Peer Learning in a Digital Farmer-to-Farmer Network: Effects on Technology Adoption and Self-Efficacy Beliefs

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Abstract

Information constraints rank high among barriers to agricultural technology adoption among small-scale farmers, particularly for complex bundles of complementary practices such as regenerative agriculture (RA). These techniques involve many components and various strategies for successful implementation, and farmers may face internal constraints to adoption even when external constraints are removed. Information communication technologies (ICTs) are emerging to extend the reach of agricultural training, with potential to deliver information through mobile and smartphones at little or no cost to farmers. The problem remains that beneficial practices like RA are varied and context-specific, requiring a high level of engagement with new information that is difficult to facilitate through ICTs. We develop a low-cost digital extension platform, ShambaChat, to facilitate peer learning through SMS communication on basic feature phones, and use a randomized control trial to evaluate the ability of this ICT to generate self-efficacy gains and promote adoption of beneficial RA practices among smallholders in Morogoro, Tanzania. We measure a positive impact of treatment on adoption and self-efficacy beliefs when farmers engage with each other through the tool, but find that participants lose interest and do not maintain activity after the first round of treatment, leading to null effects for the remainder of adoption and learning outcomes.

Résumé

Les contraintes d'information figurent parmi les obstacles à l'adoption des technologies agricoles pour les petits agriculteurs, en particulier pour les pratiques complexes complémentaires comme l'agriculture régénérative (RA). Ces techniques impliquent de nombreux composants et diverses stratégies de réussite, et les agriculteurs peuvent être confrontés à des contraintes internes à l'adoption même lorsque les contraintes externes sont supprimées. Les technologies de l'information et de la communication (TIC) offrent un potentiel de fournir des informations via les téléphones portables et les smartphones à peu ou pas de frais pour les agriculteurs. Le problème demeure que les pratiques bénéfiques telles que la RA sont variées et spécifiques au contexte, nécessitant un niveau élevé d'engagement avec de nouvelles informations qu'il est difficile de faciliter grâce aux TIC. Nous développons une plate-forme d'extension digitale, ShambaChat à faible coût pour faciliter l'apprentissage par les pairs via la communication SMS sur les téléphones de base, et utilisons un essai de contrôle randomisé pour évaluer la capacité de cette TIC à générer des gains d'auto-efficacité et à promouvoir l'adoption de pratiques de RA bénéfiques parmi les petits exploitants dans Morogoro, Tanzanie. Nous mesurons un impact positif du traitement sur l'adoption et les croyances d'auto-efficacité lorsque les agriculteurs s'engagent les uns avec les autres via l'outil, mais constatons que les participants perdent leur intérêt et ne maintiennent pas d'activité après le premier cycle de traitement, conduisant à des effets nuls pour le reste de l'adoption et les résultats d'apprentissage.

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Contribution of Authors

As the main author of this study, I developed the concept for the ShambaChat extension platform and evaluation, and the views and opinions expressed in this thesis are my own. I led the study design, and all writing, figures, and analysis produced in this report is my original work. I also contributed to the construction of the survey instrument, including all original survey modules developed for the variables of interest in this study, and coded the survey into an electronic form using XLSForms. I led the data analysis including all cleaning of data and running all models in Stata. I wrote all the final agronomic content for the extension course, managed all activity (sending and receiving messages) on the ShambaChat platform, and analyzed the content of farmers' messages using Python.

Professor Aurélie Harou is my co-author and research supervisor. She contributed to the design of the RCT and analytic methods, and provided editing, guidance, and feedback for each chapter. She helped me to frame the research question and develop rigorous methods for evaluating the treatment effects.

Professor Chris Magomba is also co-author of this study. Along with our field manager Aika Aku, he oversaw the data collection in Tanzania, and provided input for the agronomic content of the extension course. He helped with the translation of the survey and extension course into Swahili, and the translation of messages sent by farmers back into English. He was the key link to farmers in Morogoro, and provided insight on how to make this project most beneficial to them.

David Guereña at CIAT, the Big Data Platform of the CGIAR, provided agronomic expertise for designing the survey instrument, and Travis Lybbert at UC Davis provided input on eliciting self-efficacy beliefs.

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Chapter 1: Introduction

1.1 Problem Statement

Despite major gains in agricultural productivity and welfare across much of the developing world, many economies of sub-Saharan Africa (SSA) continue to lag behind in terms of output and food security (Sanchez, 2002). With 70 – 80% of the population employed in agriculture, this sector holds the key to broad-based, pro-poor economic and human development through accessible productivity gains that increase agricultural yields and incomes for smallholder farmers (Conceição et al., 2016). The success of Green Revolution advances in spurring poverty reductions through increased agricultural productivity across Asia and South America highlights the importance of making effective technologies accessible and coherent to small-scale farmers.

However, use of modern inputs remains strikingly low among smallholders in SSA, with numerous demand and supply-side factors affecting adoption. Political instability, lack of infrastructure and mechanization, and a heterogenous set of cropping systems and practices to cater to have restricted supply, resulting in high prices that render these technologies inaccessible or unprofitable for smallholders. At the same time, poorly functioning credit, goods, and insurance markets, and a lack of accessible information about these technologies have discouraged demand (Conceição et al., 2016; Francis et al., 1986; Myaka et al., 2006; Mutuku et al., 2020; Jama, 2008; Toenniessen et al,. 2008). Even where subsidies or loans are accessible and expected profits are high, smallholders may be hesitant to adopt new technologies if they doubt their ability to realize successful outcomes on their own farms (Barnett et al., 2008; Carter, 2016; Jama et al., 2017).

Additionally, Marenya and Barrett (2009) find that inorganic fertilizer application may not be profitable when soil organic matter (SOM) is low, as is common in much of SSA. Indeed, returns to fertilizer are heterogeneous and poorly documented across the diverse agro-ecological zones of SSA, and may be particularly low on rainfed plots with degraded soil resources commonly cultivated by smallholders (Conceição et al., 2016; Duflo et al., 2008; Marenya and Barrett, 2009). Since poorer farmers tend to cultivate the most degraded soils, a poverty-trap arises where low SOM makes cropland less responsive to nutrient inputs, driving farmers to continue mining nutrients from their cropland and contribute further to soil degradation – as well as inequality if better-off farmers escape this cycle more easily (Marenya and Barrett, 2009). Moreover, fertilizer use in isolation does not build long-term soil fertility or replenish the hundreds of micro- and macronutrients required for production of nutritious food crops, and improper handling of agro-chemicals can pollute water resources and cause environmental damage (Lal, 2020; Lunn-Rockliffe et al., 2020; Montgomery, 2017). Pro-poor development should recognize the limitations of Green Revolution technologies for smallholder agriculture, and seek to promote integrated soil management practices that foster and sustain healthy agro-ecosystems and bolster rural economies.

Complex bundles of complementary practices can be challenging to introduce, and adoption depends on farmers engaging deeply with information presented in a way that feels relevant and actionable. Moreover, heterogeneity of agro-ecosystems and available on-farm resources means that best-management practices are varied and context-dependent, and do not lend themselves to uniform extension across regions or even homesteads. A farmer may understand information presented to her about a new technology with theoretically high returns, but this can fail to spur adoption if she does not believe herself capable of bringing about the same outcome on her own land, either due to internal constraints such as low self-efficacy beliefs, or because the advice is not tailored to her specific agro-ecological context. Extension campaigns that initiate dialogue between farmers in existing or newly established social networks make new information more accessible by situating it in the experience of a relatable peer and providing concrete evidence of yield and profit outcomes. Farmer-to-farmer extension (F2FE) exploits this networking effect, and there is substantial evidence that learning from peers can promote technology adoption under the right conditions (BenYishay and Mobarak, 2018; Conley and Udry, 2010; Davis et al., 2012; Fisher et al., 2018; Foster and Rosenzweig, 1995; Hellin and Dixon, 2018; Nakano, 2018).

F2FE methods like farmer-field days and demonstration plots have proved effective tools for generating and sharing agricultural information, but can be logistically challenging, requiring coordination of large numbers of people and resources which may result in barriers to access, particularly in more remote regions. Additionally, the conditions under which F2FE leads to adoption, and the extent to which peer learning happens through social networks are not fully understood. Some studies suggest, for example, that farmers lack proper incentives to share information with peers (BenYishay and Mobarak, 2018; Kondylis et al., 2017), do not convey precise or detailed information that is actionable by others (Maertens and Barrett, 2012), or fall into a free-rider problem allowing others in their network to bear the cost of experimentation (Bandiera and Rasul, 2006). In recent years, information communication technologies (ICTs) have greatly expanded the accessibility and cost-effectiveness of agricultural extension, and the social-networking capacity associated with ICTs makes digital F2FE an alluring prospect. While ICTs overcome many logistical and cost barriers associated with in-person extension, the conditions under which users of a digital extension network might engage with information in a way that leads to adoption become even more challenging to meet. Particularly when considering deep cognitive engagement with complex and context-specific bundles of complementary practices and agro-ecological principles, the limitations of ICT extension loom large.

1.2 Study Objectives

This study asks whether the dynamics of farmer-to-farmer extension (F2FE) can be meaningfully preserved in a digital space, using a low-cost and accessible ICT for non-smart phones (hereafter *feature phones*). To study digital F2FE, we develop and test a simple tool, ShambaChat, for facilitating farmer engagement with complex agricultural information delivered by SMS. Through ShambaChat, smallholders are connected in chat groups with others in their region who are growing the same crop and share similar soil nutrient deficiencies. Participants receive scientifically validated information from agronomists, which they are able to discuss by text with the other farmers in their chat groups. Two members of each group are selected based on prior experience with the targeted practices at baseline. The goal of ShambaChat is to improve the efficacy of ICT extension in promoting the adoption of beneficial agricultural practices among smallholders by providing access to a digital network of peer farmers and role models. To this end, we conduct a randomized control trial (RCT) in 47 villages in Morogoro, Tanzania to evaluate the group chat feature of ShambaChat. All households in the study receive the same extension information by SMS, while treated participants are additionally placed in a 5-person chat group and encouraged to chat with each other by text about the extension information and related topics. This allows us to specifically evaluate the ability of a group chat feature to augment traditional SMS extension delivery.

The primary objective of the study is to shed light on the belief-updating process that occurs when farmers gain virtual exposure to role models with more – or simply different – experience with a given technology, and are given the opportunity to grapple with and troubleshoot new information together with a network of peers. Our first question is whether participation in the group chats increases adoption and/or knowledge of the targeted practices relative to farmers who receive the same information through one-way SMS delivery only. We then attempt to explain why the treatment could have this effect by looking at several behavioral outcomes that might be influenced by participation in the group chats. We focus on perceived-self-efficacy (PSE), or the belief in one's capacity to perform tasks successfully in a specific domain, as a potential mechanism through which peer learning might lead to adoption of new practices. If the group chats give farmers a sense that their peers are able to successfully implement certain practices, this may translate into an increase in PSE, which could in turn contribute to the decision to adopt. Even if no direct evidence of adoption outcomes is available through the group chats, general interest or enthusiasm around adopting new practices might lead to increased PSE if members feel empowered about their own capabilities by the confidence of their peers. We also use a probability assignment game to elicit a measure of farmers' subjective probability distributions (SPD) over adoption outcomes, designed to capture the effect of treatment on farmers' beliefs about the likelihood of being successful with a new practice, with success defined variously in terms of soil fertility, profit, and food security outcomes.

1.3 Summary of Results

Participation in the group chats was low overall, dropping off sharply after the first month of treatment. This suggests that farmers did not form the type of connections anticipated, which is itself a relevant finding of the study. ShambaChat users may have struggled with the technology, perhaps frustrated by the difficulty of typing messages on feature phones, or facing confusion when scrolling through messages sent between different members of their group. If users were comfortable navigating the group chats, they may still have felt awkward or uncomfortable discussing their agricultural practices with strangers, even after participating in an icebreaker. In light of this user-behavior, which is discussed at length in Section 6.2, it is unsurprising that we did not measure a significant effect of the treatment on most of the behavioral outcomes discussed above. We do not find that treated farmers update their subjective probability distributions over adoption outcomes, nor do we observe an increase in PSE as measured by the New General Self-Efficacy Scale[1].

There was, however, substantial activity in the group chats over the first month of the intervention, during which a total of 997 messages were exchanged by farmers. The content covered by the ShambaChat extension course during this month focused on legume-maize intercropping and the concept of biological nitrogen fixation – a function of legumes. It appears that while the group chats were active, participation did have a significant effect on adoption, as treated farmers are found to be 13% more likely to intercrop with a legume on their main maize plot. Moreover, in addition to general PSE, we constructed task- and outcome-specific PSE measures for several of the topics discussed in the extension course. These are mostly insignificant, but we do find a significant positive effect of treatment on PSE for the intercropping task. This measure is balanced for treatment and control groups at baseline, with an average score of 1.3 out of 4, and increases for treatment households to 1.7 at endline, remaining at 1.3 for control. This difference is significant at the 10% level according to a difference-in-differences estimation, and robust to estimation by an ordered logistic model with random effects.

Perhaps the most interesting finding of this study is that despite the initial enthusiasm and evident transfer of knowledge present during the first month of the intervention, farmers lost interest and stopped using the platform almost entirely for the second and third rounds of extension. There is no treatment effect observed for any of the adoption outcomes associated with material

[1] https://sparqtools.org/mobility-measure/new-general-self-efficacy-scale/

presented in later months, nor with the associated task-specific PSE metrics. This indicates that active use of the group chat feature may, as speculated, lead to increased adoption and PSE, but that farmers did not deem participation worthwhile after an initial trial period. If farmers do not find a technology useful, the question of whether it can facilitate meaningful connections or nuanced learning behavior becomes moot.

1.4 Contribution to the Literature

SMS delivery of extension information is an established practice, but evidence of its effectiveness is limited and results are mixed (see Section 3.4 for a complete discussion). Existing evaluations look primarily at one-way SMS extension programs that deliver agricultural advice such as reminders about timing of field tasks (e.g., Larochelle et al., 2015), or market information services (MIS) that provide price information (e.g., Fafchamps and Minton, 2012). The subset of the literature on ICTs to which we hope to contribute evaluates projects that engage participants in cognitive processes which promote learning and memory of new information (eg Tjernström et al., 2021; Guilivi et al., *working paper*). ICTs that incorporate farmer-to-farmer communication functionality exist, but are predominantly internet-based and require a smartphone or computer to access. A notable exception is WeFarm, an SMS-based platform that allows farmers to connect with each other, as well as with agronomic specialists, and access and share knowledge from a basic feature phone. However, as of yet there are no rigorous evaluations of the impacts of WeFarm on knowledge or adoption of beneficial agriculture practices (Omolo and Kumeh, 2020). Our study is the first we know of to use an experimental design to evaluate the impact of a digital farmer-to-farmer extension platform.

Additionally, we contribute to the well-developed literature on social learning processes among farmers by proposing a possible link between peer learning and perceived self-efficacy (PSE) beliefs. We develop a theory of social learning by which exposure to peer role models increases farmers' belief in their capacity to successfully adopt complex practices on their farms, and investigate this empirically by measuring the change in PSE associated with participation in a farmer-to-farmer group chat. We also propose two novel methods for eliciting domain-specific PSE for agriculture.

Finally, although we do not explicitly analyze the conditions under which farmers are able and willing to use an ICT, our assessment of the ShambaChat user experience sheds light on some of the potential limitations of ICTs for facilitating engagement with extension information. We set the stage for further research to iterate on the concept of a digital F2FE platform and ask what kinds of changes to the structure, technology, or presentation of information can be made so that farmers can benefit from innovative social learning tools.

Chapter 2: Background

2.1 Morogoro Context

We survey farming households across Morogoro Rural, one of six *wilayas*, or districts, in the Morogoro region of Tanzania. Morogoro is the third largest region in Tanzania, occupying 8.2% (72,939 sq. km) of the country's mainland area, and is home to 5.1% of the population (URT, 2012; NBST, 2014). Morogoro shares key demographic features with the rest of the country, making it an appropriate case study from which we are able to draw some implications for a wider population of rural households. 67% (69.8%) of households in Tanzania (Morogoro) are located in rural areas, and 76.9% (73.3%) of rural workers in Tanzania (Morogoro) are principally employed in own-agriculture (NBST, 2014). Rural poverty is high, with 53% (41%) or rural households living below the basic needs poverty line of $1.90 per day in 2011 in Tanzania (Morogoro) (IFPRI and Datawheel, 2017).

Over 95% of agricultural land in Tanzania and within Morogoro is rainfed, which makes the agricultural sector and therefore food security sensitive to climate change and deviations from normal rainfall patterns (Ojoyi et al., 2015; IFPRI and HarvestChoice, 2017). Maize is the most common crop grown in Morogoro as well as in Tanzania as a whole, accounting for 27% (35%) of total harvested area in Tanzania (Morogoro), and 60% of dietary calories (IFPRI and HarvestChoice, 2017; Mtaki, 2017). Maize yields are low throughout Morogoro, largely due to soil nutrient deficiencies and minimal fertilizer application. Credit constraints limit use of agricultural inputs, with less than one percent of respondent households reporting fertilizer use in 2014 (Harou et al., 2021). For this reason, we focus on maize cultivation and methods for promoting adoption of regionally appropriate practices for improving maize yields in the presence of credit and information constraints.

2.2 Agricultural Learning and Extension in Morogoro

The Sokoine University of Agriculture (SUA) is a leading provider of agricultural extension in Morogoro, and our collaborator in the present study. Agricultural extension in the region is typically provided by government and university-affiliated extension agents who visit rural villages to offer in-person trainings. At baseline in 2020, 18% of respondents in this study reported receiving such a visit at some point during the past year, and topics most commonly addressed include organic fertilizer and composting, building soil fertility, and cultivation of improved maize varieties. Around 20% of respondents are part of a farmer-based organization, although this number decreases to 10% at endline in 2021, perhaps a result of the COVID-19 pandemic. Prior to this study, fewer than 1% of respondents reported having ever received extension information by phone.

2.3 Optimal Regenerative Agriculture Practices for SSA

2.3.1 Defining Regenerative Agriculture

First popularized in the early 1980s by the Rodale Institute, a US non-profit (Massy, 2020; Rodale, 1983), Regenerative Agriculture (RA) has gained attention in recent years across academic, public, and private spheres, with an increasing number of commitments and references made to RA since 2015 (Giller et al., 2021; Newton et al., 2020; Shreefel et al., 2020). RA is defined variously in terms of agricultural practices, desired outcomes, or both. Practices associated with RA center around the use of on-farm resources such as crop residue and manure, legume intercropping, and reduced reliance on external inputs such as inorganic fertilizers and pesticides (Lal, 2020; UNCTAD 2013). RA outcomes involve environmental and socio-economic goals such as carbon sequestration, increasing biodiversity above and below ground, high-volume low-input production of nutritious food, and promotion of healthy and self-sustaining agro-ecosystems and agrarian economies (Giller et al., 2021; Newton et al., 2020; Massy, 2020; Shreefel et al., 2020).

While many of the practices and guiding principles of RA can be found within similar schools of agricultural thought such as conservation agriculture (CA) and agroecology, RA is uniquely focused on improving and maintaining soil health as the key driver of economically and environmentally sustainable food systems (Newton et al., 2020). Moreover, RA is predicated on the objective of *improving* soils and ecosystem functioning through cultivation, as opposed to conceptions of sustainable agriculture which seek merely to do no harm (Lunn-Rockliff et al., 2020). This condition makes RA a powerful vision for restoring degraded agro-ecosystems and bolstering agricultural economies in the short run through increased crop yields and nutritional diversity, reduced input costs, and improved soil resources, as well as in the long run through the generation of resilient and fertile cropland (Lunn-Rockcliffe et al., 2020; Massy, 2020; Montgomery, 2017). The approach is particularly appropriate in regions like Morogoro where degraded soils lack key nutrients and smallholders face severe credit constraints which limit uptake of inorganic fertilizer recommendations (Harou et al., 2021; Jama, 2008; Tamim et al., 2021).

2.3.2 Benefits and Challenges to Regenerative Agriculture in SSA

95% of agricultural land in sub-Saharan Africa (SSA) is managed by smallholders in low-input, rainfed cropping systems (Mutuku et al., 2020). Soil nutrient deficiencies are a key constraint on agricultural productivity in SSA (Jama, 2008; Mutuku et al., 2020; Sanchez, 2002; Snapp et al., 1998), particularly in these smallholder systems which are often located on marginalized or degraded lands (Jayne et al., 2014). Inherently low nutrient availability and high moisture-stress limit soil fertility across much of SSA, while climate change, intensifying industrial agriculture practices, and a rapidly growing population place compounding burdens on the region's soil resources (Jama, 2008; Jayne et al., 2014; Lunn-Rockcliffe et al., 2020; Place et al., 2003). The inorganic fertilizers that spurred the Green Revolution and rapidly increased agricultural production in Asia and South America since the 1960s have largely failed to take hold across Africa. On average, N fertilizer application in SSA hovers around 9kg N ha^{-1} yr^{-1}, while most staple crops draw at least 60kg N ha^{-1} yr^{-1} from the soil (Jama, 2008, Myaka et al., 2006; Place et al., 2003). The process of intensifying agricultural production to feed a growing population without replenishing nutrients has resulted in 8 million tons of soil nutrient loss annually since 1970, valued at $4 billion USD in losses per year, and left 75% of agricultural soils in SSA significantly depleted (Jama, 2008; Sanchez, 2002; Toennissen et al., 2008). Productivity losses from declining soil fertility have pushed farmers to expand into marginal land and wilderness areas, where cultivation has low returns and costly environmental externalities (Jayne et al., 2014; Toenniessen et al., 2008).

Regenerative agriculture is based on intentional management of on-farm resources, providing an avenue to combat soil nutrient deficiencies at little or no financial cost to farmers (Massy, 2018; Montgomery, 2017). Incorporating legumes into cropping systems can replace much or all of the nitrogen consumed by maize and other staple crops through biological nitrogen fixation (BNF), reducing or eliminating the need for inorganic N fertilizer inputs (Adu-Gyamfi et al., 2007; Myaka et al., 2006; Rusinamhodzi et al., 2012). The benefits of legume intercropping extend beyond BNF, providing, for example, a nutritious and marketable food and cash crop that matures during the 'hunger season' when many households have depleted their maize stocks (Adu-Gyamfi et al., 2007; Thurow, 2013). Deep-rooted pigeon peas also pull water and nutrients from below ground, making them accessible to maize and bolstering the cropping system against drought and erosion (Adu-Gyamfi et al., 2007). Intercropping requires additional labor, but costs are minimal, especially as farmers can save seeds from one year to the next, and returns are high – indeed, Rusinamhodzi et al. find that intercropped systems generated a rate of return over 300% higher than monocropped maize.

The full benefits of legume integration are seen when nitrogen-rich crop residues are returned to the soil, where they decompose and release their nutrients which can be taken up again in the next cropping cycle. Increasing the quantity of on-farm biomass is a key principle of RA, as organic matter decomposition restores nutrients and enhances biological, physical, and chemical properties of soil, particularly if sustained over time (Berazneva and Güereña., 2019; Palm et al., 2001). Several studies confirm that crop residue retention from legumes is critical for capturing the full nitrogen-fixing potential from intercropping systems, as well as providing other benefits including increased nutrient availability, nitrogen use efficiency, soil organic matter (SOM), carbon content (C), and soil moisture (Adu-Gyamfi et al., Kihara et al., 2011; Kwena et al., 2017; Murphy et al., 2016). Crop residues can be combined with other sources of organic matter such as animal manures and bedding, household food scraps, ash, charcoal, forest topsoil, leaf litter, and even human waste to make compost, a valuable organic fertilizer with established benefits for smallholder systems including improved soil structure and moisture holding capacity, increased SOM and C content, and improved nutrient retention (Demelash et al., 2014; Ndambi et al., 2019; Reetsch et al., 2020). Manure can be used alone or as an input in compost, and has the potential to replace inorganic N fertilizers in sustaining crop production under the right conditions and best management practices. Moreover, manure provides a full range of micro- and macronutrients, as well as organic matter, which provides benefits to the soil beyond N replacement (Ndambi et al., 2019; Probert et al., 1995).

The potential of manure application is well documented (e.g., Enujeke et al., 2013; Ikeh et al., 2012), but actual impacts and returns depend greatly on the quality, quantity, and management of manure resources (Kwena et al., 2017; Ndambi et al., 2019; Place et al., 2003; Probert et al., 1995; Roy and Kashem, 2014). Improper manure management can lead to contamination and health problems, and global regulatory standards currently prohibit the use of manure on crops later than 60 days before harvest (Ndambi et al., 2019; GlobalGAP 2015). Similar challenges exist around the use of other on-farm organic resources in smallholder systems. Organic matter is often of low quality, requiring large quantities to make an impact on soil health (Giller et al., 2009; Vanlauwe and Giller, 2006). While crop residue is often abundant, there are many competing uses which limit the quantity actually allocated to soil fertility management, namely fuel and animal fodder (Berazneva et al., 2015; Kwenya et al., 2017). Furthermore, most benefits of organic matter application become obvious only in the medium or long run, and risk-averse smallholders operating on short time-horizons may choose to allocate scarce resources to uses with more immediate payoffs (Berazneva and Güereña, 2019).

Many of the challenges associated with on-farm resource management boil down to information constraints. Smallholders in Malawi, for example, report that lack of information was the key constraint to adopting best-management practices for manure (Ndambi et al., 2019). Ndambi et al. propose robust extension services that facilitate knowledge sharing among farmers as the best route to overcoming this challenge. Indeed, most RA practices are knowledge-intensive, requiring deep understanding of ecosystem flows and nutrient cycling, and awareness of specific practices that harness these dynamics for crop production (Jama, 2008; Lunn-Rockliffe et al., 2020, Massy, 2020). Knowledge in an RA system can be thought of as a substitute for Green Revolution technologies, overcoming some of the constraints associated with these inputs while presenting a new set of challenges (Barrett et al., 2002; Rusinamhodzi et al., 2012). Appropriate RA practices are derived from the specific agro-ecosystems they seek to improve, looking to locally available resources, climate conditions, native species, and indigenous cropping systems to iterate on RA objectives and identify the best methods for bringing them about in each case or locale (Barrett et al., 2002, Holt-Giménez, 2006; Massy, 2020; Montgomery, 2017). There has been considerable uptake across Africa, with over 900 organizations dedicated to experimentation and dissemination of RA agroecology practices (Lunn-Rockliffe et al., 2020). Successful projects embrace fluidity in the set of appropriate RA practices, equipping farmers with the scientific principles of RA while facilitating farmer-led innovation and design of RA systems that fit farmers' specific goals and constraints (Lunn-Rockliffe et al., 2020).

Chapter 3: Literature Review

3.1 Farmer-to-Farmer Extension and Technology Adoption in SSA

Information constraints rank high among barriers to agricultural technology adoption, and farmer-to-farmer extension (F2FE) has gained prevalence as a method of engaging large and diffused networks of smallholders in agricultural learning (Fisher et al., 2018; Hellin and Dixon, 2008; Nakano et al., 2018). Successful F2FE centers farmers as agronomic innovators, as well as the nodes of communication through which critical information flows to community networks (Barrett et al., 2002; Wellard et al., 2013). This structure makes F2FE well suited to facilitating dialogue and experimentation around regenerative agriculture (RA) and adapting broad RA principles to local contexts through farmer-centered, discovery-based learning. By creating opportunities for contact between farmers engaged in similar practices, F2FE provides space for social learning and exposure to real-world evidence of adoption outcomes.

Impact evaluations of F2FE on agricultural productivity and technology diffusion are limited, and those that exist present mixed results. Established extension programs are difficult to evaluate without bias because participating farmers may differ from the general population along unobservable characteristics such as motivation or ability, in which case the demonstrated impact of the program on participants may not translate to other members of the community. Waddington et al. (2014) review 15 high-quality quantitative studies of farmer field schools (FFS) from which they ascertain largely positive impacts of FFS on participants' yields, income, and knowledge retention about targeted practices, but cannot rule out potential bias in any of the studies. They do not find evidence of diffusion of knowledge or technology adoption from participating farmers to others in their village or social networks, and long term benefits are not assessed. While not synonymous with F2FE, FFS provide participatory workshops in which farmers are led to engage with real-world agricultural challenges and work together to develop solutions that build on their own experience (Feder et al., 2004). FFS workshops are often led by farmers, and participants are encouraged or expected to bring what they learn back to their communities (Davis et al., 2012). Davis et al. (2012) conduct a rigorous longitudinal evaluation of FFS in Kenya, Tanzania, and Uganda, using quasi-experimental propensity score matching methods to identify the ex-post impact of the program on crop productivity, adoption of targeted practices, and agricultural income of participating farmers, finding significant increases in each domain. Godtland et al. (2004) also use propensity score matching to identify the impact of an FFS in Peru on knowledge of integrated pest management strategies among participating potato farmers, and find increased knowledge relative to a comparison group of non-participants matched on observable characteristics. Feder et al. (2004) use difference-in-differences estimation, another quasi-experimental identification method, to compare the change in knowledge outcomes between FFS participants and non-participants over an 8-year period, as well as the outcomes for non-participants in villages where the FFS took place. They find increased knowledge among participants, but do not see evidence of knowledge diffusion to community members (Feder et al., 2004). FFS are expensive and logistically challenging, and may not be financially viable in the absence of widespread social learning effects (Feder et al., 2004).

Several studies have looked at the mechanisms through which F2FE promotes learning and adoption of agricultural practices, hoping to identify factors that influence the success of a given F2FE initiative (Fisher et al., 2018; Kondylis et al., 2017; Maertens et al., 2020; Nakano et al., 2018; Wellard et al., 2013). Maertens et al. (2020), and Nourani (2019) model technology adoption as a two-stage social learning process in which farmers first formulate their yield expectations for a given technology based on observed yields among early-adopting peers, and then make a decision about how much effort they will expend to learn and adopt the technique on their own farms. In this way, new agricultural practices spread from farmer to farmer as evidence of their benefits and profitability works its way through social networks and members update their subjective expectations associated with adoption. The authors identify factors that make certain F2FE approaches more likely to raise farmers' expectations about a new practice enough to allocate attention to learning and adopting it. Proximity is important, for example, because the returns to a given practice depend on soil and other environmental conditions, and farmers place more weight on benefits observed within their own agroecosystem or community. Foster and Rosenzweig (1995) observe this effect in rural India, where farmers with more experienced neighbors are found to have higher adoption rates of Green Revolution technologies and higher profits. Similarly, Conley and Udry (2010) observe that pineapple farmers in Ghana modify their input use as they observe their neighbors' success with new technologies.

Kondylis et al. (2017) look for evidence of technology diffusion through social networks in a large-scale field experiment in Mozambique in which 'contact farmers' (CFs) are trained by extension agents and adopt new practices, while other farmers in their networks observe the benefits and choose whether to adopt as well. Diffusion is low overall, and the authors conclude that incentives are likely needed to motivate CFs to more actively promote the targeted practices to members of their social networks. However, some evidence of adoption is observed among farmers who grow the same types of crop as their CF, implying that social learning is most effective when similarities are present between network members. This is articulated by Wellard et al. (2013), who note in their review of community extension approaches that F2FE operates through role models, emphasizing "the positive influence of an 'ordinary' community member who has managed to achieve food security, income, and status through farming." The authors go on to suggest that F2FE works best when CFs are relatable, in terms of socioeconomic status as well as agronomic know-how, and may be less effective if they are perceived as being too far ahead of their peers in terms of technology adoption. BenYishay and Mobarak (2018) further corroborate this theory with evidence from an RCT in Malawi which compares the ability to communicate agricultural information effectively through (1) government extension workers, (2) trained 'lead farmers', or (3) untrained 'peer farmers' who are representative of the general population in terms of their characteristics and level of experience with the targeted practices. Peer farmers are found to be the most effective communicators, likely because they are perceived as relatable in terms of socio-economic status as well as agricultural conditions such as farm size and access to inputs. However, technology diffusion does not happen unless peer farmers are incentivized to share information with their social networks, implying that this process may not occur naturally or to the same extent outside the context of an organized field experiment.

Bernard et al. (2015) investigate the role model theory of learning explicitly with an RCT in rural Ethiopia exposing farmers to video testimonials produced by NGO Digital Green, which highlight local farmers and entrepreneurs who have successfully improved their socioeconomic status without assistance. The study is motivated by an idea from social cognitive theory wherein an individual's belief about her capabilities is strongly influenced by the experience of her peers, which provides a 'vicarious experience' of what is possible (Bandura, 1977; 1986). While F2FE – and vicarious experience in general – typically operates directly through real exposure to peers, the Digital Green approach proxies this through a video featuring a relatable narrator whose experience resonates with viewers. The authors investigate whether the peer learning effect can be captured through this proxy for direct contact, and find that viewers do update their beliefs about their own capacity for success after watching the video, as measured by several outcomes including investments in their children's education. Notably, the videos do not include any specific advice or information on what steps were taken by the speaker to achieve success or provide any new information on the actual returns to education, but merely drive home the point that these returns are attainable: "Individuals were well aware of educational returns… but they did not think their children would be able to achieve them. The documentaries may have shown the possibility of a brighter future for individuals of similar background." Endeavoring to understand the mechanisms through which the role model effect operates, the study looks at indicators of psychological impact. These metrics, which include locus of control, perception of poverty, and measures of aspiration, all pertain to an individual's sense of control over life outcomes. All metrics increased after viewing, with diminishing effects detected after six months.

3.2 Peer Learning Processes and Technology Adoption

A number of other studies have explored the psychological impact channels that underlie agricultural technology adoption and social learning processes (e.g. Abay et al., 2017; Malacarne 2018; 2019; McGinty et al., 2008; Taffesse and Tadesse, 2017; Ung et al., 2016). Locus of control (LoC), for example, is shown to significantly predict adoption of modern agriculture inputs among smallholders (Abay et al., 2017; Malacarne, 2018; Tafesse and Tadesse, 2017). LoC is a measure of the extent to which an individual believes that outcomes are determined by her behavior (an internal LoC) or by fate and external circumstances outside her control (an external LoC). Intuitively, the studies cited show that individuals with more internal LoC are more likely to adopt a new technology, with the goal of improving their livelihoods by taking action. Moreover, Abay et al. (2017) discuss the malleability of LoC, suggesting that if LoC can be influenced, for example by interventions like the one described above (Bernard et al., 2015), there may be potential to target this internal constraint to adoption by empowering farmers to believe in the ability of their actions to effect change. The authors also suggest that LoC may influence adoption via the farmer's expectations about the profitability of adoption, in a manner compatible with the two-stage learning model proposed by Maertens et al. (2020) and Nourani (2019).

Ung et al. (2017) explore the role of a similar psychometric variable, perceived self-efficacy (PSE), in predicting climate change adaptation behavior among households in coastal Cambodia. PSE is a concept from psychologist Albert Bandura's social cognitive theory (Bandura, 1977; 1990) which measures "the extent to which people believe that they are capable of doing specific tasks in order to achieve certain goals" (Ung et al., 2017). Ung et al. model climate change adaptation behavior with PSE as the main predictive variable, and find that households with higher PSE are significantly more likely to take steps to adapt. McGinty et al. (2008) look at self-efficacy beliefs in the context of agroforestry adoption, using a quasi-experimental design to assess the impacts of an agroforestry development initiative on PSE. The study did not find any significant effects of the program on PSE (or intention to adopt agroforestry practices), despite evidence and theoretical work suggesting that PSE, like LoC, can be altered through experience and exposure to successful outcomes in a given domain (Bandura, 1977; Wuepper and Lybbert, 2017). The authors do find, however, that self-efficacy beliefs as measured at baseline significantly predict farmers' propensity to adopt agroforestry practices.

Studies like these point to the value of understanding the psychosocial dimensions of adoption, which likely play a role in explaining the farmer decision-making process over and above socio-economic and external factors. A growing body of literature from behavioral economics provides a theoretical framework to account for the role of internal constraints like self-efficacy beliefs in adoption decisions (Carter, 2016; Wuepper and Lybbert, 2017). These models question the standard economic assumption that agents are purely rational actors using a stable set of preferences determined by prices and incomes to maximize expected utility and select the optimal investment strategy. Instead, a decision-theoretical framework emerges in which behavioral factors or "deep preferences" shape how individuals engage with economic signals and form subjective expectations about their likely outcomes which may diverge from the expected utility of a purely rational actor (Carter, 2016). Including these preference parameters allows researchers to explore potential effects of removing or reducing internal constraints on farmer adoption decisions, paving the way for empirical studies and policy interventions that explicitly target these constraints to empower marginalized communities and promote uptake of beneficial practices in agriculture and beyond.

3.3 Perceived Self-Efficacy

Bandura (1990) describes PSE as a central mechanism of agency that mediates the decision-making process, as individuals rely on beliefs about their capabilities to set goals, assess strategies, and take action in a given domain. PSE is distinct from beliefs about outcomes, in that an individual can recognize that a certain action should lead to the desired outcome, but lack the conviction that she is able to perform the action herself (Bandura, 1977). If this is the case, information about probable outcomes might not influence the behavior of a farmer who lacks the belief in her own ability to adopt the practices successfully: "The strength of people's convictions in their own effectiveness is likely to affect whether they will even try to cope with given situations" (Bandura, 1977). Bandura (1990) reviews several studies that point to the causal role of self-efficacy beliefs in decision-making and human functioning over and above ability or attitudes. Collins (1982) finds that children with higher PSE outperform low PSE children of the same ability level on problem-solving tasks, as they are more willing to grapple with the problems, and reject faulty strategies with confidence (Bandura, 1990). Similarly, Weinberg et al. (1979; 1981) find that study participants were able to run faster in an athletic competition when they were told they were competing against individuals with a recent injury, and consistently outperform a control group who were informed (accurately) that they were competing against professional athletes (Bandura, 1990; Wuepper and Lybbert, 2017). These studies illustrate the ability of self-efficacy beliefs to directly influence actions and performance attainments.

If stronger PSE is associated with higher performance attainments and motivation to pursue more challenging goals, the question becomes whether and how this attribute can be influenced and strengthened. PSE has been shown to arise from genetic and socio-cultural factors, and is shaped by shared histories as well as personal experience throughout an individual's lifetime (Espinozo Revollo and Portela, 2019; Pajares, 2006; Wuepper and Lybbert, 2017; Wuepper and Sauer, 2016). Bandura (1977) describes four information channels through which self-efficacy beliefs are formed and altered for individuals: performance accomplishments, vicarious experience, verbal persuasion, and physiological states. The gold-standard for influencing PSE is through "experiences of mastery" wherein an individual learns to overcome her initial bias about her abilities by successfully working through and completing challenging tasks. In lieu of personal experience, vicarious experience is the most effective channel for belief-updating, wherein "seeing others perform threatening activities without adverse consequences can generate expectations in observers that they too will improve if they intensify and persist in their efforts" (Bandura, 1977). There are certain conditions under which vicarious experience is more likely to impact self-efficacy beliefs. As we saw in the case of farmer-to-farmer learning, the experience of someone relatable – with shared circumstances and characteristics – provides a more impactful vicarious experience. Of course, if external constraints are binding and an individual has developed firm beliefs about her capabilities grounded in experience of repeated failures, she is likely to discount the relevance of the new experience – whether vicarious or personal.

In the case of technology adoption, while internal factors like PSE can play a role in encouraging farmers to adopt new practices, if external constraints on credit, labor, and resources persist, adoption behavior is unlikely to change. However, when external constraints are not limiting, lingering resistance to new technologies might be attributed to these behavioral factors, which policies and extension initiatives can be designed to target. Wuepper and Lybbert (2017), drawing from Just (2002), model the development of PSE as a Bayesian updating process wherein posterior PSE beliefs are a function of initial prior PSE, learning signals about capabilities, new experiences – vicarious and personal, emotions, and social persuasion. PSE can be influenced by policy interventions that provide opportunities for new experiences and positive feedback about capabilities.

3.4 ICTs for F2FE

With the expansion of cellular networks and mobile phone ownership in developing countries in recent years, information communication technologies (ICTs) have come to play a major role in disseminating extension content, overcoming some of the logistical barriers associated with in-person advisory. Providing extension information by SMS or call services is cost-effective, and the rapid proliferation of wireless infrastructure offers accessibility in remote regions. Moreover, the ability to send messages instantly and at any time enables extension providers to reach farmers with information that is critical and time-sensitive, as well as context-specific and highly pertinent to the end-user (Aker et al., 2016). The ease of social networking on digital platforms suggests that ICTs may be useful for F2FE, which is predicated on the ability to connect and communicate with others. If technology adoption is promoted through observation of peers, there is clear potential for ICTs to foster communication linkages that spur adoption among members of a digital extension network (Nakasone et al., 2014).

Perhaps because ICTs for agriculture are a relatively new phenomenon, the body of evaluative literature is limited, and results are mixed (Aker et al., 2016; Baumüller, 2018, Fabregas et al., 2021; Nakasone et al., 2014). Nakasone et al. (2013) find positive impacts of delivering price information, or market information services (MIS) to farmers by SMS, which resulted in higher farmgate prices and improved bargaining power for small scale producers. Similarly, Nyarko et al. (2013; 2021) found that MIS were associated with an 11% increase in price received for yams by farmers in Ghana. Other studies, however, find little or no impact of MIS, for example Fafchamps and Minten (2012) find no evidence that providing price information to farmers in India increased the price they received for their crops. There have been fewer assessments of ICTs that provide extension information on improved cultivation practices by SMS, and here too the results do not always find evidence of a direct impact of the ICT on technology adoption. In a randomized control trial (RCT) with farmers in India, Fafchamps and Minten (2012) find no significant effect of an SMS campaign on adoption of targeted cultivation practices. Casaburi et al. (2014), on the other hand, conduct a randomized control trial (RCT) in which sugarcane farmers in Kenya receive SMS reminders about the timing of agricultural tasks personally tailored to their planting date and local harvest cycle, and find a significant 11.5% increase in crop yields on treated plots attributed to the SMS campaign. Larochelle et al. (2017) find similar benefits from an RCT evaluating an in-person farmer-field day (FFD) accompanied by SMS follow-ups to remind participants about the timing of practices covered at the training. Farmers who received the follow-up messages retained more knowledge of the course material and were more likely to adopt the targeted practices relative to participants in the FFD who did not receive the SMS reminders. Interestingly, the knowledge gain for SMS recipients was highest for more complex practices, suggesting that the messages helped farmers engage with the more difficult course material and deepen their understanding of complicated information, which led to adoption of practices that may have felt too challenging to implement based on the FFD alone.

Aker et al. (2016) discuss several pitfalls of ICT extension which may explain the lackluster performance of many promising initiatives. A basic but often overlooked reality is the usability of technology accessible to low-income and low-digital-literacy populations. Many SMS extension campaigns attempt to reach rural households by SMS on basic feature phones, but these devices are not optimized for receiving long messages or typing detailed responses on an alpha-numeric keypad. Typical users may be more accustomed to using feature phones only for voice messaging and calls, and less likely to benefit from information provided by text (Aker et al,. 2016; Steinfield et al., 2015). Low-income households may also struggle to maintain sufficient airtime funds or battery charge, and may not be able to fix or replace broken phones, leading to discontinuous use patterns. Also, phones and SIM cards are often shared among household members or switched out when they run out of airtime or for other reasons, so an individuals' phone number tends to change frequently as we find in the present study (Aker et al., 2016; Lasdun et al., *working paper*; Steinfield et al., 2015). Aker et al. (2016) suggest that these technology barriers which make it difficult for users to engage with information presented by SMS limit the potential of ICTs to overcome information constraints for rural households. Wyche and Steinfield (2016) make a qualitative investigation of Kenyan farmers' use of the acclaimed[2] MIS platform M-Farm to understand why the service is used by less than 5% of Kenyan smallholders. They note that studies of ICTs often overlook basic realities of mobile usage patterns, which leads to "the continued development of mobile interventions which fail to gain traction with farmers because their existing practices are poorly understood" (Wyche and Steinfield, 2016). For instance, the farmers they survey used their cellphones mainly to call family and friends and strengthen existing social networks, but did not view the device as a source of agricultural information.

Additionally, while it is tempting to capitalize on the social networking potential of ICTs to promote diffusion of agriculture technologies, it is not clear that the type of interactions that typically occur in these digital spaces can lead to the psychological gains observed for in-person F2FE or community networking initiatives. For example, it can be difficult to establish trust through ICT communication alone, particularly if members of a network have never met in person (Aker et al., 2016; Moloney, 2006). Drawing on several case studies on the role of ICT in business relationships among small-scale entrepreneurs in Tanzania, Moloney (2006) posits that "mobile phones can be seen as a facilitating technology for existing, trust-based relationships," but have little value in forming new connections with strangers. Indeed, Aker et al. (2016) review the sociology literature on ICTs and trust and conclude that "the value of the mobile phone is primarily in making social networks more concrete, thereby building trust within a farmer's or trader's existing social network". For this reason, information delivered by a stranger over text may fail to resonate as reliable or relevant, further curtailing the ability of ICTs to facilitate technology diffusion across peer networks.

[2] https://www.wired.co.uk/article/mfarm

More complex ICTs involving images, voice recordings, or simulations have proven more successful in promoting technology adoption and belief updating. Guilivi et al. (2019), for example, find a significant impact of a dynamic image-based fertilizer recommendation app for smartphones, M Krishni, on adoption of urea fertilizer practices among maize farmers in Nepal, and users of the app score higher on a knowledge retention quiz compared to farmers who received the same information by SMS, voice messages, or radio. Tjernström et al. (2021) find that farmers update their allocation of farm inputs after playing MahindiMaster, an interactive game through which users learn about input returns on a virtual farm resembling their own. While these examples do not involve a peer learning component, they illustrate the potential for innovative ICTs to foster high-level cognitive engagement with information presented through ICTs, and provide us with motivation to explore an unconventional digital learning platform as a space for farmer-to-farmer knowledge sharing. There is little existing research on this subject (e.g., Kendall and Dearden, 2017; Leveau et al., 2019) and the present study aims to address this gap by looking explicitly at the connections formed among users of a digital platform designed for farmers and agronomic experts to collaboratively generate and share knowledge of regenerative agriculture practices. Kendall and Dearden (2017) identify a distinction between ICTs that offer access to information and those that provide an opportunity for communication. The latter emphasize active participation in a community of practice, facilitating knowledge-sharing among users and situating new information within social relationships and personal experience. If the technology barriers discussed above can be overcome, this approach to ICT extension may be the key to mobilizing farmers in the design and adoption of sustainable and agroecologically appropriate practices.

Chapter 4: Experimental Design

4.1 Household Selection and Data Collection

523 participating farmers were surveyed at baseline in August and September 2020 from a randomized network of 1050 households across 47 villages in Morogoro Rural. The initial randomization process occurred in 2014, when farming households were selected to participate in an experimental fertilizer recommendation initiative (Harou et al., 2021). The original randomization took place at the village and individual levels, with 47 villages selected out of all villages in Morogoro Rural that were accessible by vehicle and known to grow maize. In each village, participant households were drawn randomly from a list of all households who grew maize that year, and assigned to treatment or control groups. Data on assets, demographics, food security, and agricultural production were collected from all participating households in 2014, 2016, and 2019. The fertilizer initiative succeeded in increasing input use and maize yields among treatment households in 2016, but with little to no significant remaining effect detected in 2019 (Tamim et al., 2021).

In collaboration with the Sokoine University of Agriculture (SUA) in Morogoro, we used cellphone numbers listed in the 2019 SoilDoc survey to contact households at baseline, and were able to reach 484, or 66%, of the 733 households who listed a cellphone number in 2019. In an effort to reach more households, we reached out through community networks in each SoilDoc village and reached an additional 61 households who had not listed a number in 2019, bringing the initial number of households at baseline to 545. However, some of these households did not own their own phone – a criteria for eligibility in the ShambaChat study – or did not wish to participate, bringing the final number of households to 523, with one participating farmer per household.

The baseline survey was conducted over two 30-minute phone interviews with each household, in an effort to be less demanding on respondents in terms of time and attention. The first survey round included questions on asset ownership, housing and dwelling characteristics, patterns of food consumption, off-farm income sources, and market access and prices, as well as respondents' perceptions and attitudes towards the ongoing COVID-19 pandemic for use in a different study (Lasdun et al., *working paper*). The second survey round focused on agricultural production and climatic factors affecting production in 2020, and collected baseline levels of most variables of interest for the ShambaChat study including perceived self-efficacy, subjective probability distributions, knowledge and adoption of regenerative agriculture practices, and yields. Unfortunately, we were only able to reach 468 households for Part Two, likely because some farmers had left their villages in early September to prepare fields and lost cellphone coverage. In the interest of maintaining a large sample size, we chose to keep all 523 households in the study, despite lacking baseline values for many relevant outcome variables for the 55 participants missing Part Two.

4.2 The ShambaChat Extension Platform

To build the ShambaChat extension platform we partnered with Telerivet, a mobile communications platform that manages interactive SMS campaigns for businesses and NGOs internationally. The platform allowed us to broadcast extension messages and discussion prompts from a computer anywhere in the world directly to the cellphones of participating farmers in Morogoro. Additionally, it enabled us to group participants into 5-person chat groups – a novel functionality for feature phones – where they could respond to our extension messages and discuss the content freely over SMS. If a (treated) farmer responded to any message received through

ShambaChat, whether from us or another farmer in her group, the message was automatically forwarded to the other members of her chat group, who were able to respond in turn. On feature phones, each message arrived as a separate SMS tagged with the first three letters of the sender's name, or "SUA" for the extension messages broadcast by our team. While a bit clunky, this interface enabled users to follow a conversation, as messages were received in the order they were sent and clearly linked to the sender. To ensure privacy, all phone numbers were concealed and replaced with the three-letter nametag. Since participants were randomly allocated to chat groups and did not know each other prior to the study, we made an effort to instigate conversation by broadcasting several icebreakers to the groups encouraging members to introduce themselves with their name and village (see Appendix A for a full transcript of these messages). In theory, this technology allows for relatively easy communication between chat group members and facilitates discussion and engagement with the extension content.

The ShambaChat platform also gave us access to all the messages sent by participants in real-time, which enabled us to monitor the group chat conversations for any inappropriate content (which did not arise at any time), as well as to observe which topics were of most interest to users. We were able to send polls and survey questions to ShambaChat users and analyze the results directly through the platform. This allowed us to elicit feedback about the content and timing of messages, and to ask farmers to share how they were changing their agricultural practices to cope with the severe drought experienced during the 2021 growing season. This function of ShambaChat is discussed further in Section 6.4.

4.3 Treatment Arms

The goal of this study is to assess the specific impact of augmenting SMS extension delivery with a group chat feature, and for this reason we chose to broadcast extension messages by SMS to *all* study participants. Limiting our scope to only two treatment arms had the advantage of preserving a larger sample size when comparing outcomes between treatment and control groups, but we forego the ability to assess the impact of the extension platform more holistically relative to no intervention.

The 523 participating households were sorted into treated and control groups, with a subset of the control group consisting of 87 households in 10 randomly selected pure control villages to allow us to understand potential spillover effects – see Section 5.3. In treatment villages, we sorted all households into five-member chat groups, and then randomly assigned each chat group to either treatment or control. To ensure heterogeneity of experience within the chat groups, we included two farmers in each group who had some experience with the agricultural practices we intended to promote. To do this, we used farmer responses at baseline to identify all farmers who planted legumes in 2020 (hereafter, criteria F1) and used a soil conservation practice in 2020 (grass strips, ridges, bench terraces, drainage channels, water catchment, or other) (hereafter, criteria F2). 88 chat groups were formed from the 436 farmers in the remaining 37 treatment villages, with one member each of F1 and F2, along with three randomly selected members. We then allocated the chat groups randomly to treatment or control, with 34 control groups and 54 treatment groups. Chat groups assigned to control were dissolved, as only treated farmers would be participating in these groups during the study, leaving a total of 257 control households (across treatment and control villages) and 266 treated households at baseline.

4.4 SMS Extension Course

Given the prevalence of nitrogen deficient soils in our sample[3] and in SSA more generally, we selected a bundle of regenerative agriculture (RA) practices that seek to restore soil fertility through enhanced biological processes and ecosystem dynamics. RA practices are based on intentional management of on-farm resources, providing an avenue to combat soil nutrient deficiencies at little or no financial cost to farmers (Al-Kaisi and Lal, 2020). These practices substitute knowledge for input intensity, overcoming some of the constraints associated with promoting uptake of agricultural inputs like inorganic fertilizers, while presenting new challenges. High-quality, adaptive extension programs are key to promoting adoption of complex and context-specific technology bundles like RA, making this an appropriate topic to address through the ShambaChat platform (Lunn-Rockliffe et al., 2020).

Our team of agronomists and agricultural economists at McGill, SUA, and CIAT developed a 3-part course on RA soil building, focusing on legume-maize intercropping (Part 1), green manure and composting (Part 2), and integration of crop residues (Part 3). Each part of the course lasted one month, during which participants received 3-5 messages per day excluding weekends (see Appendix A). The messages contained information about techniques for implementing the targeted practices, the agronomic benefits of doing so, and scientific principles behind their effectiveness, as well as discussion prompts that led farmers to think more deeply about the information and encouraged them to relate it to their own experience or knowledge of similar practices. The course, including discussion prompts, was delivered by SMS to both treatment and control participants. Treated participants additionally had the ability to discuss this information with other farmers in 5-person chat-groups. To ensure farmers did not bear a cost of

[3] Soil testing was performed at each household in 2014 for a previous study, Harou et al. 2021.

participating, we paid for unlimited airtime for the duration of the study period for all households, both treatment and control.

4.5 Outcome Variables

We are interested in whether the ShambaChat group chat treatment promotes adoption of beneficial practices, and in understanding the psychological mechanisms through which peer learning can influence behavior. To this end, we measure three types of outcome variable: indicators of adoption, behavioral outcomes, and welfare outcomes.

4.5.1 Adoption Outcomes

We look at seven indicators of adoption to capture any relevant changes in production decisions in response to the treatment. The extension course focused primarily on legume nitrogen fixation and cycling organic nutrients through decomposition of on-farm organic materials, with specific practices falling into these two categories. Although we asked in great detail about adoption of each practice, the number of positive responses to specific items in most cases was too low to analyze efficiently, so we chose to aggregate into broader practices resulting in four indicators tracking adoption of legume practices, and three tracking adoption of organic materials practices.

Legumes:

i. Intercropping with legumes on main maize plot (MMP) (1): *mmp_intercr_1* takes a value of one for respondents who select one or more legume from a list of crops in response to the question "*Which of the following crops did you plant alongside maize on your MMP?*" and zero otherwise. Respondents who did not cultivate maize are omitted.

ii. Intercropping with legumes on MMP (2): *mmp_intercr_2* takes a value of one for respondents who select "*Intercropped maize with legumes"* in response to the question "*Which of the following practices did you use on you MMP?"*, and zero otherwise. Respondents who did not cultivate maize are omitted. This metric is distinct from (i) because some farmers may plant a legume alongside maize without recognizing this practice as intercropping.

iii. Other legume practices: *legume_other* takes a value of one for farmers who use cover cropping, crop rotation, or relay planting methods with legumes, and select one of these practices in response to the questions "*Which of the following practices did you use on you MMP?"*, and zero otherwise. Respondents who did not cultivate maize are omitted.

iv. Legumes on farm: *legume_onfarm* is equal to one for any farmer who selects a legume from a list of crops grown anywhere on their farm, not limited to the MMP. This variable was not collected at baseline, but we asked for recall data at endline to estimate the level in 2020. This measure includes farmers who did not cultivate maize.

Organic Materials:

i. Organic materials found or produced on farm: *organic_materials* is equal to one for farmers who find or produce an organic material, including crop residue, manure, leaf litter, or transfer of forest soil anywhere on their farm, and zero otherwise. Due to a lack of foresight when developing the survey, farmers who do not cultivate maize are omitted from this measure.

ii. Making fertilizer from on-farm organic materials: *made_org_fert* is equal to one for farmers who find or produce organic materials on their farm (*organic_materials == 1*) and state that they used this material as a fertilizer, either by incorporating it into compost or leaving it to decompose directly on the field, and zero otherwise.

iii. Applying organic fertilizer on the MMP: *org_fert_mmp* is equal to one for farmers who applied organic fertilizer on their MMP, and zero otherwise. Respondents who did not cultivate maize are omitted.

4.5.2 Behavioral Outcomes

We measure five psychometric variables in an effort to explain the process by which farmers engage with the group chat functionality of ShambaChat and change their behavior in response to the information received. These outcomes are difficult to measure and in some cases there is no standard method for doing so. For this reason we describe our methods in detail, and the survey modules presented to respondents are included in Appendix B. The distribution of responses to some of these measures can be seen in Figure 1. We construct a knowledge score based on five questions about soil fertility management practices to compare participants' knowledge of the targeted practices before and after the intervention. We also construct three measures of perceived self-efficacy, or an individual's belief about her capabilities in reference to a specific domain of functioning. Finally, we use a game to elicit a subjective probability distribution over adoption outcomes.

i. Knowledge Score (*knowledge*_score): We ask five questions about best-practices surrounding soil fertility management. Four questions specifically address the targeted practices, with a focus on identifying legume crops and applying organic fertilizers. A fifth question about seed spacing, which was not a topic covered in the extension course, is included as a control. The final score is calculated out of 16 possible points.

ii. Generalized PSE (*PSE_general*): PSE is a concept from cognitive social science, popularized by Albert Bandura (1977) as a component of his social learning theory. An individual's PSE is a measure of her beliefs about her own ability to perform tasks or behaviors which are necessary for success in a particular domain. Following Chen et al. (2001), we administer the New General Self-Efficacy (NGSE) scale, loosely adapted to the domain of agriculture. The NGSE scale consists of eight items that measure an individual's confidence in her ability to meet task demands and achieve goals. Each item is rated on a 1-5 point Likert scale, and a score, *PSE_general*, is calculated by taking the average over all items.

iii. Domain-specific PSE (*PSE_outcome_soilfertility; PSE_outcome_profits; PSE_outcome_foodsecurity; PSE_task_furrows; PSE_task_seedspacing; PSE_task_intercropping; PSE_task_manure*): We constructed a module to measure PSE for specific tasks and outcomes within the domain of RA, following the methodology of Schwarzer and Renner (2009) and Bandura (2006). Bandura argues that scales like the NGSE are too general, and fail to capture the domain-specific nature of PSE, even when loosely adapted to a domain as we do in (ii), above. Indeed, while many psychological constructs cut across all domains of functioning, PSE is linked to specific contexts and spheres of action. Despite high correlation across different domains of functioning, an individual's PSE in reference to a certain task may change as she becomes more confident in her capabilities to perform in this domain, for example through learning-by-doing, or exposure to a role model. A domain-specific PSE scale must meet certain criteria for validity (Bandura, 2006), namely:

- Should be phrased in terms of capabilities, not intentions (eg., “I am able to” instead of “I will do it”), and should measure “perceived capability to produce given attainments” (Bandura, 2006).
- Should focus on ability to perform specific tasks.
- The tasks specified in the scale should in fact be the determinants of success in the relevant domain (e.g., proper input use in fact leads to improved yields).
- The scale should reflect gradations of challenge, so that respondents can indicate their perceived level of difficulty associated with performing each task, and/or their confidence in their ability to perform them.
- The scale should elicit respondents’ beliefs about their capabilities as of now, not their expectations about potential capabilities in the future.

We include one module for domain-specific PSE, but elicit two metrics – one that covers PSE over specific outcomes, and one that looks at PSE over specific tasks. Each metric consists of 3 and 4 outcome variables, respectively, listed above.

iv. Subjective probability distribution (SPD) (*SPD_soilfertility; SPD_profits; SPD_foodsecurity*): Following Delavande et al., (2011) and Delavande (2014), we developed a thought experiment to elicit subjective probability distributions over expected intercropping outcomes. Delavande and others (e.g., Delavande and Kohler, 2009; Lybbert et al., 2007; Maffiolo and Monihan, 2018) provide a visual aid like beans or marbles to help respondents express probabilities, e.g., by putting 10 out of 20 beans on the outcome they believe has a 50% chance of occurring. Since our survey was conducted over the phone, we adapted this technique to a thought experiment in which respondents consider the probability of success among 20 identical farmers "just like you" who adopt intercropping. If exposure to relatable peer farmers increases ShambaChat users' perceived self-efficacy, they may be more confident in their ability to successfully implement the targeted practices on their own farm, leading to a higher distribution of expected outcomes.

4.5.3 Welfare outcomes

Finally, we look at three welfare outcomes to measure whether the treatment had any impact in the short run on household living standards.

i. Household assets: *asset_index* is an index of household items including productive assets such as farm tools and equipment, household assets including cellphones and electronic, vehicles, and furniture items, and livestock assets. The index is constructed using principle component analysis (PCA), see A for details.

ii. Maize yields: *maize_yields* measures self-reported yields for maize grown on households' main maize plot. The measure is adjusted for intercropping practices, and reported in kilograms per acre.

iii. Food insecurity: *food_insecurity* is a weighted average of the number of meals skipped by households members each month.

4.6 Attrition

Out of 523 households surveyed at baseline in August 2020 and included in the study, we were able to reach only 397, or 75.9%, at endline in August 2021. This represents an attrition rate of 24.1%, and could result in biased estimates if participants do not drop out of the study at random. We posit that the high rate of attrition between 2020 and 2021 is largely due to recent changes in Tanzanian laws regarding SIM card registration. A new law went into effect in February 2020, requiring Tanzanians to biometrically register their SIM card. In the months following, many individuals adjusted to the new law, resulting in high turnover of cellphone numbers. Moreover, even without the upheaval of a new law, it is well-documented that in developing countries cellphones and SIM cards are often shared among household members or switched out, so an individuals' phone number tends to change frequently (Aker et al., 2016; Steinfield et al., 2015).

We conduct two tests to determine if attrition is random. First, following Haushofer and Shapiro (2016) we verify that attrition is not correlated with treatment assignment by estimating the following equation using OLS, with standard errors clustered at the village level:

$$attrition_i = \alpha_i + \sum_{k=0}^{2} \theta_k TREAT_i^k + \varepsilon_i \tag{1}$$

where $attrition_i$ takes a value of one for farmers we did not reach at endline in 2021, and zero otherwise, and $TREAT_i^k$ takes a value of one for farmers assigned to treatment arm k, where $k = 0$ are control households in pure control villages (the omitted category), $k = 1$ are control households in treatment villages, and $k = 2$ are treated households. The results presented in Table 1 indicate that attrition is randomly distributed among the three treatment groups.

Next, we check whether any relevant household demographics or outcome variables are correlated with attrition by regressing each variable on the binary variable *attrition* defined in equation (1) above. We estimate the following equation using OLS, with standard errors clustered at the village level:

$$y_i = \alpha_0 + attrition_i + \varepsilon_i \quad (2)$$

The results of these regressions, presented in Table 2 confirm that attrition is not correlated with any relevant variables.

4.7 Baseline Balance

Despite randomization of households, we verify that all outcome variables and relevant household demographics are balanced at baseline between treatment and control groups, as well as between control households in treatment villages and control households in pure control villages. To conduct these balance tests, we regress baseline levels of outcome and demographic variables on a treatment indicator using OLS with the following specification, with standard errors clustered at the village level:

$$y_i = \alpha_0 + \theta_1 TREAT_i + \varepsilon_i \quad (3)$$

4.7.1 Balance of Treatment and Control Households

We first set the treatment indicator $TREAT_i$ equal to one for treated households and zero for all control households, and run the model specified in equation 3. The results of these regressions are reported in Table 3, where we see the mean and standard deviation in the level of each variable for treatment and control groups, respectively, and the difference in these levels. Any statistically significant difference is indicated with an asterix in Column 5. As we see, there is a significant difference in the baseline levels for knowledge score and other legume practices. The difference in outcome variables is controlled for by the first-differences estimation technique we follow in our main results section, 5.2, and we are careful to consider these baseline imbalances when conducting a cross-sectional analysis of endline data in section 5.5. Note that this imbalance does not imply selection bias, which is removed by the random allocation of households to treatment or control.

4.7.2 Balance of Control Households in Treatment and Control Villages

We also test the balance of outcome and demographic variables between control households in treatment villages, and control households in pure control villages, which will help us account for any potential spillover effects of the treatment in Section 5.3. For this test we set $TREAT_i$ equal to one for control households in treatment villages, and zero for households in control villages. Results, presented in Table 4, show that several variables are indeed unbalanced between the two control groups. These groups were initially balanced at baseline before attrition occurred. We address this imbalance in Section 5.3**.**

4.8 Intent to Treat Effects (ITT) and Compliance

Our lack of control over the way in which study participants engaged with the ShambaChat app, coupled with the reality of limited and patchy network coverage in the Morogoro region, resulted in partial or non-compliance with treatment for some households. 40 out of the 397 households interviewed at endline in 2021 reported that they did not receive any extension messages from SUA, likely due to poor cellphone coverage or switching their phone number at some point in the 6 months between the baseline data collection and the start of the messaging campaign. Of these, 17 were treated households and 23 were control. Moreover, many participants in the treatment group did not actively participate in the group chats, so it is difficult to say whether and to what extent they benefited from the treatment. In some cases they may have benefited from reading what others in their chat groups were discussing, but some chat groups had no discussion at all, in which case the experience of these treated participants would have been identical to members of the control group (who were not placed in a chat group but still received extension messages through ShambaChat). To account for this partial and non-compliance, we follow an intent-to-treat (ITT) analysis throughout this study to estimate the coefficients for all participants who were randomly assigned to the treatment group, regardless of whether or to what extent they actually received or engaged with the treatment. This approach is necessary, but likely results in an underestimation of the full treatment effect.

Chapter 5: Empirical Strategies and Results

5.1 Summary Statistics

5.1.1 Description of Household Characteristics at Baseline

The 397 households participating in our study (after attrition) are located in Morogoro Rural, a district in the Morogoro region of Tanzania, across 47 in villages which predominantly grow maize. 84% of households in our sample cultivated maize in 2020, mostly for household consumption. The average household-head is male and 45 years old. 93% of household heads have completed some education, but only 7% have completed any years beyond primary school (7 years in Tanzania). 15% of households are female-headed. 90% of households own at least one acre of land, with mean land holdings in 2020 around 6 acres, although this is skewed by a few large landholders. 92% of households own their home, which are typically constructed of stone or mud bricks with corrugated metal roofs, and 90% of maize cultivators own their own maize plot. 9% of households have electricity, and 3% have an indoor water supply. Average maize yields in 2020 were 286 kg/acre, which is low compared to 514.2kg/acre average yields recorded for Morogoro between 1994 and 2001 (Harou et al., 2021; Paavola, 2008), although this number likely suffers from reporting error.

We looked at production practices at baseline to inform the content of the extension course, aiming to target practices which were already used by a significant portion of participating households. This served as a guide for identifying regionally-appropriate practices, and provides heterogeneity in the level of experience among members of the chat groups. All baseline measures pertain to practices employed on the respondent's main maize plot (MMP). 26% of households applied some organic fertilizer on their MMP in 2020, including manure, compost, crop residue, and transfer of forest soil. 16% intercropped maize with a legume on their MMP, and 17% planted a legume in rotation or as a cover crop. According to recall data collected in 2021, 32% of households planted a legume somewhere on their farm in 2020. For reference, fewer than 5% of households used inorganic fertilizers in 2020, which is typical for Tanzania and many regions of SSA.

5.1.2 Summary of Outcome Variables

In Table 5, we present summary statistics for each outcome variable at baseline in 2020 and endline in 2021. As a result of our decision to send extension messages through ShambaChat to all study participants, both treatment and control, we are likely to see an impact on certain outcome variables, particularly adoption of the targeted practices, across all households from 2020 to 2021. These year effects are suggested by the difference estimates in Column 5 of Table 5, for which we test the significance with t-tests of the sample means in 2020 and 2021. However, since we do not control for individual fixed-effects here, or macro-level shocks occurring during the study period (for example, the COVID-19 pandemic), we cannot and do not attempt to attribute this effect to the extension campaign. Still, it is worth noting that 27% of maize-growing households intercropped maize with a legume on their main maize plot (MMP) in 2021, compared to only 16% in 2020, representing a nearly 75% increase in intercropping over the study period. Additionally, although the number of households who found or produced organic materials on their farm decreased substantially in 2021, those who did were more than twice as likely to allocate these resources to the production of organic fertilizer in 2021. Interestingly, application of organic fertilizer decreased 77%, with 26% of maize-growing households applying organic fertilizer on their MMP in 2020 compared to only 6% in 2021.

Many of the behavioral outcomes we measured also increase in 2021 relative to their baseline values. The average knowledge score increased by 1.9 points on a 16 point scale, generalized PSE scores increased 0.39 points on average on a 5 point scale, and PSE over soil fertility, profit, and food security outcomes each increased modestly as well (note that the negative change in the food *in*security variable implies an improvement in food security). To the extent that this effect is attributable to the ShambaChat extension content, we may be seeing that as farmers engage with the messages and discussion prompts, even if they are not chatting with each other, they develop a sense of self-efficacy surrounding the targeted practices and retain knowledge from the course. In the following section we are able to disentangle the year effect from the treatment effect using a model of first-differences with panel data and year fixed-effects.

5.2 Regression Estimation

We are interested in understanding the effect of incorporating a group chat feature in an SMS messaging campaign on participants' engagement with extension information. To reiterate, all households in our study received extension information and discussion prompts over SMS, and *treated households were also assigned to a 5 person chat group* where they could discuss the new information by text with other farmers in real time as they received it. In this section, we estimate the effect of this treatment on adoption outcomes, behavioral outcomes, and welfare outcomes. We follow an intent-to-treat (ITT) analysis across all models employed.

5.2.1 Technology Adoption

The regenerative agriculture methods introduced through the extension campaign can be grouped into (1) legume practices and (2) organic materials practices, and contain the 7 outcome variables described in Section 4.5. We measure the effect of treatment on each of these variables using the following first differences equation estimated by ordinary least squares (OLS), a linear probability model[4], with robust standard errors clustered at the village level:

$$\Delta y_{ij} = \alpha_0 + \beta_j TREAT_i + \Delta\varepsilon_i \tag{4}$$

where Δy_i are the difference in each of j outcome variables measured at endline (2021) and baseline (2020), $TREAT_i$ is an indicator of treatment (one for treated households; zero otherwise), ε_{iv} is an error term, and α_0 is a constant. We are interested in the coefficients β_j, which measure the average effect of the treatment on the outcome variable specified. A significant β_j would imply that the treatment had an effect on outcome j. Standard errors are clustered at the village level to account for potential correlation of outcomes within villages. Since all household characteristics are balanced across treatment and control groups, we do not include a vector of controls in this model.

For some additional intuition into the effect captured by our model, we note that with only two time periods (baseline 2020 and endline 2021), this first-differences specification is identical to a difference-in-differences (DID) model, which compares the change in the level of y_i from

[4] The adoption variables are binary, meaning they do not fit all the assumptions of an LPM which assumes a continuous distribution over a normally distributed outcome. The major problems associated with using an LPM for binary outcomes include the presence of heteroskedasticity, which can be resolved by using robust standard errors, and the fact that an LPM is capable of producing estimates outside the 0 – 1 range, in which case the estimates lack clear interpretation and are likely to be biased. However, it is common practice to use LPMs to model binary variables given a large enough sample size and use of robust standard errors, as it results in estimates that are easier to interpret (Angrist and Pischke, 2008; Woolridge, 2002). In our case, the model does not produce any values outside the 0 – 1 range, so should be unbiased and consistent.

baseline to endline between treated and control groups. The DID model is specified with the following equation:

$$y_i = \alpha_0 + \theta_j TREAT_i + \gamma_j YEAR_i + \delta_j (TREAT_i \times YEAR_i) + \varepsilon_i \tag{5}$$

Where θ_j gives the average difference in outcome between treatment and control groups across all time periods, γ_j gives the average difference in outcome over time across all treatment groups, and δ_j is the DID estimator that gives the relevant effect of the treatment over time, equivalent (when there are only two time periods) to β_j in the first-differences specification above. The DID estimator for two time periods is constructed by taking the difference in the expected value of the outcome for treated observations in each time period, minus the difference in the expected value of the outcome for control observations in each time period, as follows:

$$\begin{aligned}\delta_{DD} = (\mathrm{E}[y \mid TREAT = 1\,, YEAR = 1] - \mathrm{E}[y \mid TREAT = 1, YEAR = 0]) \\ - (\mathrm{E}[y \mid TREAT = 0\,, YEAR = 1] - \mathrm{E}[y \mid TREAT = 0, YEAR = 0])\end{aligned} \tag{6}$$

Our results, presented in Table 6 and Table 7 indicate that treatment had a positive impact on legume intercropping, statistically significant at the 5.4% level, as measured by both of our indicator variables. The first variable, found in Column 1 of Table 6 takes a value of one for all respondents who listed a legume crop as something they planted along with maize on their main maize plot (MMP). The estimate implies that treated households were 13% more likely plant a legume on their MMP in 2021 relative to control households in 2021. The second intercropping indicator, found in Column 2 of Table 6, is based on respondents' answer to the question "Did you intercrop maize with a legume on your MMP this year?". The two measures differ slightly as some farmers may have planted a legume alongside maize without recognizing this practice to be intercropping – see Section 4.5 for details. By this measure, treated farmers were 8% more likely to intercrop, significant at the 6.2% level. A possible explanation for the lower treatment effect on the second indicator is that farmers in the chat groups typically did not use the word "intercropping", but rather listed various leguminous crops that they had tried or heard about planting alongside maize. Both treated and control farmers learned explicitly about intercropping through the SMS messages. While not statistically significant at traditional levels, we note that the coefficients on other legume practices and legumes on farm are both negative, perhaps suggesting that the treatment encouraged farmers to plant legumes alongside maize instead of elsewhere on their farms.

There are no significant results for any of the organic materials practices, and overall we find that significantly fewer farmers across treatment and control groups produced or applied organic fertilizers in 2021 compared to 2020. However, the large positive coefficient on "made organic fertilizer" presented in Column 2 of Table 7 suggests that perhaps farmers in the treatment groups were more likely to allocate their on-farm organic materials as fertilizers, another topic discussed frequently in the chat groups. This coefficient is significant at the 11% level.

5.2.2 Belief Updating

We measure a series of behavioral outcomes in an effort to understand the belief updating process farmers undergo when they receive new information, chat about it with others, and decide whether or not to adopt new practices. These include a knowledge score about regenerative agriculture principles and practices, various measures of perceived self-efficacy (PSE), and measures of subjective probability distribution (SPD) over soil fertility, profit, and food security outcomes associated with adoption of the key RA practices discussed – see Section 4.5 for details. Knowledge score, general PSE, and SPD are all measured with a continuous outcome variable (or in the case of knowledge score, a well-ordered categorical variable with many categories and a normal distribution – see Figure 1) well suited to first-differences estimation with OLS, and we model these using the specification described above in Section 5.2.1, equation (4)**.** The results of these regressions are presented in Tables 8 – 10. As we see, the effect of treatment on these outcomes is not statistically significant at traditional levels. We discuss the implications and possible explanations of these results in Chapter 6.

A key variable of interest to our study is perceived self-efficacy (PSE) in the domain of regenerative agriculture. There is no standardized measurement for domain-specific PSE, only general guidelines from the psychology literature (Bandura, 2006; Schwarzer and Renner, 2009) for creating appropriate scales. We constructed two domain-specific PSE modules to investigate this trait among study participants – see Section 4.5 for a full discussion of our metrics. Both modules asked respondents to select a value from a Likert scale, resulting in categorical, non-continuous outcome variables. There is debate over whether Likert scale dependent variables can be treated as continuous and estimated with a linear probability model, as we have done for the other variables in our analysis (Sullivan and Artino, 2013). The problem arises because response items in a Likert scale, while ordinal, are not necessarily spaced at even intervals. In our case for example, we ask respondents to rank how difficult it would be to accomplish a certain task, and it is not clear that, e.g., the jump from “difficult” to “extremely difficult” is equivalent to the jump from “not at all difficult” to “somewhat difficult”. Parametric tests like OLS regression assume that the underlying population would be normally distributed, with most individuals falling near the mean level in terms of outcome. First of all, it is unclear what the mean would even be for a scale like ours, and second, there is no a priori reason to assume that most responses would be clustered around, for instance, the "moderately difficult" option. Figure 1 shows the density of responses for each PSE outcome in our data, and we clearly see that responses are not normally distributed for any of the domain-specific measures. Some econometric research maintains that parametric testing is robust to violations in the normality assumptions, and valid for use with Likert scale dependent variables even under non-optimal conditions (e.g., Norman, 2010; Sullivan and Artino, 2013). We therefore report the first-differences estimation specified in equation (4) using OLS regression with robust standard errors clustered at the village level. We find a positive coefficient of 0.323 on intercropping PSE, significant at the 10% level, indicating that treatment increased this score by .32 on a four-point scale. No other measures are significant.

However, these results, reported in Tables 11 – 12, should be interpreted with caution, particularly in the case of the task-specific PSE measures for which the Likert scale has only four items – an oversight in the design of our survey instrument (Rickards et al., 2012). For this reason, we also evaluate these outcome variables using an ordered logistic regression model with random effects given by:

$$P(Y_{it} > k \mid X_{it}, \nu_i) = H(\beta X_{it} + \nu_i - k_k) \tag{7}$$

where ν_i is an iid error term, $k_1, \dots, k_{K-1}$ are the possible levels taken by the outcome variable Y_{it} (as above), and $H(\cdot)$ is a logistic cumulative distribution function. Fixed-effects models are often preferred to random-effects models, as the latter requires a stricter condition on the individual-specific error term. Namely, the individual-specific effects must be uncorrelated with the independent variable. In our case, the randomization of households into treatment and control group should ensure that this assumption is valid, as there is no reason for any characteristics of the individual to be correlated with their treatment status – the independent variable in our case. If this assumption holds, the random-effects model is more efficient than fixed-effects (Woolridge, 2015). The results of this model, presented in Tables 13 – 14, corroborate the first-difference estimations. We find a positive treatment effect on task-specific PSE for intercropping, significant at the 1% level. The coefficient is not straightforward to interpret, but the positive sign tells us that treated households rate their PSE in the domain of intercropping higher relative to the control. No other results are significant, but the signs on all coefficients match those from the linear model.

5.2.3 Welfare Outcomes

Finally, we estimate the effect of treatment on three welfare outcomes: maize yields, food insecurity, and assets – see Section 4.5 for details. These outcomes are all modeled using the first-differences specification outlined in Section 5.2.1, equation 4, and the results are presented in Table 15. It is unsurprising that we do not see any statistically significant effect on welfare outcomes, as most of the RA methods discussed in the extension campaign take more than one season to produce a measurable effect on yields, much less assets. We might expect to see a downward trend in food insecurity if households grow a legume crop that provides food, but the positive and non-significant coefficient in Column 2 of Table 15 indicates that this is not observed.

5.3 Spillover Effects

There is potential for spillover of treatment effects to untreated households if chat group participants discuss their experience with neighbors, or if adoption of the targeted practices by treated households encourages others in the community to adopt as well – clearly a desired outcome of any agricultural education initiative (Feder et al., 2004). If these effects are present in treatment villages, our results represent a lower-bound estimate of the impact of treatment. For this reason, we included a subset of control households in randomly selected control villages, in which no households were selected for treatment (i.e. given access to the group chat feature of ShambaChat). Comparing treated households directly to control households in control villages would give us a pure treatment effect, but doing so decreases our sample size significantly. To test for spillover effects, we estimate the following first-differences equation using OLS with robust standard errors clustered at the village level:

$$\Delta y_{ij} = \alpha_0 + \sum_{k=0}^{2} \theta_{kj} TREAT_i^k + \Delta \boldsymbol{X}_i + \Delta \varepsilon_i \qquad (8)$$

where y_{ij} takes the endline value of each outcome variable, j, regressed on a series of three dummy variables, $TREAT_i^k$, corresponding to treated households ($k = 2$), control households in treatment villages ($k = 1$), and control households in pure control villages ($k = 0$), respectively. A significant θ_{1j} coefficient would indicate the presence of spillover effects, implying that control households in treatment villages absorbed some of the treatment effect on outcome j from neighboring households. However, referring to the balance table (Table 4) from section 4.7.2, we see that after attrition the control households in treatment vs control villages are not well-balanced at baseline across several outcome variables, namely legumes on farm, making organic fertilizer, PSE over soil fertility outcomes, and PSE over a seed spacing task. We must therefore take care in attributing any effect on these outcomes to spillovers from treatment. Additionally, control households are unbalanced in land-owned and ownership of MMP. We therefore include these variables in a vector of controls $\boldsymbol{X}_i$. We find evidence of spillover effects, indicated by significant θ_1 coefficient in several adoption outcomes, presented in Tables 16 – 17, namely the first legume intercropping measure (Table 16, Column 1) and the indicator for making organic fertilizer (Table 17, Column 2). Making organic fertilizer was not balanced at baseline, with control households in treatment villages significantly *less* likely to produce or find organic materials on their farms relative to control households in control villages, so this spillover effect may actually be stronger than the coefficient implies. These results suggest that control households in treatment villages may have absorbed some impact of the treatment through watching their neighbors adopt intercropping practices or discussing their experience of the ShambaChat group chats. In this case, our estimate of the treatment effect on these outcome reflects a lower-bound.

We also note the significant θ_2 coefficients for both legume intercropping measures, as well as for making organic fertilizer, which indicate positive treatment effects on these outcomes for treated households relative to control households in control villages. This suggests that the treatment effects we report in Section 5.2.1 may underestimate the true impact of treatment due to the presence of spillovers in treatment villages. A full analysis of treatment effects relative to pure control villages is outside the scope of this paper. We do not find any spillover effects across behavioral or welfare outcomes.[5]

5.4 Heterogeneous Results

We investigate whether participation in the ShambaChat group chats had the same effects for female- and male-headed households, and for the poorest and richest households.

[5] In the interest of space, these are not reported, but all results are available upon request from the author.

5.4.1 Gender

To understand the differential impact of the treatment by gender, we define a dummy variable $female$ equal to one for female-headed households and zero otherwise. We interact this term with the treatment variable and estimate the following first-differences equation with year fixed- effects We run the following equation for the seven adoption outcomes.

$$\Delta y_{ij} = \alpha_0 + \beta_j TREAT_i + \theta_j (TREAT_i \times female_i) + \Delta\varepsilon_i \qquad (9)$$

where θ_j gives the differential effect of the treatment on outcome j for female-headed households. The results of this estimation on adoption outcomes are presented in Tables 18 – 19. We see a significant differential effect for planting legumes on farm, with female-headed households in the treatment group 19% more likely to plant a legume on their farm than female-headed households in the control group. As only 22% of household heads are female, some of these estimations may lack power required to see significance, but the negative coefficients for all θ_j (except for making organic fertilizer) suggest the treatment may have been less effective for female-headed households. The treatment effect reported in Section 5.2.1 for the first intercropping measure holds, but we lose significance for the second measure when considering gender effects. There are no differential effects observed for behavioral or welfare outcomes.[6]

5.4.2 Assets

[6] In the interest of space, these are not reported, but all results are available upon request from the author.

Similarly, we estimate the differential effect of the treatment on the poorest and richest households in our sample by defining two dummy variables: $poorest$ equal to one for the bottom asset quintile and zero otherwise, and $richest$ equal to one for the top asset quintile and zero otherwise. Both indicators are based on 2020 asset levels, see Appendix C for construction of the asset index. We interact these indicators with the treatment term as in equation (9) above, but do not see a significant treatment differential for any outcome variable[7].

5.5 Robustness of Results: Cross-Sectional Analysis of Endline Data

As a robustness check, we run an intent-to-treat (ITT) analysis on a cross-section of data collected at endline in 2021. For all binary and continuous outcome variables we use a linear probability model (OLS) to estimate the following equation:

$$y_{ij} = \alpha_0 + \beta_j TREAT_i + \varepsilon_i \tag{10}$$

Results are presented in Tables 20 – 23. The significant coefficients on our two intercropping measures are not robust to this analysis, although it is worth noting that the first measure becomes significant when we account for spillovers by distinguishing between control households in treatment villages and pure control villages (see Section 5.3)[8]. The indicator for households who found or produced organic materials on their farm, presented in Column 1 of Table 21, becomes significant at the 10% level in this analysis, but as this is not supported by the first-differences analysis we do not take it as evidence of a treatment effect. As with the first-differences panel analysis, we do not see any significant results for these behavioral or welfare outcomes.

[7] In the interest of space, these are not reported, but all results are available upon request from the author.
[8] In the interest of space, these are not reported, but all results are available upon request from the author.

For the domain-specific PSE variables with categorical response structures, we conduct a cross-sectional analysis using an ordered logistic regression with proportional odds. The significant coefficient on PSE for the intercropping task is robust to this cross sectional analysis, as indicated in Column 3 of Table 24.

Chapter 6: Discussion

6.1 Summary

To summarize, we find significant and positive treatment effects on adoption of intercropping practices, as measured by two indicators, and on domain-specific PSE over an intercropping task. We find no effect on other outcome variables, including adoption of organic materials practices, knowledge retention, other metrics of PSE, subjective probability distribution over soil fertility, profit, and food security outcomes, and welfare outcomes including maize yields, assets, and food security. Our first measure of intercropping and measure of PSE over the intercropping task are robust to multiple panel data analysis techniques, but the effects on intercropping adoption do not hold in a cross sectional analysis, perhaps due to the presence of spillovers to control households in treatment villages. The presence of spillovers, detected for multiple adoption outcomes, suggests that our treatment benefited untreated households through community networks. In this section we discuss possible explanations for our findings in the context of how farmers actually engaged with the treatment. We address methodological limitations that may have impacted our results, as well as broader limitations to the use of ICTs for farmer-to-farmer extension and peer learning. Finally, we discuss further applications of the ShambaChat platform that fall outside the scope of this study.

6.2 Use of the ShambaChat Platform

The ShambaChat extension campaign was divided into three rounds, each lasting for one month and covering different (but overlapping) regenerative agriculture practices and agro-ecological principles. We found that participation in the first round, which focused on legume-maize intercropping, was highest, with 996 messages sent by farmers in the group chats. We analyzed the content of the messages using simple natural language processing techniques in Python to gain an understanding of the ShambaChat user experience. To reiterate, treated farmers received extension broadcasts and discussion prompts from our team of researchers, tagged with "SUA" for the agricultural university in Morogoro which farmers are familiar with, as well as messages from other farmers in their chat group, tagged with the first three letters of the sender's name. A reply to either message type would be forwarded to all five chat group members. 655 of the texts sent by farmers during the first round were direct responses to extension broadcasts, while the remaining 324 texts were direct replies to another member of the chat group, indicating that – at least in some groups – there was active dialogue between members. Figure 2 shows the breakdown of the types of messages sent by farmers. Most texts contained questions or advice (including answers to questions posed by other farmers or in our discussion prompts), or articulated challenges regarding the proposed practices or other factors affecting production such as pest or weather problems. Other messages contained logistical questions about how to navigate the ShambaChat platform, and introductions. Some farmers repeatedly introduced themselves, suggesting they did not understand that their chat group consisted of the same five members for the duration of the course.

A potential issue arises if farmers share misinformation in the group chats or contradict the content of the extension broadcasts, but we do not see much evidence of this occurring. In fact, 213 of the messages sent by farmers directly reinforced the extension content, while only 14 contradicted it. Only 7 messages contained objectively inaccurate information. 53 messages explicitly expressed intent to try one of the targeted practices for the first time. As we see in Figures 3 and 4, farmers sent over 200 messages about legumes – the focus of the first round of extension – and listed 14 varieties by name. This is an indication that farmers were interested in the extension content and used the group chats to deepen their engagement with the material by discussing it with their peers.

During the second round of the course, which focused on collecting on-farm organic materials and making compost, we saw a stark decline in activity in the group chats. There was a 6 week hiatus between the rounds, so it is likely that many participants lost interest during this time, and others may have lost access to their SIM card or phone. The message content from farmers was extremely limited, containing mostly introduction messages and thank you notes in response to extension broadcasts. The case was similar for the third round, which coincided with the maize harvest and focused on practices for leaving crop residues and preparing fields for the next season. We do not formally estimate the relationship between the level of group chat activity and effect of the treatment on adoption or other outcomes, but it is interesting to note that the high volume of messages and discussion surrounding the content of the first round corresponds to the treatment effect we find on adoption of intercropping practices and PSE over the intercropping task. The complete lack of discussion during the later rounds almost precludes us finding a treatment effect on other adoption variables, consistent with our null findings regarding adoption of organic materials practices and associated behavioral outcomes.

6.3 Impact of the Treatment and Methodological Limitations

If we consider the first round of extension in isolation, we see evidence of a role for PSE in the belief-updating process through which peer learning leads to adoption. Farmers engaged with information about legume intercropping through discussion with peers in a group chat, after which their PSE regarding their ability to perform an intercropping task increased, along with their likelihood of adopting the practice on their own farm. However, an identification problem emerges, as we measured endline PSE only after the adoption had taken place. It is therefore possible that adoption was spurred by some other mechanism present in the treatment, and that successful implementation of intercropping in fact contributed to the increase in PSE rather than the other way around. According to Bandura (1977, 1986), PSE is influenced most strongly by personal mastery experiences, making this interpretation of the direction of causality equally plausible. Perhaps there is mutual causality going on, with PSE playing a role on both sides of the adoption decision: social learning kickstarts a virtuous cycle wherein increased PSE from exposure to peer role models empowers farmers to adopt challenging practices, which, when completed successfully, increase PSE further through the experience of mastery. Further research could resolve this by measuring PSE after the new information is received and discussed, but before the adoption decision is made.

As previously stated, we speculate that PSE might increase from participation in the group chats simply as a result of increased exposure to the experience and attitudes of peers. However, a distinct role model effect implies that someone in the group is more experienced in the relevant domain. We took this into consideration when designing the intervention, as described in Section 4.3. Each chat group contained one farmer who had experience with legume intercropping at baseline, and one who had experience with a soil conservation practice including grass strips, ridges, bench terraces, drainage channels, or water catchment. We chose these selection criteria before the extension course was finalized, and in the end we did not end up including the soil conservation practices listed here, changing the focus instead to organic material cycling. This meant that groups only had a role model for intercropping, which is consistent with the fact that our treatment effects are stronger for the intercropping outcomes, including intercropping PSE. Further research is needed to distinguish the role model effect from the social learning effect observed from a group of peers with similar experience, perhaps building on this study to include a block of group chats with and without designated role models.

Our failure to measure outcome variables at the end of each round (due to budget and time constraints) may also have implications beyond the mutual causality problem described above. Since activity in the group chats dropped to almost zero after the first round of extension, the experience of treated and control farmers was close to identical for much of the intervention, meaning our endline measurements were effectively taken six months after the end of treatment. Such a gap between treatment and evaluation could make a big difference in the levels of the outcome variables we measure, particularly for behavioral outcomes like knowledge retention and PSE. For example, in their study of the role model effect in Digital Green's video-mediated extension program, Bernard et al. (2015; 2019) find an increase in external locus of control when they survey participants immediately after the intervention, but a much weaker effect when they follow up with the same questions six months later. It is therefore possible that we may have seen more of a treatment effect on our behavioral indicators had we been able to evaluate after each extension round.

Evaluating behavioral outcomes objectively is also a challenge, as there are not always agreed upon metrics available or replicable in the literature. For instance, domain-specific PSE – by definition – does not cut across domains of functioning, so any metric must be constructed in reference to the relevant set of tasks or outcomes under review. Since this study is the first to measure PSE over intercropping and regenerative agriculture tasks, or even agriculture more generally, we had to develop our own module for eliciting this trait. We took care to draw from the psychology literature on elicitation of domain-specific PSE, which is fairly well-developed particularly in health and education domains (Bandura, 2006; Chen et al., 2001; Schwarzer and

Renner, 2009; Wuepper and Lybbert, 2017). However, the metrics we constructed are not validated by psychologists or any external study, meaning we cannot rule out the possibility that treatment did impact these variables though we failed to detect the effect. For example, Bandura (2006) notes that a valid scale should reflect gradations of challenge by measuring efficacy beliefs for a series of progressively more challenging sub-tasks, which we were not able to do because we had not finalized the extension course at the time of baseline data collection and could not anticipate what the content would be to this level of detail. We also face econometric challenges when analyzing the data from the four or five item Likert scales we used in these measures, as discussed in Section 5.2.2.

6.4 Further Applications of the ShambaChat Platform

A major motivation in developing ShambaChat was to create a platform for innovative farmers to share solutions, with each other as well as with us. Specific techniques are often discovered or invented by farmers, who are troubleshooting agricultural problems on a daily basis – particularly in the case of broad and highly adaptable technologies like regenerative agriculture. Through ShambaChat, extension providers can learn from farmers and even incorporate farmer-generated solutions into the content of future extension campaigns. While the present study does not explicitly evaluate this function, further research could use qualitative text analysis to identify farmer-generated extension advice and explore the extent to which farmers use the platform in this way. It would also be interesting to see whether farmers act on advice from their peers, and whether they trust the information provided – for instance, are farmers more likely to trust information from an SMS sent by an extension provider or by a peer?

We made use of the information-sourcing capability of ShambaChat to check in with farmers about how their cropping practices changed in response to severe drought that affected much of Morogoro during the 2021 growing season, and to elicit farmer-generated advice on best adaptation practices and coping strategies. We used natural language processing to identify the most common suggestions from farmers, and, after verifying with an agronomist, incorporated these into the following round of extension messages. In this way, ShambaChat becomes a powerful tool for amplifying farmer voices and improving extension with highly relevant and context specific content that meets the needs of farmers in the field.

Chapter 7 – Conclusion

7.1 Limitations of ICTs for Peer Learning

Promoting adoption of complex agriculture technologies like RA requires an approach to extension that centers farmers as innovators and nodes of communication in the design and dissemination of relevant practices. Through experimentation and observation of others, farmers update their beliefs about likely outcomes associated with adoption, and exposure to success stories and positive attitudes increases farmers' confidence and willingness to try something new. The role of the extension service is therefore to facilitate the flow of information between farmers, and provide a space for robust dialogue around personal experiences with adoption. If peer learning processes operate through the mechanism of vicarious experience, whereby agents update their beliefs about their own capabilities after observing the success (or failure) of a relatable peer, extension campaigns should be designed to facilitate these experiences. As we saw in Section 3.1, F2FE initiatives have had varying degrees of success with this, depending in part on their ability to establish meaningful connections among participating farmers.

If these conditions for impactful F2FE are difficult to meet even for in-person initiatives, it is not surprising that we face challenges translating them to a digital learning environment. Anyone who has engaged with an online community, especially one composed of strangers, is aware of the communication pitfalls that arise when expressing complex ideas to an unknown audience. Considering these same dynamics playing out on feature phones, with participants who likely have varying degrees of technological literacy, it is easy to see why meaningful connections or robust dialogue may have been difficult to maintain. We surveyed 90 farmers from the treatment group who did not participate actively in the group chats after the first round of extension, to gain insight into why they didn't engage. Figure 5 gives a breakdown of the most commonly cited reasons. Many farmers told us they were too busy to reply, could not reply because of broken technology, or did not understand how to reply to the messages. All of these problems reveal a pattern common in ICT extension, where providers fail to consider the interests, needs, and technical capacities of the farmers they hope to reach (Wyche and Steinfield, 2016).

7.2 Conclusion and Policy Recommendations

Even where technology barriers can be overcome, it seems unlikely that ICTs will ever be a perfect substitute for in-person F2FE, nor will they replicate the dynamics present in community-based social networks. Of course, the present study is limited to a very rudimentary form of technology – SMS communication on feature phones – and we do not extrapolate our findings to more complex interventions. Still, for many farmers in SSA, feature phones are the predominant form of ICT available, and making use of this tool to overcome harmful information constraints should be an essential part of any development strategy for the region. The positive performance of the ShambaChat platform during the first round of extension leaves us optimistic regarding the potential benefits of a similar extension tool. We saw active discussion between farmers surrounding the content of the course, and measured a significant impact on adoption of the central practice covered during that round - intercropping. Moreover, we detected significant spillover effects, suggesting the treatment benefited other farmers through community networks. Providing extension through ShambaChat is low-cost and logistically straight-forward relative to in-person F2FE, and our results, though modest, support further development of effective uses for ICT to facilitate connections between farmers. The failure of ShambaChat to keep users engaged over multiple extension rounds points to a need for future interventions to seek guidance from farmers about what topics are of interest to them, and how to tailor the extension tool to their specific goals and level of technology and technological literacy.

Our investigation of the behavioral mechanisms by which social learning leads to adoption is rudimentary, and further collaboration between social psychologists and economists is needed to develop and validate methods for eliciting and influencing domain-specific PSE. The significant result we find for intercropping PSE contributes to a growing body of literature linking adoption behavior to internal constraints like self-efficacy beliefs (Abay et al., 2017; Bernard et al., 2015, Carter 2016, Malacarne 2018; 2019; McGinty et al., 2008; Taffesse and Tadesse, 2017; Ung et al., 2016, Wuepper and Lybbert, 2017). If our results are corroborated, they can be used to support the design of participatory learning interventions that help farmers build confidence by sharing experience and troubleshooting complex information with the help of relatable role models and peers.

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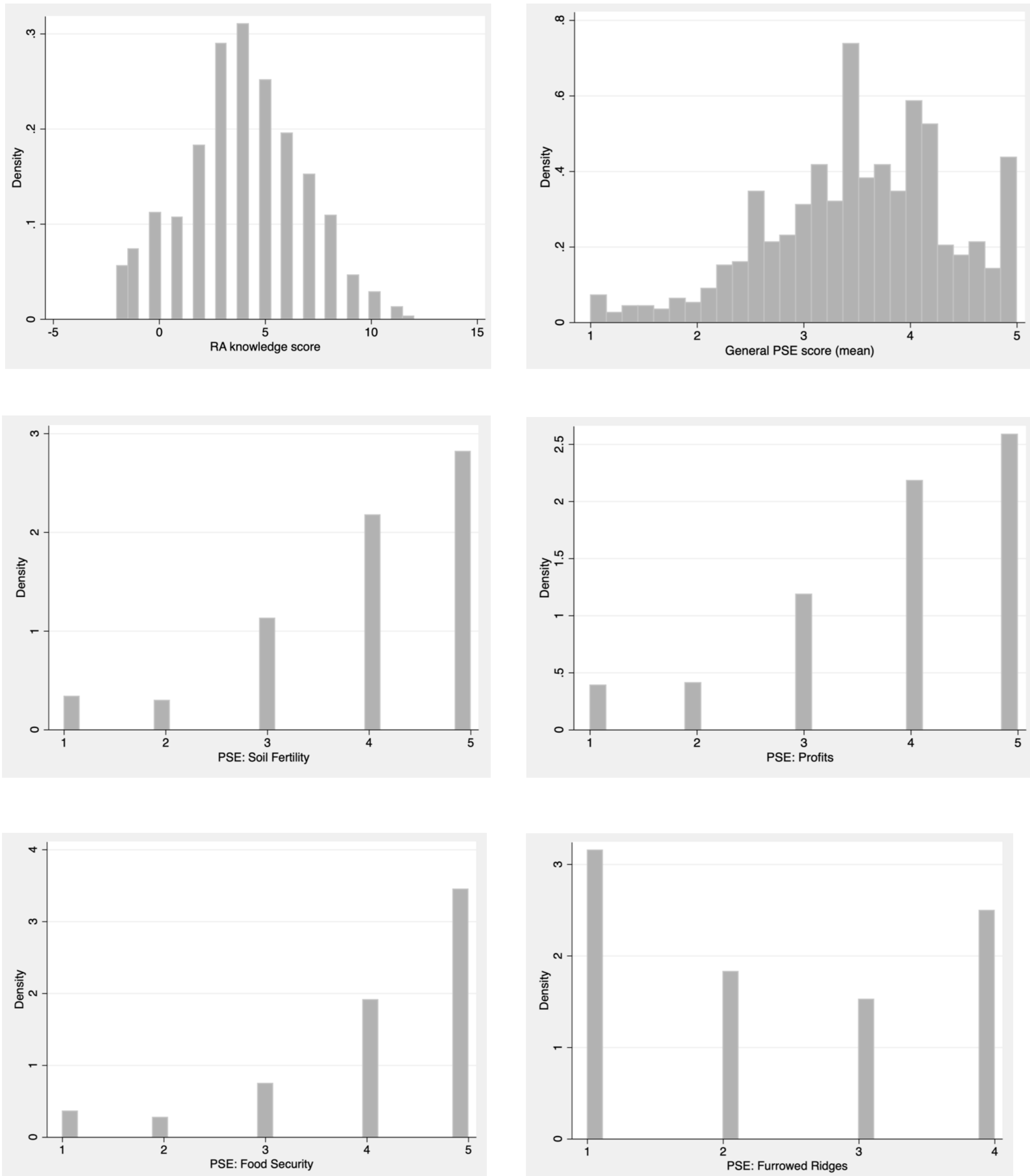
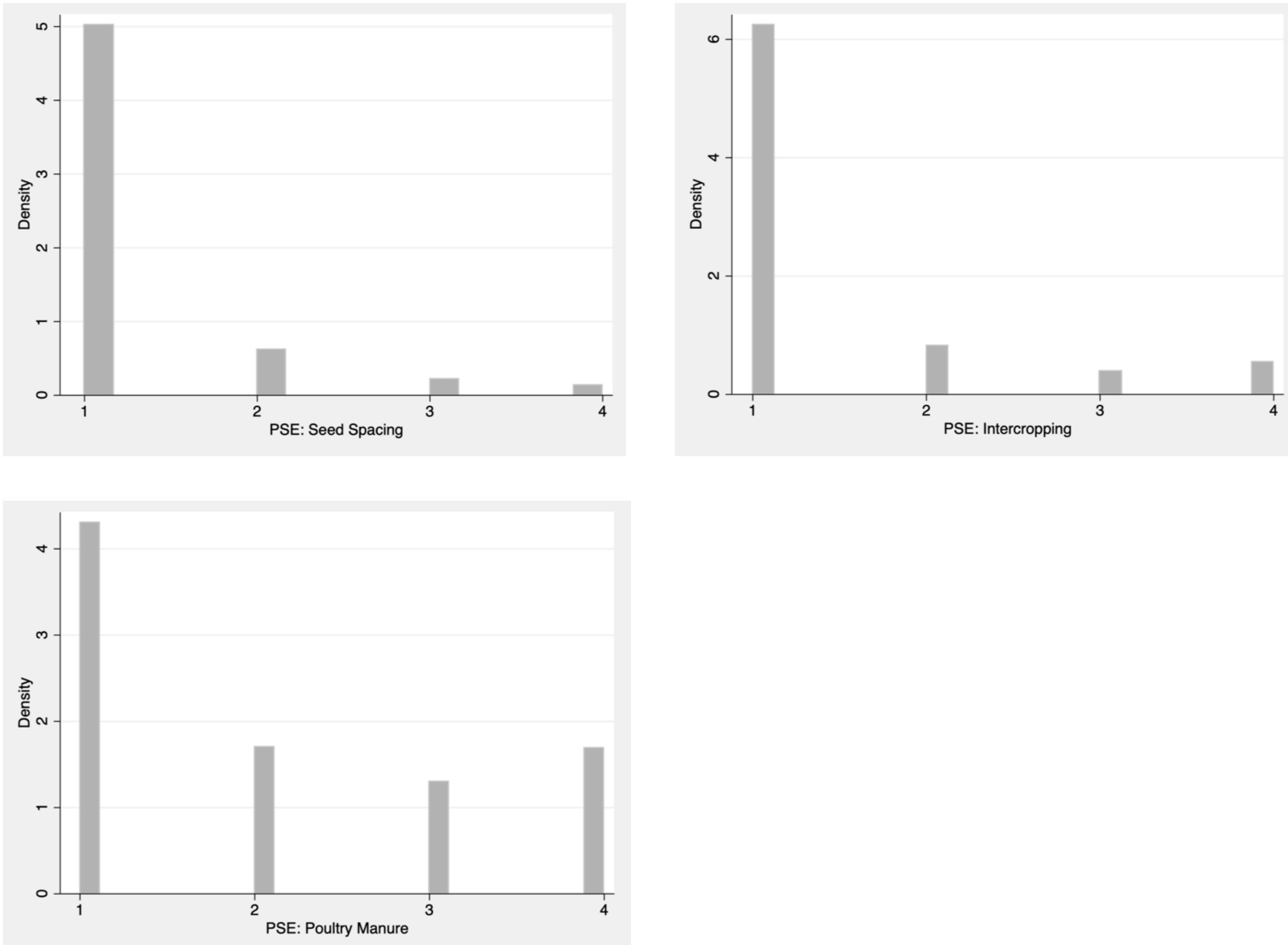
Figures

Figure 1: Distribution of Behavioral Outcome Variables





Note: This figure presents a series of histograms showing the distribution of respondent outcomes for eight metrics of PSE, and one knowledge score. The seven domain-specific PSE measurements are scored on a four or five point Likert scale, see Appendix B for details.

Figure 2: Breakdown of Messages Sent by Farmers in First Round of Extension

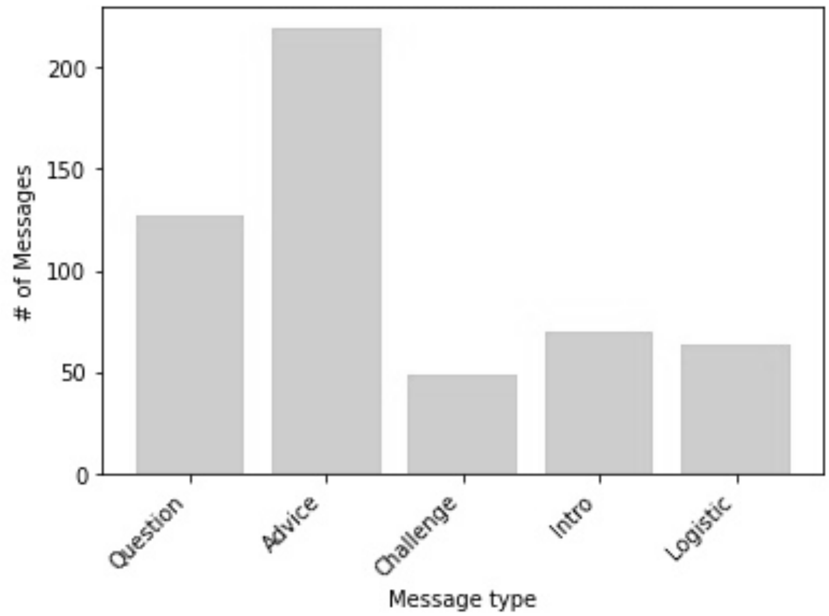


Figure 3: Topics Most Frequently Discussed by Farmers in First Round of Extension

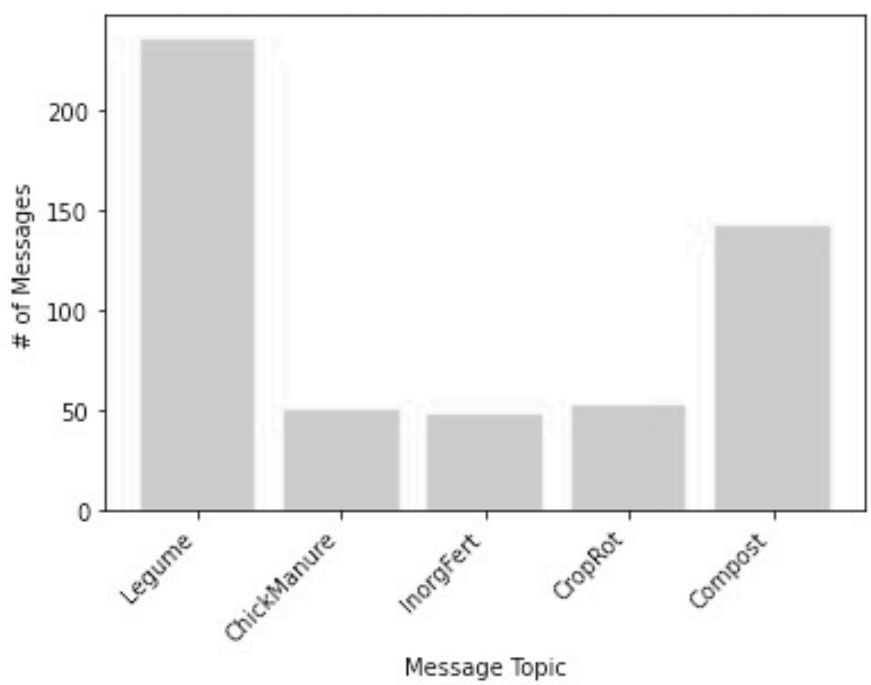


Figure 4: Frequency of Crops Mentioned by Farmers in First Round of Extension (excl maize)

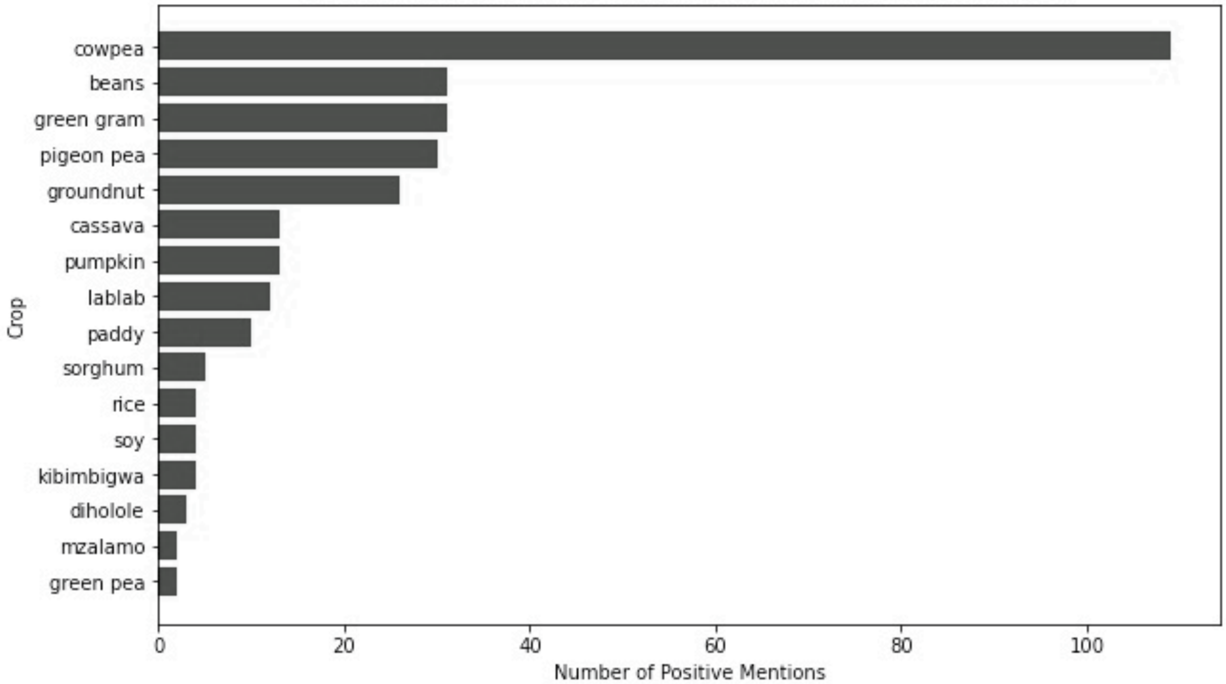
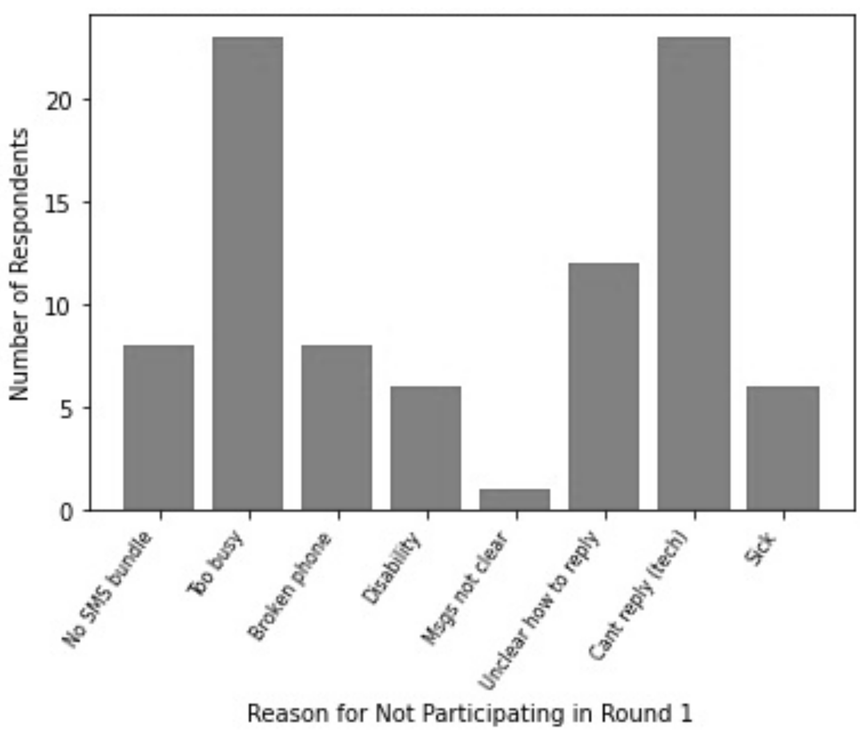


Figure 5: Reasons Most Frequently Cited for Not Participating in First Round of Extension



Tables

Table 1: Probability of Attrition by Treatment Group

VARIABLES	(1) Attrited
Control in treatment village	0.0128
	(0.0692)
Treatment	-0.00932
	(0.0572)
Constant	0.247***
	(0.0450)
Observations	523
R-squared	0.001

Robust standard errors in parentheses.
Standard errors are clustered at the village level.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2: Effect of Attrition on Outcome Variables

VARIABLES:	(1) ATTRITION:
Age of hh head	0.002
	(0.001)
Gender of hh head	0.022
	(0.057)
Education completed by hh head	0.005
	(0.009)
Dependency ratio	0.0
	(0.0)
Food insecurity index	-0.005
	(0.011)
Land owned (acres)	0.001
	(0.003)
Do you own your MMP?	0.027
	(0.065)
Asset Index	-0.004
	(0.01)
Remoteness	-0.005
	(.011)
Maize yield (kg/acre)	-0.0
	(0.0)
Intercrop w legume on MMP (1)	-0.076
	(0.052)
Intercrop w legume on MMP (2)	-0.139
	(0.057)
Other legume practices	0.039
	(0.049)
Legumes on farm	0.015
	(0.011)
Produced organic materials	0.025
	(0.045)
Made organic fertilizer on-farm	-0.037
	(0.059)
Applied organic fertilizer MMP	0.021
	(0.032)
RA knowledge score	0.001
	(0.001)
General PSE score (mean)	-0.037
	(0.026)
PSE Outcomes: Soil Fertility	0.005
	(0.018)
PSE Outcomes: Profits	0.004

	(0.216)
PSE Outcomes: Food Security	-0.004
	(0.017)
PSE Tasks: Furrowed Ridges	0.029
	(0.016)
PSE Tasks: Seed Spacing	-0.035
	(0.054)
PSE Tasks: Intercropping	-0.003
	(0.03)
PSE Tasks: Poultry Manure	-0.003
	(0.014)
SPD over soil fertility outcomes	0.0
	(0.0)
SPD over profit outcomes	0.0
	(0.0)
SPD over food security outcomes	0.0
	(0.0)

Robust standard errors in parenthesis.
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Balance of Treatment and Control Households at Baseline

Baseline 2020 Variable:	(1) Mean of Control	(2) SD of Control	(3) Mean of Treated	(4) SD of Treated	(5) Difference in Means
Village	23.15	11.59	23.97	11.80	0.812
Age of hh head	45.55	13.74	44.40	12.89	-1.148
Gender of hh head	0.17	0.38	0.14	0.35	-0.031
Education completed by hh head	6.37	1.96	6.35	2.02	-0.023
Dependency ratio	157.56	106.99	156.93	118.33	-0.624
Food insecurity index	2.26	1.89	2.08	1.77	-0.186
Land owned (acres)	6.65	8.25	6.18	7.31	-0.463
Do you own your MMP?	0.90	0.30	0.90	0.30	0.005
Asset Index	0.06	2.19	0.01	2.29	-0.051
Maize yield (kg/acre)	282.69	348.90	288.36	496.12	5.670
Intercrop w legume on MMP (1)	0.18	0.38	0.15	0.36	-0.027
Intercrop w legume on MMP (2)	0.12	0.33	0.10	0.30	-0.025
Other legume practices	0.12	0.33	0.21	0.41	0.085**
Legumes on farm	0.29	0.46	0.35	0.48	0.054
Produced organic materials	0.58	0.50	0.67	0.47	0.090
Made organic fertilizer on-farm	0.28	0.45	0.19	0.40	-0.087
Applied organic fertilizer MMP	0.26	0.44	0.26	0.44	0.001
RA knowledge score	2.64	2.41	3.27	2.33	0.632***
General PSE score (mean)	3.31	0.84	3.32	0.78	0.008
PSE Outcomes: Soil Fertility	3.84	1.25	3.90	1.16	0.067
PSE Outcomes: Profits	3.77	1.25	3.82	1.16	0.048
PSE Outcomes: Food Security	4.02	1.27	4.14	1.15	0.118
PSE Tasks: Furrowed Ridges	2.38	1.21	2.24	1.18	-0.140
PSE Tasks: Seed Spacing	1.19	0.57	1.15	0.42	-0.040
PSE Tasks: Intercropping	1.30	0.77	1.28	0.68	-0.023
PSE Tasks: Poultry Manure	2.04	1.23	1.96	1.13	-0.083
SPD over soil fertility outcomes	305.77	417.20	296.16	444.20	-9.606
SPD over profit outcomes	326.92	440.75	318.44	441.50	-8.482
SPD over food security outcomes	390.26	427.31	384.90	463.57	-5.355

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Balance of Control Households in Treatment Villages and Pure Control at Baseline

Baseline 2020 Variable:	(1) Mean of Pure Control	(2) SD of Pure Control	(3) Mean of Control in Trt Vil	(4) SD of Control in Trt Vil	(5) Difference in Means
Village	24.03	8.14	21.29	11.72	-2.741
Age of hh head	46.53	15.60	45.07	12.77	-1.463
Gender of hh head	0.20	0.41	0.15	0.36	-0.050
Education completed by hh head	6.48	1.74	6.32	2.06	-0.164
Dependency ratio	149.96	95.07	161.27	112.52	11.310
Food insecurity index	2.25	1.86	2.27	1.91	0.020
Land owned (acres)	4.77	3.75	7.56	9.61	2.788**
Do you own your MMP?	0.82	0.39	0.94	0.24	0.115*
Asset Index	-0.06	2.04	0.12	2.26	0.185
Maize yield (kg/acre)	244.45	341.57	302.79	352.78	58.349
Intercrop w legume on MMP (1)	0.22	0.42	0.15	0.36	-0.061
Intercrop w legume on MMP (2)	0.16	0.37	0.10	0.31	-0.054
Other legume practices	0.10	0.30	0.13	0.34	0.036
Legumes on farm	0.16	0.37	0.37	0.48	0.203**
Produced organic materials	0.53	0.50	0.61	0.49	0.079
Made organic fertilizer on-farm	0.48	0.51	0.19	0.39	-0.295*
Applied organic fertilizer MMP	0.31	0.47	0.24	0.43	-0.077
RA knowledge score	2.42	2.28	2.75	2.48	0.335
General PSE score (mean)	3.39	0.84	3.27	0.84	-0.111
PSE Outcomes: Soil Fertility	4.13	1.13	3.68	1.28	-0.450**
PSE Outcomes: Profits	3.95	1.17	3.68	1.29	-0.266
PSE Outcomes: Food Security	4.25	1.13	3.90	1.33	-0.353
PSE Tasks: Furrowed Ridges	2.38	1.24	2.38	1.21	-0.005
PSE Tasks: Seed Spacing	1.03	0.18	1.28	0.68	0.246**
PSE Tasks: Intercropping	1.25	0.68	1.33	0.82	0.080
PSE Tasks: Poultry Manure	2.07	1.21	2.03	1.24	-0.041
SPD over soil fertility outcomes	335.94	412.84	291.03	420.10	-44.907
SPD over profit outcomes	350.78	415.28	315.27	453.76	-35.514
SPD over food security outcomes	417.58	378.64	376.91	449.96	-40.670

*** p<0.01, ** p<0.05, * p<0.1

Table 5: Summary Statistics for Outcome Variables at Baseline and Endline

	2020			2021			
Adoption Outcomes:	**N**	**Mean**	**SD**	**N**	**Mean**	**SD**	**Difference**
Intercrop w legume on MMP (1)	303	0.16	0.37	321	0.27	0.45	0.113***
Intercrop w legume on MMP (2)	303	0.11	0.31	321	0.20	0.40	0.091***
Other legume practices	303	0.16	0.37	321	0.11	0.32	-0.053
Legumes on farm	397	0.33	0.47	397	0.31	0.47	-0.010
Produced organic materials	303	0.63	0.48	321	0.22	0.42	-0.408***
Made organic fertilizer on-farm	190	0.23	0.42	72	0.60	0.49	0.359***
Applied organic fertilizer on MMP	303	0.26	0.44	321	0.06	0.24	-0.206***

	2020			2021			
Behavioral Outcomes:	**N**	**Mean**	**SD**	**N**	**Mean**	**SD**	**Difference**
RA Knowledge score	362	2.96	2.39	397	4.86	2.77	1.903***
General PSE score	362	3.32	0.81	397	3.70	0.85	0.388***
PSE: Soil Fertility	362	3.87	1.20	397	4.14	0.98	0.270**
PSE: Profits	362	3.80	1.21	397	4.02	1.08	0.218**
PSE: Food Security	362	4.08	1.21	397	4.23	1.02	0.147
PSE: Furrowed Ridges	349	2.31	1.20	384	2.43	1.24	0.119
PSE: Seed Spacing	166	1.17	0.50	185	1.31	0.72	0.145
PSE: Intercropping	298	1.29	0.72	282	1.52	0.97	0.234*
PSE: Poultry Manure	360	2.00	1.18	384	2.08	1.17	0.076
SPD: soil fertility outcomes	397	300.88	430.63	397	372.36	446.49	72.468
SPD: profit outcomes	397	322.61	440.59	397	347.29	447.15	25.127
SPD: food security outcomes	397	387.53	445.58	397	382.18	464.15	-9.810

	2020			2021			
Welfare Outcomes:	**N**	**Mean**	**SD**	**N**	**Mean**	**SD**	**Difference**
Asset index	397	0.04	2.24	394	0.00	2.06	-0.046
Food insecurity index	397	2.17	1.83	397	2.04	1.79	-0.115
Maize yield (kg/acre)	303	285.59	429.85	321	403.40	945.06	117.532

*** p<0.01, ** p<0.05, * p<0.1

Table 6: Effect of Treatment on Adoption Outcomes – Legume Practices

VARIABLES	(1) Intercropping 1	(2) Intercropping 2	(3) Other Legume Practices	(4) Legumes on Farm
Treatment	0.126*	0.0786*	-0.0791	-0.0503
	(0.0636)	(0.0411)	(0.0528)	(0.0418)
Constant	0.0565	0.0484	-0.0161	0.0155
	(0.0493)	(0.0433)	(0.0415)	(0.0362)
Observations	252	252	252	397
R-squared	0.013	0.006	0.007	0.004

Note: The number of observations in Columns 1 – 3 reflects the number of respondents who cultivated maize in both time periods. Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Effect of Treatment on Adoption Outcomes – Organic Materials Practices

VARIABLES	(1) Organic Materials	(2) Made Organic Fertilizer	(3) Organic Fertilizer - MMP
Treatment	-0.0173	0.302	0.0116
	(0.0888)	(0.188)	(0.0655)
Constant	-0.411***	0.0769	-0.234***
	(0.0743)	(0.175)	(0.0608)
Observations	252	42	252
R-squared	0.000	0.050	0.000

Note: The number of observations Column 1 reflects the number of respondents who cultivated maize in both time periods. The number of observations in Column 2 reflects the number of respondents who produced organic materials on their farm in both time periods. Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Effect of Treatment on Behavioral Outcomes – Knowledge

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	**Knowledge Score**	**Q1**	**Q2**	**Q4**	**Q5**	**Placebo**
Treatment	-0.667	-0.00815	-0.399	-0.231	-0.0287	0.0198
	(0.508)	(0.0652)	(0.255)	(0.286)	(0.0716)	(0.0611)
Constant	2.227***	0.0625	0.812***	1.318***	0.0341	0.170**
	(0.456)	(0.0603)	(0.221)	(0.265)	(0.0572)	(0.0684)
Observations	362	362	362	362	362	362
R-squared	0.010	0.000	0.012	0.005	0.001	0.000

Note: the number of observations reflects the number of endline respondents who participated in Part 2 of the 2020 baseline survey. Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Effect of Treatment on Behavioral Outcomes – Subjective Probability Distribution

	(1)	(2)	(3)
VARIABLES	**SPD: Soil Fertility Outcomes**	**SPD: Profit Outcomes**	**SPD: Food Security Outcomes**
Treatment	-11.31	-4.816	28.58
	(56.29)	(55.90)	(54.48)
Constant	78.22	27.58	-24.36
	(49.77)	(48.57)	(51.63)
Observations	397	397	397
R-squared	0.000	0.000	0.000

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Effect of Treatment on Behavioral Outcomes – Generalized PSE

	(1)
VARIABLES	**Generalized PSE**
Treatment	0.0213
	(0.0785)
Constant	3.693***
	(0.0653)
Observations	397
R-squared	0.000

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 11: Effect of Treatment on Behavioral outcomes - Task-Specific PSE

	(1)	(2)	(3)	(4)
VARIABLES	**Furrows**	**Seed Spacing**	**Intercropping**	**Manure**
Treatment	0.255	0.271	0.323*	0.142
	(0.203)	(0.170)	(0.176)	(0.222)
Constant	-0.0625	-0.128	0.111	0.00585
	(0.176)	(0.116)	(0.125)	(0.194)
Observations	362	277	314	362
R-squared	0.005	0.034	0.015	0.002

Note: The number of observations reflects the fact that respondents who are already using a given technique were not included in the estimates. Robust standard errors in parentheses. The maximum N is 362, the number of endline respondents who in Part 2 of the 2020 baseline survey
*** p<0.01, ** p<0.05, * p<0.1

Table 12: Effect of Treatment on Outcomes – Outcome-Specific PSE

VARIABLES	(1) **Soil Fertility**	(2) **Profits**	(3) **Food Security**
Treatment	-0.123	-0.115	-0.174
	(0.165)	(0.182)	(0.184)
Constant	0.318*	0.278*	0.250*
	(0.161)	(0.155)	(0.146)
Observations	362	362	362
R-squared	0.002	0.001	0.003

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 13: Effect of Treatment on Task-Specific PSE – Ordered Logit with Random-Effects

VARIABLES	(1) **Furrows**	(2) **Seed Spacing**	(3) **Intercropping**	(4) **Manure**
Treatment	0.0719	0.706	0.674***	0.161
	(0.219)	(0.473)	(0.229)	(0.252)
Year	0.114	0.256	0.285	0.0751
	(0.236)	(0.491)	(0.331)	(0.290)
Constant – cut 1	-0.532***	2.387***	1.601***	-0.00810
	(0.122)	(0.462)	(0.183)	(0.139)
Constant – cut 2	0.300***	3.688***	2.381***	0.792***
	(0.108)	(0.594)	(0.229)	(0.153)
Constant – cut 3	1.046***	4.796***	2.985***	1.566***
	(0.142)	(0.691)	(0.226)	(0.204)
Observations	724	554	628	724
Number of respondent_id	362	277	314	362

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: Effect of Treatment on Outcome-Specific PSE - Ordered Logit with Random-Effects

VARIABLES	(1) Soil Fertility Outcomes	(2) Profit Outcomes	(3) Food Security Outcomes
Treatment	-0.174	-0.221	-0.205
	(0.282)	(0.241)	(0.225)
Year	0.461*	0.443*	0.248
	(0.265)	(0.236)	(0.261)
Constant – cut 1	-2.758***	-2.641***	-2.813***
	(0.297)	(0.246)	(0.301)
Constant – cut 2	-2.083***	-1.855***	-2.202***
	(0.266)	(0.215)	(0.262)
Constant – cut 3	-0.851***	-0.716***	-1.298***
	(0.159)	(0.145)	(0.192)
Constant – cut 4	0.531***	0.653***	0.0256
	(0.136)	(0.120)	(0.120)
Observations	724	724	724
Number of respondent_id	362	362	362

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 15: Effect of Treatment on Welfare Outcomes

VARIABLES	(1) Asset Index	(2) Food Insecurity Index	(3) Maize Yields (kg/acre)
Treatment	0.122	0.294	101.7
	(0.145)	(0.264)	(198.2)
Constant	-0.110	-0.265	91.96
	(0.128)	(0.240)	(54.92)
Observations	397	397	252
R-squared	0.002	0.005	0.002

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 16: Spillover Effects on Adoption Outcomes – Legumes

VARIABLES	(1) **Intercropping 1**	(2) **Intercropping 2**	(3) **Other Legume Practices**	(4) **Legumes on Farm**
TREAT = 1	0.193**	0.120	0.0395	-0.0144
	(0.0860)	(0.0920)	(0.0802)	(0.0903)
TREAT = 2	0.258***	0.158*	-0.0605	-0.0448
	(0.0812)	(0.0787)	(0.0795)	(0.0893)
Land Owned (acres)	0.00726**	0.00215	-0.00527***	0.00137
	(0.00279)	(0.00273)	(0.00193)	(0.00148)
Owns MMP	-0.203	-0.200	0.223*	-0.146**
	(0.123)	(0.121)	(0.128)	(0.0716)
Constant	0.0767	0.148	-0.218*	0.165*
	(0.113)	(0.114)	(0.120)	(0.0980)
Observations	252	252	252	397
R-squared	0.057	0.021	0.033	0.014

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 17: Spillover Effects on Adoption Outcomes – Organic Materials

VARIABLES	(1) **Organic Materials**	(2) **Made Organic Fertilizer**	(3) **Organic Fertilizer MMP**
TREAT = 1	0.0399	0.546*	0.108
	(0.152)	(0.269)	(0.137)
TREAT = 2	0.0141	0.716**	0.0866
	(0.141)	(0.272)	(0.130)
Land Owned (acres)	0.00491	-0.00715	0.00516***
	(0.00306)	(0.0168)	(0.00113)
Owns MMP	0.0541	0.411	0.0686
	(0.172)	(0.790)	(0.140)
Constant	-0.522**	-0.688	-0.403**
	(0.223)	(0.829)	(0.198)
Observations	252	42	252
R-squared	0.011	0.112	0.024

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 18: Heterogenous Treatment Effects on Adoption by Gender – Legumes

VARIABLES	(1) Intercropping 1	(2) Intercropping 2	(3) Other Legume Practices	(4) Legumes on Farm
Treatment	0.131*	0.0837	-0.0758	-0.0775*
	(0.0758)	(0.0599)	(0.0654)	(0.0394)
Female	0.0135	0.0241	0.0213	-0.0766*
	(0.106)	(0.114)	(0.0849)	(0.0444)
Treatment × Female	-0.0240	-0.0199	-0.0111	0.120**
	(0.149)	(0.148)	(0.117)	(0.0544)
Constant	0.0532	0.0426	-0.0213	0.0340
	(0.0569)	(0.0534)	(0.0505)	(0.0392)
Observations	252	252	252	397
R-squared	0.013	0.006	0.007	0.009

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 19: Heterogenous Treatment Effects on Adoption by Gender – Organic Materials

VARIABLES	(1) Organic Materials	(2) Made Organic Fertilizer	(3) Organic Fertilizer MMP
Treatment	0.0206	0.193	0.0329
	(0.0951)	(0.222)	(0.0819)
Female	0.191	-0.111	0.133
	(0.138)	(0.416)	(0.128)
Treatment × Female	-0.145	0.473	-0.0735
	(0.182)	(0.476)	(0.154)
Constant	-0.457***	0.111	-0.266***
	(0.0830)	(0.194)	(0.0687)
Observations	252	42	252
R-squared	0.010	0.089	0.008

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 20: Cross-Sectional Analysis of Adoption Outcomes – Legumes

VARIABLES	(1) Intercropping 1	(2) Intercropping 2	(3) Other Legume Practices	(4) Legume on Farm
Treatment	0.0632	0.00374	0.0201	-0.00615
	(0.0591)	(0.0468)	(0.0306)	(0.0566)
Constant	0.244***	0.199***	0.103***	0.320***
	(0.0433)	(0.0405)	(0.0246)	(0.0409)
Mean of Treated	0.3049	0.2012	0.1220	0.3119
	(0.4617)	(0.4021)	(0.3282)	(0.4644)
Mean of Control	0.2420	0.1975	0.1019	0.3179
	(0.430)	(0.3994)	(0.3035)	(0.4669)
Observations	319	319	319	397
R-squared	0.005	0.000	0.001	0.000

Note: the number of observations reflects that fact that 319 respondents cultivated maize in 2021.
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 21: Cross-Sectional Analysis of Adoption Outcomes – Organic Materials

VARIABLES	(1) Organic Materials	(2) Made Organic Fertilizer	(3) Organic Fertilizer - MMP
Treatment	0.0907*	0.0581	0.0162
	(0.0498)	(0.112)	(0.0281)
Constant	0.173***	0.556***	0.0513**
	(0.0432)	(0.0895)	(0.0193)
Mean of Treated	0.2683	0.0622	0.0671
	(0.4444)	(0.4903)	(0.2509)
Mean of Control	0.1720	0.5556	0.0510
	(0.3786)	(0.5064)	(0.2206)
Observations	319	71	319
R-squared	0.012	0.003	0.001

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 22: Cross-Sectional Analysis of Behavioral Outcomes – Knowledge

VARIABLES	(1) Knowledge Score	(2) Q1	(3) Q2	(4) Q4	(5) Q5	(6) Placebo
Treatment	-0.137	-0.00115	-0.0117	-0.121	-0.00274	-0.00523
	(0.451)	(0.0592)	(0.187)	(0.270)	(0.0541)	(0.0571)
Constant	4.923***	0.747***	1.907***	2.046***	0.222***	0.722***
	(0.418)	(0.0451)	(0.173)	(0.269)	(0.0459)	(0.0543)
Mean of Treated	4.792	0.748	1.9	1.921	0.223	0.713
	(2.755)	(0.436)	(1.499)	(1.387)	(0.417)	(0.453)
Mean of Control	4.938	0.749	1.918	2.051	0.221	0.723
	(2.803)	(0.435)	(1.452)	(1.559)	(0.416)	(0.449)
Observations	397	397	397	397	397	397
R-squared	0.001	0.000	0.000	0.002	0.000	0.000

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 23: Cross-Sectional Analysis of Behavioral Outcomes –Generalized PSE

VARIABLES	(1) Generalized PSE
Treatment	0.0213
	(0.0785)
Constant	3.693***
	(0.0653)
Mean of Treated	3.716
	(0.8577)
Mean of Control	3.6891
	(0.8364)
Observations	397
R-squared	0.000

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 24: Cross-Sectional Analysis of Behavioral Outcomes – Task-Specific PSE

VARIABLES	(1) Furrows	(2) Seed Spacing	(3) Intercropping	(4) Manure
Treatment	0.0763	0.502	0.666***	0.163
	(0.212)	(0.349)	(0.226)	(0.255)
Constant – cut 1	-0.567**	1.682***	1.322***	-0.123
	(0.254)	(0.349)	(0.285)	(0.271)
Constant – cut 2	0.0899	2.625***	2.098***	0.773***
	(0.199)	(0.340)	(0.368)	(0.297)
Constant – cut 3	0.931***	3.671***	2.567***	1.514***
	(0.208)	(0.450)	(0.331)	(0.347)
Mean of Treated	2.4623	1.413	1.671	2.139
	(1.282)	(0.853)	(1.089)	(1.181)
Mean of Control	2.4	1.215	1.373	2.026
	(1.199)	(0.549)	(0.822)	(1.157)
Observations	382	185	280	383

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 25: Cross-Sectional Analysis of Behavioral Outcomes – Outcome-Specific PSE

VARIABLES	(1) **Soil Fertility Outcomes**	(2) **Profit Outcomes**	(3) **Food Security Outcomes**
Treatment	-0.182	-0.236	-0.214
	(0.296)	(0.251)	(0.236)
Constant – cut 1	-3.855***	-3.228***	-3.494***
	(0.461)	(0.385)	(0.485)
Constant – cut 2	-2.709***	-2.229***	-2.543***
	(0.350)	(0.304)	(0.336)
Constant – cut 3	-1.390***	-1.318***	-1.685***
	(0.271)	(0.230)	(0.263)
Constant – cut 4	0.116	0.275	-0.166
	(0.273)	(0.272)	(0.244)
Mean of Treated	4.108	3.965	4.188
	(0.981)	(1.085)	(1.034)
Mean of Control	4.179	4.072	4.272
	(0.981)	(1.082)	(1.007)
Observations	397	397	397

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 26: Cross-Sectional Analysis of Behavioral Outcomes –Subjective Probability Distribution

VARIABLES	**(1) Soil Fertility Outcomes**	**(2) Profit Outcomes**	**(3) Food Security Outcomes**
Treatment	-22.81	-9.534	28.15
	(50.54)	(43.26)	(43.30)
Constant	383.6***	352.3***	366.6***
	(42.80)	(40.20)	(40.43)
Mean of Treated	362.129	341.708	395.916
	(470.988)	(458.803)	(480.107)
Mean of Control	382.948	353.077	367.949
	(420.551)	(435.864)	(447.817)
Observations	397	397	397
R-squared	0.001	0.000	0.001

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 27: Cross-Sectional Analysis of Welfare Outcomes

VARIABLES	(1) Asset Index	(2) Food Insecurity Index	(3) Maize Yields (kg/acre)
Treatment	0.0639	0.125	60.24
	(0.251)	(0.243)	(151.6)
Constant	-0.0325	1.985***	371.6***
	(0.205)	(0.222)	(49.77)
Mean of Treated	0.0315	2.099	431.746
	(2.262)	(1.819)	(865.667)
Mean of Control	-.0324	1.974	373.797
	(1.827)	(1.767)	(385.489)
Observations	397	397	319
R-squared	0.000	0.001	0.001

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix A: Content of Extension Course

Round 1 Extension Content:	**Discussion prompts:** *Messages in italics are sent only to chat-group participants*	**Date of sending:**
Hello, you participated in a research study in August 2020. As part of this study, you have now been selected to participate in a free course to help improve your soil, offered by SUA over SMS.. You will receive text messages with tips. The course is in 3 units: 2/1 – 2/28; 4/1 – 4/31; 7/1 – 7/31 If you participate, you will receive an unlimited texting plan each month until August 2021 as compensation for your time. Researchers will ask you some questions about the course in August, 2021. If you do NOT wish to participate, please reply "NO" to this message.	*You are also invited to a group chat with 5 maize farmers from Morogoro who have similar nitrogen deficiencies in their soil.* *You can discuss the course and any agricultural practices. You now have an unlimited text plan on your phone, so messages are free.* *Only the principal investigators at SUA and McGill University will be able to link your responses with your name.* *They will participate in the group chat to facilitate discussion. Other researchers can access the messages without linking your response to your name.* *If you do NOT wish to participate, please reply "NO" to this message*	Jan 28
	Welcome to FarmChat. This is a chat of 5 maize farmers in Morogoro. You each learned from SoilDoc that you have a nitrogen deficiency in your soil. *Introduce yourselves, and use this chat to talk about improving the nitrogen content of your soil.* *You can ask questions, share experience, and talk about methods for improving your soil that have or haven't worked for you.*	Jan 31
Make your soil healthy! Try intercropping maize with legumes, and using organic material from your farm to improve your soil. Plants need nutrients like nitrogen, which they get from the soil. When you remove the plant from the soil at harvest, you remove the nutrients too. You can replace nutrients by letting plant/animal materials decompose in your soil, or planting a legume. Then your soil will have nutrients to feed your next crop.	Have you noticed that your crop yield decreases if you use the same land year after year? Why do you think this happens? What do you normally do when you notice your land becoming less fertile?	Feb 1
Nitrogen is an important nutrient for growing maize. Legumes bring nitrogen from the air into the soil where it feeds crops.	Think about your experience with legumes. Are maize plants healthier when they're grown alongside a legume?	Feb 4

Try intercropping your maize with a legume. You will add nitrogen to the soil, reduce pests and diseases, and grow nutritious food for people and animals. Some good legume varieties include: - Pigeon pea - Beans - Ground nut - Cowpeas - Green gram - Soy beans		
Legumes are plants that absorb nutrients in the soil and help keep the soil moist. They absorb nutrients like nitrogen from the air and release them when cut. This helps increase the amount of nitrogen in your soil. If you plant them with maize, the maize can use the nitrogen to grow.	What varieties of legume have you experimented with? Do you plan to plant a legume this year? Why or why not? Which one? What kind of legume seeds are available in your local market?	Feb 5
	When is the best time to plant legumes? At the same time as maize? Or before or after? Do you plant your legume in the same row as maize, or a different row? How far apart do you put each plant?	Feb 8
Chicken manure is a great fertilizer. It has nitrogen and other nutrients. Keep chickens contained so you can collect their manure. Mix fresh and dry plant materials from your farm with manure, and let the mixture begin to decompose before adding to your field. This is called compost	Have you ever applied chicken manure as a fertilizer? Why or why not? Have you noticed an effect on your crop yields? When is the best time to apply chicken manure? At the same time as maize? Before maize is planted? After maize is planted?	Feb 9
	Do you keep your chickens contained, or let them roam free? What kind of structure or fence could you build to keep them contained?	Feb 10
Each year, maize takes nitrogen out of the soil, leaving less available for the next crop. Over time, your soil becomes unhealthy and it is hard to grow maize in it. If you replace the nitrogen by growing a legume and adding compost, your soil will stay healthy so you can keep growing maize for several years.	Have you noticed that the soil becomes less fertile after growing maize in the same place for a few years? Do you move your maize to a new plot when the soil becomes unhealthy? How often do you move it? Can you adopt practices to keep soil healthy longer? What techniques have you tried to improve your soil fertility? What techniques would you like to try this year? Next year?	Feb 11

Many farmers move their maize plot to new land when soil becomes infertile. If you do this, try growing legumes on the old plot. Then it will be ready to support maize the next year. Using compost and legume intercropping replaces the nutrients used up by maize, and keeps your soil healthy year after year.	Do you move your maize to a new plot when the soil becomes unhealthy? How often do you move your maize plot? Can you adopt practices to keep soil healthy longer?	Feb 12
	What techniques have you tried to improve your soil fertility? What techniques would you like to try this year? Next year?	Feb 15

Round 2 Extension Content[9]:	**Discussion Prompts:** *Messages in italics are sent only to chat-group participants*	**Date of Sending:**
	You have completed Part 1 of the SUA course about improving your soil. This month there will be another course, where you will receive information from SUA and be able to discuss it with the same group of farmers. *Your group is 5 maize farmers from other villages in Morogoro. You have all learned from SoilDoc that you have a nitrogen deficiency in your soil. The farmers in your group are all the same as last time.* *To chat with your group, simply reply to any SMS from us, and your message will automatically be sent to the 5 farmers in your group. If you receive a message from another farmer in your group, you can reply to it, and your message will be sent to the 5 farmers.* *Your message will automatically begin with the first 3 letters of your name, followed by ":". This is how you can easily tell which farmer in your group has sent the message you are reading.*	5/14

[9] Some of the content for this round was taken directly from a Swahili pamphlet about green manures and compost. Since we sent the Swahili version to farmers, the version here is simply a translation for reference, made using Google Translate.

	When you send a message, the other farmers will see the first 3 letters of your name in front. For example, if your name is Mohammed, your messages will start with "Moh:". You do not have to type this yourself, the phone will add it automatically. *Please use this chat to get to know each other, and talk about your farming practices and your soil. You can ask each other questions, and share advice about practices that you have tried or heard about.* *You can ask questions to the other farmers in your group, but please be aware that the agent from SUA cannot answer your questions, only the other farmers. This is for you to share advice with each other about what works for you. You will receive expert advice from SUA but cannot ask us specific questions through FarmChat.* *You have unlimited messaging paid for on your phone, so please chat as much as you want. This way you can meet other maize farmers who also have a soil nitrogen deficiency that was detected by the SoilDoc test. Together you can talk about ways of improving your soil and your yields.* *Please begin by introducing yourself to the other farmers in your group. Thank you!*	
Hello, this month you will receive messages from SUA about how to plant green manure and make compost for your farm. Thank you! Green manure is a plant that is grown for the purpose of increasing the level of organic matter and making food for soil microbes. These are fertilizers grown in the field.	Have you tried growing a green manure crop this year or in the past? Which one did you grow? Do you know anyone who planted green manure?	17
This year has been very dry in Morogoro. Green manure crops help keep moisture in the soil, and can survive with little water. This year has been very dry in Morogoro. Green manure crops help keep moisture in the soil, and can survive with little water.		5/18
If green manure is cut before or during flowering, it is fermented easily with soil microbes - within two weeks of being moist and warm - after being buried in the soil.		5/19

Instead of digging green manure into the soil, it can also be distributed and act as mulch, especially if planted with perennial crops. Green manure crops produce lots of foliage that you can add to your compost or use as a mulch directly on top of your soil.	Have you ever considered mixing green leaves in topsoil? How have you seen green manure used by farmers you know?	5/20
Green manure can be incorporated into an existing agricultural system. No additional land is required to plant fertilizer Planting green manure as part of the crop cycle is very helpful especially if planted before crops that need a lot of nutrients. Green manure is planted whenever there is no crop in the field, instead leaving the soil empty and allowing weeds to thrive and nutrients to be lost to the soil. It is also cultivated as a crop to break the cycle between species of similar crops for pest and disease control.	Have you noticed that soil becomes dry and infertile when it is left bare? Planting green manure can keep your soil healthy and moist, and add nutrients which can be used by the next crop like maize.	5/21
Green manure can be grown between crop lines such as maize, sorghum and millet. To reduce competition with the main crop, green manure is planted if the main crop is already in good condition. Planting is sometimes mixed and green manure continues to thrive during the dry season.	Do you have space between rows of maize on your maize plot? Can you plant a green manure crop in this space?	5/27
Compost is essential for the soil's ability to retain nutrients and provide nutrients to plants when needed. Anything of plant or animal origin when put on the ground decomposes and turns to some extent into clay or compost. Creating compost is a long process. But investing in compost has great benefits for the plant and feed production.	Do you know anyone who makes compost? Have you ever seen a compost pile on someone’s farm?	5/31

Compost is more than fertilizer, it creates soil. Its greatest value lies in its long term benefits to soil fertility. Compost is a highly valuable soil supplement for smallholder farmers who do not have access to natural or in-store fertilizers. Compost has been proven to be the best type of organic fertilizer in drought-prone areas.	Can you use compost to keep your soil moist during a drought?	6/3
Composting depends on the materials in the field and does not require special equipment, so it is a simple technique. But composting requires a lot of work to collect and prepare the material.	What types of organic material can you find around your farm? What can you add to your compost pile?	6/4
	Do you have time to make compost on your farm? Is making compost a valuable use of labor?	6/7
Making compost requires adequate equipment and materials and the right place. Compost is made from the same doses of animal manure and raw leaves and dried substances. Wood ash and old compost can also be included.	Can you find animal manure, raw leaves, wood ash, or other plant and animal materials to add to your compost pile? Which materials can you find on your farm or nearby?	6/9
The composting site should be close to the field, easily accessible and flat on the ground near a water source and adequate shade. If there is no natural shade, then a transfer shade is required. Making compost requires a humid environment. In dry weather, water is needed regularly to ensure proper process.		6/11
Making compost: 1.Chop the leaves of the plant to the size of a finger 2. Mix and add water to dry and green leaves separately 3. Mix different items by laying layers starting with the dried items 4. Place a metal rod on the pile and measure the temperature daily 5. When the temperature drops in the pile, turn the pile up		6/15

Making compost requires a lot of experience. But it also teaches you about many aspects of the natural processes of transforming organic matter into fertile soil.	Will you try making compost this year? Do you have any tips for other farmers who would like to try this?	6/16

Round 3 Extension Content:	**Discussion Prompts:** *Messages in italics are sent only to chat-group participants*	**Date of sending:**
Hello, welcome to the final course from SUA about improving your soil health with organic resources. You will receive information about managing crop residues and preparing your fields for the short rains growing season.	*Remember you are in a chat group with five other farmers who are also learning from SUA.* *You can chat with each other by replying to any message you receive here.* *You can tell that a message is from SUA if the SMS begins with "SUA:"* *A message is from another farmer if the SMS begins with the first 3 letters of a name, such as "Eli:" for Elizabeth.* *Use this chat to talk to each other about what practices you have tried, and what works or doesn't work on your farms. You can learn from each other and share knowledge this way.*	Aug 2
If you intercropped a legume with your maize crop, it should be ready to harvest before the maize. For smaller bean species you can easily pull out the plant and harvest the beans. After taking the bean crop, leave the entire legume plant on the field, including leaves, stems, and roots. This will act as a mulch for the maize and decompose easily into your soil.	Did you plant a legume on your maize plot this year? If so, which variety did you plant? Can you leave the legume crop residue on your field, or do you have other uses for this material?	Aug 3
Make sure to save some beans and dry them to use as seeds for next year so you don't have to buy them again! Leaving the residue as a mulch will help preserve soil moisture and reduce topsoil erosion	Do you normally save seeds from each harvest to plant next season, or do you buy new seeds each year? Do you notice dry soil eroding from water and wind when it is exposed with no mulch or crop cover? How can you prevent this?	Aug 4
Maize is ready to harvest when a black layer is visible between the maize grain and the cob	At what stage do you normally harvest your maize? What are the advantages of this?	Aug 5

Try not to harvest maize before this stage, when it is still green, as this will make it harder to store and dry. Try not to wait too long after this stage, because the maize can begin to rot and is more likely to attract pests.	Can you see a black layer between the maize grain and the cob when it is ready to harvest?	
You should not burn your maize crop residue (leaves, stems, roots, stover, and husks), because these are a valuable source of organic material which should be returned to the soil. There are two good options for managing your crop residue: 1) Composting, and 2) Leaving residue on the soil surface. We will discuss both of these options in detail when the course resumes on Monday.	Do you normally burn your crop residue? What uses do you have for maize crop residue on your farm?	Aug 6
1)Composting your maize residue: You can clear the residue off of the field at harvest, and add it to your compost pile. Cut the residue into smaller pieces to help it decompose faster. You should also add green materials, manure and water to your compost pile to help the decomposition. The compost will be ready to use on your field in a few months for the next year's long rains season.	Do you have a compost pile on your farm? If so, what do you add to your compost pile? Do you think making compost is a good way to use your maize crop residue? Why or why not?	Aug 9
Benefits of using residue for compost: mature compost is a great source of nutrients and microorganisms for your soil. Compost is easy to apply to your field and the nutrients are immediately accessible to your crops. Challenges: It will take several months for the compost to be mature and ready to use. It requires labor and knowledge to maintain your healthy compost pile.	Can you think of any other benefits or challenges of composting your maize crop residue?	Aug 10
2)Leaving maize residue on the soil surface: You can leave maize crop residue on the field after harvest. This will keep your soil covered and protected from sun and wind during the dry season.	Have you ever left maize crop residue on your field? Have you seen this practice on another farmer's field?	Aug 11

Pull out the plants and cut them up into a coarse mulch. The residue will decompose by the next long rains season. You can still plant maize or other crops during the short rains by clearing narrow rows or planting seeds directly into the soil under the residue.		
Benefits of leaving residue on soil surface: Leaving mulch will protect topsoil from eroding, and hold moisture in the soil by preventing runoff. Mulch will suppress weeds and prevent erosion, which can protect crops you plant during the short rains season. The decomposing residue will add organic matter and provide long term benefits to your soil health. This option is less labor intensive than making compost. Challenges: Leaving residue on the field can make it difficult to weed in the short term, and could make it more difficult to plant a cover crop during the short rains season.	Can you think of any other benefits or challenges of leaving your maize crop residue on your field? What will you do with your maize crop residue this year? Why?	Aug 12
Part 2: Preparing your field for the short rains season. When the rains are close, you can plant a short maturing legume crop on your plot This will keep the soil moist, add nitrogen to the soil, suppress weeds, and prevent erosion. It will also provide a nutritious food or animal fodder for your household, and green material to add to your compost or use as mulch next season.	What do you normally do with your maize plot during the short rains season? Do you think it's important to keep the soil on your field covered? What happens if you leave the soil exposed?	Aug 16
If you have left maize crop residue on the field, you can still plant a legume crop directly into the residue. Just clear a very small hole so you can see the ground and plant the seed. It will come up through the residue mulch. The residue will act as a mulch and protect the new crop. Alternatively, you can clear narrow rows across your field and plant the new crop in these rows.		Aug 17

When choosing a legume variety to plant during the short rains, there are a few things to keep in mind: The variety should be well adapted to your climate and soil, and tolerant to pests and diseases. The variety should grow fast and vigorously, and produce large quantities of leaves. It is good if the leaves are close to the ground so the crop forms a cover which will protect the soil from sun and wind, and help keep in moisture. The variety should be drought-tolerant and fast maturing.	What are some legume varieties that might be good to plant during the short rains? Why are these good options?	Aug 18
As soon as the rains start, you can plant some maize in the field as well. You can choose a short maturing maize variety, or plan to harvest green maize at the end of the short rains.	Do you normally plant maize during the short rains? Why or why not? Do you harvest green maize, or can you find a short maturing variety that is mature by the end of the season?	Aug 19
If you have successfully planted a legume crop already in the field, you can till or clear narrow strips where you will plant maize. Add the cleared legume plants to your compost pile, or use them as mulch around the new maize seedlings. The legume cover crop will protect the maize seedlings by providing shade and keeping moisture in the soil. It will also bring nitrogen from the air into the soil where it can be used by the maize crop.	What are the benefits of intercropping maize and legumes? Will you try this practice during the short rains season this year? Why or why not?	Aug 20
Thank you for participating in this SUA course! We hope you have learned some useful information about improving your soil health. There are lots of options for improving your soil. We hope you will discuss with other farmers about which practices work for you and which do not. Together we can innovate and improve our farming practices.	*Please continue to discuss with your chat group about practices you have tried or would like to learn more about!*	Aug 21

Appendix B: Survey Modules for Behavioral Outcome Variables

Knowledge:

A knowledge quiz appears in the survey as follows:

1. Which type of crop increases the nitrogen content of soil?

[ ] Grains
[ ] Vegetables
[ ] Legumes
[ ] Fruits

2. Which of the following crop varieties would supply nitrogen to maize plants when grown together in an intercropped field? *Select all that apply*

[ ] Soy beans
[ ] Groundnut
[ ] Sweet potato
[ ] Cowpeas
[ ] Beans
[ ] Tomato
[ ] Pigeon pea
[ ] Millet

3. What is the best way to plant maize seeds?

[ ] Take a handful of seeds and scatter across the surface of the field
[ ] Make small holes 5 feet apart and plant one seed in each hole
[ ] Scatter seeds along rows
[ ] Make small holes 8 inches apart along rows and plant 3 seeds in each hole

4. Which of the following are ways of improving the soil fertility on your maize plot? *Select all that apply*

[ ] Apply inorganic fertilizer
[ ] Apply compost
[ ] Intercrop maize with a legume crop
[ ] Plant a legume crop on the plot during the short rains season
[ ] Burn the crop residue left on the field after harvest
[ ] Leave crop residue on the field after harvest

5. What is the best time to apply poultry* manure to your field? **Poultry includes chickens, ducks, turkeys, and other domesticated birds*

[ ] 3 months before planting
[ ] 2-3 weeks before planting

[ ] At planting
[ ] When plants are 2 inches high
[ ] When plants are 6 inches high
[ ] After harvest

Questions 1 and 5 have one correct answer, and a total of one possible point each allocated to the total knowledge score. Questions 2 and 4 have multiple correct answers, and respondents receive one point for each correct selection, and lose one point for each incorrect selection, for a total of 5 possible points each. It is also possible to lose up to 3 points for question 2, and 1 point for question 4. Therefore, the final knowledge score takes a value between -4 and 12, inclusive. Question 3 is omitted from the knowledge score because it does not address a practice covered in the extension course. We use question 3 as a placebo to compare learning outcomes for targeted practices to general learning patterns.

Generalized PSE:

The items appear on the survey as follows:

- I will be able to achieve most of the agricultural goals that I set for myself
- When facing difficult tasks on my farm, I am certain that I will accomplish them
- In general, I think that I can obtain outcomes on my farm that are important to me
- I believe I can succeed at improving my soil and increasing the yields from my farm if I set my mind to it
- I will be able to successfully overcome many challenges on my farm
- I am confident that I can perform many different tasks on my farm
- Compared to other people, I can do most farming tasks very well
- Even when things are tough, I can make sure that my crops get adequate yields

This is adapted to the domain of agriculture from the validated New Generalized Self-Efficacy Scale (Chen et al., 2001):

- I will be able to achieve most of the goals that I set for myself
- When facing difficult tasks, I am certain that I will accomplish them
- In general, I think that I can obtain outcomes that are important to me
- I believe I can succeed at most any endeavor to which I set my mind
- I will be able to successfully overcome many challenges
- I am confident that I can perform effectively on many different tasks
- Compared to other people, I can do most tasks very well
- Even when things are tough, I can perform quite well

Domain-Specific PSE:

The module for eliciting task- and outcome-specific PSE for the domain of intercropping appears on the survey as follows:

> Many farmers and researchers around the world are promoting the practice of legume-maize intercropping, in which maize is planted in the same field as a legume crop such as pigeon pea. Growing pigeon pea provides a source of nutritious and valuable food. Pigeon pea, like all legumes, also improves the soil fertility by providing nitrogen, which is an important nutrient for maize crops. Pigeon pea plants produce a lot of vegetation, which can be left on the ground as mulch to keep the soil moist and replenish nutrients as they decompose. To intercrop successfully, the farmer should plant seeds in evenly spaced holes along furrowed rows, with maize planted along the ridges and pigeon peas in the furrow. Poultry manure may be added to the ridges 2-3 weeks before planting, to provide additional nutrients to maize plants. Researchers say that intercropping, along with application of poultry manure, provides higher economic returns to farmers, by increasing the value of their product and reducing their costs. http://www.fao.org/3/a-i5310e.pdf
>
> Now think about yourself and your own maize plot. Consider your abilities, any past experience you have with intercropping on your farm, and times you have observed these practices on someone else's farm.
>
> **1.** On a scale from 1 – 5, where 1 is strongly disagree, 3 is neither agree nor disagree, and 5 is strongly agree, how much do you agree with the following statements:
>
> If I decide to try the practices of intercropping and applying poultry manure on my farm, I will be able to:

a. … improve the soil fertility on my maize plot _____

b. … improve the profitability of my maize production ____

c. … increase my household's food security ____

2. For each component of the intercropping system (Building furrowed ridges; seed spacing; intercropping with pigeon peas; application of poultry manure), rate how difficult it would be to adopt this practice on your own main maize plot (1 = n/a I already use this practice on my own farm, 2 = Not at all difficult, 3 = Somewhat difficult, 4 = Difficult, 5 = Extremely difficult)

a. Building furrowed ridges
b. Seed spacing
c. Intercropping with pigeon peas
d. Application of poultry manure

Subjective Probability Distribution:

The subjective probability distribution module appears on the survey as follows:

Imagine 20 farms that are JUST LIKE YOURS. The farmers have the same age, education, experience, skill level, income, and commitment as you. They have the same amount of labor and resources available to them as you do. The farms are the same size and located in the same area as yours, and their initial soil quality is just like yours. Now imagine these farmers decide to try the practice of intercropping with pigeon peas on their main maize plots, and applying poultry manure. Think about all the reasons why these practices could be beneficial or costly to the farmer. These imaginary farmers face the same weather and pest conditions as you do, and must do the best they can given their circumstance.

Taking all these different possibilities into account, after 1 year, think about how many of the 20 farmers will be successful with the practices of intercropping and applying poultry manure.

1. Of the 20 farmers, after one year how many will have:
a. … Much lower soil fertility
b. … Slightly lower soil fertility
c. … The same soil fertility
d. … Slightly higher soil fertility
e. … Much higher soil fertility

2. Of the 20 farmers, after one year how many will have:
a. … Much lower profits from maize production
b. … Slightly lower profits from maize production
c. … The same profits from maize production
d. … Slightly higher profits from maize production
e. … Much higher profits from maize production

3. Of the 20 farmers, after one year how many will have:
a. … Much lower household food security
b. … Slightly lower household food security
c. … The same household food security
d. … Slightly higher household food security
e. … Much higher household food security

The SPD module yields three outcome variables corresponding to soil fertility outcomes, profit outcomes, and food security outcomes. Each variable is constructed by assigning a value to each Likert scale item, and calculating the mean SPD by taking the sum of the probability mass assigned to each item by the respondent, multiplied by the value of the Likert item.

Appendix C: Construction of the Asset Index

We construct an asset index for 2020 and 2021 applying Principle Component Analysis (PCA) to a set of household, livestock, and productive assets. This process allows us to consolidate the information present in a large number of variables into a single index. We consider all asset items owned by greater than 2 percent of households and fewer than 98 percent. The index is constructed to have a mean of 0, and is normally distributed for both years.

Table A.1: Assets Used for Construction of Asset Index

Household Assets:	**Livestock Assets:**	**Productive Assets:**
Car	Goats – adults	Power tiller
Truck	Goats – kids	Hoe
Bicycle	Sheep – adults	Shovel
Motorcycle	Lambs	Chain saw
Gas cooker	Pigs – adults	Hand saw
Refrigerator	Pigs – piglets	Barrel
Sofa	Chickens - layers	Wheel barrow
Chairs	Chickens - local	Milling machine
Tables	Chickens - broilers	Tractor
Beds	Cow (female)	Plough
Sewing machine	Bull (male)	Axe
TV	Calves	Knife
Computer	Donkey	Wood machine
Radio	Ducks	Machete
Generator	Rabbits	Sickle
Cellphone	Horse	Other
Solar panel	Oxen	
Other	Other	