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

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Job Market Paper
November 28, 2018
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Abstract

Many governments in sub-Saharan Africa attempt to increase agricultural productivity by subsidizing adoption of technologies like hybrid seeds and fertilizers. Subsidy programs often target relatively wealthy households producing surplus food to sell on the market. Yet households producing insufficient food and buying food from the market at high prices may have large incentives to adopt production technologies. To study how technology adoption incentives differ across households, I develop a theoretical model of technology adoption when buying and selling food incurs transaction costs. Technology adoption is greatest for households that can transition out of buying food or transition into selling food, with the greatest welfare improvements for households transitioning out of buying food. I test the model’s predictions using data from a randomized control trial of new, high-yielding varieties of maize developed for western Kenya. To estimate heterogeneous effects, I predict each household’s output market participation without the new varieties. Consistent with the theory, adoption of the high-yielding maize varieties is greatest for households that can transition into selling maize, and this result holds when controlling for potential confounding factors. Adoption is high for all market participation groups, however, suggesting the potential for a broad-based approach to promoting agricultural technology adoption.

*I am grateful for comments from Michael Carter, Travis Lybbert, and Kevin Novan. The main data set used in this study comes from the Western Seed Company impact evaluation commissioned by Acumen, a non-profit impact investment firm, and made possible in part by the generous support of the American people through the United States Agency for International Development Cooperative Agreement No. AID-OAA-L-12-00001 with the BASIS Feed the Future Innovation Lab and the Agricultural Technology Adoption Initiative (ATAI) administered by JPAL at MIT and the Bill and Melinda Gates Foundation. However the specific findings and recommendations remain solely the author’s and do not necessarily reflect those of USAID, the US Government, or other funders.

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1 Introduction

The number of people living in poverty worldwide decreased in recent decades, yet poverty in sub-Saharan Africa increased during the same period. This persistence in poverty is due in part to low and stagnant productivity in the agricultural sector in which most of the population works. Thus a public policy priority is to increase agricultural productivity by supporting agricultural households to adopt production technologies like hybrid seeds and fertilizers. Low adoption of productive technologies is due in part to households lacking information about these technologies. Households have a fixed cost of learning about new technologies as well as low expectations about the productivity of new technologies if previous technologies were unproductive. To encourage technology adoption despite these information problems, many governments in sub-Saharan Africa subsidize prices of agricultural production technologies for targeted agricultural households.

A crucial question for public policy is how to target subsidies to households to achieve program goals in a cost-effective manner. Subsidies for agricultural production technologies often target relatively wealthy households that produce a food surplus to sell on the market. 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). 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 food crops in developing rural economies. In developing rural economies, buying and selling staples is costly: buying staples entails costs of searching for vendors who households can purchase staples from, and selling staples entails costs of searching for 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 when buying and selling food incurs search and transport costs. The model shows technology adoption incentives are greatest for households that can transition out of buying staples or transition into selling staples with technology adoption, while incentives are low for households that would not sell many staples even with technology adoption. A prediction stemming from these results is 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.

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, where the staple food is maize. The randomized control trial was conducted by Carter et al. (2017) and randomly assigned which communities received information about new hybrid maize varieties that mature during the region’s short growing seasons. In the randomized trial, we find the information intervention 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 their purchases or sales of maize. 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.

To test the theoretical model’s prediction that a household’s expected output market participation affects its technology adoption decision, I construct a measure of each household’s expected market participation at the time of planting. I construct the proxy 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. To avoid overfitting observations I apply a leave-one-out estimation approach from Abadie et al. (2014) and Harvill et al. (2013). 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: expected market participation.

Consistent with the theory, adoption of the high-yielding maize varieties is greatest among households that can transition into selling maize. This result holds when controlling for potential confounding factors. The findings suggest that market participation is not simply a proxy for propensity to adopt new technologies, but that market participation itself is a predictor 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 relatively wealthy households that produce a food surplus to sell on the market, as shown by the program targeting criteria in table 1. The findings in this paper suggest this targeting approach may exclude many households that would be willing to adopt new production technologies. Given the nuance of technology adoption decisions, mechanisms other than targeting may allocate technologies more effectively and equitably. In particular, subsidy levels may ration technology adoption more effectively than targeting based on household characteristics in the contexts of agricultural input subsidy programs in Africa.
**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>Targeting 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>

*Maize acres only

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 output market participation for staple crops. The key insight from the model is that when market participation is costly, households value technology adoption not just as 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, households that can transition out of buying staples or into selling staples adopt the technology, with technology adoption having large impacts on household welfare for households that can transition out of buying staples. 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:

\[(1) \quad T \geq T_f\]

I model yield gains from technology adoption for a household that first concentrates the technology on land with the greatest yield gains under the new technology before applying the technology to more marginal land.\(^1\) Yield gains from technology adoption 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:

\[(2) \quad Q \equiv T \cdot x + g(T_f)\]

To adopt the new technology, the household incurs a fixed cost \(F_f\) that includes the 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. 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 financial endowment \(A\). The household’s planting season liquidity constraint is:

\[(3) \quad 1(T_f > 0) \cdot F_f + T_f \cdot P_f \leq A\]

Financial wealth that is not spent on technology adoption in the planting season is saved for the harvest season and earns an interest rate \(i\). The household’s full wealth in the harvest season is the sum of returns from savings and the value of staple production

\(^1\)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.
at price $P_c$:

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

Household staple consumption comes from staples produced plus staples bought $b$ less staples sold $m$:

$$c(b, m) = Q + b - m$$

The household spends its full wealth on staples, non-staples, and costs of transacting in staple markets. When the household buys staples ($b > 0$), it incurs a fixed cost $F_b$ representing the costs of searching for sellers. When the household sells staples ($m > 0$), 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 $\tau$ representing the cost of transporting fixed quantities of staples between the home and the market. The household’s harvest season budget constraint is:

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

### 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 $\max_{T_f \geq 0} \left( \max_{b, m \geq 0} u(c(b, m), n(b, m)) \right)$ subject to (1)-(6).

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, (6) binds such that

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

The household chooses its staples bought \( b \geq 0 \) and marketed \( m \geq 0 \) to maximize utility \( u\left(c(b, m), n(b, m)\right) \) subject to (2), (4), (5), and 7. Optimal market participation satisfies the problem’s first-order necessary conditions

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

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

where \( \mu^*_b \) is the Lagrange multiplier for purchases and \( \mu^*_m \) 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 and endowments of financial and land wealth:

\[ (b^*, m^*) = (b^*(T_f; T, A), m^*(T_f; T, A)) \]
(8) and (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:

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

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)-(5), (7), (10), and (11). The problem’s first-order necessary condition for a solution is:

\[
\frac{\partial V}{\partial T_f}(T_f^*; T, A) - \lambda^* - \rho^* \cdot P_f + \mu_f^* = 0
\]
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, $\rho^*$ is the shadow value of liquidity in the planting season, and $\mu^*_f$ 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 (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 problem would simplify greatly if technology adoption did not incur a fixed cost, in which case the 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.

### 2.3 Numerical Analysis of a Technology Adoption Intervention

The numerical analysis simulates an intervention that increases households’ expectations about a production technology’s physical yield. I simulate the effects of an information intervention for two cases. The benchmark case is similar to standard models of technol-
ogy adoption in that neither buying nor selling staples incurs transaction costs. In the second case, both buying and selling staples incur transaction costs, as is the case in the setting for the subsequent empirical analysis.

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 per unit of land $CV/T$. Compensating variation is the amount of money the household would have to be given 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 worse off when taking on the fixed costs of technology adoption and negative for households that are better 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 have a high yield. The simulation mirrors the subsequent empirical analysis, a randomized control trial that provides information about new, high-yielding varieties of maize to some communities and no information to other communities. I parameterize the simulations using data from the randomized control trial, including households’ expected yield gains from technology pre-intervention as well as estimated yield gains from technology adoption post-intervention. Estimated yield gains from technology adoption post-intervention are more than three times larger than households’ expected yield gains from technology adoption pre-intervention, as shown by the productivity parameter values in in table 2.

\[ V(0; T, A \cdot [1 + i]) \equiv V(T_f^* | CV = 0; T, A - F_t - T_f^* | CV = 0 \cdot P_f \cdot [1 + i] + CV) \]

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 2: Parameter values for the numerical analysis (costs and prices in 2015 Kenyan shillings, with ~100 Kenyan shillings per US dollar)

<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&lt;sup&gt;a,b&lt;/sup&gt;</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>11310.94</td>
</tr>
<tr>
<td>- Buying</td>
<td>$F_b$</td>
<td>0.00</td>
<td></td>
<td>1904.46</td>
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<tr>
<td>Proportional transaction cost&lt;sup&gt;a,c&lt;/sup&gt;</td>
<td>$\tau$</td>
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<table>
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<th>Symbol</th>
<th>Value</th>
<th>Figures 1 &amp; 2</th>
<th>Graphs a &amp; b</th>
<th>Graphs c &amp; d</th>
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<tbody>
<tr>
<td>Yield from land endowment&lt;sup&gt;a&lt;/sup&gt;</td>
<td>$\chi$</td>
<td>300.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yield gain function</td>
<td>$g(T_f)$</td>
<td>$\alpha \cdot</td>
<td>T_f</td>
<td>^\beta$</td>
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<tr>
<td>- Marginal return parameter</td>
<td>$\beta$</td>
<td>0.95</td>
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<tr>
<td>- Productivity parameter&lt;sup&gt;d&lt;/sup&gt;</td>
<td>$\alpha$</td>
<td>188.76</td>
<td>600.00</td>
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<tr>
<td>Fixed adoption cost</td>
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<td>Technology price</td>
<td>$P_f$</td>
<td>10,800.00</td>
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<tr>
<td>Interest rate of return</td>
<td>$i$</td>
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<tr>
<td>Staple price&lt;sup&gt;a,d&lt;/sup&gt;</td>
<td>$P_c$</td>
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<td>Utility function</td>
<td>$u(c, n)$</td>
<td>$\frac{1}{1-R} \cdot [c^\gamma \cdot n^{1-k}]$</td>
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<td></td>
<td></td>
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<tr>
<td>- Consumption share parameter&lt;sup&gt;a,e&lt;/sup&gt;</td>
<td>$\gamma$</td>
<td>0.19</td>
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<tr>
<td>- Relative risk aversion&lt;sup&gt;f&lt;/sup&gt;</td>
<td>$R$</td>
<td>2.68</td>
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</table>

<sup>a</sup>Calculated from my own data.

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

<sup>c</sup>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).

<sup>d</sup>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).

<sup>e</sup>This is based on a staple budget share of 0.16 (compared with 0.60 for Park (2006)).

<sup>f</sup>I derive the coefficient of relative risk aversion with respect to non-staple consumption $R = [R_Y + \gamma]/[1 + \gamma]$ where $R_Y = -Y \cdot (\partial^2 V/\partial Y^2)/(\partial V/\partial Y) = 3$ 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 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).
2.3.1 Adoption without Transaction Costs in Output Markets

I first study the case where market participation does not incur transaction costs, as is the case in standard models of technology adoption. For this case I plot household market participation and compensating variation as a function of endowments of financial and land wealth in figure 1.

Graph 1a shows expected market participation when households believe the production technology has low yields such that no households adopt the technology. The partition between households that buy staples and households that sell staples is defined by the set of endowment duplets that make the household indifferent between buying and selling, that is endowments that satisfy \( \frac{\partial u}{\partial n_c} / \frac{\partial u}{\partial n} = p_c \) from (8). Above the partition, households have high financial wealth relative to land wealth so that they buy staples. Below the partition, households have low financial wealth relative to land wealth such that they sell staples. Since no households would adopt the technology in this case, compensating variation is positive for all households as shown in graph 1b. Compensating variation decreases with land wealth because applying the technology on more land offsets more of the fixed costs of technology adoption. Compensating variation does not vary with market participation itself because output market participation does not incur transaction costs in this case.

Graph 1c shows expected market participation when households believe the production technology has high yields. The dashed line indicates that the increase in expected yield induces some households to adopt the technology such that they transition from not adopting and buying staples to adopting and being autarkic with respect to staple markets. Compensating variation is negative for these households, as shown in graph 1d. Even with high expected yield gains from technology adoption, two groups of households would be worse off when adopting the technology \((\text{CV} > 0)\). 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.
Figure 1: Adoption-marketing regimes with no transaction costs in output markets

**Market participation**

1a. Pre-intervention:
Low expected yield

\[ \text{Initial wealth} \]

1b. Pre-intervention:
Low expected yield

\[ \text{Initial wealth} \]

1c. Post-intervention:
High expected yield

\[ \text{Initial wealth} \]

1d. Post-intervention:
High expected yield

\[ \text{Initial wealth} \]

Notes: \( M(\alpha_L) \) is market participation with a low expected yield gain from technology adoption. \( M(\alpha_H) \) is market participation with a high expected yield gain from technology adoption. \( M(\alpha)<0 \) for buyer households; \( M(\alpha)=0 \) for autarkic households; \( M(\alpha)>0 \) for seller households. Initial wealth and compensating variation measured in 2015 Kenyan shillings (about 100 shillings per US dollar).
even when applying the technology on all of their land; for these households, $\mu_i \geq 0$ in (12). Compensating variation does not vary with market participation itself because output market participation does not incur transaction costs in this case.

2.3.2 Adoption with Transaction Costs in Output Markets

I now study technology adoption and market participation when buying and selling in staple output markets incurs transaction costs. 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. I estimate the proportional costs of transacting in staple markets using data from the randomized control trial, and find the buying price of maize is about 25 percent greater than the selling price of maize during the period with most maize transactions. Given these costs, I plot household technology adoption and expected market participation as a function of endowments of financial and land wealth in figure 2.

Graph 2a shows expected market participation when households believe the production technology has low yields such that no households adopt the technology. Households with high financial wealth relative to land wealth buy staples, households with low financial wealth relative to land wealth sell staples, and households in between are autarkic with respect to staple output markets. Since no households would adopt the technology in this case, compensating variation is positive for all households as shown in graph 2b. While compensating variation decreases with land wealth as before, compensating variation varies with market participation due to transaction costs when buying and selling staples. In particular, compensating variation is close to zero for households that are autarkic or on the margin between being autarkic and selling staples.

Graph 2c shows expected market participation when households believe the produc-

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3 Appendix A details the approach for estimating the price wedge between buying and selling prices for maize using my data.
Figure 2: Adoption-marketing regimes with transaction costs in output markets

Market participation

2a. Pre-intervention:
Low expected yield

\[ M(\alpha_{L}) < 0 \]

\[ M(\alpha_{L}) = 0 \]

\[ M(\alpha_{L}) > 0 \]

2b. Pre-intervention:
Low expected yield

2c. Post-intervention:
High expected yield

\[ M(\alpha_{L}) < 0 \]

\[ M(\alpha_{H}) < 0 \]

\[ M(\alpha_{L}) = 0 \]

\[ M(\alpha_{H}) = 0 \]

\[ M(\alpha_{L}) > 0, M(\alpha_{H}) > 0 \]

2d. Post-intervention:
High expected yield

Notes: \( M(\alpha_{L}) \) is market participation with a low expected yield gain from technology adoption. \( M(\alpha_{H}) \) is market participation with a high expected yield gain from technology adoption. \( M(\alpha) < 0 \) for buyer households; \( M(\alpha) = 0 \) for autarkic households; \( M(\alpha) > 0 \) for seller households. Initial wealth and compensating variation measured in 2015 Kenyan shillings (about 100 shillings per US dollar).
tion technology has high yields. The dashed lines indicate high yields induce some households to adopt the technology and change their market participation. In the top-left corner, some households transition 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. Compensating variation is negative for households adopting the production technology, as shown in graph 2d. Notably, compensating variation per unit land is most negative for households that would transition from not adopting and buying staples to adopting and being autarkic with respect to staple markets, as indicated by the dark blue region in graph 2d. Three types of households do not adopt the technology. The first two – households with little financial or land wealth – are similar to the benchmark case shown in graph 1d.4 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.

2.4 Summary of Results

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, as can be seen by comparing graphs 1a and 2a. This prediction reproduces a result from the literature on output market participation, and is central to the model’s

4But 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.
main prediction about the interdependence between technology adoption and market participation of agricultural households.

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, which would not be predicted by a model without transaction costs. First, the model predicts the technology is adopted by households that can transition from being buyers to autarkic with respect to staple output markets as well as those that can transaction from being autarkic to sellers; comparing graphs 2c and 2d shows this result. Second, the model predicts the technology is adopted by few households that would remain autarkic even with technology adoption, as can be seen by comparing graphs 1d and 2d.

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 randomized control trial conducted with a local seed company generated variation in information about productive hybrid maize varieties developed 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. 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 hybrids from Western Seed Company, as shown in figure 3. 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 control 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.

We collected data using 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. Figure 4 shows the timing of the randomized intervention relative to the recall periods for the household surveys.

For this analysis, the primary outcome of interest is whether or not the household planted hybrid maize varieties from Western Seed Company in the 2015 main season.

5The 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

Randomization
- Seed Control
  - 1 Site per Strata
- Seed Treatment
  - 1 Site per Strata

Random Sampling
- Sample
  - 50 Households per Site
  - Sample
  - 50 Households per Site

Site 1
Site 2
Strata 1
The explanatory variable of interest is household market participation. We collected data on maize sales for each season of the study period, including total quantity sold and the price received for the largest sale. We 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.

3.2 Participation in Maize Markets

Testing predictions from the theoretical model requires a measure of market participation without treatment. Since I do not observe such a measure for treatment households, I construct a measure using observations of market participation without treatment for control group households.

I define market participation of household $h$ in strata $p$ at time $t$ as an ordered outcome based on the household’s net marketed surplus of maize ($\text{maize marketed } m_{hpt}$ less maize bought $b_{hpt}$). As net marketed surplus increases, the household transitions

---

6I only observe maize bought in the final time period ($t = 3$). For the other periods I replace maize bought
from being a net buyer, to an autarkic, to a net seller household with respect to maize markets:

\[
\text{MP}_{hpt} \equiv \begin{cases} 
1 & \text{if } m_{hpt} - b_{hpt} < 0 \\
2 & \text{if } m_{hpt} - b_{hpt} = 0 \\
3 & \text{if } m_{hpt} - b_{hpt} > 0 
\end{cases}
\]

(13) In the data we observe market participation for a given household often varies from year to year. Among control group households, 28 percent are net buyers in each of the three years of the study and 13 percent are net buyers in two of the three years of the study; 13 percent are net sellers in each of the three years and 19 percent are net sellers in two of the three years. The remaining 27 percent of households are approximately autarkic, as their market participation behavior is not dominated by either buying or selling.

I assume observed market participation is determined by latent market participation \( \text{MP}^*_h \). I assume the model for latent market participation of household \( h \) in strata \( p \) at time \( t \) is

\[
(14) \quad \text{MP}^*_h = \psi_{pt} + T_{hp1} \psi_{T_{pt}} + L_{hp1} \psi_{L_{pt}} + T_{hp1} L_{hp1} \psi_{TL_{pt}} + U_{hpt}
\]

where \( T_{hp1} \) is maize acres at baseline, \( L_{hp1} \) is household size at baseline, and \( U_{hpt} \) is an error term. \( \psi_{pt} \) is a location-time-specific effect, \( \psi_{T_{pt}} \) is the effect of the household land endowment on market participation that varies by location and time period, \( \psi_{L_{pt}} \) is the effect of household characteristics on market participation that varies by location and time period, \( \psi_{TL_{pt}} \) is the interaction effect of household land endowment and characteristics on market participation that varies by location and time period. I estimate with maize bought in a typical period (\( b_{hpt} = b_{hp}, \forall t \in \{1, 2\} \)).
(14) by maximum likelihood assuming an ordered probit model.  

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 overfit predictions. Overfitting control household observations would result in endogenous stratification whereby treatment effect estimates based on these predictions would be biased (Abadie et al. 2014). To avoid over-fitting 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.

Since time is a predictor of market participation in (14), predicted market participation can vary from year to year for a given household, just as we observe among households in the control group. I group households by their distribution of predicted market participation across years. I define a household predicted to be a net buyer in all years a “deep buyer”, and a household predicted to be a net buyer in most years a “shallow buyer” that may transition into autarky by increasing their maize production. Similarly, I define a household predicted to be a net seller in all years a “deep seller”, and households predicted to be a net seller in most years a “shallow sellers” that may transition into selling by increasing their maize production. I define the remaining households as autarkic households.

Appendix B details the estimation approach.
4 Technology Adoption by Market Participation

The theoretical model predicts technology adoption varies with expected market participation. I test these predictions using data from the randomized control trial in western Kenya. First, I estimate how the effect of the information intervention on technology adoption varies with expected market participation when not controlling for other household characteristics. These estimates tell us the potential for increasing 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 that were held constant in the theoretical model.

For each set of estimates, I use two proxies for expected market participation. First, I proxy for expected market participation using observed market participation at baseline as measured by net marketed surplus ($MP_{hp1}$). For this proxy, I define market participation groups 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 described in the previous sub-section. Although realized market participation in a single year may misrepresent a household’s expected market participation, this cross-sectional data may be similar to the information available to programs for applying targeting criteria for technology adoption programs. Second, I proxy for expected market participation using predicted market participation ($\hat{MP}_{hpt}$) as defined in the previous sub-section. Predicted market participation is my preferred proxy since it is more closely linked to the concept of the household’s expected market participation in the theoretical model.

---

8For example, 13 percent of control group households are net sellers each year. The proxy indicator for this group equals one for the top 13 percent of sellers at baseline, which includes all households with at least 450 kilograms of maize sold.
4.1 Effects of Targeting Technologies by Market Participation

For programs targeting technology adoption interventions, a first step for determining the optimal targeting strategy would be estimating differences in adoption rates across households. In this sub-section I estimate how a household’s expected market participation without technology adoption predicts the impacts of a technology adoption program, which I call the targeting effect of market participation on technology adoption.

I model adoption of Western Seed Company hybrid maize varieties in 2015 as a linear function of expected market participation and its interaction with randomly assigned information about the varieties. The model for household $h$ in village $v$ and strata $p$ is

$$a_{hvp} = \mu^t_p + m_{hvp} \gamma^t + d_{vp} m_{hvp} \eta^t + \epsilon_{hvp}$$

where $a_{hvp}$ is technology adoption (1 for adopters, 0 otherwise), $\mu^t_p$ is a strata fixed effect, $m_{hvp}$ is a vector of indicators of expected market participation without treatment, and $d_{vp}$ is random assignment to receive the seed information (1 if assigned, 0 otherwise).\(^9\)

The vector $\eta^t$ contains the parameters of interest: the effect of the information intervention on adoption for households with a given expected market participation. Note that (15) does not control for household characteristics. Allowing household characteristics to vary with expected market participation is analogous to a technology adoption program targeting households on certain criteria without being able to hold constant other household characteristics. In this way, estimates of $\eta^t$ give the expected effect on technology adoption of targeting a household in a given expected market participation group. This targeting effect is not the marginal effect of being in a given market participation group, since other household characteristics can vary with market participation,

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\(^9\)The main effect of random assignment is absorbed by the interaction between random assignment and expected market participation.
let alone a causal effect of market participation.

Table 3, column 1 shows estimates of (15) when proxying for expected market participation with observed market participation at baseline; estimates of $\eta_{te}$ are listed under the heading “Interaction effects”. All market participation groups have large increases in adoption due to the information program, and all but one of these estimates is different from zero with statistical significance. Parameters are not estimated precisely enough to reject a null hypothesis of equality of interaction effects. Yet it is still useful to compare differences in parameter estimates for each group given the theoretical model’s predictions and the potential implications for targeting technology adoption programs. The information intervention had the largest effect on adoption for deep seller households selling at least 450 kilograms of maize, increasing adoption by 24 percentage points. The information intervention had the next largest effect for shallow seller households selling less than 450 kilograms of maize, increasing adoption by 19 percentage points. The information intervention had the smallest effect on adoption for autarkic households, increasing adoption by 12 percentage points.

Table 3, column 2 shows estimates of (15) when proxying for expected market participation with predicted market participation. Since these estimates use a predicted variable as a dependent variable, I use bootstrap estimates of the standard deviation of the parameter estimates. As before, the information intervention increases adoption for all market participation groups but the effects are imprecisely estimated. The information intervention increases adoption most for shallow sellers that expect to be net sellers in most but not all years, increasing adoption by 22 percentage points. Since these are the households that are most likely to transition into selling in all years with technology adoption, the large effect for this group is consistent with the theoretical model’s prediction that adoption incentives are large for households that can change their market participation as a result of technology adoption.

While the information program increased technology adoption more for some mar-
Table 3: Technology adoption by market participation (N=1086)

<table>
<thead>
<tr>
<th></th>
<th>Targeting (1)</th>
<th>Targeting (2)</th>
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<th>Marginal (4)</th>
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<td>Interaction effects</td>
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<td>0.17***</td>
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<td>(0.08)</td>
<td>(0.04)</td>
<td>(0.10)</td>
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<td>0.22***</td>
<td>0.12</td>
<td>0.24**</td>
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<td>(0.05)</td>
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<td>Autarkic</td>
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<td>0.16*</td>
<td>0.06</td>
<td>0.16</td>
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<td>(0.04)</td>
<td>(0.08)</td>
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<td>(0.09)</td>
</tr>
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<td>Buyer - Shallow</td>
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<td>0.17***</td>
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<td>(0.04)</td>
<td>(0.09)</td>
<td>(0.08)</td>
</tr>
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<td>0.14**</td>
<td>0.08</td>
<td>0.12</td>
</tr>
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<td>(0.08)</td>
<td>(0.05)</td>
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<tr>
<td>Other controls</td>
<td>No</td>
<td>No</td>
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<td>Yes</td>
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</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 71 villages;
standard errors (2) and (4) are bootstrapped.
Significance: * = 10%, ** = 5%, *** = 1%
ket participation groups than for others, all groups had large increases in adoption due to the information program. This is an important finding given the theoretical model’s result that welfare effects of technology adoption are greatest for households that can transition from not adopting the technology and buying staples to adopting the technology and being autarkic with respect to staple markets. While buyers did not have the largest increase in adoption due to the technology adoption program, their large increase in adoption may have large impacts on their household welfare. These findings from the theoretical and empirical analysis suggest some tension between targeting buyers who may have large welfare gains from technology adoption and targeting sellers with somewhat larger increases in adoption due to the technology adoption program.

4.2 Marginal Effects of Market Participation on Technology Adoption

The prediction that technology adoption varies with expected market participation comes from a theoretical model that assumes households are identical in all ways other than their endowments of financial and land wealth. To test the theoretical model’s predictions more directly, I estimate the marginal effects of market participation on technology adoption by controlling for household characteristics and their interactions with the information intervention.

I model adoption of Western Seed hybrid maize varieties in 2015 as a linear function of baseline household characteristics and their interactions with randomly assigned information about the varieties. The model for household h in village v and strata p is

\[
\alpha_{hvp} = \mu_p^{me} + m_{hvp}' \gamma^{me} + d_v m_{hvp}' \eta^{me} + x_{hvp}' \theta^{me} + d_v x_{hvp}' \beta^{me} + \epsilon_{hvp}^{me}
\]

where \( x_{hvp} \) is a column vector of control variables and all other variables are defined
as in (15). The vector $\eta^{me}$ contains the parameters of interest: the difference in adoption due to the information intervention for households with a given expected market participation, controlling for household characteristics.

Table 3, column 3 shows estimates of (16) when proxying for expected market participation with observed market participation at baseline. Controlling for household characteristics gives marginal effect estimates of market participation that are smaller in magnitude and less precisely estimated than targeting effect estimates of market participation (column 1). But differences in marginal effect estimates between expected market participation groups are similar in magnitude to differences in targeting effect estimates. This finding suggests market participation is not simply a proxy for propensity for technology adoption, but is itself a predictor of technology adoption. In particular, being a deep seller appears to be a predictor of technology adoption rather than a proxy for propensity to adopt.

Table 3, column 4 shows estimates of (16) when proxying for expected market participation with predicted market participation. As with the other proxy, adding control variables reduces the magnitude of the point estimates while increasing the standard errors of these estimates. But controlling for household characteristics does not change the pattern in differences in adoption between these groups in terms of either adoption in the control group or interactions with assignment to seed information and access. In particular, being a shallow seller seems to be a predictor of technology adoption rather than a proxy for propensity to adopt. This finding is consistent with the theoretical model’s prediction that adoption incentives are large for households that can change their market participation as a result of technology adoption.

The control variables proxy are 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 ex ante expectation is that each is positively correlated with both adoption of hybrids and selling maize.
5 Conclusion

To stimulate sustained technology adoption and productivity growth in agriculture, many governments in sub-Saharan Africa 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. This paper studies how adoption of production technologies and its welfare impacts relate to a common criterion for targeting subsidies to agricultural households: producing surplus food to sell on the market.

I study how incentives for technology adoption differ across households by developing a theoretical model of technology adoption when buying and selling food incurs transaction costs. The model shows that when market participation is costly, households value technology adoption not just as an income source but also as a means of either reducing costs of buying staples or overcoming costs of selling staples. Welfare gains from technology adoption are greatest for households that can transition out of buying staples or transition into selling staples with technology adoption. A prediction stemming from this result is 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.

I test the theoretical model’s predictions of how technology adoption varies with expected market participation using data from a randomized control trial of information about high-yielding maize varieties developed for western Kenya, where the main staple is maize. Consistent with the theory, adoption of the high-yielding maize varieties is greatest among households that can transition into selling maize. This result holds when controlling for potential confounding factors. The findings suggest that market participation is not simply a proxy for propensity to adopt new technologies, but that market participation itself is a predictor of technology adoption.

The findings in this paper inform targeting of development programs, especially
agricultural programs targeted by participation in output markets for staples. Technology adoption is positive and non-trivial for all market participation groups and the theoretical analysis shows the largest welfare impacts of technology adoption are for households that typically buy staples from the market. Yet these households would be excluded from input subsidy programs targeting relatively wealthy households that produce a food surplus to sell on the market. Given the nuance of technology adoption decisions, mechanisms other than targeting may allocate technologies more effectively and equitably. In particular subsidy levels may ration technology adoption more effectively than targeting based on land wealth or other household characteristics in the contexts of agricultural input subsidy programs in Africa.
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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 in western Kenya.

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>
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<th>Main Rains</th>
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<th>Jul</th>
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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

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

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 strata 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 4 shows estimates of (17) 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 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
### Table 4: Village prices by season, market, and treatment

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366 village-season-market observations (66 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.
test whether community assignment to receive information about the hybrids affects prices, I estimate

\[
\text{price}_{vpt} = \sum_{q=1}^{P} \mathbf{1}(p = q)\phi_q^0 + \text{buy}^0 + \sum_{s=2}^{3} \left\{ \mathbf{1}(t = s) \cdot (\lambda_s^0 + \text{buy}^0) \right\} + \\
+ d_v \cdot \left[ \phi^1 + \text{buy}^1 + \sum_{s=2}^{3} \left\{ \mathbf{1}(t = s) \cdot (\lambda_s^1 + \text{buy}^1) \right\} \right] + \text{error}_p
\]

where \( d_v = 1 \) for households in the seed treatment communities (0 otherwise). Parameters with the superscript \(^0\) have the same interpretation as in (17) 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 4 shows estimates of (18) 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 \( v \)

\[
\text{price}_v = \sum_{q=1}^{C} \mathbf{1} (\text{cluster} = q)\phi_q + \sum_{r=2}^{3} \mathbf{1} (\text{year} = r)\xi_r + \sum_{s=2}^{12} \mathbf{1} (\text{month} = s)\zeta_s + \text{error}_v
\]

where \( \phi_q \) 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 confi-
idence 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 market conditions in the empirical setting approximate the theoretical model’s assumptions.
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.
Appendix B: Predicting Market Participation

Since market participation is an ordered outcome in (13), I model it using a general approach for ordered outcome variables. The model of observed market participation is

\begin{equation}
MP_{hpt} \equiv \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}
\end{equation}

where $MP^*_hpt$ is defined by (14), $\alpha_1$ 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

\begin{equation}
\Pr(MP_{hpt} = 1) = F\left(\alpha_1 - \left[MP^*_hpt(\psi) - U_{hpt}\right]\right)
\end{equation}

\begin{equation}
\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)
\end{equation}

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

where $F$ is the cumulative distribution function of $U_{hpt}$. Then I estimate parameters $(\psi, \alpha)$ that, subject to (14) and (13)-(21), 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 | \psi, \alpha) \right)
\end{equation}