

# Pricing and Allocation of New Agricultural Technologies<sup>1</sup>

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# The Role of Prices in Allocating Goods

- ▶ In a first best world, market prices efficiently allocate goods
- ▶ Subsidies: a policy tool for lowering prices
  - Can increase take-up of goods with high expected benefits
  - But the allocative efficiency consequences are not clear
- ▶ Buyers can be heterogeneous in many ways:
  - Benefits from using the good
  - Constraints preventing take-up
  - The sign of the correlation between these two (if any) is unknown

# Studying Prices as an Allocation Mechanism in an Agricultural Setting

1. Agricultural input subsidies take up 10% or more of total government spending in some developing countries (Wiggins and Brooks 2012)
2. Heterogeneity in returns due to farm management skills, farm characteristics, access to complementary inputs, etc.
3. Uncertainty implies that expected returns at the time of purchase may differ from realized returns
4. Two separate decisions: take-up  $\neq$  adoption

# This Paper...

## Research Question:

- ▶ Do higher prices screen out buyers with lower benefits?
  - At various prices, do farmers who choose not to buy a new agricultural technology have lower than average returns?

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- ▶ Two-stage randomized controlled trial (RCT)
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## Contribution:

- ▶ The first experimental evidence on whether agricultural input prices sort farmers based on their returns to adoption Literature

## Brief Context

- ▶ An improved wheat seed called *BARI-Gom-33*
- ▶ The RCT is implemented in Bangladesh:
  - *BARI-Gom-33* is resistant to a contagious crop disease called wheat blast



Photo credit: Guillermo Vargas

Map

# Preview of Results

## 1. Results on demand and adoption

- Demand is highly elastic, but buyers paying higher prices are not more likely to plant distributed seeds
- Subsidies do **not** distort allocation away from those most likely to plant the seeds

## 2. Results on revenues and profits

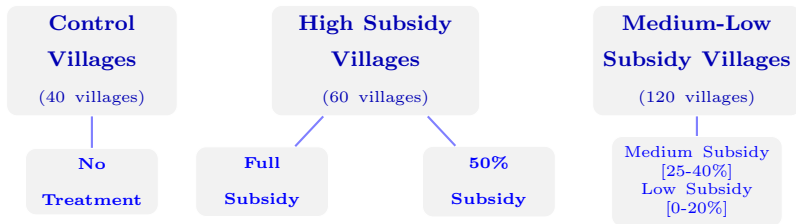
- Negative treatment effects on revenues and profits
- Realized returns of the self-selected non-buyers (who eventually receive the seed for free) are similar to the realized returns of framers who got free seeds at random

## 3. A possible mechanism

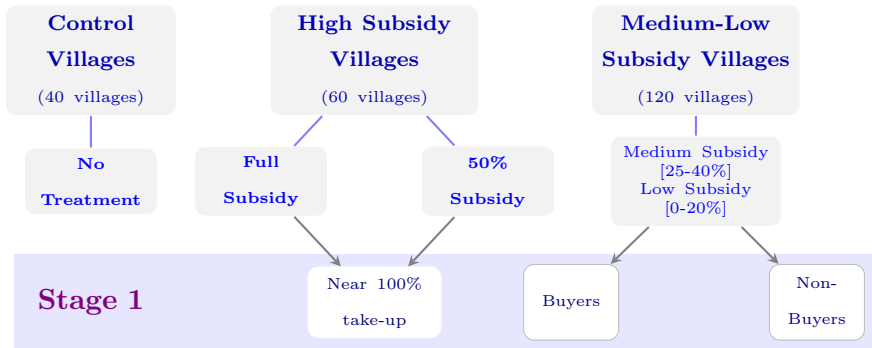
- Heterogeneity analysis suggests that credit constraints partially explain why farmers who are *willing* to plant the seeds but are not *able* to buy them

1. Introduction
2. Experimental Design
3. Empirical Strategy
4. Results on Take-up and Adoption
  - Similar effects on adoption regardless of purchase decision
5. Results on Revenues and Profits
  - No evidence of positive selection based on realized returns
6. Year 2 Results
  - Partially persistent treatment effects on adoption
7. A Potential Mechanism
  - Heterogeneity in the characteristics of non-buyers and the response to stage-two treatment

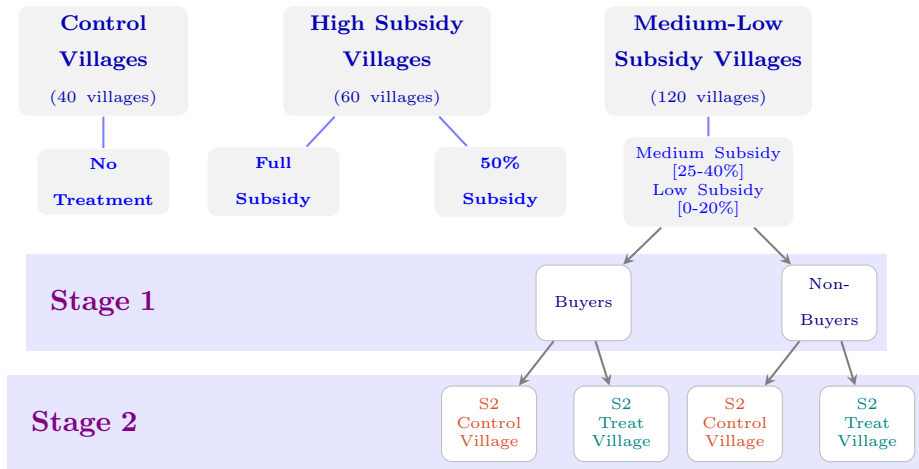
# Two-stage Experimental Design



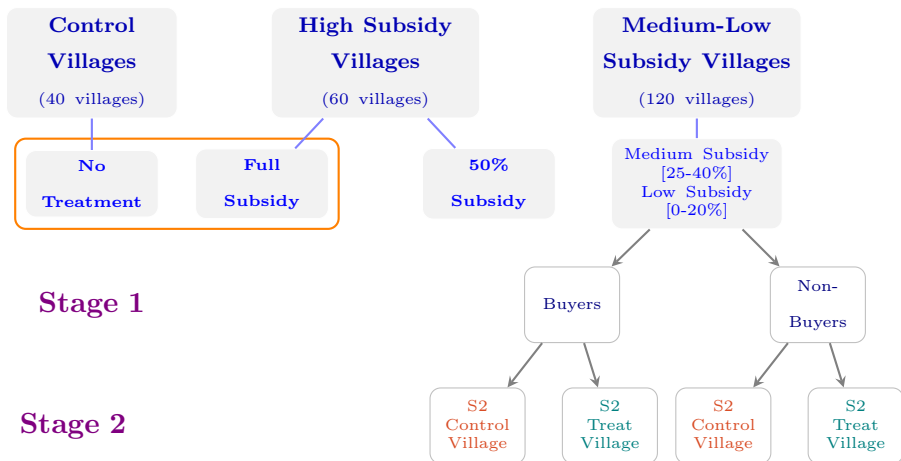
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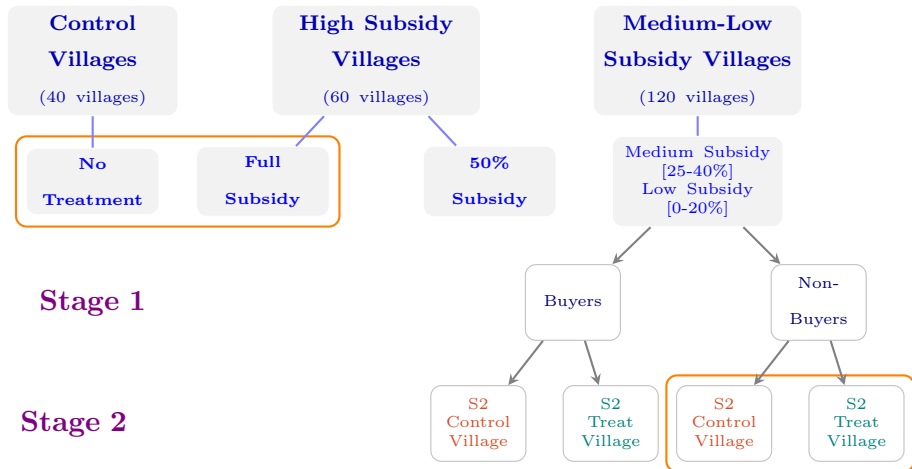
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# Empirical Strategy

## Test for Selection Effects (1/2)

$$Y_{ijs} = \gamma_1 Free_j + \gamma_2 S1\text{-NonBuyer}_{ij} * S2\text{-Treat}_j \\ + \gamma_3 S1\text{-NonBuyer}_{ij} * S2\text{-Control}_j + \alpha_s + \epsilon_{ijs}$$

- ▶  $Y_{ijs}$  outcome of interest (e.g., adoption, wheat area, revenues, and profits)
- ▶ Omitted group = pure control villages
- ▶  $\alpha_s$  strata fixed effects Wheat intensity
- ▶ Probability weights to account for the differences in the sampling probabilities of non-buyers

# Empirical Strategy

## Test for Selection Effects (2/2)

$$Y_{ijs} = \gamma_1 \text{Free}_j + \gamma_2 \text{S1-NonBuyer}_{ij} * \text{S2-Treat}_j \\ + \gamma_3 \text{S1-NonBuyer}_{ij} * \text{S2-Control}_j + \alpha_s + \epsilon_{ijs}$$

- ▶  $\gamma_1$  measures treatment effects for the entire population
- ▶  $\gamma_2 - \gamma_3$  measures net effect of stage-two treatment on non-buyers
- ▶  $\gamma_1 = \gamma_2 - \gamma_3$  tests whether the self-selected non-buyers obtained similar, lower, or higher outcomes
  - $\gamma_1 > \gamma_2 - \gamma_3$  implies positive self-selection
  - $\gamma_1 < \gamma_2 - \gamma_3$  implies negative self-selection

# Empirical Strategy

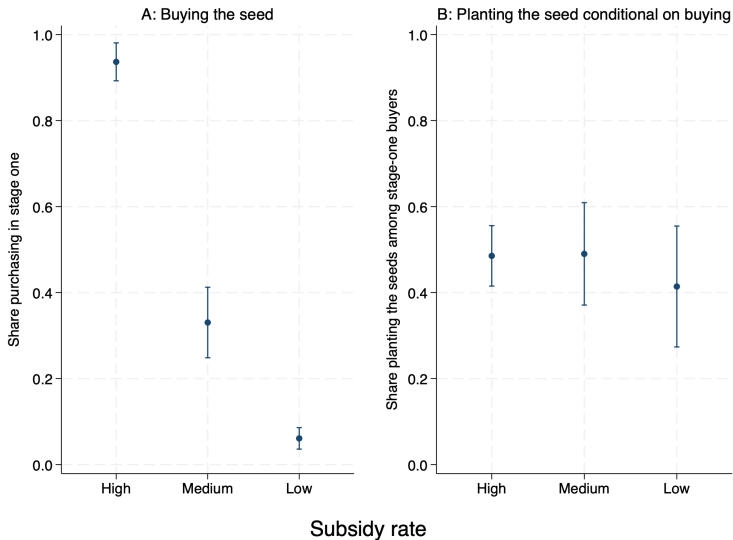
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  - $\gamma_1 > \gamma_2 - \gamma_3$  implies positive self-selection
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- ▶ Additional specifications: include buyers separately, and/or interact stage-two treatment and control with a dummy for stage-one subsidy level Alternative specification Power calculation

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# Elastic Demand in Contrast with Flat Usage Rate



# Impacts on Adoption and Wheat Cultivation

## Similar Causal Effects Regardless of Purchase Decision

	(1) Adoption	(2) Growing Wheat	(3) Share of Wheat Area
Free distribution village ( $\gamma_1$ )	0.41*** (0.04)	0.28*** (0.04)	0.09*** (0.02)
S1 Non-buyer x S2 Treat ( $\gamma_2$ )	0.35*** (0.04)	0.23*** (0.04)	0.06*** (0.02)
S1 Non-buyer x S2 Control ( $\gamma_3$ )	0.03 (0.03)	0.00 (0.04)	0.00 (0.02)
S1 Buyer x S2 Treat	0.39*** (0.05)	0.27*** (0.05)	0.09*** (0.02)
S1 Buyer x S2 Control	0.32*** (0.06)	0.23*** (0.06)	0.08*** (0.02)
Strata FE	Yes	Yes	Yes
R-squared	0.265	0.192	0.118
p-value $\gamma_1 = \gamma_2 - \gamma_3$	0.07	0.23	0.30
CI: $\gamma_1 - \gamma_2 + \gamma_3$	(-0.01, 0.20)	(-0.05, 0.18)	(-0.03, 0.08)
Control Villages' Mean	0.02	0.15	0.06
Number of observations	4,611	4,611	4,611

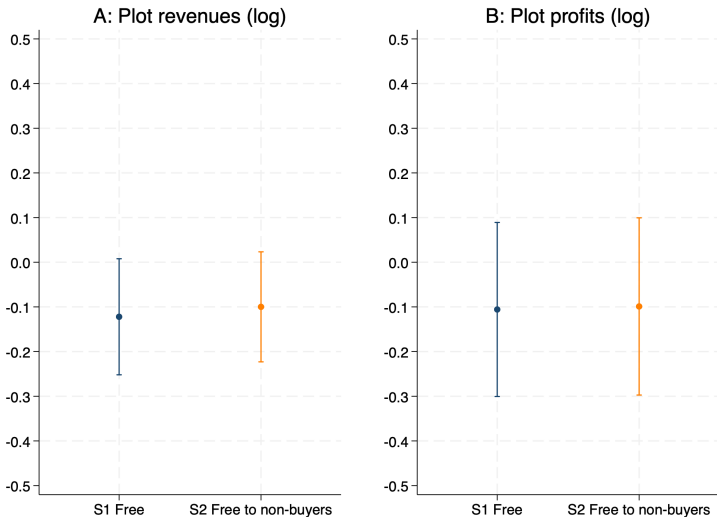
Adoption medium vs low subsidy

Baseline wheat cultivation

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# Impacts on Revenues and Profits

No Evidence of Positive Selection Based on Realized Returns



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# Adoption and Disadoption in Year 2

## Similar Causal Effects on (Dis-)Adoption

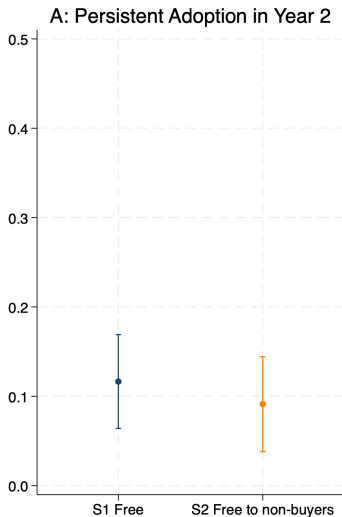
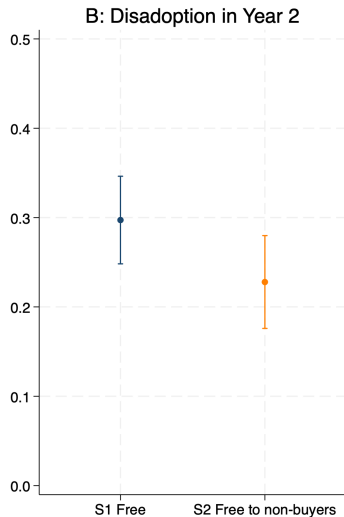


Table: Year 2 results

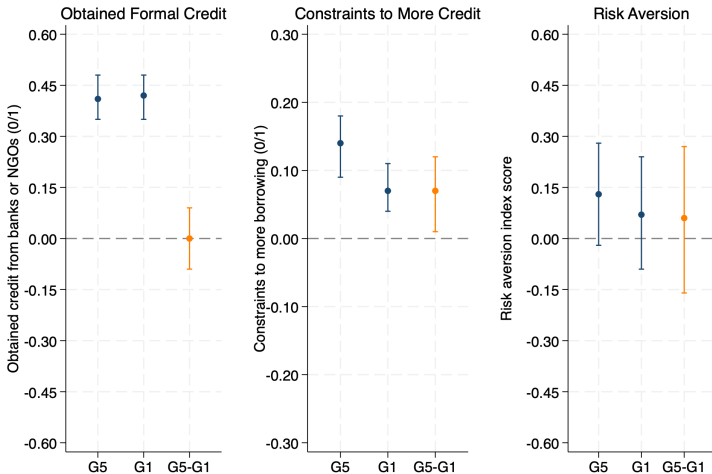


Spillover effects

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# Heterogeneity in Treatment Effects on Growing Wheat

## Characteristics of farmers who are most responsive to free distribution



G5 = 20% Most affected G1 = 20% Least affected, CI: 90% level

## Conclusion

- ▶ The experimental design allows for a comparison between the causal effects of free distribution on two groups:
  1. farmers who receive the seed for free in stage one
  2. farmers who choose not to buy the seed in stage one

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  2. farmers who choose not to buy the seed in stage one
- ▶ Results suggest that prices do **not** screen farmers based on returns to adoption
  - One explanation: ability to pay may be different from the revealed willingness-to-pay due to credit constraints
  - The credit constraint mechanism is consistent with empirical results as well as a theoretical model

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- ▶ Results suggest that prices do **not** screen farmers based on returns to adoption
  - One explanation: ability to pay may be different from the revealed willingness-to-pay due to credit constraints
  - The credit constraint mechanism is consistent with empirical results as well as a theoretical model
- ▶ Policy implication:
  - Subsidies do not distort allocation to farmers with lower returns
  - Prices *alone* cannot serve as a targeting tool in targeting dissemination to high-return farmers

Thank You!

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# Contribution to the Literature

## **This paper examines whether prices allocate agricultural inputs efficiently**

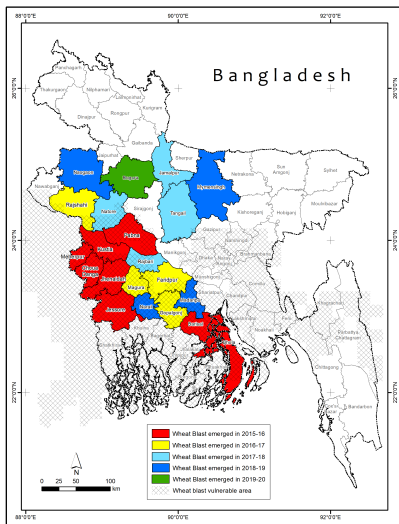
- ▶ The debate on how prices allocate resources:
  - Subsidies could correct under-utilization (Cohen and Dupas 2010; Kremer and Miguel 2007)
  - But higher WTP could be associated with higher benefits (Ashraf, Berry, and Shapiro 2010; Berry, Fischer, and Guiteras 2020; Lybbert et al. 2017; Beaman, Karlan, et al. 2023)

## I look at this trade-off in the context of agricultural inputs

- ▶ The dissemination of agricultural technologies to targeted farmers
  - Input subsidy programs relying on local expert opinion (Carter, Laajaj, and Yang 2021; Abate et al. 2018; Giné et al. 2022)
  - Theory-based targeting relying on social networks (Beaman, BenYishay, et al. 2021)

I study self-selection as a targeting mechanism induced by price changes

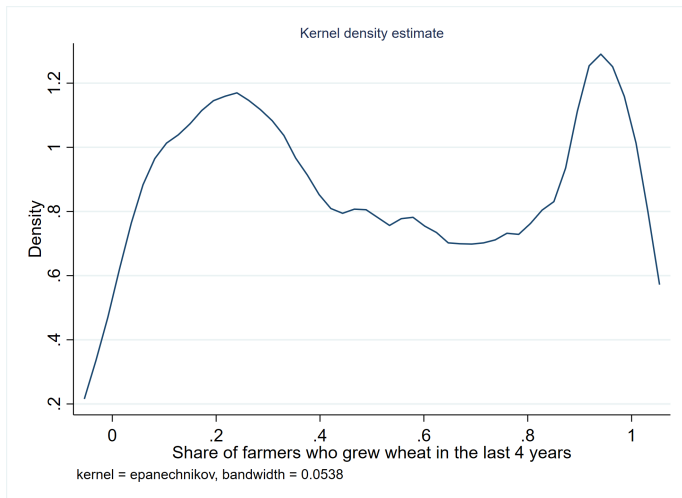
# Districts Map



Wheat blast vulnerability by district during 2016-2019

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# Village-level Intensity of wheat cultivation



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# Alternative Regression Specifications

## Two Separate Regressions

First, stage-one free distribution treatment:

$$Y_{ijs} = \gamma_1 \text{Free}_j + \alpha_s + \epsilon_{ijs} \quad (1)$$

- ▶ Omitted group = pure control villages

Second, stage-two free distribution to non-buyers:

$$Y_{ijs} = \delta_1 \text{S2-Treat}_j + \alpha_s + \epsilon_{ijs} \quad (2)$$

- ▶ Omitted group = non-buyers in stage-two control villages

My preferred specification stacks the two regression equations to test for:  $\gamma_1 = \delta_1$  (where  $\delta_1$  is the same as  $\gamma_2 - \gamma_3$  in the stacked equation)

# Power Calculation

## Ex-post Power Calculation Estimates

First, stage-one free distribution treatment:

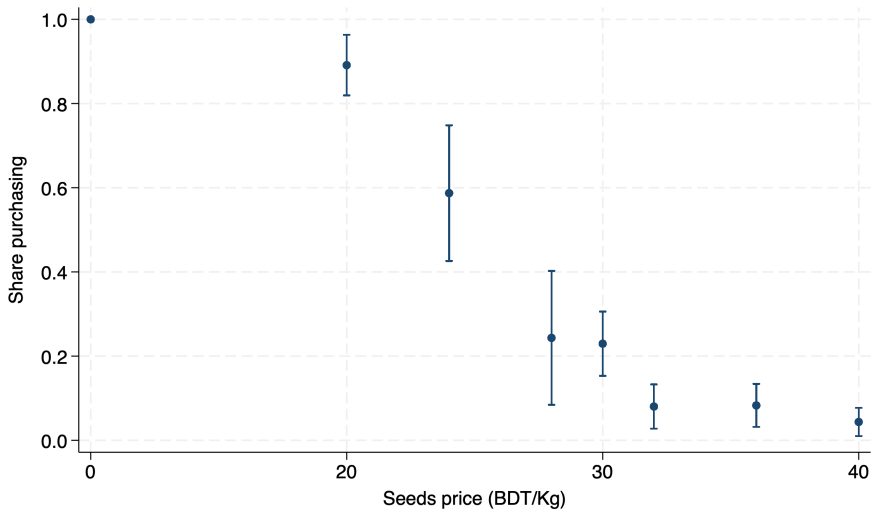
1. MDE for wheat cultivation: 0.19 SD
2. MDE for plot revenues: 0.25 SD
3. MDE for plot profits: 0.16 SD

Second, stage-two free distribution to non-buyers:

1. MDE for wheat cultivation: 0.19 SD
2. MDE for plot revenues: 0.26 SD
3. MDE for plot profits: 0.16 SD

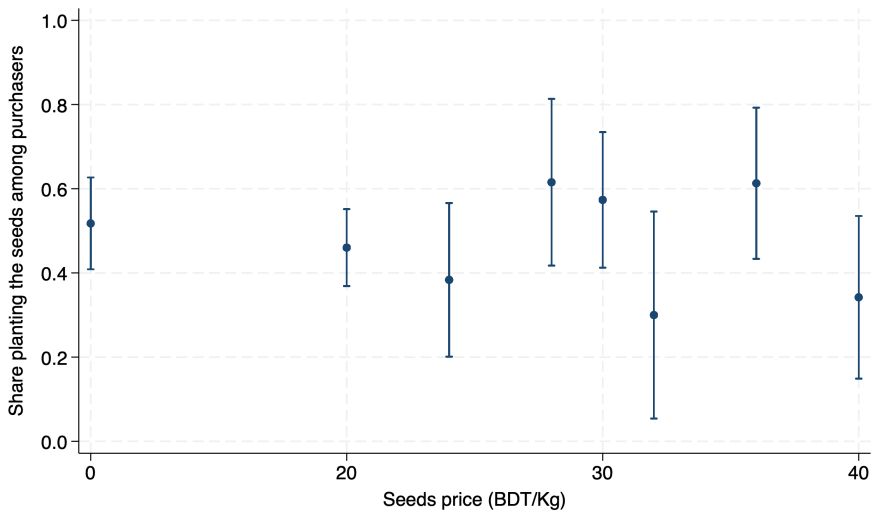
Intracluster correlation (ICC) was estimated at baseline and updated using follow-up data.

# Inverse Demand Curve



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# Share of Buyers Planting the Seeds



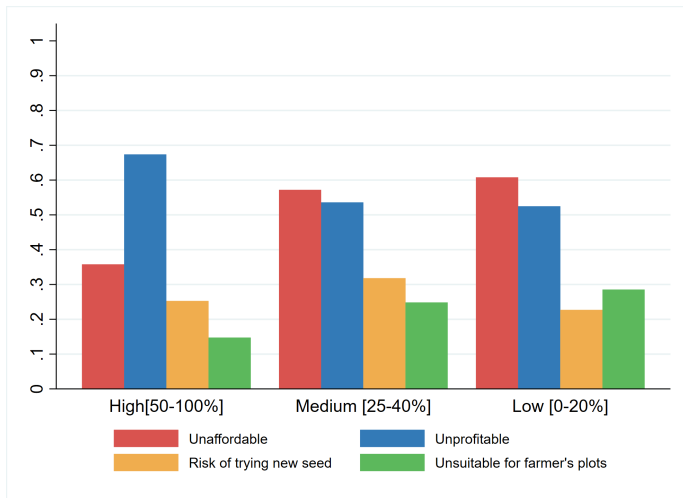
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## First-Stage to the Encouragement Design

	(1)	(2)
	All villages	Excluding S2T Villages
High Subsidy [50-100%]	0.89*** (0.03)	0.89*** (0.03)
Medium Subsidy [25-40%]	0.28*** (0.05)	0.28*** (0.07)
Strata FE	Yes	Yes
F-statistic	526.19	470.42
R-squared	0.792	0.825
Low-Subsidy Villages' Mean	0.06	0.04
Number of farmers per village	25	25
Number of villages	180	123

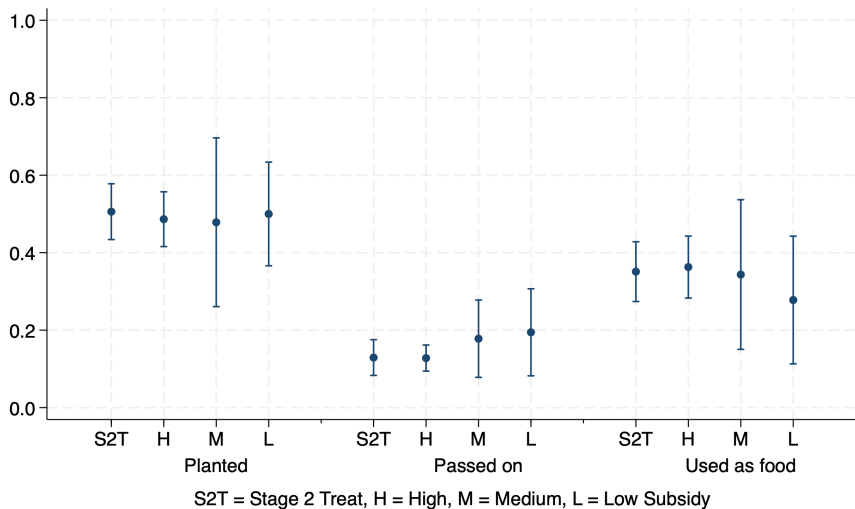
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# Stated Reasons for Not Buying the Seeds at Stage One



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# What Did Seed Buyers Do with the Seeds?



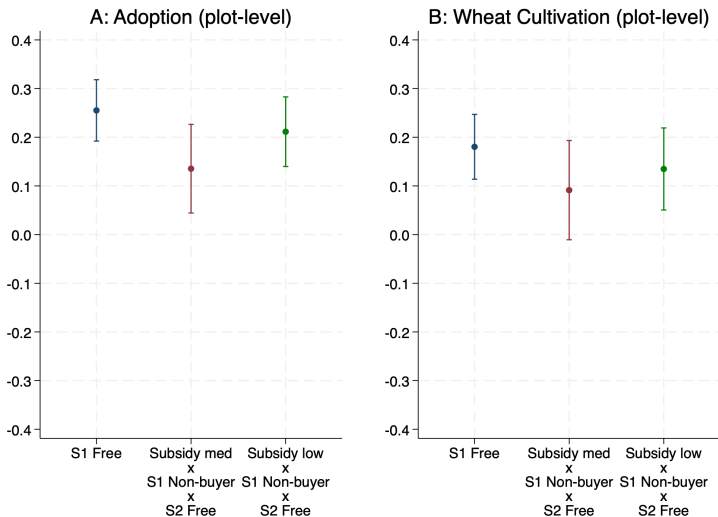
# Uses of Distributed Seeds Among Buyers

	Planted the seeds		Passed it on		Used it as food	
	(1)	(2)	(3)	(4)	(5)	(6)
	Excluding S2T	All T villages	Excluding S2T	All T villages	Excluding S2T	All T villages
Medium Subsidy [25-40%]	-0.06 (0.07)		0.04 (0.05)		0.05 (0.06)	
Low Subsidy [0-20%]	0.04 (0.09)		-0.03 (0.05)		-0.01 (0.09)	
S1 Buyer: S2 Control		-0.02 (0.06)		-0.01 (0.04)		0.05 (0.06)
S1 Buyer: S2 Treat		0.02 (0.06)		0.08* (0.04)		-0.11 (0.07)
S1 Non-buyer: S2 Treat		0.00 (0.04)		-0.00 (0.03)		0.00 (0.05)
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.209	0.179	0.052	0.080	0.270	0.202
p-value $S2T_{buyer} = S2C'_{buyer}$		0.50		0.08		0.04
High-Subsidy Villages' Mean	0.49	0.49	0.13	0.13	0.36	0.36
Number of observations	1,674	3,046	1,674	3,046	1,674	3,046

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# Impacts on Adoption and Wheat Cultivation

## Non-Buyers in Medium-Subsidy vs Low-Subsidy Villages

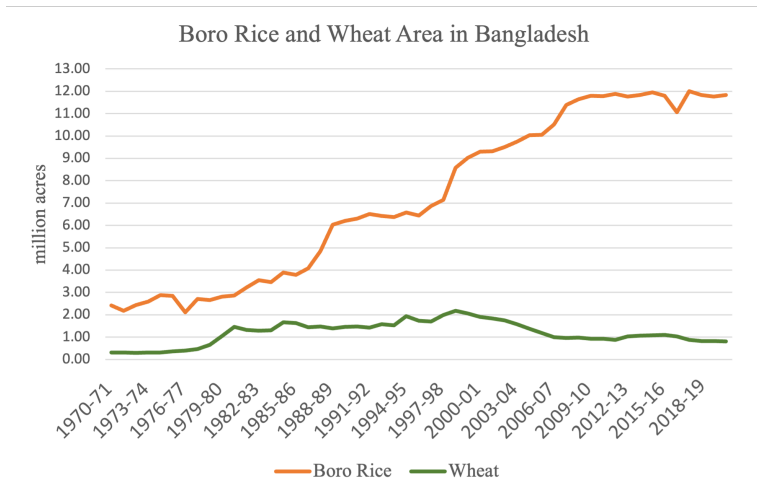


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# Heterogeneity by Baseline Wheat Cultivation Back

	(1)	(2)	(3)
	Adoption	Growing Wheat	Share of Wheat Area
Free distribution village ( $\gamma_1$ )	0.31*** (0.04)	0.25*** (0.04)	0.07*** (0.01)
Free distribution x B-line wheat	0.29*** (0.05)	0.10 (0.07)	0.06 (0.04)
S1 Non-buyer x S2 Treat ( $\gamma_2$ )	0.31*** (0.03)	0.24*** (0.03)	0.07*** (0.01)
S1 Non-buy x S2 Treat x B-line wheat	0.13*** (0.04)	-0.00 (0.05)	0.00 (0.03)
S1 Non-buyer x S2 Control ( $\gamma_3$ )	0.03 (0.02)	0.01 (0.03)	-0.00 (0.01)
S1 Non-buy x S2 Control x B-line wheat	0.02 (0.04)	0.05 (0.06)	0.03 (0.03)
Baseline wheat cultivation	-0.04 (0.03)	0.12*** (0.04)	0.05** (0.02)
Strata FE	Yes	Yes	Yes
R-squared	0.290	0.226	0.160
Control Villages' Mean	0.02	0.15	0.06
Number of observations	4,611	4,611	4,611

# Changes in Boro Rice and Wheat Area Over 50 years



Source: Bangladesh Bureau of Statistics

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## How Do I Measure Profits at the Plot Level?

- ▶ Consistent method for selecting reference plot among treatment and control farmers: baseline plot ranking exercise
- ▶ My measure of profits accounts for total production costs:
  - shadow costs for subsidized (as well as stored) seeds
  - shadow cost of family labor (Agness et al. 2022)

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# Summary Statistics: Plot Revenues & Profits

		Follow-up		Baseline	
		Mean/SD	N	Mean/SD	N
<b>Wheat</b>	Revenues ('000 BDT/acre)	45.52 (14.26)	893	32.84 (10.00)	1,670
	Profits ('000 BDT/acre)	14.29 (15.39)	893	-4.20 (16.93)	1,670
<b>Boro Rice</b>	Revenues ('000 BDT/acre)	76.27 (16.19)	1,642	68.68 (12.32)	1,335
	Profits ('000 BDT/acre)	29.19 (19.26)	1,642	27.45 (16.90)	1,335
<b>Onion</b>	Revenues ('000 BDT/acre)	158.52 (53.07)	930	187.14 (56.57)	493
	Profits ('000 BDT/acre)	75.28 (54.38)	930	92.12 (61.40)	493
<b>Maize</b>	Revenues ('000 BDT/acre)	158.92 (31.90)	391	82.71 (17.64)	434
	Profits ('000 BDT/acre)	102.34 (30.07)	391	34.82 (22.55)	434
<b>Mustard</b>	Revenues ('000 BDT/acre)	44.36 (17.10)	366	39.82 (16.05)	264
	Profits ('000 BDT/acre)	23.33 (14.22)	366	10.47 (21.91)	264
<b>Lentil</b>	Revenues ('000 BDT/acre)	51.75 (20.10)	236	48.33 (14.01)	328
	Profits ('000 BDT/acre)	27.92 (19.24)	236	20.08 (16.72)	328

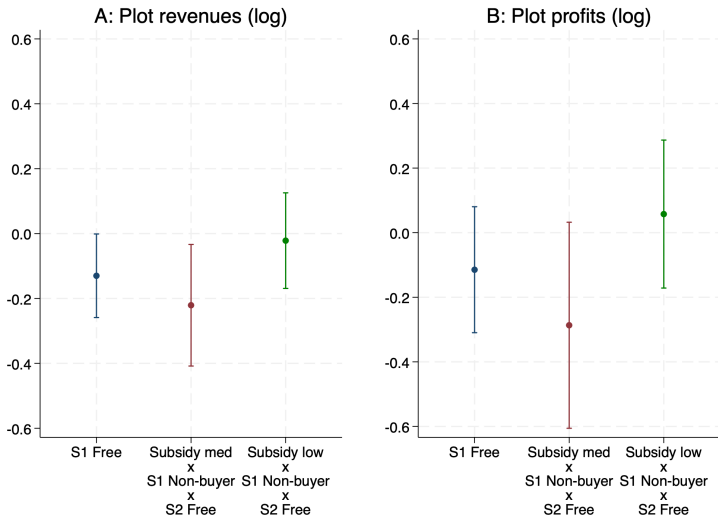
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## BARI-Gom-33 Seed Is Associated with High Wheat Yield

	Log Yield			
	(1)	(2)	(3)	(4)
BARI Gom 33 plot	0.04 (0.03)	0.04 (0.03)	0.11* (0.05)	0.10** (0.04)
Baseline yield (kg/acre)		0.00* (0.00)		-0.00 (0.00)
Farmer FE	No	No	Yes	Yes
Strata FE	Yes	Yes	No	No
Baseline plot ranking dummies	Yes	Yes	Yes	Yes
R-squared	0.128	0.130	0.592	0.637
Average wheat yield (kg/acre)	1,559	1,559	1,559	1,559
Number of observations	1,577	1,528	385	363

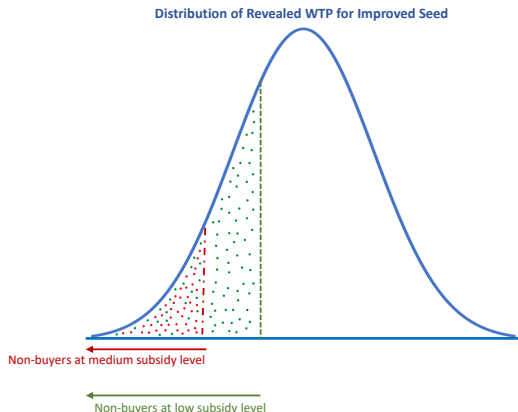
# Impacts on Revenues and Profits

## Non-Buyers in Medium-Subsidy vs Low-Subsidy Villages



# A Novelty of the Two-Stage Experimental Design (1/2)

## Infer Returns of *Induced* Buyers at the Medium Subsidy



$$F(Q^{seeds} \mid buy_{low} = 0) = P(buy_{med} = 0)F(Q^{seeds} \mid buy_{med} = 0) \\ + (1 - P(buy_{med} = 0))F(Q^{seeds} \mid buy_{med} = 1)$$

## A Novelty of the Two-Stage Experimental Design (2/2)

Infer Returns of *Induced* Buyers at the Medium Subsidy

$$F(Q^{seeds} | buy_{low} = 0) = P(buy_{med} = 0)F(Q^{seeds} | buy_{med} = 0) \\ + (1 - P(buy_{med} = 0))F(Q^{seeds} | buy_{med} = 1)$$

- ▶  $P(buy_{med} = 0)$  estimated from demand elicitation in stage one
- ▶  $F(Q^{seeds} | buy_{low} = 0)$  and  $F(Q^{seeds} | buy_{med} = 0)$  estimated from stage-two randomization
- ▶ The inferred value of expected profits among *induced buyers at the medium subsidy* is 50,000 BDT/acre (relative to average profits of 40,000 BDT/acre in control villages)

# Adoption and Disadoption in Year 2

## Similar Causal Effects on (Dis-)Adoption

	(1)	(2)	(3)	(4)
	Year 2 Any Adoption	Persistent Adoption	New Adoption	Disadoption
Free distribution village ( $\gamma_1$ )	0.07* (0.04)	0.12*** (0.03)	-0.05** (0.02)	0.30*** (0.03)
S1 Non-buyer x S2 Treat ( $\gamma_2$ )	0.09*** (0.03)	0.10*** (0.02)	-0.01 (0.02)	0.25*** (0.03)
S1 Non-buyer x S2 Control ( $\gamma_3$ )	0.00 (0.02)	0.01 (0.02)	-0.01 (0.02)	0.02 (0.02)
S1 Buyer x S2 Treat	0.17*** (0.04)	0.13*** (0.03)	0.03 (0.03)	0.26*** (0.04)
S1 Buyer x S2 Control	0.08 (0.05)	0.11*** (0.04)	-0.03 (0.03)	0.21*** (0.05)
Strata FE	Yes	Yes	Yes	Yes
R-squared	0.186	0.109	0.125	0.181
p-value $\gamma_1 = \gamma_2 - \gamma_3$	0.64	0.54	0.11	0.07
CI: $\gamma_1 - \gamma_2 + \gamma_3$	(-0.12, 0.07)	(-0.06, 0.11)	(-0.11, 0.01)	(-0.01, 0.15)
Control Villages' Mean	0.09	0.00	0.09	0.01
Number of observations	4,601	4,594	4,594	4,594

# Spillover Effects on Adoption and Wheat Cultivation

	Adoption		Growing wheat	
	(1)	(2)	(3)	(4)
	Year 1	Year 2	Year 1	Year2
Treatment village x Treated farmer	0.23*** (0.02)	0.13*** (0.02)	0.11*** (0.02)	0.02 (0.01)
Treatment village	0.03 (0.02)	-0.07*** (0.02)	0.06** (0.03)	0.03 (0.03)
Strata FE	Yes	Yes	Yes	Yes
R-squared	0.136	0.160	0.111	0.182
Control Villages' Mean	0.02	0.09	0.15	0.21
Number of observations	6,929	6,916	6,929	6,916

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## Spillover Effects on Year 2 (Dis)adoption

	(1)	(2)	(3)
	Persistent Adoption	New Adoption	Disadoption
Treatment village x Treated farmer	0.07*** (0.01)	0.05*** (0.01)	0.15*** (0.01)
Treatment village	0.00 (0.01)	-0.07*** (0.02)	0.03* (0.01)
Strata FE	Yes	Yes	Yes
R-squared	0.081	0.103	0.086
Control Villages' Mean	0.00	0.09	0.01
Number of observations	6,908	6,908	6,908

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## A Potential Mechanism: Heterogeneity

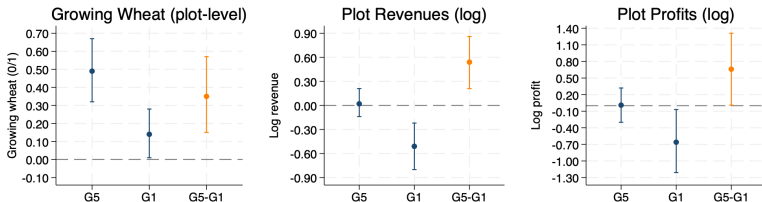
What are the characteristics of farmers who are most responsive to free distribution?

- ▶ First, use machine learning (ML) methods to predict the conditional average treatment effect (CATE)
- ▶ Second, sort observations into groups: group average treatment effect (GATES)
  - $G_1$ : 20% of the observations with the lowest predicted CATE
  - $G_5$ : 20% of the observations with the highest predicted CATE
- ▶ Third, examine the characteristics of the group with the highest predicted CATE versus that of the group with the lowest predicted CATE (Chernozhukov et al. 2023)

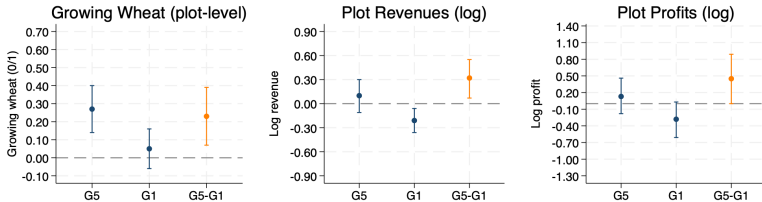
Apply this heterogeneity analysis to non-buyers in the stage-two treatment villages as well as treated farmers in the free-distribution villages.

# GATES of the Main Outcomes

## A: Stage-One Unconditional Free Distribution



## B: Stage-Two Free Distribution to Non-Buyers



G5 = 20% Most affected G1 = 20% Least affected

## What is CATE?

Let  $Z$  be a vector of covariates and  $D$  be a treatment indicator, we can start with a very general model of the form:

$$Y = b_0(Z) + Ds_0(Z) + U, \quad E[U|Z, D] = 0,$$

where

$$b_0(Z) = E[Y|D = 0, Z]$$

is the baseline conditional average (BCA), and

$$s_0(Z) = E[Y|D = 1, Z] - E[Y|D = 0, Z]$$

is the conditional average treatment effect (CATE).

Both  $b_0(Z)$  and  $s_0(Z)$  can be predicted using ML algorithms

# Implementation Steps for Machine Learning Algorithms

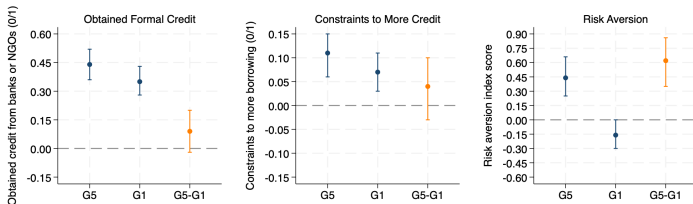
Consider  $S$  splits that divide the observations (usually 50-50) into training sample and validation sample. Over each split, apply the following steps using ML methods (e.g., random forest, elastic net, gradient boosting):

1. Use the training sample to train  $E[Y|D = 0, Z]$  and  $E[Y|D = 1, Z]$
2. Use the validation sample to predict  $E[Y|D = 0, Z]$  and  $E[Y|D = 1, Z]$
3. The predicted CATE is the difference between the predicted values of  $E[Y|D = 1, Z]$  and  $E[Y|D = 0, Z]$  for this split

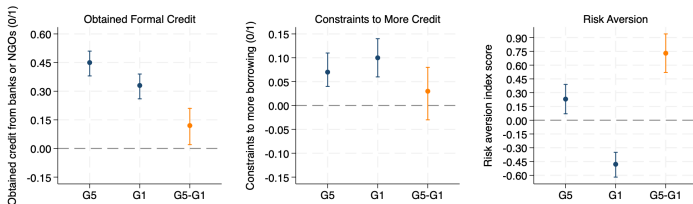
Repeat steps 1 - 3 for 100 or more splits. The end result is the median of the predicted CATE across all splits.

# Heterogeneity in Treatment Effects on Plot Profits

A: Stage-One Unconditional Free Distribution



B: Stage-Two Free Distribution to Non-Buyers



G5 = 20% Most affected G1 = 20% Least affected