Transaction Costs, Technology Adoption, and Input Subsidies in African Agriculture: Theory and Evidence from Western Kenya*

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Abstract

Many governments in sub-Saharan Africa attempt to increase food security by subsidizing adoption of technologies like hybrid seeds and fertilizers. Subsidies often target relatively wealthy households that sell the staple crops that they produce. But when selling staples incurs transaction costs, households on the margin of selling staples may have the greatest incentives to adopt new technologies that allow them to overcome transaction costs of selling output. Similarly, households on the margin of buying staples may adopt new technologies that reduce their costs of buying staples from the market. I formalize this intuition by modeling a household’s adoption of an agricultural technology when it is costly to transact in output markets. The model shows households near the margins of selling or buying staples have the greatest incentives to adopt new technologies. I test this prediction using data from a randomized control trial of high-yielding maize varieties developed for western Kenya. Randomized access to hybrid seeds increases adoption most for sellers of maize and least for autarkic households, with differences in adoption driven by market participation. The theoretical and empirical analyses show that when output markets have transaction costs, output market participation is important to technology adoption decisions.

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1 Introduction

Food insecurity is higher in sub-Saharan Africa than in any other region, with one-fifth of the population undernourished and an average daily food deficit of 130 kilocalories per capita (FAO, 2018a,b). A potential means of increasing food security is by increasing agricultural productivity through adoption of technologies like hybrid seeds and fertilizers. But agricultural technology adoption and productivity in the region are low due to a combination of lack of suitable technologies for agroclimatic environments at the regional-level and constraints to adoption at the household-level. When lack of access to productive technologies historically makes households pessimistic about the productivity of new technologies, inducing them to adopt new technologies that are in fact productive in their local growing conditions can be difficult. To support technology adoption in this context, governments in sub-Saharan Africa increasingly subsidize prices of agricultural inputs for households.

Although an objective of agricultural input subsidy programs is to increase regional food security, governments often target subsidies to households that are relatively food secure and wealthy. This targeting approach is supported by economic models of technology adoption that predict technology adoption increases with farmer wealth for technologies with risk, cost, or scale effects (Foster & Rosenzweig, 2010). In models where a new technology incurs fixed costs of acquiring it or learning how to apply it, either liquidity constraints or lack of insurance for a risky technology can prevent adoption by poor households (Dercon & Christiaensen, 2011). In these models technology adoption is greatest for wealthy households that are not expected to be constrained by the risk or fixed costs of adoption.

A crucial question for public policy is whether targeting agricultural input subsidies to wealthier households is effective. While this targeting approach raises concerns that programs have a regressive effect on the distribution of income across agricultural households, a more fundamental economic question is whether less wealthy households are
actually less likely to adopt agricultural technologies. In particular predictions of technology adoption across the wealth distribution may differ in a model that accounts for connections between several key features of staple crops in developing rural economies. In developing rural economies, buying and selling staples is costly: buying staples entails costs of finding vendors who households can purchase staples from, and selling staples entails costs of finding traders who households can sell staples to (Key et al., 2000; Renkow et al., 2004). Additionally, costs of transporting staples to and from rural areas make buying prices greater than selling prices for staple crops (Key et al., 2000; Renkow et al., 2004). In this context, technology adoption is not just an income source but is also a means of either reducing costs of buying staples or overcoming costs of selling staples.

In this paper I formalize the intuition that transaction costs in output markets incentivize technology adoption by developing a theoretical model of technology adoption and output market participation by an agricultural household. Market participation in the model is a function of household wealth, in particular the ratio of liquid wealth to land wealth: as liquid wealth declines relative to land wealth, households transition from being buyers, to autarkic, to sellers with respect to staple output markets. While the aforementioned models predict technology adoption increases with household wealth, in my model transaction costs in staple output markets lead technology adoption to not monotonically increase in total household wealth or in land wealth’s share of total wealth. The model shows that when households receive full information about the technology’s productivity, households near the margins of selling or buying staples have the greatest incentives to adopt new technologies.

I test the theoretical model’s predictions of how technology adoption varies with expected market participation using data from western Kenya, where the main staple is maize. I use data from a randomized control trial conducted by Carter et al. (2017) that randomly assigned which communities had first access to new hybrid maize varieties.
that mature during the region’s short growing seasons. In the randomized trial, we find access to the varieties causes yields to increase by 40 percent but incomes to remain unchanged on average. Even without large income impacts, the theoretical model in this paper predicts technology adoption could be driven by households valuing the technology’s effect on output market participation. Households in the study sample span the spectrum from net buyer, to autarkic, to net seller households with respect to maize markets. Additionally, 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. The economic importance and market conditions for maize in the study setting are similar to those for staples in much of sub-Saharan Africa.

The theoretical model predicts that a household’s expectations about future market participation affect its technology adoption decision. Testing this hypothesis empirically requires measuring each household’s expected market participation at the time of planting. My first proxy for this is observed market participation at baseline, which is highly correlated with household market participation across years. I also construct a proxy that approximates the structural heterogeneity variable of interest – expected market participation – in two steps. First, I use multiple years of data to predict expected market participation of the household based on its land endowment in its locality in a given year. Second, I categorize households by their distribution of predicted market participation over these years. Thus this proxy variable is similar to the driver of heterogeneous adoption in the theoretical model.

I estimate both the unconditional effects of targeting technologies by market participation as well as the conditional marginal effects of market participation on technology adoption. Targeting effects are greatest for “deep seller” households that sell the largest quantities of maize, followed by “shallow seller” households selling small quantities of maize. Targeting effects are smallest for autarkic households. While differences in targeting effects for deep sellers and other market participation groups are large in magnitude,
the differences are greater for conditional marginal effect estimates when holding other factors constant. Thus market participation does not just proxy for propensity to adopt new technologies – it is a driver of technology adoption.

This study shows costs of market participation can affect household responses to interventions in these markets or related markets. This relates to two studies of how endogenous participation in markets prior to introduction of new technologies can characterize heterogeneous responses to these technologies. Carter & Yao (2002) find the intensity of participation in land rental markets affects responses to the “technology” of improved land transfer rights. Henderson & Isaac (2016) find the intensity of participation in credit markets shapes the effects of contract farming, a “technology” with a fixed cost. In this paper I find participation in staple markets under a status quo technology is predictive of adoption of hybrid maize that increases agricultural productivity.

The findings in this paper inform targeting of development programs, especially agricultural programs targeted by participation in output markets for staples. Most input subsidy programs target land rich, commercial households that are not expected to be constrained by fixed costs of adoption or selling output, as shown by the program eligibility criteria in table 1. While the empirical analysis in this paper finds these households adopt hybrid maize at the greatest rates, the theoretical analysis shows this outcome is a function of costs specific to the study setting; more generally, the theoretical model shows households near the margins of selling or buying staples have the greatest incentives to adopt new technologies. Given the nuance of technology adoption decisions, mechanisms other than targeting may allocate technologies most effectively and equitably. In a recent study of a technology for preparing land for planting rice in India, Lybbert et al. (2018) find price discounts more effectively allocate technologies than targeting based on land wealth or other characteristics. In the setting for the present study and for many agricultural input subsidy programs in Africa, subsidy levels may ration technology adoption more effectively than targeting based on household characteristics.
Table 1: Agricultural input subsidies often target households with greater landholdings and semi-commercial market orientation

<table>
<thead>
<tr>
<th>Start</th>
<th>Country</th>
<th>Eligibility criteria</th>
<th>Subsidy %</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Acres owned</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Min</td>
<td>Max</td>
</tr>
<tr>
<td>2002</td>
<td>Zambia</td>
<td>2.5</td>
<td></td>
</tr>
<tr>
<td>2005</td>
<td>Malawi</td>
<td>1.0*</td>
<td></td>
</tr>
<tr>
<td>2007</td>
<td>Kenya</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td>2007</td>
<td>Rwanda</td>
<td>0.5</td>
<td></td>
</tr>
<tr>
<td>2008</td>
<td>Tanzania</td>
<td>2.5</td>
<td></td>
</tr>
<tr>
<td>2008</td>
<td>Zambia</td>
<td>2.5*</td>
<td></td>
</tr>
<tr>
<td>2009</td>
<td>Mozambique</td>
<td>1.2*</td>
<td>12.5*</td>
</tr>
<tr>
<td>2011</td>
<td>Zimbabwe</td>
<td>1.2</td>
<td></td>
</tr>
<tr>
<td>2012</td>
<td>Nigeria</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td>2019</td>
<td>Uganda</td>
<td>3.0</td>
<td>5.0</td>
</tr>
</tbody>
</table>

Notes: 2002 Zambia is the Fertilizer Support Programme (Druilhe & Barreiro-Hurlé, 2012; Mason & Tembo, 2014; Mason et al., 2013; Minde et al., 2008; World Bank, 2010); 2005 Malawi is the Agricultural Input Support Programme (Druilhe & 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 & Barreiro-Hurlé, 2012); 2007 Rwanda is the Crop Intensification Programme (Druilhe & Barreiro-Hurlé, 2012); 2008 Tanzania is the National Agricultural Input Voucher System (Druilhe & Barreiro-Hurlé, 2012; Pan & Christiaensen, 2012); 2008 Zambia is the Farmer Input Support Programme (Mason & 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).

2 Model of Technology Adoption with Transaction Costs

In this section I develop an agricultural household model to study how market conditions and household endowments shape technology adoption and market participation for staple crops. The key insight from the model is that when market participation is costly, households value technology adoption not just an income source but also 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, the section
concludes with a numerical analysis of technology adoption using parameter estimates from my data and the market participation literature. Under this parameterization, the technology is not adopted by households that are solidly autarkic with respect to staple output markets or by households with too little liquid or land wealth to take on the fixed costs of technology adoption. The theoretical model shows that when output markets have transaction costs, output market participation is important to technology adoption decisions.

2.1 Preferences, Technology, Endowments, and Costs

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. I assume that under the status quo technology, the land endowment \(T\) yields \(x\) staples per unit. The household can plant land to a new technology \(T_f\) that includes hybrid seeds and complementary inputs like fertilizer. The household’s land endowment constrains its land planted with the new technology:

\[
T \geq T_f
\]

I model yield gains from technology adoption for a household that first concentrates the technology on fields generating the greatest yield gains under the new technology before applying the technology to more marginal land. This model is consistent with agronomic best practices as well as variability in yield responsiveness to seeds and fertilizers due to different soil quality across fields even for a single household. Yield gains are represented by the function \(g(T_f)\), which equals zero without use of the technology.
(g(0) = 0) and increases at a decreasing rate. Household staple production is:

$$Q \equiv T \cdot x + g(T_f)$$

(2) To adopt the new technology, the household incurs fixed costs of searching for sellers of quality inputs, transporting inputs from the market to the home, and learning best practices for using the new technology. I denote the total value of these fixed costs $F_f$. Additionally, the household pays the market price $P_f$ for each unit of land planted under the new technology. Total expenditures on the fixed costs and unit costs of technology adoption can be no greater than the household’s liquidity endowment $A$. The household’s planting season liquidity constraint is:

$$1(T_f > 0) \cdot F_f + T_f \cdot P_f \leq A$$

(3) Liquidity that is not spent on technology adoption in the planting season is saved for the harvest season and earns an interest rate of return $i$. The household’s full income in the harvest season is the sum of returns from savings and the value of staple production at price $P_c$:

$$Y \equiv A - 1(T_f > 0) \cdot F_f - T_f \cdot P_f \cdot [1 + i] + Q \cdot P_c$$

(4) The household spends its full income on staples, non-staples, and costs of transacting in staple markets. When the household buys staples ($b > 0$), it incurs fixed costs of searching for sellers and transporting purchases from the market to the home; I denote the total value of these fixed costs $F_b$. When the household sells staples ($m > 0$), it
incurs fixed costs of searching for buyers, preparing harvest for sale, and transporting harvests to a selling point; I denote the total value of these fixed costs $F_m$. Additionally, transactions incur a proportional cost $\tau$ determined through competition between agents who transport fixed quantities of maize between transaction points in the village to the market hub where prices are determined. The household’s harvest season full income constraint is:

\[(5) \quad c \cdot P_c + n + 1(b > 0) \cdot F_b + 1(m > 0) \cdot F_m + [b + m] \cdot \tau \leq Y\]

2.2 Sequential Technology Adoption and Market Participation

The household makes sequential technology adoption and market participation choices to maximize its utility from consuming staples and non-staples subject to its constraints. The household’s problem is max $T_f \geq 0$ \(\max b, m \geq 0 u\left(c(b, m), n(b, m)\right)\) subject to (1)-(5) and

\[(6) \quad c = Q + b - m\]

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. I then solve the household’s technology adoption problem in the planting season.

2.2.1 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. Since utility increases with both staple and non-staple consumption, (5) binds. Then the household chooses its staples bought $b \geq 0$
and marketed \( m \geq 0 \) to maximize utility \( u(c(b, m), n(b, m)) \) subject to (2), (4), (6), and

\[
(7) \quad n(c) \equiv Y - \left[ c \cdot P_c + 1(b > 0) \cdot F_b + 1(m > 0) \cdot F_m + [b + m] \cdot \tau \right]
\]

Optimal market participation satisfies the problem’s first-order necessary conditions

\[
(8) \quad \frac{\partial u}{\partial c} - \frac{\partial u}{\partial n} \cdot [P_c + \tau] + \mu^*_b = 0
\]

\[
(9) \quad -\frac{\partial u}{\partial c} + \frac{\partial u}{\partial n} \cdot [P_c - \tau] + \mu^*_m = 0
\]

where each function is evaluated at optimal market participation \((b^*, m^*)\), \( \mu^*_b \) is the Lagrange multiplier for purchases, and \( \mu^*_m \) is the Lagrange multiplier for sales.

(8) and (9) show that household consumption and utility from consumption vary with staple production in two ways. First, staple production contributes to household income. 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 purchases and sales of staples given technology adoption and land and liquidity endowments are:

\[
(10) \quad (b^*, m^*) = (b^*(T_f; T, A), m^*(T_f; T, A))
\]
The household’s indirect utility from consumption in the harvest season is:

\[(11) \quad V(T_f; T, A) \equiv u\left(c(b^*, m^*), n(b^*, m^*)\right)\]

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.

### 2.2.2 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. In the planting season the household chooses technology adoption \(T_f \geq 0\) to maximize indirect utility \(V(T_f; T, A)\) subject to (1)-(6), (10), and (11). The problem’s first-order necessary condition for a solution is:

\[(12) \quad \frac{\partial V}{\partial T_f}(T_f^*; T, A) - \lambda^* + \mu_f^* = 0\]

where \(T_f^* = T_f^*(T, A)\) is the optimal level of technology adoption given household endowments. \(\lambda^*\) is the shadow value of land for applying the new technology in the planting season and \(\mu_f^*\) is the Lagrange multiplier for technology adoption, with both evaluated at the optimal level of technology adoption.

The fixed costs of technology adoption and output market participation imply that
each household has not one but six solutions to (12), one for each combination of technology adoption and output market participation. Of these six candidate solutions, the optimal combination maximizes the household’s indirect utility. Without fixed costs of technology adoption, the household would adopt an initially infinitesimal amount when the marginal value product of that adoption exceeds its marginal cost given household market participation without technology adoption. 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. I highlight this result using numerical analysis in the next sub-section.

2.3 Numerical Analysis of Technology Adoption

In my numerical analysis of technology adoption I consider two cases. In the first case, neither buying nor selling staples incur transaction costs, as is the case in standard models of technology adoption in the literature. In the second case, both buying and selling staples incur transaction costs. For each case I study adoption both when households have pessimistic beliefs about the physical yield gain from technology adoption as well as when households have realistic beliefs about the physical yield gain from technology adoption. Taken together, these four cases show how transaction costs in staple output markets shape technology adoption decisions of agricultural households.

I parameterize the household model with estimates from my data and the output market participation literature, as summarized in table 2.¹ The key parameters that vary across the two cases are fixed and proportional transaction costs in staple output

¹Appendix A details the approach for estimating the price wedge between buying and selling prices for maize using my data.
markets: all costs are zero in figure 1 and positive in figure 2. In both figures, the top panel shows technology adoption when households are pessimistic about the physical yield gain from technology adoption and the bottom panel shows technology adoption when households are realistic about the physical yield gain from technology adoption.

2.3.1 Adoption without Transaction Costs in Output Markets

I first study how costs of technology adoption shape technology adoption and market participation. To isolate this effect, I study cases where market participation does not incur transaction costs, as is the case in standard models of technology adoption in the literature.

For these cases I plot household technology adoption and market participation as a function of endowments of land and liquidity in figure 1. The top panel shows the household’s technology adoption and expected market participation when it is pessimistic about the physical yield gain from technology adoption. In this case, no households adopt the technology. Households with high liquidity wealth relative to land wealth buy staples and households with low liquidity wealth relative to land wealth sell staples.

The bottom panel shows the household’s technology adoption and expected market participation when it has full information about the physical returns to technology adoption. Even with full information, two groups of households do not adopt the technology. First, liquidity-poor households cannot take on the fixed costs of technology adoption. Second, land-poor households cannot make up for the fixed costs of adoption even when applying the technology on all of their land; for these households, $\mu_f > 0$ in (12). Since land poor households do not adopt the technology in this scenario, their production of staples only comes from their land endowment. Most land poor households buy staples from the market, with only the most liquidity poor households in this group selling staples. The partition between buying and selling is defined by the set
Table 2: Parameter values for the numerical analysis

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>Value</th>
<th>Figure 1</th>
<th>Figure 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed transaction cost(^a,b)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- Selling</td>
<td>(F_m)</td>
<td>0.00</td>
<td></td>
<td>1131.94</td>
</tr>
<tr>
<td>- Buying</td>
<td>(F_b)</td>
<td>0.00</td>
<td></td>
<td>1904.46</td>
</tr>
<tr>
<td>Proportional transaction cost(^a,c)</td>
<td>(\tau)</td>
<td>0.00</td>
<td></td>
<td>3.20</td>
</tr>
<tr>
<td>Yield from land endowment(^a)</td>
<td>(\chi)</td>
<td>300.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yield gain function</td>
<td>(g(T_f))</td>
<td>(\alpha \cdot [T_f]^\beta)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>- Marginal return parameter</td>
<td>(\beta)</td>
<td>0.95</td>
<td></td>
<td></td>
</tr>
<tr>
<td>- Productivity parameter(^a)</td>
<td>(\alpha)</td>
<td>188.76</td>
<td></td>
<td>600.00</td>
</tr>
<tr>
<td>Fixed adoption cost</td>
<td>(F_f)</td>
<td>6,607.70</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Technology price</td>
<td>(P_f)</td>
<td>10,800.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Interest rate of return</td>
<td>(i)</td>
<td>0.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Staple price(^a,d)</td>
<td>(P_c)</td>
<td>28.50</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Utility function</td>
<td>(u(c, n))</td>
<td>(\frac{1}{1-R} \cdot [c^Y \cdot n]^1-R)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>- Consumption share parameter(^a,c)</td>
<td>(\gamma)</td>
<td>0.19</td>
<td></td>
<td></td>
</tr>
<tr>
<td>- Relative risk aversion(^f)</td>
<td>(R)</td>
<td>2.68</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\(^a\) Calculated from my own data.

\(^b\) Derived from estimates by Renkow et al. (2004) of ad valorem equivalent fixed transaction costs for maize markets in western Kenya.

\(^c\) 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).

\(^d\) 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).

\(^e\) This is based on a staple budget share of 0.16 (compared with 0.60 for Park (2006)).

\(^f\) I derive the coefficient of relative risk aversion with respect to non-staple consumption

\[ R = \left[ R_Y + \gamma \right] / \left[ 1 + \gamma \right] \] where

\[ R_Y = -Y \cdot \left( \frac{\partial^2 V}{\partial Y^2} \right) / \left( \frac{\partial V}{\partial Y} \right) = 3 \] 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 of \(\gamma\) 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).
Figure 1: Adoption-marketing regimes with no transaction costs in output markets
of endowment duplets that make the household indifferent between buying and selling, that is endowments that satisfy $\frac{\partial u}{\partial c} / \frac{\partial u}{\partial n} = P_c$ from (8). Above the partition, liquidity increases household consumption of staples more than it increases production so that households buy staples. Below the partition, land increases production more than it increases consumption so that households sell staples.

2.3.2 Adoption with Transaction Costs in Output Markets

I now study how costs of market participation shape technology adoption and market participation. To isolate this effect, I study cases where buying and selling in staple output markets incurs transaction costs.

For these cases I plot household technology adoption and expected market participation as a function of endowments of land and liquidity in figure 2. The top panel shows the household’s technology adoption and expected market participation when it is pessimistic about the physical yield gains from technology adoption. In this case, no households adopt the technology. Households with high liquidity wealth relative to land wealth buy staples, households with low liquidity wealth relative to land wealth sell staples, and households in between are autarkic with respect to staple output markets.

The bottom panel shows the household’s technology adoption and expected market participation with full information about the physical yield gain from technology adoption. Three types of households do not adopt the technology. The first two – liquidity-poor and land-poor households – are similar to the first case. 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. The third type of non-adopting
Figure 2: Adoption-marketing regimes with transaction costs in output markets

Technological pessimism

Technological realism
household is defined by its autarky with respect to staple output markets. In particular, these households are not marginally autarkic, that is near the threshold of either buying or selling. These households produce a sufficient amount of staples without technology adoption to meet household demand but do not produce enough to enter the market as sellers with technology adoption.

2.4 Summary of Results

The household model shows how technology adoption for staple crop production varies with transaction costs in staple output markets. The main result for empirical study is that 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. When households receive full information to update pessimistic beliefs about physical returns to the technology, the model predicts the technology is not adopted by households that are solidly autarkic with respect to staple output markets, nor by households with too little land or liquidity to take on the fixed costs of technology adoption. Estimating market participation effects on technology adoption requires an empirical measure of a household’s proximity to thresholds of market participation. I propose two such measures in the next section.

3 Data and Market Participation

I test the theoretical model’s predictions of how technology adoption varies with expected market participation using data from a randomized control trial in western Kenya. Western Kenya is an ideal setting to study differences in technology adoption by household participation in output markets for the main staple, maize. Hybrid maize adoption is low and a field experiment conducted with a local seed company generated random variation in access to new, productive hybrid maize varieties adapted for the region.
Additionally, buyers and sellers face different effective output prices for maize due to a time-invariant wedge between buying and selling prices and higher prices in the buying season. Further, households span the spectrum from buyer, to autarkic, to seller households with respect to maize markets.

### 3.1 Data from Randomized Control Trial

Data come from a randomized control trial with agricultural households in western Kenya for an impact evaluation of Western Seed Company hybrid maize varieties by Carter et al. (2017). The study sample includes 1200 households in western Kenya, where adoption of hybrid maize varieties lags behind other regions of the country.\(^2\) Hybrid maize from Western Seed Company is new to this region of Kenya and its early maturity is well-suited to the short growing seasons in the region.

The impact evaluation randomized two interventions to encourage adoption of maize hybrids from Western Seed Company, as shown in figure 3. First, communities were randomly selected for Western Seed’s promotional activities from the population of potential communities. The promotional activities included agronomic information about the hybrid maize varieties in 2013 and a seed delivery program in 2015. The promotional activity in 2013 was specifically designed for households to update their beliefs about the physical yield gain from the hybrid maize technology. Second, within each community households were randomly selected to receive fertilizer in 2014 to relieve fertilizer costs as a constraint to hybrid maize adoption in the early stages of the study.

We collected data using three rounds of household surveys to capture baseline characteristics in late 2013, midline impacts of the interventions in early 2015, and endline impacts of the interventions in early 2016. Figure 4 shows the timing of the randomized

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\(^2\)The full sample also includes 600 households in 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 central Kenya, therefore I focus my analysis on the 1200 households sampled from western Kenya.
Figure 3: Randomized interventions and sampling

Sample from Western Kenya
24 Demonstration Sites

Stratification Based on Growing Conditions
12 Strata

Strata 1

Randomization

Seed Control
1 Site per Strata

Seed Treatment
1 Site per Strata

Random Sampling

Sample
50 Households per Site

Fertilizer Control
25 Households

Fertilizer Treatment
25 Households

Fertilizer Control
25 Households

Fertilizer Treatment
25 Households

Randomization

Pure Control Group
300 Households

Fertilizer Treatment Only
300 Households

Seed Treatment Only
300 Households

Seed and Fertilizer
300 Households
interventions relative to the recall periods for the household surveys.

For this analysis, the primary outcome of interest is whether or not the household planted Western Seed Company hybrids in the 2015 main season. The explanatory variable of interest is household market participation. We collected maize sales data for each season of the study period, including total quantity sold and the price of largest sale. We collected maize purchase data during the endline survey, including total quantity and price of purchases over four-month periods from February 2015 to January 2016. During the same endline survey, households also reported whether their purchases differed from a typical year and, if so, whether they expected this difference along with the quantity of maize purchased in a typical year.

3.2 Participation in Maize Markets

I use variation in market participation for a given household over time to characterize their market participation. I use variation in this characterization across households to estimate how rates of technology adoption differ between market participation classifications. I summarize variation in market participation over time and across households in table 3. Each row shows the percent of the control group with each combination of
market participation during the study period. Twenty-eight percent of households were net buyers each year while thirteen percent were net sellers each year. Households that bought or sold in most but not all years fall roughly along the margins of market participation defined in the theoretical model: thirteen percent of households mostly buy and are on the margin of being autarkic with respect to maize markets; nineteen percent of households mostly sell and are on the margin of between being autarkic and being a seller with respect to maize markets. I classify the remaining twenty-seven percent of households as being autarkic with respect to maize markets.

Testing predictions from the theoretical model requires a measure of market participation without treatment. One predictor of this is household participation in maize markets in the baseline year of the study. I split the sample along this dimension in table 3. The first column shows that of households that were deep buyers of maize at baseline (bought more than 90 kilograms), almost seventy-five percent bought maize in each of the study years and more than twenty-five percent were maize buyers in two of the three study years. Households that were shallow buyers of maize at baseline (bought less than 90 kilograms) had a similar distribution across market participation groups over the study years. The similar distributions of market participation between deep buyers and shallow buyers make these poor proxies for differentiating between households that always buy maize and households that mostly buy maize. The remaining proxies appear better at differentiating between groups, with autarky at baseline proxying for autarky during the study, shallow sales (less than 450 kilograms) proxying for selling in most years, and deep sales (more than 450 kilograms) proxying for selling in all years.

I also construct an alternative proxy for market participation by predicting market participation without treatment for each household. I define market participation as an ordered outcome that increases from being a net buyer, to an autarkic, to a net seller.

\[\text{I only observe staples bought in the final year of the study. I assume staples bought in the other years equal staples bought in a typical year.}\]
household with respect to maize markets. I assume observed market participation is determined by latent market participation $MP_{hpt}^*$. I assume the model for latent market participation of household $h$ in strata $p$ at time $t$ is

$$MP_{hpt}^* = \psi_{pt} + T_{hp1}\psi_{pt}^T + X_{hp}\psi_t^X + T_{hp1}X_{hp}\psi_t^{TX} + U_{hpt}$$

where $T_{hp1}$ is maize acres per capita at baseline, $X_{hp}$ is a vector of time-invariant household characteristics, and $U_{hpt}$ is an error term. $\psi_{pt}$ is a location-time-specific effect, $\psi_{pt}^T$ is the effect of the household land endowment on market participation that varies by location and time period, $\psi_t^X$ is the effect of household characteristics on market participation that varies by time period, and $\psi_t^{TX}$ is the interaction effect of household land endowment and characteristics on market participation that varies by time period. I estimate (13) by maximum likelihood assuming an ordered probit model.4

For each treatment household, I predict market participation without treatment by first estimating the model using three years of household-year observations from the control group only. I then use these estimates to predict market participation for each household-year observation in the treatment group.

For control households, applying the same procedure would result in endogenous stratification whereby control group data would be overfit so that treatment effect estimates based on these predictions would be biased (Abadie et al. 2014). To avoid overfitting the control group data, I follow the general leave-one-out estimation approach from Abadie et al. (2014) and Harvill et al. (2013). To predict market participation without treatment for control household $h$, I first estimate the model using three years of household-year observations from all control households other than $h$. I then use these leave-one-out estimates to predict market participation in each year for household $h$.

In table 4 I split the sample along the dimension of predicted market participation

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4 Appendix B details the estimation approach.
(\(\hat{MP}_{hp}\)). The first column shows that of households predicted to buy maize each year, about two-thirds bought maize in each of the study years. Households predicted to buy maize in two of the three study years are evenly distributed across buying each year, buying most years, and being autarkic. The difference in distributions between the first two columns makes the prediction of buying in each year a stronger proxy for buying in each season than was being a deep buyer at baseline. However households predicted to be autarkic or to sell in most seasons have similar distributions of actual market participation over the study years, making them weaker proxies. Compared to baseline market participation, predicted market participation seems to be a stronger proxy for differentiating between solid and marginal buyers but a weaker proxy for autarky and selling.

4 Market Participation Effects on Technology Adoption

I test the theoretical model’s predictions of how technology adoption varies with expected market participation using data from the randomized control trial in western Kenya. First, I estimate how technology adoption varies with expected market participation when not controlling for other household characteristics. These estimates are analogous to the potential to increase technology adoption by using market participation as a criterion for targeting agricultural technology adoption programs. Second, I estimate the effect of market participation on technology adoption when controlling for potential confounding factors.

4.1 Effects of Targeting Technologies by Market Participation

The first question of the empirical analysis is whether a household’s expected market participation without technology adoption predicts technology adoption. To estimate the targeting effect of market participation on technology adoption, I model adoption
Table 3: Market participation shares: Observed (row) by baseline (column)

<table>
<thead>
<tr>
<th>Observed</th>
<th>Buy-Deep</th>
<th>Buy-Shallow</th>
<th>Autarky</th>
<th>Sell-Shallow</th>
<th>Sell-Deep</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buy always</td>
<td>17</td>
<td>12</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>28</td>
</tr>
<tr>
<td>Buy mostly</td>
<td>6</td>
<td>5</td>
<td>0</td>
<td>2</td>
<td>0</td>
<td>13</td>
</tr>
<tr>
<td>Autarky</td>
<td>0</td>
<td>0</td>
<td>21</td>
<td>4</td>
<td>2</td>
<td>27</td>
</tr>
<tr>
<td>Sell mostly</td>
<td>0</td>
<td>1</td>
<td>6</td>
<td>10</td>
<td>3</td>
<td>19</td>
</tr>
<tr>
<td>Sell always</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>7</td>
<td>6</td>
<td>13</td>
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<tr>
<td>Total</td>
<td>23</td>
<td>17</td>
<td>27</td>
<td>22</td>
<td>10</td>
<td>100</td>
</tr>
</tbody>
</table>

N: 278

Deep means buying >90 kg or selling >450 kg.

Table 4: Market participation shares: Observed (row) by predicted (column)

<table>
<thead>
<tr>
<th>Observed</th>
<th>Buy always</th>
<th>Buy mostly</th>
<th>Autarky</th>
<th>Sell mostly</th>
<th>Sell always</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buy always</td>
<td>21</td>
<td>5</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>28</td>
</tr>
<tr>
<td>Buy mostly</td>
<td>6</td>
<td>4</td>
<td>2</td>
<td>1</td>
<td>0</td>
<td>13</td>
</tr>
<tr>
<td>Autarky</td>
<td>4</td>
<td>4</td>
<td>6</td>
<td>6</td>
<td>6</td>
<td>27</td>
</tr>
<tr>
<td>Sell mostly</td>
<td>1</td>
<td>1</td>
<td>7</td>
<td>5</td>
<td>5</td>
<td>19</td>
</tr>
<tr>
<td>Sell always</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>1</td>
<td>8</td>
<td>13</td>
</tr>
<tr>
<td>Total</td>
<td>32</td>
<td>14</td>
<td>19</td>
<td>14</td>
<td>21</td>
<td>100</td>
</tr>
</tbody>
</table>

N: 278
of Western Seed maize hybrids in 2015 as a linear function of expected market participation and its interaction with randomly assigned information about and access to the varieties.\footnote{The main effect of random assignment is absorbed by the interaction between expected market participation and assigned access.} The model for farmer $h$ in village $v$ is

\[(14) \quad a_{hv} = \sum_{q=1}^{p} 1(\text{strata} = q) \mu_{q}^{te} + m_{hv}^{'} \gamma^{te} + d_{v} m_{hv}^{'} \eta^{te} + \epsilon_{hv}^{te}\]

where $a_{hv}$ is technology adoption (1 for adopters, 0 otherwise), $\mu_{q}^{te}$ is a strata fixed effect, $m_{hv}$ is expected market participation without treatment, and $d_{v}$ is assigned seed information and access (1 if assigned, 0 otherwise).

The coefficient vector of interest is $\eta^{te}$, with each element being the linear effect of assignment on adoption for a group of households defined by expected market participation, all else changing. I estimate $\eta^{te}$ when proxying for expected market participation ($m_{hv}$) with market participation observed at baseline ($MP_{hp}$) as well as market participation predictions ($\hat{MP}_{hp}$). The comparison of these proxies in the previous section suggests market participation at baseline is a stronger proxy for autarky and selling while the market participation prediction is a stronger proxy for differentiating between consistent and marginal buyers.

I show estimates of (14) when proxying for expected market participation with market participation observed at baseline in table 5, column 1. For deep sellers, seed access increases adoption by 24 percentage points, the largest effect for any market participation group. Shallow sellers have the next greatest adoption response to seed access at 19 percentage points. Autarkic households have the smallest adoption response to seed access at 12 percentage points. Shallow and deep buyers have adoption responses of 13-14 percentage points; these similar adoption responses are consistent with these proxies representing similar distributions of market participation (as shown in table 3).
Table 5: Technology adoption by market participation (N=1086)

<table>
<thead>
<tr>
<th>Interaction effects</th>
<th>Targeting</th>
<th>Marginal</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Obs Pres</td>
<td>Obs Pred</td>
<td></td>
</tr>
<tr>
<td>Seller - Deep</td>
<td>0.24**</td>
<td>0.10**</td>
</tr>
<tr>
<td></td>
<td>(0.08)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>Seller - Shallow</td>
<td>0.19***</td>
<td>0.23**</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td>(0.07)</td>
</tr>
<tr>
<td>Autarkic</td>
<td>0.12**</td>
<td>0.16***</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>Buyer - Shallow</td>
<td>0.13**</td>
<td>0.18**</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>Buyer - Deep</td>
<td>0.14</td>
<td>0.15*</td>
</tr>
<tr>
<td></td>
<td>(0.08)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>Main effects</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Seller - Shallow</td>
<td>-0.04</td>
<td>-0.09</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.05)</td>
</tr>
<tr>
<td>Autarkic</td>
<td>-0.03</td>
<td>-0.11**</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>Buyer - Shallow</td>
<td>-0.06</td>
<td>-0.10*</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td>(0.05)</td>
</tr>
<tr>
<td>Buyer - Deep</td>
<td>-0.05</td>
<td>-0.08</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>Reference mean</td>
<td>0.11</td>
<td>0.09</td>
</tr>
<tr>
<td>Strata controls</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Other controls</td>
<td>No</td>
<td>No</td>
</tr>
</tbody>
</table>

Outcome variable: WSC hybrid adoption (0/1) in 2015.
Observed: Deep means selling >450 kg or buying >90 kg.
Predicted: Deep means selling all years or buying all years.
Other controls are: indicators for midaltitude zone, male HH head, credit unconstrained, hybrid user, and fertilizer treatment; maize acres and HH size demeaned by strata.
Standard errors in parentheses clustered by village.
Significance: * = 10%, ** = 5%, *** = 1%
To disentangle effects of targeting shallow buyers from those of targeting deep buyers, I estimate (14) when proxying for expected market participation with market participation predictions. I show the results in table 5, column 2. For shallow buyers, seed access increases adoption by 18 percentage points, compared with 15 percentage points for deep buyers. Shallow buyers have a slightly greater adoption response to seed access than deep buyers.

Taken together, the estimates suggest technology adoption increased most when targeting seed information and access to households that were deep sellers of maize, followed by households that were shallow sellers of maize. Autarkic households had the smallest response to the seed promotion interventions. Buyers of maize were slightly more responsive than autarkic households, with shallow buyers slightly more responsive than deep buyers. These are estimates of the potential gains from targeting technology adoption programs by market participation when allowing all other household characteristics to vary with market participation. To test the prediction from the theoretical model that market participation changes technology adoption of households, I control for household characteristics that vary with market participation in the next sub-section.

4.2 Marginal Effects of Market Participation on Technology Adoption

To estimate the marginal effect of market participation on technology adoption, I model adoption of Western Seed maize hybrids in 2015 as a linear function of baseline household characteristics and their interactions with randomly assigned information about and access to the varieties. The model for farmer h in village v is

$$a_{hv} = \sum_{q=1}^{p} \mathbf{1}(\text{strata} = q)\mu_{q}^{me} + m_{hv}^{\gamma_{me}} + d_{v}m_{hv}^{\eta_{me}} + x_{hv}^{\gamma_{me}} + d_{v}x_{hv}^{\beta_{me}} + e_{hv}^{me}$$
where $x_{hv}$ is a column vector of control variables.\textsuperscript{6}

The coefficient vector of interest is $\eta^{me}$. Each element of the vector is the linear effect of assignment on adoption for a group of households defined by expected market participation, all else constant.

I show estimates of (15) when proxying for expected market participation with market participation observed at baseline in table 5, column 3. Recall that market participation at baseline is a strong proxy for being a consistent seller, marginal seller, or autarkic household, but a poor proxy for differentiating between consistent and marginal buyers. The marginal effect on adoption from being a deep seller is the largest effect, followed by effects of being a shallow seller, buyer, and autarkic.

The marginal effects of market participation on adoption follow the same pattern of estimated effects of targeting by market participation (column 1), but differ in subtle and insightful ways. The main effect of the control variables ($\theta^{me}$) controls for greater rates of adoption among deep sellers in the control group, which decreases interaction effects by 3-6 percentage points relative to the interaction effect for deep sellers. The interaction effect between control variables and randomized assignment ($\beta^{me}$) decreases interaction effects of market participation by 2-3 percentage points for deep seller, shallow seller, and autarkic households; these households appear to be slightly better resourced to adopt new technologies than buyer households. Overall, the greater resources of deep seller households increases adoption in the control group more than the interaction effect relative to other market participation groups. This makes the marginal effect estimate of being a deep seller greater than the targeting effect estimated in the previous subsection. Being a deep seller seems to be a driver of technology adoption rather than a

\textsuperscript{6}The control variables proxy for drivers of adoption identified by Jack (2011): midaltitude agroclimatic zone proxies for greater expected profitability, maize acres (demeaned by pair) proxies for lesser exposure to land market inefficiencies, household size (demeaned by pair) and male household head proxy for lesser exposure to labor market inefficiencies, credit unconstrained proxies for lesser exposure to financial market inefficiencies, and past hybrid use proxies for lesser exposure to informational inefficiencies. I define control variables such that my \textit{ex ante} expectation is that each is positively correlated with both adoption of hybrids and selling maize.
proxy for propensity to adopt. But the advantages of targeting deep sellers with the largest marginal effect on response to treatment is muted by the greater propensity of deep sellers to adopt regardless of whether they are targeted.

I show estimates of (15) when proxying for expected market participation with market participation predictions in table 5, column 4. Recall that market participation predictions are a strong proxy for differentiating between consistent and marginal buyers. Adding control variables does not change estimated differences between these groups in terms of either adoption in the control group or interactions with assignment to seed information and access. The marginal effect on adoption from being a shallow buyer is slightly greater than the effect of being a deep buyer.

5 Conclusion

To stimulate sustained technology adoption and productivity growth in agriculture, governments in sub-Saharan Africa increasingly subsidize prices of agricultural technologies like hybrid seeds and fertilizers. A crucial question for public policy is how to design and target subsidies to households to achieve program goals in a cost-effective manner. Most agricultural input subsidy programs is to increase regional food security target subsidies to households that are relatively food secure and wealthy. The theoretical model in this paper shows that when market participation is costly, households value technology adoption not just an income source but also as a means of either reducing costs of buying staples or overcoming costs of selling staples. In particular, the technology is not adopted by households that are solidly autarkic with respect to staple output markets, nor by households with too little liquid or land wealth to take on the fixed costs of technology adoption. The model provides a nuanced analysis of technology adoption when output market participation is costly.

I test the theoretical model’s predictions of how technology adoption varies with ex-
ected market participation using data from a randomized control trial of high-yielding maize varieties developed for western Kenya, where the main staple is maize. I estimate both the unconditional effects of targeting technologies by market participation as well as the conditional marginal effects of market participation on technology adoption. Targeting effects are greatest for “deep seller” households that sell the largest quantities of maize, followed by “shallow seller” households selling small quantities of maize. Targeting effects are smallest for autarkic households. While differences in targeting effects for deep sellers and other market participation groups are large in magnitude, the differences are greater for conditional marginal effect estimates when holding other factors constant. Thus market participation does not just proxy for propensity to adopt new technologies – it is a driver of technology adoption.

The findings in this paper inform targeting of development programs, especially agricultural programs targeted by participation in output markets for staples. Most input subsidy programs target land rich, commercial households that are not expected to be constrained by fixed costs of adoption or selling output. While the main empirical finding in this paper is that these households adopt new technologies at the greatest rates, two caveats for targeting are warranted. First, technology adoption is still positive and non-trivial for other market participation groups. Second, commercial producers are a small share of agricultural households in this study setting. Given these factors, the potential for inclusive agricultural technology adoption programs still exist. In particular, given the nuance of technology adoption decisions, mechanisms other than targeting may allocate technologies most effectively and equitably. In the setting for the present study and for many agricultural input subsidy programs in Africa, subsidy levels may ration technology adoption more effectively than targeting based on land wealth or other household characteristics.
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Lunduka, Rodney, Ricker-Gilbert, Jacob, & Fisher, Monica. 2013. What are the farm-level impacts of Malawi’s farm input subsidy program? A critical review. *Agricultural Economics (United Kingdom), 44*(6), 563–579.


Appendix A: Output Markets for Maize 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 control trial.

Figure 5 shows the frequency of sales of maize grain by season, year, and month. The top panel shows the main months for selling maize after the harvest from the main rains are August through October. The bottom panel shows the main months for selling maize after the harvest from the short rains are January and February. The final row shows the recall periods for buying data from 2015-2016. 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).

Maize grain prices differ between buying and selling markets and vary over the course of the year. Figure 6 plots mean buying prices by four-month periods and mean selling prices by month. Selling prices peak during the rainy seasons between maize harvests, from October-November and April-June. Buying prices are greater than selling prices, suggesting transaction costs exist in maize markets. It is difficult to estimate the magnitude of transaction costs from the summary statistics in figure 6, however. Defining time-invariant transaction costs as the difference in purchase price and highest monthly sales price during that period would overweight high selling prices and underestimate transaction costs. Furthermore, these summary statistics pool price differences across communities, whereas transaction costs should be estimated from differences in buying and selling prices within communities.

To estimate transaction costs and seasonal price fluctuations, I use the following
Figure 5: Maize sales frequency by season, year, and month

<table>
<thead>
<tr>
<th>Main Rains</th>
<th>Feb</th>
<th>Mar</th>
<th>Apr</th>
<th>May</th>
<th>Jun</th>
<th>Jul</th>
<th>Aug</th>
<th>Sep</th>
<th>Oct</th>
<th>Nov</th>
<th>Dec</th>
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<tbody>
<tr>
<td>12-13</td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>13-14</td>
<td>12</td>
<td>14</td>
<td>10</td>
<td>6</td>
<td>12</td>
<td>26</td>
<td>90</td>
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<td>(4)</td>
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<td>(2)</td>
<td>(1)</td>
<td>(1)</td>
<td>(3)</td>
<td>(3)</td>
<td>(12)</td>
<td>(28)</td>
<td>(21)</td>
<td>(11)</td>
<td>(11)</td>
<td>(8)</td>
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<tr>
<td>16</td>
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Notes: The top panel shows Main Rains, the middle panel shows Short Rains, and the bottom panel shows Purchase Periods. Thick-bordered cells indicate times of data collection; for example, the data on the short season of 2012/13 and the main season of 2013 were collected in Oct and Nov 2013. Shading of cells follows the percentage of largest sales within a given month and season: the darkest shade indicates over 17% of largest sales in that season occurred in that month; the medium shade indicates 7-17% of largest sales in that season occurred in that month; the lightest shade indicates less than 7% of largest sales in that season occurred in that month; lack of shading indicates bad data, as sales in these months are infeasible given the timing of data collection and maize harvest in each season.
Figure 6: Maize grain unit values: Monthly means from Dec14-Jan16

Notes: Means for village-level observations measured in Kenyan shillings per kilogram.
model of prices in village $v$ in strata $p$ at time period $t$

$$(16) \quad \text{price}_{vpt} = \sum_{q=1}^{p} 1(p = q)\phi_q + \text{buy} \delta + \sum_{s=2}^{3} \left\{ 1(t = s) \cdot [\lambda_s + \text{buy} \delta_s] \right\} + \text{error}_p$$

where $\phi_q$ is the average selling price in strata $q$ in February through May ($t = 1$), $\delta$ is the average of the selling price less the buying price across pairs in February through May, $\lambda_s$ is the average of the selling price at time $t = s$ less the selling price at $t = 1$, and $\delta_s$ is the average of the buying price at time $t = s$ less the buying price at $t = 1$.

Table 3 shows estimates of (16) in 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 figures 5 and 6. 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 percent 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 price. A violation of this that would be problematic for the empirical analysis would be if households in a community with access to the hybrids expect prices to decline as other households in the community adopt the hybrids. To test whether
Table 6: Village prices by season, market, and treatment

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<td>Oct15-Jan16</td>
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<td>Jun15-Sep15 × Purchase price</td>
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<td>Oct15-Jan16 × Treatment</td>
<td>0.7</td>
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<tr>
<td></td>
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<td>(1.0)</td>
</tr>
<tr>
<td>Purchase price × Treatment</td>
<td>-1.8</td>
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<td></td>
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<td>(1.7)</td>
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<tr>
<td>Jun15-Sep15 × Purchase price × Treatment</td>
<td>-1.5</td>
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<tr>
<td></td>
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<td>(2.5)</td>
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<tr>
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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.
community assignment to access the hybrids affects prices, I estimate

$$\text{(17)} \quad \text{price}_{vpt} = \sum_{q=1}^{P} \mathbf{1}(p = q)\phi_{q}^{0} + \text{buy}_{0}^{\delta} + \sum_{s=2}^{3} \left\{ \mathbf{1}(t = s) \cdot [\lambda_{s}^{0} + \text{buy}_{s}^{\delta}] \right\} +

+ d_{v} \cdot \left[ \phi^{1} + \text{buy}_{1}^{\delta} + \sum_{s=2}^{3} \left\{ \mathbf{1}(t = s) \cdot [\lambda_{s}^{1} + \text{buy}_{s}^{\delta}] \right\} \right] + \text{error}_{p}$$

where $d_{v}$ is assigned access to the hybrids (0 if not assigned, 1 otherwise). Parameters with the superscript 0 have the same interpretation as in (16) for the communities without access to the hybrids ($d_{v} = 0$). A parameter with the superscript 1 is the additive effect of being assigned access to the hybrids ($d_{v} = 1$).

Table 7 shows estimates of (17) in 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 $v$

$$\text{(18)} \quad \text{price}_{v} = \sum_{q=1}^{C} \mathbf{1}(\text{cluster} = q)\varphi_{q} + \sum_{r=2}^{3} \mathbf{1}(\text{year} = r)\xi_{r} + \sum_{s=2}^{12} \mathbf{1}(\text{month} = s)\zeta_{s} + \text{error}_{v}$$

where $\varphi_{q}$ is the average selling price in cluster $q$ in August at baseline ($(\text{year}, \text{month}) = (1, 1)$), $\xi_{r}$ is the average of selling prices in year $r$ less the baseline year conditional on cluster and month, and $\zeta_{s}$ is the average of selling prices in month $s$ less the baseline year condition on cluster and year.

Figure 7 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
**Figure 7**: 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.

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 with access to maize hybrids 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.
Appendix B: Predicting Market Participation

I define market participation of household \( h \) in strata \( p \) at time \( t \) along the spectrum of staple surplus (staples marketed \( m_{hpt} \) less staples bought \( b_{hpt} \)):

\[
(19) \quad MP_{hpt} = \begin{cases} 
1 & \text{if } m_{hpt} - b_{hpt} < 0 \\
2 & \text{if } m_{hpt} - b_{hpt} = 0 \\
3 & \text{if } m_{hpt} - b_{hpt} > 0 
\end{cases}
\]

I only observe staples bought in the final time period \( (t = 3) \). For the other periods I replace staples bought with staples bought in a typical period \( (b_{hpt} = b_{hp}, \forall t \in \{1, 2\}) \).

Since market participation is an ordered outcome in (19), I model it using a general approach for ordered outcome variables. The model of observed market participation is

\[
(20) \quad MP_{hpt} = \begin{cases} 
1 & \text{if } MP^*_{hpt} < \alpha_1 \\
2 & \text{if } \alpha_1 < MP^*_{hpt} < \alpha_2 \\
3 & \text{if } MP^*_{hpt} > \alpha_2 
\end{cases}
\]

where \( MP^*_{hpt} \) is defined by (13), \( \alpha_1 \) is the threshold between net buyer and autarkic households, and \( \alpha_2 \) is the threshold between autarkic and net seller households.

Taking probabilities in (20) gives the probability of each outcome

\[
(21) \quad Pr(MP_{hpt} = 1) = F\left(\alpha_1 - \left[MP^*_{hpt}(\psi) - U_{hpt}\right]\right)
\]

\[
Pr(MP_{hpt} = 2) = F\left(\alpha_2 - \left[MP^*_{hpt}(\psi) - U_{hpt}\right]\right) - F\left(\alpha_1 - \left[MP^*_{hpt}(\psi) - U_{hpt}\right]\right)
\]

42
\[
\Pr(MP_{hpt} = 3) = 1 - F\left(\alpha_2 - \left[ MP^*_hpt(\psi) - U_{hpt} \right] \right)
\]

where \(F\) is the cumulative distribution function of \(U_{hpt}\). Then I estimate parameters \((\psi, \alpha)\) that maximize the log-likelihood function

\begin{equation}
\mathcal{L}(\psi, \alpha) = \sum_{h=1}^{N} \sum_{t=1}^{3} \sum_{j=1}^{3} \mathbf{1}(MP_{hpt} = j) \cdot \ln\left( \Pr(MP_{hpt} = j \mid \psi, \alpha) \right)
\end{equation}

subject to (13) and (19)-(21).