Effects of Economic and Social Incentives on Bureaucratic Quality: Experimental Evidence from Sierra Leone

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Using a field experiment implemented in Sierra Leone with community-level service providers, we examine the individual and joint effects of selection, local monitoring, and incentivized payment mechanisms. We find evidence consistent with past literature that social pressure improves quality of service provision. These gains, however, are no better than gains from simple direct payment mechanisms with lower social costs. We find no effects of varying selection mechanisms. Analysis of a structural model identifies conditions under which selection and social or economic incentives are more or less likely to be effective and help make sense of our design-based findings. Our model-based analysis suggests that the null result on selection is because of high social embededness even for candidates not selected by communities and a low correlation between embeddedness and intrinsic motivation. Social sanctions would increase performance of workers with higher social sensitivity, whereas financial incentive scheme are particularly effective when workers are more embedded in the communities they serve. JEL Codes: I15, I18, J33, M52, O15, O55.

1 Introduction

Recruiting and incentivizing service providers, such as health workers, teachers, and agricultural extension workers, remains a central challenge for many developing country governments. How to improve the quality of service provision closely relates to how the bureaucracy is organized (cf. Bandiera et al. (2022), Deserranno et al. (2024)). This is at the core of economics given the central place institutions play in economic development (Acemoglu and Robinson 2013).

We contribute to recent work on "personnel economics" that examines interacting institutional features that affect the types of people fulfilling bureaucratic functions and the incentives they have to perform well (Finan, Olken, and Pande 2017). We focus specifically on one key aspect of recruitment – *who* gets to recruit bureaucrats – and two approaches to incentivizing bureaucrats – one focused on community monitoring and one on pay-for-performance. We experimentally examine the individual and joint effects of these three features using a factorial design.

Research on *recruitment* strategies includes work by (Dal Bó, Finan, and Rossi 2013), who find that that higher wages attract more qualified and competent candidates during a government recruitment process in Mexico. Ashraf, Bandiera, and Jack (2014) and Deserranno (2017) assess recruitment strategies aimed at attracting applicants with different personal motivations: materially motivated workers and socially motivated workers. This work primarily assesses differences in the types of workers that result from different forms of self-selection. We differ from these studies by focusing not on different incentivizes conditional on self-selection, but by varying the selector, building on the idea that different types of selectors have different incentives but also different access to information about possible candidates.

Turning to incentive schemes, recent studies have highlighted the potential benefits of *social* incentives, showing how service provision can be enhanced by involving beneficiary communities in the process of service delivery, for example related to health Christensen et al. (2021), related to education Molina et al. (2016), and to combat corruption (Fiala and Premandan 2018; Olken 2007). Beneficiaries may provide information about the needs and priorities of the community, have a stake in outcomes, and may hold service providers to account through social pressures. Work by Björkman and Svensson (2009) in Uganda and Christensen et al. (2021) in Sierra Leone suggest that when baseline service provision is low, empowered community members can push local workers into higher performance resulting in better health outcomes. In another context, Olken (2007) argues that state audits are effective in reducing corruption

not because violators were afraid of being prosecuted by the state (they rarely were), but because evidence of this corruption would be reported to community members.

Finally, *financial* incentives schemes have shown to be effective in improving performance in the education sector (see Duflo, Hanna, and Ryan (2012), and a well-established literature on firms: e.g. (Bandiera, Barankay, and Rasul 2011)). Closest to our study is Ashraf, Bandiera, and Jack (2014) who observe higher performance from private non-financial rewards (in their case condom sale performance scores) compared to financial incentives for health promotion. Christensen et al. (2021) show that non-financial rewards to clinic staff increases clinic utilization and satisfaction with service provision. Few studies, however, have assessed the interaction of selection and financial rewards. Leaver et al. (2021) use a two-stage experiment to identify the effect of teacher selection and performance using variations in financial incentives in employment contracts. At the recruitment stage, potential teachers are randomly assigned to a fixed wage or 'pay-for-performance' offer. In the second stage, teachers are re-randomized into both contract types. They find that pay for performance selection plus incentive increases pupil learning most.

In this paper, we study the individual and joint effects of service provider selection, and social and financial incentives in the context of a randomized intervention in Sierra Leone. We focus on so-called Community Animal Health Workers (CAHWs). CAHWs were installed in 300 rural communities, randomly selected, as part of the Government of Sierra Leone (GoSL) strategy to improve health conditions and preparedness in the wake of the Ebola epidemic. The pandemic had caught the country by surprise and revealed that fine grained systems to detect and manage outbreaks timely were lacking. After the crisis, GoSL launched a "One Health" program, aiming to increase preparedness by investing in the integration of both human and animal health systems. Part of the program was to increase capacity at local levels to increase animal husbandry practices and health (lowering the risk of spillover events) and improve local reporting of disease symptoms (increasing the probability of detecting outbreaks early). GoSL recruited and trained CAHWs to provide basic animal health services and execute health surveillance activities to detect and prevent diseases.

The program is similar to other localized development programs. Since 1990s development policy has been looking at local delivery models for better service provision. These programs have become increasingly popular and rely on locally-recruited actors to deliver a variety of public service interventions or undertake government tasks. Predominantly, these interventions have focused on health and agriculture using extension type agents, such as Community Health Workers (CHWs) and Health Volunteers engaged in providing care at local levels as the lowest level of the bureaucracy. In the agriculture sector, extension workers have

fulfilled similar roles. A core challenge to these programs has been their financial sustainability. Many ministries in developing countries are under-resourced and cannot afford to permanently add workers to the payroll. A central question is therefore which recruitment and incentive scheme produces the highest service provision quality.

For agricultural extension workers, governments and donors have been experimenting with new ways to increase program sustainability, relying on a entrepreneurial worker models, where workers are recruited and trained, and are officially part of the government system (like CHWs), but for their income rely on local remuneration for their services. For example, such so-called "agripreneur" programs have been launched in several developing countries, often funded by the World Bank, and other donors. Over the past decades, also CAHW programs have been launched in several countries (Catley 2020).

Here we assess CAHW performance on their service provision quality, which here is taken as their surveillance behavior performance. As part of their training, CAHWs learn about recognizing animal diseases symptoms, which can reflect underlying diseases. CAHWs report these symptoms on surveillance forms, designed by the Ministries for this intervention, to Ministry supervisors. We assess both the quantity and the quality of these submitted surveillance reports. As secondary outcomes, we also assess impacts on local margins including animal health, good husbandry practices and integration of the CAHW in their communities.

This paper makes several contributions.

First, despite existing evidence supporting community-based mechanisms, we do not know if these community monitoring mechanisms are more or less effective than performance-based payment schemes. Nor do we have a good understanding of the conditions under which they work most effectively. To our knowledge there has been no study to date that benchmarks social sanctions against financial rewards where service providers are paid for their performance.[1] We find that these two strategies, which we calibrated to be equally costly to the policy maker in our intervention, have comparable effects in terms of surveillance performance, with slightly higher (though not significantly different) estimates for pay for performance.

Second, while the effects of social and financial incentives have been studied separately, they can in practice appear together. This raises the question of how they interact, and in particular whether the presence

[1]Most existing studies compare different types of non-financial rewards (see Finan, Olken, and Pande (2017) for a review), or aim to assess what mechanism (reducing information asymmetry, joint action planning, interface meetings) are at work (see Raffler, Posner, and Parkerson (2024)).

of one crowds out the effects of the other (Frey and Oberholzer-Gee 1997). We find weak evidence suggesting moderate crowding out across all pairs of treatments, though we can never reject the null of no interactions.

Third, it is an open question whether and to what extent schemes to incentivize service providers depend on recruitment strategies. Different incentive schemes may matter not because of the incentives they provide workers on the margin but because of (self-)selection by workers with different personal characteristics (e.g. public service motivation) and embeddedness (e.g. social-political ties). We find that varying who selects service providers does not impact performance.

Fourth, we develop a theoretical model which we structurally estimate. Doing so allows us to build on observed patterns across all treatment combinations to inform us when and why interventions make a difference. Analysis of the model helps us understand not only why some interventions made a difference but also why others did not. The model suggests that the selection intervention failed to impact service provision quality because of the limited variation in embeddedness across different candidate pools and the limited relation between embeddedness and intrinsic motivations. In addition, we learn that social sanctions would improve performance for those workers with higher social sensitivity, and financial incentive scheme are more effective when workers are more embedded in the communities they serve.

The paper is structured as follows. In Section 2 we present a model on how recruitment and incentives interact and generate testable hypotheses which we use to guide the analysis of our experimental design introduced in Section 3. Section 4 presents the results of our main hypotheses test using a design-based approach. Section 5 presents the results using a model-based approach and we use the structural model to make inferences regarding the "causes" and external validity of our estimated effects. We conclude in Section 6.

2 A Theory for Service Provider Performance

To formalize our thinking about recruitment and incentives, we use a principal-agent framework with public service motivation following Francois (2000). We model how recruitment procedures and incentive structures affect the performance of a service provider (a CAHW in this study) with both material and non-material motivations.

We seek to understand the effects of three treatments on the behavior of public servants.

treatment	label
T1	Agent is selected by community (T1 = 1) or by chief (T1 = 0)
T2	Community can impose social sanctions on agent (T2 = 1) or not (T2=0)
T3	Agents receive pay for performance (T3 = 1) or not (T3=0)

2.1 Model

The game features a worker ('he') and a unit-mass continuum of villagers ('she'). Their interaction is divided into three stages: selection, monitoring and assessment.

A worker is characterized by two attributes: embeddedness (denoted by $\eta \in \{\underline{\eta}, 1\}$) and intrinsic motivation (denoted by $\mu \in \{0, \overline{\mu}\}$).[2] The value $\theta = (\eta, \mu)$ represents a worker's *type*. Embeddedness captures the number of strong kinship relationship that tie the worker to the village, intrinsic motivation captures the extent to which the worker is motivated to exert effort in the absence of external incentive (both pecuniary and non-pecuniary).

We assume that the worker's type under chief ($T1 = 0$) selection is drawn form a candidate pool represented in Table 2. The parameter $\rho \in (-1, 1)$ captures the correlation between embeddedness and intrinsic motivation.

$\mu \backslash \eta$	$\underline{\eta}$	1
0	$\frac{1+\rho}{4}$	$\frac{1-\rho}{4}$
$\overline{\mu}$	$\frac{1-\rho}{4}$	$\frac{1+\rho}{4}$

Table 2: The candidate pool under chief selection: embeddedness (η) and intrinsic motivation (μ)

Under villager selection ($T_1 = 1$), the worker is drawn from the subset of the candidate pool with high embeddedness. Table 3 displays the posterior probability of each type as a function of the selection

[2] We set high embeddedness to one and low intrinsic motivation to zero for analytic simplicity. This normalization does not affect our results.

treatment T_1. The chief is more likely to select workers with high intrinsic motivation if and only if the correlation ρ is negative. In other words, ρ captures the extent to which the village's selection advantage *relative to the chief* on embeddedness extends to intrinsic motivation.

	$T_1 = 0$ Chief Selection	$T_1 = 1$ Village Selection
$\Pr\{\eta = 1 \mid T_1\}$	$\frac{1}{2}$	1
$\Pr\{\mu = \overline{\mu} \mid T_1\}$	$\frac{1}{2}$	$\frac{1+\rho}{2}$

Table 3: The effect of the selection treatment on the posterior worker type.

The worker's (deterministic) performance depends on both embeddedness η and effort $e \in [0, 1]$:

$$\pi = e\eta$$

This captures the idea that highly embedded workers have better knowledge of the village and higher levels of trust with the population, and that those advantages improve performance (holding effort constant) and raise the return of effort.

The worker also produces a stochastic *performance signal* σ, which is high ($\sigma = 1$) with probability π or low ($\sigma = 0$) with probability $1 - \pi$:

$$\Pr(\sigma = 1) = \pi$$

Effort is associated with a cost $c(e) = \frac{e^2}{2\kappa}$ which captures the value of the worker's alternative use of time (e.g., tending to one's farm and enjoy leisure). The parameter κ captures the wage elasticity of effort.

Before the worker's effort choice, a villager is randomly and publicly selected to choose a social sanctioning plan $s(\sigma)$: each villager chooses this plan *as if* she was the sole principal of the worker.[3] Since effort and performance are unobservable to the villager, social sanctioning only depends on the performance signal σ:

$$s = (s(0), s(1)) \in [-T_2, T_2]^2.$$

[3]In a more descriptively accurate game, the provision of shame among villagers should be modeled as a public good provision game. We abstract from this layer of strategic considerations for three reasons: first, our results would be qualitatively unaffected; second, it would significantly increase the complexity of the model; third, the implementation of our intervention—specifically, the presence of community action plans—limits the empirical relevance of these considerations.

The level of performance-contingent social sanctioning $s(\sigma)$ captures the effect of a broad array of behaviors that the villagers adopt towards the worker to either reward ($s(\pi) < 0$) or punish ($s(\pi) > 0$) him. These behaviors have material and psychological consequences not only for the worker, but also for the villager. Community monitoring ($T_2 = 1$) provides villagers with opportunities to deploy social sanctioning: with community monitoring ($T_2 = 1$), $s(\sigma) \in [-1, 1]$, without community monitoring ($T_2 = 0$) social sanctioning is effectively unavailable ($s(0) = s(1) = 0$).[4]

A high-performing worker receives additional income under a pay-for-performance treatment (T_3). We assume that the worker receives zero when either (i) pay-for-performance is absent ($T_3 = 0$), or the worker's performance signal is low ($\sigma = 0$). Conversely, under pay-for-performance ($T_3 = 1$) and high performance signal ($\sigma = 1$), the worker receives a payment normalized to one.

In addition to his extrinsic payoff, the worker also enjoys an intrinsic payoff μ when the realization of the performance signal is high, in line with the interpretation of μ as intrinsic motivation. The payoff of the worker is then

$$w(e; s, \sigma; \theta) = \sigma(T_3 + \mu) - \phi s(\sigma) T_2 - \frac{e^2}{2\kappa},$$

where ϕ captures the worker's sensitivity to social sanctioning.

To ensure that effort is interior, we assume that κ is sufficiently small:

Assumption 1. $\kappa < \frac{1}{\mu + 2\phi + 1}$.

The villager benefits from the worker's performance (capturing improvements in animal health that come from more frequent inspections as well as improved surveillance). The villager also suffers a psychological cost of sanctioning the worker, which captures guilt and/or conflict-aversion. The parameter γ represents the villager's own susceptibility to guilt.[5] The villager's payoff is then

$$u(\pi, s) = \pi - \gamma s.$$

[4] The latter assumption is obviously stark, since villagers can rely on direct (albeit imperfect) observation of the worker's activity to potentially sanction and reward. Hence, s should be interpreted as the *additional* social sanctioning/reward that comes with the availability of good information about the worker's performance and a dedicated community meeting to discuss it.

[5] One could also assume that the cost of sanctioning also depends on the worker's embeddedness η. We explore this possibility in the Appendix.

In the baseline model, we assume that the susceptibility to guilt γ is drawn from a binary distribution (we relax this assumption in the Appendix) with support $\{0, \overline{\gamma}\}$, with $\Pr(\gamma = 0) \equiv \zeta \in (0, 1)$. We assume that $\overline{\gamma}$ is sufficiently large to ensure variation in equilibrium shaming behavior:

Assumption 2. $\overline{\gamma} > \frac{\phi\kappa}{1-\kappa(\overline{\mu}+2\phi+1)}$.

We interpret ζ as the strength of village-level norms. Table 4 summarizes the model parameters.

Table 4: Model parameters, choices, and outcomes.

Symbol	Name	Interpretation
$\mu \in \{0, \overline{\mu}\}$	(Intrinsic) motivation	Strength of motivation
$\eta \in \{\underline{\eta}, 1\}$	Embeddedness	Strength of a worker's ties to the community
$\theta = (\mu, \eta)$	Worker's type	
$\rho \in [-1, 1]$	Type correlation	$Corr(\mu, \eta)$
ϕ	Social sensitivity	The worker's susceptibility to social sanctioning
$\gamma \in \{0, \overline{\gamma}\}$	Guilt	The villager's psychological cost of social sanctioning
$\zeta \in [0, 1]$	Strength of village-level norms	Probability of low-guilt villager
κ	Productivity	Effort elasticity to wage
$e \in [0, 1]$	Effort	How hard the worker works
$\pi \in [0, 1]$	Performance	Outcome of worker's activity ($\pi = e\eta$)
$\sigma \in \{0, 1\}$	Performance signal	Public signal of performance ($\Pr(\sigma = 1) = \pi$)
$s(\sigma) \in [-1, 1]$	Social sanctioning plan	Villager commits to it before observing σ

Timeline. The sequence of events is as follows:

1. The worker is selected by either the village ($T_1 = 1$) or the chief ($T_1 = 0$) and privately observes his type.
2. The villagers and the worker learn whether the latter is subject to community monitoring ($T_2 = 1$) and/or pay-for-performance ($T_3 = 1$).
3. If $T_2 = 1$, a villager with observable guilt parameter γ is chosen to commit to a conditional plan of social sanctioning $\{s(\sigma)\}_{\sigma\in\{0,1\}}$.
4. The worker chooses effort e.
5. The worker's performance signal σ is realized.

6. If $T_2 = 1$, the villager implements the announced social sanctioning $s(\sigma)$ and if $T_3 = 1$ and $\pi = 1$, a payment is made. Payoffs are realized and the game ends.

Solution concept. A (sequential) equilibrium in this context is a pair of strategies $\{s, e(s;\theta)\}$ such that (i) effort is individually rational for each type given the sanctioning strategy, (ii) the sanctioning strategy maximizes the villager's expected payoff given its expectations about the worker's type and its anticipated effect on the workers' effort $\hat{e}(s;\theta)$, and (iii) the villager's expectations are correct ($\hat{e}(s;\theta) = e(s;\theta)$ for each θ) :

$$e(s;\theta) \in \arg\max_{e\in[0,1]} \mathbb{E}_{\pi}\Big\{w(e,s,\sigma;\theta)\Big\}$$
$$s \in \arg\max_{\{(s(0),s(1))\in[-T_2,T_2]^2\}} \mathbb{E}_{\theta,\pi}\Big\{u(\pi,s) \mid \hat{e}(s;\theta)\Big\}$$

2.1.1 Analysis

Optimal effort. Owing to Assumption 1 we obtain that optimal effort equals

$$e(s;\theta) = \kappa\eta \max\Big\{\mu + T_3 + T_2\phi(s(0) - s(1)), 0\Big\} \tag{1}$$

All else equal, effort is nondecreasing in intrinsic motivation and embeddedness, and is higher under pay-for-performance due to the monetary payment. Effort also increases in the *social reward* $s(0) - s(1)$, which is the reduction in shaming associated with good performance.

Optimal shaming. First, notice that a villager's *expected payoff* is function of the worker's effort and type is given by:

$$v(e,s) = \eta e - \gamma[e\eta s(1) + (1 - e\eta)s(0)] \tag{2}$$

Substituting Equation (1) into Equation (2), we obtain that the villager-optimal scheme solves

$$\max_{s(\sigma)\in[-1,1]^2} \mathbb{E}_{\theta}\{v(e(s;\theta),s)\}.$$

The villager always chooses to praise the worker after observing a high performance signal ($s(1) = -1$). In the Appendix we show that, under the assumptions, the villager will choose maximal shaming $s(0) = 1$ after observing the low performance signal if her susceptibility to guilt is low ($\gamma = 0$) and minimal shaming $s(0) = -1$ otherwise.

Lemma 1. *In equilibrium,* $s^* \equiv (s^*(0), s^*(1)) = \begin{cases} (1,-1) & if \gamma = 0 \\ (-1,-1) & otherwise. \end{cases}$

In the Appendix, Proposition 1 shows that under more general assumptions about the village level distribution of guilt, there exists a critical level of susceptibility above which the villager still rewards the worker upon observing a low signal, and below which they inflict maximal social shaming.[6]

We can now compute the expected performance as a function of the three dimensions of uncertainty of the model: the worker's type (whose distribution depends on $T1$) and the villager's guilt:

$$\pi^*(T_1, T_2, T_3) = \mathbb{E}_{\gamma,\theta}\{\eta e(s^*; \gamma, \theta) \mid T_1, T_2, T_3\}$$

where

$$e(s^*; \gamma, \theta) = \begin{cases} \kappa\eta(\mu + T_3 + T_2 2\phi) & \text{if} \quad \gamma = 0 \\ \kappa\eta(\mu + T_3) & \text{otherwise.} \end{cases} \tag{3}$$

We can now study the effect of the various treatments on the worker's expected performance.

2.1.2 Empirical Implications

Baseline effect of village selection. We begin with the simplest case: when community monitoring and pay-for-performance are both absent ($T_2 = T_3 = 0$), $s(0) = s(1) = 0$ and thus effort equals $\eta\mu$. As a result, we obtain that $\pi^*(T_1, 0, 0) = \mathbb{E}_\theta\{\eta^2\mu | T_1\}$: the effect of going from chief selection to village selection is then entirely driven by the change in the induced type distribution. Since higher embeddedness raises one's productivity, embeddedness and intrinsic motivation are complements.

Under village selection, all types have high embeddedness, while the posterior intrinsic motivation is given by $\Pr(\mu = \overline{\mu} | \eta = 1) = \kappa\frac{1+\rho}{2}$. As a consequence, expected performance under village selection equals

[6] Interestingly, the critical threshold depends on the selection procedure $T1$—which changes the villager's expectations about the workers' embeddedness and intrinsic motivation—and on the presence of pay-for-performance T_3. See the Appendix for detail.

$$\pi^*(1,0,0) = \mathbb{E}_\eta \left\{ \kappa\eta^2 \middle| 1 \right\} = \kappa\overline{\mu}\frac{1+\rho}{2}$$

Under chief selection, conversely, types are drawn from the full type distribution:

$$\pi^*(0,0,0) = \mathbb{E}_\eta \left\{ \kappa\eta^2 \middle| 0 \right\} = \kappa\overline{\mu}\left(\frac{1+\rho}{4} + \underline{\eta}^2\frac{1-\rho}{4}\right)$$

As a result,

$$\pi^*(1,0,0) - \pi^*(0,0,0) = \kappa\overline{\mu}\left(\frac{1+\rho}{4} - \underline{\eta}^2\frac{1-\rho}{4}\right) = \frac{\kappa\overline{\mu}}{4}\left(\underbrace{1-\underline{\eta}^2}_{\substack{\text{Increased}\\ \text{embeddedness}}} + \underbrace{\rho(1+\underline{\eta}^2)}_{\substack{\text{Change in}\\ \text{intrinsic motivation}}}\right) \tag{4}$$

This brings us to the following observation:

Observation 1. *In the absence of extrinsic incentives ($T_2 = T_3 = 0$), performance is higher under village selection if and only if $\rho \geq -\frac{1-\underline{\eta}^2}{1+\underline{\eta}^2}$.*

Village selection yields higher effort and better output than chief selection unless (i) embeddedness is not too consequential relative to intrinsic motivation ($\underline{\eta}$ is large) and (ii) embeddedness crowds out intrinsic motivation (ρ is negative and sufficiently large).

The effect of pay-for-performance. Using (3), we have that

$$\pi^*(T_1,T_2,T_3) = \mathbb{E}_\theta \left\{ \kappa\eta^2 \left(\mu + T_3 + T_2 2\phi\zeta\right) \middle| T_1 \right\} \tag{5}$$

We can see that pay-for-performance increases expected performance, via the material extrinsic incentive of the payment.[7]

$$\pi^*(T_1,T_2,1) - \pi^*(T_1,T_2,0) = \kappa\mathbb{E}_\eta \left\{\eta^2 | T_1\right\} > 0 \tag{6}$$

[7] With a continuous guilt distribution, there is also an indirect effect that operates through a higher likelihood of social sanctioning for poor performance, which reinforces the baseline effect. See Appendix for details.

Notice that, since expected embeddedness η is higher under village selection, the effect of pay-for-performance should be higher under village selection than under chief selection. In the baseline model, instead, the effect of pay-for-performance does not vary with community selection.[8]

Observation 2. *Pay-for-performance increases expected performance. Moreover, the effect*
(i) is stronger under village selection than under chief selection;
(ii) is independent of community monitoring.

The effect of community monitoring. Inspection of (5) reveals that the main effect of community monitoring is to introduce a probability of being shamed for poor performance:

$$\pi^*(T_1, 1, T_3) - \pi^*(T_1, 0, T_3) = 2\phi\zeta\kappa\mathbb{E}_\eta\left\{\eta^2|T_1\right\} > 0 \tag{7}$$

The size of this effect depends on the selection procedure. Since expected embeddedness η is higher under village selection, the effect of community monitoring should be higher under village selection. In the baseline model, instead, the effect of community monitoring does not vary with pay-for-performance.[9]

Observation 3. *Community monitoring increases expected performance. Moreover, the effect*
(i) is stronger under village selection than under chief selection;
(ii) is independent of pay-for-performance.

Overall effect of village selection. Using again (3), we obtain

$$\begin{aligned}\pi^*(1, T_2, T_3) - \pi^*(0, T_2, T_3) = \\ = \pi^*(1,0,0) - \pi^*(0,0,0) - \mathbb{E}_\theta\left\{\kappa\eta^2\mu\middle|0\right\} + (T_3 + T_2 2\phi\zeta)\left[\mathbb{E}_\eta\left\{\kappa\eta^2\middle|1\right\} - \mathbb{E}_\eta\left\{\kappa\eta^2\middle|0\right\}\right]\end{aligned}$$

Since village selection is associated with higher embeddedness, the second term of the expression is always positive. The first term, instead, corresponds to the effect of village selection absent extrinsic incentives

[8] In the Appendix, we show that with a continuous distribution of guilt, the interaction between pay-for-performance and village selection is always positive without community monitoring but is ambiguous with community monitoring. The conditions, however, are rather knife-edge.

[9] In the Appendix, we show that with a continuous distribution of guilt, the interaction between community monitoring and pay-for-performance is positive. We also show that in that case, the interaction between community monitoring and village selection can be negative. The conditions, however, are again rather knife-edge: as long as village selection increases performance when $T_2 = T_3 = 0$ ($\rho \geq -\frac{1-\eta^2}{1-\underline{\eta}^2}$) or $\underline{\eta}$ not too large, the interaction between community monitoring and village selection is positive.

$(T_2 = T_3 = 0)$. As a consequence, if village selection improves performance absent extrinsic incentives, then village selection must also improve performance in the presence of extrinsic incentives.[10]

Observation 4. *If village selection increases expected performance in absence of extrinsic incentives $(T_2 = T_3 = 0)$, it increases expected performance under all incentive configurations (T_2, T_3).*

Table 5 below summarizes the expected performance (divided by the common cost term κ) under each of the eight treatment cells.

$(T_2, T_3) \backslash T_1$	$T_1 = 0$			$T_1 = 1$		
$\frac{\pi^*(T_1,0,0)}{\kappa}$	$\frac{\overline{\mu}}{2}\frac{1+\rho+\underline{\eta}^2(1-\rho)}{2}$			$\frac{\overline{\mu}}{2}(1+\rho)$		
$\frac{\pi^*(T_1,0,1)}{\kappa}$	$\frac{\overline{\mu}}{2}\frac{1+\rho+\underline{\eta}^2(1-\rho)}{2}$	$+\frac{1+\underline{\eta}^2}{2}$		$\frac{\overline{\mu}}{2}(1+\rho)$	$+1$	
$\frac{\pi^*(T_1,1,0)}{\kappa}$	$\frac{\overline{\mu}}{2}\frac{1+\rho+\underline{\eta}^2(1-\rho)}{2}$	$+(1+\underline{\eta}^2)\phi\zeta$		$\frac{\overline{\mu}}{2}(1+\rho)$	$+2\phi\zeta$	
$\frac{\pi^*(T_1,1,1)}{\kappa}$	$\frac{\overline{\mu}}{2}\frac{1+\rho+\underline{\eta}^2(1-\rho)}{2}$	$+(1+\underline{\eta}^2)\phi\zeta$	$+\frac{1+\underline{\eta}^2}{2}$	$\frac{\overline{\mu}}{2}(1+\rho)$	$+2\phi\zeta$	$+1$

Table 5: Expected performance as a function of the treatment.

Notice that each value has at most three components. For example, we can see how performance under both incentive schemes and village selection ($\pi^*(T_1, 1, 1)$) is driven by (i) intrinsic motivation, (ii) the fear of social sanctioning, and (iii) the monetary incentive. Crucially, each these components is influenced by the selection procedure, which changes the distribution of types.

In the Appendix, we provide the mapping between the model parameters and each of the regression coefficients of a fully interacted linear model with the three treatment variables.

2.2 Hypotheses

Using the model on how recruitment and incentives interact we generate testable hypothesis which we use to guide the analysis of our experimental design.

Hypothesis 1: Village selection increases performance.

[10] This result also obtains with a continuous distribution of guilt.

Explanation: Village selection (T1=1) increases performance relative to chief selection (T1=0) (as long as embeddedness does not crowd-out intrinsic motivation too much).

Hypothesis 2: Community monitoring increases performance. Explanation: Community monitoring (T2=1) incentivizes worker performance through the associated probability of being publicly shamed for poor performance.

Hypothesis 3: Pay-for-performance increases performance.

Explanation: Pay for performance (T3=1) increases performance due to the probability of receiving a monetary reward.

Hypothesis 4: There is a positive interaction between village selection and pay-for-performance.

Explanation: More productive workers (i.e. those with higher embeddedness, T1=1) are more responsive to extrinsic incentives (T3=1).

Hypothesis 5: There is a positive interaction between village selection and community monitoring.

Explanation: More productive workers (i.e. those with higher embeddedness, T1=1) are more responsive to extrinsic incentives (T2=1). For more embedded workers, effort yields a more effective mitigation against the risk of social sanctioning.

In the Appendix, we show that this result continues to hold even if we allow villagers to experience stronger guilt when imposing social sanctions on more embedded workers.

Hypothesis 6: There is a positive interaction between pay-for-performance and community monitoring.

In the Appendix, we show that this result does not depend on how one models community monitoring. However, we also show that it can be potentially reversed by sufficiently large concavity in the marginal value of effort, via a more traditional crowding out of competing incentives. When the marginal effect of effort on expected performance is sufficiently decreasing, the increase in performance associated with social sanctioning is higher in the absence of pay-for-performance.

While we believe that our model strikes an adequate balance between tractability and descriptive accuracy, the possibility of this crowding out of incentives does make us a bit more cautious about Hypothesis 6 relative to the rest of theory's implications.

3 Context and Study Design

3.1 Epidemics and Health in Rural Sierra Leone

The absence of basic health services and a high-quality disease surveillance system can have long-lasting welfare consequences. For example, during the 2014-2015 Ebola Virus Disease outbreak in Sierra Leone, the lack of timely and high quality information about Ebola aggravated the outbreak Glennerster, MCleod, and Suri (Jan 30, 2015). More than 7 out of 10 emerging infectious diseases, including Ebola, spill over from (wild)animals Milbank and Vira (2022). In Sierra Leone, the threat of zoonosis is likely to increase in the years to come, in part due to increased deforestation. This implies that public health programs and surveillance systems that focus exclusively on human diseases might be ill equipped to handle health threats in a globalized world. In response, policymakers in Sierra Leone are working to integrate the Global One Health Agenda into national policy. The One Health perspective emphasizes the importance of both human and animal health and environmental conditions (e.g. Kahn 2006).

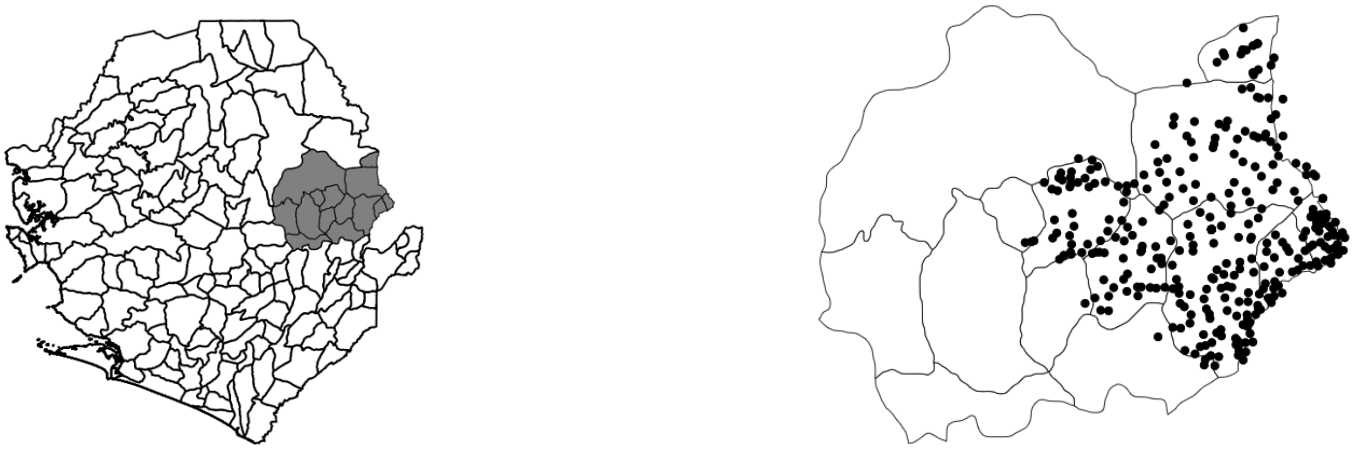
As part of this agenda, the Sierra Leonean Ministry of Health (MOH) and the Ministry of Agriculture (MAF) recruited, trained and installed so-called Community Animal Health Workers (CAHWs) that provided basic health services and executed health surveillance activities to detect and prevent (animal) diseases.

3.2 The One Health Intervention

In collaboration with the Ministry of Health and Sanitation (MOH) and the Ministry of Agriculture, Forestry and Food Security (MAF) of the Government of Sierra Leone (GoSL), we implemented a cluster-randomized study designed to test the impact of One Health program.

GoSL identified eligible rural villages in seven Chiefdoms in Kono District, a region dependent on livestock rearing (Figure 1). Next, within each Chiefdom, GoSL created a list of all villages with a trained Community Health Worker (CHW). CHWs are health workers that are responsible for human health in the community, including health surveillance. In total, 375 villages were listed from 424 villages. Of these, five villages functioned as pilot villages, and seven villages turned out to no longer exist, bringing the study population to 363 villages.

We co-designed the community One Health program with GoSL, which consisted of multiple components. In each village, individuals were recruited to become a Community Animal Health Worker (CAHW). While



(a) Kono District (b) Study villages

Figure 1: Map of the study villages

many community members had experience raising and caring for animals, CAHWs did not formally exist in Sierra Leone before the program. CAHWs are a voluntary workers responsible for monitoring and reporting animal disease symptoms, as well as preventative and curative treatment of sick animals within the community. Their set up mirrors that of Community Health Workers (CHW) common throughout many Low Income Countries. Recruitment was conducted with the Ministry of Agriculture and involvement of local leaders and community members. Eligibility criteria of candidates included: literacy, numeracy, animal rearing experience, residence in the community, good health and availability to participate in a multi-week training session. Subsequently, CAHWs participated in a 21-day training , taught by veterinary doctors overseen by MAF, which provided the skills and knowledge on the basics of animal husbandry, disease prevention and treatment. In addition, the training focused on disease surveillance and reporting. CAHWs were tasked to report to Ministry supervisors on suspect symptoms of common animal diseases, using a reporting form. CAHW also participated in an additional two-day training on One Health for which the community CHW was also present, stressing the need for a joint human and animal-oriented approach to disease prevention. After successfully completing the training, the CAHW received a starting kit with tools and basic animal drugs to provide treatments to sick animals. Subsequently, the CAHW was installed in her respective community during a village meeting. At the meeting, the overall One Health program was introduced to the wider community, specifying the roles and responsibilities of the CAHW, and the community was asked to create a One Health platform consisting of all actors responsible for health in the community: the CHW, a traditional health worker, and the CAHW. In the following months, the CAHW provided basic animal health services, demonstrated and provided information on best practices for animal husbandry behaviors and report suspected disease symptoms to ministry supervisors. CAHWs

did disease reporting on large ruminants (cows, bulls), small ruminants (sheep, goats), pigs, birds (chicken, ducks, fowls), and dogs. An example of a reporting form can be found in Appendix Figure 7. In Voors et al. (2024), we show that on average the program had very high take up (during the program less than 5% of CAHWs dropped from the program) and performance throughout. In addition, the overall CAHW program made meaningful changes in relevant local outcomes. Compared to control villages animal health and good health behaviors as well as animal stocks increased due to the CAHW program. From planner's perspective it matters if we can improve CAHW performance based on how CAHWs are recruited and incentivised.

3.3 Experimental Design

As part of the intervention, we randomly assign CAHW program villages to three different experiments following a $2 \times 2 \times 2$ factorial design.

For the *recruitment experiment*, we asked both the community and the Paramount chief to make a list of preferred CAHW candidates. This design allows us to directly identify which candidates would have represented each village had the village fallen into the other treatment. However, only in about 100 villages were both types of candidates available. Here we block randomly assigned whether a candidate selected by the Paramount Chiefs was trained and installed or the candidate selected by the community. Using data on pre-intervention data on population size, ethnic fractionalization, distance to nearest principal health unit (PHU), distance to phone coverage, average wealth, number of households with livestock, community health worker (CHW) presence, duration of community nomination process and community – paramount Chief ties, GPS coordinates as geographic variables, and the village's recruitment treatment status, to create blocks of four villages.[11] Note that due to a smaller sample we have less power to experimentally test the effect of recruitment and its interaction with incentive schemes. In all other village we just have one candidate, either selected by the state/Paramount Chief or village. Specifically, in 112 villages the CAHW was recruited by state authorities in collaboration with the Paramount Chief. In 175 villages, the community selected the CAHW. In our analysis below we assess treatment effects both for the experimental and full sample (also including the endogenously selected candidates)

The recruitment took place ahead of the training, and before the incentive treatments (discussed below) were announced. It is possible that either candidates performed better during the training. In that

[11] Blocks are formed using the package "blocktools" in R, which seeks to minimize multivariate distance between units in a block.

Table 6: No Financial Incentives

T1	No Community Monitoring	Community monitoring	Total
Chief selects	28	28	56
Community selects	44	44	88
Total	72	72	144

Table 7: Pay for Performance

T1	No Community Monitoring	Community monitoring	Total
Chief selects	27	29	56
Community selects	44	43	87
Total	71	72	143

case, this treatment variation captures both the effect of selection as well as a differential impact of the training. Attendance data and post training test scores however reveal no differences between both types of candidates.

We use a factorial design to identify the independent and joint effect of *community monitoring* and *pay for performance*. Specifically, after the training and community installation of new CAHWs, villages were block randomly assigned to the community monitoring and pay for performance treatments (or both) before program onset followed a two-by-two factorial design. As blocks we used the same variables as above conditioning also on whether villages were part of the recruitment lottery or not.

3.3.1 Recruitment Experiment

To assess the impact of recruitment strategies, in a random subset of communities, CAHWs were recruited following a "business-as-usual" scenario, where state authorities collaborate with Paramount Chiefs to select CAHW candidates from the project community. In other communities, MAF facilitators traveled to villages and held a village meeting where CAHW candidates were selected with full community participation. The treatment resulted in modest differences in the type of CAHW. Using a baseline survey of all CAHWs we find very few differences in CAHW characteristics (see Appendix Table 14), both when looking at the full sample (Column 1 and 2) and experimental subsample (Column 3 and 4). Using a household baseline survey, we find that community selected candidates are perceived to be slightly more socially embedded,

and integrated in their communities (see Appendix Table 15). For example both types of CAHWs are well known, live in the village and 50% of respondents are family members of CAHWs.

3.3.2 Community Monitoring Experiment

This experiment manipulated whether the CAHW was monitored by the community (CM). That is, in a random half of all villages, the community was actively engaged in monitoring CAHW performance (mimicking the central components of the Björkman and Svensson (2009) project). This monitoring involves: 1) the creation of joint action plans, 2) the organization of interface meetings between the community and CAHWs, and 3) decreasing information asymmetry in worker performance. CAHWs and the community signed a "statement of expectations"; a copy was laminated and put up for public display. To assess health worker performance veterinary experts from MAF assessed Type 1 and Type 2 errors in surveillance reports by CAHWs (see "Validation Exercise" below). Each CAHW was assigned a relative rank (compared to all other CAHWs) as well as an overall quality score. This information was then presented to community members during village meetings where all members of the community were invited to attend. This allowed community members to reward or impose social sanctions on health workers representing their community. These incentives included items like helping to work on the CAHWs farm, gifting money or assets, etc, see Appendix Table 20. Social sanctions, locally talked about as motivation, included calling a village meeting, refusing to help CAHW, reporting the CAHW to the chief, etc, see Appendix Table 21. Treatment communities were more likely to implement these types of sanctions, see Appendix Table 22. On average, CM villages are 6.5%-9.9% more likely to have motivated or rewarded their CAHW.

3.3.3 Pay for Performance Experiment

This experiment manipulates whether the CAHW is paid for performance (P4P). Based upon their performance, all CAHWs were assigned a relative rank. CAHWs in those villages selected for the pay-for-performance treatment, received feedback on performance in private by the Ministry. The CAHWs were paid based on their performance, broken into three brackets: the lowest third received nothing; middle Le 225,000; and the top received Le 450,000. CAHWs in villages not assigned to this treatment did not receive any payments. Importantly, to enable a direct comparison between this treatment and the community-monitoring treatment, we keep the total cost per community the same. ## Data and Sample

Data were collected before, during and after the intervention. Appendix Table 7.2 gives a timeline of the program and data collection activities.

1. **Chief survey**. Baseline data from the village chiefs was collected during July 2017 before program start.

2. **CAHW baseline data** were collected with all nominated CAHWs, up to two per village.

3. **Household baseline data** were collected during October and November 2017. In each village, a census was done of all inhabited dwellings and obtained a list of the top animal rearing households from the village chief. We targeted eight households per village: six randomly selected households, and respondents from the two households holding most animals within the community. The head of the household was interviewed in each household. In total the household survey includes data from 2,072 households in 284 villages. Appendix Table 16 presents baseline information for surveyed households pooling across treatment arms. The majority of respondents were male (76%), married (80%), around 45 years old and had lived in the village for 28 years. About 20% of respondents received any formal education, and 85% were illiterate. About half of the households were Christian (51%), while the other half were Muslim (49%). The vast majority of respondents (89%) care for animals (predominantly chickens, goats and sheep), and 90% cares for animals.

4. **Household endline data** were collected during March and April 2020, at the end of the program. About two years after CAHWs were recruited, we returned to the same households that were also interviewed for the baseline survey. We re-interviewed 2,078 households in 285 villages. Attrition at the household level is 10% with no differences across treatment arms (see Appendix Table 17). The endline survey captures local outcomes relating to animal husbandry, animal health knowledge and practices, household wealth, and perspectives on the integration of CAHWs into their communities.

5. **Reporting forms** A core task of CAHWs is to fill out monitoring forms each time they inspect or treat animals from animal owners. In this surveillance form, CAHWs fill out fields for: community member name, community, chiefdom, animal type and animal symptoms, see example form in Appendix Figure 7. These monitoring forms inform MAF and the Research Team about the state of animal health in the communities, and helps to quickly identify disease spread and outbreaks. To collect forms every second month, ministry runners went out to each community. Runners recorded whether CAHWs could be found, and whether forms could be collected, and if not why. Surveillance

forms were brought to a central location to be digitalized and stored. We use this data to create a surveillance effort index (see below).

6. **Validation exercise** To assess surveillance quality we organised several validation exercises. These measures were developed in conjunction with local and international health experts and policy makers, and carefully piloted. In a field practical, we asked CAHWs to come to a central location and assess their technical knowledge across two activities: *Animal Station Exam* where: CAHWs observed upto three sick animals, diagnosed their health problems, and fill in a disease reporting form and *Form Review*: We took five randomly selected recently submitted disease surveillance forms and an evaluator assesses whether forms were filled out correctly and assessed overall comprehension of form completion. We also organised village visits. A MAF representative visited the CAHWs respective village and implemented: *Sick Animal Observation* where evaluators verified if sick animals found in a village had been reported by CAHWs (ie false negatives) and *Monitoring Form Follow-Up* where evaluators used a previously filed reporting forms, and interviewed owners of reported animals to verify if CAHWs have accurately reported sick animals (ie false positives). Based on the scores we created a surveillance quality index, a normalised and added index based on the four sub-components (ie the animal knowledge exam, form review, sick animal observation in the field and monitoring form follow-up). This validation exercise was implemented two times during the study period. we implemented four evaluation exercises using: a field practical and a village visit. Based on thee scores CAHWs were assigned three relative ranks (low, middle and high) compared to all other CAHWs. The scores of the first round were used in the community monitoring and pay for per formance treatments. Scores for the second round are used below to assess impacts of threatments on surveillance quality at the end of the program.

3.3.4 Outcome: Service Provider Performance

Our main measure of CAHW performance uses data from the reporting forms and creates an effort index comprising (i) the number of reports submitted by the CAHW, (ii) the number of animals reported on and (iii) the fraction of times our runners could find the CAHW during their (unannounced) visit. We standardize each measure by dividing them by the 95th percentile value, and assigning a value of one to those with higher values. We then combine these three variables into one measure of CAHW performance by taking a mean. The measures have a relatively high internal correlation (with a Cronbach's Alpha of 0.62), see Figure 2.

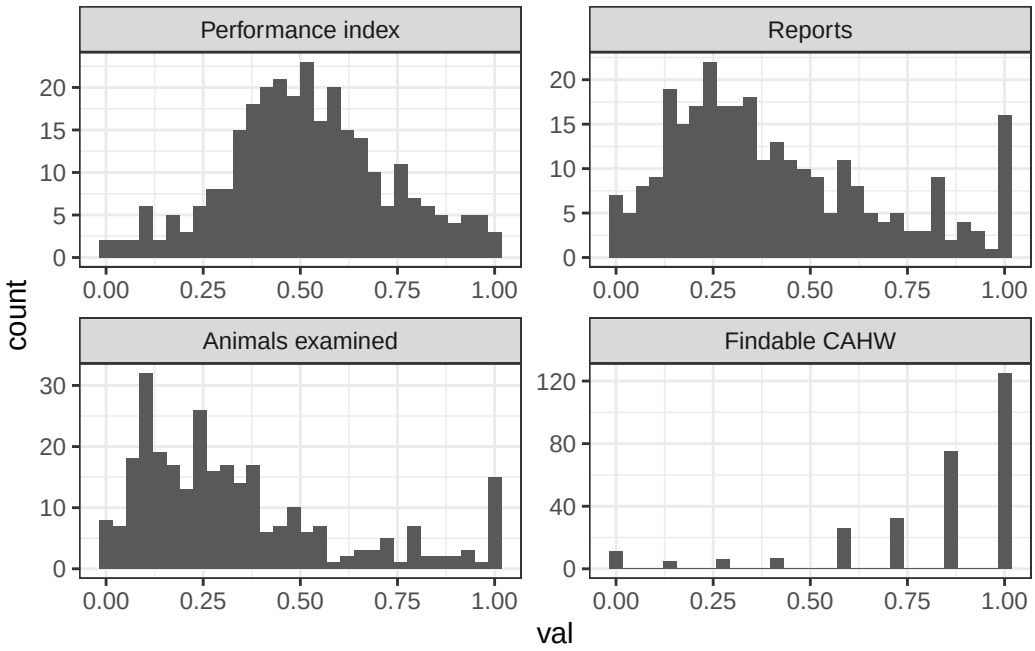


Figure 2: Components of the performance index

3.3.5 Estimation

Our estimand is the ITT. To estimate treatment effects, we use a linear model with randomization block fixed effects (see above). We first estimate short models for each treatment arm separately:

$$p_c = \alpha_k + \beta^{\mathrm{T}} \mathbb{1}(T)_c + X_c + \epsilon_c$$

where outcome p_c is the performance of a CAHW (defined above) in community c; T is an indicator variable equal to one for villages assigned to a treatment, α_k are block Fixed Effects, and ϵ_c is the ususal idiosyncratic error term. We also estimate a full long model with all treatment interactions, and adding an indicator for whether a village was part of the experimental variation in the selection experiment (n=100).

4 Experimental Results

4.1 Main results: Service Provider Performance

The main design based results are shown in Table 8. These tables present de-meaned effects of our surveillance effort index (which ranges 0-1). There are no effects of selection, the performance of workers

selected by the community do not score higher compared to those selected by Chiefs. Column 1 and 4 present data on the full sample, estimates for the restricted experimental sample which yields similar results, see Appendix Table 24. Turning to incentives, there is a positive treatment effect of both CM and P4P, see Columns 2-5. Specifically, community monitoring increases surveillance effort by 0.05 or 0.24 SD. We find a comparable impact of financial incentives: CAHWs in this arm score 0.06 higher, or 0.29 SDs. There is little difference across short (Columns 1 -3) and long models (Columns 4 and 5). Comparing to other studies the impact of CM and P4P is a substantial effect. Raffler, Posner, and Parkerson (2024) find an effect of 0.07 SD (s.e. = 0.026) on "treatment quality". Christensen et al. (2021) found an effect of CM on "health service delivery index" of 0.041 SD (though not precisely estimated, with s.e. = 0.079), and for Non Financial Incentives of 0.022 SDs. Appendix Figure 8 shows the shift in the distribution of our index. CM (blue) and P4P (red) both add high performers, shifting away from the lower end of the tail, especially for P4P.

We find that effects are similar for each sub-indicator: the number of reports submitted, the number of animals reported on and if CAHWs were present during MAF form collection visits. All effects are between 0.04 and 0.06 units, or 0.19 - 0.29 SDs (see Appendix Table 22). On average in the CM arm, CAHWs submit 12 more reports, report on 39 more animals and are present 6% more of the time, with similar quantities for the P4P arm, see Appendix Table 23.

As a robustness, in Column 2 of Appendix Table 24 we also report CM x P4P analyses without the recruitment treatment and with randomization strata fixed effects. The results are qualitatively similar.

4.2 Surveillance Quality

Our measure of performance relates largely to effort by the CAHW invested in surveillance activities. This effort measure closely fits our model and is a relevant quantity to allow health agencies to respond more timely to suspected events. To what degree does increase effort relate to increase surveillance quality? The surveillance reports contains both type 1 and type 2 errors. False positives may be large if CAHW felt inclined to report even if no symptoms were observed. Both margins matter for containing pandemics, ie failing to report events has large consequences and triggering responses to false events is costly. Looking at records, we observe both the event of a disease *and* the effort in recording it. To validate our main measure of performance we assess treatmetns effects on our direct behavioral measure (see Validation Exercise above) in Table 9.

Table 8: Main results

	T1	T2	T3	All	All (FE)
T1 (selection)	0.011			0.009	
	(0.028)			(0.024)	
T2 (community monitoring)		0.050**		0.051**	0.050**
		(0.025)		(0.024)	(0.025)
T3 (pay for performance)			0.063**	0.060**	0.063**
			(0.024)	(0.024)	(0.024)
T1 x T2				−0.062	−0.057
				(0.049)	(0.049)
T1 x T3				−0.039	−0.042
				(0.049)	(0.049)
T2 x T3				−0.034	−0.032
				(0.048)	(0.049)
T1 x T2 x T3				0.014	0.013
				(0.097)	(0.098)
Two candidates (T1)				0.063**	
				(0.025)	
Constant				0.497***	
				(0.015)	
Control Mean	0.519	0.493	0.489	0.423	0.423
Control SD	0.202	0.214	0.201	0.191	0.191
Observations	287	287	287	287	287

Note: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

The outcome is a normalised index based on the four sub-component measures we used (ie the animal knowledge exam, form review, sick animal observation in the field and monitoring form follow-up). We find results generally constistent with the overall main results on surveillance effort. There is no effect of selection (Column 1 and 4), and a positive effect of CM and P4P of 0.15-0.21 SDU. Results on CM are less precisely estimated, however throughout we cannot reject the null of no difference between CM and P4P.

5 A Structural approach

The estimates of the treatment effects studied so far test propositions that are suggested by the model. Since our model provides predictions for effort as a function of parameters and treatments we can make inferences about model parameters on the basis of observed outcomes in different treatment conditions.

To estimate model parameters we integrate our model into an empirical model with chiefdom level fixed effects $ _{j}$ and random errors and estimate model parameters using stan.

$$e_{ij} = \alpha_j + \kappa \times p(T_1, T_2, T_3 | \bar{\mu}, \underline{\eta}, \rho, \nu, \phi, \zeta) + \epsilon_i$$

We place a flat prior on all model parameters (subject to the ranges of the parameters). Posterior estimates on model parameters are then shown in Figure 3.

The distributions are rather wide for most parameters, but they nevertheless show movement. Critically our posterior on the upper bound for intrinsic motivation moves down, relative to our flat prior. The lower bound on embeddedness has increased, implying a narrow range for this distribution. The posterior on type correlation is essentially flat. We update our beliefs on susceptibility to guilt upwards and our beliefs about social sensitivity downwards. Finally we have relative tight posteriors on our scaling parameter and the distribution of the error term.

Table 9: Main Results Surveilance Quality

	T1	T2	T3	All	All (FE)
T1 (selection)	0.046			0.117	
	(0.134)			(0.119)	
T2 (community monitoring)		0.151		0.150	0.152
		(0.120)		(0.118)	(0.120)
T3 (pay for performance)			0.208*	0.202*	0.206*
			(0.119)	(0.118)	(0.120)
T1 x T2				−0.354	−0.354
				(0.241)	(0.243)
T1 x T3				0.112	0.104
				(0.241)	(0.243)
T2 x T3				0.177	0.162
				(0.236)	(0.240)
T1 x T2 x T3				0.155	0.198
				(0.485)	(0.489)
Two candidates (T1)				0.110	
				(0.126)	
Constant				−0.039	
				(0.070)	
Control Mean	−0.059	−0.075	−0.101	−0.289	−0.289
Control SD	0.993	0.916	1.100	0.958	0.958
Observations	287	287	287	287	287

Note: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

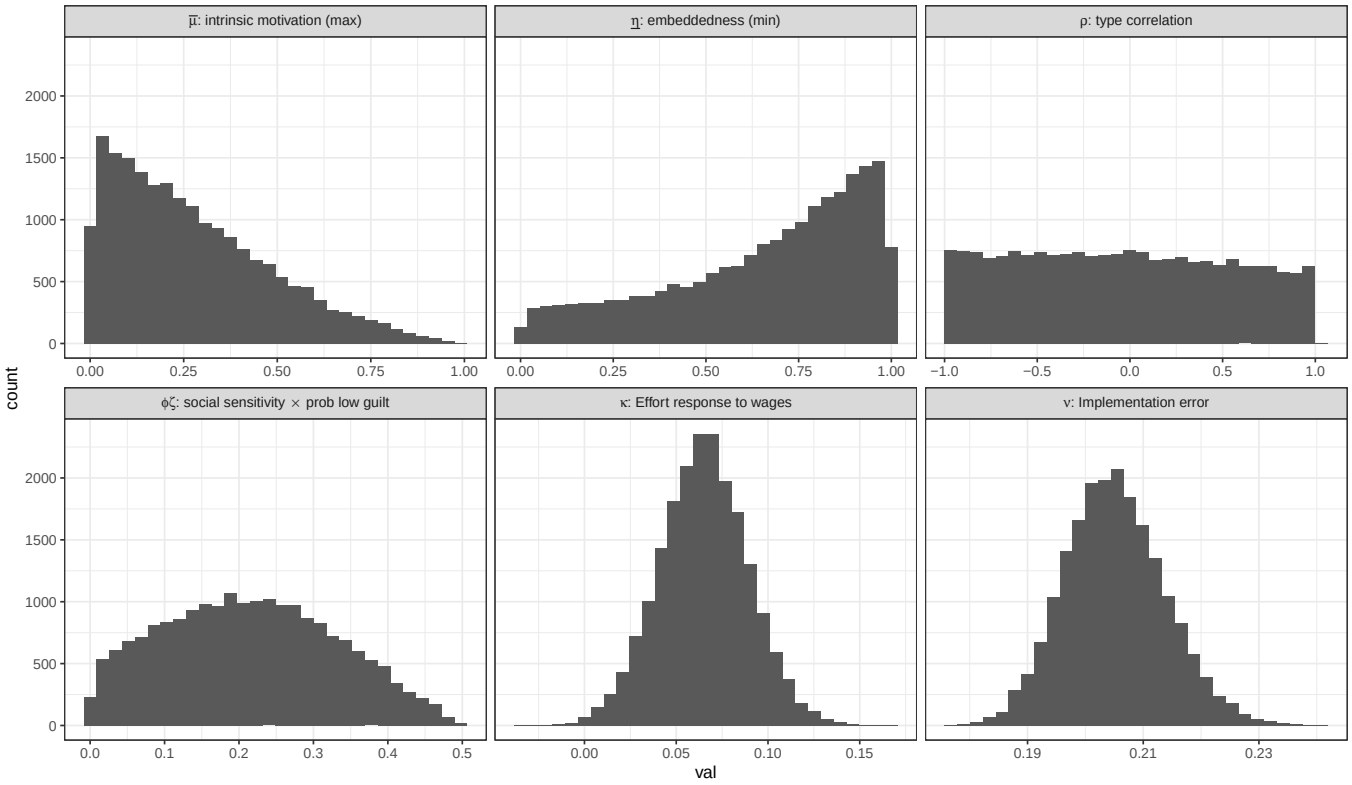


Figure 3: Posterior distributions on model parameters

5.1 Experiments

With our structural model in hand we are in a position to ask counterfactual questions about what prevents or augments the effects of institutional features, where and when interventions might be more or less effective, and whether interventions that seek to target fundamental parameters are likely to improve outcomes or improve the effects of treatments.

For each set of experiments we calculate our posterior effects for different treatments (selection, community monitoring and pay for performance) when different parameters are fixed to particular (near) extreme values. In all cases we look at the effect of a treatment relative to chief-selection and no incentives condition. This allows us to ask counterfactual questions under the model, asking: how would we expect effects to be different in different conditions?

5.1.1 Experiments: T1 selection

We start by focusing on T1, community selection. Where and when might we expect stronger selection effects? Under the model these effects might depend on type correlation, motivation, and embeddedness. To assess the importance of these conditions we show our posterior estimates for treatment effects when these different parameters are fixed to different high and low values. Results are shown in Figure 4.

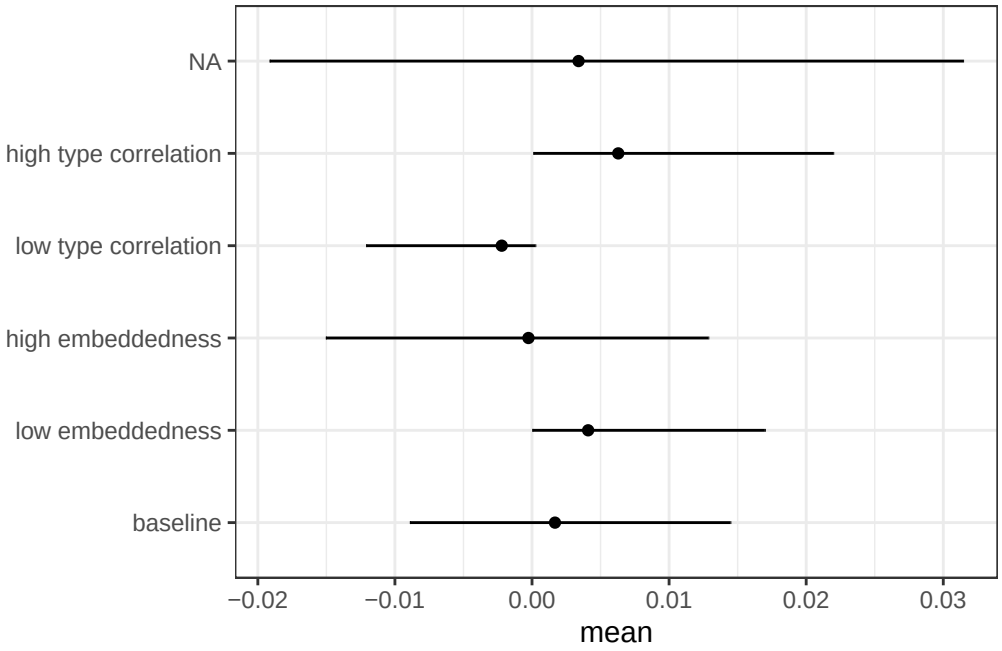


Figure 4: When might selection matter?

We see that we would expect an effect of village selection if there were a higher correlation between embeddedness and intrinsic motivation—as in that case villages would be more likely to choose highly motivated individuals than chiefs—or if chief-selected candidates were less embedded. In all cases, however, the estimated effects are small. Thus while this analysis can explain why we observe no effects given our beliefs about the distribution of types, it also suggests that we should not expect dramatic differences elsewhere.

5.1.2 Experiments: T2 Community Monitoring

Our second experiment examines conditions under which the effect of community oversight of the form studied by Björkman and Svensson (2009) are likely to be stronger or weaker. Under our model, the effect depends on embeddedness and social sensitivity.

Results from experiments varying these parameters are shown in Figure 5.

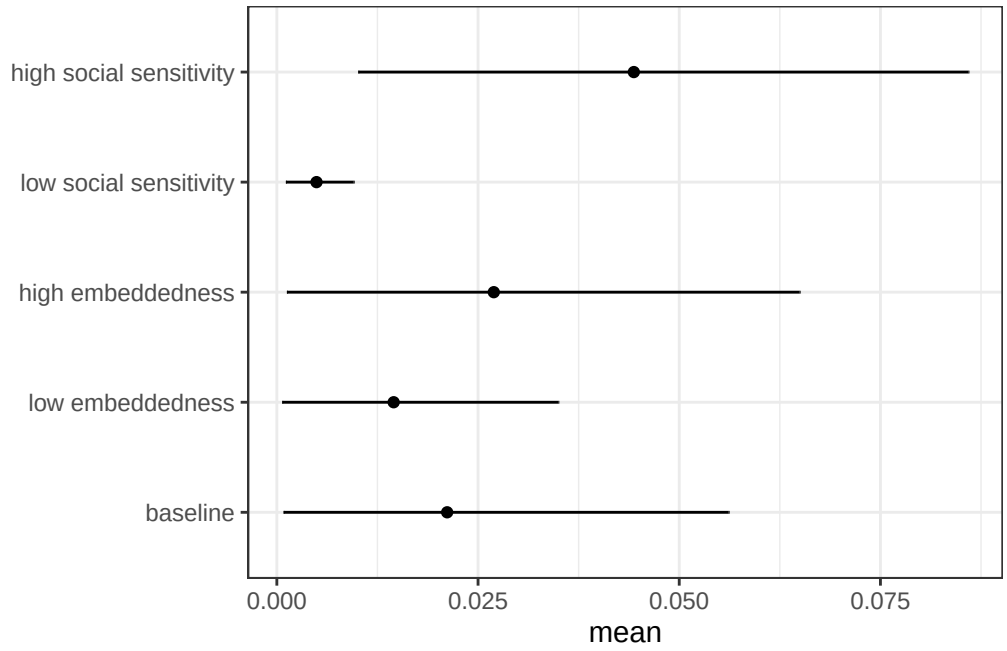


Figure 5: When might community sanctions work?

We see here that expectations are positive in all cases, as required by the model. Estimated effects would essentially double if social sensitivity were high. High embeddedness affects expectations also but the importance of this feature is substantively weaker.

5.1.3 Experiments: T3 Pay for Performance

In our third experiment we examine conditions under which the effect of payment for performance are stronger or weaker. Under the model effects might depend on embeddedness.

Results from experiments varying these parameters are shown in Figure 6. Here we see only modest changes in expectations about treatment effects as a function of embeddedness.

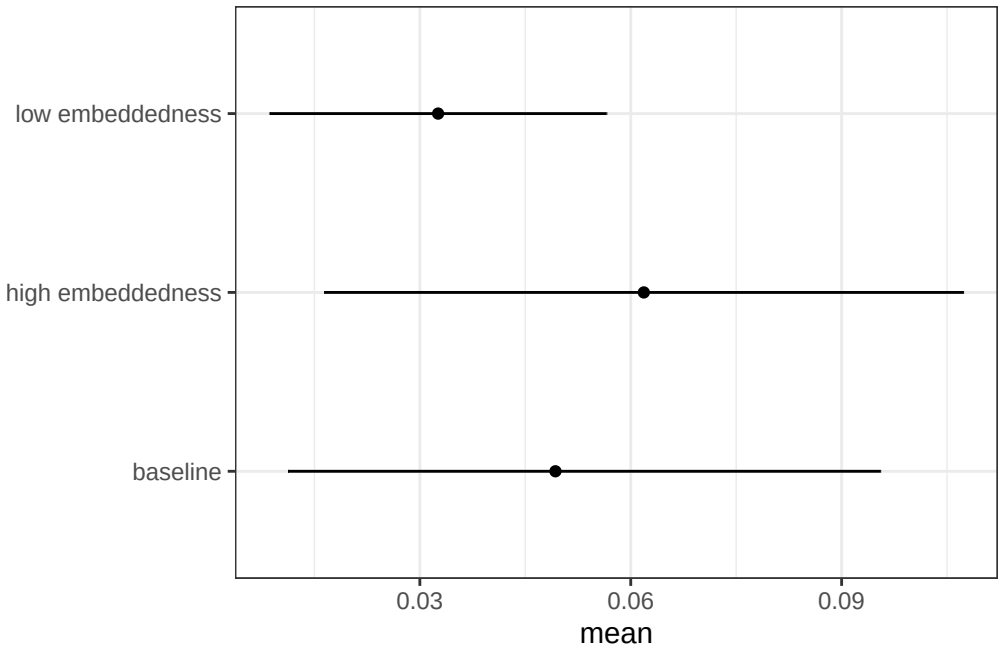


Figure 6: When is payment most effective?

6 Conclusion

We use a field experiment implemented in Sierra Leone to examine the joint effects of local selection, local monitoring, and incentivized payment mechanisms. We find no evidence that community selection of candidates makes a difference in this context. We do find evidence consistent with past literature that social pressure improves worker quality. The effects are larger than reported elsewhere. These gains are however similar to simple direct payment mechanisms that involve similar direct but lower social costs, i.e. the cost of community members joining several meetings with the CAHW to learn about performance as well as the time costs of implementing the social incentives (the material costs entail an in-kind transfer to the CAHW so from a social perspective represent no net loss).

Analysis of a structural model identifies conditions under which social or economic incentives are more or less likely to be effective. We use this analysis to make sense of both our null effect and the two positive effects. This analysis suggests that the null result on selection may arise because of high social embeddedness even for candidates not selected by communities and a low correlation between embeddedness and effectiveness.

7 Appendices

7.1 Model supplementary material

7.1.1 Baseline Model: Proofs

Proof of Lemma 1. Substituting (1) into (2) yields that, when $T_2 = 1$ the villager's expected payoff as a function of her social sanctioning plan $s = (s(0), s(1))$

$$\begin{aligned} V(s;\gamma) =& \mathbb{E}_\theta \left\{ \eta e(s;\theta) \middle| T_1 \right\} [1 - \gamma s(1) + \gamma s(0))] - \gamma s(0) \\ =& \mathbb{E}_\theta \left\{ \kappa \eta^2 \max \left\{ \mu + T_3 + \phi(s(0) - s(1)), 0 \right\} \middle| T_1 \right\} [1 - \gamma s(1) + \gamma s(0))] - \gamma s(0) \end{aligned}$$

First, in equilibrium we mist have $s(0) \geq s(1)$ (otherwise the villager can strictly improve the worker's expected performance without increasing her guilt). Second

$$\frac{\partial V(s;\gamma)}{\partial s(1)} = -\gamma \mathbb{E}_\theta \left\{ e(s;\theta) \middle| T_1 \right\} + \frac{\partial \mathbb{E}_\theta \left\{ e(s;\theta) \middle| T_1 \right\}}{\partial s(1)}.$$

Since both terms are strictly negative, the optimal social sanctioning plan always involves $s(1) = -1$ (maximal praise following a high performance signal). Second, is immediate to see that when $\gamma = 0$, the optimal social sanctioning plan also involves $s(0) = 1$ (maximal shaming following a low performance signal. Finally, when $\gamma = \overline{\gamma}$, we have

$$\begin{aligned} V(s(0), -1; \overline{\gamma}) =& \mathbb{E}_\theta \left\{ \kappa \eta^2 [\mu + T_3 + \phi(s(0) + 1)] \middle| T_1 \right\} [1 + \overline{\gamma} + \overline{\gamma} s(0)] - \overline{\gamma} s(0) \\ =& \kappa \mathbb{E}_\theta \left\{ \eta^2 [\mu + T_3 + \phi] \middle| T_1 \right\} [1 + \overline{\gamma} + \overline{\gamma} s(0)] + \kappa \phi s(0) \mathbb{E}_\theta \left\{ \eta^2 \middle| T_1 \right\} [1 + \overline{\gamma} + \overline{\gamma} s(0)] - \overline{\gamma} s(0) \end{aligned}$$

First, notice that the expression is convex in $s(0)$. Hence, we just need to show that under the assumptions $V(-1, -1; \overline{\gamma}) > V(1, -1; \overline{\gamma})$, i.e.,

$$
\begin{aligned}
2\overline{\gamma} &> \kappa \mathbb{E}_\theta \left\{ \eta^2 [\mu + T_3 + \phi] \middle| T_1 \right\} 2\overline{\gamma} + \kappa \phi \mathbb{E}_\theta \left\{ \eta^2 \middle| T_1 \right\} 2[1 + \overline{\gamma}] \\
\leftrightarrow \overline{\gamma} &> \kappa \mathbb{E}_\theta \left\{ \eta^2 [\mu + T_3 + \phi] \middle| T_1 \right\} \overline{\gamma} + \kappa \mathbb{E}_\theta \left\{ \eta^2 \middle| T_1 \right\} \phi [1 + \overline{\gamma}] \\
\leftrightarrow \overline{\gamma} \Big[1 - \kappa \mathbb{E}_\theta \left\{ \eta^2 [\mu + T_3 + 2\phi] \middle| T_1 \right\} \Big] &> \kappa \mathbb{E}_\theta \left\{ \eta^2 \middle| T_1 \right\} \phi
\end{aligned}
$$

which is implied by Assumptions 1 (left-hand is positive) and 2. □

7.1.2 Model Parameters and Regression Coefficients

The table below summarizes the relationship between the model quantities and the regression coefficients of

$$
Y_i = \delta \mathbf{T}' + \epsilon_i
$$

where

$$
\mathbf{T} = [1 \quad T_1 \quad T_2 \quad T_3 \quad T_1 T_2 \quad T_1 T_3 \quad T_2 T_3 \quad T_1 T_2 T_3]
$$

δ_0	δ_1	δ_2	δ_3	δ_4	δ_5	δ_6	δ_7
$\kappa \frac{\underline{\mu}}{2} \frac{1+\rho+\underline{\eta}^2(1-\rho)}{2}$	$\kappa \frac{\underline{\mu}}{2} \frac{1+\rho-\underline{\eta}^2(1-\rho)}{2}$	$\kappa(1+\underline{\eta}^2)\phi\zeta$	$\kappa \frac{1+\underline{\eta}^2}{2}$	$\kappa\phi\zeta \left[1-\underline{\eta}^2\right]$	$\kappa \frac{1-\underline{\eta}^2}{2}$	0	0

Table 10: Model Parameters and Regression Coefficients.

ME_{CoS}	$\delta_1 + \frac{\delta_4+\delta_5}{2} + \frac{\delta_7}{4}$
ME_{SS}	$\delta_2 + \frac{\delta_4+\delta_6}{2} + \frac{\delta_7}{4}$
ME_{PP}	$\delta_3 + \frac{\delta_5+\delta_6}{2} + \frac{\delta_7}{4}$
$IA_{CoS,SS}$	$\delta_4 + \frac{\delta_7}{2}$
$IA_{CoS,PP}$	$\delta_5 + \frac{\delta_7}{2}$
$IA_{SS,PP}$	$\delta_6 + \frac{\delta_7}{2}$
$IA_{CoS,SS,PP}$	δ_7

Table 11: Marginal and Interaction Effects and Regression Coefficients

7.1.3 Relaxing Binary Guilt Distribution

To economize notation, in the rest of the Appendix we set $\kappa = 1$. Let

$$\gamma^\dagger(T_1, T_3) \equiv \begin{cases} \frac{\phi}{1-\frac{\overline{\mu}}{2}(1+\rho)-(2\phi+T_3)} & T_1 = 1 \\ \frac{\phi}{\frac{2}{1+\underline{\eta}}-\frac{\overline{\mu}}{2}\frac{1+\rho+\underline{\eta}^2(1-\rho)}{1+\underline{\eta}}-\frac{1+\underline{\eta}^2}{1+\underline{\eta}}(2\phi+T_3)} & T_1 = 0 \end{cases}$$

Proposition 1. *The villager's optimal sanctioning strategy is given by*

$$(s_0, s_1) = \begin{cases} (-1,-1) & \text{if} \quad \gamma \geq \gamma^\dagger(T_1, T_3) \\ (1,-1) & \text{otherwise.} \end{cases}$$

Proof. We begin with the case of village selection ($T_1 = 1$). First, notice that we can write

$$\begin{aligned}
V(s_0, s_1) &= \mathbb{E}_{\theta,\pi}\Big\{v(\hat{e}(s;\theta), \pi, s)\Big|T_1 = 1, \hat{e}(s;\theta) = e(s;\theta)\Big\} \\
&= \mathbb{E}_{\theta,\pi}\Big\{e(s;\theta) - \gamma s_\pi\Big|\eta = 1\Big\} \\
&= \mathbb{E}_{\theta}\Big\{e(s;\theta) - \Pr(\pi = 1)\gamma s_1 - \Pr(\pi = 0)\gamma s_0\Big|\eta = 1\Big\} \\
&= \mathbb{E}_{\theta}\Big\{e(s;\theta) - \eta e(s;\theta)\gamma s_1 - (1 - \eta e(s;\theta))\gamma s_0\Big|\eta = 1\Big\} \\
&= \mathbb{E}_{\mu|\eta=1}\Big\{e(s;\theta) + e(s;\theta)\gamma(s_0 - s_1) - \gamma s_0\Big\} \\
&= \mathbb{E}_{\mu|\eta=1}\Big\{\max\{\mu + \phi(s_0 - s_1) + T_3, 0\}\Big\}(1 + \gamma(s_0 - s_1)) - \gamma s_0
\end{aligned}$$

where the last line follows from substituting $e(s;\theta) = \max\{\mu + \phi(s_0 - s_1) + T_3, 0\}$.

We proceed in three steps: (i) we show that the villager-optimal social sanctioning must be such that $s_0 \geq s_1$, (ii) we show that the villager-optimal social sanctioning must be such that $s_1 = -1$, and (iii) we characterize the optimal s_0.

(i) Suppose that $s' = (s'_0, s'_1)$ with $s'_0 < s'_1$ is villager optimal and consider $s'' = (s'_0, s'_0)$. We have that

$$\begin{aligned}
V(s'_0, s'_1) &< \mathbb{E}_{\mu|\eta=1}\Big\{\max\{\mu + \phi(s'_0 - s'_1) + T_3, 0\}\Big\} - \gamma s'_0 \\
&< \mathbb{E}_{\mu|\eta=1}\Big\{\mu + T_3\Big\} - \gamma s'_0 \\
&< \mathbb{E}_{\mu}\Big\{\mu \mid \eta = 1\Big\} + T_3 - \gamma s'_0 \\
&= V(s'_0, s'_0)
\end{aligned}$$

(ii) Since the villager-optimal sanctioning scheme satisfies $s_0 \geq s_1$, it must always induce positive effort ($\max\{\mu + \phi(s_0 - s_1) + T_3, 0\} = \mu + \phi(s_0 - s_1) + T_3$). We can then rewrite the problem as

$$\max_{s\in\{(x,y)\in[-1,1]^2|y\geq x\}} \Big(\frac{1+\rho}{2}\overline{\mu} + \phi(s_0 - s_1) + T_3\Big)(1 + \gamma(s_0 - s_1)) - \gamma s_0$$

Differentiating with respect to s_1 yields

$$-\phi(1 + \gamma(s_0 - s_1) - \gamma\Big(\frac{1+\rho}{2}\overline{\mu} + \phi(s_0 - s_1) + T_3\Big) < 0$$

Hence, in any villager optimal scheme we must have $s_1 = -1$. (iii) In light of the above, the villager optimal s_0 solves

$$\max_{s_0 \in [-1,1]} \Big(\frac{1+\rho}{2}\overline{\mu} + \phi(s_0+1) + T_3 \Big)(1+\gamma(s_0+1)) - \gamma s_0$$

Since the objective function is strictly convex in s_0, the villager optimal s_0 is either 1 or -1, depending on the sign of $V(-1,-1) - V(1,-1)$. We can then verify that

$$\begin{aligned}
& V(-1,-1) - V(1,-1) \geq 0 \\
\leftrightarrow \quad & \Big(\frac{1+\rho}{2}\overline{\mu} + T_3 \Big) + \gamma \geq \Big(\frac{1+\rho}{2}\overline{\mu} + 2\phi + T_3 \Big)(1+2\gamma) - \gamma \\
\leftrightarrow \quad & 2\gamma \geq \Big(\frac{1+\rho}{2}\overline{\mu} + 2\phi + T_3 \Big) 2\gamma + 2\phi \\
\leftrightarrow \quad & \gamma \geq \frac{\phi}{1 - 2\phi - \frac{1+\rho}{2}\overline{\mu} - T_3} \equiv \gamma^\dagger(1, T_3)
\end{aligned}$$

We now consider the case of chief selection ($T_1 = 0$). Substituting Equation 1 into the villager's objective function, we obtain

$$\begin{aligned}
V(s_0, s_1) &= \max_s \mathbb{E}_{\theta,\pi} \Big\{ v(\hat{e}(s;\theta), \pi, s) \Big| T_1 = 0, \hat{e}(s;\theta) = e(s;\theta) \Big\} \\
&= \max_s \mathbb{E} \Big\{ e(s;\theta)(1 + \gamma\eta(s_0 - s_1)) - \gamma s_0 \Big\} \\
&= \max_s \mathbb{E}_{\eta,\mu} \Big\{ \eta \max\{\mu + \phi(s_0 - s_1) + T_3, 0\}(1 + \gamma\eta(s_0 - s_1)) \Big\} - \gamma s_0 \\
&= \max_s \mathbb{E}_{\eta,\mu} \Big\{ \max\{\mu + \phi(s_0 - s_1) + T_3, 0\}\eta(1 + \gamma\eta(s_0 - s_1)) \Big\} - \gamma s_0
\end{aligned}$$

Using the same steps as the case of $T_1 = 1$, we obtain that since the objective is strictly convex in both s_0 and s_1, the solution is one of the four vertices of the square $[-1,1]^2$. Notice also that $V(-1,-1) - V(1,1) = 2\gamma > 0$, and that

$$V(-1,-1) - V(-1,1) = \mathbb{E}_{\eta,\mu} \Big\{ (\mu + T_3)\eta - \max\{\mu - 2\phi + T_3, 0\}\eta(1 - 2\gamma\eta) \Big\} > 2$$

Hence, the optimal incentive scheme is either $(-1,-1)$ or $(1,-1)$. After writing

$$\begin{aligned}
V(-1,-1) - V(1,-1) &= \mathbb{E}_{\eta,\mu}\Big\{(\mu + T_3)\eta - (\mu + 2\phi + T_3)\eta(1 + 2\gamma\eta)\Big\} + 2\gamma \\
&= -\mathbb{E}_{\eta,\mu}\Big\{(\mu + 2\phi + T_3)2\gamma\eta^2 + 2\phi\eta\Big\} + 2\gamma \\
&= -\mathbb{E}_{\eta,\mu}\Big\{2\gamma\eta^2\mu + (2\phi + T_3)2\gamma\eta^2 + 2\phi\eta\Big\} + 2\gamma, \\
&= 2\gamma\Big[1 - \mathbb{E}_{\eta,\mu}\{\eta^2\mu\} - (2\phi + T_3)\mathbb{E}_{\eta}\{\eta^2\}\Big] - 2\phi\mathbb{E}_{\eta}\{\eta\}.
\end{aligned}$$

We obtain

$$\gamma^{\dagger}(0, T_3) \equiv \frac{\phi}{\frac{2}{1+\underline{\eta}} - \frac{\overline{\mu}}{2}\frac{1+\rho+\underline{\eta}^2(1-\rho)}{1+\underline{\eta}} - \frac{1+\underline{\eta}^2}{1+\underline{\eta}}(2\phi + T_3)}$$

This concludes the proof. □

We now prove an ancillary Lemma.

Lemma 2. *Whenever* $\rho \geq -\frac{1-\underline{\eta}^2}{1+\underline{\eta}^2}$,
(i) village selection improves social sanctioning: $\gamma^{\dagger}(1, T_3) - \gamma^{\dagger}(0, T_3) > 0$,
(ii) $\gamma^{\dagger}(1, T_3) - \gamma^{\dagger}(0, T_3)$ *is higher under pay-for-performance.*

Proof. Notice that we can re-write $\gamma^{\dagger}$ as follows, with $\Psi(T_3) \equiv 1 - 2\phi - \frac{\overline{\mu}}{2} - T_3$:

$$\begin{aligned}
\gamma^{\dagger}(1, T_3) &= \frac{\phi}{\Psi(T_3) - \frac{\overline{\mu}}{2}\rho} \\
\gamma^{\dagger}(0, T_3) &= \frac{\phi}{\Psi(T_3)\frac{1+\underline{\eta}^2}{1+\underline{\eta}} + (1 - \underline{\eta})\left(1 - \frac{\overline{\mu}}{2}\rho\right)}
\end{aligned}$$

Part (i). After some rearranging, we obtain that the sign of $\gamma^{\dagger}(1, T_3) - \gamma^{\dagger}(0, T_3)$ is equal to the sign of

$$(1 - \eta)\left(1 - \frac{\underline{\eta}}{1 + \underline{\eta}}\Psi(T_3)\right) + \rho\frac{\overline{\mu}}{2}\eta$$

Imposing $\rho \geq -\frac{1-\underline{\eta}^2}{1+\underline{\eta}^2}$ yields the following lower bound:

$$(1-\eta)\left(1-\frac{\underline{\eta}}{1+\underline{\eta}}\Psi(T_3)\right)-\frac{1-\underline{\eta}^2}{1+\underline{\eta}^2}\frac{\overline{\mu}}{2}\eta=(1-\eta)\left(1-\frac{\underline{\eta}}{1+\underline{\eta}}\Psi(T_3)-\frac{\underline{\eta}+\underline{\eta}^2}{1+\underline{\eta}^2}\frac{\overline{\mu}}{2}\right)$$
$$>(1-\eta)\left[1-\frac{\underline{\eta}+\underline{\eta}^2}{1+\underline{\eta}^2}\left(\Psi(T_3)+\frac{\overline{\mu}}{2}\right)\right]>0$$

where the second inequality follows from the fact that $\Psi(T_3)<1-\frac{\overline{\mu}}{2}$.

Part (ii). To show that $\gamma^\dagger(1,T_3)-\gamma^\dagger(0,T_3)$ increases in T_3, it is sufficient to show that the difference decreases in Ψ (where we omit the dependence of T_3 for expositional clarity:

$$\begin{aligned}\frac{\partial}{\partial\Psi}[\gamma^\dagger(1,T_3)-\gamma^\dagger(0,T_3)]&=\frac{\partial}{\partial\Psi}\left(\frac{\phi}{\Psi-\frac{\overline{\mu}}{2}\rho}-\frac{\phi}{\Psi\frac{1+\underline{\eta}^2}{1+\underline{\eta}}+(1-\underline{\eta})\left(1-\frac{\overline{\mu}}{2}\rho\right)}\right)\\&=-\phi\left(\Psi-\frac{\overline{\mu}}{2}\rho\right)^{-2}+\frac{1+\underline{\eta}^2}{1+\underline{\eta}}\phi\left(\Psi\frac{1+\underline{\eta}^2}{1+\underline{\eta}}+(1-\underline{\eta})\left(1-\frac{\overline{\mu}}{2}\rho\right)\right)^2\\&=\phi^{-1}\left(-\gamma^\dagger(1,T_3)^2-\frac{1+\underline{\eta}^2}{1+\underline{\eta}}\gamma^\dagger(0,T_3)^2\right)<0,\end{aligned}$$

where the last inequality follows from part (i). □

Proof of Observation 2. The first part of the statement follows by inspection of Inequality 6.

Part (i) without community monitoring follows from the fact that

$$\mathbb{E}_\eta\left\{\eta^2|T_1=1\right\}=1>\frac{1+\underline{\eta}^2}{2}=\mathbb{E}_\eta\left\{\eta^2|T_1=0\right\}.$$

When community monitoring is present, the claim holds whenever

$$\left(1+2\phi\frac{\gamma^\dagger(1,1)-\gamma^\dagger(1,0)}{\overline{\gamma}}T_2\right)>\left(1+2\phi\frac{\gamma^\dagger(0,1)-\gamma^\dagger(0,0)}{\overline{\gamma}}T_2\right)\frac{1+\underline{\eta}^2}{2}\tag{8}$$

It is immediate to see that, since $\underline{\eta}<1$, the inequality holds as long as ϕ is small enough. To show that when $\rho\geq-\frac{1-\underline{\eta}^2}{1+\underline{\eta}^2}$ the inequality also holds regardless of ϕ, notice that a sufficient condition for inequality (8) is

$$\gamma^\dagger(1,1)-\gamma^\dagger(1,0)>\gamma^\dagger(0,1)-\gamma^\dagger(0,0)\leftrightarrow\gamma^\dagger(1,1)-\gamma^\dagger(0,1)>\gamma^\dagger(1,0)-\gamma^\dagger(0,0)\tag{9}$$

which follows from part (ii.) of Lemma 2.

Part (ii) Follows from the fact that $\gamma^{\dagger}(T_1,1)-\gamma^{\dagger}(T_1,0)>0$. □

Observation 5. *Community monitoring increases expected performance. Moreover, the effect*

(i) is stronger under village selection provided that ρ is sufficiently large;

(ii) is stronger under pay-for-performance.

Proof of Observation 5. The first part of the statement follows by inspection of Inequality 7.

Part (i) Notice that

$$\pi^*(1,1,T_3)-\pi^*(1,0,T_3)=2\phi\frac{\gamma^{\dagger}(1,T_3)}{\overline{\gamma}}\mathbb{E}_{\eta}\left\{\eta^2|T_1=1\right\}=2\phi\frac{\gamma^{\dagger}(1,T_3)}{\overline{\gamma}}$$
$$\pi^*(0,1,T_3)-\pi^*(0,0,T_3)=2\phi\frac{\gamma^{\dagger}(0,T_3)}{\overline{\gamma}}\mathbb{E}_{\eta}\left\{\eta^2|T_1=0\right\}=2\phi\frac{\gamma^{\dagger}(0,T_3)}{\overline{\gamma}}\frac{1+\underline{\eta}^2}{2}$$

It's immediate to see that whenever $\gamma^{\dagger}(1,T_3)>\gamma^{\dagger}(0,T_3)$, $\pi^*(1,1,T_3)>\pi^*(0,1,T_3)$. We also show that even when $\rho=-1$, the condition can still hold:

$$\pi^*(1,1,T_3)-\pi^*(1,0,T_3)\Big|_{\rho=-1}=\frac{2\phi}{\overline{\gamma}}\frac{1}{\Psi+\frac{\overline{\mu}}{2}}$$
$$\pi^*(0,1,T_3)-\pi^*(0,0,T_3)\Big|_{\rho=-1}=\frac{2\phi}{\overline{\gamma}}\frac{\frac{1+\underline{\eta}^2}{2}}{\Psi\frac{1+\underline{\eta}^2}{1+\underline{\eta}}+(1-\underline{\eta})\left(1+\frac{\overline{\mu}}{2}\right)}=\frac{2\phi}{\overline{\gamma}}\frac{1}{\Psi\frac{2}{1+\underline{\eta}}+2\frac{1-\underline{\eta}}{1+\underline{\eta}^2}\left(1+\frac{\overline{\mu}}{2}\right)}$$

Hence, in this case $\pi^*(1,1,T_3)-\pi^*(1,0,T_3)>\pi^*(0,1,T_3)-\pi^*(0,0,T_3)$ as long as

$$\Psi+\frac{\overline{\mu}}{2}<\Psi\frac{2}{1+\underline{\eta}}+2\frac{1-\underline{\eta}}{1+\underline{\eta}^2}\left(1+\frac{\overline{\mu}}{2}\right)\leftrightarrow\frac{\overline{\mu}}{2}\frac{2\underline{\eta}-1+\underline{\eta}^2}{1+\underline{\eta}^2}<(1-\underline{\eta})\left(\Psi\frac{1}{1+\underline{\eta}}+\frac{2}{1+\underline{\eta}^2}\right)$$

which holds whenever $\underline{\eta}$ is sufficiently small.

Part (ii) Follows from the fact that $\gamma^{\dagger}(T_1,1)-\gamma^{\dagger}(T_1,0)>0$. □

Proof of Observation 4. Using again equation (5), we obtain:

$$\pi^*(1,T_2,T_3)-\pi^*(0,T_2,T_3)=\pi^*(1,0,0)-\pi^*(0,0,0)$$
$$+\frac{2\phi}{\overline{\gamma}}\left(\gamma^\dagger(1,T_3)-\frac{1+\underline{\eta}^2}{2}\gamma^\dagger(0,T_3)\right)T_2+y\left(1-\frac{1+\underline{\eta}^2}{2}\right)T_3$$

First, notice that $y\left(1-\frac{1+\underline{\eta}^2}{2}\right)>0$. Condition $\rho\geq-\frac{1-\underline{\eta}^2}{1+\underline{\eta}^2}$ is necessary and sufficient for $\pi^*(1,0,0)-\pi^*(0,0,0)>0$. By part (i.) of Lemma 2, is also sufficient for $\gamma^\dagger(1,T_3)-\frac{1+\underline{\eta}^2}{2}\gamma^\dagger(0,T_3)>0$. □

7.1.4 The interaction between monetary and social incentives

In our baseline model, the interaction between T_2 and T_3 is weakly positive: if the distribution of villager guilt is continuous, Observation 5 implies that the effect of community monitoring is higher under pay-for-performance. Intuitively, it is easier for a villager to commit to impose a social sanction upon observing a low performance signal when the likelihood of that event is lower. Since pay-for-performance ($T_3=1$)increases expected performance, when $T_3=1$ a villager expects a lower level of expected guilt relative to the case in which $T_3=0$.

How robust is this result? Here we focus on two direction: the first if the possibility of decreasing returns in the worker's effort, the second is the possibility that villagers experience guilt upfront, not ex-post.

Upfront guilt. Suppose that, instead of committing to a social sanctioning scheme, the villager commits to a level of *shaming effort* $a\in[0,1]$ that expands the gap between the social reward and the social cost associated with the two signal levels: $s(0)=a$ and $s(1)=-a$, and that shaming effort results in an upfront cost of $\frac{a^2}{2\gamma}$, where γ is, for simplicity, a fixed parameter.

In this context, the worker is able to observe (or correctly conjecture) the value of a. Expected effort then is equal to $e(\theta,a)=\eta[\mu+T_3+2\phi aT_2]$. Anticipating this, under $T_2=1$, the villager's optimal effort a^* solves the following problem

$$\max_{a\in[0,1]}\left\{\mathbb{E}_\theta\{\eta e(\theta,a)|T_1\}-\frac{a^2}{2\gamma}\right\}$$
$$\max_{a\in[0,1]}\left\{\mathbb{E}_\theta\{\eta^2[\mu+T_3]|T_1\}+2\phi a\mathbb{E}_\theta\{\eta^2|T_1\}-\frac{a^2}{2\gamma}\right\}$$

which yields $a^* = 2\gamma\phi\mathbb{E}_\theta\{\eta^2|T_1\}$. Notice that since a^* is independent of T_3, we have no crowding out of incentives: $\pi^*(T_1, 1, T_3) - \pi^*(T_1, 0, T_3)$ is independent of T_3.

Decreasing returns. Now consider the baseline model and assume that, instead of being linear, the effect of effort on expected performance is concave: $\pi = \eta h(e)$, where $h(\cdot)$ is strictly concave. Since payoffs are as in the baseline model, it is easy to see that effort solves

$$\max\left\{\eta h(e)[\mu + T_3 - \phi T_2 s(1)] - (1 - \eta h(e))\phi T_2 s(0) - \frac{e^2}{2}\right\}$$

It is also easy to see that, as in the baseline model, we have $s(1) = -1$ and $s(0) = 2\mathbb{I}\{\gamma = 0\} - 1$. Hence, we have that equilibrium effort $e^*(\gamma; \theta)$ solves

$$\eta h'(e)[\mu + T_3 + 2\phi T_2 \mathbb{I}\{\gamma = 0\}] - e = 0$$

and expected performance equals

$$\pi^*(T_1, T_2, T_3) = \mathbb{E}_\theta\{\eta e^*(0; \theta)T_1\}\zeta + \mathbb{E}_\theta\{e^*(\overline{\gamma}; \theta)|T_1\}(1 - \zeta)$$

It is immediate to see that, since $h'(e)$ is decreasing,

$$\frac{\partial e^*(0;\theta)}{\partial T_2} = -\frac{\eta h'(e) 2\phi}{\eta h''(e)[\mu + T_3 + 2\phi T_2 \mathbb{I}\{\gamma = 0\}] - 1}$$

is both positive and decreasing in T_3. Thus $\pi^*(T_1, 1, T_3) - \pi^*(T_1, 0, T_3)$ is positive and decreasing in T_3. As a result, we have crowding out. Intuitively, because of decreasing returns on effort, the marginal effect of social sanctioning is higher without pay-for-performance.

7.1.5 Relaxing Additive Separability

Consider the following more general formulation of the worker's utility:

$$w = z(y, n) - \frac{e^2}{2}$$

depends on (i) the cost of effort (normalized to one in the baseline model), (ii) a material reward y, and (iii) a non-material reward n, which includes both intrinsic and extrinsic components (shaming by villagers): $n = \gamma\pi - \phi s$.

We assume that

1. z is strictly increasing in both arguments
2. $0 < z(0, -\phi) < z(y, \overline{\mu} + \phi) < 1$, to ensure that effort is interior

The following result shows that even when z has increasing differences—that is, the marginal utility of higher material reward increases with the non-material reward—, the effect of pay for performance can still be higher under chief selection.

Let $ATE_3(T_1, T_2) = \pi^*(T_1, T_2, 1) - \pi^*(T_1, T_2, 0)$ be the average effect of pay-for-performance.

Lemma 3. *When z has increasing differences, there exists ρ_0 such that whenever $\rho < \rho_0$, pay-for-performance is more effective under village selection:*

$$ATE_3(1, 0) < ATE_3(0, 0).$$

Proof. Under the assumptions, when $T_2 = 0$ the worker's individually optimal effort maximizes $e\eta z(yT_3, \gamma) + (1 - e\eta)z(0, 0)$

$$e(s, \theta) = \eta\Big[z(yT_3, \mu) - z(0, 0)\Big]$$

Hence, under village selection, we have

$$\pi^*(1, 0, T_3) = \frac{1+\rho}{2} z(yT_3, \overline{\mu}) + \frac{1-\rho}{2} z(yT_3, 0) - z(0, 0)$$

while under chief selection, we have

$$\begin{aligned}
\pi^*(1, 0, T_3) =& \frac{1}{2}\Big(\frac{1+\rho}{2} z(yT_3, \overline{\mu}) + \frac{1-\rho}{2} z(yT_3, 0) - z(0, 0)\Big) \\
&+ \frac{\eta}{2}\Big(\frac{1-\rho}{2} z(yT_3, \overline{\mu}) + \frac{1+\rho}{2} z(yT_3, 0) - z(0, 0)\Big) \\
=& \frac{1+\rho+\underline{\eta}(1-\rho)}{4} z(yT_3, \overline{\mu}) + \frac{1-\rho+\underline{\eta}(1+\rho)}{4} z(yT_3, 0) + \frac{1+\underline{\eta}}{2} z(0, 0)
\end{aligned}$$

We then obtain that

$$ATE_3(1,0) = \frac{1+\rho}{2}[z(y,\overline{\mu}) - z(0,\overline{\mu})] + \frac{1-\rho}{2}[z(y,0) - z(0,0)]$$

and

$$ATE_3(0,0) = \frac{1+\rho+\underline{\eta}(1-\rho)}{4}[z(y,\overline{\mu}) - z(0,\overline{\mu})] + \frac{1-\rho+\underline{\eta}(1+\rho)}{4}[z(y,0) - z(0,0)]$$

Under increasing differences, it is immediate to see that $ATE_3(0,0) > ATE_3(1,0)$ whenever $1+\rho < \frac{1+\rho+\underline{\eta}(1-\rho)}{2}$, that is $1+\rho < \underline{\eta}(1-\rho)$, which implies that $\rho_0 = -\frac{1-\underline{\eta}}{1+\underline{\eta}}$.

□

7.1.6 Embeddedness-Dependent Guilt

Suppose that the villager's utility is given by

$$u(\pi, s) = \pi - \eta\gamma s$$

Then the villager's expected payoff becomes

$$v(e,s) = \eta e(s) - \gamma\eta^2 e(s)s_1 - \gamma\eta(1-\eta e(s))s_0$$

and her objective function

$$V(s_0, s_1) = \mathbb{E}_\theta\Big\{\eta e(s,\theta)(1+\gamma\eta(s_0 - s_1)) - \gamma\eta s_0\Big\}$$

Under village selection, this boils down to the same exact expression as in the baseline model. Conversely, under chief selection, we have

$$\begin{aligned} V(s_0, s_1) &= \mathbb{E}_\theta\Big\{e(s,\theta)(\eta + \gamma\eta^2(s_0 - s_1)) - \gamma\eta s_0\Big\} \\ &= \mathbb{E}_\theta\Big\{\max\{\mu + \phi(s_0 - s_1) + T_3\}\eta(\eta + \gamma\eta^2(s_0 - s_1)) - \gamma\eta s_0\Big\} \end{aligned}$$

Relative to the baseline model, we obtain a qualitatively similar expression. Community monitoring is still more effective under village selection.

7.1.7 Falsification Tests

- Embedded workers should generally be more responsive to anything that increases the return of effort, because effort and embeddedness are complement;
- All things equal, it is easier for villagers to commit to providing a positive social reward (i.e., commit to shaming) under pay for performance: basically, the idea that these people are paid reduces the chances that in equilibrium I will have to shame the worker;
- For the same reason, it is easier to commit to shaming a worker whom I know is very susceptible to social pressure (high ϕ) .

7.1.8 The Role of Effort

The table below summarizes expected *effort* under each treatment cell in the more general model with continuous guilt.

$(T_2,T_3)\backslash T_1$	$T_1=0$			$T_1=1$		
$\pi^*(T_1,0,0)$	$\frac{\overline{\mu}}{2}\frac{1+\rho+\underline{\eta}(1-\rho)}{2}$			$\frac{\overline{\mu}}{2}(1+\rho)$		
$\pi^*(T_1,0,1)$	$\frac{\overline{\mu}}{2}\frac{1+\rho+\underline{\eta}(1-\rho)}{2}$	$+\frac{1+\underline{\eta}}{2}$		$\frac{\overline{\mu}}{2}(1+\rho)$	$+1$	
$\pi^*(T_1,1,0)$	$\frac{\overline{\mu}}{2}\frac{1+\rho+\underline{\eta}(1-\rho)}{2}$	$+(1+\underline{\eta})\phi\zeta\frac{\phi}{\overline{\gamma}}\gamma^\dagger(0,0)$		$\frac{\overline{\mu}}{2}(1+\rho)$	$+2\frac{\phi}{\overline{\gamma}}\gamma^\dagger(1,0)$	
$\pi^*(T_1,1,1)$	$\frac{\overline{\mu}}{2}\frac{1+\rho+\underline{\eta}(1-\rho)}{2}$	$+(1+\underline{\eta})\frac{\phi}{\overline{\gamma}}\gamma^\dagger(0,1)$	$+\frac{1+\underline{\eta}}{2}$	$\frac{\overline{\mu}}{2}(1+\rho)$	$+2\frac{\phi}{\overline{\gamma}}\gamma^\dagger(1,1)$	$+1$

Table 12: Expected effort as a function of the treatment.

Observation 6. *For each $(T_2,T_3)\in\{0,1\}^2$, there exist thresholds $\rho^l(T_2,T_3)$ and $\rho^h(T_2,T_3)$ such than when $\rho\in(\rho^l(T_2,T_3),\rho^h(T_2,T_3))$, village selection increases performance and decreases effort.*

Proof

Follows from the fact that since $\underline{\eta}\in(0,1)$, the effect of T_1 on effort equals, using the notation on Table 8

$$e^*(1,T_2,T_3)-e^*(0,T_2,T_3)=\begin{cases}\frac{\overline{\mu}}{2}\frac{1+\rho-\underline{\eta}(1-\rho)}{2}\\ +\frac{\phi}{\overline{\gamma}}\left[2\gamma^\dagger(1,0)-(1+\underline{\eta})\gamma^\dagger(0,0)\right]T_2\\ +\frac{1-\underline{\eta}}{2}T_3\\ \frac{\phi}{\overline{\gamma}}\left[2\gamma^\dagger(1,1)-2\gamma^\dagger(1,0)-(1+\underline{\eta})\gamma^\dagger(0,1)-(1+\underline{\eta})\gamma^\dagger(0,0)\right]T_2T_3\end{cases}$$

The only difference between $e^*(1,T_2,T_3)-e^*(0,T_2,T_3)$ and $\pi^*(1,T_2,T_3)-\pi^*(0,T_2,T_3)$ is that $\underline{\eta}$ is not squared. To prove the claim, we just need to show that the difference $e^*(1,T_2,T_3)-e^*(0,T_2,T_3)$ is submodular in (ρ,η) (omitting the dependence of $\gamma^\dagger(0,T_3)$ and $\gamma^\dagger(1,T_3)$ on η). We obtain

$$\frac{\partial^2}{\partial\rho\partial\eta}=-\frac{\overline{\gamma}}{4}-\frac{\phi}{\overline{\gamma}}\frac{\partial\gamma^\dagger(0,0)}{\partial\rho}T_2+\frac{\phi}{\overline{\gamma}}\left[-\frac{\partial\gamma^\dagger(0,1)}{\partial\rho}+\frac{\partial\gamma^\dagger(0,0)}{\partial\rho}\right]T_2T_3$$

Since both $\gamma^\dagger(0,0)$ and $\gamma^\dagger(0,1)$ are increasing in ρ, the result holds: whenever village selection improves expected effort, it also increases expected performance.

7.1.9 Additional information on type

In this section, we assume that, in addition to ((T_1,T_2,T_3)) the analyst (but not the actors in the model) can observe a noisy signal of the worker's type

$q=(q_\mu,q_\eta)\in\mathbb{R}^2$, with $q_\mu\sim\mathcal{N}(\chi_0+\chi_1\mu),\tau_\mu^{-2})$ and $q_\eta\sim\mathcal{N}(\psi_0+\psi_1\eta,\tau_\eta^{-2})$.

The precision parameters τ_μ and τ_η capture the accuracy of each component of the signal, while the parameters $(\chi_0,\chi_1,\psi_0,\psi_1)$ allow us to scale the measure into the type space.

As a result, we can build an expanded version of Table 5 in which $\pi^*(T_1,T_2,T_3)$ is replaced by $\pi^*(T_1,T_2,T_3,q)$.

It is convenient to define $P_0(\theta\mid T_1)$ as the prior belief about the worker's type as a function the treatment and $P(\theta\mid T_1,q)$ as the posterior belief as a function of the signal and the treatment. Using the fact that

$$P(\theta;T_1,q)=\frac{\Pr(q\mid\theta,T_1)P_0(\theta\mid T_1)}{\sum_{\theta'\in\{0,\overline{\mu}\}\times\{\underline{\eta},1\}}\Pr(q\mid\theta',T_1)P_0(\theta'\mid T_1)}$$

We have the following:

$$P_0(0,\underline{\eta} \mid T_1) = (1-T_1)\frac{1+\rho}{4} \tag{10}$$

$$P_0(\overline{\mu},\underline{\eta} \mid T_1) = (1-T_1)\frac{1-\rho}{4} \tag{11}$$

$$P_0(0,1 \mid T_1) = (1-T_1)\frac{1-\rho}{4} + T_1\frac{1-\rho}{2} \tag{12}$$

$$P_0(\overline{\mu},1 \mid T_1) = (1-T_1)\frac{1+\rho}{4} + T_1\frac{1+\rho}{2} \tag{13}$$

Using the normal distribution and the properties of the exponential function, we obtain

$$\Pr(q \mid \theta, T_1) = \frac{\tau_\mu \tau_\eta}{2\pi} \exp\left(-\frac{(q_\mu - \chi_0 - \chi_1\mu)^2\tau_\mu^2 + (q_\eta - \psi_0 - \psi_1\eta)^2\tau_\eta^2}{2}\right) \tag{14}$$

From which we obtain

$$P(\theta; T_1, q) = \frac{\exp\left(-\frac{(q_\mu-\chi_0-\chi_1\mu)^2\tau_\mu^2+(q_\eta-\psi_0-\psi_1\eta)^2\tau_\eta^2}{2}\right) P_0(\theta \mid T_1)}{\sum_{\theta' \in \{0,\overline{\mu}\}\times\{\underline{\eta},1\}} \exp\left(-\frac{(q_\mu-\chi_0-\chi_1\mu')^2\tau_\mu^2+(q_\eta-\psi_0-\psi_1\eta')^2\tau_\eta^2}{2}\right) P_0(\theta' \mid T_1)} \tag{15}$$

We then use these quantities to compute expected performance using the following formula:

$$\pi^*(T_1,T_2,T_3;q) = \left\{ \begin{array}{l} \overline{\mu}\underline{\eta}^2 P(\overline{\mu},\underline{\eta} \mid T_1,q) + \overline{\mu} P(\overline{\mu},1 \mid T_1,q) \\ + \left[\begin{array}{c} P(0,\underline{\eta} \mid T_1,q)\underline{\eta}^2 + P(\overline{\mu},\underline{\eta} \mid T_1,q)\underline{\eta}^2 \\ + P(0,1 \mid T_1,q) + P(\overline{\mu},1 \mid T_1,q) \end{array} \right] [2\phi\zeta T_2 + T_3] \end{array} \right\} \tag{16}$$

which allows us to replicate Table 5 for each possible signal (q).

Moment restrictions Notice that we can use our knowledge of the type space to link the *empirical distribution* of the type signals to the values of the scaling parameters:

$$\mathbf{E}\{q_\mu | T_1\} = \chi_0 + \chi_1\frac{\overline{\mu}}{2}(1+T_1\rho)$$

$$\mathbf{E}\{q_\eta | T_1\} = \psi_0 + T_1\psi_1 + (1-T_1)\psi_1\frac{1+\underline{\eta}}{2}$$

We can also use the empirical correlation between realized q_μ and q_η to impose restrictions on ρ.

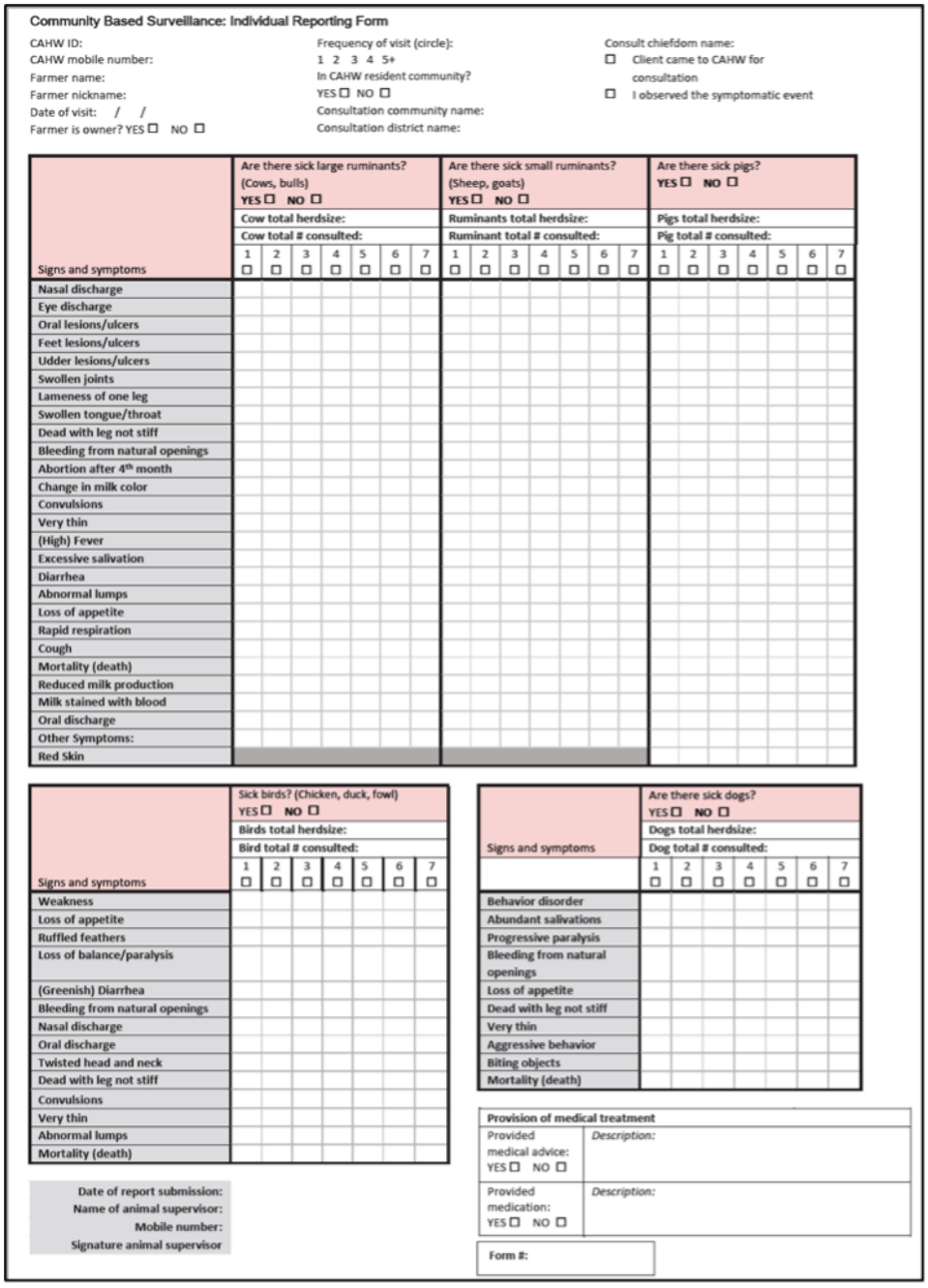
7.2 Timeline

Table 13: Timeline of project activities

Stage	Description	Date
1	Chief survey. Collect baseline data on villages. Used for treatment assignment.	July 2017
2	CAHWs nominations by the Paramount Chiefs and communities	July 2017
3	CAHW baseline survey. Baseline survey and tests for eligibility. If the village had a CAHW suggested by both the PC and the community, the survey would take place with both.	July 2017
4	Treatment assignment	August 2017
5	CAHW training for 23 days. Across 10 sites in Koidu, by 20 MAFFS facilitators.	August 2017
6	Household baseline survey. Survey with eight individuals per village.	Oct - Nov 2017
7	Installation of the CAHWs in each village. CAHW introduction to their community. Also included intro of the OH platform and assignment to incentive scheme. In total, 284/287 CAHWs were installed.	November 2017
8	CAHW performance round 1. Data collected from field practical and field visits. Field practical: A total of 267/287 CAHWs participated in this exercise. Those who did not scored 0. 8 of 267 had not sent in any form: they get the same score as during the animal exercise. Village visit: Visited 287 villages. 20 CAHWs had not submitted any filled forms so could not be judged: 'Communities with no monitoring forms to follow-up' (20 obs.) get the standardized mean value as their final score	| Field practical: Feb 2018;

9	Village visits: In CM treatments: Community feedback meeting 1. Review OH project, the statement of expectations, and the 'report card'. In P4P treatments: Enumerators delivered the incentive payments to the CAHWs in person, but in public in the P4P&CM treatments.	July 2018
10	CAHW performance round 2. Data collected from field practical and field visits. A total of 276 (out of 287) CAHWs participated. (As part of the village visits: they also did CAHW satisfaction surveys, and Town Chief Animal Census)	Practical: Nov 2018; Village visits: Mar - Apr 2019
11	Village visits: In CM treatments: see above In P4P treatments: see above	Oct - Nov 2019
12	Household endline data, including the COVID-19 behavioral measure.	Mar - Apr 2020

7.3 Figures



Community Based Surveillance: Individual Reporting Form

CAHW ID:
CAHW mobile number:
Farmer name:
Farmer nickname:
Date of visit: / /
Farmer is owner? YES ☐ NO ☐

Frequency of visit (circle):
1 2 3 4 5+
In CAHW resident community?
YES ☐ NO ☐
Consultation community name:
Consultation district name:

Consult chiefdom name:
☐ Client came to CAHW for consultation
☐ I observed the symptomatic event

Signs and symptoms	Are there sick large ruminants? (Cows, bulls) YES ☐ NO ☐ Cow total herdsize: Cow total # consulted: 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7 ☐	Are there sick small ruminants? (Sheep, goats) YES ☐ NO ☐ Ruminants total herdsize: Ruminant total # consulted: 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7 ☐	Are there sick pigs? YES ☐ NO ☐ Pigs total herdsize: Pig total # consulted: 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7 ☐
Nasal discharge			
Eye discharge			
Oral lesions/ulcers			
Feet lesions/ulcers			
Udder lesions/ulcers			
Swollen joints			
Lameness of one leg			
Swollen tongue/throat			
Dead with leg not stiff			
Bleeding from natural openings			
Abortion after 4th month			
Change in milk color			
Convulsions			
Very thin			
(High) Fever			
Excessive salivation			
Diarrhea			
Abnormal lumps			
Loss of appetite			
Rapid respiration			
Cough			
Mortality (death)			
Reduced milk production			
Milk stained with blood			
Oral discharge			
Other Symptoms:			
Red Skin			

Signs and symptoms	Sick birds? (Chicken, duck, fowl) YES ☐ NO ☐ Birds total herdsize: Bird total # consulted: 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7 ☐
Weakness	
Loss of appetite	
Ruffled feathers	
Loss of balance/paralysis	
(Greenish) Diarrhea	
Bleeding from natural openings	
Nasal discharge	
Oral discharge	
Twisted head and neck	
Dead with leg not stiff	
Convulsions	
Very thin	
Abnormal lumps	
Mortality (death)	

Signs and symptoms	Are there sick dogs? YES ☐ NO ☐ Dogs total herdsize: Dog total # consulted: 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7 ☐
Behavior disorder	
Abundant salivations	
Progressive paralysis	
Bleeding from natural openings	
Loss of appetite	
Dead with leg not stiff	
Very thin	
Aggressive behavior	
Biting objects	
Mortality (death)	

Provision of medical treatment	
Provided medical advice: YES ☐ NO ☐	*Description:*
Provided medication: YES ☐ NO ☐	*Description:*

Form #:

Date of report submission:
Name of animal supervisor:
Mobile number:
Signature animal supervisor

Figure 7: Animal Disease Surveillance Form

7.4 Additional tables

7.4.1 Summary statistics

Table 18: Summary statistics for outcome variables

measure	mean	min	max	sd
Performance index	0.52	0	1	0.21
Reports	0.41	0	1	0.27
Animals examined	0.34	0	1	0.27
Findable CAHW	0.81	0	1	0.25

Table 14: Baseline CAHW Survey

	All 287		Primary stratum only	
	Community (N= 170)	PC (N= 100)	Community (N= 50)	PC (N= 50)
Female	0.10	0.09	0.14	0.13
Age	28.48	29.34	28.82	30.11
Married	0.71	0.70	0.78	0.64
Kono tribe	0.75	0.72	0.76	0.74
Education (1-15)	10.52	10.06	10.18	9.94
Assets	12.56	12.97	12.32	12.72
Hours worked with animals	17.23	20.80	19.00	12.00
Extraversion	6.79	6.94	5.96	7.11
Agreeableness	7.08	7.06	6.70	6.83
Conscientiousness	7.91	7.88	7.40	7.87
Neuroticism	2.72	3.21	2.98	3.26
Openness	5.91	6.08	6.20	6.30
Years lived in village	12.29	13.72	14.04	14.26
Nights sleep in village	6.76	6.80	6.82	6.91
Plannning on staying in village	0.75	0.75	0.61	0.76
Nr Family in the village	8.81	9.72	9.82	9.47
Are or connected to leaders	0.51	0.50	0.36	0.49

Note:

CAHW Survey

Table 15: Baseline Household Survey

	All 287 with CAHWs		Primary stratum only	
	Community (N= 1000)	PC (N= 75)	Community (N= 360)	PC (N= 330)
Do you know the CAHW?	0.96	4.43	0.97	8.74
Social position of CAHW in village (higher is lower)	1.92	2.14	1.93	2.29
CAHW is family	0.49	0.52	0.48	0.44
CAHW is immediate family	0.15	0.13	0.12	0.11
CAHW lives in the village	0.91	0.87	0.95	0.86
How often CAHW in the village	5.70	5.54	5.76	5.40
How frequently talk to the CAHW (1 = daily, 6 = never)	1.34	1.57	1.28	1.67
CAHW eligible to be a PC	0.49	0.48	0.50	0.43
How connected with the PC (lower is better connected)	3.39	3.34	3.23	3.23
Days per week CAHW working on CAHW things	2.99	2.65	3.00	2.51
Satisfaction with CAHW helping community (1=not at all, 5=a lot)	4.43	4.27	4.44	4.02
CAHW part of decision making group (1=not at all, 5=a lot)	4.04	3.85	4.12	3.76
Willing to work on CAHW's farm (1=not at all, 5=a lot)	2.19	2.01	2.09	2.01

Note: Household baseline survey

Table 16: HouseholdBaseline Charateristics

	N Obs	Mean	SD	Median	Min	Max
Respondent gender (1 = Female)	2714	0.24	0.42	0	0.0	1
Respondent age (0-100)	2704	45.37	16.26	42	18.0	100
Marital status (1 = Married)	2696	0.80	0.40	1	0.0	1
Years in community (0-100)	2558	27.50	19.07	25	0.5	100
Education (1 = Has formal education)	2711	0.20	0.40	0	0.0	1
Literacy (1 = Illiterate)	2712	0.85	0.36	1	0.0	1
Christian (1 = Yes)	2714	0.51	0.50	1	0.0	1
Muslim (1 = Yes)	2714	0.49	0.50	0	0.0	1
Cares for animals (1 = Yes)	2715	0.89	0.31	1	0.0	1

[a] Household survey

Table 17: Survey Attrition

	DV = Perc. Attrition
Intercept	0.099***
	(0.029)
T1 CAHW Selection	−0.015
	(0.027)
T2 Community Monitoring	−0.009
	(0.027)
T3 Pay-for-Performance	−0.028
	(0.027)
N Obs	285
R^2	0.005
Adjusted R^2	−0.005

Note: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table 19: Social Sanctions

	(1) Rewarded CAHW	(2) Motivated CAHW
Community Monitoring	0.097***	0.065**
	(0.027)	(0.026)
Observations	1602	1640
Clusters	270	269
Control Mean	0.273	0.215
Control SD	0.446	0.446

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

7.4.2 Manipulation Check T2

Table 20: How did you reward CAHW?

	Freq.	Percent
NA	709	0.388
Work on CAHWs farm for a day	651	0.356
Dont Know	347	0.190
Give Money	182	0.100
Compensate the CAHW with fowl/other animal	181	0.099
Not include CAHW for public labor	160	0.087
Other	124	0.068
Recommend the CAHW for other projects as a good worker	96	0.052
Community will contribute to buying animal medicine	88	0.048

Note:
Frequency Table of endline household survey question If the CAHW was not performing their duties how SHOULD they be motivated?

Table 21: How did you motivate CAHW?

	Freq.	Percent
NA	709	0.388
Dont Know	388	0.212
Call CAHW at elders meeting and ask why	360	0.197
Call a community meeting to find out why	330	0.180
Report the CAHW to MAF or Town Chief	329	0.180
No longer receive help on farm	202	0.110
Other	113	0.062
Help the CAHW buy medicine	39	0.021
Fines	32	0.017
Wont recommend the CAHW for other jobs	26	0.014
Help CAHW reduce his workload	10	0.005

Table 22: Subcomponents of Performance Index (standardized)

	reports	animals	findable	all
T2 (community monitoring)	0.05	0.04	0.06	0.05*
	(0.03)	(0.03)	(0.03)	(0.02)
T3 (pay for performance)	0.08**	0.06*	0.04	0.06**
	(0.03)	(0.03)	(0.03)	(0.02)
T2 x T3	−0.04	−0.03	−0.02	−0.03
	(0.06)	(0.06)	(0.06)	(0.05)
R^2	0.29	0.25	0.25	0.28
Adj. R^2	0.04	−0.01	−0.02	0.03
Num. obs.	287	287	287	287
RMSE	0.26	0.27	0.26	0.21

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

7.4.3 Alternative specifications

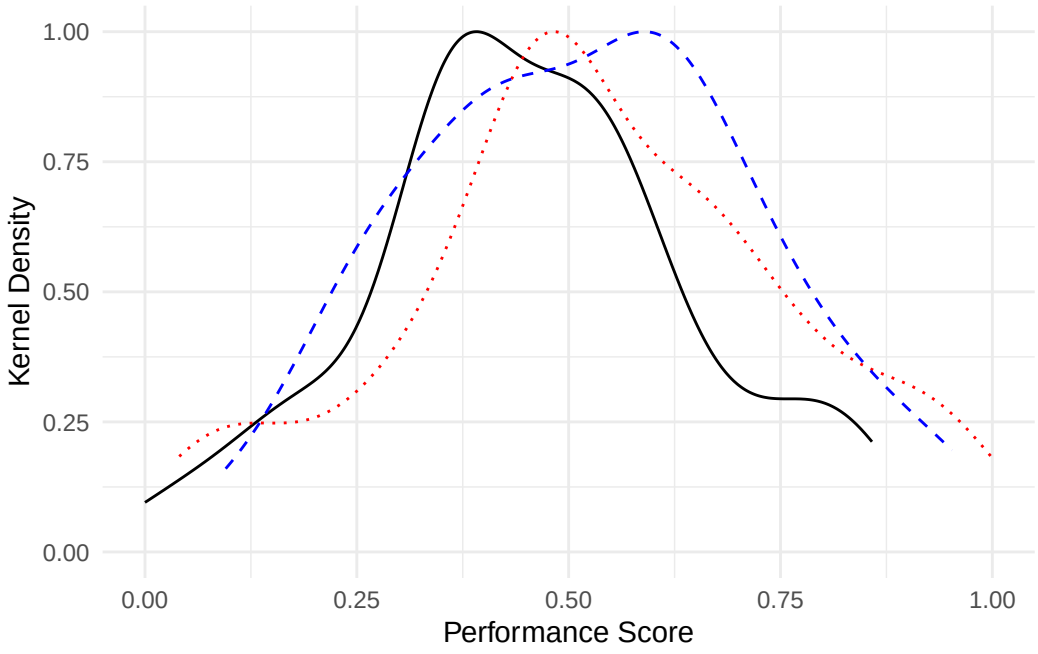


Figure 8: Changes in distributions

Table 23: Subcomponents of Performance Index (unstandardized)

	reports	animals	findable	all
T2 (community monitoring)	11.55	38.67	0.06	16.76
	(6.27)	(26.79)	(0.03)	(10.46)
T3 (pay for performance)	17.55**	50.00	0.04	22.53*
	(6.18)	(27.47)	(0.03)	(10.61)
T2 x T3	−2.15	−19.06	−0.02	−7.08
	(12.25)	(47.96)	(0.06)	(18.90)
Control Mean	58.17	129.67	0.75	62.86
Control SD	45.80	118.09	0.27	51.01
Num. obs.	287	287	287	287
R^2	0.31	0.32	0.25	0.32
Adj. R^2	0.06	0.08	−0.02	0.08

Note: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

7.4.4 Model based estimates of treatment effects

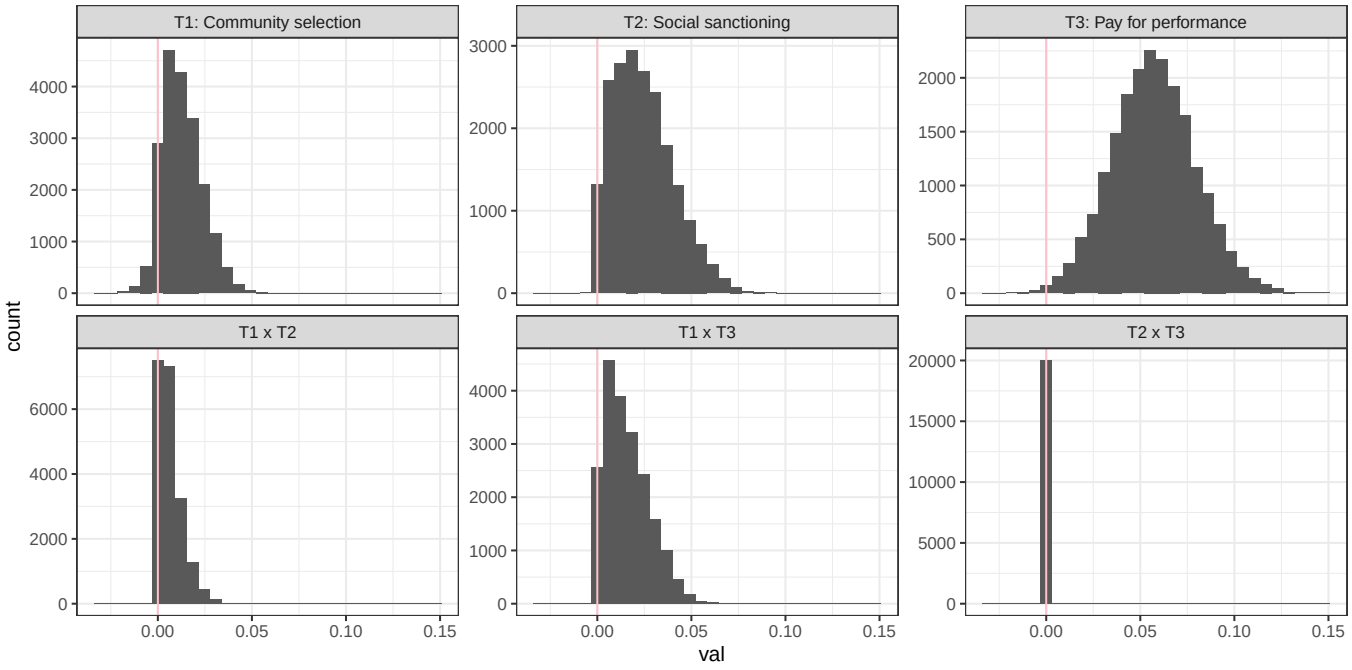


Figure 9: Posterior distributions on causal effects: close but note forced direction on interactions

Table 24: Additional specifications

	T1 (sub)	T23sat
T1 (selection)	0.01	
	(0.04)	
T2 (community monitoring)		0.05*
		(0.02)
T3 (pay for performance)		0.06**
		(0.02)
T2 x T3		−0.03
		(0.05)
R^2	0.54	0.28
Adj. R^2	0.03	0.03
Num. obs.	100	287
RMSE	0.20	0.21

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

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