Technology Adoption and Market Participation in Smallholder Agriculture*

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Abstract

This paper studies whether the adoption of a technology that increases the production of a staple crop differs between households who are buyers, sellers, or self-sufficient with respect to the staple crop. I develop a theoretical model that shows that if buying or selling staples incurs large fixed costs, technology adoption varies with market participation; if fixed costs are small, however, technology adoption does not vary with market participation. Whether technology adoption varies by market participation has implications for how to target interventions promoting technology adoption such as input subsidy programs. I estimate how adoption varies with market participation using data from a randomized controlled trial of high-yielding varieties of maize developed for western Kenya. Treatment effects across market participation groups are neither large nor statistically significant. These results suggest that transaction costs in output markets are not large enough to shape the pattern of adoption of a production technology.

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1 Introduction

The global poor disproportionately reside in rural sub-Saharan Africa, work in agriculture, and are spatially dispersed (Bank, 2018). Spatial dispersion makes participation in markets costly due to transaction costs, in particular transportation costs or search costs (de Janvry et al., 1991; Key et al., 2000). A well-studied market with transaction costs in rural sub-Saharan Africa is the output market for staple crops (Barrett, 2008; Renkow et al., 2004). One implication of transaction costs in the output market for a staple crop is that they can cause an agricultural household to select out of the market as either a seller or a buyer.

A second implication of transaction costs in the output market for a staple crop is that they create a household-specific shadow value of staple output (de Janvry et al., 1991; Key et al., 2000). Proportional transaction costs, for example due to transportation costs, create a price wedge such that the staple buying price is greater than the staple selling price. Fixed transaction costs, for example due to search costs, make the relationship between staple production and household utility non-convex; that is, output has locally increasing returns for a household near the threshold of being autarkic or a seller with respect to output markets (Barrett, 2008; Key et al., 2000). In this way, an agricultural household's market participation, on both the extensive and intensive margins, signals the shadow value of their output.

Transaction costs in output markets have been shown to affect the supply response of households (de Janvry et al., 1991; Key et al., 2000). More recent studies on production decisions of agricultural households in sub-Saharan Africa focus on the discrete decision of a household to adopt a new production technology (Suri and Udry, 2022). This paper studies the intersection of these literatures: how do transaction costs in output markets affect an agricultural household's incentive to to adopt a new production technology? The interdependence between output market participation and technology adoption is a subject of interest in both the market participation literature (Barrett, 2008; Renkow et al., 2004) and the technology adoption literature (Suri and Udry, 2022). The relationship between market participation and technology adoption is of interest for understanding both the economic decision-making of agricultural households and potential implications for the targeting of programs promoting technology adoption.

This paper studies the relationship between technology adoption and market participation both theoretically and empirically. Section 2 develops and analyzes a theoretical model of technology adoption in which buying and selling staples incurs fixed costs. The household model shows that transaction costs in output markets incentivize technology adoption such that technology adoption is both an income source as well as a means of either reducing costs of buying staples or overcoming costs of selling staples. Incentives for technology adoption are greatest for land poor households near the threshold of becoming self-sufficient or sellers, as well as land rich households that are sellers. When fixed costs in output markets are large, the model predicts that when households receive full information about a technology's productivity, adoption will be greatest among households near the margins of buying or selling staples, as well as households already selling staples. When fixed costs are small, however, technology adoption does not vary with market participation.

Section 3 extends the theoretical analysis to study the policy relevance of the interdependence between technology adoption and market participation for a common policy for promoting technology adoption: input subsidies. A temporary subsidy can stimulate long-term technology adoption if a household learns from adopting the technology at a subsidized price and increases its expected yields from subsequent technology adoption compared to its initially pessimistic beliefs (Carter et al., 2014). To encourage technology adoption in this context, many governments in sub-Saharan Africa subsidize prices of agricultural production technologies for targeted agricultural households. Due to the costs of subsidies to the government, many agricultural subsidy programs target particular households to receive the subsidy. Yet there remains debate about the effectiveness of agricultural subsidy programs, including how to target and design these programs (Giné et al., 2022). Key features of subsidy programs are targeting based on household land wealth and design of the subsidy level, with programs tending to target households with relatively greater land wealth that produce food on a semi-commercial basis, as shown in Table 1.

Section 3 models input subsidy program targeting and design by an optimizing policymaker. The policymaker chooses input subsidy program targeting and design for a population of households distributed over the land-financial wealth space that choose technology adoption on both the extensive and intensive margin following the model developed in Section 2. I model the policymaker's problem over two seasons. In season one, the household is pessimistic about the physical returns from adopting inputs and chooses its level of input adoption given a subsidy level. In season two, the household has full information about the input's productivity and can adopt at the full market price up to the level that was adopted under the season one subsidy. The policymaker maximizes season two household expenditures on inputs less season one program expenditures on subsidies. I parameterize the model with estimates from data collected in surveys with agricultural households in western Kenya. Under the empirical endowment distribution, households are concentrated at low levels of land and wealth endowments. With transaction cost estimates from the literature, the optimal program provides an 86% subsidy to households in the top 18% of the land endowment distribution; households adopting the technology by the optimal subsidy are primarily sellers of staples without the subsidy program, providing a rationale for governments to specifically target sellers. Without transaction costs, however, the optimal program provides an 87% subsidy to households in the top 6% of the land endowment distribution, and adoption does not vary by market participation.

Section 4 describes the context for the empirical analysis. Data come from a randomized controlled trial in western Kenya (Bird et al., 2022). The randomized controlled trial randomly assigned communities to receive information about new hybrid maize varieties of the staple crop, maize, that mature during the region's short growing seasons. The theoretical model in this paper predicts that technology adoption could be driven by households valuing the technology's effect on their purchases or sales of maize. In the study sample, buyers pay higher prices for maize than they would receive as a seller due to both a time-invariant wedge between buying and selling prices as well as higher prices in the buying season. Additionally, households vary in their participation in output markets for maize from net buyers, to autarkic, to net sellers.

Section 5 estimates the relationship between technology adoption and market participation in the context of the randomized controlled trial. For households that sold maize in the year prior to the study, treatment increases average technology adoption on the extensive margin by 18 percentage points (pp) off of a base of just 2 percent adoption by sellers in the control group. For households that were autarkic or buyers with respect to maize markets in the year prior to the study, the treatment effect differed from sellers by just 1-3pp, a small difference both economically and statistically. In terms of total adoption relevant to policymakers, treatment effects are relatively larger for seller households but do not differ from autarkic or buyer households with statistical significance. The larger point estimate on total adoption is consistent with sellers having more land on which to apply the productive technology, which is consistent with the theoretical model as well as descriptive statistics in the study sample. The results suggest that, in the study context, transaction costs in output markets are not large enough to shape the pattern of adoption of a production technology.

The theoretical and empirical analyses in this paper contribute to our understanding of the interdependence between technology adoption and market participation in smallholder agriculture. The theoretical analysis in this paper shows that the relationship between technology adoption and market participation is ambiguous, and depends on the magnitude of fixed costs of transacting in output markets. When transaction costs are sufficiently large, this deters technology adoption by households that would remain autarkic even when adopting the productive technology. When transaction costs are small, however, technology adoption does not vary with market participation. The empirical analysis in this paper does not find statistically significant differences in a technology adoption intervention's effects across market participation groups, consistent with a context with relatively small fixed costs of transacting in output markets.

Whether technology adoption varies with market participation also is relevant for policies promoting technology adoption such as input subsidies, as shown by the policy simulation in Section 3. Most input subsidy programs target relatively wealthy households that produce a food surplus to sell on the market, as shown by the program targeting criteria in Table 1. The optimality of this approach critically depends on the assumption that technology adoption is greater for sellers of staples, and may implicitly assume relatively large fixed costs of transacting in output markets. The empirical analysis in this paper, however, does not find statistically significant differences in a technology adoption intervention's effects across market participation groups, consistent with a context with relatively small fixed costs of transacting in output markets. Thus the findings in this paper suggest that targeting input subsidies primarily to sellers of staples may exclude many households that would be willing to adopt new production technologies.

2 Economics of Technology Adoption and Market Participation

This section studies the relationship between technology adoption and market participation in smallholder agriculture in theory. Appendix A presents the theoretical household model of technology adoption and output market participation for staple crops as a formal optimization problem. The model studies adoption of a production technology when entering output markets as a seller or buyer incurs transaction costs. The insight from the model is that when market participation is costly, households value technology adoption both as an income source as well as a means of either reducing costs of buying staples or overcoming costs of selling staples. To see how significant these costs are in technology adoption decisions, this section presents a numerical analysis parameterized with estimates from western Kenya, the context for the subsequent empirical analysis.

Table 1: Agricultural input subsidies often target households with greater landholdings and semi-commercial market orientation

Start	Country	Targeting criteria			Subsidy %
		Acres owned*		Other	
		Min	Max		
2002	Zambia	2.5		Cooperatives	50-60
2005	Malawi	1.0		Productive poor	64-95
2007	Kenya	1.0			100
2007	Rwanda	0.5			75:50:25
2008	Tanzania		2.5	Female	50
2008	Zambia	2.5		Cooperatives	75-79
2009	Mozambique	1.2	12.5	Progressive	73
2011	Zimbabwe	1.2			90
2012	Nigeria	1.0		Non-commercial	50
2019	Uganda	3.0	5.0	Farmer groups	67:50:33

Notes: *Maize acres only for 2005 Malawi, 2008 Zambia, and 2009 Mozambique. 2002 Zambia is the Fertilizer Support Programme (Druilhe and Barreiro-Hurlé, 2012; Mason and Tembo, 2014; Mason et al., 2013; Minde et al., 2008; World Bank, 2010); 2005 Malawi is the Agricultural Input Support Programme (Druilhe and Barreiro-Hurlé, 2012; Kilic et al., 2015; Lunduka et al., 2013; Minde et al., 2008); 2007 Kenya is the National Accelerated Agricultural Input Programme (Druilhe and Barreiro-Hurlé, 2012); 2007 Rwanda is the Crop Intensification Programme (Druilhe and Barreiro-Hurlé, 2012); 2008 Tanzania is the National Agricultural Input Voucher System (Druilhe and Barreiro-Hurlé, 2012; Pan and Christiaensen, 2012); 2008 Zambia is the Farmer Input Support Programme (Mason and Smale, 2013; Mason et al., 2013); 2009 Mozambique is the Farm Input Subsidy Programme (Carter et al., 2013); 2011 Zimbabwe is the Electronic Voucher Program (FAO, 2012); 2012 Nigeria is the Growth Enhancement Support Scheme (Wossen et al., 2017); 2019 Uganda is the Agriculture Cluster Development Project (World Bank, 2015).

The numerical analysis simulates an intervention that increases household expectations about a production technology's physical yield. Table A.1 shows the parameter values for the numerical analysis, which come from the market participation literature and from household survey data collected in western Kenya. Estimated yield gains from technology adoption post-intervention are more than three times larger than households' expected yield gains from technology adoption pre-intervention. I derive fixed costs of transacting in staple markets using estimates by Renkow et al. (2004) for maize in western Kenya, the same crop and region studied in the subsequent empirical analysis; the fixed cost of selling is about 113 US dollars and the fixed cost of buying is about 19 US dollars. Kirimi et al. (2011) note, however, increased competition in the maize marketing sector over time that would be consistent with a trend of transaction costs decreasing over time. I still estimate, however, substantial proportional costs of transacting in staple markets using data from western Kenya; during the harvest period, the period with the most maize transactions, the buying price of maize is about 25% greater than the selling price of maize.[1]

The numerical analysis simulates two outcomes. The first outcome is output market participation, which is a function of the household's endowment of financial and land wealth as well as its expected yield gains from technology adoption. The second outcome is the household's compensating variation from incurring the fixed costs of technology adoption. Compensating variation is the amount of money the household would have to give up to be indifferent between its consumption when not adopting the technology and its consumption when taking on the fixed costs of technology adoption. Thus compensating variation is positive for households that are better off when taking on the fixed costs of technology adoption and negative for households that are worse off when taking on the fixed costs of technology adoption.

The simulation shows household behavior both pre-intervention, when they expect the technology to have a low yield, and post-intervention, when they expect the technology to

[1] Appendix B details the approach for estimating the price wedge between buying and selling prices for maize using my data.

have a high yield. The simulation mirrors the subsequent empirical analysis, a randomized controlled trial that provides information about new, high-yielding varieties of maize to some communities and no information to other communities.

Fig. 1 plots household market participation and technology adoption as functions of endowments of financial wealth and land wealth. Fig. 1A shows market participation at baseline, in the absence of a new production technology. Households with low land wealth relative to financial wealth buy staples, households with high land wealth relative to financial wealth sell staples, and households in between are autarkic with respect to staple output markets.

Fig. 1B shows that compensating variation is positive for households adopting the production technology. Notably, compensating variation is greatest for households that can transition out of buying staples, transition into selling staples, or continue selling staples with technology adoption. Three types of households do not adopt the technology. First, households with little financial wealth cannot take on the fixed costs of technology adoption. Second, households with little land wealth cannot make up for the fixed costs of adoption even when applying the technology on all of their land; for these households.[2] The third group of non-adopting households are autarkic with respect to staple output markets and are not near the threshold of either buying or selling staples. These households produce a sufficient amount of staples without technology adoption to meet household demand but would not sell enough staples with technology adoption to make up for the fixed costs of both technology adoption and market participation.

Fig. 1C shows market participation after the new production technology becomes available. The dashed lines indicate that high yields induce some households to adopt the technology and change their market participation. In the top-left corner, some households transition

[2]But with proportional transaction costs in output markets, both groups of non-adopters differ slightly. Higher buying prices due to transaction costs reduces the land wealth threshold for non-adoption, that is more land-poor households adopt the technology than in the case without transaction costs. Lower selling prices due to transaction costs increases the liquidity wealth threshold for non-adoption, that is fewer liquidity-poor households adopt the technology than in the case without transaction costs.

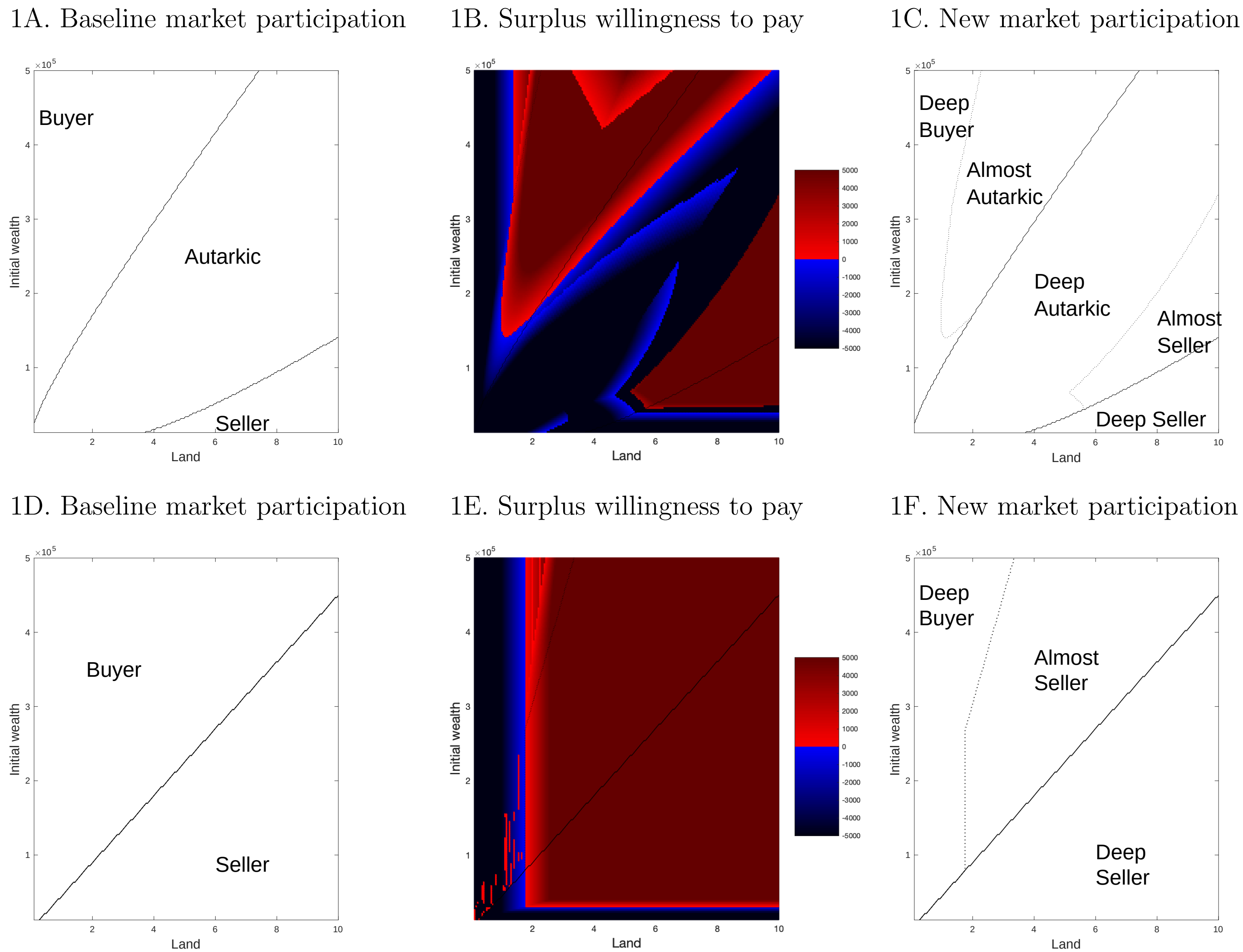
from not adopting and buying staples to adopting and being autarkic with respect to staple markets. In the bottom-right corner, some households transition from not adopting and being autarkic to adopting and selling staples.

The household model generates several predictions about household market participation and technology adoption when buying and selling staples is costly. First, transaction costs prevent some households from participating in markets as either a buyer or seller of staples. This prediction reproduces a result from the literature on output market participation, and is central to the model's main prediction about the interdependence between technology adoption and market participation of agricultural households.

The main results for empirical study relate to the household's technology adoption decision depending on both its staple surplus without technology adoption and its change in staple surplus due to technology adoption, as shown by comparing Figs. 1B and 1C. The technology is adopted by households that can transition from being buyers to autarkic with respect to staple output markets, households that can transaction from being autarkic to sellers, and households that remain sellers. Additionally, the technology is adopted by few households that would remain autarkic even with technology adoption.

Importantly, the prediction that technology adoption varies with output market participation would not come from a model without relatively large transaction costs in output markets. I study the case with no transaction costs in output markets in Figs. 1D-F. In Fig. 1D, households with low land wealth relative to financial wealth buy staples and households with high land wealth relative to financial wealth sell staples; absent transaction costs in output markets, no households are autarkic with respect to output markets. Fig. 1E shows that compensating variation from incurring the fixed costs of technology adoption, which is positive for households adopting the production technology. Adoption is mainly constrained by the fixed costs of technology adoption limiting adoption by households that are land poor or financially poor. Adoption is not, however, shaped by output market participation in the absence of transaction costs.

Figure 1: **Outcomes and distributions in wealth-land space.** Initial wealth and surplus willingness to pay (compensating variation) for the technology measured in 2015 Kenyan shillings (about 100 shillings per US dollar). Graphs A-C show numerical results with transaction costs in output markets. Graphs D-F show numerical results without transaction costs in output markets.



3 Policy Relevance for Targeting and Designing Input Subsidies

This section shows how, in theory, interdependence between technology adoption and market participation can have policy implications for targeting and designing programs to promote technology adoption. In particular, I study targeting and design of an agricultural input subsidy program by a policymaker who maximizes net benefits from the program. Targeting is based on household land wealth such that the policymaker sets targeting criteria with a minimum land wealth and maximum land wealth. Program design is based on the subsidy level. I measure benefits from the program by input investment by agricultural households in the season after the subsidy program.

The policy problem includes two periods of technology adoption by agricultural households. In the first period, the program offers subsidies to households that have initially pessimistic expectations about physical returns from input adoption. In the second period, the subsidy is removed but households that adopted in the first period have fully updated beliefs about the technology's productivity. This updating only applies to the land area on which they applied the technology during the subsidy period, however, such that technology adoption after the subsidy in period two cannot exceed technology adoption under the subsidy in period one. Conditional on household decisions, the policymaker chooses program targeting and design. In particular, I study an agricultural input subsidy program with targeting by household land wealth and design by subsidy level.[3]

Non-convexity of the household's indirect utility function makes technology adoption a non-monotonic function of household endowments and requires targeting subsidies to discrete

[3] To focus on targeting and subsidies, the policy model assumes away other program features that may be sensitive to the interdependence of technology adoption and market participation. First, the model has no maximum size of input package subsidized, which is a common policy in practice. Second, I study a one-season subsidy whereas the number of seasons could be endogenous to the policymaker. Third, the model is not set up to compare outcomes from the subsidy intervention with alternative interventions such as relaxing household capital constraints or reducing transaction costs (for example, through infrastructure investment).

categorizations of households.[4] This also corresponds with how governments target and design subsidy programs in practice. I estimate an empirical endowment distribution in two steps. First, I approximate the distribution of land by fitting a lognormal distribution to the data from western Kenya. Second, I approximate the distribution of income as a function of land.[5] Fig. 2 plots the difference in probability weights between the empirical distribution and the uniform distribution in land-wealth endowment space. The uniform distribution overweights land and wealth rich households relative to the empirical distribution. The mode of the empirical distribution is at low levels of land and wealth endowments, levels such that technology adoption is sub-optimal regardless of subsidy size given the numerical model. For the policymaker, the important feature of the empirical endowment distribution is that households are concentrated at low levels of land wealth, which places more weight on lower levels of the land and wealth distributions when evaluating the costs and benefits of subsidy programs.

Appendix B mathematically defines the policymakers' cost, benefit, and welfare functions. Costs of the program come from subsidizing inputs. Benefits of the program come from input investment in the season after the subsidy program. Finally, the policymaker chooses program targeting and design to maximize welfare as defined by the difference between benefits and costs. The welfare function is not necessarily convex over the choice variables due to fixed costs of technology adoption and output market participation in the household problem. Therefore I use numerical analysis to solve the policymaker's targeting and design problem.

Fig. 3 shows a program's net benefits under an optimal subsidy when transaction costs in

[4] As with the household problem, the policy problem would simplify greatly if household technology adoption and market participation did not incur fixed costs. In that case, household technology adoption would be a monotonic function of endowments. Then the policymaker could implicitly choose a continuous optimal subsidy function defined over explicitly chosen parameters of a gamma distribution defined over land wealth such that the optimal subsidy would vary continuously over land wealth rather than making discrete jumps.

[5] I estimate that the distribution of households in land space is $Lognormal(-0.0546374, 0.664421)$. I estimate that the distribution of households in income space is $Lognormal(11.18413 + 0.0156138 \cdot \log(T), 1.202856)$.

output markets are relatively large. Since subsidies have positive net impacts when targeting some households but negative net impacts when targeting other households, the policy trade-off is between including households with net positive impacts and excluding households with net negative impacts. Under the empirical endowment distribution when transaction costs in output markets are relatively large, the optimal policy is an 86% subsidy targeted to households with at least 1.8 units (acres) of land, the top 18% of the land distribution. Not all households satisfying the targeting criterion for land adopt, however, motivating policymakers to apply other targeting criteria such as those in Table 1. In particular, policymakers may seek to only target "deep sellers" in order to avoid targeting deep autarkic households that would select out of the program. Indeed, this is the approach of half of the countries with agricultural input subsidies listed in Table 1 (Malawi, Mozambique, Uganda, and Zambia). Only targeting "deep sellers" has two main potential shortcomings, however. First, selection out of the program by households comes at no cost to the program, whereas applying an additional targeting criterion requires program resources to further verify eligibility of households. Second, explicitly targeting "deep sellers" assumes that transaction costs in output markets are sufficiently large to cause technology adoption to differ meaningfully between market participation groups.

In contrast, Fig. 4 shows a program's net benefits under an optimal subsidy when transaction costs in output markets are non-existent. The optimal policy is an 87% subsidy targeted to households with at least 2.8 units (acres) of land, the top 6% of the land distribution. Despite the targeting criterion for land being more restrictive than the case with transaction costs, adoption without transaction costs is higher due to more households selecting into the program. Importantly, without transaction costs there is no need to apply additional targeting criteria such as proxies for market participation. In fact, applying such criteria when transaction costs do not shape technology adoption would reduce program benefits, both for the policymaker and for individual households.

Figure 2: **Empirical probability less the uniform probability.** Under a uniform endowment distribution, each cell would have a probability weight around 1×10^{-4}.

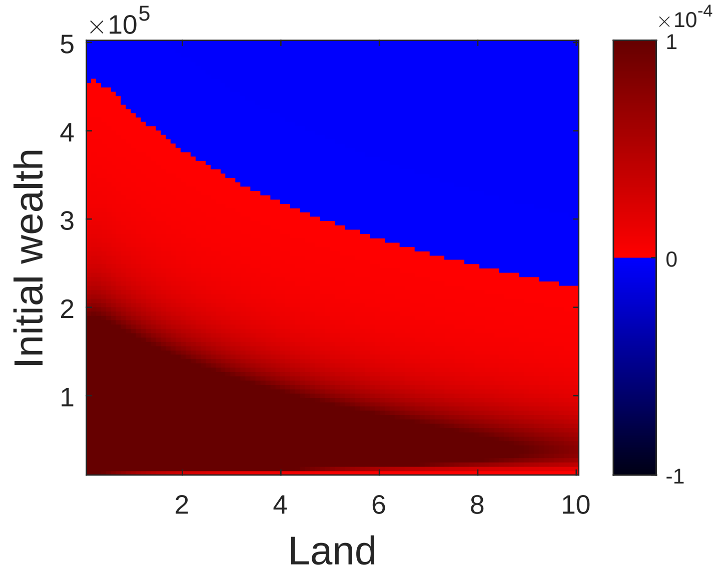


Figure 3: **Net program benefits when transaction costs in output markets are relatively large under the optimal subsidy of 86%.** The optimal program when transaction costs in output markets are relatively large offers subsidies to households with more than 1.8 units of land, making up 18% of the population; for a population of one million, the aggregate net benefit is 1.28 million USD**.**

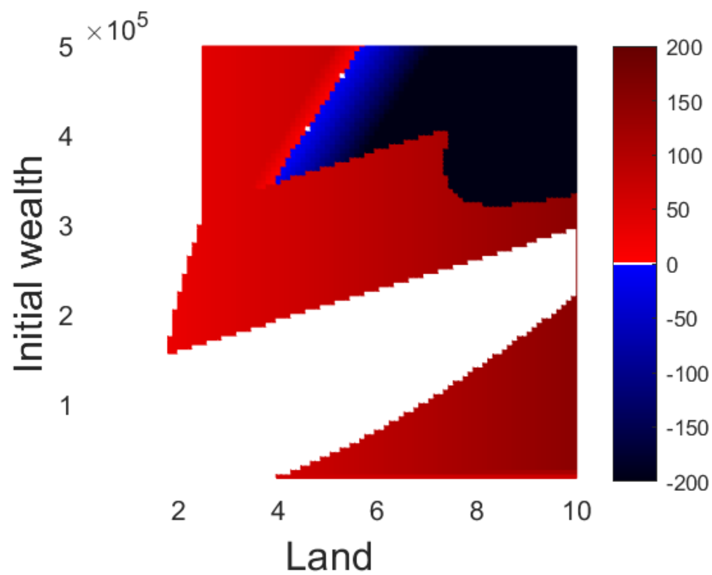
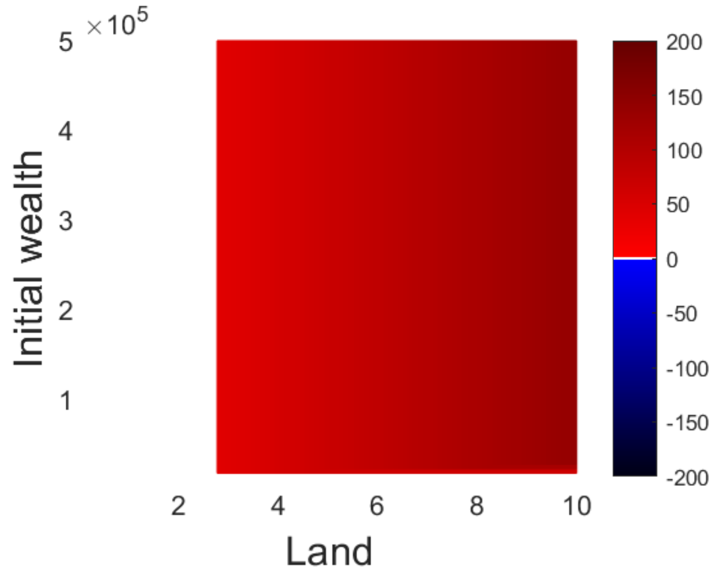


Figure 4: **Net program benefits when transaction costs in output markets are non-existent under the optimal subsidy of 87%.** The optimal program when transaction costs in output markets are non-existent offers subsidies to households with more than 2.8 units of land, making up 6% of the population; for a population of one million, the aggregate net benefit is 2.76 million USD.



4 Randomized Controlled Trial in Western Kenya

I empirically estimate the interdependence between technology adoption and market participation in the context of western Kenya, where the main staple crop is maize. Data come from a randomized controlled trial with agricultural households in western Kenya for an impact evaluation of Western Seed Company hybrid maize varieties (Bird et al., 2022). The study sample includes 700 households in the moist mid-altitude (henceforth, mid-altitude) agro-ecological zone of western Kenya, where adoption of hybrid maize varieties lags behind other regions of the country.[6] Hybrid maize varieties from Western Seed Company are new to this region of Kenya and their early maturity is well-suited to the short growing seasons in the region.

The impact evaluation randomized an intervention to encourage adoption of maize hy-

[6]The full sample also includes 1100 households in the moist transitional agro-ecological zones of western and central Kenya, where hybrid maize adoption is almost universal and maize is a smaller proportion of household expenditures. These characteristics make the theory in this paper less applicable to the moist transitional zones, therefore I focus my analysis on the 700 households sampled from the mid-altitude zone.

brids from Western Seed Company. The experimental design is shown in Fig. 5. Western Seed Company identified potential communities where they could establish demonstration sites to provide information about the varieties to households in the communities. The randomized controlled trial stratified potential demonstration sites into pairs of sites with similar growing conditions, then randomly assigned one of the communities to receive a demonstration site (the "seed treatment") and one of the communities to not receive a demonstration site (the "seed control"). Seed treatment communities received the demonstration sites and agronomic information about the hybrid maize varieties in 2013. The promotional activity in 2013 was specifically designed for households to update their beliefs about the physical yield gain from the hybrid maize technology.

Data come from three rounds of household surveys. Surveys collected data on baseline characteristics in late 2013, midline impacts of the intervention in early 2015, and endline impacts of the intervention in early 2016. Fig. 6 shows the timing of the randomized intervention relative to the timing of the household surveys.

For the empirical analysis, the outcome of interest is household adoption of hybrid maize varieties from Western Seed Company in either of the two post-treatment main seasons (2014 or 2015). Outcomes include adoption on the extensive margin (0/1) and total adoption (in kilograms).

The explanatory variable of interest is household market participation. Surveys collected data on maize sales for each season of the study period, including total quantity sold and the price received for the largest sale. Surveys collected data on maize purchases during the endline survey, including total quantity and price of purchases over four-month periods from February 2015 to January 2016. Households also reported whether their purchases during this time period differed from a typical year and, if so, reported the quantity of maize that they purchase in a typical year. I construct my preferred measure of market participation from the difference between a household's baseline sales of maize and its typical purchases of maize, neither of which should be affected by assignment to treatment.

Figure 5: **Randomized interventions and sampling**

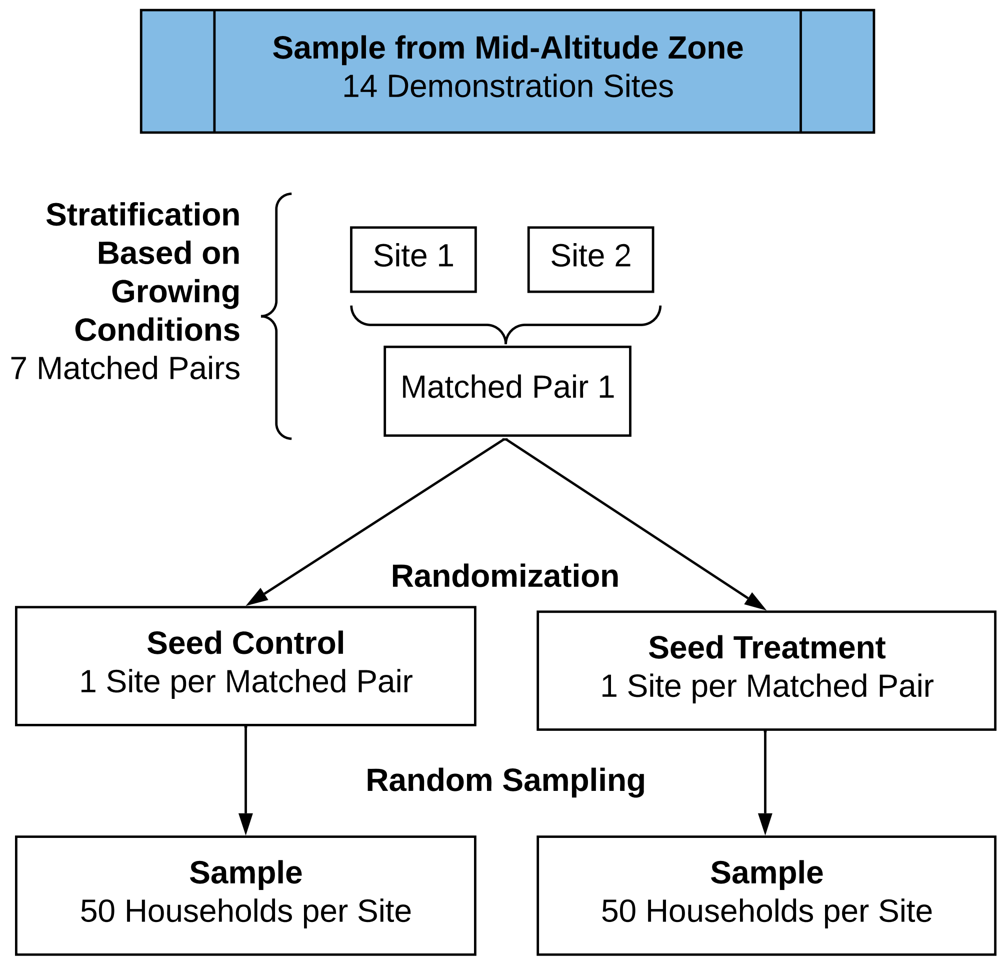
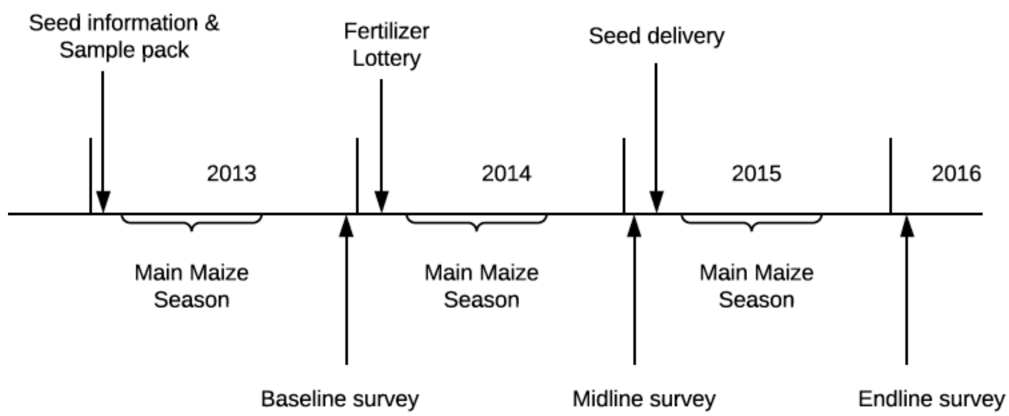


Figure 6: **Study timeline**



5 Treatment Effects by Market Participation

I test the theoretical model's predictions of how technology adoption varies with expected market participation using data from the randomized controlled trial in western Kenya. I model an outcome for household i in village v, site s, matched pair p, and time period t as

$$Outcome_{ivspt} = \rho Treat_s + \sum_k [\delta^k Treat_s MP^k_{ivsp} + \gamma^k MP^k_{ivsp}] + [\nu_p + E_{ivspt}] \qquad (1)$$

where $Treat_s = 1$ for households near sites randomly assigned to receive the seed information (= 0 otherwise), $MP^k_{ivsp} = 1$ for households with baseline market participation k, ν_p is a matched pair fixed effect, and E_{ivspt} is an error term clustered by village. The parameters of interest are δ^k: the difference in the effect of the information intervention on adoption for households with expected market participation k relative to the omitted category of market participation.

This section presents summary statistics and estimates of Eq. (1) for two different definitions of market participation. The first definition is based on the extent of market participation and places each household in one of three categories based on baseline market participation: net seller, autarkic, or net buyer household. This is my preferred empirical measure as the relatively small number of categories leaves a relatively large number of households in each category, making estimates less sensitive to the value of any one observation. A shortcoming of studying the extent of market participation is that it deviates from the theoretical model in which household technology adoption also depends on the household's intensity of market participation. Therefore I also present a second set of results based on the intensity of market participation that further sub-divides households into "deep" and "almost" market participants.

5.1 Extent of Market Participation

Table 2 shows summary statistics, stratified by the extent of market participation at baseline and treatment assignment. Relative to all other groups, sellers have the most experience using hybrid maize varieties. Since the theoretical model assumes household size is constant across households, I summarize per capita measures for acres in total and in maize, maize yield and harvest, and income. Going from buyer to autarkic to seller households, we see large increases in acres in total and in maize, maize harvest, and income, with the increase in maize income being proportionally much larger than the increase in total income. These trends are consistent with the theoretical model. To further relate these measures to the theoretical model, I show the ratio of total income to acres (total and maize) as well as the value of maize production as a share of full income. Going from buyer to seller households, the ratio of income to acres decreases and the value of maize production as a share of full income increases, consistent with the theoretical model.

Beyond farm size, income, and household size, the theoretical model abstracts away from other factors that may differ across households and relate to both their market participation and technology adoption. The remainder of Table 2 summarizes a number of these factors for the sample. Going from buyer to seller, several measures of household welfare improve; in particular, the probability of poverty and realized food insecurity decrease while dietary diversity increases.

Finally, Table 2 summarizes variables related to the randomized controlled trial and the outcome of interest in this study: adoption of Western Seed Company hybrids. A cross-cutting fertilizer treatment that is not the focus of this paper is well-balanced across market participation groups. Adoption of Western Seed Company hybrids is greater in the treatment group. I now turn to estimating differences in adoption due to assignment to treatment in a regression framework.

Table 3 shows estimates of Eq. (1) with the omitted category of market participation being seller households. Column (1) shows estimates with the outcome variable being an

Table 2: Summary statistics for mid-altitude sub-sample

	Buyer		Autarkic		Seller	
	(1)	(2)	(3)	(4)	(5)	(6)
	Control	Treat	Control	Treat	Control	Treat
Hybrid user in main season	0.21	0.21	0.25	0.32	0.31	0.32
Dry maize yield (kg/ac)	147.53	216.73	219.10	229.95	254.93	389.22
Acres (total)	1.63	0.99	1.62	1.60	2.28	2.07
Acres (maize)	1.34	0.82	1.23	1.31	1.76	1.67
Household size	6.33	5.71	5.40	6.07	5.77	6.23
Per capita measures						
Acres (total)	0.29	0.20	0.33	0.29	0.47	0.41
Acres (maize)	0.24	0.16	0.26	0.24	0.39	0.34
Maize harvest (kg)	29.20	28.57	48.77	44.98	93.73	90.85
Maize income (100 ksh)	8.40	8.22	14.04	12.94	26.97	26.14
Income (100 ksh)	155.37	174.57	256.14	208.84	277.93	339.15
Income (100000 ksh/ac total)	0.79	1.73	1.13	1.02	0.82	1.19
Income (100000 ksh/ac maize)	0.95	2.31	1.43	1.25	1.03	1.58
Maize income share	0.09	0.24	0.09	0.12	0.13	0.12
Poverty probability	0.37	0.35	0.28	0.28	0.28	0.31
Food insecure	0.81	0.75	0.63	0.61	0.58	0.48
Dietary diversity (0-12)	5.82	6.43	6.36	6.51	6.80	6.84
HH head: Male	0.66	0.59	0.61	0.64	0.68	0.67
Fertilizer treatment	0.45	0.45	0.51	0.51	0.53	0.56
Adopted Western Seed	0.01	0.16	0.02	0.20	0.02	0.19
Observations	120	124	101	84	79	82

indicator for adopting Western Seed and using data from both midline and endline years. As seen in Table 2, contamination of the control group is not an issue as adoption of Western Seed is virtually non-existent in the control group across market participation groups. On average across the midline and endline years, treatment increases adoption by deep sellers by 18 percentage points (pp), an estimate that is large and statistically significant. Relative to sellers, all other market participation groups have average treatment effects that are smaller by 1-3pp, a small difference in economic terms. The effect of the interaction between treatment and other market participation groups does not differ from zero independently or jointly at conventional levels of statistical significance. Thus, differences in adoption by market participation are neither economically large nor different from zero with statistical significance. This pattern of results holds across both post-intervention years, as shown by the similar estimates for the pooled sample, midline sub-sample, and endline sub-sample in columns (1)-(3).

While technology adoption on the extensive margin studied in columns (1)-(3) relates to the model of household technology adoption in Section 2, technology adoption in total is the policy-relevant outcome in the model of program targeting in section 3. For example, a private sector program such as those by Western Seed presumably would seek to target their technology to the greatest proportion of households with the greatest expected expenditures on their product. For a public sector program such as an input subsidy modeled in section 3, policymakers seek to increase expenditures on inputs.

Table 3, columns (4)-(6) present treatment effects on quantity of Western Seed used (in kilograms). The treatment effect on total adoption is greatest for sellers relative to other market participation groups at 0.88 kilograms. The treatment effect on total adoption is lower for other market participation groups by 0.20 kilograms, corresponding with a decrease of 23%. The decrease in adoption in total when going from sellers to other market participation groups is larger in magnitude than the decrease in adoption on the extensive margin in columns (1)-(3). This is consistent with the interpretation that sellers are not more

Table 3: Treatment effects on technology adoption

	Western Seed (0/1)			Western Seed (kg)		
	(1)	(2)	(3)	(4)	(5)	(6)
Seed treatment, $\hat{\rho}$	0.18***	0.18***	0.18***	0.88**	0.95**	0.82*
	(0.04)	(0.05)	(0.04)	(0.26)	(0.29)	(0.34)
Interaction effects, $\hat{\delta}^k$						
Autarkic	-0.01	-0.06	0.04	-0.20	-0.47	0.07
	(0.04)	(0.04)	(0.05)	(0.36)	(0.38)	(0.54)
Buyer	-0.03	-0.04	-0.02	-0.20	-0.26	-0.14
	(0.05)	(0.05)	(0.06)	(0.33)	(0.36)	(0.40)
Direct effects, $\hat{\gamma}^k$						
Autarkic	0.00	0.01	-0.01	-0.01	0.10	-0.11
	(0.02)	(0.02)	(0.03)	(0.20)	(0.12)	(0.38)
Buyer	-0.02	-0.02	-0.02	-0.23	-0.09	-0.37
	(0.02)	(0.01)	(0.03)	(0.16)	(0.07)	(0.30)
Mean, Control Seller	0.02	0.01	0.03	0.19	0.05	0.33
F-test p-value, null: $\delta^k = 0, \forall k$	0.86	0.36	0.62	0.80	0.45	0.80
Observations	1178	589	589	1178	589	589
Midline	Yes	Yes	No	Yes	Yes	No
Endline	Yes	No	Yes	Yes	No	Yes

Models control for matched pair.

Standard errors in parentheses clustered by 42 villages.

Significance: * = 10%, ** = 5%, *** = 1%

likely to adopt Western Seed hybrids but, among those who adopt, they adopt more intensively than adopters of other market participation groups. As with the extensive margin of adoption, for total adoption the effect of the interaction between treatment and other market participation groups does not differ from zero independently or jointly at conventional levels of statistical significance.

5.2 Intensity of Market Participation

A shortcoming of studying the extent of market participation is that it breaks from the theoretical model in which household technology adoption also depends on the household's intensity of market participation. To study the intensity of market participation, I define "deep" and "almost" market participants based on quantities of net marketed surplus to create a distribution of market participation similar to the observed market participation across years in the control group. For example, 11% of control group households are net sellers each year.[7] The proxy indicator for this group equals one for the top 11% of sellers at baseline, which includes all households with over 270 kilograms of maize sold. Such cross-sectional data may be similar to the information available to programs for applying targeting criteria for technology adoption programs.

Table 4 shows summary statistics, stratified by the intensity of market participation at baseline and treatment assignment. Stratifying by intensity of market participation effectively sub-divides both buyer and seller households into two categories each of buyer and seller households. As a result, the pattern of summary statistics stratified by the intensity of market participation is similar to the pattern of summary statistics stratified by the extent of market participation in Table 2. Going from deep buyer and almost autarkic households to deep seller households, we see large increases in acres in total and in maize, maize yield and harvest, and income, with the increase in maize income being proportionally much larger

[7] 11% are net sellers in each of the three years and 17% percent are net sellers in two of the three years; 30% are net buyers in each of the three years of the study and 15% are net buyers in two of the three years of the study; the remaining 27% percent of households are approximately autarkic, as their market participation behavior is not dominated by either buying or selling.

than the increase in total income. These trends are consistent with the theoretical model. Going from deep buyers to deep sellers, the ratio of income to acres decreases and the value of maize production as a share of full income increases. As with the pattern in Table 2, the pattern in Table 4 is consistent with the theoretical model.

The remainder of Table 4 also is similar to Table 2. Going from deep buyer to deep seller, several measures of household welfare improve; in particular, the probability of poverty and realized food insecurity decrease while dietary diversity increases. Both seed and fertilizer treatments are well-balanced across market participation groups. Adoption of Western Seed Company (WSC) hybrids is greater in the treatment group, with the greatest rates of adoption for deep sellers.

A key difference for the analysis stratified by intensity of market participation is that further sub-dividing the sample leaves relatively small sub-samples for each market participation group. In particular, I only define 51 households as deep sellers, 32 in treatment and 19 in control. Given that the outcome variable for the analysis is a 0/1 indicator of technology adoption, and the average treatment effect across market participation groups in Table 3 is relatively small, this makes each deep seller observation potentially pivotal when estimating differences in technology adoption relative to other market participation groups. With this caveat in mind, I turn to interpreting regression estimates of treatment effects across market participation groups.

Table 5 shows estimates of Eq. (1) with the omitted category of market participation being "deep seller" households. Column (1) shows estimates with the outcome variable being an indicator for adopting Western Seed and using data from both midline and endline years. As seen in Table 4, contamination of the control group is not an issue as adoption of Western Seed is virtually non-existent in the control group across market participation groups. On average across the midline and endline years, treatment increases adoption by deep sellers by 23pp, an estimate that is large and statistically significant. Relative to deep sellers, all other market participation groups have average treatment effects that are smaller by 6-9pp; these estimates correspond with the treatment effect decreasing by 29-39%. This relatively large effect, however, is sensitive to individual observations due to the small sample for deep sellers; relatedly, the effect of the interaction between treatment and other market participation groups does not differ from zero independently or jointly at conventional levels of statistical significance, however. Thus, differences in adoption by market participation are economically large but do not differ from zero with statistical significance. This pattern of results holds across both post-intervention years, as shown by the similar estimates for the pooled sample, midline sub-sample, and endline sub-sample in columns (1)-(3).

Table 5, columns (4)-(6) present treatment effects on quantity of Western Seed used (in kilograms). The treatment effect on total adoption is greatest for deep sellers relative to other market participation groups at 1.41 kilograms. The treatment effect on total adoption is lower for other market participation groups by 0.65-0.89 kilograms, corresponding with a decrease of 46-63%. Thus the decrease in adoption in total when going from deep sellers to other market participation groups is larger in magnitude than the decrease in adoption on the extensive margin in columns (1)-(3). This is consistent with the interpretation that deep sellers both are more likely to adopt Western Seed hybrids and, among those who adopt, adopt more intensively relative to other market participation groups. As with the extensive margin of adoption, for total adoption the effect of the interaction between treatment and other market participation groups is economically large but does not differ from zero independently or jointly at conventional levels of statistical significance.

Table 4: Summary statistics for mid-altitude sub-sample

	Deep Buyer		Almost Autarkic		Deep Autarkic		Almost Seller		Deep Seller	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Control	Treat	Control	Treat	Control	Treat	Control	Treat	Control	Treat
Hybrid user in main season	0.26	0.21	0.11	0.22	0.25	0.32	0.29	0.21	0.40	0.49
Dry maize yield (kg/ac)	128.98	222.21	185.10	205.78	219.10	229.95	224.94	210.77	349.64	668.04
Acres (total)	1.68	1.08	1.53	0.81	1.62	1.60	2.04	1.88	3.05	2.38
Acres (maize)	1.42	0.89	1.19	0.67	1.23	1.31	1.52	1.63	2.53	1.75
Household size	6.78	5.92	5.45	5.29	5.40	6.07	5.58	6.08	6.37	6.47
Per capita measures										
Acres (total)	0.28	0.20	0.30	0.20	0.33	0.29	0.41	0.40	0.66	0.43
Acres (maize)	0.24	0.16	0.25	0.17	0.26	0.24	0.33	0.35	0.57	0.31
Maize harvest (kg)	26.71	26.13	34.32	33.52	48.77	44.98	68.80	59.07	172.47	140.51
Maize income (100 ksh)	7.68	7.52	9.88	9.65	14.04	12.94	19.80	17.00	49.63	40.43
Income (100 ksh)	152.84	193.57	160.50	136.57	256.14	208.84	197.96	314.31	530.48	377.94
Income (100000 ksh/ac total)	0.77	1.98	0.83	1.23	1.13	1.02	0.70	1.22	1.21	1.14
Income (100000 ksh/ac maize)	0.93	2.33	0.99	2.29	1.43	1.25	0.92	1.47	1.37	1.73
Maize income share	0.07	0.07	0.14	0.58	0.09	0.12	0.11	0.11	0.19	0.13
Poverty probability	0.36	0.35	0.41	0.36	0.28	0.28	0.29	0.33	0.22	0.28
Food insecure	0.85	0.80	0.72	0.66	0.63	0.61	0.65	0.62	0.37	0.25
Dietary diversity (0-12)	5.76	6.43	5.92	6.41	6.36	6.51	6.67	6.56	7.21	7.28
HH head: Male	0.74	0.63	0.50	0.51	0.61	0.64	0.63	0.78	0.84	0.50
Fertilizer treatment	0.42	0.40	0.50	0.56	0.51	0.51	0.57	0.58	0.42	0.53
Adopted Western Seed	0.01	0.16	0.01	0.16	0.02	0.20	0.03	0.16	0.00	0.23
Observations	80	83	40	41	101	84	60	50	19	32

Deep Buyer households bought more than 77 kilograms of maize at baseline.

Almost Autarkic households bought maize at baseline but less than 77 kilograms.

Deep Autarkic households neither bought nor sold maize at baseline.

Almost Seller households sold maize at baseline but less than 270 kilograms.

Deep Seller households sold more than 270 kilograms of maize at baseline.

Table 5: Treatment effects on technology adoption

	Western Seed (0/1)			Western Seed (kg)		
	(1)	(2)	(3)	(4)	(5)	(6)
Seed treatment, $\hat{\rho}$	0.23**	0.21**	0.24***	1.41**	1.19*	1.62**
	(0.07)	(0.07)	(0.07)	(0.47)	(0.51)	(0.52)
Interaction effects, $\hat{\delta}^k$						
Almost Seller	-0.08	-0.06	-0.10	-0.84	-0.43	-1.25
	(0.08)	(0.10)	(0.08)	(0.59)	(0.64)	(0.67)
Deep Autarkic	-0.06	-0.10	-0.02	-0.72	-0.72	-0.73
	(0.06)	(0.08)	(0.06)	(0.51)	(0.59)	(0.60)
Almost Autarkic	-0.08	-0.09	-0.07	-0.89	-0.85	-0.93
	(0.09)	(0.09)	(0.10)	(0.55)	(0.59)	(0.63)
Deep Buyer	-0.07	-0.06	-0.08	-0.65	-0.34	-0.96
	(0.07)	(0.07)	(0.07)	(0.52)	(0.61)	(0.52)
Direct effects, $\hat{\gamma}^k$						
Almost Seller	-0.00	-0.01	0.01	0.12	-0.08	0.32
	(0.02)	(0.02)	(0.02)	(0.15)	(0.10)	(0.29)
Deep Autarkic	-0.00	-0.00	0.00	0.08	0.03	0.13
	(0.02)	(0.02)	(0.03)	(0.16)	(0.13)	(0.28)
Almost Autarkic	-0.01	-0.02	-0.00	-0.13	-0.13	-0.12
	(0.02)	(0.02)	(0.03)	(0.10)	(0.09)	(0.14)
Deep Buyer	-0.03	-0.03	-0.02	-0.15	-0.16	-0.13
	(0.02)	(0.02)	(0.03)	(0.11)	(0.09)	(0.16)
Mean, Control Deep Seller	0.00	0.00	0.00	0.00	0.00	0.00
F-test p-value, null: $\delta^k = 0, \forall k$	0.87	0.69	0.65	0.56	0.49	0.34
Observations	1178	589	589	1178	589	589
Midline	Yes	Yes	No	Yes	Yes	No
Endline	Yes	No	Yes	Yes	No	Yes

Models control for matched pair. Almost means selling <=270 kg or buying <=77 kg.
Standard errors in parentheses clustered by 42 villages.
Significance: * = 10%, ** = 5%, *** = 1%

6 Conclusion

This paper contributes to a growing literature on agricultural technology adoption in sub-Saharan Africa by studying how the impact of an intervention promoting adoption of production technologies varies with an agricultural household's output market participation. The paper is motivated by the theoretical insight that when participating in output markets for staple crops is costly, this may deter some households from adopting productive technologies but also may create an incentive for other households to adopt productive technologies, specifically those that can transition to becoming self-sufficient or sellers by adopting a productive technology. The paper develops a formal theoretical model of an agricultural household to derive this result and uses an empirical context in western Kenya to study its implications for the design of policies to support technology adoption by smallholders and whether it is consistent with agricultural technology adoption by smallholders.

I study the policy implications of the interdependence of technology adoption and market participation by conducting a numerical analysis of the targeting and design of a common policy for promoting technology adoption in sub-Saharan Africa: input subsidies. The policymaker's targeting and design problem nests the agricultural household model of technology adoption. Heterogeneous technology adoption across households is due to differences in household endowments of land and financial wealth as well as transaction costs in agricultural output markets. As household characteristics change along an observable criterion for targeting – land wealth – incentives to adopt change as well. As a result program impacts vary with targeting and subsidy level, and optimal subsidy targeting and level are interdependent. Under parameter values that include relatively large fixed costs of selling and buying the staple, the optimal policy is to offer an 86% subsidy to households in the top 18% of the land distribution. Households targeted by the optimal subsidy are primarily sellers of staples without the subsidy program, as well as some household that transition into selling or being autarkic with technology adoption. Under parameter values without fixed costs of selling and buying the staple, however, the optimal policy is to offer an 87% subsidy to households in the top 6% of the land distribution. Without transaction costs, adoption does not vary with market participation and thus there is no incentive for the policymaker to further target the subsidy based on market participation.

I test the theoretical model's predictions of how technology adoption varies with expected market participation using data from a randomized controlled trial of information about high-yielding maize varieties developed for western Kenya, where the main staple is maize. For households that sold maize in the year prior to the study, treatment increases average technology adoption by 18pp off of a base of just 2 percent adoption by sellers in the control group. For households that were autarkic or buyers with respect to maize markets in the year prior to the study, the treatment effect differed from sellers by just 1-3pp, a small difference both economically and statistically. The results suggest that, in the study context, transaction costs in output markets are not large enough to shape the pattern of adoption of a production technology.

The theoretical and empirical analyses in this paper contribute to our understanding of the interdependence between technology adoption and market participation in smallholder agriculture. The theoretical analysis shows that the relationship between technology adoption and market participation is ambiguous, and depends on the magnitude of fixed costs of transacting in output markets. When transaction costs are sufficiently large, this deters technology adoption by households that would remain autarkic even when adopting the productive technology. This is relevant for policies promoting technology adoption such as input subsidies, as this may make it optimal to target sellers of staples already producing sufficient amounts to make it economically optimal to enter output markets as sellers, as shown by the policy simulation in Section 3. The empirical analysis, however, does not find statistically significant differences in a technology adoption intervention's effects across market participation groups, consistent with a context with relatively small fixed costs of transacting in output markets. Thus the findings in this paper suggest that targeting input subsidies primarily to sellers of staples may exclude many households that would be willing to adopt new production technologies.

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Appendix A: Household Model of Technology Adoption and Market Participation

The household model is a sequential model of technology adoption in a planting season and output market participation in a harvest season. The household derives utility from consuming staples c and non-staples n in the harvest season. For both staples and non-staples, utility increases with consumption at a decreasing rate and as consumption approaches zero the marginal utility from consumption approaches infinity.

The household produces staples from its land endowment and its technology adoption. Under the status quo technology, each household i has a land endowment T_i that yields x staples per unit. In season t the household can plant land to a technology $T^f_{i,t}$ that includes hybrid seeds and complementary inputs like fertilizer. The household's land endowment constrains its land planted with the technology:

$$T_i \geq T^f_{i,t} \tag{A.1}$$

I model yield gains from technology adoption as a linear function of adoption; this is consistent with agronomic best practices and implicitly assumes uniform responsiveness to seeds and fertilizers across fields for a single household (Bird et al., 2022). Household staple production is:

$$Q(T_i, T^f_{i,t}) \equiv T_i \cdot x + T^f_{i,t} \cdot \alpha \tag{A.2}$$

To adopt the new technology, the household incurs a fixed cost F^f that accounts for searching for sellers of quality inputs and transporting inputs from the market to the home. Additionally, the household pays the market price P^f for each unit of land planted under the new technology, which may be subsidized at a rate s_t. Total expenditures on the fixed costs and unit costs of technology adoption can be no greater than the household's initial endowment of financial wealth A_i. The household's planting season liquidity constraint is:

$$\mathbf{1}\big(T^f_{i,t} > 0\big) \cdot [F^f + T^f_{i,t} \cdot P^f \cdot [1 - s_t]] \leq A_i \tag{A.3}$$

Financial wealth that is not spent on technology adoption in the planting season is saved for the harvest season and earns an interest rate r. The household's full wealth in the harvest season is the sum of returns from savings and the value of staple production at price P^c:

$$Y_{i,t} \equiv \Big[A_i - \mathbf{1}\big(T^f_{i,t} > 0\big) \cdot [F^f + T^f_{i,t} \cdot P^f \cdot [1 - s_t]]\Big] \cdot [1 + r] + Q(T_i, T^f_{i,t}) \cdot P^c \tag{A.4}$$

Household staple consumption comes from staples produced plus staples bought $b_{i,t}$ less staples sold $m_{i,t}$:

$$c(b_{i,t}, m_{i,t}) = Q(T_i, T^f_{i,t}) + b_{i,t} - m_{i,t} \tag{A.5}$$

When the household buys staples ($b_{i,t} > 0$), it incurs a fixed cost F^b representing the costs of searching for sellers. When the household sells staples ($m_{i,t} > 0$), it incurs a fixed cost F^m that includes costs of searching for buyers and preparing harvest for sale. Additionally, transactions incur a proportional cost τ representing the cost of transporting fixed quantities of staples between the home and the market.

The household spends its full wealth on staples, non-staples, and costs of transacting in staple markets.[8] The household's harvest period budget constraint is:

$$c(b_{i,t}, m_{i,t}) \cdot P^c + n + \mathbf{1}\big(b_{i,t} > 0\big) \cdot F^b + \mathbf{1}\big(m_{i,t} > 0\big) \cdot F^m + [b_{i,t} + m_{i,t}] \cdot \tau \leq Y_{i,t} \tag{A.6}$$

[8]In the harvest period, households also could face an initial liquidity constraint preventing outlays on transaction costs from exceeding savings from the planting season. In the model this would reduce market participation by households with low financial wealth. I abstract from this possibility by assuming households can pool money in the harvest season so that transaction costs and consumption expenditures occur simultaneously rather than sequentially.

Since utility increases with both staple and non-staple consumption, Eq. (A.6) binds:

$$n(b_{i,t}, m_{i,t}) = Y_{i,t} - \Big[c(b_{i,t}, m_{i,t}) \cdot P^c + \mathbf{1}\big(b_{i,t} > 0\big) \cdot F^b + \mathbf{1}\big(m_{i,t} > 0\big) \cdot F^m + [b_{i,t} + m_{i,t}] \cdot \tau\Big] \quad \text{(A.7)}$$

The household chooses sequential technology adoption and market participation to maximize its utility from consuming staples and non-staples subject to its constraints. The household's problem is

$$\max_{T^f_{i,t} \geq 0} \Bigg(\max_{b_{i,t}, m_{i,t} \geq 0} u\Big(c(b_{i,t}, m_{i,t}), n(b_{i,t}, m_{i,t})\Big)\Bigg)$$

subject to Eq. (A.1)-(A.5) and (A.7).

In the planting season the household knows transacting in staple markets in the harvest season incurs fixed and proportional costs. I solve the household's problem recursively starting with the household's market participation problem in the harvest season.

Market Participation in the Harvest Season

In the harvest season the household consumes staples and non-staples given the prices it faces, its income, and its staple production. The household chooses its staples bought $b_{i,t} \geq 0$ and marketed $m_{i,t} \geq 0$ to maximize utility $u\Big(c(b_{i,t}, m_{i,t}), n(b_{i,t}, m_{i,t})\Big)$ subject to (A.2), (A.4)-(A.5), and (A.7). Optimal market participation satisfies the problem's first-order necessary conditions

$$\frac{\partial u}{\partial c}\Big(c(b^*_{i,t}, m^*_{i,t}), n(b^*_{i,t}, m^*_{i,t})\Big) - \frac{\partial u}{\partial n}\Big(c(b^*_{i,t}, m^*_{i,t}), n(b^*_{i,t}, m^*_{i,t})\Big) \cdot \Big[P^c + \tau\Big] + \mu^{b*} = 0 \quad \text{(A.8)}$$

$$-\frac{\partial u}{\partial c}\Big(c(b^*_{i,t}, m^*_{i,t}), n(b^*_{i,t}, m^*_{i,t})\Big) + \frac{\partial u}{\partial n}\Big(c(b^*_{i,t}, m^*_{i,t}), n(b^*_{i,t}, m^*_{i,t})\Big) \cdot \Big[P^c - \tau\Big] + \mu^{m*} = 0 \quad \text{(A.9)}$$

where μ^{b*} is the Lagrange multiplier for purchases and μ^{m*} is the Lagrange multiplier for sales. Both of these multipliers are evaluated at the household's optimal purchases and sales of staples given technology adoption, endowments, and the subsidy level:

$$\big(b^*_{i,t}, m^*_{i,t}\big) = \big(b^*_{i,t}(T^f_{i,t}|T_i, A_i, s_t), m^*_{i,t}(T^f_{i,t}|T_i, A_i, s_t)\big) \tag{A.10}$$

Eq. (A.8) and (A.9) show that household consumption and utility from consumption vary with staple production in two ways. First, staple production contributes to household wealth in the harvest season. Second, staple production determines whether the household is a buyer, autarkic, or a seller with respect to staples, which in turn determines the household's effective staple price.

The household's indirect utility from consumption in the harvest season is:

$$V(T^f_{i,t}|T_i, A_i, s_t) \equiv u\Big(c(b^*_{i,t}, m^*_{i,t}), n(b^*_{i,t}, m^*_{i,t})\Big) \tag{A.11}$$

The household's indirect utility function is non-convex over endowments due to the fixed cost of transacting in staple output markets. The fixed cost of buying staples causes households near the threshold of buying staples to exit the market and instead reduce their staple consumption, thereby increasing their marginal utility of staple consumption. The fixed cost of selling staples causes households near the threshold of selling staples to exit the market and instead increase their staple consumption, thereby decreasing their marginal utility of staple consumption. Thus households on the thresholds of being autarkic or sellers with respect to staple markets may have large incentives to adopt technologies that increase their staple production.

Technology Adoption in the Planting Season

In the planting season the household chooses technology adoption in order to maximize utility from consuming staples and non-staples in the harvest season subject to its constraints. Formally the planting period problem is

$$\max_{T^f_{i,t} \geq 0} V(T^f_{i,t}|T_i, A_i, s_t)$$

subject to Eq. (A.1)-(A.5), (A.7), and (A.10)-(A.11). The problem's first-order necessary condition for a solution is:

$$\frac{\partial V}{\partial T_f}(T_{i,t}^{f*}|T_i, A_i, s_t) - \lambda^* - \rho^* \cdot P^f \cdot [1 - s_t] + \mu^{f*} = 0 \tag{A.12}$$

where λ^* is the shadow value of land for applying the new technology in the planting season, ρ^* is the shadow value of liquidity in the planting season, and μ^{f*} is the Lagrange multiplier for technology adoption, all evaluated at the optimal level of technology adoption. Because the indirect utility function is non-convex, a given household does not have a unique solution to its technology adoption program. The fixed costs of technology adoption and output market participation imply that each household considers not one but six potential solutions to Eq. (A.12), one for each combination of technology adoption and output market participation. Of these six potential solutions, the household chooses the optimal combination that maximizes its indirect utility. The household's optimal technology adoption is

$$T_{i,t}^{f*} = T_{i,t}^{f*}(T_i, A_i, s_t)$$

The problem would simplify greatly if technology adoption did not incur a fixed cost; in that case a household could adopt an initially infinitesimal amount when the marginal value product of that adoption exceeds its marginal cost given household market participation without technology adoption. But with fixed costs of technology adoption, the household's initial adoption must exceed a minimum adoption level so that the initial technology adoption decision also depends on its marginal effect on the household's probability of being a buyer, autarkic, or a seller with respect to staple markets. Thus the household's decision to adopt the technology depends on both its staple surplus without technology adoption and its change in staple surplus due to technology adoption. Given the complexity of the household problem, I use numerical analysis to show the implications of these costs for household technology adoption, using the model and parameter values in Table A.1. The numerical analysis simulates an intervention that increases household expectations about a production technology's physical yield. I simulate two outcomes. The first outcome is output market participation, which is a function of the household's endowment of financial and land wealth as well as its expected yield gains from technology adoption. The second outcome is the household's compensating variation from incurring the fixed costs of technology adoption. Compensating variation is the amount of money the household would have to give up to be indifferent between its consumption when not adopting the technology and its consumption when taking on the fixed costs of technology adoption.[9] Thus compensating variation is positive for households that are better off when taking on the fixed costs of technology adoption and negative for households that are worse off when taking on the fixed costs of technology adoption.

Appendix B: Maize Output Markets in Western Kenya

The analysis in this paper assumes households incur costs when transacting in staple markets. Ideally I would estimate transaction costs based on simultaneous purchases and sales of maize grain by farmers in the same location. I approximate this ideal using data from the randomized controlled trial in western Kenya.

The main months for selling maize after the harvest from the main rains are August through October. The main months for selling maize after the harvest from the short rains are January and February. Buying data from 2015-2016 include three recall periods. Purchase Period 1 corresponds with the short rains harvest (February through May), Purchase Period 2 corresponds with the lean season between harvests (June through September), and Purchase Period 3 corresponds with the harvest season from the main rains (October through January).

[9] In a slight abuse of notation, $CV_{i,t}$ is defined by the equality

$$V(0; T_i, A_i \cdot [1+r]) \equiv V(T_{i,t}^{f*}|_{CV_{i,t}=0}; T_i, [A_i - F^f - T_{i,t}^{f*}|_{CV_{i,t}=0} \cdot P^f] \cdot [1+r] - CV_{i,t})$$

where the last argument indicates financial wealth in the harvest season, whereas previously the last argument referred to financial wealth in the planting season.

Table A.1: Parameter values for the numerical analysis (monetary values in 2015 Kenyan shillings, with ~100 Kenyan shillings per US dollar)

Parameter	Symbol	Value
Utility function	$u(c, n)$	$\frac{1}{1-R} \cdot [c^{\gamma} \cdot n]^{1-R}$
- Consumption share parameter[a,b]	γ	0.19
- Relative risk aversion[c]	R	2.68
Yield from land endowment[a]	x	300.00
Yield gain parameter[a]		
- Low	α	188.76
- High	α	600.00
Fixed adoption cost	F^f	$6,607.70$
Technology price	P^f	$10,800.00$
Subsidy rate	s_t	0.00
Interest rate of return	r	0.00
Staple price[a,d]	P^c	28.50
Fixed transaction cost[e]		
- Selling	F^m	$11,310.94$
- Buying	F^b	$1,904.46$
Proportional transaction cost[a,f]	τ	3.20

[a]Calculated from my own data.

[b]Based on a staple budget share of 0.16 (compared with 0.60 for Park (2006)).

[c]I derive the coefficient of relative risk aversion with respect to non-staple consumption $R = [R_Y + \gamma]/[1 + \gamma]$ where $R_Y \equiv -Y \cdot (\partial^2 V/\partial Y^2)/(\partial V/\partial Y) = 3$ is relative risk aversion with respect to income that is consistent with values in the literature (Barrett, 1996; Park, 2006). The functional form for utility implies a constant coefficient of relative risk aversion for staples $R_c = [R - 1] \cdot \gamma + 1$. My derivation and small value for γ implies relative risk aversion $(R, R_c) = (2.68, 1.32)$ that is much less than the *ad hoc* values $(R, R_c) = (3, 4)$ from Park (2006).

[d]I assume the market price is the mean of mean buying and selling prices for maize in the period with most transactions in my data (June to September).

[e]Derived from *ad valorem* equivalent fixed transaction costs for maize markets in western Kenya estimated by Renkow et al. (2004).

[f]This is half of the price wedge between buying and selling prices for maize in the period with most transactions in my data (June to September).

Fig. A.1 plots maize grain unit values as monthly means from December 2014 through January 2016.

To estimate transaction costs and seasonal price fluctuations, I use the following model of prices in village v in matched pair p at time period t

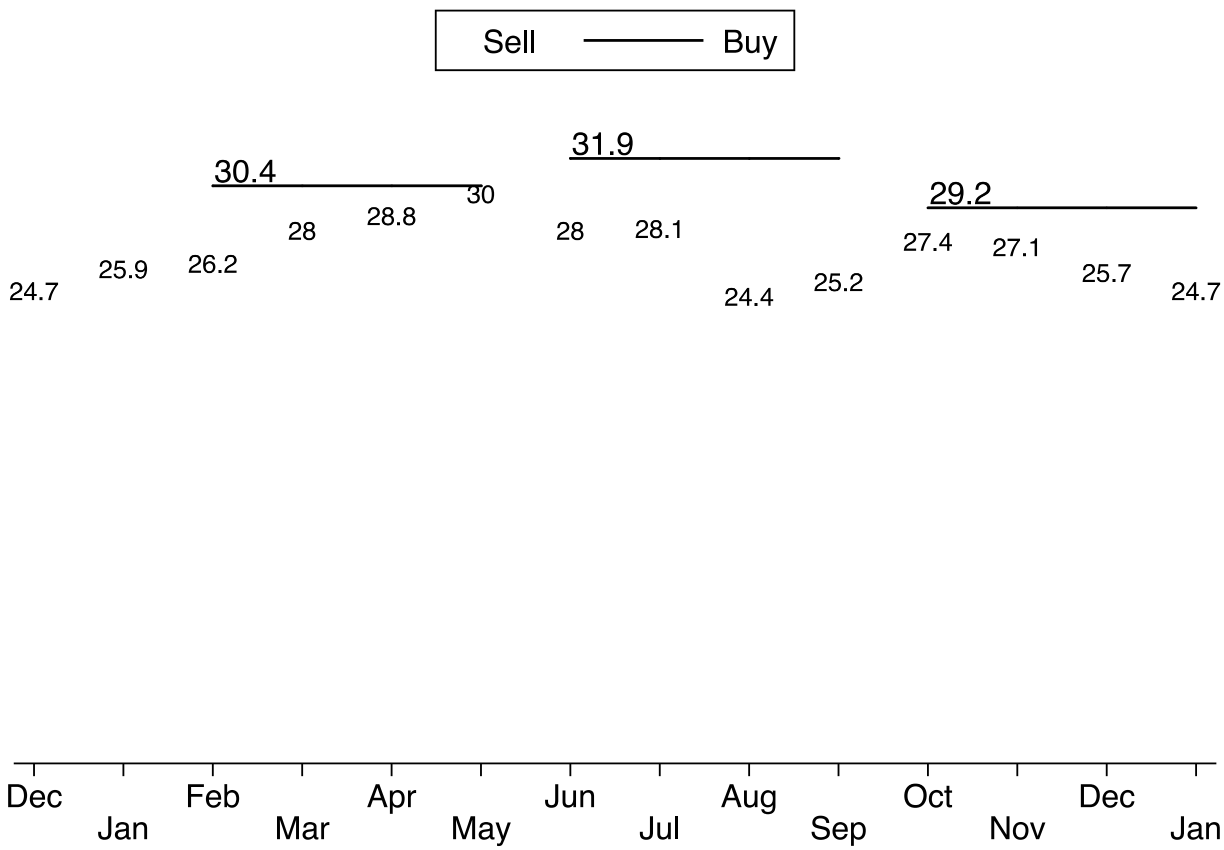
$$price_{vpt} = \sum_{q=1}^{P} \phi_q \mathbf{1}(p = q) + \delta buy + \sum_{s=2}^{3} \Big\{ [\lambda_s + \delta_s buy] \mathbf{1}(t = s) \Big\} + error_{vpt} \tag{A.13}$$

where ϕ_q is the average selling price in matched pair q in February through May ($t = 1$), δ is the average of the selling price less the buying price across matched pairs in February through May, λ_s is the average of the selling price at time $t = s$ less the selling price at $t = 1$, and δ_s is the average of the buying price at time $t = s$ less the buying price at $t = 1$.

Estimates of Eq. (A.13) are shown in Table A.2, column (1). Time-invariant transaction costs defined as the smallest average difference between purchase and sales prices in a given period are approximately 2.2 Kenyan shillings per kilogram, the price wedge from October through January. The price wedge increases to 6.4 Kenyan shillings per kilogram during the period from June through September. This is likely because this period includes the most expensive lean season purchases in June and July as well as the cheapest sales in the harvest season in August and September, as shown in Fig. A.1. In other words if the seasonal price trend repeated in the following year, a household that sold at harvest and then bought in the subsequent lean season would pay a price in the lean season that is 25% greater than the price they received in the harvest season. Defining this difference as the total difference between selling and buying prices and assuming symmetry implies a total transaction cost of $\tau = 3.2$ Kenyan shillings relative to an average market price of 28.5 Kenyan shillings from June through September.

The analysis in this paper assumes staple prices are exogenous so that technology adoption and staple production for an individual household are not correlated with the output

Figure A.1: Maize grain unit values: Monthly means from Dec14-Jan16



Notes: Means for village-level observations measured in Kenyan shillings per kilogram.

price. A violation of this assumption that would be problematic for the empirical analysis would be if households in a community with information about the hybrids expect prices to decline as other households in the community adopt the hybrids. To test whether community assignment to receive information about the hybrids affects prices, I estimate

$$price_{vpt} = \sum_{q=1}^{P} \phi_q^0 \mathbf{1}(p = q) + \delta^0 buy + \sum_{s=2}^{3} \Big\{ [\lambda_s^0 + \delta_s^0 buy] \mathbf{1}(t = s) \Big\} + \tag{A.14}$$

$$+ \Big[\phi^1 + \delta^1 buy + \sum_{s=2}^{3} \Big\{ [\lambda_s^1 + \delta_s^1 buy] \mathbf{1}(t = s) \Big\} \Big] d_v + error_{vpt}$$

where $d_v = 1$ for households in the seed treatment communities (0 otherwise). Parameters with the superscript ^{0} have the same interpretation as in Eq. (A.13) for the communities without access to the hybrids ($d_v = 0$). A parameter with the superscript ^{1} is the additive effect of being assigned assess to the hybrids ($d_v = 1$).

Estimates of Eq. (A.14) are shown in Table A.2, column (2). Price wedges do not vary with treatment suggesting prices are not determined locally, markets are integrated, and barriers to trader entry are limited.

Finally, to see whether seasonal price trends are similar across years, I estimate the model of sales price in village v

$$price_v = \sum_{q=1}^{C} \varphi_q \mathbf{1}(cluster = q) + \sum_{r=2}^{3} \xi_r \mathbf{1}(year = r) + \sum_{s=2}^{12} \zeta_s \mathbf{1}(month = s) + error_v \tag{A.15}$$

where φ_q is the average selling price in site q in August at baseline $((year, month) = (1, 1))$, ξ_r is the average of selling prices in year r less the baseline year conditional on site and month, and ζ_s is the average of selling prices in month s less the baseline year condition on site and year.

Fig. A.2 plots regression estimates of changes in sales prices by month with confidence intervals. Average seasonality of prices are similar to the trends in 2015-2016, but the confidence intervals suggest trends vary somewhat between years.

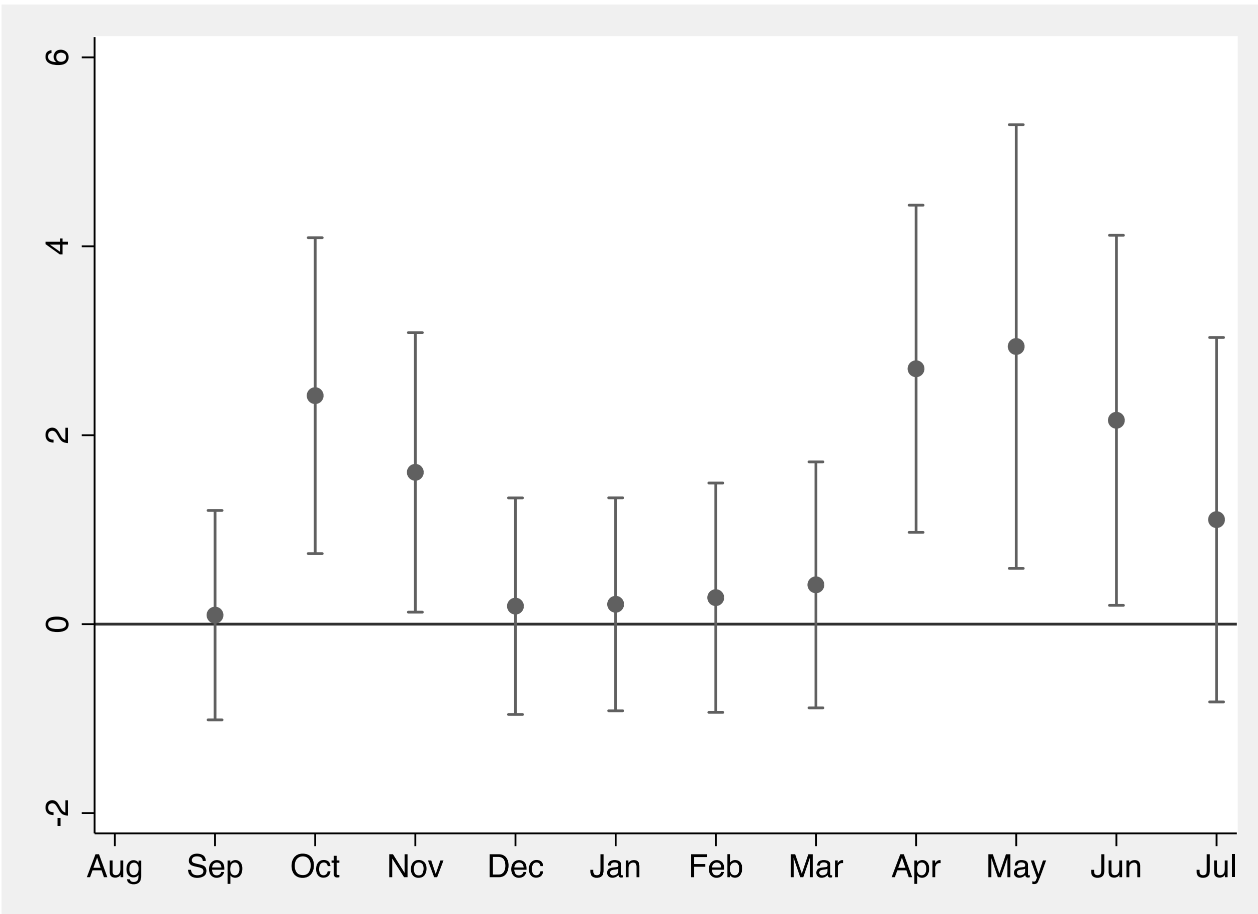
In conclusion, buying and selling prices for maize in western Kenya are significantly different. About half of the difference can be attributed to time-invariant transaction costs, while the other half can be attributed to seasonal fluctuations in buying and selling prices. Communities assigned to receive information about the hybrid maize varieties through the randomized control trial did not have economically meaningful differences in buying or selling prices from communities without access to the hybrids. Thus the the market conditions in the empirical setting approximate the theoretical model's assumptions.

Table A.2: Village prices by season, market, and treatment

	(1)	(2)
Jun15-Sep15	-2.8***	-2.7*
	(0.7)	(1.3)
Oct15-Jan16	-1.0	-1.4*
	(0.7)	(0.7)
Purchase price	2.6***	3.5**
	(0.6)	(1.1)
Jun15-Sep15 × Purchase price	3.8***	4.5***
	(0.7)	(1.2)
Oct15-Jan16 × Purchase price	-0.4	-0.4
	(0.9)	(1.0)
Treatment		1.3
		(1.1)
Jun15-Sep15 × Treatment		-0.2
		(1.9)
Oct15-Jan16 × Treatment		0.7
		(1.0)
Purchase price × Treatment		-1.8
		(1.7)
Jun15-Sep15 × Purchase price × Treatment		-1.5
		(2.5)
Oct15-Jan16 × Purchase price × Treatment		0.1
		(1.9)
Reference sales price	28.1	27.5
Strata controls	Yes	Yes

366 village-season-market observations (60 dropped with no transactions).
Dependent variable is maize grain price in Kenyan shillings per kilogram.
Standard errors clustered by pair (Significance: *=10%, **=5%, ***=1%)
F-test of no treatment effect in (4) has p-value of .08.

Figure A.2: Maize grain unit values: Seasonal trends



Notes: Dots are estimated monthly marginal effect estimates relative to the October mean of 28.6 Kenyan shillings per kilogram from a regression of village-level observations. Bars indicate 95 percent confidence intervals around these estimates.

Appendix C: Targeting and Designing Input Subsidies

I study an agricultural input subsidy program with targeting by household land wealth and design by subsidy level. In the notation of the household problem, the policymaker targets households with a minimum land wealth T^0 and maximum land wealth T^1 from the joint probability distribution for endowments $\phi \equiv \phi(T_i, A_i)$. Program design is based on the subsidy level s_1.

Costs of the program come from subsidizing inputs:

$$C(T^0, T^1, s_1|\phi) \equiv s_1 \cdot \int_{T^0}^{T^1} \int_{A} P^f \cdot T^{f*}_{i,1}(T_i, A_i, s_1)\phi dA_i dT_i$$

Benefits of the program come from input investment in the season after the subsidy program. Aggregate benefits are

$$B(T^0, T^1, s_1|\phi) \equiv w \cdot \int_{T^0}^{T^1} \int_{A} P^f \cdot T^{f*}_{i,2}(T_i, A_i, s_1)\phi dA_i dT_i$$

where w is the policymaker's benefit from the outcome of interest; in the numerical analysis I make the simplifying assumption $w = 1$.[10]

Finally, the policymaker chooses program targeting and design to maximize welfare as defined by the difference between benefits and costs:[11]

$$\max_{T^0, T^1, s_1} W(T^0, T^1, s_1|\phi) \equiv B(T^0, T^1, s_1|\phi) - C(T^0, T^1, s_1|\phi)$$

The welfare function is not necessarily convex over the choice variables due to fixed costs of technology adoption and output market participation in the household problem. Therefore I use numerical analysis to solve the policymaker's targeting and design problem.

[10] w can be scaled to include single season benefits as well as persistent effects in subsequent seasons, assuming persistent effects exist.

[11] Alternatively, costs for the policymaker may be constrained by a program budget $\bar{C}$. Then the policymaker's problem would be $\max_{T^0,T^1,s_1} B(T^0, T^1, s_1|F^m, F^b, \tau, \phi)$ subject to $C(T^0, T^1, s_1|F^m, F^b, \tau, \phi) \leq \bar{C}$.