The Demand for Health: Why do people want antibiotic and steroid, but not vaccination ?

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14.771

The demand for Health: Low level and high elasticity...

- Households seem to be willing to pay a lot for curative care: Expenditure on private health care in India (budget share, half of the visits to private doctors). e.g. in Udaipur 8% of the households recorded total expenditures on health of more than Rs 5,000 (ten times the monthly budget per capita for the average family)
- However, low take up and surprisingly large price elasticities for preventive health for technology we know to be highly effective: bednets, immunization, deworming etc. Figure
- We have seen a recent example of that with the COVID-19 vaccine, and not just in the developing world...

The extra people who buy when it is cheaper are in fact investing in their health

- Two counterarguments to that in the policy world:
  - Heterogeneity in returns: low prices draw people who have very little use for the product and will not undertake complementary action (e.g. using the net): no health impact.
  - sunk cost fallacy: treatment effect of getting a low price (which would discourage complementary action)
- Cohen and Dupas, Dupas (2010), Ashraf-Berry-Shapiro investigate this issue.
- little evidence that of this. Cohen Dupas find No elasticity of use conditional on take up : Conditional usage, so relative elasticity of effective coverage is very large Effective coverage

However....

- The sensitivity to price appears to be surprisingly large.
- Likewise, large reaction to small positive incentives for immunization. Banerjee et al. "Conditional lentils transfers"
  - 130 villages
  - 60 get randomly assigned to receive regular immunization camp
  - 30 of those get small incentives to get immunized (1 kg of lentils/1 set of plates)
  - Pretty large impact of the camp..But larger impact of the lentils ▸ complete immunization ▸ number of shots
- Thornton find the samething for getting your result of an HIV test.

Price Effects

- Small negative price: Banerjee-Duflo etc.. Immunization in India
  - 130 villages
  - 60 get randomly assigned to receive regular immunization camp
  - 30 of those get small incentives to get immunized (1 kg of lentils/1 set of plates)
  - Pretty large impact of the camp..But larger impact of the lentils ▸ complete immunization ▸ number of shots

Why these high price elasticities?

- These are just two examples, but there are many others.
- Basis for the "Conditional Cash transfer approach" (e.g. Progresa, Mexico), which has become very popular in many countries: cash transfer is conditional on health.
- Puzzling in light of health demand model we started with:
  - Large benefits
  - People care about their health (they spend money on treatment)
  - Prices (or opportunity cost) are not that high to begin with

Low take up and High elasticity: possible Explanation (1) Present bias

- This could explain high elasticity to price of preventive care: small cost today discourage actions, but could be undone by small benefit today (e.g. a bag of lentils).
- Subsidies for preventive care could be justified, not only by externalities, but "internalities".

Implication of present bias

- Other policies that would be effective in this context: default option (you have to opt out NOT to get your child immunize); helping people to commit (Karlan and Gine: CARES in the philippines: people put money in a savings account which they forfeit if they start smoking. 10% of people took up program when offered, and those offered where 3% more likely to stop smoking than those not offered).
- Problem with this explanation: is it plausible that people are *that* fooled by themselves, and really think they will immunize their children in the future?

Low take up and High elasticity: possible Explanation (2) Information

- We observe large sensitivity to relevant information
  - e.g. Dupas (2007): Pregnancies with older partners decline significantly when teenager are informed that older men are less likely to have HIV than younger men. ▸ table
  - Dupas (2010) tests by comparing purchase of a *second* bednet (at 150 ksh) of those who were offered a first bednet for free or against payment: those who pay less the first time are more likely to pay the second time. ▸ period 1 ▸ period 2
- However, learning about health is very difficult (Das and Sanchez, 2002): many diseases are "self-limiting", in the sense that symptoms will go away by themselves (at least temporarily) : learning about doctor quality is really hard.
- Particularly difficult to link cause and effects with preventive case, especially when the behavior has externalities.

Low take up and High elasticity: possible Explanations (3): Trust

- Mistrust of government (message changes; in India: forced sterilization). Two recent studies highlight that:
  - Lowes and Montero (2021): Places where french government undertook massive and missguided sleeping sickness vaccination campaign still have low trust in medicine today than comparable palces in same country that were under british rule, and less childhoold immunization
  - Martinez-Bravo and Stegmann (2021) CIA vaccine ruse (to find Osama bin Laden) also leads to decrease in immunization.
- Very little impact of not well defined "behavioral change" message
  - e.g. Kremer and Miguel: No impact of a campaign to convince kids to wear shoes and stop fishing in the lake to avoid catching worms.
  - Duflo-Dupas-Kremer (2018): No impact of the "ABCD" Campaign in upper primary school in Kenya, which tried to convince kids to forgo sex till marriage

Low Take up and High elasticity: possible explanations (4): social equilibrium

- People understand that the benefit of immunization are mainly social
- And they have no way to signal they are of the "right type"
- Karing (2020): Sierra Leone. Given silicon bracelets to show that you have completed the sequence
- Bracelets are popular and increase immunization
- How do you know that it is about signaling per se? What else could it be? how could we test it ?
- Nice feature of experiment: introduce a treatment with uninformative bracelets
- These bracelets are about as effective: this really could be about tiny incentives , not social signaling. More research to do!

The role of the social network

- With many of the above explanations (information, trust, conveying the social norm) social network are likely to play a key role
- Common idea: influential people.
- First possibility: Stars
  - Alatas et al (Indonesia): messages on twitters send by stars are more likely to be retweeted
  - Banerjee et al (COVID-19 protection) "The Banerjee effect". Video messages sent by Abhijit via text message affect symptom reporting and self-reported social distancing.
- We could also use locally influential people (see Biden "immunization corps") Problem: who is influential?
  - Network theory suggests ideas: people with high centrality.
  - Research suggests that shortcuts may not work (people with many friends, people who live in central location).

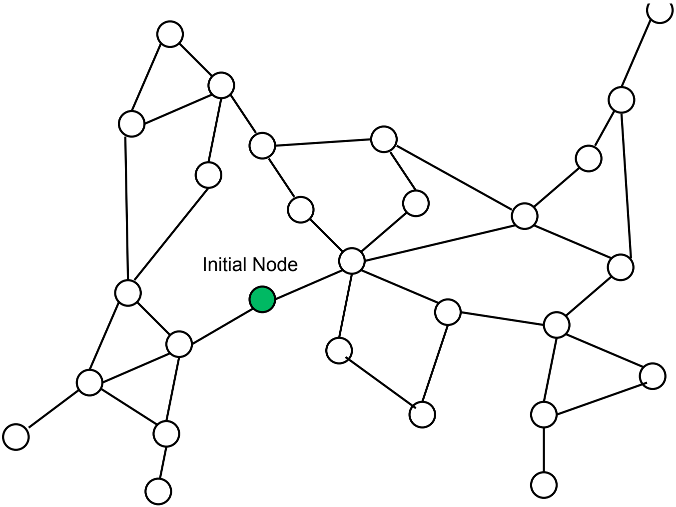
Gossips

- what is the idea of Gossips?
- How about asking a few people in the network? perhaps surprisingly, this is not a suggestion in the literature (in economics or marketing). We do know that community members are good at identifying the poor (Alatas et al), or the productive (Hussam et al). Yet far from automatic that members of a social network should know who is central
    - hard to know how central others are outside of immediate circle
    - research suggests network members have poor image of network, beyond immediate friends

A simple process

Information diffusion: 4 periods, probability of passing=0.5

diffusion centrality: $DC_i(0.5, 4)$



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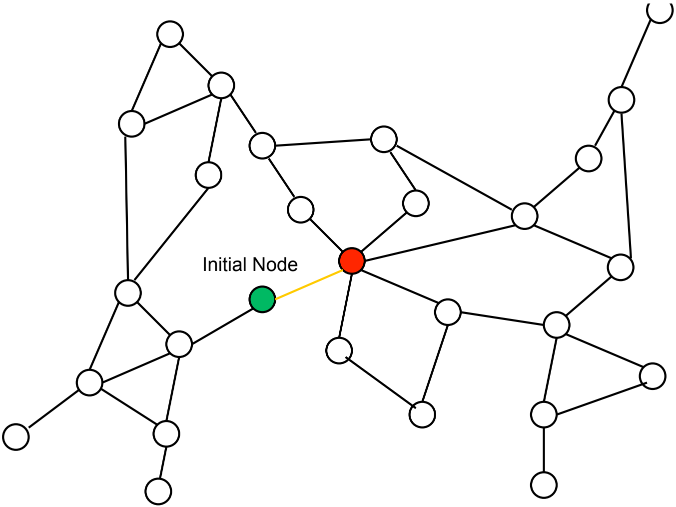

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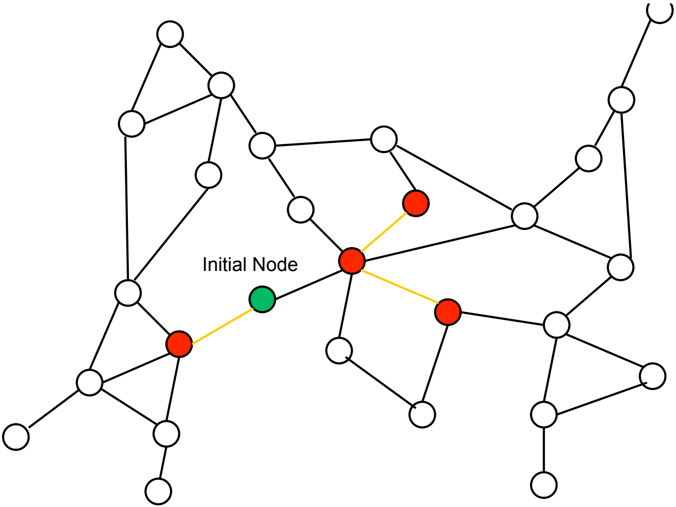

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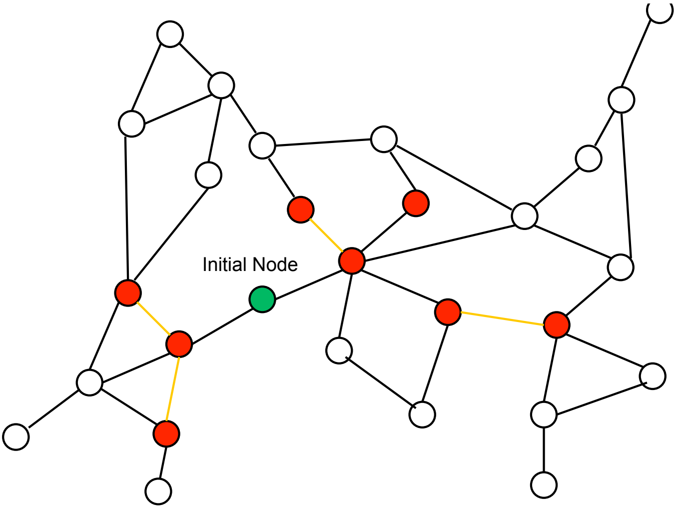

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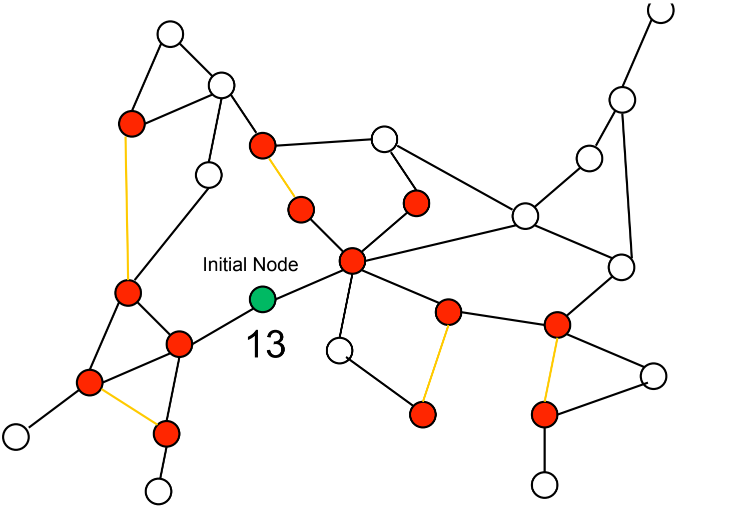

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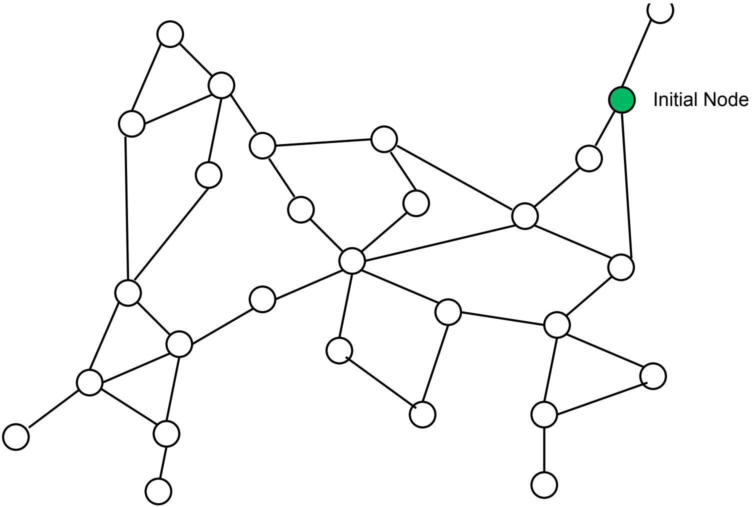

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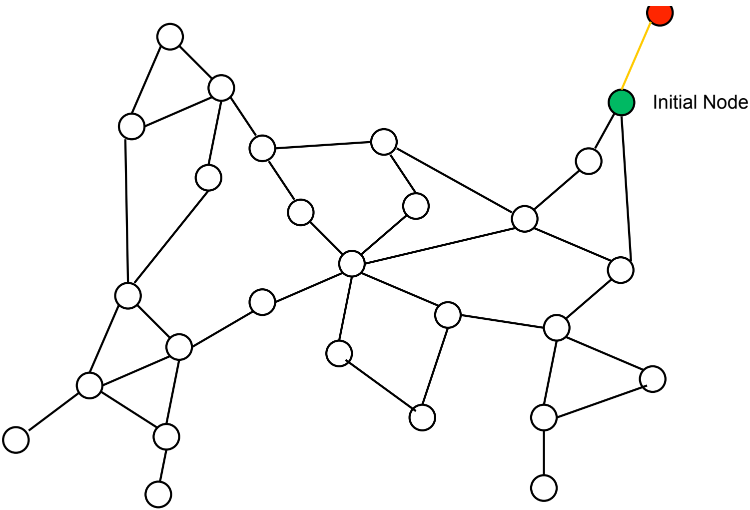

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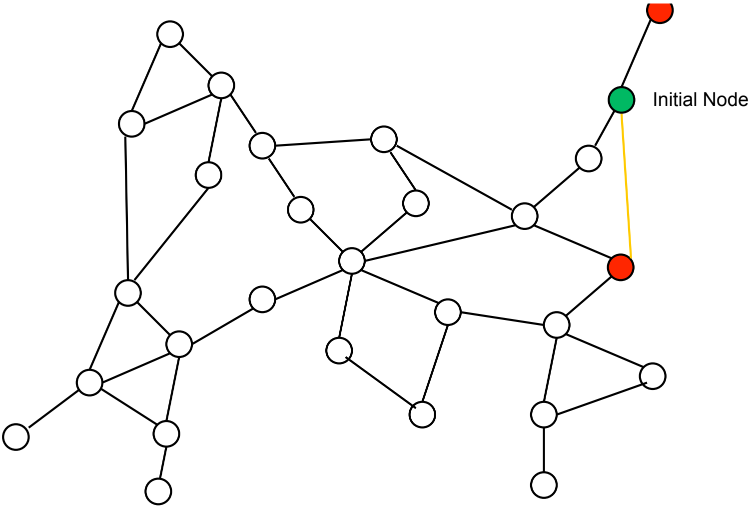

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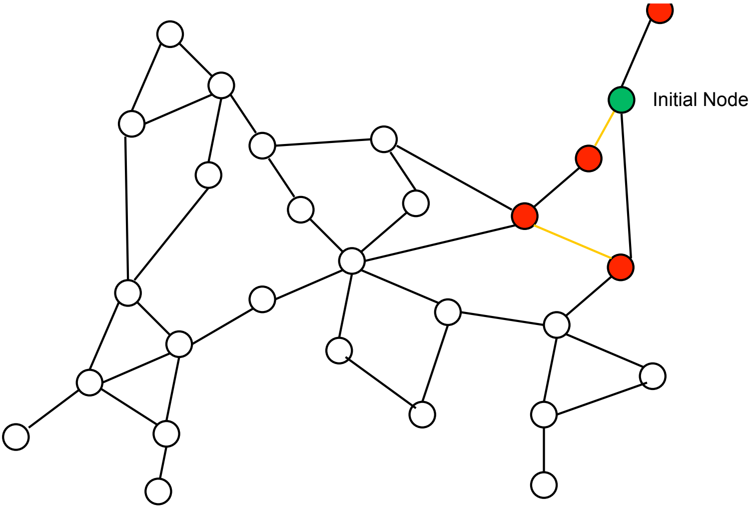

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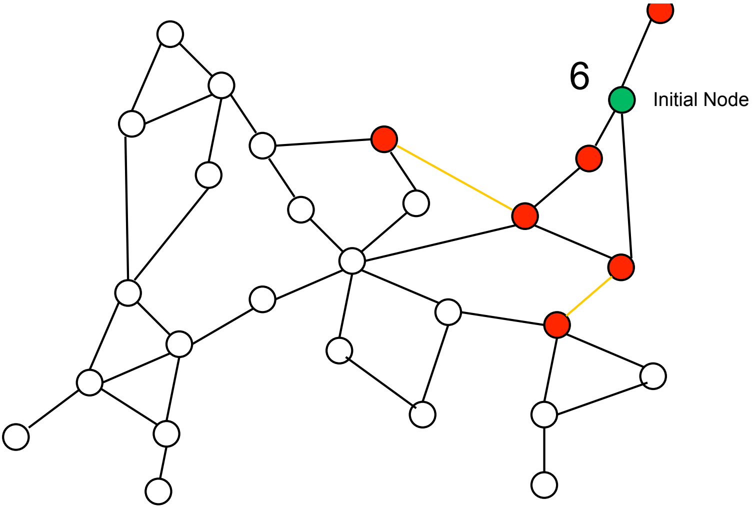

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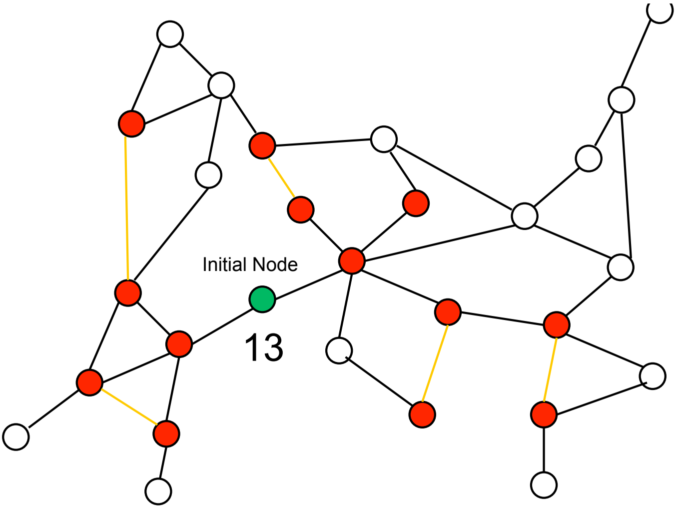


diffusion centrality

$$DC(\mathrm{g}; q, T) := \left(\sum_{t=1}^{T} (q\mathrm{g})^t \right) \cdot 1.$$

- DC_i is the total expected number of times information starting at i hits all others

Can network member identify those with high DC?

- BCDJ ('13) and Beaman et al. ('14) show value of hitting injection point with high EV centrality
- But it is very expensive to collect network data
  - not a scalable policy solution
- What about asking members of the network?
- Ex ante, should not expect people to know who may be central
  - eigenvector centrality depends on macro-structure of the network
  - people are bad at knowing network structure at arms length (Carley and Krackhardt, 1996; Krackhardt and Kilduff, 1999; Breza, Chandrasekhar, and Tahbaz-Salehi, 2016)
- On the other hand, if they knew, they could also know other things about these people that makes them even better to pass some type of information: they could do even better than picking network central people.

how could people learn?

compare the process a from how listeners rank others (gossip centrality) to that from the sender's perspective (diffusion centrality)

gossip

- “Matt changed jobs”, “Esther bought a goat,” spreads randomly
- Probability q that news is passed from one node to another
- Keep track of how many times hear news about Matt, Esther...

network gossip

Let

$$\mathrm{M}(\mathrm{g}; q, T) := \left(\sum_{t=1}^{T} (q\mathrm{g})^t \right).$$

$M(\mathrm{g}; q, T)_{ij}$ is expected number of times j hears a piece of information originating from i.

Define *network gossip heard* by node j to be

$$NG(\mathrm{g}; q, T)_j = M(\mathrm{g}; q, T)_{\cdot j}.$$

Conceptual difference:

- Diffusion centrality tracks how well info spreads from a given node
- Network gossip tracks how relatively often j hears about info originating from other nodes

how well can this do?

Every individual's rankings of others under network gossip will be **according to the ranking of diffusion centrality** for large enough T and q.

Theorem: If g is irreducible and aperiodic, and if $q \geq 1/\lambda_1$, then as $T \to \infty$

- every individual j's ranking of others under $NG(\mathrm{g}; q, T)_j$ will be according to the ranking of diffusion centrality, $DC(\mathrm{g}; q, T)$,
- and hence according to eigenvector centrality, $e(\mathrm{g})$.

Intuition:

- much more likely to hear about a central node's gossip relative to a nearby, non-central friend with enough communication periods.

Diffusing a message about immunization

- Large scale project undertaken in collaboration with the government of Haryana, India
- Objective is to increase demand for immunization [in a context with low immunization rate]
- We developed and deployed in a large sample of villages a e-health application on Android. Serves as set up for several experiments:
    - Incentives
    - Reminders
    - "Seed" intervention
- Experiment size:
    - 7 districts (pop 8 mil)
    - Each of 2360 villages covered (140 PHCs, 755 SCs)
    - 295,038 unique children covered (administrative data)
    - 471,608 vaccines administered

Design of the Seed intervention

- (well) before the tablets and incentive treatment started, we visited 516 (out of about 900 in this arm) villages in the experiment and ask random households to nominate up to 4 people.
- Villages were randomly selected to be:
  1. Gossip
  2. Trusted
  3. Trusted Gossip
- Then we selected randomly 5 of the people who had been nominated, and enrolled them as seed

Gossip

"Who are the people in this village, who when they share information, many people in the village get to know about it. For example, if they share information about a music festival, street play, fair in this village, or movie shooting many people would learn about it. This is because they have a wide network of friends/contacts in the village and they can use that to actively spread information to many villagers. Could you name four such individuals, male or female, that live in the village (within OR outside your neighborhood in the village) who when they say something many people get to know?"

Trusted

"Who are the people in this village that you and many villagers trust, both within and outside this neighborhood, trust? When I say trust I mean that when they give advice on something, many people believe that it is correct and tend to follow it. This could be advice on anything like choosing the right fertilizer for your crops, or keeping your child healthy. Could you name four such individuals, male or female, who live in the village (within OR outside your neighborhood in the village) and are trusted?"

Trusted Gossip

"Who are the people in this village, both within and outside this neighborhood, who when they share information, many people in the village get to know about it. For example, if they share information about a music festival, street play, fair in this village, or movie shooting many people would learn about it. This is because they have a wide network of friends/contacts in the village and they can use that to actively spread information to many villagers. Among these people, who are the people that you and many villagers trust? When I say trust I mean that when they give advice on something, many people believe that it is correct and tend to follow it. This could be advice on anything like choosing the right fertilizer for your crops, or keeping your child healthy. Could you name four such individuals, male or female, that live in the village (within OR outside your neighborhood in the village) who when they say something many people get to know and are trusted by you and other villagers?"

Intervention

- We visited them once before anything else to get their consent to get messaged once a month. We told them about the importance of immunization and suggest they spread it.
- From then on, we messaged them once a month with text messages that say the following:
    - In Incentive villages: Vaccination protects your child from 10 types of diseases and ensures complete physical and mental development of the child . Families with children below 12 months of age will receive a free mobile recharge worth TK as a gift for vaccinating their child. Please share this information with your friends and family members and encourage them to immunize their child at the nearest immunization session camp.
    - In No incentive villages: Vaccination protects your child from 10 types of diseases and ensures complete physical and mental development of the child . Please share this information with your friends and family members and encourage them to immunize their child at the nearest session camp.

results

	Log(Number of Children received Penta1)	Log(Number of Children received Penta2)	Log(Number of Children received Penta3)	Log(Number of Children received Measles)
	(1)	(2)	(3)	(4)
Gossip	0.146	0.192	0.190	0.181
	(0.100)	(0.097)	(0.094)	(0.086)
Trusted	0.141	0.159	0.149	0.119
	(0.092)	(0.088)	(0.088)	(0.083)
Trusted Gossip	0.129	0.146	0.178	0.124
	(0.093)	(0.089)	(0.086)	(0.078)
Slope	0.135	0.143	0.159	0.148
	(0.085)	(0.082)	(0.081)	(0.074)
Flat	-0.013	0.025	0.085	0.044
	(0.098)	(0.096)	(0.090)	(0.084)
Control Mean	9.02	7.43	6.35	4.37
Observations (village x month)	3,543	3,468	3,406	3,175

Putting it all together

Banerjee et al (2020) "Selecting the Most effective nudge"

- Nudges as tools
  - Common instrument 1: Cash/in kind incentives
  - Common instrument 2: Reminders
  - Newer to toolkit: leverage social networks

The Policy Design Question

- Evidence that each strategy *may* improve take-up
- But we need to know
  1. Which strategy is the most effective (largest increase)
  2. Which strategy is the most cost effective (largest increase/$)
- More subtly
  1. What dosage should we use?
  2. And what *combinations* of policies should we use?

Typical Approaches

Meta-analyses:

- Collect estimates from different papers and put them on a common scale
  (E.g., Campbell Collaborative; Cochrane Review; J-PAL)
- Problem:
  - Populations and interventions may vary considerably across studies
  - When different interventions tested in different contexts, impossible to assess interactions between policy options
  - Makes running a single large scale RCT in the relevant context with direct (internal) comparisons a relevant pre-launch strategy

Problem 1: An Awkward Choice

1. Restrict the number of interventions (or combos) (McKenzie, 19)
2. Include all combos but perhaps lose power
   - In practice researchers often pool options ex-post but this can be misleading (e.g., Muralidharan et al., 19)
3. A push in the literature space towards assuming the conclusion.

Problem 2: Biased Estimates of Best Policies

Andrews et al. (2021):

- Estimate a collection of policy effects: $\hat{\eta}_1, \ldots, \hat{\eta}_K$.
- Each of the form: $\sqrt{n}(\hat{\eta}_j - \eta_j^0) = \sqrt{n}\hat{\epsilon}_j \quad \mathcal{N}(0, V)$.
- But then

$$\max_j\{\sqrt{n}\hat{\eta}_j\} = \max_j\{\sqrt{n}\eta_j^0 + \sqrt{n}\hat{\epsilon}_j\}$$

What We Do: TVA Pooling and Pruning

1. Write problem for *treatment variant aggregation* (TVA)
   - TVA pools variants that have no differences in effects
   - TVA prunes variants that are irrelevant
2. Use the Puffer transformation to implement LASSO (Rohe, 14; Jia and Rohe, 15)
   - Naive LASSO fails: no irrepresentability for TVA.
   - Puffer pre-conditioning recovers this consistently for our crossed-RCT design
3. Post-processing
   - Pooled and pruned estimates consistent/asymptotically normal (Javanmard and Montanari '13)
   - Estimate effect of best policy adjusting for winner's curse (Andrews et al., 21 - approximate unbiasedness)
     - Fluke risk: adjustment penalizes more when comparison set larger
     - Similar variant risk: when variants of same policy have similar effects, don't want to run a race

Interventions

1. Incentives crossed 2×2
   - Flat vs Slope: linear or convex incentives
   - High vs Low: total for completion is INR 450 vs 250

2. Reminders
   - Personalized SMS (and call) stating that it is the time to get the VVV vaccine for your children AAA, BBB, etc., noting the vaccination camp is open and they should go.
   - If incentives are available, the message notes this as well.

3. Immunization Ambassadors
   - *Random* seeds: 6 ambassador randomly from the census.
   - *Information hub* seed: respondents were asked to identify who is good at relaying information.
   - *Trusted* seed: respondents were asked to identify those who are generally trusted to provide good advice about health or agricultural questions

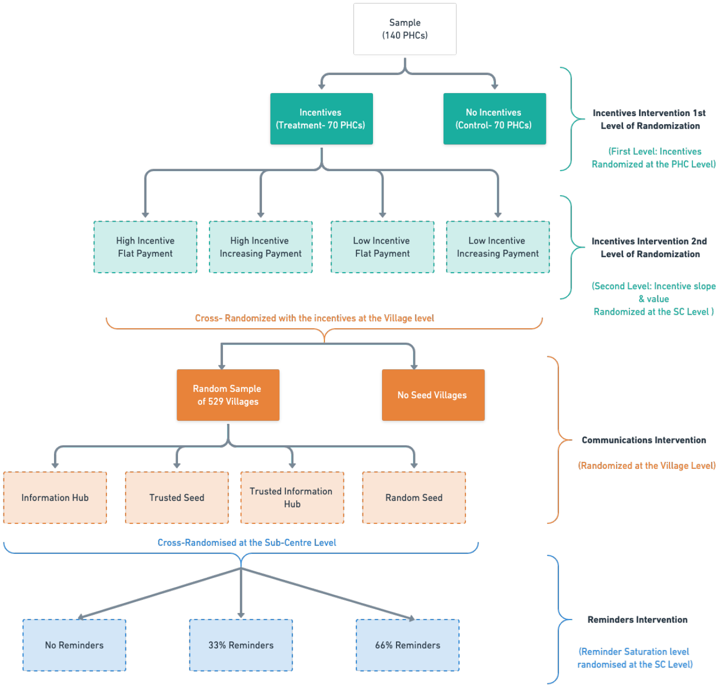
Application: Immunization Policy Design

Environment: Haryana, India

- 2360 villages; 914 at risk for all treatments
- 295,038 children

Design: 75 unique policy combinations

- Incentives: $\{$none$\}$ + $\{$linear, convex$\}$ $\times$ $\{$low, high$\}$
- Reminders: $\{$none, low, high$\}$
- Seeding: $\{$none, random, info hubs, trusted, trusted info hubs$\}$



Sample
(140 PHCs)
Incentives
(Treatment- 70 PHCs)
No Incentives
(Control- 70 PHCs)
Incentives Intervention 1st Level of Randomization
(First Level: Incentives Randomized at the PHC Level)
High Incentive Flat Payment
High Incentive Increasing Payment
Low Incentive Flat Payment
Low Incentive Increasing Payment
Incentives Intervention 2nd Level of Randomization
(Second Level: Incentive slope & value Randomized at the SC Level)
Cross- Randomized with the incentives at the Village level
Random Sample of 529 Villages
No Seed Villages
Information Hub
Trusted Seed
Trusted Information Hub
Random Seed
Communications Intervention
(Randomized at the Village Level)
Cross-Randomised at the Sub-Centre Level
No Reminders
33% Reminders
66% Reminders
Reminders Intervention
(Reminder Saturation level randomised at the SC Level)

Intervention Main Effects

In the entire sample, 2360 villages, we run the following regression:

$$y_{dsvt} = \alpha + \beta' \text{Incentive}_s + \gamma' \text{SMS}_s + \delta' \text{Ambassador}_v \\ + \lambda \text{Ambassador Sample}_v + \upsilon_{dt} + \epsilon_{dsvt}$$

- y_{dsvt} is the number of measles shot given in month t in village v in sub-center (SC) s, and district d,
- Ambassador Sample$_v$ is a dummy indicating that a village is part of the Ambassador sample,
- Ambassador$_v$ is a vector of the 4 possible ambassador interventions (randomly chosen, nominated as "information hub," nominated as "trusted information hub," and nominated as "trusted"),
- Incentive$_s$ is a vector of incentive interventions (low slope, high slope, low flat, high flat),
- SMS$_s$ is a vector of SMS interventions (33% or 66%),
- υ_{dt} is a set of district-time dummies (since the intervention was stratified at the district level). ϵ_{dsvt} represents the error term.

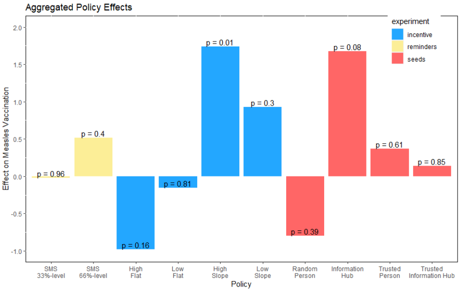
Intervention Main Effects

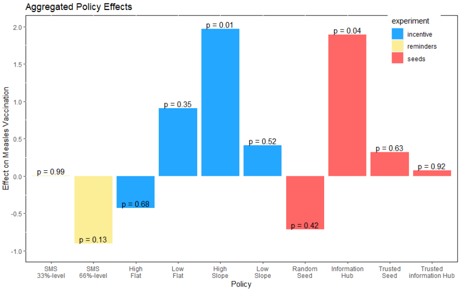
Focus sample, 917 villages, we run:

$$y_{dsvt} = \alpha + \beta' \text{Incentive}_s + \gamma' \text{SMS}_s + \delta' \text{Ambassador}_v + \upsilon_{dt} + \epsilon_{dsvt}.$$

In all specifications, we weight these village-level regressions by village population, and standard errors are clustered at the SC level.

Uninteracted results





Control means: 5.29 (A) and 7.32 (B)

Procedure

1. Define what is allowed to potentially "pool" (treatment profile)
2. Specify the regression as in the "marginal" way (a little tricky).
3. Use Puffer transform to make LASSO possible
4. Post Lasso on selected variables
5. Winner curse correction

Smart Pooling regression

The smart pooling specification looks like

$$\begin{aligned}
y_{dsvt} = {} & \alpha_0 + \alpha_{SMS}\text{SMS}_s + \alpha_{H,SMS}\text{High SMS}_s \\
& + \alpha_{Slope}\text{Slope}_s + \alpha_{H,Slope}\text{High Slope}_s + \alpha_{Flat}\text{Flat}_s + \alpha_{H,Flat}\text{High Flat}_s \\
& + \alpha_R\text{Random}_v + \alpha_H\text{Info Hub (All)}_v + \alpha_T\text{Trust}_v + \alpha_{TH}\text{Trusted Info Hub}_v \\
& + \alpha'_X X_{sv} + v_{dt} + \epsilon_{dsvt},
\end{aligned}$$

where we have explicitly listed some of the variables in "single arm" treatment profiles. X_{sv} is a vector of the remaining 64 smart pooling variables in "multiple arm" treatment profiles, and v_{dt} is a set of district-time dummies.

Policy Effects on Immunization

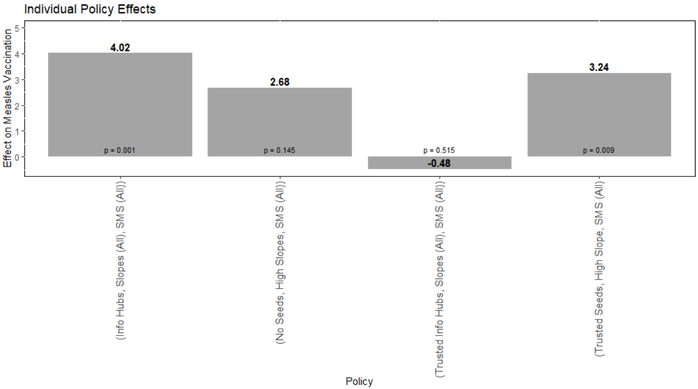


Figure: Effects of the smartly pooled and pruned combinations of reminders, incentives, and seeding policies on number of measles vaccinations relative to control (7.32). The specification is weighted by village population, controls for district-time fixed effects, and clusters standard errors at the subcenter level.

Policy Effects on Immunization per $

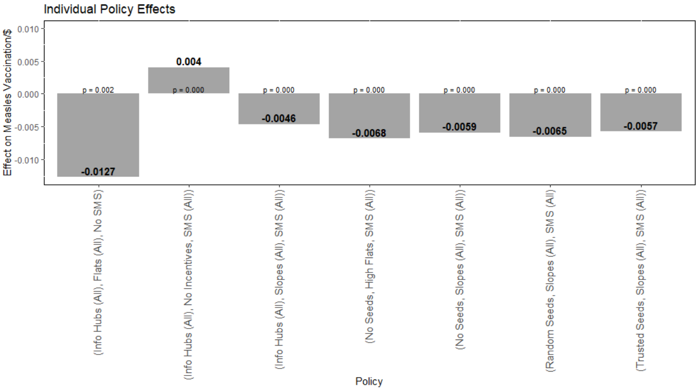


Figure: Effects of the smartly pooled and pruned combinations of reminders, incentives, and seeding policies on the number of Measles vaccines per $1 relative to control (0.0436 shots per $1). The specification is weighted by village population, controls for district-time fixed effects, and clusters standard errors at the subcenter level.

Effect of Best Policy

Table: Best Policies

	(1) # Measles Shots	(2) # Measles Shots per \$1
WC Adjusted Treatment Effect	3.26	0.004
Confidence Interval (95%)	[0.32,6.25]	[0.003, 0.005]
Control Mean	7.32	0.0435
Observations	204	814
Optimal Policy	(Information Hubs, SMS, Slope)	(Information Hubs POOLED, SMS)

Notes: Estimation using Andrews et al. (2020); hybrid estimation with $\alpha = 0.05, \beta = 0.005$. The specifications are weighted by village population and account for district-time fixed effects as well as variance clustered at the subcenter level.

What We Find

- Number of immunizations
  - Smart pooling selects 4 policies
  - Best policy (Info Hub, Any Reminder, Any Convex Incentive)
  - Increases immunization by 44% relative to status quo
- Number of Immunizations per $
  - Smart pooling and pruning selects 7 policies
  - No incentive schemes are selected
  - Best policy (Info Hub, Any Reminder, No Incentives)
  - Increases immunization/$ by 9.1% relative to status quo

Policy prescription

- Do Gossip+SMS everywhere
- But Most effective policy is not cost effective compared to status quo. Are there are places we can identify where it is more effective
- Standard problem of "predictive medicine"
- There are many potential covariates, how do we know which is a true one, vs a fluke...
- Standard answer: pre-analysis plan... but what if you don't know
- Alternative: ML. Problem is, we don't have tool for consistently estimating Causal Average treatment effect..
- Solution: give up on the full CATE, just estimate features of it.

First Step: Proxy Predictors

- We shall rely on random data splitting into a main sample, indexed by M, and an auxiliary sample, indexed by A. Here (A, M) form a random partition of $\{1, ..., N\}$.
- From the auxiliary sample A, we obtain **Generic ML** estimates of the baseline and treatment effects, which we call ML proxies

$$z \mapsto B(z) = B(z; \mathrm{Data}_A)$$

and

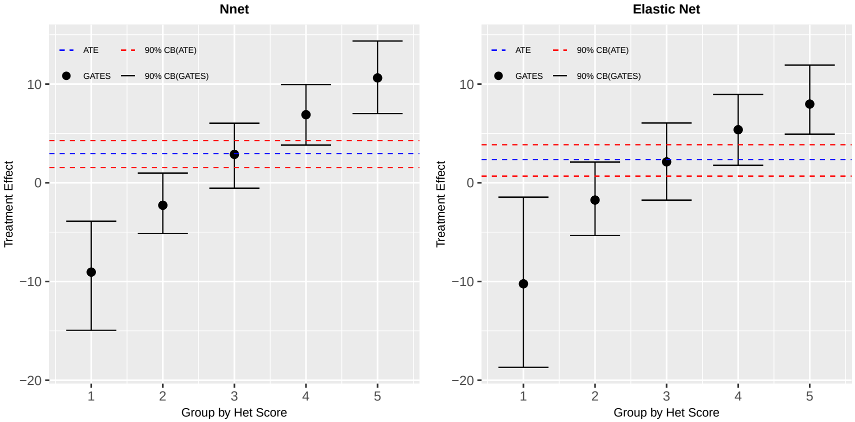
$$z \mapsto S(z) = S(z; \mathrm{Data}_A).$$

- Generic ML include random forest, neural network, lasso, elastic net, etc ...
- We treat $B(Z)$ and $S(Z)$ agnostically as possibly biased and noisy predictors of $b_0(Z)$ and $s_0(Z)$.

Second Step: From ML Proxies to Target Parameters

- We target *key features of* CATE and not the CATE itself:
    (1) Best linear predictor (**BLP**) of CATE $s_0(Z)$ using ML proxy $S(Z)$;
    (2) Group average treatment effects sorted (**GATES**) by the groups induced by ML proxy $S(Z)$;
    (3) Classification Analysis (**CLAN**): Average characteristics of the units in most and least affected groups (note that one must be careful reading too much into the CLAN: it is descriptive not structural!)
- We estimate and develop valid inference for these features using the main sample M

GATES by Quintiles of ML Proxies



CIs are simultaneous across groups

GATES of 20% Most and Least Affected Groups

	Most Affected (G_5)	Least Affected (G_1)	Difference
		Nnet	
GATE $\gamma_k := \hat{\mathrm{E}}[s_0(Z) \mid G_k]$	11.71	-7.94	**19.39**
	(8.314,15.24)	(-12.03,-3.468)	(13.67,25.19)
	[0.000]	[0.000]	[0.000]
Control Mean $:= \hat{\mathrm{E}}[b_0(Z) \mid G_k]$	3.796	12.84	-8.989
	(3.310,4.249)	(12.37,13.29)	(-9.620,-8.317)
	[0.000]	[0.000]	[0.000]
		Elastic Net	
GATE $\gamma_k := \hat{\mathrm{E}}[s_0(Z) \mid G_k]$	9.291	-5.793	**15.08**
	(6.910,11.69)	(-8.399,-2.990)	(11.07,18.99)
	[0.000]	[0.001]	[0.000]
Control Mean $:= \hat{\mathrm{E}}[b_0(Z) \mid G_k]$	-0.474	10.99	-11.330
	(-1.169,0.204)	(10.22,11.72)	(-12.21,-10.45)
	[0.358]	[0.000]	[0.000]

Notes: Medians over 250 splits. 90% confidence interval in parenthesis.

Classification Analysis: Baseline Immunization Variables

	Elastic Net 20% Most (δ_5)	Elastic Net 20% Least (δ_1)	Elastic Net Difference ($\delta_5 - \delta_1$)	Nnet 20% Most (δ_5)	Nnet 20% Least (δ_1)	Nnet Difference ($\delta_5 - \delta_1$)
Num vaccines to pregnant mother	2.187	2.313	-0.125	2.190	2.281	-0.097
	(2.141,2.234)	(2.271,2.356)	(-0.189,-0.059)	(2.151,2.232)	(2.243,2.320)	(-0.154,-0.039)
	-	-	[0.000]	-	-	[0.002]
Num vaccines to kids since birth	4.069	4.636	-0.571	4.277	4.723	-0.451
	(3.921,4.206)	(4.511,4.766)	(-0.761,-0.383)	(4.171,4.384)	(4.610,4.829)	(-0.594,-0.300)
	-	-	[0.000]	-	-	[0.000]
Num of polio drops	2.946	2.994	-0.048	2.960	3.000	-0.039
	(2.933,2.959)	(2.982,3.007)	(-0.066,-0.030)	(2.950,2.969)	(2.989,3.008)	(-0.051,-0.026)
	-	-	[0.000]	-	-	[0.000]
Children with immunization card	0.799	0.924	-0.123	0.897	0.928	-0.031
	(0.769,0.829)	(0.896,0.953)	(-0.165,-0.081)	(0.880,0.913)	(0.908,0.947)	(-0.053,-0.012)
	-	-	[0.000]	-	-	[0.006]
Children with 5 or more vaccines since birth	0.375	0.499	-0.121	0.391	0.519	-0.130
	(0.342,0.410)	(0.468,0.531)	(-0.169,-0.076)	(0.363,0.422)	(0.492,0.547)	(-0.168,-0.087)
	-	-	[0.000]	-	-	[0.000]

- Villages with low levels of pretreatment immunization are most affected by the incentives
- Nothing mechanical in this result. It could have been the opposite.
- Policy recommendation: prioritize these villages under budget constraints

Cost effectiveness

	Elastic Net			Nnet		
	Mean in Treatment ($\hat{\mathrm{E}}[X \mid D = 1, G_k]$)	Mean in Control ($\hat{\mathrm{E}}[X \mid D = 0, G_k]$)	Difference	Mean in Treatment ($\hat{\mathrm{E}}[X \mid D = 1, G_k]$)	Mean in Control ($\hat{\mathrm{E}}[X \mid D = 0, G_k]$)	Dif
Imm. per dollar (G_1)	0.034	0.047	-0.013	0.033	0.047	-0.0
	(0.030,0.037)	(0.045,0.048)	(-0.017,-0.009)	(0.029,0.036)	(0.045,0.049)	(-0
	-	-	[0.000]	-	-	[0.0
Imm.per dollar (G_2)	0.031	0.044	-0.013	0.035	0.044	-0.0
	(0.027,0.036)	(0.042,0.046)	(-0.018,-0.008)	(0.031,0.039)	(0.042,0.046)	(-0
	-	-	[0.000]	-	-	[0.0
Imm.per dollar (G_3)	0.037	0.043	-0.007	0.037	0.043	-0.0
	(0.033,0.041)	(0.041,0.046)	(-0.011,-0.002)	(0.034,0.041)	(0.041,0.045)	(-0
	-	-	[0.015]	-	-	[0.0
Imm. per dollar (G_4)	0.039	0.039	-0.001	0.037	0.041	-0.0
	(0.036,0.042)	(0.036,0.042)	(-0.005,0.004)	(0.034,0.041)	(0.038,0.044)	(-0
	-	-	[1.000]	-	-	[0.1
Imm. per dollar (G_5)	0.036	0.034	0.002	0.036	0.035	0.0
	(0.032,0.040)	(0.030,0.039)	(-0.004,0.007)	(0.033,0.040)	(0.031,0.038)	(-0
	-	-	[1.000]	-	-	[0.8

- Policy is as cost-effective as the status quo (control) for G_4, G_5, i.e. for the demographics for which it has greatest impact.

Discussion

- For the most affected group, increase of about 300% in immunization. Is it plausible?
  - Banerjee et al (2015) find that incentive increase complete immunization rate from 16% to 38%: same order of magnitude
  - Parents in this group report that 38% of Children have received 5 shots or more. Quadrupling would give us a number above 1... But it is almost surely a large overestimate.
- For the least affected group, decrease in immunization. Is it plausible?
  - Incentives are small. Gneezi at al show that small incentive can decrease intrinsic motivation.
  - Trust in immunization is delicate: perhaps people are wondering why the government needs to pay them to do this?
  - An important result that needs to be probed. Highlights the importance to look for heterogeneity when conducting policy experiment.

Concluding thoughts

- Demand for health is fascinating
- Lots of we don't understand, still....
- It makes for a complicated supply response.

References I

- Alatas, V., Purnamasari, R., Wai-Poi, M., Banerjee, A., Olken, B.A. and Hanna, R., 2016. Self-targeting: Evidence from a field experiment in Indonesia. Journal of Political Economy, 124(2), pp.371-427.
- Andrews, I., Kitagawa, T. and McCloskey, A., 2019. Inference on winners (No. w25456). National Bureau of Economic Research.
- Ashraf, N., Berry, J. and Shapiro, J.M., 2010. Can higher prices stimulate product use? Evidence from a field experiment in Zambia. American Economic Review, 100(5), pp.2383-2413.
- Banerjee, A., Chandrasekhar, A.G., Duflo, E. and Jackson, M.O., 2019. Using gossips to spread information: Theory and evidence from two randomized controlled trials. The Review of Economic Studies, 86(6), pp.2453-2490.
- Banerjee, A., Chandrasekhar, A.G., Dalpath, S., Duflo, E., Floretta, J., Jackson, M.O., Kannan, H., Loza, F.N., Sankar, A., Schrimpf, A. and Shrestha, M., 2021. Selecting the Most Effective Nudge: Evidence from a Large-Scale Experiment on Immunization (No. w28726). National Bureau of Economic Research.
- Banerjee, A.V., Duflo, E., Glennerster, R. and Kothari, D., 2010. Improving immunisation coverage in rural India: clustered randomised controlled evaluation of immunisation campaigns with and without incentives. Bmj, 340.
- Banerjee, A., Alsan, M., Breza, E., Chandrasekhar, A.G., Chowdhury, A., Duflo, E., Goldsmith-Pinkham, P. and Olken, B.A., 2020. Messages on COVID-19 prevention in India increased symptoms reporting and adherence to preventive behaviors among 25 million recipients with similar effects on non-recipient members of their communities (No. w27496). National Bureau of Economic Research.
- Breza, E., Chandrasekhar, A.G. and Tahbaz-Salehi, A., 2018. Seeing the forest for the trees? An investigation of network knowledge (No. w24359). National Bureau of Economic Research.
- Carley, K.M. and Krackhardt, D., 1996. Cognitive inconsistencies and non-symmetric friendship. Social networks, 18(1), pp.1-27.
- Cohen, J. and Dupas, P., 2010. Free distribution or cost-sharing? Evidence from a randomized malaria prevention experiment. The Quarterly Journal of Economics, pp.1-45.

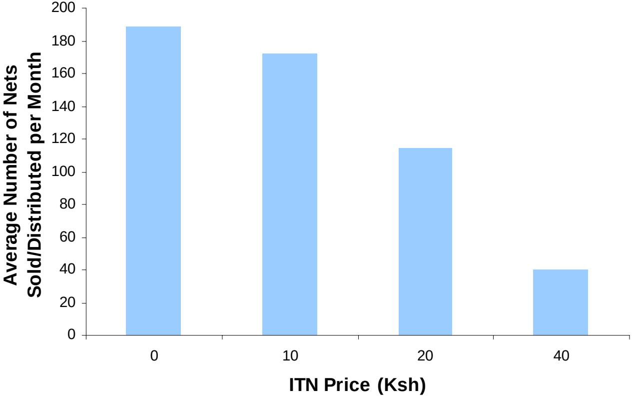
References II

- Das, J. and Sánchez-Páramo, C., 2002. Short but not sweet: new evidence on short duration morbidities from India. Available at SSRN 636333.
- Duflo, E., Dupas, P. and Kremer, M., 2015. Education, HIV, and early fertility: Experimental evidence from Kenya. American Economic Review, 105(9), pp.2757-97.
- Dupas, P., 2011. Do teenagers respond to HIV risk information? Evidence from a field experiment in Kenya. American Economic Journal: Applied Economics, 3(1), pp.1-34.
- Dupas, P., 2014. Short-run subsidies and long-run adoption of new health products: Evidence from a field experiment. Econometrica, 82(1), pp.197-228.
- Dupas, P. and Miguel, E., 2017. Impacts and determinants of health levels in low-income countries. In Handbook of economic field experiments (Vol. 2, pp. 3-93). North-Holland.
- Giné, X., Karlan, D. and Zinman, J., 2010. Put your money where your butt is: a commitment contract for smoking cessation. American Economic Journal: Applied Economics, 2(4), pp.213-35.
- Gneezy, U. and Rustichini, A., 2000. Pay enough or don't pay at all. The Quarterly journal of economics, 115(3), pp.791-810.
- Hussam, R., Rigol, N. and Roth, B., 2017. Targeting high ability entrepreneurs using community information: Mechanism design in the field. Unpublished Manuscript.
- Jia, J. and Rohe, K., 2015. Preconditioning the lasso for sign consistency. Electronic Journal of Statistics, 9(1), pp.1150-1172.
- Karing, A., 2021. Social signaling and childhood immunization: A field experiment in sierra leone.
- Krackhardt, D. and Kilduff, M., 1999. Whether close or far: Social distance effects on perceived balance in friendship networks. Journal of personality and social psychology, 76(5), p.770.
- Kremer, M. and Miguel, E., 2007. The illusion of sustainability. The Quarterly journal of economics, 122(3), pp.1007-1065.
- Lowes, S. and Montero, E., 2021. The legacy of colonial medicine in Central Africa. American Economic Review, 111(4), pp.1284-1314.

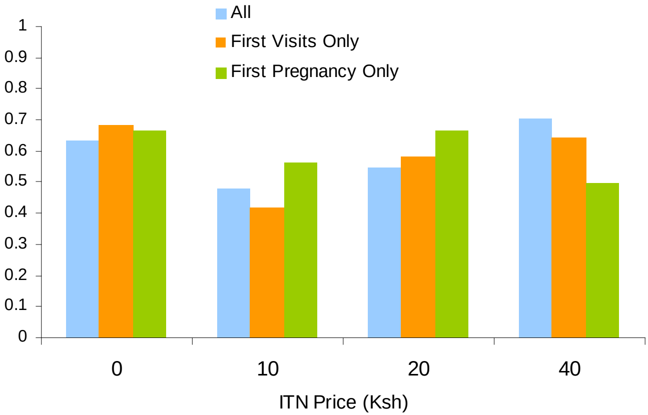
References III

- Martinez-Bravo, M. and Stegmann, A., 2021. In vaccines we trust? The effects of the CIA's vaccine ruse on immunization in Pakistan. Journal of the European Economic Association.
- McKenzie, D. 2019. Be careful with inference from 2-by-2 experiments and ther cross-cutting designs.
- Muralidharan, K., Romero, M. and Wüthrich, K., 2019. Factorial designs, model selection, and (incorrect) inference in randomized experiments (No. w26562). National Bureau of Economic Research.
- Rohe, K., 2014. A note relating ridge regression and ols p-values to preconditioned sparse penalized regression. arXiv preprint arXiv:1411.7405.
- Thornton, R.L., 2008. The demand for, and impact of, learning HIV status. American Economic Review, 98(5), pp.1829-63.

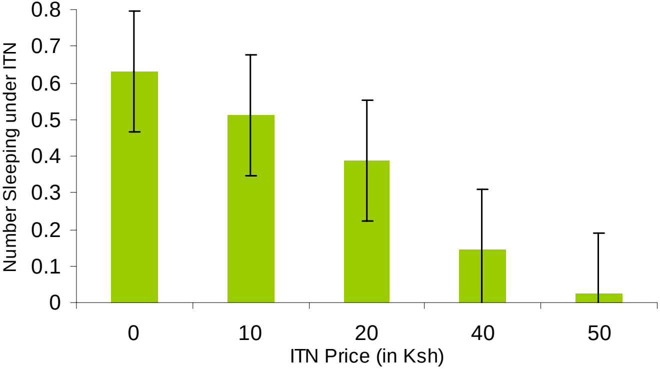
Results: Demand
Monthly Net Sales by ITN Price



Results: Usage Share Observed Using ITN at follow-up



Effective Coverage: Share of Prenatal Clients Sleeping Under ITN, by Price



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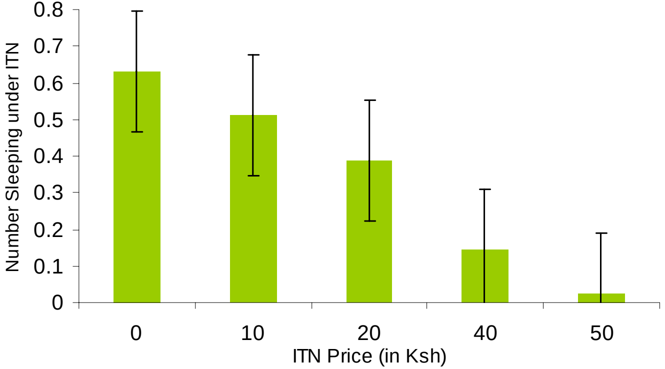
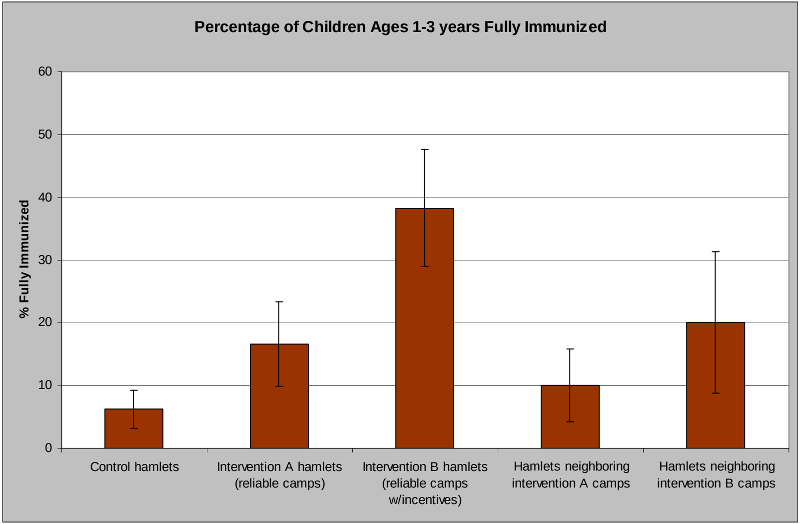


Figure 2: Percentage of children 1-3 years fully immunized by intervention status



Note: Fully immunized is defined as reporting 5 or more immunizations. Weighted means are reported, and the bars reflect the 95% clustered confidence interval.

Figure 3: Number of immunizations received by children 1-3 years

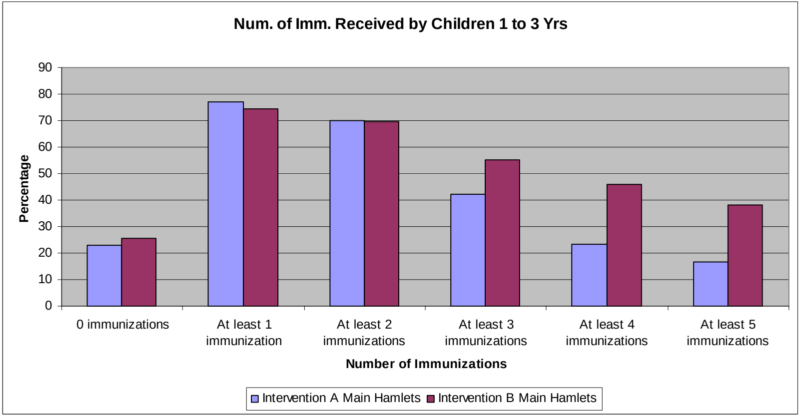


Table 7
Overall Treatment Effect on Incidence of Childbearing by Adult Men

	Comparison Group Base=100	Treatment Group	# Averted	Treatment Effect
# Observed Teen Pregnancies	100	68.6	31.4	-31.4%
Share of Observed Pregnancies by Adult Men	48%	24%		-23.2%
# Observed Pregnancies by Adult Men	47.6	16.7	30.9	-64.8%
# Observed Pregnancies by Young Men	52.4	51.9	0.5	-1.0%
Share of Cross-Generational Pregnancies among Averted Pregnancies			98%	

Notes: Treatment = Relative Risks Information Campaign. First row: treatment effect on number of teen pregnancies reported from Table 5 (-0.17/0.53). Second row: treatment effect on share of pregnancies by adult men reported from Table 6, regression (3).

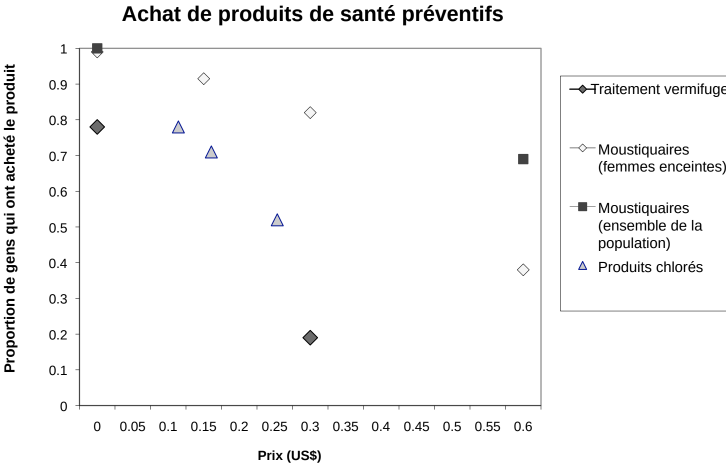

Achat de produits de santé préventifs
Proportion de gens qui ont acheté le produit
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0.5
0.55
0.6
Prix (US$)
Traitement vermifuge
Moustiquaires (femmes enceintes)
Moustiquaires (ensemble de la population)
Produits chlorés

Figure 2

Panel A: Share of study households that purchased the LLIN in Phase 1

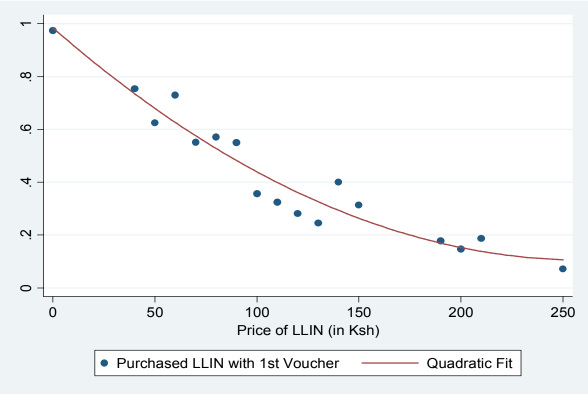
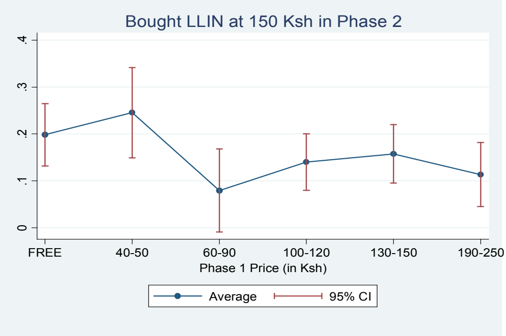
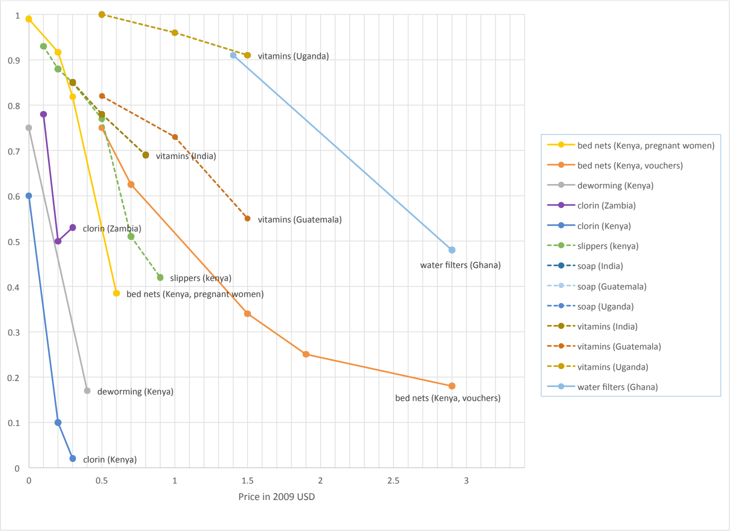


Figure 4

Redemption of 2nd LLIN Voucher (uniformly priced at 150Ksh), by 1st LLIN voucher price gro





1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0
0.5
1
1.5
2
2.5
3
Price in 2009 USD
vitamins (Uganda)
vitamins (India)
vitamins (Guatemala)
clorin (Zambia)
water filters (Ghana)
slippers (kenya)
bed nets (Kenya, pregnant women)
deworming (Kenya)
bed nets (Kenya, vouchers)
clorin (Kenya)
bed nets (Kenya, pregnant women)
bed nets (Kenya, vouchers)
deworming (Kenya)
clorin (Zambia)
clorin (Kenya)
slippers (kenya)
soap (India)
soap (Guatemala)
soap (Uganda)
vitamins (India)
vitamins (Guatemala)
vitamins (Uganda)
water filters (Ghana)

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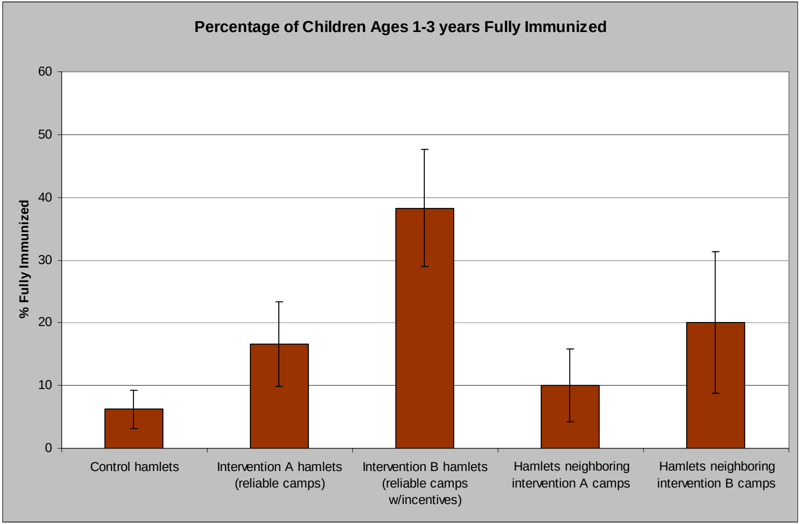

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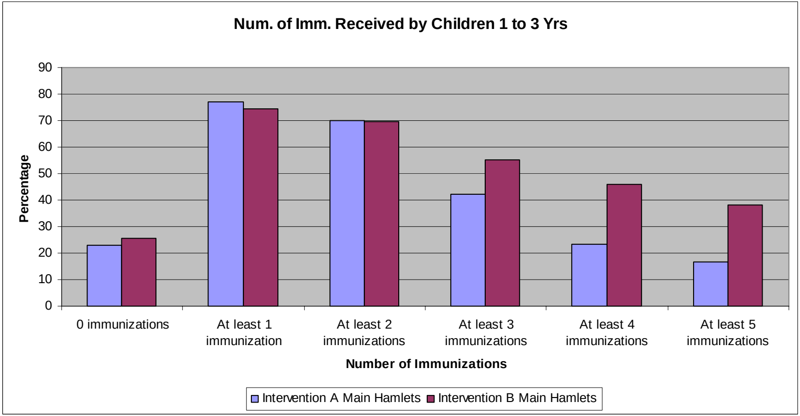

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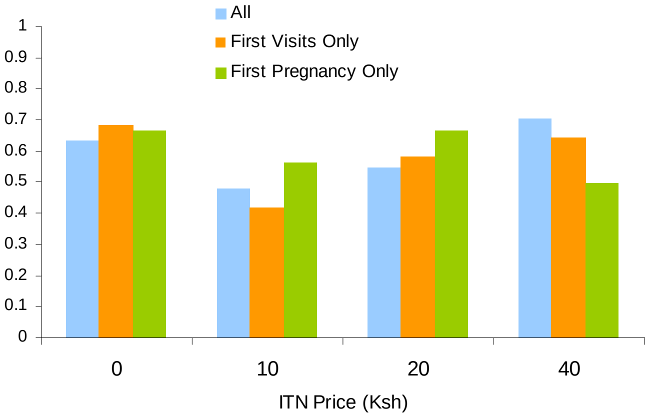

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