Development Economics

Health

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AEA Continuing Education

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Roadmap

1. The Health-Productivity Relationship
2. Demand for Health Care
3. Supply of Health Care

Economic Impact of Disease

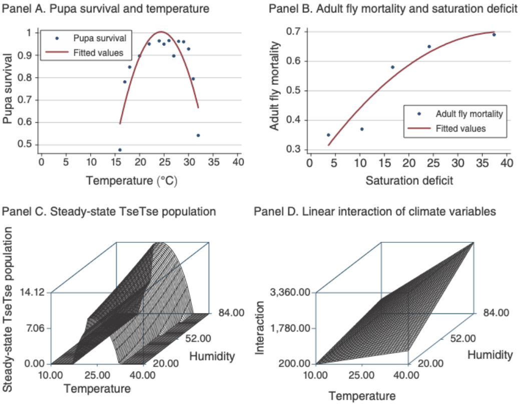
Developing countries often have high burden of disease

- e.g., Malaria, African trypanosomiasis (sleeping sickness), Intestinal worms (helminth)
- Many considered "neglected tropical diseases" by WHO
  - Often difficult to control, vector-borne, animal reservoirs

Alsan (2015) studies the economic impacts of sleeping sickness on pre-colonial and modern-day economic outcomes in Africa

- Transmitted by TseTse fly, only found in Africa
- Livestock particularly vulnerable to disease
- Livestock essential for intensive farming, plough use
- $\implies$ Disease limits economic opportunity

Identification Strategy: TseTse Suitability



- TseTse fly suitability non-monotonic function of environmental conditions (temperature and humidity)
- Creates TseTse Suitability Index (TSI) using 1871 climate data

Pre-Colonial Impacts of TseTse Exposure

	Main effect TSI (β) (1)	Africa interaction TSI (δ) (2)	Africa total TSI ($\beta+\delta$) (3)
Panel A. Agriculture			
Large domesticated animals	0.036	−0.214***	−0.177***
	(0.030)	(0.039)	(0.029)
Intensive agriculture	−0.015	−0.075*	−0.090***
	(0.041)	(0.043)	(0.022)
Plow use	0.069**	−0.070*	−0.0007
	(0.030)	(0.035)	(0.019)
Female participation in agriculture	−0.039	0.247***	0.208***
	(0.065)	(0.088)	(0.063)
Panel B. Institutions			
Indigenous slavery	−0.003	0.105**	0.102***
	(0.042)	(0.049)	(0.020)
Centralization	0.010	−0.116**	−0.106**
	(0.027)	(0.051)	(0.049)

- Column 1: placebo impacts of TSI in tropics *outside* of Africa
- Column 2: differential impacts of TSE in Africa
- Farming suitability positively correlated with TSI
- Result: TSI reduces draft animals, plough use, intensive agriculture, political centralization

Contemporary Effects of TseTse Exposure

	(1)	(2)	(3)	(4)	(5)
Panel A. Dependent variable is the log mean luminosity					
TSI	–0.480**	–0.441*	–0.744***	–0.452*	–0.296
	(0.236)	(0.234)	(0.228)	(0.252)	(0.246)
Historical centralization					1.083***
					(0.247)
Panel B. Dependent variable is the log number of cattle					
TSI	–1.270**	–1.172**	–1.491***	–0.639*	–0.648*
	(0.473)	(0.447)	(0.390)	(0.320)	(0.323)
Historical centralization					–0.060
					(0.319)
Climate controls	Yes	Yes	Yes	Yes	Yes
Malaria index	No	Yes	Yes	Yes	Yes
Other geographic controls	No	No	Yes	Yes	Yes
Country fixed effects	No	No	No	Yes	Yes
Observations	665	665	665	665	665
Number clusters	48	48	48	48	48

- Panel A: Nighttime lights (proxy for economic activity) lower in high TSI areas
- Panel B: High TSI correlated with lower livestock ownership today
- $\Longrightarrow$ Large, persistent impacts of disease on economic outcomes

The Health - Productivity Relationship: Adults

Micro-evidence that improved health ↑ productivity in adults

- Anemia and Deworming in Indonesia (WISE study) (Thomas et al 2006)
  - Reductions in anemia, ↑ labor supply, earnings, psycho-social benefits
  - Why aren't people making this investment themselves?
- Malaria
  - Free bednets in Zambia (Fink and Masiye 2015)
    - 14.7% increase in self-reported farm output
  - Testing and treatment among Nigerian cane cutters (Dillon et al 2014)
    - ITT effect of being sampled for test; 15% higher productivity
- Air pollution in Indian garment factories (Adhvaryu et al 2014)
  - 1sd more PM2.5 decreases productivity by 6%

The Health - Productivity Relationship: Children

Classic study on deworming in Kenyan schools by Miguel and Kremer (2004)

- Intestinal worms pervasive in developing countries (hookworm, whipworm, shistosomiasis, roundworm), especially affect children
  - Kenya sample of primary students: $> 90\%$ had some level of infection, $30\% - 50\%$ had moderate-to-severe infection
- Worm larvae passed in feces $\implies$ externalities for others in community

RCT giving free deworming medicines and education to students

- 75 schools, 30,00 children aged 6-18
- Treatment 1: intervention began in 1998
- Treatment 2: intervention began in 1999
- Treatment 3: intervention began in 2001

Short-run results

JANUARY TO MARCH 1999, HEALTH AND HEALTH BEHAVIOR DIFFERENCES BETWEEN GROUP 1 (1998 TREATMENT) AND GROUP 2 (1998 COMPARISON) SCHOOLS[a]

	Group 1	Group 2	Group 1 – Group 2
Panel A: Helminth Infection Rates			
Any moderate-heavy infection, January–March 1998	0.38	–	–
Any moderate-heavy infection, 1999	0.27	0.52	-0.25^{***}
Panel B: Other Nutritional and Health Outcomes			
Sick in past week (self-reported), 1999	0.41	0.45	-0.04^{**}
			(0.02)

School Participation

	Group 1 (25 schools)	Group 2 (25 schools)	Group 3 (25 schools)	
Panel A:				
First year post-treatment (May 1998 to March 1999)	*1st Year Treatment*	*Comparison*	*Comparison*	*Group 1 – (Groups 2 & 3)*
Girls <13 years, and all boys	0.841	0.731	0.767	0.093^{***}
				(0.031)

- Large decrease in infection, increase in school attendance
- However, no impacts on cognitive ability or test scores (puzzle)

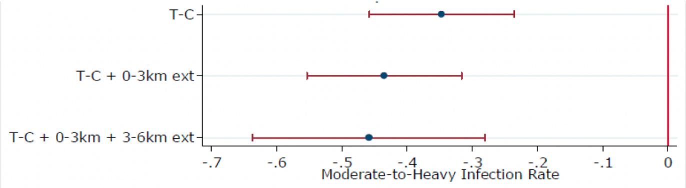
Short-Run Results: Externalities

Recall, treatment at school level

- Stronger externalities if more nearby schools also treated.

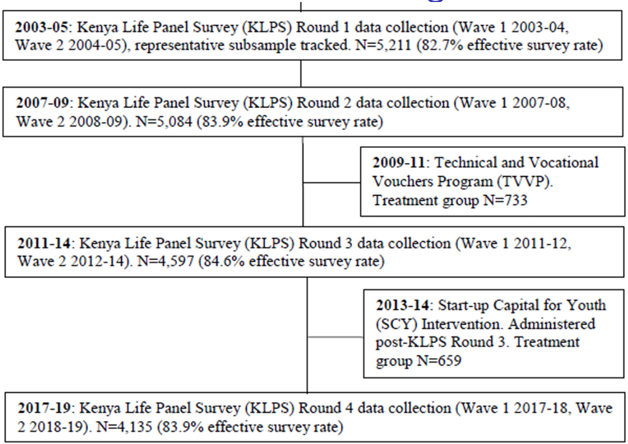
$$Y_{ijt} = a + \beta_1 \cdot T_{1it} + \beta_2 \cdot T_{2it} + X'_{ijt}\delta + \sum_d (\gamma_d \cdot N^T_{dit}) + \sum_d (\phi_d \cdot N_{dit})$$
$$+ u_i + e_{ijt}.$$

- N_{dit} number of nearby students (d - distance radius)
- N^T_{dit} number of treated (Group 1) nearby students
- Total effect: $\beta_T + \gamma_d N^T_{dit}$



- Positive externality on others at 0-3km, effect 10pp larger
- Ozier (2018) finds positive impacts on children 0-2 in treated locations (pure externality). 0.3sd increase in cognitive ability 10 years post-intervention

Longer-run results



- Follow-up data collection allows long-run tracking.
  - Baird et al (2016) QJE: 10-year impacts
  - Hamory et al (2021) PNAS: 20-year impacts
- Recall, Treatment 3 group eventually got treated, LR effect is of 2-3 *additional* years of deworming

20-year impacts: Hamory et al (2021)

	Treatment (λ_1)			Full sample	
	(1)	(2)	(3)	(4)	(5)
	Full sample	Male	Older	Control mean	Number of obs.
A: Earnings and wealth					
Log annual individual earnings	0.09	0.06	0.19**	6.73	7,698
	(0.06)	(0.07)	(0.08)		
Wage earnings (annual)	81	138	162*	887	13,628
	(68)	(110)	(89)		
Self-employment profit (annual)	41*	51	70*	212	13,638
	(24)	(48)	(39)		
Individiual farming profit (annual)	−0	1	−3	9	13,707
	(2)	(3)	(3)		
Nonzero earnings	0.02*	0.04**	0.02	0.59	13,794
	(0.01)	(0.02)	(0.02)		
Hourly earnings	0.14*	0.22	0.32*	1.07	6,096
	(0.08)	(0.15)	(0.16)		
Per capita household wealth (KLPS-4)	69	102	253***	522	4,085
	(50)	(97)	(89)		

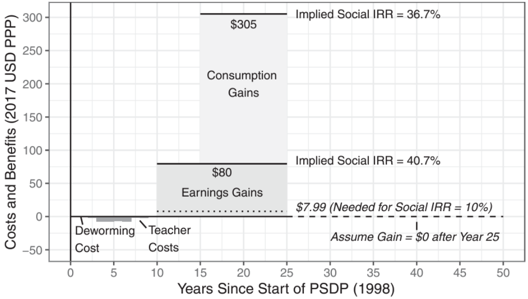
- Baird et al (2016): women better health, women more secondary education, men more primary education
- 20-year impacts: large increase in earnings, especially for older students at treatment
- Greater likelihood of working, self-employment earnings

20-year impacts: Hamory et al (2021)

	Treatment (λ_1)			Full sample	
	(1) Full sample	(2) Male	(3) Older	(4) Control mean	(5) Number of obs.
B: Labor supply, occupation, and sectoral choice					
Urban residence	0.04**	0.06**	0.03	0.45	13,793
	(0.02)	(0.03)	(0.03)		
Total hours worked (last 7 d)	1.04	2.20**	1.79**	24.19	13,807
	(0.66)	(0.92)	(0.91)		
Hours worked—agriculture (last 7 d)	−0.87**	−0.57	−0.46	3.99	13,807
	(0.43)	(0.62)	(0.56)		
Hours worked—nonagriculture (last 7 d)	1.91***	2.77***	2.24**	20.20	13,807
	(0.65)	(0.94)	(1.08)		
Employed—agriculture/fishing	-0.003	−0.001	0.004	0.043	13,768
	(0.008)	(0.013)	(0.012)		
Employed—services/wholesale/retail	0.002	0.012	−0.002	0.230	13,761
	(0.014)	(0.020)	(0.019)		
Employed—construction/trade contractor	0.004	0.011	−0.007	0.033	13,760
	(0.007)	(0.014)	(0.009)		
Employed—manufacturing	−0.001	0.002	0.002	0.026	13,760
	(0.004)	(0.007)	(0.006)		

- Treated individuals more likely to live in urban area, have moved out of agriculture
- Annual consumption \$305 higher (p-value < 0.1), unreported

20-year impacts: Hamory et al (2021)



- Extremely cost-effective intervention, long run gains in consumption and earnings lead to high Social IRR
  - Costs of program implementation + costs of extra teachers
- Externalities make this an underestimate of benefit to cost:
  - e.g., Ozier (2018) effect on 0-2 year olds

Roadmap

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Health Care Demand

Health expenditures

- The poor do spend substantial resources on health expenditures, especially for treatment
- However, low adoption for some health investments, particularly preventive care
    - e.g., Vaccines, insecticide-treated bed nets
    - 20% cost sharing lowered deworming take-up from 75% to 18% (Kremer and Miguel 2007)
- Often low trust in health institutions
    - e.g., forced sterilization campaigns in 1970's India

Colonial Medicine and Modern-Day Health Take-Up

Lowes and Montero "The Legacy of Colonial Medicine in Central Africa" AER (2021)

- Study French colonial campaign to eradicate sleeping sickness 1921-1956
- Gave medical exams to millions of villagers, "forced to receive injections of medications with dubious efficacy and with serious side effects including blindness, gangrene and death"
- Research question: what is the legacy of those brutal treatments on modern-day demand for health care?
- Empirical strategy:
  - Digitize colonial records to measure campaign intensity
  - Modern-day outcomes (DHS): vaccinations, consent to blood test for anemia/HIV

Colonial Medicine and Modern-Day Health Take-Up

FIGURE 1. MAP OF CAMEROON AND FORMER FRENCH EQUATORIAL AFRICA

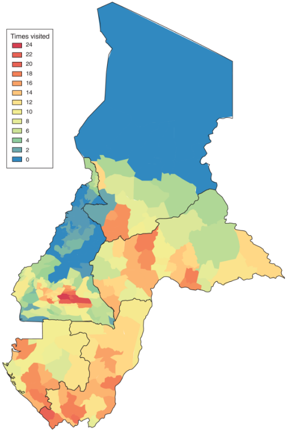
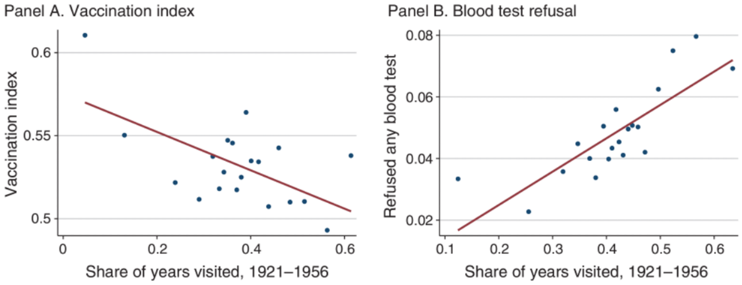


FIGURE 2. SLEEPING SICKNESS VISITS BETWEEN 1921–1956

Source: Lowes and Montero (2021)

Colonial Medicine and Modern-Day Health Take-Up



Source: Lowes and Montero (2021)

- Less trust in vaccines / bloodtests in places with more campaign exposure
- Results robust to IV strategy – correlation between cassava production and sleeping sickness (vs. millet) recognized by colonial regime

Other Impediments to Demand

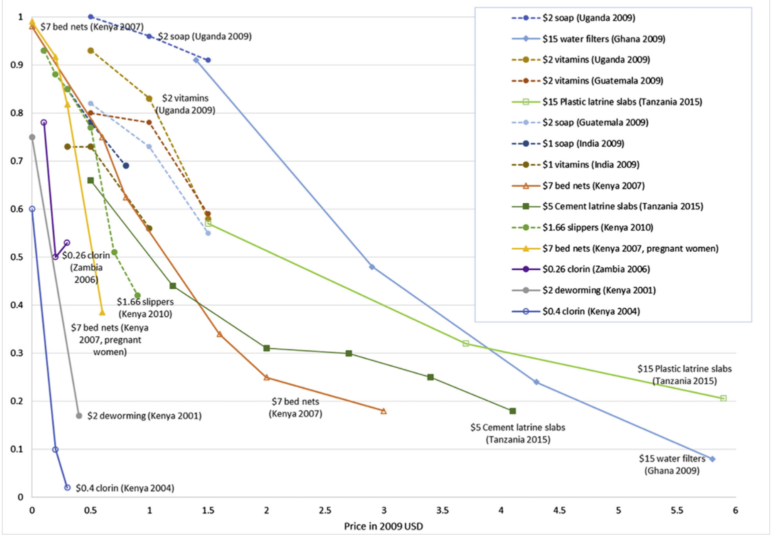
Hard to Learn about Health

- Preventative investments useful at undetermined time in future, may never need
  - Hard to know if lack of disease from vaccine or luck
- Many diseases self-limiting, best treatment is no treatment
  - Stories of over-treatment to cater to patients: e.g., glucose drip, antibiotics

Externalities (Miguel and Kremer 2004)

- Complements with peer adoption: e.g., learn about benefits from network, norms over use
- Substitutes with peer adoption: e.g., peer adoption improves local disease environment

Willingness to Pay for Preventative Health



Take-up declines steeply with price. Suggests need for steep subsidies to stimulate demand

Source: Dupas and Miguel (2017)

Willingness to Pay for Treatment

	Took ACT (1)
Panel A. Pooled impact	
Any ACT subsidy	0.187***
	(0.038)
Panel B. Impact by subsidy level	
B1. ACT subsidy = 92 percent	0.225***
	(0.053)
B2. ACT subsidy = 88 percent	0.161***
	(0.050)
B3. ACT subsidy = 80 percent	0.178***
	(0.048)
p-value: B1 = B2 = B3 = 0	0.000***
p-value: B1 = B2 = B3	0.531
DV mean (control group)	0.190

Source: Cohen, Dupas and Schaner (2015)

- RCT in Kenya, malaria treatment
- ACTs (artemisinin combination therapies) best available treatment
- Randomize subsidies for ACTs
- In contrast with preventative products, take-up does not decrease as quickly with price
- Also show that increasing price improves targeting (unreported)
  - (users more likely to actually have malaria)

Non-Price Interventions and Take-up of Preventative Care

Childhood vaccines typically free, provided by public health sector; cost effective, tested way to prevent disease

- However, low completion rates
- Unicef and WHO (2019): 20 million children fail to receive standard immunizations annually

Banerjee et al (2023) try numerous policy ideas in Haryana, India for increasing completion of childhood vaccines:

- 915 villages, 3 types of interventions
  - Simple SMS reminders
  - Incentives (high vs. low, steeply increasing vs. flat)
  - Use of community members as information "seeds" (Information hubs - network targeting, random, trusted)
- Try 75 total policy combinations (crossed design)
- Also design new method *treatment variant aggregation* (TVA) to select best intervention out of large set

Vaccine Takeup

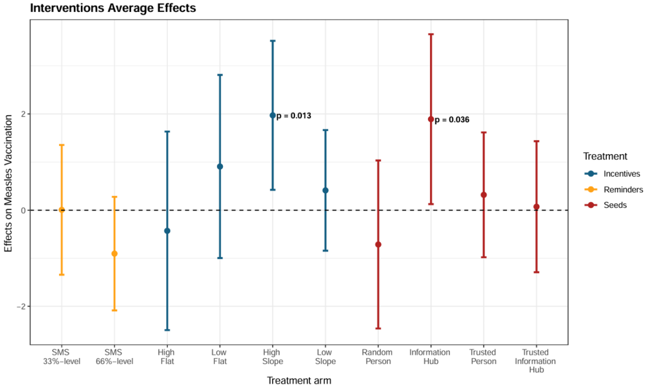


FIGURE 6. Effects on the number of measles vaccinations relative to control (7.32) by reminders, incentives, and seeding policies, restricted to the vil-

Source: Banerjee et al 2022

- Most effective policy: incentives, ambassadors who are information hubs, and reminders
- Most cost-effective policy: information hubs, ambassadors, and SMS reminders but no incentives

Social Signaling and Vaccine Takeup

Anne Karing (2023) studies whether social signaling can be used to increase vaccination

- Context: Sierra Leone, 58% completion rate of 1st year vaccines
- 92% think community would view mother who took children to get vaccinated positively

RCT gives some HHs a way to signal vaccine compliance publicly to others

- Control: No bracelet
- Uninformative bracelet: yellow or green "1st visit" bracelet to all
- Signal at 4: exchange bracelet for "4th visit" at V4
- Signal at 5: exchange bracelet for "5th visit" at V5

Figure A1: Different Bracelets handed out across Three Signaling Treatme

Social Signaling and Vaccine Take-up

- Karing shows that mothers correctly infer that green bracelet in S4 and S5 treatments indicates higher vaccine probability
- Does this, in turn, lead to change in actual vaccinations?

Dependent variable:	**1 Vaccine** (1)	**2 Vaccines** (2)	**3 Vaccines** (3)	**4 Vaccines** (4)	**5 Vaccines** (5)	**Total # of vaccines** (6)
Panel B:	Effects of Signals on Vaccination by Age One Year					
Signal at 4	0.002	0.009**	0.013	0.019	0.033	0.075
	(0.003)	(0.004)	(0.009)	(0.017)	(0.033)	(0.057)
Signal at 5	0.002	0.009**	0.019**	0.035**	0.094***	0.159***
	(0.003)	(0.004)	(0.008)	(0.016)	(0.033)	(0.057)
Uninformative Bracelet	0.003	0.010***	0.011	0.008	0.029	0.061
	(0.003)	(0.004)	(0.008)	(0.017)	(0.035)	(0.059)
Distance	0.000	-0.000	-0.002**	-0.008***	-0.015***	-0.025***
	(0.000)	(0.001)	(0.001)	(0.002)	(0.004)	(0.006)
Control Group mean	0.993	0.984	0.959	0.917	0.687	4.541
Observations	4897	4897	4897	4897	4897	4897
$S_4 > 0$: p(UI = S4)	0.499	0.804	0.807	0.445	0.890	0.754
$S_5 > 0$: p(UI = S5)	0.547	0.950	0.225	0.075	0.031	0.039
p(S4 = S5)	0.971	0.863	0.328	0.172	0.017	0.033
Joint F-Test	0.575	0.055	0.132	0.132	0.016	0.019
Controls	Yes	Yes	Yes	Yes	Yes	Yes

- Signal at 5 increases total vaccines by 1 by 0.16 (mean 4.5)
- Biggest difference going from 4 to 5

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Health Care Supply

Stylized facts

- Low-quality health products common in market
- Low quality health service delivery by govt'
  - High absenteeism, low effort
- Low quality health service delivery by private sector
  - High fraction of providers with no formal training
  - Heterogeneity in knowledge of providers

Low-quality supply possible ingredient in low demand

Fake Drugs Prevalent

	Drug stores selling fake drugs
	(1)
All districts	36.8%
	($N = 57$)
By district	
Bushenyi	40.0%
Mbale	33.3%
Mbarara	53.3%
Mpigi	26.1%
By local competition	
Monopoly	30.8%
Competition	38.6%

Source: Bjorkman Nyqvist et al 2021

- Context: Uganda, market for antimalarial ACTs
- Authors sent covert shoppers to drug stores, tested quality in lab
- Finding: 37% of tested drugs fake or low-quality
- 28% of Households believe nearest drug store sells fake drugs

Low Quality Providers Prevalent

Madhya Pradesh, India

	Madhya Pradesh (5 districts, 100 markets)			SP sample villages (3 districts, 46 markets)		
	All (1)	Inside village (2)	Outside village (3)	All (4)	Inside village (5)	Outside village (6)
Panel A. Composition of markets based on census of providers						
Total	11.68	3.97	7.71	16.02	4.65	11.37
	(12.06)	(4.49)	(12.17)	(15.81)	(5.41)	(16.42)
Public MBBS	0.45	0.05	0.40	0.50	0.02	0.48
	(0.97)	(0.22)	(0.93)	(1.11)	(0.15)	(1.11)
Public alternative qualification	0.22	0.07	0.15	0.24	0.07	0.17
	(0.48)	(0.29)	(0.39)	(0.52)	(0.33)	(0.44)
Public paramedical	1.58	1.13	0.45	1.98	1.30	0.67
	(1.90)	(1.46)	(1.33)	(2.12)	(1.49)	(1.59)
Public unqualified	1.71	0.68	1.03	2.07	0.67	1.39
	(1.75)	(1.04)	(1.54)	(2.05)	(1.12)	(1.94)
Total public	3.96	1.93	2.03	4.78	2.07	2.72
	(3.20)	(2.28)	(2.63)	(3.53)	(2.45)	(3.17)
Private MBBS	0.40	0.00	0.40	0.59	0.00	0.59
	(1.57)	(0.00)	(1.57)	(2.15)	(0.00)	(2.15)
Private alternative qualification	1.92	0.23	1.69	2.67	0.33	2.35
	(3.65)	(0.66)	(3.65)	(4.86)	(0.90)	(4.89)
Private unqualified	5.40	1.81	3.59	7.98	2.26	5.72
	(6.01)	(2.23)	(6.14)	(7.88)	(2.74)	(8.32)
Total private	7.72	2.04	5.68	11.24	2.59	8.65
	(10.54)	(2.69)	(10.81)	(14.31)	(3.38)	(14.87)

- Large private market, Poor qualifications (MBBS = MD)

Source: Das et al (2016) AER

Low Quality Providers Prevalent

Survey methodology to measure quality of provider-patient interactions

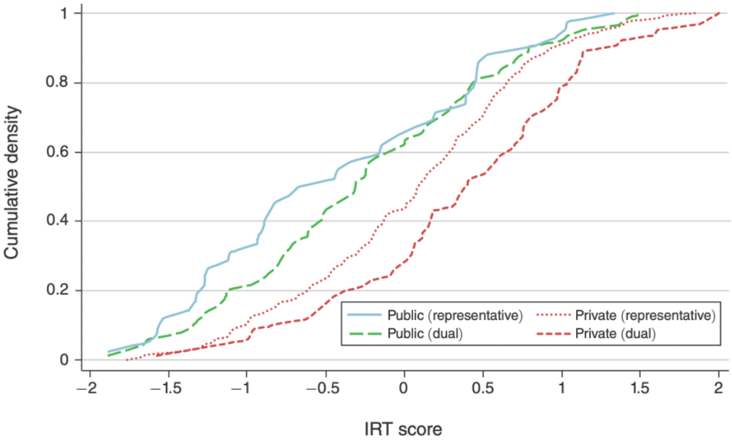
- Standardized Patients (SPs)
- Trained community members visit providers, present with set of symptoms
- SP records information about interaction
  - Time spent, questions asked, tests offered, treatment offered

Das et al (2016) explore three types of cases among public and private practitioners

- (1) unstable angina in 45 year old male;
- (2) asthma in 25 year old female/male;
- (3) dysentery in a child (at home), presented by father

Quality of care

Index of checklist items



- Quality of care substantially better from private providers
- Even true *within* provider

Source: Das et al (2016)

Treatment Patterns

Banerjee et al (2023) explore patterns of treatment in India with SP methodology

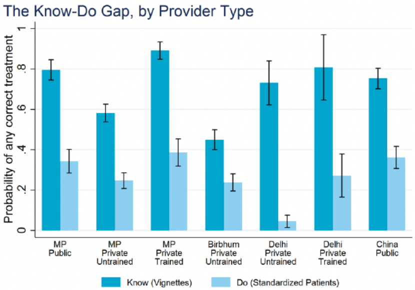
	(1) Any correct treatment	(2) Correct treatment	(3) Over-treatment	(4) Incorrect treatment	(5) Gave an antibiotic (excl. diarrhea)	(6) Gave a steroid (excl. asthma)	(7) Referred to another provider	(8) Number of cases
MP	0.302	0.048	0.255	0.698	0.350	0.032	0.180	939
Birbhum	0.237	0.015	0.222	0.763	0.331	0.015	0.321	396
Delhi	0.108	0.008	0.100	0.892	0.540	0.092	0.104	250
Mumbai	0.292	0.033	0.258	0.708	0.566	0.198	0.086	1,583
Patna	0.310	0.051	0.259	0.690	0.679	0.096	0.057	1,019
China	0.361	0.237	0.124	0.639	0.512	0.000	0.191	299
Kenya	0.524	0.211	0.313	0.476	0.548	0.016	0.164	166

- Substantial avoidable costs from incorrect treatment

The Know-Do Gap

Banerjee et al (2023) further show a large “Know-Do Gap” among practitioners

- Know: responses to vignettes about hypothetical patients
- Do: actions with standardized patients



- Incorrect treatment can’t all be explained by lack of practitioner knoweledge

Impacts of Training: Patient Trust

Banerjee et al (2023) randomize practitioners into training program

- No impacts on practitioner knowledge
- Highly publicized, so credible signal of practitioner ability

	(1) Checklist in SPs	(2) Any correct treatment	(3) Time spent (mins)	(4) Fees charged (USD)
	ITT Estimates			
Treatment group	0.040***	0.073*	0.239*	0.067
	(0.011)	(0.038)	(0.140)	(0.078)
Training attendance				
R2	0.089	0.053	0.119	0.035
Number of observations	790	790	790	790
Mean of dependent variable: Control	0.273	0.520	3.252	0.689
Mean of dependent variable: Treatment	0.313	0.594	3.495	0.757

- Increase in correct treatment, higher quality care (also increased revenues for practitioner)

Fake Drugs: How to Drive them Out?

Recall Bjorkman Nyqvist et al (2021) study on fake drugs

Unit of analysis	Village	
	Number of drug stores selling fake drugs in the village	
Dependent variable:	(1)	(2)
NGO entry	−0.263**	−0.194*
	(0.118)	(0.105)
Observations	99	99
R-squared	0.229	0.378
District FE	Yes	Yes
Controls	No	Yes
Dep. Var. mean in control	0.420	0.420

	Dependent variable: household believes nearest drug store sells fake drugs			
	(1)	(2)	(3)	(4)
NGO entry	−0.065**	−0.082**	0.019	0.023
	(0.028)	(0.037)	(0.031)	(0.029)
NGO entry ∗ post-survey			−0.112**	−0.119**
			(0.051)	(0.050)
Observations	674	674	2397	2397

Randomized intervention:

- Entry by trusted NGO
- Sells authentic ACTs at lower prices (+ other health services)

Question:

- What happens to fake drugs in local shops?

Results:

- NGO presence reduces fakes by 50%
- Prices fall (unreported)
- HHs beliefs improve (ctrl mean 30% fake), use more ACTs (unreported)

Health: Take-aways

- Strong direct link from health to economic outcomes
- However, demand often low for preventative goods
- More work needed to decompose origins of low demand
  - Why don't individuals take profitable health investments?
  - Place where cash transfers unlikely to change health investments at the margin
  - How to make benefits more salient?
- Monetary and non-monetary incentives can improve vaccine take-up
- Open question: how can health systems combat legacy of mistrust?