GR 6307
Public Economics and Development

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

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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:

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

  2. Low types don't mimic high types:

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

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

$$\underbrace{N_H \pi_{HS} \left(p_{HS} - p\right)}_{\text{profits from } H \text{ types}} + \underbrace{N_L \pi_{LS} \left(p_{LS} - p\right) \left(1 - \phi_L \left(t_L\right)\right)}_{\text{profits from } L \text{ types who pass}}$$

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

- 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 $G\left(\gamma\right)$. As a result, $R\left(\mathcal{R}, \gamma\right)$ 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

$$\underbrace{\int N_H \pi_{HS}\left(R\left(\mathcal{R},\gamma\right)\right) H dG\left(\gamma\right)}_{\text{(expected) social value of slots to } H}$$

$$+\underbrace{\int N_L \pi_{LS}\left(R\left(\mathcal{R},\gamma\right)\right)\left[1-\phi_L\left(t_L\left(R\left(\mathcal{R},\gamma\right)\right)\right)\right] L dG\left(\gamma\right)}_{\text{social value of slots to } L \text{ who pass test}}$$

$$+\underbrace{\int N_L \pi_{LF}\left(R\left(\mathcal{R},\gamma\right)\right)\phi_L\left(t_L\left(R\left(\mathcal{R},\gamma\right)\right)\right) L dG\left(\gamma\right)}_{\text{social value of slots to } L \text{ who fail test}}$$

$$-\underbrace{\int \left(\nu+\delta\right) N_H t_H\left(R\left(\mathcal{R},\gamma\right)\right) dG\left(\gamma\right)}_{\text{social cost of testing } H}-\underbrace{\int \left(\nu+\delta\right) N_L t_L\left(R\left(\mathcal{R},\gamma\right)\right) dG\left(\gamma\right)}_{\text{social cost of testing } L}$$

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	
	$y_H > y_L$	$y_H \leq y_L$
$h > l$	Case I: Alignment	Case III: Inability to Pay
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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

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

- Note the IC constraint for the L types:

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

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”

$$
\begin{aligned}
p_H &= p_L = l \\
\pi_H &= 0,\ \pi_L = 1/N_L \\
t_H &= 0,\ t_L = 0
\end{aligned}
$$

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

3. “lottery”

$$
\begin{aligned}
p_H &= p_L = h \\
\pi_H &= \pi_L = 1/\left(N_L + N_H\right) \\
t_H &= 0,\ t_L = 0
\end{aligned}
$$

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 $\mathbf{v}$

$$R(a, y) \equiv x\left(\gamma_a \mathbb{E}\left[v_a | a, y\right] - \gamma_y \mathbb{E}\left[v_y | a, y\right]\right), \ \gamma_a \geq 0, \ \gamma_y \geq 0$$

- $\Rightarrow$ 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

$$\max_{a \in A} (v_a + v_y y) a - C(a) + \mu_a \mathbb{E}\left[v_a | a, y\right] + \mu_y \mathbb{E}\left[v_y | a, y\right]$$

Benabou & Tirole 2006: Choice of a

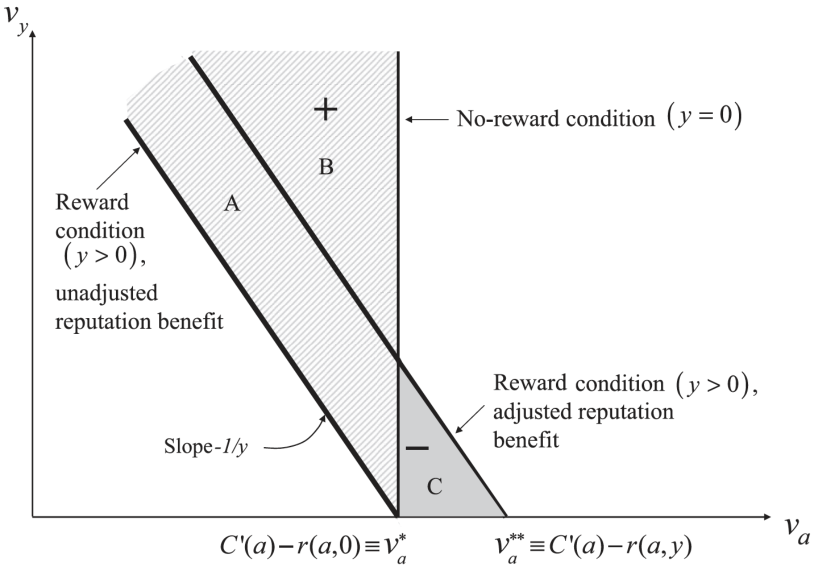
- The agent's optimal choice satisfies the FOC

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

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

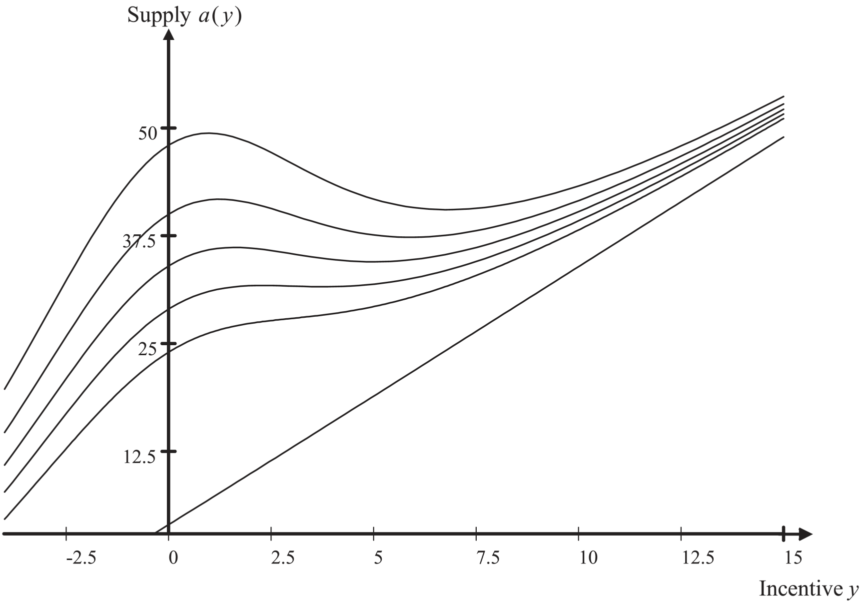
$$\bar{a}'(y) = \frac{\bar{v}_y}{k} + \bar{\mu}_a \rho'(y) - \bar{\mu}_x \chi'(y)$$

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:

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

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

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

- Increasing x has 2 effects:

1. Direct *amplifying* effect with sign $sign\left(\mu_a \rho\left(y,x\right) - \mu_y \chi\left(y,x\right)\right)$
   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 $\rho\left(y,x\right)$ and $\chi\left(y,x\right)$ 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}

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

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, $b^*_{ij} = \frac{1}{2}\left(\pi_i - \theta_{ij}\right)$
3. If the outside option is high, then $b^*_{ij} = \sqrt{2\left(\bar{u}_{ij} - \underline{w}\right)} - \theta_{ij}$

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*

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

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

Theory

Financial Incentives

Non-financial Incentives

Recruitment & Selection

Open Questions

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*

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

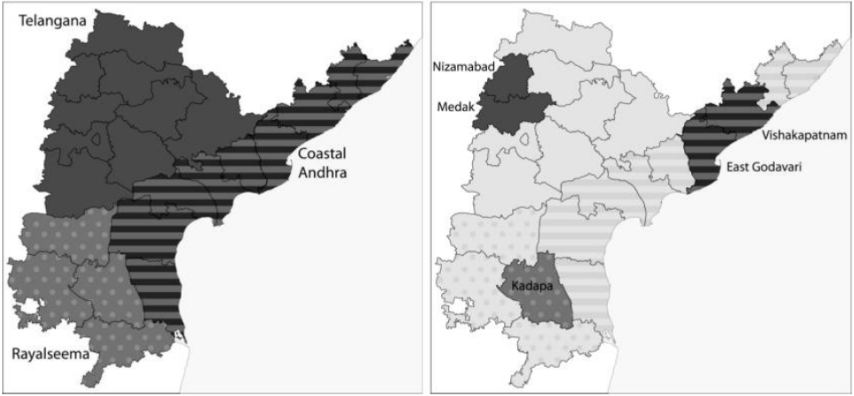


FIG. 1.—*A*, Andhra Pradesh (AP); *B*, district sampling (stratified by sociocultural regions of AP).

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

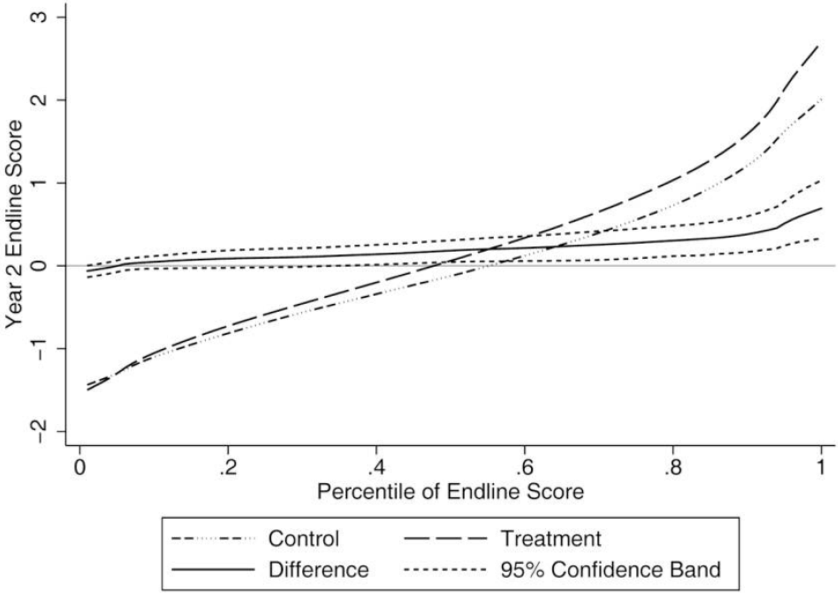
Muralidharan & Sundararaman 2011: Heterogeneity

- How does the distribution of test scores change:

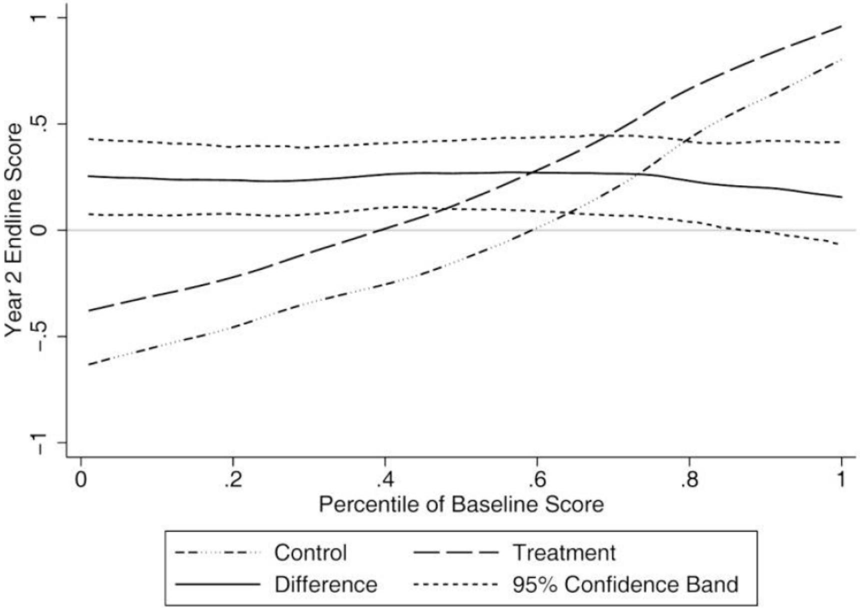
$$\delta(\tau) = G_n^{-1}(\tau) - F_m^{-1}(\tau)$$

  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:

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



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*

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

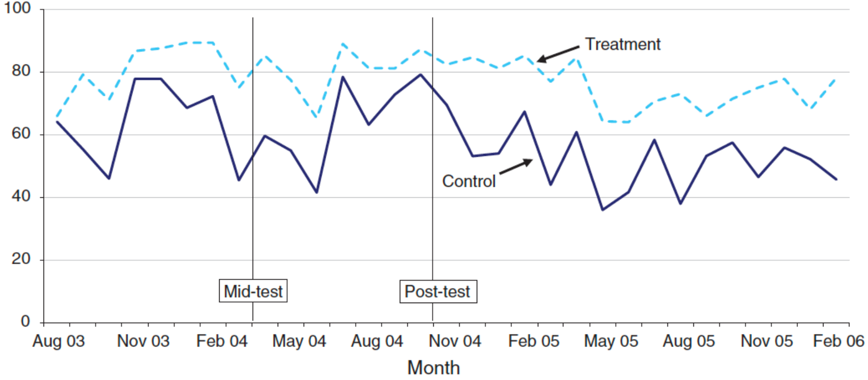
Duflo et al. 2012: Data

- 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

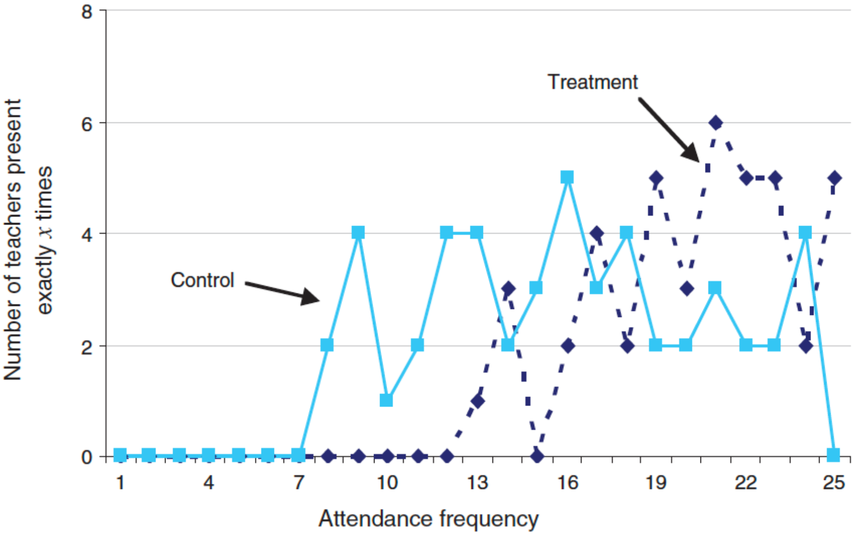


Duflo et al. 2012: Attendance Increased

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

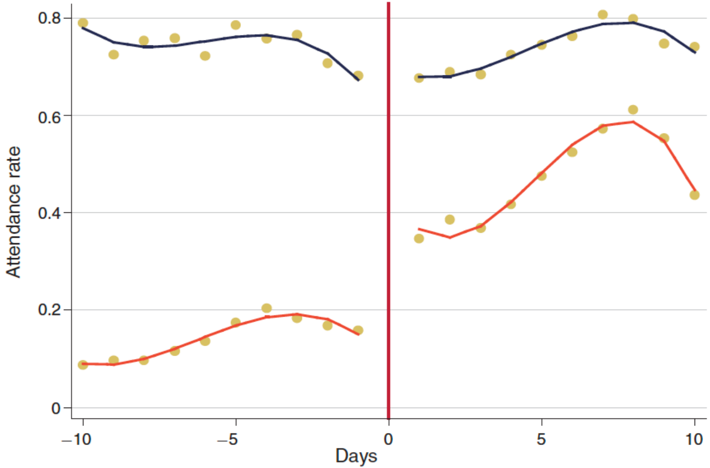


FIGURE 3. RDD REPRESENTATION OF TEACHER ATTENDANCE AT THE START AND END OF THE MONTH

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

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

where $\mathbf{1}_{im} (d > 10)$ 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:

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

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

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

- 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

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

- 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.

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

  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

Papers

Karthik and Sandip's 2011
Khan Khwaja Olken
auditors reputation paper

Outline

Theory

Financial Incentives

Non-financial Incentives

Recruitment & Selection

Open Questions

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Recruitment & Selection
- Ashraf et al.

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Theory

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Non-financial Incentives

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Open Questions

Open Questions

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