Agricultural Technology Adoption and Staple Price Risk in Kenya

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Abstract

Agricultural development is often proposed as an approach to reduce rural poverty in less developed countries, yet many agricultural development interventions exclude poor farmers if they are are expected to be less responsive to interventions. I study whether land poor agricultural households will respond more than wealthier households to an intervention that increases production of staple foods due to its effect on household exposure to staple price risk. The empirical setting is a randomized control trial in western Kenya in which farmers were randomly assigned to receive inorganic fertilizer and access to hybrid seeds for maize, the staple food. Control group farmers produce less maize than they consume and face price risk as buyers of maize on average. Treatment decreases exposure to price risk among land poor households on average. Policymakers underestimate the willingness of land poor households to adopt agricultural technologies when they do not account for the role of price risk in household decision-making.

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Agricultural development is often proposed as an approach to reduce rural poverty in less developed countries, yet the poor are excluded from many agricultural development interventions. The paradox arises from the perception that an intervention's effectiveness decreases as it targets poorer households. For example, agricultural development in sub-Saharan Africa is increasingly supported by government subsidies for yield-increasing seeds and fertilizers for farmers to produce staple grains. Yet the potential of these programs to reduce poverty is diminished if they target subsidies to wealthier farmers perceived to be most willing to adopt the subsidized technologies.

The prevailing perception that an intervention's effectiveness decreases as it targets poorer households demands economic scrutiny. Consider subsidies for yield-increasing seeds and fertilizers that aim to increase technology adoption. If the direct effect of subsidies on household welfare mainly comes from increasing grain harvests, changes in household grain management due to these production technologies may factor into households' agricultural technology adoption decisions. Since technology adoption decisions are taken when grain prices are unknown, net buyers of grain have an added incentive to increase production to avoid price risk as buyers of grain while net sellers of grain have a reduced incentive to increase production since it will increase their exposure to price risk [Barrett, 1996, Bellemare et al., 2013, Finkelshtain and Chalfant, 1991, 1997]. Thus targeting poorer households that are more likely to face price risk as a buyer of maize may yield a multiplier effect on household welfare by both increasing income and decreasing exposure to price risk that they would face as buyers of maize. Policymakers may underestimate the willingness of land poor households to adopt agricultural technologies when they do not account for the role of price risk in household decision-making.

I study the role of maize price risk in adoption of maize production technologies in western Kenya. The study setting is a randomized control trial where randomized treatments include provision of high quality inorganic fertilizer and the opportunity to buy high-yielding hybrid seeds. Treatments decrease the proportion of households buying maize and increase the proportion of households selling maize. Households expected to buy less maize after receiving the technology adoption treatment, suggesting that maize production decisions may be affected by their potential to change household participation in maize markets. The treatment effect on household exposure to maize price risk is consistent with technology adoption decreasing exposure to maize price risk for households with smaller farm sizes and increasing exposure to maize price risk for households with larger farm sizes.

My empirical approach builds on methodologies from the literature on decision-making of agricultural households facing price risk [Barrett, 1996, Bellemare et al., 2013, Finkelshtain and Chalfant, 1991]. The measure of household exposure to price risk is household willingness to pay to stabilize the price of maize grain, which is a product of the household's coefficient of absolute price risk aversion and the variance of local maize prices.

The research contributes to two debates in the agricultural development field. First, a broad discussion about what socioeconomic impacts to expect from agricultural technology adoption largely focuses on two extremes, with profitability for risk-neutral households on the one hand and food security of risk-averse households on the other. I argue instead that households are distributed across this spectrum according to their ability to draw on their endowments to cope with stochastic shocks. Thus profitability may be a relevant adoption criterion for some households but not others. I focus on two main impacts of technology adoption for staple food production: 1) increased income (due to greater profitability) and 2) decreased price risk aversion.

These insights contribute to a second debate over what types of farmers should be targeted by interventions to promote agricultural technology adoption for staple food production. Targeting poorer households that are more likely to face price risk as a buyer of maize may yield a multiplier effect on household welfare by both increasing income and decreasing exposure to price risk that they would face as buyers of maize. If households anticipate these effects, poorer households may factor price risk into their adoption decision and thereby value adoption more than wealthier farmers.

I begin with a theoretical model of technology adoption by an agricultural household with preferences over price risk (section 1). I estimate a measure of willingness to pay to stabilize the price of a staple grain using data from a randomized control trial in western Kenya along with supplementary panel data from the region (section 2). In the main study sample, technology adoption and grain purchases decrease with farm size while grain sales increase with farm size (section 3). Control group farmers tend to produce less maize than they consume and face price risk as buyers of maize. Technology adoption treatments decrease household exposure to price risk, especially among land poor households. Price risk appears to motivate technology adoption by land poor farmers (section 4).

1 A Technology Adoption Model with Price Risk

I study an agricultural household that chooses its production and consumption to maximize utility from consuming a bundle of goods, with a subset of goods both produced and consumed by the household. Technology adoption and production decisions for staple food crops that agricultural households both produce and consume depend on price risk. When price risk is present, production and willingness to pay to stabilize the price of the staple depends on whether the agricultural household is a net seller or buyer of the staple [Finkelshtain and Chalfant, 1991].

I focus on the effect of price risk on production of a single crop by building on the household model developed by Barrett. My model formalizes the idea that price risk may encourage technology adoption for households that would be net buyers of staple goods without technology adoption and deter technology adoption for households that would be net sellers of staple goods without technology adoption. The link between theory and empirics is a measure of household willingness to pay to stabilize the price of the staple, which is derived from the theoretical model following Bellemare et al. The willingness to pay measure from my model is simply a proxy for household exposure to price risk and should not be thought of as a valuation of an actual price stabilization policy, which is the focus of Bellemare et al.

Consider an agricultural household's problem of choosing whether to adopt an agricultural technology in the planting season, observing the staple price, and then choosing consumption during the harvest season. Since the staple price is unknown at the time of the planting decision but known at the time of the harvest season consumption decision, the problem is characterized by temporal uncertainty (Chavas and Larson). Solving the problem recursively, households adopt the technology based on its expected impact on household income and marketed surplus. The household problem is represented as a picture in figure 1.

1.1 The Agricultural Household Model

Assume the household objective in the harvest season is to maximize expected utility from consuming a staple consumption good q_c and a non-staple composite good q_n. For each good, marginal utility of consumption is strictly positive at all consumption levels, strictly decreases with consumption, and approaches infinity as consumption of that good approaches zero. Let the harvest season prices for staple consumption good be p_c and the price of the non-staple composite good be p_n.

In the planting season the household chooses whether to adopt a production technology x. The production process is represented by a function $f(x,T)$ that is stepwise and increasing in the production technology and linear and increasing in farm size T.

The household input investment and staple consumption problem can be represented by the following model.

$$\max_{x\epsilon\{0,1\}} E_{p_c}\left\{\max_{q_c,q_n\geq 0} u(q_c,q_n)\right\} \tag{1}$$

subject to

$$p_n q_n + p_c q_c \leq y^*$$

$$y^* \equiv p_c f(x,T) + I + Z - P_x x$$

$$0 \leq Z - P_x x$$

where $E_{p_c}\left\{.\right\}$ is the operator for taking expectations with respect to the stochastic staple price, y^* is full household income, I is exogenous income in the harvest season, and Z is exogenous income in the planting season.

1.1.1 The Harvest Season Consumption Problem

I begin the analysis by defining harvest season utility conditional on the realized staple price and technology adoption determined in the previous planting season. The household's indirect utility function is

$$V(p, y|x) \equiv \max_{q_c, q_n \geq 0} u(q_c, q_n)$$

$$subject\ to$$

$$q_n + p[q_c - f(x, T)] = i + z - p_x x$$

where prices and income are normalized by the price of the non-staple good.

1.1.2 The Planting Season Technology Adoption Problem

(1) can be represented with the indirect utility function from the harvest season consumption problem, following Barrett, as shown below.

$$\max_{x \epsilon \{0,1\}} E_p \Big\{ V(p, y|x) \Big\} \tag{2}$$

subject to

$$y \equiv pf(x, T) + i + z - p_x x$$

$$0 \leq z - p_x x$$

where $E_p\left\{.\right\}$ is the operator for taking expectations over the normalized staple price. The household solves (2) by adopting the technology if the expected utility from adopting exceeds the expected utility from not adopting:

$$E_p\left\{V(p, y|x = 1)\right\} > E_p\left\{V(p, y|x = 0)\right\} \tag{3}$$

1.2 Technology Adoption and Staple Price Risk

I isolate the role of price risk in the technology adoption decision by expressing household indirect utility as a function of income and willingness to pay to stabilize the price of the staple WTP, following Bellemare et al. I implicitly define willingness to pay conditional on the technology adoption decision with the expression

$$E_p\left\{V(p, y|x)\right\} \equiv V(\mu, y - WTP|x) \tag{4}$$

where y is exogenous income that is uncorrelated with stochastic prices and μ is the mean price. I approximate the righthandside of (4) with a first-order Taylor series expansion

$$V(\mu, y - WTP|x) \approx V(\mu, y|x) - V_y(\mu, y|x)WTP|_x \tag{5}$$

where V_y is the partial derivative of the indirect utility function with respect to income and willingness to pay is conditional on the technology adoption decision.

Price risk explicitly enters the technology adoption decision by replacing each side of inequality (3) with the corresponding approximation from the righthandside of (5). The household adopts the technology if:

$$V(\mu, y|x=1) - V_y(\mu, y|x=1)WTP|_{x=1} > V(\mu, y|x=0) - V_y(\mu, y|x=0)WTP|_{x=0}$$

Rearranging terms gives the technology adoption condition

$$[V(\mu, y|x=1) - V(\mu, y|x=0)] + V_y(\mu, y|x=0)[WTP|_{x=0} - \gamma WTP|_{x=1}] > 0 \quad (6)$$

where $\gamma \equiv {}^{V_y(\mu,y|x=1)}/_{V_y(\mu,y|x=0)} > 0$ is positive and weakly less than 1 assuming marginal utility from income is weakly decreasing with technology adoption.

The first term in (6) represents technology adoption's welfare effects in a world without price risk. The second term represents technology adoption's welfare effects due to its effect on household exposure to price risk. The remainder of the sub-section shows that the second term is positive for land poor households and negative for land rich households when price risk exists.

1.2.1 An Economic Interpretation of the Willingness to Pay Measure

I approximate willingness to pay to stabilize the price of the staple by approximating both sides of (4) with Taylor series expansions, following Bellemare et al.

$$WTP = -\frac{1}{2}\sigma \frac{V_{pp}(\mu, y)}{V_y(\mu, y)} \quad (7)$$

is the approximation where σ is the variance of the staple price. If price risk exists, the household's willingness to pay to stabilize the price of the staple depends on the curvature of its indirect utility function with respect to prices and income. In particular, willingness to pay to stabilize the price of staple depends on the household's coefficient of absolute price risk aversion derived by Barrett, Bellemare et al.

$$A(p,y) \equiv -\frac{V_{pp}(p,y)}{V_y(p,y)} \tag{8}$$

$$A(p,y) = -\frac{m(p,y)}{p}[\beta(p,y)[\eta(p,y) - R] + \epsilon(p,y)]$$

is the coefficient of absolute price risk aversion where $\beta(p,y)$ is the budget share of net marketed surplus, R is the Arrow-Pratt coefficient of relative income risk aversion, $\eta(p,y)$ is the elasticity of net marketed surplus with respect to income, and $\epsilon(p,y)$ is the elasticity of net marketed surplus with respect to price.[1]

To interpret the economic components of willingness to pay to stabilize the price of the staple, I re-write (8) in the form of a Slutsky equation:

$$A(p,y) = \frac{m(p,y)}{p}\beta(p,y)[R - \eta(p,y)] - \frac{m(p,y)}{p}\epsilon(p,y)$$

The first term is the effect of income on price risk aversion and the second term is the effect of substitution between net marketed surplus and consumption of the staple on price risk aversion. Constant elasticities of net marketed surplus with respect to income and prices imply that the income effect is quadratic in net marketed surplus and the substitution effect is linear in net marketed surplus. If net marketed surplus is inelastic with respect to income relative to the coefficient of relative income risk aversion, an income increase decreases the budget share of net marketed surplus so that the income effect contributes to price risk aversion for both net buyers and net sellers of the staple. If the staple is an ordinary good, a price increase leads net buyers of the staple to substitute away from price risk by decreasing purchases and

[1] $\beta(p,y) = {}^{pm(p,y)}/_{y}$; $R = {}^{-yV_{yy}(p,y)}/_{V_y(p,y)}$; $\eta(p,y) = \frac{\partial m(p,y)}{\partial y}\frac{y}{m(p,y)}$; $\epsilon(p,y) = \frac{\partial m(p,y)}{\partial p}\frac{p}{m(p,y)}$.

net sellers of the staple to substitute toward price risk by increasing sales.

1.2.2 Technology Adoption's Effect on Exposure to Staple Price Risk

(6), (7), and (8) lead to 2 sufficient conditions for signing technology adoption's welfare effects due to its effect on household exposure to price risk.

1. If willingness to pay to stabilize the staple price is non-negative without technology adoption and decreases with technology adoption, then technology adoption's effect on household exposure to price risk has a positive welfare effect.

2. If willingness to pay to stabilize the staple price is non-positive without technology adoption and increases with technology adoption, then technology adoption's effect on household exposure to price risk has a negative welfare effect.

Figure 2 on page 22 illustrates these conditions. The vertical axis is willingness to pay to stabilize the staple price as a percent of income and the horizontal axis is farm size in acres. In this illustration, households can be categorized into three groups based on technology adoption's welfare effects due to its effect on household exposure to price risk. Households with a farm size smaller than T1 have a positive willingness to pay without technology adoption that decreases with technology adoption so that condition 1 holds. Households with farm sizes between T1 and T2 have a negative willingness to pay without technology adoption that increases with technology adoption so that condition 2 holds. Households with farm sizes greater than T2 satisfy neither of the sufficient conditions for signing technology adoption's welfare effects due to its effect on household exposure to price risk.

2 Empirical Framework and Data

The main empirical analysis estimates the effect of technology adoption on willingness to pay to stabilize the staple price. The first step of the analysis estimates coefficients of absolute price risk aversion. The second step uses these estimates to construct willingness to pay measures and estimates how it varies with technology adoption.

2.1 Empirical Framework

Constructing a coefficient of absolute price risk aversion at the household-level requires 6 variables. Three of these variables can be observed directly: price, net marketed surplus, and net marketed surplus's share of household income. I use cross-sectional observations of these variables from data collected as part of the Western Seed Company impact evaluation, which is described in subsubsection 2.2.1 on the next page.

A fourth variable's value must be assumed: the Arrow-Pratt coefficient of relative income risk aversion. Barrett assumes this coefficient is in the range of 1.5 to 2.5 whereas Bellemare et al. assume the coefficient equals 1. I adopt $R = 1$.

The remaining 2 variables can be estimated from data: elasticities of net marketed surplus with respect to income and price. In the theoretical model, income and price variables are annual measures so that the relevant elasticities must be identified by year-to-year variation (Bellemare et al.). I estimate the elasticities from panel data from western Kenya using the following reduced form marketed surplus function for farmer i in district d in year t :

$$m_{idt} = \eta y_{idt} + \epsilon p_{idt} + \gamma_i + \alpha_{dt} + u_{idt} \tag{9}$$

where m_{idt} is net marketed surplus, y_{idt} is household income, p_{idt} is the staple price, γ_i is a household fixed effect, α_{dt} is a district-year fixed effect, and u_{idt} is an error term. To estimate elasticities, I transform net marketed surplus, household income, and price by the inverse hyperbolic sine transformation.

2.2 Data

My empirical framework requires cross-sectional and panel data. I construct willingness to pay to stabilize the price of the staple for cross-sectional observations from a randomized control trial in western Kenya using elasticities estimated from panel data from the same area and collected by the same Kenyan research institute.

2.2.1 Western Seed Company Impact Evaluation

The Western Seed Company impact evaluation collected data on agricultural households in Kenya in 2013, 2015, and 2016. The evaluation was conducted in central and western Kenya by the Tegemeo Institute and the University of California at Davis. Surveys coincided with a randomized control trial that was stratified with 600 households in central Kenya and 1200 households in western Kenya. Households are mapped in figure 3 on page 23 with circles indicating clusters of 50 study households. I study only the western sub-sample, where randomized interventions were a seed information treatment and a fertilizer treatment.

The information treatment in year one was randomly assigned to half of the sampled clusters. The treatment was assigned through pair-wise cluster randomization with one cluster per pair randomly assigned to the information treatment. In treated clusters, study households received a 250 gram sample pack of hybrid maize seed from

Western Seed Company in order to test the seeds on-farm. Sample packs were very small – enough for planting 0.025 acres, compared with a sample median of 1.000 acres planted with maize at baseline – and was not expected to affect household income in year one. The aim of this intervention was to encourage farmers to purchase seed in year two when the seed would be sold by local retailers for the first time.

The fertilizer treatment in year two was randomly assigned to half of the households in each cluster. Treated households received a 50 kilogram bag of fertilizer customized to local soil quality in order to relax liquidity constraints and encourage adoption of complementary hybrid maize seeds. The treatment was randomly assigned at the farmer level and stratified by cluster so that half of the farmers who received the information treatment received the fertilizer treatment as well and half of the farmer who did not receive the information treatment received the fertilizer treatment.

Surveys collected pre-treatment baseline data in 2013, midline impacts in 2015, and endline impacts in 2016. Impacts were due to the initial information and fertilizer interventions as well as a seed delivery program to information treatment clusters to encourage uptake of Western Seed Company hybrid maize seed. The timeline of events is illustrated in figure 4 on page 24.

The timeline of events relative to outcomes of interest is illustrated in figure 5 on page 25. My analysis uses data on harvests and utilization of harvests, which are collected for each field cultivated by each household in the sample; fields are defined as contiguous areas under the same crop mix in a given season. For each field, farmers use common units to report harvest, consumption, sales, and post-harvest losses for maize grain. I convert these quantities to kilograms using crop-unit conversion factors from the Tegemeo Institute. For fields from which some of the harvest was sold, farmers also report the following for the largest sale from that field's harvest: a) quantity, b) month of sale, c) buyer, and d) unit value or total value received. Maize sales are common in September/October after the main rains and in January/February after the short rains, as shown in figure 6 on page 26.

I collected data on purchases of maize grain/meal for home consumption at endline to determine the household's status as a net buyer or seller of maize. Time periods covered by the purchases module follow the technology adoption treatments and therefore would reflect impacts of treatments on staple purchases. Time periods were defined as four-month periods as in the long-running panel survey for the Tegemeo Agricultural Policy Research and Analysis Project conducted with rural Kenyan households by the Tegemeo Institute and Michigan State University, which is described in greater detail in subsubsection 2.2.2.

I construct income measures for the period from June through January given the available data. Household income is the sum of net salary and business income and gross agricultural, livestock product, and milk income less the costs of seeds, fertilizers, other agricultural inputs, land preparation, and hired labor on the main maize field in the main season.

2.2.2 Tegemeo Agricultural Policy Research and Analysis Project (TAPRA)

I use panel data to estimate marketed surplus equation (9) with household-level fixed effects using data from the Tegemeo Agricultural Policy Research and Analysis Project (TAPRA). TAPRA is a four-round panel household survey of a representative sample of Kenyan farm households in 2000, 2004, 2007 and 2010 by the Tegemeo Institute and Michigan State University. I use TAPRA data collected in 2004, 2007, and 2010, which were the only years when purchase prices were collected in the farm household survey. I estimate (9) using data from the sub-sample of households in the former provinces of Nyanza and Western, which overlap geographically with the

Western Seed Company impact evaluation study sample in western Kenya. In these areas 536 households were surveyed in more than one survey out of the three surveys conducted in 2004, 2007, and 2010.

2.2.3 Food and Agriculture Organization of the United Nations Data

A final variable needed to estimate willingness to pay to stabilize the price of maize is the variance of maize prices in Kenya. I use annual data from the Food and Agriculture Organization of the United Nations to estimate the variance of maize prices in Kenya. Nominal annual producer prices for maize in Kenyan shillings per ton are available for 1991-2015. I convert these prices to Kenyan shillings per kilogram. A monthly consumer price index for Kenya is available for 2000-2015. I average the consumer price index across months for each year and divide the consumer price index for all years by the 2015 value to create a consumer price index factor relative to 2015. For years 2000-2015 I divide the annual maize price in Kenyan shillings per kilogram by the annual average consumer price index factor relative to 2015 to obtain annual maize prices in 2015 values.

3 Empirical Results

I begin by presenting descriptive results on the relationship between market participation, technology adoption, and farm size. The empirical probability of buying dry maize decreases with farm size while the empirical probability of selling dry maize increases with farm size, as shown in figure 7 on page 27. Past use of hybrid maize seed (figure 8) and inorganic fertilizer (figure 9) both increase with farm size. Thus the market participation and farm size relationships are consistent with extensive production as well as intensive production increasing with farm size.

While the seed treatment increased adoption of Western Seed maize hybrids, adoption does not vary with farm size at midline (figure 10) but increases with farm size at endline (figure 11). Inorganic fertilizer use on maize decreases with farm size (figure 12), contradicting the conventional wisdom that households with high propensities for selling output are more likely to adopt new production technologies.

The household model represented as a picture in figure 1 suggests two links that must be established in order to conclude that price risk motivates technology adoption. First, technology adoption must change market participation, and households must expect this effect. Second, changes in market participation must affect household welfare through its exposure to price risk. The remainder of this section analyzes each of these relationships.

3.1 Technology Adoption and Market Participation

I study the effect of technology adoption on four categories of market participation following harvests in the midline year: 1) *sellers* of maize post-harvest; 2) *buyers* of food in the subsequent lean season, 3) *seller-buyers* that did both; 4) *autarkic* households that did neither. A visual representation of these groups is given in table 1. Among households with low maize acreage per capita the fertilizer treatment led to an 8 percentage point decrease in households buying maize, as shown in table 2. Among households with high maize acreage per capita the fertilizer treatment led to an 8 percentage point decrease in households being autarkic with respect to maize markets and a 6 percentage point increase in households being sellers in maize markets, as shown in table 3. Full regression output is in the appendix (section 8).

More households assigned to receive randomized treatments expected to purchase less maize grain over the following year, as shown in table 4. Treatments led to larger percentage point increases in Western Seed, fertilizer use, and maize sales at midline among typical purchasers of maize than among typical non-purchasers, as shown in tables 5 and 6. While treatment effects on Western Seed use among typical non-purchasers caught up to treatment effects on typical purchasers at endline, peristent effects on fertilizer use and maize sales are greater among typical purchasers. Additional descriptive statistics on maize grain purchases and technology adoption are given in the appendix (section 8).

3.2 Market Participation and Welfare

I use TAPRA data to estimate (9) with household and district-round fixed effects. Results using nominal prices and income are given in table 7. The elasticity of maize marketed surplus is inelastic and positive with respect to own price and household income, as shown in column (1). Columns (2) and (3) show that households cultivating fewer maize acres per capita than the median from the Western Seed sample – likely net buyers of maize – have maize marketed surplus that is slightly more responsive to prices and less responsive to income than likely net sellers of maize. I ignore these differences and use estimates from the full sample in column (1) to construct the measure of willingness to pay to stabilize the price of maize.

Figure 13 on page 33 plots willingness to pay to stabilize the price of maize against baseline farm size for each of the treatment groups in the Western Seed Company impact evaluation; the willingness to pay measure is transformed by the inverse hyperbolic sine function. Farmers in the Control group have a positive willingness to pay across farm sizes, indicating households are expected net buyers of maize without technology adoption in this sample. Thus condition 1 from the theoretical model is empirically relevant in this setting. The Seed and Fertilizer treatment decreased willingness to pay relative to the Control group over virtually all of the farm size distribution, implying positive welfare effects of technology adoption due to decreased exposure to price risk. The Seed Only treatment decreased willingness to pay relative to the Control group for households with farm sizes between 1.5 and 4 acres, implying positive welfare effects of technology adoption due to decreased exposure to price risk in this range. The Fertilizer treatment decreased willingness to pay relative to the Control group for households with farm sizes smaller than 2 acres, implying positive welfare effects of technology adoption due to decreased exposure to price risk in this range.

4 Conclusion

Land poor agricultural households may be more willing than wealthier households to adopt agricultural technologies that increase production of a food staple. The mechanism driving this effect is that these technologies decrease exposure to staple price risk for households that would otherwise be net buyers of food staples. Using data from a randomized control trial, I find that control group farmers tend to produce less maize than they consume and face price risk as buyers of maize. Technology adoption treatments decrease exposure to price risk among land poor households on average. Technology adoption for maize production appears to be motivated by expected decreases in maize purchases for land poor households. Policymakers underestimate the willingness of land poor households to adopt agricultural technologies when they do not account for the role of price risk in agricultural technology adoption decisions.

5 Acknowledgements

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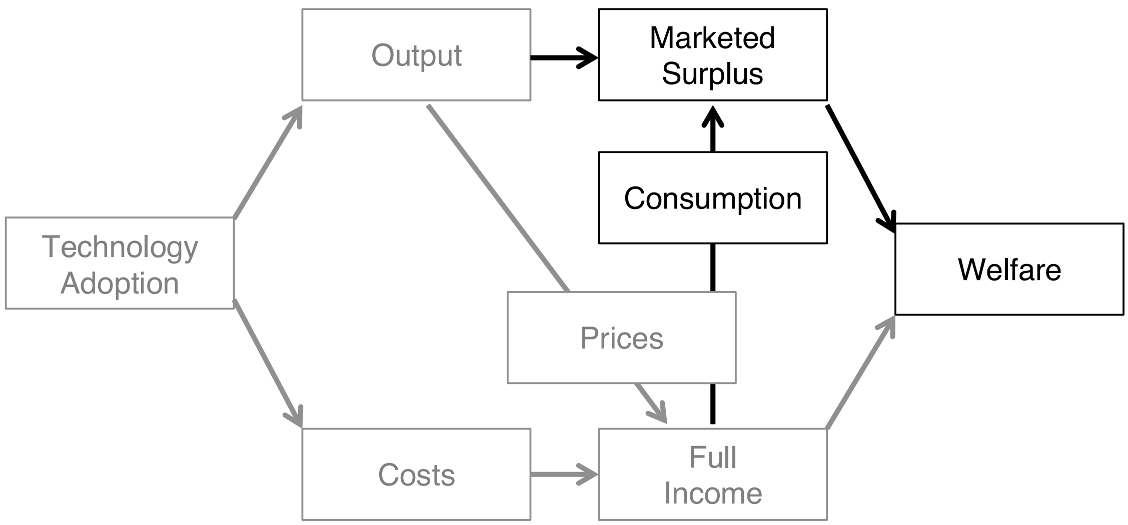
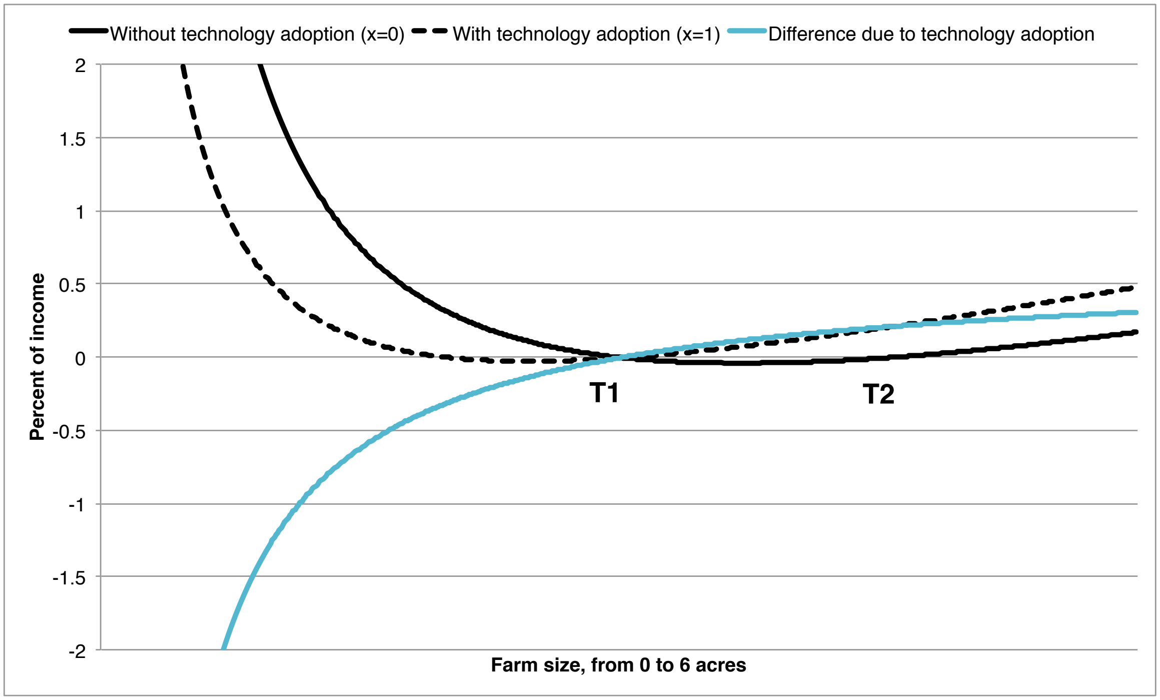
6 Figures

Figure 1: Technology adoption with and without price risk aversion



Notes: Gray represents the literature's focus on expected profitability as a driver of technology adoption. Black represents the new focus of this analysis on expected marketed surplus affecting technology adoption.

Figure 2: Illustration of willingness to pay to stabilize the price of the staple and technology adoption



Notes: The vertical axis is willingness to pay to stabilize the staple price as a percent of income and the horizontal axis is farm size in acres. In this illustration, households can be categorized into 3 groups based on technology adoption's welfare effects due to its effect on household exposure to price risk: (1) Households with a farm size smaller than T1 have a positive willingness to pay without technology adoption that decreases with technology adoption; (2) Households with farm sizes between T1 and T2 have a negative willingness to pay without technology adoption that increases with technology adoption; (3) Households with farm sizes larger than T2 realize an ambiguous welfare effect through technology adoption's effect on price risk.

Figure 3: Sample of interest is Western Midaltitude and Western Transitional

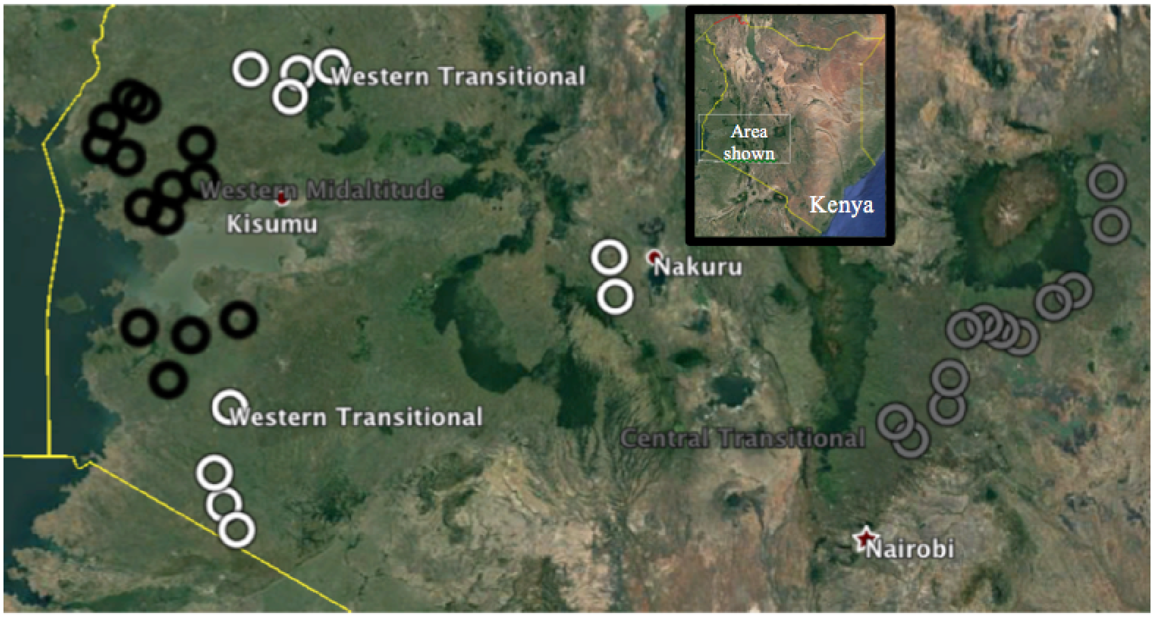


Figure 4: Timeline of treatments and data collection

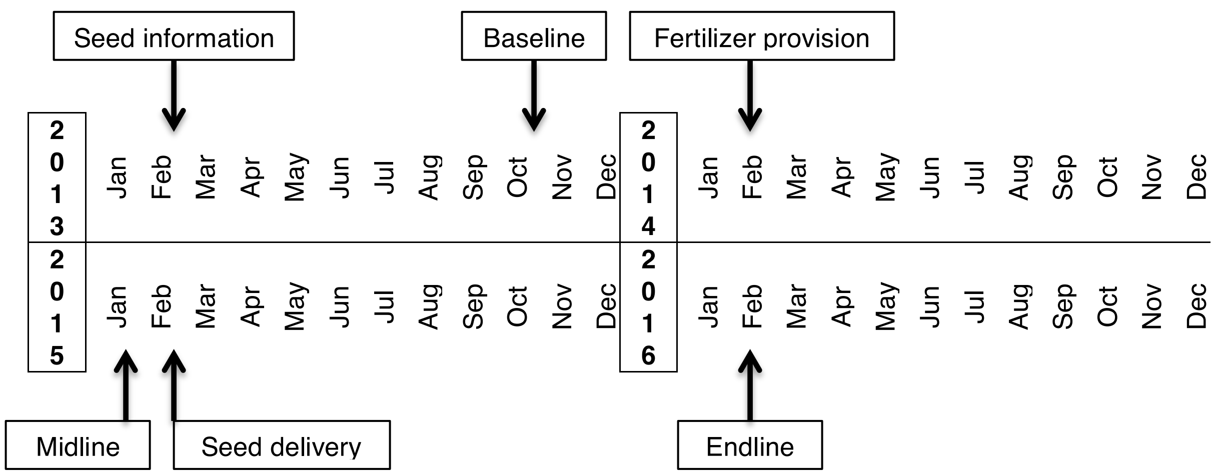


Figure 5: Timeline of grain management

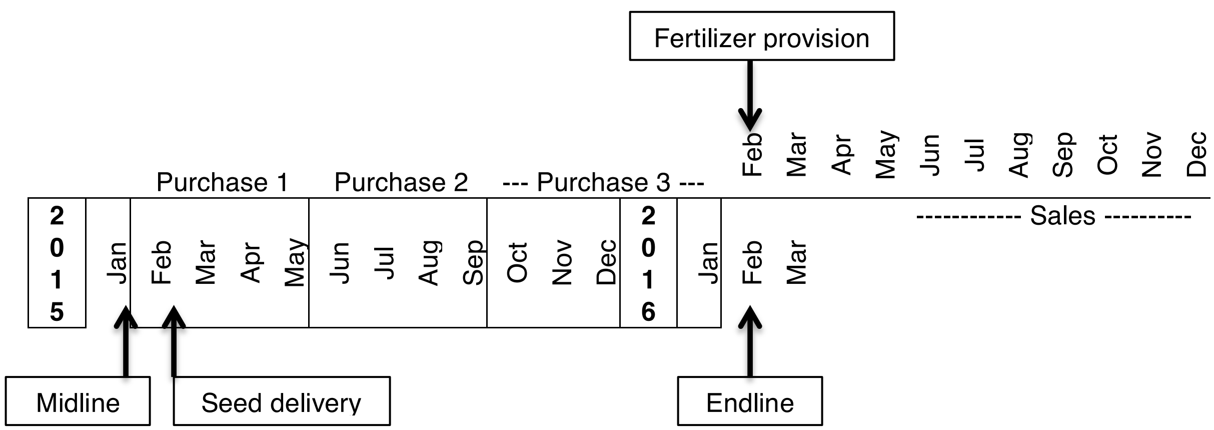


Figure 6: Maize sales after main (short) rains are common in Sep/Oct (Jan/Feb)

Year	Month							
2012	Oct	2 (0.78)						
	Nov	8 (3.11)						
	Dec	14 (5.45)						
2013	Jan	39 (15.18)	10 (3.02)					
	Feb	72 (28.02)	12 (3.63)					
	Mar	48 (18.68)	14 (4.23)					
	Apr	40 (15.56)	10 (3.02)					
	May	15 (5.84)	6 (1.81)					
	Jun	4 (1.56)	12 (3.63)					
	Jul	5 (1.95)	26 (7.85)					
	Aug	5 (1.95)	90 (27.19)					
	Sep	5 (1.95)	119 (35.95)					
	Oct		20 (6.04)	5 (2.76)				
	Nov		8 (2.42)	11 (6.08)				
	Dec		4 (1.21)	25 (13.81)				
2014	Jan			59 (32.6)				
	Feb			46 (25.41)				
	Mar			20 (11.05)	2 (0.47)			
	Apr			7 (3.87)	2 (0.47)			
	May			2 (1.1)	2 (0.47)			
	Jun			3 (1.66)	11 (2.59)			
	Jul			1 (0.55)	13 (3.06)			
	Aug			0 (0)	63 (14.82)			
	Sep			2 (1.1)	105 (24.71)			
	Oct				75 (17.65)	5 (1.98)		
	Nov				48 (11.29)	8 (3.17)		
	Dec				59 (13.88)	37 (14.68)		
2015	Jan				38 (8.94)	67 (26.59)		
	Feb				7 (1.65)	50 (19.84)		PURCHASE PD 1
	Mar					37 (14.68)		
	Apr					25 (9.92)	4 (0.82)	
	May					8 (3.17)	4 (0.82)	
	Jun					6 (2.38)	13 (2.67)	PURCHASE PD 2
	Jul					3 (1.19)	14 (2.88)	
	Aug					3 (1.19)	59 (12.14)	
	Sep					3 (1.19)	135 (27.78)	
	Oct						102 (20.99)	PURCHASE PD 3
	Nov						54 (11.11)	
	Dec						51 (10.49)	
2016	Jan						40 (8.23)	
	Feb						7 (1.44)	
	Mar						4 (0.82)	

Notes: Seasons are separated by columns beginning with the short season of 2012/13 and ending with the main season of 2015. The rightmost column indicates which months are grouped together in the recall periods used in the purchases module of the endline survey. Two-by-two cell boxes indicate the months when data were collected for those seasons; 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 7: Buying decreases and selling increases with farm size (y-axis=percent participating at endline)

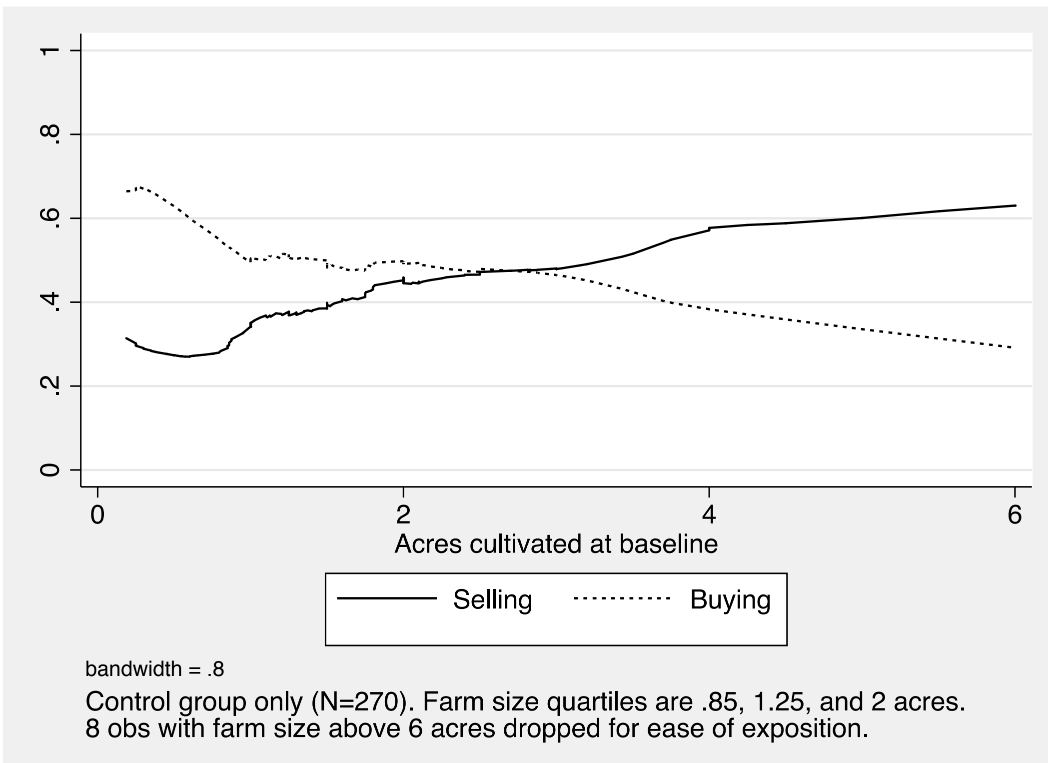


Figure 8: Hybrid use increases with farm size (y-axis=use in ten seasons prior to baseline)

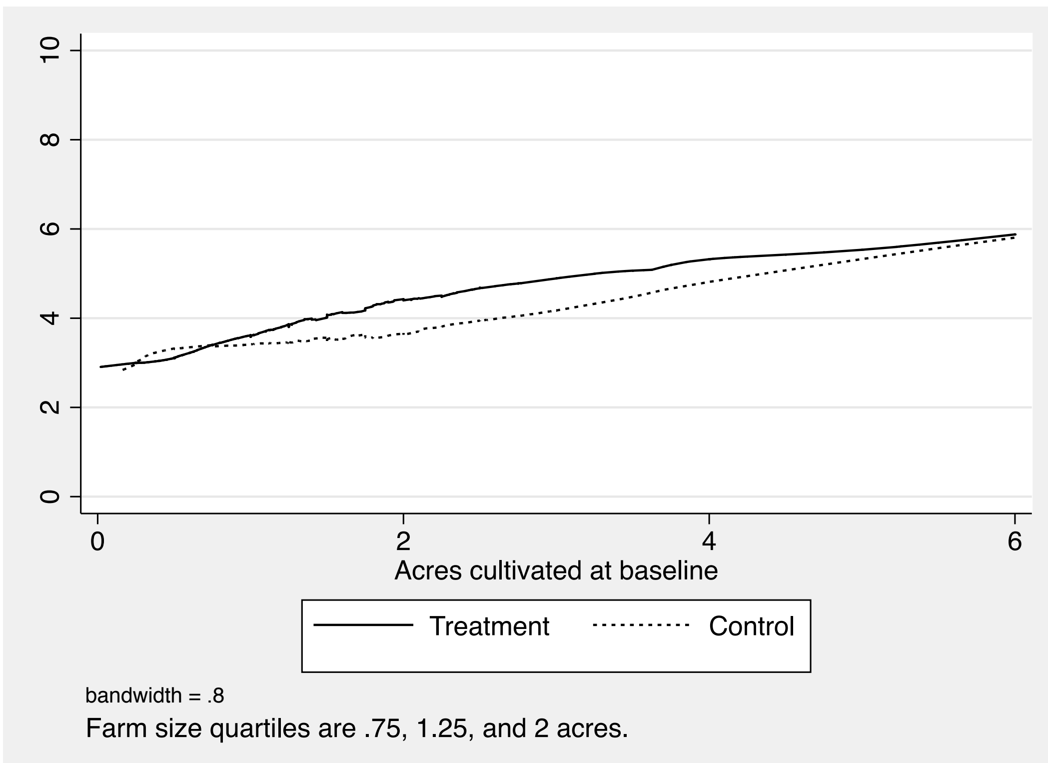


Figure 9: Fertilizer use does not clearly vary with farm size (use in ten seasons prior to baseline)

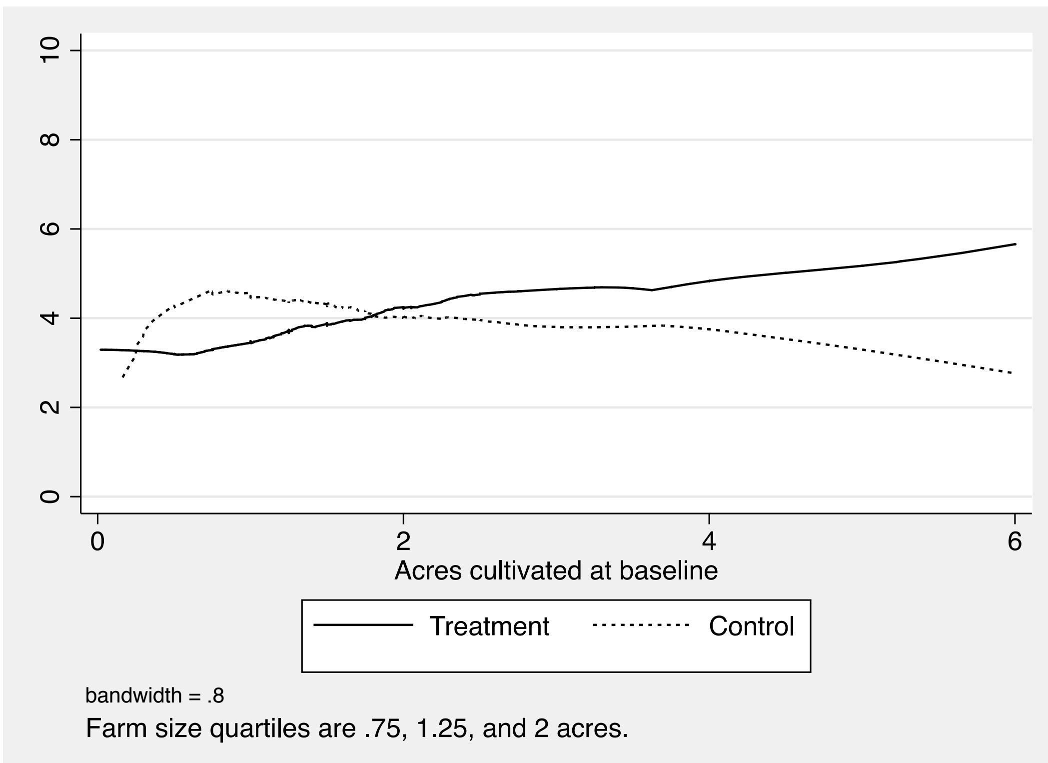


Figure 10: Western Seed maize hybrid use at midline does not clearly vary with farm size (y-axis=percent adopting)

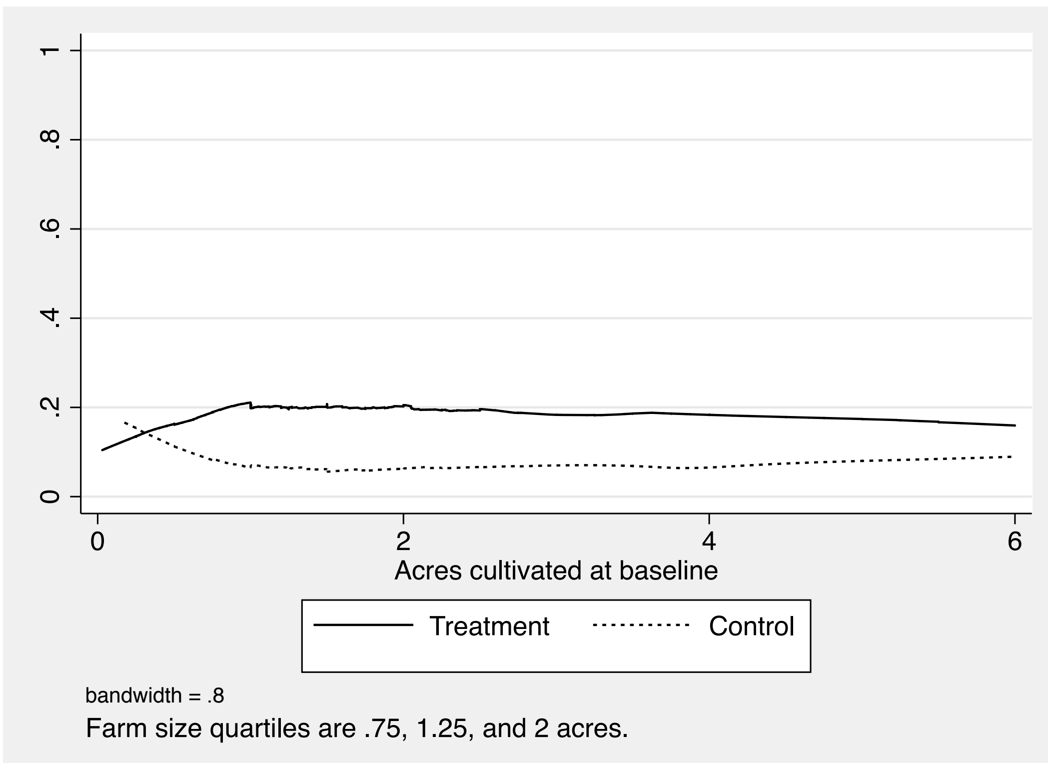


Figure 11: Western Seed maize hybrid use at endline increases with farm size (y-axis=percent adopting)

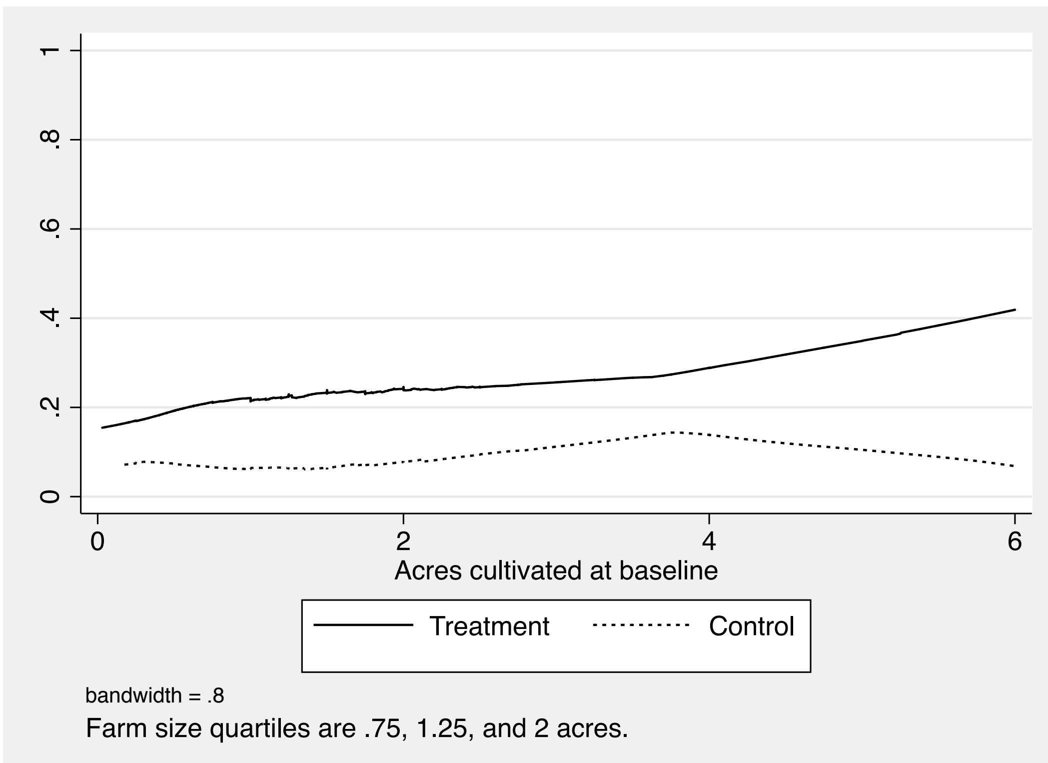


Figure 12: Fertilizer use on maize at endline decreases with farm size in the control group (y-axis=percent adoption)

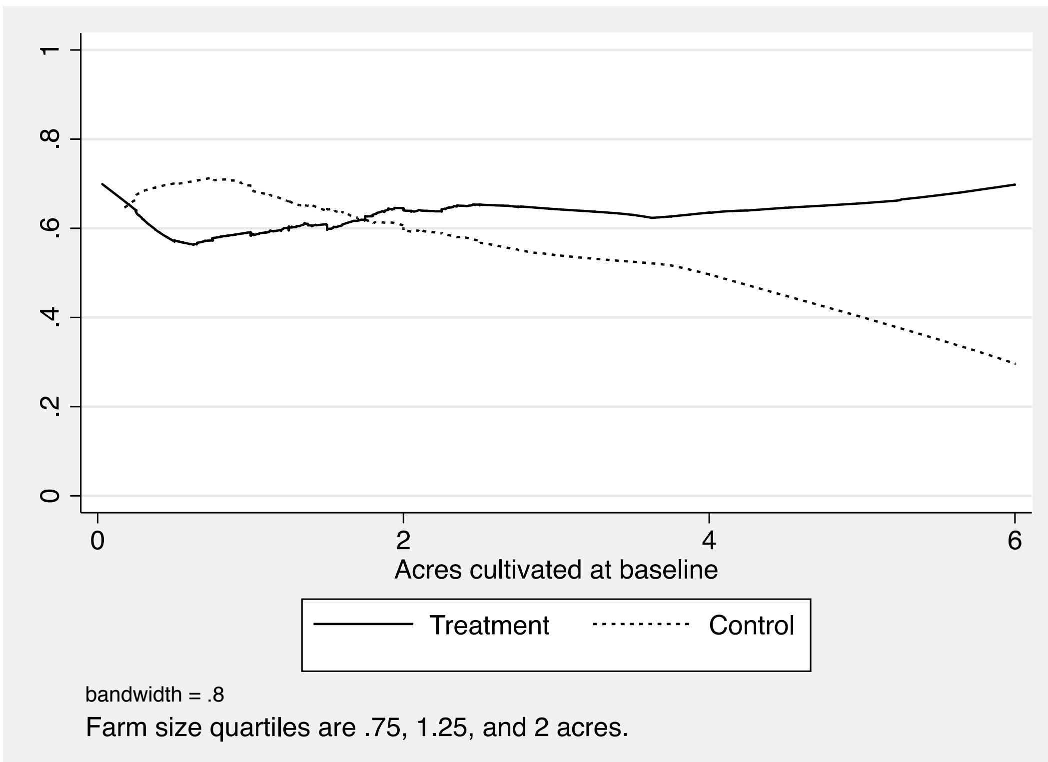
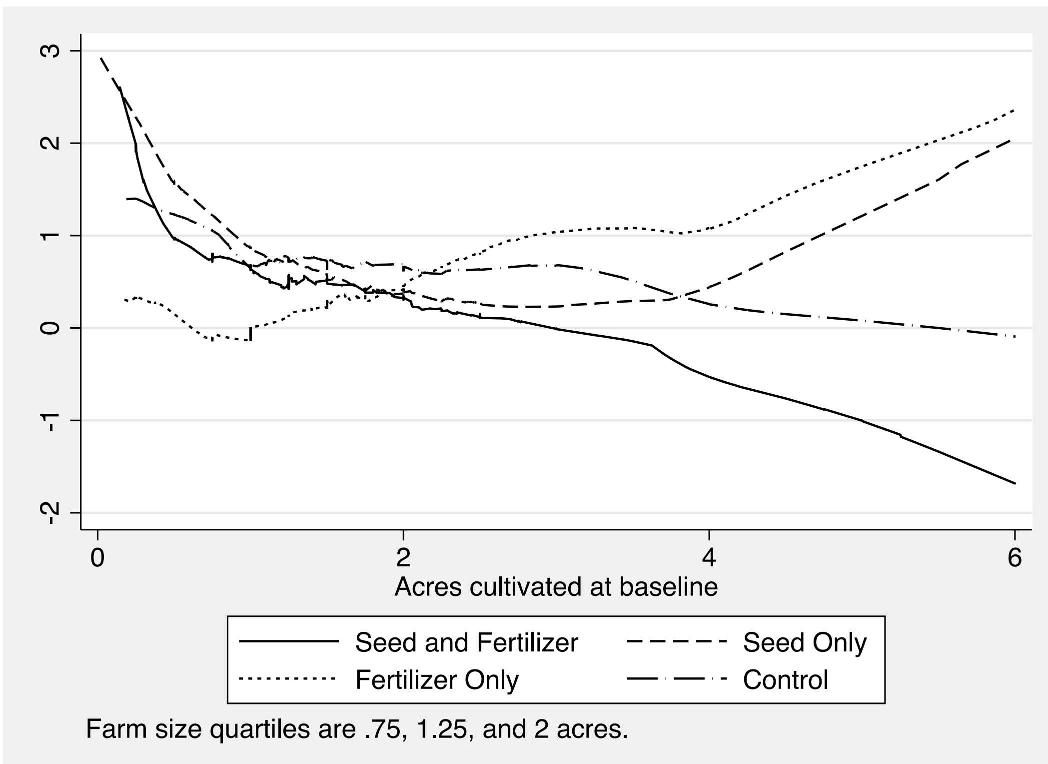


Figure 13: Willingness to pay to stabilize the price of maize grain



7 Tables

Table 1: Market Participation Regimes

		Buy high	
		No	Yes
Sell low	No	Autarkic	Buyer
	Yes	Seller	Seller-Buyer

Table 2: Impact by Land Per Capita: Below Median

	Buyer	Autarkic	Seller	Seller-Buyer
Control group mean	0.30	0.34	0.25	0.11
Fertilizer marginal effect				
- Point estimate	-0.08	-0.03	0.06	0.05
- Standard error	0.04	0.04	0.04	0.03
R-squared	0.40	0.41	0.38	0.16

OLS regression with standard errors clustered by village (N=517).
Regressors: Indicators for treatment, pair, baseline seasonal food insecurity; baseline maize yield, acreage, harvest; baseline non-maize ag income, predicted poverty, household dietary diversity score.

Table 3: Impact by Land Per Capita: Above Median

	Buyer	Autarkic	Seller	Seller-Buyer
Control group mean	0.17	0.40	0.36	0.06
Fertilizer marginal effect				
- Point estimate	0.00	-0.08	0.06	0.02
- Standard error	0.03	0.04	0.04	0.02
R-squared	0.30	0.46	0.49	0.10

OLS regression with standard errors clustered by village (N=520).
Regressors: Indicators for treatment, pair, baseline seasonal food insecurity; baseline maize yield, acreage, harvest; baseline non-maize ag income, predicted poverty, household dietary diversity score.

Table 4: Purchases of Maize Grain Compared to Typical Year

	Treatment Group				
Purchases	Seed & Fert	Seed	Fert	Control	Total
Less - expected	48	38	25	32	143
Less - unexpected	23	24	17	20	84
Same	159	159	178	165	661
More - unexpected	18	26	29	22	95
More - expected	30	35	28	38	131
Total	278	282	277	277	1114

Table 5: Share of Typical Non-Purchasers

	Seed & Fert	Seed	Fert	Control
Midline				
Western Seed	0.16	0.15	0.05	0.08
Fert on maize	0.91	0.72	0.92	0.72
Sold maize	0.50	0.43	0.52	0.48
Endline				
Western Seed	0.22	0.27	0.06	0.11
Fert on maize	0.70	0.66	0.68	0.73
Sold maize	0.57	0.57	0.59	0.48

Table 6: Share of Typical Purchasers

	Seed & Fert	Seed	Fert	Control
Midline				
Western Seed	0.24	0.20	0.08	0.09
Fert on maize	0.86	0.49	0.91	0.51
Sold maize	0.36	0.26	0.33	0.21
Endline				
Western Seed	0.23	0.22	0.10	0.07
Fert on maize	0.60	0.51	0.60	0.48
Sold maize	0.36	0.25	0.37	0.28

Table 7: Maize price and income elasticity estimates from fixed effects

	Maize Acres per Capita		
	(1)	(2)	(3)
	All	Small	Large
Maize price	0.17	0.30	0.10
	(0.20)	(0.41)	(0.23)
Income	0.05**	0.03	0.06**
	(0.02)	(0.06)	(0.03)
F-statistic	2.72	0.45	2.83
R-squared	0.01	0.00	0.01
Observations	1538	482	1056

All specifications include district-round fixed effects as controls. Income in Kenyan shillings. Maize price in Kenyan shillings/kilogram. Maize price is household average weighted by volume for sellers and district average weighted by volume for non-sellers. All variables transformed by inverse hyperbolic sine function.

8 Appendix

Table 8: Impact by Land Per Capita: Below Median

	Harvest	Buyer	Autarkic	Seller	Seller-Buyer
Treatment (0/1)					
Seed	-0.20	0.08	-0.08	-0.03	0.03
	(0.15)	(0.05)	(0.06)	(0.06)	(0.04)
Fertilizer	0.37***	-0.07	-0.07	0.08	0.06
	(0.13)	(0.06)	(0.07)	(0.06)	(0.04)
Seed*Fertilizer	-0.07	-0.02	0.09	-0.04	-0.03
	(0.18)	(0.08)	(0.08)	(0.08)	(0.06)
Maize Production, Baseline					
Yield	-0.45	-0.01	0.08	-0.07	0.00
	(0.27)	(0.08)	(0.08)	(0.07)	(0.06)
Acres	-0.89	-0.06	0.10	-0.09	0.05
	(0.54)	(0.18)	(0.21)	(0.17)	(0.14)
Harvest	0.61**	-0.02	-0.08	0.10	-0.00
	(0.30)	(0.08)	(0.09)	(0.08)	(0.07)
Non-Maize Ag Income, Baseline	0.10**	-0.02	-0.01	0.02	0.00
	(0.04)	(0.01)	(0.02)	(0.01)	(0.01)
Welfare, Baseline					
Poverty (0-1)	-0.97***	0.01	0.08	-0.09	0.00
	(0.19)	(0.08)	(0.11)	(0.09)	(0.07)
Dietary Diversity (0-12)	0.00	-0.01	0.01	0.01	-0.02*
	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)
Seasonal Food Insecurity, Baseline					
Pre-Short (0/1)	-0.28**	0.10*	0.08*	-0.13***	-0.05
	(0.12)	(0.05)	(0.05)	(0.04)	(0.04)
Post-Short (0/1)	-0.07	-0.04	-0.10*	0.06	0.09*
	(0.13)	(0.06)	(0.05)	(0.04)	(0.04)
Pre-Main (0/1)	0.08	0.06	-0.11**	0.00	0.05
	(0.09)	(0.05)	(0.05)	(0.04)	(0.03)
Post-Main (0/1)	0.09	0.02	-0.02	-0.03	0.02
	(0.12)	(0.05)	(0.06)	(0.05)	(0.04)
Fertilizer marginal effect					
- Point estimate	0.33	-0.08	-0.03	0.06	0.05
- Standard error	0.09	0.04	0.04	0.04	0.03
Dep var mean, Control	3.75	0.30	0.34	0.25	0.11
R-squared	0.94	0.40	0.41	0.38	0.16

OLS regression with pair indicator variables as controls (N=517).

Harvest is kilograms of maize per capita plus one transformed by the natural logarithmic function.

Standard errors are clustered by village.

* = 10% significance, ** = 5% significance, *** = 1% significance

Table 9: Impact by Land Per Capita: Above Median

	Harvest	Buyer	Autarkic	Seller	Seller-Buyer
Treatment (0/1)					
Seed	-0.12	-0.02	0.05	-0.03	-0.00
	(0.14)	(0.05)	(0.06)	(0.06)	(0.03)
Fertilizer	0.19	0.02	-0.07	0.03	0.01
	(0.14)	(0.05)	(0.05)	(0.05)	(0.03)
Seed*Fertilizer	0.07	-0.03	-0.02	0.05	0.00
	(0.22)	(0.06)	(0.08)	(0.08)	(0.04)
Maize Production, Baseline					
Yield	0.81	-0.00	-0.10	0.16	-0.05
	(0.51)	(0.11)	(0.16)	(0.13)	(0.05)
Acres	1.20*	-0.02	-0.18	0.28*	-0.08
	(0.63)	(0.13)	(0.19)	(0.16)	(0.06)
Harvest	-0.59	-0.02	0.06	-0.09	0.05
	(0.51)	(0.11)	(0.15)	(0.13)	(0.04)
Non-Maize Ag Income, Baseline	-0.04	-0.02**	0.05***	-0.02	-0.01
	(0.04)	(0.01)	(0.01)	(0.01)	(0.01)
Welfare, Baseline					
Poverty (0-1)	-1.17***	0.18**	-0.17	-0.12	0.11
	(0.20)	(0.09)	(0.10)	(0.09)	(0.07)
Dietary Diversity (0-12)	-0.02	0.00	-0.02	0.01	0.01*
	(0.03)	(0.01)	(0.02)	(0.01)	(0.01)
Seasonal Food Insecurity, Baseline					
Pre-Short (0/1)	0.05	0.00	-0.04	0.05	-0.02
	(0.11)	(0.04)	(0.05)	(0.05)	(0.02)
Post-Short (0/1)	0.06	0.04	-0.10	0.03	0.03
	(0.13)	(0.05)	(0.06)	(0.06)	(0.04)
Pre-Main (0/1)	-0.19	0.05	-0.06	0.00	0.01
	(0.13)	(0.03)	(0.05)	(0.05)	(0.03)
Post-Main (0/1)	0.00	0.04	0.01	-0.05	-0.01
	(0.14)	(0.04)	(0.06)	(0.06)	(0.03)
Fertilizer marginal effect					
- Point estimate	0.22	0.00	-0.08	0.06	0.02
- Standard error	0.10	0.03	0.04	0.04	0.02
Dep var mean, Control	4.39	0.17	0.40	0.36	0.06
R-squared	0.95	0.30	0.46	0.49	0.10

OLS regression with pair indicator variables as controls (N=520).
Harvest is kilograms of maize per capita plus one transformed by the natural logarithmic function.
Standard errors are clustered by village.
* = 10% significance, ** = 5% significance, *** = 1% significance

Table 10: Typical Non-Purchasers Continued to Not Purchase Maize Grain

	Treatment Group				
Purchases	Seed & Fert	Seed	Fert	Control	Total
Less - expected	0	0	0	2	2
Less - unexpected	0	0	0	1	1
Same	125	121	138	114	498
More - unexpected	5	9	13	9	36
More - expected	9	10	11	13	43
Total	139	140	162	139	580

Table 11: Typical Purchasers Changed Maize Grain Purchases

	Treatment Group				
Purchases	Seed & Fert	Seed	Fert	Control	Total
Less - expected	48	38	25	30	141
Less - unexpected	23	24	17	19	83
Same	34	38	40	51	163
More - unexpected	13	17	16	13	59
More - expected	21	25	17	25	88
Total	139	142	115	138	534

Table 12: Harvest is Reason for Expecting Less Maize Grain Purchases

	Treatment Group				
Reason	Seed & Fert	Seed	Fert	Control	Total
Harvest	37	33	19	26	115
Consumption	8	3	4	1	16
Marketing	3	2	2	5	12
Total	48	38	25	32	143