Material and Informational Constraints to the Adoption of Digital Farm Input Subsidies*

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Abstract

We study the adoption of an electronic voucher subsidy for agricultural inputs by members of farmer organizations in Uganda. We randomly assign farmer organizations to have their members offered a status quo subsidy, a higher subsidy, or no subsidy. Adoption does not increase significantly due to the status quo subsidy but increases substantially due to the high subsidy. For farmers who at baseline did not use the inputs subsidized by the voucher, adoption increases with their farmer organization's leader's experience with the inputs and social similarity to the member. The results are consistent with material and information constraints limiting adoption of the electronic voucher subsidy, particularly for the intended beneficiaries of the subsidy program: farmers with limited experience with improved inputs, for whom a subsidy lowers the cost of learning by doing and may induce sustained technology adoption. While digital payment schemes can lower the costs of delivering payments from governments to people, they do not by themselves eliminate the need to tend to basic economic constraints of liquidity and information.

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1 Introduction

Digital technologies loom large in the delivery and design of any number of development interventions, ranging from social protection to micro-insurance schemes. Already by 2017, fully 37% of recipients of government-to-people (G2P) payments in low-income countries received their payments digitally (Baur-Yazbeck et al., 2019); by 2025, this share was 73% (Klapper et al., 2025). G2P digital payments lower administrative costs and can offer a number of side benefits as well, including providing beneficiaries an entry point to the formal financial system and potentially being more inclusive (Muralidharan et al., 2016). While we do not question these benefits of G2P-based interventions, this paper's key message is that basic constraints of liquidity and trust continue to limit the effectiveness of interventions intended to alter behavior even when digital tools deliver the intervention.

This paper specifically examines a farm input subsidy program in Uganda that utilized G2P technologies to deliver partial input subsidies through electronic vouchers ("e-vouchers") to eligible beneficiaries. The Ugandan Agriculture Cluster Development Project (ACDP) was intended to subsidize the cost of experimentation and learning for farmers with little prior experience using high yielding inputs. In contrast to the direct delivery of free inputs, which the government of Uganda had sporadically done,[1] the e-voucher of ACDP was intended to stimulate the private market for inputs, rather than suppress it as direct input delivery can do. In the spirit of the Carter et al. (2021) finding that temporary subsidies can spur post-subsidy demand for inputs, the ACDP e-vouchers offered subsidies for only 3 seasons, with the subsidy basis declining from season to season.

While these features of ACDP are consistent with the best practices for farm input subsidy programs laid out by Morris et al. (2007),[2] its use of an agile G2P system did not erase the importance of the basic non-digital constraints that confront any program

[1] Operation Wealth Creation is an initiative that was launched in 2013 by the president that, among other things, provided free inputs to farmers.

[2] Morris et al. (2007) outline ten guiding principles for subsidies to be market-smart, including favoring market-based solutions and devising an exit strategy.

intended to provide information and ultimately change behavior. In this paper we examine how two basic constraints shaped the uptake of the ACDP e-voucher and ultimately limited whatever impacts it had. The first constraint is a liquidity constraint that shapes farmer's ability and willingness to pay for an unproven technology. In Carter et al. (2021)'s RCT of a similar voucher subsidy (delivered via a paper voucher not an e-voucher), only 41% of farmers redeemed the voucher. Of those not redeeming the vouchers, most reported that their non-use was due to insufficient funds to make the required matching payment (the Mozambique program studied by Carter et al. (2021) offered a 73% subsidy, requiring the farmer to pay 27% of the cost of an input bundle). Analyzing the ACDP e-voucher, where the level of the first season subsidy was varied from 67% to 90%, we find that the largest subsidy payment increased program enrollment by 20 to 25 percentage points relative to the lower subsidy level.

The second non-digital constraint to ACDP e-voucher uptake is the social and other characteristics of the local leader who delivered the core messages about the ACDP program to farmers. We find that having a group leader who is more sophisticated (in the sense of having greater prior experience with the subsidized inputs) and more socially similar to their farmers is correlated with higher uptake of the ACDP program. Sub-sample analysis reveals that these average estimates are driven by farmers who, prior to the subsidy program, had limited experience with the inputs subsidized by the e-voucher, suggesting that these farmers otherwise face information constraints to adoption. These findings are especially important because while it is possible to digitally deliver core messages intended to induce behavioral change, the recent meta-study of Fabregas et al. (2025) shows digital delivery of key messages has a remarkably small impact on farmer behavior and technology adoption.[3] Indeed, trust remains one of the key constraints to adoption of new digital payments technologies (Blumenstock et al., 2015; Mas and Radcliffe, 2011; Suri, 2017), which may compound the high levels of social trust the program relies upon to induce experimentation with new agricultural

[3]Fabregas et al. (2025) note that these programs may still be cost effective given their low costs of implementation.

technologies.

Stepping back, this study contributes to the literature on digitizing development interventions intended to induce long-lasting behavioral change, in particular government-implemented agriculture input subsidy programs in sub-Saharan Africa. In sub-Saharan Africa, agricultural productivity and adoption of agricultural technologies such as improved seed varieties and fertilizers are low and stagnant (Carter et al., 2021; Suri and Udry, 2022). A common policy intervention to increase agricultural technology adoption and productivity is an agricultural input subsidy (Carter et al., 2021; Jayne et al., 2018; Pan and Christiaensen, 2012). An economic rationale for subsidies is that they can lower the cost of experimenting with technologies for farmers with limited experience using them, however subsidy programs are prone to "leakage" from subsidies being accessed by farmers who would have purchased the inputs at unsubsidized prices (Jayne et al., 2018).

To reduce these leakages, the modes of delivering subsidies to farmers have evolved over time, with universal subsidies replaced by targeted subsidies to individual farmers with paper vouchers (Pan and Christiaensen, 2012) and paper vouchers replaced by electronic vouchers (Wossen et al., 2017). We focus on take-up of the subsidy program, which in input subsidy programs in sub-Saharan Africa is far from universal (Carter et al., 2021; Jayne et al., 2018). The barriers to subsidy adoption can be meaningful constraints, as documented by Kumar et al. (2023). Our results suggest that these constraints still bind in the context of an electronic voucher subsidy program. In particular, we find that the level of subsidy relaxes material constraints to program participation and characteristics of delivery agents relax information constraints to program participation. This effect is strongest for the intended beneficiaries of the subsidy program: farmers with limited experience with improved inputs, for whom a subsidy lowers the cost of learning by doing and may induce sustained technology adoption.

Our study also has implications for targeting interventions in networks, which is the subject of a large and growing literature (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). In particular, our results are consistent with the flow of information being a binding constraint on subsidy adoption for farmers. Similar to Riley et al. (2025), we find important heterogeneity in uptake based on group leader characteristics; these "focal members" of existing groups play a key role in sustained technology adoption.

The remainder of this paper is structured as follows. Section 2 describes our empirical context. Section 3 estimates average and heterogeneous effects of the randomized subsidy treatments on farmer participation in the e-voucher subsidy program in Uganda. After a brief review of the literature, on leader characteristics and information dissemination, Section 4 studies the dissemination of information about the e-voucher subsidy program. Section 5 concludes.

2 Empirical Context and Experimental Design

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

2.1 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 highest value 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).[4]

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 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, a farmer was eligible to be offered the e-voucher subsidy if they met 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

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

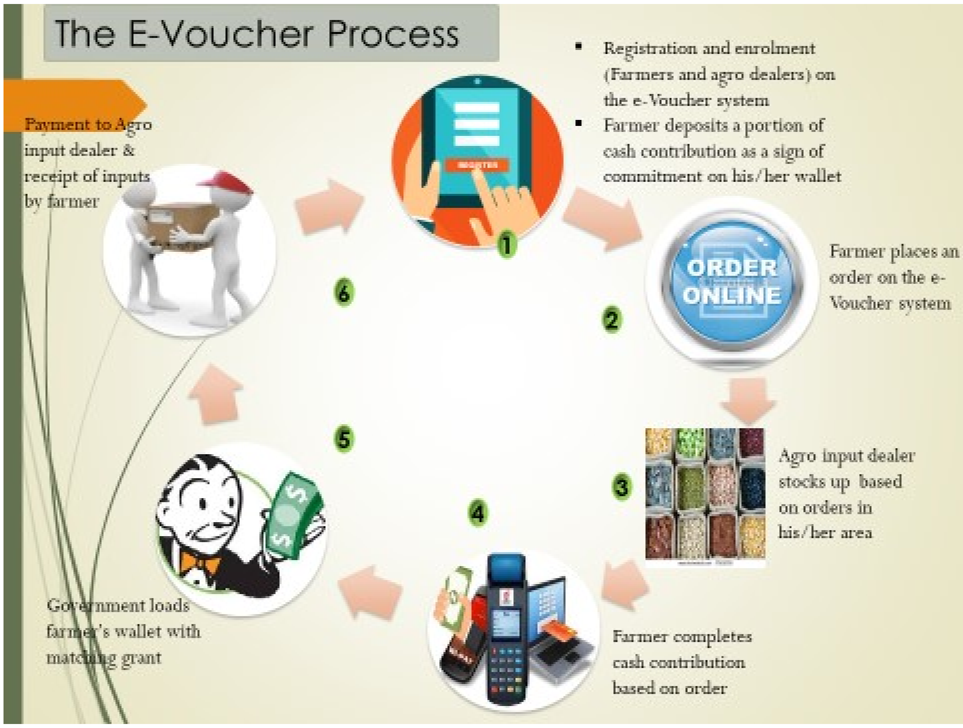

Figure 1: ACDP's Electronic Voucher Management System
(Source: https://www.agriculture.go.ug/the-agriculture-cluster-development-project-acdp/)

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.

2.2 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.[5] We weight our sample across crops to be representative of the relative importance of each crop in the ACDP program,

[5]We exclude cassava, which is more difficult to measure due to its long growing period and its ability to be stored in the ground.

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.[6]

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: Treatment (subsidy pilot) to sixteen organizations per sub-county; 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 eight organizations each to the following treatment arms:

1. 67 percent subsidy (followed by 50 and 33 percent subsidies in subsequent seasons);

2. 90 percent subsidy (followed by 50 and 10 percent subsidies in subsequent seasons).[7]

2.3 Data

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

[6] Our sample of sub-counties is as follows: in eastern Uganda, two sub-counties from the pilot district for maize; in southwestern Uganda, one sub-county from the pilot district for beans; in central Uganda, one sub-county from the district neighboring the pilot district for coffee (due to the pilot covering all sub-counties in the pilot district for coffee); in 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).

[7] 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 the 90 percent subsidy and control (no subsidy pilot) on a computer; the remaining organizations in the rice sub-county were eligible for the 67 percent subsidy as part of the pilot program.

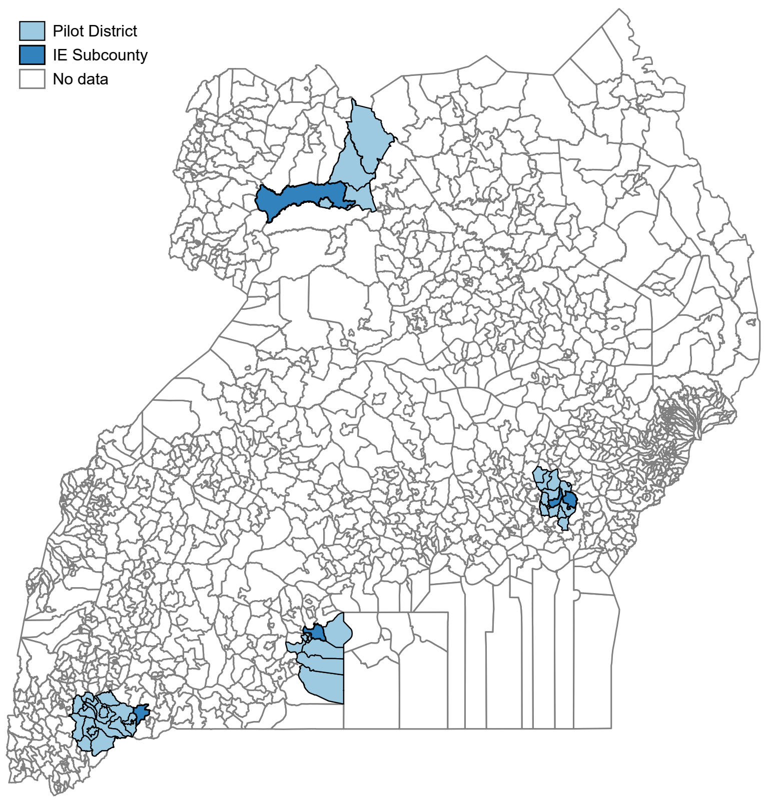

Figure 2: Locations of ACDP Pilot District Sub-counties and RCT Sub-counties

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 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 assigned to the 67 percent subsidy, the 90 percent subsidy, and the control (no subsidy pilot).

The second data source is a baseline household survey conducted in 2019. The survey focused on farmer recall of agricultural data from 2018, which includes 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.

We merge these three data sets together to construct our analysis data set. 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 prespecified 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.

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, and 90 percent. 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.

3 Treatment Effects on Subsidy Pilot Enrollment

This section estimates average and heterogeneous treatment effects of subsidy assignment on subsidy pilot enrollment.

3.1 Average Treatment Effects

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

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

where Y_{ifg} is an indicator for program participation, $Treatment_{fg}$ is a vector of indicators for subsidy 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.

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 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

	All	Control	67% Subsidy	90% Subsidy
Agriculture (0/1)				
- Main crop is target	0.68	0.67	0.69	0.69
- 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

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, we explore our data based on our observations of implementation of the ACDP subsidy pilot and the randomized controlled trial. In particular, 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 the 67 percent subsidy have relatively small treatment effects, and farmers assigned to the 90 percent subsidy have relatively large treatment effects.

Farmers assigned to the control group may 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

	(1) All	(2) Maize1	(3) Maize2	(4) Beans	(5) Coffee	(6) Rice
67% Subsidy	0.065	0.034	0.039	0.107	0.184	-0.015
	(0.036)	(0.039)	(0.095)	(0.053)	(0.089)	(0.041)
90% Subsidy	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 effect estimates: Enrollment (0/1)

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 the 67 percent subsidy 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 the 67 percent subsidy rather than the 90 percent subsidy. These anecdotes are consistent with what we find from comparing, for each farmer who enrolled in ACDP, 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 the 90 percent subsidy. 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 the 90 percent subsidy having relatively large treatment effects, most of the farmers assigned to the 90 percent who enrolled in ACDP actually enrolled under the 67 percent subsidy; these farmers drive 50-75% of the treatment effect estimate for the 90 percent subsidy. In other words, most of the treatment effect estimate for the 90 percent subsidy 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 the 67 percent subsidy is not due entirely to the difference in input prices for these farmers relative to those randomly assigned to the 90 percent subsidy. If that were the case, farmers assigned to the 90 percent subsidy would not enroll under the 67 percent subsidy at such high rates. The low treatment effect for the 67 percent subsidy may be due to additional factors other than price, such as random assignment to the 67 percent subsidy changing a farmer's attitude toward ACDP.

3.2 Heterogeneous Treatment Effects

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

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

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 the 67 percent subsidy causes enrollment to increase by only 7.6 percentage points relative to the control (47%), and assignment to the 90 percent subsidy 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 order through ACDP.

Columns (3) and (4) present estimates of heterogeneous treatment effects by female. For farmers assigned to the control group or the 67 percent subsidy, 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 the 90 percent subsidy, female has a large, positive effect on participation such that being female is associated with a 8.7 percentage point increase in enrollment; this effect, however, is not different from zero at the 5 percent significance level.

			Female=1		Livestock		Land	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Enroll	Order	Enroll	Order	Enroll	Order	Enroll	Order
67% Subsidy	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)
90% Subsidy	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)
Covariate			0.003	-0.004	0.023	0.001	-0.000	0.002
			(0.028)	(0.027)	(0.019)	(0.017)	(0.003)	(0.002)
67% Subsidy × Covariate			-0.002	-0.012	0.019	0.026	0.009	0.005
			(0.053)	(0.049)	(0.028)	(0.025)	(0.005)	(0.004)
90% Subsidy × Covariate			0.087	0.056	0.037	0.077*	0.023**	0.024**
			(0.061)	(0.052)	(0.034)	(0.031)	(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

Covariates are a female indicator, number of livestock groups owned, and land.
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 by covariate (excl. Rice sub-county)

Columns (5) and (6) present estimates of heterogeneous treatment effects by livestock wealth. For farmers assigned to the control group or the 67 percent subsidy, 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 the 90 percent subsidy, 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 the 67 percent subsidy, 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 the 90 percent subsidy, 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.

We build on the estimates of our heterogeneous treatment effects by allowing treatment effects to vary with more covariates. The motivation for this is twofold. 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 the 67 percent subsidy, and column (3) is the 90 percent subsidy. Across sub-samples, households that include a leader of a farmer organization enroll at greater rates at a magnitude of 14.7-16.8 percentage points. The relationship between enrollment and being a leader of a farmer organization is large in magnitude: it is roughly half of the average treatment effect of the 90 percent subsidy 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 B.

	(1) Control	(2) 67% Subsidy	(3) 90% Subsidy
Female	0.0307	-0.0136	0.144***
	(0.0296)	(0.0359)	(0.0384)
Land	-0.00173	0.00883*	0.00842
	(0.00453)	(0.00427)	(0.00668)
Livestock groups owned	0.0175	0.0320	0.0303
	(0.0150)	(0.0192)	(0.0187)
Leader of farmer organization	0.161**	0.168**	0.147*
	(0.0518)	(0.0634)	(0.0722)
Main crop is target	-0.0244	0.0581	0.0716
	(0.0539)	(0.0624)	(0.0712)
Pesticides	0.0982*	-0.0481	-0.0402
	(0.0406)	(0.0478)	(0.0471)
Inorganic fertilizers	-0.0104	-0.00116	0.0307
	(0.0411)	(0.0500)	(0.0518)
Improved seed	0.0345	-0.0927*	0.0951*
	(0.0382)	(0.0449)	(0.0450)
Household size	0.0148*	0.00605	0.00999
	(0.00578)	(0.00668)	(0.00690)
Food Insecurity Score	-0.00390	-0.00122	-0.00368
	(0.00259)	(0.00282)	(0.00340)
Respondent has more than primary education	0.00570	-0.00502	0.0298
	(0.0325)	(0.0385)	(0.0435)
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

These findings naturally lead to the question of whether and how information about ACDP flows from farmer group leaders to farmer group members, a question that we study in the next section.

4 Leader Characteristics and Information Dissemination

In addition to the material constraints that may limit adoption of improved technologies, farmers may also confront informational constraints, including technical information on how to implement a novel technology or information on the returns to a technology. In this case, farmers may learn from the people around them.[8] The benefits of sharing information include material incentives (Balew et al., 2022; Bandiera et al., 2023) as well as social incentives (Gauri et al., 2017). 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 that they seek to reach (Ashraf and Bandiera, 2018). After a brief review of the literature on the effect of leader characteristics on behavioral change, this section develops two measures of the characteristics of the farmer group leaders who were central to the rollout of the ACDP program. We label these measures leader "sophistication" and "similarity." While we were unable to randomly manipulate leader characteristics, we cautiously use the observed variation in leader characteristics to explore their association with program uptake.

4.1 Who Learns from Whom

The potential for the benefits and costs of sharing information to vary with the identify of the agent and the group that they seek to reach seek motivates studies of social learning focused on heterogeneity along these dimensions. Cheng (2022) highlights a tension in the literature:

[8] 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.

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. Social learning is a key function of member organizations, and our work contributes to the literature on the functioning of member organizations. Our work is closely related to Ambler et al. (2021), which studies the flow of information within existing farmer groups. The authors 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.[9]

Another strand of the literature 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, studies the leaders of Village Savings and Loan Associations (VSLAs) in Uganda, and finds 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) finds 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) finds 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. In our setting, however, we estimate a trade-off in leader characteristics between sophistication and

[9] By contrast, Behaghel et al. (2020) find that heterogeneity does not impede social learning from "contact farmers" among dairy farmers in Uganda.

similarity to the membership at large.

4.2 Empirical Measures of Sophistication and Similarity for the ACDP Input Subsidy Program

We construct farming sophistication and socioeconomic similarity measures as detailed below. For each household, the leader we link to is the farmer group chair (if the chair was surveyed), or the group secretary if the chair was not surveyed.[10]

4.2.1 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 (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.

[10]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.

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 A4. 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.

4.2.2 Socioeconomic Similarity

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 empirically, we construct a measure of socioeconomic similarity.

We construct a Gower dissimilarity matrix for all individuals within the same sub-county. 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. The Gower dissimilarity measure is bounded between 0 and 1 and increases with dissimiliarity. We take the opposite of this value as the measure of similarity in our model.

4.3 Leadership Sophistication, Social Similarity, and Program Enrollment

While we were unable to generate experimental variation in farmer group leadership characteristics, the ACDP program offers the opportunity to provisionally learn about the impact of leader characteristics on the efficacy of the program. To do this, we estimate the following model of program enrollment for member i of farmer group f in sub-county g:

$$\begin{aligned} Y_{ifg} = {} & \alpha_1 Sophistication_{fg} + \alpha_2 Similarity_{ifg} \\ & + \alpha_3 Sophistication_{fg} Similarity_{ifg} + \theta_g + \Omega X_{ifg} + E_{ifg} \end{aligned} \tag{3}$$

where Y_{ifg} is an indicator for program participation, $Sophistication_{fg}$ is the farming sophistication index for group f's leader, $Similarity_{ifg}$ is the socioeconomic similarity between member i and the leader of their group f, θ_g is a sub-county fixed effect, X_{ifg} is a vector of household-level controls and E_{ifg} is an error term.[11] We include the interaction of farming sophistication and socioeconomic similarity to explore potential complementarities, and in some specifications we control for the household's own farming sophistication index.

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 6.1 percentage point increase in the likelihood that the household enrolls; a one standard deviation increase in the similarity between the household and their leader is associated with a more muted 2.9 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

[11] The household-level controls are: an indicator for being female; total landholdings; number of livestock groups owned; an indicator equal to one if the main crop grown on any parcel is the target crop in that district; indicators equal to one if the household used any pesticides, inorganic fertilizers, or improved seeds; household size; household food insecurity score, and; an indicator equal to one if the respondent has more than a primary education.

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 effect of sophistication and similarity is relatively small. Additionally, controlling for a household's own farming sophistication does not change the leader coefficient estimates and itself is not different from zero with statistical significance at the 5 percent level. In columns (3) and (4), we restrict the sample to only groups assigned to treatment; the results are, if anything, slightly stronger. By contrast, in columns (5) and (6), leader characteristics are statistically unrelated to household enrollment for the control sub-sample. Fig. 3 plots the coefficients from a regression of enrollment on leader characteristics, as well as sub-county fixed effects, separately for each treatment arm. It is clear that the statistically significant relationships documented in Table 5 are driven almost entirely by assignment to the 90 percent subsidy, which is unsurprising given the average treatment effect estimates in Table 2.[12]

In order to rule out alternative explanations for the group leader dynamics we explore above, we control for additional variables, such as the group size (Table A12), the group's original purpose as indicated by the name of the group (Table A12), gender (Table A13), experience with extension services (Table A15), similarity to other (non-leader) members of the group (Tables A16 and A17), and spatial measures of distance to district offices (Table A18) or dispersion of households within the group (Table A19). In general, we find that although these controls may be statistically significant, they do not in general meaningfully change the coefficients on socioeconomic similarity to the leader nor the farming sophistication of the leader, as can be seen in Fig. 5. We also look at the interaction of some of these controls with our leader measures, which again are often not significant.

[12]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 A11, we reclassify enrolled households to the group that they listed when enrolling in ACDP. When we re-estimate Eq. (3) using the leaders of these reclassified groups, the correlation with leader farming sophistication is stronger.

	Full Sample		Treatment		Control	
	(1)	(2)	(3)	(4)	(5)	(6)
Similarity	0.0294**	0.0283*	0.0466***	0.0429**	0.00400	0.00414
	(0.0111)	(0.0112)	(0.0141)	(0.0142)	(0.0159)	(0.0161)
Sophistication	0.0612***	0.0622***	0.0679***	0.0698***	0.00250	0.00238
	(0.0110)	(0.0111)	(0.0133)	(0.0133)	(0.0181)	(0.0182)
Similarity × Sophistication		0.0210*		0.0297*		0.00519
		(0.0106)		(0.0125)		(0.0186)
HH Sophistication		0.0339		0.0366		-0.00311
		(0.0357)		(0.0423)		(0.0617)
Observations	1458	1458	962	962	496	496
Sub-County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

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

Table 5: Leader Characteristics in Information Dissemination. Linear Probability Model 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 similarity to the farmer group leader constructed using the opposite of the Gower dissimilarity measure; farming sophistication indices 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.

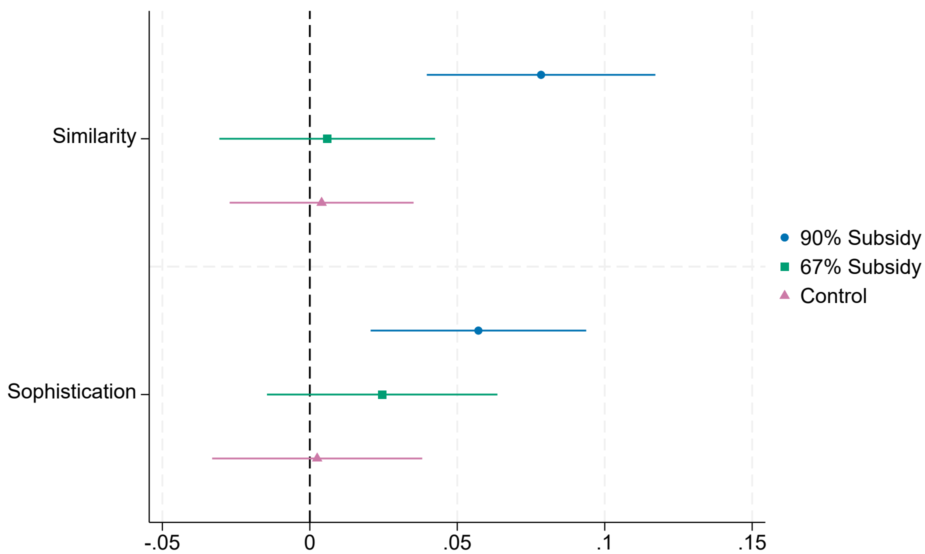

Figure 3: Coefficient plot of leader characteristics in information dissemination, estimated separately for each treatment arm. Linear Probability Model estimated separately for households assigned to each treatment arm (excluding the rice district), with household socioeconomic similarity to the farmer group leader constructed using the opposite of the Gower dissimilarity measure; farming sophistication indices 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 and a vector of household controls.

4.4 Heterogeneity by Baseline Input Use

The positive relationship between program enrollment and leader characteristics among those assigned to the 90 percent subsidy suggests that leaders relax a constraint to program enrollment for members of their organizations. Given the roll-out of information about ACDP through leaders of farmer groups, it is plausible that farmer group leaders relax an information constraint. Multiple potential information constraints exist in this context, however, in particular: 1) information about the program's existence and/or enrollment procedures, and 2) information about the production technologies subsidized by the program.

This section studies the role of leaders in relaxing these two information constraints by estimating Eq. (3) separately for each combination of treatment assignment and baseline use of any improved agricultural input subsidized by ACDP (specifically seed, pesticide, or inorganic fertilizer). If the primary constraint that leaders remove is information about the program's existence, then we would expect to see a strong relationship between enrollment and leader characteristics for prior input users who already know the effectiveness of the inputs. If instead the primary information constraint that leaders remove concerns the productivity of the subsidized technology, then we would expect to see a strong relationship between enrollment and leader characteristics for non-users consistent with leaders convincing members to experiment with using these inputs, potentially for the first time.

Table 6 and Fig. 4 present estimates of Eq. (3) separately by treatment assignment and prior input use. The bottom of the table reports the share of farmers enrolled in ACDP for each sub-sample, which increases with assignment to treatment (especially the 90 percent subsidy) for both users and non-users.[13] Sub-sample estimates of the relationship between enrollment and leader characteristics reveal that the positive correlation between having a more sophisticated or similar leader and enrollment that we estimate on average is driven by farmers assigned to the 90 percent subsidy who did not use improved inputs prior to ACDP.

[13] Appendix A presents differences in adoption as treatment effect estimates from estimating Eq. (1) separately by treatment assignment and prior input use.

	90% Subsidy		67% Subsidy		Control	
	(1)	(2)	(3)	(4)	(5)	(6)
	Non-Users	Users	Non-Users	Users	Non-Users	Users
Similarity	0.0965***	0.0534	0.00121	0.0166	0.0153	-0.0144
	(0.0273)	(0.0294)	(0.0227)	(0.0346)	(0.0186)	(0.0321)
Sophistication	0.0952***	0.0217	0.00737	0.0323	0.0322	-0.0487
	(0.0252)	(0.0299)	(0.0263)	(0.0321)	(0.0210)	(0.0356)
HH Sophistication	0.0216	0.0909	0.0728	-0.160	-0.0172	-0.612
	(0.124)	(0.244)	(0.0924)	(0.272)	(0.0668)	(0.369)
Observations	248	181	334	199	319	177
Share Enrolled	0.414	0.525	0.194	0.275	0.110	0.208
Sub-County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

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

Table 6: Leader Characteristics in Information Dissemination by Treatment Assignment and Baseline Input Use. Linear Probability Model with the outcome variable of a dummy equal to one if the household was matched to ACDP enrollment data. All independent variables are standardized. Household socioeconomic similarity to the farmer group leader is constructed using the opposite of the Gower dissimilarity measure. Farming sophistication indices are constructed using principal components analysis. The farmer group leader household is the group chairperson if they were interviewed, or the secretary if not.

These results are consistent with leaders not only passing on information that the program exists, but also convincing their members to experiment with new inputs. They are also consistent with the finding in Riley et al. (2025) that group leader experience is to some extent a substitute for own experience with a novel technology.

This result is encouraging for the farmer group dissemination model of an agricultural input subsidy like ACDP, which is designed to encourage new adoption of improved technologies. Delivering subsidies to individual farmers through their farmer groups, particularly if the leaders of those groups are sophisticated farmers and/or socially similar to their members, seems successful to relax information constraints for farmers with the least information about the subsidized inputs.

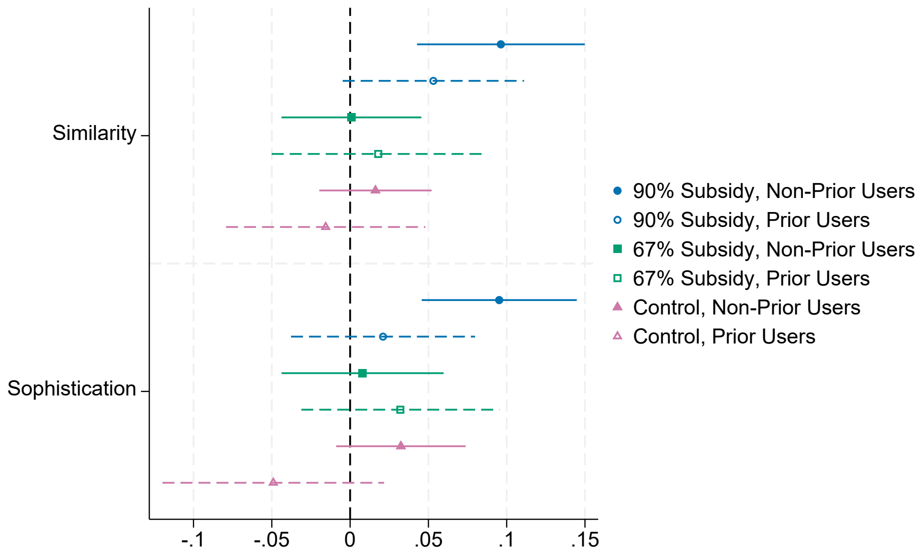

Figure 4: Coefficient plot of leader characteristics in information dissemination, estimated separately for each treatment arm and baseline input use. Linear Probability Model estimated separately for prior input user and non-user households assigned to each treatment arm (excluding the rice district), with household socioeconomic similarity to the farmer group leader constructed using the opposite of the Gower dissimilarity measure; farming sophistication indices 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 and a vector of household controls.

5 Conclusion

In this paper, we 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 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.

Finally, the findings of this study have implications for the digitization of development programs. In the context of the program that we study, an agricultural input subsidy, a primary motivation for digitization is to reduce leakages of subsidies to farmers who would use the agricultural subsidies even without a subsidy. Our results suggest that these are the very farmers for whom digitization works best; that is, their participation in the subsidy program is least sensitive to our proxy for access to program information, their farmer organization's leader's characteristics. In contrast, leader characteristics appear to relax constraints to program participation for the intended beneficiaries of the subsidy program: farmers with limited experience with improved inputs, for whom a subsidy lowers the cost of learning by doing and may induce sustained technology adoption. For these farmers, we anticipate that the material and information constraints to program participation studied in this paper will continue to bind unless subsidy programs evolve in this era of digitized learning subsidies in their modes of delivery and/or design.

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	(1) All	(2) Non-Users	(3) Users
A (67-50-33)	0.076	0.067*	0.031
	(0.039)	(0.031)	(0.069)
B (90-50-10)	0.304***	0.179***	0.306***
	(0.054)	(0.045)	(0.070)
Reference Mean	0.161	0.118	0.231
Observations	1865	1085	780

Users used either improved seeds, pesticides, or inorganic fertilizer at baseline.
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 A1: Heterogeneous treatment effect estimates by baseline input use (excl. Rice sub-county)

A Heterogeneous Treatment Effects by Baseline Input Use

Table A1 presents estimates of Eq. (1). Assignment to treatment (especially the 90 percent subsidy) increases the likelihood of enrolling in the program for both users and non-users.

B 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 predict 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.

Table A2: 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	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

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, 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.

Table A3: Predicting leader status: Logistic regression estimates (post-LASSO)

label_hh_leader	
Main crop is target	0.47*
	(0.23)
Pesticides	0.17
	(0.21)
Improved seed	0.20
	(0.20)
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	1.31***
	(0.35)
Vocational education	1.46**
	(0.45)
Observations	1865

Standard errors in parentheses

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

Imposing these assumptions on our data leaves us with an estimation sample of 36 farmer organizations assigned to the control, 29 farmer organizations assigned to the 67 percent subsidy, and 27 farmer organizations assigned to the 90 percent subsidy. For the control group, being a leader increases enrollment by 25.0 percentage points from a base of 12.5% enrollment for members selected by our propensity score matching estimation approach. For the 67% subsidy, being a leader increases enrollment by 19.0 percentage points from a base of 25.9% enrollment for members selected by our propensity score matching estimation approach. For the 90 percent subsidy, being a leader increases enrollment by 5.6 percentage points from a base of 61.1% enrollment for members selected by our propensity score matching estimation approach.

To conclude, being a leader increases enrollment by 5.6-25.0 percentage points across treatment and control sub-samples. This effect is large in magnitude relative to our large average treatment effect on enrollment for the 90 percent subsidy (Table 3, column (1)).

C 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 A4. 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 A4: 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.

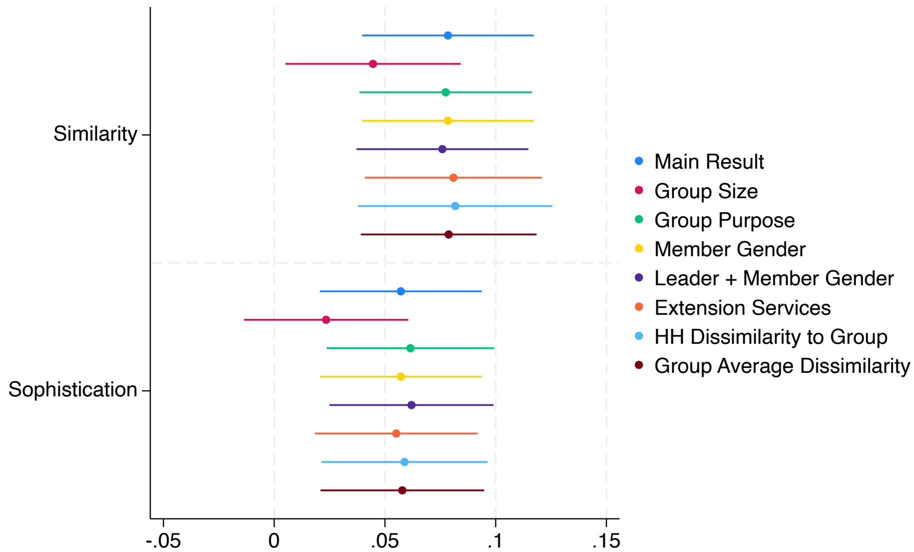

Figure 5: Coefficient plot of leader characteristics in information dissemination, estimated separately with additional controls (see appendix for more information). Linear Probability Model estimated separately for households assigned to the 90 percent subsidy treatment arm (excluding the rice district), 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 similarity to the farmer group leader constructed using the opposite of the Gower dissimilarity measure; farming sophistication indices 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 and a vector of household controls.

D Robustness

D.1 Heterogeneous Treatment Effects by Sub-County

D.2 Heterogeneous Treatment Effects by Leader Characteristics

An alternative 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 A9 and A10. As we saw in tables **??** and **??**, leader farming sophistication and dissimilarity to member households only predict takeup in groups assigned to treatment. This is also visible in tables A9 and A10, where beyond the level differences between treatment and control groups (with particularly higher enrollment among those assigned to

	(1)	(2)	(3)	(4)	(5)
	All	Maize1	Maize2	Beans	Coffe
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.0294**	-0.0107	-0.0419	-0.0986***	0.020
	(0.0111)	(0.0159)	(0.0234)	(0.0227)	(0.034
FG Leader Farming Sophistication Index (std)	0.0612***	0.0459**	-0.0120	0.136***	0.135*
	(0.0110)	(0.0154)	(0.0233)	(0.0226)	(0.034
Mean	0.278	0.166	0.336	0.207	0.46
Observations	1458	530	403	318	207
Sub-County Fixed Effects	Yes	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

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

Table A5: Leader Characteristics in Information Dissemination by Sub-County. Linear Probability Model estimated 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.

	(1)	(2)	(3)	(4)	(5)
	All	Maize1	Maize2	Beans	Coffee
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.0784***	-0.0725*	-0.119*	-0.111*	0.0055
	(0.0197)	(0.0333)	(0.0488)	(0.0516)	(0.0369
FG Leader Farming Sophistication Index (std)	0.0572**	0.107***	-0.0627	0.140**	0.0108
	(0.0186)	(0.0277)	(0.0495)	(0.0418)	(0.0398
Mean	0.465	0.235	0.405	0.482	0.868
Observations	429	147	112	101	69
Sub-County Fixed Effects	Yes	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

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

Table A6: Leader Characteristics in Information Dissemination by Sub-County, 90 Percent Subsidy Treatment. Linear Probability Model estimated 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.

	(1) All	(2) Maize1	(3) Maize2	(4) Beans	(5) Coffee
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.00589	0.0142	-0.00373	-0.0297	-0.0976
	(0.0186)	(0.0290)	(0.0400)	(0.0365)	(0.0708)
FG Leader Farming Sophistication Index (std)	0.0245	-0.00586	0.0427	-0.0132	0.0623
	(0.0199)	(0.0325)	(0.0381)	(0.0463)	(0.0689)
Mean	0.227	0.153	0.327	0.105	0.339
Observations	533	196	156	114	67
Sub-County Fixed Effects	Yes	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

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

Table A7: Leader Characteristics in Information Dissemination by Sub-County, 67 Percent Subsidy Treatment. Linear Probability Model estimated 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.

	(1) All	(2) Maize1	(3) Maize2	(4) Beans	(5) Coffee
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.00400	0.00193	-0.0457	0.0373*	-0.00933
	(0.0159)	(0.0271)	(0.0412)	(0.0150)	(0.0542)
FG Leader Farming Sophistication Index (std)	0.00250	0.0482	-0.0251	0.00888	-0.0298
	(0.0181)	(0.0293)	(0.0413)	(0.0188)	(0.0598)
Mean	0.146	0.120	0.276	0.0194	0.144
Observations	496	187	135	103	71
Sub-County Fixed Effects	Yes	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

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

Table A8: Leader Characteristics in Information Dissemination by Sub-County, Control. Linear Probability Model estimated 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.

the 90 percent subsidy, 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 for the 67 percent).

D.3 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 A11, we see that the correlation between leader farming sophistication and enrollment is even stronger than that in table **??**. 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.

D.4 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 A12), the group's original purpose as indicated by the name of the group (table A12), gender (table A13), experience with extension services (table A15), similarity to other (non-leader) members of the group (tables A16 and A17), and spatial measures of distance to district offices (table A18) or dispersion of households within the group(table A19). 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

	(1)	(2)	(3)
	Enroll	Enroll	Enroll
HH Socioeconomic Dissimilarity to FG Leader (std)	0.0000669	-0.000804	-0.00130
	(0.0190)	(0.0190)	(0.0190)
FG Leader Farming Sophistication Index (std)	0.0215	0.0219	0.0185
	(0.0216)	(0.0216)	(0.0216)
67-50-33	0.0828**	0.0861***	0.0833**
	(0.0255)	(0.0257)	(0.0255)
90-50-10	0.258***	0.260***	0.257***
	(0.0274)	(0.0278)	(0.0274)
67-50-33 × HH Socioeconomic Dissimilarity to FG Leader (std)	-0.00341	-0.00961	-0.00226
	(0.0264)	(0.0267)	(0.0264)
90-50-10 × HH Socioeconomic Dissimilarity to FG Leader (std)	-0.0690**	-0.0602*	-0.0686**
	(0.0264)	(0.0277)	(0.0265)
67-50-33 × FG Leader Farming Sophistication Index (std)	-0.00269	-0.00261	0.00335
	(0.0290)	(0.0290)	(0.0292)
90-50-10 × FG Leader Farming Sophistication Index (std)	0.0443	0.0448	0.0477
	(0.0278)	(0.0278)	(0.0278)
HH Socioeconomic Dissimilarity to FG Leader (std)		-0.00720	
× FG Leader Farming Sophistication Index (std)		(0.0213)	
67-50-33 × HH Socioeconomic Dissimilarity to FG Leader (std)		-0.0250	
× FG Leader Farming Sophistication Index (std)		(0.0283)	
90-50-10 × HH Socioeconomic Dissimilarity to FG Leader (std)		-0.00814	
× FG Leader Farming Sophistication Index (std)		(0.0258)	
HH Farming Sophistication Index (std)			0.0483
			(0.0391)
67-50-33 × HH Farming Sophistication Index (std)			-0.0484
			(0.0258)
90-50-10 × HH Farming Sophistication Index (std)			-0.0282
			(0.0264)
Observations	1458	1458	1458
Sub-County Fixed Effects	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes

Standard errors in parentheses

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

Table A9: 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 and a vector of household controls.

	(1) Enroll	(2) Enroll	(3) Enroll
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.000376	-0.00127	-0.00214
	(0.0193)	(0.0193)	(0.0193)
FG Leader Farming Sophistication Index (std)	0.0218	0.0221	0.0186
	(0.0219)	(0.0219)	(0.0220)
Treatment	0.169***	0.171***	0.168***
	(0.0226)	(0.0228)	(0.0225)
Treatment × HH Socioeconomic Dissimilarity to FG Leader (std)	-0.0440	-0.0394	-0.0436
	(0.0234)	(0.0234)	(0.0233)
Treatment × FG Leader Farming Sophistication Index (std)	0.0471	0.0486	0.0511*
	(0.0252)	(0.0252)	(0.0253)
HH Socioeconomic Dissimilarity to FG Leader (std)		-0.00968	
× FG Leader Farming Sophistication Index (std)		(0.0216)	
Treatment × HH Socioeconomic Dissimilarity to FG Leader (std)		-0.0147	
× FG Leader Farming Sophistication Index (std)		(0.0240)	
HH Farming Sophistication Index (std)			0.0621
			(0.0395)
Treatment × HH Farming Sophistication Index (std)			-0.0398
			(0.0228)
Observations	1458	1458	1458
Sub-County Fixed Effects	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes

Standard errors in parentheses

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

Table A10: 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 and a vector of household controls.

	(1)	(2)	(3)
	Enroll	Enroll	Enroll
HH socioeconomic dissimilarity to recoded FG leader	0.00466	0.00474	0.00346
	(0.0120)	(0.0120)	(0.0120)
Reclassified FG Leader Farming Sophistication Index	0.111***	0.110***	0.111***
	(0.0120)	(0.0120)	(0.0120)
HH socioeconomic dissimilarity to recoded FG leader		0.0229*	
× Reclassified FG Leader Farming Sophistication Index		(0.0113)	
HH Farming Sophistication Index (std)			0.0587
			(0.0394)
Observations	1299	1299	1299
Sub-County Fixed Effects	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes

Standard errors in parentheses

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

Table A11: 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 and a vector of household controls.

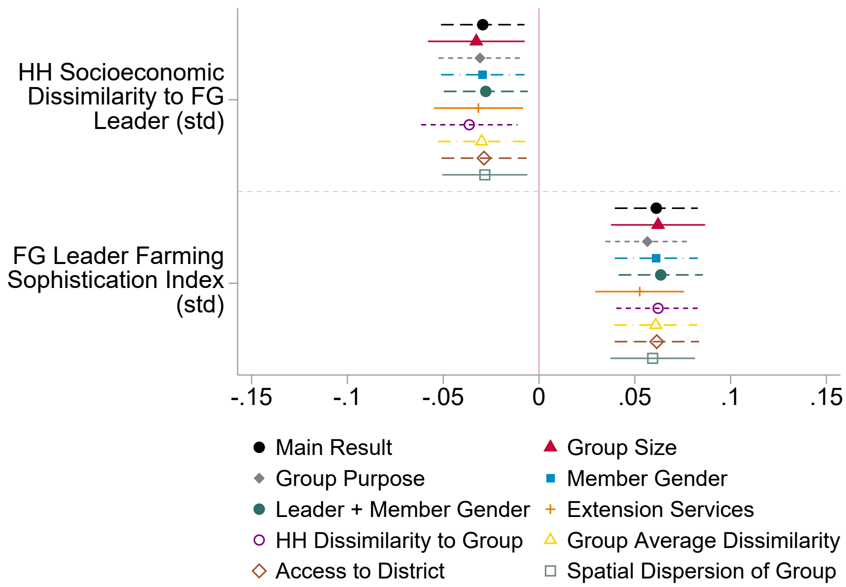

Figure 6: Coefficient plot of leader characteristics in information dissemination, estimated separately with additional controls (see appendix for more information). Linear Probability Model estimated separately for households in all treatment arms (excluding the rice district), with the outcome variable 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 and a vector of household controls.

of the leader (as seen in Fig. 5 for the 90% subsidy stream, Fig. 6 for the full sample, and Fig. 7 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 percent subsidy 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 A12, 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

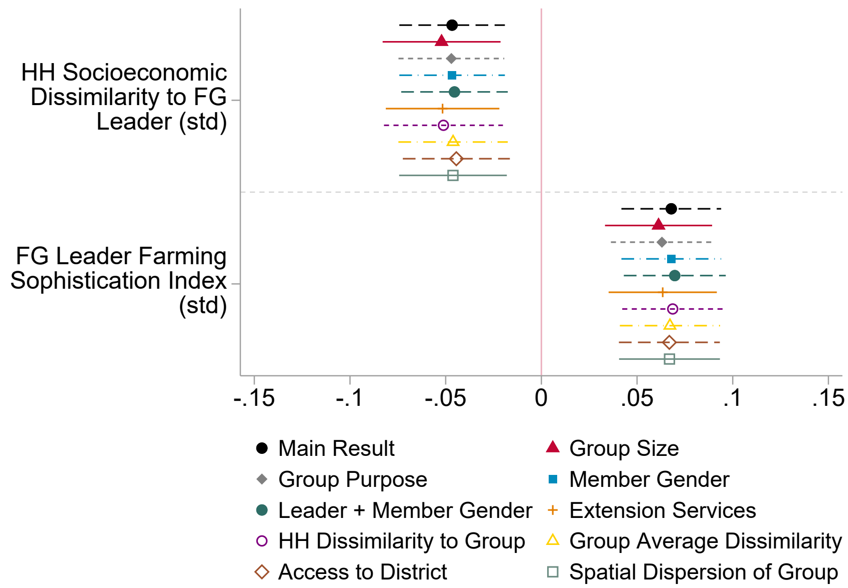

Figure 7: Coefficient plot of leader characteristics in information dissemination, estimated separately with additional controls (see appendix for more information). Linear Probability Model estimated separately for households assigned to treatment (excluding the rice district), with the outcome variable 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 and a vector of household controls.

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 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 A13, 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 A15, we control for a dummy equal to one if the household reports having received

	(1) Enroll	(2) Enroll	(3) Enroll
Panel A: Full Sample			
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.0327*	-0.0308**	-0.0346**
	(0.0129)	(0.0110)	(0.0128)
FG Leader Farming Sophistication Index (std)	0.0621***	0.0566***	0.0573***
	(0.0125)	(0.0112)	(0.0125)
Administrative listed number of members in FG	-0.00317***		-0.00347***
	(0.000741)		(0.000746)
FG Name indicates Farmer Group		0.0480*	0.0740**
		(0.0241)	(0.0276)
FG Name indicates Women's Group		0.0687*	0.0752
		(0.0349)	(0.0446)
FG Name indicates Savings Group		0.142***	0.149***
		(0.0289)	(0.0320)
Observations	1152	1458	1152
Panel B: Treated Groups			
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.0521***	-0.0470***	-0.0504**
	(0.0157)	(0.0141)	(0.0157)
FG Leader Farming Sophistication Index (std)	0.0612***	0.0630***	0.0560***
	(0.0143)	(0.0136)	(0.0144)
Administrative listed number of members in FG	-0.00416***		-0.00461***
	(0.000826)		(0.000835)
FG Name indicates Farmer Group		0.0747*	0.104**
		(0.0341)	(0.0361)
FG Name indicates Women's Group		0.0458	0.0831
		(0.0489)	(0.0566)
FG Name indicates Savings Group		0.0887*	0.121**
		(0.0370)	(0.0399)
Observations	817	962	817
Panel C: 90-50-10 Treatment Arm			
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.0446*	-0.0774***	-0.0398
	(0.0201)	(0.0198)	(0.0203)
FG Leader Farming Sophistication Index (std)	0.0234	0.0615**	0.0281
	(0.0189)	(0.0193)	(0.0191)
Administrative listed number of members in FG	-0.00918***		-0.00891***
	(0.00111)		(0.00113)
FG Name indicates Farmer Group		0.0522	-0.00768
		(0.0577)	(0.0583)
FG Name indicates Women's Group		0.0477	0.0930
		(0.0761)	(0.0876)
FG Name indicates Savings Group		-0.0743	-0.0509
		(0.0587)	(0.0591)
Observations	379	429	379

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

Table A12: All specifications include subcounty fixed effects and a vector of household controls

	(1)	(2)	(3)	(4)	(5)
	Enroll	Enroll	Enroll	Enroll	Enroll
Panel A: Full Sample					
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.0294**	-0.0278*	-0.0233	-0.0278*	-0.0292*
	(0.0111)	(0.0112)	(0.0126)	(0.0111)	(0.0120)
FG Leader Farming Sophistication Index (std)	0.0612***	0.0635***	0.0628***	0.0644***	0.0647***
	(0.0110)	(0.0112)	(0.0112)	(0.0112)	(0.0113)
Female	0.0441	0.0353	0.0190	0.0350	0.0423
	(0.0230)	(0.0241)	(0.0319)	(0.0238)	(0.0336)
Group leader is female		0.0302	0.00241		
		(0.0243)	(0.0431)		
Female × Group leader is female			0.0429		
			(0.0550)		
Any group leader is female				0.0368	0.0462
				(0.0237)	(0.0387)
Female × Any group leader is female					-0.0155
					(0.0504)
Observations	1458	1458	1458	1458	1458
Panel B: Treated Groups					
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.0466***	-0.0454**	-0.0397*	-0.0456**	-0.0444**
	(0.0141)	(0.0142)	(0.0160)	(0.0141)	(0.0151)
FG Leader Farming Sophistication Index (std)	0.0679***	0.0697***	0.0690***	0.0700***	0.0699***
	(0.0133)	(0.0136)	(0.0136)	(0.0136)	(0.0136)
Female	0.0657*	0.0601	0.0386	0.0615*	0.0539
	(0.0299)	(0.0311)	(0.0416)	(0.0305)	(0.0444)
Group leader is female		0.0204	-0.0137		
		(0.0312)	(0.0538)		
Female × Group leader is female			0.0540		
			(0.0695)		
Any group leader is female				0.0220	0.0133
				(0.0304)	(0.0479)
Female × Any group leader is female					0.0148
					(0.0629)
Observations	962	962	962	962	962
Panel C: 90-50-10 Treatment Arm					
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.0784***	-0.0759***	-0.0705**	-0.0787***	-0.0784***
	(0.0197)	(0.0198)	(0.0221)	(0.0196)	(0.0209)
FG Leader Farming Sophistication Index (std)	0.0572**	0.0620**	0.0623**	0.0652***	0.0652***
	(0.0186)	(0.0188)	(0.0189)	(0.0188)	(0.0188)
Female	0.137**	0.112*	0.0887	0.109*	0.106
	(0.0444)	(0.0473)	(0.0640)	(0.0456)	(0.0688)
Group leader is female		0.0698	0.0349		
		(0.0462)	(0.0792)		
Female × Group leader is female			0.0554		
			(0.102)		
Any group leader is female				0.110*	0.107
				(0.0451)	(0.0744)
Female × Any group leader is female					0.00465
					(0.0970)
Observations	429	429	429	429	429

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

Table A13: All specifications include subcounty fixed effects and a vector of household controls.

	(1) Enroll	(2) Enroll
Panel A: Full Sample		
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.0368**	-0.00529
	(0.0112)	(0.0173)
FG Leader Farming Sophistication Index (std)	0.0520***	-0.000917
	(0.0111)	(0.0181)
Group Leader is Enrolled in ACDP	0.239***	0.238***
	(0.0227)	(0.0225)
Group Leader is Enrolled in ACDP		-0.0517*
× HH Socioeconomic Dissimilarity to FG Leader (std)		(0.0225)
Group Leader is Enrolled in ACDP		0.0846***
× FG Leader Farming Sophistication Index (std)		(0.0230)
Observations	1366	1366
Panel B: Treated Groups		
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.0535***	-0.0271
	(0.0141)	(0.0234)
FG Leader Farming Sophistication Index (std)	0.0673***	-0.0164
	(0.0134)	(0.0240)
Group Leader is Enrolled in ACDP	0.237***	0.230***
	(0.0296)	(0.0294)
Group Leader is Enrolled in ACDP		-0.0372
× HH Socioeconomic Dissimilarity to FG Leader (std)		(0.0291)
Group Leader is Enrolled in ACDP		0.122***
× FG Leader Farming Sophistication Index (std)		(0.0292)
Observations	921	921
Panel C: 90-50-10 Treatment Arm		
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.0824***	-0.117**
	(0.0197)	(0.0378)
FG Leader Farming Sophistication Index (std)	0.0408*	0.0831*
	(0.0190)	(0.0410)
Group Leader is Enrolled in ACDP=1	0.193***	0.201***
	(0.0535)	(0.0538)
Group Leader is Enrolled in ACDP		0.0517
× HH Socioeconomic Dissimilarity to FG Leader (std)		(0.0459)
Group Leader is Enrolled in ACDP		-0.0558
× FG Leader Farming Sophistication Index (std)		(0.0472)
Observations	417	417

Standard errors in parentheses

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

Table A14: All specifications include subcounty fixed effects and a vector of household controls.

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 A16 explores the household's dissimilarity to non-leader members of their group. Column (1) replaces the leader characteristics with the household's own: as we have seen above in Table 5, 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 A17 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.

Then, in tables A18 and A19, we look at geographic measures of proximity. Table A18 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 A19 controls for the distance between the household and all other members of their group, as well as the average geographic distance between members

	(1) Enroll	(2) Enroll	(3) Enroll
Panel A: Full Sample			
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.0295**	-0.0296**	-0.0294**
	(0.0111)	(0.0110)	(0.0111)
FG Leader Farming Sophistication Index (std)	0.0603***	0.0606***	0.0579***
	(0.0110)	(0.0110)	(0.0111)
Extension (past 6 months)	0.0756*		0.0739*
	(0.0308)		(0.0308)
Extension (ACDP)		0.209***	
		(0.0477)	
Group Leader Attended a 2 Day Training			0.0476
			(0.0276)
Observations	1458	1458	1458
Panel B: Treated Groups			
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.0472***	-0.0472***	-0.0473***
	(0.0140)	(0.0140)	(0.0140)
FG Leader Farming Sophistication Index (std)	0.0656***	0.0671***	0.0662***
	(0.0132)	(0.0132)	(0.0133)
Extension (past 6 months)	0.129**		0.130**
	(0.0405)		(0.0406)
Extension (ACDP)		0.219***	
		(0.0619)	
Group Leader Attended a 2 Day Training			-0.0138
			(0.0325)
Observations	962	962	962
Panel C: 90-50-10 Treatment Arm			
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.0814***	-0.0804***	-0.0828***
	(0.0197)	(0.0196)	(0.0200)
FG Leader Farming Sophistication Index (std)	0.0555**	0.0576**	0.0554**
	(0.0185)	(0.0185)	(0.0186)
Extension (past 6 months)	0.117*		0.116*
	(0.0554)		(0.0555)
Extension (ACDP)		0.162*	
		(0.0740)	
Group Leader Attended a 2 Day Training			0.0222
			(0.0522)
Observations	429	429	429

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

Table A15: All specifications include subcounty fixed effects and a vector of household controls.

	(1) Enroll	(2) Enroll	(3) Enroll
Panel A: Full Sample			
HH Farming Sophistication Index (std)	0.0305	0.0328	0.0347
	(0.0364)	(0.0358)	(0.0358)
HH average socioeconomic dissimilarity to others in group	-0.0166	0.0146	0.0159
	(0.0120)	(0.0148)	(0.0148)
FG Leader Farming Sophistication Index (std)		0.0622***	0.0625***
		(0.0111)	(0.0111)
HH Socioeconomic Dissimilarity to FG Leader (std)		-0.0364**	-0.0386**
		(0.0128)	(0.0129)
HH average socioeconomic dissimilarity to others in group			-0.0156
× FG Leader Farming Sophistication Index (std)			(0.0114)
Observations	1719	1458	1458
Panel B: Treatment Groups			
HH Farming Sophistication Index (std)	0.0492	0.0374	0.0387
	(0.0430)	(0.0425)	(0.0426)
HH average socioeconomic dissimilarity to others in group	-0.0368*	0.00954	0.0104
	(0.0149)	(0.0180)	(0.0180)
FG Leader Farming Sophistication Index (std)		0.0686***	0.0687***
		(0.0134)	(0.0134)
HH Socioeconomic Dissimilarity to FG Leader (std)		-0.0512**	-0.0526**
		(0.0158)	(0.0159)
HH average socioeconomic dissimilarity to others in group			-0.0114
× FG Leader Farming Sophistication Index (std)			(0.0135)
Observations	1145	962	962
Panel C: 90-50-10 Treatment Arm			
HH Farming Sophistication Index (std)	-0.0240	-0.0412	-0.0374
	(0.0581)	(0.0589)	(0.0590)
HH average socioeconomic dissimilarity to others in group	-0.0509*	0.0109	0.0169
	(0.0203)	(0.0270)	(0.0276)
FG Leader Farming Sophistication Index (std)		0.0588**	0.0579**
		(0.0191)	(0.0191)
HH Socioeconomic Dissimilarity to FG Leader (std)		-0.0817***	-0.0847***
		(0.0223)	(0.0225)
HH average socioeconomic dissimilarity to others in group			-0.0205
× FG Leader Farming Sophistication Index (std)			(0.0188)
Observations	564	429	429

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

Table A16: All specifications include subcounty fixed effects and a vector of household controls.

	(1) Enroll	(2) Enroll	(3) Enroll
Panel A: Full Sample			
HH Farming Sophistication Index (std)	0.0276	0.0354	0.0372
	(0.0363)	(0.0357)	(0.0358)
Average socioeconomic dissimilarity between members in FG	-0.0129	-0.000478	-0.00195
	(0.0110)	(0.0118)	(0.0119)
FG Leader Farming Sophistication Index (std)		0.0609^{***}	0.0610^{***}
		(0.0111)	(0.0111)
HH Socioeconomic Dissimilarity to FG Leader (std)		-0.0300^{**}	-0.0299^{**}
		(0.0116)	(0.0116)
Average socioeconomic dissimilarity between members in FG $\times$ FG Leader Farming Sophistication Index (std)			-0.0163 (0.0116)
Observations	1720	1458	1458
Panel B: Treatment Groups			
HH Farming Sophistication Index (std)	0.0441	0.0390	0.0400
	(0.0429)	(0.0425)	(0.0424)
Average socioeconomic dissimilarity between members in FG	-0.0340^{*}	-0.00493	-0.00833
	(0.0142)	(0.0153)	(0.0155)
FG Leader Farming Sophistication Index (std)		0.0672^{***}	0.0669^{***}
		(0.0133)	(0.0133)
HH Socioeconomic Dissimilarity to FG Leader (std)		-0.0461^{**}	-0.0460^{**}
		(0.0146)	(0.0146)
Average socioeconomic dissimilarity between members in FG $\times$ FG Leader Farming Sophistication Index (std)			-0.0204 (0.0143)
Observations	1145	962	962
Panel C: 90-50-10 Treatment Arm			
HH Farming Sophistication Index (std)	-0.0301	-0.0405	-0.0374
	(0.0583)	(0.0589)	(0.0588)
Average socioeconomic dissimilarity between members in FG	-0.0286	0.00750	0.0121
	(0.0205)	(0.0243)	(0.0245)
FG Leader Farming Sophistication Index (std)		0.0578^{**}	0.0537^{**}
		(0.0188)	(0.0189)
HH Socioeconomic Dissimilarity to FG Leader (std)		-0.0788^{***}	-0.0747^{***}
		(0.0202)	(0.0203)
Average socioeconomic dissimilarity between members in FG $\times$ FG Leader Farming Sophistication Index (std)			-0.0385 (0.0238)
Observations	564	429	429

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

Table A17: All specifications include subcounty fixed effects and a vector of household controls.

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.

Finally, in table A20, we control for all the various dimensions of robustness simultaneously. Column (1) presents results for the full sample; column (2) for members of groups assigned to treatment, and column (3) for those assigned to the 90 percent initial subsidy treatment arm. The coefficient on farmer group leader farming sophistication is relatively stable; the coefficient on the household's socioeconomic dissimilarity to their leader is if anything larger in magnitude. However, when we restrict to the much smaller 90 percent subsidy sub-sample, multicollinearity inflates the standard errors such that statistical significance is lost.

Tables A16-A18 are inspired by models of the effect of nonrandom exposure to exogenous shocks (Borusyak and Hull, 2023). In our context, the nonrandom exposure is the degree of transmission of information from a farmer group leader to a farmer group member, and the exogenous shock is the random assignment of a farmer group to an intended treatment. To implement this approach, we control for the socioeconomic dissimilarity and farming sophistication of a farmer group's counterfactual leader.

To determine a farmer group's counterfactual leader, we build on the propensity score matching approach in Appendix A. Specifically, we define a single leader of each farmer group as the group's chairperson or, if we have no data on the chairperson, the group's secretary. We then estimate the relationship between being the single leader of a farmer group and farmers' observable characteristics. These estimates allows us to predict the propensity to be the single leader of a farmer group. For groups with common support between the leader and members on the propensity measure, we match the single leader of a farmer group with the member of the farmer group with the most similar member in terms of propensity to lead. We define this member of the farmer group as the group's counterfactual leader.

	(1) Enroll	(2) Enroll
Panel A: Full Sample		
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.0287*	-0.0324**
	(0.0113)	(0.0113)
FG Leader Farming Sophistication Index (std)	0.0615***	0.175***
	(0.0112)	(0.0340)
Access to District Capital, 2015	0.123	0.212
	(0.148)	(0.150)
FG Leader Farming Sophistication Index (std)		-0.246***
× Access to District Capital, 2015		(0.0697)
Observations	1416	1416
Panel B: Treatment Groups		
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.0444**	-0.0502***
	(0.0142)	(0.0143)
FG Leader Farming Sophistication Index (std)	0.0669***	0.186***
	(0.0134)	(0.0408)
Access to District Capital, 2015	0.217	0.237
	(0.196)	(0.195)
FG Leader Farming Sophistication Index (std)		-0.260**
× Access to District Capital, 2015		(0.0841)
Observations	946	946
Panel C: 90-50-10 Treatment Arm		
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.0663**	-0.0761***
	(0.0203)	(0.0202)
FG Leader Farming Sophistication Index (std)	0.0609**	0.236***
	(0.0187)	(0.0526)
Access to District Capital, 2015	0.711*	0.825**
	(0.286)	(0.284)
FG Leader Farming Sophistication Index (std)		-0.396***
× Access to District Capital, 2015		(0.112)
Observations	424	424

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

Table A18: All specifications include subcounty fixed effects and a vector of household controls.

	(1) Enroll	(2) Enroll
Panel A: Full Sample		
Average distance from HH to other group members, standardized	0.00775	0.0141
	(0.0212)	(0.0222)
Average distance between members of FG, standardized	0.0144	0.00569
	(0.0217)	(0.0229)
HH Socioeconomic Dissimilarity to FG Leader (std)		-0.0283*
		(0.0113)
FG Leader Farming Sophistication Index (std)		0.0593***
		(0.0112)
Observations	1698	1438
Panel B: Treatment Groups		
Average distance from HH to other group members, standardized	0.0182	0.0322
	(0.0237)	(0.0247)
Average distance between members of FG, standardized	-0.00961	-0.0174
	(0.0243)	(0.0257)
HH Socioeconomic Dissimilarity to FG Leader (std)		-0.0462**
		(0.0143)
FG Leader Farming Sophistication Index (std)		0.0669***
		(0.0134)
Observations	1134	952
Panel C: 90-50-10 Treatment Arm		
Average distance from HH to other group members, standardized	0.0137	0.0125
	(0.0466)	(0.0516)
Average distance between members of FG, standardized	0.0329	0.0274
	(0.0448)	(0.0494)
HH Socioeconomic Dissimilarity to FG Leader (std)		-0.0689***
		(0.0204)
FG Leader Farming Sophistication Index (std)		0.0560**
		(0.0188)
Observations	558	424

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

Table A19: All specifications include subcounty fixed effects

	(1) Enroll	(2) Enroll	(3) Enroll
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.0554***	-0.0623**	-0.0373
	(0.0157)	(0.0189)	(0.0303)
FG Leader Farming Sophistication Index (std)	0.0553***	0.0569***	0.0465
	(0.0139)	(0.0163)	(0.0249)
Access to District Capital, 2015	-0.0936	0.405	0.968*
	(0.188)	(0.260)	(0.440)
Average distance from HH to other group members (std)	0.0225	0.0340	0.0179
	(0.0235)	(0.0259)	(0.0606)
Average distance between members of FG (std)	-0.0218	-0.0262	-0.0694
	(0.0258)	(0.0289)	(0.0802)
Administrative listed number of members in FG	-0.00364***	-0.00466***	-0.00781***
	(0.000782)	(0.000881)	(0.00130)
FG Name indicates Farmer Group	0.0803*	0.149***	0.0893
	(0.0320)	(0.0423)	(0.0752)
FG Name indicates Women's Group	0.181**	0.188**	0.274
	(0.0549)	(0.0686)	(0.157)
FG Name indicates Savings Group	0.134***	0.0913*	-0.0939
	(0.0360)	(0.0444)	(0.0684)
Group leader is female	0.00569	0.0113	0.0423
	(0.0320)	(0.0397)	(0.0611)
Received extension services in past 6 months	0.0465	0.102*	0.0983
	(0.0383)	(0.0486)	(0.0688)
2 day training on input use	0.171**	0.214**	0.0955
	(0.0607)	(0.0749)	(0.0941)
Group Leader Attended a 2 Day Training	0.111**	0.0927*	0.0620
	(0.0348)	(0.0424)	(0.0723)
HH average socioeconomic dissimilarity to others in group	0.0301	0.0244	-0.0265
	(0.0221)	(0.0254)	(0.0389)
Average socioeconomic dissimilarity between members in FG	0.0144	0.00610	0.0497
	(0.0199)	(0.0251)	(0.0364)
Observations	992	721	323
Sub-County Fixed Effects	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes
Sample	Full	Treated Groups	90% Treatment Arm

Standard errors in parentheses

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

Table A20: All specifications include subcounty fixed effects

Table A21: Enrollment and Leader Characteristics in 90% Treatment (explanatory variables standardized by sub-county)

	(1)	(2)	(3)	(4)	(5)	(6)
HH Socioeconomic Dissimilarity to FG Leader (std)	-0.074**	-0.135***	-0.061*	-0.126***	-0.061*	-0.127***
	(0.023)	(0.029)	(0.024)	(0.029)	(0.024)	(0.029)
FG Leader Farming Sophistication Index (std)	0.087***	0.097***	0.081***	0.089***	0.081***	0.089***
	(0.023)	(0.025)	(0.023)	(0.025)	(0.023)	(0.025)
HH Socioeconomic Dissimilarity to FG Counterfactual Leader (std)		0.113***		0.123***		0.124***
		(0.032)		(0.033)		(0.033)
FG Counterfactual Leader Farming Sophistication Index (std)		-0.005		0.002		0.002
		(0.025)		(0.026)		(0.026)
HH Farming Sophistication Index (std)					-0.009	0.014
					(0.069)	(0.068)
Observations	311	311	311	311	311	311
Sub-County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes	Yes

Standard errors in parentheses

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

Table A22: Enrollment and Leader Characteristics in 67% Treatment (explanatory variables standardized by sub-county)

	(1)	(2)	(3)	(4)	(5)	(6)
HH Socioeconomic Dissimilarity to FG Leader (std)	0.000	-0.017	0.006	-0.005	0.005	-0.005
	(0.023)	(0.027)	(0.024)	(0.027)	(0.024)	(0.027)
FG Leader Farming Sophistication Index (std)	0.079*	0.084*	0.090*	0.102*	0.090*	0.103*
	(0.036)	(0.041)	(0.037)	(0.042)	(0.037)	(0.042)
HH Socioeconomic Dissimilarity to FG Counterfactual Leader (std)		0.045		0.031		0.028
		(0.029)		(0.030)		(0.030)
FG Counterfactual Leader Farming Sophistication Index (std)		-0.035		-0.036		-0.037
		(0.030)		(0.031)		(0.031)
HH Farming Sophistication Index (std)					0.081	0.077
					(0.071)	(0.071)
Observations	359	359	359	359	359	359
Sub-County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes	Yes

Standard errors in parentheses

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

Table A23: Enrollment and Leader Characteristics in Control (explanatory variables standardized by sub-county)

	(1)	(2)	(3)	(4)	(5)	(6)
HH Socioeconomic Dissimilarity to FG Leader (std)	0.013	0.023	0.015	0.022	0.015	0.022
	(0.018)	(0.022)	(0.018)	(0.022)	(0.018)	(0.022)
FG Leader Farming Sophistication Index (std)	0.005	-0.003	0.007	0.000	0.007	-0.000
	(0.020)	(0.022)	(0.021)	(0.022)	(0.021)	(0.022)
HH Socioeconomic Dissimilarity to FG Counterfactual Leader (std)		-0.022		-0.017		-0.016
		(0.023)		(0.025)		(0.025)
FG Counterfactual Leader Farming Sophistication Index (std)		0.024		0.019		0.020
		(0.020)		(0.020)		(0.020)
HH Farming Sophistication Index (std)					-0.018	-0.023
					(0.066)	(0.068)
Observations	395	395	395	395	395	395
Sub-County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes	Yes

Standard errors in parentheses

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