Lecture 05:
Randomized controlled trials III – Spillovers

PPHA 34600
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From last time: we can handle non-compliance

What can we estimate with non-compliance?

- **ITT**: $\bar{Y}(R_i = 1) - \bar{Y}(R_i = 0)$
- **LATE**: $\frac{\bar{Y}(R_i=1) - \bar{Y}(R_i=0)}{\pi^C}$
  - Under constant treatment effects: equal to ATE, ATT
  - With heterogeneous treatment effects: need not equal ATE or ATT

There are many interesting flavors of RCT

Experimental designs for ease of implementation:

Oversubscription design

- You only have budget to treat N units. Start with a pool of $2N$, and randomly select half.
- Attractive for policymakers with concerns about equity

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- You're eventually going to treat everyone, but can't treat everyone immediately. Randomly assign half of your units to get treatment first; wait long enough to treat the second half to measure impacts.
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Randomized encouragement design (we've seen this already!)

- Layer randomization on top of something already available to everyone, to encourage take-up.
- Attractive for policymakers with concerns about equity

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Experimental designs for ease of estimation:

Stratified design

- Randomize *within* a group (e.g. gender; rural/urban status; etc)
- Ensures balance on stratified variables
- Increases statistical power
- Estimation: include strata fixed effects (required with $P \neq 0.5$)
- Most stringent version: pair-wise matched randomization

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- Do group-level, rather than unit-level, randomization
- Mitigates concerns about spillovers
- Can be useful from an equity perspective

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Randomized saturation design

- Two-step design to *estimate* spillovers

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Experimental designs for the sake of implementation:

- Oversubscription design
- Randomized roll-out design
- Randomized encouragement design

Experimental designs for the sake of estimation:

- Stratified design
- Randomized saturation design

→ These both help us think about **spillovers**

We typically invoke a no-spillovers assumption

The Stable Unit Treatment Value Assumption (SUTVA):

- Has an awkward name
- Formally says:

$$\text{If } D_i = D_i^{'}, \text{ then } Y_i(\mathbf{D}) = Y_i(\mathbf{D}^{'})$$

- In words:
  Treatment status of all other units j doesn't affect potential outcomes of unit i
- In other words: no spillovers

This has been running around behind everything we've done so far!

What goes wrong when SUTVA is violated?

Consider a randomized typhoid vaccination campaign:

- No intervention with control individuals
- Treated individuals are vaccinated
- Outcomes of interest: disease prevalence

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If we estimate the treatment effect as $\overline{disease}(1) - \overline{disease}(0)$, we **underestimate treatment**

This messes us up!

Illustrating SUTVA issues with fake data

	Vaccinated	Unvaccinated
Direct effects	-0.9	0
Spillover effects	0	-0.5
Total treatment effect	-0.9	-0.5

Measuring $\hat{\tau}^{ATE}$ as $\bar{Y}(1) - \bar{Y}(0) = -0.9 + 0.5 = -0.4$...

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... but $\tau^{ATE} = -0.9$!

How do we deal with this?

Unlike with non-compliance, there's no nice stats trick, but you can still:

1. Treat your ATE as an upper (lower) bound
   - This is often still useful! Think the true effect is 0, but with SUTVA you estimate 0.001?

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2. Design your RCT to avoid these concerns
   - "Cluster-randomized" designs are common
   - Instead of randomizing individuals, randomize villages or markets
   - Choose clusters far away from each other to minimize SUTVA issues

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   - "Cluster-randomized" designs are common
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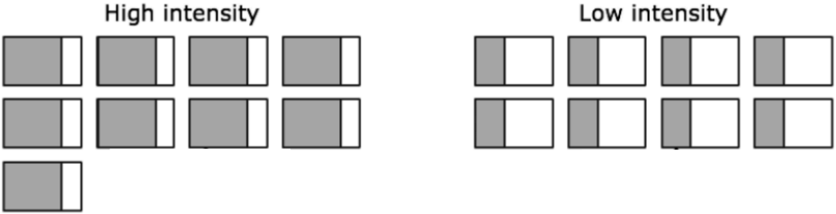
   - Choose clusters far away from each other to minimize SUTVA issues
3. Design your RCT to measure spillovers
   - We often care a lot about the size of spillovers

Randomized saturation design

These designs have **two** randomization steps:

1. Randomize clusters into treatment intensities (including pure control)
    - Lets us compare high-vs.-low intensity places
2. Randomize units within clusters
    - Lets us compare treatment-vs.-control units

Randomized saturation design: cartoon edition



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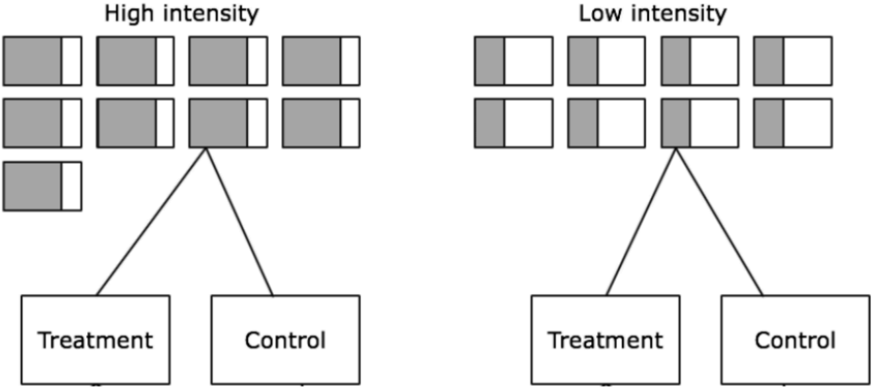

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- **Step 1:** Randomly assign clusters a treatment saturation $\pi_c \in [0, 1]$
  - $\rightarrow$ Choose from a pre-determined set of saturations! (eg $\pi \in \{0.25, 0.75\}$)
  - $\rightarrow$ You also need to have a pure control cluster: $\pi_c = 0$

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- **Step 2:** In each cluster, randomly assign $\pi_c \cdot N_c$ units into treatment
  - → Now D_{ic} is the treatment status for unit i in cluster c

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This results in three types of units:

- Treated individual: $D_{ic} = 1$ as usual
- Pure control: $D_{ic} = 0$ and $\pi_c = 0$
- Within-cluster control: $D_{ic} = 0$ and $\pi_c > 0$

RS designs open the door to new treatment parameters

In the most general model:

$$Y_{ic} = f(D_{ic}, D_{jc}; X_{ic}, \varepsilon_{ic})$$

In words: Y_{ic} depends on **both** D_{ic} **and** D_{jc}

→ This allows SUTVA violations

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$$Y_{ic} \perp D_{jd} \text{ for all } d \neq c$$

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To make the RS design useful, we impose a restriction:

$$Y_{ic} \perp D_{jd} \text{ for all } d \neq c$$

- **In words:** i's potential outcome is unaffected by other-cluster units
- **In other words:** There is no cross-cluster interference
- Note that Y_{ic} can still depend on Y_{jc} for $i \neq j$

RS designs open the door to new treatment parameters

Intent to treat (ITT):

$$\tau^{ITT}(\pi) = E[Y_{ic}|D_{ic} = 1, \pi_c = \pi] - E[Y_{ic}|D_{ic} = 0, \pi_c = 0]$$

$\rightarrow$ Difference between those offered treatment and **pure controls**

$\rightarrow$ Why don't we compare with $D_{ic} = 0, \pi_c = \pi$?

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- $\rightarrow$ $\tau^{ITT}(\pi) = \tau^{ATE}(\pi)$ with perfect compliance

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Spillover on the non-treated (SNT):

$$\tau^{SNT}(\pi) = E[Y_{ic}|D_{ic} = 0, \pi_c = \pi] - E[Y_{ic}|D_{ic} = 0, \pi_c = 0]$$

$\rightarrow$ Difference between control units in **treated clusters** and pure controls

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Total causal effect (TCE):

$$\tau^{TCE}(\pi) = E[Y_{ic}|\pi_c = \pi] - E[Y_{ic}|\pi_c = 0] = \pi\tau^{ITT}(\pi) + (1 - \pi)\tau^{SNT}(\pi)$$

→ Overall cluster difference between treated and control clusters

→ $D_{ic} = 1, \pi_c > 0$ units get τ^{ITT}; $D_{ic} = 0, \pi_c > 0$ units get τ^{SNT}

We can break the ITT down into two components

1. <u>Direct effect of treatment</u>:

   - AKA the **Treatment on the Uniquely Treated (TUT)**:

$$\tau^{TUT} = E[Y_{ic}|D_{ic} = 1, \pi_c = 0] - E[Y_{ic}|D_{ic} = 0\pi_c = 0] = \tau^{ITT}(\pi_c = 0)$$

→ this is the ITT were we to only treat one unit (no spillovers!)

→ Note that this **isn't** a function of π

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2. Spillover effect of treatment:

   - AKA the **Spillover on the Treated (ST)**:

$$\tau^{ST}(\pi) = E[Y_{ic}|D_{ic} = 1, \pi_c = \pi] - E[Y_{ic}|D_{ic} = 1\pi_c = 0]$$

→ this is the saturation-dependent spillover effect (only spillovers!)

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$$\tau^{ITT}(\pi) = \tau^{TUT} + \tau^{ST}(\pi)$$

Estimation in the RSD

Though these parameters are complicated, estimation is easy:

$$Y_{ic} = \alpha + \sum_{\pi \neq 0} \tau^{trt} D_{ic} \cdot \mathbf{1}[\pi_c = \pi] + \sum_{\pi \neq 0} \tau^{ctrl} S_{ic} \cdot \mathbf{1}[\pi_c = \pi] + \varepsilon_{ic}$$

where:
Y_{ic} is the outcome for unit i in group c
$D_{ic} \cdot \mathbf{1}[\pi_c = \pi]$ is an indicator for a treated unit with saturation π_c
$S_{ic} \cdot \mathbf{1}[\pi_c = \pi]$ is an indicator for a control unit with saturation π_c
ε_{ic} is an error term

$\rightarrow$ All groups are compared to **pure controls**

Computing relevant parameters

From this estimating equation:

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We can get many parameters of interest:

$\hat{\tau}^{ITT}(\pi) = \hat{\tau}_{\pi}^{trt}$

$\hat{\tau}^{SNT}(\pi) = \hat{\tau}_{\pi}^{ctrl}$

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The randomized saturation design enables us to estimate spillover effects!

An example: Timed loans for Kenyan maize farmers

Policy issue:

- Farmers are selling corn when prices are low and buying when high
- This causes large welfare losses

Program:

- Farmers were (randomly) offered a storage-linked loan at harvest
- **Research question:**
  What is the effect of the loan on the use of storage for arbitrage?

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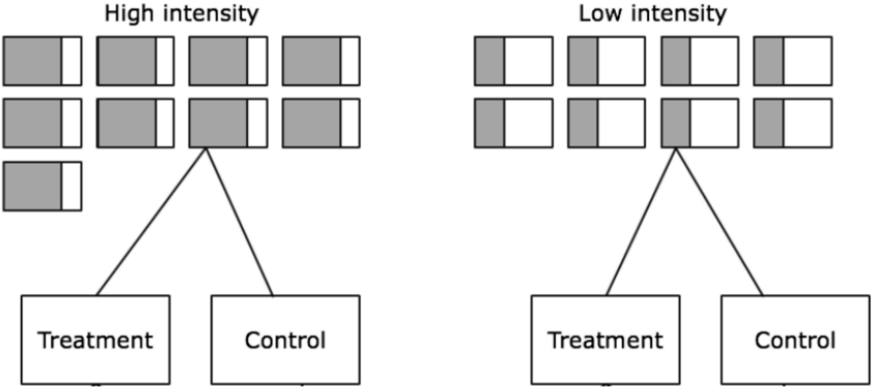
The authors implement a randomized saturation design

Randomized saturation design: Kenyan maize edition



Estimating treatment effects: Kenyan maize edition

The authors estimate (a slightly extended version of):

$$Y_{ij} = \alpha + \beta T_j + \varepsilon_{ij}$$

where:
Y_{ij} is the outcome for person i in group j
T_j is a treatment indicator
ε_{ij} is an error term

→ What treatment parameter of interest does $\hat{\beta}$ capture?

The ever-important balance check

Baseline characteristic	Treat	Control	Obs	T - C *std diff*	*p-val*
Male	0.30	0.33	1,589	-0.08	0.11
Number of adults	3.00	3.20	1,510	-0.09	0.06
Children in school	3.00	3.07	1,589	-0.04	0.46
Finished primary school	0.72	0.77	1,490	-0.13	0.02
Finished secondary school	0.25	0.27	1,490	-0.04	0.46
Total cropland (acres)	2.44	2.40	1,512	0.01	0.79
Number of rooms in household	3.07	3.25	1,511	-0.05	0.17
Total school fees	27,240	29,814	1,589	-0.06	0.18
Average monthly consumption (Ksh)	14,971	15,371	1,437	-0.03	0.55
Average monthly consumption/capita (log)	7.97	7.96	1,434	0.02	0.72
Total cash savings (Ksh)	5,157	8,021	1,572	-0.09	0.01
Total cash savings (trim)	4,732	5,390	1,572	-0.05	0.33
Has bank savings acct	0.42	0.43	1,589	-0.01	0.82
Taken bank loan	0.08	0.08	1,589	-0.02	0.73
Taken informal loan	0.24	0.25	1,589	-0.01	0.84
Liquid wealth (Ksh)	93,879	97,281	1,491	-0.03	0.55
Off-farm wages (Ksh)	3,917	3,797	1,589	0.01	0.85
Business profit (Ksh)	2,303	1,802	1,589	0.08	0.32
Avg %Δ price Sep-Jun	133.49	133.18	1,504	0.00	0.94
Expect 2011 LR harvest (bags)	9.36	9.03	1,511	0.02	0.67
Net revenue 2011 (Ksh)	-3,304	-4,089	1,428	0.03	0.75
Net seller 2011	0.32	0.30	1,428	0.05	0.39
Autarkic 2011	0.07	0.06	1,589	0.03	0.51
% maize lost 2011	0.02	0.01	1,428	0.03	0.57
2012 LR harvest (bags)	11.18	11.03	1,484	0.02	0.74
Calculated interest correctly	0.71	0.73	1,580	-0.03	0.50
Digit span recall	4.57	4.58	1,504	-0.01	0.89
Maize giver	0.26	0.26	1,589	-0.00	0.99

ITT results: Number of maize bags stored

	Y1		Y2		Pooled	
	(1) Overall	(2) By rd	(3) Overall	(4) By rd	(5) Overall	(6) By rd
Treat	0.57***		0.55***		0.56***	
	(0.14)		(0.13)		(0.10)	
Treat - R1		0.87***		1.24***		1.05***
		(0.28)		(0.24)		(0.18)
Treat - R2		0.75***		0.30*		0.55***
		(0.17)		(0.17)		(0.12)
Treat - R3		0.11		0.08		0.09
		(0.08)		(0.34)		(0.16)
Observations	3836	3836	2944	2944	6780	6780
Mean DV	2.67	2.67	1.68	1.68	2.16	2.16
SD DV	3.51	3.51	2.87	2.87	3.23	3.23
R squared	0.37	0.37	0.21	0.21	0.33	0.33
P-Val Treat	<0.01		<0.01		<0.01	
P-Val Treat FWER	<0.01		<0.01		<0.01	
P-Val Treat - R1		<0.01		<0.01		<0.01
P-Val Treat - R1 FWER		<0.01		<0.01		<0.01
P-Val Treat - R2		<0.01		0.07		<0.01
P-Val Treat - R2 FWER		<0.01		0.17		<0.01
P-Val Treat - R3		0.18		0.81		0.56
P-Val Treat - R3 FWER		0.33		0.91		0.63

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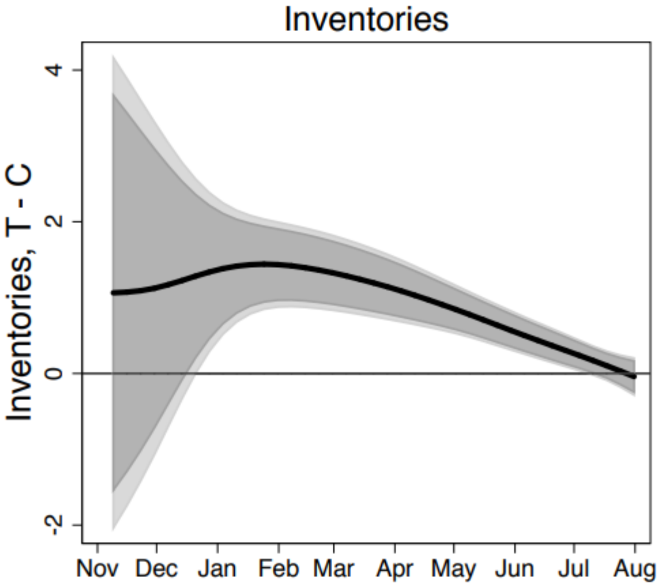
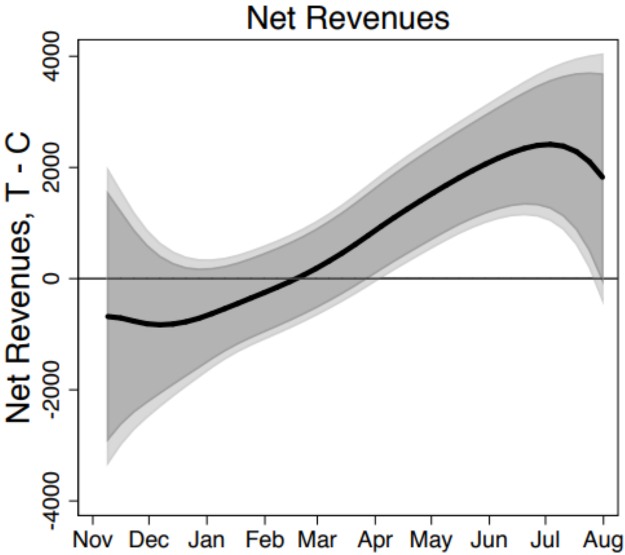


ITT results: Net revenue (Ksh)

	Y1		Y2		Pooled	
	(1) Overall	(2) By rd	(3) Overall	(4) By rd	(5) Overall	(6) By rd
Treat	265		855***		533***	
	(257)		(302)		(195)	
Treat - R1		-1165***		16		-614**
		(323)		(445)		(272)
Treat - R2		510		1995***		1188***
		(447)		(504)		(337)
Treat - R3		1370***		565		999***
		(413)		(403)		(291)
Observations	3795	3795	2935	2935	6730	6730
Mean DV	334	334	-3434	-3434	-1616	-1616
SD DV	6055	6055	6093	6093	6359	6359
R squared	0.03	0.04	0.07	0.08	0.12	0.12
P-Val Treat	0.30		0.01		0.01	
P-Val Treat FWER	0.38		0.01		0.01	
P-Val Treat - R1		<0.01		0.97		0.02
P-Val Treat - R1 FWER		<0.01		0.97		0.04
P-Val Treat - R2		0.26		<0.01		<0.01
P-Val Treat - R2 FWER		0.38		<0.01		<0.01
P-Val Treat - R3		<0.01		0.16		<0.01
P-Val Treat - R3 FWER		<0.01		0.26		<0.01

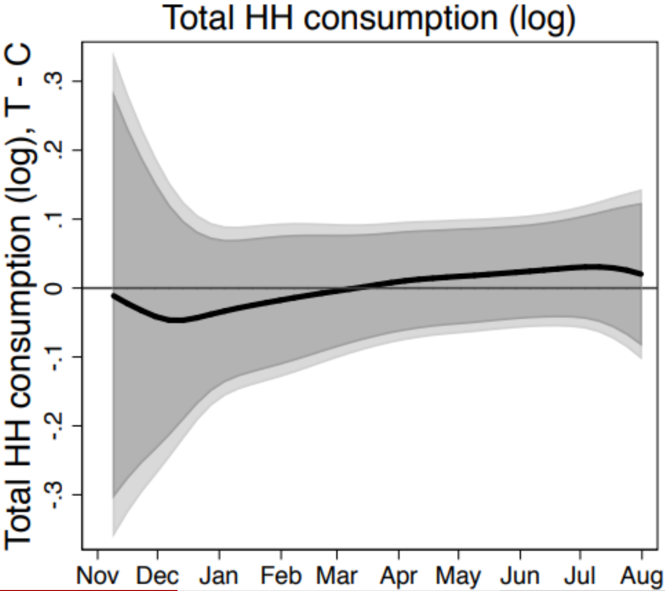
ITT results: Net revenue by month



ITT results: Household consumption (logs)

	Y1		Y2		Pooled	
	(1) Overall	(2) By rd	(3) Overall	(4) By rd	(5) Overall	(6) By rd
Treat	0.01		0.06*		0.04	
	(0.03)		(0.04)		(0.02)	
Treat - R1		-0.03		0.06		0.01
		(0.05)		(0.05)		(0.03)
Treat - R2		0.03		0.08*		0.05*
		(0.04)		(0.04)		(0.03)
Treat - R3		0.04		0.05		0.04
		(0.04)		(0.05)		(0.03)
Observations	3792	3792	2944	2944	6736	6736
Mean DV	9.48	9.48	9.61	9.61	9.55	9.55
SD DV	0.63	0.63	0.63	0.63	0.64	0.64
R squared	0.03	0.03	0.05	0.05	0.06	0.06
P-Val Treat	0.68		0.08		0.13	
P-Val Treat FWER	0.69		0.10		0.13	
P-Val Treat - R1		0.49		0.17		0.69
P-Val Treat - R1 FWER		0.49		0.26		0.69
P-Val Treat - R2		0.48		0.08		0.09
P-Val Treat - R2 FWER		0.49		0.17		0.13
P-Val Treat - R3		0.36		0.27		0.16
P-Val Treat - R3 FWER		0.47		0.35		0.21

ITT results: Household consumtion by month



Going beyond the ITT: Kenyan maize edition

We want to know about effects on markets (not just people):

$$p_{mst} = \alpha + \beta_1 H_s + \beta_2 \text{month}_t + \beta_3 (H_s \times \text{month}_t) + \varepsilon_{mst}$$

where:

p_{mst} is the price in market m, sublocation s, month t
H_s is an indicator for high-intensity sublocations
month_t is a monthly time trend
ε_{ij} is an error term

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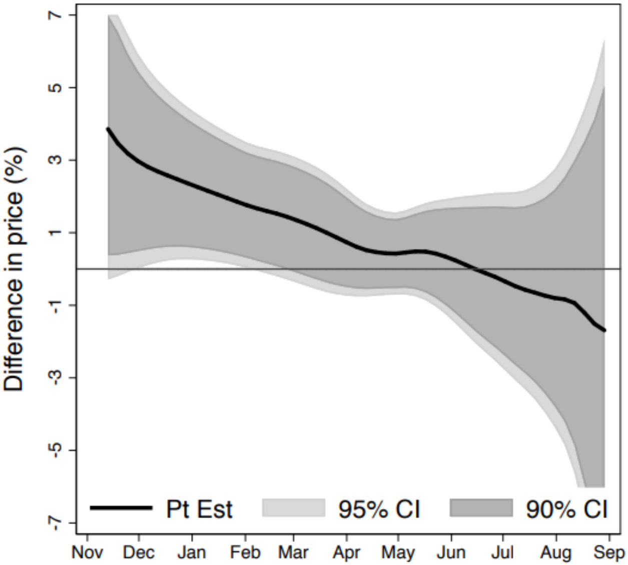
This estimating equation exploits the RS design to measure differential effects by saturation!

ITT results: Market prices

	Main Specification (3km)			Robustness (Pooled)	
	Y1	Y2	Pooled	1km	5km
High	4.41*	2.85	3.97**	2.79	3.77*
	(2.09)	(1.99)	(1.82)	(1.72)	(1.82)
Month	1.19***	1.22***	1.36***	1.33***	1.54***
	(0.36)	(0.38)	(0.35)	(0.34)	(0.29)
High Intensity * Month	-0.57	-0.48	-0.57	-0.52	-0.83**
	(0.42)	(0.46)	(0.39)	(0.39)	(0.37)
Observations	491	381	872	872	872
R squared	0.08	0.03	0.06	0.06	0.06
P-val High	0.052	0.172	0.044	0.124	0.056
P-val High Bootstrap	0.096	0.196	0.084	0.152	0.112
P-val Month	0.005	0.005	0.001	0.001	0.000
P-val Month Bootstrap	0.040	0.000	0.034	0.022	0.000
P-val High*Month	0.193	0.316	0.158	0.200	0.038
P-val High*Month Bootstrap	0.176	0.316	0.170	0.218	0.056

ITT results: Market prices by month



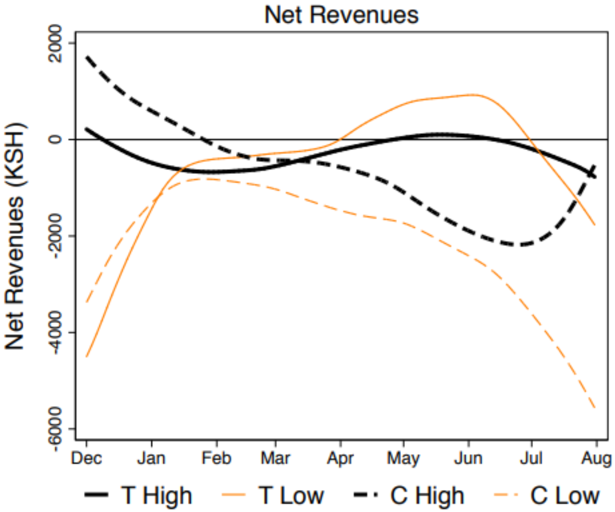
Given the price effects, what happens to everything else?

How do treatment effects vary with intensity?

$$Y_{ijs} = \alpha + \beta_1 T_j + \beta_2 H_s + \beta_3 (T_j \times H_s) + \varepsilon_{ijs}$$

- Same LHS var as the ITT, but now separately by intensity

General equilibrium effects



General equilibrium effects

	Low Saturation	High Saturation
1. Direct gains/HH (Ksh)	3,304	854
2. Indirect gains/HH (Ksh)	0	495
3. Ratio of indirect to direct gains	0.00	0.58
4. Direct beneficiary population (HH)	247	495
5. Total local population (HH)	3,553	3,553
6. Total direct gains (Ksh)	816,984	422,248
7. Total indirect gains (Ksh)	0	1,757,880
8. Total gains (direct + indirect; Ksh)	816,984	2,180,128
9. Fraction of gains direct	1.00	0.19
10. Fraction of gains indirect	0.00	0.81

Recap

TL;DR:

1. RCTs are (still) great!
2. Spillovers make things complicated
3. We can still make progress on (some) treatment parameters