Using Farmer Groups to Share Information*

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Abstract

We study material and informational constraints to adoption of a subsidy for agricultural inputs in Uganda. We randomly assign farmer organizations to be offered no subsidy, a status quo subsidy, or a higher initial subsidy. Material constraints to adoption bind for some farmers: the status quo subsidy has no significant effect on adoption, but the high subsidy substantially increases adoption. Informational constraints to adoption also bind for some farmers: group leaders are more likely to adopt than general members, and member adoption increases with leader experience with improved agricultural inputs as well as social similarity to the member.

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1 Introduction

In sub-Saharan Africa, agricultural productivity and adoption of agricultural technologies such as improved seed varieties and fertilizers is low and stagnant (Suri and Udry, 2022). A common policy intervention to increase agricultural technology adoption and productivity is an agricultural input subsidy (Jayne et al., 2018). Agricultural input subsidies can have large impacts on agricultural technology adoption and producitivity: the first randomized controlled trial (RCT) of a government-implemented agricultural input subsidy estimates that, for farmers in Mozambique induced by a subsidy to adopt agricultural inputs, subsidized inputs increase yields by 80% (Carter et al., 2021).

Yet even for subsidies of agricultural inputs with demonstrable impacts, adoption is far from universal. In the RCT in Mozambique, of the farmers assigned to be eligible for the subsidy of 73%, the subsidy was adopted by only 41% of farmers (Carter et al., 2021). The context and findings of the Mozambique study suggest two primary constraints to the adoption of agricultural input subsidies. The first constraint is material. In surveys in Mozambique, most farmers self-report that lack of money was the reason for not adopting the agricultural input subsidy (Carter et al., 2021). The second constraint is informational. Carter et al. (2021) find substantial technology adoption due to spillover of information about agricultural inputs from subsidy recipients to others in their social networks, implying that information can be a binding constraint to technology adoption even within a population of farmers eligible for an agricultural input subsidy in sub-Saharan Africa.

This paper studies the roles of material and informational constraints to adoption of a government-implemented agricultural input subsidy in sub-Saharan Africa. In particular, we study an electronic voucher ("e-voucher") subsidy for agricultural inputs in Uganda. The e-voucher subsidy was the primary component of the Government of Uganda's Agriculture Cluster Development Project (ACDP) and was piloted in 2019, the year of interest for our study. The e-voucher subsidy phased out over the course of three seasons, with the subsidy amount decreasing with each season. Farmers accessed e-voucher subsidies as individuals, but to be eligible for the e-voucher a farmer was required to be a member of a farmer organization. In practice, farmer organizations were a critical entry point for the Government of Uganda to identify eligible farmers and share information about the e-voucher program.

We study the role of material constraints to adoption of an agricultural input subsidy by randomly assigning farmers eligible for the e-voucher subsidy to different subsidy levels by farmer organization. The research design yields three intended treatment sub-samples: a control group to receive no subsidy, a treatment group to receive a subsidy of 67 percent in season one (followed by 50 percent in season two and 33 percent in season three), and a treatment group to receive a subsidy of 90 percent in season one (followed by 50 percent in season two and 10 percent in season three). The 67 percent subsidy increases subsidy adoption relative to the control by only 6.5 percentage points (26%) and this estimate is not different from zero with statistical significance at standard significance levels. The 90 percent subsidy increases subsidy adoption relative to control by 27.2 percentage points (108%) and this estimate is different from zero with statistical significance at the 0.1% confidence level. Our estimates of average treatment effects of subsidies on adoption suggest that material constraints are binding for some farmers.

We study the role of informational constraints to adoption of an agricultural input subsidy by drawing on insights from the field and from the literature on social learning. In practice, farmer organizations were a critical entry point for the Government of Uganda to identify eligible farmers and to share information about the e-voucher program. To investigate this in our data, we estimate differences in adoption between leaders and members of farmer organizations as well as estimate the relationship between leader characteristics and member adoption. Conditional correlational regression estimates indicate that leaders adopt the subsidy at a rate that is 14.8-16.2 percentage points greater than members, a large effect that is largely robust to estimation approach (including propensity score matching). Additionally, we estimate that, for those assigned to the 90% subsidy, adoption of the e-voucher subsidy by a member of a farmer organization increases with the leader of their organization's: (1) sophistication (i.e. experience) with improved agricultural inputs and (2) social similarity to them. These estimates are large, different from zero with statistical significance, and robust to controlling for a number of other observable characteristics of farmer organizations. This speaks directly to a trade-off highlighted in the literature on social learning and leadership (Cheng, 2022); although more representative leaders have been shown to improve internal group functioning (Deserranno et al., 2019; Nourani et al., 2021), we find that leader sophistication has a stronger relationship with member adoption of this external program.

Taken together, the findings of this study lend insight into the impacts of the intensive margins of agricultural input subsidy design and implementation. In doing so, our study contributes most directly to three literatures related to implementing economic programs in a developing country context. First, the study contributes to the literature on government-implemented agricultural input subsidy programs in sub-Saharan Africa (Carter et al., 2021; Jayne et al., 2018), suggesting that the level of subsidy is an important component of adoption. Second, the study relates to targeting interventions in networks (Balew et al., 2022; Bandiera et al., 2023; Beaman and Dillon, 2018; Beaman et al., 2021; BenYishay et al., 2020; Carter et al., 2021; Cheng, 2022; Galeotti et al., 2020; Mekonnen et al., 2022; Takahashi et al., 2020; Varshney et al., 2022), finding that the flow of information is a binding constraint on adoption. Third, the study relates to broader work on the governance of community organizations (Arcand and Wagner, 2016; Ashraf and Bandiera, 2018; Deserranno et al., 2019; Francesconi and Wouterse, 2015; Nourani et al., 2021), speaking to a trade-off in leader characteristics between sophistication and similiarity to the membership at large.

The remainder of this paper is structured as follows. Section 2 reviews the literature on social learning, particularly about agricultural technologies in a developing country context. Section 3 describes our empirical context. Section 4 estimates average and heterogeneous effects of the randomized subsidy treatments on farmer participation in the e-voucher subsidy program in Uganda. Section 5 studies the dissemination of information about the e-voucher subsidy program. Section 6 concludes.

2 Literature Review

Our paper contributes to a long history of work on social learning, particularly for agricultural technology adoption. Low adoption of improved agricultural technologies which are known to be profitable is an ongoing puzzle. Risk aversion and liquidity constraints may prevent farmers from experimenting with new technologies; the ACDP program's subsidy was intended to address these constraints for farmers. However, there may also be informational constraints, including technical information on how to implement a novel technology or information on the returns to a technology (van Campenhout, 2012). Particularly if the latter binds, farmers may learn from the people around them. Cheng (2022) describes three mechanisms by which social learning occurs (incidentally, these are also three reasons it is difficult to study empirically): a peer's actions as well as exogenous characteristics may influence an individual's actions, but peers behave similarly because they share traits and face the same environment.

The choice to pass on information can be understood as a strategic act, with both benefits and costs that have been studied in the literature. Several papers, such as Balew et al. (2022) and Bandiera et al. (2023), experimentally incentivize the sharing of information (that is, externally shape the benefits); Balew et al. (2022) find that these incentives increase the effort exerted to share information, but have no impact on the likelihood that recipients act on their new information (by experimenting with new agricultural technologies). The benefits of sharing information can take the form of material incentives, such as in Balew et al. (2022), but more often social recognition and prestige; these social incentives are less likely to crowd out any intrinsic motivation to share information (Gauri et al., 2017).[1] Bandiera et al. (2023) find evidence, however, that delivery agents are able to extract rents

[1] Gauri et al. (2017) also finds that social recognition has a larger impact on information passing in areas with higher initial capacity, suggesting potential complementarities between sophistication and the social ties between members of a group.

from non-poor connections they pass information on to (in addition to the low financial incentives provided by their experiment).[2]

The costs of sharing information include the effort exerted by the agent, which may be affected by the identity of the agent and the group they seek to reach (Ashraf and Bandiera, 2018). In particular, Cheng (2022) highlights a tension in the literature: delivery agents that are themselves more sophisticated are more effective in communicating information about complex technologies, but heterogeneity between the agent and recipients hampers social learning. Often in practice, the agent charged with passing on information is a local leader. Local leaders should have more information on local conditions (such as the distribution of shocks and individual returns to inputs), so they could target new technologies to maximize aggregate returns and then redistribute afterwards (Basurto et al., 2020). In a different context, higher quality leaders construct more public goods and generally perform better (Lim, 2020). Existing social connections are easier to pass information on to; Bandiera et al. (2023) find that more connected delivery agents reach more farmers overall, particularly among their own ties. Similarly, Chen et al. (2010)'s work in Uganda finds a stronger marginal effect of local information providers for more connected agents.

Turning to the role of heterogeneity in social learning, our work is closely related to that of Ambler et al. (2021), who look at the flow of information within existing farmer groups. They find that decisions made by leaders are less influential in shaping behavior than those made by peers; social comparison effects can hamper the relevance of information passed on by someone socially different from the farmer. By contrast, Behaghel et al. (2020) find that heterogeneity does not impede social learning from 'contact farmers' among dairy farmers in Uganda.

Social learning is a key function of farmer groups, as well as other types of local or-

[2]Alatas et al. (2019) argue, however, that this form of elite capture happens more often when there are in fact additional benefits remaining once the very poor have been addressed; they calculate that the extent of elite capture is relatively small in welfare terms. Pan and Christiaensen (2012) similarly look at the tension between poverty alleviation and agricultural productivity in targeting input vouchers in Tanzania. They find that leaders are distributing vouchers to the less poor, but targeting is better in areas with a higher share of beneficiaries, higher trust in the community, and that are not served by external extension agents.

ganizations. Our work contributes to the literature on the functioning of farmer groups. One strand in particular focuses on the leaders of these groups: are they representative of the broader membership, and how does their representativeness impact the group's effectiveness? Deserranno et al. (2019), for example, look at the leaders of Village Savings and Loan Associations (VSLAs) in Uganda, and find that leaders elected (rather than selected through public discussion) are more representative of the economic status of their group (that is, less wealthy, with less education and business training); they are also more effective in distributing benefits to all members of the group. In a similar vein, Nourani et al. (2021) find that democratically-run farmer groups in Malawi with closer social ties are more cooperative than their counterparts dominated by elite leaders, and are especially better at aggregating preferences and sharing information within the group. This is consistent with evidence from Beath et al. (2014) that the democratic selection of leaders limits elite capture. Both Deserranno et al. (2019) and Nourani et al. (2021) suggest a potential trade-off, however: although more representative leaders are beneficial for the functioning within the group (and in particular the distribution of resources within the group), these leaders are less educated, and Nourani et al. (2021) find that the program facilitator from an external NGO interacts more with more elite leaders. It could be that more skillful or sophisticated leaders are better placed to link the group to the external world.

This paper also contributes to a broader literature on the functioning of farmer groups in developing country contexts, such as Francesconi and Wouterse (2015). Farmer groups or other rural producer organizations exist in every country in Sub Saharan Africa, and serve an important political role given their legibility to government (presenting clear homogeneous demands) (Engelsma). Farmer organizations that can solve collective action problems in the non-political domain (such as selling produce jointly) can credibly mobilize politically, hence the common targeting of benefits such as agricultural input subsidies to farmer groups.

3 Empirical Context and Experimental Design

This section first describes Uganda's Agriculture Cluster Development Project and its agricultural input subsidy pilot in 2019, which is focus of our study. The section then describes the randomized controlled trial designed around the subsidy pilot.

3.1 Uganda's Agriculture Cluster Development Project

The Government of Uganda's Ministry of Agriculture, Animal Industry and Fisheries (MAAIF) implemented the Agriculture Cluster Development Project (ACDP) with financial support from the World Bank in the form of a loan of 150 million USD. The goal of ACDP was to increase the production and sales by smallholder farmers in Uganda of major agricultural commodities. ACDP specifically targeted four major food crops (maize, beans, rice, and cassava) as well as the country's greatest high value agricultural crop (coffee). ACDP's target was to reach 450,000 farm households across 12 geographic clusters of the country, spanning over 57 districts (MAAIF, 2018).[3]

ACDP's primary component was an electronic voucher (e-voucher) subsidy for agricultural inputs. The subsidy was designed to phase out over the course of three seasons, starting with a subsidy in season one of 67 percent, in season two of 50 percent, and in season three of 33 percent. ACDP's goal was for farmers using the subsidy to increase agricultural yields by 50 percent. While this yield growth goal was high, it appeared achievable in Uganda based on estimates from MAAIF (2012), experimental trials (Kaizzi et al., 2012a,b), and on-farm trials (Sebuwufu et al., 2015; Sibiko, 2012).

Fig. 1 summarizes the electronic voucher management system, including the process for a farmer to redeem the subsidy. A farmer first enrolls in the system by making an initial down payment on their co-payment for agricultural inputs. The farmer later orders inputs on the e-voucher system. Motivations for administering the subsidy through an e-voucher include reducing leakage of subsidies from intended beneficiary farmers as well as linking

[3]This is about 9% of the country's farm population of approximately 5 million farm households.

farmers to private agro-input dealers. A potential downside, however, is the potentially steep learning curve for integrating both farmers and private agro-input dealers into the e-voucher management system.

In districts targeted by ACDP, eligibility for the e-voucher subsidy was for individual farmers meeting the following criteria (MAAIF, 2018):

1. Be a member of a registered farmer association/cooperative;
2. Be Ugandan and in possession of a valid National Identity card;
3. Be willing to commit at least one acre of the land for the project commodity;
4. Be willing to co-fund purchase of inputs.

In practice, the critical eligibility criterion was: 1. Be a member of a registered farmer association/cooperative. This is because MAAIF identified farmers for the program by contacting a farmer organization's leader (chairperson or secretary), with the leader serving as a point person to share information about the program with the organization's members.

MAAIF piloted the e-voucher subsidy program in 2019. The pilot included five districts, one for each of the five commodities targeted by ACDP. Pilot districts were drawn from five separate geographic clusters defined by ACDP. Within each pilot district, MAAIF piloted the e-voucher in a subset of administrative levels below the district called sub-counties.

3.2 Randomized Controlled Trial of the Subsidy Pilot

In collaboration with MAAIF and the World Bank, we designed and implemented a randomized controlled trial (RCT) of the e-voucher subsidy pilot. The RCT focuses on four of the five crops targeted by ACDP: maize, beans, coffee and rice; we exclude cassava, which is more difficult to measure due to its long growing period and its ability to be stored in the ground. We weight our sample across crops to be representative of the relative importance

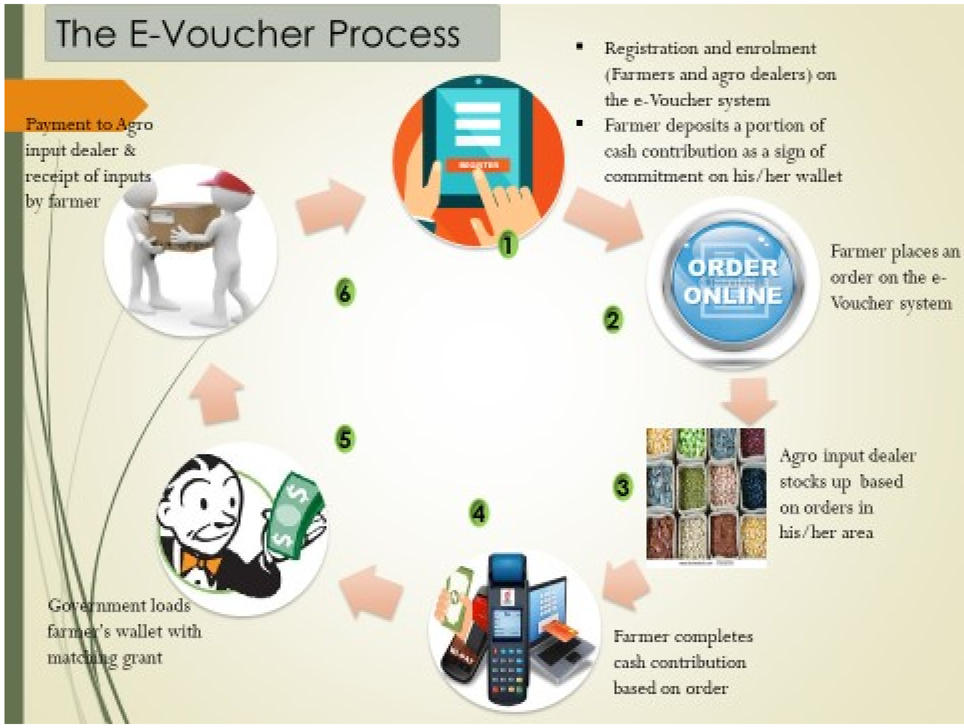

Figure 1: ACDP's Electronic Voucher Management System
(Source: https://www.agriculture.go.ug/the-agriculture-cluster-development-project-acdp/)

of each crop in the ACDP program, which devotes the most resources to maize, followed by beans and coffee, followed by rice.

Fig. 2 maps, for each pilot district for our four crops of interest, its sub-counties (light blue) as well as the sub-counties sampled for the RCT (dark blue). In an attempt to minimize disruption of the pilot program and minimize risk of contaminating the RCT, where possible we do not conduct the RCT in sub-counties selected for the pilot program but instead in otherwise similar sub-counties near the pilot sub-counties. Our sample of sub-counties is as follows.

- East Uganda: two sub-counties from the pilot district for maize
- Southwest Uganda: one sub-county from the pilot district for beans
- Central Uganda: one sub-county from the district neighboring the pilot district for coffee; this is due to the pilot covering all sub-counties in the pilot district for coffee

- Northern Uganda: one sub-county from the pilot district for rice; this was a pilot sub-county due to the pilot covering all sub-counties in the pilot district for rice

Within each sub-county sampled for the RCT, in 2018 MAAIF and district-level agricultural extension agents conducted a census of all existing farmer organizations. Among farmer organizations within a sub-county, we randomly assigned on a computer:

1. Treatment (subsidy pilot) to sixteen organizations per sub-county;

2. Control (no subsidy pilot) to the remaining organizations in each sub-county (MAAIF agreed to offer the subsidy to these organizations after the study period).

Among the sixteen treatment farmer organizations within a sub-county, MAAIF invited each organization's leaders to participate in a public lottery to randomly assign:

1. Subsidy Stream A (67/50/33) to eight organizations;

2. Subsidy Stream B (90/50/10) to eight organizations.

We modified this experimental design slightly for the rice sub-county due to the relatively small size of rice in the ACDP program and to minimize disruption to the pilot program from conducting the RCT within a rice pilot sub-county. First, the sample size for the rice sub-county is half that of the other sub-counties. Second, in the rice sub-county we randomly assigned four organizations each to Subsidy Stream B and Control on a computer; the remaining organizations in the rice sub-county were eligible for Subsidy Stream A as part of the pilot program.

3.3 Data Sources

Our empirical analysis uses three data sources. The first data source is the farmer organization census conducted in RCT sub-counties by MAAIF and district-level agricultural extension agents in 2018, the year before the 2019 pilot. The census included, for each organization, the organization's name, number of members, and the name and phone number

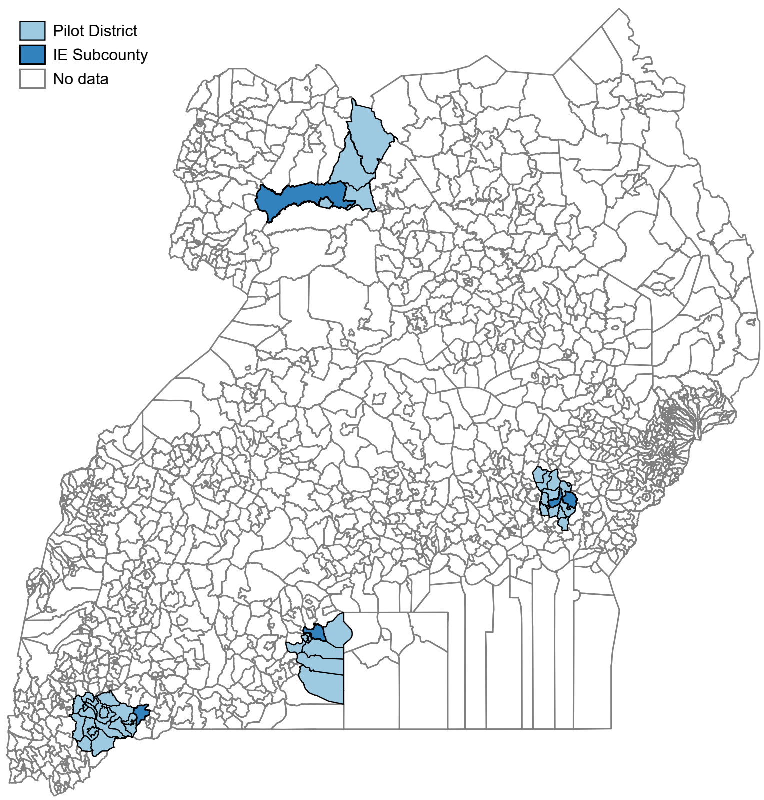

Figure 2: Locations of ACDP Pilot District Sub-counties and RCT Sub-counties

of the organization's chairperson and secretary. In total, the farmer organization census includes data for 133 farmer organizations in the RCT sub-counties, including organizations in Subsidy Stream A, Subsidy Stream B, and Control.

The second data source is a baseline household survey conducted in 2019. The survey focused on farmer recall of agricultural data from 2018, the two seasons prior to ACDP's pilot subsidy program. We conducted baseline household surveys with a random sample of farmers from each treatment group and a random sample of farmers from randomly selected control groups in each RCT sub-county.

The third data source is administrative data from the e-voucher management system on individuals who participated in ACDP in 2019. These data include both enrollment in the subsidy program as well as orders of agricultural inputs through the subsidy program.

Our analysis data set merges these three data sources together. Our total number of observations is 2189. For some names of individuals sampled from the sampled farmer organization rosters, there is no match to that name in the household roster from the baseline survey. As a result, these observations lack data on demographic information for the sampled farmer, in particular gender and education. Additionally, some household surveys are incomplete and lack data on variables such as livestock wealth. Since we pre-specified heterogeneity analyses by both gender and livestock wealth, in our analysis we omit observations with missing values for either of these variables. The total number of observations in the final analysis data set is 2100.

4 Treatment Effects on Subsidy Pilot Enrollment

This section estimates pre-specified regression models of average and heterogeneous treatment effects of subsidy assignment on subsidy pilot enrollment. Additionally, the section provides context for each of these sets of estimates.

4.1 Average Treatment Effects: Estimates

Our pre-specified regression model of average treatment effects of subsidy assignment on program participation for individual i in farmer group f in sub-county g is

$$Y_{ifg} = \rho Treatment_f + \gamma_g + \varepsilon_{ifg} \tag{1}$$

where Y_{ifg} is an indicator for program participation, $Treatment_f$ is a vector of indicators for subsidy stream treatment assignment, γ_g is a sub-county fixed effect to account for randomization being stratified by sub-county, and ε_{ifg} is an error term. We estimate standard errors clustered by the unit of randomization, the farmer group.

Before presenting regression estimates of average treatment effects on subsidy pilot enrollment, we first present summary statistics at baseline in Table 1. Among sample farmers, use of improved inputs is low: use of improved seed for any crop is 22%, use of pesticides is 23%, and use of inorganic fertilizers is 17%. To estimate the effect on input use of subsidies, we randomly assign sample farmers to different subsidies: 0 percent ("Control"), 67 percent ("A (67-50-33)"), and 90 percent ("B (90-50-10)"). At baseline, observable characteristics have mean values that are fairly similar across subsidy treatment arms. Balance on observable characteristics gives us confidence that we also have balance on unobservable characteristics such that the randomized treatment assignment is an exogenous instrument for farmer participation in ACDP's pilot input subsidy program in Uganda. The remainder of this section presents estimates of the effect of subsidies on farmer participation in ACDP's pilot input subsidy program in Uganda.

Table 2 presents estimates of average treatment effects of subsidy assignment on program participation. In Table 2, we define program participation as a 0/1 indicator for enrollment in ACDP's subsidy pilot. Column (1) presents estimates for the full sample. For the full sample, enrollment for the control group is unexpectedly high, with 25.1% of farmers assigned to the control enrolling in the program. Assignment to the 67 percent subsidy treatment

	All	Control	A (67-50-33)	B (90-50-10)
Agriculture (0/1)				
- Main crop is target	0.68	0.67	0.69	0.69
- Improved seed: Target	0.18	0.17	0.17	0.21
- Improved seed	0.22	0.20	0.21	0.26
- Pesticides	0.23	0.20	0.25	0.25
- Inorganic fertilizers	0.17	0.17	0.18	0.16
Landholdings (acres)				
- Total	3.46	3.07	4.10	3.21
Household attributes				
- Household size	6.57	6.43	6.60	6.68
- Livestock groups owned	1.03	1.01	0.95	1.13
Respondent attributes				
- Female	0.60	0.60	0.58	0.61
- Age	43.68	43.07	42.89	45.12
Observations	2100	706	707	687

Table 1: Baseline characteristics by randomized treatment assignment

increased enrollment relative to the control group by only 6.5 percentage points (26%), and this estimate is not different from zero with statistical significance at the 5% level. Assignment to the 90 percent subsidy treatment, however, increased enrollment relative to the control group by a substantial 27.2 percentage points (108%), and this estimate is different from zero with statistical significance at the 0.1% level.

While our parameter of interest is the effect of input prices on a farmer's participation in ACDP, parameter estimates in column (1) could be due in part to factors other than input prices. To investigate potential mechanisms underlying our estimates of our pre-specified model, in the next section we explore our data based on our observations of implementation of the ACDP subsidy pilot and the randomized controlled trial.

4.2 Average Treatment Effects: Context

In this section, we provide some context around the three main findings from Table 2, column (1): farmers assigned to the control group have high enrollment, farmers assigned to subsidy stream A have relatively small treatment effects, and farmers assigned to subsidy stream B

	(1) All	(2) Maize1	(3) Maize2	(4) Beans	(5) Coffee	(6) Rice
A (67-50-33)	0.065	0.034	0.039	0.107	0.184	-0.015
	(0.036)	(0.039)	(0.095)	(0.053)	(0.089)	(0.041)
B (90-50-10)	0.272***	0.112	0.115	0.466**	0.721***	0.026
	(0.049)	(0.071)	(0.100)	(0.131)	(0.057)	(0.025)
Control Mean	0.251	0.132	0.304	0.034	0.153	0.962
Observations	2100	643	490	365	367	235

Column (1) controls for fixed effects for randomization strata (sub-county).
Standard errors clustered by randomization unit (farmer group) in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: Average treatment effects estimates: Enrollment (0/1)

have relatively large treatment effects.

Farmers assigned to the control group have high enrollment due to the randomized controlled trial (RCT) being implemented imperfectly by government officials. In the context of ACDP, the lead government officials implementing ACDP in the field are agricultural extension officers at the sub-county level. To explore the potential for sub-county-level differences in implementation, we re-estimate Eq. (1) for each of the five sub-counties in our sample. Sub-county is the level at which the randomization is stratified, meaning that, within each sub-county sub-sample, random assignment is uncorrelated with farmer characteristics in expectation.

Table 2, columns (2)-(6) show that farmers assigned to the control group have high enrollment in the full sample due in large part to the rice pilot sub-county for ACDP. In the rice pilot sub-county for ACDP, enrollment in ACDP among control group farmers is nearly universal (96.2%). While we did not anticipate control group contamination to this degree, the rice district was most vulnerable to contamination of the control in the RCT's implementation. The rice district was the only district where we conducted the RCT within a pilot sub-county rather than a non-pilot sub-county, meaning that the default for non-study farmers in the rice district was to be eligible for ACDP whereas the default for non-study farmers in other districts was to be ineligible for ACDP. Since the rice sub-county effectively did not implement the RCT for the outcome of interest, program enrollment, we exclude the rice sub-county for the remainder of the analysis.

Farmers assigned to subsidy stream A having relatively small treatment effects may be due in part to treatment assignment of a farmer group changing more than the price of inputs. In particular, treatment assignment of a farmer group may change the attitudes of its members toward the program. Anecdotally, while stakeholders agreed that public lotteries would be perceived as fair and transparent, some farmers expressed frustration about assignment to subsidy stream A rather than subsidy stream B. These anecdotes are consistent with what we find from comparing, for each farmer, their farmer group membership prior to ACDP with the farmer group that they enrolled in ACDP under: program participants not complying with treatment assignment tend to enroll under farmer groups assigned to subsidy stream B. In this way, treatment assignment changed not only the assigned subsidy assignment, but also, in some cases, a farmer's attitude toward ACDP and their membership in a farmer group.

Finally, despite farmers assigned to subsidy stream B having relatively large treatment effects, most of the farmers assigned to subsidy stream B who enrolled in ACDP actually enrolled under subsidy stream A; these farmers drive 50-75% of the treatment effect estimate for subsidy stream B. In other words, most of the treatment effect estimate for subsidy stream B is driven by farmers who anticipated receiving a 90 percent subsidy based on their random assignment, were only offered a 67 percent subsidy due to imperfect implementation of the randomized controlled trial, yet still enrolled under the the 67 percent subsidy.

This context suggests that the relatively low treatment effect estimate for random assignment to subsidy stream A is not due entirely to the difference in input prices for these farmers relative to those randomly assigned to subsidy stream B. If that were the case, farmers assigned to subsidy stream B would not enroll under subsidy stream A at such high rates. The low treatment effect for subsidy stream may be due to additional factors other than price, such as random assignment to subsidy stream A changing a farmer's attitude toward ACDP.

4.3 Heterogeneous Treatment Effects: Estimates

Our pre-specified regression model of heterogeneous treatment effects on program participation for individual i in farmer group f in sub-county g is

$$Y_{ifg} = \rho Treatment_f + \Omega X_{ifg} + \delta Treatment_f X_{ifg} + \gamma_g + \varepsilon_{ifg} \tag{2}$$

where X_{ifg} is an observable characteristic (female, livestock wealth, or land wealth) and all other notation is the same as Eq. (1). We estimate standard errors clustered by the unit of randomization, the farmer group.

Table 3 presents estimates of heterogeneous treatment effects on program participation. Column (1) provides a benchmark for these results by re-estimating Eq. (1) for non-rice sub-counties. For the non-rice sub-sample, assignment to the control causes enrollment of 16.1%, assignment to subsidy stream A causes enrollment to increase by only 7.6 percentage points relative to the control (47%), and assignment to subsidy stream B causes enrollment to increase by 30.4 percentage points relative to the control (189%). Column (2) shows that for the outcome of an indicator for whether a farmer ordered inputs through ACDP, the magnitudes of these estimates are similar but their values attenuate toward zero. Attenuation is expected between the outcomes of enrollment and orders, as enrollment is a necessary but not sufficient condition for farmers to orders through ACDP.

Columns (3) and (4) present estimates of heterogeneous treatment effects by female. For farmers assigned to the control group or subsidy stream A (67-50-33), females have no difference in participation in ACDP relative to males. Since these groups have similar average treatment effects (columns (1) and (2)), it is not surprising that these groups have similar heterogeneous treatment effects. For farmers assigned to subsidy stream B (90-50-10), female has a large, positive effect on participation such that being female is associated

	(1) Enroll	(2) Order	(3) Enroll	(4) Order	(5) Enroll	(6) Order	(7) Enroll	(8) Order
A (67-50-33)	0.076	0.061	0.077	0.068	0.059	0.036	0.049	0.045
	(0.039)	(0.036)	(0.050)	(0.047)	(0.037)	(0.031)	(0.043)	(0.039)
B (90-50-10)	0.304***	0.240***	0.251***	0.206***	0.262***	0.156***	0.241***	0.174***
	(0.054)	(0.046)	(0.062)	(0.049)	(0.057)	(0.045)	(0.062)	(0.050)
Female=1			0.003	-0.004				
			(0.028)	(0.027)				
A (67-50-33) × Female=1			-0.002	-0.012				
			(0.053)	(0.049)				
B (90-50-10) × Female=1			0.087	0.056				
			(0.061)	(0.052)				
Livestock groups owned					0.023	0.001		
					(0.019)	(0.017)		
A (67-50-33) × Livestock groups owned					0.019	0.026		
					(0.028)	(0.025)		
B (90-50-10) × Livestock groups owned					0.037	0.077*		
					(0.034)	(0.031)		
Land							-0.000	0.002
							(0.003)	(0.002)
A (67-50-33) × Land							0.009	0.005
							(0.005)	(0.004)
B (90-50-10) × Land							0.023**	0.024**
							(0.008)	(0.009)
Reference Mean	0.161	0.116	0.163	0.127	0.117	0.091	0.091	0.091
Observations	1865	1865	1865	1865	1865	1865	1865	1865

Regression models control for fixed effects for randomization strata (sub-county).
Standard errors clustered by randomization unit (farmer group) in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Heterogeneous treatment effect estimates (excl. Rice sub-county)

with a 8.7 percentage point increase in enrollment; this effect, however, is not different from zero at the 5 percent significance level.

Columns (5) and (6) present estimates of heterogeneous treatment effects by livestock wealth. For farmers assigned to the control group or subsidy stream A (67-50-33), livestock wealth has no effect on participation in ACDP. Since these groups have similar average treatment effects (columns (1) and (2)), it is not surprising that these groups have similar heterogeneous treatment effects. For farmers assigned to subsidy stream B (90-50-10), livestock wealth has a small, positive effect on participation such that each additional livestock group owned is associated with a 3.7 percentage point increase in enrollment; this effect, however, is not different from zero at the 5 percent significance level.

Columns (7) and (8) present estimates of heterogeneous treatment effects by land wealth. For farmers assigned to the control group or subsidy stream A (67-50-33), land wealth has no effect on participation in ACDP. Since these groups have similar average treatment effects (columns (1) and (2)), it is not surprising that these groups have similar heterogeneous treatment effects. For farmers assigned to subsidy stream B (90-50-10), land wealth has a small, positive effect on participation such that each acre of land is associated with a 2.3 percentage point increase in enrollment; this effect is different from zero at the 0.1 percent significance level.

The finding that participation in ACDP increases with land wealth is consistent with land wealth complementing the ACDP input subsidy and spurring increased production on relatively large farms. An alternative, and potentially complementary, explanation for participation in ACDP increasing with land wealth could be that information about ACDP flows more to wealthier individuals within a community. In particular, given the implementation of ACDP through farmer groups, there could be potential for greater participation by farmer group leaders and their network neighbors, both of which may be more likely to have greater wealth. The remainder of the paper studies information flow about ACDP to farmer group leaders and from farmer group leaders to farmer group members.

4.4 Heterogeneous Treatment Effects: Context

In this section, we build on the estimates of our pre-specified model of heterogeneous treatment effects in Section 4.3 by allowing treatment effects to vary with more covariates than those than we pre-specified. The motivation for this is two-fold. First, given the program's implementation through farmer groups and their leaders, we have reason to believe that being a farmer group leader will have a meaningful impact on enrollment. Second, exploring the data in this way may generate new hypotheses or insights for future analysis.

Table 4 presents estimates of a correlational regression with an outcome variable of enrollment and explanatory variables of observable characteristics. We estimate the correlational regression for three sub-samples defined by treatment assignment: column (1) is the control group, column (2) is subsidy stream A (67-50-33), and column (3) is subsidy stream B (90-50-10). Across sub-samples, households that include a leader of a farmer organization enroll at greater rates at a magnitude of 14.7-16.9 percentage points. The relationship between enrollment and being a leader of a farmer organization is large in magnitude: it is roughly half of the treatment effect of subsidy stream B on enrollment (Table 3, column (1)). No other variable in Table 4 has as sizable a correlation with enrollment consistently across sub-samples as being a leader of a farmer organization.

Estimates in Table 4 are suggestive evidence in support of our hypothesis from observations in the field that using farmer groups to share information about ACDP shaped patterns of enrollment in ACDP. Additionally, we show that our estimate of this effect is robust to estimation approach, which we show with propensity score matching estimates in Appendix A. The remainder of the paper studies information flow about ACDP from farmer group leaders to farmer group members.

5 Leaders' Information Dissemination

Turning to our next question, we explore how leaders disseminate information about the program to their group members. Two features of leaders may lower the costs of passing on information about an agricultural input subsidy to their members. First, if the leader themselves has experience with the inputs in the package, they should find it easier to communicate their value (and their information may be more credible to members); more educated leaders may also find it easier to understand and communicate the e-Voucher system (Nourani et al., 2021). We term this dimension the leader's farming sophistication. Secondly, there is a large literature that finds social learning is aided by close social ties and socioeconomic similarity (Cheng, 2022). We capture this dimension empirically by constructing a measure of socioeconomic dissimilarity between each member household and their farmer group leader.

We construct farming sophistication and socioeconomic dissimilarity measures as detailed below. For each household, the leader we link to is the farmer group chair (if the chair was

	(1)	(2)	(3)
	Control	A (67-50-33)	B (90-50-10)
Female	0.0308	-0.0129	0.149***
	(0.0297)	(0.0359)	(0.0383)
Land	-0.00190	0.00858*	0.00823
	(0.00454)	(0.00428)	(0.00665)
Livestock groups owned	0.0183	0.0324	0.0326
	(0.0151)	(0.0192)	(0.0186)
Leader of farmer organization	0.162**	0.169**	0.147*
	(0.0519)	(0.0633)	(0.0719)
Main crop is target	-0.0222	0.0572	0.0633
	(0.0540)	(0.0624)	(0.0710)
Pesticides	0.0988*	-0.0550	-0.0410
	(0.0407)	(0.0481)	(0.0469)
Inorganic fertilizers	-0.00787	-0.00346	0.0369
	(0.0414)	(0.0500)	(0.0516)
Improved seed	0.0788	-0.181*	-0.0930
	(0.0791)	(0.0851)	(0.0860)
Improved seed: Target	-0.0538	0.113	0.228*
	(0.0843)	(0.0921)	(0.0890)
Household size	0.0143*	0.00598	0.0105
	(0.00583)	(0.00668)	(0.00687)
Food Insecurity Score	-0.00385	-0.00106	-0.00362
	(0.00259)	(0.00283)	(0.00339)
Respondent has more than primary education	0.00506	-0.00794	0.0338
	(0.0325)	(0.0386)	(0.0433)
Observations	627	632	606

Regression models control for fixed effects for randomization strata (sub-county).
Standard errors clustered by randomization unit (farmer group) in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Correlates of enrollment by treatment assignment

surveyed), or the group secretary if the chair was not surveyed.[4] We then estimate a model of program enrollment for member i of farmer group f in sub-county g:

$$Y_{ifg} = \alpha_1 Sophistication_f + \alpha_2 Dissimilarity_{if} + \alpha_3 Sophistication_f Dissimilarity_{if} + \theta_g + E_{ig} \tag{3}$$

where Y_{ifg} is an indicator for program participation, $Sophistication_f$ is a the farming sophistication index for group f's leader, $Dissimilarity_{if}$ is the socioeconomic dissimilarity between member i and the leader of their group f, θ_g is a sub-county fixed effect to account for randomization being stratified by sub-county, and E_{ifg} is an error term. We include the interaction of farming sophistication and socioeconomic dissimilarity to explore potential complementarities, and in some specifications we control for the household's own farming sophistication index.

5.1 Farming Sophistication Index

We expect that adoption of the ACDP program is more likely for farmers who have used the subsidized inputs in the past. In addition, a group leader who has used these inputs is a more credible source of information about their value, and therefore is more likely to encourage adoption among their group members (Ambler et al., 2021). We conceptualize this underlying trait as the individual's farming sophistication, which is expressed in using various agricultural inputs, as well as the individual's education.

To empirically approximate this underlying farming sophistication, we use principal components analysis (PCA). We take the the first component of dummy variables from our household survey capturing whether the household used a given agricultural input (pesti-

[4] We were able to link 97 groups (1602 households) to their farmer group chair, and 67 groups (1094 households) to their farmer group secretary. Using the secretary when the chair was not identified gives us 107 groups with a leader identified, comprising 1,751 households. We have also explored robustness to alternate ways of measuring leader characteristics, such as the maximum farming sophistication of the identified leaders (or minimum socioeconomic dissimilarity), results available upon request.

cides, inorganic fertilizer, improved seeds for any crop), a dummy indicating if the household grew the target crop for that district, the number of types of livestock owned by the household, and a dummy indicating if the farmer group member has more than a primary school education. We conduct the PCA for all surveyed households, calling the first component the 'household farming sophistication index,' and then match the leader's farming sophistication index to all members of their group.

Empirically, this index is significantly positively correlated with the use of agricultural inputs, education, and the number of livestock groups owned, as seen in table A3. This gives us confidence to interpret the first component as a measure of farming sophistication. Note, however, that many households in our survey use none of the inputs included; the index is therefore somewhat bottom-censored.

5.2 Socioeconomic Dissimilarity Measure

There is also strong evidence that social proximity facilitates learning (Cheng, 2022). Although we do not have a direct network measure of social proximity, there is a wealth of evidence that people select friends who are similar to them, and that heterogeneity in socioeconomic characteristics can hamper social learning (Cheng, 2022; Deserranno et al., 2019). To capture this heterogeneity between households empirically, we construct a measure of socioeconomic dissimilarity.

We construct a Gower dissimilarity matrix for all individuals within the same subcounty. The pairwise dissimilarity measure is computed based on each household's total landholdings, total area of purchased parcels, household size, Progress out of Poverty wealth Index (Schreiner, 2012), a Food Consumption Score (Wiesmann et al., 2009), and Household Food Insecurity Access Score, as well as the farmer group member's age, a dummy indicating if they are female, and a dummy indicating if they have more than a primary school education. The Gower measure of dissimilarity is used as it will work with a mix of binary and continuous data; additionally, it does not exclude observations with missing values for some variables.

From this matrix, we identify the household's dissimilarity to their farmer group chair (or secretary if the chair was not identified in the survey), as well as their average dissimilarity to all households within the farmer group. We additionally compute the average dissimilarity of all members in the group, as an overall measure of group closeness.

5.3 Leader Characteristics in Information Dissemination

Table 5 presents estimates of the relationship between a household's enrollment in ACDP and their farmer group leader's traits. In column (1), we see that a one standard deviation increase in the farming sophistication index of the farmer group leader is associated with a 6 percentage point increase in the likelihood that the household enrolls; a one standard deviation decrease in the dissimilarity between the household and their leader is associated with a more muted 2.3 percentage point increase in the likelihood the household enrolls. Both of these signs are consistent with theory, but the relative magnitude is striking: leader sophistication demonstrates a stronger relationship than similarity. This is in contrast to work by Deserranno et al. (2019), where more representative leaders are conducive to (internal) group functioning. However, the external, information-seeking role of leaders in disseminating the ACDP program may help explain the relative value of leader sophistication in this context.

In column (2), the interaction of sophistication and dissimilarity is insignificant; in column (3), controlling for a household's own farming sophistication is similarly insignificant and does not change the leader coefficients. In table 6, we restrict the sample to only groups assigned to treatment; the results are, if anything, slightly stronger. By contrast, in table 7 which only includes control groups (where there should have been fewer outreach efforts by program staff), leader characteristics are statistically unrelated to household enrollment. Figure 3 plots the coefficients from a regression of enrollment on leader characteristics, as well as subcounty fixed effects, separately for each treatment arms. It is clear that the statistically significant relationships documented in table 5 are driven almost entirely by the 90-50-10

	(1) Enroll	(2) Enroll	(3) Enroll
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.0266*	-0.0256*	-0.0268*
	(0.0110)	(0.0111)	(0.0111)
FG Leader Farming Sophistication Index (std)	0.0603***	0.0607***	0.0610***
	(0.0110)	(0.0111)	(0.0111)
HH Socioeconomic Dissimilarity to FG Leader (std)		-0.00867	
× FG Leader Farming Sophistication Index (std)		(0.0102)	
HH Farming Sophistication Index (std)			-0.00697
			(0.0110)
Observations	1458	1458	1458
Sub-County Fixed Effects	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Leader Characteristics in Information Dissemination, Full Sample. Linear Probability Model estimated on the full sample (excluding the rice district), with the outcome variable of a dummy equal to one if the household was matched to ACDP enrollment data. All independent variables are standardized, with household socioeconomic dissimilarity to the farmer group leader being constructed using the Gower dissimilarity measure; farming sophistication indices being constructed using principal components analysis, and the farmer group leader household identified as the group chairperson if they were interviewed, or the secretary if not. All specifications include sub-county fixed effects.

subsidy stream, which is unsurprising given the results in table 2. This is further suggestive that control group noncompliance occurred outside of the assigned farmer group structure: perhaps households were members of multiple farmer groups, so learned about the program through a different, treated group. Indeed, in table A6, we reclassify enrolled households to the group that they listed when enrolling in ACDP. When we re-estimate equation (5) using the leaders of these reclassified groups, the correlation with leader farming sophistication is stronger.

5.4 Robustness

In order to rule out alternate explanations for the group leader dynamics we explore above, we control for additional variables, such as the group size (table A7), the group's original purpose as indicated by the name of the group (table A7), gender (table A8), experience with

	(1) Enroll	(2) Enroll	(3) Enroll
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.0435**	-0.0406**	-0.0446**
	(0.0139)	(0.0141)	(0.0140)
FG Leader Farming Sophistication Index (std)	0.0647***	0.0657***	0.0666***
	(0.0133)	(0.0133)	(0.0134)
HH Socioeconomic Dissimilarity to FG Leader (std)		-0.0162	
× FG Leader Farming Sophistication Index (std)		(0.0121)	
HH Farming Sophistication Index (std)			-0.0219
			(0.0140)
Observations	962	962	962
Sub-County Fixed Effects	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Leader Characteristics in Information Dissemination, Treatment Groups. Linear Probability Model estimated on the sample of all households assigned to treatment (excluding the rice district), with the outcome variable of a dummy equal to one if the household was matched to ACDP enrollment data. All independent variables are standardized, with household socioeconomic dissimilarity to the farmer group leader being constructed using the Gower dissimilarity measure; farming sophistication indices being constructed using principal components analysis, and the farmer group leader household identified as the group chairperson if they were interviewed, or the secretary if not. All specifications include sub-county fixed effects.

	(1)	(2)	(3)
	Enroll	Enroll	Enroll
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.0000260	0.0000635	-0.000599
	(0.0158)	(0.0159)	(0.0159)
FG Leader Farming Sophistication Index (std)	0.00162	0.00188	-0.000365
	(0.0179)	(0.0180)	(0.0180)
HH Socioeconomic Dissimilarity to FG Leader (std)		0.00392	
× FG Leader Farming Sophistication Index (std)		(0.0171)	
HH Farming Sophistication Index (std)			0.0173
			(0.0152)
Observations	496	496	496
Sub-County Fixed Effects	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Leader Characteristics in Information Dissemination, Control Groups. Linear Probability Model estimated on the sample of all households assigned to control (excluding the rice district), with the outcome variable of a dummy equal to one if the household was matched to ACDP enrollment data. All independent variables are standardized, with household socioeconomic dissimilarity to the farmer group leader being constructed using the Gower dissimilarity measure; farming sophistication indices being constructed using principal components analysis, and the farmer group leader household identified as the group chairperson if they were interviewed, or the secretary if not. All specifications include subcounty fixed effects.

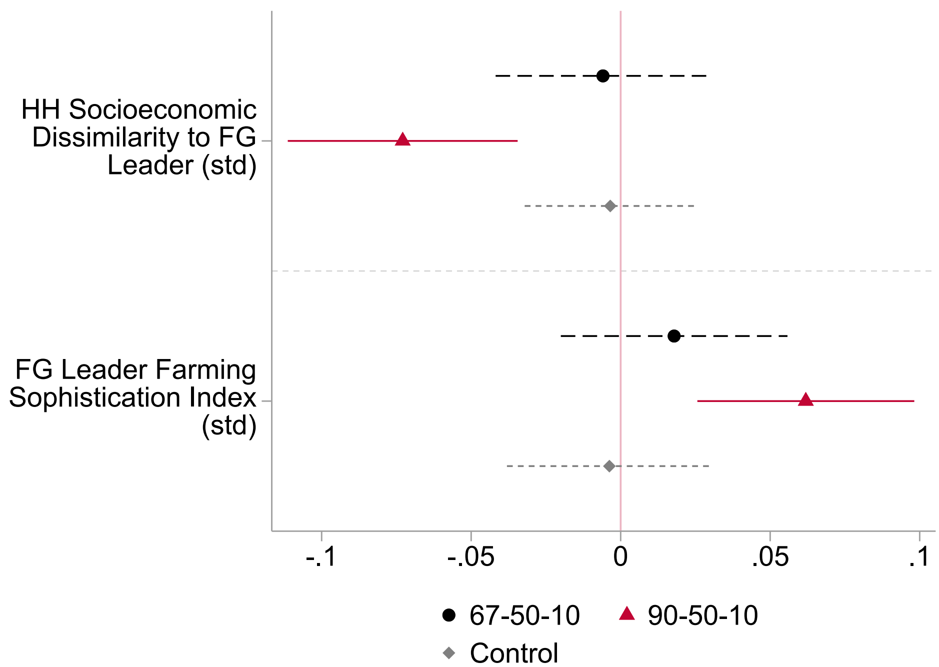

Figure 3: Coefficient plot of leader characteristics in information dissemination, estimated separately for each treatment arm. Linear Probability Model estimated separately for households assigned to each treatment arm (excluding the rice district), with the outcome variable of a dummy equal to one if the household was matched to ACDP enrollment data. All independent variables are standardized, with household socioeconomic dissimilarity to the farmer group leader being constructed using the Gower dissimilarity measure; farming sophistication indices being constructed using principal components analysis, and the farmer group leader household identified as the group chairperson if they were interviewed, or the secretary if not. All specifications include sub-county fixed effects.

extension services (table A9), similarity to other (non-leader) members of the group (tables A10 and A11), and spatial measures of distance to district offices (table A12) or dispersion of households within the group(table A13). In general, we find that although these controls may be statistically significant, they do not in general meaningfully change the coefficients on socioeconomic dissimilarity to the leader nor the farming sophistication of the leader, as can be seen in figure 4. We also look at the interaction of some of these controls with our leader measures, which again are often not significant.

6 Conclusion

In this paper, we have studied adoption of an agricultural input subsidy program in Uganda. Farmers were randomly assigned to receive the subsidy at one of two initial subsidy levels, or to a control group; this assignment happened through farmer groups. We find that relative to the control group, those assigned to the lower initial subsidy of 67 percent were 6.5 percentage points more likely to enroll in the program (a difference which is not statistically significant). By contrast, those assigned to the higher 90 percent initial subsidy were 27.2 percentage points more likely to enroll in the program than the control group. This suggests that material (e.g. liquidity) constraints are binding for the adoption of agricultural inputs in Uganda.

Beyond this, however, informational constraints may prevent farmers from adopting the program. In particular, the program was implemented through farmer organizations: members of farmer organizations were eligible for the subsidy, and information was shared through the farmer group structure. We therefore explore how well information about the program flowed through farmer groups. First, we find that farmer group leaders were significantly more likely to adopt the program than general members. Second, we find that among those assigned to the higher subsidy level, adoption is significantly correlated with both their leader's sophistication (experience) with agricultural inputs and social similarity to the

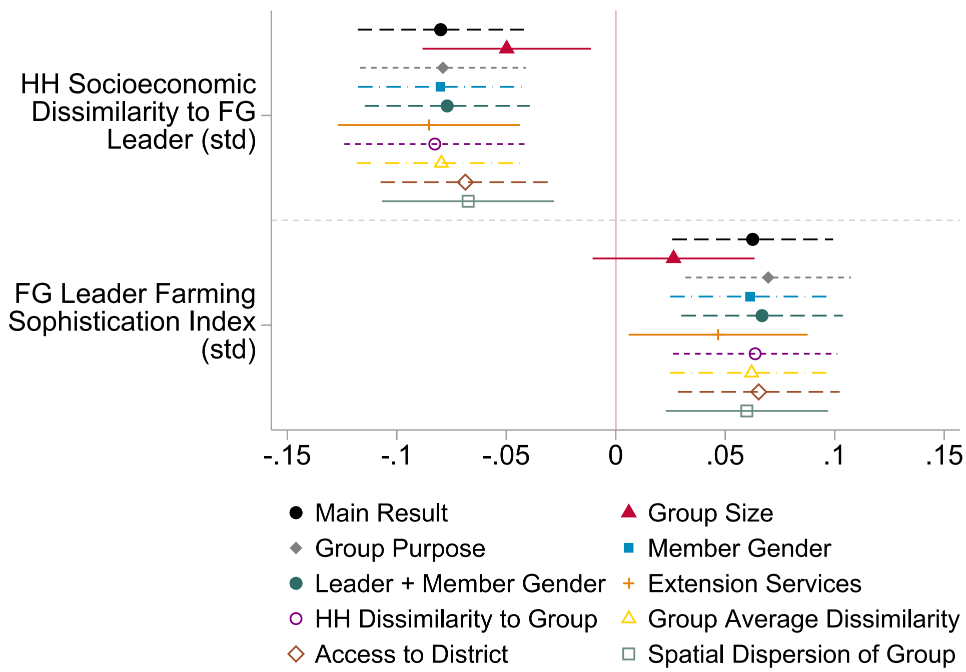

Figure 4: Coefficient plot of leader characteristics in information dissemination, estimated separately with additional controls (see appendix for more information). Linear Probability Model estimated separately for households assigned to the 90% subsidy treatment arm (excluding the rice district), with the outcome variable of a dummy equal to one if the household was matched to ACDP enrollment data. All independent variables are standardized, with household socioeconomic dissimilarity to the farmer group leader being constructed using the Gower dissimilarity measure; farming sophistication indices being constructed using principal components analysis, and the farmer group leader household identified as the group chairperson if they were interviewed, or the secretary if not. All specifications include sub-county fixed effects.

member. This latter result speaks to a trade-off in the literature on social learning; we find that leader sophistication is a stronger predictor of adoption of this external program than social similarity, which has been shown to improve internal group functioning (Deserranno et al., 2019; Nourani et al., 2021).

This paper contributes to the literature on agricultural input subsidies in Sub-Saharan Africa, which have been shown to have substantial impacts on yields and yet lower than expected adoption (Carter et al., 2021). We find that material constraints may prevent adoption of even subsidized inputs, which suggests that high initial subsidies are important. However, informational constraints also seem to bind, suggesting that more attention should be paid to program administration and dissemination. In particular, implementing a subsidy program through existing farmer groups may introduce social incentives that constrain adoption.

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A Leader's Informational Advantage

We estimate the causal effect of being a leader on enrollment in ACDP with a propensity score matching estimator. The validity of our propensity score matching estimates critically depends on our ability to predict whether a household has a leader of a farmer organization based on the household's observable characteristics. Summary statistics in Table A1 show that leaders do indeed look different than members (non-leaders): leaders use more agricultural inputs, have greater landholdings, are less likely to be female, and are slightly older.

We predict whether a household has a leader of a farmer organization based on observable characteristics of the household using a logistic regression model. To improve our predictions, we use LASSO to select variables for the model. To avoid over-fitting our predictions, we perform LASSO on ten different sub-samples. Each sub-sample omits 10% of the farmer organizations in our sample, and uses the remaining 90% of farmer organizations to whether a household has a leader of a farmer organization for the omitted 10%. We do not present all 10 sets of logistic regression estimates here, but instead give a sense of which variables are predictive of farmer group leadership by present logistic regression estimates (post-LASSO) for the full sample in Table A2.

To estimate the effect of being a leader on enrollment in ACDP, we make three assumptions. First, we assume that matches only occur within a farmer organization. This assumption removes differences across farmer organizations as a confounding factor in the estimation approach, but still leaves our estimates vulnerable to unobservable characteristics correlated with both a household having a leader of a farmer organization and enrolling in ACDP. Second, we impose common support, meaning that our estimates only include observations from farmer organizations in which we predict a leader and a member to be similarly likely to be the leader of an organization based on their observable characteristics. This assumption improves the internal validity of our estimates by eliminating biases from comparing farmers who are dissimilar to one another based on observable characteristics,

Table A1: Baseline characteristics by randomized treatment assignment and leader status

	Control		A (67-50-33)		B (90-50-10)	
	Member	Leader	Member	Leader	Member	Leader
Agriculture (0/1)						
- Main crop is target	0.73	0.75	0.71	0.82	0.72	0.74
- Improved seed: Target	0.18	0.33	0.18	0.29	0.23	0.31
- Improved seed	0.22	0.37	0.23	0.35	0.28	0.38
- Pesticides	0.21	0.33	0.28	0.22	0.26	0.48
- Inorganic fertilizers	0.19	0.21	0.20	0.22	0.17	0.31
Landholdings (acres)						
- Total	2.48	2.64	2.77	4.58	2.78	2.69
Household attributes						
- Household size	6.33	6.46	6.55	7.12	6.63	6.02
- Livestock groups owned	1.00	1.19	0.94	1.12	1.07	1.31
Respondent attributes						
- Female	0.60	0.54	0.61	0.43	0.61	0.60
- Age	43.60	46.37	43.71	46.31	45.63	48.93
Observations	575	52	581	51	564	42

but limits the external validity of our estimates by restricting our parameter of interest to the sub-population of farmer organizations with leaders and members who are similar to one another. Third, we impose 1-to-1 matching so that each leader is only compared to a single member of their farmer organization.

Imposing these assumptions on our data leaves us with an estimation sample of 33 farmer organizations assigned to the control, 29 farmer organizations assigned to subsidy stream A (67-50-33), and 21 farmer organizations assigned to subsidy stream B (90-50-10). For the control group, being a leader increases enrollment by 18.2 percentage points from a base of 12.1% enrollment for members selected by our propensity score matching estimation approach. For subsidy stream A (67-50-33), being a leader increases enrollment by 12.1 percentage points from a base of 22.4% enrollment for members selected by our propensity score matching estimation approach. For subsidy stream B (90-50-10), being a leader increases enrollment by 9.5 percentage points from a base of 52.4% enrollment for members selected by our propensity score matching estimation approach.

To conclude, being a leader increases enrollment by 9.5-18.2 percentage points across

Table A2: Predicting leader status: Logistic regression estimates (post-LASSO)

label_hh_leader	
Main crop is target	0.46
	(0.24)
Pesticides	0.17
	(0.21)
Improved seed	0.12
	(0.42)
Improved seed: Target	0.10
	(0.44)
Customary	0.04
	(0.02)
Purchased	0.02
	(0.03)
Mailo	0.10
	(0.10)
Livestock groups owned	0.18*
	(0.09)
Female	-0.10
	(0.18)
Secondary education	1.04***
	(0.20)
Tertiary education	1.32***
	(0.35)
Vocational education	1.46**
	(0.45)
Observations	1865

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

treatment and control sub-samples. This effect is large in magnitude relative to our large average treatment effect on enrollment for subsidy stream B of 30.4 percentage points (Table 3, column (1)).

B Measures of Sophistication and Similarity

The farming sophistication index we construct is the first principal component of dummy variables from our household survey capturing whether the household used a given agricultural input (pesticides, inorganic fertilizer, improved seeds for any crop), a dummy indicating if the household grew the target crop for that district, the number of types of livestock owned by the household, and a dummy indicating if the farmer group member has more than a primary school education. We conduct the PCA for all surveyed households, calling the first component the 'household farming sophistication index,' and then match the leader's farming sophistication index to all members of their group.

Empirically, this index is significantly positively correlated with the use of agricultural inputs, education, and the number of livestock groups owned, as seen in table A3. This gives us confidence to interpret the first component as a measure of farming sophistication. Note, however, that many households in our survey use none of the inputs included; the index is therefore somewhat bottom-censored.

	(1)
	HH Farming Sophistication Index (std)
Main crop is target	0.0626*
	(0.0273)
Pesticides	0.594***
	(0.0333)
Inorganic fertilizers	0.923***
	(0.0374)
Improved seed	0.698***
	(0.0330)
Livestock groups owned	0.133***
	(0.0128)
Respondent has more than primary education	0.722***
	(0.0282)
Constant	-0.793***
	(0.0285)
Observations	2100

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A3: Correlations of underlying measures and Farming Sophistication Index. OLS regression of the standardized farming sophistication index (constructed via PCA) on a dummy equal to one if the main crop grown on any parcel is the target crop in that district, a series of dummies equal to one if the household used pesticides, inorganic fertilizer, or improved seeds on any parcel, the number of livestock groups owned by the household, and a dummy equal to one if the respondent has more than a primary level of education.

C Robustness

C.1 Heterogeneous Treatment Effects by Leader Characteristics

An alternate way of examining the role of farmer group leader characteristics in disseminating information about ACDP is to interact assigned treatment status with leader characteristics, as in tables A4 and A5. As we saw in tables 6 and 7, leader farming sophistication and dissimilarity to member households only predict takeup in groups assigned to treatment. This is also visible in tables A4 and A5, where beyond the level differences between treatment and control groups (with particularly higher enrollment among those assigned to the 90-50-10 stream, as documented above), leader farming sophistication has a significantly higher correlation with enrollment in treatment groups, and dissimilarity between the household and leader is marginally significantly more negatively predictive of enrollment (especially in the 67-50-33 stream).

C.2 Reclassifying Households

Due to the fact that households can belong to multiple farmer groups, we examine not only the leader of the group that we found the household to survey through, but also the group that they listed when enrolling in the eVMA (if they did so). Perhaps households learned about the program through an alternate, treated group of which they were a member; therefore, the characteristics of that group's leader may matter more. This recategorization is not our preferred specification, as we are only able to link households that enrolled with an alternate group. However, in table A6, we see that the correlation between leader farming sophistication and enrollment is even stronger than that in table 5. This is consistent with learning from these alternate group leaders. Note that group leaders were not interviewed for more of the reclassified groups than the originally assigned groups, hence the difference in sample sizes between this and the specifications in the main text.

	(1) Enroll	(2) Enroll	(3) Enroll
HH Socioeconomic Dissimilarity to FG Leader (std)	0.00338	0.00335	0.00281
	(0.0191)	(0.0191)	(0.0191)
FG Leader Farming Sophistication Index (std)	0.0209	0.0211	0.0187
	(0.0216)	(0.0216)	(0.0217)
67-50-33	0.0809**	0.0833**	0.0818**
	(0.0255)	(0.0258)	(0.0255)
90-50-10	0.261***	0.264***	0.261***
	(0.0274)	(0.0278)	(0.0274)
67-50-33	-0.00562	-0.00873	-0.00475
× HH Socioeconomic Dissimilarity to FG Leader (std)	(0.0265)	(0.0268)	(0.0265)
90-50-10	-0.0706**	-0.0654*	-0.0711**
× HH Socioeconomic Dissimilarity to FG Leader (std)	(0.0265)	(0.0277)	(0.0265)
67-50-33	-0.00787	-0.00831	-0.00137
× FG Leader Farming Sophistication Index (std)	(0.0291)	(0.0291)	(0.0292)
90-50-10	0.0468	0.0470	0.0496
× FG Leader Farming Sophistication Index (std)	(0.0278)	(0.0279)	(0.0279)
HH Socioeconomic Dissimilarity to FG Leader (std)		0.00447	
× FG Leader Farming Sophistication Index (std)		(0.0207)	
67-50-33 × HH Socioeconomic Dissimilarity to FG Leader (std)		-0.0203	
× FG Leader Farming Sophistication Index (std)		(0.0283)	
90-50-10 × HH Socioeconomic Dissimilarity to FG Leader (std)		-0.0140	
× FG Leader Farming Sophistication Index (std)		(0.0256)	
HH Farming Sophistication Index (std)			0.0195
			(0.0183)
67-50-33 × HH Farming Sophistication Index (std)			-0.0483
			(0.0259)
90-50-10 × HH Farming Sophistication Index (std)			-0.0288
			(0.0262)
Observations	1458	1458	1458
Sub-County Fixed Effects	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A4: Leader Characteristics in Information Dissemination, Full Sample. Linear Probability Model estimated on the full sample (excluding the rice district), with the outcome variable of a dummy equal to one if the household was matched to ACDP enrollment data. Except for treatment stream dummies, all independent variables are standardized, with household socioeconomic dissimilarity to the farmer group leader being constructed using the Gower dissimilarity measure; farming sophistication indices being constructed using principal components analysis, and the farmer group leader household identified as the group chairperson if they were interviewed, or the secretary if not. All specifications include sub-county fixed effects.

	(1) Enroll	(2) Enroll	(3) Enroll
HH Socioeconomic Dissimilarity to FG Leader (std)	0.00302	0.00301	0.00243
	(0.0194)	(0.0194)	(0.0194)
FG Leader Farming Sophistication Index (std)	0.0207	0.0210	0.0184
	(0.0219)	(0.0220)	(0.0220)
Treatment	0.170***	0.173***	0.170***
	(0.0226)	(0.0228)	(0.0226)
Treatment	-0.0457	-0.0434	-0.0462*
× HH Socioeconomic Dissimilarity to FG Leader (std)	(0.0235)	(0.0236)	(0.0235)
Treatment	0.0471	0.0477	0.0512*
× FG Leader Farming Sophistication Index (std)	(0.0253)	(0.0254)	(0.0254)
HH Socioeconomic Dissimilarity to FG Leader (std)		0.00441	
× FG Leader Farming Sophistication Index (std)		(0.0211)	
Treatment × HH Socioeconomic Dissimilarity to FG Leader (std)		-0.0181	
× FG Leader Farming Sophistication Index (std)		(0.0240)	
HH Farming Sophistication Index (std)			0.0189
			(0.0186)
Treatment			-0.0399
× HH Farming Sophistication Index (std)			(0.0228)
Observations	1458	1458	1458
Sub-County Fixed Effects	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A5: Leader Characteristics in Information Dissemination, Full Sample. Linear Probability Model estimated on the full sample (excluding the rice district), with the outcome variable of a dummy equal to one if the household was matched to ACDP enrollment data. Except for a dummy equal to one for treatment groups, all independent variables are standardized, with household socioeconomic dissimilarity to the farmer group leader being constructed using the Gower dissimilarity measure; farming sophistication indices being constructed using principal components analysis, and the farmer group leader household identified as the group chairperson if they were interviewed, or the secretary if not. All specifications include sub-county fixed effects.

	(1)	(2)	(3)
	Enroll	Enroll	Enroll
HH socioeconomic dissimilarity to recoded FG leader	0.00653	0.00540	0.00643
	(0.0119)	(0.0118)	(0.0119)
Reclassified FG Leader Farming Sophistication Index	0.112^{***}	0.111^{***}	0.112^{***}
	(0.0119)	(0.0118)	(0.0119)
HH socioeconomic dissimilarity to recoded FG leader		0.0292^{**}	
$\times$ Reclassified FG Leader Farming Sophistication Index		(0.0106)	
HH Farming Sophistication Index (std)			-0.00519
			(0.0115)
Observations	1299	1299	1299
Sub-County Fixed Effects			

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A6: Leader Characteristics in Information Dissemination, Full Sample with reclassified groups. Linear Probability Model estimated on the full sample (excluding the rice district), with the outcome variable of a dummy equal to one if the household was matched to ACDP enrollment data. All independent variables are standardized, with household socioeconomic dissimilarity to the farmer group leader being constructed using the Gower dissimilarity measure; farming sophistication indices being constructed using principal components analysis. Households are reclassified to the group name they listed at enrollment in ACDP, or retained in their original assigned group if they did not enroll, and the farmer group leader household is identified as the group chairperson if they were interviewed, or the secretary if not. All specifications include sub-county fixed effects.

C.3 Alternate Specifications and Additional Controls

In order to rule out alternate explanations for the group leader dynamics we explore above, we control for additional variables, such as the group size (table A7), the group's original purpose as indicated by the name of the group (table A7), gender (table A8), experience with extension services (table A9), similarity to other (non-leader) members of the group (tables A10 and A11), and spatial measures of distance to district offices (table A12) or dispersion of households within the group(table A13). In general, we find that although these controls may be statistically significant, they do not in general meaningfully change the coefficients on socioeconomic dissimilarity to the leader nor the farming sophistication of the leader (as seen in figure 4 for the 90% subsidy stream, figure 5 for the full sample, and figure 6 for all treated groups). We also look at the interaction of some of these controls with our leader measures, which again are often not significant. Each table includes three panels: the first uses the full sample, the second, only treated groups, and the third, only those in the 90-50-10 treatment arm which saw the highest levels of enrollment. This last, however, restricts our sample size substantially, so estimates are at times less precise.

In table A7, we control both for group size (as listed on the administrative records that also identified group leaders, rather than the number of surveyed members of the group which is only a sample of larger groups) and group purpose. Group purpose was identified from the group name: if the group name was "[Village] Women's Group", for example, we identify it as a women's group; if it was "[Village] Women's VSLA", then it would receive a value of 1 for both women's group and savings group. In columns (1) and (3), we see that the number of members in the group is negatively and statistically significantly associated with member enrollment, but controlling for this in panels A and B does not substantively affect the primary coefficients of interest. In panel C, when we restrict the sample to only those treated at the 90% level, the leader farming sophistication index coefficient halves in magnitude and is no longer statistically significant. Columns (2) and (3), where we control for three (non-mutually exclusive) categories of farmer groups, we find that compared to

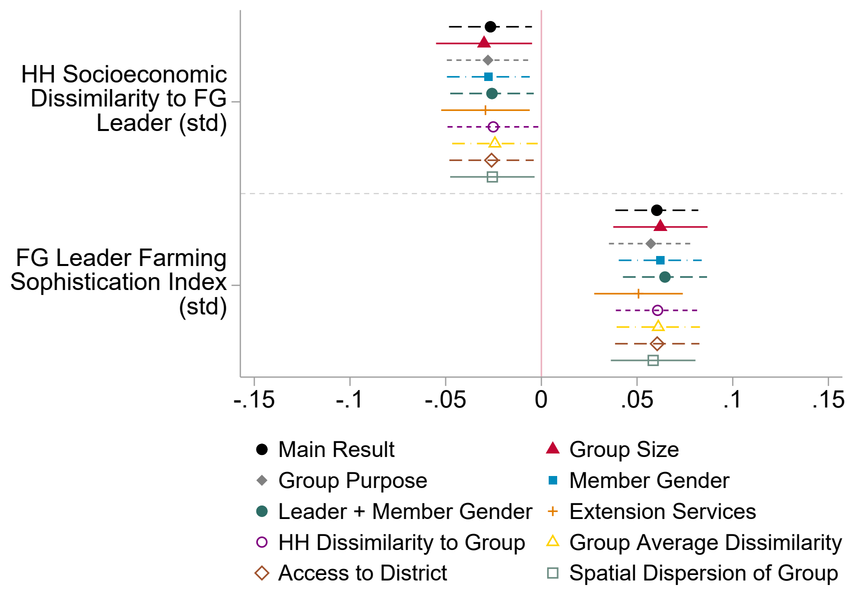

Figure 5: Coefficient plot of leader characteristics in information dissemination, estimated separately with additional controls (see appendix for more information). Linear Probability Model estimated separately for households in all treatment arms (excluding the rice district), with the outcome variable of a dummy equal to one if the household was matched to ACDP enrollment data. All independent variables are standardized, with household socioeconomic dissimilarity to the farmer group leader being constructed using the Gower dissimilarity measure; farming sophistication indices being constructed using principal components analysis, and the farmer group leader household identified as the group chairperson if they were interviewed, or the secretary if not. All specifications include sub-county fixed effects.

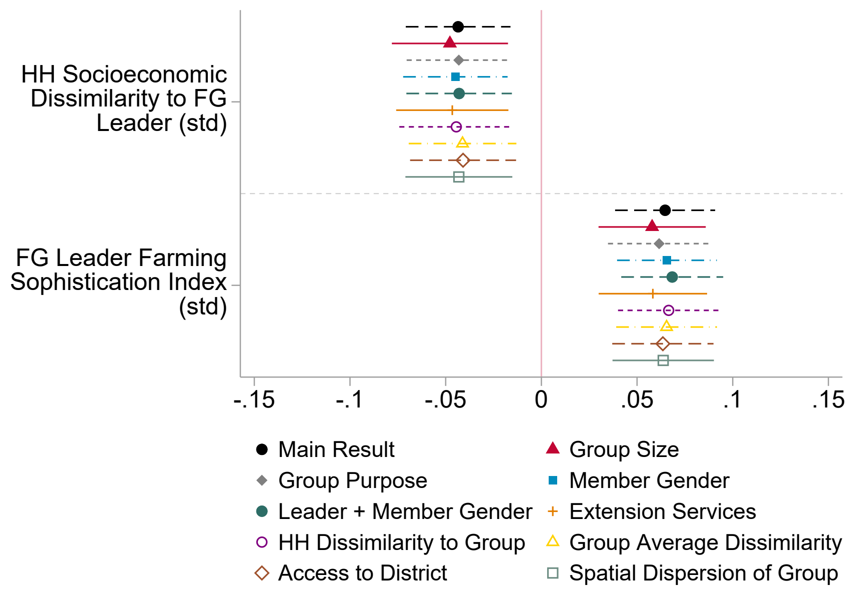

Figure 6: Coefficient plot of leader characteristics in information dissemination, estimated separately with additional controls (see appendix for more information). Linear Probability Model estimated separately for households assigned to treatment (excluding the rice district), with the outcome variable of a dummy equal to one if the household was matched to ACDP enrollment data. All independent variables are standardized, with household socioeconomic dissimilarity to the farmer group leader being constructed using the Gower dissimilarity measure; farming sophistication indices being constructed using principal components analysis, and the farmer group leader household identified as the group chairperson if they were interviewed, or the secretary if not. All specifications include sub-county fixed effects.

groups without a name that indicates a farmer group, a women's group, or a savings group, groups that fall into one of these categories have higher enrollment. This is particularly true for savings groups, perhaps due to the regular meetings savings groups have facilitating information dissemination. It may also be that groups named only in local languages (so we cannot necessarily tell group purpose from the name) have lower enrollment for some reason. Nevertheless, our primary coefficients of interest are robust to the inclusion of these controls.

In table A8, we explore the role of gender in disseminating information about the program. We control for the gender of the farm group member in all specifications; in general, women are more likely to enroll, but this does not change the group leader effects and if anything strengthen the role of socioeconomic dissimilarity in predicting enrollment. In columns (2) and (3) we also control for the gender of the group leader (the chair, if they were identified, or the secretary if no chair was found). In columns (4) and (5), we instead define a more inclusive variable equal to one if either the chair or the secretary is female. In general, the gender of the leader is statistically insignificant, and there do not seem to be marked interaction effects of household and leader gender. All specifications retain the main effects of interest, where household socioeconomic dissimilarity to the farmer group leader is negatively correlated with enrollment, while the farming sophistication of that leader positively predicts enrollment.

Table A9, we control for a dummy equal to one if the household reports having received extension services of any kind in the past six months (in columns (1) and (3), as well as a dummy equal to one if they report having received ACDP-specific extension services in the past (column (2)). Both of these are strongly predictive of enrollment, unsurprisingly, but do not change the role of leader characteristics. In column (3), we additionally look at if the group leader reported attending a 2-day ACDP training, which does seem positively correlated with member enrollment (although only marginally significant in the full sample), but this is not the primary driver of our leader effects documented above.

Table A10 explores the household's dissimilarity to non-leader members of their group.

	(1)	(2)	(3)
	Enroll	Enroll	Enroll
Panel A: Full Sample			
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.0299*	-0.0279*	-0.0316*
	(0.0128)	(0.0110)	(0.0127)
FG Leader Farming Sophistication Index (std)	0.0622***	0.0572***	0.0581***
	(0.0126)	(0.0112)	(0.0125)
Administrative listed number of members in FG	-0.00326***		-0.00352***
	(0.000738)		(0.000744)
FG Name indicates Farmer Group		0.0536*	0.0812**
		(0.0241)	(0.0276)
FG Name indicates Women's Group		0.0908**	0.0908*
		(0.0341)	(0.0438)
FG Name indicates Savings Group		0.150***	0.156***
		(0.0287)	(0.0317)
Observations	1152	1458	1152
Panel B: Treated Groups			
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.0478**	-0.0431**	-0.0454**
	(0.0155)	(0.0139)	(0.0153)
FG Leader Farming Sophistication Index (std)	0.0579***	0.0615***	0.0539***
	(0.0143)	(0.0136)	(0.0144)
Administrative listed number of members in FG	-0.00450***		-0.00488***
	(0.000816)		(0.000823)
FG Name indicates Farmer Group		0.0786*	0.109**
		(0.0339)	(0.0358)
FG Name indicates Women's Group		0.0865	0.109*
		(0.0476)	(0.0554)
FG Name indicates Savings Group		0.111**	0.136***
		(0.0364)	(0.0391)
Observations	817	962	817
Panel C: 90-50-10 Treatment Arm			
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.0498*	-0.0789***	-0.0460*
	(0.0196)	(0.0193)	(0.0197)
FG Leader Farming Sophistication Index (std)	0.0264	0.0696***	0.0306
	(0.0188)	(0.0192)	(0.0190)
Administrative listed number of members in FG	-0.00962***		-0.00926***
	(0.00108)		(0.00112)
FG Name indicates Farmer Group		0.0736	0.00925
		(0.0565)	(0.0560)
FG Name indicates Women's Group		0.108	0.120
		(0.0725)	(0.0854)
FG Name indicates Savings Group		-0.0442	-0.0291
		(0.0576)	(0.0577)
Observations	379	429	379

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A7: All specifications include subcounty fixed effects

	(1) Enroll	(2) Enroll	(3) Enroll	(4) Enroll	(5) Enroll
Panel A: Full Sample					
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.0277*	-0.0258*	-0.0201	-0.0259*	-0.0266*
	(0.0110)	(0.0111)	(0.0125)	(0.0111)	(0.0119)
FG Leader Farming Sophistication Index (std)	0.0621***	0.0646***	0.0636***	0.0654***	0.0655***
	(0.0111)	(0.0112)	(0.0112)	(0.0112)	(0.0113)
Female	0.0542*	0.0443	0.0227	0.0442	0.0482
	(0.0226)	(0.0238)	(0.0318)	(0.0234)	(0.0334)
Group leader is female		0.0326	-0.00379		
		(0.0241)	(0.0429)		
Female × Group leader is female			0.0563		
			(0.0550)		
Any group leader is female				0.0383	0.0433
				(0.0236)	(0.0385)
Female × Any group leader is female					-0.00843
					(0.0504)
Observations	1458	1458	1458	1458	1458
Panel B: Treated Groups					
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.0449**	-0.0430**	-0.0368*	-0.0434**	-0.0422**
	(0.0139)	(0.0140)	(0.0158)	(0.0140)	(0.0149)
FG Leader Farming Sophistication Index (std)	0.0656***	0.0684***	0.0676***	0.0684***	0.0683***
	(0.0133)	(0.0136)	(0.0136)	(0.0136)	(0.0136)
Female	0.0812**	0.0722*	0.0480	0.0750*	0.0674
	(0.0292)	(0.0306)	(0.0415)	(0.0299)	(0.0441)
Group leader is female		0.0300	-0.00758		
		(0.0307)	(0.0533)		
Female × Group leader is female			0.0599		
			(0.0695)		
Any group leader is female				0.0285	0.0199
				(0.0300)	(0.0474)
Female × Any group leader is female					0.0146
					(0.0628)
Observations	962	962	962	962	962
Panel C: 90-50-10 Treatment Arm					
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.0801***	-0.0770***	-0.0719***	-0.0803***	-0.0803***
	(0.0191)	(0.0192)	(0.0214)	(0.0190)	(0.0203)
FG Leader Farming Sophistication Index (std)	0.0613**	0.0668***	0.0670***	0.0692***	0.0692***
	(0.0185)	(0.0188)	(0.0188)	(0.0187)	(0.0188)
Female	0.119**	0.0921*	0.0690	0.0915*	0.0917
	(0.0422)	(0.0448)	(0.0626)	(0.0436)	(0.0675)
Group leader is female		0.0779	0.0443		
		(0.0450)	(0.0777)		
Female × Group leader is female			0.0537		
			(0.101)		
Any group leader is female				0.103*	0.103
				(0.0444)	(0.0737)
Female × Any group leader is female					-0.000446
					(0.0960)
Observations	429	429	429	429	429

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A8: All specifications include subcounty fixed effects

	(1) Enroll	(2) Enroll	(3) Enroll
Panel A: Full Sample			
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.0265*	-0.0266*	-0.0266*
	(0.0110)	(0.0110)	(0.0110)
FG Leader Farming Sophistication Index (std)	0.0590***	0.0591***	0.0566***
	(0.0110)	(0.0110)	(0.0111)
Extension (past 6 months)	0.0778*		0.0762*
	(0.0305)		(0.0305)
Extension (ACDP)		0.195***	
		(0.0476)	
Group Leader Attended a 2 Day Training			0.0479
			(0.0277)
Observations	1458	1458	1458
Panel B: Treated Groups			
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.0439**	-0.0435**	-0.0439**
	(0.0139)	(0.0139)	(0.0139)
FG Leader Farming Sophistication Index (std)	0.0622***	0.0634***	0.0623***
	(0.0133)	(0.0133)	(0.0134)
Extension (past 6 months)	0.127**		0.127**
	(0.0404)		(0.0404)
Extension (ACDP)		0.190**	
		(0.0618)	
Group Leader Attended a 2 Day Training			-0.00433
			(0.0325)
Observations	962	962	962
Panel C: 90-50-10 Treatment Arm			
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.0824***	-0.0806***	-0.0851***
	(0.0192)	(0.0192)	(0.0195)
FG Leader Farming Sophistication Index (std)	0.0605**	0.0629***	0.0603**
	(0.0186)	(0.0186)	(0.0186)
Extension (past 6 months)	0.129*		0.126*
	(0.0547)		(0.0548)
Extension (ACDP)		0.133	
		(0.0734)	
Group Leader Attended a 2 Day Training			0.0415
			(0.0516)
Observations	429	429	429

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A9: All specifications include subcounty fixed effects

Column (1) replaces the leader characteristics with the household's own: as we have seen above in tables 5 and 6, the household's own farming sophistication index is not significantly predictive of enrollment. Additionally, the average dissimilarity between the household and all non-leader members of their group is statistically insignificant. The leader sophistication, however remains stable, and does the leader socioeconomic dissimilarity in both treatment samples. Table A11 then looks at the overall level of similarity between members of a group, to see if group cohesion might explain our leader results. Once again, however, there is no statistically significant correlation with enrollment, and the leader coefficients remain significant.

Finally, in tables A12 and A13, we look at geographic measures of proximity. Table A12 computes the household's access to the district capital [cite muller crepon x2], as a proxy for the household's ability to learn information about government programs outside of the ACDP farmer group structure. When we restrict to only the 90% subsidy treatment arm, it does seem like households with more access to the district are more likely to enroll, but this does not attenuate the leader effects and if anythign strengthens them. However, there may be some substitution between information sources: households with more geographic access to the district exhibit a weaker relationship with group leader farming sophistication, as seen in column (3). Table A13 controls for the distance between the household and all other members of their group, as well as the average geographic distance between members of the group (measures which are, by construction, collinear, but are jointly insignificant). Neither of these measures are statistically related to enrollment, and controlling for them does not meaningfully change the coefficients on leader characteristics.

	(1) Enroll	(2) Enroll	(3) Enroll
Panel A: Full Sample			
HH Farming Sophistication Index (std)	0.0202	-0.00596	-0.00635
	(0.0108)	(0.0114)	(0.0114)
HH average socioeconomic dissimilarity to others in group	-0.0206	-0.00396	-0.00388
	(0.0108)	(0.0124)	(0.0124)
FG Leader Farming Sophistication Index (std)		0.0608***	0.0609***
		(0.0111)	(0.0111)
HH Socioeconomic Dissimilarity to FG Leader (std)		-0.0251*	-0.0259*
		(0.0122)	(0.0122)
HH average socioeconomic dissimilarity to others in group			-0.00809
× FG Leader Farming Sophistication Index (std)			(0.0113)
Observations	1719	1458	1458
Panel B: Treatment Groups			
HH Farming Sophistication Index (std)	0.00467	-0.0218	-0.0219
	(0.0136)	(0.0145)	(0.0145)
HH average socioeconomic dissimilarity to others in group	-0.0329*	-0.000381	-0.000289
	(0.0134)	(0.0153)	(0.0153)
FG Leader Farming Sophistication Index (std)		0.0665***	0.0665***
		(0.0135)	(0.0135)
HH Socioeconomic Dissimilarity to FG Leader (std)		-0.0445**	-0.0449**
		(0.0152)	(0.0152)
HH average socioeconomic dissimilarity to others in group			-0.00436
× FG Leader Farming Sophistication Index (std)			(0.0136)
Observations	1145	962	962
Panel C: 90-50-10 Treatment Arm			
HH Farming Sophistication Index (std)	0.0228	-0.00738	-0.00684
	(0.0186)	(0.0208)	(0.0208)
HH average socioeconomic dissimilarity to others in group	-0.0486**	0.00574	0.0102
	(0.0183)	(0.0222)	(0.0228)
FG Leader Farming Sophistication Index (std)		0.0637***	0.0631**
		(0.0191)	(0.0191)
HH Socioeconomic Dissimilarity to FG Leader (std)		-0.0826***	-0.0848***
		(0.0210)	(0.0212)
HH average socioeconomic dissimilarity to others in group			-0.0152
× FG Leader Farming Sophistication Index (std)			(0.0189)
Observations	564	429	429

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A10: All specifications include subcounty fixed effects

	(1) Enroll	(2) Enroll	(3) Enroll
Panel A: Full Sample			
HH Farming Sophistication Index (std)	0.0182	-0.00542	-0.00555
	(0.0106)	(0.0111)	(0.0111)
Average socioeconomic dissimilarity between members in FG	-0.0200	-0.0102	-0.0117
	(0.0106)	(0.0113)	(0.0114)
FG Leader Farming Sophistication Index (std)		0.0611***	0.0611***
		(0.0111)	(0.0111)
HH Socioeconomic Dissimilarity to FG Leader (std)		-0.0243*	-0.0242*
		(0.0114)	(0.0114)
Average socioeconomic dissimilarity between members in FG			-0.0150
$\times$ FG Leader Farming Sophistication Index (std)			(0.0116)
Observations	1720	1458	1458
Panel B: Treatment Groups			
HH Farming Sophistication Index (std)	0.00364	-0.0192	-0.0193
	(0.0134)	(0.0143)	(0.0143)
Average socioeconomic dissimilarity between members in FG	-0.0399**	-0.0150	-0.0184
	(0.0136)	(0.0145)	(0.0147)
FG Leader Farming Sophistication Index (std)		0.0654***	0.0652***
		(0.0134)	(0.0134)
HH Socioeconomic Dissimilarity to FG Leader (std)		-0.0412**	-0.0411**
		(0.0143)	(0.0143)
Average socioeconomic dissimilarity between members in FG			-0.0190
$\times$ FG Leader Farming Sophistication Index (std)			(0.0143)
Observations	1145	962	962
Panel C: 90-50-10 Treatment Arm			
HH Farming Sophistication Index (std)	0.0172	-0.00463	-0.00305
	(0.0183)	(0.0203)	(0.0203)
Average socioeconomic dissimilarity between members in FG	-0.0415*	-0.00635	-0.00280
	(0.0194)	(0.0225)	(0.0226)
FG Leader Farming Sophistication Index (std)		0.0620**	0.0583**
		(0.0189)	(0.0191)
HH Socioeconomic Dissimilarity to FG Leader (std)		-0.0796***	-0.0766***
		(0.0197)	(0.0198)
Average socioeconomic dissimilarity between members in FG			-0.0326
$\times$ FG Leader Farming Sophistication Index (std)			(0.0238)
Observations	564	429	429

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A11: All specifications include subcounty fixed effects

	(1) Enroll	(2) Enroll
Panel A: Full Sample		
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.0252*	-0.0294*
	(0.0115)	(0.0115)
FG Leader Farming Sophistication Index (std)	0.0614***	0.192***
	(0.0111)	(0.0332)
Access to District Capital, 2015	0.128	0.230
	(0.147)	(0.148)
FG Leader Farming Sophistication Index (std)		-0.284***
× Access to District Capital, 2015		(0.0684)
Observations	1437	1437
Panel B: Treatment Groups		
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.0397**	-0.0463**
	(0.0146)	(0.0146)
FG Leader Farming Sophistication Index (std)	0.0659***	0.191***
	(0.0133)	(0.0396)
Access to District Capital, 2015	0.269	0.291
	(0.195)	(0.194)
FG Leader Farming Sophistication Index (std)		-0.276***
× Access to District Capital, 2015		(0.0823)
Observations	955	955
Panel C: 90-50-10 Treatment Arm		
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.0660**	-0.0771***
	(0.0205)	(0.0205)
FG Leader Farming Sophistication Index (std)	0.0663***	0.217***
	(0.0186)	(0.0500)
Access to District Capital, 2015	0.705*	0.793**
	(0.285)	(0.283)
FG Leader Farming Sophistication Index (std)		-0.345**
× Access to District Capital, 2015		(0.106)
Observations	430	430

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A12: All specifications include subcounty fixed effects

	(1) Enroll	(2) Enroll
Panel A: Full Sample		
Average distance from HH to other group members, standardized	0.00417	0.00874
	(0.0213)	(0.0223)
Average distance between members of FG, standardized	0.0165	0.00498
	(0.0218)	(0.0230)
HH Socioeconomic Dissimilarity to FG Leader (std)		-0.0247*
		(0.0116)
FG Leader Farming Sophistication Index (std)		0.0594***
		(0.0111)
Observations	1721	1459
Panel B: Treatment Groups		
Average distance from HH to other group members, standardized	0.0125	0.0231
	(0.0238)	(0.0249)
Average distance between members of FG, standardized	-0.00958	-0.0163
	(0.0244)	(0.0257)
HH Socioeconomic Dissimilarity to FG Leader (std)		-0.0419**
		(0.0147)
FG Leader Farming Sophistication Index (std)		0.0662***
		(0.0133)
Observations	1146	961
Panel C: 90-50-10 Treatment Arm		
Average distance from HH to other group members, standardized	-0.00559	-0.00561
	(0.0468)	(0.0516)
Average distance between members of FG, standardized	0.0556	0.0555
	(0.0453)	(0.0496)
HH Socioeconomic Dissimilarity to FG Leader (std)		-0.0637**
		(0.0207)
FG Leader Farming Sophistication Index (std)		0.0611**
		(0.0186)
Observations	565	430

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A13: All specifications include subcounty fixed effects