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

Bjorn Van Campenhout, Els Lecoutere and David J. Spielman

May 5, 2017

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.

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 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 five districts from the East known for their maize production: Jinja, Mayuge, Iganga, Luuka and Kamuli. 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

	subcounties	parishes	villages
Jinja	11	69	631
Mayuge	7	56	272
Iganga	12	66	382
Luuka	7	33	209
Kamuli	13	72	1031
Total	50	269	3131

Table 1: Administrative structure of study area

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 location and we want to consider power in the context of multiple treatments. In addition, it also allows us to determine the optimal number of observations within each treatment combination. The algorithm that was used to perform the power calculations can be found in the git repository.

We start by first finding the optimal distribution of the total sample size over the different treatment groups, given the hypotheses we want to test, keeping total sample size fixed. Depending on the hypotheses on wants to test and the effect sizes expected for particular treatment combinations, it may be more efficient to allocate relatively more observations to a particular treatment combination that just dividing all observations equally over all treatment combinations (in our case, if we fix sample size at 1000 observations, we would allocate 100 observations to each treatment combination). For instance, the treatment combination where both messenger and receivers are the couple features in three of the four hypotheses we will test. In addition, it is expected to have the largest effect size, so additional observations in this treatment group will increase power much more than adding observations in other treatment combination cells.

We developed a simple algorithm to find the optimal allocations to the different cells using a grid search. In particular, we estimate power to detect the four main hypotheses simultaneously for all possible allocations of observations to the different cells.

Power calculations are based on yield data taken from the fourth wave of the Uganda National Panel Survey. In particular, we calculate average yields of maize (defined as quantity harvested per hectare planted) during the second season of 2013 at the household level[1]. We will sample from this distribution for the power calculations. Mean yields in the sample was about 1.3 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 stratifying at this level on statistical power.

In addition, the main power calculations will be based on the first set of research questions (related to the gender composition of the messenger and the receiver), as the hypotheses we formulate here are most complex and the factorial design allows us to recycle observations for the third factor related to adding IVR to the video content. Not only do the two gender related factors in the first set of research question both have three levels (male, female, and both), we are also interested in particular interactions between the two factors, which needs to be accounted for when determining sample size. For the third factor, which is the one related to adding IVR to the video treatment, we are only interested in the main effects and there are only two levels (video and video + IVR). Therefore, in this factor, we can allocate half of the households that get to see any kind of video to one level

[1] Using this survey may provide an overly pessimistic view. Experience with UNPS data suggests the yield data is very noisy. In addition, the for the first set of power calculations, we relied on rice yield data we collected ourselves in a previous study. When this data was used, we obtained substantially higher power for the same hypotheses.

fo the factor and half to the other level. For reasonable effect sizes, these sample sizes are likely to result in sufficient power.

In terms of impact, it is expected that agricultural extension information messages delivered by a man and a woman and received by both the man and woman farmer will be most effective because of gender matching effects, in combination with the projection of a household approach to farming in the message and the higher likelihood that both the woman and man farmer participate in decision making about adoption with equal information. The latter effect is expected to be at work when the man and woman farmer receive the message together, regardless of the messenger composition. The projection of a household approach is present when the message is delivered by a man and a woman, regardless of recipient composition. The gender matching effect is only at work when the gender of the messenger and recipient is matched. It is expected that the effectiveness of the typical case of extension information messages delivered by a man and received by a man will be lower than the cases in which other effects can realize.

The corresponding expected effect size for each treatment combination on average yield at the household level is summarized in Figure 1. They range from no increase from the control in the treatment combination where the receiver is the woman and the messengers is a male and vice versa to a 25.0 percent increase for the treatment combination where the video messages is shown to the couple and the message in the video is also delivered by a couple. In this last case, we expecte yields to increase from 1323 kg/ha to 1654 kg/ha.

Kondylis et al. (2016) find evidence of gender bias in awareness, knowledge and adoption of pit planting in Mozambique. In particular, they find that among men who received information from a male messenger, the proportion that are aware of pit planting is 10 percentage points higher. This proportion is 6.5 percentage points higher for actual adoption. Female awareness, knowledge and adoption is the same irrespective of the presence of a male extension worker. However, if a female extension worker is added, awareness, knowledge and adoption among female farmers also increases by roughly the same proportions. We use these results to get an idea about the gender matching effect. In particular, we model a 7.5 percent increase in yields when messenger and recipient is male and when messenger and recipient is female.

Lambrecht, Vanlauwe, and Maertens (2016) investigate the effect of participating in extension training as a couple. In particular, they investigate whether participation of female farmers in an agricultural extension programme in South-Kivu increases adoption of three technologies: improved legume varieties, row planting and mineral fertiliser. Joint male and female programme participation leads to the highest adoption rates. We therefore model an 10 percent increase in yields for farmers that view the video as a couple.

Doss and Morris (2001) find that adoption of agricultural technologies among female farmers is lower than among male farmers. They find that this is due to gender-linked differences in access to complementary inputs, such as access to information. Kondylis et al. (2016) also find that women do not seem to benefit from male extension workers. We therefore assume no effect in our power calculations for the subset of farmers that get to see a video where the messenger is of the opposite gender.

Pan, Smith, and Sulaiman (2015) use a regression discontinuity approach to evaluate an inovative extension model that relies heavily on model farms. They find production increases by about 21 percent.

Finally, we expect the highest effect when both spouses are provided the information by a model farmer couple.

The expected effect sizes are based on the interplay of the three effects mentioned above: gender matching effect, a knowledge-is-power-effect, and the projection of a household approach. For instance, the effects on the diagonal in Figure 1 are higher because here the gender matching effect is playing: We expect that men learn more from other man and women learn more from other women, which in turn would lead to higher yields among gender matched subsamples. The expected effects emanating from the gender composition of the receiver is related to information deficiencies. This can be directly when women are also important actors in agriculture. For instance, Kabunga, Dubois, and Qaim (2012) find that female farmers are less likely to adopt the tissue banana culture technology in Kenya, but that they would have an equal chance to adopt innovations, provided that they acquire sufficient knowledge about the innovation. In addition, knowledge may also affect technology adoption and subsequent yields through changes in relative bargaining power of the actors. This is expected to increase yields especially when both male and female are given access to information. We also expect larger effects when the message is brought by a couple, as a cooperative approach to farmering is likely to reduce inefficiencies within the farm household. In some cells, various effects may be applicable: the reason why the largest effect is expected with both husband and spouse receive the

Control 1609 kg/ha		Messenger		
		Male	Female	Both
Receiver	Male	1770 kg/ha 10.0 %	1716 kg/ha 6.67 %	1824 kg/ha 13.3 %
	Female	1663 kg/ha 3.33 %	1877 kg/ha 16.7 %	1931 kg/ha 20.0 %
	Both	1984 kg/ha 23.4 %	2038 kg/ha 26.7 %	2091kg/ha 30.0 %

Figure 1: Expected Effect Sizes

message together from a couple is because there all three effects are playing.

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 2. 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 2 as the yellow curve.

A third question relates to the recipient. Here we also want to find a

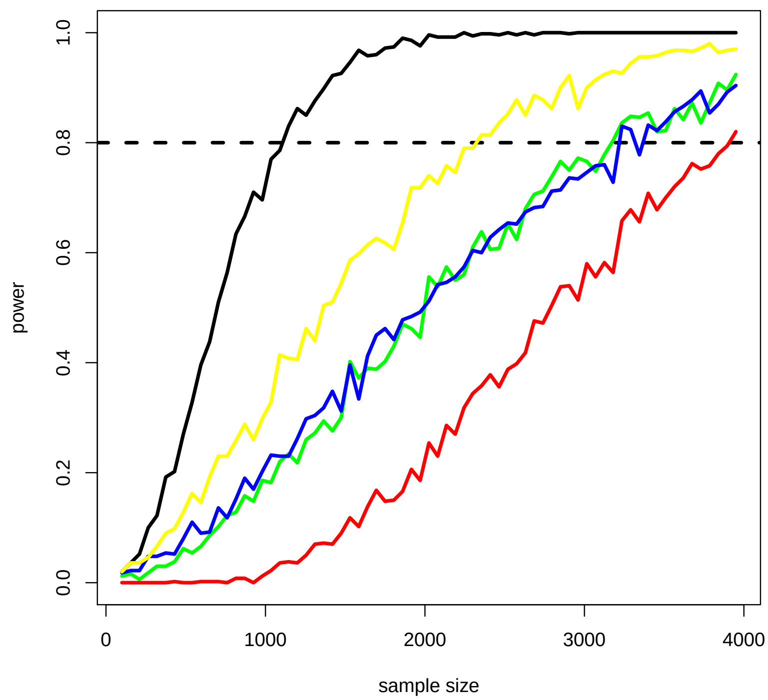

Figure 2: Power curves

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 2.

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.

A second outcome variable we will investigate relates more to equity within the household. The gender productivity gap, where women managed plots are farmed less extensively than male managed plots resulting in significanlty lower yields, has been observed throughout subsaharan africa and for a variety of crops (Udry, 1996). In Uganda, Duponchel (2015) find that female managed plots are almost 20 percent less productive than male managed plots. The gap is caused by a general lack of access to production factors compared to men. For instance, women may be forced to farm on inherently lower productivity plots and they may have less access to productivity enhancing tools, technologies and inputs such as fertilizer. Knowledge related to crop intensification is one such factor where access between men and women differs, and so finding out how changing particular attributes to extension videos affect this gap is an important outcome.

Using data from the latest UNPS, we also find a significant gender gap among maize farmers in Uganda. Male farmers obtain yields of about 1427 kg per hectare. Women managed maize plots only get about 1385 tons. We thus model a difference of about 42 kg per hectare, with a standard error of about 40 kg per hectare. The difference we find seems lower that what others find. For instance, Larson et al. (2015) find the gender gap to be about double of what we find, although they base their analysis on male versus female headed households, while we look at the gender of the person that manages the plot. According to FAO, female managed plots are in general 20-30 percent less productive. Duponchel (2015) estimate the gap to be 23 percent, but they aggregate all crops by weighing by prices and expressing yields in monetary terms. Peterman et al. (2011) estimate it as high as 50 percent.

There is no literature we are aware of that looks at the effect of the gender composition of the messenger and the gender composition of the receiver of agricultural extension messages on the agricultural productivity gap. Therefore, we will use our best judgment to determine expected effect sizes. Starting from a baseline situation where maize yields are about 42 kg/ha higher on male managed plot, showing a video to a man only is likely to further increase this gap (+30 percent). Due to the homophily effect, we expect that the increase in male productivity is smaller when the messenger is a woman, and so the gap will increase less (+10 percent). Finally, if the message is brought by a couple and a household approach to farming is projected, the man may be encouraged to share some of the knowledge with his wife. However, we expect the increase in yield on male managed plots to still be higher than any potential increase of yield on the female managed plot. As such, we expect the effect on the yield gap to be marginally positive (10%).

When the information is shown to the woman but not to the man, it is expected that yields on female managed plots will increase, while yields on male managed plots are likely to remain the same. This would mean that the gap reduces. Again due to the homophily effect, we expect women to learn most form women, and so the reduction in the gap will be highest when the messenger is also a women (-30 %). The reduction will be smallest when the information is given by a man (-10 %). Finally, if the woman is sensitized on the importance of a household approach to farming, some of the information may be shared with the husband, also reducing the effect on the gap somewhat (-20 %).

When the information is given to the couple, we expect little or no effect on the gap if the message is given by either male or female. We may expect a slight increase in the gap if the information is given to the male (+5%) and a slight decrease if he information is given by a female (-5%), but the effect is likely to be too small to detect, so we put it on zero in the simulations. Finally, if both spouses have all the information and the message is given that the household farm should be managed as a unit, we expect that the gap reduces by half (-50%).

With respect to intra-household outcomes, we are interested in three hypotheses. First we want to test the importance asymmetric information, and we will test if the gap significantly differs between households where the man was shown the video and households where the woman was shown the video. Second, we want to test if there is a difference depending on whether a household cooperative approach was promoted or the information was borough by an individual. Finally, we also want to separately compare changes in the gender yield gap for households that are both shown the video that also projects a household approach to all the other households[2].

On the basis of the above, we come to the following division of observations across the different treatment cells.

Assignment to Treatment

Fieldwork

Instruments

The treatments consist of the provision of information that is assumed to increase maize productivity through encouraging adoption of modern technologies and recommended practices.

In general, we would like to have a treatment that contains information that relevant to all participants in the experiment. For instance, if we decide to promote labour saving technologies, careful attention should be given to who's labour this technology affects. We may therefore decided to include a labour saving technology related to ploughing, which is predominantly a male activity, while also including

For example

[2] To make the grid search manageable, we again took some groups together when dividing observations {(YMM,YMF),(YFM,YFF), (YBM,YBF), (YMB,YFB), (YBB), (Ctrl)}. Within each group, we simply took the average expected effect size.

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).

Deliverable and Calendar

References

Banerjee, A., A. Banerjee, and E. Duflo. 2011. *Poor Economics: A Radical Rethinking of the Way to Fight Global Poverty*. Poor Economics: A Radical Rethinking of the Way to Fight Global Poverty. PublicAffairs.

Bernard, T., S. Makhija, K. Orkin, A. S. Taffesse, and D. J. Spielman. 2016. *Video-based agricultural extension: Analysis of a pilot project in Ethiopia.* Project note, International Food Policy Research Institute.

de Janvry, A., E. Sadoulet, and T. Suri. 2016. "Field experiments in developing country agriculture." *Handbook of Economic Field Experiments* .

Doss, C. R. and M. L. Morris. 2001. "How does gender affect the adoption of agricultural innovations?: The case of improved maize technology in Ghana." *Agricultural Economics* 25 (1): 27 – 39.

Duponchel, D. A. D. B. K. D. M. 2015. *Investigating the Gender Gap in Agricultural Productivity: Evidence from Uganda.* The World Bank.

Jack, B. K. 2013. *Market inefficiencies and the adoption of agricultural technologies in developing countries.* Tech. rep.

Kabunga, N. S., T. Dubois, and M. Qaim. 2012. "Heterogeneous information exposure and technology adoption: The case of tissue culture bananas in Kenya." *Agricultural Economics* 43 (5): 473–486.

Kondylis, F., V. Mueller, G. Sheriff, and S. Zhu. 2016. "Do Female Instructors Reduce Gender Bias in Diffusion of Sustainable Land Management Techniques? Experimental Evidence From Mozambique." *World Development* 78 (C): 436–449.

Lambrecht, I., B. Vanlauwe, and M. Maertens. 2016. "Agricultural extension in Eastern Democratic Republic of Congo: does gender matter?" *European Review of Agricultural Economics* 43 (5): 841.

Larson, D. F., S. Savastano, S. Murray, and A. Palacios-López. 2015. "Are women less productive farmers? How markets and risk affect fertilizer use, productivity, and measured gender effects in Uganda." .

Meinzen-Dick, R., A. Quisumbing, J. Behrman, P. Biermayr-Jenzano, V. Wilde, M. Noordeloos, C. Ragasa, and N. Beintema. 2011. *Engendering agricultural research, development and extension*, vol. 176. Intl Food Policy Res Inst.

Pan, Y., S. C. Smith, and M. Sulaiman. 2015. *Agricultural extension and technology adoption for food security: Evidence from Uganda.* Tech. rep., IZA Discussion Papers.

Peterman, A., A. Quisumbing, J. Behrman, and E. Nkonya. 2011. "Understanding the complexities surrounding gender differences in agricultural productivity in Nigeria and Uganda." *Journal of Development Studies* 47 (10): 1482–1509.

Udry, C. 1996. "Gender, agricultural production, and the theory of the household." *Journal of political Economy* 104 (5): 1010–1046.