

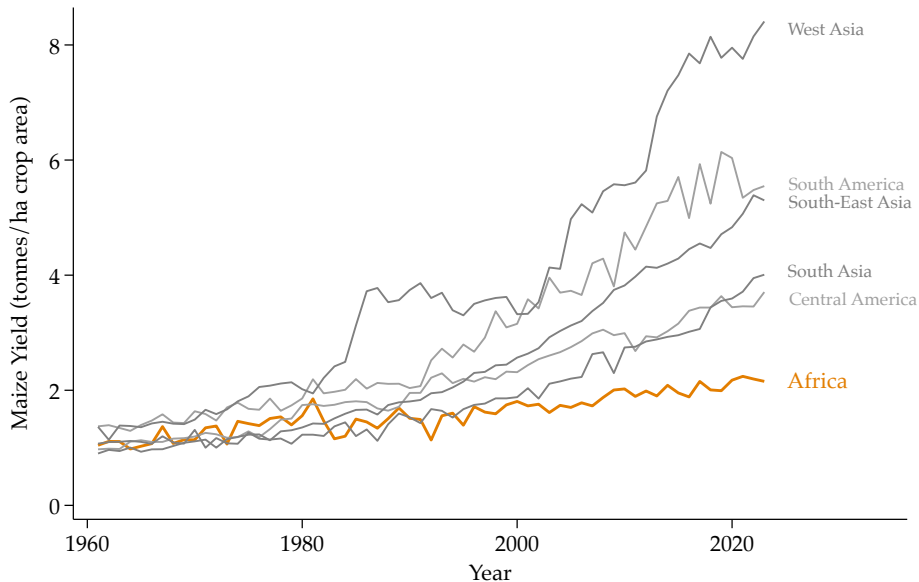
Liquidity Constraints and Capital Allocation in Agriculture:

Theory and Evidence from Uganda

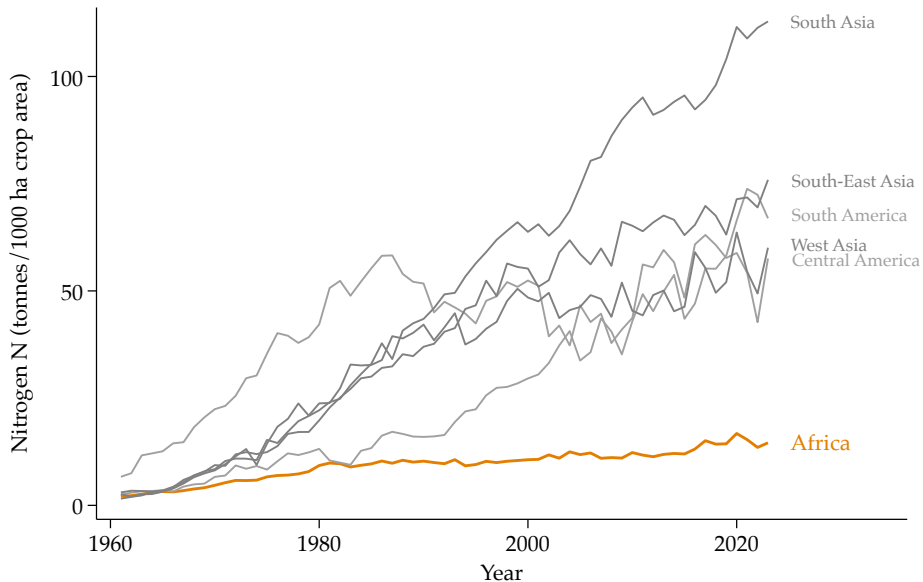
K. Burchardi, J. De Quidt, B. Lerva, S. Tripodi

NBER SI, July 2026

Background: Agricultural Output in Africa



Background: Fertilizer Adoption in Africa



Our Paper: The Market for Fertilizer

- 1 How well are fertilizer markets functioning in *status quo*?
 - Subsidy of 30% encourages adoption by a subgroup farmer with high returns.
 - Average profit impacts are substantially below market price.

Our Paper: The Market for Fertilizer

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- Cash transfers increase profits.
- Cash transfers imply that optimal subsidy is 0%.

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③ Is it optimal to address the distortion at the source?

- It might not be if the government's cost of funds is high.

Plan for Today

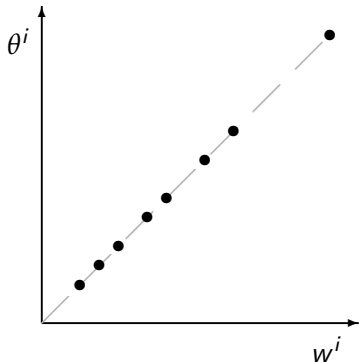
- 1 Theory
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Theory

Consider an *investment good* yielding a heterogeneous return θ^i .

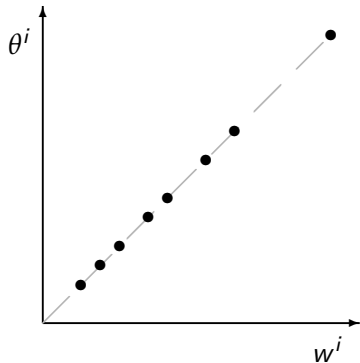
How to ensure the investment good is allocated to individuals with highest return?

Theory: Allocation with Markets



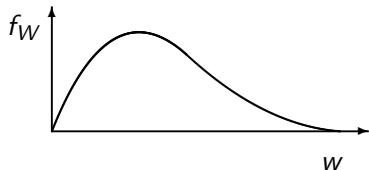
What is the investor's willingness-to-pay, w^i ?

Theory: Allocation with Markets

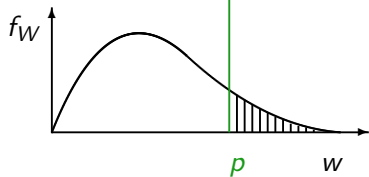
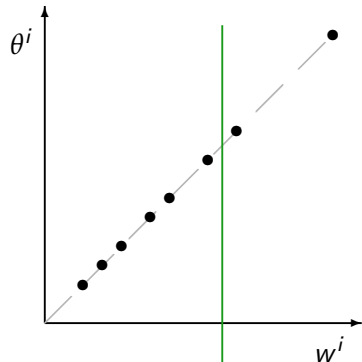


What is the investor's willingness-to-pay, w^i ?

→ Absent distortions: $w^i = \theta^i$.



Theory: Allocation with Markets



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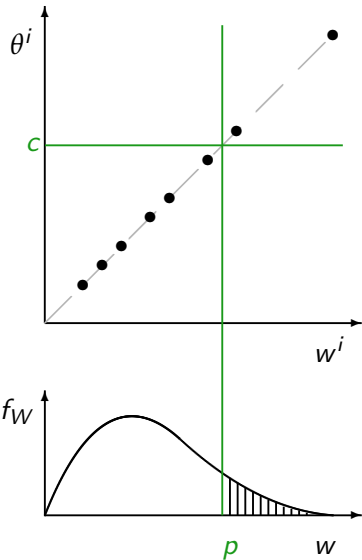
→ Absent distortions: $w^i = \theta^i$.

Perfect Markets: Charging price p ,
projects with $w^i \geq p$ receive investment good:

$w^i \geq p$ if and only if $\theta^i \geq p$.

Selection effect of markets.

Theory: Allocation with Markets



What is the investor's willingness-to-pay, w^i ?

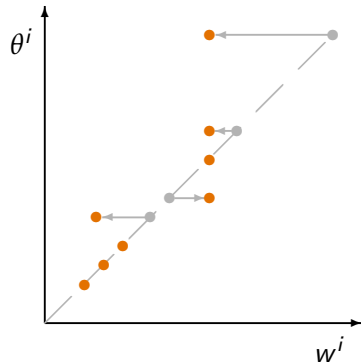
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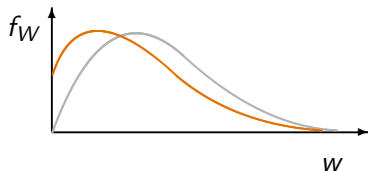
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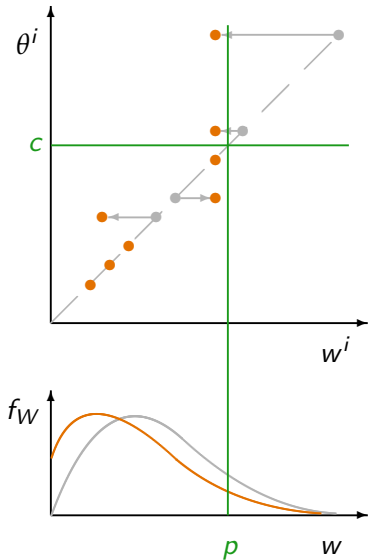
Distortions, such as...

- insurance constraints,
- information constraints,
- behavioural constraints,
- *liquidity constraints*,

... correspond to horizontal shift.



Theory: Allocation with Markets

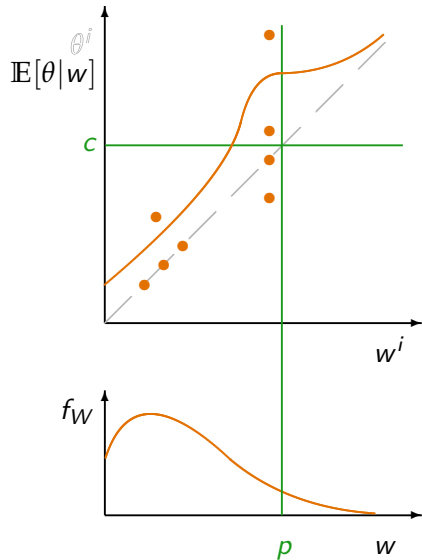


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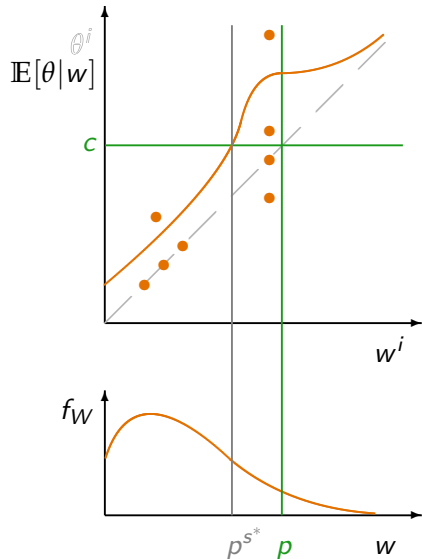
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Surplus with price p' is

$$S(p') = \int_{p'}^{\infty} (\mathbb{E}[\theta | w] - c) f_W(w) dw.$$

Theory: Allocation with Markets



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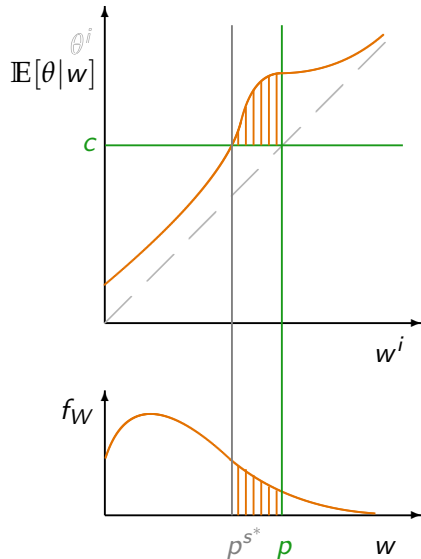
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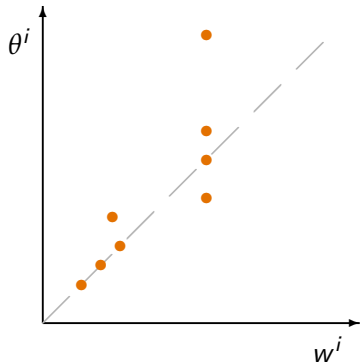
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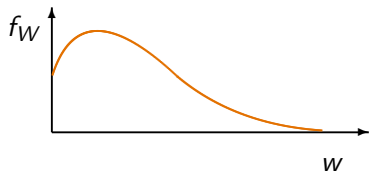
1.a Optimal subsidy: p' that maximises surplus.

1.b Free fertilizer: $S(0) - S(p)$.

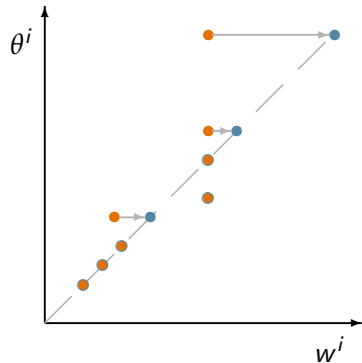
Theory: Allocation with Markets



Relaxing **liquidity constraints** ($l \in \{0, 1\}$):



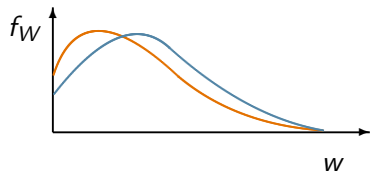
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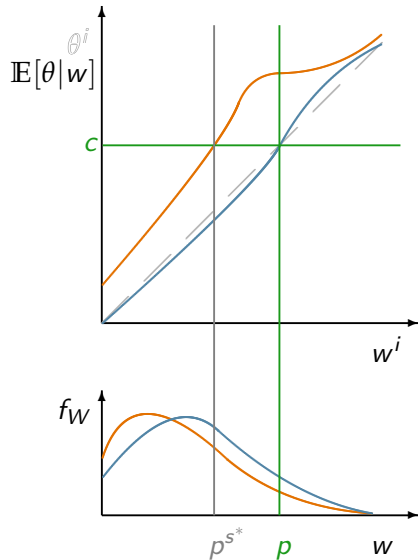
Relaxing **liquidity constraints** ($l \in \{0, 1\}$):

→ Shifts w^i to right.

→ FOSD shift of $f_{W(l)}(w)$.



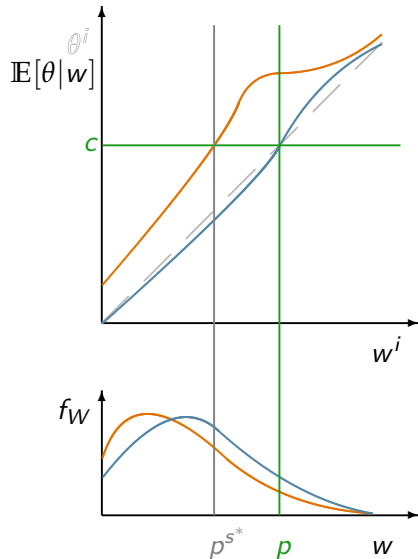
Theory: Allocation with Markets



Relaxing **liquidity constraints** ($l \in \{0, 1\}$):

- Shifts w^i to right.
- FOSD shift of $f_{W(l)}(w)$.
- $\mathbb{E}[\theta(l) | w(l)]$ changes.
 - Write surplus $S(p'; l)$.

Theory: Allocation with Markets



Relaxing **liquidity constraints** ($l \in \{0, 1\}$):

- Shifts w^i to right.
- FOSD shift of $f_{W(l)}(w)$.
- $\mathbb{E}[\theta(l) | w(l)]$ changes.
 - Write surplus $S(p'; l)$.

2.a Adoption in this scenario.

2.b Direct profit impacts: $S(p; 1) - S(p; 0)$.

2.c Optimal subsidy in this scenario.

$\mathbb{E}[\theta(1) | w(1)]$, $f_{W(1)}(w)$,

$\mathbb{E}[\theta(0) | w(0)]$, $f_{W(0)}(w)$

are the **target moments of experimental design**.

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Multiple Price List

Possible r	Purchase
200k UGX	
.	.
.	.
140k UGX	
120k UGX	
100k UGX	
.	.
.	.
0k UGX	

Multiple Price List

Possible r	Purchase
200k UGX	NO
.	.
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Scratchcard Price Revelation

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200k UGX	NO
.	.
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Iff $r^i \leq w^i$, purchase fertilizer at r^i .

- Version of Becker-DeGroot-Marschak (BDM, 1964).
- Incentive-compatible mechanism to elicit w^i .

Random Price

- 13 / 38

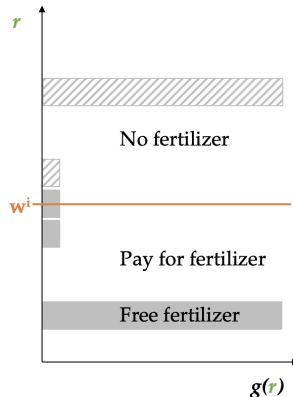
Multiple Price List

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.	.
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Scratchcard Price Revelation



Random Price



Iff $r^i \leq w^i$, purchase fertilizer at r^i .

- Version of Becker-DeGroot-Marschak (BDM, 1964).
- Incentive-compatible mechanism to elicit w^i .
- Randomization of treatment conditional on w : identify $\mathbb{E}[\theta(0)|w(0)]$.

Experimental Design

Multiple Price List

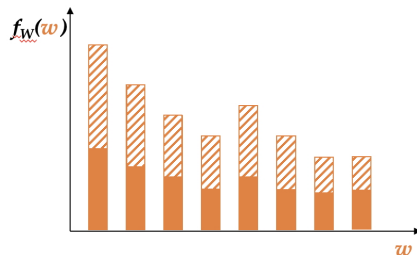
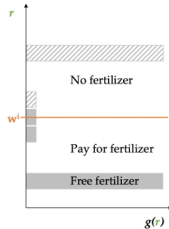
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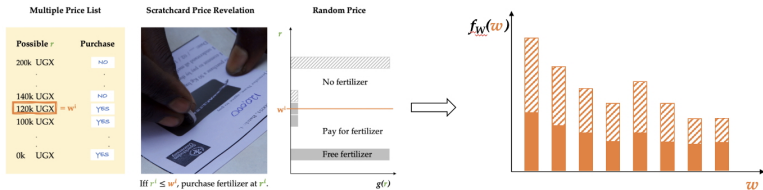


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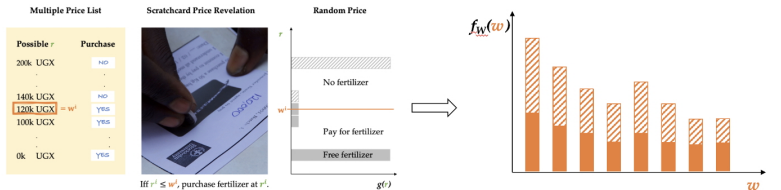


- BDM is a “selective trial”, see *Chassang, Padró i Miguel, Snowberg (2012)*.
- Related applications: *Berry, Fischer, Guiteras (2019)*, *Berkouwer and Dean (2022)*.

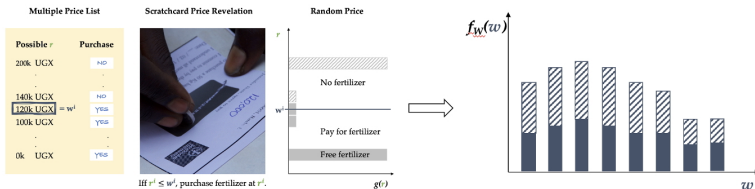


Lottery

Losers: 5k UGX



Winners: 200k UGX



- Lottery prize money equal to market price of the investment good: **liquidity constraints relaxed**.
- Also incentivise attendance.

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Estimation: Regression

$$\begin{aligned} y^{iv} = & \sum_w \alpha_{w,0} \mathbb{1}[w^i = w, l^i = 0] + \sum_w \beta_{w,0} \mathbb{1}[w^i = w, l^i = 0] \mathbb{1}[r^i = 0] \\ & + \sum_w \alpha_{w,1} \mathbb{1}[w^i = w, l^i = 1] + \sum_w \beta_{w,1} \mathbb{1}[w^i = w, l^i = 1] \mathbb{1}[r^i = 0] \\ & + \zeta X^{iv} + \epsilon^{iv}, \end{aligned}$$

- where $\beta_{w,l}$ are coefficients of primary interest,
- X^{iv} always includes village fixed effects and baseline farm size,
- and the sample excludes observations with $0 < r^i \leq w^i$.

[Baseline Farm Control]

Estimators

- 1 Average treatment effect of the fertilizer bundle on outcome y^{iv} amongst the farmer adopting at price p , and within the lottery $l \in \{0, 1\}$ groups:

$$\hat{ATE}_F(p; l) = \frac{\sum_{w \geq p} \hat{f}(w; l) \cdot \hat{\beta}_{w,l}}{\sum_{w \geq p} \hat{f}(w; l)}.$$

- 2 Average impact of lottery on outcome y^{iv} :

$$\hat{ATE}_L = \sum_w \hat{f}(w; 1) \cdot \hat{\alpha}_{w,1} - \hat{f}(w; 0) \cdot \hat{\alpha}_{w,0}.$$

$\hat{f}(w; l)$ is the empirical distribution of willingness to pay given l , taken as fixed.

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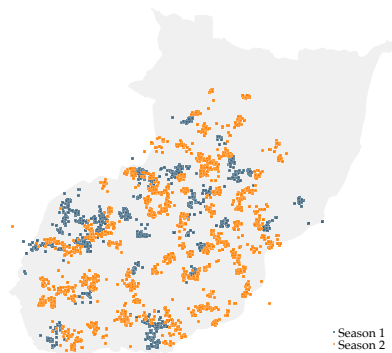
Setting

- **Where?**
Maize farmers in Eastern Ugandan districts of Tororo, Manafa, Mbale (Duflo et al., 2008).
- **What?**
50kg DAP / 50kg CAN; 1 acre; 200k UGX.
- **When?**
1st season of 2017 (S1) and 2018 (S2).

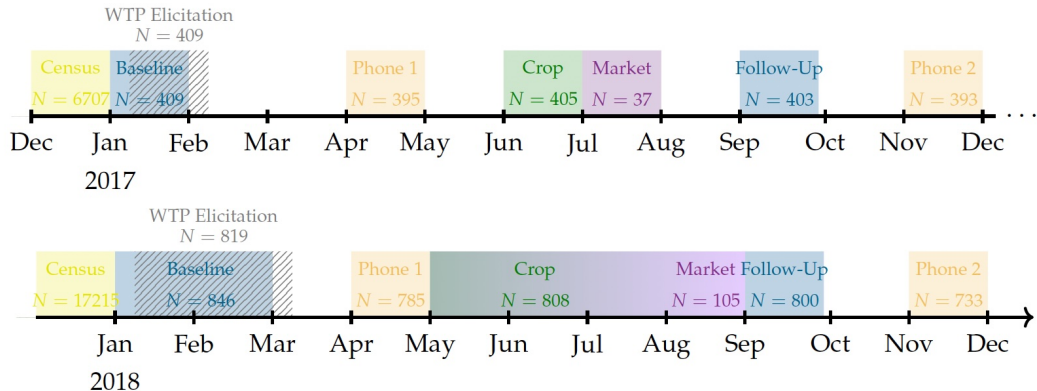


Sampling

- 1 Sample of 51/102 rural villages, stratified by pop. density.
- 2 Conducted *census* of households.
- 3 Eligible households (i) engaged in commercial farming, (ii) cultivate maize, (iii) self-report cultivating 2 to 6 acres and (iv) have mobile money account.
- 4 Select 408/816 eligible households.



Measurement

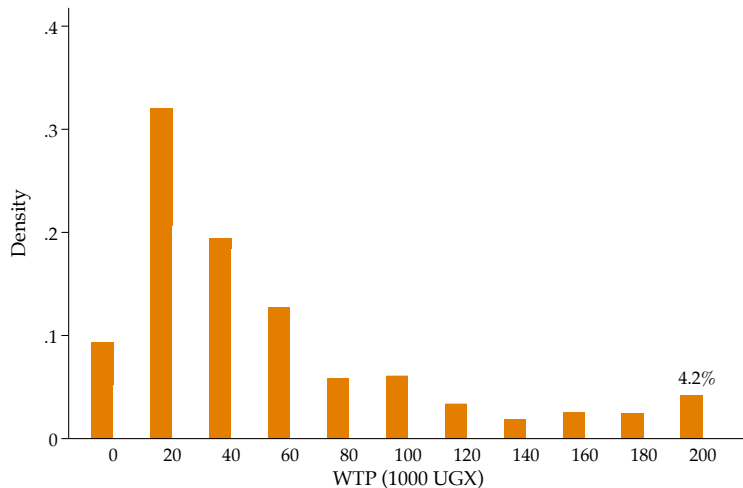


[WTP, Planting Time] [Implementation] [Plot Size Measurement] [Quadrants] [Optimal Survey Design]

Plan for Today

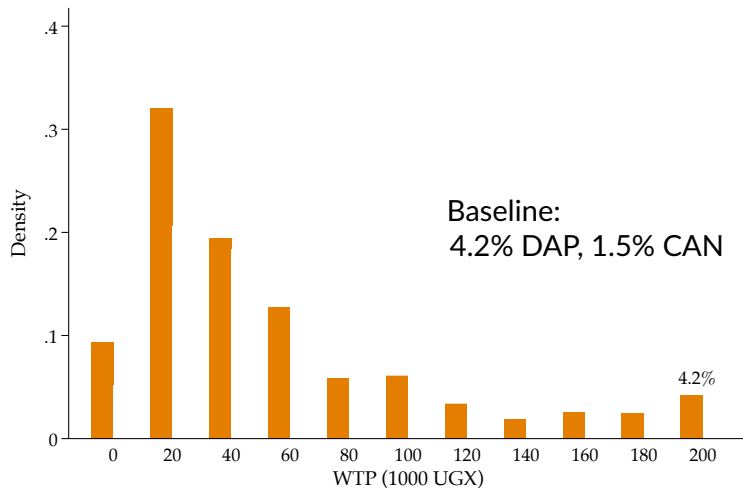
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Results: Willingness to Pay



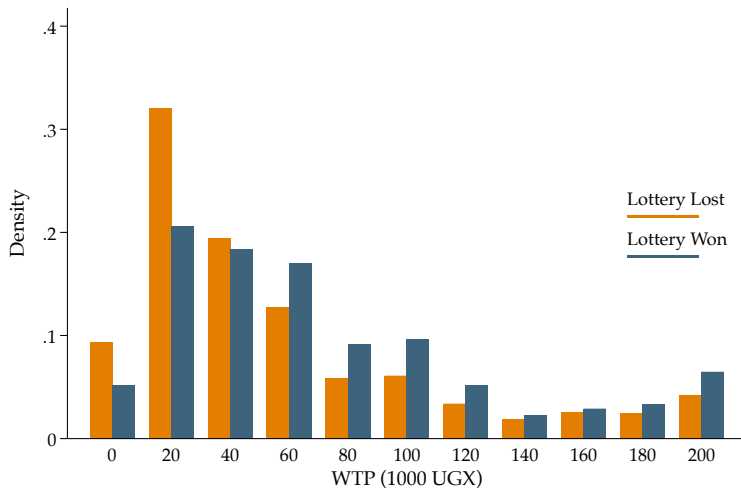
Average WTP | Lottery Lost = 56k UGX

Results: Willingness to Pay



Average WTP | Lottery Lost = 56k UGX

Results: Willingness to Pay



Average WTP | Lottery Lost = 56k UGX ; Average WTP | Lottery Won = 72k UGX

Results: Profit Impact of Fertilizer

	(1)	(2)	(3)	(4)	(5)	(6)
	Revenue	Costs				Profits
		Non-L. (maize)	Hired L. (all crops)	Fam. L. (all crops)	(2)+(3)+(4)	
$\hat{ATE}_F$ (0; Lottery Lost)	139.0 (24.6) [0.000]	2.85 (8.00) [0.721]	41.53 (16.16) [0.010]	29.82 (20.92) [0.154]	74.19 (28.28) [0.009]	65.00 (31.18) [0.037]
N (Lottery Lost/Won)	684/410	686/410	686/410	686/408	686/408	684/408
Mean Y in Control	331.3	98.11	123.62	294.91	516.65	

[Land] [Seeds & Fertilizer] [Labour] [Quadrants] [Long-Run Adoption]

Results: Profit Impact of Fertilizer

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$\hat{ATE}_F$ (0; Lottery Won)	110.0 (35.7) [0.002]	10.88 (11.59) [0.348]	35.76 (25.46) [0.160]	30.29 (30.02) [0.313]	74.72 (39.61) [0.060]	34.73 (47.19) [0.462]
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Duflo, Kremer, Robinson (2008):

- Find – at best – 136% gross return over the season (CAN only).
- With comparable output measure, we find 55%-70% return.
- With appropriate profit measure, we find 17%-32% return.
- All do not include fertiliser cost.

[Weather Patterns]

Results: Profit Impact of Lottery

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$\hat{ATE}_L$	79.7 (30.1) [0.008]	20.44 (10.13) [0.044]	19.92 (15.41) [0.196]	-12.26 (25.29) [0.628]	30.09 (33.26) [0.366]	50.28 (37.94) [0.185]
N (Lottery Lost/Won)	684/410	686/410	686/410	686/408	686/408	684/408
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Results: Profit Impact of Lottery

	(1)	(2)	(3)	(4)	(5)	(6)
	Revenue					Profits
$\hat{ATE}_L$	79.7 (30.1) [0.008]					50.28 (37.94) [0.185]

Karlan, Osei, Osei-Akoto and Udry (QJE, 2014):

- 420\$ grant in Ghana increases costs by 2\$ and profits by 65\$.

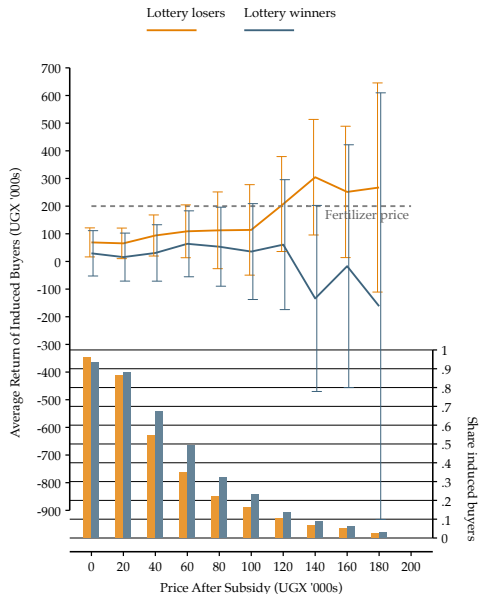
Beaman, Karlan, Thuysbaert, Udry (ECMA, 2023):

- 140\$ grant in Mali increases output by 66\$ and “gross profits” by 39\$.
(Does not subtract the value of own, family and unpaid labor.)

Results: Marginal Treatment Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
w	0k	20k	40k	60k	80k	100k	120k	140k	160k	180k	200k
$\hat{\beta}_{w;0}$	99 (101)	17 (50)	66 (72)	103 (75)	108 (148)	-47 (202)	10 (172)	453 (273)*	238 (174)	267 (230)	
$\hat{\beta}_{w;1}$	259 (151)*	-35 (110)	-56 (127)	84 (134)	99 (161)	0 (165)	391 (161)**	-431 (256)*	150 (194)	-162 (469)	
$\hat{f}(w; 0)$	0.099	0.318	0.190	0.132	0.056	0.060	0.034	0.018	0.027	0.023	0.042
$N(w; 0)$	69	237	143	94	43	45	25	14	19	18	31
$\hat{f}(w; 1)$	0.052	0.202	0.187	0.169	0.089	0.095	0.050	0.024	0.028	0.033	0.072
$N(w; 1)$	24	91	82	75	40	43	23	11	13	14	30

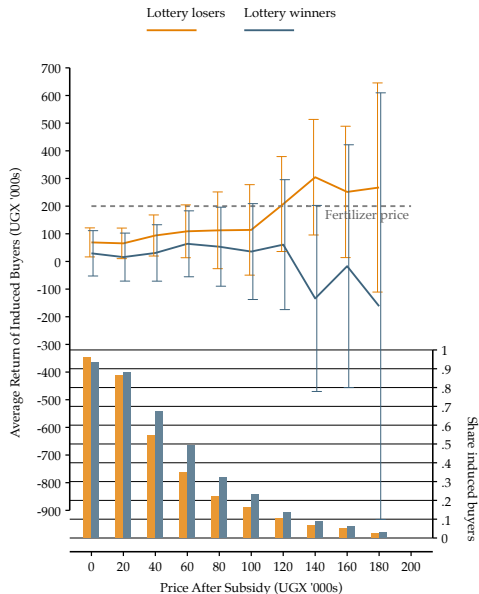
Results: Optimal Subsidy



1 Market Allocation

- For $W \geq 140k$ UGX find large returns in constrained group.

Results: Optimal Subsidy



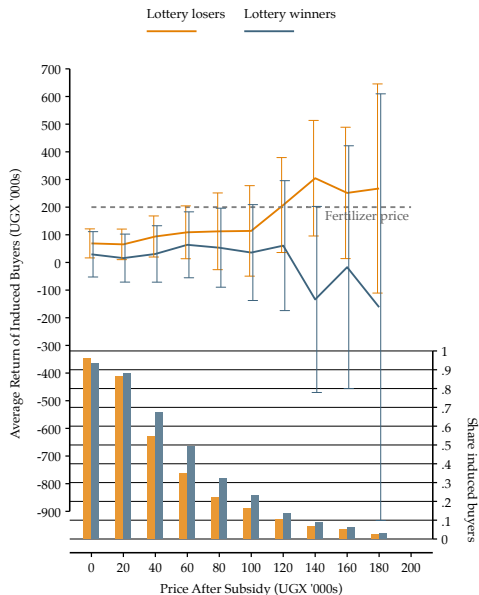
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- Large positive returns realised with optimal subsidy of 60k UGX.
- 7% induced to buy.

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1 Market Allocation

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2 Subsidy in Status Quo

- Large positive returns realised with optimal subsidy of 60k UGX.
- 7% induced to buy.

3 Subsidy in Unconstrained Scenario

- Optimal subsidy is 0 in unconstrained group.

Lipsey and Lancaster (1956).

Plan for Today

- 1 Theory
- 2 Experimental Design
- 3 Estimation
- 4 Setting, Sampling and Measurement
- 5 Results
- 6 Optimal Policy**

Taking Stock

Summary of Findings:

- 1 A 30% subsidy is a second-best policy.
- 2 A lottery payout implies that constrained farmers with high returns increase their willingness to pay, removing the motive for a subsidy.
- 3 A lottery payout increased farm profits.

Should a policy maker focus on correcting any distortions created by liquidity constraints through a subsidy, or should she focus on relaxing liquidity constraints?

Policy Environment

Government Options:

- Allocate transfers of 195k UGX randomly to a share d of the population.
- Offer a single bundle of DAP and CAN to each household at a subsidized price.

Assumptions:

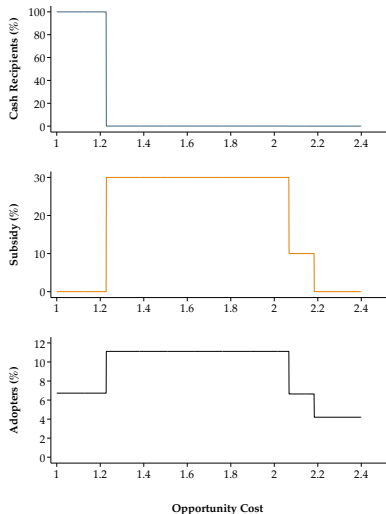
- No general equilibrium effects.
- $\hat{\mathbb{E}}[\theta(I)|w(I)]$ same if the farmer purchased at a price equal to their WTP.
- Fertilizer adoption is a binary decision.

Policy Maker's Optimisation

A policy maker will want to choose d and s to maximise:

$$\begin{aligned} W(d, s) = & (1 - d) \left(S(p - s; 0) - S(p; 0) - (\gamma - 1)s \int_{p-s}^{\infty} f_{W(0)}(w) dw \right) \\ & + d \left(S(p - s; 1) - S(p; 1) - (\gamma - 1)s \int_{p-s}^{\infty} f_{W(1)}(w) dw \right) \\ & + d (S(p; 1) - S(p; 0) - (\gamma - 1)195k \text{ UGX}) . \end{aligned}$$

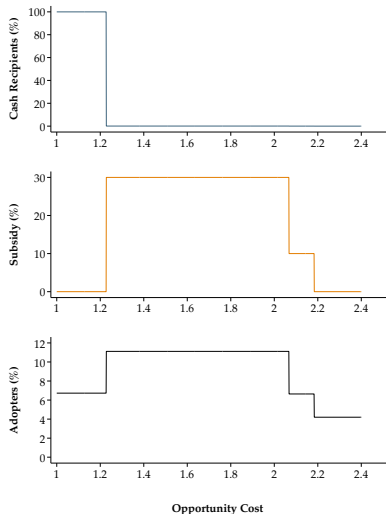
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Four regimes:

- 1 At highest opportunity cost: nothing.
Adoption: 4.2%.
- 2 At high opportunity cost: 10% subsidy.
Adoption: 6.6%; gross return: 2.18.
- 3 At medium opportunity cost: 30% subsidy.
Adoption: 11.1%; gross return: 2.09.
- 4 At low opportunity cost: cash transfers.
Adoption: 6.7%; gross return: 1.25.

Results: Optimal Policy



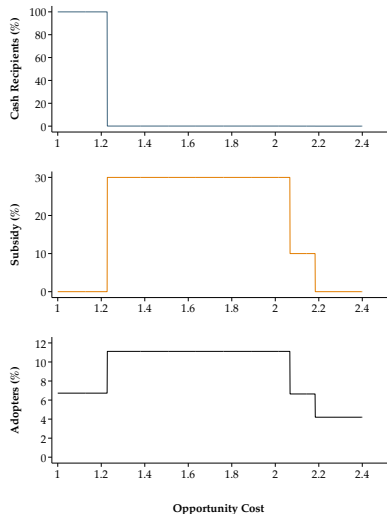
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Lessons:

- Might explain prevalence of subsidy schemes.
- Higher adoption with 30% subs. than cash; second-best à la Lipsey and Lancaster (1956).

Summary

- 1 How well are fertilizer markets functioning in *status quo*?
 - Average profit impacts are substantially below market price.
 - Subsidy of 30% encourages adoption by a subgroup farmer with high returns.
- 2 Can we address the distortion at the source?
 - Cash transfers increase adoption.
 - Cash transfers increase profits.
 - Cash transfers imply that optimal subsidy is 0%.
- 3 Is it optimal to address the distortion at the source?
 - It might not be if the government's cost of funds is high.

Appendix

Introduction: Potash

Introduction: Phosphate

Experiment: BDM Pilot

Experiment: WTP & Planting

Experiment: R Distribution

Estimation: Baseline Control

Measurement: Optimal Survey

Measurement: Plot Size

Measurement: Quadrants

Setting: Weather Patterns

Results: Long-Run Adoption

Results: Land

Results: Inputs

Results: Labour

Results: Quadrants

Results: Compliers

Results: Long-Run Adoption

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	End of Season		Next Season				
	Fertilizer Left		Fertilizer Used		Expenditure (UGX)		
	DAP	CAN	DAP	CAN	DAP	CAN	Any
$\hat{ATE}_F$ (Lottery Lost)	0.226 (0.025) [0.000]	0.240 (0.025) [0.000]	0.306 (0.031) [0.000]	0.281 (0.029) [0.000]	2484 (1233) [0.044]	1448 (975) [0.138]	3535 (2424) [0.145]
$\hat{ATE}_F$ (Lottery Won)	0.211 (0.029) [0.000]	0.238 (0.035) [0.000]	0.391 (0.044) [0.000]	0.370 (0.038) [0.000]	3627 (2115) [0.087]	2335 (1167) [0.046]	7085 (3573) [0.048]
$\hat{ATE}_L$	0.000 (0.012) [0.984]	0.018 (0.018) [0.325]	0.032 (0.028) [0.260]	0.005 (0.021) [0.827]	-432 (1489) [0.772]	-619 (839) [0.461]	-315 (2673) [0.906]
N (Lottery Lost/Won)	663/395	663/395	663/395	663/395	663/395	663/395	663/395
Mean Y in Control	0.000	0.000	0.054	0.042	2083	1097	5863

- Very large effects on long-run adoption.
- Not driven by income effect of fertilizer; suggests learning.

[Main Results] [Appendix Overview]

Results: Average Treatment Effects

	(1)	(2)	(3)	(4)	(5)
	Land Operation (sqm)			Land Rentals (sqm)	
	Total	Cultivated	Fallow	Rented Out	Rented In
$\hat{ATE}_F$ (Lottery Lost)	207.6 (198.8) [0.297]	503.9 (244.1) [0.039]	-92.8 (179.7) [0.606]	-138.7 (126.6) [0.274]	4.8 (136.6) [0.972]
$\hat{ATE}_F$ (Lottery Won)	344.6 (227.7) [0.131]	625.3 (312.2) [0.045]	-108.0 (204.4) [0.597]	-150.4 (132.4) [0.256]	212.1 (184.0) [0.249]
$\hat{ATE}_L$	-62.7 (200.7) [0.755]	263.3 (285.5) [0.357]	-115.3 (190.3) [0.545]	-134.3 (125.4) [0.284]	190.6 (159.8) [0.233]
N (Lottery Lost/Won)	701/415	701/415	701/415	701/415	701/415
Mean Y in Control	9037.5	7378.6	978.8	555.4	563.2

[Main Results] [Appendix Overview]

Results: Average Treatment Effects

	(1)	(2)	(3)	(4)	(5)	(6)
	Seeds		Fertilizer			
	Used Improved	Expenditure (UGX)	Used Any	Used DAP	Used CAN	Expenditure (UGX)
$\hat{ATE}_F$ (Lottery Lost)	0.120 (0.034) [0.000]	-530 (6578) [0.936]	0.793 (0.023) [0.000]	0.809 (0.023) [0.000]	0.796 (0.023) [0.000]	-315.8 (189.8) [0.096]
$\hat{ATE}_F$ (Lottery Won)	0.145 (0.049) [0.003]	5153 (8734) [0.555]	0.715 (0.031) [0.000]	0.695 (0.033) [0.000]	0.735 (0.034) [0.000]	-234.2 (251.9) [0.353]
$\hat{ATE}_L$	0.083 (0.039) [0.036]	12645 (8168) [0.122]	0.131 (0.029) [0.000]	0.114 (0.026) [0.000]	0.101 (0.023) [0.000]	-157.3 (342.2) [0.646]
N (Lottery Lost/Won)	701/415	701/415	701/415	701/415	701/415	701/415
Mean Y in Control	0.268	36608	0.104	0.060	0.041	407.4

[Main Results] [Appendix Overview]

Results: Average Treatment Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Task:	Clearing	Ploughing	Planting	Fertilizer	Pesticides	Weeding	Irrigating	Harvest	All	All
Panel A, Family:	Hours								Hours	
$\hat{ATE}_F$ (Lottery Lost)	-3.846 (11.558) [0.739]	6.302 (8.790) [0.474]	7.097 (7.655) [0.354]	36.80 (2.51) [0.000]	3.183 (0.947) [0.001]	3.834 (12.289) [0.755]	-0.247 (0.187) [0.188]	10.23 (7.86) [0.194]	64.22 (37.83) [0.090]	
$\hat{ATE}_F$ (Lottery Won)	3.102 (14.966) [0.836]	8.087 (11.174) [0.469]	4.104 (10.996) [0.709]	39.48 (4.68) [0.000]	0.585 (1.189) [0.623]	7.968 (16.954) [0.639]	-0.034 (0.282) [0.906]	-3.06 (10.65) [0.774]	54.55 (52.03) [0.295]	
$\hat{ATE}_L$	-9.880 (11.825) [0.404]	-11.502 (8.363) [0.169]	0.171 (9.387) [0.985]	2.78 (2.67) [0.298]	1.460 (1.042) [0.161]	-12.549 (15.109) [0.406]	0.011 (0.234) [0.964]	5.68 (9.43) [0.548]	-20.46 (43.81) [0.641]	
N (Lottery Lost/Won)	701/413	701/413	701/413	701/413	701/413	701/412	701/413	701/413	701/413	
Mean Y in Control	99.070	55.080	95.894	2.68	3.734	171.155	0.427	92.81	524.26	
Panel B, Hired:	Number								Hours	Costs
$\hat{ATE}_F$ (Lottery Lost)	-0.021 (0.071) [0.765]	0.517 (0.271) [0.056]	0.887 (0.354) [0.012]	1.188 (0.158) [0.000]	0.072 (0.058) [0.215]	1.149 (0.411) [0.005]	0.000 (0.003) [0.896]	1.037 (0.308) [0.001]	43.90 (13.48) [0.001]	41528 (16155) [0.010]
$\hat{ATE}_F$ (Lottery Won)	-0.136 (0.146) [0.352]	0.469 (0.465) [0.314]	0.999 (0.678) [0.141]	0.905 (0.268) [0.001]	0.134 (0.097) [0.169]	1.072 (0.740) [0.148]	0.006 (0.007) [0.357]	0.973 (0.621) [0.117]	34.84 (23.99) [0.147]	35765 (25457) [0.160]
$\hat{ATE}_L$	0.149 (0.121) [0.220]	0.336 (0.300) [0.262]	0.582 (0.389) [0.135]	0.106 (0.119) [0.371]	-0.079 (0.051) [0.123]	0.974 (0.440) [0.027]	-0.002 (0.002) [0.315]	0.798 (0.335) [0.018]	24.75 (13.32) [0.064]	19920 (15408) [0.196]
N (Lottery Lost/Won)	701/412	701/412	701/412	701/412	701/412	701/412	701/412	701/412	701/412	701/415
Mean Y in Control	0.153	1.769	2.962	0.114	0.119	4.222	0.003	2.072	96.13	123623

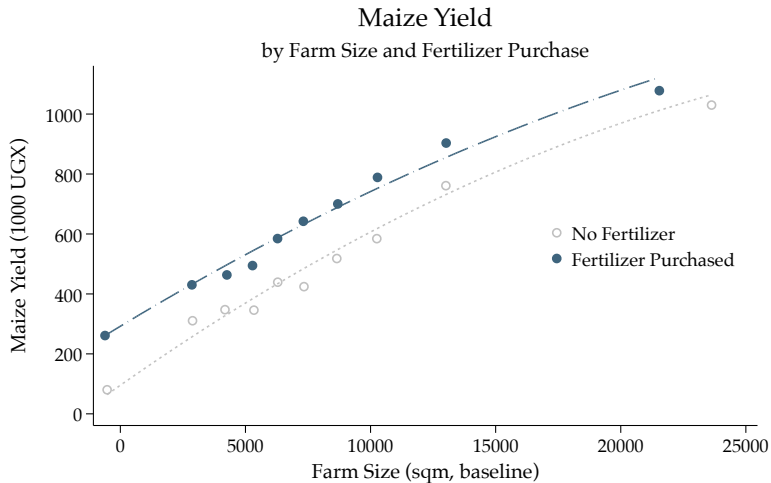
[Main Results] [Appendix Overview]

Results: Average Treatment Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All Quadrants				Maize Quadrants					
	Intercr.	Line-S.	M. Cult.	Maize Pl.	Maize Pl.	Expect.	Exp. Pl.	Disease	Armyw.	Infested Pl.
$\hat{ATE}_F$ (Lottery Lost)	-0.017 (0.021) [0.404]	0.096 (0.021) [0.000]	0.074 (0.020) [0.000]	0.729 (0.148) [0.000]	0.437 (0.153) [0.004]	0.083 (0.018) [0.000]	0.804 (0.159) [0.000]	-0.032 (0.029) [0.277]	-0.016 (0.022) [0.458]	-0.071 (0.079) [0.367]
$\hat{ATE}_F$ (Lottery Won)	-0.074 (0.026) [0.005]	0.074 (0.029) [0.011]	0.045 (0.027) [0.091]	0.583 (0.209) [0.005]	0.592 (0.240) [0.014]	0.117 (0.024) [0.000]	1.020 (0.245) [0.000]	-0.097 (0.037) [0.009]	-0.020 (0.032) [0.541]	-0.077 (0.110) [0.482]
$\hat{ATE}_L$	0.005 (0.023) [0.823]	0.020 (0.024) [0.400]	0.018 (0.022) [0.408]	0.211 (0.155) [0.174]	0.112 (0.177) [0.528]	0.004 (0.020) [0.819]	0.154 (0.163) [0.345]	-0.029 (0.035) [0.408]	-0.006 (0.027) [0.833]	-0.036 (0.095) [0.705]
N (Lottery Lost/Won)	695/411	695/411	695/411	695/411	641/382	641/382	641/382	641/382	641/382	641/382
Mean Y in Control	0.267	0.461	0.528	2.625	4.747	0.581	2.916	0.397	0.172	0.650

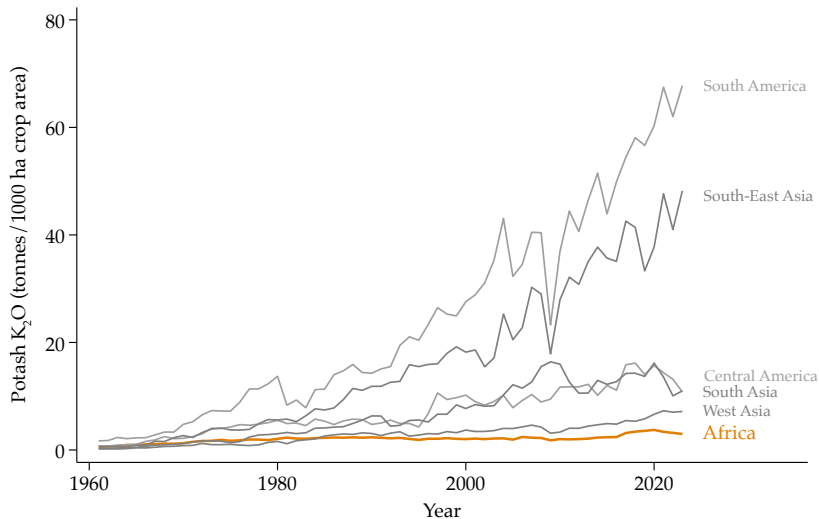
[Main Results] [Appendix Overview]

Maize Yield and Farm Size

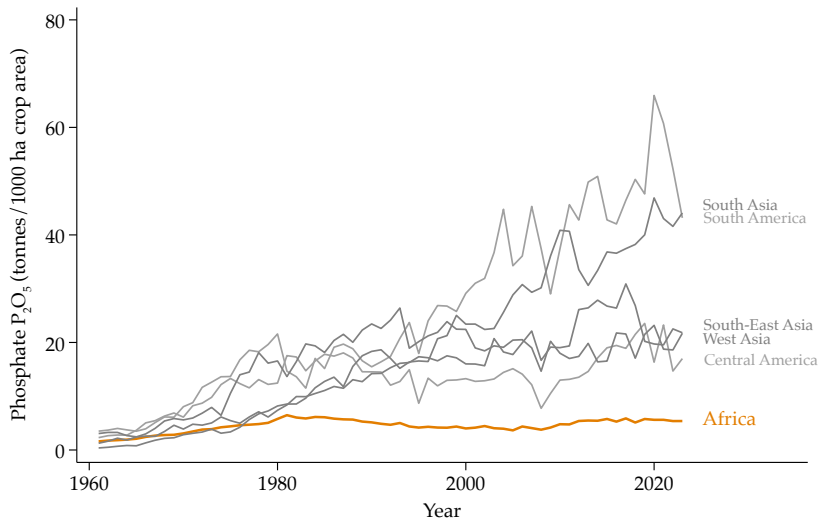


[Estimation Equation] [Appendix Overview]

Background: Fertilizer Adoption in Africa



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Marginal Treatment Effects

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- 3 Can recover other quantities of interest, e.g.

- $\int_P^{W_{max}} \Delta^{MTE}(w) dF(w)$: ATE for buyers at price P .
- $\int_P^{P'} \Delta^{MTE}(w) dF(w)$: LATE of price change from P' to P .

[Experimental Design]

Implementation Challenges: Understanding

Berry et al. (2015) use approach with water filters in Ghana. BDM demand curve similar to take-it-or-leave-it offers.

Implementation Issues:

- People do not always bid truthfully in strategy-proof mechanisms like BDM: more dominant strategy play in ascending than second-price sealed-bid auctions.

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- Worry about auctioneer misbehaviour. Participants will not bid truthfully if they suspect price manipulation.
- With uniform price, low power for 'extreme' WTP.
- With actual randomisation of R , no stratification.

Pilot Experiment

Pilot Experiment:

- 1 WTP elicitation in setting where optimal bid is known: instantly-redeemable cash voucher worth 1400 UGX (\$0.40).
- 2 Test different mechanisms to compare performance.

Test population: rural village residents in Eastern Uganda.

Pilot Experiment

Test 3 design features:

- **BDM** vs **ascending MPL**.

Pilot Experiment

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 - Public: scratchcard with 11 boxes, subject scratches one.
We show examples, can scratch all boxes after, enumerators “do not know” the price locations.
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We show examples, can scratch all boxes after, enumerators “do not know” the price locations.
 - Preassigned: scratchcard with single box.
“The price has been randomly selected by the computer and enumerator does not know it.”
- **Unstated vs stated price distribution.**
 - Unstated: “The price might be 0, 200, ..., up to 2,000 UGX.”
 - Stated: “... Each of these values appears exactly once/is equally likely to be on your scratchcard.”

Pilot Experiment

Treatments

- 1 BDM, public randomization, stated uniform prices
- 2 MPL, public randomization, stated uniform prices
- 3 MPL, preassigned price, stated uniform prices
- 4 MPL, preassigned price, unstated price distribution

Main observables:

- Participant's cash on hand
- Bid for voucher
- Optimal bid = 1 if $bid \in \{1200, 1400\}$ or all cash if constrained.

Pilot Experiment: Soap Auction

After the voucher, we also sell a bar of soap worth 2000 UGX (\$0.55) using the same mechanism ($P \in \{0, 400, \dots, 4000\}$).

Data

- Bid for bar of soap
- Participant belief about market price of soap (at end of survey)
- “Optimal bid” = 1 if $\text{bid} \in \{\text{marketprice}(\text{rounded}), \text{marketprice} - 400\}$, or (cash on hand + voucher profit) if constrained.

Note: only “optimal”. True optimal bid equals market price only if a) participant would buy soap in the market and b) no transaction costs.

Pilot Experiment: Implementation Details

Multiple design features to aid trust and understanding

- Give participants an instantly redeemable 100 UGX voucher at start, to demonstrate voucher mechanism.
- Explain mechanism in concrete and intuitive terms.
- For a hypothetical 1600 UGX voucher, ask participant to compute win/lose outcomes and profits for different bid-price combinations.
- Check participant comprehension of price range (& distribution in stated treatments).
- After WTP elicited, check participant knows what would happen for different price draws.
- Allow to change bid if desired (nobody does).
- Final confirmation.
- Price revelation.

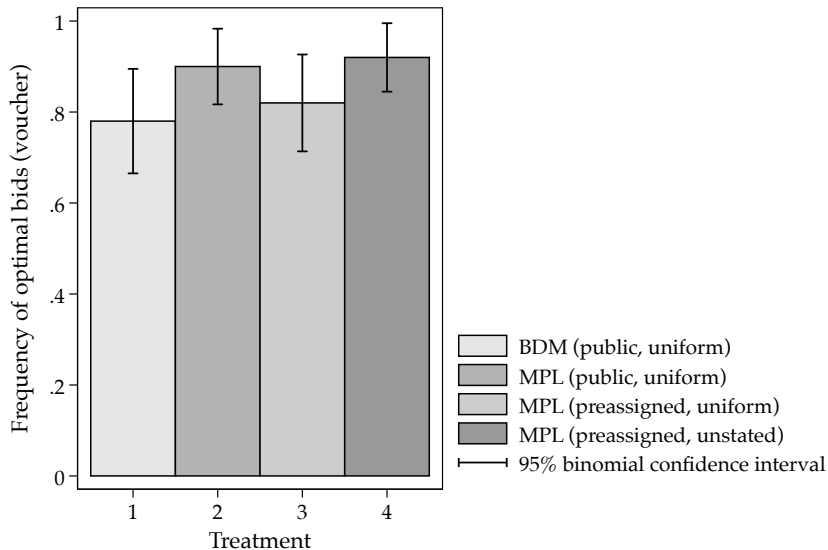
Pilot Experiment: Implementation Details

Participants:

- Recruit from 7 rural villages in Mbale District (Eastern Region) Uganda.
- Mobilizers visit village 1 day before, ask chairperson to suggest 35 participants.
- Interviews continue until $N = 200$.
- Simple randomization (50 per treatment).

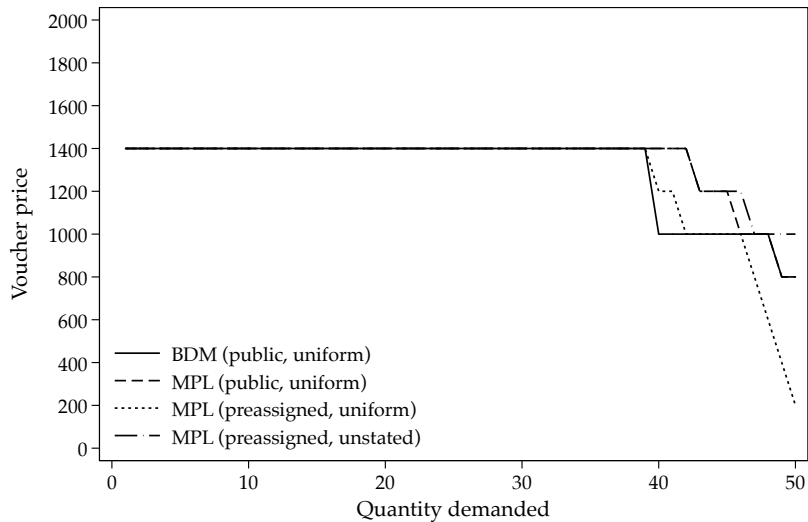
Pilot Experiment: Results

Optimal bidding for voucher. Chi-squared (3 d.f.) p-value = 0.15



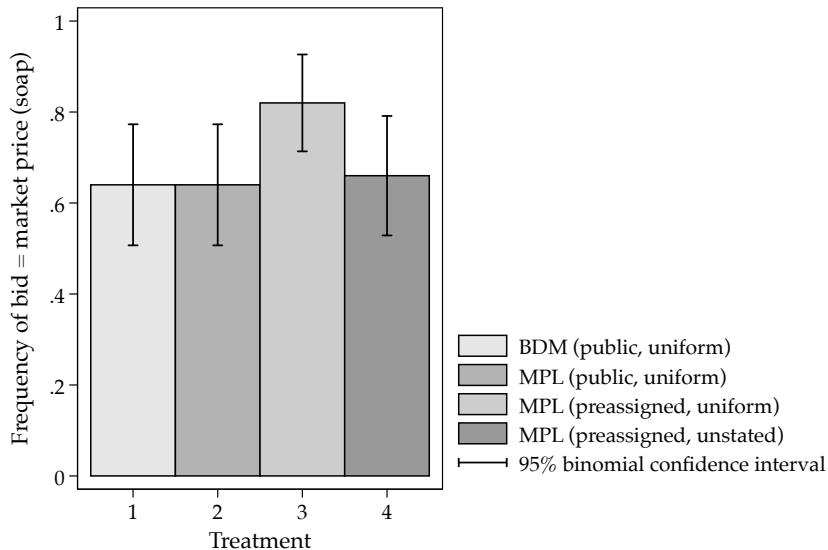
Pilot Experiment: Results

Demand for voucher



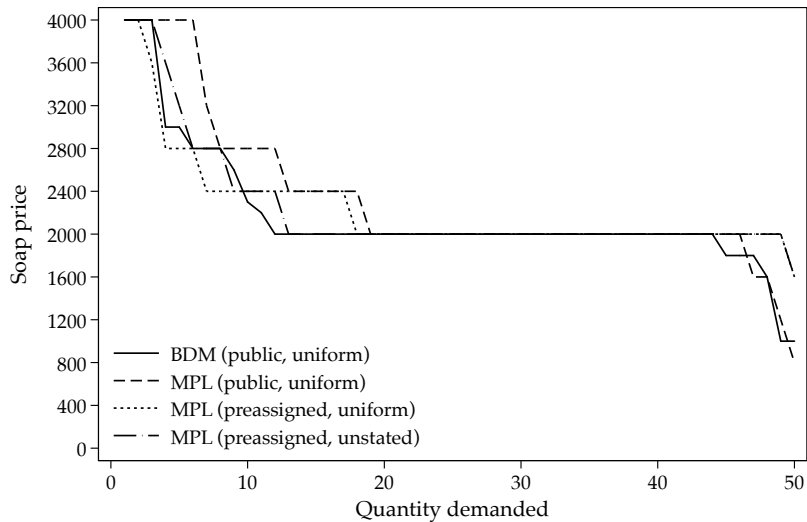
Pilot Experiment: Results

"Optimal" bidding for soap. Chi-squared (3 d.f.) p-value = 0.15



Pilot Experiment: Results

Demand for soap

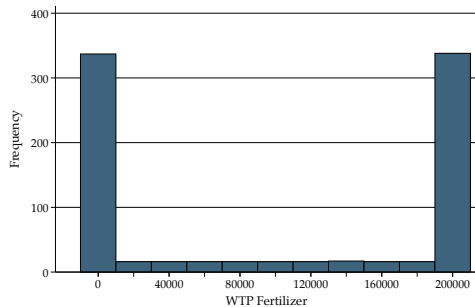
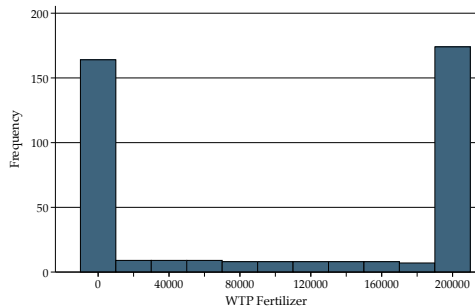


Pilot Experiment: Summary of Findings

- All mechanisms performed surprisingly well, no clear differences.
 - Contrast with earlier results.
- Gives confidence in ability to measure WTP.
- MPL (preassigned, unstated) seems safe to use.

[Appendix Overview]

Price Distribution



[Appendix Overview]

Optimal Survey Design

Aim: Measure outcome y_i in population of interest $\mathcal{P}$.

Problem: Prohibitively costly. Could measure y_i in $\mathcal{P}_y \subset \mathcal{P}$.

Standard: Measure $\mathbf{x}_i$ that maybe proxies for y_i , $y_i = f(\beta\mathbf{x}_i, \epsilon_i)$,
and use it instead of y_i .

Optimal Survey Design

How to use $\mathbf{x}_i$ optimally? How to choose $\mathbf{x}_i$?

(Carneiro, Lee, Wilhelm, 2017)

Optimal Survey Design: Part 1

How to use $\mathbf{x}_i$ optimally?

1. Measure y_i for $\mathcal{P}_y$ and $\mathbf{x}_i$ for $\mathcal{P}$.
2. Find $\hat{f}(\mathbf{x}_i) = \arg \min_{g(\mathbf{x}) \in \mathcal{C}(\mathbf{x})} L(y_i, g(\mathbf{x}_i)).$
3. Predict $\hat{y}_i = \hat{f}(\mathbf{x}_i)$ for all $i \notin \mathcal{P}_y$.

Optimal Survey Design: Part 1

How to use $\mathbf{x}_i$ optimally?

1. Measure y_i for $\mathcal{P}_y$ and $\mathbf{x}_i$ for $\mathcal{P}$.
2. Find $\hat{f}(\mathbf{x}_i) = \arg \min_{g(\mathbf{x}) \in \mathcal{C}(\mathbf{x})} L(y_i, g(\mathbf{x}_i)).$
 - $L(y_i, g(\mathbf{x}_i))$ usually MSE.
3. Predict $\hat{y}_i = \hat{f}(\mathbf{x}_i)$ for all $i \notin \mathcal{P}_y$.

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 - Machine learning good at this!
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Optimal Survey Design: Part 1

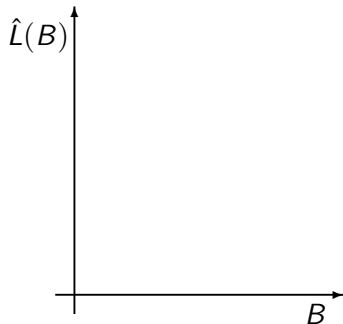
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 - $L(y_i, g(\mathbf{x}_i))$ usually MSE.
 - Machine learning good at this!
 - Evaluate $L(y_i, \hat{f}(\mathbf{x}_i))$ in $\mathcal{P}_{\text{Test}} \subset \mathcal{P}_y$.
3. Predict $\hat{y}_i = \hat{f}(\mathbf{x}_i)$ for all $i \notin \mathcal{P}_y$.

Optimal Survey Design: Part 2

How to choose $\mathbf{x}_i$?

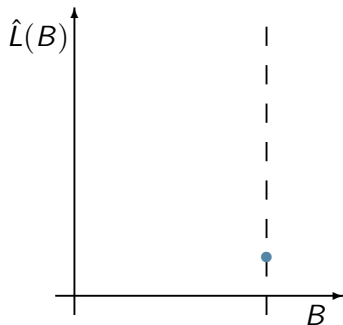
1. Prices p_j for each x_{ij} .
 $\rightarrow B(\mathbf{x}_i; \mathbf{p}) := \sum_{i \in \mathcal{P}} \mathbf{p}' \mathbf{x}_i.$



Optimal Survey Design: Part 2

How to choose $\mathbf{x}_i$?

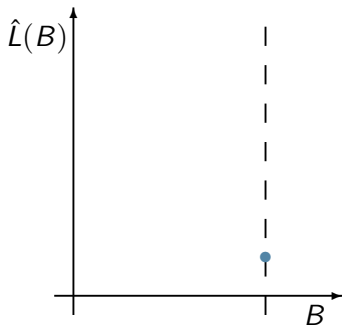
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Optimal Survey Design: Part 2

How to choose $\mathbf{x}_i$?

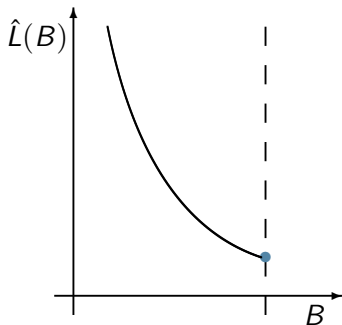
1. Prices p_j for each x_{ij} .
 $\rightarrow B(\mathbf{x}_i; \mathbf{p}) := \sum_{i \in \mathcal{P}} \mathbf{p}' \mathbf{x}_i.$
2. For all $B < B(\mathbf{x}_i; \mathbf{p})$:
find subset of variables $\mathbf{z}$ that minimises
 $L(y_i; \hat{f}(\mathbf{z}_i))$, s.t. $B(\mathbf{z}; \mathbf{p}) \leq B$; evaluate
 $L(y_i; \hat{f}(\mathbf{z}_i))$ in $\mathcal{P}_{\text{Test}^*} \subset \mathcal{P}_y$.



Optimal Survey Design: Part 2

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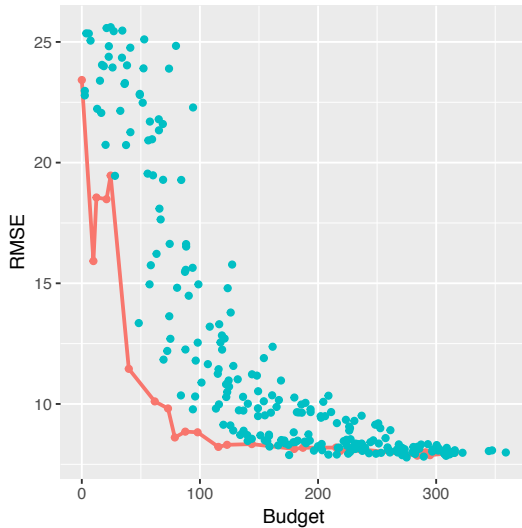


Optimal Survey Design: Our Example



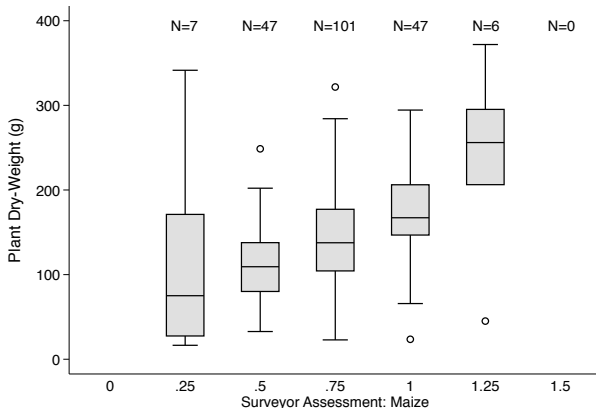
Optimal Survey Design: Our Example

Budget–Error trade-off, Training data



Optimal Survey Design: Our Example

FIGURE 1: ENUMERATOR EXPECTATIONS AND REALIZED MAIZE YIELD.



Notes: The figure depicts box plots of realized dry yield per plant in a quadrant, at each discrete level of enumerator expectations. *Plant Dry-Weight (g)* is measured in grams and calculated as the average weight (at 12% moisture) of sampled maize ears in a quadrant multiplied by the observed number of ears per plant. The enumerators' expectations are the enumerators' assessment of the expected yield per plant of maize plants in a quadrant relative to the yield of healthy plant. Answers were given as shares from a discrete set of options, $s \in \{0\%, 25\%, 50\%, 75\%, 100\%, 125\%, 150\%\}$. The grey area of each box plot depicts the 25th to 75th percentile range, and the inside black line depicts the median. Above each box plot the number of observations at the is stated. All data is at the quadrant level.

Optimal Survey Design: Our Example

TABLE 2: CORRELATION OF YIELD MEASURES

	Realized Yield	Enumerator Assessment	Farmer-Reported
Realized Yields	1.000		
Enumerator Assessment	0.816	1.000	
Farmer-Reported	0.395	0.463	1.000

Notes: The table reports the pair-wise Pearson's correlation coefficient between any two measures of yields, using information from the 69 plots for which all information is available. *Realized Yield* is based on a combination of Crop-Cutting and Pre-Harvest Crop Assessment data with the key ingredient being the measured dry-weight of ears; *Enumerator Assessment* is solely based on Pre-Harvest Crop Assessment with the key ingredient being the enumerator assessment of yield per plants; and *Farmer Reported* is based on the farmers' self-reported yield in the Follow-Up Survey.

[Timeline] [Appendix Overview]

Measuring Plot Sizes

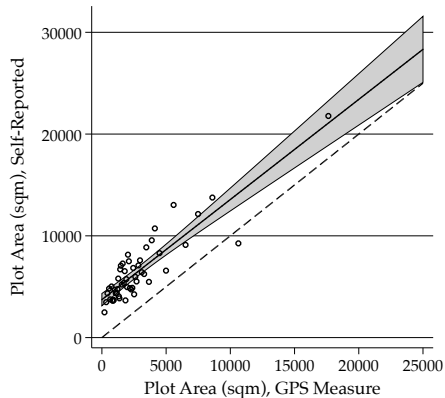
Figure 3: Crop Assessment Field Tracks



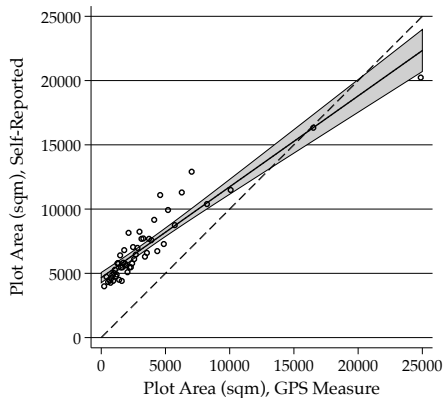
Measuring Plot Sizes

Figure 4: Land Size Measurement

(a) Season 1



(b) Season 2



Quadrant Placement

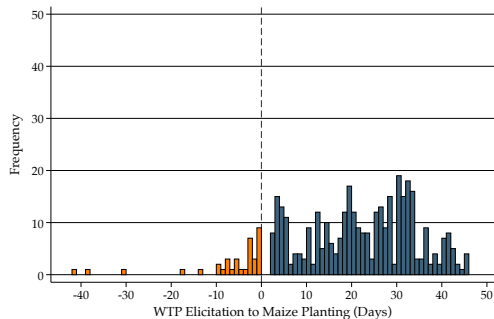


[Timeline] [Appendix Overview]

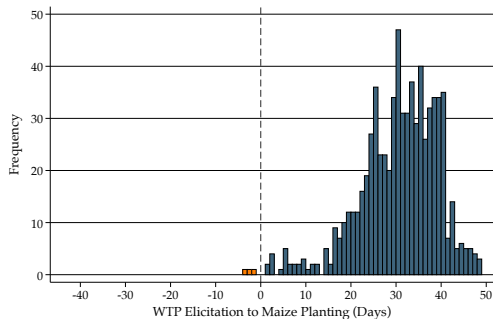
Planting Time

Figure 5: WTP Elicitation to Maize Planting

(a) Season 1

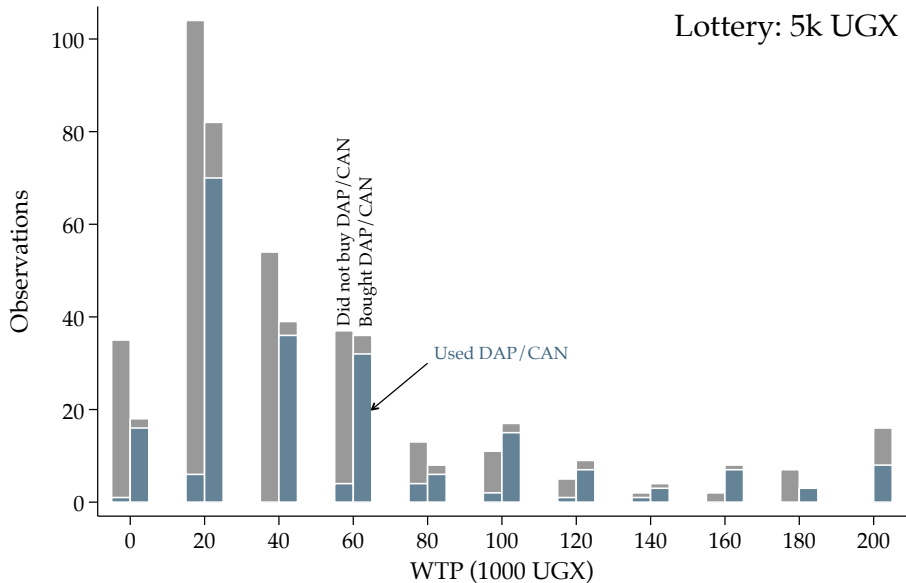


(b) Season 2

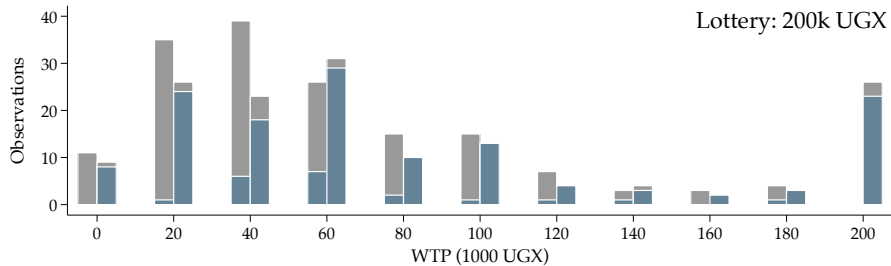
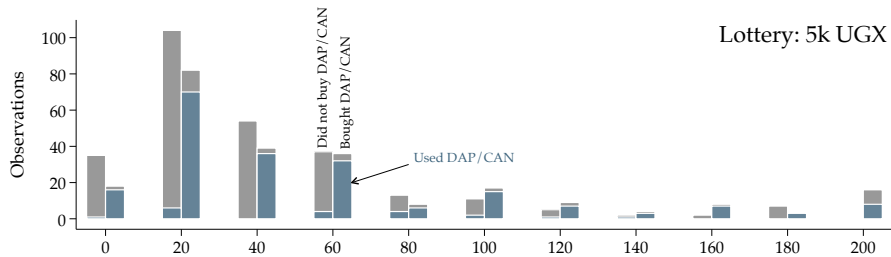


[Timeline] [Appendix Overview]

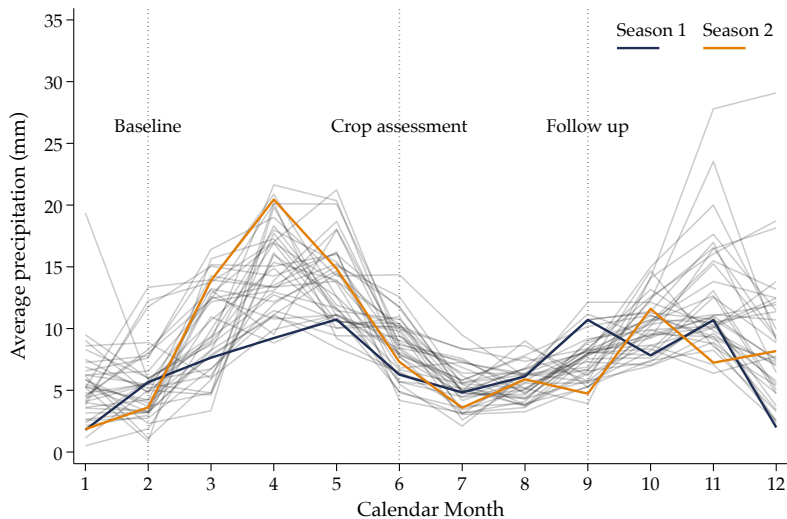
First Stage (Lottery: 5k)



First Stage



Weather Patterns 1981-2018



[Results] [Appendix Overview]