

Increasing Adoption and Varietal Turnover of Seed—A Pre-Analysis Plan for Consumer and Producer Side Interventions

Bjorn Van Campenhout*, Leocardia Nabwire†, Berber Kramer‡,
Carly Trachtman§

January 27, 2023

Abstract

To increase adoption of new agricultural technologies, both push (supply side) and pull (demand side) factors are important. A popular supply side intervention to increase adoption of a particular technology is some level of subsidy. However, it is often argued that if something was subsidized (or even provided for free), it may not be used for the intended purpose. In this paper, we test if farmers that receive a sample of a new improved seed variety are more likely to adopt it in the future than a control group of farmers who did not get a free sample. Furthermore we test whether farmers learn differently from seed that was obtained for free than if they had to pay a (small) price for it. The latter is investigated using a Becker–DeGroot–Marschak (BDM) auction such that we can disentangle the selection effect, whereby farmers that are prepared to pay a price are likely to be more motivated to learn from it for subsequent adoption decisions, from the sunk cost effect, where a product that has a price attached to it is valued more. In addition to the supply side intervention, we also test the relative effectiveness of a demand sided intervention to increase adoption of improved seed varieties. In particular, we cross-randomize an intervention where households are demonstrated how to prepare the new seed variety and get the ability to taste it.

Keywords: technology adoption, subsidies, screening effect, sunk cost effect, demonstration.

JEL: Q16, H24, O33, D91

*Development Strategy and Governance Division, International Food Policy Research Institute, Leuven, Belgium

†Development Strategy and Governance Division, International Food Policy Research Institute, Kampala, Uganda

‡Markets Trade and Institutions Division, International Food Policy Research Institute, Nairobi, Kenya

§Markets Trade and Institutions Division, International Food Policy Research Institute, Washington DC, USA

1 Motivation

In development economics, long run change often requires both push and pull factors simultaneously creating to a new equilibrium. For example, value chain upgrading often involves some kind of acceleration in the demand of the underlying commodity downstream (for instance after opening up of a new export market) and a matched supply side disruption upstream (such as a technological innovation that increases productivity). Similar arguments may hold for the adoption of a new technology, where farmers may change behavior in response to both the supply of the new technology and an increase in demand for the commodity that emanates from the new technology.

A popular supply side intervention to introduce a new agricultural technology is some level of subsidy. Private sector actors such as seed companies or agro-input dealers often use trail packs, as they realize farmers may be reluctant to try out a new product. Public actors may think commercial seed are out of reach of poor households and want to kick-start large scale adoption by providing the initial investment. The case for free (or subsidized) inputs also stems from potential externalities: it is well established that one of the most effective ways to increase technology adoption is through peer learning, and both private and public partners may attempt to leverage social learning (Conley and Udry, 2010; Bandiera and Rasul, 2006). Furthermore, informal seed systems used by farmers often suffer from decades of seed degeneration due to recycling of seed introduced during colonial times (McGuire and Sperling, 2016). Injecting new seed varieties can be an important strategy to improve the overall seed stock in the informal sector. For instance, public research organizations often invest in open pollinating varieties (OPVs) that can be recycled to some extent without losing vigor.

At the same time, it is often argued that providing goods or services for free distorts the utility people attach to it. As a result, the good or service remains unused, is resold, or otherwise used in unintended ways. Examples include the use of free bed-nets for fishing or the use of subsidized chlorine for cleaning (instead of drinking water treatment) (Cohen and Dupas, 2010; Ashraf, Berry, and Shapiro, 2010).

There are at least three ways in which charging a price may lead to increased usage. The first is a *screening effect*, whereby only people who really value the product will acquire the product (while those who do not intend to use it will be less likely to buy it). A second is more psychological in nature and conjectures that people are prone to *sunk cost effects*, and as a result, paying a positive price for something leads one to appreciate it more (regardless of whether you really want it or not). Finally, prices may also provide a *signal for quality*.

In general, studies on subsidized inputs in the health sector focus most on intended use as the primary outcome. In our case, intended use is considered an intermediary outcome; we are most interested in the learning that emanates from the (subsidized) seed pack as evidenced by subsequent adoption of the seed in the next year when the seed is not subsidized anymore. Kremer, Rao, and Schilbach (2019) note that learning about new technologies requires costly

experimentation and costly attention, and so individuals would benefit from decreasing the costs of learning. The fact that learning is also costly means the same mechanisms (a screening effect and/or a sunk cost effect) may also affect the extent to which farmers learn. That is, if a seed is valued less because it is provided for free, it may also be that farmers put in less effort and complementary investment when experimenting, and pay less attention to outcomes. Examples include planting subsidized seed on sub-optimal plots or mixing subsidized seed with farmer-saved seed, which would make learning harder.

Studies on adoption often focus solely on the supply side, and it is assumed that supply related attributes such as high yield or drought resistance are also the traits that farmers seek. As such, in information dissemination and marketing of new seeds, these attributes are singled out. However, previous exploratory data analysis suggests that both ease of cooking and taste are also important characteristics that determine the choice of what varieties to adopt.

In this research, we evaluate the relative effectiveness of two interventions designed to increase varietal turnover of maize seed in Uganda. A first intervention targets the supply side and consists of providing farmer with the technology at a subsidized (up to 100 percent) price. A second intervention targets the demand side. Here we create demand for maize by cooking demonstrations where farmers can familiarize themselves with maize derived from the improved seed varieties and taste (Low et al., 2007).

The above also suggests that the size of the subsidy and the relative magnitude of screening and sunk cost effects are important unknowns when evaluating supply interventions to promote seed varietal turnover. As such, the intervention that targets the supply side has three treatment arms. In one treatment arm, a seed trial pack is provided for free. In a second treatment arm, a two stage pricing design is used, where we first ask farmers how much they are willing to pay to identify the screening effect, and then provide a discount to isolate the sunk cost effect. The third treatment arm is the control group, who does not get access to (free or discounted) seed.

This document serves as a pre-analysis plan for the study that will be registered in a public repository. It provides background information, outlines hypotheses which will be tested, tools that will be used in the field, power calculations and sample size projections on which sampling is based, outcome variables that will be used to assess impact, and specification that will be estimated. As such, it will provide a useful reference in evaluating the final results of the study (Humphreys, Sanchez de la Sierra, and van der Windt, 2013; Dufflo et al., Working Paper).

2 Relation to the literature

As the use of seed trial packs touches on many constraints, our study touches on various strands of the literature. For instance, providing free or subsidized seed directly to farmers removes access related constraints, such as situations where agro-input dealers would not have sufficient stocks of seed at the right

moment (Shiferaw, Kebede, and You, 2008). Seed trial packs are often distributed to enable farmers to overcome aversion to risk, ambiguity, or other forms of uncertainty (Chavas and Nauges, 2020; Boucher et al., 2021). The amount of subsidy also removes financial constraints (Abate et al., 2016). The opportunity to learn from trial packs may also be a substitute for information provided by agricultural advisory services (Shiferaw et al., 2015; Van Campenhout, Spielman, and Lecoutere, 2021). As mentioned above, new technologies are also sometimes subsidized by governments in the hope that model farmers set up demonstration plots to encourage peer learning (Conley and Udry, 2010)

That said, there are surprisingly few studies that directly evaluate the effectiveness of seed trial packs to accelerate technology adoption. Biedny et al. (2020) find that in Tanzania, adding trial packs to demonstration plots in the context of village based agricultural advisors does not significantly affect input sales, orders received, or learning. In many studies, the impact of seed packs itself are not the subject of research, but rather some attribute of the seed (like the risk reduction potential, eg. Boucher et al., 2021).

Also related is Morgan, Mason, and Maredia (2020), who compare different extension approaches, one of which involves the use of trial packs. Their outcome is not subsequent adoption of the new technology, but the willingness to pay, which is elicited using a BDM. As such, their interest is more in explaining dis-adoption once new technologies are sold through traditional market channels. They find that, in the southern highlands of Tanzania, bean farmers' willingness to pay is not affected by seed trial packs.

The relationship between effectiveness and the size of the subsidy, and in particular the hypothesis that free good may be less effective than paid for goods, has been studied in the context of public health interventions, such as the adoption of insecticide treated bednets. To our knowledge, we are the first to address this question in the context of agricultural technology adoption. The use of BDM to isolate screening and sunk cost effects is also not very common. As far as we know, it was only done by Berry, Fischer, and Guiteras (2020), but in the final version of their paper the analysis was deferred to the online appendix because of no significant effects and space constraints. However, a BDM may be a better way to identify sunk cost effects and selection effect than the two stage pricing designs used in Cohen and Dupas (2010) and Ashraf, Berry, and Shapiro (2010). Indeed, Ashraf, Berry, and Shapiro (2010) argue that their procedure only correlates to WTP (while a BDM directly measures WTP). Recent research also suggests that BDM seems to work pretty well in practice (Burchardi et al., 2021).

There seem to be even less studies that look at demand side interventions to spur technology adoption. In general, demand side interventions such as cooking demonstrations are primarily concerned about nutrition education (eg. Reicks et al., 2014). Experiential interventions like tasting rarely go all the way back to decisions on what to plant.

3 Methods and experimental design

We use a standard field experiment to test the effectiveness of free trial packs and the consumer side interventions. To do so, we will use a cluster randomized control trial that takes the form of a 2x2 factorial design. Each factor has a control and a treatment level and the clusters will be villages, in which a fixed number of households will be selected.

The first factor corresponds to the supply side treatment. In the treatment level of this factor, farmers in treatment villages receive a free sample of a new improved seed variety (bazooka). In the control level of this factor, farmers do not receive a free sample pack (but they do get something of similar value (a so-called token of appreciation) to account for potential income effects). The second factor corresponds to the demand side intervention. In the treatment level of this factor, farmers in treatment villages will be exposed to a cooking demonstration where farmers are provided with the opportunity to taste food prepared using the promoted variety. In the control level of this factor, we will not organize these kind of events.

To test whether farmers learn differently from seed that was obtained for free than if they had to pay a (small) price for it, we use a randomized two-stage pricing design to isolate the sunk-cost effect from the screening effect (Ashraf, Berry, and Shapiro, 2010; Cohen and Dupas, 2010). In such designs, subjects are offered a service or good for a particular price in a first stage. In a second stage, a discount is applied to that price. Regressing outcomes (such as whether the product is used for the intended purpose) on the price while controlling for the discount gives an estimate of the screening effect of the price; regressing outcomes on the discount while controlling for the price gives an estimate of the sunk cost effect.

A standard Becker-DeGroot-Marschak (BDM) auction is essentially a two stage pricing design and can be used to disentangle the sunk cost and screening effect (Becker, DeGroot, and Marschak, 1964). In such an auction, farmers are asked to name the highest price they are prepared to pay for a particular good. Participants then enter a lottery where a price is drawn from a particular distribution. If the price the farmer was prepared to pay is higher than the price drawn, the farmer gets the item at the draw price. The difference between the farmer's reservation price and the price drawn is then an unexpected discount, and so the BDM provides us with the two components necessary to disentangle the screening and sunk cost effects: the willingness-to-pay and the transaction price (Berry, Fischer, and Guiteras, 2020).

To study screening and sunk cost effects, we confine ourselves to the treatment factor of the seed trial intervention (that is, half of the sample that is used to power the 2x2 factorial design). In this subset, we match to each treated household a household that will be offered seed at a non-zero transaction cost. While all households in the treatment factor of the seed pack intervention will be subjected to a BDM, we will make sure that half of these individuals will receive a 100 percent discount (that is, make sure that the price the computer draws is zero). In reality, we will also have to take into account that some farm-

ers may be naming a reservation price that is likely to be below the price drawn by the lottery. This problem can be controlled by making sure the computer always draws a price that is below the farmer reservation price. At the same time, if farmers get the opportunity to learn this, they are likely to underbid.

4 Treatments

For the first factor, the treatment level will consist of a seed trial pack that the household receives. This trial pack will be an improved seed variety (hybrid seed) that is available in the market but at the same time not yet widely adopted by farmers. The control level for this factor will simply be the absence of a seed trial pack, that is, these household will not receive a seed trial pack. However, in both treatment and control groups, we will inform farmers about the existence of the improved seed variety and the benefits of using them, to be able to isolate the effect of the trail pack from merely knowledge effects.

For the second factor, the treatment level consists of an event where farmers are shown how easy it is to prepare food grown with the improved variety and farmers are allowed to taste. Also here, control level for this factor will again be the absence of these events, that is, households in control villages will not be exposed to such events.

5 Power calculations

We use simulations to determine sample size. Simulation is a far more flexible, and far more intuitive way to think about power analysis. Even the smallest tweaks to an experimental design are difficult to capture in a formula (adding a second treatment group, for example), but are relatively straightforward to include in a simulation. In our case, we generate data with a simulated treatment effect of a given size n times (for the number of simulations), and then count how often (z) we can find a significant effect ($p < 0.05$). We do this for different sample sizes (eg 100, 200, 300, ... 1000) and pick the sample size where z/n is about .80. As we have a clustered design, we perform a grid search over 2 dimensions: number of villages and number of households per village.

We use the following assumptions for the power calculations. The primary outcome we use is a binary indicator for use of improved seed at the farmer level. Using data previously collected as part of a different project from 3450 smallholder maize farmers located in 345 villages, we find that about 64 percent of farmers indicate that they are already using improved seed. However, this is likely to be an overestimate as these farmers were sample from clients of agro-input dealers, and the question asked was if the farmer had ever used improved seed. We thus use a baseline seed use rate of 32 percent, which is closer to mean of 34 percent reported in the same area in [Van Campenhout, Spielman, and Lecoutere \(2021\)](#). Inter cluster (within village) correlation for this outcome has been estimated to be 0.15. We assume similar treatment effects for both the

	Ctrl	Free seed	Seed Auction
Ctrl	27 clusters (540 HH)	27 clusters (540 HH)	27 clusters (540 HH)
Consumption	27 clusters (540 HH)	27 clusters (540 HH)	27 clusters (540 HH)

Figure 1: Design

seed trial treatment and the consumption (a 13.5 percentage point increase). For the interaction effect, we assume a 23.5 percentage point increase. We use HC3 standard errors clustered at the village level for the power calculations. R code can be found [here](#).

After running a series of power simulation where we optimize power for samples that vary over 2 dimensions (villages and households per village), we converged to a sample consisting of 110 villages with 20 households in each village. In this design, 55 villages or 1,100 households will receive a free trial pack and 55 villages or 1,100 households will be exposed to the consumption side treatment. Half of these will overlap, that is, about 27 villages or 540 households will receive both treatments. With this setting, we are not powered to detect the three effects simultaneously. In only 66 percent of cases we are able to estimate a positive effect at the five percent significance level for both treatments and their interaction. However, if we consider the treatments separately, we hit conventional power levels for both treatments, and get up to 0.97 for the interaction effect. We are certain to identify at least one of the three parameters of interest (seed packs, consumer intervention, or the interaction). The design, with sample sizes, is illustrated in Figure 1.1

We will not run formal power calculations for the BDM based experiment (but we will once the final sample is known calculate minimal detectable effect sizes for reference). As mentioned above, we will just add an extra column to the 2x2 design.

6 Estimation and inference

We will use ANCOVA models to assess impact. As randomization happened at the village level, we estimate a similar equation:

$$Y_{1ij} = \alpha + \beta_S T_i^S + \beta_D T_i^D + \beta_I T_i^S T_i^D + \delta Y_{0ij} + \varepsilon_{ij} \quad (1)$$

where T_i^S is a dummy for the supply side intervention treatment status of village i and T_i^D is a dummy for the demand side intervention treatment status of village i . We also allow for an interaction effect between the two treatments and control for baseline outcomes to improve precision.

Factorial designs have recently been criticized for the proliferation of under-powered studies and replication failure ([Muralidharan, Romero, and Wüthrich, 2019](#)). While in the previous section we ran power calculations based on models

with a complete set of interactions (as on equation 1), we may still want to try boosting power by pooling observations across the orthogonal treatment in the event that we find a treatment effect that appears smaller than the minimal detectable effect size that we assumed during power calculations. To do so, we will consider the orthogonal treatment as a co-variate we adjust for, and interact the treatment variable with the demeaned orthogonal treatment. This give a more robust version of the treatment estimate that corresponds to the coefficient estimate of the treatment of interest after dropping the interaction with orthogonal the treatment:

$$Y_{1ij} = \alpha + \beta_M T_i^M + \beta_O (T_i^O - \bar{T}^O) + \beta_I T_i^M (T_i^O - \bar{T}^O) + \delta Y_{0ij} + \varepsilon_{ij} \quad (2)$$

Where now T_i^M is a dummy for the main treatment and T_i^O is a dummy for the orthogonal treatment (which enters in deviations from its means).

Because we will test for treatment effects on a range of outcome measures, we will deal with multiple outcomes and multiple hypotheses testing by means of two approaches. Firstly, we follow a method proposed by [Anderson \(2008a\)](#) and aggregate different outcome measures within each domain into single summary indices. Each index is computed as a weighted mean of the standardized values of the outcome variables. The weights of this efficient generalized least squares estimator are calculated to maximize the amount of information captured in the index by giving less weight to outcomes that are highly correlated with each other. Combining outcomes in indices is a common strategy to guard against over-rejection of the null hypothesis due to multiple inference. However, it may also be interesting to see the effect of the intervention on individual outcomes. An alternative strategy to deal with the multiple comparisons problem is to adjust the significance levels to control the Family Wise Error Rates (FWER). The simplest such method is the Bonferroni method. However, the Bonferroni adjustment assumes outcomes are independent, and so can be too conservative when outcomes are correlated. We therefore use a Bonferroni adjustment which adjusts for correlation ([Sankoh, Huque, and Dubey, 1997](#); [Aker et al., 2016](#))

7 Timeline

There are two maize growing seasons in the area we are planning to work. One is running from march/april to june/July, the other from August/Sept to November/December.

Ideally we would distribute trail packs together with baseline data collection about one month before planting. As such, the best time would be around February 2023.

8 Context

The study will be implemented in Eastern Uganda in an area known as the Busoga Kingdom. We will sample from 4 districts that have relatively low

6. Has used quality maize seed on any plot in last season - 1 is yes (q25a)
7. Has used the promoted seed (bazooka) on a randomly chosen plot in the last season (q31)
8. Where did you obtain the seed from for the maize planted on the randomly selected plot in the previous season? (q32) - more formal (eg agro-input dealer, operation wealth create) is better
9. How often was the seed that was used on the randomly selected plot recycled? (q34)
10. Maize yields on a randomly chosen plot in last season - production/size of plot (q29, q50, q51)

9.2 Outcomes at midline

We plan to do a midline survey in August 2023. As mentioned above, at midline, we are particularly interested in the use of trial packs and whether something was learned from it. As such, only households that received a trial pack (either free or subsidized) will be asked the questions below. However, all households will be revisited, as at this time the consumption side treatment will be implemented.

1. Was trial pack used as seed on the farm? (as opposed to sold, eaten,...)
2. How was the seed trial package was used? (pure on separate plot, mixed with landraces, mixed with bazooka from other source, mixed with other improved seed,...)
3. Was it intercropped?
4. What seed/plant spacing was used for the trail pack?
5. Number of seeds per hill usedfor the trail pack?
6. Did you apply organic manure to the soil for the trail pack?
7. Did you apply DAP ****(black in color)**** or NPK (brown in color) for the trail pack?
8. Did you apply Urea ****(white in color)**** for the trail pack?
9. How many times did you weed the trial pack maize plot?
10. How many days after planting did you do first weeding on the trail pack plot?
11. Did you use any pesticides, herbicides or fungicides on the trail pack plot?
12. When did you plant the trail pack seed?

13. Did you re-sow where seeds did not germinate on the trial seed plot? If so, what seed variety did you used of gap filling
14. area planted with trial pack?
15. production from trial pack?
16. yields from trial pack plot?
17. perceptions related to the quality of the trial pack seed (bazooka).
18. Were you happy with the bazooka?
19. What seed are you planning to use in next season?

9.3 Outcomes at endline

9.3.1 Primary outcomes

The main aim of the project is to find ways to increase varietal turnover. Most primary outcomes are therefore related to seed use in years subsequent to the intervention. We define 10 primary outcomes that will also be combined in a summary index test following [Anderson \(2008b\)](#). Therefore, all primary outcomes have an unambiguous expected effect.

1. has used quality maize seed (hybrid/OPV obtained from credible source and not recycled too often) on any plot in last season - 1 is yes (q25a)
2. has used Bazooka on any plot in last season in last season - 1 is yes (q25aa)
3. has used improved seed (hybrid/OPV obtained from credible source and not recycled too often) on a randomly chosen plot in the last season - 1 is yes (q31)
4. has used the promoted seed (bazooka) on a randomly chosen plot in the last season - 1 is yes (q31)
5. extensive margin improved seed use on random plot (kg improved seed (OPV or hybrid)) (q38) - more is better
6. intensive margin improved seed use on random plot (kg improved seed (OPV or hybrid)/area planted) (q38/q29) - more is better
7. How often was the seed that was used on the randomly selected plot recycled? (q34) - less is better
8. Where did you obtain the seed from for the maize planted on the randomly selected plot in the previous season? (q32) - more formal (eg agro-input dealer, operation wealth create) is better
9. Would you use this seed that was used on the randomly selected plot in the previous season again in the future? - 1 is yes (q37)

10. maize yields on a randomly chosen plot in last season - production/size of plot (q29, q50, q51) - more is better

9.3.2 Secondary outcome

We define a range of secondary outcomes. These are outcomes to explore impact pathways. There are also some outcomes for which effects are not a-priori known.

1. rating of taste of seed variety used on randomly selected field - 1 is good (4) or very good (5) taste of variety - producer intervention impact pathway (q35g)
2. Seed variety that was planted on the randomly selected crop in the previous season (to test if farmers has experience - consumption intervention impact pathway)?
3. was it intercropped? (q30) - if yes, ask for secondary crop (q30a) and percentage allocations (q30b)
4. crop residue use (cr_use_grp)
5. cost of the seed (q39)
6. where was the seed obtained from? (q32)
7. Was the female co-head involved in the decision to use a particular type of seed on the randomly selected plot? (q34a)
8. Was the female co-head involved in the decision on what happened to the crops harvested on the randomly selected plot? (q34aa)
9. How much maize from the randomly selected plot was kept for own consumption? (q55a)
10. How much was kept for seed in the next agricultural season? (q56)
11. What seed/plant spacing was used on random plot? (q40)
12. Number of seeds per hill used on random plot? (q41)
13. Did you apply organic manure to the soil on random plot? (q42)
14. Did you apply DAP **(black in color)** or NPK (brown in color) on random plot? (q43)
15. Did you apply Urea **(white in color)** on random plot? (q44)
16. How many times did you weed on random plot? (q45)
17. How many days after planting did you do first weeding on random plot? (q46)

18. Did you use any pesticides, herbicides or fungicides on random plot? (q47)
19. When did you plant the seed on random plot? (q48)
20. Did you re-sow where seeds did not germinate on random plot? (q49)
21. Indicate time use (total man days per season) for male co-head, female co-head, other HH members, hired in for:
 - Field preparation
 - Planting
 - Weeding
 - Spraying
 - Harvesting
22. maize yields on a randomly chosen plot in last season - production/size of plot (q29, q50, q51)
23. Did you sell any maize that you harvested from this randomly selected plot? (q53)
24. How many bags of maize did you sell from this randomly selected plot? (q54)
25. Q24. Are you a member of a farmer group, association or cooperative that is involved in maize production? (q24)
26. Wealth - consumption of most commonly consumed items
27. Food security (R111 and R112)
28. Subjective well-being, relative to others (R409) and over time (R110)

Ethical clearance

This research received clearance form Makerere’s School of Social Sciences Research Ethics Committee () as well as from IFPRI IRB (). The research was also registered at the Ugandan National Commission for Science and Technology ().

Transparency and replicability

To maximize transparency and allow for replicability, we use the following strategies:

- pre-analysis plan: the current document provides an ex-ante step-by-step plan setting out the hypothesis we will test, the intervention we will implement to test these hypotheses, the data that will be collected and specifications we will run to bring the hypotheses to the data. This pre-analysis plan will be pre-registered at the AEA RCT registry.

- revision control: the entire project will be under revision control (that is time stamped track changes) and committed regularly to a public repository (github).
- mock report: After baseline data is collected, a pre-registered report will be produced and added to the AEA RCT registry and GitHub. This report will differ from the pre-analysis plan in that it already has the tables filled with simulated data (drawn from the baseline). The idea is that after the endline, only minimal changes are necessary (basically connecting a different dataset) to obtain the final result, further reducing the opportunity of specification search.

Funding

This research is part of the [OneCG Market Intelligence Initiative](#) which is funded by a [consortium of donors](#).

References

- Abate, G. T., S. Rashid, C. Borzaga, and K. Getnet. 2016. “Rural Finance and Agricultural Technology Adoption in Ethiopia: Does the Institutional Design of Lending Organizations Matter?” *World Development* 84: 235–253.
- Aker, J. C., R. Boumnijel, A. McClelland, and N. Tierney. 2016. “Payment mechanisms and antipoverty programs: Evidence from a mobile money cash transfer experiment in Niger.” *Economic Development and Cultural Change* 65 (1): 1–37.
- Anderson, M. L. 2008a. “Multiple inference and gender differences in the effects of early intervention: A reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects.” *Journal of the American statistical Association* 103 (484): 1481–1495.
- . 2008b. “Multiple Inference and Gender Differences in the Effects of Early Intervention: A Reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects.” *Journal of the American Statistical Association* 103 (484): 1481–1495.
- Ashraf, N., J. Berry, and J. M. Shapiro. 2010. “Can Higher Prices Stimulate Product Use? Evidence from a Field Experiment in Zambia.” *American Economic Review* 100 (5): 2383–2413.
- Bandiera, O. and I. Rasul. 2006. “Social Networks and Technology Adoption in Northern Mozambique*.” *The Economic Journal* 116 (514): 869–902.
- Becker, G. M., M. H. Degroot, and J. Marschak. 1964. “Measuring utility by a single-response sequential method.” *Behavioral Science* 9 (3): 226–232.

- Berry, J., G. Fischer, and R. Guiteras. 2020. “Eliciting and Utilizing Willingness to Pay: Evidence from Field Trials in Northern Ghana.” *Journal of Political Economy* 128 (4): 1436–1473.
- Biedny, C., N. M. Mason, S. S. Snapp, A. Nord, J.-C. Rubyogo, and J. Lwehabura. 2020. “Demonstration plots, seed trial packs, bidirectional learning, and modern input sales: Evidence from a field experiment in Tanzania.” .
- Boucher, S. R., M. R. Carter, J. E. Flatnes, T. J. Lybbert, J. G. Malacarne, P. Marenya, and L. A. Paul. 2021. *Bundling Genetic and Financial Technologies for More Resilient and Productive Small-scale Agriculture*. Tech. rep., National Bureau of Economic Research.
- Burchardi, K. B., J. de Quidt, S. Gulesci, B. Lerva, and S. Tripodi. 2021. “Testing willingness to pay elicitation mechanisms in the field: Evidence from Uganda.” *Journal of Development Economics* 152: 102701.
- Chavas, J.-P. and C. Nauges. 2020. “Uncertainty, Learning, and Technology Adoption in Agriculture.” *Applied Economic Perspectives and Policy* 42 (1): 42–53.
- Cohen, J. and P. Dupas. 2010. “Free Distribution or Cost-Sharing? Evidence from a Randomized Malaria Prevention Experiment*.” *The Quarterly Journal of Economics* 125 (1): 1–45.
- Conley, T. G. and C. R. Udry. 2010. “Learning about a New Technology: Pineapple in Ghana.” *American Economic Review* 100 (1): 35–69.
- Duflo, E., A. Banerjee, A. Finkelstein, L. F. Katz, B. A. Olken, and A. Sautmann. Working Paper. “In Praise of Moderation: Suggestions for the Scope and Use of Pre-Analysis Plans for RCTs in Economics.”
- Humphreys, M., R. Sanchez de la Sierra, and P. van der Windt. 2013. “Fishing, Commitment, and Communication: A Proposal for Comprehensive Nonbinding Research Registration.” *Political Analysis* 21 (1): 1–20.
- Kremer, M., G. Rao, and F. Schilbach. 2019. “Behavioral development economics.” In “Handbook of Behavioral Economics: Applications and Foundations 1,” vol. 2, 345–458. Elsevier.
- Low, J. W., M. Arimond, N. Osman, B. Cunguara, F. Zano, and D. Tschirley. 2007. “A Food-Based Approach Introducing Orange-Fleshed Sweet Potatoes Increased Vitamin A Intake and Serum Retinol Concentrations in Young Children in Rural Mozambique.” *The Journal of Nutrition* 137 (5): 1320–1327.
- McGuire, S. and L. Sperling. 2016. “Seed systems smallholder farmers use.” *Food Security* 8 (1): 179–195.
- Morgan, S. N., N. M. Mason, and M. K. Maredia. 2020. “Lead-farmer extension and smallholder valuation of new agricultural technologies in Tanzania.” *Food Policy* 97: 101955.

- Muralidharan, K., M. Romero, and K. Wüthrich. 2019. *Factorial designs, model selection, and (incorrect) inference in randomized experiments*. Tech. rep., National Bureau of Economic Research.
- Reicks, M., A. C. Trofholz, J. S. Stang, and M. N. Laska. 2014. “Impact of Cooking and Home Food Preparation Interventions Among Adults: Outcomes and Implications for Future Programs.” *Journal of Nutrition Education and Behavior* 46 (4): 259–276.
- Sankoh, A. J., M. F. Huque, and S. D. Dubey. 1997. “Some comments on frequently used multiple endpoint adjustment methods in clinical trials.” *Statistics in medicine* 16 (22): 2529–2542.
- Shiferaw, B., T. Kebede, M. Kassie, and M. Fisher. 2015. “Market imperfections, access to information and technology adoption in Uganda: challenges of overcoming multiple constraints.” *Agricultural Economics* 46 (4): 475–488.
- Shiferaw, B. A., T. A. Kebede, and L. You. 2008. “Technology adoption under seed access constraints and the economic impacts of improved pigeonpea varieties in Tanzania.” *Agricultural Economics* 39 (3): 309–323.
- Van Campenhout, B., D. J. Spielman, and E. Lecoutere. 2021. “Information and Communication Technologies to Provide Agricultural Advice to Smallholder Farmers: Experimental Evidence from Uganda.” *American Journal of Agricultural Economics* 103 (1): 317–337.