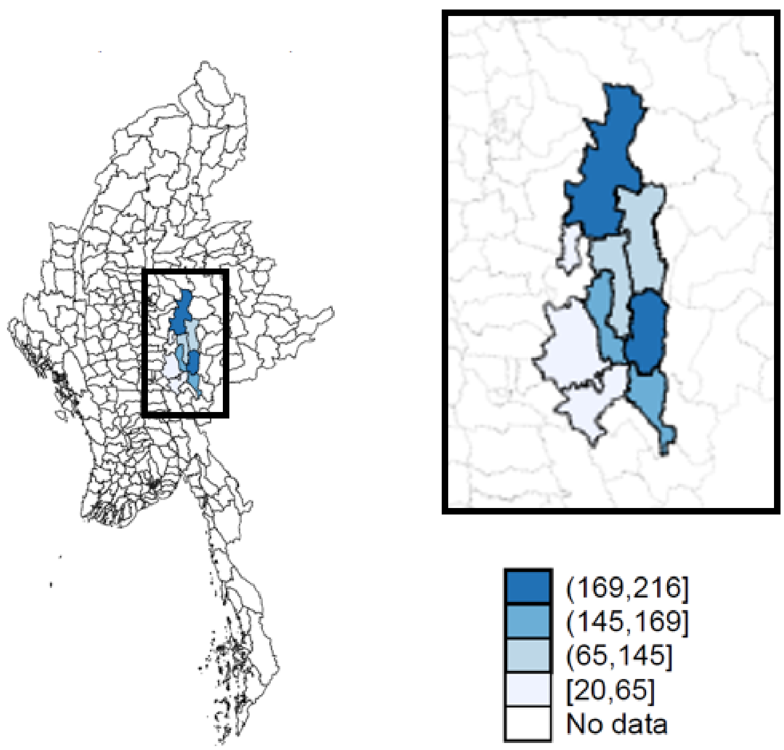
Damage from FAW can be mitigated with timely identification and proper control methods (Tambo et al., 2019). FAW control strategies include agronomic practices (minimum till, regular weeding, or intercropping with certain crops), mechanical methods (handpicking of larvae, light traps, or pheromone lures), and chemical controls (spraying of pesticides) which are often the most common practice (Rajil et al., 2019; Tambo et al., 2020b). Pesticide use for FAW control, like other integrated pest management practices, is framed around action thresholds. If farmers observe FAW incidence rates above the thresholds, they are recommended to apply pesticides. But below the thresholds, farmers are recommended to use less costly methods of control. Because there are different thresholds at different growth stages in maize, proper FAW control is information intensive, and farmers often have incomplete knowledge. Cited avenues for increasing farmer knowledge of FAW control include agricultural extension agents, media sources, and farm neighbors (Kumela, 2018; Tambo et al., 2020a).

3. DATA AND EXPERIMENTAL DESIGN

3.1 Data

Within Myanmar this study focuses on 9 townships in southern Shan and northern Kayah states for their high densities of maize farmers (shown in Figure 1 with the final sample achieved in each township). The Department of Population provided an initial sample frame of 80 Enumeration Areas (EAs) or villages in these regions designed to be representative of rural households. Military checkpoints and movement restrictions made travel into and out of the study area infeasible. To conduct a listing of maize-growing households with active cellphones in each village, we leveraged local connections living in the region to visit village leaders, and where feasible, visit households. A total of 4,273 households that grew maize and owned a cellphone were listed. To ensure that cellphone numbers were correct and working, to register households in our survey, and to collect basic household information and assess farmer knowledge, we attempted to reach each listed household via phone call in early June 2021. We successfully connected with 1617 maize-growing households in 61 villages,[1] which we call our registry which serves as our sample frame for our experimental design.

Figure 1. Study region map, final sample by township



Source: Author calculations

[1] The number of maize farming households in each village ranged from 9 to 40.

The data used for this article come from three rounds of phone interviews covering the 2021 monsoon production season conducted in June (pre-intervention), September (post-intervention), and December 2021, respectively. The survey instruments included the following modules: demographics and household characteristics, including maize farming practices and production during the 2020 season (June); extension (June); detailed knowledge assessments (June and September); and maize production practices and harvest quantities in monsoon 2021 (December). Not all households had fully harvested their maize by the December interview. In those cases, we asked farmers about their expected harvest quantities on their unharvested maize areas.

To assess farmer knowledge of FAW and control practices, we asked farmers 13 questions covering three key themes: scouting and identification, control actions and action thresholds, and pesticide controls (full list of knowledge questions in Appendix Table A1). To reduce the probability of farmers correctly answering questions without a real understanding of the subject, most questions were open-ended (i.e., not true-false or multiple choice). For analysis, we create simple indices as the sum of correct responses to questions in each of the three thematic areas and overall (the three themes combined).

There was some attrition between the registry and the baseline, as well as across interview rounds such that the final sample for analysis consists of 1114 households (Table 1). The attrition rates highlight the challenges in reaching rural households via cellphone, especially in the context of Myanmar during the military coup. With a steep decline of trust under military control, farmers may have been more likely to ignore calls from unknown numbers. Comparisons of attrition households to those successfully reached for interviews show no evidence of biases across treatment groups (Appendix Table A2).

Table 1. Household samples and attrition by round and by treatment assignment

	Households interviewed			Attrition	
	Registry (June 2021) (1)	Round 1 (June 2021) (2)	Sample for analysis (3)	Registry to Round 1 [(1) - (2)] (4)	Round 1 to Sample for analysis [(2) - (3)] (5)
All	1617	1267	1114	350	153
By treatment assignment					
Control	526	418	362	108	56
T1 - Direct SMS	533	414	370	119	44
T2 - Lead farmer SMS	558	435	382	123	53

'Registry' is the list of all farmers for whom we were able to confirm an active cellphone number. 'Sample for analysis' is the panel observations with data from each of the three interview rounds. 'Attrition' observations are households dropped from the sample due to unsuccessful attempts to reach them for follow-up interviews.

3.2 Experimental design

To identify the causal effect of each extension program, we randomly assigned villages to one of three groups: direct SMS, lead-farmer SMS, or control. By randomizing at the village level (as opposed to the farmer level) we reduce potential spillovers of information from the treatment groups to the control group. Randomization ensures that receipt of information and the extension method are orthogonal to household characteristics by design. Still, it can be helpful to test for significant differences across the groups to establish whether the groups are well-balanced prior to the interventions.

Table 2 shows that our sample is indeed well-balanced across treatment group assignment. For each of the 27 variables tested, we fail to reject the null that the averages for all three groups are equal. Especially important to this study, variables on cellphone ownership and use, knowledge, and maize production and practices are not significantly different across groups.

Table 2. Sample descriptives and balance tests of random group assignment

	All sample (n=1114)		Control group (n=362)		T1: SMS group (n=370)		T2: Lead Farmer group (n=382)		Test of equal means: C=T1=T2
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	p-value
Household characteristics									
# of household members									
Total	4.9	(1.7)	5.1	(1.8)	4.9	(1.8)	4.8	(1.7)	0.370
Male	2.4	(1.2)	2.5	(1.2)	2.4	(1.2)	2.3	(1.2)	0.248
Female	2.5	(1.2)	2.5	(1.2)	2.5	(1.2)	2.5	(1.2)	0.823
Self-reported occurrence of violence in area since coup (%)	17.3	(37.9)	16.9	(37.5)	15.9	(36.7)	19.1	(39.4)	0.938
Land area owned (acres)	9.4	(8.9)	9.8	(9.1)	9.2	(7.8)	9.2	(9.8)	0.869
Respondent information									
Female respondent (%)	16.9	(37.5)	16.6	(37.2)	19.2	(39.4)	14.9	(35.7)	0.585
Respondent age	39.2	(12.1)	39.8	(12.6)	38.8	(11.8)	38.9	(12.0)	0.672
Education (%)									
Completed high school or above	17.1	(37.7)	16.9	(37.5)	17.3	(37.9)	17.3	(37.9)	0.990
Never attended school	5.0	(21.9)	6.4	(24.4)	4.1	(19.7)	4.7	(21.2)	0.436
Monastery only	13.8	(34.5)	13.3	(34.0)	12.2	(32.7)	16.0	(36.7)	0.638
Able to read/type cell messages in Burmese (%)	91.4	(28.1)	92.0	(27.2)	93.5	(24.7)	88.7	(31.6)	0.114
Mobile Phone Ownership and Usage (HH level)									
# of Operating cellphones owned	2.2	(1.2)	2.3	(1.2)	2.2	(1.2)	2.2	(1.2)	0.619
# of Smartphones owned	1.8	(1.2)	1.9	(1.2)	1.7	(1.2)	1.7	(1.1)	0.262
Typical spending per month on mobile (HH level), Kyat	14,250	(13,625)	15,041	(14,035)	13,842	(12,279)	13,897	(14,449)	0.525
Knowledge (pre-intervention)									
Know about FAW (%)	90.5	(29.4)	93.1	(25.4)	87.0	(33.6)	91.4	(28.1)	0.121
Overall Knowledge Index [0,13]	2.36	(1.52)	2.40	(1.56)	2.32	(1.65)	2.35	(1.36)	0.938
Sub-Index: Scouting and Identification Knowledge [0,5]	0.92	(0.84)	0.89	(0.81)	0.91	(0.89)	0.95	(0.80)	0.825
Sub-Index: Action Threshold Knowledge [0,4]	0.83	(0.86)	0.88	(0.93)	0.79	(0.83)	0.81	(0.81)	0.795
Sub-Index: Pesticides Knowledge [0,4]	0.61	(0.73)	0.62	(0.69)	0.62	(0.76)	0.60	(0.72)	0.951
Maize history									
Experience (# years since HH first cultivated, including 2021)	12.3	(8.3)	12.0	(7.4)	12.8	(9.3)	12.1	(8.1)	0.732
Experienced FAW in last 3 years, all HHs (%)	60.3	(48.9)	60.5	(49.0)	61.1	(48.8)	59.4	(49.2)	0.889
2020 Monsoon Season									
Acreage cultivated, all crops	9.0	(8.7)	9.6	(10.0)	9.0	(7.7)	8.5	(8.2)	0.748
Acreage cultivated, maize only	6.5	(7.6)	7.5	(9.4)	6.2	(6.1)	5.9	(7.0)	0.416
Maize yield (kg/acre)	1,866	(823)	1,831	(795)	1,832	(824)	1,935	(847)	0.589
Planted purchased maize seed, %	99.1	(9.7)	99.4	(7.5)	99.2	(9.2)	98.6	(11.8)	0.642
Quantity of urea applied on maize plots (in 50 kg bags)	5.8	(8.1)	6.4	(9.0)	5.5	(7.1)	5.6	(8.2)	0.770
Quantity of compound fertilizer applied on maize plots (in 50 kg bags)	9.7	(13.8)	10.9	(15.1)	9.2	(12.6)	8.9	(13.5)	0.707

Test of equal means across group assignment is an F-test of equality across groups with village clustered standard errors. All variables are pre-intervention.

3.3 Information interventions

FAW control in maize – and pest control more generally – is complex, and potential crop damage inflicted varies by maize growth stage. Thus, recommended control actions are conditional on plant growth stage as well as the level (or severity) of pest infestation. To understand these complexities and to make appropriate recommendations on controlling FAW, we sought advice from the Plant Protection Division of the Ministry of Agriculture, Livestock, and Irrigation, as well as literature from the Food and Agriculture Organization, and the United States Agency for International Development in Myanmar. To design the topics and messages for our information interventions, we partnered with a company that operated a well-known farmer cellphone application in Myanmar.

After deliberations, we settled on four messages in our information interventions with three content themes – (i) FAW identification and scouting, (ii) pest incidence action thresholds and control methods, (iii) and pesticide toxicity and safety (Appendix Figure A1 shows the full set of messages in English). Message 1 contained an introduction to the program along with pesticide safety information. Messages 2, 3, and 4 contained information on each of the three themes. Message 1 was sent in mid-June. This was followed by three thematic messages. We timed each of the thematic messages following the modal maize production calendar such that the messages were sent at the relevant maize growth stage between the third week in June to the second week of July. Each message contained information on pesticide action thresholds for the specific growth stage – early vegetative, early whorl, and late whorl.

These messages were delivered to farmers in a local language in one of two ways depending on treatment group assignment. In the direct SMS treatment group, we sent messages directly to farmers' cellphones using the confirmed and active numbers. In the lead-farmer treatment group, we sent messages to lead-farmers – identified by village leaders during the household listing exercise – that were tasked with disseminating the information to the farmers in their villages. Lead-farmers were called prior to the program to confirm that they were reachable via cellphone, to explain the program, and to obtain their consent to participate as lead farmers.[2] We provided a list of the other interviewed farmers in their villages along with cellphone contact information so lead farmers could provide them with information. Lead farmers were compensated for their participation with a 15,000 MMK (US$9.30, approximately two times daily wage rate for casual labor) token of appreciation at the onset of the program – given to build trust and to fund the cost of message delivery to other farmers – and an additional 1,000 MMK (US$0.60) payment per message delivered to farmers. We counted all information delivery methods to village farmers – in-person, phone call, or SMS – equally in compensating lead farmers.

This lead-farmer program is a departure from the conventional lead farmer method in that there was no in-person training with the lead-farmers. Lead-farmers received information through SMS, which we acknowledge is not the ideal lead-farmer implementation method for many contexts. In Myanmar during the coup, this approach allowed us to quickly get information to farmers through a local and likely more trusted contact at a time when trust of outsiders was low. In other similar

[2] All lead farmers in the lead farmer treatment group were successfully reached prior to information dissemination and each agreed to participate in the program.

fragile state contexts, this may also be an attractive option especially because the method has low variable costs and can be easily scaled to other villages, crops, or sectors.

4. EMPIRICAL FRAMEWORK

4.1 Extension impacts on farmer knowledge

Knowledge is the mechanism through which our extension programs may change behavior. To test the causal impacts of the extension interventions on farmer knowledge we use the following intention-to-treat (ITT) regression:

$$Y_{i,v} = T_v \boldsymbol{\beta} + \varepsilon_{i,v} \,, \qquad (1)$$

where $Y_{i,v}$ is the dependent variable of interest, in this case an index of FAW knowledge at the endline survey for farmer i in village v; T_v is a vector of indicator variables for treatment group assignment – SMS, lead farmer, or control group (the excluded category captured as an intercept); and $\varepsilon_{i,v}$ is an iid error term clustered at the village level. We estimate (1) by ordinary least squares linear projection model which provides solid estimates of average effects on the outcome despite not matching the data generation process (Wooldridge, 2010).

$\boldsymbol{\beta}$ is the coefficient vector of interest and will show the average difference in outcomes causally attributed to treatment group assignment. However, as shown later in section 5a, many farmers assigned to treatment did not actually receive information. To estimate the outcome changes for those farmers that did receive extension treatment – more specifically, for the compliers that received extension only through group assignment – we use the following instrumental variables local average treatment effect (LATE) estimation:

$$SMS_{i,v} = T_v \boldsymbol{\beta^{SMS}} + \varepsilon_{i,v}^{SMS} \,, \qquad (2)$$

$$LF_{i,v} = T_v \boldsymbol{\beta^{LF}} + \varepsilon_{i,v}^{LF} \,, \qquad (3)$$

$$Y_{i,v} = \beta_0 + \beta_1 \widehat{SMS_{i,v}} + \beta_2 \widehat{LF_{i,v}} + \varepsilon_{i,v} \,, \qquad (4)$$

In the first stage (equations 2 & 3) we use random treatment assignment to instrument for actual receipt of extension through SMS ($SMS_{i,v}$) and the lead farmer SMS program ($LF_{i,v}$). Random assignment ensures that the instruments pass the exclusion restriction. In the second stage, the outcome variable is regressed on the predicted receipt of each extension type ($\widehat{SMS_{i,v}}$ and $\widehat{LF_{i,v}}$). The result is a causal estimate of the impact of complying with each extension type on the outcomes of interest. Again, standard errors are clustered at the village level following our experimental design.

4.2 Practices and outcomes

Knowledge changes are central to any extension program, but they are intermediate goals toward changes in behaviors and outcomes. While control practices taken after observing FAW are of interest, and a focal point of the extension messages, we cannot make direct comparisons in control practices across groups conditional on reporting FAW because we rely on self-reported FAW incidence data and the extension interventions included messages on FAW scouting and identification. Thus, reporting FAW is not orthogonal to the treatment group assignment, i.e., the treatments themselves likely impact the condition (reporting FAW) required for these practices to be implemented.

However, we are able to estimate ITT and LATE regressions for differences in practices or outcomes for the entire sample and not conditional on observing FAW. Specifically, we test for differences in scouting and maize yields across treatment groups. By not conditioning on reporting FAW, we avoid biasing our sample and we preserve the causal interpretation of the treatment group estimates because randomization ensures that non-treatment related factors including actual – not reported – FAW incidence are balanced in expectation across treatment assignment.

4.3 Damage control

The overarching objective of our extension programs was more effective FAW control, but econometric estimates of pest control efficacy are complicated by the fact that control methods do not directly increase crop production, they reduce losses from pest pressure. Damage control estimations explicitly model these impacts by separating the productive inputs – i.e., variables that directly influence yield – and damage control inputs (Lichtenberg & Zilberman 1986). Under the usual assumption of separability,[3] this can be represented as:

$$Q = f(x)g(z)\,, \tag{5}$$

where $f(x)$ is the production function with input vector x, and $g(z)$ is the damage control function with damage control input vector z.

There is no consensus on the best damage control estimation method and there are tradeoffs to each approach. We elect to use a two-stage estimation procedure following the damage control examples of Kuosmanen et al. (2006) and Iqbal and Sial (2018) that can test damage control input effects for multiple groups, in our case treatment assignments.[4] The general approach is to first estimate technical efficiency of each farmer using non-parametric data envelopment analysis (DEA). Then the second stage is to regress damage control variables on the technical efficiency scores. Two-stage methods have several benefits over parametric production function estimation of damage control. Principal among them is that DEA, unlike parametric methods, does not require functional form assumptions which can drive differences in estimated results (Saha, Shumway and Havenner, 1997; Carrasco-Tauber and Moffitt, 1992). Still, the DEA estimation procedure assumes a common production possibility frontier across farmers and requires that all

[3] For separability to hold, the production function must have constant returns to scale and independence between damage control input efficacy and direct inputs. Kuosmanen et al. (2006) show that these assumptions are not as restrictive as previously assumed, and that they do not imply zero marginal rate of substitution between direct and damage control inputs.

[4] For a more detailed discussion of the damage control estimation methods see Kuosmanen (2006).

input variables be strictly positive. In many contexts, a main drawback of using DEA is that it does not produce readily accessible (i.e., parametric) estimates of the impacts of inputs x on production Q. However, this is not a large concern in our application as the focus of the extension interventions was entirely on effective damage control - $g(z)$ in equation 5 – not on direct input productivity or response.

In the first stage, we estimate the technical inefficiency scores of each household using DEA where the output is maize yield in kilograms per acre and the production input vector includes the plot size in acres, and per acre variables for total input costs and total labor days (both hired and household).[5] The DEA procedure produces Farrell technical inefficiency scores $\widehat{\theta_{i,v}}$, which take values [1, ∞) where 1 is on the production possibility frontier and higher values reflect greater inefficiency in input use.

The second-stage estimation is our primary interest, where we estimate the damage control impacts by regressing the log of technical inefficiency scores on pesticide use with the following form:

$$\ln\left(\widehat{\theta_{i,v}}\right) = \alpha + PestExp_i^{T_v}\boldsymbol{\delta} + Z_i\boldsymbol{\mu} + \varepsilon_{i,v} \quad , \qquad (6)$$

where $PestExp_i^{T_v}$ is a vector of the total expenditure of pesticides per acre applied on the plot for each treatment group (T_v) as a separate variable, including but not limited to pesticides applied in control of FAW[6]; Z_i is a vector of weed control variables; and, as above, $\varepsilon_{i,v}$ is an iid error term clustered at the village level. The coefficient vector $\boldsymbol{\delta}$ is our primary interest as it shows the relationships of pesticide use and log technical inefficiency for each group.

To test for possible nonlinear impacts of pesticide expenditures, we also use the inverse hyperbolic sine (IHS) transformation of $PestExp_i$ which approximates the natural log transformation but includes values of zero. In this case, it is especially important to include the zero values of pesticide expenditure because not using pesticides when it is not economical – when incidence rates are below the action threshold – is an important part of our extension messaging. It is also important to include the full sample in testing for pesticide efficacy because the extension interventions could show benefits even for those plots where there was no observed FAW. One possible avenue for such an effect is in reducing uncertainty and decreasing pesticide use when no FAW is present. Thus, IHS is the preferred transformation, though interpretation of the coefficients is often not straightforward (Bellemare and Wichman, 2020).

We note that excluding pest pressure information can introduce bias in estimated productivities of damage control inputs (Norwood and Mara 2003). However, we choose to exclude information on self-reported FAW pressure from our damage control estimations to avoid biasing the treatment effect estimates as described above.

[5] More detail on the first-stage estimation is in the appendix. As a robustness check on this first-stage specification, we disaggregate the variables in the production input vector x_i to include the plot size (acres), per acre household labor days, and expenditures per acre on maize seed, urea fertilizer, compound fertilizer, and hired labor. However, to satisfy the strict positivity requirement we must introduce a separate issue by arbitrarily setting zero values to one.

[6] Pesticide expenditures are commonly used as a variable of pesticide use (see for example Kuosmanen et al., 2006 and Iqbal and Sial, 2018) in part because pesticide quantities are not easily calculated. Pesticides come in several formulations and with different concentrations of active ingredients.

The distribution of $\ln(\widehat{\theta_{i,v}})$ is truncated at 0, so we estimate (6) by Tobit regression following (Banker and Natarajan, 2008). Simar and Wilson (2007) argue that a bias corrected first-stage DEA (that moves even the most efficient households off the production possibility frontier) followed by a truncated normal regression is the appropriate estimation method for the data generating process. Following Liu et al. (2021) we employ both estimation methods as a robustness check but with one modification. We elect to cluster our standard errors at the village level according to our experimental design (Abadie et al., 2022) rather than implement the second-stage bootstrap procedure proposed by Simar & Wilson (2007) which controls for potential serial correlation biases (from the first to second stage) but does not account for clustered sample designs. We consider the possibility of underestimating the standard errors and therefore overstating statistical significance as the larger error to avoid.

5. RESULTS AND DISCUSSION

5.1 Compliance & reaching farmers

Both information delivery methods show large room for improvement in reaching farmers (Table 3), but the reasons for low compliance differ across methods. As one might expect, the SMS extension method had greater compliance than the lead-farmer method. Cellphone company data shows that all intended messages were successfully sent out to farmers' cellphone lines, and 90 percent of the messages that we could track were successfully delivered.[7] Undelivered messages (10 percent) are then a factor in low compliance, but unopened, and later expired, or otherwise ignored messages are likely a more important influence. At a time of low trust following a coup by a military that historically spies on their people, unsolicited messages may not have been welcomed in some cases. In follow-up calls, we received reports of some farmers blocking or screening messages from unknown numbers.

Table 3. Treatment Group Compliance

Group	Sample Assignment	Sample that Took-up Treatment	Compliance Rate (%)
Control	362	--	--
SMS	370	111	30.0
Lead Farmer	382	83	21.7
Total Observations	1114	194	

Source: Fall armyworm phone survey

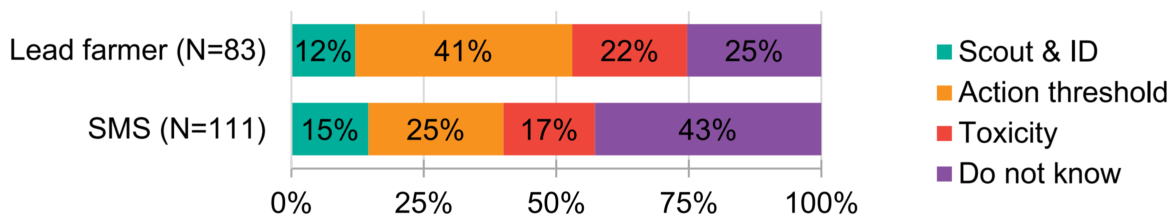
For the lead-farmer intervention, we confirmed that all lead-farmers received their messages, along with their local farmer lists. However, they did not relay that information to all the intended recipients. The low compliance in the lead farmer extension intervention is more likely a selection problem where lead-farmers chose with whom to share information. Delivering the messages requires effort and time: after the intervention three quarters of lead farmers interviewed reported delivering information to farmers only once on average, despite being sent 4 separate messages at separate times that were intended to be shared individually, and despite the incentive of 1,000

[7] Note that telecommunications restrictions imposed in Myanmar limited the messages that we could track and we only have delivery information for 54 percent of all messages sent out.

MMK payment per message delivered to farmers (delivering 8 messages in a day would provide a return greater than the prevailing daily wage rate). The most common lead-farmer information sharing method as reported by local farmers was telephone calls (69 percent) followed by in-person conversations (30 percent) and then SMS (5 percent).

To begin our assessment of what farmers learned from the interventions, we asked them to report the main topic of the information received. Farmers complying with the lead-farmer extension program were much more likely to report pesticide action thresholds for FAW as the main message – 41 percent compared to just 25 percent for SMS compliers (Figure 2). A strikingly high percentage of the SMS group farmers reported that they do not know the main message (43 percent). The same figure for the lead-farmer group was just 25 percent, and the improvement over the SMS group appears to be driven only by in-person information delivery. Within the lead-farmer group, about 40 percent of farmers reached by either phone calls or SMS reported not knowing the main topic, compared to just 14 percent of those that had in-person conversations with lead farmers. Although these estimates suffer from selection biases, emphasizing in-person delivery of information within the lead-farmer mechanism is worth further study.

Figure 2. Reported main topic of information received among compliers of each extension method



Source: Author calculations

5.2 Effects on farmer knowledge, scouting, and yield

Despite low compliance, both extension treatment groups show significant knowledge improvements over the control group. Each treatment group coefficient in the ITT and LATE regressions on knowledge indices are positive (Table 4) thus showing higher average knowledge scores in each index for both extension treatments relative to the control group. In the overall knowledge index, both treatment groups show significant effects, and the knowledge gains are of similar magnitudes for both groups. In the LATE estimates which scale the effects to show the causal average impact for those that received information, overall knowledge scores are higher by 1.76 points in the lead-farmer group and 1.39 for the SMS group, amounting to a more than 50 percent increase over the control group average scores. Thus, the knowledge regressions reveal that both direct SMS and a lead-farmer SMS program can effectively transfer information to farmers when conventional extension channels are cut, and internet is blocked.

Yet, there are important differences in where the farmers show knowledge gains across delivery mechanisms. The Scout & ID index (which captures knowledge of scouting practices and FAW identification) shows similar magnitude effects for the SMS and lead-farmer groups, though the estimates are not significantly different from control group. We note that, among the component indices, the Scout & ID index had the highest average knowledge of the control group, thus the interventions may have had relatively little room to improve farmer knowledge. This result is consistent with previous research and a Bayesian model of updating knowledge (Goeb and Lupi, 2021).

Table 4. Intention-to-treat (ITT) and local average treatment effect (LATE) estimates of treatment on knowledge indices

	Knowledge indices							
Dep Var	Overall [0,13]		Scout & ID [0,5]		Action Threshold [0,4]		Toxicity [0,4]	
Estimator	ITT (1)	LATE (2)	ITT (3)	LATE (4)	ITT (5)	LATE (6)	ITT (7)	LATE (8)
SMS assignment	0.416**		0.157		0.098		0.161**	
	(0.166)		(0.107)		(0.066)		(0.066)	
	[0.011]		[0.104]		[0.159]		[0.036]	
Lead Farmer assignment	0.383**		0.124		0.199***		0.06	
	(0.184)		(0.083)		(0.067)		(0.068)	
	[0.018]		[0.136]		[0.004]		[0.380]	
SMS treated		1.388**		0.524		0.328		0.536**
		(0.545)		(0.348)		(0.224)		(0.217)
Lead Farmer treated		1.761**		0.57		0.916***		0.275
		(0.865)		(0.375)		(0.335)		(0.314)
Control group mean	2.74	2.74	1.23	1.23	0.95	0.95	0.56	0.56
Underidentification test	-	24.68***	-	24.68***	-	24.68***	-	24.68***
Coefficient equality test: SMS = LF	0.87	0.68	0.77	0.91	0.194	0.086	0.213	0.427
N	1114	1114	1114	1114	1114	1114	1114	1114
R-Squared	0.015		0.011		0.010		0.014	

Note: Cluster robust SEs at the village level in parentheses. Randomization inference test p-values in brackets. For LATE analysis, "SMS Treated" and "LF Treated" variables are instrumented by "SMS Assignment" and "LF Assignment". * p<.1, ** p<.05, *** p<.01. Underidentification test is the Kleibergen-Paap rk LM statistic. Estimators in columns 1, 3, 5, and 7 are ordinary least squares. Estimators in columns 2, 4, 6, and 8 are instrumental variables.

In the Action Threshold index (which captures knowledge of economic threshold knowledge for pesticide use on FAW) the lead-farmer group had significantly higher knowledge scores than the control group. Compliers of the lead-farmer program show average scores 2.8 times that of SMS group, and significantly higher than the SMS compliers (column 6). This confirms the main message results above, and together they suggest that the in-person information delivery was important for knowledge improvements. Conversely, the SMS group demonstrated higher knowledge scores in the Toxicity index (which shows knowledge of toxicity understanding and identification).

Lead farmers may selectively share the information messages that they feel are most important, while the farmers that receive SMS messages may more easily retain information that is clear and easily understood. This pattern across knowledge indices appears to follow previous research on pesticide information in Africa showing that more complicated messages can be delivered more effectively in-person by trusted sources and that simple messages can be communicated through less formal mechanisms (Goeb and Lupi, 2021; Goeb et al., 2022c).

As explained in section 4.b we are limited in what practices and outcomes for which we can test for causal changes. Table 5 shows two such tests for scouting for FAW and maize yield. Both extension programs show higher shares of farmers scouting than the control group, though an already high share of the control group farmers (73 percent) scouted for pests in their maize plots, implying little room for information to increase scouting. Despite similar knowledge index changes across treatments, the lead-farmer group scouted at a higher rate than both the SMS group (significantly different and six times higher in the LATE estimate[8]) and the control group (random inference test significantly different in the ITT estimate). One possible explanation is that the knowledge change on toxicity action threshold – which shows strong improvements for the lead-farmer group – also led to an increase in scouting through a heightened concern or awareness to the risks and need to take action.

Overall yields are not significantly different across the three groups. Although the lead-farmer average yield is 81 kg/ac more than the control group and 153 kg/ac more than the SMS group, there are wide standard errors of the estimates and yields have wide standard deviations (nearly 50 percent of the mean in 2020, Table 2).

Table 5. Intention-to-treat (ITT) and local average treatment effect (LATE) estimates of treatment on scouting for fall armyworm and maize yield

Dep Var	Scouted for FAW [0,1]		Yield (kg/ac)	
Estimator	ITT	LATE	ITT	LATE
	(1)	(2)	(3)	(4)
SMS assignment	0.014		-72.05	
	(0.041)		(96.920)	
	[0.704]		[0.183]	
Lead Farmer assignment	0.064		81.358	
	(0.042)		(126.127)	
	[0.082]		[0.182]	
SMS treated		0.047		-240.168
		(0.136)		(323.096)
Lead Farmer treated		0.294		374.445
		(0.195)		(595.564)
Control group mean	0.73	0.73	1,390	1,390
Underidentification test		24.68***		24.68***
Coefficient equality test: SMS = LF	0.15	0.099	0.24	0.29
N	1114	1114	1114	1114
R-Squared	0.004		0.008	

Note: Cluster robust SEs at the village level in parentheses. Randomization inference test p-values in brackets. For LATE analysis, "SMS Treated" and "LF Treated" variables are instrumented by "SMS Assignment" and "LF Assignment". * p<.1, ** p<.05, *** p<.01. Underidentification test is the Kleibergen-Paap rk LM statistic. Estimators in columns 1 and 3 are ordinary least squares. Estimators in columns 2 and 4 are instrumental variables.

[8] Table A4 in the appendix shows that scouting is significantly associated with observing fall armyworm. While the differences in reported fall armyworm rates are insignificant across group assignments, failing to reject the null hypothesis (that the reported incidence rate is the same across groups) is not evidence that the null is true. The significant differences in scouting rates, together with scouting's significant effects on reporting fall armyworm validate our decisions not to condition on reporting fall armyworm in our analyses.

5.3 Effects on maize technical inefficiency and damage control

We now turn to the main results of interest, tests for the efficacy of pesticide use in damage control estimations (Table 6).9 The lead-farmer group is the only group to consistently show significant improvements in maize technical efficiency (or significant decreases in technical inefficiency) from pesticide use. The control group shows significant benefits from pesticides in one of four estimates while the SMS group results are insignificant in all four estimates. For the lead-farmer group, a 1,000 MMK increase in pesticide expenditure leads to an approximate yield increase of 0.8-1.1 percent (columns 1 and 3). Because pesticides do not have a direct effect on maize production, yield improvement stems from more effective control of pests through improved timing and selection of pesticides.

Table 6. Average partial effects of pesticide expenditures by treatment assignment

	Ln (Technical inefficiency scores)			
	Two-stage DEA		Bias corrected DEA	
	(1)	(2)	(3)	(4)
Pesticide expenditure by group ('000 MMK/ac)				
Control assignment	-0.005**		-0.002	
	(0.002)		(0.003)	
SMS assignment	-0.003		0.000	
	(0.003)		(0.003)	
Lead Farmer assignment	-0.011***		-0.008**	
	(0.004)		(0.004)	
Inverse hyperbolic sine of pesticide expenditure by group ('000 MMK/ac)				
Control assignment		-0.031		-0.01
		(0.020)		(0.021)
SMS assignment		-0.015		0.002
		(0.017)		(0.015)
Lead Farmer assignment		-0.071**		-0.053*
		(0.028)		(0.028)
Covariates	Yes	Yes	Yes	Yes
Coefficient equality tests p-value				
SMS = LF	0.139	0.099	0.085	0.079
Control = LF	0.265	0.254	0.234	0.218
Control = SMS	0.594	0.549	0.545	0.630
Number of Observations	1112	1112	1112	1112

Notes: Cluster robust SEs at the village level in parentheses. Significance: * p<.1, ** p<.05, *** p<.01. Covariates are weed pressure variables: indicators for high and low weed pressure, and the number of complete weedings conducted on the plot. Coefficient equality tests are chi-squared tests. Columns 1 and 2 are estimated by Tobit regression and columns 3 and 4 are estimated by truncated regression (second stage).

In three of four estimates, the lead-farmer group had significantly more effective pesticide use than the SMS group. This aligns with the significantly higher knowledge scores on pesticide action thresholds for the lead-farmer group. For the SMS group, the overall knowledge improvement but insignificant differences in action threshold knowledge do not lead to effective pesticide use in maize. We note that we fail to reject the null of equal efficacy in pesticide expenditures between control and treatment groups in each estimation. However, the coefficients are 2 to 5 times larger in magnitude for the lead-farmer group. Given the low compliance, it may be reasonable to expect

[9] Summary statistics of variables by group are presented in Appendix Table A3.

larger and more significant effects from reaching more farmers with information through the lead-farmer mechanism.

5.4 Robustness checks, extensions, and limitations

We conduct alternative estimations to test the sensitivity of our results to two estimation decisions. First, we restrict the sample to only the maize plots that were fully harvested at the time of interview. This drops our sample size nearly in half, and our power along with it, but it removes any potential error or bias from farmers reporting expectations for a portion of their maize plots that were not yet harvested at the time of interview. Results in Appendix Table A5 show similar effect sizes and significance despite the lower power. We conclude that our decision to increase power by using harvest volumes comprised partially of expectations at the end of the growing season does not meaningfully change our results.

Our second robustness check is to use an alternative specification of the first stage DEA estimation. In the alternative specification, we disaggregate the variables in the production input vector to include the plot size (acres), per acre household labor days, and expenditures per acre on maize seed, urea fertilizer, compound fertilizer, and hired labor. However, to satisfy the strict positivity requirement we must introduce a separate issue by arbitrarily setting zero values to one.[10] Results in Appendix Table A6 show similar estimates as those shown in Table 6. The only meaningful difference is the damage control effects for the control group are significant in the bias-corrected DEA regressions, though the lead-farmer group estimates are still larger with lower p-values. Thus, our preferred DEA first-stage specification is not driving the estimated impacts of damage control efficacy.

To put our estimates into context we take an admittedly imperfect step to compare the relative cost efficacies of each extension program (Table 7). We use a naïve approach to estimate the benefits of each program by assuming an increase in pesticide expenditures equivalent to US$1 for all farmers and apply the average partial effect estimate for each group from Table 6, column 1.

The fixed costs of the design and management are the same for both methods, and the variable costs end up being quite similar as well: $816 for the SMS method and $796 for the lead-farmer method, mostly in lead-farmer incentives for distributing information. Lower compliance in the lead-farmer program means that the costs per farmer reached are higher than in the SMS method. However, the higher maize yield improvements in pesticide efficacy for the lead-farmer method imply a much larger benefit from the extension program from an assumed average increase in pesticide use of $1. The larger benefits drive much higher estimated returns for the lead-farmer extension method. The net value per targeted farmer was $23 for the lead-farmer method and $6 for the SMS method.

[10] The changes made are in the input expenditure variables which are defined in MMK and have mean values of more than 20,000 each. Thus, one is sufficiently small as an arbitrary value and close in meaning to zero.

Table 7. Costs and benefits comparisons of SMS and lead-farmer extension methods

	Extension method	
	SMS	Lead-farmer
Costs		
Fixed costs		
Message design & development	$ 3,000	$ 3,000
Management	$ 2,000	$ 2,000
Variable costs		
SMS delivery costs	$ 816	$ 20
Lead-farmer communications		$ 25
Lead-farmer payment		$ 771
Costs per farmer targeted		
Total	$ 15.72	$ 15.22
Variable	$ 2.21	$ 2.14
Costs per farmer reached		
Total	$ 52.40	$ 70.07
Variable	$ 7.35	$ 9.83
Estimated benefits from 1USD increase in pesticide use		
Maize		
Total	$ 10,106	$ 34,499
Per targeted farmer	$ 27	$ 90
Net value		
Total	$ 2,368	$ 8,964
Per targeted farmer	$ 6	$ 23
Benefit-cost ratio		
Total	0.4	1.5
Variable costs	2.9	11.0

Notes: Costs exclude researcher time. Estimated benefits calculated as $\widehat{APE_j} * 1.62 * Y_i * A_i$ where $\widehat{APE_j}$ is the average partial effect estimate for treatment group j (column 1 in Table 6); 1.62 is USD to MMK exchange rate divided by 1000; Y_i is the maize yield for farmer i; and A_i is the area of the maize plot. Net value is the value of additional maize output using the sample average maize price minus the assumed pesticide cost increase.

While this paper contributes to our understanding of extension methods in times of crisis, there are limitations to our analysis, and we highlight three of them for further discussion here. First, there is room for improvement in the implementation of our tested interventions, most notably we had low compliance. While this does not affect the validity of estimates calculated as average effects across group assignment (not information receipt), it does lower both the average effects and statistical power, and in that way, may underrepresent the impacts of such programs if they are able to reach more farmers with timely delivery of information around their specific growing calendars. To address low compliance, we present the LATE estimates where possible. There is scope to further research lead farmers' decision to share SMS messages with target farmers and incentive structures to positively influence that decision. Second, we rely on self-reported FAW incidence which is affected by the extension programs themselves through scouting and identification. Thus, we are not able to test the impacts of our interventions on the intermediate behaviors to control FAW. Given the context and fully remote nature of this study, there is little we could have done to eliminate this problem. Indeed, it is a problem for most pest incidence studies, but future research could address it with regular plot monitoring. Third, in our damage control estimations and our cost-benefit estimates we focus on maize production as the key outcome. However, there may be other important outcomes that we are not able to measure, e.g., environmental impacts, health risks, or gross margins. These remain areas for future research contributions.

6. CONCLUSION

In this paper, we have explored the effects of two remote farmer extension programs to reduce the economic costs of an emergent pest during a crisis when traditional extension methods were infeasible due to political instability and COVID-19. By randomly assigning villages to receive either no information, information through SMS, or information through a novel SMS-based lead-farmer method, we ensure exogenous group assignment and therefore causal effect estimates. We conducted this experiment in Myanmar in 2021 during a military coup, and the information campaign addressed fall armyworm, a new threat to maize production.

Our results show that both extension programs improved farmer knowledge, but in different ways. The SMS-group learned more in pesticide toxicity while the lead-farmer group learned more in pesticide action thresholds. Both effect sizes are 96 percent of the control group knowledge scores. These results are broadly in-line with previous findings on pesticide extension and knowledge (Goeb and Lupi, 2021; Goeb et al., 2022c). Importantly, the knowledge changes did not lead to noticeable improvement in practices for the SMS group, but the lead-farmer group was 6 percent more likely to scout than the control group. More importantly, the lead-farmer group used pesticides more effectively than the SMS group and the control group.

Altogether, our results show the importance of information on pesticide action thresholds in the management of FAW, particularly when delivered by a peer-farmer within the community. Perhaps more important for policy, our results demonstrate that lead-farmer information dissemination mechanisms can be effective – and more effective than direct SMS campaigns – in a time of high distrust and crisis. Messages from unknown sources may not be an effective way to deliver information to farmers in such contexts. In particular, in-person delivery of information by lead farmers may be most impactful, though more research is needed there to understand the modes of communication they used and how to incentivize them to relay the messages to more farmers. The larger effect estimates of the lead-farmer method imply greater aggregate returns on expenditures relative to the SMS-group.

Both interventions can be easily scaled to reach more farmers at low marginal costs, making them attractive investments at a larger scale than our experiment. However, implementing the direct SMS method requires a large database of farmer phone numbers to contact which is not cost-free to obtain. Governments could, at lower cost, allow farmers to self-select into a registry to receive such messages, of course with the tradeoff that only the registered farmers would benefit. Yet, this research shows that disseminating information through lead farmers, even without the ability to train lead farmers in person, could have a greater impact without the need for large farmer registries. Instead, governments or NGOs could work with extension staff to identify appropriate lead farmers and incentivize them to share information within their villages.

We had low compliance in our information interventions and there is much room for design improvements to reach a larger share of the intended recipients and to increase impact. Future research should explore such design issues including making messages more targeted and direct, other innovative information delivery mechanisms through a known number, or different incentive schemes for lead farmer information sharing including higher payments for in-person information delivery.

Lastly, extension information may be a relatively fast and low-cost way to improve farmer welfare in the face of a new production threat and in fragile states, but future research should compare the impacts and cost effectiveness of other farm interventions. Cash transfers may be a particularly important intervention to test in contexts of insecurity or in the presence of new threats requiring cash expenditures for new inputs and in conflict areas where cellphone applications could be used for the safe transfer of money.

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APPENDIX

Table A.1 Knowledge assessments

Question	Response options
Scouting and identification	
What is the recommended route/pattern to follow when scouting for FAW?	Open-ended
Where does fall armyworm mostly lay eggs?	Open-ended
What is the most common sign of fall armyworm damage on leaves?	Open-ended
What part of maize plant do young fall armyworm larvae most often show damage and frass?	Open-ended
How do you identify fall armyworm appearance and distinguish from other caterpillar pests?	Open-ended
Action threshold	
Out of 100 maize plants, how many should show FAW damage before applying chemical…	
At the establishment stage of maize growth (seeding to 2 weeks),	(0-100), don't know
At the early whorl stage (knee high, 2-4 weeks old),	(0-100), don't know
At the late whorl stage (shoulder high, 5-8 weeks old)	(0-100), don't know
After which maize growth stage, is it no longer recommended to apply pesticides?	Open-ended, # of weeks
Pesticides	
Do you know that there are beneficial insects that help control Fall armyworm?	Yes/no
How do you identify the toxicity (health risk) of a pesticide from its container?	Open-ended
How toxic/harmful to humans is a GREEN label pesticide under usual use?	Very / Somewhat/ Not very
How toxic/harmful to humans is a RED label pesticide under usual use?	Very / Somewhat/ Not very
Total knowledge index is sum total of correct responses. Three sub-indices are the sum of correct responses within each category.	

Table A.2 Attrition bias tests across treatment groups

HH Attrited	(1) Coef.	SE	(2) Coef.	SE	(3) Coef.	SE	(4) Coef.	SE
Group Assignment								
SMS	-0.027	(0.032)	-0.029	(0.032)	-0.031	(0.032)	-0.034	(0.032)
Lead Farmer	0.010	(0.035)	0.011	(0.035)	0.008	(0.034)	0.009	(0.035)
Demographic Characteristics								
No. of HH Members			0.011*	(0.006)	0.011*	(0.006)	0.016**	(0.007)
Female Farmer			0.027	(0.029)	0.025	(0.029)	0.028	(0.03)
Farmer Age			-0.002**	(0.001)	-0.002***	(0.001)	-0.002*	(0.001)
Attended Monastery School			-0.028	(0.03)	-0.026	(0.03)	-0.027	(0.031)
Attended High School or More			-0.052*	(0.028)	-0.053*	(0.029)	-0.049*	(0.029)
Did not attend school			0.027	(0.057)	0.030	(0.057)	0.030	(0.058)
Farm Characteristics								
Land area owned (acres)			-0.001	(0.001)	0.000	(0.002)	0.000	(0.002)
Violence in area since coup			0.048	(0.031)	0.046	(0.03)	0.043	(0.031)
Maize Cultivation Experience					0.001	(0.001)	0.001	(0.001)
Maize Area Cultivated in 2021					-0.003	(0.002)	-0.003	(0.002)
Experienced pests in last 3 years					-0.066	(0.048)	-0.068	(0.049)
Information/Social Network Characteristics								
Aware of FAW							-0.01	(0.037)
No. of Cellphones Owned							-0.019*	(0.011)
Read/type SMS messages in Burmese							0.057	(0.043)
Has agricultural apps on phones							0.025	(0.025)
Constant	0.199***	(0.022)	0.244***	(0.058)	0.305***	(0.067)	0.246***	(0.083)
N	1,382		1,382		1,382		1,382	
R-squared	0.0015		0.0144		0.0182		0.023	

Note: Cluster robust SEs at the village level in parentheses. * p<.1, ** p<.05, *** p<.01

Table A.3 Output, input, and damage control variables for a household's main maize plot, by group assignment

	All sample (n=1114)		Control group (n=362)		T1: SMS group (n=370)		T2: Lead Farmer group (n=382)	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Maize yield on main plot (kg/ac)	1395.8	(690.5)	1390.4	(630.4)	1321.9	(624.2)	1472.4	(792.3)
Input variables								
Area of main plot (ac)	4.1	(3.7)	4.5	(4.4)	4.2	(3.4)	3.6	(3.4)
Input costs ('000 MMK/ac)	135.3	(97.9)	137.3	(94.0)	131.0	(71.7)	137.5	(121.0)
Total labor (days/ac)	11.2	(9.9)	10.7	(8.6)	11.4	(11.1)	11.6	(9.7)
Damage control variables								
Pesticide expenditure ('000 MMK/ac)	9.0	(11.3)	8.8	(11.8)	7.9	(9.8)	10.2	(12.0)
Low weed pressure on plot (i)	0.2	(0.4)	0.2	(0.4)	0.2	(0.4)	0.2	(0.4)
High weed pressure on plot (i)	0.5	(0.5)	0.5	(0.5)	0.4	(0.5)	0.5	(0.5)
Number of complete weedings	1.4	(0.7)	1.4	(0.7)	1.4	(0.8)	1.4	(0.7)

Notes: Total labor includes both hired and household labor. Input costs exclude pesticide expenditures. (i) denotes indicator variable where 1=yes, 0=no.

Table A.4 Relationships of scouting and group assignment to reporting fall armyworm

Dep Variable	Report Fall Armyworm			
	(1)	(2)	(3)	(4)
Scout	0.206***		0.202***	0.216***
	(0.037)		(0.038)	(0.080)
SMS assignment		-0.013	-0.016	0.000
		(0.054)	(0.053)	(0.084)
		[0.745]		
Lead Farmer assignment		0.066	0.053	0.068
		(0.056)	(0.055)	(0.082)
		[0.127]		
Scout X SMS				-0.022
				(0.097)
Scout X LF				-0.021
				(0.097)
Control group mean	0.49	0.49	0.49	0.49
Coefficient equality test: SMS = LF		0.135	0.155	0.38
Coefficient equality test: Scout X SMS = Scout X LF				0.984
N	1114	1114	1114	1114
R-Squared	0.031	0.005	0.035	0.035

Note: Cluster robust SEs at the village level in parentheses. Randomization inference test p-values in brackets. * p<.1, ** p<.05, *** p<.01.

Table A.5 Only fully harvested plots - Average partial effects of pesticide expenditures by treatment assignment

Sample	ln (Technical inefficiency scores)			
	Two-stage DEA		Bias corrected DEA	
	(1)	(2)	(3)	(4)
Pesticide expenditure by group ('000 MMK/ac)				
Control assignment	-0.004		-0.002	
	(0.004)		(0.005)	
SMS assignment	0.000		0.002	
	(0.004)		(0.005)	
Lead Farmer assignment	-0.012***		-0.009**	
	(0.004)		(0.004)	
Inverse hyperbolic sine of pesticide expenditure by group ('000 MMK/ac)				
Control assignment		-0.035		-0.02
		(0.030)		(0.032)
SMS assignment		-0.004		0.010
		(0.024)		(0.025)
Lead Farmer assignment		-0.077**		-0.060*
		(0.038)		(0.037)
Covariates	Yes	Yes	Yes	Yes
Coefficient equality tests p-values				
SMS = LF	0.074	0.122	0.085	0.121
Control = LF	0.266	0.409	0.284	0.424
Control = SMS	0.495	0.431	0.56	0.47
Number of Observations	637	637	637	637

Notes: Cluster robust SEs at the village level in parentheses. Significance: * p<.1, ** p<.05, *** p<.01. Covariates are weed pressure variables: indicators for high and low weed pressure, and the number of complete weedings conducted on the plot. Coefficient equality tests are chi-squared tests.

Table A.6 Alternative DEA specification: Average partial effects of pesticide expenditures by treatment assignment

Sample	Ln (Technical inefficiency scores)			
	Two-stage DEA		Bias corrected DEA	
	(1)	(2)	(3)	(4)
Pesticide expenditure by group (‘000 MMK/ac)				
Control assignment	-0.005**		-0.004*	
	(0.002)		(0.002)	
SMS assignment	-0.003		-0.001	
	(0.003)		(0.002)	
Lead Farmer assignment	-0.011***		-0.009**	
	(0.004)		(0.004)	
Inverse hyperbolic sine of pesticide expenditure by group (‘000 MMK/ac)				
Control assignment		-0.031		-0.031*
		(0.020)		(0.016)
SMS assignment		-0.015		-0.009
		(0.017)		(0.013)
Lead Farmer assignment		-0.071**		-0.064***
		(0.028)		(0.024)
Covariates	Yes	Yes	Yes	Yes
Coefficient equality tests p-values				
SMS = LF	0.139	0.099	0.061	0.038
Control = LF	0.265	0.254	0.215	0.231
Control = SMS	0.594	0.549	0.382	0.29
Number of Observations	1112	1112	1112	1112

Notes: Cluster robust SEs at the village level in parentheses. Significance: * p<.1, ** p<.05, *** p<.01. Covariates are weed pressure variables: indicators for high and low weed pressure, and the number of complete weedings conducted on the plot. Coefficient equality tests are chi-squared tests.

Appendix Figure 1. Messages sent to farmers (English)

Message 1
Your household was recently called by phone about maize management practices. One aspect of management is to control fall armyworm, a caterpillar pest that can cause significant losses in maize. To help you control this pest, we will send you messages by SMS 4 times during the growing season. This is the first message. <u>These messages are sent by MSU, based on guidance from the Dept of Plant Protection and ImpactTerra (GoldenPaddy).</u>
FAW cannot be eradicated, it can only be managed and controlled. Pesticides are a useful tool to control FAW, but to maximize your farm profits, you should only spray if you observe FAW presence ABOVE the recommended action threshold according to growth stages
Pesticide safety is essential. Always use pesticides safely by wearing PPE (e.g., gloves, boots), choosing less toxic pesticides, and following recommended safety and mixing practices provided on the packaging.
Pesticides vary in their toxicity. The color labels at the bottom of pesticide labels signal the toxicity class. Red is Highly hazardous and Green is much less hazardous. When possible you should use less toxic pesticides.

Message 2
This is message number 2 on how to control Fall Armyworm. <u>These messages are sent by MSU, based on guidance from the Dept of Plant Protection and ImpactTerra (GoldenPaddy).</u>
Scouting is necessary for quick detection of the presence of FAW. And **should be done once every week at the seedling and early vegetative stages**

- **Walk** through the maize field at least 5 meters from the edges of your field
- **Scout zigzags** the field, stopping at five different locations
- At each stop, **assess at least 10 plants** looking for signs of FAW feeding. Common signs include:
    - Eggs underneath leaves
    - Larvae or frass inside the whorl
    - Glass-pane eating on leaves

At 0-2 weeks stage: If you find FAW signs on 5 or more plants out of 50, then you should apply a biological pesticide such as B.t. or neem, so that you do not harm natural enemies. Always apply pesticides safely by wearing PPE (e.g., gloves, boots),
If you find FAW signs on less than 5 plants out of 50, It is not profitable to spray. pick up and destroy the eggs and larva by hand

Message 3
This is message number 3 on how to control Fall Armyworm. <u>These messages are sent by MSU, based on guidance from the Dept of Plant Protection and ImpactTerra (GoldenPaddy).</u>
At the early whorl stage (2-4) weeks, you should continue to scout for FAW once every week using the zig-zag pattern, stopping at 5 locations inside your field, and examining at least 10 plants at each location
Common signs still include:

- Eggs underneath leaves
- Larvae or frass inside the whorl
- Glass-pane eating on leaves

You can distinguish FAW from other caterpillars because FAW has a Y-shape on its head, and 4 prominent dots on its back
At 2-4 weeks: If you find FAW signs on 10 or more plants out of 50, then you should apply a **recommended pesticides** by Department of Plant Protection such as products with the active ingredients indoxacarb or emamectin benzoate products (e.g., Awba- Nget Gyi Taung; Awba-Alarm; or Armor Top Star). Pesticides vary in their toxicity. The color labels at the bottom of pesticide labels signals the toxicity class. Red is Highly hazardous and Green is much less hazardous. When possible you should use less toxic pesticides.
If you find FAW signs on less than 10 plants out of 50, it is not profitable to spray a pesticide

Message 4
This is the 4th and final message on how to control Fall Armyworm. <u>These messages are sent by MSU, based on guidance from the Dept of Plant Protection and ImpactTerra (GoldenPaddy).</u>
Scouting should continue weekly. Continue to use a zig-zag pattern or a ladder pattern, check 5 spots, and at least 10 plants per spot
Common signs of FAW to look for include

- Eggs underneath leaves
- Larvae or frass inside the whorl
- Glass-pane eating on leaves

At the late whorl stage, when **20 or more plants out of 50** show signs of FAW, you should apply a **recommended pesticides** by Department of Plant Protection such as products with the active ingredients indoxacarb or emamectin benzoate products (e.g., Awba- Nget Gyi Taung; Awba-Alarm; or Armor Top Star). Always apply pesticides safely by wearing PPE (e.g., gloves, boots).
If you find signs of FAW on less than 20 plants out of 50, it is not profitable to apply a pesticide. You may hand pick.
After your maize reaches the tasseling stage, you are not recommended to apply a pesticide to your maize. It could be dangerous and poisonous for the applicators and the natural enemies. So, pick up by hand and destroy or crush the eggs or caterpillars.

Data Envelopment Analysis

The first-stage Data Envelopment Analysis method can be expressed as the following maximization problem for farm o with n other farms:

$$\max_{\rho} \theta$$

Subject to:

$$\theta_{y_o} \leq \sum_{i=1}^{n} \rho_i y_i$$

$$x_o^k \geq \sum_{i=1}^{n} \rho_i x_i^k \text{ , } for\ k = 1, 2, 3$$

$$\rho_i \geq 0$$

where θ is the maximized technical efficiency score, and the optimization chooses farm specific weights ρ to form linear combinations of other observed farms (i.e., not farm o) outputs y and inputs x. We have only one output in our problem (maize yield in kg/ac) and three inputs (plot size, input costs per acre, and total labor days). The constraints ensure that the optimized output for farm o is within a linear combination of observed farm outputs, and also that the linear combination of input use for the other farms does not exceed that of farm o.

The maximization produces Farrell output-oriented technical efficiency scores, $\hat{\theta}$, taking values between one and infinity, where one is on the frontier and higher scores reflect greater inefficiency of input use. As explained in Kuosmanen et al. (2006), under usual assumptions, the DEA procedure produces consistent estimates of the first (non-damage control) component of production $f(x)$ in equation (5). More accurately, $\hat{\theta}$ is a consistent estimate of $Q\ /\ f(x)$, which we use to form our outcome variable for the damage control estimation in the second stage.

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