ICT-mediated agricultural knowledge transfer in Uganda: What works?

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Abstract

In information dissemination campaigns by agricultural extension services, seemingly small attributes, such as how the message is framed, the way it is delivered or who it is delivered to can result in significant differences in outcomes, such as knowledge transferred and adoption of recommended practices. In the context of ICT-mediated knowledge transfer, this study investigates the role of the gender composition of the person(s) who provide the information and the gender/age composition of the person(s) who receive the information in making the information transfer more effective. In addition, we investigate if framing the message using social and behavioral change communication (SBCC) techniques as opposed to the more traditional, teacher-student model has a higher impact. Additionally, video as a way to deliver extension information is compared to more demand-driven ICT solutions, such as Interactive Voice Response (IVR). Effectiveness is assessed in terms of knowledge gain, increased adoption, yield increase, and poverty reduction. We propose to do this using field experiments, where farmers are randomly assigned to particular interventions.

Motivation

Banerjee, Banerjee, and Duflo (2011)'s influential book surveying two decades of research on the incredibly multi-faceted and complex economic lives of the poor concludes that they often lack critical pieces of information and believe things that are not true. In many instances, a simple piece of information makes a big difference. However, not every information campaign is effective, and often, seemingly small attributes, such as how the message is framed, the way it is delivered, or who it is delivered by and to, can result in significant differences in impact (Jack, 2013). Understanding the effect of these attributes through rigorous evaluation research should therefore be an essential part of any knowledge exchange model.

We propose an evaluation that will address key questions on the effectiveness of ICT-enabled extension and advisory service approach in Uganda. The questions are related to the gender/age composition of the receiver and the messenger of the information message, the way in which the message is framed, and the way it is delivered. The questions will be answered through field experiments, where farmers are randomly assigned to a group that receives particular interventions (de Janvry, Sadoulet, and Suri, 2016). Since we want to test more than one research hypothesis and are particularly interested in comparing the effectiveness of various attributes of an ICT-enabled extension approach, we opt for a factorial design. In such a design, farmers get a particular combination of interventions and, in general, a smaller sample size is needed to answer a fixed number of research questions.

We will work with maize farmers in southeast Uganda. Short videos that explain simple yet effective ways to increase maize productivity, such as best practices in row spacing and plant density, will be developed and shown to selected members within farm households. An alternative technology to deliver the same information, such as Interactive Voice Response (IVR), will be developed and implemented by a partner (Human Network International). Power calculations suggest we would need a sample of about 3,600 farmers, which will be drawn from six districts. The videos will be shown to farmers at the beginning of the main season, which starts in September 2017, and an endline survey will collect information on outcomes after harvesting, which ends in February 2018. We expect to collect endline data during March 2018 and to have results ready by July 2018.

The results of this study is expected to inform agricultural extension system reform currently underway in Uganda. Uganda's new director of extension services signaled a role for digital extension within the future extension strategy. While the subject of this research study is maize intensification, we believe the findings can be readily extended to include similar interventions on different crops and subjects, including extension on post-harvest storage and handling, agricultural value addition, or agricultural commodity marketing.

Research Questions

This research aims to answer which attributes of an agricultural extension information campaign are most important for its effectiveness. In particular, we will investigate attributes related to the gender composition of both messenger and recipient of the messages. In addition, we will look at the effect of framing the same information in different ways. Finally, we will also look at the model of delivery of the information.

Gender Composition of Messenger and Receiver

Research suggests the gender and age composition of both messenger and receiver are important in making information effective. However, agricultural extension information services are generally biased toward men. Most often, extension officers are male who target the main decision maker with respect to agriculture within households, which is also often considered to be the male farmer. The assumption that extension messages given to one household member will trickle down to the rest of the household, including women and younger household members, may be false. Men do not necessarily discuss production decisions or transfer extension knowledge to women household members, especially if extension messages were focusing on men's priorities and crops (Meinzen-Dick et al., 2011). Gender matching effects, where men learn more from other men and women learn more from other women, have also been found in the context of agricultural extension services (Doss and Morris, 2001). At the same time, farms are essentially run and managed at the household level, and it may therefore be more effective if information is targeted at this level. For instance, Lambrecht, Vanlauwe, and Maertens (2016) found joint male and female program participation leads to higher adoption rates of fertilizer in Eastern DR Congo. The analysis of a Digital Green project in Ethiopia also concluded that there is much to be learned from observing the interactions between men and women who learn about the same technologies and practices (Bernard et al., 2016).

We therefore want to investigate the relative importance of (i) the gender composition of the messenger, and (ii) the gender as well as age composition of the audience for effective agricultural extension information messages to encourage sustainable crop intensification in smallholder household farms and for improving gender equity in household farming. In particular, we will compare outcomes between:

- households that are shown a video with agricultural extension information where the animator is an individual "peer" farmer (ie. a man or a women) and households that were shown a video providing the same information by a couple of peer farmers (ie. man and woman who are shown to participate as equals in the family farm and deliver the message as a couple);

- households in which one adult individual (husband or wife) is shown a video with agricultural extension information and households in which the couple (husband and wife) is shown a video with the same information;

- households where the gender composition of (the individual) messenger(s) and (individual) audience is matched and households where the gender composition of the messenger and audience differ.

For this research question, we will be particularly interested in how these interventions reverberate through intra-household decision-making and the allocation of time and resources to agriculture between the different individuals within the farm household. The outcomes of interest will therefore be disaggregated by gender and age, and interpreted in light of the interplay between efficiency at the household farm level, equity within the farming household and women's and youth's empowerment.

Framing of Message

Apart from the conventional factors that affect smallholder farmers (such as access to credit, land and labor availability, and risk management and coping mechanisms), personal characteristics are also important in determining behavioral change. Less tangible factors, such as a farmer's attitude toward farming as a business instead of just for subsistence, are often correlated with a range of desirable outcomes. For instance, Bernard et al. (2015) found that showing videos of successful "role model" farmers increases aspirations and reduces fatalism (i.e. absence of locus of control). Ongoing work by Abay, Blalock, and Berhane (2017) documents robust correlations between locus of control and agricultural technology adoption behaviour.

We will ask if videos featuring successful practices using social and behavioural change communications and social marketing techniques commonly used in public health campaigns, such as the SunSmart Slip-Slop-Slap campaign against skin cancer in Australia (1988) and CDC's campaign on breastfeeding, are better at changing behavior than alternative ways of framing the same information, which are more traditional and based on a teacher-student model. Social marketing applies commercial marketing strategies to develop activities aimed at changing or maintaining people's behavior for the benefit of individuals and society as a whole. These techniques and strategies are thought to be especially apt at making people feel that something is good or appropriate to them, or that they really need it. In a way, it aims to increase a farmer's aspirations and expand the options within the mental models that farmers form.

Different ICT Channels

The tools and technologies through which the information is transferred are also likely to influence effectiveness. There are many different ways of delivering agricultural extension messages through ICT. Broadly, one can differentiate between two different approaches. In one approach, extension resembles the traditional teacher-pupil model, where the farmer is assumed to absorb knowledge from experts. Showing videos to farmers or pushing information over a mobile phone would fall into this category. A second approach relies more on a consultative model, where the farmer is assumed to know his or her information needs are and requests this information from a service provider. Call centers and Interactive Voice Response (IVR) technology are examples of this second approach. In a third research question, we will compare the effectiveness in terms of changing knowledge, practices and outcome such as yields and poverty of video messages to more or less demand based options such as IVR. In particular, we will compare videos to videos augmented with IVR and videos augmented with IVR where the recepient is also provided with reminders of the existence of the IVR service.

Outcomes

The effectiveness of the different interventions will be judged by their effect on a range of outcomes at the farm household level. Therefore, a first set of outcomes will investigate changes in knowledge due to the interventions. It is further assumed that knowledge translates into increased adoption of the technologies. We will investigate both adoption as a binary outcome (yes/no), but also look at adoption intensity (adopted on share of total cultivated area, application rates, etc.). This, in turn, is expected to benefit agricultural production (yield). Finally, we expect this will affect household wellbeing, through increased consumption and income derived from marketing of more, better quality crops. We will therefore include consumption expenditure as a proxy for wellbeing.

Defining the outcomes will enable us to compare the cost-effectiveness of each intervention (e.g., is showing a video to a woman more cost effective than showing it to a couple in terms of its effect on productivity?). We will also collect information that is relevant for the particular attributes we focus on. For instance, showing extension information to the wife instead of the husband may result in substantially different labor allocation effects: women may prefer labor saving innovations, while men may focus more on yield increasing investments. Therefore, in the context of poorly functioning labor markets, we may want to include school attendance of adolescent girls.

Research Strategy

The questions will be answered through field experiments, where farmers are randomly assigned to a group that receives particular interventions (de Janvry et al., 2017). An identification strategy that is based on randomization allows us to quantify the causal linkage between an intervention and the outcomes. In particular, we establish the causal link between extension videos and the knowledge gained, between extension videos and yield changes, and between extension videos and poverty (measured by income). Note that this is different from looking at the direct causal link between for instance yield and poverty. In other words, if we find videos affect learning and videos affect poverty, we cannot be sure poverty is affected by another attribute related to our video (eg motivation). In a way, field experiments estimate a reduced form of relationships, and looking into the exact causal chain would require a full mediation analysis with an adapted design, such as those discussed in Imai et al. (2013). However, the study would still be useful in learning about the likely impact pathways. For one, we will include intermediate outcomes related to different pathways based on theory and previous research: Finding that videos have an effect on poverty and on measures of motivation but not on knowledge may make us more confident that the impact works through non-cognitive channels. Furthermore, we can explore causal links between intermediate outcomes and final outcomes (such as the effect of knowledge on yields) using statistical techniques (such as instrumenting knowledge by treatment assignment).

The research design itself will take the form of a mixed level factorial design. To answer the first research question, we define two different factors, each with three levels. The first factor relates to the messenger and has three levels (male, female and male+female). Similarly, the second factor relates to the recipient of the message and also has these three levels (male, female and male+female). The second research question will be added to the design as an extra factor, but this factor only has 2 levels (information given in an objective way, information provided using social marketing techniques). The third research question, where video is now augmented with a demand-driven technology such as IVR, corresponds to adding an extra factor with two levels (no IVR, IVR, IVR + reminders). In practice, we therefore add the IVR treatment to one third of the participants who get to see a video and we add the IVR+reminders treatment to one third of the sample that gets the treatment. Finally, we will add a pure control group to the design, such that we do not only investigate relative effectiveness of the different attributes, but also relative to someone who did not get to see a video at all.

The interventions will be targeted at the individual (household) level as opposed to group screenings. Videos will be shown in the house or in the field if necessary. This option guarantees consistency in the treatment and requires the least amount of observations. The videos will be developed in house by the research team and produced by a professional media production company such as NOTV. For IVR, we will partner with Human Network International. Human Network International's 3-2-1develops content for farmers on a variety of crops and agricultural practices, and make the service available to farmers for free or at low cost.

Crop and Technology

The interventions for which we will investigate various attributes will be on maize intensification. Maize is widely consumed, yet its value to weight ratio is sufficiently high to also make it an important commodity. Therefore, increasing maize productivity at the farm household level has the potential to lead to improvements in both nutritional outcomes and income. Maize yields

	subcounties	parishes	villages
Bugiri	11	68	465
Kapchorwa	7	39	287
Mayuge	7	56	272
Mbale	14	48	564
Sironko	10	78	767
Tororo	17	76	776
Total	66	365	3131

Table 1: Administrative structure of study area

in Uganda are relatively low. While on-station trials report potential yields average about 3.8 metric tons per hectare (improved varieties, no fertilizer used), according to the latest UNPS data, average maize yields are much lower, at about 0.92 tons per hectare for the main growing season of 2014. There is a lot of variation in yields, with the top 10 percent of best farmers getting yields in excess of 2.3 metric tons. At the same time, the use of modern inputs such as inorganic fertilizer and modern technologies such as row planting is very low in Uganda. For example, use of inorganic fertilizer averages only 1 kg of nutrient per hectare per year, compared to Kenya (32 kg/ha); Rwanda (29 kg/ha); and Tanzania (6 kg/ha). Using the latest UNPS data, only 6 percent of maize plots are planted using improved seed varieties. This suggests substantial scope to increase yields through the use of modern inputs and recommended practices.

Sampling

Sampling Frame

Maize is especially important in the East. We will sample from six districts from the East known for their maize production: Bugiri, Kapchorwa, Mayuge, Mbale, Sironko and Tororo. We will exclude trading centres and in Sironko and Kapchorwa, we will also exclude areas that are too high on the mountain slope. Table 1 gives an idea of how villages are distributed over parishes, which are in turn allocated to subcounties within each of the 6 districts in our study.

Our study population consists of maize farmers within this region. Because of cost considerations, however, we will use two-stage cluster sampling to obtain a representative sample of this population. In particular, we will first randomly select parishes. Within each parish, we will then list all the households, from which we will then sample households to be included in the study. At the same time, we suspect that outcomes within parishes will be correlated, for instance due to local weather conditions, or development programs that are implemented in certain areas. Therefore, we try to turn our two-stage cluster sampling approach into a strength by using the first level of the clustering as blocking variables. In other words, in each parish, we will makes sure all possible treatment combinations are administered (and only once in each parish). From the research strategy above, we learn that we have a total of 55 different treatment combinations (3*3*2*3+1).

Statistical Power

We determine sample size by running various power analyses for different research questions with different underlying assumptions. Instead of determining power analytically, we use simulation techniques. Simulation allows us to sample from actual data on outcome variables instead of from a theoretical distribution with an assumed mean and standard deviation. It is also straightforward to build in flexibility in terms of specifications one plans to use for inference. In our case, we want to incorporate control variables for the parishes and we want to consider power in the context of multiple treatments. The algorithm that was used to perform the power calculations can be found in the git repository. We run 500 simulations for each candidate sample size and increase sample size by 55 households as this is the size of our blocs.

Power calculations are based on yield data taken from a baseline study that was done as part of the Pasic project. In particular, we interviewed rice growers in the area where we will also do the maize study (Bugiri, Butaleja and Tororo). From this study, we will use rice yield estimates as a proxy for outcomes in the maize study. We will sample from this distribution for the power calculations. Mean yields in the sample was about 1.6 tons per hectares with a standard deviation of about .9. We will also use location data from this study to get an idea of the impact of using parishes for blocking on statistical power.

In addition, the main power calculations will be based on the first re-

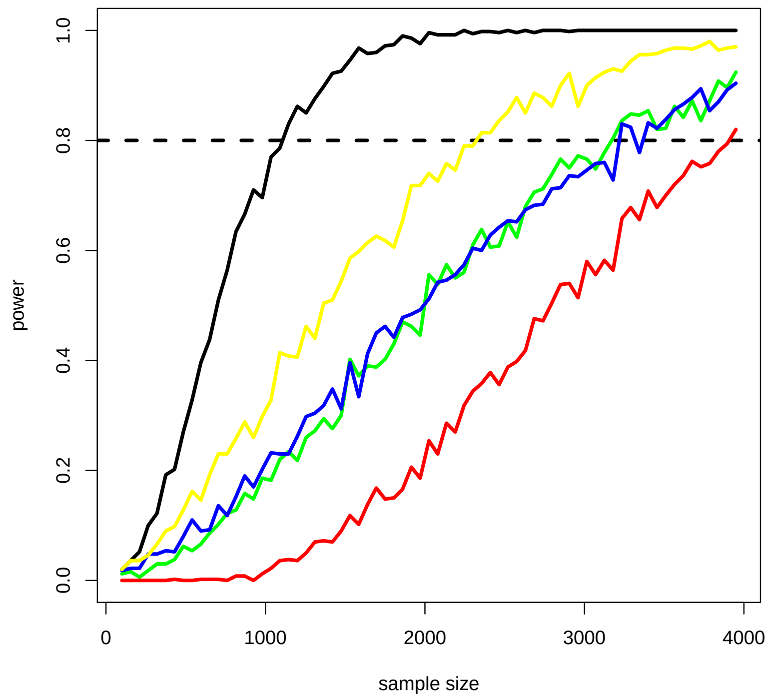

Figure 1: Power curves

search question (related to the gender composition of the messenger and the receiver), as the hypotheses we formulate here are most complex, requiring different interactions and hence many cells. We also expect the effects from these two factors and its interactions to be relatively small.

At one extreme, we could calculate sample size required to identify all possible treatment combinations. For instance, we can compare control to MM, control to FM, control to MF etc. We can already test various hypotheses here, requiring at least one or a few of these to be significant, or a more stringent test where we require all of the treatments to turn up significant. Or we can even go one step further and require also that some or even all the differences between the treatments are significant (eg the different between MM and MF). Testing all interactions in this way would require a sample size well above what is possible. We therefore will base our power calculations on comparing groups of treatments based on the research questions outlined above.

A first and obvious question will be to find out if videos work, irrespective of who they are shown to and who features in the video. We thus calculate sample size by taking all treatment arms and interactions in our factorial design together and we simply test the different between treatment and control. This scenario is shown as the black curve in Figure 1. From the figure, we learn that we would need a sample size of about 1100 observations to test this with sufficient power (.8).

A second question is related to the gender composition of the animator, where we expect that when the message is brought by a couple leads to better outcomes then when the message is given by an individual (either a male or a female farmer). We calculate sample size that is needed to determine a significant difference in yields between these two groups and plot this in Figure 1 as the yellow curve.

A third question relates to the recipient. Here we also want to find a significant difference in outcomes between households that were shown the video as a couple and households in which the video was only shown to one individual in the household. The results of these power simulations is shown as the blue line in figure 1.

The fourth question relates to the gender matching effect. Here we compare if households where the gender of the recipient and the gender of the messenger (including the BB cell) differ from the effect obtained by households where there is no matching (FM and MF). This is shown as the green line in the figure.

Finally, we investigate the most stringent option and we combine the above four research question and estimate power needed for finding all these effects together. This is summarized in the red line. Here we see we would need about 4000 observations to get sufficient power. We will settle for something in-between the red line and the blue and green lines and include about 3500 farmers in our study. Taking into account the fact that we will work in blocks of 55 farmers, this means we would sample about 64 parishes.

Assignment to Treatment

Fieldwork

Instruments

Empirical Analysis

Variables

Balancing Checks

Treatment Effects

Intent to Treat

Treatment on the Treated

Heterogeneous Effects

Standard Error Adjustments

While our main outcome variables are ultimately household welfare and potato yields, we will also estimate the impact of our interventions on a range of intermediate variables. The fact that we have many such variables may lead to the so-called "look elsewhere" effect, where one is bound to find significant effects simply due to the sheer number of parameters. Therefore, some form of multiple-inference correction is in order. In general, there are two ways in which to avoid false positives that result of multiple hypothesis testing. One can either reduce the number of hypothesis, or one can make the statistical test stricter by for instance reducing the significance threshold (such as the Bonferroni adjustment). We will address false positive arising from multiple hypothesis testing using both ways.

First of all, we will use the groupings presented in the section that lists the variables to create indices (directly related to yield, sales, welfare, crowding in other intensification methods,...). At the most basic level, each of the indices is a weighted mean of the several standardized outcomes within each group. In particular, for each variable within each group, we make sure positive direction always means better, otherwise we switch sign. We then demean the outcome and standardize by scaling by the control group standard deviation.

We then create weighted averages for the outcomes in each group at the household level, using as weights the inverse of the co-variance matrix of the transformed outcomes within the group. This is done for each of the groups. The resulting variables can then be used to assess the impact of the particular intervention using the specifications outlined above.

However, we may be interested in identifying differential effects within each of the groups. For example, we may want to differentiate between the effect on potato sales immediately after the harvest and potato sales during the lean season. We will therefore also use Family Wise Error Rate Control. In particular, we will use the free step-down re-sampling method of **?**. Finally, we will also drop outcomes from our analysis for which 95 percent of observations are the same value. This is done to reduce the influence of outcomes with limited variation.

Research Team

The research will be led by Bjorn Van Campenhout (b.vancampenhout@cgiar.org), Els Lecoutere (els.lecoutere@uantwerpen.be) and David Spielman (d.spielman@cgiar.org). Research assistance will be provided by Wilberforce Walukano (W.Walukano@cgiar.org) and Marc Charles Wanume (wcharli@gmail.com).

Deliverables and Calendar

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