Experiential Learning in Health

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Economics of Health Inequality

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Motivation

Motivation

How do we learn about health?

- Experts
  - Inequities in trust (Alsan and Wanamaker, 2018; Banerjee et al, 2023; Lowes and Montero, 2021; Martinez-Bravo and Stegmann, 2021)
  - Inequities in access
- Laypeople
  - Can improve issues of trust (Alsan and Eichmeyer, 2024)
  - Can improve issues of information dissemination (Banerjee et al., 2019)
  - Inequities in information in the network
  - Inequities in information sharing
- Experiences
  - Large literature about experiential learning in agriculture
    - Bound by limited attention (Hanna et al., 2014)
    - Internalizing neighbor's experiences (Foster and Rosenzweig, 1995; Conley and Udry, 2010)
  - Similarities between learning in agriculture and health
    - Noisy, uncertain outcomes

Motivation

Experiential learning about health

- Cons
  - Difficult to observe outcomes
  - Difficult to attribute outcomes to inputs
  - Misattribution could bias beliefs
- Pros
  - Trustworthy
  - Unconstrained by social marginalization

Preview of results:

1. Aiding individuals in experiential learning about health technology (chlorine tablets) $\rightarrow$ technology adoption and improved health
2. Experiential learning and social learning are complementary
   - Only learn about health technology from others if you have both sender and receiver have gone through experiential learning
   - Can learn from positive signals in the network $\rightarrow$ moderates potential for negative draws from nature to lead to misattribution

Outline

Outline:

1. Brief literature review: learning about health and agriculture
2. **Paper 1** (Akram and Mendelsohn, 2021) : Diaries to Increase the Adoption of Chlorine tablets for Water Purification by Poor Households
   - Can experiential information improve take-up of health technologies relative to expert information alone?
     - Setting: chlorine tablets in peri-urban Karachi, Pakistan
     - Recording diarrhea leads to higher rates of chlorine adoption than standard information about chlorine efficacy from CHW
     - Experiential + Expert information > Expert information
3. **Paper 2** (Akram et al., in progress): Title Forthcoming
   - How does experiential learning about health work?
     - Stronger signals versus many signals?
     - Habit formation as a confounder?
     - Complementarities with social learning?
   - Policy 1: (a) get people to adopt, versus (b) **direct attention**
   - Policy 2: (a) **saturate treatment**, versus (b) seed treatment

Literature Review

Learning by Doing: Agriculture

Farmers learn through experimentation... (Foster and Rosenzweig, 1995)

- Farmers are more likely to adopt technologies (high-yield varietals in the Green Revolution in India) if they experiment with them
- Farmers are more likely to adopt technologies if their neighbors use them and experience high yields

... but attention is bound (Hanna et al., 2014)

- Encouraging experimentation did not lead to changes in behavior without showing farmers a summary of changes in inputs/outputs
- Information is not useful without noticing

Learning by Doing: Health

Learning by doing among providers: Volume-outcome relationship

- Meta-analysis: positive and stat. sig. relationship, but magnitudes vary, and cannot rule out selective referrals (Halm et al., 2002)
- Non-elective C-sections: 1SD $\uparrow$ in recent experience $\Rightarrow \downarrow$ 13.8% NICU admission (Facchini, 2022)

Learning by observing among patients (Bennett et al., 2018)

- Standard hygiene instruction versus showing microbes under a microscope – seeing is believing
  - $\rightarrow$ improved hygiene (visible check of hands, nails, feet, and clothes)
  - $\rightarrow$ improved health (child anthropometrics)
  - $\rightarrow$ effects moderated by stronger traditional beliefs, which teach that overconsumption and heat cause diarrhea

Akram and Mendelsohn (2021)

Setting

Preventive health behaviors: Long-term, persistent use $\rightarrow$ amenable to learning by doing

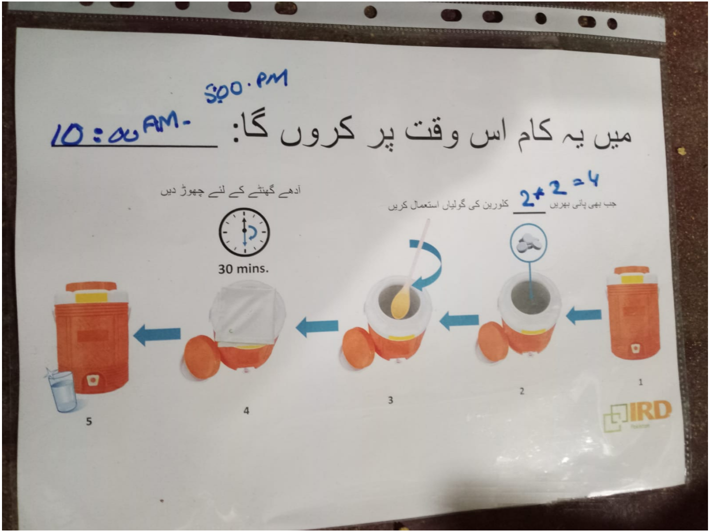
Technology: Chlorine tablets (effective water purification technology)

- 7.1% of Pakistani households use any water purification technology (Pakistan DHS, 2017-18)
- 34% take-up with free distribution (Dupas et al., 2016)
- Requires daily use

Setting: peri-urban Karachi

- Data from our baseline (Akram et al., forthcoming)
  - 21% do nothing to clean drinking water
  - 64.5% use (largely ineffective) methods to filter particles
  - 14.5% use a method to disinfect (mostly boiling)
  - 75% report dirt in drinking water (baseline)
  - Enumerator observed dirt in drinking water in 16% (38%) of households during baseline (any survey)

Setting



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1
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IRD

Info-Tool

Hypothesis – Health effects of water purification through chlorine table are not immediately observable, so:

Making these effects easier to observe

$\Longrightarrow$ learning about efficacy over time through repeated use

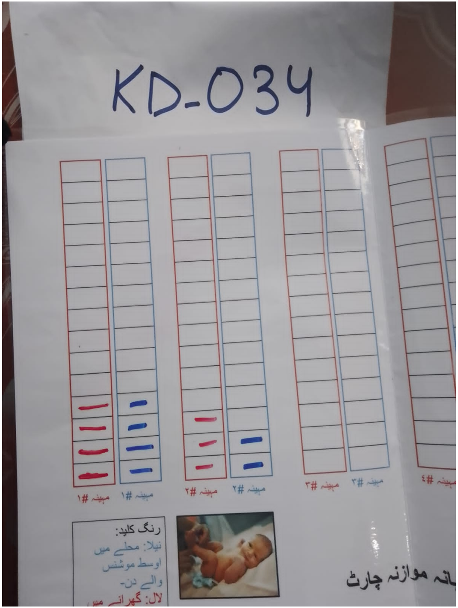
$\Longrightarrow$ long-run behavioral change

Test of learning: Short-term drawing attention to health signals $\Rightarrow$ long-term behavioral change

Treatment – cluster-randomized (neighborhoods):

- Pen-and-paper chart for caregivers to track children's diarrhea
- Every 2 weeks: Comparison bar chart with expected diarrhea rate (from epidemiological literature: Luby et al., 2006)
- Comparison: Active Control (chlorine distribution and consultation)

Info-Tool



Timeline

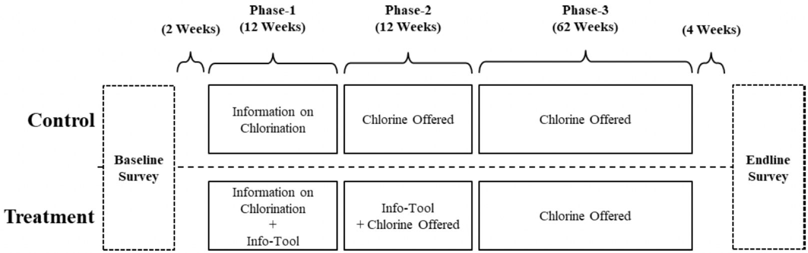


Figure 2. Experiment Structure

Figure 1: Akram and Mendelsohn (2021): Timeline

Results

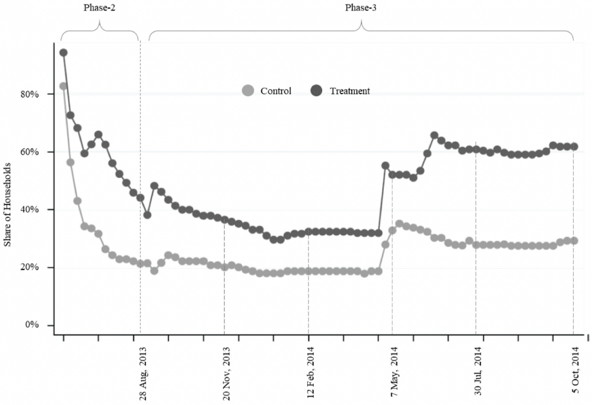


Figure 3. Observed Weekly Acceptance Rates

Figure 2: Akram and Mendelsohn (2021): Chlorine Acceptance

Results

Table 3. Presence of Chlorine in Drinking Water

Variables	(1) Baseline	(2) Baseline	(3) Endline	(4) Endline
Treatment	0.05	0.05	0.57***	0.55***
	(0.06)	(0.03)	(0.06)	(0.06)
Observations	299	289	266	258
R-squared	0.00	0.70	0.33	0.42
Mean in control	0.26	0.26	0.29	0.29
Characteristics included	NO	YES	NO	YES

Figure 3: Akram and Mendelsohn (2021): Chlorine Residual Presence

Results

Table 4. Anthropometric Measures of Children 0–5 Years of Age

Variables	(1) Weight (kg)	(2) Weight (kg)	(3) Height (cm)	(4) Height (cm)
Treatment	1.060*	2.154*	2.689***	3.834***
	(0.589)	(1.080)	(0.888)	(0.975)
Observations	785	767	782	765
R-squared	0.00	0.08	0.01	0.07
Mean in control	13.18	13.18	94.89	94.89
Vector of controls included	NO	YES	NO	YES
Age categories included	0–5	0–5	0–5	0–5

Figure 4: Akram and Mendelsohn (2021): Child Anthropometrics

Akram et al. (forthcoming)

Motivation

Agha Ali Akram (Mathematica)
Gabriella Fleischman (Harvard Kennedy School)
Akib Khan (Uppsala University)
Reshmaan Hussam (Harvard Business School)

Understanding how experiential learning about health works

- What does Info-Tool actually do?
    - Create **stronger signals** → learning → long-term adoption
    - Early adoption (novelty, etc.) → **more signals** → learning → long-term adoption
        - Many signals: less variable information (on average more accurate), but learning constrained by limited attention
        - Stronger signals: may overweight unrepresentative signals
    - Early adoption (novelty, etc.) → **habit formation** → long-term adoption
    - Social learning (neighborhood-clustered randomization)

Motivation

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Understanding how experiential learning about health works

- What does Info-Tool actually do?
  - **Stronger signals** versus **early adoption** → treatment arm with early subsidies conditional on use (Incentives arm)
    - Within Incentives: **Habit formation** versus **learning** → not addressing
  - Individual **experiential learning** versus **social learning** → individual-level randomization, spillovers by treated neighbors

Experimental Design: Incentives Arm

Design borrowed from Hussam et al. (2022)

Short-term incentives $\Rightarrow$ short-term use
$\Rightarrow$ habit formation or learning through signal aggregation
$\Rightarrow$ long-run behavioral change

Treatment:

- Offer paper tokens for empty chlorine tablet wrappers
- Tokens redeemable for children's goods (lowest value: stickers, highest value: backpack)
- Possible to game $\Longrightarrow$
  - Main outcome: objective tests for chlorine residual in drinking water
  - Conduct unscheduled audits
- Income effect held constant (unconditional lottery for gifts in other treatment groups)

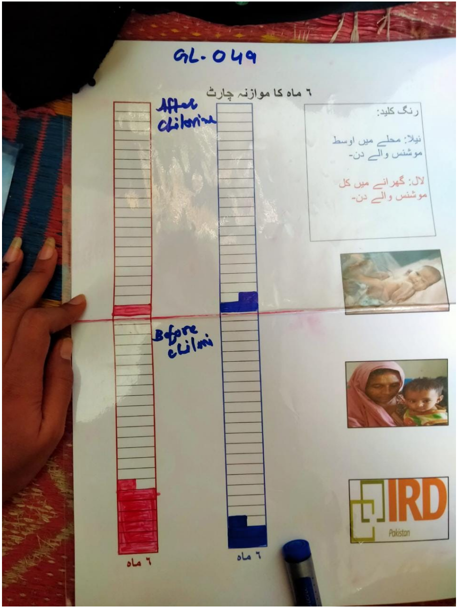
Experimental Design: Info-Tool

Design borrowed from Akram and Mendelsohn (2021)

Treatment:

- Pen-and-paper chart for caregivers to track children's diarrhea
- Every 2 weeks: Comparison bar chart with control diarrhea rate
- One time: 3-month difference-in-difference bar charts after treatment period ends
- Individual-level randomization $\rightarrow$ random variation in treatment status of neighbors

Experimental Design: Info-Tool



Experimental Design: Timeline

<table>
<tr><th></th><th>Month 1</th><th>Pre-Treatment: Months 2-4</th><th>Treatment: Months 5-7</th><th>Post-Treatment: Months 8-18</th><th>Month 19</th></tr>
<tr><td>Chlorine</td><td rowspan="4">Baseline Survey</td><td></td><td>Chlorine Distribution</td><td rowspan="3">Chlorine Distribution</td><td rowspan="4">Endline Survey</td></tr>
<tr><td>Incentives</td><td></td><td>Chlorine Distribution + Incentives</td></tr>
<tr><td>Info-Tool</td><td>Info-tool Training</td><td>Chlorine Distribution + Info-tool</td></tr>
<tr><td>Control</td><td colspan="3"></td></tr>
<tr><td></td><td></td><td>Twice-monthly visits for child health data</td><td>Twice-monthly visits for child health and chlorine presence data</td><td>Once-monthly visits for child health and chlorine presence data</td><td></td></tr>
</table>

Sample: 1800 caregivers in peri-urban Karachi

- At least one child $<$ 5 years old
- Children drink from same water vessel as parents
- Water vessel is large enough for appropriate use of chlorine table

Model

Naive DeGroot Learning:

$$\hat{S}_i^t = \frac{\sum_{j=1}^{J} \alpha_{ij}^t s_{ij}^t}{d_i^t + 1}$$

$\hat{S}_i^t$: individual i's net information in time t
s_{ij}: information sent to individual i from individual j (my own signal: s_{ii})
α_{ij}: weight that individual i gives signal s_{ij}
d_i^t: individual i's degree (number of network connections) in time t

Our model of experiential and social learning:

$\rightarrow$ model of complementarities in experiential and social learning

$\rightarrow$ simplest version: consider the role of **strong signals** (assume away early adoption stories)

Model

Our model of social and experiential learning:

$$\hat{S}_i^T = \frac{\sum_{t=0}^{T} \sum_{j=1}^{J} \alpha_{ij}^t \cdot a_{ij}^t \cdot s_{ij}^t}{\sum_{t=0}^{T} \sum_{j=1}^{J} a_{ij}^t}$$

$\hat{S}_i^t$: individual i's net information in time t
s_{ij}: information sent to individual i from individual j (my own signal: s_{ii})
α_{ij}: weight that individual i gives signal s_{ij}

$a_{ij}^t \in \{0, 1\}$: i received a signal from j in time t

only consider signals if i receives a signal from j in period t

$a_{ii}^t = 1 \Rightarrow$ I adopt chlorine in period t

New observations enter each time period

Model: Defining Signal Weights

Assumption: Signal weights are the believed probability that a signal is accurate, $\alpha_{ij}^t \in [0, 1]$, where:

$$\alpha_{ij}^t = \alpha_{ij}^t(\gamma_j^t, \omega_{\gamma_j,i}^t, \cdot)$$

$$\omega_{\gamma_j,i}^t = \omega_{\gamma_j,i}^t(\gamma_i^{t-1}, \gamma_i^{t-2}, ..., \gamma_i^0, \cdot)$$

- γ_j^t: j's technology to observe signals in time t
- $\omega_{\gamma_j,i}^t$: i's time t trust in γ_j^t (j's time t signal-observation technology)
  - depends on technologies I have used in the past
- Assume other reasons to be skeptical towards a signal from j in time t are exogenous
  - I was distracted in time $t \to$ low α_{ii}^t
  - I think j exaggerates often $\to$ low $\alpha_{ij}^t, \forall t$

Model

Adopt chlorine if:

$$\hat{S}_i^t > c_i^t$$

c_i^t: cost of using chlorine

$\rightarrow$ new decision each period (not forward-thinking, multi-period decision)
$\rightarrow$ passive learner, not active experimenter

Model $\rightarrow$ Treatments

Chlorine Only, Incentives, and Info-Tool:

- free distribution and delivery of chlorine table in months 4-18
- $\downarrow c_i^t, t \in (4, 18)$
- $\uparrow$ chlorine adoption relative to Pure Control

Incentives:

- gifts conditional on chlorine use in months 4-6
- $\downarrow c_i^t, t \in (4, 6)$
- $\uparrow$ contemporaneous chlorine adoption relative to Chlorine Only

Model $\to$ Treatments

Info-Tool:

- chart to record children's diarrhea rates in months 1-6
- $\uparrow \alpha_{ii}^{t}, t \in (1, 6)$ via γ_i^t
- $\uparrow$ heterogeneity by early period health signals relative to Chlorine Only and Incentives
- $\uparrow$ chlorine use in $t > 6$ relative to Incentives and Chlorine
- $\uparrow \alpha_{ij}^{t}, j \in IT$ via $\omega_{\gamma_j, i}$
- $\uparrow$ heterogeneity by spillovers from IT households relative to Chlorine Only and Incentives
- $\uparrow$ importance of friends' health signals in explaining spillover effects

Variable Definitions

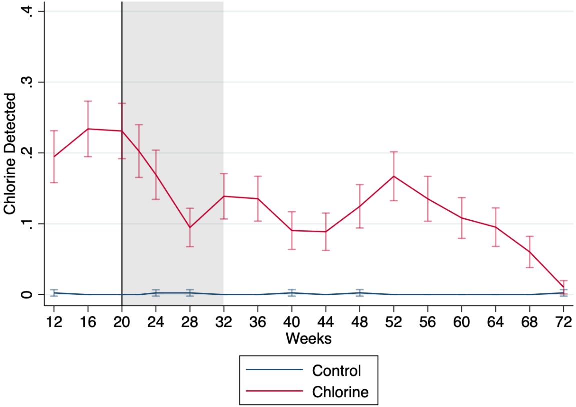
Heterogeneity by:

- Health Signals: Predicted health improvement after chlorine distribution
  - Actual health improvement

$$\frac{\text{Diarrhea}_{t=1,2,3} - \text{Diarrhea}_{t=4,5,6}}{n_{children} \times n_{visits}}$$

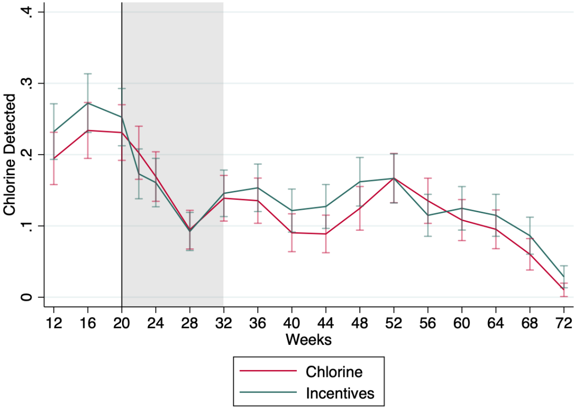
  - Endogenous to treatment status $\Rightarrow$ construct lasso-predicted measures using baseline variables in Pure Control sample
  - Improved = predicted health improvement is above median
- Spillovers: Anyone in Info-Tool group lives within 20m
  - Recentered to purge estimates of OVB (Boryusak and Hull, 2022)
  - 20m selected using BIC-minimizing radius (Eggers et al., 2020)

Model Predictions: Overall Chlorine Use



✓Higher use in chlorine groups than Pure Control, $\forall t$

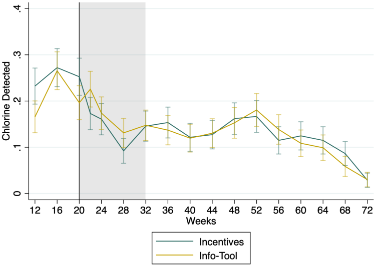
Model Predictions: Overall Chlorine Use

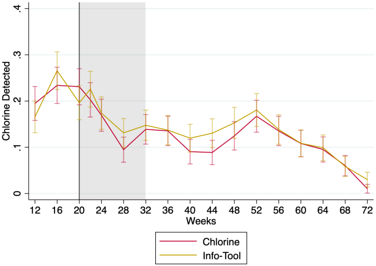


✓Higher use in chlorine groups than Pure Control, $\forall t$

✓Higher short-term use in the Incentives group

Model Predictions: Overall Chlorine Use



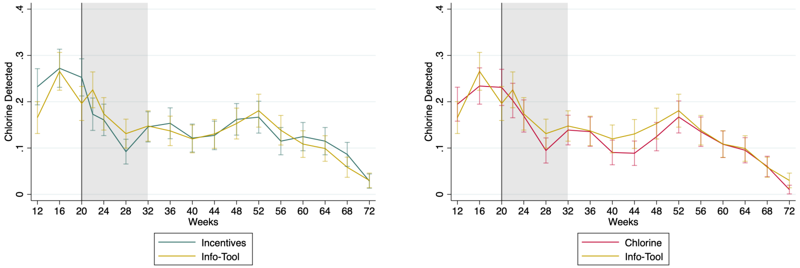


✓Higher use in chlorine groups than Pure Control, $\forall t$

✓Higher short-term use in the Incentives group

✓Higher medium-term use in the Info-Tool group

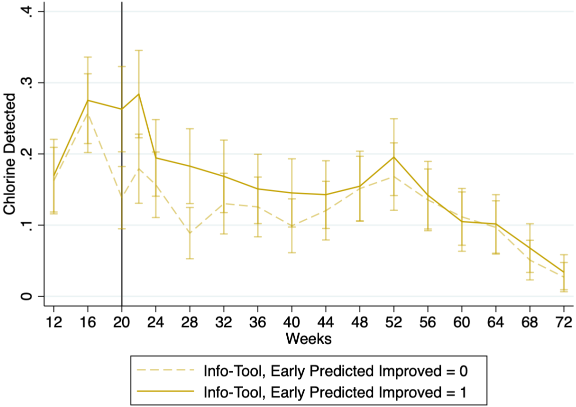
Model Predictions: Overall Chlorine Use



Take-away: Strong signals explains IT increased use one quarter, but effects fade out

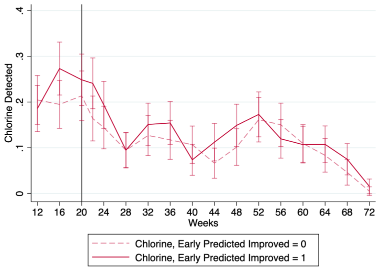
Tables

Model Predictions: Health Signal Heterogeneity



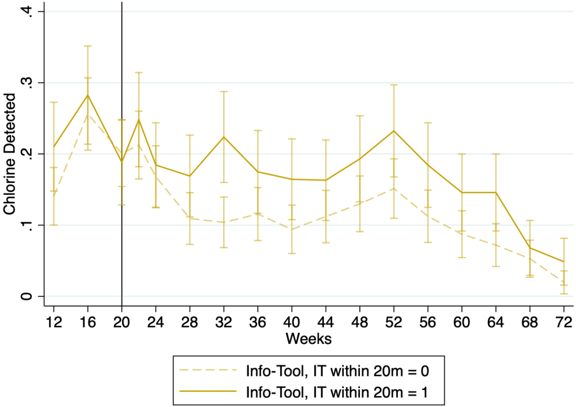
Suggestive: Info-Tool short-term responsiveness to early health signals

Model Predictions: Health Signal Heterogeneity



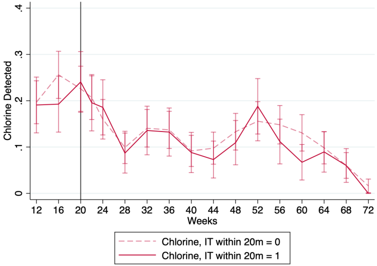
Suggestive: Info-Tool short-term responsiveness to early health signals

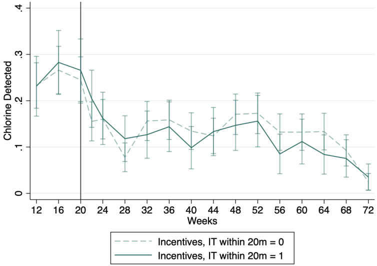
Model Predictions: IT Spillover Heterogeneity



✓Info-Tool responsiveness to IT spillovers

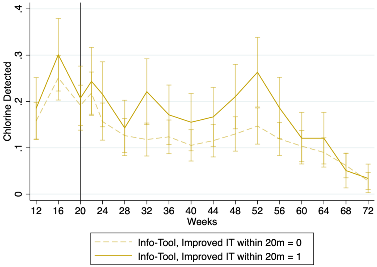
Model Predictions: IT Spillover Heterogeneity

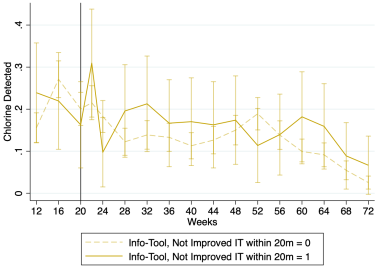




✓Info-Tool responsiveness to IT spillovers

Model Predictions: IT Spillover Heterogeneity

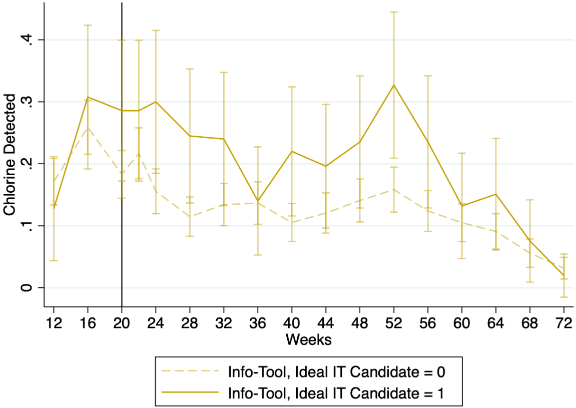




✓Info-Tool responsiveness to IT spillovers

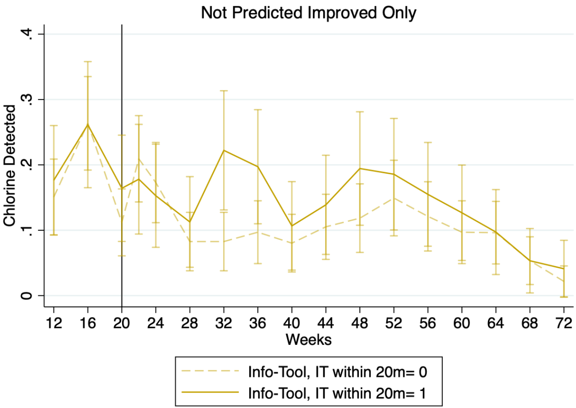
✓IT-to-IT spillovers driven by predicted improved neighbors

Improved IT with Improved Neighbors



Ideal IT candidate: Early positive health signals + neighbors with early positive health signals

Not Improved IT with IT Neighbors



Complementarity between experiential and social learning moderates the potential for negative draws from nature to lead to misattribution

What Explains Info-Tool Success?

Info-Tool sends stronger signals

- Explains immediate post-treatment higher chlorine use

Info-Tool leads to early adoption

- Can rule out early adoption as driving mechanism in Q2
- Can't rule out frequent adoption in the long run

Info-Tool generates social learning

- Yes, but only *complementary* to experiential learning
- Complementarity between learning through noticing and social learning generates persistence
  - → Optimal policy: saturate learning-through-noticing intervention
  - → May explain extremely high rates of chlorine use in Akram and Mendelsohn (2021)

Alternative Explanation: Conversations

Our model: IT generates $\uparrow \alpha_{ij}^{t}, j \in IT$

$$\hat{S}_i^T = \frac{\sum_{t=0}^{T} \sum_{j=1}^{J} \alpha_{ij}^{t} \cdot a_{ij}^{t} \cdot s_{ij}^{t}}{\sum_{t=0}^{T} \sum_{j=1}^{J} a_{ij}^{t}}$$

Alternative model: IT generates $\uparrow a_{ij}^{t}, j \in IT$

$$\hat{S}_i^T = \frac{\sum_{t=0}^{T} \sum_{j=1}^{J} \alpha_{ij}^{t} \cdot a_{ij}^{t} \cdot s_{ij}^{t}}{\sum_{t=0}^{T} \sum_{j=1}^{J} a_{ij}^{t}}$$

Alternative Explanation: Conversations

	Number of Friends: Discussed Water Purification			Number of Friends: Discussed Health		
	IV	OLS	OLS	IV	OLS	OLS
Boils, Bleaches, or Chlorinates Water	0.388***	0.213***		0.035	-0.019	
	(0.107)	(0.030)		(0.124)	(0.034)	
Chlorine			0.078*			0.011
			(0.040)			(0.046)
Incentives			0.177***			-0.006
			(0.040)			(0.046)
Info-Tool			0.100**			0.027
			(0.040)			(0.046)
Observations	1575	1575	1575	1575	1575	1575
Control Mean	0.245	0.245	0.307	1.018	1.018	1.007

Standard errors in parentheses
* $p < .1$, ** $p < 0.05$, *** $p < 0.01$

Table 1: Conversations about Health and Water Purification

No differences in frequency of conversations about health/water purification across treatment groups

Alternative Explanation: Social Norms

	Believes Guest Would Accept Chlorinated Water			Number of Friends Believes Uses Chlorine		
	IV	OLS	OLS	IV	OLS	OLS
Boils, Bleaches, or Chlorinates Water	0.360***	0.217***		0.157***	0.096***	
	(0.078)	(0.021)		(0.049)	(0.013)	
Chlorine			0.081***			0.032*
			(0.029)			(0.018)
Incentives			0.145***			0.052***
			(0.030)			(0.018)
Info-Tool			0.102***			0.058***
			(0.029)			(0.018)
Observations	1575	1575	1575	1573	1573	1573
Control Mean	0.657	54.891	0.673	0.043	0.043	0.055

Standard errors in parentheses
* $p < .1$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Social Norms

No differences in expectations of others to chlorinate or accept chlorinated water across treatment groups

Health Results

	(1) Index (Anthropometry)	(2) Height-for-Age	(3) Weight-for-Height	(4) Weight-for-Age	(5) MUAC-for-Age
Chlorine-Only	0.081**	0.020	0.009	0.082	0.025
	(0.039)	(0.084)	(0.099)	(0.081)	(0.064)
Incentives	0.031	0.023	-0.097	0.069	0.062
	(0.042)	(0.078)	(0.101)	(0.079)	(0.065)
Info-Tool	0.109***	-0.001	0.077	0.187**	0.079
	(0.039)	(0.080)	(0.101)	(0.080)	(0.066)
Observations	2616	2371	2439	2492	1954
Endline Control Mean	-0.019	-1.773	-0.291	-1.407	-1.453
P-values:					
Chlorine = Incentives	0.191	0.970	0.307	0.878	0.558
Chlorine = Info-Tool	0.445	0.805	0.501	0.200	0.396
Incentives = Info-Tool	0.044	0.759	0.095	0.142	0.792

Table 3: Child Health: Endline

Health Results

	(1) Boils Water	(2) Uses Chlorine	(3) Boils or Chlorinates
Chlorine	-0.061***	0.366***	0.294***
	(0.022)	(0.031)	(0.033)
Incentives	-0.060***	0.360***	0.300***
	(0.022)	(0.031)	(0.033)
Info-Tool	-0.045**	0.365***	0.321***
	(0.022)	(0.031)	(0.032)
Observations	1575	1575	1575
Control Means			
Endline Mean	0.158	0.104	0.255
Baseline Mean	0.144	0.004	0.148

Standard errors in parentheses
* $p < .1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Endline Water Treatment Method (Self-Reported)

Health Results

	(1) Index (Anthropometry)	(2) Height-for-Age	(3) Weight-for-Height	(4) Weight-for-Age	(5) MUAC-for-Age
Boils, Bleaches, or Chlorinates Water	0.244**	0.043	-0.008	0.379*	0.200
	(0.113)	(0.208)	(0.261)	(0.213)	(0.185)
Observations	2616	2371	2439	2492	1954
Endline Control Mean	-0.019	-1.773	-0.291	-1.407	-1.453
Weak-IV robust F statistic	118.78	126.82	120.83	121.59	94.61
C-statistic p-value	0.025	0.530	0.424	0.130	0.056

Table 5: Child Health: IV

Instrumented: ‘boils, bleaches, or chlorinates water’
Instrument: ‘any treatment group’

Health Results

Intervention	Paper	HAZ	WHZ	WAZ	Muac-for-age
Chlorinated Water	Akram et al., forthcoming	0.043	-0.008	0.379	0.200
Handwashing	Hussam et al., 2022	0.272	–	0.203	0.078
Hygiene	Bennett et al., 2018	0.290	–	0.270	–
Nutrient Supplements	Sazawal et al., 2013	0.180	–	0.030	–
	Soofi et al., 2022	0.290	0.050	0.260	–
ECD	Bos et al., 2024	-0.024	0.230	0.137	–

Table 6: Benchmarking Child Health Estimates

Caregiver Results

Inequity as a potential unintended consequence of...

- ... chlorine distribution, by household bargaining power
  - Baseline: 79% involved in HH decision-making about child health
  - Baseline: 50% are sole HH decision-maker about child health
  - Endline: 11% say do not use chlorine because men do not allow it
- ... Info-tool, by education
  - Interpreting Info-Tool may require numeracy/literacy skills
  - 30% ever attended school
- ... Info-tool, by social capital
  - Social learning only positively impacts people with social capital

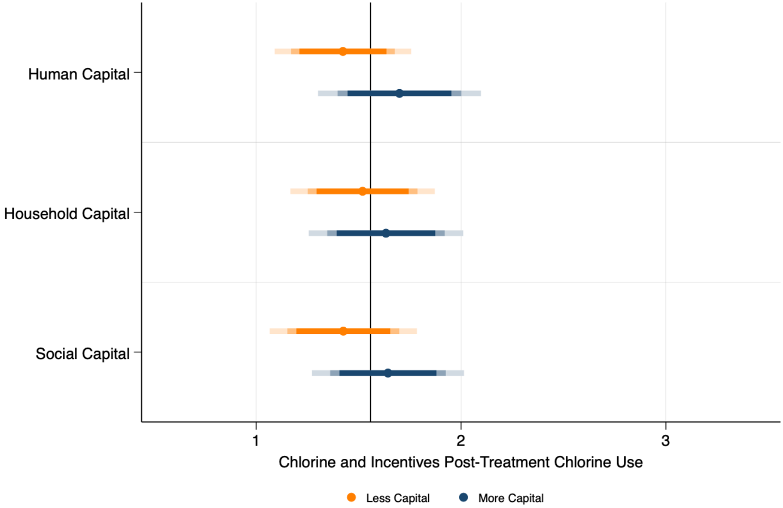
Caregiver Results

Equity Analysis

- Three forms of capital
  - Human capital: education, health
  - Household capital: decision-making power in the household
  - Social capital: number of friends I list, if I am listed in others' networks, if I am listed as a network-central individual by others
- PCA: 3 social network questions, 4 household decision-making questions, 1 education question, 1 health question
  - Component 1: Loads onto decision-making questions → measure of household capital
  - Component 2: Loads onto health and education → measure of human capital
  - Component 3: Loads onto social network questions → measure of social capital
    - Social network questions collected at endline only – social capital is possibly an outcome
    - Look at engagement with relatives only (unlikely affected by treatment)

Caregiver Results

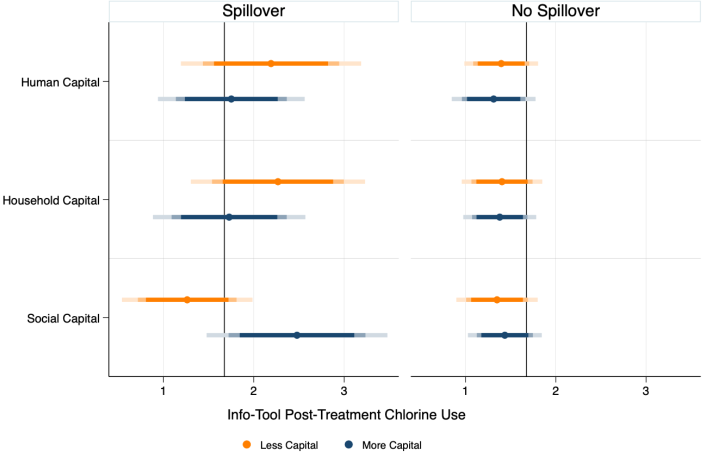
Equitable use in Chlorine and Incentives (pooled)



Caregiver Results

Not creating inequities by human capital or bargaining power (if anything, progressive)

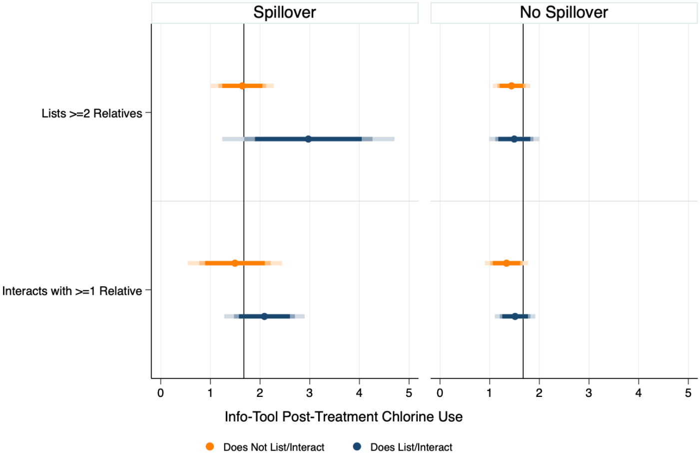
Inequity in access social learning



Caregiver Results

Pattern holds when looking at engagement with relatives only

Unlikely that engagement with relatives changes so dramatically from this treatment



Demand

Low take-up with free distribution alone

$\rightarrow$ Not only an access problem ...

But access is still the first and foremost issue

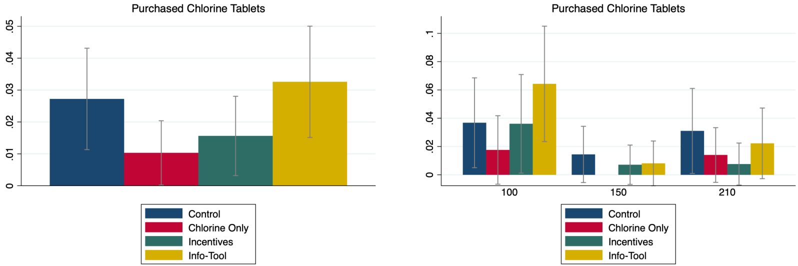


Figure 5: Take-it-or-leave-it Demand Exercise

Conclusion

Learning by doing in health

- Evidence that "practice makes perfect" among providers
- Can we use learning by doing to effectively change health behaviors?
  - Yes!
  - Limited attention important
  - Complementarity between learning by doing and learning from others
- Does learning by doing exacerbate or close inequities?
  - Important role of social learning $\rightarrow$ induces inequity by social capital
  - Potentially progressive with regards to human and household capital
    - "Seeing is believing" – improved trust among people least likely to trust experts?
    - Limited attention binds differentially by human capital/household decision-making power?

Conclusion

Thank You!

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Appendix

Chlorine Use

	(1)	(2)	(3)	(4)	(5)
	Q1	Q2	Q3	Q4	Q5
Chlorine	0.617***	0.551***	0.268***	0.367***	0.222***
	(0.049)	(0.043)	(0.036)	(0.037)	(0.031)
Incentives	0.705***	0.525***	0.343***	0.382***	0.278***
	(0.048)	(0.043)	(0.036)	(0.037)	(0.031)
Info-Tool	0.586***	0.622***	0.337***	0.416***	0.233***
	(0.049)	(0.043)	(0.036)	(0.037)	(0.031)
Observations	1653	1802	1802	1802	1802
P-values:					
Incentives = Info-Tool	0.015	0.024	0.864	0.359	0.146
Chlorine = Info-Tool	0.524	0.098	0.056	0.190	0.711
Incentives = Chlorine	0.072	0.552	0.037	0.691	0.068

Standard errors in parentheses
* $p < .1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Chlorine Use: Aggregate Specification

Back

Chlorine Use

	(1)	(2)	(3)	(4)	(5)
	Q1	Q2	Q3	Q4	Q5
Chlorine	0.220***	0.149***	0.103***	0.140***	0.086***
	(0.015)	(0.011)	(0.012)	(0.013)	(0.010)
Incentives	0.251***	0.142***	0.129***	0.144***	0.107***
	(0.015)	(0.010)	(0.013)	(0.012)	(0.011)
Info-Tool	0.205***	0.164***	0.126***	0.157***	0.087***
	(0.013)	(0.011)	(0.012)	(0.012)	(0.010)
Observations	4711	6354	4719	4673	4674
P-values:					
Incentives = Info-Tool	0.017	0.102	0.813	0.420	0.129
Chlorine = Info-Tool	0.450	0.283	0.126	0.300	0.947
Incentives = Chlorine	0.117	0.610	0.077	0.810	0.133

Standard errors in parentheses
* $p < .1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Chlorine Use: Panel Specification

Chlorine Use

	(1) Q1		(2) Q2		(3) Q3		(4) Q4		(5) Q5	
Chlorine × Not Improved	0.555***	(0.069)	0.482***	(0.061)	0.271***	(0.051)	0.376***	(0.053)	0.224***	(0.044)
Chlorine × Improved	0.677***	(0.069)	0.616***	(0.061)	0.262***	(0.051)	0.358***	(0.052)	0.216***	(0.044)
Incentives × Not Improved	0.677***	(0.068)	0.508***	(0.060)	0.403***	(0.050)	0.364***	(0.052)	0.326***	(0.043)
Incentives × Improved	0.734***	(0.069)	0.544***	(0.061)	0.282***	(0.051)	0.400***	(0.053)	0.228***	(0.044)
Info-Tool × Not Improved	0.509***	(0.069)	0.559***	(0.060)	0.327***	(0.050)	0.415***	(0.052)	0.245***	(0.043)
Info-Tool × Improved	0.662***	(0.070)	0.688***	(0.062)	0.346***	(0.052)	0.416***	(0.053)	0.220***	(0.044)
Observations	1653		1802		1802		1802		1802	
P-values:										
Chlorine $\times Improved = Chlorine \times NotImproved$	0.214		0.121		0.910		0.807		0.892	
Incentives $\times Improved = Incentives \times NotImproved$	0.559		0.674		0.094		0.626		0.115	
Info-Tool $\times Improved = Info - Tool \times NotImproved$	0.119		0.136		0.799		0.986		0.698	

Standard errors in parentheses
* $p < .1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Chlorine Use: Aggregate Specification

Chlorine Use

	(1)		(2)		(3)		(4)		(5)	
	Q1		Q2		Q3		Q4		Q5	
Chlorine × Not Improved	0.197***	(0.021)	0.132***	(0.014)	0.102***	(0.016)	0.141***	(0.017)	0.085***	(0.014)
Chlorine × Improved	0.239***	(0.021)	0.164***	(0.016)	0.102***	(0.017)	0.137***	(0.018)	0.086***	(0.016)
Incentives × Not Improved	0.235***	(0.021)	0.138***	(0.013)	0.147***	(0.019)	0.132***	(0.016)	0.120***	(0.017)
Incentives × Improved	0.266***	(0.021)	0.146***	(0.014)	0.109***	(0.017)	0.153***	(0.020)	0.092***	(0.015)
Info-Tool × Not Improved	0.174***	(0.018)	0.152***	(0.015)	0.122***	(0.017)	0.151***	(0.018)	0.088***	(0.013)
Info-Tool × Improved	0.237***	(0.020)	0.178***	(0.016)	0.129***	(0.018)	0.158***	(0.017)	0.086***	(0.014)
Observations	4711		6354		4719		4673		4674	
P-values:										
Chlorine $\times Improved = Chlorine \times NotImproved$	0.162		0.123		0.995		0.867		0.935	
Incentives $\times Improved = Incentives \times NotImproved$	0.303		0.675		0.132		0.414		0.213	
Info-Tool $\times Improved = Info - Tool \times NotImproved$	0.020		0.227		0.768		0.790		0.900	

Standard errors in parentheses
* $p < .1$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Chlorine Use: Panel Specification

Chlorine Use

	(1) Q1		(2) Q2		(3) Q3		(4) Q4		(5) Q5	
Chlorine × No Spillover	0.604***	(0.061)	0.533***	(0.054)	0.249***	(0.045)	0.352***	(0.046)	0.219***	(0.039)
Chlorine × Spillover	0.643***	(0.084)	0.584***	(0.073)	0.302***	(0.061)	0.396***	(0.063)	0.229***	(0.052)
Incentives × No Spillover	0.680***	(0.060)	0.498***	(0.053)	0.356***	(0.045)	0.401***	(0.046)	0.292***	(0.038)
Incentives × Spillover	0.752***	(0.082)	0.574***	(0.073)	0.322***	(0.061)	0.351***	(0.063)	0.256***	(0.052)
Info-Tool × No Spillover	0.567***	(0.061)	0.558***	(0.054)	0.309***	(0.045)	0.365***	(0.046)	0.202***	(0.039)
Info-Tool × Spillover	0.620***	(0.083)	0.734***	(0.073)	0.386***	(0.061)	0.504***	(0.063)	0.289***	(0.052)
Observations	1653		1802		1802		1802		1802	
P-values:										
Chlorine $\times$ *Spillover* $=$ *Chlorine* $\times$ *NoSpillover*	0.706		0.578		0.489		0.567		0.870	
Incentives $\times$ *Spillover* $=$ *Incentives* $\times$ *NoSpillover*	0.483		0.402		0.648		0.524		0.577	
Info-Tool $\times$ *Spillover* $=$ *Info* $-$ *Tool* $\times$ *NoSpillover*	0.611		0.053		0.313		0.076		0.182	

Standard errors in parentheses
* $p < .1$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Chlorine Use: Aggregate Specification

Chlorine Use

	(1) Q1		(2) Q2		(3) Q3		(4) Q4		(5) Q5	
Chlorine × No Spillover	0.212***	(0.018)	0.145***	(0.013)	0.095***	(0.015)	0.134***	(0.016)	0.085***	(0.013)
Chlorine × Spillover	0.232***	(0.025)	0.156***	(0.017)	0.118***	(0.018)	0.149***	(0.019)	0.089***	(0.017)
Incentives × No Spillover	0.241***	(0.019)	0.134***	(0.012)	0.133***	(0.016)	0.152***	(0.016)	0.114***	(0.015)
Incentives × Spillover	0.267***	(0.025)	0.157***	(0.017)	0.122***	(0.020)	0.126***	(0.020)	0.095***	(0.018)
Info-Tool × No Spillover	0.194***	(0.017)	0.146***	(0.013)	0.115***	(0.015)	0.137***	(0.014)	0.075***	(0.011)
Info-Tool × Spillover	0.227***	(0.023)	0.197***	(0.019)	0.145***	(0.023)	0.186***	(0.024)	0.108***	(0.018)
Observations	4711		6354		4719		4673		4674	
P-values:										
Chlorine $\times Spillover = Chlorine \times NoSpillover$	0.536		0.616		0.328		0.537		0.848	
Incentives $\times Spillover = Incentives \times NoSpillover$	0.391		0.284		0.678		0.305		0.424	
Info-Tool $\times Spillover = Info - Tool \times NoSpillover$	0.255		0.031		0.263		0.077		0.112	

Standard errors in parentheses
* $p < .1$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Chlorine Use: Panel Specification