GR 6307
Public Economics and Development

3. The Personnel Economics of the Developing State: Delivering Services to the Poor

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Spring 2018

Outline

Outline

Theory

- Aghion & Tirole (JPE 1997) *Formal and Real Authority in Organizations*
- Banerjee, Hanna & Mullainathan (2012) *Corruption*
- Benabou & Tirole (AER 2006) *Incentives and Prosocial Behavior*
- Besley & Ghatak (AER 2005) *Competition and Incentives with Prosocial Agents*

Aghion & Tirole (1997): Model Setup

- Principal-agent framework: Agent is choosing among $n \geq 3$ a priori identical projects.
- Project k has profit B_k for the principal and private benefit b_k for the agent.
- They can also do nothing: $B_0 = b_0 = 0$
- Congruence:
  - Choosing the principal's preferred project gives her B and the agent βb.
  - Choosing the agent's preferred project gives him b and the principal αB.
  - $0 < \alpha, \beta \leq 1$ are exogenous parameters

Aghion & Tirole (1997): Model Setup

- Principal is risk neutral. Utility is

$$B_k - w$$

  w is wage paid to the agent
- Agent is risk averse and has limited liability: $w \geq 0$. Utility is

$$u(w) + b_k$$

  Agent is so risk averse that w can't depend on outcomes
- Initially, nobody knows projects' payoffs. Gathering information is costly.
- If agent pays cost $g_A(e)$ he learns the payoffs of all projects with probability e. With probability $1 - e$ he learns nothing.
- Principal can pay cost $g_P(E)$ to learn payoffs with probability E. With probability $1 - E$ she learns nothing.

Aghion & Tirole (1997): Authority

1. *P-formal authority:* The principal has formal authority. She may overrule the agent's recommendation.
2. *A-formal authority:* The agent picks his preferred project and cannot be overruled by the principal.

- Contracts specify an allocation of formal authority to either the principal or the agent.
- *Real authority:* Who actually gets to make the decision? Either because agent has formal authority or because P is just "rubber-stamping" agent's recommendation
- Timing:
  1. Prinicpal proposes a contract
  2. Parties gather information
  3. The party without formal authority communicates a subset of the projects' payoffs (s)he has learned
  4. The controlling party picks a project

Aghion & Tirole (1997): Utilities

- Under *P*-formal authority, the utilities are:

$$u_P = \underbrace{EB}_{\text{P picks her preferred project}} + \underbrace{(1-E)\,e\alpha B}_{\text{A suggests his preferred project}} - g_P(E)$$

$$u_A = \underbrace{E\beta b}_{\text{P picks her preferred project}} + \underbrace{(1-E)\,eb}_{\text{A suggests his preferred project}} - g_A(e)$$

- Under *A*-formal authority, the utilities are:

$$u_P^d = \underbrace{e\alpha B}_{\text{A picks his preferred project}} + \underbrace{(1-e)\,EB}_{\text{P suggests her preferred project}} - g_P(E)$$

$$u_A^d = \underbrace{eb}_{\text{A picks his preferred project}} + \underbrace{(1-e)\,E\beta b}_{\text{P suggests her preferred project}} - g_A(e)$$

Aghion & Tirole (1997): Basic Tradeoff

- In this model there is a basic tradeoff between loss of control and initiative.
- The reason is that efforts are *strategic substitutes:* The more effort the principal makes, the less the agent wants to (&vv).
- To see this, the FOCs for effort when the principal has formal authority are

$$(1 - \alpha e)\, B = g_P'(E)$$
$$(1 - E)\, b = g_A'(e)$$

- Both of these reaction curves slope *down*.
- Imagine the principal's effort became more costly: $g_P' \uparrow$
  - Probability of learning the best project goes down. The principal loses real authority (control)
  - The reduction in E will encourage initiative by the agent:, $e \uparrow$. The principal gains

Aghion & Tirole (1997): Delegation

- If the principal cedes formal authority to the agent the effort FOCs become

$$(1-e)\,B = g_P'\,(E)$$
$$(1-\beta E)\,b = g_A'\,(e)$$

- These yield an equilibrium $\left(E^d, e^d\right)$ where
  - $e < e^d$: Greater initiative by the agent
  - $E > E^d$: Loss of formal *and* real authority to the agent.
  - Less effort required from principal
  - Agent is better off $\rightarrow$ slackens participation constraint so could lower wage

Aghion & Tirole (1997): Span of Control

- Consider a principal with multiple agents where the principal doesn't want to delegate.
- How many agents to hire? How to encourage effort among many agents?
- m identical agents. Each one solving the problem above.
- Principal's disutility is $g_P\left(\sum_i E_i\right)$, agents' tasks are independent. Fixed cost f per agent.

$$u_P = \sum_i \left[E_i B + (1 - E_i)\, e_i \alpha B - f\right] - g_P\left(\sum_i E_i\right)$$

Aghion & Tirole (1997): Span of Control

- Assume a symmetric equilibrium, each agent gets the same effort E from the principal. FOCs are

$$(1-\alpha e)\,B = g'_P\,(mE)$$
$$(1-E)\,b = g'_A\,(e)$$

  with solution $\{E\,(m)\,, e\,(m)\}$.

- Principal's utility from m agents is

$$u_P\,(m) \equiv mR\,(E\,(m)\,, e\,(m)) - g_P\,(mE\,(m))$$

  where $R\,(E\,(m)\,, e\,(m)) \equiv E\,(m)\,B + [1-E\,(m)]\,e\,(m)\,\alpha B - f$ is revenue per agent.

Aghion & Tirole (1997): Span of Control

- The optimal team size m then satisfies

$$\frac{du_P}{dm} = \underbrace{\underbrace{R\left(E\left(m\right), e\left(m\right)\right)}_{\text{extra revenue}} - \underbrace{E\left(m\right) g_P'\left(mE\left(m\right)\right)}_{\text{overload cost}}}_{\text{Marginal profit}<0}$$

$$+ \quad \underbrace{m\frac{\partial R}{\partial e}\frac{\partial e}{\partial m}}_{\text{initiative effect }>0} \quad = 0$$

- Principal commits to overhiring, being overloaded and underinvesting in E in order to encourage initiative e

Aghion & Tirole (1997): Wages and Effort

- Now reintroduce wage effects in the model where the principal has formal authority.
- How do changes in wages affect real authority?
- Suppose that two of the projects are relevant and give the principal profits of B and 0. This implies $\alpha = \beta =$probability they have the same preferred project.
- The agent gets a wage $w \geq 0$ when the principal's profit is B
- Principal's net gain is now $B - w$
- If the agent has information and real authority, his average net payoff is

$$\tilde{b} = \begin{cases} \underbrace{b}_{\text{choose preferred proj}} + \underbrace{\alpha u(w)}_{\text{w/pr } \alpha \text{, congruence}} & \text{if } u(w) < b \\ \underbrace{u(w)}_{\text{choose principal's preferred proj}} + \underbrace{\alpha b}_{\text{w/pr } \alpha \text{, congruence}} & \text{if } u(w) \geq b \end{cases}$$

Aghion & Tirole (1997): Wages and Effort

- Now the FOCs are

$$(1 - \alpha e)\tilde{B} = g'_P(E)$$
$$(1 - E)\tilde{b} = g'_A(e)$$

- Denote solution to this as $\{E(w), e(w)\}$. Then by backward induction solve for w

$$\frac{du_P}{dw} = \underbrace{(1 - E)\alpha(B - w)\frac{de}{dw}}_{\text{additional effort}} - \underbrace{[E + (1 - E)e\alpha]}_{\text{higher wage bill}}$$

- Higher wages increase real authority:
  1. Stronger incentives $\rightarrow$ agent more likely to make a recommendation
  2. Principal monitors less $\rightarrow$ less likely to overrule the agent

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Banerjee *et al.* 2012: Setup

- The government is allocating “slots” through a bureaucrat
- Continuum of slots of size 1 to be allocated to population of size $N > 1$
- 2 types of agents, H and L with masses N_H, N_L.
- Social value of a slot for type H if H, L for type L, $H > L$
- private benefits are l, and h, and ability to pay is $y_h \leq h$ and $y_l \leq l$ due to credit constraints.

Banerjee *et al.* 2012: Setup

- Testing technology. Test for an amount of time t
- probability type L fails (outcome F) is $\phi_L(t)$, $\phi'_L(t) \geq 0$
- Type H never fails (always get outcome S) if she wants to pass.
- Both can opt to deliberately fail
- Cost of testing is νt to the bureaucrat and δt to the applicant

Banerjee *et al.* 2012: Possible Mechanisms

- Bureaucrats announce direct mechanisms that they commit to ex ante.
- A mechanism is a vector $R = (t_x, p_{xr}, \pi_{xr})$
  - t_x amount of testing of each announced type $x = H, L$
  - π_{xr} is the probability of getting a slot if announce type x and get result $r = F, S$
  - p_{xr} is the price paid by xr
- Restrict to winner-pay mechanisms
- 2 incentive compatibility constraints:
  1. High types prefer not to mimic low types:

$$\pi_{HS}\left(h - p_{HS}\right) - \delta t_H \geq \pi_{LS}\left(h - p_{LS}\right) - \delta t_L$$

  2. Low types don't mimic high types:

$$\begin{aligned}&\pi_{LS}\left(l - p_{LS}\right)\left[1 - \phi_L\left(t_L\right)\right] + \pi_{LF}\left(l - p_{LF}\right)\phi_L\left(t_L\right) - \delta t_L \\ \geq &\pi_{HS}\left(l - p_{HS}\right)\left[1 - \phi_L\left(t_H\right)\right] + \pi_{HF}\left(l - p_{HF}\right)\phi_L\left(t_H\right) - \delta t_H\end{aligned}$$

Banerjee *et al.* 2012: Possible Mechanisms

- Clients can also walk away $\rightarrow$ 2 participation constraints:
  1. High types don't walk away

$$\pi_{HS}\left(h - p_{HS}\right) - \delta t_H \geq 0$$

  2. Low types don't walk away

$$\pi_{LS}\left(l - p_{LS}\right)\left[1 - \phi_L\left(t_L\right)\right] + \pi_{LF}\left(l - p_{LF}\right)\phi_L\left(t_L\right) - \delta t_L \geq 0$$

- There is only a mass 1 of slots so

$$N_H\pi_{HS} + N_L\pi_{LS}\left[1 - \phi_L\left(t_L\right)\right] + N_L\pi_{LF}\phi_L\left(t_L\right) \leq 1$$

- Finally the clients can't borrow, so they can't pay more than they have

$$p_{Hr} \leq y_H,\ r = F, S$$
$$p_{Lr} \leq y_L,\ r = F, S$$

- Define $\mathbf{R}$ as the set of rules R that satisfy these constraints

Banerjee et al. 2012: Rules

- The government sets rules $\mathcal{R} = (T_x, P_{xr,}\Pi_{xr})$
  - T_x are permitted tests t_x
  - P_{xr} are permitted prices for each type
  - Π_{xr} are permitted assignment probabilities π_{xr}
- Assume that $\mathcal{R}$ is feasible: There's at least one $R \in \mathbf{R}$ satisfying the rules.
- If $\mathcal{R}$ is not a singleton, then the bureaucrat has *discretion*.
- Government also chooses p a price the bureaucrat has to pay the government for each slot he gives out.

Banerjee et al. 2012: Bureaucrats

- For each mechanism $R \in \mathbf{R} \cap \mathcal{R}$ that follow the rules, the bureaucrat's payoff is

$$\underbrace{N_H \pi_{HS} (p_{HS} - p)}_{\text{profits from } H \text{ types}} + \underbrace{N_L \pi_{LS} (p_{LS} - p) (1 - \phi_L (t_L))}_{\text{profits from } L \text{ types who pass}}$$
$$+ \underbrace{N_L \pi_{LF} (p_{LF} - p) \phi_L (t_L)}_{\text{profits from } L \text{ types who fail}} - \underbrace{\nu N_H t_H - \nu N_L t_L}_{\text{costs of testing}}$$

- If the bureaucrat uses a mechanism $R \in \mathbf{R} \cap \mathcal{R}^c$ that's against the rules, there's an extra cost γ of breaking the rules.
- Assume γ comes from a distribution $G(\gamma)$. As a result, $R(\mathcal{R}, \gamma)$ will be the mechanism chosen by a bureaucrat with corruption cost γ when the rule is $\mathcal{R}$

Banerjee et al. 2012: The Government

- Assume the government only cares about social value of slots (Could generalize. How?)
- Government's objective is to choose the rules $\mathcal{R}$ to maximize

$$
\begin{aligned}
&\underbrace{\int N_H \pi_{HS}\left(R\left(\mathcal{R},\gamma\right)\right) H dG\left(\gamma\right)}_{\text{(expected) social value of slots to } H} \\
&+ \underbrace{\int N_L \pi_{LS}\left(R\left(\mathcal{R},\gamma\right)\right)\left[1-\phi_L\left(t_L\left(R\left(\mathcal{R},\gamma\right)\right)\right)\right] L dG\left(\gamma\right)}_{\text{social value of slots to } L \text{ who pass test}} \\
&+ \underbrace{\int N_L \pi_{LF}\left(R\left(\mathcal{R},\gamma\right)\right)\phi_L\left(t_L\left(R\left(\mathcal{R},\gamma\right)\right)\right) L dG\left(\gamma\right)}_{\text{social value of slots to } L \text{ who fail test}} \\
&- \underbrace{\int \left(\nu+\delta\right) N_H t_H\left(R\left(\mathcal{R},\gamma\right)\right) dG\left(\gamma\right)}_{\text{social cost of testing } H} - \underbrace{\int \left(\nu+\delta\right) N_L t_L\left(R\left(\mathcal{R},\gamma\right)\right) dG\left(\gamma\right)}_{\text{social cost of testing } L}
\end{aligned}
$$

Banerjee et al. 2012: 4 Cases

Valuation of Slot	Agent's Relative Ability to Pay	
	$y_H > y_L$	$y_H \leq y_L$
$h > l$	Case I: Alignment	Case III: Inability to Pay
$h \leq l$	Case II: Unwillingness to Pay	Case IV: Misalignment

- Case I: Social and private value rankings align
  1. Pure market case $H = h = y_H$, $L = l = y_L$
  2. Choosing an efficient contractor: H types are more efficient, make more money $h > l$. Also probably $y_H = h$ and $y_L = l$
  3. Allocating import licenses: H types make most profits. But credit constraints might bind: $y_H < h = H$ and $y_L < l = L$

Banerjee et al. 2012: 4 Cases

Valuation of Slot	Agent's Relative Ability to Pay	
	$y_H > y_L$	$y_H \leq y_L$
$h > l$	Case I: Alignment	Case III: Inability to Pay
$h \leq l$	Case II: Unwillingness to Pay	Case IV: Misalignment

- Case II: Seems pretty unlikely.
    1. A merit good? e.g. subsidized condoms. H are high risk types. But they like risk so $h < l$. Could also be richer so $y_H > y_L$.

Banerjee et al. 2012: 4 Cases

Valuation of Slot	Agent's Relative Ability to Pay	
	$y_H > y_L$	$y_H \leq y_L$
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- Case III: Social and pivate values are aligned, but the high value types can't afford it as much as the low value types
  1. Hospital beds. H needs bed urgently (e.g. cardiac vs cosmetic surgery). $H = h > L = l$. But no reason to assume H can afford more. e.g. $y_H = y_L = y$
  2. Targeting subsidized food to the poor. $H = h > L = l$ but $y_H < y_L$
  3. Allocating government jobs. Best candidates also value job the most (possibly because of private benefits!). But constrained in how much they can pay for the job up front.

Banerjee et al. 2012: 4 Cases

Valuation of Slot	Agent's Relative Ability to Pay	
	$y_H > y_L$	$y_H \leq y_L$
$h > l$	Case I: Alignment	Case III: Inability to Pay
$h \leq l$	Case II: Unwillingness to Pay	Case IV: Misalignment

- Case IV: The government wants to give the slots to those who value it the least
    1. Law enforcement: Slot is avoiding jail $H > 0 > L$, $y_H = y_L = y$, $h = l > 0$
    2. Driving licenses. Bad drivers more likely to get in trouble, so $H > 0 > L$, $y_H = y_L = y$. $h < l$
    3. Procurement: Imagine there are high and low quality firms. The slot is the contract. Want to buy from high quality firms $(H > L)$ even though costs higher $(l > h)$. Without credit constriants, $y_H = h$ and $y_L = l$

Banerjee et al. 2012: Alignment

- Assume $N_H < 1$ but $L > 0$ so optimal to give leftover slots to L
- We will analyze 4 possible mechanisms:

1. The socially optimal mechanism
2. All slots to the highest bidder: The *auction* mechanism
3. Pay to avoid missing out on a slot: The *monopoly* mechanism
4. Using testing to deter mimicry: The *testing* mechanism

- We will characterize each mechanism and show when the bureaucrat will pick each one

Banerjee et al. 2012: Alignment

- Candidate solution:

$$p_H = y_L + \epsilon,\ p_L = y_L$$
$$\pi_H = 1,\ \pi_L = \frac{1 - N_H}{N_L}$$
$$t_H = t_L = 0$$

- Low types can't mimic (can't afford p_H). High types won't mimic as long as

$$\underbrace{h - (y_L + \varepsilon)}_{\text{slot for sure at } p_H} \geq \underbrace{\frac{1 - N_H}{N_L}(h - y_L)}_{\text{slot w/pr } (1-N_H)/N_L \text{ at price } p_L}$$

Banerjee et al. 2012: Alignment

- This can always be guaranteed for small enough ϵ
- Affordable to H since $y_H > y_L$
- Feasible since π_L chosen to satisfy slot constraint
- Let E be set of ϵs such that this mechanism is in $\mathcal{R}$
- Will the bureaucrat choose $\epsilon \in E$? Given the fixed cost of breaking the rules, if he breaks them, he'll maximize his profits.

Banerjee et al. 2012: Alignment

- How can the bureaucrat extract more rents? Given π_L the highest price he can charge Hs is

$$p_H = p_H^* = \min\left\{y_H, y_L + (h - y_L)\,\frac{N-1}{N_L}\right\}$$

- $\Rightarrow$ Auction mechanism

$$p_H = p_H^*,\ p_L = y_L$$
$$\pi_H = 1,\ \pi_L = \frac{1-N_H}{N_L}$$
$$t_H = t_L = 0$$

Banerjee et al. 2012: Alignment

- The auction mechanism still leave Hs positive surplus: $p_H^* < y_H$. Can the bureaucrat extract more?
- He needs to satisfy the mimicry constraint. So he can play with π_L to do this and maybe get more money.
- $\Rightarrow$ the Monopoly mechanism.

$$p_H = \tilde{p}_H \leq y_H,\ p_L = y_L$$
$$\pi_H = 1,\ \pi_L = \min\left\{\frac{h - \tilde{p}_H}{h - y_L}, \frac{1 - N_H}{1 - N_L}\right\}$$
$$t_H = t_L = 0$$

- Note, this mechanism is inefficient whenever $\pi_L < (1 - N_H) \,/\, (1 - N_L)$. Slots are wasted

Banerjee et al. 2012: Alignment

- Will the bureaucrat prefer the auction or monopoly mechanism?
- The profits to the bureaucrat from the monopoly mechanism are
$$N_H\left(\tilde{p}_H - p\right) + N_L \frac{h - \tilde{p}_H}{h - y_L}\left(y_L - p\right)$$
- Note that at $\tilde{p} = y_L + \left(h - y_L\right)\left(N - 1\right)/N_L$ he gets the auction mechanism profit
- Profits are increasing in $\tilde{p}_H$ iff
$$N_H > N_L \frac{y_L - p}{h - y_L}$$
- If this condition holds, the monopoly mechanism with $\tilde{p}_H = y_H$ dominates.

Banerjee et al. 2012: Alignment

- Finally, consider the testing mechanism:

$$p_H = \min\left\{y_H, h - (h - l)\frac{1 - N_H}{N_L}\right\},\ p_{LS} = p_{LF} = y_L$$

$$\pi_H = 1,\ \pi_{LS} = \pi_{LF} = \frac{1 - N_H}{N_L}$$

$$t_H = 0,\ t_L = \max\left\{0, \frac{1}{\delta}\min\left\{(h - y_L)\frac{1 - N_H}{N_L} - (h - y_H),\right.\right.$$
$$\left.\left.(l - y_L)\frac{1 - N_H}{N_L}\right\}\right\}$$

- Aim: Use testing to relax the IC constraint that Hs don't mimic Ls

Banerjee et al. 2012: Alignment

- Note testing here is completely wasteful: Nothing depends on the outcome.
  - H types more likely to pass, so don't want to reward passing (trying to discourage pretending to be L)
  - H types can fail on purpose, so don't want to reward failing
- Testing relaxes the IC constraint though:

$$h - p_H \geq (h - y_L)\,\frac{1 - N_H}{N_L} - \delta t_L$$

  - RHS decreasing in t_L so can increase p_H
- Can't go past y_H so

$$\delta t_L \leq h - y_H - (h - y_L)\,\frac{1 - N_H}{N_L}$$

- Also can't scare away all the Ls

$$\delta t_L \leq (l - y_L)\,\frac{1 - N_H}{N_L}$$

Banerjee et al. 2012: Alignment

- This doesn't exhaust all possible mechanisms, but they're useful archetypes. So which one will the bureaucrat choose?
- Scenario 1: Suppose that $(h - y_L)\frac{N-1}{N_L} + y_L \geq y_H$. Now the auction mechanism extracts the most rents. The government gives the bureaucrat full discretion and sets p to divide the surplus between them.
- Scenario 2: $(h - y_L)\frac{N-1}{N_L} + y_L < y_H$ but testing is a) easy: $\nu = 0$, and b) effective, $y_H \leq h - (h - l)\frac{1-N_H}{N_L}$.
  - Government can set a rule that price must be below $(h - y_L)\frac{N-1}{N_L} + y_L$ and there cannot be any testing. Bureaucrats with high γ will follow this rule and choose the auction mechanism. Those with low γ will break it and choose either the testing or monopoly mechanism. In equilibrium there are both bribes and inefficiency.
  - Note that therefore the optimal rules depend on the degree of corruptibility of the bureaucrats.

Banerjee et al. 2012: Alignment

- Scenario 3: $(h - y_L)\,\frac{N-1}{N_L} + y_L < y_H$ but testing is hard: $\nu \gg 0$ so bureaucrats don't use red tape.
- Without rules the bureaucrats choose either auction or monopoly mechanism.
- They choose the monopoly mechanism (which the govt dislikes) if

$$N_H > N_L \frac{y_L - p}{h - y_L}$$

  - Government can set low p to avoid monopoly mechanism
- Government may prefer to cap the price again. There will be bribery, and also inefficiency amongst those choosing the monopoly mechanism.

Banerjee et al. 2012: Inability to Pay

- Focus on Banerjee (1997) special case: $L > 0$, $N_H < 1$, $h > l$, $y_H = y_L = y < l$, $\phi_L(t) = 0$
- Three mechanisms:

1. Auction mechanism:

$$p_H = y,\ p_L = l - \frac{N_L}{1 - N_H}(l - y)$$
$$\pi_H = 1,\ \pi_L = \frac{1 - N_H}{N_L}$$
$$t_H = t_L = 0$$

- H types prefer paying the higher price and getting the slot for sure.

Banerjee et al. 2012: Inability to Pay

2. Testing mechanism:

$$p_H = y,\ p_L = y$$
$$\pi_H = 1,\ \pi_L = \frac{1 - N_H}{N_L}$$
$$t_H = \frac{N_H + N_L - 1}{N_L}\left(l - y\right),\ t_L = 0$$

- Satisfy the IC constraint by making H types do the test, even though they're guaranteed to pass.

3. Lottery mechanism:

$$p_H = y,\ p_L = y$$
$$\pi_H = \pi_L = \frac{1}{N_H + H_L}$$
$$t_H = 0,\ t_L = 0$$

Banerjee et al. 2012: Inability to Pay

- Scenario: $\nu = 0$.
- With no rules, the bureaucrat prefers the lottery $\Rightarrow$ inefficient allocation of slots
- Suppose rule is set to require $\pi_H = 1$, $\pi_L = (1 - N_H)/N_L$.
- Now bureaucrat uses the testing mechanism. Yields same payoff as lottery.
- To stop this the government can set rule that the auction mechanism must be followed.
  - Bureaucrats with high γ will follow the rule. Bureaucrats with low γ will use the testing mechanism.
  - Bribery and red tape.
- Alternatively the government could have the rule be the lottery.
  - No corruption and no red tape. But misallocation

Banerjee et al. 2012: Misalignment

- Focus on the following case:
  - $N_H > 1$: Slots are scarce.
  - $y_L = l > h = y_H$: social and private values are misaligned
  - $L < 0$: Low types should not have a slot.
- Consider three types of mechanisms the bureaucrat might use

Banerjee et al. 2012: Misalignment

1. “testing + auction”

$$p_{HS} = p_H^*,\ p_{HF} = p_L = l$$
$$\pi_{HS} = 1/N_H,\ \pi_{HF} = \pi_L = 0$$
$$t_H = t_H^*,\ t_L = 0$$

where t_H^* and p_H^* solve

$$h - \delta t_H^* - p_H^* = 0$$
$$(1 - \phi_L(t_H))(l - p_H^*) - \delta t_H^* = 0$$

- Note the IC constraint for the L types:

$$(1 - \phi_L(t_H))(l - p_H^*) - \delta t_H^* \leq 0$$

they have to prefer not getting the slot to pretending to be H and getting it with some probability

Banerjee et al. 2012: Misalignment

2. “auction”

$$p_H = p_L = l$$
$$\pi_H = 0,\ \pi_L = 1/N_L$$
$$t_H = 0,\ t_L = 0$$

Noone is tested, but the allocation is terrible: Only Ls get slots

3. “lottery”

$$p_H = p_L = h$$
$$\pi_H = \pi_L = 1/\left(N_L + N_H\right)$$
$$t_H = 0,\ t_L = 0$$

Banerjee et al. 2012: Misalignment

- What should the government do?
- With no rules the bureaucrats choose the auction mechanism. Terrible!
- Government could set rules to be the testing + auction mechanism.
  - Bureaucrats with low γ break rules and use the auction mechanism.
- Government could set rules to be the lottery
  - Bureaucrats make more money $\rightarrow$ smaller incentive to deviate$\rightarrow$ fewer bureaucrats give all slots to Ls
  - But some slots go to L types even when rules are followed.

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Benabou & Tirole 2006: Introduction

- People often do things that are costly to themselves and primarily benefit others. Why?

1. Rewards and punishments for prosocial behavior sometimes backfire.
2. Social pressure and norms successfully use honor and shame to direct behavior
3. People care about their *self-image*. People want to think they are prosocial.

- Develop a theory of prosocial behavior.
  - Heterogeneity in degree of altruism/greed
  - desire for social reputation/self-respect
- People's behavior has 3 motivations *intrinsic, extrinsic,* and *reputational.*

Benabou & Tirole 2006: Model

- Agents are choosing how much to participate in a pro-social activity.
- Choose a from choice set $A \subset \mathbb{R}$ incurring cost $C(a)$
- Monetary reward is ya, $y \lesseqgtr 0$
- Agents' types are
  - v_a: intrinsic valuation
  - v_y: extrinsic valuation
  - $\mathbf{v} \equiv (v_a, v_y) \in \mathbb{R}^2$. continuous density $f(\mathbf{v})$ and mean $(\bar{v}_a, \bar{v}_y)$
- Direct benefit of participating is

$$(v_a + v_y y)\, a - C(a)$$

Benabou & Tirole 2006: Model

- Participation decisions also create reputational costs/benefits.
- Assume these depend linearly on observers' posterior expectations of the agent's type $\mathbf{v}$

$$R\left(a,y\right)\equiv x\left(\gamma_{a}\mathbb{E}\left[v_{a}|a,y\right]-\gamma_{y}\mathbb{E}\left[v_{y}|a,y\right]\right),\ \gamma_{a}\geq0,\ \gamma_{y}\geq0$$

- $\Rightarrow$ people want to be seen as *prosocial* $\gamma_a \geq 0$ and *disinterested* $\gamma_y \geq 0$
- $x > 0$ measures the visibility/salience of actions. Defining $\mu_a = x\gamma_a$ and $\mu_y = x\gamma_y$, agents solve

$$\max_{a\in A}\left(v_{a}+v_{y}y\right)a-C\left(a\right)+\mu_{a}\mathbb{E}\left[v_{a}|a,y\right]+\mu_{y}\mathbb{E}\left[v_{y}|a,y\right]$$

Benabou & Tirole 2006: Choice of a

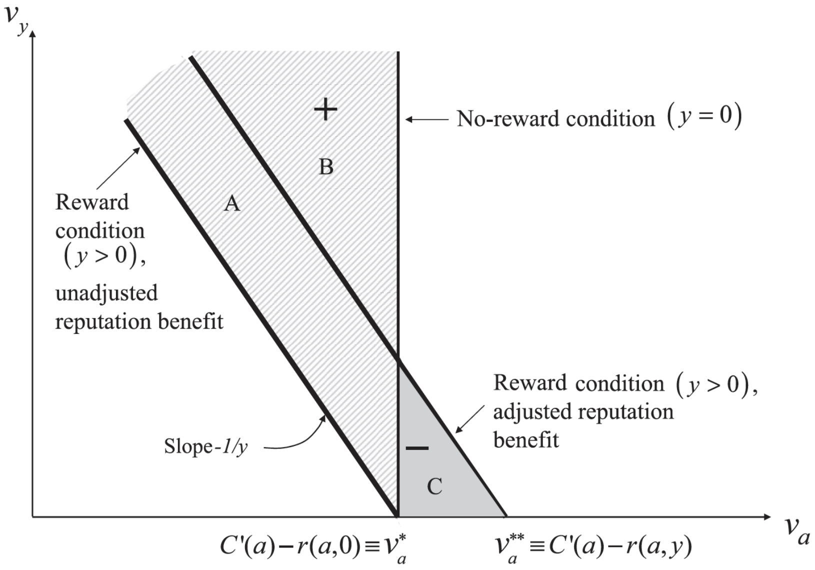
- The agent's optimal choice satisfies the FOC

$$C'(a) = v_a + v_y y + r(a, y; \boldsymbol{\mu})$$
$$r(a, y; \boldsymbol{\mu}) \equiv \mu_a \frac{\partial \mathbb{E}[v_a | a, y]}{\partial a} - \mu_y \frac{\partial \mathbb{E}[v_y | a, y]}{\partial a}$$

1. Observing a reveals the *sum* of intrinsic, extrinsic & reputational concerns $\rightarrow$ signal extraction problem
2. A higher incentive y makes a more informative about v_y but less about v_a
3. $\boldsymbol{\mu}$ makes inference about v_a and v_y noisier. This gets worse when actions are more visible (higher x)

Benabou & Tirole 2006: Analysis

- Start with the case where μ_a and μ_y are fixed.



Benabou & Tirole 2006: Analysis

- Add a few assumptions: $A = \mathbb{R}$, $C(a) = ka^2/2$,

$$\mathbf{v} \equiv \begin{pmatrix} v_a \\ v_y \end{pmatrix} \sim \mathcal{N}\begin{pmatrix} \bar{v}_a & \sigma_a^2 & \sigma_{ay} \\ \bar{v}_y & \sigma_{ay} & \sigma_y^2 \end{pmatrix}, \quad \bar{v}_a \lesseqgtr 0,\ \bar{v}_y > 0$$

- Start with case where $\boldsymbol{\mu}$ is fixed. Implies that

$$\bar{r}(a, y) \equiv \bar{\mu}_a \frac{\partial \mathbb{E}[v_a|a, y]}{\partial a} - \bar{\mu}_y \frac{\partial \mathbb{E}[v_y|a, y]}{\partial a}$$

- With normal $\mathbf{v}$, the posteriors are

$$\mathbb{E}[v_a|a, y] = \bar{v}_a + \rho(y)[ka - \bar{v}_a - \bar{v}_y y - \bar{r}(a, y)]$$
$$\mathbb{E}[v_y|a, y] = \bar{v}_y + \chi(y)[ka - \bar{v}_a - \bar{v}_y y - \bar{r}(a, y)]$$

where $\rho(y) = \frac{\sigma_a^2 + y\sigma_{ay}}{\sigma_a^2 + 2y\sigma_{ay} + y^2\sigma_y^2}$ and $y\chi(y) \equiv 1 - \rho(y)$

- Equilibrium solves these two differential equations.

Benabou & Tirole 2006: Signal Extraction

PROPOSITION 1: *Let all agents have the same image concern* $(\bar{\mu}_a, \bar{\mu}_y)$. *There is a unique (differentiable-reputation) equilibrium, in which an agent with preferences* (v_a, v_y) *contributes at the level*

$$a = \frac{v_a + v_y y}{k} + \bar{\mu}_a \rho(y) - \bar{\mu}_y \chi(y)$$

The reputational returns are $\partial \mathbb{E}[v_a|a,y]/\partial a = \rho(y)k$ *and* $\partial \mathbb{E}[v_y|a,y]/\partial a = \chi(y)k$, *resulting in a net value* $\bar{r}(y) = k(\bar{\mu}_a \rho(y) - \bar{\mu}_y \chi(y))$, *independent of* a.

- How do extrinsic incentives affect inference and behavior? higher y increases direct payoff, but decreases both dimensions of signaling. e.g. when $\sigma_{ay} = 0$

$$\rho(y) = \frac{1}{1 + y^2\sigma_y^2/\sigma_a^2} \quad \chi(y) = \frac{y\sigma_y^2/\sigma_a^2}{1 + y^2\sigma_y^2/\sigma_a^2}$$

- $\Rightarrow$ Higher y is like increasing the noise to signal ratio σ_y/σ_a
- When $\sigma_{ay} \neq 0$, a positive correlation amplifies this.

Benabou & Tirole 2006: Crowd-out

- Aggregate supply of the public good $\bar{a}(y) = \int_i a_i di$ has slope

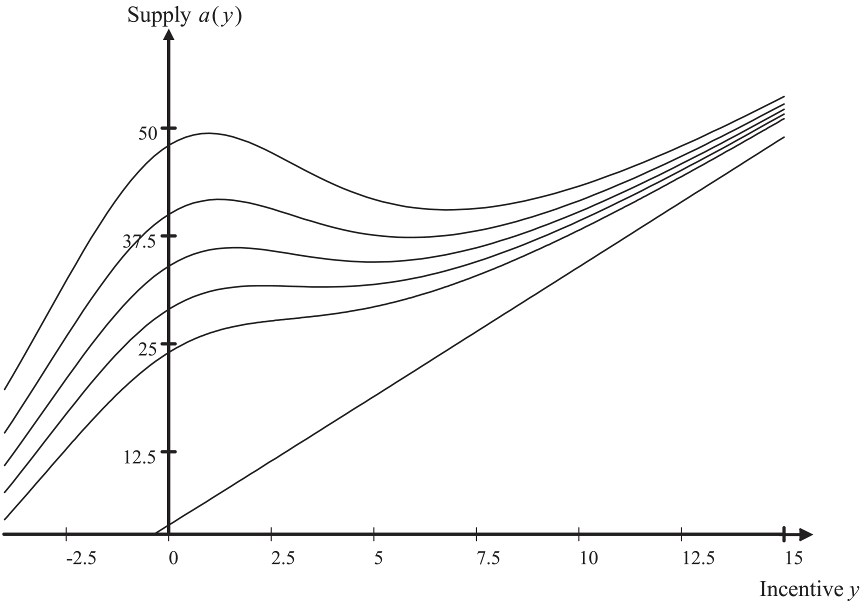
$$\bar{a}'(y) = \frac{\bar{v}_y}{k} + \bar{\mu}_a \rho'(y) - \bar{\mu}_x \chi'(y)$$

PROPOSITION 2 (Overjustification and crowding out): *Let $\sigma_{ay} = 0$ and define $\theta \equiv \sigma_y / \sigma_a$. Incentives are counterproductive, $\bar{a}'(y) < 0$, at all levels such that*

$$\frac{\bar{v}_y}{k} < \bar{\mu}_a \frac{2y\theta^2}{\left(1 + y^2\theta^2\right)^2} + \bar{\mu}_y \frac{\theta^2\left(1 - y^2\theta^2\right)}{\left(1 + y^2\theta^2\right)^2}$$

Consequently, for all $\bar{\mu}_a$ above some thershold $\mu_a^* \geq 0$, there exists a range $[y_1, y_2]$ such that $\bar{a}(y)$ is decreasing on $[y_1, y_2]$ and increasing everywhere else on $\mathbb{R}$. If $\bar{\mu}_y < \bar{v}_y / k\theta^2$, then $\mu_a^* > 0$ and $0 < y_1 < y_2$; as $\bar{\mu}_a$ increases, y_1 falls and y_2 rises, so $[y_1, y_2]$ widens. If $\bar{\mu}_y > \bar{v}_y / k\theta^2$, then $\mu_a^* = 0$ and $y_1 < 0 < y_2$; as $\bar{\mu}_a$ increases both y_1 and y_2 rise and, for $\bar{\mu}_a$ large enough, $[y_1, y_2]$ again widens.

Benabou & Tirole 2006: Crowd-out



Benabou & Tirole 2006: Image Rewards

- We have studied how extrinsic incentives (y) affect participation. Can providing visibility to contributions (x) do a better job of encouraging participation?
- Yes, but: When we have a homothetic increase in μ_a, μ_y this works, but with heterogeneity people may suspect that contributors are just doing it to look good: That they are *image-motivated*. This dampens incentives to participate.
- Allow image concerns also to be heterogeneous:

$$\left(\begin{array}{c} \mu_a \\ \mu_y \end{array} \right) \sim \mathcal{N} \left(\begin{array}{c} \bar{\mu}_a \\ \bar{\mu}_y \end{array} , \left[\begin{array}{cc} \omega_a^2 & \omega_{ay} \\ \omega_{ay} & \omega_y^2 \end{array} \right] \right), \ \bar{\mu}_a, \bar{\mu}_y \geq 0$$

  and v and $\boldsymbol{\mu}$ are independent.

Benabou & Tirole 2006: Image Rewards

- The first order condition for the choice of a is still

$$C'(a) = v_a + v_y y + r(a, y; \boldsymbol{\mu})$$

- Now the reputational concern term in the first order condition $r(a, y; \boldsymbol{\mu})$ is also normally distributed, with mean $\bar{r}(a, y; \boldsymbol{\mu})$ and variance

$$\Omega(a, y)^2 \equiv \left(\frac{\partial \mathbb{E}[v_a | a, y]}{\partial a} - \frac{\partial \mathbb{E}[v_y | a, y]}{\partial a} \right) \times \begin{pmatrix} \omega_a^2 & \omega_{ay} \\ \omega_{ay} & \omega_y^2 \end{pmatrix} \times \begin{pmatrix} \frac{\partial \mathbb{E}[v_a | a, y]}{\partial a} \\ -\frac{\partial \mathbb{E}[v_y | a, y]}{\partial a} \end{pmatrix}$$

Benabou & Tirole 2006: Image Rewards

- Updating still satisfies

$$\mathbb{E}\left[v_a|a,y\right] = \bar{v}_a + \rho\left(a,y\right)\left[ka - \bar{v}_a - \bar{v}_y y - \bar{r}\left(a,y\right)\right]$$
$$\mathbb{E}\left[v_y|a,y\right] = \bar{v}_y + \chi\left(a,y\right)\left[ka - \bar{v}_a - \bar{v}_y y - \bar{r}\left(a,y\right)\right]$$

but now

$$\rho\left(a,y\right) \equiv \frac{\sigma^2 + y\sigma_{ay}}{\sigma_a^2 + 2y\sigma_{ay} + y^2\sigma_y^2 + \Omega\left(a,y\right)^2}$$
$$\chi\left(a,y\right) \equiv \frac{y\sigma^2 + \sigma_{ay}}{\sigma_a^2 + 2y\sigma_{ay} + y^2\sigma_y^2 + \Omega\left(a,y\right)^2}$$

- Equilibrium solves these differential equations.
  - But note they are now nonlinear because of the Ω^2 term.
  - Restrict attention to equilibria in the class where $\Omega \perp a$. This keeps reputations linear in a

Benabou & Tirole 2006: Image Rewards

PROPOSITION 4: (1) *A linear-reputation equilibrium corresponds to a fixed point* $\Omega(y)$, *solution to*

$$\frac{\Omega(y)^2}{k^2} = \omega_a^2 \rho(y)^2 - 2\omega_{ay}\rho(y)\chi(y) + \omega_y^2 \chi(y)^2$$

The optimal action chosen by an agent with type $(\mathbf{v}, \boldsymbol{\mu})$ *is then*

$$a = \frac{v_a + v_y y}{k} + \mu_a \rho(y) - \mu_y \chi(y)$$

and the marginal reputations are $\partial \mathbb{E}[v_a|a,y]/\partial a = \rho(y)k$ *and* $\partial \mathbb{E}[v_y|a,y]/\partial a = \chi(y)k$, *with a net value of* $r(y;\boldsymbol{\mu}) = [\mu_a \rho(y) - \mu_y \chi(y)]k$ *for the agent.*
(2) There always exists such an equilibrium, and if $\omega_{ay} = 0$ *it is unique (in the linear reputation class)*

- Fixed point intuition:
  - The more variable image motives are, the noisier behavior is as a signal of v_a, v_y, reducing $\rho(y)$ and $\chi(y)$.
  - But the variance is endogenous to behavior which takes into account its effect on signal-extraction.

Benabou & Tirole 2006: Image Rewards

- Image rewards give rise to an offsetting *overjustification effect*. To see this, consider scaling all the reputational weights $\boldsymbol{\mu} = (\mu_a, \mu_y)$ up by a prominence factor x holding the material incentive y constant.
- Aggregate supply is

$$\bar{a}(y, x) = \frac{\bar{v}_a + \bar{v}_y y}{k} + x \left[\bar{\mu}_a \rho(y, x) - \bar{\mu} \chi(y, x) \right]$$

- Increasing x has 2 effects:

1. Direct *amplifying* effect with sign $sign(\mu_a \rho(y, x) - \mu_y \chi(y, x))$
   1.1 For socially minded people with $\mu_a \gg \mu_y$ this increases incentives to contribute
   1.2 For people worried not to look greedy $\mu_a \ll \mu_y$ this decreases incentives.
2. Indirect *dampening* effect. Increasing x increases the noise Ω $\rightarrow$ people attribute behavior more to image-seeking $\rho(y, x)$ and $\chi(y, x)$ shrink $\rightarrow$ people respond less to image rewards.

Outline

Theory

- Aghion & Tirole (JPE 1997) *Formal and Real Authority in Organizations*
- Banerjee, Hanna & Mullainathan (2012) *Corruption*
- Benabou & Tirole (AER 2006) *Incentives and Prosocial Behavior*
- Besley & Ghatak (AER 2005) *Competition and Incentives with Prosocial Agents*

Besley & Ghatak 2005: Introduction

- Money is not the only way that workers are motivated
- Many organizations, especially in the non-profit & public sectors have a “mission”
- (some) workers too care about the mission of the organization they work with.
- Build a model to study this.
  - Matching on mission $\rightarrow$ less need for explicit incentives
  - But, entrenches conservatism/resistance to innovation.

Besley & Ghatak 2005: Principal-Agent Setup

- A firm = a risk-neutral principal, and a risk-neutral agent.
- Principal needs agent to do a project.
- Project outcome is high $\rightarrow Y_H$ or low $\rightarrow Y_L < Y_H$
- Probability of high outcome is effort by agent e.
- Effort is non-contractible and costs agent $e^2/2$
- Agent has limited liability so requires wage $\underline{w} \geq 0$ every period.

Besley & Ghatak 2005: Organizational Mission

- 3 types of principals $i \in \{0, 1, 2\}$
- If project succeeds, principal gets $\pi_i > 0$.
- Type 0 principals are "standard": π_0 is purely monetary. Think of them as the private sector, the "**Profit-oriented sector**"
- Types 1 and 2: Part of π_1, π_2 are nonpecuniary payoffs: Think of them as non-profits/govt, the "**Mission-oriented sector**"
- Assume $\pi_1 = \pi_2 = \hat{\pi} \rightarrow$ this is a model of horizontal matching: no productivity differences across orgs when there is efficient matching.

Besley & Ghatak 2005: Intrinsic Motivation

- 3 types of agents $j \in \{0, 1, 2\}$
- Agents get a nonpecuniary benefit θ_{ij} from working at a type i organization
- Type 0s don't care: $\theta_{i0} = 0$,
- Types 1 and 2 are "Motivated Agents": Get $\bar{\theta}$ from working at "their" type, $\underline{\theta}$ from working at the other type. $\bar{\theta} > \underline{\theta} \geq 0$

$$\theta_{ij} = \begin{cases} 0 & \text{if } i = 0 \text{ and/or } j = 0 \\ \underline{\theta} & \text{if } i \in \{1,2\}, j \in \{1,2\}, i \neq j \\ \bar{\theta} & \text{if } i \in \{1,2\}, j \in \{1,2\}, i = j \end{cases}$$

- Assume: $\max\left\{\pi_0, \hat{\pi} + \bar{\theta}\right\} < 1$ to guarantee interior solutions for effort in all matches

Besley & Ghatak 2005: Optimal Contracts

- Contracts have 2 terms
  1. A fixed wage w_{ij} paid regardless of the project outcome
  2. A bonus b_{ij} if the outcome is Y_H
- Consider the first-best as a benchmark. Effort is contractible and solves

$$\max_e e\left[\pi_i + \theta_{ij}\right] + (1-e)\left[0\right] - e^2/2$$

- First-best optimal effort:

$$e = \pi_i + \theta_{ij}$$

- Generates total surplus

$$\frac{\left(\pi_i + \theta_{ij}\right)^2}{2}$$

Besley & Ghatak 2005: Optimal Contracts

- In the second best, effort is not contractible. Principal solves

$$\max_{[b_{ij},w_{ij}]} u_{ij}^P = (\pi_i - b_{ij})\, e_{ij} - w_{ij}$$

- Subject to 3 constraints:
  - limited liability: Agent gets at least $\underline{w}$:

$$b_{ij} + w_{ij} \geq \underline{w} \quad w_{ij} \geq \underline{w}$$

  - participation: Agent prefers this to outside option

$$u_{ij}^a = e_{ij}\,(b_{ij} + \theta_{ij}) + w_{ij} - \frac{1}{2}e_{ij}^2 \geq \bar{u}_j$$

  - Incentive compatibility: Agent picks e_{ij}

$$e_{ij} \in \arg\max_{e_{ij}\in[0,1]} \left\{ e_{ij}\,(b_{ij} + \theta_{ij}) + w_{ij} - \frac{1}{2}e_{ij}^2 \right\}$$

which simplifies to $e_{ij} = b_{ij} + \theta_{ij}$ as long as this is $\in [0,1]$

Besley & Ghatak 2005: Optimal Contracts

- Assume the project is always worth trying:

$$\frac{1}{4}\left[\min\left\{\pi_0, \hat{\pi}\right\}\right]^2 - \underline{w} > 0$$

- Define $\bar{v}_{ij}$ as the value of the reservation payoff to an agent of type j such that a principal of type i makes zero expected profits under the optimal contract. And define $\underline{v}_{ij}$ as the lowest $\bar{u}_j$ for which the participation constraint binds.

Besley & Ghatak 2005: Optimal Contracts

PROPOSITION 1: *Suppose Assumptions 1 and 2 hold. An optimal contract* $\left(b_{ij}^{*}, w_{ij}^{*}\right)$ *between a principal of type* i *and an agent of type* j *given a reservation payoff* $\bar{u}_j \in [0, \bar{v}_{ij}]$ *exists, and has the following features:*

1. *The fixed wage is set at the subsistence level:* $w_{ij}^{*} = \underline{w}$
2. *The bonus payment is characterized by*

$$b_{ij}^{*} = \begin{cases} \max\left\{0, \frac{\pi_i - \theta_{ij}}{2}\right\} & \textit{if } \bar{u}_j \in \left[0, \underline{v}_{ij}\right] \\ \sqrt{2\left(\bar{u}_j - \underline{w}\right)} - \theta_{ij} & \textit{if } \bar{u}_j \in \left[\underline{v}_{ij}, \bar{v}_{ij}\right] \end{cases}$$

3. *The optimal effort level solves:* $e_{ij}^{*} = b_{ij}^{*} + \theta_{ij}$

Besley & Ghatak 2005: Optimal Contracts

- Gives rise to 3 cases

1. If the agent is more motivated than the principal and the outside option is low, $b_{ij}^{*} = 0$
2. If the principal is more motivated than the agent and the outside option is low, $b_{ij}^{*} = \frac{1}{2}(\pi_i - \theta_{ij})$
3. If the outside option is high, then $b_{ij}^{*} = \sqrt{2(\bar{u}_{ij} - \underline{w})} - \theta_{ij}$

Besley & Ghatak 2005: Optimal Contracts in the Profit-Oriented Sector

COROLLARY 1: *In the profit-oriented sector* $(i = 0)$*, the optimal contract is characterized by the following:*

(a) *The fixed wage is set at the subsistence level, i.e.,* $w^*_{0j} = \underline{w}$ $(j = 0, 1, 2)$

(b) *The bonus payment is characterized by*

$$b^*_{0j} = \begin{cases} \frac{\pi_0}{2} & \text{if } \bar{u}_j \in \left[0, \underline{v}_{0j}\right] \\ \sqrt{2\left(\bar{u}_j - \underline{w}\right)} & \text{if } \bar{u}_j \in \left[\underline{v}_{0j}, \bar{v}_{0j}\right] \end{cases}$$

for $j = 0, 1, 2$

(c) *The optimal effort level solves:* $e^*_{0j} = b^*_{0j}$ $(j = 0, 1, 2)$

Besley & Ghatak 2005: Optimal Contracts in the Mission-oriented sector

COROLLARY 2: *Suppose that* $\bar{u}_0 = \bar{u}_1 = \bar{u}_2$*. Then, in the mission-oriented sector* $(i = 1, 2)$*, effort is higher and the bonus payment is lower if the agent's type is the same as that of the principal.*

- bonuses and intrinsic motivation are perfect substitutes

COROLLARY 3: *Suppose that* $\bar{u}_0 = \bar{u}_1 = \bar{u}_2$*. Then, in the mission-oriented sector* $(i = 1, 2)$ *bonus payments and effort are negatively correlated in a cross section of organizations*

- This is a selection effect: Places with better match will have lower bonuses because of corollary 2.

Besley & Ghatak 2005: Competing for Workers

- What happens when the different sectors are competing for workers?
- Define $\mathcal{A}_p = \{p_0, p_1, p_2\}$ as the set of types of the principals. $\mathcal{A}_a = \{a_0, a_1, a_2\}$ is the set of types of the agents.
- A matching process is a matching function $\mu : \mathcal{A}_p \cup \mathcal{A}_a \to \mathcal{A}_p \cup \mathcal{A}_a$ such that
  1. $\mu(p_i) \in \mathcal{A}_a \cup \{p_i\} \ \forall p_i \in \mathcal{A}_p$
  2. $\mu(a_j) \in \mathcal{A}_p \cup \{a_j\} \ \forall a_i \in \mathcal{A}_a$
  3. $\mu(p_i) = a_j \iff \mu(a_j) = p_i \, \forall (p_i, a_j) \in \mathcal{A}_p \times \mathcal{A}_j$
- n_i^p = number of principals of type i. Analogously n_j^a
- Assume $n_1^a = n_1^p$ and $n_2^a = n_2^p$.
- However, allow *unemployment* $(n_0^a > n_0^p)$ and *full employment* $(n_0^a < n_0^p)$

Besley & Ghatak 2005: Competing for Workers

- Assume that the individuals on the long side of the market gets none of the surplus.
- This pins down the outside options. For any set of outside options, proposition 1 tells us the optimal contracts.

PROPOSITION 2: *Consider a matching μ and associated optimal contracts $\left(w_{ij}^{*}, b_{ij}^{*}\right)$ for $i = 0, 1, 2$ and $j = 0, 1, 2$. Then this matching is stable only if $\mu\left(p_i\right) = a_i$ for $i = 0, 1, 2$*

- Assume that when the two sectors are competing it's still worth having mission-oriented production (surplus is high enough):

$$\bar{\theta} + \hat{\pi} \geq \pi_0$$

Besley & Ghatak 2005: Competing for Workers: Full Employment

PROPOSITION 3: *Suppose that $n_0^a < n_0^p$ (full employment in the profit-oriented sector). Then the following matching μ is stable: $\mu(a_j) = p_j$ for $j = 0, 1, 2$ and the associated optimal contracts have the following features:*

(a) *The fixed wage is set at the subsistence level, i.e. $w_{ij}^* = \underline{w}$ for $j = 0, 1, 2$*

(b) *The bonus payment in the mission-oriented sector is*

$$b_{11}^* = b_{22}^* = \frac{1}{2}\max\left\{\max\left\{\bar{\theta}, \hat{\pi}\right\}, \pi_0 + \sqrt{\pi_0^2 - 4\underline{w}} - \bar{\theta}\right\}$$

and the bonus payment in the profit-oriented sector is

$$b_{00}^* = \frac{\pi_0 + \sqrt{\pi_0^2 - 4\underline{w}}}{2}$$

(c) *The optimal effort level solves: $e_{jj}^* = b_{jj}^* + \bar{\theta}$ for $j = 1, 2$ and $e_{00}^* = b_{00}^*$.*

Besley & Ghatak 2005: Competing for Workers: Full Employment

- Competition for workers and incentives interact in important ways

1. *matching effect*. Less heterogeneity in contracts compared to a world in which principals and agents don't match assortatively. When the participation constraint doesn't bind, incentive pay is lower.
2. *outside option effect.* Full employment drives profit-oriented principals' payoff to zero. Motivated agent's reservation utility is what she'd get by switching to the profit-oriented sector.
   2.1 When productivity is high in the profit-oriented sector, the mission-oriented sector has to pay more and use incentive pay more.
   2.2 Even with a binding participation constraint, incentive pay is lower in the mission-oriented sector than in the profit-oriented sector

Besley & Ghatak 2005: Competing for Workers: Unemployment

PROPOSITION 4: *Suppose that $n_0^a > n_0^p$ (unemployment in the profit-oriented sector). Then the following matching μ is stable: $\mu(a_j) = p_j$ for $j = 0, 1, 2$ and the associated optimal contracts have the following features:*

(a) The fixed wage is set at the subsistence level $w_{ij}^* = \underline{w}$ for $j = 0, 1, 2$;

(b) *The bonus payment in the mission-oriented sector is:*

$$b_{11}^* = b_{22}^* = \frac{\max\{\bar{\theta}, \hat{\pi}\} - \bar{\theta}}{2}$$

and the bonus payment in the profit-oriented sector is

$$b_{00}^* = \frac{\pi_0}{2}$$

(c) *The optimal effort level solves: $e_{ij}^* = b_{ij}^* + \bar{\theta}$ for $j = 1, 2$ and $e_{00}^* = b_{00}^*$*

Besley & Ghatak 2005: Competing for Workers

- Now there's only a matching effect.
- Application of BG framework to public sector bureaucracy
  - Lower powered incentives due to mission-oriented production
  - If an election changes the mission, may reduce productivity of bureaucracy
  - If private-sector opportunities improve $\rightarrow$ more high-powered incentives in bureaucracy
  - Lack of innovation: In profit-oriented sector, any innovation that increases π_0 will be adopted. However, in a mission-oriented organization, only innovations that increase $\pi_i + \theta_{ij}$ will be adopted. If the innovation increases π_i but decreases θ_{ij} it may not be adopted.

Outline

Outline

Financial Incentives

- Muralidharan & Sundararaman (JPE 2011) *Teacher Performance Pay: Experimental Evidence from India*
- Duflo, Hanna & Ryan (AER 2012) *Incentives Work: Getting Teachers to Come to School*
- Khan, Khwaja & Olken (QJE 2016) *Tax Farming Redux: Experimental Evidence on Performance Pay for Tax Collectors*
- Duflo Greenstone Pande & Ryan (QJE 2013): *Truth-telling by Third-party Auditors and the Response of Polluting Firms: Experimental Evidence from India*

Muralidharan & Sundararaman 2011: Introduction

- Randomized evaluation of teacher performance pay
- Large scale experiment in Andhra Pradesh, India
- Can we really measure teacher performance?
- Teacher incentive programs can backfire (multitasking, teaching to the test etc.)
- How should bonus contracts be set up?
- Are bonuses a cost-effective way to increase performance?

Muralidharan & Sundararaman 2011: Model

- Teachers do 2 tasks
  1. T_1: teaching using curricular best practices
  2. T_2: activities to increase scores on exams (drills, teaching to the test, cheating)
- t_1 and t_2 denote time allocated to these tasks. Human capital gains are

  $$H = f_1 t_1 + f_2 t_2 + \varepsilon$$

  where f_1, f_2 are marginal products and ε is noise outside teacher's control
- Planner cannot observe H, t_1 or t_2 but observes performance measure P (e.g. test scores)

  $$P = g_1 t_1 + g_2 t_2 + \phi$$

Muralidharan & Sundararaman 2011: Model

- Principal offers a wage contract depending on P: e.g. $w = s + bP$
- Teacher's utility is

$$U = \mathbb{E}[w] - C(t_1, t_2; \bar{t})$$

  where $\bar{t}$ is an effort norm. Teachers suffer a psychic cost if $t_1 + t_2 < \bar{t}$
- Optimal bonus b^* depends on functional form of C, but when t_1 and t_2 are substitutes, easy to construct examples s.t. $b^* = 0$: better to accept the output generated by the norm $\bar{t}$ than to distort input allocation.
- But, if $\bar{t}$ is small, then gains from increasing effort can exceed costs of distorting effort. Plausible in India: Absenteeism is very high.
- Moreover, if f_1/f_2 is not too much greater than 1, less substitution. Plausible in India: Tests are central to the system so best practice may be to teach to the test.

Muralidharan & Sundararaman 2011: Experiment

A

	India	AP
Gross enrollment (Ages 6-11) (%)	95.9	95.3
Literacy (%)	64.8	60.5
Teacher absence (%)	25.2	25.3
Infant mortality (per 1,000)	63	62

Muralidharan & Sundararaman 2011: Experiment

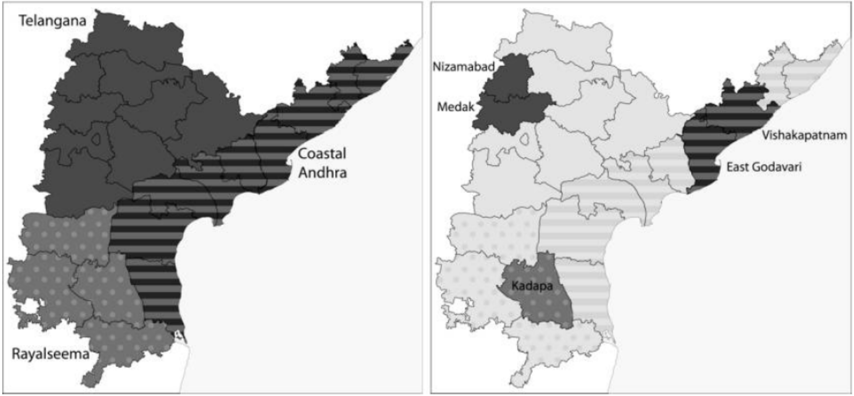


FIG. 1.—*A*, Andhra Pradesh (AP); *B*, district sampling (stratified by sociocultural regions of AP).

Muralidharan & Sundararaman 2011: Experiment

- Work in Andhra Pradesh: 5th most populous state in India. Population > 80 million
- State consists of 3 sociocultural regions and 23 districts
- Within each district randomly sample one division (out of 3-5 in each district)
- within each division randomly sample 10 mandals (out of 10-15 in each division)
- In each of the 50 mandals, randomly sample 10 schools with probabilities proportional to enrolment.
- Sample is now representative of a typical **child** attending a government-run primary school

Muralidharan & Sundararaman 2011: Experiment

TABLE 1
Incentives

	Incentives (Conditional on Improvement in Student Learning)		
Inputs	None	Group Bonus	Individual Bonus
None	Control (100 schools)	100 schools	100 schools
Extra contract teacher	100 schools		
Extra block grant	100 schools		

	Control (1)	Group Incentive (2)	Individual Incentive (3)	p-Value (Equality of All Groups) (4)
	A. Means of Baseline Variables			
School-level variables:				
1. Total enrollment (baseline: grades 1–5)	113.2	111.3	112.6	.82
2. Total test takers (baseline: grades 2–5)	64.9	62.0	66.5	.89
3. Number of teachers	3.07	3.12	3.14	.58
4. Pupil-teacher ratio	39.5	40.6	37.5	.66
5. Infrastructure index (0–6)	3.19	3.14	3.26	.84
6. Proximity to facilities index (8–24)	14.65	14.66	14.72	.98
Baseline test performance:				
7. Math (raw %)	18.5	18.0	17.5	.69
8. Math (normalized; in SD)	.032	.001	−.032	.70
9. Telugu (raw %)	35.1	34.9	33.5	.52
10. Telugu (normalized; in SD)	.026	.021	−.046	.53

	B. Means of End Line Variables			
Teacher turnover and attrition:				
Year 1 (relative to year 0):				
11. Teacher attrition (%)	.30	.34	.30	.54
12. Teacher turnover (%)	.34	.34	.32	.82
Year 2 (relative to year 0):				
13. Teacher attrition (%)	.35	.38	.34	.57
14. Teacher turnover (%)	.34	.36	.33	.70
Student turnover and attrition:				
Year 1 (relative to year 0):				
15. Student attrition from baseline to end-of-year tests	.081	.065	.066	.15
16. Baseline math test score of attritors (equality of all groups)	−.17	−.13	−.22	.77
17. Baseline Telugu test score of attritors (equality of all groups)	−.26	−.17	−.25	.64
Year 2 (relative to year 0):				
18. Student attrition from baseline to end-of-year tests	.219	.192	.208	.23
19. Baseline math test score of attritors (equality of all groups)	−.13	−.05	−.14	.56
20. Baseline Telugu test score of attritors (equality of all groups)	−.18	−.11	−.21	.64

Muralidharan & Sundararaman 2011: Bonuses

- Bonuses based on average improvement in test scores

$$\text{Bonus} = \begin{cases} Rs.500 \times (\%\text{gain in avg test scores} - 5\%) & \text{if gain} > 5\% \\ 0 & \text{otherwise} \end{cases}$$

- In group incentive schools, all teachers got the same bonus based on school-level average improvement
- In individual incentive schools, based on average test score of the specific teacher.
- Slope (Rs.500) set so expected payment would equal additional spending in input treatments

Muralidharan & Sundararaman 2011: Tests

- To reduce cheating, tests conducted by external teams
- Baseline test (June-July 2005) tested math and language
- At the end of year one (March-April 2006), two rounds of tests separated by 2 weeks
  - round 1 (Lower endline, LEL) tested competencies up to previous school year
  - round 2 (higher endline, HEL) tested material from the current school year's syllabus
- Same procedure repeated at the end of year 2
- Scores in year 0 normalized to distribution across all schools
- Scores in years 1 and 2 normalized to distribution in control schools

Muralidharan & Sundararaman 2011: Results

- Teacher attrition: no significant difference in teacher attrition across schools (worried teachers try to select into incentive schools for e.g.)
- Student attrition: 7.1% attrition at year 1. 20.6% at year 2. Higher attrition for lower test score children. But balanced across treatments.

$$T_{ijkm}(Y_n) = \alpha + \gamma T_{ijkm}(Y_0) + \delta \text{Incentives} + \beta Z_m + \varepsilon_k + \varepsilon_{jk} + \varepsilon_{ijk}$$

where T_{ijkm} is score of student i in grade j at school k in mandal m. Y_0 denotes baseline tests and $Y_n$indicates test at end of n years. Z_m are mandal dummies

Muralidharan & Sundararaman 2011: Results

TABLE 3
IMPACT OF INCENTIVES ON STUDENT TEST SCORES
Dependent Variable: Normalized End-of-Year Test Score

	YEAR 1 ON YEAR 0		YEAR 2 ON YEAR 0	
	(1)	(2)	(3)	(4)
	A. Combined (Math and Language)			
Normalized lagged test score	.503***	.498***	.452***	.446***
	(.013)	(.013)	(.015)	(.015)
Incentive school	.149***	.165***	.219***	.224***
	(.042)	(.042)	(.047)	(.048)
School and household controls	No	Yes	No	Yes
Observations	42,145	37,617	29,760	24,665
R^2	.31	.34	.24	.28

Muralidharan & Sundararaman 2011: Results

	B. Math			
Normalized lagged test score	.492***	.491***	.414***	.408***
	(.016)	(.016)	(.022)	(.022)
Incentive school	.180***	.196***	.273***	.280***
	(.049)	(.049)	(.055)	(.056)
School and household controls	No	Yes	No	Yes
Observations	20,946	18,700	14,797	12,255
R^2	.30	.33	.25	.28
	C. Telugu (Language)			
Normalized lagged test score	.52***	.510***	.49***	.481***
	(.014)	(.014)	(.014)	(.014)
Incentive school	.118***	.134***	.166***	.168***
	(.040)	(.039)	(.045)	(.044)
School and household controls	No	Yes	No	Yes
Observations	21,199	18,917	14,963	12,410
R^2	.33	.36	.26	.30

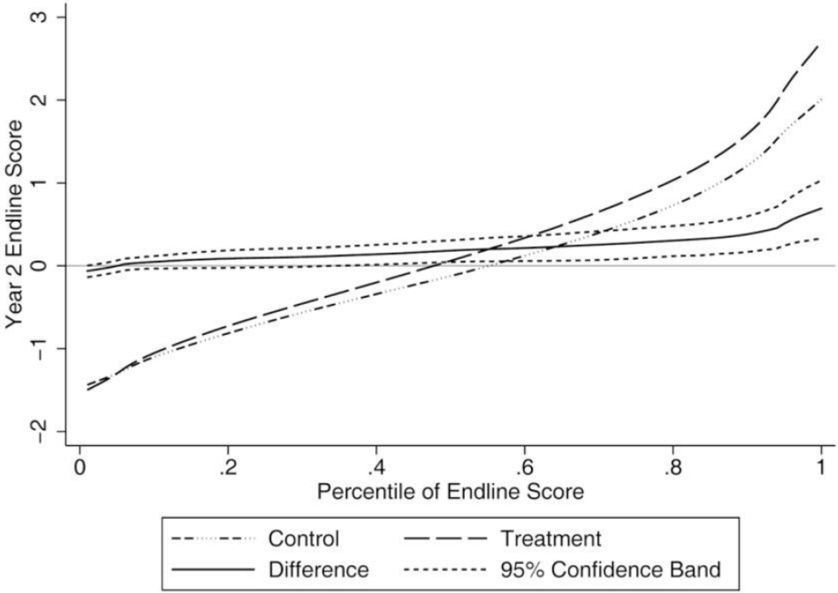
Muralidharan & Sundararaman 2011: Heterogeneity

- How does the distribution of test scores change:

$$\delta\left(\tau\right)=G_n^{-1}\left(\tau\right)-F_m^{-1}\left(\tau\right)$$

  where G_n is treatment distribution, F_m control
- NB This is a quantile treatment effect not a treatment effect at different quantiles
- Treatment effect at different quantiles: Estimate nonparametric reg of endline scores on baseline scores separately for treatment and control.
- Heterogeneity by observables:

$$\begin{aligned}T_{ijkm}\left(Y_n\right)=\alpha+\gamma T_{ijkm}\left(Y_0\right)+\delta_1\text{Incentives}+\delta_2\text{Characteristic}\\+\delta_3\text{Incentives}\times\text{Characteristic}+\beta Z_m+\varepsilon_k+\varepsilon_{jk}+\varepsilon_{ijk}\end{aligned}$$


Year 2 Endline Score
3
2
1
0
-1
-2
0
.2
.4
.6
.8
1
Percentile of Endline Score
Control
Treatment
Difference
95% Confidence Band

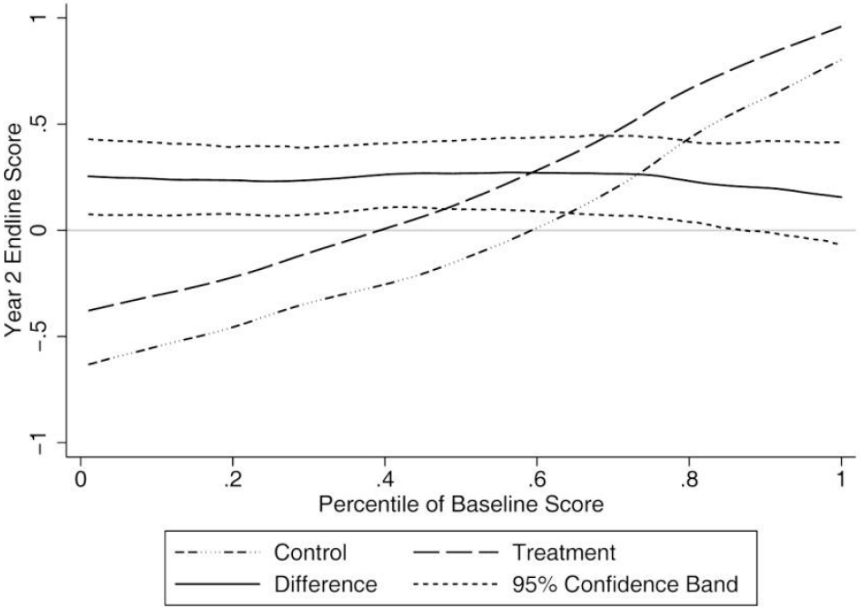

Year 2 Endline Score
1
.5
0
−.5
−1
0
.2
.4
.6
.8
1
Percentile of Baseline Score
Control
Treatment
Difference
95% Confidence Band

TABLE 6
HETEROGENOUS TREATMENT EFFECTS
A. HOUSEHOLD AND SCHOOL CHARACTERISTICS

	Log School Enrollment (1)	School Proximity (8–24) (2)	School Infrastructure (0–6) (3)	Household Affluence (0–7) (4)	Parental Literacy (0–4) (5)	Scheduled Caste/Tribe (6)	Male (7)	Normalized Baseline Score (8)
	Two-Year Effect							
Incentive	−.198	−.019	.28**	.09	.224***	.226***	.233***	.219***
	(.354)	(.199)	(.130)	(.073)	(.054)	(.049)	(.049)	(.047)
Covariate	−.065	−.005	.025	.017	.068***	−.066	.029	.448***
	(.058)	(.010)	(.038)	(.014)	(.015)	(.042)	(.027)	(.024)
Interaction	.083	.018	−.02	.038**	−.003	−.013	−.02	.006
	(.074)	(.014)	(.040)	(.019)	(.019)	(.056)	(.034)	(.031)
Observations	29,760	29,760	29,760	25,231	25,226	29,760	25,881	29,760
R^2	.244	.244	.243	.272	.273	.244	.266	.243
	One-Year Effect							
Incentive	−.36	−.076	.032	.004	.166***	.164***	.157***	.149***
	(.381)	(.161)	(.110)	(.060)	(.047)	(.045)	(.044)	(.042)
Covariate	−.128**	−.016*	−.001	.017	.08***	.007	.016	.502***
	(.061)	(.008)	(.025)	(.013)	(.012)	(.035)	(.020)	(.021)
Interaction	.103	.017	.041	.042**	−.013	−.06	.002	.000
	(.081)	(.011)	(.031)	(.017)	(.016)	(.048)	(.025)	(.026)
Observations	42,145	41,131	41,131	38,545	38,525	42,145	39,540	42,145
R^2	.31	.32	.32	.34	.34	.31	.33	.31

B. Teacher Characteristics (Pooled Regression Using Both Years of Data)

	Education (1)	Training (2)	Years of Experience (3)	Salary (Log) (4)	Male (5)	Teacher Absence (6)	Active Teaching (7)	Active or Passive Teaching (8)
Incentive	−.113	−.224	.258***	1.775**	.031	.15***	.084	.118
	(.163)	(.176)	(.059)	(.828)	(.091)	(.050)	(.054)	(.074)
Covariate	.003	−.051	−.001	−.034	−.084	−.149	.055	.131
	(.032)	(.041)	(.003)	(.066)	(.057)	(.137)	(.078)	(.093)
Interaction	.086*	.138**	−.009**	−.179*	.09	.013	.164*	.064
	(.050)	(.061)	(.004)	(.091)	(.069)	(.171)	(.098)	(.111)
Observations	53,737	53,890	54,142	53,122	54,142	53,609	53,383	53,383
R^2	.29	.29	.29	.29	.29	.29	.29	.29

Impact of Incentives on Nonincentive Subjects
Dependent Variable: Normalized End Line Score

	Year 1		Year 2	
	Science	Social Studies	Science	Social Studies
	A. Reduced-Form Impact			
Normalized baseline math score	.215***	.224***	.156***	.167***
	(.019)	(.018)	(.023)	(.024)
Normalized baseline language score	.209***	.289***	.212***	.189***
	(.019)	(.019)	(.023)	(.024)
Incentive school	.112**	.141***	.113**	.18***
	(.052)	(.048)	(.044)	(.050)
Observations	11,786	11,786	9,143	9,143
R^2	.26	.31	.19	.18

Group versus Individual Incentives
Dependent Variable: Normalized End-of-Year Test Score

	Year 1 on Year 0			Year 2 on Year 0		
	Combined (1)	Math (2)	Telugu (3)	Combined (4)	Math (5)	Telugu (6)
Individual incentive school	.156***	.184***	.130***	.283***	.329***	.239***
	(.050)	(.059)	(.045)	(.058)	(.067)	(.054)
Group incentive school	.141***	.175***	.107**	.154***	.216***	.092*
	(.050)	(.057)	(.047)	(.057)	(.068)	(.052)
F-statistic p-value (testing group incentive school = individual incentive school)	.765	.889	.610	.057	.160	.016
Observations	42,145	20,946	21,199	29,760	14,797	14,963
R^2	.31	.299	.332	.25	.25	.26

Impact of Inputs versus Incentives on Learning Outcomes
Dependent Variable: Normalized End-of-Year Test Score

	Year 1 on Year 0			Year 2 on Year 0		
	Combined (1)	Math (2)	Language (3)	Combined (4)	Math (5)	Language (6)
Normalized lagged score	.512***	.494***	.536***	.458***	.416***	.499***
	(.010)	(.012)	(.011)	(.012)	(.016)	(.012)
Incentives	.15***	.179***	.121***	.218***	.272***	.164***
	(.041)	(.048)	(.039)	(.049)	(.057)	(.046)
Inputs	.102***	.117***	.086**	.085*	.089*	.08*
	(.038)	(.042)	(.037)	(.046)	(.052)	(.044)
F-statistic p-value (inputs = incentives)	.178	.135	.298	.003	.000	.044
Observations	69,157	34,376	34,781	49,503	24,628	24,875
R^2	.30	.29	.32	.225	.226	.239

Outline

Financial Incentives

- Muralidharan & Sundararaman (JPE 2011) *Teacher Performance Pay: Experimental Evidence from India*
- Duflo, Hanna & Ryan (AER 2012) *Incentives Work: Getting Teachers to Come to School*
- Khan, Khwaja & Olken (QJE 2016) *Tax Farming Redux: Experimental Evidence on Performance Pay for Tax Collectors*
- Duflo Greenstone Pande & Ryan (QJE 2013): *Truth-telling by Third-party Auditors and the Response of Polluting Firms: Experimental Evidence from India*

Duflo et al. 2012: Introduction

- Access to primary school has increased dramatically in low-income countries, but school quality hasn't
  - 65% of children in grades 2-5 in Indian government schools in 2006 couldn't read a simple paragraph (Pratham 2006)
  - 24% of teachers in India are absent in unannounced visits (Kremer et al 2005)
- This paper: Experiment and structural model of direct monitoring of para-teachers' attendance in India.
- Ambiguous effect on presence.
  - Standard labor supply model predicts more effort, but only if strong enough incentives
  - Incentives could crowd out intrinsic motivation (Benabou & Tirole 2006).
  - Teachers may stop working after reaching target income (Fehr & Goette 2007)

Duflo et al. 2012: Introduction

- Will presence increase learning?
  - Multitasking means incentives for presence could crowd out other dimensions of effort (Holmstrom & Milgrom 1991).
  - Incentives may demotalize teacher or reduce their intrinsic motivation to teach.
- But if the main reason people fon’t show up is the opportunity cost of being at the school and the marginal cost of teaching once you’re at the school is low, this might just work.

Duflo et al. 2012: Setting & Experiment

- The setting are rural nonformal education centers (NFEs) in Udaipur, Rajasthan, India.
- In september 2003 Seva Mandir, the operator chose 120 schools for the experiment.
  - In 60 schools the teachers got a camera and were told that one of the students had to take a photograph of the teacher with the children at the start and the end of the day. Cameras had a tamper-proof date & time function.
  - The other 60 schools are controls
- Teachers' base salary was Rs. 1,000 for at least 20 days of work per month.
- Treatment teachers got a Rs. 50 bonus for every day in excess of 20 days and a Rs. 50 fine for each day of the 20 that they skip. Fines capped at Rs. 500

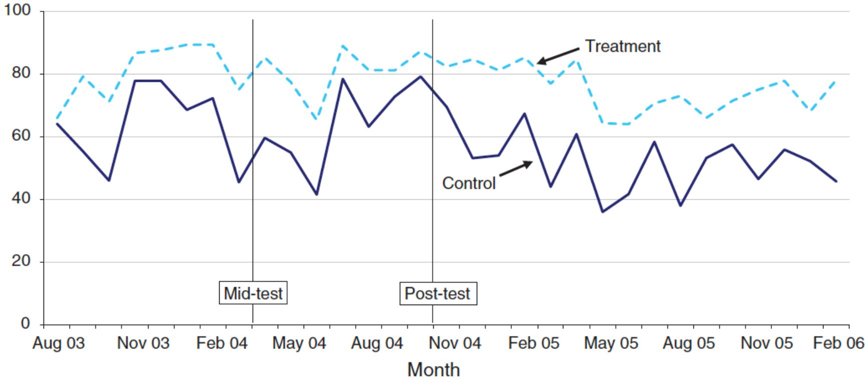
Duflo et al. 2012: Data

- Attendance data
  1. 1 random, unannounced visit to each school each month.
  2. Camera and payment data for treatment schools
- Additional data from random checks. How many children, whether anything on the board, whether the teacher was talking to the children, and roll call.
- 3 basic competency exams.Oral exams testing simple math, basic Hindi vocabulary. Written exam testing addition, multiplication, ability to construct sentences, and reading comprehension.
  1. a pretest in August 2003
  2. a mid-test in April 2004
  3. a post-test in September 2004

Table 1—Baseline Data

	Treatment (1)	Control (2)	Difference (3)
Panel A. Teacher attendance			
School open	0.66	0.64	0.02
			(0.11)
	41	39	80
Panel B. Student participation (random check)			
Number of students present	17.71	15.92	1.78
			(2.31)
	27	25	52
Panel C. Teacher qualifications			
Teacher test scores	34.99	33.54	1.44
			(2.02)
	53	54	107
Panel D. Teacher performance measures (random check)			
Percentage of children sitting within classroom	0.83	0.84	0.00
			(0.09)
	27	25	52
Percent of teachers interacting with students	0.78	0.72	0.06
			(0.12)
	27	25	52
Blackboards utilized	0.85	0.89	−0.04
			(0.11)
	20	19	39
F-stat (1,110)			1.21
p-value			(0.27)
Panel E. Baseline test scores			
Took written exam	0.17	0.19	−0.02
			(0.04)
	1,136	1,094	2,230
Total score on oral exam	−0.08	0.00	−0.08
			(0.07)
	940	888	1,828
Total score on written exam	0.16	0.00	0.16
			(0.19)
	196	206	402

Duflo et al. 2012: Attendance Increased

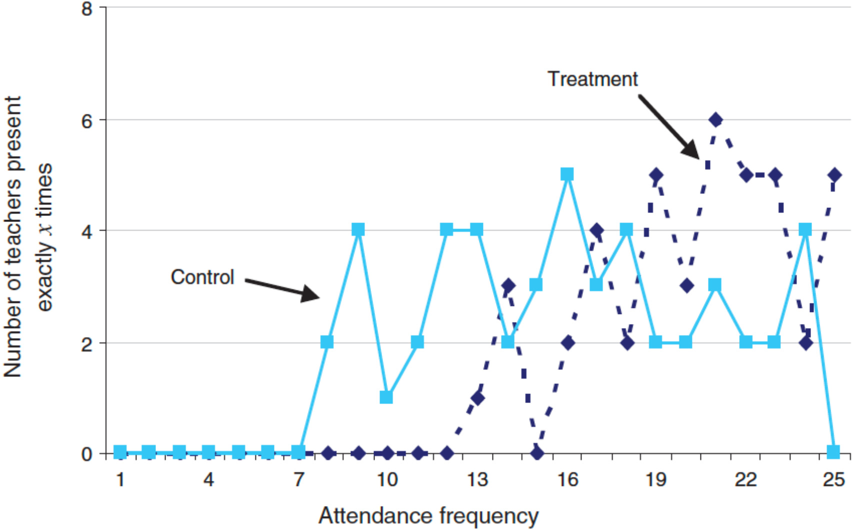


Duflo et al. 2012: Attendance Increased

Table 2—Teacher Attendance

September 2003–February 2006			Difference between treatment and control schools		
Treatment (1)	Control (2)	Diff (3)	Until mid-test (4)	Mid- to post-test (5)	After post-test (6)
Panel A. All teachers					
0.79	0.58	0.21	0.20	0.17	0.23
		(0.03)	(0.04)	(0.04)	(0.04)
1,575	1,496	3,071	882	660	1,529
Panel B. Teachers with above median test scores					
0.78	0.63	0.15	0.15	0.15	0.14
		(0.04)	(0.05)	(0.05)	(0.06)
843	702	1,545	423	327	795
Panel C. Teachers with below median test scores					
0.78	0.53	0.24	0.21	0.14	0.32
		(0.04)	(0.05)	(0.06)	(0.06)
625	757	1,382	412	300	670

Duflo et al. 2012: Attendance Increased



Duflo et al. 2012: Financial Incentives

- People in the treatment group got both financial incentives and monitoring, so difficult to disentangle the two
- The cap of Rs. 500 on the fine makes the incentive scheme non-linear permiting an assessment of the financial incentives independent of the monitoring as follows:
  - Imagine a teacher who was sick a lot one month and missed most of the first 20 days of school. Assume on day 21 he has worked 5 days and has 5 days to go. Even if he works all 5 days, he will earn Rs. 500, the same as if he works none. At the start of the next month the clock resets, so he has an incentive to start working again.
  - Now imagine a teacher who has worked 10 days by the 21st day of the month. She earns Rs. 50 for every day she works. No different before or after the end of the month.

Duflo et al. 2012: Financial Incentives

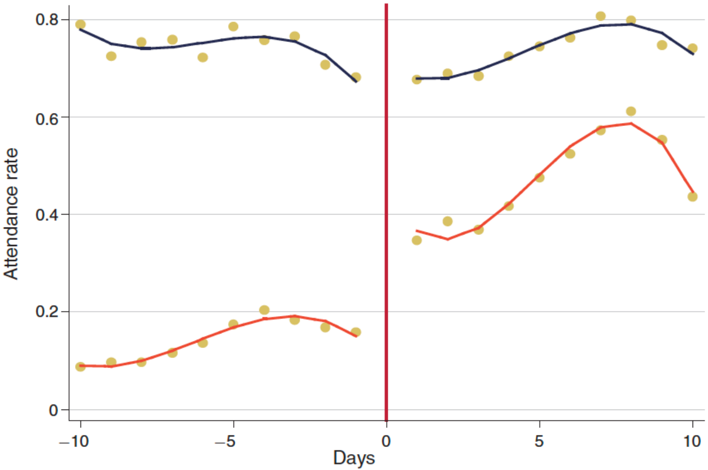


FIGURE 3. RDD REPRESENTATION OF TEACHER ATTENDANCE AT THE START AND END OF THE MONTH

Notes: The top lines represent the months in which the teacher is in the money, while the bottom lines represent the months in which the teacher is not in the money. The estimation includes a third-order polynomial of days on the left and right side of the change of month.

Duflo et al. 2012: Financial Incentives

- For teachers in the treatment group. create a dataset of attendance records around the end of the month. The last day of a month and the first day of the next month form a pair m
- $Work_{itm}$ is a dummy for working in day t of pair m

$$
\begin{aligned}
Work_{itm} = \alpha + \beta \mathbf{1}_{im}\left(d > 10\right) + \gamma Firstday_t \\
+ \lambda \mathbf{1}_{im}\left(d > 10\right) \times Firstday_t + v_i + \mu_m + \epsilon_{itm}
\end{aligned}
$$

where $\mathbf{1}_{im}\left(d > 10\right)$ is a dummy =1 in both t if the teacher is “in the money” and $Firstday_t$ indicates the first day of the month

Duflo et al. 2012: Financial Incentives

Table 3—Do Teachers Work More When They are "In the Money"?

	(1)	(2)	(3)	(4)
Beginning of month	0.19	0.12	0.46	0.39
	(0.05)	(0.06)	(0.04)	(0.03)
In the money	0.52	0.37	0.6	0.48
	(0.04)	(0.05)	(0.03)	(0.01)
Beginning of the month × in the money	−0.19	−0.12	−0.34	−0.3
	(0.06)	(0.06)	(0.04)	(0.02)
Observations	2,813	2,813	27,501	27,501
R^2	0.06	0.22	0.08	0.16
Sample	First and last day of month	First and last day of month	First ten and last ten days of month	First ten and last ten days of month
Third-order polynomial on days on each side			X	X
Teacher fixed effects		X		X
Month fixed effects		X		X
Clustered standard errors	X		X	

Duflo et al. 2012: Dynamic Labor Supply Model

- Teachers on day $t = \{1, \ldots, T_m\}$ of month m value consumption C_{tm} and leisure L_{tm}

$$U_{tm} = U\left(C_{tm}, L_{tm}\right) = \beta C_{tm}\left(\pi_m\right) + \left(\mu_{tm} - P\right) L_{tm}$$

  where P is nonpecuniary cost of missing work.
- Consumption depends on earned income π_m, β turns rupees of consumption into utility.
- L_{tm} is 1 if the teacher doesn't attend work, and zero otherwise.
- Leisure coefficient has deterministic and stochastic parts

$$\mu_{tm} = \mu + \epsilon_{tm}$$

  where ϵ_{tm} is assumed to be normal.

Duflo et al. 2012: Dynamic Labor Supply Model

- Not attending school has two costs: P and a probability $p_m(t, d)$ of being fired that depends on the number of days worked d by time t in month m. If they are fired, teachers get F, their outside option.
- Income in the treatment group is

$$\pi_m = 500 + 50 \max\{0, d_{m-1} - 10\}$$

while in the control group π_m is Rs. 1000.

- Control group has simple binary choice. Bellman equation on every day except last day of the month:

$$V_m(t, d; \epsilon_{tm}) = p_m(t, d) F + [1 - p_m(t, d)] \times \max\{\mu - P + \epsilon_{tm} + EV_m(t + 1, d; \epsilon_{t,m+1}), EV_m(t + 1, d + 1; \epsilon_{t,m+1})\}$$

Duflo et al. 2012: Dynamic Labor Supply Model

- Treatment group have a very different problem to solve since they face incentives for attendance.
- In periods $t < T_m$

$$\begin{aligned}V_m(t, d; \epsilon_{tm}) = p_m(t, d) + (1 - p_m(t, d)) \times \\ \max\{\mu - P + \epsilon_{tm} + EV_m(t+1, d; \epsilon_{t,m+1}) \\ , EV_m(t+1, d+1; \epsilon_{t,m+1})\}\end{aligned}$$

- In period T_m

$$\begin{aligned}V_m(T_m, d; \epsilon_{T_m,m}) = p_m(T_m, d) F + [1 - p_m(T_m, d)] \times \\ \max\{\mu - \bar{P} + \epsilon_{T_m,m} + \beta\pi(d) \\ + EV_{m+1}(1, 0; \epsilon_{t,m+1}) \\ , \beta\pi(d+1) + EV_{m+1}(1, 0; \epsilon_{t,m+1})\}\end{aligned}$$

Duflo et al. 2012: Estimation

- In period T_m, EV_{m+1} doesn't depend on action in T_m so we can solve the model backwards.
- Need to make some assumptions about μ and the distribution of ϵ
- In the data noone ever gets fired, so assume that teachers perceive $p_m(t,d) = 0$
- Model 1: iid errors. Simplest case. In period $t < T$

$$\begin{aligned}
\mathbb{P}(work; t, d, \theta) &= \mathbb{P}(\mu + \epsilon_{tm} + EV(t+1, d) < EV(t+1, d+1)) \\
&= \mathbb{P}(\epsilon_{tm} < EV(t+1, d+1) - EV(t+1, d) - \mu) \\
&= \Phi(EV(t+1, d+1) - EV(t+1, d) - \mu)
\end{aligned}$$

Duflo et al. 2012: Estimation

- Each value function can be computed using backword recursion.
- Let w_{imt} be an indicator for working on day t in month m. Then the log likelihood is

$$LLH(\theta) = \sum_{i=1}^{N} \sum_{m=1}^{M_i} \sum_{t=1}^{T_m} \left[w_{imt} \mathbb{P}(work; t, d, \theta) + (1 - w_{imt}) (1 - \mathbb{P}(work, t, d, \theta)) \right]$$

- This likelihood is concave and can be evaluated quickly, no numerical integration is needed. Just need to evaluate it at many points.

Duflo et al. 2012: Estimation

- Now introduce some serial correlation in two ways.
- Approach 1: Serially correlated preference shocks

$$\mu_{mt} = \mu + w_{m,t-1}\gamma$$

- Now the likelihood is

$$LLH(\theta) = \sum_{i=1}^{N}\sum_{m=1}^{M_i}\sum_{t=1}^{T_m}\left[w_{imt}\mathbb{P}\left(work; t, d, \theta, w_{m,t-1}\right)\right.$$
$$\left. + \left(1 - w_{imt}\right)\left(1 - \mathbb{P}\left(work, t, d, \theta, w_{m,t-1}\right)\right)\right]$$

- Approach 2: Serially correlated cost shocks:

$$\epsilon_{mt} = \rho\epsilon_{m,t-1} + \nu_{mt}$$

- Can't estimate this by ML, need to use Method of Simulated Moments. Match sequences of attendance of length 5.

Duflo et al. 2012: Estimation

- Extend the above in 2 ways

1. Incorporate observables into μ. Use attendance in control group in same geographic block and teacher's score on the admission exam to shift μ
2. Relax assumption that the outside option is the same for everyone. Estimate fixed effects μ_i or random coefficients μ_{im} drawn from normal distribution or from a mixture of two normally distributed types.

Parameter	Model I (1)	Model II (2)	Model III (3)	Model IV (4)	Model V (5)	Model VI (6)	Model VII (7)	Model VIII (8)
β	0.049	0.027	0.055	0.057	0.013	0.017	0.017	0.016
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
μ_1	1.564		1.777	1.778	−0.428	−0.304	−0.160	−0.108
	(0.013)		(0.013)	(0.021)	(0.045)	(0.042)	(0.092)	(0.057)
ρ			0.422	0.412	0.449			
			(0.030)	(0.021)	(0.043)			
σ_1^2				0.043	0.007	0.252	0.418	0.235
				(0.012)	(0.019)	(0.015)	(0.052)	(0.028)
μ_2					1.781			
					(0.345)			
σ_2^2					0.050			
					(0.545)			
ρ					0.024			
					(0.007)			
Yesterday shifter						0.094	0.024	0.095
						(0.010)	(0.009)	(0.014)
Attendance								−0.132
								(0.095)
Test score								−0.005
								(0.002)
Heterogeneity	None	FE	None	RC	RC	RC	RC	RC
Three-day window	No	No	No	No	No	No	Yes	No

Duflo et al. 2012: Counterfactual Policies

- With the model we can do counterfactuals. Authors use model V.
- Find the cost minimizing combination of the bonus size and the threshold to get a bonus that yield a particular number of expected work days.

Expected days worked (1)	Bonus cutoff (2)	Bonus (3)	Expected cost (4)	Test score gain over control group (13 days) (5)
14	0	0	500	0.04
15	21	25	521	0.07
16	22	75	664	0.11
17	21	75	672	0.15
18	20	75	755	0.18
19	20	100	921	0.22
20	20	125	1,112	0.26
21	16	225	2,642	0.29
22	11	275	4,604	0.33

Duflo et al. 2012: Teacher performance

TABLE 6—TEACHER PERFORMANCE

	September 2003–February 2006			Difference between treatment and control schools		
	Treatment (1)	Control (2)	Diff. (3)	Until mid-test (4)	Mid- to post-test (5)	After post-test (6)
Percent of children sitting within classroom	0.72	0.73	−0.01	0.01	0.04	−0.01
			(0.01)	(0.89)	(0.03)	(0.02)
	1,239	867	2,106	643	408	983
Percent of teachers interacting with students	0.55	0.57	−0.02	−0.02	0.05	−0.04
			(0.02)	(0.04)	(0.05)	(0.03)
	1,239	867	2,106	643	480	983
Blackboards utilized	0.92	0.93	−0.01	−0.03	0.01	−0.01
			(0.01)	(0.02)	(0.02)	(0.02)
	990	708	1,698	613	472	613

Notes: Teacher Performance Measures from Random Checks include only schools that were open during the random check. Standard errors are clustered by school.

TABLE 7—CHILD ATTENDANCE

	September 2003–February 2006			Difference between treatment and control schools		
	Treatment (1)	Control (2)	Diff (3)	Until mid-test (4)	Mid- to post-test (5)	After post-test (6)
Panel A. Attendance conditional on school open						
Attendance of students present at pretest exam	0.46	0.46	0.01	0.02	0.03	0.00
			(0.03)	(0.03)	(0.04)	(0.03)
	23,495	16,280	39,775			
Attendance for children who did not leave NFE	0.62	0.58	0.04	0.02	0.04	0.05
			(0.03)	(0.03)	(0.04)	(0.03)
	12,956	10,737	23,693			
Panel B. Total instruction time (presence)						
Presence for students present at pretest exam	0.37	0.28	0.09	0.10	0.10	0.08
			(0.03)	(0.03)	(0.04)	(0.03)
	29,489	26,695	56,184			
Presence for student who did not leave NFE	0.50	0.36	0.13	0.10	0.13	0.15
			(0.03)	(0.04)	(0.05)	(0.04)
	16,274	17,247	33,521			

Duflo et al. 2012: Student Achievement

- Run treatment regressions of scores in mid- and end-term exams. Test scores are highly autocorrelated so gain lots of precision by controlling for pre-scores.

$$
\begin{aligned}
Score_{ijk} = {} & \beta_1 + \beta_2 Treat_j + \beta_3 Pre\_Writ_{ij} + \beta_r Oral\_Score_{ij} \\
& + \beta_5 Written\_Score_{ij} + \varepsilon_{ijk}
\end{aligned}
$$

  where Pre_Writ_{ij} is a dummy for taking the written test at baseline (they did either the written or oral test), $Oral\_Score_{ij}$ is the score on the oral exam (or 0 if did the written exam) and $Written\_Score_{ij}$ is the score on the written exam (or 0 if did the oral exam).

TABLE 9—ESTIMATION OF TREATMENT EFFECTS FOR THE MID- AND POST-TEST

Mid-test				Post-test			
Took written (1)	Math (2)	Lang. (3)	Total (4)	Took written (5)	Math (6)	Lang. (7)	Total (8)
Panel A. All children							
0.04	0.15	0.16	0.17	0.06	0.21	0.16	0.17
(0.03)	(0.07)	(0.06)	(0.06)	(0.04)	(0.12)	(0.08)	(0.09)
1,893	1,893	1,893	1,893	1,760	1,760	1,760	1,760
Panel B. With controls							
0.04	0.13	0.14	0.14	0.06	0.18	0.14	0.15
(0.03)	(0.07)	(0.06)	(0.06)	(0.04)	0.13	0.08	0.09
1,752	1,752	1,752	1,752	1,760	1,760	1,760	1,760
Panel C. Took pretest oral							
	0.14	0.13	0.15		0.2	0.13	0.16
	(0.08)	(0.06)	(0.07)		(0.14)	(0.09)	(0.10)
	1,550	1,550	1,550		1,454	1,454	1,454
Panel D. Took pretest written							
	0.19	0.28	0.25		0.28	0.28	0.25
	(0.12)	(0.11)	(0.11)		(0.18)	(0.11)	(0.12)
	343	343	343		306	306	306

Outline

Financial Incentives

- Muralidharan & Sundararaman (JPE 2011) *Teacher Performance Pay: Experimental Evidence from India*
- Duflo, Hanna & Ryan (AER 2012) *Incentives Work: Getting Teachers to Come to School*
- Khan, Khwaja & Olken (QJE 2016) *Tax Farming Redux: Experimental Evidence on Performance Pay for Tax Collectors*
- Duflo Greenstone Pande & Ryan (QJE 2013): *Truth-telling by Third-party Auditors and the Response of Polluting Firms: Experimental Evidence from India*

Khan et al 2016: Introduction

- Focus on a bureaucrat (tax inspector) who has to assess, enforce, and audit property taxes.
- One possibility: sell the right to collect taxes to the bureaucrat and then let the bureaucrat keep most/all of the revenue: "Tax Farming" common throughout history (Rome, France etc.)
- But this is a setting where the bureaucrat and the citizen might collude.
  - performance incentives affect division of rents without necessarily increasing revenue.
  - e.g. if collusion is costless, then performance pay increases bribes without increasing revenue since taxpayer now has to compensate the inspector for the foregone bonus.
- Conduct an experiment in Punjab, Pakistan to investigate these issues.

Khan et al 2016: Setting

- Punjab population >80 million. Very low property tax collection.
- Tax levied on the Gross Annual Rental Value (GARV) of the property. Determined by a formula with size of land and buildings as inputs.
- Different rates for owner-occupied and rental properties. And for residential and commercial. This is main way tax evasion happens.
- Tax administered in “circles”: geographic areas covering 2-10K houses.
  - Each circle has 3 officers: An “inspector” (boss) a “clerk” (records) and a “constable” (assists inspector)
  - Each year they send the taxpayer a bill.

Khan et al 2016: Model

- Taxpayer has true tax liability τ_i^*. Inspector knows τ_i^* but can choose to report $\tau_i < \tau_i^*$
- Inspector receives incentive payment $r\tau_i$
- Colluding to underreport is costly
  - taxpayer cost: $\alpha\left(\tau_i^* - \tau_i\right)$
  - inspector cost: $\beta\left(\tau_i^* - \tau_i\right)$
- Taxpayer and inspector Nash bargain over bribe b_i
- If they don't agree a bribe, the taxpayer gets $-\tau_i^*$ and the inspector gets $r\tau_i^*$
- If they agree, the taxpayer gets $-\tau_i - \alpha_i\left(\tau_i^* - \tau_i\right) - b_i$ and the inspector gets $r\tau_i - \beta\left(\tau_i^* - \tau_i\right) + b_i$

Khan et al 2016: Model

- Joint surplus is

$$\underbrace{\tau_i^* - \tau_i - \alpha_i\left(\tau_i^* - \tau_i\right) - b_i}_{\text{taxpayer}} + \underbrace{r\left(\tau_i - \tau_i^*\right) - \beta_i\left(\tau_i^* - \tau_i\right) + b_i}_{\text{inspector}}$$

$$= \quad -\tau_i\left(1 - \alpha_i - \beta_i - r\right) + \tau_i^*\left(1 - \alpha_i - \beta_i - r\right)$$

- Two cases

$$\tau_i = \begin{cases} 0 & \text{if } r + \alpha_i + \beta_i < 1 \\ \tau_i^* & \text{if } r + \alpha_i + \beta_i > 1 \end{cases}$$

- With bargaining weight γ_i on the taxpayer

$$b_i = \left[\left(\beta_i + r\right)\gamma_i + \left(1 - \gamma_i\right)\left(1 - \alpha_i\right)\right]\tau_i^*$$

Khan et al 2016: Model

- What happens to total revenue T? Denote $f(\alpha, \beta, \tau^*)$ joint dist of α, β, τ^*

$$\frac{dT}{dr} = \underset{r+\alpha+\beta=1, \tau^* \in (0,\infty)}{\int\int\int} \tau^* f(\alpha, \beta, \tau^*)\, d\alpha d\beta d\tau^*$$
$$= \underset{\alpha, \tau^*}{\int\int} \tau^* f(\alpha, 1-r-\alpha, \tau^*)\, d\alpha d\tau^*$$

- If we increase r the effect depends on how many people are on the margin between the two cases
- Simplifying assumptions to note
  - linearity
  - τ^* known, no effort by bureaucrat
  - outside option is τ^* so no extortion/overtaxation

Khan et al 2016: Experiment

- Treatment 1: *Revenue* based performance pay:

$$\text{Bonus}_c = \alpha_c \max\{\text{Revenue}_c - \text{Benchmark}_c, 0\}$$

- Benchmark calculated from 3-year averages of historical collection plus normal rate of increase.
- α_c was 40% for lowest 50% of circles, 30% between 50th and 75th percentiles, 20% at the top.
- Note incentive depends only on revenue, not whether it's more money from existing houses or finding new houses to bring into the tax net.
- Bonus divided 40%-30%-30% between inspector, constable & clerk.

Khan et al 2016: Experiment

- Treatment 2. *Revenue Plus* performance pay:
- Same as above, but also incentives to address multitasking
- Pay adjusted according to taxpayer satisfaction (survey of 21,000 households) and assessment accuracy $(1 - |\text{survey } GARV/\text{official } GARV|)$
- Circles ranked and divided into three equal-sized groups
- Top group got another bonus of 0.75$\times$base pay
- Bottom group lost 0.75$\times$base pay (subject to total experimental payments >0)

Khan et al 2016: Experiment

- Treatment 3. *Flexible bonus*:
- Bonuses analogous to private sector.
- Performance Evaluation Committee ranks the circles and divided into 3 groups.
- Same adjustments to payout as in Revenue Plus treatment
- Treatment 4: *Information only* in year 2. Same treatment (monitoring, reports, meetings etc) except no payments
- Treatment 5: *Supervisors performance pay* in year 2. Similar to Revenue treatment, but for the supervisors (only 26 treatments, 25 controls though)

Khan et al 2016: Experiment

Experimental Design

	Randomization		Implementation	
	Year 1	Year 2	Year 1	Year 2
Revenue	53	72	47	68
Revenue plus	54	74	48	68
Flexible bonus	54	73	49	67
Information	0	70	0	66
Control	322	194	338	213

Khan et al 2016: Measurement

- 2 main data sources
  1. Administrative data at the circle-level
  2. Survey data at property/taxpayer-level to measure accuracy of tax assessment, customer satisfaction and corruption.
- Create a measure of under/overtaxation

$$TaxGap = \frac{GARV_{\text{Inspector}} - GARV_{\text{Survey}}}{GARV_{\text{Inspector}} + GARV_{\text{Survey}}}$$

  sample mean is -0.10 suggesting undertaxation
- Use absolute value of $TaxGap$ as measure of inaccuracy (mean 0.34)
- Bribes are common: Respondents report average bribes of Rs.2000 (US$20) which $\sim$ 50% of reported property taxes paid

Khan et al 2016: Estimation

- Small amount of attrition (refuse to participate/transferred out) so use 2SLS: Instrument actual treatment status with randomization outcome

$$\ln Y_{cst} = \alpha_s + \beta Treatment_{cst} + \gamma \ln Y_{cs0} + \epsilon_{cst}$$

  where Y_{cst} is outcome in circle c in stratum s at time t. $Treatment_{cst}$ is continuous between 0 & 1 representing fraction of treated circle staff present in circle c in the last quarter of year t.
- For survey-based outcomes estimate

$$Y_{ics} = \alpha_s + \beta Treatment_{cs} + \epsilon_{ics}$$

	(1)	(2)	(3)	(4)	(5)	(6)
	Year 1			Year 2		
	Total	Current	Arrears	Total	Current	Arrears
Panel A: Main treatment						
Any treatment	0.091***	0.073***	0.152**	0.094***	0.091***	0.113
	(0.028)	(0.027)	(0.069)	(0.031)	(0.032)	(0.083)
Panel B: Subtreatments						
Revenue	0.118***	0.109***	0.134	0.129***	0.152***	0.005
	(0.035)	(0.034)	(0.099)	(0.043)	(0.044)	(0.133)
Revenue plus	0.080	0.086*	0.072	0.093**	0.081*	0.175
	(0.053)	(0.052)	(0.110)	(0.045)	(0.049)	(0.114)
Flexible bonus	0.071*	0.024	0.243**	0.056	0.035	0.148
	(0.038)	(0.035)	(0.098)	(0.041)	(0.042)	(0.108)
N	481	481	481	482	482	479
Mean of control group	15.671	15.379	14.030	15.745	15.518	13.915
Rev. vs. multitasking p	0.323	0.193	0.830	0.233	0.049	0.262
Objective vs. subjective p	0.530	0.090	0.212	0.220	0.084	0.634
Equality of schemes p	0.562	0.143	0.433	0.359	0.086	0.527
Joint significance p	0.004	0.010	0.073	0.012	0.005	0.305

	(1) Quality	(2) Satisfaction	(3) Inaccuracy	(4) Tax gap
Panel A: Main treatment				
Any treatment	−0.006	−0.011	0.004	0.007
	(0.022)	(0.022)	(0.012)	(0.022)
Panel B: Subtreatments				
Revenue	0.006	−0.006	0.002	−0.022
	(0.036)	(0.037)	(0.017)	(0.029)
Revenue plus	0.040	0.029	0.028*	0.015
	(0.026)	(0.027)	(0.016)	(0.032)
Flexible bonus	−0.060*	−0.053*	−0.016	0.029
	(0.031)	(0.032)	(0.018)	(0.031)
N	6050	6050	9870	9870
Sample	Phase 1	Phase 1	Full	Full
Mean of control group	0.538	0.555	0.339	−0.103
Rev. vs. multitasking p	0.683	0.876	0.813	0.159
Objective vs. subjective p	0.015	0.064	0.099	0.315
Equality of schemes p	0.014	0.059	0.090	0.344
Joint significance p	0.035	0.129	0.160	0.533

Khan et al 2016: Collusion

- The model suggests that the incentive payments will alter the nature of collusion

1. How many properties get revalued? i.e. how often does collusion break down?
2. How does collusion change? if collusion breaks down, tax should go up and bribes should go down. If collusion doesn't break down bribes + tax should go up. How shared depends on γ
3. When does collusion break down? Which properties are the ones the inspectors reassess?

Impacts on Number of Reassessed Properties

	(1) Total number of section 9 properties added to tax rolls in treatment period	(2) Number of new properties added to tax rolls in treatment period	(3) Number of reassessed properties added to tax rolls in treatment period
Treatment	83.0*	74.0**	9.0
	(45.27)	(34.39)	(22.35)
N	234	234	234
Mean of control group	96.7	36.7	60.0

Impacts on Tax Payments and Corruption, by Reassessed Status

	(1) Self-reported tax payment	(2) Bribe payment	(3) Frequency of bribe payment	(4) Perception of corruption
Panel A: General population sample only				
Treatment	−62.81	594.1*	0.2021**	0.0113
	(264.7)	(341.7)	(0.0951)	(0.0254)
N	11,586	5,993	4,802	6,050
Mean of control group	4,069.425	1,874.542	0.683	0.644
Panel B: Reassessed and general population sample				
Reassessed * treatment	1,884*	−557.4	−0.1592*	−0.0031
	(1,083)	(380.1)	(0.0942)	(0.0221)
Reassessed	2,763***	−66.38	0.0137	−0.0191*
	(572.9)	(177.5)	(0.0403)	(0.0107)
N	16,353	8,207	6,993	8,268
Sample	Full	Phase 1	Phase 1	Phase 1
Mean of control group in gen. pop. sample	3928.252	1874.542	0.683	0.644

Selection Effects on Reassessments

	(1) GARV	(2) Number of floors	(3) Last renovation was ≤ 2 years ago	(4) Land area (sq. feet)	(5) Total covered area (sq. feet)	(6) Main Road	(7) Tax Category	(8) Percent of property commercial	(9) Percent of property commercial and rented	(10) Tax Liability
Reassess * treatment	20,137.796	0.002	−0.005	−32.599	852.092	−0.002	−0.226**	0.018	0.075**	3,897.980
	(16,187.550)	(0.050)	(0.020)	(82.473)	(771.516)	(0.048)	(0.088)	(0.037)	(0.029)	(3,539.474)
Reassess	24,683.609***	0.078***	0.094***	37.396	−156.619	0.064***	0.212***	0.217***	0.176***	5,503.481***
	(7,944.915)	(0.026)	(0.011)	(57.199)	(379.299)	(0.024)	(0.044)	(0.019)	(0.015)	(1,754.013)
N	15,090	16,352	16,354	16,352	16,352	16,352	15,090	16,226	16,227	15,090
Mean of control group in gen. pop. sample	36,808.77	1.57	0.02	301.13	2,779.82	0.46	3.78	0.35	0.17	6,642.00

Notes. Property-level 2SLS regressions. Specifications follow equation (12) of the main text and includes a control for whether the response came from the short version of the questionnaire. This table looks at selection effects on property characteristics. The characteristics labeled components of GARV are those that directly enter into the formula used to calculate GARV. Tax category (column (7)) is seven-tiered categorical variable with 7 being the most expensive tax bracket and 1 being the cheapest. Standard errors are clustered by robust partition, the partition of circles such that all circles that merged or split with each other are included within the same partition. * $p<.10$, ** $p<.05$, *** $p<0.01$.

Selection Effects on Reassessments

	(1) Approximate age of owner	(2) Owner's level of education	(3) Per capita wages	(4) Predicted expenditure given assets	(5) Connected to politician	(6) Connected to politician, government, police
Reassess * treatment	−0.348	−0.523*	−821.749	110.798	0.021*	0.005
	(0.799)	(0.317)	(1,078.191)	(213.234)	(0.012)	(0.027)
Reassess	−0.656*	0.303*	13.126	−94.529	−0.013**	0.005
	(0.398)	(0.157)	(510.006)	(122.380)	(0.006)	(0.014)
N	13,406	16,254	13,765	13,954	16,354	16,354
Mean of control group in gen. pop. sample	50.70	9.19	16,281.55	6,292.58	0.05	0.36

Khan et al 2016: Results

- Evidence broadly consistent with model:
  - Inspectors do reassess houses and bring in new ones
  - where reassessed, more likely to pay more tax, pay less bribes
  - Suggestive evidence it's richer, more powerful people who get reassessed
- Was this worthwhile for the benefit? We can do a cost-benefit assessment

Khan et al 2016: Cost-Benefit

Cost-Effectiveness of Incentives

	(1) Additional revenue	(2) Cost of incentives	(3) ROI
Panel A: Information in controls			
Any treatment	124,961,461	108,387,160	15.29
Revenue	50,578,024	37,349,784	35.42
Revenue plus	40,671,290	35,549,342	14.41
Flexible bonus	30,555,313	35,488,035	−13.90
Panel B: Information out of controls			
Any treatment	140,973,016	108,387,160	30.06
Revenue	56,269,064	37,349,784	50.65
Revenue plus	45,539,845	35,549,342	28.10
Flexible bonus	35,571,720	35,488,035	0.24

Outline

Financial Incentives

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- Duflo Greenstone Pande & Ryan (QJE 2013): *Truth-telling by Third-party Auditors and the Response of Polluting Firms: Experimental Evidence from India*

Duflo et al 2013: Introduction

- Third-party audits are a common mechanism to monitor compliance with regulations
  - financial accounting of firms
  - food safety, health care, flowers etc in consumer & commodity markets
  - environmental regulation
- Usually, the auditor is chosen by, pair by, and reports to the audited firm.
- Creates a conflict of interest: Report the truth or report what is beneficial for your client?
- Conduct an experiment in India to investigate whether this can be overcome.

Duflo et al 2013: Setting

- Study conducted in Gujarat: 5% of India's population but 9% of manufacturing employment and 19% of output
- 3 of the 5 most polluted rivers in India are in Gujarat. Air pollution dangerous for human health in the cities.
- Gujarat Pollution Control Board (GPCB) has a stringent regulatory framework for pollution control.
- 2 Main instruments to enforce regulations
    1. Inspections (Duflo et al 2018 next week)
    2. third-party environmental audits.

Duflo et al 2013: Audits

- Plants with high pollution potential must submit a yearly environmental audit
- Auditors
  - visit each plant for about one day in each of three seasons of the year.
  - Observe environmental management practices and measure pollution.
  - Compile findings into a standardized format.
  - Submit report to the plant and to GPCB by February 15 of the following year.
- Auditors:
  - audit at most 15 plants a year and audit a plant at most 3 years in a row.
  - Auditors with inaccurate reports are liable to be decertified.
- Firms
  - no audit report $\rightarrow$ can have water & electricity cut off.
  - Reports showing noncompliance with regs $\rightarrow$can be closed or fined (fines happen often)

Duflo et al 2013: Experiment

- Work with GPCB to implement a modified auditing system
- 663 small/medium scale plants in Ahmedabad & Surat selected
- Just before 2009 audits, randomly assigned half to audit treatment
- Then collect detailed data on each plant to determine eligibility $\rightarrow$ 473 plants, of which 49.2% in the treatment group.
- Treatment plants assigned to the audit treatment in year 1 (2009) and year 2 (2010)
- Notified by letter from GPCB that their audit rules had changed.

Duflo et al 2013: Treatment

- Treatment with 3 components

1. *Assignment and Fixed Pay*. Auditors randomly assigned to treatment plants and paid a flat fee (Rs. 45,000)
2. *Backchecks*. Randomly selected 20% of readings to be redone by technical staff from engineering colleges roughly 10 days after auditor's visit.
3. *Incentive Pay.* In year 2 added explicit incentive pay for auditor accuracy.
   3.1 Calculate δ_p: difference between audit and backcheck for pollutant p. Average it: $\Delta_{\text{Water}} = \sum_{p \in \text{Water}} \delta_p$, $\Delta_{\text{Air}} = \sum_{p \in \text{Air}} \delta_p$, $\Delta_{\text{All}} = \left(\Delta_{\text{Water}} + \Delta_{\text{Air}}\right)/2$
   3.2 Rank auditors: Least accurate quartile get Rs. 35,000 per audit. Next least accurate quartile get Rs. 40,000. Most accurate half get Rs. 52,500 (NB average pay unchanged)

Submission of Audit Reports

	(1) Treatment	(2) Control	(3) Difference
Panel A: 2009			
Audit submitted	163	177	
Total plants	233	240	
Share submitted	0.70	0.74	−0.038
			(0.041)
Panel B: 2010			
Audit submitted	164	153	
Total plants	233	240	
Share submitted	0.70	0.64	0.066
			(0.043)

	(1) Treatment	(2) Control	(3) Difference
Panel A: Plant characteristics			
Capital investment INR 50 m to 100 m (= 1)	0.092	0.14	−0.051
	[0.29]	[0.35]	(0.033)
Located in industrial estate (= 1)	0.57	0.53	0.042
	[0.50]	[0.50]	(0.051)
Textiles (= 1)	0.88	0.93	−0.030
	[0.33]	[0.26]	(0.025)
Effluent to common treatment (= 1)	0.41	0.35	0.078
	[0.49]	[0.48]	(0.049)
Wastewater generated (kl/day)	420.5	394.6	35.4
	[315.9]	[323.4]	(31.6)
Lignite used as fuel (= 1)	0.71	0.77	−0.024
	[0.45]	[0.42]	(0.029)
Diesel used as fuel (= 1)	0.29	0.25	0.038
	[0.45]	[0.43]	(0.046)
Air emissions from flue gas (= 1)	0.85	0.87	−0.0095
	[0.35]	[0.33]	(0.016)
Air emissions from boiler (= 1)	0.93	0.92	0.026
	[0.26]	[0.27]	(0.027)
Bag filter installed (= 1)	0.24	0.34	−0.10**
	[0.43]	[0.47]	(0.046)
Cyclone installed (= 1)	0.087	0.079	0.0010
	[0.28]	[0.27]	(0.027)
Scrubber installed (= 1)	0.41	0.41	−0.018
	[0.49]	[0.49]	(0.050)

Panel B: Regulatory interactions in year prior to study			
Whether audit submitted (= 1)	0.82	0.81	0.022
	[0.38]	[0.39]	(0.038)
Any equipment mandated (= 1)	0.42	0.49	−0.047
	[0.50]	[0.50]	(0.047)
Any inspection conducted (= 1)	0.79	0.78	0.016
	[0.41]	[0.42]	(0.042)
Any citation issued (= 1)	0.28	0.24	0.035
	[0.45]	[0.43]	(0.045)
Any water citation issued (= 1)	0.12	0.12	−0.0031
	[0.33]	[0.33]	(0.034)
Any air citation issued (= 1)	0.027	0.0052	0.021*
	[0.16]	[0.072]	(0.013)
Any utility disconnection (= 1)	0.098	0.094	0.0029
	[0.30]	[0.29]	(0.031)
Any bank guarantee posted (= 1)	0.033	0.026	0.0045
	[0.18]	[0.16]	(0.017)
Observations	184	191	

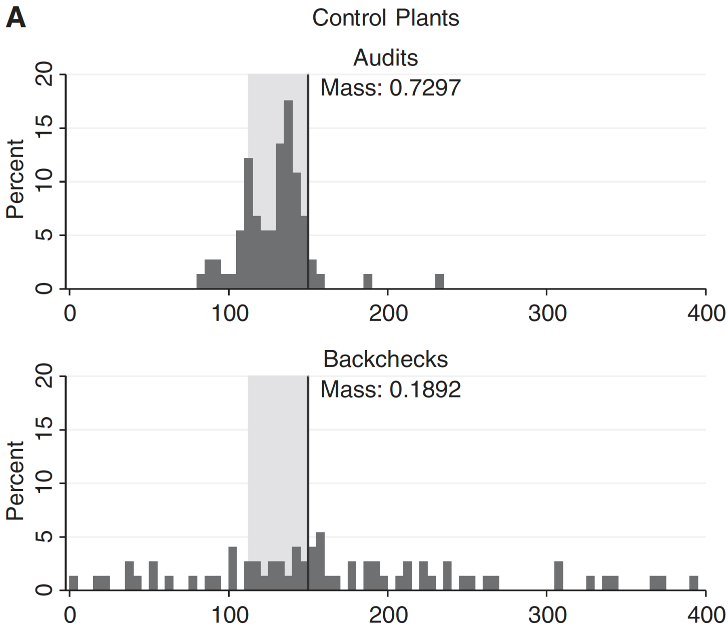
Duflo et al 2013: Misreporting in Control Group

- Do auditors misreport?

1. Compare distribution of pollution scores in audit reports to backcheck data
2. Regression version. Stack data from audit and backchecks and run

$$\mathbf{1}\left\{\text{Compliant}\right\}_{ij} = \beta_1 \mathbf{1}\left\{\text{AuditReport}\right\} + \alpha_r + \epsilon_{ij}$$

where $\mathbf{1}\left\{\text{Compliant}\right\}_{ij}$ denotes pollutant i at plant j being between 75% and 100% of the regulatory standard.


A
Control Plants
Audits
Mass: 0.7297
Percent
0
5
10
15
20
0
100
200
300
400
Backchecks
Mass: 0.1892
Percent
0
5
10
15
20
0
100
200
300
400

Compliance in Audits Relative to Backchecks, Control Group Only

	(1) All pollutants	(2) Water pollutants	(3) Air pollutants
Panel A: Dependent variable: Narrow compliance (dummy for pollutant between 75% and 100% of regulatory standard)			
Audit report (= 1)	0.270***	0.297***	0.230***
	(0.025)	(0.034)	(0.033)
Control mean in backchecks	0.097	0.110	0.077
Panel B: Dependent variable: Compliance (dummy for pollutant at or below regulatory standard)			
Audit report (= 1)	0.288***	0.273***	0.311***
	(0.023)	(0.033)	(0.032)
Control mean in backchecks	0.557	0.538	0.586
Observations	1132	688	444

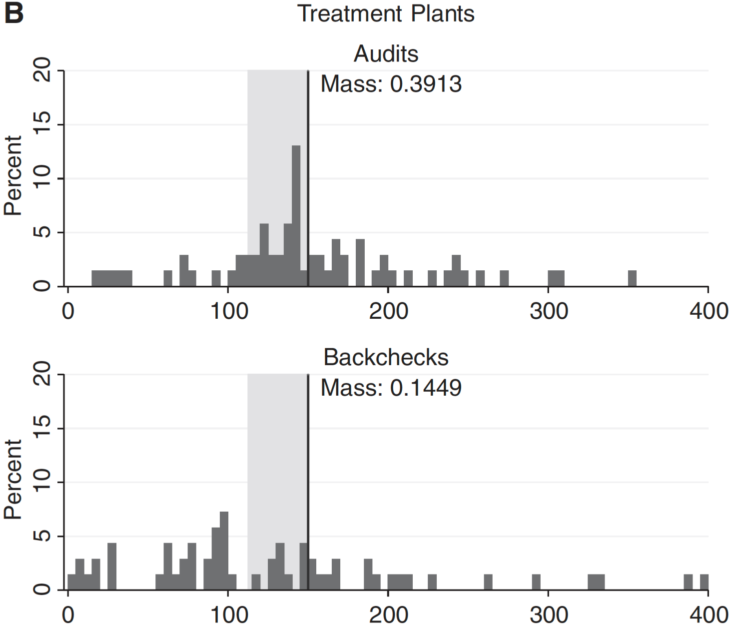
Duflo et al 2013: Treatment Effects on Misreporting

- Does the treatment improve auditors' reporting?

1. Compare distribution of pollution scores in audit reports and backcheck data
2. Run difference in difference regression

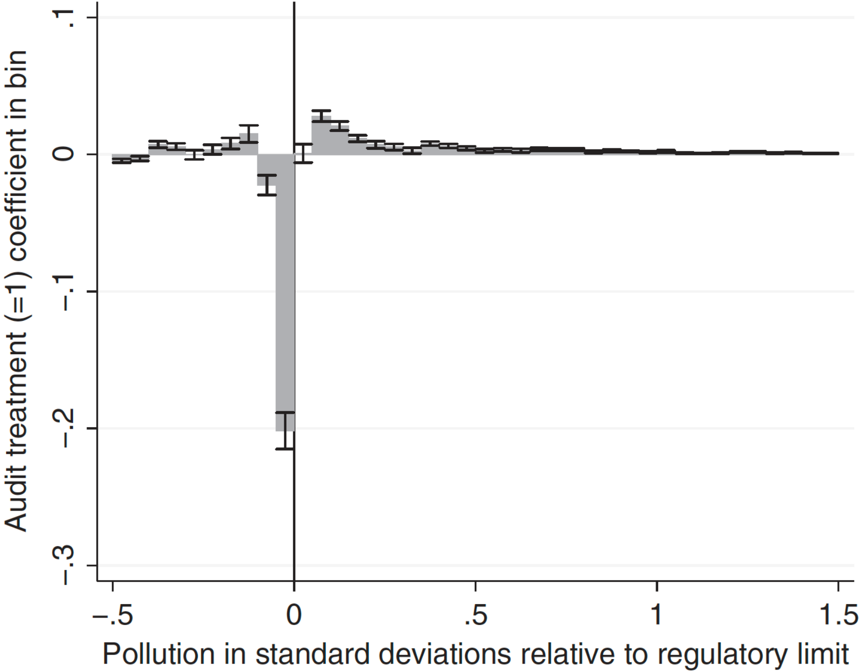
$$\mathbf{1}\{\text{Compliant}\}_{ij} = \beta_1 \mathbf{1}\{\text{AuditReport}\} \times T_j + \beta_2 \mathbf{1}\{\text{AuditReport}\} + \beta_3 T_j + \alpha_r + \epsilon_{ij}$$

B


Treatment Plants
Audits
Mass: 0.3913
Percent
0
5
10
15
20
0
100
200
300
400
Backchecks
Mass: 0.1449
Percent
0
5
10
15
20
0
100
200
300
400

Compliance in Audits Relative to Backchecks by Treatment Status

	(1) All pollutants	(2) Water pollutants	(3) Air pollutants
Panel A: Dependent variable: Narrow compliance (dummy for pollutant between 75% and 100% of regulatory standard)			
Audit report × Treatment group	–0.185***	–0.212***	–0.143***
	(0.034)	(0.044)	(0.046)
Audit report (= 1)	0.270***	0.297***	0.230***
	(0.025)	(0.034)	(0.033)
Treatment group (= 1)	–0.0034	–0.013	0.011
	(0.0176)	(0.025)	(0.024)
Control mean in backchecks	0.097	0.110	0.077
Panel B: Dependent variable: Compliance (dummy for pollutant at or below regulatory standard)			
Audit report × Treatment group	–0.234***	–0.166***	–0.345***
	(0.039)	(0.050)	(0.056)
Audit report (= 1)	0.288***	0.273***	0.311***
	(0.023)	(0.033)	(0.032)
Treatment group (= 1)	0.058*	0.0075	0.145***
	(0.034)	(0.0477)	(0.041)
Control mean in backchecks	0.557	0.538	0.586
Observations	2236	1378	858


Audit treatment (=1) coefficient in bin
.1
0
−.1
−.2
−.3
−.5
0
.5
1
1.5
Pollution in standard deviations relative to regulatory limit

Duflo et al 2013: Plant Responses

- Do plants reduce pollution now that the auditors tell the truth?
- In endline survey (after year 2) gather new pollution measurements from all plants, not just those who submit audit reports
- Estimate effects on pollution

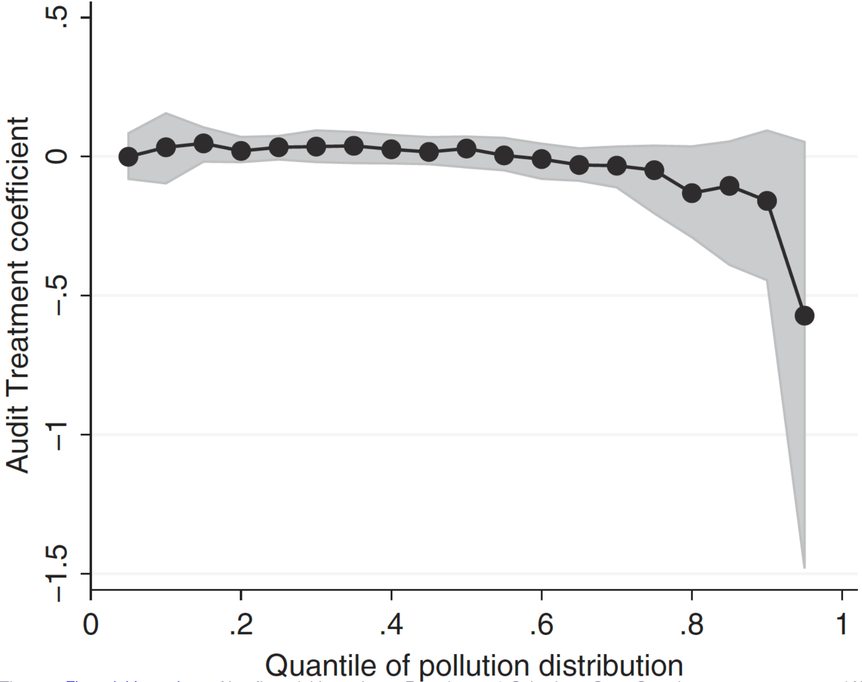
$$y_{ij} = \alpha_r + \beta T_j + \epsilon_{ij}$$

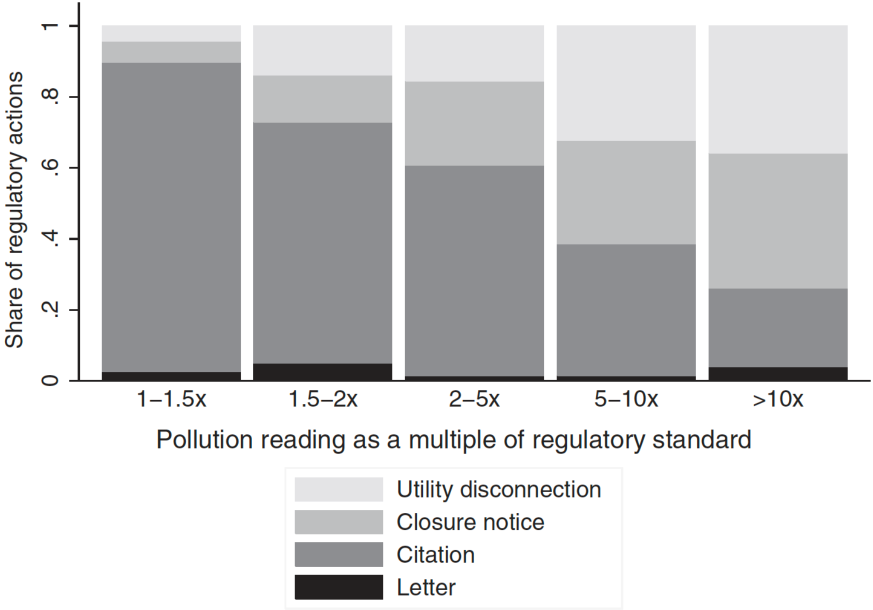
- Also estimate quantile regressions:

$$Q_{y_{ij}|X_j}(\tau) = \beta T_j + \alpha_r + \epsilon_{ij}$$

Endline Pollutant Concentrations on Treatment Status

	(1) All pollutants	(2) Water pollutants	(3) Air pollutants
Panel A: Dependent variable: Level of pollutant in endline survey, all pollutants (standard deviations relative to backcheck mean)			
Audit treatment assigned (= 1)	–0.211**	–0.300*	–0.053
	(0.099)	(0.159)	(0.057)
Control mean	0.076	0.114	0.022
Observations	1439	860	579
Panel B: Dependent variable: Compliance (dummy for pollutant in endline survey at or below regulatory standard)			
Audit treatment assigned (=1)	0.027	0.039	0.002
	(0.027)	(0.039)	(0.028)
Control mean	0.573	0.516	0.656
Observations	1,439	860	579


Audit Treatment coefficient
.5
0
−.5
−1
−1.5
0
.2
.4
.6
.8
1
Quantile of pollution distribution



Share of regulatory actions
0
.2
.4
.6
.8
1
1–1.5x
1.5–2x
2–5x
5–10x
>10x
Pollution reading as a multiple of regulatory standard
Utility disconnection
Closure notice
Citation
Letter

Outline

Theory

Financial Incentives

Non-financial Incentives

Recruitment & Selection

Open Questions

Outline

Non-financial Incentives

- Ashraf Bandiera & Jack (JPubE 2014) *No Margin, No Mission? A Field Experiment on Incentives for Public Service Delivery*
- Duflo, Greenstone, Pande & Ryan (WP 2017): *The Value of Regulatory Discretion: Estimates from Environmental Inspections in India*
- Khan, Khwaja & Olken (WP 2018) *Making Moves Matter: Experimental Evidence on Incentivizing Bureaucrats through Performance-Based Postings*

Ashraf et al 2014: Introduction

- Evidence on performance pay for pro-social tasks is mixed (teachers papers)
- Theory says that intrinsic motivation will interact with extrinsic incentives (Benabou & Tirole, Besley & Ghatak)
- Design an experiment to compare effects of intrinsic and extrinsic motivation and their interaction.

Ashraf et al 2014: Context

- Work with Society for Family Health (SFH), a public health NGO working in Lusaka, Zambia
- SFH program to distribute female condoms through hair salons. Study ran 12/09-12/10
- Hair salons:
  - familiarity between stylists and clients permits targeting and, duting styling, a captive audience to explain benefits to.
  - Many many salons throughout salons: census found 2500 for a population of $\sim$2 million people in Lusaka
- Agents have to exert effort to diffuse information
  - about HIV
  - about the product, which is unfamiliar to many

Ashraf et al 2014: Rrecruitment

1. SFH attempts to invite 1,222 stylists to a 1-day training program
2. 981 can be reached and get the letter
3. 771 accept and do the training
4. 747 join up. They get
   4.1 12 packs at a subsidized price of 2,000 ZMK (US$.033 per pack)
   4.2 a range of promotional materials
   4.3 access to more packs at 500 ZMK per pack
   4.4 Retail price set at 500 ZMK per pack, same as male condoms

Summary statistics.

	Mean	Median	Min	Max	sd	N
Panel A: outcome variables						
Packs sold (restocked)	9.01	0.00	0.00	216.00	18.08	771
Packs sold (calculated)	13.90	12.00	0.00	148.00	15.77	771
Promoter attention	2.52	2.56	0.00	3.00	0.30	725
Promoter interest	2.15	2.12	0.00	3.00	0.38	697
Logbook filled	0.47	0.50	0.00	1.00	0.23	725
Total displays (promotional material)	2.26	2.20	0.00	8.00	0.90	726
Panel B: control variables						
Salon is a barbershop (0–1)	0.44	0.00	0.00	1.00	0.50	771
Salon is near a bar (0–1)	0.88	1.00	0.00	1.00	0.32	770
Salon size (number of employees)	1.75	2.00	1.00	9.00	0.99	770
Number of trained salons in the same area	4.46	3.00	1.00	30.00	5.06	173
Stylist sells other products in salon (0–1)	0.27	0.00	0.00	1.00	0.45	771
Stylist is in bottom quartile of asset distribution (0–1)	0.21	0.00	0.00	1.00	0.40	771
Stylist's socio-economic status is low (0–1)	0.19	0.00	0.00	1.00	0.40	771
Stylist's dictator-game donation (Kwacha)	5728.94	5000.00	0.00	40,000.00	3744.67	767
Stylist's reported work motivation is intrinsic (0–1)	0.58	1.00	0.00	1.00	0.49	771
Stylist's religion is Catholic (0–1)	0.23	0.00	0.00	1.00	0.42	771
Panel C: other descriptors						
Monthly income of the salon (Kwacha)	332,569	250,000	0	10,000,000	572,050	700
Stylist can read and write in at least one language (0–1)	0.94	1.00	0.00	1.00	0.23	771
Stylist can read and write in English (0–1)	0.85	1.00	0.00	1.00	0.35	770
Total number of products sold	0.47	0.00	0.00	6.00	0.94	771

Ashraf et al 2014: Treatments

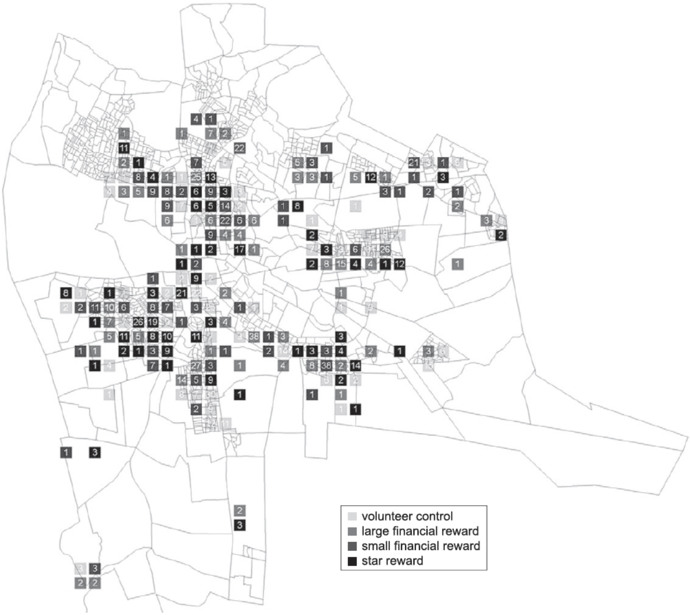
- 4 treatment groups

1. *Control* group recruited as volunteers. No incentives
2. *Large financial-margin* treatment receive 450 ZMK for each pack sold, a 90% margin over retail
3. *Small financial-margin* treatment get 50 ZMK for each pack sold, a 10% margin.
4. *Non-financial reward (star)* treatment. Get a thermometer display and each sale is rewarded with a star stamped on the thermometer. Stylists told if they sell >216 packs they will get a certificate at a ceremony

- Rewards paid only on restocks, not the original 12 packs.

Ashraf et al 2014: Randomization

- Treatment is at the neighborhood level. All salons in each neighborhood in the same treatment arm
- Census of hair salons with GPS coordinates and characteristics
- Make a grid: 650m x 650m cells with 75m buffers on all sides.
- grid cells are the unit of randomization
- salons in the buffer zones not invited to join
- Final sample: 205 cells with 1222 hair salons in them
- Balance randomization on variables likely to affect sales (type, size, location)
  - do 1,000 random draws
  - for each draw calculate the t-stats on all the differences in the attributes.
  - the maximum t-stat is this draw's score
  - choose the draw with the lowest score: "minmax t-stat method" (see Bruhn & McKenzie 2009 for discussion of this and other balancing methods)

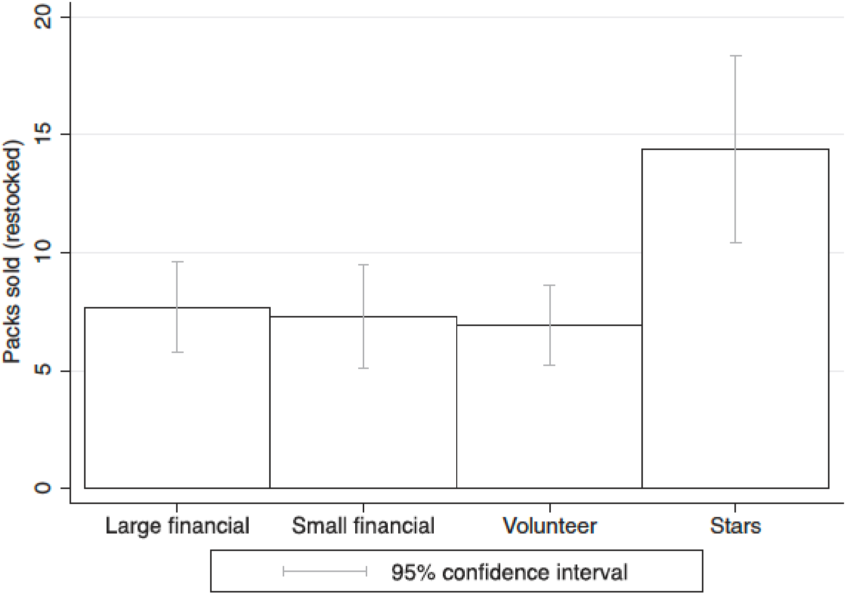

volunteer control
large financial reward
small financial reward
star reward

Ashraf et al 2014: Estimation

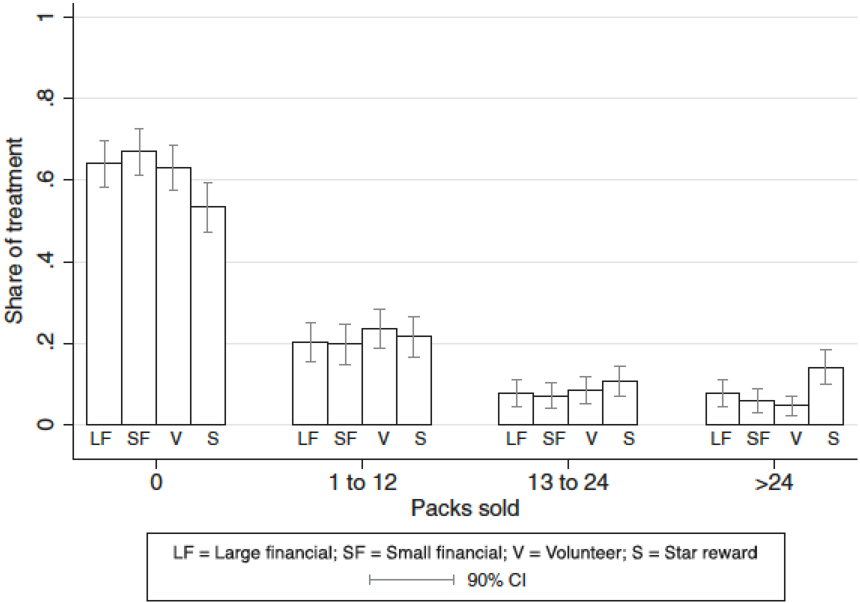
- To evaluate impact on sales, estimate

$$y_{ic} = \alpha + \sum_{j=1}^{3} \delta_{0j} \text{treat}_c^j + \mathbf{X}_i \eta_i + u_{ic}$$

- Not everyone who was invited got the letter, and not everyone who got the letter came to the training. To look for selection, estimate same equation with participation on lhs. No effects of the treatments.
- The buffer zones are there to deal with spillovers. But
  1. People move around. Stylists only kept their treatment status if moved within a neighborhood, or to another neighborhood with the same treatment status
  2. People talk. Gathered data on relationships with other stylists. Median only has 1. during first 4 months, 60-80% of stylists make one new connection to a stylist, but none after 4 months.



Packs sold (restocked)
0
5
10
15
20
Large financial
Small financial
Volunteer
Stars
95% confidence interval


Share of treatment
0
.2
.4
.6
.8
1
LF SF V S
LF SF V S
LF SF V S
LF SF V S
0
1 to 12
13 to 24
>24
Packs sold
LF = Large financial; SF = Small financial; V = Volunteer; S = Star reward
90% CI

Average treatment effects on sales.

Dependent variable	Packs sold (restocked)		Packs sold (calculated)	=1 if sells at least one pack	=1 if sells 12 or more packs	=1 if sells 24 or more packs
Mean in control group	*6.93*	*6.96*	13.30	*.368*	*.341*	*.128*
	(1)	(2)	(3)	(4)	(5)	(6)
Large financial reward	0.769	1.187	−0.653	−0.003	0.01	0.031
	[1.618]	[1.759]	[1.848]	[0.067]	[0.063]	[0.042]
Small financial reward	0.378	0.826	−0.135	−0.025	−0.018	0.011
	[1.528]	[1.530]	[1.603]	[0.066]	[0.060]	[0.040]
Star reward	7.482***	8.022***	6.283**	0.114*	0.128*	0.101**
	[2.448]	[2.639]	[2.451]	[0.066]	[0.065]	[0.049]
Salon is a barbershop (0–1)		2.751*	3.193**	0.101**	0.098**	0.031
		[1.600]	[1.467]	[0.039]	[0.040]	[0.031]
Salon is near a bar (0–1)		0.544	0.772	−0.048	−0.031	−0.005
		[2.108]	[1.971]	[0.074]	[0.063]	[0.050]
Salon size (log number of employees)		2.379	1.195	−0.082	−0.069	0.037
		[2.950]	[2.917]	[0.063]	[0.063]	[0.049]
Number of trained salons in the same area		0.02	0.069	0.001	0.000	−0.001
		[0.087]	[0.094]	[0.003]	[0.003]	[0.002]
Stylist sells other products in salon (0–1)		5.110***	2.758*	0.084**	0.085**	0.073**
		[1.701]	[1.542]	[0.039]	[0.041]	[0.035]
Stylist in the bottom quartile of asset distribution (0–1)		1.303	0.448	0.006	−0.001	0.018
		[1.743]	[1.639]	[0.051]	[0.052]	[0.036]
Stylist's socio-economic status is low (0–1)		−1.048	−0.962	−0.008	−0.012	−0.042
		[1.411]	[1.212]	[0.046]	[0.047]	[0.029]
Stylist's dictator-game donation above the median (0–1)		3.353***	2.210**	0.152***	0.143***	0.016
		[1.125]	[1.115]	[0.031]	[0.032]	[0.028]
Stylist's reported work motivation is intrinsic (0–1)		−0.541	−0.458	−0.035	−0.034	−0.03
		[1.298]	[1.166]	[0.036]	[0.035]	[0.031]
Stylist's religion is Catholic (0–1)		−3.567**	−3.163***	−0.085**	−0.074*	−0.035
		[1.370]	[1.185]	[0.041]	[0.040]	[0.033]
Constant	6.929***	0.175	8.176**	0.355***	0.313***	0.086
	[1.123]	[4.002]	[3.957]	[0.098]	[0.093]	[0.073]
R-squared	0.0285	0.0631	0.0526	0.0499	0.0482	0.0267
Observations	771	765	743	765	765	765
Large financial = small financial (p-value)	0.803	0.823	0.747	0.694	0.578	0.583
Large financial = stars (p-value)	0.00719	0.0108	0.00502	0.0517	0.0501	0.145
Small financial = stars (p-value)	0.00365	0.00548	0.00725	0.018	0.0119	0.0502

Ashraf et al 2014: Effort

Average treatment effects on effort measures.

Dependent variable	Total displays	Logbook filled	Promoter attention	Promoter interest	Average standardized effect
Mean in control group	2.285	0.479	2.498	2.111	
Standard deviation in control group	*1.19*	*0.28*	*0.41*	*0.42*	
	(1)	(2)	(3)	(4)	(5)
Large financial reward	0.071	0.028	−0.004	0.024	0.029
	[0.102]	[0.029]	[0.034]	[0.035]	[0.033]
Small financial reward	−0.101*	0.007***	0.021	0.049	−0.006
	[0.126]	[0.028]	[0.044]	[0.049]	[0.050]
Star reward	0.264**	0.067**	−0.036	0.094**	0.097**
	[0.127]	[0.029]	[0.034]	[0.044]	[0.042]
Controls	Yes	Yes	Yes	Yes	Yes
R-squared	0.099	0.0232	0.0317	0.0603	
Observations	722	722	721	694	726
Large financial = small financial (p-value)	0.151	0.5	0.529	0.603	0.49
Large financial = stars (p-value)	0.108	0.189	0.32	0.128	0.108
Small financial = stars (p-value)	0.0118	0.0582	0.167	0.437	0.07

Ashraf et al 2014: Motivation

- Expect different effects according to how pro-socially motivated people are.
  - Play dictator game: At signup agents told that on-top of 40,000 ZMK show-up fee, they'll get 12,500 ZMK to donate to a well known HIV/AIDS charity or keep. Amount donated measures prosociality.
- We also expect different effects for high/low socio-economic status (utility is concave).
  - measure with education level and English speaking ability (19% classified as low status)
- Allow treatment effects to be heterogeneous by motivation.

$$y_{ic} = \alpha + \mathbf{X}_i \beta + \gamma \sigma_i + \sum_{j=1}^{3} \delta_{0j} \text{treat}_c^j (1 - \sigma_i) + \sum_{j=1}^{3} \delta_{1j} \text{treat}_c^j \sigma_i + u_{ic}$$

where $\sigma_i = 1$ if the agent's donation in the dictator game is above the median; or $\sigma_i = 1$ if low socio-economic status

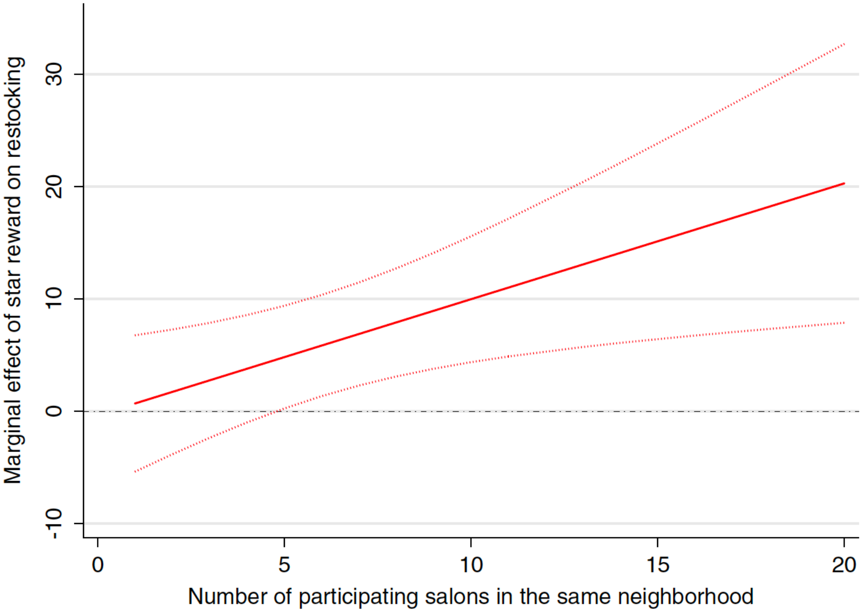
Heterogeneous treatment effects, by stylist motivation.

Dependent variable is packs sold (restocked)		
Motivation variable	Stylist's dictator game donation is above the median	Stylist's socio-economic status is low
Mean in control group = 6.96	(1)	(2)
Motivation variable	0.778*	−3.984**
	[1.518]	[1.605]
Effect of large financial when motivation variable = 0	−2.215	0.806
	[1.633]	[2.095]
Effect of small financial when motivation variable = 0	1.141	−0.041
	[1.933]	[1.705]
Effect of stars when motivation variable = 0	4.537	7.462**
	[2.859]	[3.021]
Effect of large financial when motivation variable = 1	3.462	3.542**
	[2.476]	[1.780]
Effect of small financial when motivation variable = 1	0.352	4.741*
	[1.889]	[2.858]
Effect of stars when motivation variable = 1	10.480***	11.110***
	[3.411]	[3.126]
Controls	Yes	Yes
R-squared	0.07	0.064
Observations	765	765
Large financial: p-value of the null that difference by motivation variable = 0	0.029	0.326
Small financial: p-value of the null that difference by motivation variable = 0	0.731	0.146
Stars: p-value of the null that difference by motivation variable = 0	0.091	0.350

Ashraf et al 2014: Signaling

- The signaling value of the stars might be higher when there are more peers in the neighborhood to see them
- Experiment is balanced on number of salons, so exploit random variation in the number of peers.

$$y_{ic} = \alpha + \mathbf{X}_i\beta + \gamma N_c + \sum_{j=1}^{3}\delta_{0j}\text{treat}_c^j + \sum_{j=1}^{3}\delta_{1j}\text{treat}_c^j \times N_c + u_{ic}$$


Marginal effect of star reward on restocking
-10
0
10
20
30
0
5
10
15
20
Number of participating salons in the same neighborhood

Outline

Non-financial Incentives

- Ashraf Bandiera & Jack (JPubE 2014) *No Margin, No Mission? A Field Experiment on Incentives for Public Service Delivery*
- Duflo, Greenstone, Pande & Ryan (WP 2017): *The Value of Regulatory Discretion: Estimates from Environmental Inspections in India*
- Khan, Khwaja & Olken (WP 2018) *Making Moves Matter: Experimental Evidence on Incentivizing Bureaucrats through Performance-Based Postings*

Duflo et al 2017: Introduction

- Pollution is high despite strict standards for emissions.
- Why aren't the standards enforced?
- Typical explanations: Lack of resources, corruption
- Gujarat Pollution Control Board (GPCB) has limited resources, so uses discretion to pick which plants to inspect.
- How does the regulator choose who to inspect? Would removing that discretion help or hurt enforcement?
- Experiment and structural model in Gujarat to investigate these issues

Duflo et al 2017: Context

- Industrial plants are subject to stringent air and water emissions standards
- GPCB inspects plants to observe its condition, environmental management, and often collects pollution samples.
- Regulation mandates routine inspection. Every 90 days for large- or medium-scale plants, and once a year for small-scale plants.
- At baseline, 42% of control plants inspected less than prescribed.
- Penalties can be harsh. Regulator can mandate installation of abatement equipment, require a bond be posted against future performance, order utilities disconnected.

Duflo et al 2017: Experiment

- Experiment increased inspection frequency between August 2009 and May 2011
- Identified population of 3,455 red-category (high pollution) small- and medium-scale plants in 3 regions (Ahmedabad, Surat & Valsad).
- Drew sample of 960 plants:
  - all 473 audit-eligible plants in Ahmedabad and Surat (see Duflo et al 2013)
  - random sample of 488 plants from the remaining audit-ineligible population.
- Randomly assign inspection treatment stratifying by region $\times$ audit-treatment-status.
- 481 plants assigned to inspection guaranteed at least one annual inspection and up to 4 a year.
  - In Q1 assigned an initial inspection, and then each quarter inspected again w/pr 0.66,
  - Additional inspections done by 3 recently retired GPCB scientists rehired for the project

Table A3: Inspection Treatment Covariate Balance

	Control (1)	Treatment (2)	Difference (3)
Panel A. Plant Characteristics			
Capital investment Rs. 50m to Rs. 100m (=1)	0.087	0.071	-0.017
	[0.28]	[0.26]	(0.017)
Located in industrial estate (=1)	0.33	0.37	0.032
	[0.47]	[0.48]	(0.027)
Textiles (=1)	0.45	0.45	-0.0092
	[0.50]	[0.50]	(0.020)
Dyes and Intermediates (=1)	0.13	0.16	0.027
	[0.34]	[0.36]	(0.022)
Effluent to common treatment (=1)	0.37	0.35	-0.021
	[0.48]	[0.48]	(0.031)
Waste water generated (kl / day)	192.1	196.8	4.30
	[310.9]	[316.4]	(16.2)
Air emissions from boiler (=1)	0.50	0.52	0.019
	[0.50]	[0.50]	(0.020)

Panel B. Regulatory Interactions in Year Prior to Study			
Number of inspections	1.22	1.25	0.026
	[1.32]	[1.32]	(0.079)
Inspections below prescribed (=1)	0.42	0.39	-0.031
	[0.49]	[0.49]	(0.029)
Number of pollution readings	3.64	3.92	0.28
	[5.65]	[5.58]	(0.31)
Pollution reading ever collected (=1)	0.40	0.44	0.048*
	[0.49]	[0.50]	(0.027)
Any pollution reading above limit (=1)	0.34	0.38	0.031
	[0.48]	[0.48]	(0.026)
Citations	0.22	0.20	-0.023
	[0.51]	[0.55]	(0.034)
Closure warnings	0.056	0.052	-0.0044
	[0.31]	[0.32]	(0.020)
Closure directions	0.075	0.077	0.0019
	[0.31]	[0.34]	(0.021)
Bank guarantees posted	0.019	0.029	0.010
	[0.15]	[0.21]	(0.012)
Equipment mandates	0.24	0.25	0.0082
	[0.54]	[0.53]	(0.029)
Any utility disconnection (=1)	0.010	0.0021	-0.0083
	[0.10]	[0.046]	(0.0051)
Observations	480	480	

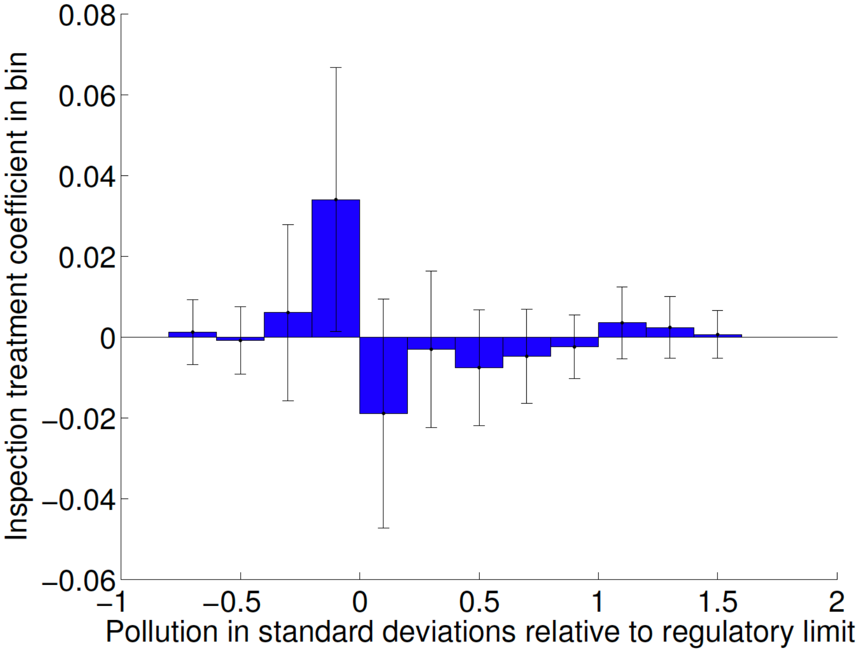
	Control	Treatment	Difference
Panel A. Inspections by Treatment Status			
Number inspections assigned in treatment, annual	0	2.12	2.12***
	[0]	[0.57]	(0.026)
Total inspections, annual over treatment	1.40	3.11	1.71***
	[1.59]	[1.77]	(0.11)
Initial inspections, annual over treatment	1.28	2.79	1.50***
	[1.38]	[1.52]	(0.094)
Observations	480	480	
Panel B. Perceived Inspections by Treatment Status			
Perceived Inspections, 2008	2.53	2.66	0.13
	[1.42]	[1.40]	(0.10)
Perceived Inspections, 2009	2.78	3.16	0.38***
	[1.44]	[1.37]	(0.100)
Perceived Inspections, 2010	2.92	3.62	0.71***
	[1.58]	[1.46]	(0.11)
Total perceived notices and closures received, 2010	0.27	0.30	0.025
	[0.64]	[0.70]	(0.048)
Observations	388	403	

Panel C. Regulatory Actions by Treatment Status

Pollution reading ever collected at plant (=1)	0.60	0.38	0.21***
	[0.49]	[0.49]	(0.032)
Any pollution reading above limit at plant (=1)	0.55	0.34	0.22***
	[0.50]	[0.47]	(0.031)
Number of pollution readings above limit at plant	2.84	1.17	1.67***
	[3.67]	[2.58]	(0.20)
Total citations	0.35	0.15	0.20***
	[0.69]	[0.42]	(0.037)
Total water citations	0.12	0.046	0.071***
	[0.37]	[0.22]	(0.020)
Total air citations	0.042	0.021	0.021*
	[0.20]	[0.14]	(0.011)
Total closure warnings	0.17	0.094	0.077***
	[0.48]	[0.34]	(0.027)
Total closure directions	0.20	0.16	0.042
	[0.54]	[0.48]	(0.033)
Total bank guarantees	0.065	0.060	0.0042
	[0.25]	[0.27]	(0.017)
Total equipment mandates	0.040	0.027	0.013
	[0.23]	[0.19]	(0.014)
Total utility disconnections	0.042	0.040	0.0021
	[0.20]	[0.22]	(0.013)
Observations	480	480	

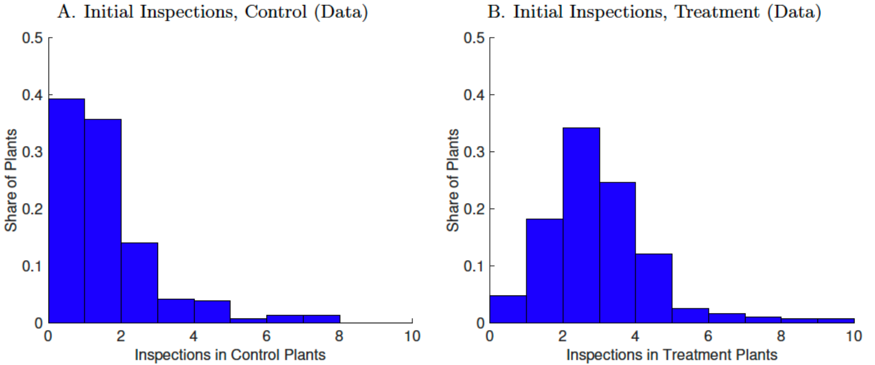
Table 2: Endline Pollution and Compliance on Treatments

	(1)	(2)	(3)	(4)
	Panel A. Plant-level Costs			
	Capital costs		Maintenance costs	
	(USD '000s)	Any (=1)	(USD '000s)	Any (=1)
Inspection treatment (=1)	-0.221	0.0213	0.838*	0.00974
	(0.453)	(0.0344)	(0.499)	(0.0224)
Plant characteristics	Yes	Yes	Yes	Yes
Audit experiment	Yes	Yes	Yes	Yes
Control Mean	2.050	0.567	0.264	0.108
Observations	791	791	791	791



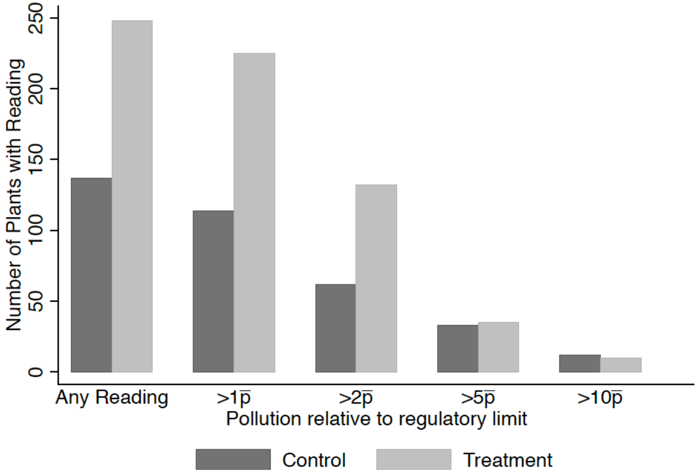
0.08
0.06
0.04
0.02
0
−0.02
−0.04
−0.06
Inspection treatment coefficient in bin
−1
−0.5
0
0.5
1
1.5
2
Pollution in standard deviations relative to regulatory limit

Treatment doesn't increase inspection of severe violators



Treatment doesn't increase inspection of severe violators

Figure 2: Regulatory Targeting of Extreme Polluters



Duflo et al 2017: Model

- Build a model of regulator-plant interactions with 2 stages

1. Targeting stage
   1.1 regulator chooses an inspection targeting rule
   1.2 plants choose whether to run abatement equipment
   1.3 regulator observes a signal of plant pollution and inspects plants by applying the targeting rule
2. Penalty stage
   2.1 Regulator acts as a regulatory machine, following exogenous rules for follow-up
   2.2 plants play a dynamic game against the machine, deciding whether to comply or risk future penalties

Duflo et al 2017: Targeting Stage

- Plant j has latent pollution in period m of

$$\log \tilde{P}_{jm} = \phi_0 + \phi_1 X_j + u_{1j} + u_{2jm}$$

  where X_j are plant observables, and the shocks are normal: $u_{1j} \sim \mathcal{N}\left(0, \sigma_1^2\right)$ and $u_{2jm} \sim \mathcal{N}\left(0, \sigma_2^2\right)$.
- Regulator sets a targeting rule $\mathcal{I}\left(u_{1j} | X_j, T_j, \theta_T\right)$ that assigns annual number of routine inspections as a function of the shock u_{1j}, plant characteristics, treatment status, and targeting parameters θ_T.
- Plants, know $\mathcal{I}\left(\cdot|\cdot\right)$, their X_j,T_j and u_{1j} so can calculate how often they will be inspected.
- Plants also know their abatement cost c_j, $\log c_j \sim \mathcal{N}\left(\mu_c, \sigma_c^2\right)$ and decide whether to Run their equipment (which the regulator doesn't observe), which reduces their pollution to

$$\log P_{jm} = \log \tilde{P}_{jm} + \phi_2 Run, \quad \phi_2 < 0$$

Duflo et al 2017: Targeting Stage

- Summarize the costs of regulation to plants by a penalty value function $V_0\left(P_{jm}\right)$ giving the money value to the plant of an initial inspection that finds pollution P_{jm} (expected value of all regulatory actions in penalty stage)
- If a plant expects to be inspected I_j times, the abatement equipment will be run if benefit exceeds maintenance costs

$$Run^* = \mathbf{1}\left\{I_j \times \left(V_0\left(P_{jm}\right) - V_0\left(\tilde{P}_{jm}\right)\right) > c_j\right\}$$

Duflo et al 2017: Targeting Stage

- The regulator wants to set a rule that maximizes total abatement.
- The rule depends on parameters $\lambda, \beta, \rho \in \theta_T$ but we assume β & ρ are exogenous, so regulator picks (vector) λ to solve

$$\lambda^* \in \arg\max_{\lambda} \sum_{j=1}^{N} \int \int \mathbb{P} \left(\mathcal{I} \left(u_{1j} | X_j, T_j, \theta_T \right) \left[V_0 \left(P_{jm} \right) - V_0 \left(\tilde{P}_{jm} \right) \right] \right) \times \tilde{P}_{jm} \left(1 - e^{\phi_2} \right) dF \left(U_2 \right) dF \left(U_1 \right)$$

such that

$$\sum_{j=1}^{N} \int \mathcal{I} \left(u_{1j}, X_j, T_j, \theta_T \right) dF \left(U_1 \right) = N \bar{I}$$

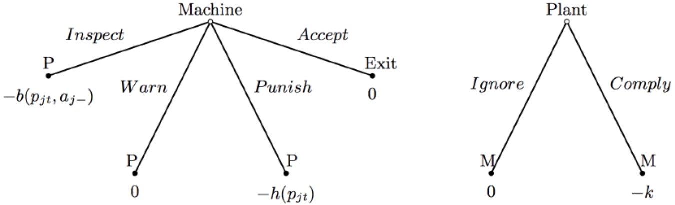
- For estimation assume

$$\mathcal{I} \left(u_{1j} | X_j, T_j, \theta_T \right) = \lambda_2 \Phi \left(\frac{\lambda_1 + X_j' \beta_1 + T_j' \beta_2 + u_1}{\rho} \right)$$

Duflo et al 2017: Penalty Stage

- We want to estimate the value function $V_0(P_{jm})$ by modeling the game after an initial inspection as a dynamic discrete choice problem.
- Game starts in round 1 with an initial inspection.
- In subsequent rounds, plant j and the regulatory machine R alternate moves.
- When the plant moves,
  - it can $Comply$ or $Ignore$ the regulatory machine.
  - Complying means paying to install abatement equipment.
  - Acts to minimize regulatory cost
- When the regulatory machine moves,
  - it has four actions $a_{R_t} : Inspect, Warn, Punish, Accept$
  - Regulatory machine: fixed probabilities of any action conditional on state (assume known to the plant)

Duflo et al 2017: Penalty Stage



A. Actions of the Regulatory Machine B. Actions of the Plant

The figure gives the actions of the regulatory machine and plant at each node and the terminal nodes give the payoffs in each round for the plant. The penalty stage begins with an inspection where the Regulatory Machine (M) observes p_{j1}. The machine can take four actions. If M *Inspects*, M gets a new signal of pollution and the plant may have to offer a bribe with payoff $-b(p_{jt}, a_{j-})$. If M *Warns*, there is no cost to the plant. If *M Punishes*, the plant faces a cost $-h(p_{jt})$. After each of these moves the plant *Ignores* or *Complies* and *M* moves again. If M *Accepts*, the stage ends.

Duflo et al 2017: Estimating Penalty Stage

- Scanned and coded up 9,624 documents on interactions with plants.
- Use maximum likelihood to estimate the game
- The state space is the pollution reading, the last two actions by the regulator and the plant, and the game round t.
- Estimate transition probabilities using count estimator
- Estimate action probabilities for the regulatory machine conditional on the state using multinomial logit.

Duflo et al. 2017: Estimating Penalty Stage

- Have to specify
- the cost of inspections $b(p_{jt}, a_{j-}) = (1 - \mathbf{1}\{a_{j-} = Comply\}) \times (\nu_1 \mathbf{1}\{\bar{p} < p_{jt} < 2\bar{p}\} + \nu_2 \mathbf{1}\{2\bar{p} \leq p_{jt} < 5\bar{p}\} + \nu_3 \mathbf{1}(5\bar{p} \leq p_{jt}))$
  - $h(p_{jt})$ cost if regulator picks punish:
    - $-\tau_0$
    - $-\tau_1 \mathbf{1}\{\bar{p} < p_{jt} < 2\bar{p}\} - \tau_2 \mathbf{1}\{2\bar{p} \leq p_{jt} < 5\bar{p}\} - \tau_3 \mathbf{1}\{5\bar{p} \leq p_{jt}\}$
  - k, cost of abatement equipment: $k = \$17,000$, average cost observed in data
- Now for each action a_{jt} we know the within-round payoff $\pi_j(a_{jt}|st)$

Duflo et al 2017: Estimating Penalty Stage

- The plant's utility of taking action a_{jt} in state s_t is now

$$v_j(a_{jt}) = \underbrace{\pi_j(a_{jt}|s_t) + e_j(a_{jt}|s_t)}_{\text{payoff today}}$$
$$+ \delta \sum_{s_{t+1}} \underbrace{f(s_{t+1}|a_{jt}, s_t)}_{\text{state transition prob}} \sum_{a_{R,t+1}} \underbrace{\mathbb{P}(a_{R,t+1}|s_{t+1})}_{\text{machine's action prob}} \times$$
$$\left\{ \underbrace{\pi_j(a_{R,t+1}|s_{t+1})}_{\text{payoff from } a_{R,t+1}} + \delta \sum_{s_{t+2}} \underbrace{f(s_{t+2}|a_{R,t+1}, s_{t+1})}_{\text{state transition prob}} V_j(s_{t+2}) \right\}$$

  where $e_j(a_{jt}|s_t)$ are utility shocks with type-I EV distribution and δ is the discount factor
- The machine's action probabilities and the state transition probabilities are known to the plant

Duflo et al 2017: Estimating Penalty Stage

- Yields value of the state

$$V_j\left(s_t\right) = \max_{a \in A_p} v_j\left(a_{jt} | s_t\right)$$

- By backward induction, solve for the state values given $\theta_p = \{\tau, \nu\}$

Duflo et al 2017: Estimating Penalty Stage

- Now we have the actions the plant will take for any parameters and probabilities.
- Estimate the state transitions with

$$\hat{f}\left(s'|a_{jt}, s_t\right) = \frac{\sum_{j,c,t} \mathbf{1}\left(s_{j,t+1} = s'|s_{jt}, a_{jt}\right)}{\sum_{j,c,t} \mathbf{1}\left(s_{jt}, a_{jt}\right)}$$

- Estimate the conditional action probabilities with

$$\mathbb{P}\left(a_{Rt} = a|s_t\right) = \frac{\exp\left(q\left(s_t\right)'\omega_a\right)}{\sum_{a'} \exp\left(q\left(s_t\right)'\omega_a\right)}$$

- Now, the likelihood of observing a set of n chains of regulator actions is

$$\mathcal{L}\left(\theta_p\right) = \prod_n \prod_{t=1}^{T_{jn}} \mathbb{P}\left(a_{jnt}|s_{jnt}, \theta_P\right)$$

which can be maximized numerically

Duflo et al 2017: Estimating the Targeting Stage

- Parameters to estimate

$$\theta_T = \left\{ \underbrace{\phi}_{\text{pollution}}, \underbrace{\beta, \lambda_1, \lambda_2}_{\text{targeting rule}}, \underbrace{\mu_c}_{\text{mean abatement cost}}, \underbrace{\sigma_1, \sigma_2}_{\text{pollution shocks}} \right\}$$

- Estimate by GMM using data on the number of inspections N_j, observables X_j, treatment status T_j, pollution P_j and abatement costs of abaters $c_j \times Run$ and the estimated $\hat{V}_0(p_j)$ from the penalty stage

Duflo et al 2017: Estimating the Targeting Stage

- Moments to use

1. Pollution equation: Let $Z_j = \begin{bmatrix} 1 & X_j & T_j \end{bmatrix}$
$$g_1(\phi) = Z_j' \left(\log P_j - \phi_0 - \phi_1 X_j - \phi_2 Run\right)$$
2. Expected inspections
$$g_2(\lambda, \beta) = \mathbf{1}' \left(\mathbb{E}\left[\mathcal{I}\left(u_{1j} | X_j, T_j, \lambda, \beta, \rho\right)\right] - I_j\right)$$
$$g_3(\lambda, \beta) = \mathbf{1}' \left(\mathbb{E}\left[\mathcal{I}^2\left(u_{1j} | X_j, T_j, \lambda, \beta, \rho\right)\right] - I_j^2\right)$$
3. Proabability and cost of runnning abatement equipment
$$g_4(\phi, \mu, \sigma) = \mathbb{P}\left(Run = 1 | \phi, \mu, \sigma\right) - \frac{1}{N} \sum_j \mathbf{1}\left\{c_j > 0\right\}$$
$$g_5(\phi, \mu, \sigma) = \mathbb{E}\left[c_j | Run = 1, \phi, \mu, \sigma\right] - \frac{1}{\sum_j \mathbf{1}\left\{c_j > 0\right\}} \sum_j \mathbf{1}\left\{c_j > 0\right\} c_j$$

Duflo et al 2017: Estimating the Targeting Stage

4. Variance of pollution shocks and covariance with inspections

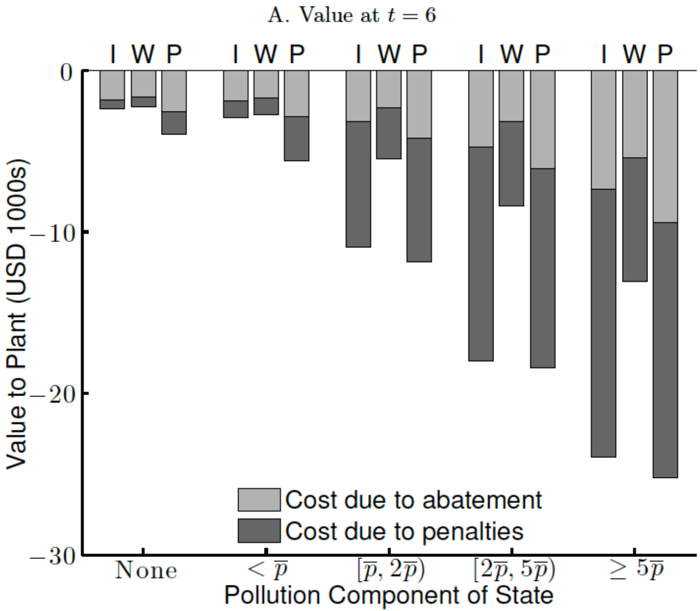
$$g_6(\beta,\phi,\sigma) = \mathbb{E}\left[\varepsilon_2^2|\beta,\phi,\sigma\right] - \sum_j \hat{\varepsilon}_2^2/N = \sigma_1^2 + \sigma_2^2 - \sum_j \hat{\varepsilon}_2^2/N$$

$$g_7(\beta,\phi,\sigma) = \mathbb{E}\left[\varepsilon_2 \cdot \mathcal{I}|\theta\right] - \sum_j \hat{\varepsilon}_{2j} \times I_j/N$$

- stack all these moments to form $g(\theta_T) = \begin{bmatrix} g_1' & g_2' & \ldots & g_7' \end{bmatrix}$
- Minimize gWg' to estimate $\hat{\theta}_T$.

Table 3: Structure of Penalty Stage Actions

Round	Regulatory Action				Plant Action			
	Inspect	Warn	Punish	Accept	Ignore	Comply	N	% left
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1	100.0	0.0	0.0	0.0			7423	100.0
2					99.6	0.4	7423	
3	1.0	9.5	2.2	87.3			7423	100.0
4					92.8	7.2	941	
5	23.3	4.8	5.3	66.6			941	12.7
6					91.1	8.9	314	
7	18.8	11.8	9.9	59.6			314	4.2
8					83.5	16.5	127	
9	21.3	5.5	18.1	55.1			127	1.7
10					82.5	17.5	57	
11	26.3	3.5	10.5	59.6			57	0.8
12					87.0	13.0	23	
13	26.1	4.3	8.7	60.9			23	0.3
14					77.8	22.2	9	
15+	16.7	8.3	0.0	75.0	100.0	0.0	9	0.1
Total without inspections	0.0	4.6	1.6	42.7	50.2	0.9	7824	
Total	31.0	3.2	1.1	29.4	34.6	0.6	25217	


A. Value at $t = 6$
I W P
Value to Plant (USD 1000s)
0
−10
−20
−30
Cost due to abatement
Cost due to penalties
None
$< \overline{p}$
$[\overline{p}, 2\overline{p})$
$[2\overline{p}, 5\overline{p})$
$\geq 5\overline{p}$
Pollution Component of State

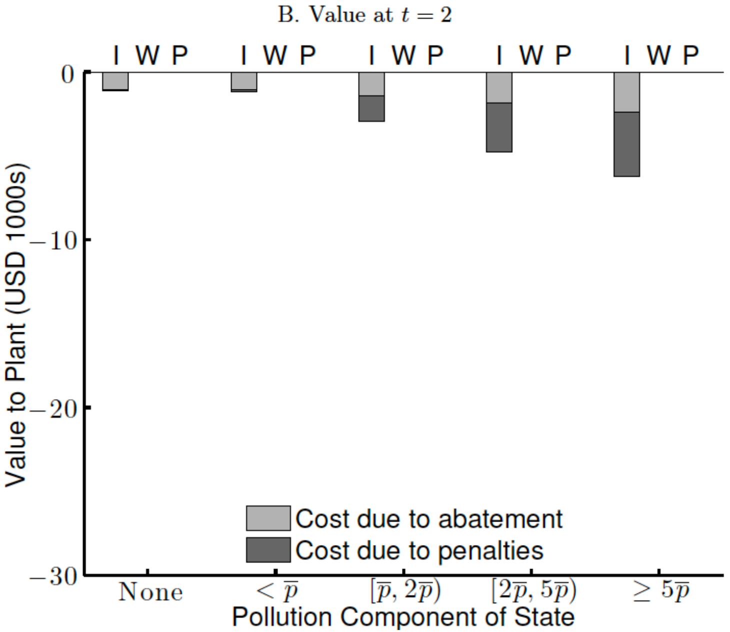

B. Value at $t = 2$
I W P
0
−10
−20
−30
Value to Plant (USD 1000s)
Cost due to abatement
Cost due to penalties
None
$< \overline{p}$
$[\overline{p}, 2\overline{p})$
$[2\overline{p}, 5\overline{p})$
$\geq 5\overline{p}$
Pollution Component of State

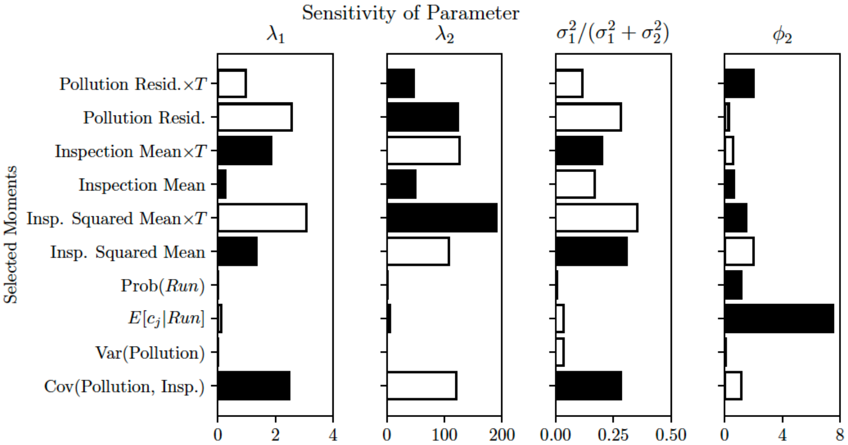
Table 4: Multinomial Logit Model of Action Choice Conditional on State

Party to move:	Regulatory Machine			Plant
	Inspect	Warn	Punish	Comply
	(1)	(2)	(3)	(4)
Lagged regulatory actions				
Warn, lag 1	0.33	-2.05***	-2.10***	-0.23
	(0.23)	(0.32)	(0.31)	(0.30)
Punish, lag 1	1.80***	-2.22***	-0.53*	1.29***
	(0.23)	(0.56)	(0.30)	(0.26)
Lagged plant actions				
Firm: Comply, lag 1	-1.80***	-1.03**	-0.82**	-0.53
	(0.32)	(0.47)	(0.37)	(0.66)
Last observed pollution reading				
0-1x	-0.38	-0.25	0.052	-0.18
	(0.23)	(0.16)	(0.24)	(0.38)
1-2x	-0.20	0.55***	0.37**	0.39*
	(0.16)	(0.098)	(0.18)	(0.23)
2-5x	-0.17	0.84***	0.70***	0.74***
	(0.17)	(0.10)	(0.17)	(0.22)
5x+	0.27	0.63***	1.15***	0.90***
	(0.21)	(0.16)	(0.21)	(0.26)

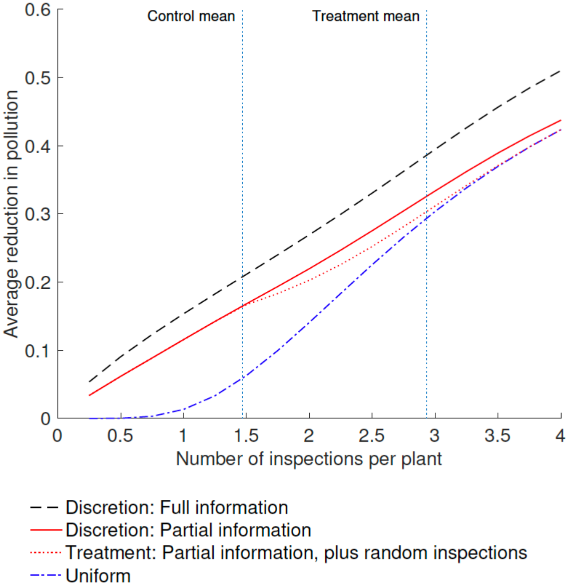
Table 6: Estimates of Targeting Stage Parameters

	Constrained		Unconstrained	
	Initial Inspections	Log Pollution	Initial Inspections	Log Pollution
	(1)	(2)	(3)	(4)
Panel A. Targeting and Pollution Equations				
Inspection treatment	0.095		0.162	
	(0.009)		(0.025)	
Run equipment (=1)		-1.902		-0.711
		(0.160)		(0.308)
Inspection targeting shift parameter (λ_1)	-0.395		-0.220	
	(0.003)		(0.066)	
Inspection targeting level parameter (λ_2)	33.022		10.064	
	(1.876)		(3.137)	
Constant		0.212		-0.009
		(0.109)		(0.102)
Panel B. Distributions of Pollution and Maintenance Cost Shocks				
Standard deviation of observed pollution shock (σ_1)	0.069		0.111	
	(0.003)		(0.022)	
Standard deviation of unobserved pollution shock (σ_2)	1.033		0.864	
	(0.047)		(0.042)	
Mean of log maintenance cost (μ_c)	2.388		1.833	
	(0.061)		(0.334)	
Panel C. Test of Targeting Optimality Constraints				
Distance metric test statistic χ^2_2	16.1039			
Test p-value	0.0003			

Figure 5: Sensitivity of Targeting Parameters to Moments



Value of Discretion: Abatement by Information Regime and Budget Constraint



Outline

Non-financial Incentives

Ashraf Bandiera & Jack (JPubE 2014) *No Margin, No Mission? A Field Experiment on Incentives for Public Service Delivery*

Duflo, Greenstone, Pande & Ryan (WP 2017): *The Value of Regulatory Discretion: Estimates from Environmental Inspections in India*

Khan, Khwaja & Olken (WP 2018) *Making Moves Matter: Experimental Evidence on Incentivizing Bureaucrats through Performance-Based Postings*

Khan et al 2018: Introduction

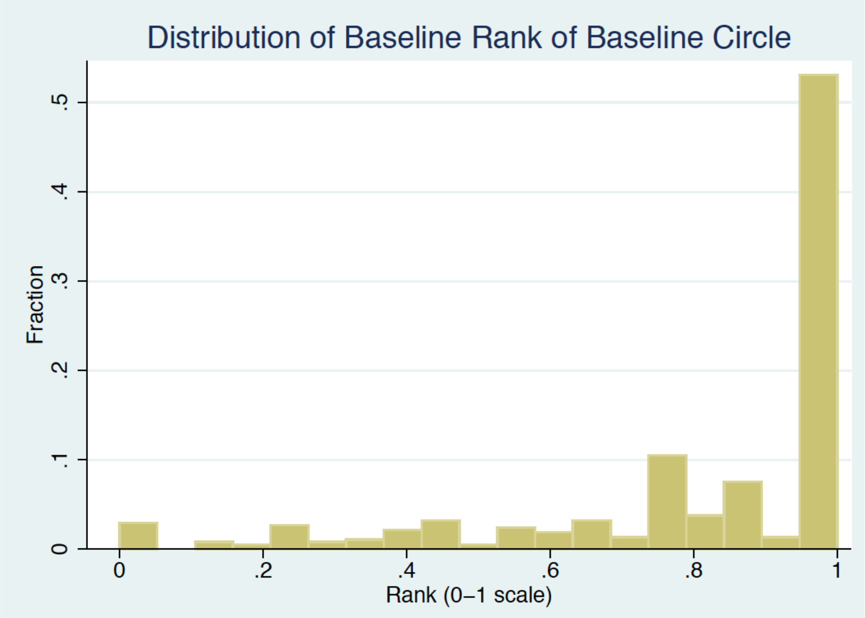
- Incentivizing workers in the government is doubly hard.
  - Scope for performance pay often limited
  - promotion often mechanical
  - punishment hard
- One thing we might try and leverage is transfers
  - bureaucrats are transfered all the time, but largely because of personal/political connections, idiosyncratic preferences, or arbitrariness
- Run an experiment in Punjab, Pakistan with property tax inspectors to test this.
- Design and implement a *performance-ranked serial dictatorship* (PRSD) mechanism

Khan et al 2018: Context

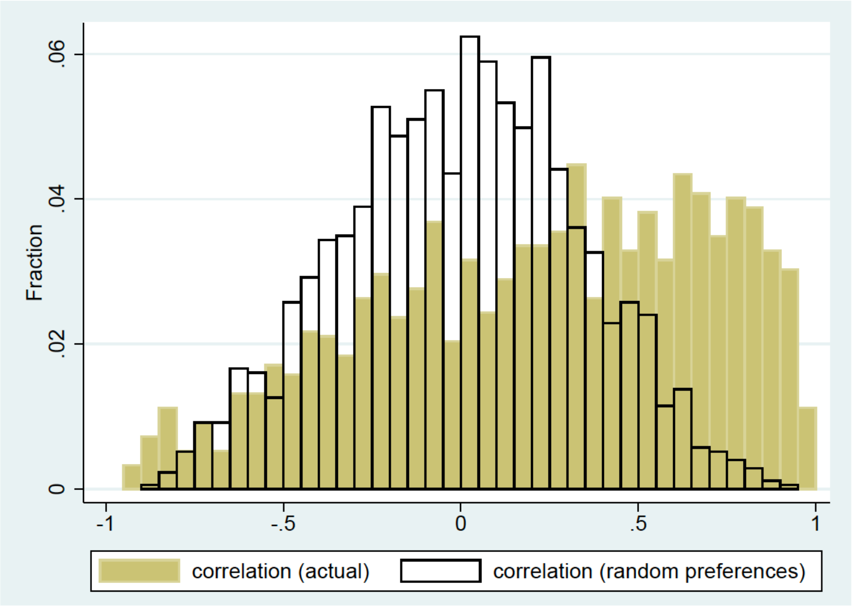
- Study urban property tax in Punjab, Pakistan (population 110 million)
- Same tax setting as in Khan et al 2016.
- About 1/3 inspectors is transferred each year
- Inspectors care about where they are posted, the circles are very heterogeneous.
  - Size: 90th %ile has 3x properties of 10th %ile
  - Ease of collecting taxes, opportunities for corruption
  - Amenities
- Current transfer process is opaque and subject to political influence, so limited use as incentive.

Khan et al 2018: Data

- Admin data on tax performance
  - quarterly inspector reports showing collections and tax base
- Preference data.
  - ask inspectors to rank all circles (average 10) in their district.
  - Told preferences would be used in treatments (incentive compatible to reveal true preferences) but before told treatment status
- Calculate the allocation that makes no inspector worse off, and no inspector or group of inspectors would want to deviate (Shapley & Scarf, 1974). 15% of inspectors would move, and these individuals would move 30%iles up their preference ordering.
- 15% relatively small, suggests that the incentive scheme will create both winners and losers.


Distribution of Baseline Rank of Baseline Circle
Fraction
0
.1
.2
.3
.4
.5
0
.2
.4
.6
.8
1
Rank (0–1 scale)

(b) Distribution of pairwise rank correlations



Khan et al 2018: Treatment

- Worked with Excise & Taxation department on the "Merit-Based Transfers and Postings" (MBTP) scheme
- Inspectors in MBTP scheme randomized into groups of 10 circles within districts.
- Inspectors told they would be ranked based on performance, and then based on ranking they would be given a choic of circles within their group.
- Performance based on 2 measures (randomized)
  1. Recovery: y-o-y percentage increase in tax collected
  2. Demand: y-o-y percentage increase in assessed tax base

Khan et al 2018: Modeling Incentives

- Inspector i gets utility u_{ij} from being assigned to circle j.
- Denote overall preference matrix by $\mathbf{P}$
- growth rate in revenue is $y_i = y_{i0} + e_i + \epsilon_i$, $\epsilon_i \sim iid$ with sd σ_ϵ
- For a vector of outcomes $\mathbf{y}$, the PRSD mechanism yields an allocation $r_i(\mathbf{y}, \mathbf{P})$
- If effort has convex cost $c(e_i)$ then each inspector maximizes

$$\max_{e_i} \sum_{j=1}^{J} u_{ij} \mathbb{P}(j = r_i(\mathbf{y}, \mathbf{P})) - c(e_i)$$

$\Rightarrow$ effort choice satisfies

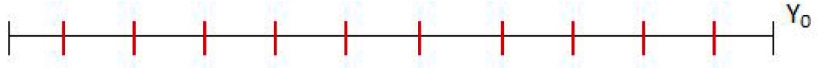
$$\frac{d\mathbb{E}[u]}{de_i} = \sum_{j=1}^{J} u_{ij} \frac{\partial \mathbb{P}(j = r_i(y_i, \mathbf{y}_{-i}, \mathbf{P}))}{\partial y_i} = c'(e_i)$$

Khan et al 2018: Influences on Incentives

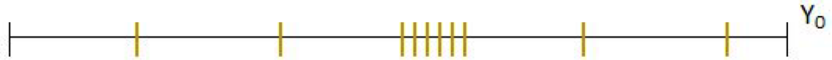
1. Preferences $\mathbf{P}$
   1.1 imagine everyone has the same preferences. Then all that matters is the inspector's rank in the performance distribution. $r_i = Rank\left(y_i, \mathbf{y}\right)$
   1.2 Imagine nobody shares a first-choice with anyone else. Then they all get their first choice, and scheme provides *no incentives*
2. Distribution of y_0.
   2.1 If they are all close together, then small effort changes can change ranks: strong incentives.
   2.2 If they are far apart, need lots of effort to change rank: weak incentives
3. Preferences u_{ij}
   3.1 With common preferences and common y_0, Lazear & Rosen (1981) show that you can replicate the efficient piece rate with a tournament
   3.2 With general preferences, it's not clear how close we are to a piece rate.

(a) When y_0 is concentrated, the marginal return to effort is high for all inspectors.

(b) When y_0 is spread out, marginal returns to effort are low.



(c) Within a group variation: inspectors with y_0 close together face strong incentives, whereas those with y_0 far apart face weaker.

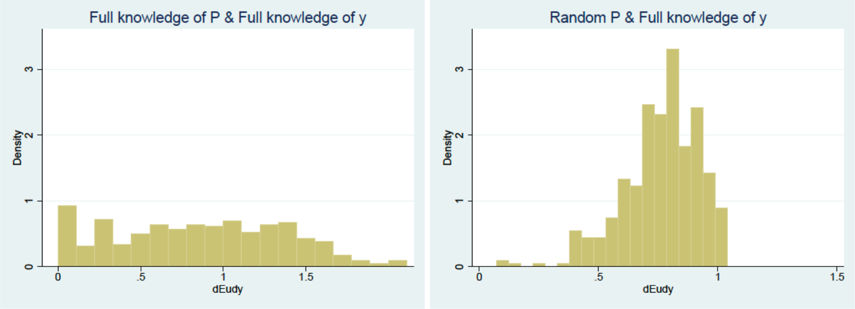


Khan et al 2018: Marginal return to effort

- Simulate the model under different assumptions about what the inspectors know about $\mathbf{P}$ and $\mathbf{y}_0$
- For a given effort vector $\mathbf{e}$, solve for the Nash equilibrium efforts.
- Need to parameterize
  - u_{ij}: take ordinal preferences and linearize $u_{ij} = 1$ for top circle and $u_{ij} = 0$ for bottom circle
  - $\mathbf{y}_0$: regress revenue changes on 2 lags of revenu and tax base in the control group. get $\mathbf{y}_0$ and σ_ϵ^2.
- Evaluate the lhs of the FOC $d\mathbb{E}\left[u\right]/de_i$ at $\mathbf{e} = 0$ under different assumptions:

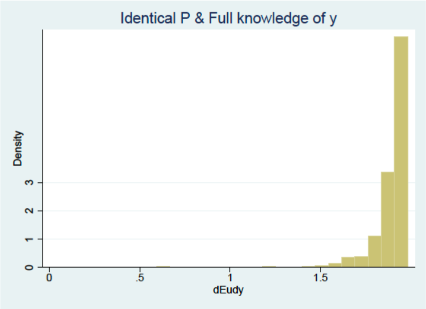
Khan et al 2018: Marginal return to effort

(a) Full Knowledge of P and y (b) Assuming random preferences P, full knowledge of y

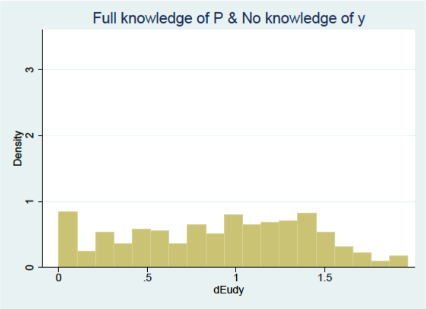


Khan et al 2018: Marginal return to effort

(c) Assuming identical preferences P, full knowledge of y

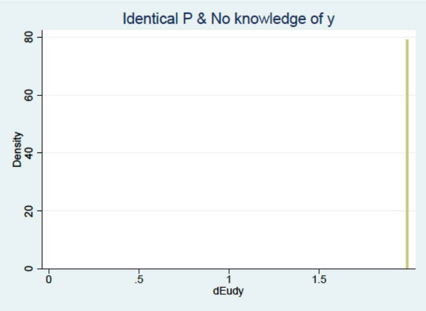


(d) Full knowledge of P, no knowledge of y

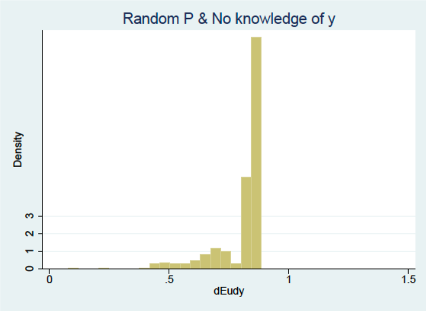


Khan et al 2018: Marginal return to effort

(e) Assuming identical preferences P, no knowledge of y



(f) Assuming random preferences P, no knowledge of y



Khan et al 2018: Experiment

- At start of year 1, circles randomly assigned into groups of 9-11 circles within metropolitan area. $\Rightarrow$ 41 groups.
- Randomized into treatment, control. Within treatment into recovery/demand measure of performance.
- In year 2, groups rerandomized into treatment/control stratifying by year-1 treatment status.

	Year 2 Control	Year 2 Treatment	Total
Year 1 Control	207	50	257
Year 1 Treatment	72	81	153
(Not included in Year 1 lottery)	96	19	115
Total	375	150	525

Khan et al 2018: Estimation

- Estimate treatment effects in circle c with

$$\log y_{ct} = \alpha_t + \gamma_t \log y_{c0} + \beta TREAT_c + \epsilon_{ct}$$

- Using model simulations, ge predicted equilibrium effort $\tilde{e}_i$ from each inspector and estimate

$$\begin{aligned}\log y_{ct} = \alpha_t + \alpha_g + \gamma_t \log y_{c0} + \beta_1 TREAT_c \times \tilde{e}_i \\ + \beta_2 \tilde{e}_i + \beta_3 TREAT_c \times X_c + \beta_4 X_c + \epsilon_{ct}\end{aligned}$$

- Estimate effect of re-randomizing with

$$\begin{aligned}\log y_{ct} = \alpha + \gamma \log y_{c0} + \beta_1 TREAT\_Y1_c + \beta_2 TREAT\_Y2_c \\ + \beta_3 TREAT\_Y1_c \times TREAT\_Y2_c + \varepsilon_{ct}\end{aligned}$$

Khan et al 2018: Revenue Results

Table 3: Treatment Effect on Log Tax Revenue

	Year 1 (Y1 Q4)			Year 2 (Y2 Q4)			Pooled		
	(1) Total	(2) Current	(3) Arrears	(4) Total	(5) Current	(6) Arrears	(7) Total	(8) Current	(9) Arrears
Treatment	0.049	0.048	0.065	0.092	0.069	-0.074	0.061	0.054	0.026
	(0.022)	(0.023)	(0.056)	(0.042)	(0.040)	(0.119)	(0.020)	(0.021)	(0.052)
	[0.009]	[0.023]	[0.259]	[0.036]	[0.142]	[0.594]	[0.002]	[0.004]	[0.653]
N	405	405	396	251	251	244	656	656	640
Mean growth in controls	0.117	0.154	-0.048	0.309	0.408	-0.337	0.203	0.268	-0.177

Notes: OLS regressions of log of tax revenue on treatment assignment. The unit of observation is a circle, as defined at the time of randomization. Specification controls for baseline values (FY 2013). Robust standard errors in parentheses. Standard errors are clustered by circle. Randomization inference based p-values in brackets.

	(1)	(2)	(3)	(4)
Panel A: Full knowledge of P, Y				
Treatment * Eq. effort	0.027	0.045	0.035	0.074*
	(0.023)	(0.039)	(0.023)	(0.040)
Treatment * Tax base at baseline		-0.046		-0.086
		(0.052)		(0.055)
Treatment * Recovery rate at baseline			-0.180	-0.246*
			(0.133)	(0.136)
Eq. effort	0.002	-0.001	-0.003	-0.014
	(0.015)	(0.017)	(0.016)	(0.016)
Panel B: Random P, full knowledge of Y				
Treatment * Eq. effort	0.020	0.037	0.051*	0.111**
	(0.025)	(0.032)	(0.028)	(0.045)
Treatment * Tax base at baseline		-0.036		-0.104**
		(0.044)		(0.053)
Treatment * Recovery rate at baseline			-0.217*	-0.332**
			(0.132)	(0.141)
Eq. effort	0.016	0.016	0.011	-0.010
	(0.024)	(0.028)	(0.026)	(0.027)

	(1)	(2)	(3)	(4)
Panel C: Assume identical P, full knowledge of Y				
Treatment * Eq. effort	-0.007	-0.008	0.012	0.012
	(0.020)	(0.021)	(0.027)	(0.028)
Treatment * Tax base at baseline		-0.019		-0.038
		(0.036)		(0.037)
Treatment * Recovery rate at baseline			-0.185	-0.207
			(0.143)	(0.143)
Eq. effort	0.007	0.009	0.004	0.003
	(0.012)	(0.014)	(0.013)	(0.013)
Panel D: Full knowledge of P, no knowledge of Y				
Treatment * Eq. effort	0.024	0.037	0.023	0.047
	(0.024)	(0.040)	(0.026)	(0.038)
Treatment * Tax base at baseline		-0.037		-0.062
		(0.049)		(0.050)
Treatment * Recovery rate at baseline			-0.170	-0.207
			(0.137)	(0.139)
Eq. effort	-0.003	-0.005	-0.006	-0.012
	(0.013)	(0.014)	(0.013)	(0.014)
N	652	652	652	652
Mean of control group	16.078	16.078	16.078	16.078

	Y1 Preferences (Treatment)				Allocation		Difference in allocation			
	(1)		(2)		(3)		(4)		(5)	
	All circles		Top inspectors' circles		Treated inspectors		Treatment - Control (Revenue)		Treatment - Control (Tax base)	
	b / se	Mean	b / se	Mean	b / se	Mean	b / se	Mean	b / se	Mean
Log of tax base (Current)	0.167**	15.870	0.343*	15.873	0.312*	15.906	0.537*	16.055	0.173	16.050
	(0.070)		(0.177)		(0.179)		(0.304)		(0.278)	
Log of tax base (Arrears)	0.137	14.254	0.173	14.228	0.219	14.224	0.355	14.492	-0.092	14.552
	(0.128)		(0.413)		(0.407)		(0.677)		(0.667)	
Growth in tax base (Current)	0.001	0.101	0.004	0.099	0.011	0.094	0.006	0.113	-0.024	0.109
	(0.008)		(0.035)		(0.036)		(0.073)		(0.040)	
Growth in tax base (Arrears)	0.055	-0.321	-0.117	-0.335	-0.068	-0.361	-0.022	-0.362	-0.199	-0.317
	(0.086)		(0.199)		(0.220)		(0.414)		(0.216)	
Log of revenue (Current)	0.180**	15.565	0.376**	15.566	0.338*	15.605	0.635**	15.737	0.235	15.735
	(0.072)		(0.177)		(0.172)		(0.309)		(0.304)	
Log of revenue (Arrears)	0.151	13.848	0.113	13.814	0.152	13.821	0.669	14.023	-0.193	14.086
	(0.123)		(0.328)		(0.337)		(0.626)		(0.430)	
Growth in revenue (Current)	-0.003	0.142	0.024	0.140	0.029	0.138	0.057	0.172	0.040	0.158
	(0.011)		(0.036)		(0.037)		(0.067)		(0.060)	
Growth in revenue (Arrears)	0.068	-0.331	-0.192	-0.351	-0.164	-0.359	0.144	-0.353	-0.355	-0.312
	(0.093)		(0.220)		(0.242)		(0.435)		(0.231)	
Any unofficial payment	0.050*	0.395	0.040	0.395	0.034	0.404	-0.039	0.387	0.196	0.375
	(0.026)		(0.081)		(0.079)		(0.134)		(0.139)	
Log of unofficial payment rate	-0.043	0.704	-0.219*	0.728	-0.211*	0.705	-0.378	0.692	-0.402*	0.698
	(0.041)		(0.128)		(0.122)		(0.237)		(0.218)	
Log average p.c. expenditure	0.066	8.614	0.097	8.611	0.082	8.631	0.141	8.652	0.262	8.625
	(0.046)		(0.096)		(0.101)		(0.157)		(0.171)	
Properties for commercial use	-0.004	0.322	-0.072	0.325	-0.072	0.328	-0.016	0.367	-0.092	0.356
	(0.016)		(0.051)		(0.049)		(0.079)		(0.113)	
Properties for residential use	-0.006	0.424	0.114*	0.419	0.119*	0.413	0.056	0.377	0.150	0.381
	(0.015)		(0.068)		(0.068)		(0.102)		(0.153)	
Num of properties (in hundreds)	-5.497	65.585	-15.182**	68.221	-11.301*	63.547	-4.070	75.349	-30.497***	74.123
	(3.594)		(7.654)		(6.780)		(14.674)		(11.300)	
Log of average property value	0.204*	7.630	0.487	7.608	0.489	7.631	0.062	7.869	1.450**	7.809
	(0.114)		(0.347)		(0.341)		(1.103)		(0.573)	
N	1184		136		123		197		199	

	(1) Total	(2) Current	(3) Arrears
Y1 Treatment (β_1)	0.109	0.085	0.128
	(0.038)	(0.040)	(0.100)
	[0.003]	[0.020]	[0.200]
Y2 Treatment (β_2)	0.081	0.055	-0.074
	(0.043)	(0.041)	(0.119)
	[0.064]	[0.235]	[0.592]
Y1 AND Y2 Treatment (β_3)	-0.150	-0.085	-0.061
	(0.067)	(0.068)	(0.178)
	[0.014]	[0.203]	[0.733]
N	403	403	392
$\beta_1 = \beta_2$	0.564	0.560	0.167
$\beta_1 + \beta_3 = 0$	0.401	0.999	0.655
Mean growth in controls	0.309	0.408	-0.337

Outline

Papers

Do gooders
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Outline

Recruitment & Selection

Ashraf et al.

Outline

Open Questions

- ?