Policy Research Working Paper 9013

Targeting Inputs

Experimental Evidence from Tanzania

Xavier Giné
Shreena Patel
Bernardo Ribeiro
Ildrim Valley

WORLD BANK GROUP
Development Economics
Development Research Group
September 2019

Abstract

Input subsidy programs (ISP) often have two conflicting targeting goals: selecting individuals with the highest marginal return to inputs on efficiency grounds, or the poorest individuals on equity grounds, allowing for a secondary market to restore efficiency gains. To study this targeting dilemma, this paper implements a field experiment where beneficiaries of an ISP were selected via a lottery or a local committee. In lottery villages, the study finds evidence of a secondary market as beneficiaries are more likely to sell inputs to non-beneficiaries. In contrast, in non-lottery villages, the study finds evidence of displacement of private fertilizer sales yet no elite capture. The impacts of the ISP on agricultural productivity and welfare are limited, suggesting that resources should be directed at complementary investments, such as improving soil quality and irrigation.

This paper is a product of the Development Research Group, Development Economics. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://www.worldbank.org/prwp. The authors may be contacted at xgine@worldbank.org.

Targeting Inputs: Experimental Evidence from Tanzania*

Xavier Giné
World Bank

Shreena Patel
Millenium Challenge Corporation

Bernardo Ribeiro
World Bank

Ildrim Valley
World Bank

Keywords: input subsidies, fertilizer, trade-off.

JEL codes: C93, D24, O12, O13, Q12, Q18.

---

* Giné: xgine@worldbank.org. Patel: shreena@gmail.com. Ribeiro: bbarbozaribeiro@worldbank.org. Valley: ivalley@worldbank.org. We thank Madhur Gautam, Arianna Legovini and David Rohrbach for their constant encouragement and support and Cristina Martínez for superb research assistance. We are grateful to Michael Carter, Aparajita Goyal, Florence Kondylis, Hanan Jacoby and Sandra McCoy for very helpful comments and to DIME and 3ie for funding. The views expressed in this paper are those of the authors and should not be attributed to the World Bank, its executive directors, or the countries they represent.

1. Introduction

Agricultural input subsidies have long been suggested as a way to increase yields in places with low agricultural investment such as Sub-Saharan Africa. Critics have argued that subsidies are expensive, and they may distort the market and divert resources from other complementary investments, such as R&D, irrigation infrastructure and soil improvements. The recurring instances of food shortages and rising food prices in developing countries, however, have led to a renewed interest in agricultural input subsidies (Duflo, Kremer and Robinson, 2011; Bardhan and Mookherjee, 2011; Jayne and Rashid, 2013; Goyal and Nash, 2017). Subsidy programs are appealing because they encourage changes in farming practices that result in short-term increases in productivity and food security while putting downward pressure on food prices (Carter et al. 2014). Input subsidies alleviate farmers' credit constraints directly and may also produce a demonstration effect for neighboring farmers, reducing their perception of risk and disseminating information to farmers who were previously unaware of these technologies (Feder et al., 1985; Suri 2011; Karlan et al., 2014; Bold et al., 2017). From a political economy perspective, subsidies provide a demonstrable way for politicians to show their support to constituents (Bueno de Mesquita et al., 2003; Banful, 2011; Mason and Smale, 2013; Kilic et al., 2015; Mason et al., 2017).

A key issue in the design of any transfer program is how to target its beneficiaries. The literature has largely been concerned with the targeting of *cash* transfer programs or the delivery of public goods and services, to the poorest individuals. One way to achieve this targeting is through decentralization (Bardhan and Mookharjee, 2005; 2006). Proponents argue that decentralization increases accountability since elected officials will be subject to electoral sanctions by local citizens. In addition, local authorities may be able to implement programs in a more accurate and cost-effective way, perhaps because relevant targeting information is only available locally. In some instances, attempts by central government agencies to target the poor using mean- or proxy mean-tests could be worse than allowing the community to identify beneficiaries (Alderman, 2002; Alatas et al., 2012) or even to allow them to self-select (Jack, 2013). Critics argue however that decentralization may result in elite capture. While decentralization can harness greater accountability when local democratic institutions work properly, when these institutions are subject to special interest capture by powerful elites, then benefits can be more easily diverted towards the elite (Bardhan and Mookherjee, 2005).

In this paper we are concerned with the targeting of a program that subsidizes *inputs* and like many other "smart" input subsidy programs (ISPs), it involves a potential trade-off between efficiency and equity (Jayne and Rashid, 2013; Wiggins and Brooks, 2010 and Pan and Christiansen, 2012). If efficiency were the main goal, the program should target constrained farmers with the highest marginal productivity for input use, so that productivity and demonstration effects were maximized. In contrast, if equity were the main goal, the program should target the poorest individuals, although yield gains may not materialize if these farmers are not the most productive. In this case, the emergence of a secondary market could restore efficiency gains while compensating the poorest (Holden and Lunduka, 2012), but program implementers typically oppose the transfer of benefits. In sum, the weights placed on these two conflicting objectives by a potential ISP may result in different populations targeted by the program and thus to different impacts on agricultural productivity and welfare.

To balance concerns of efficiency and equity, ISPs typically focus on small-holder farmers. While there certainly may be productive small-holder farmers for whom both goals are satisfied, there will also be unproductive farmers among the eligible small-holder farmers. Differentiating between productive and unproductive farmers is difficult since productivity is typically not observable. In practice, ISPs may end up targeting the better off farmers that were already purchasing improved inputs from the private market, and for whom productivity gains from input subsidies are limited. Thus, public ISPs may fail to identify high productivity farmers with credit constraints, and at the same time displace private investment among non-constrained farmers.

The government-led ISP that we study in Tanzania has these two competing goals of efficiency and equity. According to World Bank (2009a), the program aims to contribute to higher food production and productivity (efficiency) by improving resource-constrained farmers' food security and livelihood (equity). The targeting of the program is decentralized and done by a local committee elected by the community. This committee may have superior information about the landholdings and agricultural productivity of prospective beneficiaries, but it may also try to allocate subsidies to committee members or to well-connected villagers (Pan and Christiansen, 2012; Kilic et al., 2015; Mason et al., 2017).

To study the extent to which this ISP achieved both goals and the scope for elite capture, we conduct a field experiment using the roll-out of the program by manipulating the identification of eligible households and the selection of beneficiaries among eligible farmers through a public lottery. In

particular, we implement a 2x2 design with two interventions. The first intervention promotes transparency in the identification of eligible households by conducting a public village-wide meeting where all adult members of the community identify the eligible farmers. The second intervention promotes transparency and fairness in the selection of beneficiaries among eligible farming households by introducing a public lottery. These two interventions randomly sort villages into 3 treatment groups and a control group: (i) villages with a public meeting and a lottery; (ii) villages with a public meeting without a public lottery, where beneficiaries were selected by the program committee; (iii) villages without the public meeting where eligible households were identified by the program committee and with a public lottery to choose the beneficiaries; and (iv) the control group of villages where the local committee identifies eligible farmers and selects beneficiaries, that is, the committee has full discretion over the allocation of vouchers.

This design allows us to assess whether the eligibility criteria, if implemented properly, would effectively select poor and productive farming households. In particular, whether village committees use these eligibility criteria when identifying eligible individuals (with or without a public meeting), and whether the most productive farmers are chosen as beneficiaries among the eligible (with or without lottery selection). In addition, the design can be used to measure the impact of the subsidy program on agricultural and welfare outcomes.

Our findings are as follows. First, the eligibility criteria do target individuals with low landholdings, suggesting that the program effectively selects the poor. Second, village committees do follow the program eligibility criteria when identifying eligible farmers, even in the absence of a public meeting. As part of the study, we asked every village committee to prepare a list of all eligible farmers that were not yet beneficiaries of the program. This list was used by the team as a starting point to conduct the village meeting where farmers not in the list could be added as eligible and farmers in the list that were not deemed as eligible could be removed. Since the village meeting resulted in few changes to the original list, we conclude that it already included most eligible farmers.

Third, unlike Pan and Christiansen (2012) who study the first year of the same program in a nearby region, we find no evidence of elite capture since none of the new beneficiaries in non-lottery villages are members of the local committee. In fact, new beneficiaries are as likely to be connected to local government officials or village influentials as non-beneficiaries are (Alatas et al., 2019).

The fact that public meetings did not affect the pool of eligible farmers from where beneficiaries were later drawn, allows us to focus on the comparison between villages with a lottery and those without it. In non-lottery villages where beneficiary selection was done directly by local committees, we find significant ex-ante and ex-post input and yield differences between beneficiaries and non-beneficiaries, suggesting that beneficiaries were significantly better off and with access to improved inputs, even in the absence of the subsidies. These differences in input use and yields translated into differences in household income and food security. The fact that beneficiaries in non-lottery villages were more likely to report having purchased the inputs in the marketplace prior to the intervention suggests that the subsidy program crowded out private investment and that it did not target the farmers with the highest marginal returns to inputs (Jayne et al., 2013). In contrast, there are no ex-ante differences in the characteristics of beneficiaries compared to non-beneficiaries in lottery villages, as predicted by randomization. There are also no ex-post differences in yields, household income or food security between beneficiaries and not. In lottery villages, however, a secondary market for vouchers seemed to emerge as beneficiaries are more likely to report having given inputs to non-beneficiaries.

Due to the ex-ante differences between beneficiaries and non-beneficiaries in non-lottery villages, we use baseline characteristics and Propensity Score Matching (PSM) techniques to select a comparable group of beneficiaries and non-beneficiaries. We find small and insignificant impacts of the program in non-lottery villages, suggesting that the significant differences between beneficiaries and non-beneficiaries using the full sample were largely due to the ex-ante differences between both groups. In lottery villages we find that non-beneficiaries have marginally higher yields and are able to sell a larger share of the agricultural production to the market than their counterparts in non-lottery village, a result also consistent with the development of a secondary market.

These limited impacts suggest that emphasis on ISPs to increase fertilizer use seems somewhat misplaced. While local committees were not captured by local elites, they failed to target constrained farmers with high marginal productivity. Vouchers were allocated to farmers who already used fertilizers, thus crowding out private investment and reducing the impact on poverty reduction. In contrast, declining soil fertility associated with rising land pressures and continuous cultivation, poor soil management practices, and rainfed farming conditions hold more potential as explanations for the limited ability of Tanzanian farmers to use fertilizer profitably, and public resources should be directed at addressing these complementary investments (Jayne and Rashid, 2013; Goyal and Nash, 2017).

The remainder of the paper is organized as follows. Section 2 describes the context of our intervention. Section 3 describes the experimental design and the data collected. Section 4 describes the empirical framework and the results. Section 5 concludes.

2. Context

Agriculture is central to the Tanzanian economy and is inextricably linked to food security, household income, poverty reduction, and health. It accounts for 27 percent of GDP, 80 percent of employment, 75 percent of rural household incomes, and provides over 95 percent of Tanzania's annual food requirement (World Bank, 2009b). Agricultural productivity, however, is a persistent challenge for most small-holder farmers in Tanzania and across Africa. Agriculture is almost entirely rainfed, crop yields are 20–30 percent of potential, and the use of improved inputs is low (Duflo et al. 2008; Suri, 2011).

In an effort to increase agricultural productivity following the 2007/8 food crisis, the Ministry of Agriculture, Food Security and Cooperatives of Tanzania (MAFC) launched the National Agricultural Input Voucher Scheme (NAIVS) with funding from the World Bank. The goal of the voucher scheme was to boost food production and reduce pressure on food staple prices. In addition, the program aimed to bolster food security by encouraging smallholder farmers to adopt improved seed varieties and experiment with the use of chemical fertilizers, at a time when the costs of grain shortfalls and associated prices of grain imports were particularly high.

NAIVS aimed to provide vouchers for 50 percent subsidies on fertilizers and improved seeds to 2.5 million farming households growing rice and maize in 65 districts in the Southern and Northern Highlands and the Western region. The subsidy package for maize farmers included improved seeds, basal fertilizer (DAP), and top-dressing fertilizer (urea) for one acre of land. Farmers received one voucher for each of the three inputs, which could be redeemed at registered agro-dealers in their village or nearby villages. By presenting the voucher, beneficiary farmers only needed to pay in cash the remaining "top-up" value of the inputs, that is, the difference between the market price of the inputs and the face value of the voucher (subsidy). The expectation of the program was that farmers would continue to purchase improved inputs once convinced of their benefits.[1] At the time of the study in 2010, the total

[1] Beneficiaries of the program were supposed to receive vouchers for a maximum of three years so that they would learn about the improved inputs and then begin purchasing them on their own after graduating from the program. The three-year graduation policy, however, was not enforced. According to our data, 60 percent of households that had been in the program for three years still claimed to receive vouchers in the fourth year (World Bank, 2014).

cost of inputs was USD 68 and the voucher provided a subsidy of USD 35.[2] See Section A1 of the Online Appendix for details on subsidized input package and input pricing.

The NAIVS program also strengthened the supply chain through the emergence of new agro-dealers at the village level. According to our data, 80 percent of village agro-dealers reported having started their business in 2008 (when the voucher program started), or later. Moreover, 80 percent of agro-dealers surveyed in 2012 also reported being registered for the NAIVS program.

The eligibility criteria for NAIVS followed the Abuja Declaration of 2006 stressing a commitment to "smart" subsidies that supported the development of private sector fertilizer markets and targeted smallholder farmers with currently low but potentially profitable fertilizer use (Burke et al., 2017; Morris et al., 2007). In particular, farmers (i) had to cultivate no more than 1 hectare of maize or rice, (ii) should not have used chemical fertilizer or improved seeds in the previous 5 years, and (iii) were able to afford the top-up payment. Furthermore, among eligible farmers, priority was given to female-headed households.[3]

These eligibility criteria underscore the dual objectives of the subsidy program—to increase the usage of improved seed and inorganic fertilizer to boost food production (efficiency) while targeting the small landholders to increase food security among the poor (equity).

In every village, the beneficiary selection process and voucher distribution were overseen by the Village Voucher Committee (VVC) formed by 3 men and 3 women elected by the village. According to the NAIVS guidelines, the VVC was only elected once and thus perhaps less subject to elite capture as it was not accountable to electoral pressure. According to column 2 of Panel A in Table 1, while almost all VVCs were made up of 3 men and 3 women, virtually none of its members were elected. Rather, they were typically appointed by local government officials. Panel B of Table 1 reports the characteristics of VVC members. Most VVC members were married (90 percent), lived in a house with a concrete floor

[2] Each voucher had a face value of approximately 50 percent of the market price of the input. Because vouchers were printed before farmers bought their inputs, the level of subsidy reflected in the vouchers' face value was only an approximation, based on projected input prices when the vouchers are printed. If market prices moved higher (lower) than the projection, the level of subsidy to the farmer was less (more) than 50 percent.

[3] If the household head and his sons cultivate different land, and total landholdings of each individual meets the eligibility criteria, then they could all be eligible and end up receiving two or more packages of vouchers. Head and spouse will not qualify separately, but head and children (mostly sons) could. In our data, however, we did not encounter multiple beneficiaries from the same household.

(63 percent), and cultivated less than 1 hectare (56 percent). In addition, roughly 90 percent of VVC members could read and write, and they were knowledgeable of their responsibilities and the NAIVS eligibility criteria. Table OA3 in the Online Appendix compares the characteristics of VVC members (column 3) to those of a random sample of villagers (column 1) and a random sample of NAIVS-eligible households that were not yet beneficiaries at baseline (column 2). Columns 6, 7 and 8 report the p-value of these comparisons. Compared to the average villager, VVC members tend to have similar housing quality but smaller landholdings (column 7). In comparison with households eligible for the subsidy program, however, VVC members appear to be better off, living in better housing and having more cultivable land (column 8).

Before selecting beneficiaries, the VVC was tasked with preparing a list of eligible farmers. In practice, they used the list of farmers kept by government officials and selected those that met the eligibility criteria. Once the list was finalized, the VVC selected from it as many beneficiary farmers as the number of packs of three vouchers that were allocated to the village.

The allocation of vouchers across villages in a district, across districts in a region and across regions in the country was done by the District, Regional, and National Voucher Committees, respectively. In this paper we focus on the allocation of vouchers within a village, and not across villages, districts, or regions. See Section A2 of the Online Appendix for details on the institutional arrangement of the NAIVS program.

3. Experimental design and data

3.1 Interventions

The experiment is designed to explore the efficiency-equity trade-off faced in the targeting of NAIVS and the scope for elite capture when eligibility identification and beneficiary selection are decentralized. We do so by manipulating the identification of eligible farmers and selection of beneficiaries among those eligible. We exploit the fact that the number of vouchers available to be distributed to new beneficiaries increased from the 2009/10 season to the 2010/11 season. In 2008, MAFC estimated that 2.5 million households would be eligible for the program, but the government had distributed vouchers to only 1.5 million households during the 2009/10 season and was planning to expand the program to 2 million households in the 2010/11 season.

The original plan was to conduct the experiment in three districts, one in each of two regions in the north (Arusha and Kilimanjaro), and in one region in the south (Morogoro), all with bi-modal rainfall that allows for two cropping seasons.[4] From each of the three districts, we sampled around 40 villages that planned to receive an increase in the number of vouchers.

While preparing for the launch of the intervention, the team of researchers and MAFC staff that helped design the intervention was in direct communication with the NAIVS regional authorities in Arusha. Villages in Arusha that expected an increase in the number of vouchers were told to wait for a delegation from MAFC before any new beneficiary was identified. In Kilimanjaro and Morogoro, however, communication problems prevented such coordination and by the time the MAFC teams visited the selected villages to implement the intervention, the VVC in those villages had already identified and notified the new beneficiaries. As a result, while the team visited all three study regions, the intervention was only successfully implemented in Arusha. In the analysis of Section 4, we thus restrict the analysis to the 46 Arusha villages where a factorial 2x2 design with the following experimental arms was implemented.

Eligibility Identification: To increase transparency in the identification of eligible households, in half of the study villages, a 2-3-person team led by a representative of MAFC and the VVC facilitated a public meeting of the Village Assembly to identify eligible households to receive the new 2010 voucher allocation, following the strict enforcement of NAIVS eligibility criteria. The number of new packs of three vouchers received by village *i* in 2010/11 season (X_i^{2010}) was not known at the time of the intervention. During this meeting, the MAFC team publicly read the names in the list of eligible farmers prepared by the VVC and checked with the Village Assembly that each farmer complied with the eligibility criteria and whether no two members of the same household were listed. Once every name in the list had been read, the MAFC team asked the Village Assembly to name any farmers who they believed were eligible but had not been previously mentioned and were not yet beneficiaries of the voucher program.

On average, about 80 individuals attended the Village Assembly (either for the eligibility identification or the beneficiary selection). This validation process took around one hour and a half, on average. In

[4] The research team chose these regions with bi-modal rains due to the later start date of the planting season which allowed for the interventions prior to the distribution of the 2010/11 vouchers.

practice, the resulting list was not different from the original list produced by the VVC, suggesting that few names were added or subtracted. The list, however, always contained more individuals than the actual number of voucher packs each village ended up receiving. This means that only a subset of farmers in the list of eligible farmers would become new beneficiaries.

Beneficiary Selection: To increase transparency and fairness in the selection of beneficiaries, in half of the study villages, the intervention team facilitated a public lottery to select X_i^{2010} new voucher beneficiaries from the list of eligible farmers. In the presence of the Village Assembly, the names of all eligible farmers were placed in a basket and beneficiaries were randomly selected. This list of beneficiaries was then ratified by the Village Assembly and displayed publicly in a prominent place in the village. In practice, it took close to two hours to conduct the lottery.

Figure 1 describes the 2x2 factorial design that divides study villages into four bins according to the interventions implemented in each village. While the public meeting with the Village Assembly allows us to assess whether the identification of eligible households is done following the program eligibility criteria, the lottery assesses whether the farmers with highest marginal returns to inputs are selected as beneficiaries among the eligible households and the scope of elite capture. These interventions answer the following questions: Do VVC members identify all potential eligible households, regardless of their productivity? And among the eligible households, do they select only productive households, or their friends and kin?

3.2 Data

This paper uses survey data from 4 different sources. First, in every study village we conducted a *villager* household survey of 16 households drawn at random. This survey asked basic socioeconomic characteristics, beneficiary status and whether the household met the NAIVS eligibility criteria. Second, we conducted a survey with one male and one female member of the VVC to assess their understanding of the eligibility criteria, the process of beneficiary selection and their socioeconomic characteristics. Third, we collected village level data related to access to services, prices and the implementation of the NAIVS program. The respondent for the village survey was the Village Executive Officer or VEO, a government-appointed official in the village. Finally, we administered surveys to 10 *eligible* households that had not received vouchers in the 2009/10 season. Five of these eligible households would receive vouchers in the 2010/11 season while the other five would not. To draw this sample, we used the VVC

records of eligible households that were compiled from the list of farmers kept by the village extension officer, when available. This list of eligible farmers recorded the name and gender of the household head as well as the area of land under cultivation of maize and rice. The VVC checked the farmer list against the eligibility criteria to come up with the list of eligible farmers.

The baseline data collection took place in January and February of 2011 immediately after the implementation of the village-level interventions in the three regions of Arusha and Kilimanjaro in the North, and Morogoro Region in the South.

In Arusha we collected baseline data for 460 households. Since the intervention was only successfully implemented in the 46 Arusha villages, at endline we doubled the number of observations for the eligible household survey, resulting in a sample of 920 households. The criteria used to draw the additional sample were the same as in the baseline eligible survey: eligible beneficiaries were defined as those that began participating in NAIVS during the 2010/11 planting season, and eligible non-beneficiaries were defined as those that were eligible to participate in 2010/11 but were not selected as beneficiaries. Table OA4 in the Online Appendix suggests that the baseline sample and the additional sample are comparable. Endline data were collected in July and August of 2012. The households that participated in the baseline villager survey were also revisited.

Table 1 reports the mean of village level characteristics in Panel A from the village survey, VVC member characteristics in Panel B from the VVC survey and household member characteristics in Panel C from the villager survey. Column 1 of Table 1 reports the data source, column 2 reports mean characteristics across all villages, columns 3 and 4 report the means in lottery and non-lottery villages, respectively, and columns 6 and 7 report the means in meeting and no-meeting villages. Columns 5 and 8 show balance across experimental arms by reporting the p-values associated with a t-test that the differences in characteristics are different from zero.[5]

According to column 2 of Panel A in Table 1, there are on average 407 eligible farmers per village and about 67 percent of them were beneficiaries in 2010. Only 9 percent of households have access to electricity. About 59 percent of villages have a health clinic or hospital and almost all have a primary

[5] The p-values reported account for clustering at the village level. Since the number of clusters (villages) is 47, we use the t-asymptotic wild cluster bootstrap procedure described in Cameron et al. (2008).

school (not shown). On average, villages have 1 agro-dealer and the NAIVS subsidy as a share of the total cost of inputs is 48.6 percent.

The villager survey included a couple of questions regarding the social and/or political connections of respondents. In particular, respondents were asked whether they were related to or socialized with government or NAIVS officials such as the Ward Executive Officer (WEO), the VEO, the District Agriculture and Livestock Development Officer (DALDO), or any VVC member or village influential such as the hamlet, village or ward chairs.[6] Column 2 of Panel C in Table 1 reports that 22 percent of villagers were related to government officials or influential, and 21 percent socialized with them regularly. In addition, 68 percent of villagers had used improved seeds during the 2009/10 season and 48 percent had used inorganic fertilizer (mostly urea).

We find no differences across treatment arms in any of the panels in Table 1. We report the p-value of a joint F-test that all the characteristics reported in a given panel do not predict being assigned to a lottery (column 5) or an open meeting village (column 8). None of the p-values reported is significant at conventional levels (the lowest p-value is 0.385). The different treatment arms thus appear to be balanced.

4. Results on Targeting and Impacts

4.1 Targeting

We use the villager survey to first study whether the eligibility criteria successfully identified the poor. While only the eligible household survey instrument collected food security, we use landholdings as a proxy for poverty as they were collected across all surveys. Using the eligible household survey, we find that the correlation between landholdings and food security is 0.13 and highly significant (p-value is 0.000). Figure 2 shows the distribution of landholdings and the average landholdings among eligible households, that is, those that cultivated less than 1 hectare, and not-eligible households. We find that the NAIVS eligibility criteria successfully targeted farmers at the bottom of the distribution of

[6] The DALDO, WEO and VEO are appointed by the district government. In contrast, the village or ward chairman are hereditary titles. We also asked at baseline the political party supported by the head of the household. Although there are no differences between the different treatment groups, 90 percent of the respondents reported supporting the same party, Chama Cha Mapinduzi (CCM), the ruling party in Tanzania at the time of the study. Only around 7 percent reported supporting the main opposition party (Chadema) and 2 percent chose not to answer.

landholdings. The average eligible household owns 0.8 hectares corresponding to the 28th percentile while the average non-eligible household owns 1.3 hectares which corresponds to the 69th percentile of the distribution of landholdings.

Figure 3 reports the targeting by landholdings. In particular, it reports the percentage of beneficiaries in each landholding quintile from the villager survey, for the start of the program in 2008/09 as well as the year of the intervention 2010/11. At the start of the NAIVS program, households with more land were also more likely to become beneficiaries. Participation in NAIVS among farmers in the lowest landholding quintile was only 5 percent and it increased to 10 percent among farmers in the highest quintile. This finding is consistent with results from Zambia and Malawi (Jayne et al., 2016; Goyal and Nash, 2017). By the year of the intervention, however, the probability of participation was roughly constant at around 15 to 20 percent across landholding quintiles.

Table 2 complements Figure 3 as it also reports improvements in the targeting of NAIVS between the start of the program in 2008/09 and the year of the intervention 2010/11. Panel A of Table 2 reports data from all villages, Panel B from study villages in Arusha, and Panel C and Panel D from non-study villages in Kilimanjaro and Morogoro, respectively. We focus on three of the eligibility criteria that can proxy for liquidity constraints, namely, whether the beneficiary had used hybrid seeds or chemical fertilizer prior to the start of the NAIVS program and whether they cultivated less than 1 hectare. Recall that eligible individuals should not have used improved inputs prior to becoming a beneficiary since purchasing inputs at market prices would signal that they are not credit constrained and thus may not have the highest marginal returns. Based on these three eligibility criteria, Table 2 reports the percentage of beneficiaries that meet all three criteria. In all panels, the targeting of NAIVS improves over time as the percentage of new beneficiaries who are eligible increases from the first year of NAIVS, 2008/09 to the 2010/11 season. In study villages, the percentage of beneficiaries who are eligible increases from 24 percent in 2008/09 to 46 percent in 2010/11. Following Galasso and Ravallion (2005) and Pan and Christiansen (2012), we define the targeting differential T_v in village v as:

$$T_v = \frac{B_{Ev}}{E_v} - \frac{B_{NEv}}{NE_v}$$

where B_{Ev} are the number of eligible beneficiaries in village v, E_v is the number of eligible individuals in village v, B_{NEv} is the number of beneficiaries that are not eligible while NE_v is the number of non-

eligible individuals in village v. The targeting differential can range from $T_v = -1$, where the program in village v fully covers all non-eligible individuals with no benefits going to eligible individuals, to $T_v = 1$, where only eligible individuals are beneficiaries and they are all covered by the program. We find that the targeting differential has improved in the 2010/11 season compared to the start of the program, and that the targeting in study villages in Arusha is worse compared to Morogoro but much better than in Kilimanjaro. In fact, targeting in Kilimanjaro by 2010/11 was only 6 percent (0 percent would be consistent with lack of targeting, that is, when eligibility status plays no role in who becomes a beneficiary). In contrast, the targeting in Arusha by 2010/11 is 30 percent.

Table OA5 in the Online Appendix uses data collected at baseline to compare baseline characteristics of eligible households in the three regions of Arusha, Kilimanjaro and Morogoro. Households in Arusha appear to be richer and more educated than those in either of the other two regions. This perhaps explains the overall higher use of improved seeds and chemical fertilizer prior to 2008/09 in our study villages compared to villages in Kilimanjaro or Morogoro. Taking together the results of Table 2 and Online Appendix Table OA5, households and villages may not be readily comparable across regions but the trends in targeting over time are roughly similar.

Table 3 uses data from the eligible survey to compare the characteristics of eligible households that became beneficiaries to those that did not in lottery villages (columns 3-4) and in non-lottery villages (columns 7-8). Column 1 of Table 2 reports the data sources, column 2 the mean of the characteristics of all eligible farmers interviewed in lottery villages, and column 6 reports the analogous mean for eligible farmers interviewed in villages without the lottery. P-values associated with a t-test that the characteristics of beneficiaries and non-beneficiaries are different from zero in lottery and no lottery villages are reported in columns 5 and 9, respectively, and calculated using the t-asymptotic wild cluster bootstrap procedure (Cameron et al., 2008).

According to column 5, we find no statistically significant differences in the characteristics of beneficiaries and non-beneficiaries in lottery villages, except for past maize yields. While beneficiaries appear to have higher yields during the year prior to the intervention, non-beneficiaries seem to have used fertilizer more often compared to beneficiaries, although the difference in fertilizer use is not statistically significant. In contrast, in non-lottery villages beneficiaries appear to be younger, more able

to read and write, have higher Raven's test scores (which is a proxy for raw intelligence), and have higher food security than non-beneficiaries.

In addition, around 18 and 16 percent of respondents reported, respectively, being related and socializing with government officials or village influentials. Interestingly, beneficiaries are comparable to non-beneficiaries in both lottery and non-lottery villages (p-values of t-tests that individuals are related or socialize with government officials or influentials are 0.486 and 0.558, respectively in lottery villages and 0.467 and 0.731, respectively in non-lottery villages). This result suggests an absence of elite capture in the targeting process, as we will argue more precisely in Section 5.

More generally, a joint F-test that all the characteristics reported in Table 3 do not predict beneficiary status in lottery villages is not statistically significant at conventional levels (p-value is 0.903) but it is highly significant in non-lottery villages (p-value is 0.008).

This indicates that in lottery villages there are no statistical differences between beneficiaries and non-beneficiaries, as randomization would suggest. In contrast, in non-lottery villages where the VVC chose beneficiaries among eligible, beneficiaries are systematically different from non-beneficiaries in a way that the VVC appears to be targeting more educated and better off farmers.

The last 3 columns of Table 3 compare the characteristics of eligible households in villages which held public meetings to identify eligible farmers (column 11) to those that did not (column 12). As column 13 suggests, none of the characteristics appear significant, suggesting that conducting the public meeting did not affect the pool of individuals identified as eligible. The p-value associated to the joint F-test that all variables jointly determine eligibility with a public meeting is 0.946.[7] This result is perhaps unsurprising because according to the MAFC team that conducted the meetings, few changes were made to the list of eligible farmers prepared by the VVC in all study villages. We conclude that the public meeting did not alter the identification of eligible households significantly.

4.2 Impacts

By virtue of the experimental design, and given that the village meeting had no impact on the

[7] Due to differences in the number of observations between baseline and endline surveys we replicate the results of Table 1 restricting the sample to 427 of the 460 households surveyed at both baseline and endline and find similar results.

identification of eligible farmers, the intent to treat (ITT) effects of being a beneficiary of the ISP via the lottery can be estimated with the following equation:

$$Y_{ij} = \alpha_{ij} + \beta_B Beneficiary_{ij} + \beta_L Lottery_j + \beta_{BxL} Beneficiary_{ij} \text{ x } Lottery_j + \varepsilon_{ij}, \quad (1)$$

where Y_{ij} is a given outcome for household *i* in village *j*, $Beneficiary_{ij}$ is a dummy variable that takes value 1 if household *i* in village *j* was selected as a beneficiary according to the administrative data and $Lottery_j$ is a dummy variable that takes value 1 if a public lottery was used to select beneficiaries in village *j*. The term ε_{ij} is a mean-zero error. Since the treatment assignment of lottery was done at the village level, we take seriously the fact that the number of villages (clusters) may be small and compute p-values using the t-asymptotic wild cluster bootstrap procedure described in Cameron et al. (2008).[8] In the tables we report the p-values (and not the standard errors) associated with the test that the estimated coefficient is zero. Equation 1 is estimated via OLS when the dependent variable is binary to facilitate the interpretation of the coefficients. Alternatively, we use Tobit specifications when the dependent variable is truncated.

In Tables OA9 and OA10 of the Online Appendix, we report the results of running the following specification that allows for the impacts of the two different interventions separately:

$$Y_{ij} = \alpha_{ij} + \beta_B Beneficiary_{ij} + \beta_{ML} ML_j + \beta_L Lottery_j + \beta_M Meeting_j + \beta_{BxML} Beneficiary_{ij} \text{ x } ML_j + \beta_{BxL} Beneficiary_{ij} \text{ x } Lottery_j + \beta_{BxM} Beneficiary_{ij} \text{ x } Meeting_j + \varepsilon_{ij}, \quad (2)$$

where now the dummy variable $Meeting_j$ indicates whether village *j* had a public meeting to identify eligible farmers, and ML_j represents the interaction of village meeting and lottery selection of beneficiaries for village *j*.

The coefficients of interest in Equation 1 are the β coefficients and measure the impact of the lottery intervention. Specifically, β_B measures the impact of the program on beneficiaries in non-lottery villages

[8] Unlike standard bootstrap methods that compute the Wald statistic from the bootstrap estimated standard error, the t-asymptotic procedure directly bootstraps the Wald statistic to form inference. This bootstrap procedure provides asymptotic refinement over standard methods of inference for OLS with clustered data. Moreover, it provides a more accurate cluster-robust inference when the number of clusters is small.

relative to non-beneficiaries in the same villages. Coefficient β_L measures the impact of the program on non-beneficiaries in lottery villages compared to non-beneficiaries in non-lottery villages. Finally, the coefficient β_{BxL} measures the differential impact of the program on beneficiaries in lottery villages relative to non-beneficiaries in these same villages.

Table 3 makes clear that in lottery villages, the randomization produces two groups (beneficiaries and non-beneficiaries) that have similar observable and unobservable characteristics. In non-lottery villages, however, the VVC chose beneficiaries that were more educated and better off. As a result, differences in outcomes between beneficiaries and non-beneficiaries could be driven by the program or by pre-existing differences in observable and unobservable characteristics between the two groups (Lalonde, 1986). As a result, when assessing the impact of the program on agricultural and welfare outcomes, we use propensity score matching to find a valid control group in non-lottery villages. We thus also report estimates of Equation 1 restricting to the matched sample of beneficiaries and non-beneficiaries with similar observable characteristics before the intervention.

We note also that less productive beneficiaries in lottery villages may have given away or sold part of the subsidized inputs to perhaps non-beneficiaries in the control group. Because such a market for inputs did not develop in non-lottery villages, we can assess its impact on agricultural and welfare outcomes in lottery villages by using the matched sample and comparing non-beneficiaries in lottery villages to non-beneficiaries in non-lottery villages.

Before we describe the impacts of NAIVS on agricultural and welfare outcomes, we first focus on the impacts of the lottery and of being a beneficiary on awareness of the program, implementation and satisfaction, displacement of sales and the scope of elite capture among the sample of eligible households.

4.2.1 Program awareness and implementation

Column 1 of Table 4 presents the OLS estimate of Equation 1 using as dependent variable a dummy that takes value of 1 if the respondent reports being aware of the NAIVS program in the village. The coefficient β_B on the dummy variable *Beneficiary* indicates that beneficiaries were roughly 10 percentage points more aware of the program than non-beneficiaries (p-value is 0.007), suggesting that some farmers might have learned about the program only after being selected as beneficiaries.

Awareness of the NAIVS program among non-beneficiaries in non-lottery villages is high at 86 percent. In addition, there seems to be no difference in awareness between non-beneficiaries in lottery and non-lottery villages as the coefficient β_L on the dummy variable *Lottery* is small and not statistically significant.

Column 2 of Table 4 reports whether the farmer was asked about his or her ability to afford the top-up when the VVC assessed his or her eligibility for the NAIVS program. This is important because the VVC reported to us anecdotally that they "knew" who could and could not pay and only offered the vouchers to those that could pay. Put differently, the ability to pay the top-up could have been used by the VVC as an excuse to target the program to specific individuals. Indeed, becoming a beneficiary increases the probability of being asked about the ability to pay for the top-up by roughly 8 percentage points (a 54 percent increase from a base of 15 percent among non-beneficiaries in non-lottery villages). This increase, however, is only weakly statistically significant at conventional levels (p-value is 0.093) and there is no difference among non-beneficiaries in lottery and non-lottery villages.

Columns 3 and 5 of Table 4 use as dependent variable whether beneficiaries report receiving the pack of vouchers in the seasons 2010/11 and 2011/12, respectively. Since we use administrative data to determine the beneficiary status of individuals, there are differences between the administrative data and the self-reported voucher allocation. Indeed, according to columns 3 and 5, around 22 percent in 2010/11 and 24 percent in 2011/12 of individuals classified as non-beneficiaries, respectively, claimed to receive vouchers in non-lottery villages. As expected, becoming a beneficiary increases significantly the probability of reporting having received the pack of three vouchers. This increase corresponds to around 34 percentage points in 2010/11 and 17 percentage points in 2011/12. While treatment compliance is far from perfect, beneficiaries in lottery villages are equally likely to receive the vouchers compared to beneficiaries in non-lottery villages. This suggests that the VVC did not interfere with the (random) allocation of vouchers generated by the lottery and distributed vouchers to beneficiaries once they were identified similarly in both lottery and non-lottery villages.

While columns 3 and 5 assess whether beneficiaries according to the administrative data actually received the packs of vouchers, we can restrict the sample to self-reported beneficiaries and examine the number of different inputs they claim to have purchased with vouchers, out of the three possible inputs. We find that beneficiaries purchase on average 2.3 inputs, irrespective of whether the lottery took place

to select beneficiaries. We know from MAFC administrative data that all agro-dealers claimed to the partner bank NMB that *all* of the vouchers distributed in 2010/11 had been redeemed, and so there is a discrepancy between the number of inputs that beneficiaries purchased with vouchers, and the number of vouchers claimed by agro-dealers for payment (see Section A.2 of the Online Appendix for details of the process that agro-dealers followed to redeem the vouchers collected from beneficiaries). This suggests that agro-dealers either forced farmers to sign and turn over all three vouchers while only selling two of the three inputs on average, or agro-dealers allowed the face value of one voucher to be used as top-up for the purchase of the two inputs. For example, for the purchase of urea, the farmer would hand out the urea and DAP voucher and use all or part of the face value of the DAP voucher towards payment of the urea top-up.

We also checked whether the quantity of inputs purchased with vouchers corresponds to the package designed by MAFC and find that it is the case. That is, for each input purchased, farmers bought the amount stipulated by the program (enough for 1 acre of land), but they only purchased two of the three inputs, on average, even though agro-dealers claimed that farmers had redeemed all three vouchers.

Column 4 of Table 4 reports satisfaction with the selection process of beneficiaries. The dependent variable takes value 1 if the respondent reported being very satisfied with the selection of voucher beneficiaries in 2010/11. We find that, unsurprisingly, beneficiaries are 16 percentage points more likely to report being satisfied with the selection process compared to non-beneficiaries. Interestingly, non-beneficiaries in lottery villages are 11 percentage points more likely to report being satisfied with the selection process than non-beneficiaries in non-lottery villages (an increase of 18 percent from a base of 62 percent). In fact, in lottery villages there is no difference in satisfaction between beneficiaries and non-beneficiaries (p-value is 0.396). Arguably, respondents in lottery villages may think that a lottery is a fairer method of choosing beneficiaries compared to selection by the VVC.

4.2.2 Displacement of sales

While column 4 of Table 4 shows higher satisfaction among farmers when a lottery is used to select beneficiaries, the lottery could randomly select as beneficiaries less productive farmers, and as a result, one would expect more transfers of inputs from (less productive) beneficiaries to (more productive) non-beneficiaries in a secondary market for inputs.

Column 1 of Table 5 thus studies the extent to which inputs purchased with vouchers were given to other farmers. Each observation in the specification in column 1 of Table 5 corresponds to a link between a respondent and a friend. The dependent variable is a dummy variable that takes the value of 1 if the respondent reported giving agricultural inputs to a non-beneficiary friend.[9] Column 1 shows evidence consistent with the emergence of a secondary market for inputs in lottery villages, where beneficiaries are 9 percentage points more likely than non-beneficiaries to give inputs to others (p-value is 0.017). Similarly, non-beneficiaries in lottery villages are 9 percentage points less likely to give inputs to others compared to non-beneficiaries in non-lottery villages (p-value is 0.014). In sum, while the lottery produced an allocation that is more equitable, a secondary market for inputs seemed to emerge to mitigate the potential efficiency losses.

In non-lottery villages, the VVC targeted younger, more educated and richer farmers (see Table 2). It is therefore important to ask whether beneficiaries in non-lottery villages were already buying inputs at market prices prior to becoming beneficiaries, in which case, the ISP only reduced the cost of acquiring inputs, crowding out private investment.

Columns 2 and 3 of Table 5 look at the extent of crowding out. The dependent variables are dummies that take the value of 1 if the respondent reported having used inorganic fertilizers (column 2) and improved seeds (column 3) in 2009/10, the season prior to the intervention. There is some evidence of crowding out for fertilizer but not for improved seeds. In non-lottery villages, beneficiaries are 13 percentage points more likely to have used inorganic fertilizer in the previous season compared to non-beneficiaries (column 2 of Table 5). In contrast, in lottery villages, it is the non-beneficiaries who appear more likely to have used fertilizer in the past, compared to the beneficiaries. This last result is probably a fluke since Table 2 reports that thanks to the randomization by the lottery, there were no major differences between beneficiaries and non-beneficiaries in lottery villages. We thus conclude that columns 2 and 3 are suggestive of input displacement, especially in non-lottery villages.

We note, however, that this crowding out may have been facilitated by the growth of NAIVS as the increased demand for improved inputs from the vouchers led to the development of a network of agro-dealers that made inputs available at the village level. As mentioned in Section 2, 80 percent of village agro-dealers reported having started their business around the time that NAIVS started or later and most

[9] The number of contacts is the number of reported friends. Some respondents reported more than one friend while others reported none. In total, 294 respondents reported 523 friends. There are no differences between lottery and non-lottery villages in the probability of reporting one or more friends.

were registered to handle vouchers for the NAIVS program. Prior to the program, most agro-dealers were located in towns.

4.2.3 Elite capture

Being a decentralized institution, the VVC may be subject to elite capture, that is, members of the VVC or their friends and relatives could have influenced the allocation of vouchers, tilting it to their own benefit. In non-lottery villages, therefore, the VVC may have targeted their own members, or their relatives and friends who may also happen to be more educated and richer as seen in Table 2.

To assess the extent of elite capture, we use two variables reported in Table 2 that were collected at baseline and that capture social connections between respondents and local authorities. In column 4 of Table 5, the dependent variable is a dummy that takes the value of one if the respondent holds the position or is related to Ward Executive Officer (WEO), the VEO, the District Agriculture and Livestock Development Officer (DALDO) or any VVC member or village influential such as the hamlet, village or ward chairs. In column 5, the dependent variable is a dummy that takes the value of one if the respondent has social interactions with office holders and other authority figures. Finally, in column 6, the dependent variable is a dummy that takes value of one if the individual reports having paid to become a beneficiary of NAIVS at the time of the intervention in 2010/11.

In columns 4-6, the point estimates are neither economically large nor statistically significant at conventional levels. All these government officials and influentials would be classified as formal elites in Alatas et al. (2019). They find some elite capture of formal elites but that eliminating it would result in less than 1 percent of welfare gains. These results contrast those in Pan and Christiansen (2012) who observed that households with members holding elected positions or in the VVC in the Kilimanjaro region were significantly more likely to be selected as beneficiaries during the 2008/09 season, the first season of NAIVS. Table 2 reports the percentage of beneficiaries that were related to government officials or influentials both for the initial 2008/09 season as well as the 2010/11 season when the intervention was implemented. Interestingly, in the Kilimanjaro region we find that 43 percent of beneficiaries in 2008/09 were related to government officials or influentials. This number is comparable to the 58 percent in Pan and Christiansen (2012). In the 2010/11 season the percent of beneficiaries that are connected is 30 percent. In contrast, in our study villages, only 21 percent of beneficiaries were related to government officials or influentials in 2008/09 and 22 percent in 2010/11.

We can further assess the extent of elite capture and mistargeting of NAIVS over time in our study villages in Arusha compared to those in Kilimanjaro by running the main specification in Alatas et al. (2019):

$$Y_{ij} = \alpha + \beta_1 Related_{ij} + \beta_2 Eligible_{ij} + \varepsilon_{ij} \ , \tag{3}$$

where Y_{ij} is a dummy that indicates whether household i in village j reported being a NAIVS beneficiary, $Related_{ij}$ is a dummy that takes the value of 1 if the head of household i in village j reports holding the position or being related to the DALDO, WEO, VEO, VVC member, Village Chair or Hamlet chair, and $Eligible_{ij}$ is a dummy that indicates whether household i in village j is eligible in the 2008/09 season for the NAIVS program (i.e. had not used improved inputs prior to the start of NAIVS and had cultivated less than 1 Ha of land). We use baseline and follow-up data from the Villager survey and report the OLS estimates of Equation 3 in Table 6. We run separate regressions for the 2008/09 and 2010/11 seasons in Arusha (columns 1 and 2, respectively) and Kilimanjaro (columns 3 and 4, respectively).

In Arusha villages, being related to government officials or influentials is not correlated with being a NAIVS beneficiary in either 2008/09 season (column 1) or 2010/11 season (column 2). In both columns, the coefficient β_1 is small and not statistically different from zero at conventional levels. In contrast, political connections played a role in voucher distribution in the 2008/09 season in Kilimanjaro (column 3), consistent with the findings of Pan and Christiansen (2012), Kilic et al. (2015) from Malawi and Mason et al. (2017) from Zambia. Column 3 reports that being related to government officials or influentials increased the probability of receiving vouchers by 3.2 percentage points, an increase of 60 percent over the mean of 5.4 percent among non-eligible individuals that were not related to government officials or influentials. By 2010/11, however, the elite capture is no longer significant. Table 6 confirms the results that elite capture was only present in Kilimanjaro, especially in the 2008/09 season, but not in Arusha.

Table 6 also complements the findings in Table 2 and Figure 3 that targeting improved over time, especially in Arusha villages. For a well targeted program, one would expect a positive correlation between eligibility and being a beneficiary. In the 2008/09 season, however, being eligible for the NAIVS program was actually negatively correlated with self-reported beneficiary status (column 1). By

the 2010/11 season, the correlation between eligibility and becoming a beneficiary during that season was positive and significant, as expected. In contrast, eligibility played no role in Kilimanjaro for neither season. The coefficient β_2 on the dummy $Eligible_{ij}$ in columns 3 and 4 are negative and not statistically different from zero. This finding reinforces the point that the implementation of NAIVS was different in Arusha compared to Kilimanjaro.

4.2.4 Agricultural and welfare impacts

Columns 1-6 of Table 7 report various agricultural outcomes using the full sample of 920 farmers at endline. The dependent variable in column 1 is a dummy that indicates whether or not the household cultivated maize during the 2010/11 season. In columns 2-6, each observation corresponds to a plot. The dependent variable in column 2 is area planted, in column 3 is basal fertilizer use in kilograms (DAP) while in column 4 it is total fertilizer use in kilograms, including DAP and urea. Columns 3 and 4 run a Tobit specification because there is a large percentage of zeros. Column 5 reports results on crop failure while column 6 on log yield (Kg/acre) over total area planted area.

We find that in non-lottery villages beneficiaries are slightly less likely to grow maize (3.2 percentage points over a high average of 95% of maize growing households), and that beneficiaries are not more likely to cultivate larger plots in either lottery nor non-lottery villages. In non-lottery villages, beneficiaries use around one more bag (50kg) of basal (DAP) fertilizer and about half of a bag of top-dressing fertilizer compared with non-beneficiaries. In contrast, beneficiaries and non-beneficiaries in lottery villages do not differ significantly in their use of basal fertilizer (bootstrapped p-value is 0.916) although the difference in their use of fertilizer in general is marginally significant (bootstrapped p-value is 0.099). Beneficiaries in non-lottery villages are also 6.1 percentage points less likely to report crop failure, and they report 70 percent higher yields that translate into an increase of 187 Kg per acre.

Given that we examine a range of agricultural outcomes we follow Kling, Liebman, and Katz (2007), among others, and construct an index summary measure of standardized treatment effects. In particular, we rescale each agricultural outcome in columns 2 to 6 of Table 7 such that larger values indicate more desirable values and convert each measure to a z-score such that $z_{ijk} = \left(y_{ijk} - \mu_k\right)/\sigma_k$, where μ_k and σ_k are the mean and standard deviation of variable y_{ijk}, and we construct the index as $Z_{ij} = \sum_k z_{ijk}/k$. Column 7 reports a 38 percentage point increase in the index among beneficiaries in non-lottery villages

compared to non-beneficiaries, while in lottery villages, the difference is not significant (bootstrapped p-value is 0.534).

We note however that the significant pre-existing differences between beneficiaries and non-beneficiaries in non-lottery villages, and the potential secondary market that allowed input transfers between beneficiaries and non-beneficiaries make the causal interpretation of the coefficients β_B and β_L from Equation 1 impossible. Simply put, we do not know how much of the impacts between beneficiaries and non-beneficiaries in non-lottery villages are due to the NAIVS program or to pre-existing differences in characteristics. Similarly, the secondary market in lottery villages may have attenuated the true impact of the program.

We make progress by restricting the sample in non-lottery villages to households that are similar in observable characteristics at baseline. In particular, we predict beneficiary status in non-lottery villages by running a logit model with all the baseline characteristics reported in Table 2. We note that the sample is thus restricted to individuals with baseline data. We then calculate the propensity score of households in non-lottery villages and choose households who have similar predicted probabilities of becoming a program beneficiary.[10] We finally estimate the propensity score of households in lottery villages using the logit estimates of non-lottery villages and restrict the lottery sample to the ones who share a common support with the non-lottery households.

By design, matched beneficiaries and non-beneficiaries in non-lottery villages should be comparable. Columns 1 to 6 of Table OA6 in the Online Appendix reports summary statistics of households in the matched sample. Columns 7 and 8 report that beneficiaries and non-beneficiaries are similar on observable characteristics in lottery and non-lottery villages, respectively (the p-value of a joint F-test that all the characteristics do not predict beneficiary status is 0.425 and 0.824, respectively). In addition, column 9 shows that beneficiaries in lottery and non-lottery villages are also comparable on observables in the matched sample (p-value is 0.605). In column 10 the same holds when comparing non-beneficiaries from lottery and non-lottery villages (p-value is 0.679). This suggests that when running

[10] The matching algorithm chooses the nearest neighbor in the control group (with replacement) to be part of the new sample. We also drop a few households who were beneficiaries in the 2010/11 season but had no comparable households in the control group. After also dropping households in lottery villages with propensity scores out of the score support in non-lottery villages, the algorithm selects a total of 330 households (out of 427 at baseline). All results presented here are robust to different algorithm specifications (e.g. Kernel matching, k-nearest neighbors etc.). Results upon request.

the specification in Equation 1 using the matched sample, the coefficient β_B recovers the causal impact of the program while β_L recovers the impact of the secondary market on non-beneficiaries in lottery villages.

Column 8 of Table 7 reports for completeness the results using the index of agricultural outcomes using the sample of 427 households with data in both the baseline and endline samples. The point estimates are comparable to those in column 7 using the full sample and somewhat less precisely estimated due to the lower power. Panel A of Table OA7 in the Online Appendix reports the individual items of the index for the sample of 427 households with baseline and endline data. Overall, the results in Panel A of Table OA7 in the Online Appendix are comparable to those in columns 1 to 6 of Table 7.

Column 9 of Table 7 reports the impact of NAIVS on agricultural outcomes using the matched sample. Compared to the results on column 7, we see that the point estimates are smaller in magnitude and not statistically significant. This suggests that the impacts detected in column 7 are mostly driven by the ex-ante differences between beneficiaries and non-beneficiaries in non-lottery villages, rather than the NAIVS program.

Panel B of Table OA7 in the Online Appendix report the individual items of the agricultural index for the matched sample. Column 4 suggests that beneficiaries only increase total fertilizer use by 7.6 Kg from a base of 18.3 Kg among non-beneficiaries in non-lottery villages. This increase is small and not statistically significant. Since roughly the same proportion of beneficiaries in the matched sample report receiving the vouchers as in the full sample (column 3 of Table 4) we conclude that the increase in fertilizer use due to the NAIVS is small. Using maize yields and input use we estimate a nutrient use efficiency of 8.2 Kg of maize per Kg of nitrogen from a base production of 383 Kg of maize.[11] This estimate is consistent with the response rates from other evaluations of ISPs in Sub-Saharan African countries in the range of 8–24 kg of maize per kg of nitrogen applied reviewed in Goyal and Nash (2017). In contrast, evidence from "researcher-managed" farm trials in East and Southern Africa produced estimates ranging from 18 to 40 kg of maize per kg of nitrogen (Tscharntke et al. 2012; Vanlauwe et al. 2011). Given the prevailing fertilizer and farmgate maize prices in our study area, while the estimates in the range of 18–40 kg of maize per kg of nitrogen would almost always result in highly

[11] We find the same nutrient use efficiency of 8.2 Kg of maize per Kg of nitrogen when using the matched sample.

profitable returns to farmers, our estimate of nitrogen use efficiency implies that the net value of output produced from incremental fertilizer does not exceed the cost of the NAIVS program per farmer.

Goyal and Nash (2017) suggest that the potential for positive impacts of ISPs on fertilizer use is greatest when they are administered in areas where the private sector has been inactive and among households that cannot afford fertilizer at commercial prices (Jayne et al. 2013; Mason and Jayne 2013; Mather and Jayne 2015; Ricker-Gilbert et al. 2011). In contrast, we study the impact of NAIVS in a region where the private sector was already active and the program targeted households that were already purchasing fertilizers at commercial prices.

Corral et al. (in preparation) in Mexico and, in particular, Harou et al. (in preparation) using data from Tanzania provide another explanation for the low use of fertilizer. They provide plot-specific soil testing and find evidence of important within-village variation in soil nutrient deficiencies. As a result, the blanket NAIVS fertilizer recommendations may not be relevant for the majority of farmers in their sample given the diversity in soil nutrient limitations.

Columns 1 to 3 of Table 8 report welfare outcomes using the full sample. The dependent variable in column 1 is the share of the agricultural production sold to the market, column 2 reports the log of household income and column 3 reports the principal component analysis (PCA) of answers to five questions related to food security.

Column 1 shows that beneficiaries in lottery villages sell 19 percentage points more of their production compared to non-beneficiaries, and in non-lottery villages, beneficiaries sell approximately 25 percentage points more. Interestingly, non-beneficiaries in lottery villages report selling higher share of their output too (compared to non-beneficiaries in non-lottery villages) although the increase is only marginally significant (p-value is 0.128). While there are no differences in household income (column 2), beneficiaries in non-lottery villages report higher food security than non-beneficiaries, but there are no statistically significant differences between beneficiaries and non-beneficiaries in lottery villages (column 3). Due to the large number of missing observations for household income, we use the percentage of output sold and the first component of the PCA of food security to construct a standardized index analogous to that of columns 7 to 9 in Table 7. Column 4 of Table 8 reports the standardized index. Similar to results in columns 1 to 3, we find that beneficiaries in non-lottery

villages are better off than non-beneficiaries. Interestingly, we find that non-beneficiaries in lottery villages are also better off compared to non-beneficiaries in non-lottery villages.

Column 5 reports the results using the same index of column 4 but restricting the sample to the 381 households with data from both baseline and endline.[12] The only point estimate that is statistically significant is that of β_L, capturing the difference among non-beneficiaries in lottery villages compared to non-lottery villages. The improvements in welfare among non-beneficiaries in lottery villages is consistent with a secondary market for inputs we observed in lottery villages. Panel A of Table OA8 in the Online Appendix reports the three individual items of the welfare index for the sample of households with baseline and endline data.

Column 6 of Table 8 reports the impact of NAIVS on welfare outcomes using the matched sample. Compared to the results in column 4, we again see that the estimate of β_L is large and significant. Column 6 of Table OA7 suggests that the improved access to inputs thanks to the secondary market allowed non-beneficiaries in lottery villages to have yields 9.4 percent higher compared to their counterparts in non-lottery villages. This increase in yield translated into a significantly higher percentage of production sold to the market (column 1 of Table OA8).

In summary, in non-lottery villages where local village officials chose beneficiaries, farmers targeted were not those with the highest marginal returns as they were already purchasing improved inputs in the absence of the program. This fact combined with the low returns to fertilizer in general, resulted in limited overall impacts. In lottery villages we find no differences between beneficiaries and non-beneficiaries, although non-beneficiaries fare better than their counterparts in non-lottery villages, a finding consistent with the emergence of a secondary market for inputs.

5 Conclusion

The government-run ISP in Tanzania that we study, like many other ISPs in Africa, has two conflicting goals: contributing to higher food production and productivity, and improving resource-constrained farmers' food security and livelihood. Put differently, it aims to target productive but liquidity-constrained farmers. Since landholdings are observable and a good proxy for liquidity constraints while

[12] The number of observations is smaller than in column 8 of Table 7 because we have respondents with missing data for the share of production sold to the market.

productivity is unobserved, in practice the eligibility criteria rely heavily on landholdings. The targeting of the program is decentralized and done by a local committee in the hope that it possesses information about farmer productivity only available locally. Decentralized institutions, however, can be subject to capture by local elites or may target better off farmers that were accessing inputs in the market prior to the program. This may exacerbate crowding out of commercial inputs, reducing the impact of the program on total fertilizer use and crop production.

We designed a field experiment with a 2x2 factorial design to study the targeting and program impacts when beneficiary selection was carried out via a public lottery or a local committee. We find that the program effectively selected the poor and that local committees implemented the eligibility criteria properly. Among those eligible, however, local committees did not target more connected farmers, but rather better off farmers that were more likely to report having purchased the inputs in the marketplace prior to the intervention. The program thus did not target farmers with the highest marginal returns to inputs. In contrast, in villages where beneficiaries were selected via a lottery, there were no ex-ante differences between beneficiaries and non-beneficiaries, as predicted by randomization, and because some of the beneficiaries were unproductive, a secondary market for vouchers seemed to emerge to allow those beneficiaries to sell inputs to productive non-beneficiaries.

Using Propensity Score Matching techniques, we control for any ex-ante observable differences between beneficiaries and non-beneficiaries and find limited impacts on input use and subsequent agricultural production and welfare in non-lottery villages. In lottery villages, non-beneficiaries fare better than their counterparts in non-lottery villages.

Policy discussions of low fertilizer use in Africa have tended to overemphasize failures in credit markets and underemphasize factors that limit fertilizer profitability, such as declining soil fertility associated with rising land pressures and continuous cultivation, poor soil management practices, and rainfed farming conditions. This has led to the widespread view that low fertilizer use in Africa primarily reflects market access problems that can be overcome through input subsidy programs, when these results suggest that public resources would perhaps be best directed at addressing these complementary factors.

Although Africa's fertilizer use is often compared unfavorably with that of Asia, during the "Green Revolution" fertilizer use was only high in irrigated areas or areas with significant potential for water

control, and where the risks of fertilizer use were relatively low but the expected returns were higher (Gautam 2015). In addition, farmers faced domestic prices for fertilizers below world market prices, suggesting that fertilizer use was profitable in the absence of subsidies (Rashid et al., 2013). In contrast, drought-prone rainfed areas in Asia had relatively low fertilizer use comparable to many areas in Africa (Jayne and Rashid, 2013).

After eight years, the NAIVS program was discontinued in 2016 due to lack of funding, two years after the closing of the World Bank loan. Of the 10 Sub-Saharan African countries with an existing ISP in 2010 (Jayne et al., 2016), only the ones in Zambia and Malawi are currently still active.

References

Alatas, V., A. Banerjee, R. Hanna, B. A. Olken, and J. Tobias. 2012. "Targeting the Poor: Evidence from a Field Experiment in Indonesia." *American Economic Review* 102 (4): 1206-40.

Alatas, V., A. Banerjee, R. Hanna, B. A. Olken, R. Purnamasari, and M. Wai-Poi. 2019. “Does elite capture matter? Local elites and targeted welfare programs in Indonesia.” *AEA Papers and Proceedings* 109: 334-339.

Alderman, H. 2002. “Do local officials know something we don’t? Decentralization of targeted transfers in Albania.” *Journal of Public Economics* 83 (3): 375-404.

Bardhan, P., and D. Mookherjee. 2005. “Decentralizing antipoverty program delivery in developing countries.” *Journal of Public Economics* 89 (4): 675-704

____. 2006. “Decentralization and Accountability in Infrastructure Delivery in Developing Countries.” *Economic Journal* 116: 101–127.

____. 2011. "Subsidized Farm Input Programs and Agricultural Performance: A Farm-Level Analysis of West Bengal's Green Revolution, 1982-1995." *American Economic Journal: Applied Economics*, 3(4): 186-214.

Bold, T., K. C. Kaizzi, J. Svensson, and D. Yanagizawa-Drott. 2017. “Lemon Technologies and Adoption: Measurement, Theory and Evidence from Agricultural Markets in Uganda.” *Quarterly Journal of Economics* 132 (3): 1055-1100.

Bueno de Mesquita, B., S. Smith, R. M. Siverson, and J. D. Morrow. 2003. *The Logic of Political Survival.* Cambridge, MA: MIT Press.

Burke, W. J., T. S. Jayne, and J. R. Black. 2017. “Factors explaining the low and variable profitability of fertilizer application to maize in Zambia.” *Agricultural Economics* 48: 115-126.

Cameron, C., J. Gelbach, and D. Miller. 2008. “Bootstrap-based Improvements for Inference with Clustered Errors.” *Review of Economics and Statistics* 90(3): 414-27.

Carter, M., R. Laajaj, and D. Yang. 2014. "Subsidies and the Persistence of Technology Adoption: Field Experimental Evidence from Mozambique." *NBER Working Paper* w20465.

Corral, C., X. Giné, A. Mahajan, and E. Seira. “A Multiple Intervention Approach to Improve Agricultural Yields.” In Preparation.

Dulfo, E., M. Kremer, and J. Robinson. 2008. “How high are rates of return to fertilizer? Evidence from field experiments in Kenya.” *American Economic Review: Papers and Proceedings* 98 (2): 482-88.

Duflo, E., M. Kremer, and J. Robinson. 2011. “Nudging Farmers to Use Fertilizer: Theory and Experimental Evidence from Kenya.” *American Economic Review* 101(6): 2350-90.

Feder, G., R. E. Just, and D. Zilberman. 1985. "Adoption of Agricultural Innovations in Developing Countries: a survey." *Economic Development and Cultural Change* 33(2) 255-298.

Goyal, A., and J. Nash. 2017. *Reaping Richer Returns: Public Spending Priorities for African Agriculture Productivity Growth.* Africa Development Forum series. Washington, D.C.: World Bank.

Harou, A., N. Amuri, M. Madajewicz, C. Magomba, H. Michelson, K. Tschirhart, J. M. Semoka, and C. Palm. “When does information make a difference? A field experiment with farm-specific soil information in Tanzania..” In preparation.

Holden, S., and R. Lunduka. 2012. “Do fertilizer subsidies crowd out organic manures? The case of Malawi.” *Agricultural Economics* 43 (3): 303-14.

Jack, B. K. 2013. "Private Information and the Allocation of Land Use Subsidies in Malawi." *American Economic Journal: Applied Economics* 5(3): 113-35.

Jayne, T.S., D. Mather, N. Mason, and J. Ricker-Gilbert. 2013. “How do fertilizer subsidy programs affect total fertilizer use in sub-Saharan Africa? Crowding out, diversion and benefit/cost assessments,” *Agricultural Economics* 44: 687-703.

Jayne, T.S., N. M. Mason, W. J. Burke, and J. Ariga. 2016. “Agricultural input subsidy programs in Africa: An assessment of recent evidence.” Michigan State University International Development Working Paper 145.

Jayne, T.S., and S. Rashid. 2013. “Input subsidy programs in sub-Saharan Africa: a synthesis of recent evidence,” *Agricultural Economics* 44: 547-562.

Karlan, D., R. Osei, I. Osei-Akoto, and C. Udry. 2014. “Agricultural Decisions after Relaxing Credit and Risk Constraints.” *Quarterly Journal of Economics* 129(2): 597-652.

Kilic, T., E. Whitney, and P. Winters. 2015. "Decentralised Beneficiary Targeting in Large-Scale Development Programmes: Insights from the Malawi Farm Input Subsidy Programme." *Journal of African Economies* 24 (1): 26–56.

Kling, R., J. B. Liebman, and L. F. Katz. 2007. "Experimental Analysis of Neighborhood Effects." *Econometrica* 75:83-119.

Lalonde, R. J. 1986. "Evaluating the econometric evaluations of training programs with experimental data." *American Economic Review* 76 (4): 604-620.

Mason, N. M., and M. Smale. 2013. "Impacts of Subsidized Hybrid Seed on Indicators of Economic Well-Being Among Smallholder Maize Growers in Zambia." *Agricultural Economics* 44 (6): 659–70.

Mason, N. M., and T. S. Jayne. 2013. "Fertilizer subsidies and smallholder commercial fertilizer purchases: Crowding out, leakage, and policy implications for Zambia." *Journal of Agricultural Economics* 64 (3): 558-62.

Mason, N. M, T. S. Jayne, and N. van de Walle. 2017. "The Political Economy of Fertilizer Subsidy Programs in Africa: Evidence from Zambia" *American Journal of Agricultural Economics* 99(3): 705–731.

Mather, D., and T. S. Jayne. 2015. "Fertilizer subsidies and the role of targeting in crowding out: An assessment of smallholder fertilizer demand in Kenya." Selected paper for the 29th International Conference of Agricultural Economists, Milan, Italy, August 8-14.

Morris, M., V. Kelly, R. Kopicki, and D. Byerlee. 2007. *Fertilizer Use in African Agriculture: Lessons Learned and Good Practice Guidelines*. Washington, D.C.: World Bank.

Pan, L., and L. Christiaensen. 2012. Who is vouching for the input voucher? Decentralized targeting and elite capture in Tanzania." *World Development* 40 (8): 1619-33.

Rashid, S., P. Dorosh, M. Malek, and S. Lemma. 2013. "Modern input promotion in sub-Saharan Africa: Insights from Asian green revolution." *Agricultural Economics* 44(6): 705-721.

Ricker-Gilbert, J., T. S. Jayne, and E. Chirwa. 2011. "Subsidies and crowding out: A double-hurdle model of fertilizer demand in Malawi." *American Journal of Agricultural Economics* 93 (1): 26-42.

Suri, T. 2011. "Selection and Comparative Advantage in Technology Adoption." *Econometrica* 79(1): 159–209.

Tscharntke, T., Y. Clough, T. Wanger, L. Jackson, I. Motzke, I. Perfecto, J. Vandermeer, and A. Whitbread. 2012. "Global food security, biodiversity conservation, and the future of agriculture intensification." *Biological Conservation* 151 (1): 53-59.

Vanlauwe, B., J. Kihara, P. Chivenge, P. Pypers, R. Coe, and J. Six. 2011. "Agronomic use efficiency of N fertilizer in maize-based systems in sub-Saharan Africa within the context of integrated soil fertility management." *Plant and Soil* 339 (1-2): 35-50.

Wiggins, S., and J. Brooks. 2010. The Use of Input Subsidies in Developing Countries. In *Agricultural Policies for Poverty Reduction.* Paris: OECD.

World Bank. 2009a. "Accelerated Food Security Program of the United Republic of Tanzania under the Global Food Crisis Response Program. Report No: 48549-TZ. Washington, D.C.

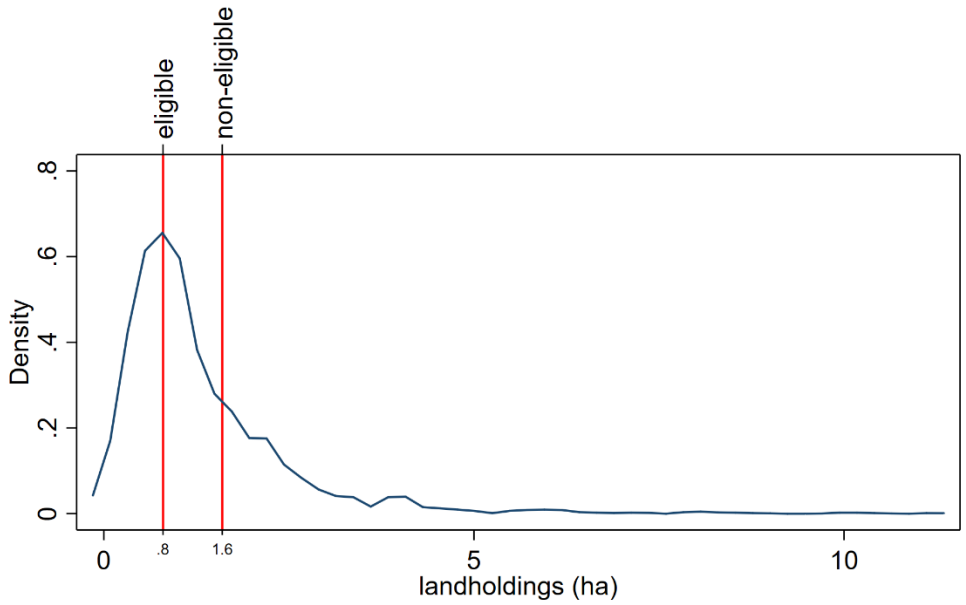
World Bank. 2009b. "Conditional Cash Transfers: Reducing Present and Future Poverty". Washington, D.C.: World Bank.

Figure 1: Experimental Design

	SELECTION OF BENEFICIARIES (AMONG ELIGIBLE FARMERS)		
IDENTIFICATION OF ELIGIBLE FARMERS		Lottery	Non-lottery
	Village meeting ("Meeting")	**A Villages (12)** Interventions #1 and #2 Village meeting produces a list of eligible farming households and X_i^{2010} beneficiaries are chosen using a lottery	**C Villages (11)** Intervention # 1 only Village meeting produces a list of eligible farming households and selects X_i^{2010} beneficiaries
	No village meeting ("No Meeting")	**B Villages (12)** Intervention # 2 only VVC produces the list of all eligible farming households and X_i^{2010} beneficiaries are chosen using a lottery	**D Villages (11)** No interventions VVC produces the list of all eligible farming households and select X_i^{2010} beneficiaries as per usual process

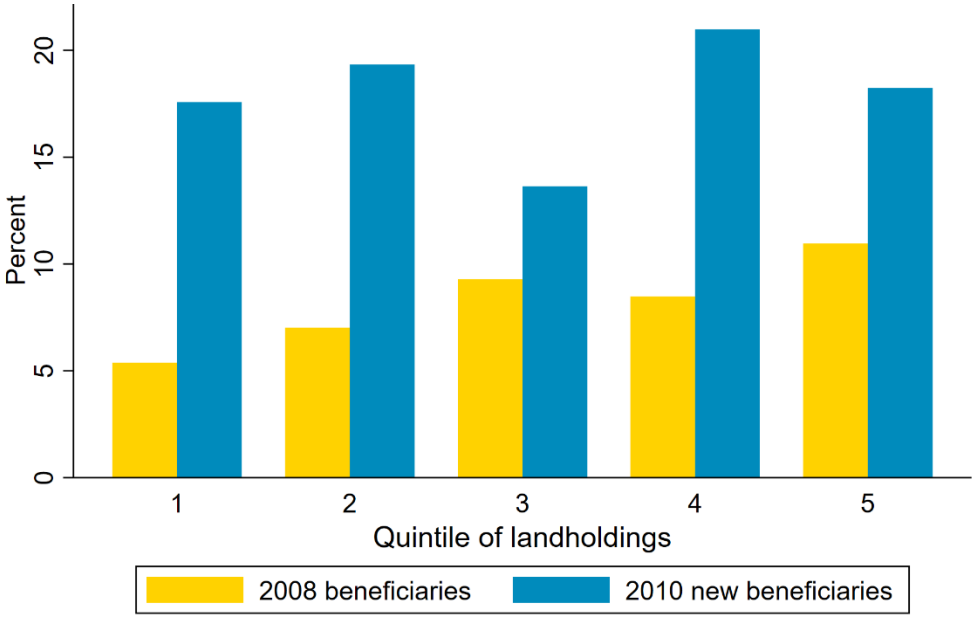
Note: This figure shows the number of villages in Meru (Arusha) in each of the experimental arms.
X_i^{2010} = Number of vouchers to new beneficiaries allocated to village *i* in 2010

Figure 2: Distribution of landholdings, eligible and non-eligible farmers



Source: Baseline villager survey. Only regions of Arusha, Kilimanjaro and Morogoro

Figure 3: Share of NAIVS beneficiaries by landholding quintile



Source: Baseline villager survey. Only regions of Arusha, Kilimanjaro and Morogoro

Table 1. Orthogonality Checks

	Data Source	All villages	Lottery (L)	No Lottery (NL)	P-value: L = NL	Meeting (M)	No Meeting (NM)	P-value: M = NM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Village level								
Number of eligible farmers in 2009/10	Baseline	406.5	413.5	398.7	*0.768*	376.6	436.3	*0.229*
Share of beneficiaries among eligible farmers in 2009/10	Baseline, Follow-up	0.668	0.667	0.668	*0.986*	0.694	0.641	*0.502*
Total village cultivable land (000s acres)	Baseline	2.1	1.8	2.6	*0.226*	1.8	2.5	*0.262*
Total village cultivable land that is irrigated (000s acres)	Baseline	0.492	0.464	0.524	*0.824*	0.332	0.653	*0.231*
Number of HHs involved in agricultural activities in 2009/10	Baseline	518.2	509.0	528.2	*0.864*	468.2	568.2	*0.371*
Share of HHs with access to electricity	Baseline	0.090	0.086	0.094	*0.842*	0.081	0.098	*0.682*
Village has health clinic or hospital (0/1)	Baseline	0.587	0.667	0.500	*0.261*	0.522	0.652	*0.380*
VVC has 3 women and 3 men (0/1)	Baseline	0.957	1	0.909	*0.137*	0.957	0.957	*1.000*
VVC members were elected (0/1)	Baseline	0.043	0.042	0.045	*0.951*	0.000	0.087	*0.155*
Rains were good in 2009/10 (0/1)	Baseline	0.804	0.833	0.773	*0.614*	0.739	0.870	*0.275*
Maize price at the beginning of harvest 2009/10 (TSH/Kg)	Baseline	325.7	334.2	316.4	*0.569*	320.9	330.4	*0.760*
Number of agrodealers in the village	Baseline	1.2	1.1	1.2	*0.933*	1.2	1.2	*1.000*
Program subsidy as percent of input package	Baseline	0.486	0.477	0.495	*0.459*	0.482	0.490	*0.743*
Number of observations		46	24	22		23	23	
P-value of joint F-test that all coefficients are 0					*0.929*			*0.385*
Panel B: Village Voucher Committee (VVC) survey								
Age of respondent	Baseline	46.0	45.3	46.7	0.485	45.1	46.7	0.444
Respondent is male (0/1)	Baseline	0.506	0.511	0.500	0.921	0.488	0.522	0.756
Respondent is married (0/1)	Baseline	0.899	0.872	0.929	0.385	0.884	0.913	0.651
Respondent can read and write (0/1)	Baseline	0.921	0.894	0.952	0.309	0.930	0.913	0.767
House has concrete floor (0/1)	Baseline	0.629	0.638	0.619	0.853	0.605	0.652	0.647
Cultivates 1 Ha or less (0/1)	Baseline	0.562	0.596	0.524	0.500	0.581	0.543	0.722
Number of changes in VVC composition since its creation	Baseline	1.4	1.2	1.7	0.356	1.4	1.4	0.907
Responsabilities correctly named by VVC member (up to 7)	Baseline	5.4	5.5	5.2	0.450	5.2	5.5	0.269
Correctly named program elibility criteria (0/3)	Baseline	2.7	2.7	2.6	0.513	2.7	2.7	0.863
Number of observations		89	46	43		43	46	
P-value of joint F-test that all coefficients are 0					*0.884*			*0.983*
Panel C: Villager household survey								
Head of household is male (0/1)	Baseline	0.826	0.855	0.790	*0.049*	0.833	0.817	*0.630*
Head of household is married (0/1)	Baseline	0.845	0.855	0.832	*0.404*	0.857	0.831	*0.350*
Is related to government officials or influentials (0/1)	Baseline	0.218	0.212	0.225	*0.833*	0.247	0.186	*0.241*
Socializes with government officials or influentials (0/1)	Baseline	0.211	0.205	0.219	*0.816*	0.240	0.180	*0.253*
House has concrete floor (0/1)	Baseline	0.580	0.632	0.518	*0.118*	0.568	0.594	*0.720*
Cultivates 1 Ha or less (0/1)	Baseline	0.503	0.480	0.530	*0.432*	0.505	0.500	*0.934*
Used improved seeds in 2009/10 (0/1)	Baseline	0.676	0.680	0.671	*0.448*	0.682	0.669	*0.826*
Used inorganic fertilizer in 2009/10 (0/1)	Baseline	0.482	0.477	0.488	*0.885*	0.458	0.509	*0.929*
Maize yield (Kgs/acre) in 2009/10	Baseline	555.2	578.9	526.9	*0.886*	528.0	585.0	*0.474*
Head of household is a beneficiary (0/1)	Baseline	0.465	0.478	0.451	*0.661*	0.468	0.463	*0.929*
Number of Observations		734	400	334		384	350	
P-value of joint F-test that all coefficients are 0					*0.881*			*0.975*

Note: In Panel A, we use village-level data from Village Survey to compare Arusha villages in different treatment arms (except the number of agrodeales in the village, computed sing data from th VVC survey). Panel B compares Arusha villages using data from the VVC survey, which interviewed up to 2 VVC members per village. In Panel C, we compare Arusha villages using household-level data from the Baseline Villager Household Survey. The data source (baseline or follow-up) can be found in Column 1. In Column 2, we report the average in all villages. In Columns 3-5, we compare lottery and non-lottery villages by reporting averages for the two groups of villages and the p-value of the equality t-test. In Columns 6-8, we compare meeting and non-meeting villages, also reporting averages and p-values. At the bottom of each panel we report the number of observations and the the p-value of a joint F-test that all coefficients of a regression of lottery status (Column 5) or meeting dummy (Column 8) against characteristics are zero. All p-values in Panel C are computed using the t-asymptotic wild cluster bootstrap procedure described in Cameron et al. (2008). Clustering was done at the village level. Range of values for categorical variables are given in parenthesis. (0/1) indicates dummy variables, equal to one if the response is yes. See Appendix

Table 2. Targeting of NAIVS over time

	2008/09 season	2010/11 season
	(1)	(2)
Panel A: All villages		
% of beneficiaries who are eligible	27%	46%
Targeting differential	-6%	30%
% of beneficiaries who are related to government officials or influentials	25%	22%
Panel B: Villages in the study (Arusha)		
% of beneficiaries who are eligible	24%	46%
Targeting differential	-10%	30%
% of beneficiaries who are related to government officials or influentials	21%	22%
Panel C: Villages not in the study (Kilimanjaro)		
% of beneficiaries who are eligible	57%	64%
Targeting differential	-2%	6%
% of beneficiaries who are related to government officials or influentials	43%	30%
Panel D: Villages not in the study (Morogoro)		
% of beneficiaries who are eligible	7%	31%
Targeting differential	-2%	51%
% of beneficiaries who are related to government officials or influentials	27%	14%

Note: Data come from baseline and follow-up Villager survey. Arusha (north) villages were part of the study, while villages in Kilimanjaro (also in the north) and Morogoro (south) were not part of the whole study. Beneficiary status is self-reported by survey respondents.

Table 3. Characteristics of eligible households

	Data Source	Lottery				No Lottery				P-value: Lottery vs. No Lottery	Meeting (M)	No Meeting (M)	P-value: M = NM
		Total	Beneficiary (B)	Non-benef. (NB)	P-value: B = NB	Total	Beneficiary (B)	Non-benef. (NB)	P-value: B = NB				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Head of household is male (0/1)	Baseline	0.655	0.647	0.664	*0.801*	0.588	0.604	0.571	*0.600*	*0.078*	0.622	0.624	*0.962*
Age of household head	Baseline	49.6	49.3	49.9	*0.793*	47.7	46.0	49.6	*0.092*	*0.381*	48.2	49.2	*0.630*
Head of household is married (0/1)	Baseline	0.825	0.802	0.850	*0.315*	0.814	0.811	0.816	*0.926*	*0.835*	0.804	0.835	*0.560*
Head of household can read and write (0/1)	Baseline	0.753	0.733	0.776	*0.580*	0.765	0.840	0.684	*0.029*	*0.820*	0.766	0.752	*0.789*
Raven's index (0/3)	Follow-up	1.021	1.056	0.983	*0.359*	1.045	1.150	0.934	*0.098*	*0.748*	1.063	1.002	*0.424*
Related to government officials or influentials (0/1)	Baseline	0.179	0.198	0.159	*0.486*	0.132	0.113	0.153	*0.467*	*0.211*	0.153	0.161	*0.845*
Socializes with government officials or influentials (0/1)	Baseline	0.157	0.172	0.140	*0.558*	0.123	0.113	0.133	*0.731*	*0.348*	0.129	0.151	*0.554*
House has concrete floor (0/1)	Follow-up	0.506	0.506	0.507	*0.989*	0.439	0.449	0.427	*0.438*	*0.266*	0.487	0.461	*0.665*
Food security PCA index	Baseline	0.108	0.023	0.200	*0.482*	-0.119	0.256	-0.524	*0.007*	*0.193*	-0.053	0.049	*0.580*
Cultivates 1 Ha or less (0/1)	Follow-up	0.613	0.618	0.607	*0.805*	0.598	0.612	0.582	*0.565*	*0.762*	0.598	0.613	*0.759*
Maize yield (Kgs/acre) in 2009/10	Baseline	696.4	768.4	618.5	*0.094*	718.5	733.8	700.2	*0.785*	*0.811*	668.4	746.4	*0.416*
Used agricultural inputs in 2009/10 (0/1)	Baseline	0.659	0.629	0.692	*0.315*	0.618	0.660	0.571	*0.182*	*0.554*	0.660	0.619	*0.556*
Number of Observations	Baseline	223	116	107		204	106	98			209	218	
	Follow-up	480	251	229		440	227	213			460	460	
P-value of joint F-test that all coefficients are 0					*0.903*				*0.008*	*0.565*			*0.946*

Note: This table shows descriptive statistics using individual level data from the household survey. Column 1 describes when the data were collected, either at baseline or follow-up. Column 2 reports averages in lottery villages and Columns 3-5 compare beneficiaries and non-beneficiaries of the NAIVS voucher program in 2010/11 in lottery villages. We report analogous figures for no lottery villages in Columns 6-9. In Column 10 we report the p-values of the mean comparison between individuals in lottery and no lottery villages. Columns 11-13 compare households in meeting and no meeting villages. Due to implementation issues, the number of surveyed households at baseline is lower than that at follow-up. P-value of joint F-test corresponds to the p-value of a joint F-test that all coefficients of a regression of beneficiary status (Columns 5 and 9) or meeting dummy (Column 13) against characteristics are zero. All p-values are computed using the t-asymptotic wild cluster bootstrap procedure described in Cameron et al. (2008). Clustering was done at the village level. Range of values for categorical variables are given in parenthesis. (0/1) indicates dummy variables, equal to one if the response is yes. See Appendix Table 1 for definition of variables.

Table 4. NAIVS program awareness and implementation

	Awareness of NAIVS program	Asked about ability to pay in 2010/11	Household received vouchers in 2010/11	Satisfaction with selection of beneficiaries in 2010/11	Household received vouchers in 2011/12
	(1)	(2)	(3)	(4)	(5)
Beneficiary	0.097***	0.079*	0.339***	0.156***	0.171***
	0.007	*0.093*	*0.000*	*0.009*	*0.000*
Lottery	0.036	0.042	0.072	0.110**	0.049
	0.320	*0.267*	*0.171*	*0.035*	*0.382*
Lottery x Beneficiary	-0.020	-0.008	-0.062	-0.116	0.016
	0.619	*0.883*	*0.343*	*0.112*	*0.788*
Number of households	920	920	920	920	920
R-squared	0.029	0.011	0.100	0.019	0.039
Mean of dep. var. for NB in NL vil.	0.859	0.146	0.216	0.615	0.235
P-val of B = NB in L villages	*0.005*	*0.033*	*0.000*	*0.396*	*0.000*

Note: This table reports the estimation of the following specification: $y_{ij} = \alpha_{ij} + \beta_1 Beneficiary_{ij} + \beta_2 Lottery_j + \beta_3 Lottery_j * Beneficiary_{ij} + \varepsilon_{ij}$, where i indexes the individual (household) and j indexes the village. $Beneficiary_{ij}$ is a dummy that takes value of 1 if the individual i in village j is a beneficiary of the NAIVS voucher program in 2010/11. $Lottery_j$ is a dummy that takes value of 1 if beneficiaries in village j were chosen using a lottery. The models presented here represent an intention to treat analysis and are not adjusted for any baseline covariates. Dependent variables are constructed based on questions asked on follow-up household survey. The dependent variable in Column 1 is a dummy that indicates whether respondent is aware of the presence of the NAIVS program in his or her village. Column 2 reports the results using a dummy that codes whether the respondent was asked about his or her ability to pay for the voucher top-up in 2010/11. In Columns 3 and 5, the dependent variables are dummies that indicate if respondent reports receiving vouchers in 2010/11 and 2011/12, respectively. For those regressions, respondents self-report receiving or not voucher and the answers may differ from administrative data used to assign beneficiary status. In Column 4, the dependent variable is a dummy variable that indicates whether the respondent reports being very satisfied with the selection of voucher beneficiaries in 2010/11. P-values are computed using the t-asymptotic wild cluster bootstrap procedure described in Cameron et al. (2008) and reported below the coefficients. Clustering was done at the village level. ***,**,* denote statistical significance at the 1, 5 and 10 percent level, respectively. See Appendix Table 1 for definition of variables.

Table 5: Displacement and elite capture

	Gives inputs to others	Used inorganic fertilizers in 2009/10	Used improved seeds in 2009/10	Related to government officials and influentials	Socializes with government officials and influentials	Paid to become beneficiary in 2010/11
	(1)	(2)	(3)	(4)	(5)	(6)
Beneficiary	-0.024	0.129*	0.031	-0.040	-0.019	0.004
	0.605	*0.077*	*0.634*	*0.465*	*0.735*	*0.838*
Lottery	-0.086**	0.135	0.119	0.006	0.008	0.012
	0.014	*0.139*	*0.129*	*0.915*	*0.886*	*0.269*
Lottery x Beneficiary	0.112**	-0.265***	-0.042	0.079	0.052	0.002
	0.041	*0.005*	*0.663*	*0.309*	*0.518*	*0.910*
Number of contacts	523					
Number of households	294	427	427	427	427	920
R-squared	0.017	0.019	0.010	0.007	0.004	0.003
Mean of dep. var. for NB in NL vil.	0.103	0.286	0.469	0.153	0.133	0.009
P-val of B = NB in L villages	*0.017*	*0.031*	*0.875*	*0.490*	*0.562*	*0.694*

Note: In Column 1, we report the estimation of the following specification: $y_{ijk} = \alpha_{ijk} + \beta_1 Beneficiary_{ij} + \beta_2 Lottery_j + \beta_3 Lottery_j * Beneficiary_{ij} + \varepsilon_{ijk}$, where i indexes the individual (household), j indexes the village and k indexes another individual reported to be in the respondent's network. In Columns 2-6 we report the estimation of the following specification: $y_{ij} = \alpha_{ij} + \beta_1 Beneficiary_{ij} + \beta_2 Lottery_j + \beta_3 Lottery_j * Beneficiary_{ij} + \varepsilon_{ij}$, where i indexes the individual (household) and j indexes the village. $Beneficiary_{ij}$ is a dummy that takes value of 1 if the individual i in village j is a beneficiary of the NAIVS voucher program in 2010/11. $Lottery_j$ is a dummy that takes value of 1 if beneficiaries in village j were chosen among the eligible households though a lottery. The models presented here represent an intention to treat analysis and are not adjusted for any baseline covariates. The dependent variable in Column 1 is a dummy variable that takes value 1 if the respondent reported giving agricultural inputs to a non-beneficiary friend. The dependent variables in Column 2 and 3 are dummy variables that take value 1 if the respondent reports using improved seeds and inorganic fertilizers in 2009/10, respectively, using household survey data collected at baseline. In Columns 4 and 5, the dependent variables are dummies that takes value 1 if respondent reports also at baseline holding the position of or being related to and having regular social interaction with DALDO, WEO, VEO, VVC member, or Village or Hamlet Chair, respectively. The dependent variable in Column 6 is a dummy variable that takes value 1 if respondent reports at follow-up household survey having paid to become a voucher beneficiary in 2010/11. Data for the Columns 1 and 6 were collected using household survey at follow-up while data in Columns 2-5 come from household survey at baseline. P-values are computed using the t-asymptotic wild cluster bootstrap procedure described in Cameron et al. (2008) and reported below the coefficients. Clustering was done at the village level. ***,**,* denote statistical significance at the 1, 5 and 10 percent level, respectively. See Appendix Table 1 for definition of variables.

Table 6. Elite capture and targeting, Arusha vs. Kilimanjaro

	(1)	(2)	(3)	(4)
	Arusha		Kilimanjaro	
	2008 beneficiaries	2010 new beneficiaries	2008 beneficiaries	2010 new beneficiaries
Related to government officials or influentials	-0.004	-0.004	0.032*	0.051
	(0.896)	(0.904)	(0.097)	(0.381)
Eligible in 2008/09 season	-0.083***	0.074**	-0.028	-0.068
	(0.003)	(0.016)	(0.142)	(0.219)
Observations	734	666	544	256
R-squared	0.012	0.009	0.011	0.011
Mean dep. var. non eligible non related	0.193	0.155	0.054	0.244

Note: Data come from baseline and follow-up Villager survey. Arusha (north) villages were part of the study, while villages in Kilimanjaro (also in the north) were not part of the whole study. Beneficiary status is self-reported by survey respondents.

Table 7. Agricultural Outcomes

	Grows maize	Area planted (acres)	Basal fertilizer per acre (Kg)	Total fertilizer per acre (Kg)	Crop failure	Log total yield	Standardized index of agricultural outcomes		
							Full sample	Baseline sample	Matched sample
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Beneficiary	-0.032*	-1.589	51.215***	21.951**	-0.061**	0.699***	0.379***	0.322**	0.101
	0.080	*0.233*	*0.002*	*0.017*	*0.047*	*0.008*	*0.001*	*0.041*	*0.596*
Lottery	-0.010	-0.816	22.782	6.952	-0.048	0.526	0.191	0.295*	0.115
	0.769	*0.540*	*0.212*	*0.578*	*0.238*	*0.185*	*0.164*	*0.062*	*0.583*
Lottery x Beneficiary	0.053**	0.557	-49.853**	-12.975	0.050	-0.292	-0.332***	-0.422**	-0.216
	0.032	*0.711*	*0.015*	*0.223*	*0.162*	*0.353*	*0.010*	*0.028*	*0.363*
R-squared	0.005				0.006		0.020	0.018	0.004
Mean of dep. var. for NB in NL vil.	0.953	3.67	2.85	12.94	0.151	4.31	-0.139	-0.154	0.033
P-val of B = NB in L villages	*0.238*	*0.168*	*0.916*	*0.099*	*0.579*	*0.030*	*0.534*	*0.355*	*0.386*
Model	OLS	Tobit	Tobit	Tobit	OLS	Tobit	OLS	OLS	OLS
Percentage of censured observations		0.04	0.89	0.64		0.15			
Number of plots		1,139	1,139	1,139	1,139	1,139	1,139	531	414
Number of households	920	920	920	920	920	920	920	427	330

Note: This table reports the estimation of the following specifications: $y_{ijk} = \alpha_{ijk} + \beta_1 Beneficiary_{ij} + \beta_2 Lottery_j + \beta_3 Lottery_j * Beneficiary_{ij} + \varepsilon_{ijk}$, where i indexes the individual (household), j indexes the village and k indexes plots. $Beneficiary_{ij}$ is a dummy that takes value of 1 if the individual i in village j is a beneficiary of the NAIVS voucher program in 2010/11. $Lottery_j$ is a dummy that takes value of 1 if beneficiaries in village j were chosen using a lottery. The specifications presented here are not adjusted for any baseline covariates. The dependent variable in Column 1 is a dummy that indicates whether or not the household grew maize in 2010/11. Column 2 reports area planted in acres for all plots. Columns 3 and 4 report use of basal fertilizer (DAP) and total fertilizer (basal + top-dressing or urea) per acre in kilograms, respectively. Dependent variable in Column 5 is a dummy indicating crop failure. Column 6 reports log yield (Kg/Area planted) including plots with crop failure. Outlier plots with yields over 4000 kg per area are dropped from the regressions. The dependent variable in columns 7 to 9 is a standardized index of agricultural outcomes based on the items in columns 2 to 6, replacing crop failure with crop success, that is, the reverse of crop failure so that larger values indicate more desirable values. In Column 7, we use the full sample of households interviewed at follow-up. In Column 8, we restrict the sample to households with baseline and endline data. In Column 9, we use the matched sample, that is, we restrict the sample in Column 8 to beneficiaries and non-beneficiaries with the same common support based on a nearest neighbor propensity score matching algorithm. P-values are computed using the t-asymptotic wild cluster bootstrap procedure described in Cameron et al. (2008) and reported below the coefficients. Clustering was done at the village level. ***,**,* denote statistical significance at the 1, 5 and 10 percent level, respectively. See Appendix Table 1 for definition of variables.

Table 8. Welfare Outcomes

	Percent of output sold	Log total household income	Food security PCA index	Welfare standardized index		
				Full sample	Baseline sample	Matched sample
	(1)	(2)	(3)	(4)	(5)	(6)
Beneficiary	0.249***	-0.594	0.403**	0.288**	0.290	0.314
	0.001	*0.145*	*0.033*	*0.026*	*0.121*	*0.233*
Lottery	0.162	0.257	0.318	0.220*	0.458**	0.520**
	0.128	*0.500*	*0.223*	*0.090*	*0.012*	*0.025*
Lottery x Beneficiary	-0.058	0.744	-0.281	-0.131	-0.237	-0.319
	0.544	*0.117*	*0.282*	*0.413*	*0.338*	*0.307*
R-squared			0.010	0.018	0.037	0.032
Mean of dep. var. for NB in NL vil.	0.125	12.583	-0.758	-0.199	-0.320	-0.340
P-val of B = NB in L villages	*0.000*	*0.525*	*0.552*	*0.118*	*0.759*	*0.981*
Model	Tobit	Tobit	OLS	OLS	OLS	OLS
Percentage of censured observations	0.597	0.038				
Number of households	828	547	920	828	381	299

Note: This table reports the estimation of the following specifications: $y_{ij} = \alpha_{ij} + \beta_1 Beneficiary_{ij} + \beta_2 Lottery_j + \beta_3 Lottery_j * Beneficiary_{ij} + \varepsilon_{ij}$, where i indexes the individual (household) and j indexes the village. $Beneficiary_{ij}$ is a dummy that takes value of 1 if the individual i in village j is a beneficiary of the NAIVS voucher program in 2010/11. $Lottery_j$ is a dummy that takes value of 1 if beneficiaries in village j were chosen using a lottery. The models presented here are not adjusted for any baseline covariates. Column 1 reports a percentage of production that is sold. Column 2 reports on log of total household income, including non-agricultural activities. Dependent variable in Column 3 is constructed using the households reported worry for scarcity of food, number of meals per day, size of meals, and consumption of least preferred foods; higher values represent higher food security. The dependent variable in all columns 4-6 is a standardized index of agricultural outcomes and it was constructed base on questions asked on follow-up household survey. The index components are (i) percentage of production that is sold and (ii) food security index, where higher values represent higher food security. In Column 4, we use the sample of households interviewed at follow-up with non-missing values of the dependent variables in Column 1 and 3. In Column 5, we restrict the sample to households with baseline and endline data. In Column 6, we use the matched sample, that is, we restrict the sample in Column 5 to beneficiaries and non-beneficiaries with the same common support based on a nearest neighbor propensity score matching algorithm. P-values are computed using the t-asymptotic wild cluster bootstrap procedure described in Cameron et al. (2008) and reported below the coefficients. Clustering was done at the village level. ***,**,* denote statistical significance at the 1, 5 and 10 percent level, respectively. See Appendix Table 1 for definition of variables.

Appendix Table 1: Definition of variables

Variable	Survey	Description
Panel A: Village survey		
Village level data		
Number of eligible farmers in 2009/10	Baseline	Number of farmers in the village that fulfill the 2 main program criteria: (i) cultivate no more than 1 hectare of maize or rice, (ii) not have used chemical fertilizer or improved seeds in the previous 5 years
Share of beneficiaries among eligible farmers in 2009/10	Baseline, Follow-up	Number of farmers in the village who are program beneficiaries in 2009/10, as a share of number of farmers in the village that are eligible in 2009/10 (see variable above)
Number of HHs involved in agricultural activities in 2009/10	Baseline	Number of households involved in agricultural activities as their main occupation in 2009/10
VVC has 3 women and 3 men	Baseline	Equals 1 if Village Voucher Committee (VVC) has 3 female and 3 male members.
VVC members were elected	Baseline	Equals 1 if VVC members were selected though an election
Rains were good in 2009/10	Baseline	Equals 1 if the long rains (masika) in 2009/10 in the village were as expected or more than expected.
Maize price at the beginning of harvest 2009/10 (TSH/Kg)	Baseline	Maize price (TSH/Kg) at the beginning of the long rains harvest in 2009/10
Program subsidy as percent of input package	Baseline	Average price of input package discounted the top-up amount (TSH), as a share of full price of input package (TSH)
Panel B: Villager household survey		
Household level data		
Is related to government officials or influentials	Baseline	Equals to 1 if the household head reports holding the position of or being related to DALDO, WEO, VEO, VVC member, Village Chair or Hamlet chair.
Socializes with government officials or influentials	Baseline	Equals to 1 if household head reports having regular social interaction with DALDO, WEO, VEO, VVC member, village or hamlet chairperson.
Used improved seeds in 2009/10	Baseline	Equals to 1 if household head reports using any improved seeds on any parcel in the long rainy season of 2009/10.
Used inorganic fertilizer in 2009/10	Baseline	Equals to 1 if household head reports using any inorganic fertilizer on any parcel in the long rainy season of 2009/10.
Maize yield (Kgs/acre) in 2009/10	Baseline	Maize yield (KG/acre) in the long rainy season of 2009/10. Include zeros (crop failure) and uses harvested area instead of planted area. At baseline, we did not collected data on planted area per plot. Yields over 4000 KGs/acre were removed from the sample.
Village level data		
% of beneficiaries who are eligible	Baseline	Percent of household heads who report being a program beneficiary, as a share of total number of village respondents.
Targeting differential	Baseline	Computed as number of eligible beneficiaries in a village divided by the number of eligible farmers minus the number of non-eligible beneficiaries in the village divided by the number of non-eligible farmers.
% of beneficiaries who are related to government officials or influentials	Baseline	Percent of household heads who report being a program beneficiary and holding the position of or being related to DALDO, WEO, VEO, VVC member, Village Chair or Hamlet chair, as a share of household head who self-report being a program beneficiary.

Panel C: Village Voucher Committee (VVC) member survey		
Household level data		
Number of changes in VVC composition since its creation	Baseline	Number of VVC members that have been changed or replaced since the committee was formed.
Responsibilities correctly named by VVC member	Baseline	Number of responsibilities correctly named by VVC member (up to 7). VVC responsibilities are: (i) inform village farmers about the targeting criteria and selection of beneficiaries, (ii) prepare list of beneficiaries, (iii) select beneficiary farmers from the list given number of vouchers allocated to village, (iv) submit list of beneficiary farmers to the Village Government and Council for approval, (v) inform approved farmers and request applications, (vi) distribute vouchers and (vii) monitor the use of inputs by voucher recipients
Correctly named program eligibility criteria	Baseline	Equals 1 if VVC member correctly listed the program eligibility criteria, namely (i) cultivate no more than 1 hectare of maize or rice, (ii) not have used chemical fertilizer or improved seeds in the previous 5 years and (iii) top-up affordability
Village level data		
Number of agrodealers in the village	Baseline	Average number of agrodealers in the village reported by VVC members in each village
Panel D: Household survey		
Household level data		
Raven's index	Follow-up	Number of correct answers given by the household head in a Raven's test. Assumes value of 0, 1, 2 or 3.
PCA food security index	Follow-up	Index of food security based on Principal Component Analysis (PCA) of answers to the following questions: a) How often did you worry that your household would not have enough food in the past 30 days? b) How often in the past 30 days were you or any household member not able to eat the kinds of foods you preferred because of a lack of resources? c) How many meals per day do you/your household eat on average during the following time periods? d) Were the meals consumed during the lean period smaller or different than meals consumed during the last 30 days? e) How many days per month did you or someone in your household go to bed hungry in the following time periods? Higher values of the index correspond to higher levels of food security
Paid to become beneficiary in 2010/11	Follow-up	Equals to 1 if household head reports having paid to become a NAIVS voucher beneficiary in 2010/11.
Is related to government official or influential	Baseline	Equals to 1 if the household head reports holding the position of or being related to DALDO, WEO, VEO, VVC member, Village Chair or Hamlet chair.
Awareness of NAIVS program	Follow-up	Equals to 1 if household head reports being aware of NAIVS program in his or her village.
Attended meeting where eligible households were identified in 2010/11	Follow-up	Equals to 1 if household head reports having attended the village or hamlet meeting where eligible households were identified in 2010/11.
Asked about ability to pay in 2010/11	Follow-up	Equals to 1 if household head reports being asked by the VVC or village hamlet official if he or she could afford the voucher top-up in 2010/11.
Household received vouchers in 2010/11	Follow-up	Equals to 1 if household reports having received vouchers in 2010/11.
Satisfaction with selection of beneficiaries in 2010/11	Follow-up	Equals to 1 if household head reports being very satisfied with the selection of beneficiaries in 2010/11.
Household received vouchers in 2011/12	Follow-up	Equals to 1 if household reports having received vouchers in 2011/12.
Used improved seeds in 2009/10	Baseline	Equals to 1 if household head reports using any improved seeds on any parcel in the long rainy season of 2009/10.
Used inorganic fertilizer in 2009/10	Baseline	Equals to 1 if household head reports using any inorganic fertilizer on any parcel in the long rainy season of 2009/10.
Used agricultural inputs in 2009/10	Baseline	Equals to 1 if household head reports using any inorganic fertilizer or any improved seeds on any parcel in the long rainy season of 2009/10.
Welfare standardized index	Follow-up	Standardized sum of 2 welfare outcome variables, also standardized: (i) percent of output sold and (ii) PC food security index.

Plot level data		
Percent of output sold	Follow-up	Plot level data. Total quantity harvested and sold as share of total quantity harvested in the long rainy season of 2010/11.
Maize yield (Kgs/acre) in 2009/10	Follow-up	Plot level data. Maize yield (KG/acre) for any type of maize seed during the long rainy season of 2009/10.
Kg of Basal Fert. per acre	Follow-up	Plot level data. KG of basal fertilizer used per acre of area planted in the long rainy season of 2010/11.
Kg of Fertilizer per acre	Follow-up	Plot level data. KG of top-dressing fertilizer used per acre of area planted in the long rainy season of 2010/11.
Crop Failure	Follow-up	Plot level data. Dummy variable. Equals to 1 if yield is zero. in the long rainy season of 2010/11.
Log Total Yield	Follow-up	Plot level data. Log of the total yield (KG/acre) in the long rainy season of 2010/11. Include zeros (crop failure) and uses planted area. Yields over 4000 KGs/acre were removed from the sample.
Standardized index of agriculture outcomes	Follow-up	Plot level data. Standardized sum of 5 agricultural outcome variables, also standardized before the sum: (i) area planted, (ii) kilograms of basal fertilier per acre, (iii) kilograms of total fertilizer per acre, (iv) dummy that takes value of 1 if yield is positive (1 - crop failure) and (v) log total yield.
Link level data		
Gives inputs to others	Follow-up	Link level data. Based on self-reported data on network of neighboring farmers in the village that the household head would go for advice of that would come to him/her for advice. Variable contains one observation for each link reported. Dummy variable. Equals to one if the household head reports giving any fertilizer and/or seed to a member of his/her network during 2010/11 planting season.

Online Appendix for

Targeting Inputs: Experimental Evidence from Tanzania

by Xavier Giné, Shreena Patel, Bernardo Ribeiro and Ildrim Valley

NOT FOR PRINT PUBLICATION

Contents:

Section A. Background on NAIVS

Section A1. Subsidized input package

The input package consisted of three vouchers:

1) Nitrogenous fertilizer—one bag of urea.

2) Phosphorous fertilizer. Option 1: one bag of DAP; Option 2: two bags of Minjingu Rock Phosphate (MRP) with nitrogen supplement (also called Minjingu mazao), depending on the farmer's choice.[1]

3) Seed (10 kilograms of a hybrid or open-pollinated maize variety or a rice variety)[2] sufficient for half of a hectare of maize (Table A.1).

Table OA1: Maize input packages proposed for NAIVS (for 1 ha)

Options	N source	P source	Seed
Option 1	1 bag urea	1 bag DAP	10 kg OPV or hybrid seed
Option 2	1 bag urea	2 bags MRP+10N	10 kg OPV or hybrid seed

Table OA2: Input prices in the Arusha villages in 2009/10 (TZS)

	Median value of subsidy voucher	Median top-up payment required	Median total input cost
DAP (50 kg)	12,000	16,500	25,000
Urea (50 kg)	23,000	17,000	42,000
Hybrid or OPV maize seed (10 kg)	17,000	17,000	34,000

Source: VVC member baseline survey
* As a point of reference in December 2010 $1 USD = 1480 TZS

Section A2. Institutional Arrangements

The National Agricultural Input Voucher Scheme (NAIVS) was overseen and implemented by the Ministry of Agriculture, Food Security and Cooperatives of Tanzania (MAFC) in collaboration with other public agencies and private sector participants.

NAVIS Oversight

The NAIVS National Forum was the apex organization and endorsed the allocation of vouchers across targeted districts based on the adopted guidelines and selection criteria guidelines for NAIVS implementation. The forum endorsed the NAIVS annual work plan and budgets

[1] DAP is the most commonly used basal fertilizer in Tanzania. MRP, manufactured in Northern Tanzania, is technically less efficient, because a certain amount of nitrogen is needed for plants to absorb phosphorus. MRP+N was a new product at the time of the study in 2011, technically equivalent to DAP, but produced in very limited quantities.
[2] The seed provided in the package was sufficient to plant half of a hectare (100 percent) of maize and one-quarter of a hectare (50 percent) of direct-seeded rice. The lesser quantity of rice was proposed because rice is a self-pollinating crop, and good quality seed can easily be multiplied by farmers themselves, thus encouraging the spread of new rice varieties.

proposed by the National Voucher Steering Committee (NVSC). Membership in the forum included public sector representatives at the national, regional and district level as well as representatives of the private sector, particularly fertilizer companies, seed companies, agro-dealer associations, farmer organizations, and civil society organizations. The forum's broad membership was intended to encourage the participation of all concerned groups and to ensure transparency in implementing the voucher system. The forum was chaired by the Minister of MAFC and met twice a year.

The NVSC provided policy guidance and oversees project implementation. The NVSC met every two months and was chaired by the Permanent Secretary of MAFC and included representatives of the Ministry of Finance, Prime Minister's Office, Regional Administration and Local Government, directors of relevant MAFC departments, and representations of national farmer organizations, agribusinesses that produce, import and market inputs, civil society, and the partner bank National Microfinance Bank (NMB). The NVSC set the criteria for allocating vouchers and guidelines for implementation of NAIVS at all levels, and reviewed the integrity of the voucher system, approved annual work plans, and addressed all implementation issues.

The Agricultural Input Section (AIS) was a section within the Directorate of Crop Development Department of the MAFC and was responsible for day-to-day management of NAIVS and for providing support to NVSC. The Head of Agricultural Input Section (HAIS) served as the NVSC Secretary. He was assisted by staff from other departments and sections of MAFC including one planning officer, one fertilizer and soil nutrition management specialist, one monitoring and evaluation officer, one accounting officer, one procurement officer, and one communication specialist.

NAIVS implementation

At regional level, the Regional Voucher Committee (RVC) supported districts and monitored the implementation of the voucher scheme in the region. The RVC was responsible for allocating vouchers to districts based on established criteria; estimating demand for agricultural inputs, based on historical input-use data, and providing this information to AIS; reviewing information collected from each district, including data on production, cropped area, input use, prices and marketable surplus; informing districts about their voucher allocations and initiating further allocation of vouchers to Wards and Villages by the local government authorities; helping to monitor implementation of the voucher scheme; and compiling NAIVS progress reports from the districts to submit to the NVSC Secretariat.

The District Voucher Committee (DVC) was made up of the District Agriculture and Livestock Officer (DALDO) and representatives of farmer groups, agro-dealers, and civil society and NMB and established under the chairmanship of the District Commissioner. In close collaboration with the respective district NAIVS Forum, the DVC implemented the voucher scheme in its respective district. In addition to allocating vouchers to wards and villages based on established criteria, the DVC monitored implementation at the village level and prepared and submitted implementation progress reports to the RVC for transmittal to AIS at the national level.

Finally, the Village Assembly (VA), in consultation with the Village Council and Village Government, organized the election of the Village Voucher Committee (VVC) members (three

men and three women), who were charged with recommending beneficiary farmers and, when endorsed by the VA, issuing the vouchers assigned to the village by the DVC to them. The VVC also monitored the use of inputs by voucher recipients and reported regularly to the Village Council and Village Government.

The VVC informed the community about the objectives of the voucher scheme; the process and procedures used to select participants; and the implementation rules. The VVC then prepared a list of farmers who cultivated not more than one hectare and who grew maize and/or rice. It identified farmers who were diligent, operated their fields full-time, and met the other criteria. Once the list was finalized, the VVC selected from it as many beneficiary farmers as number of 3-pack vouchers were allocated to the village. In subsequent years, the VVC could use the list to allocate additional packs of vouchers that were received.

Partnerships with the private sector

After vouchers were issued to farmers, farmer linked with an agro-dealer who could supply the desired inputs. For each input, farmer were expected to pay the difference between the voucher face value and the prevailing market price (i.e. the "top-up" amount), which at the prevailing market prices, was equivalent to about half the market price. Agro-dealers redeemed vouchers by depositing them with the National Microfinance Bank.

Agro-dealers. Agro-dealers were informed of the number and types of vouchers to be issued to farmers and encouraged to make inputs available at the village. Agro-dealers willing to participate in NAIVS had to complete a training course provided by the NGO Citizens Network for Foreign Affairs (CNFA) and had to register with the program. Agro-dealers obtained inputs from wholesalers or importers through their established commercial channels. Agro-dealer associations could identify key obstacles to the smooth flow of inputs from the sources to the users and to engage with key stakeholders on addressing these obstacles.

National Microfinance Bank. NMB's local branches credited agro-dealers' accounts in the amount of the face value of the vouchers they redeemed, using funds transferred from MAFC to NMB for this purpose. NMB verified the authenticity of the voucher, recorded the transaction, and informed MAFC that the transaction had been completed. NMB maintained and safeguarded all records and vouchers for a minimum of five years.

Private fertilizer companies. Input suppliers imported fertilizers according to projected demand and their assessment of the market, including the additional demand induced by NAIVS, and then distributed inputs through their own regional networks and independent agro-dealers.

The private seed industry. Seed companies were fully involved in supplying the certified seed included in the input package that farmers purchased with their vouchers.

Table OA3: Descriptive statistics of VVC members

	Baseline villager survey respondents	Baseline HH survey respondents	VVC member			P-value of t-test that (1) = (2)	P-value of t-test that (1) = (3)	P-value of t-test that (2) = (3)	P-value of t-test that (4) = (5)
			All	Lottery Villages	Non-lottery Villages				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Household head is male (0/1)	0.826	0.613	0.710	0.719	0.700	0.000	0.024	0.141	0.873
Household head is married (0/1)	0.845	0.813	0.871	0.844	0.900	0.154	0.582	0.266	0.517
House has concrete floor (0/1)	0.580	0.459	0.613	0.688	0.533	0.000	0.619	0.022	0.220
Has cultivable land smaller than 1 Ha (0/1)	0.503	0.748	0.613	0.656	0.567	0.000	0.096	0.024	0.477
Number of observations	734	460	62	32	30				
P-value of joint F-test that all coefficients are 0						*0.000*	*0.003*	*0.014*	*0.471*

Note: This table reports means of characteristics of baseline villager survey respondents (Column 1), baseline household survey respondents (Column 2) and VVC members (Columns 3-5, data collected at baseline). Columns 6-9 show p-values of the equality t-tests. In the villager and eligible surveys, questions were asked about the household head. In order to appropriate compare the data in Columns 1 and 2, Columns 3-5 restrict the data to VVC member who were head of their households (around 70% of respondents). (0/1) indicates dummy variables, equal to one if the response is yes. See Appendix Table 1 for definition of variables.

Table OA4. Characteristics of eligible households, baseline vs. additional sample

	Data source (1)	Total (2)	Baseline sample (3)	Additional sample (4)	P-value (3) = (4) (5)
Head of household is male (0/1)	Follow-up	0.520	0.553	0.491	*0.061*
Age of household head	Follow-up	51.2	50.9	51.4	*0.615*
Head of household is married (0/1)	Follow-up	0.637	0.651	0.625	*0.408*
Head of household can read and write (0/1)	Follow-up	0.728	0.747	0.712	*0.233*
House has concrete floor (0/1)	Follow-up	0.474	0.471	0.477	*0.857*
Number of Observations		920	460	460	
P-value of joint F-test that all coefficients are 0					*0.469*

Note: This table shows descriptive statistics using individual level data from the household survey. Column 1 describes when the data were collected, either at baseline or follow-up. Column 2 reports averages for the full sample. Column 3 reports the averages for the baseline sample while column 4 reports the averages for the additional sample interviewed at endline. In Column 5 we report the p-values of the mean comparison between the baseline and additional sample. P-value of joint F-test corresponds to the p-value of a joint F-test that all coefficients of a regression of having baseline data (being in the baseline sample) against characteristics are zero. All p-values are computed using the t-asymptotic wild cluster bootstrap procedure described in Cameron et al. (2008). Clustering was done at the village level. Range of values for categorical variables are given in parenthesis. (0/1) indicates dummy variables, equal to one if the response is yes. See Appendix Table 1 for definition of variables.

Table OA5: Descriptive statistics of Arusha vs. other regions

Characteristics	Arusha	Kilimanjaro	Morogoro	P-value of F-test
	(1)	(2)	(3)	(4)
Panel A: Village characteristics				
Number of agro-dealers	1.02	0.06	0.27	*0.024*
Number of Observations	46	16	15	
Panel B: Household characteristics				
Household head age	48.68	51.39	41.88	*0.000*
Household head is male (0/1)	0.613	0.509	0.502	*0.001*
Household head is married (0/1)	0.813	0.494	0.262	*0.000*
Household head can read and write (0/1)	0.754	0.885	0.825	*0.000*
House roof made of corrugated iron sheet (0/1)	0.930	0.865	0.390	*0.000*
House has concrete floor (0/1)	0.459	0.400	0.147	*0.000*
Total area cultivable land owned (acres)	2.08	2.29	5.57	*0.000*
Is related to government officials or influentials (0/1)	0.157	0.268	0.180	*0.000*
Number of Observations	460	340	400	

Note: This table reports means of characteristics of baseline household survey respondents in Arusha, Kilimanjaro and Morogoro regions. (0/1) indicates dummy variables, equal to one if the response is yes. See Appendix Table 1 for definition of variables.

Table OA6. Characteristics of eligible households, matched sample

	Lottery			No Lottery			P-value of t-test			
	Total	Beneficiary (B)	Non-benef. (NB)	Total	Beneficiary (B)	Non-benef. (NB)	(2) = (3)	(5) = (6)	(2) = (5)	(3) = (6)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Head of household is male (0/1)	0.663	0.649	0.677	0.642	0.640	0.646	*0.686*	*0.945*	*0.888*	*0.657*
Age of household head	49.4	49.5	49.3	45.5	46.3	43.9	*0.916*	*0.271*	*0.287*	*0.019*
Head of household is married (0/1)	0.813	0.784	0.844	0.825	0.809	0.854	*0.262*	*0.454*	*0.715*	*0.869*
Head of household can read and write (0/1)	0.751	0.722	0.781	0.832	0.820	0.854	*0.433*	*0.752*	*0.145*	*0.441*
Raven's index (0/3)	0.917	0.887	0.948	1.06	1.09	1.000	*0.622*	*0.693*	*0.180*	*0.795*
Related to government officials or influentials (0/1)	0.155	0.175	0.135	0.146	0.124	0.188	*0.485*	*0.440*	*0.397*	*0.468*
Socializes with government officials or influentials (0/1)	0.155	0.175	0.135	0.146	0.124	0.188	*0.485*	*0.440*	*0.397*	*0.468*
House has concrete floor (0/1)	0.539	0.526	0.552	0.504	0.494	0.521	*0.741*	*0.774*	*0.729*	*0.776*
Food insecurity PCA index	-0.291	-0.115	-0.468	-0.298	-0.322	-0.254	*0.215*	*0.875*	*0.493*	*0.560*
Has cultivable land larger than 1 Ha (0/1)	0.389	0.392	0.385	0.445	0.427	0.479	*0.932*	*0.526*	*0.632*	*0.284*
Maize yield (Kgs/acre) in 2009/10	676.1	733.1	619.0	745.8	750.2	737.1	*0.254*	*0.932*	*0.899*	*0.345*
Used agricultural inputs in 2009/10 (0/1)	0.658	0.629	0.688	0.664	0.640	0.708	*0.353*	*0.494*	*0.903*	*0.834*
Number of Observations	193	97	96	137	89	48	193	137	186	144
P-value of joint F-test that all coefficients are 0							*0.425*	*0.824*	*0.605*	*0.679*

Note: This table shows descriptive statistics using individual level data from the baseline household survey. The sample is restricted to households in non-lottery who are similar in observable characteristics based on a nearest neighbor propensity score matching algorithm. In lottery villages we also restrict the sample to households who share the propensity score distribution support of households in no lottery villages. Column 1 reports averages in lottery villages. Columns 2 and 3 report averages for beneficiaries and non-beneficiaries of the NAIVS voucher program in 2010/11 in lottery villages. We report analogous figures for non-lottery villages in Columns 4-6. In Columns 7-10 we report the p-values of the mean comparison between different groups. P-value of joint F-test corresponds to the p-value of a joint F-test that all coefficients of a regression of beneficiary status (Columns 7 and 8) or lottery dummy (Column 9 and 10) against characteristics are zero. All p-values are computed using the t-asymptotic wild cluster bootstrap procedure described in Cameron et al. (2008). Clustering was done at the village level. Range of values for categorical variables are given in parenthesis. (0/1) indicates dummy variables, equal to one if the response is yes. See Appendix Table 1 for definition of variables.

Table OA7. Agricultural Outcomes using Propensity Score Matching

	Grows maize	Area planted (acres)	Basal fertilizer per acre (Kg)	Total fertilizer per acre (Kg)	Crop failure	Log total yield
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Full Baseline Sample						
Beneficiary	-0.035	-3.435	30.655*	15.463	-0.092**	1.001**
	0.244	*0.211*	*0.060*	*0.238*	*0.037*	*0.031*
Lottery	-0.006	-2.477	26.611	9.183	-0.119**	1.151**
	0.862	*0.373*	*0.167*	*0.553*	*0.018*	*0.013*
Lottery x Beneficiary	0.047	1.776	-48.595**	-17.156	0.117**	-0.896*
	0.260	*0.566*	*0.038*	*0.274*	*0.026*	*0.084*
R-squared	0.005				0.020	
Mean of dep. var. for NB in NL vil.	0.959	5.89	3.08	14.70	0.186	3.97
P-val of B = NB in L villages	*0.638*	*0.292*	*0.290*	*0.849*	*0.385*	*0.649*
Model	OLS	Tobit	Tobit	Tobit	OLS	Tobit
Percentage of censured observations		0.04	0.88	0.64		0.15
Number of plots		531	531	531	531	531
Number of households	427	427	427	427	427	427
Panel B: Matched Baseline Sample						
Beneficiary	-0.026	-6.142	32.151	7.575	-0.032	0.761
	0.440	*0.240*	*0.203*	*0.670*	*0.596*	*0.102*
Lottery	-0.010	-5.368	31.212	3.100	-0.069	0.936**
	0.791	*0.300*	*0.294*	*0.876*	*0.222*	*0.035*
Lottery x Beneficiary	0.037	4.347	-41.644	-7.094	0.066	-0.801
	0.449	*0.414*	*0.182*	*0.717*	*0.342*	*0.135*
R-squared	0.002				0.006	
Mean of dep. var. for NB in NL vil.	0.958	8.92	2.71	18.33	0.136	4.13
P-val of B = NB in L villages	*0.749*	*0.304*	*0.620*	*0.961*	*0.311*	*0.883*
Model	OLS	Tobit	Tobit	Tobit	OLS	Tobit
Percentage of censured observations		0.041	0.884	0.618		0.138
Number of plots		414	414	414	414	414
Number of households	330	330	330	330	330	330

Note: This table reports the estimation of the following specifications: $y_{ijk} = \alpha_{ijk} + \beta_1 Beneficiary_{ij} + \beta_2 Lottery_j + \beta_3 Lottery_j * Beneficiary_{ij} + \varepsilon_{ijk}$, where i indexes the individual (household), j indexes the village and k indexes plots. $Beneficiary_{ij}$ is a dummy that takes value of 1 if the individual i in village j is a beneficiary of the NAIVS voucher program in 2010/11. $Lottery_j$ is a dummy that takes value of 1 if beneficiaries in village j were chosen using a lottery. The models presented here are not adjusted for any baseline covariates. Dependent variables are constructed based on questions asked on follow-up household survey. Data are restricted to baseline respondents in both panels. Panel A reports results using full baseline sample of households. In Panel B the sample is restricted to households in non-lottery who are similar in observable characteristics based on a nearest neighbor propensity score matching algorithm. The sample in Panel B also include households in lottery village who share the propensity score distribution support of households in no lottery villages. The dependent variable in Column 1 is a dummy that indicates whether or not the HH grew maize in 2010/11. Column 2 reports area planted. Columns 3 and 4 report use of basal fertilizer (DAP) and total fertilizer (basal + top-dressing or urea) per acre in kilograms, respectively. Dependent variable in Column 5 is a dummy indicating crop failure. Column 6 reports log yield (Kg/Area) including plots with crop failure. The outlier plots with yields over 4000 kg per area planted or harvested are dropped out of the regressions. P-values are computed using the t-asymptotic wild cluster bootstrap procedure described in Cameron et al. (2008) and reported below the coefficients. Clustering was done at the village level. ***,**,* denote statistical significance at the 1, 5 and 10 percent level, respectively. See Appendix Table 1 for definition of variables.

Table OA8. Welfare Outcomes using Propensity Score Matching

	Percent of output sold	Log total household income	Food security PCA index
	(1)	(2)	(3)
Panel A: Full Baseline Sample			
Beneficiary	0.277*	-0.381	0.425
	0.054	*0.348*	*0.187*
Lottery	0.324**	0.300	0.459
	0.023	*0.514*	*0.178*
Lottery x Beneficiary	-0.117	0.155	-0.400
	0.495	*0.815*	*0.320*
R-squared			0.013
Mean of dep. var. for NB in NL vil.	0.090	12.7	-0.737
P-val of B = NB in L villages	*0.105*	*0.702*	*0.928*
Model	Tobit	Tobit	OLS
Percentage of censured observations	0.64	0.03	
Number of households	381	260	427
Panel B: Matched Baseline Sample			
Beneficiary	0.377**	-0.695	0.279
	0.019	*0.201*	*0.596*
Lottery	0.415**	-0.213	0.431
	0.011	*0.634*	*0.393*
Lottery x Beneficiary	-0.270	0.527	-0.286
	0.171	*0.517*	*0.594*
R-squared			0.008
Mean of dep. var. for NB in NL vil.	0.069	13.1	-0.641
P-val of B = NB in L villages	*0.310*	*0.813*	*0.979*
Model	Tobit	Tobit	OLS
Percentage of censured observations	0.622	0.033	
Number of households	299	212	330

Note: This table reports the estimation of the following specification: $y_{ij} = \alpha_{ij} + \beta_1 Beneficiary_{ij} + \beta_2 Lottery_j + \beta_3 Lottery_j * Beneficiary_{ij} + \varepsilon_{ij}$, where i indexes the individual (household) and j indexes the village. $Beneficiary_{ij}$ is a dummy that takes value of 1 if the individual i in village j is a beneficiary of the NAIVS voucher program in 2010/11. $Lottery_j$ is a dummy that takes value of 1 if beneficiaries in village j were chosen using a lottery. The models presented here are not adjusted for any baseline covariates. Dependent variables are constructed base on questions asked on follow-up household survey. Data are restricted to baseline respondents in both panels. Panel A reports results using full baseline sample of households. In Panel B the sample is restricted to households in non-lottery who are similar in observable characteristics based on a nearest neighbor propensity score matching algorithm. The sample in Panel B also include households in lottery village who share the propensity score distribution support of households in no lottery villages. Column 1 reports a percentage of maize production that is sold. Column 2 reports on log of total household income, including non-agricultural activities. Dependent variable in Column 3 is constructed using the households reported worry for scarcity of food, number of meals per day, size of meals, and consumption of least preferred foods; higher values represent lower food security. P-values are computed using the t-asymptotic wild cluster bootstrap procedure described in Cameron et al. (2008) and reported below the coefficients. Clustering was done at the village level. ***,**,* denote statistical significance at the 1, 5 and 10 percent level, respectively. See Appendix Table 1 for definition of variables.

Table OA9: NAIVS program awareness and implementation

	Awareness of NAIVS program	Asked about ability to pay in 2010/11	Household received vouchers in 2010/11	Satisfaction with selection of beneficiaries in 2010/11	Household received vouchers in 2011/12
	(1)	(2)	(3)	(4)	(5)
Beneficiary	0.092	0.065	0.295***	0.197***	0.161**
	0.105	*0.399*	*0.000*	*0.000*	*0.044*
Meeting & Lottery village	0.063	0.044	0.094	0.217***	0.092
	0.256	*0.499*	*0.160*	*0.004*	*0.183*
Lottery village	0.033	0.027	0.064	0.168**	-0.017
	0.528	*0.642*	*0.369*	*0.011*	*0.803*
Meeting village	0.023	-0.013	0.013	0.161**	-0.025
	0.717	*0.835*	*0.884*	*0.034*	*0.787*
Beneficiary x M&L	-0.033	-0.035	-0.067	-0.228**	-0.063
	0.603	*0.674*	*0.445*	*0.016*	*0.481*
Beneficiary x Lottery	0.004	0.048	0.033	-0.085	0.112
	0.949	*0.598*	*0.696*	*0.297*	*0.238*
Beneficiary x Meeting	0.011	0.028	0.090	-0.079	0.018
	0.872	*0.766*	*0.344*	*0.495*	*0.841*
Number of households	920	920	920	920	920
R-squared	0.031	0.013	0.104	0.032	0.043
Mean of Dep Var in Control	0.887	0.172	0.267	0.715	0.264
P-val of B = Non-B in…					
Meeting & Lottery village	*0.553*	*0.546*	*0.039*	*0.267*	*0.200*
Lottery village	*0.019*	*0.063*	*0.000*	*0.082*	*0.000*
Meeting village	*0.020*	*0.118*	*0.000*	*0.255*	*0.011*

Note: This table reports the estimation of the following specification: $y_{ij} = \alpha_{ij} + \beta_1 Beneficiary_{ij} + \beta_2 ML + \beta_3 L_j + \beta_4 M_j + \beta_5 Beneficiary_{ij} * ML_j + \beta_6 Beneficiary_{ij} * L_j + \beta_7 Beneficiary_{ij} * M_j + \varepsilon_{ij}$, where i indexes the individual (household) and j indexes the village. $Beneficiary_{ij}$ is a dummy that takes value of 1 if the individual i in village j is a beneficiary of the NAIVS voucher program in 2010/11. Variables ML_j, L_j and M_j are dummies that take value of 1 if village j is under both interventions, only second intervention and only first intervention, respectively. The models presented here represent an intention to treat analysis and are not adjusted for any baseline covariates. Dependent variables are constructed based on questions asked on follow-up household survey. The dependent variable in Column 1 is a dummy that indicates whether respondent is aware of the presence of the NAIVS program in his or her village. Column 2 reports the results using a dummy that codes whether the respondent was asked about his or her ability to pay for the voucher top-up in 2010/11. In Columns 3 and 5, the dependent variables are dummies that indicates if respondent reports receiving vouchers in 2010/11 and 2011/12, respectively. For those regressions, respondents self-report receiving or not voucher and the answers may differ from administrative data used to assign beneficiary status. In Column 4, the dependent variable in Column 4 is a dummy variable that indicates whether the respondent reports being very satisfied with the selection of voucher beneficiaries in 2010/11. P-values are computed using the t-asymptotic wild cluster bootstrap procedure described in Cameron et al. (2008) and reported below the coefficients. Clustering was done at the village level. ***,**,* denote statistical significance at the 1, 5 and 10 percent level, respectively. See Appendix Table 1 for definition of variables.

Table OA10: Displacement and elite capture

	Gives inputs to others	Used inorganic fertilizers in 2009/10	Used improved seeds in 2009/10	Related to government officials and influentials	Socializes with government officials and influentials	Paid to become beneficiary in 2010/11
	(1)	(2)	(3)	(4)	(5)	(6)
Beneficiary	-0.0418	0.242*	-0.008	-0.146*	-0.125	0.008
	0.659	*0.053*	*0.929*	*0.082*	*0.142*	*0.720*
Meeting & Lottery village	-0.104	0.236*	0.171*	-0.063	-0.079	0.017
	0.209	*0.090*	*0.058*	*0.455*	*0.373*	*0.321*
Lottery village	-0.140*	0.188	0.089	-0.078	-0.057	0.008
	0.082	*0.142*	*0.429*	*0.362*	*0.515*	*0.635*
Meeting village	-0.0737	0.152	0.022	-0.149*	-0.148*	-0.000
	0.376	*0.303*	*0.848*	*0.060*	*0.068*	*0.956*
Beneficiary x M&L	0.0953	-0.381***	-0.011	0.183	0.165	-0.011
	0.316	*0.005*	*0.936*	*0.108*	*0.152*	*0.673*
Beneficiary x Lottery	0.169	-0.375**	0.005	0.188	0.149	0.008
	0.101	*0.015*	*0.970*	*0.111*	*0.210*	*0.714*
Beneficiary x Meeting	0.0331	-0.232	0.094	0.218**	0.217*	-0.008
	0.730	*0.103*	*0.464*	*0.039*	*0.057*	*0.769*
Number of contacts	523					
Number of households	294	427	427	427	427	920
R-squared	0.025	0.028	0.016	0.019	0.017	0.004
Mean of Dep Var in Control	0.140	0.401	0.554	0.134	0.115	0.018
P-val of B = Non-B in…						
Meeting & Lottery village	*0.180*	*0.007*	*0.756*	*0.034*	*0.062*	*0.927*
Lottery village	*0.068*	*0.199*	*0.980*	*0.629*	*0.763*	*0.224*
Meeting village	*0.796*	*0.923*	*0.337*	*0.302*	*0.231*	*0.801*

Note: In Column 1, we report the estimation of the following specification: $y_{ijk} = \alpha_{ijk} + \beta_1 Beneficiary_{ij} + \beta_2 ML_j + \beta_3 L_j + \beta_4 M_j + \beta_5 Beneficiary_{ij}*ML_j + \beta_6 Beneficiary_{ij}*L_j + \beta_7 Beneficiary_{ij}*M_j + \varepsilon_{ijk}$, where i indexes the individual (household), j indexes the village and k indexes another individual reported to be in the respondent's network. Columns 2-6 report the estimation of the following specification $y_{ij} = \alpha_{ij} + \beta_1 Beneficiary_{ij} + \beta_2 ML_j + \beta_3 L_j + \beta_4 M_j + \beta_5 Beneficiary_{ij}*ML_j + \beta_6 Beneficiary_{ij}*L_j + \beta_7 Beneficiary_{ij}*M_j + \varepsilon_{ij}$, where i indexes the individual (household) and j indexes the village. $Beneficiary_{ij}$ is a dummy that takes value of 1 if the individual i in village j is a beneficiary of the NAIVS voucher program in 2010/11. Variables ML_j, L_j and M_j are dummies that take value of 1 if village j is under both interventions, only second intervention and only first intervention, respectively. The models presented here represent an intention to treat analysis and are not adjusted for any baseline covariates. The dependent variable in Column 1 is a dummy variable that takes a value 1 if the respondent reported giving agricultural inputs to a non-beneficiary friend. The dependent variables in Column 2 and 3 are dummy variables that take value of 1 if the respondent reports using improved seeds and inorganic fertilizers in 2009/10, respectively, using household survey data collected at baseline. In Columns 4 and 5, the dependent variables are dummies that takes value of 1 if respondent reports holding the position of or being related to and having regular social interaction with DALDO, WEO, VEO, VVC member, or Village or Hamlet Chair. The dependent variable in Column 6 is a dummy variable that takes value of 1 if respondent reports at follow-up household survey having paid to become a voucher beneficiary in 2010/11. Data for the Columns 1 and 6 were collected using household survey at follow-up while data in Columns 2-6 come from household survey at baseline. P-values are computed using the t-asymptotic wild cluster bootstrap procedure described in Cameron et al. (2008) and reported below the coefficients. Clustering was done at the village level. ***,**,* denote statistical significance at the 1, 5 and 10 percent level, respectively. See Appendix Table 1 for definition of variables.