O-Ring Theory of Enforcement

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Very very rough draft; I'm begging you, do not circulate.

Abstract

Why are some countries more corrupt than others? One possibility is that some have regulations that are too complex to effectively be implemented by their resource-constrained enforcement agencies. I write a model of government enforcement of an externality-averting provision that predicts that moving away from the more complex "first-best" provision to a less complex "second-best" provision actually increases externality reduction by decreasing corruption.

Work on the microfoundations of corruption has focused on the incentives of individual agents — usually officials and/or firms — to engage in corrupt behavior (Becker and Stigler, 1974). It is no surprise therefore that interventions targeted at reducing corruption have often targeted those very incentives — e.g., the costs of enforcement by the officer, the punishments for failing to do so, and the benefits for succeeding (Olken, 2007; Duflo et al., 2013; Khan et al., 2016). These studies usually take law itself as given; i.e., the design of the law is exogenous, while its enforcement is the object of study. But what if corruption is a function of the law itself?

Here I take that possibility seriously. I propose a model in which the complexity of a law — the number of regulations it contains — determines the probability of its enforcement. Specifically, each regulation–firm interaction is treated as a new draw from a Bernoulli distribution: with some probability, the firm will bribe the government official to ignore this particular regulation. The more regulations, the more opportunities for the official to succumb to bribery — or, put more cynically, the more regulatory weapons with which the official can extract bribes. The key assumption of the model is that, for any given official, corruption is all or nothing: a bribed officer does not enforce any regulations.

This evokes the "O-ring" production function proposed by Kremer (1993), in which the successful production of one unit of output depends on the successful completion of all of the requisite discrete tasks: one mistake and the entire unit is ruined. One implication of this model is that, if they're profit-maximizing, firms with low-skilled workers choose to remain smaller and specialize in goods that are simple to produce; otherwise, too many mistakes would be made and lots of output would go to waste. In the case of corruption, my slightly modified version of the Kremer model suggests that countries with low state capacity should choose to have fewer regulations and laws that are simple to enforce; otherwise, too many bribes would be paid and lots of regulations would go unenforced.

One domain in which corruption is crucial is environmental regulation. A central role of the government is to correct externalities, and pollution is a classic example thereof; without intervention, the socially efficient outcome is not achieved. Pollution is dramatically worse in poor countries than it is in rich ones; is this because of less stringent pollution laws (reflecting different preferences, different marginal costs, or different benefits) or less effective enforcement (Greenstone and Jack, 2015)? The former becomes less and less likely as, on paper, environmental regulations in low- and middle-income countries converge qualitatively towards that of rich countries (Olken and Pande, 2012).[1] However, levels of enforcement are not comparable between rich and poor countries. My model highlights two possible explanations for the discrepancy: (1) low state capacity, and (2) overly-complex regulations. I hope to test the importance of the latter in the context of lead-acid battery recycling.

Lead-acid battery recycling is a highly profitable yet highly polluting industry. Recent work in economics has found that living near battery-recycling plants has a negative causal relationship with health outcomes (Tanaka et al., 2022; Ipapa, 2023). This is no surprise given the fairly comprehensive understanding of the impact of lead poisoning on health outcomes, and the public health literature correlating this industry with lead poisoning (Aizer et al., 2018; Ericson et al., 2016). Despite the existence of laws with a *de jure* mandate to force this industry to reduce its pollution, lead-acid battery recyclers operate *de facto* unregulated in many developing countries (Mahzab et al., 2024). However, as the challenge of lead poisoning in low- and middle-income countries receives more attention, this is starting to change (Larsen and Sánchez-Triana, 2023). Some momentum has emerged to enable regulators in low- and middle-income countries to strengthen laws regulating this industry — and to better enforce those that are already on the books.

The present study aims to empirically test the hypothesis that reducing the complexity of environmental regulations can enhance enforcement effectiveness and reduce corruption in the context of lead-acid battery recycling by implementing a randomized control trial that varies the number of regulations an officer is tasked with enforcing. If successful, this

[1] I do not substantiate this claim here; however it is an empirical one, so, with time, I hope to be able to do so.

suggests that more attention should be directed at ensuring that regulations are appropriate for the context in which they are to be implemented; sometimes, the best law on paper may not be the best law in practice.

1 Model

In this very simple model, I abstract away from the microfoundations of corruption, instead focusing on the reduced-form outcome with which a policymaker might be directly concerned: how much stuff gets enforced. Consider an industry that creates a classic externality, such as pollution. A benevolent government (the principal) writes a regulation whose goal is to correct that externality. The regulation is made up of a series of provisions, whose enforcement is carried out by corruptable officers (the agents).

I treat corruption as little more than a coinflip: when an officer inspects a firm, they choose either to enforce the provision — which entails checking whether a firm is compliant, and, if not, imposing the appropriate penalty — or to accept a bribe and ignore the provision. Assume, for now, that the officer accepts a bribe with exogenous probability π. The key insights to the model results from the fact that I model provision enforcement as Leontief: if an officer accepts a bribe for one provision, then he will not enforce *any* of the provisions. In other words, provisions are o-rings: if one piece fails, the whole thing is useless.

The intuition is the following: a government official that is taking bribes to ignore the pollution coming out of a firm's smokestack is likely also going to ignore that firm's worker safety violations. Similarly, a firm that is paying an official to ignore worker safety violations is not going to be concerned about that same officer cracking down on the pollution coming from the firm's smokestack, and therefore will not bother to comply with the provision on smokestack emissions. In both versions of the story, any corruption "breaks" the o-ring, causing enforcement (and therefore compliance) to collapse.

The situation I'm modeling is a bit of a caricature, but it's meant to capture what I've gathered is a relatively common practice: some big agency — e.g., UNEP, WHO, the US EPA, the World Bank, the IMF — writes some model regulation which, implicitly or explicitly, is tied to aid. Developing countries then adopt the regulation whole cloth. The regulation, of course, is perfect: it contains all the consensus best practices for the given industry. The problem is that it is inappropriate for many developing country contexts — such governments are incapable of enforcing a regulation this complex. My hypothesis is that these countries would be *better off* with a regulation that was *worse* — so long as it is simpler to enforce.

Consider a regulation that corrects a classic externality, such as pollution. Let the regulation consist of a number of provisions that sum to Q. Let q be the subset of provisions that are enforced. Enforced provisions are goods; the utility that the regulation creates for society is an increasing, concave function of the number of provisions that are enforced:

$$U = f(q),$$

where $f'(q) > 0$ (the more enforced provisions, the better) and $f''(q) < 0$ (each additional enforced provision is less valuable than the previous one). To illustrate, take the example of pollution provisions: the more stringent the provision, the more pollution is reduced; but the marginal benefit of each additional provision is less than the last, since the first few provisions plucked all the low-hanging abatement fruit.

Now we turn to enforcement. We assume that a regulation is enforced by N identical officers who evenly split the provisions such that the number of provisions each officer enforces is Q/N. Suppose that for each provision, there are two possible outcomes: with probability $\pi \in (0, 1)$, the officer responsible for that provision is bribed and so the provision goes unenforced; with probability $1 - \pi$, the officer is not bribed and the provision gets enforced. In order to highlight the novelty of my model, I abstract away from any variation (endogenous or exogenous) in π, or any trading off of enforcement effort against the risk of getting caught.

Consider each officer to be an independent "o-ring": upon bribery, an officer becomes entirely corrupt, so every provision for which that officer is responsible goes unenforced. Each provision is another opportunity to be bribed. Therefore, the probability that an officer enforces all their provisions — i.e., goes entirely unbribed — is

$$(1 - \pi)^{Q/N}.$$

Then the expected number of provisions that are enforced by each officer is given by

$$\frac{Q}{N} (1 - \pi)^{Q/N}.$$

Because all the officers are identical and there are N of them, the total expected number of enforced provisions is given by

$$\mathbb{E}[q] = N \cdot \left(\frac{Q}{N} (1 - \pi)^{Q/N} \right) = Q (1 - \pi)^{Q/N}.$$

To make the model solvable by my unskilled hands, assume $f(q) = ln(q)$. Then the total expected utility is given by

$$\begin{aligned} U &= ln\left(Q\,(1-\pi)^{Q/N}\right) \\ &= ln(Q) + \frac{Q}{N} ln\,(1-\pi) \end{aligned}$$

The social planner's problem is to maximize total expected utility. Suppose π and N are given exogenously, so Q is the only choice variable. Then the first-order condition is given by

$$\frac{dU}{dQ} = \frac{1}{Q} + \frac{ln\,(1-\pi)}{N} = 0.$$

Solving for Q yields our optimum, Q^*.

$$Q^* = -\frac{N}{ln\,(1-\pi)}.$$

For ease of interpretation, let us define $\gamma = -ln(1-\pi)$ as some measure of corruption; note that $\pi \in (0,1)$, so $ln(1-\pi) < 0$ and is a decreasing function of π. Therefore $\gamma > 0$ and is an increasing function of π, i.e., as probability of being bribed increases, the measure of corruption increases. Therefore, utility is maximized at

$$Q^* = \frac{N}{\gamma}.$$

Let us note two things about this result. The first is that, despite this being an unconstrained maximization problem and utility being a monotonically increasing function of q, we successfully identified a maximum. That is, utility is suboptimal if Q is too low *or too high*. This captures the intuition that if there are too many items on an officer's plate, they become more susceptible to corruption, opening the door to the possibility that the number of provisions that actually get enforced might actually *increase* if there were *fewer* provisions.

The other thing worth noting is that the optimal number of provisions is increasing in number of officers N and decreasing in corruption γ. We might interpret N and γ to be two sides of the "state capacity" coin: N represents the size of the state, and γ represents the ability of each individual officer. That is, the more officers there are, and the better they are at their jobs, then the more stringent the provisions should be.

If a government has N officers to enforce this provision, then the optimal number of provisions, Q^*, ends up being a decreasing function of π and an increasing function of N. The insights that fall out of this model are very intuitive. The most obvious one is that a country with highly corruptible officers (high π) are better off with simpler provisions (small Q^*) that reduce the number of opportunities for bribery, while a country with officers who are difficult to bribe can afford to have more complex provisions — exactly analogous to the result in Kremer (1993), which is that countries with high-skill workers can specialize in producing more complex goods. A second insight is that a state can offset the corruption effect of having more officers by having them enforce fewer provisions — which evokes a simple story about state capacity.

2 Context and Intervention

A non-governmental organization (NGO) is in the process of creating a new, internationally-recognized standard for recycled lead. The standard will be based on an existing "Standard Operating Procedures" document, produced by industry experts, which spells out in great detail the assorted pollution abatement techniques of lead-acid battery recycling (Manhart and Wilson, 2021). The NGO aims to ascertain which of the techniques described in the Standard Operating Procedures are the most cost-effective at abating lead pollution.

Meanwhile, in 2024 Nigeria added the National Environmental (Battery Control) Regulations to their National Environmental Standards and Regulations Enforcement Agency (NESREA) (Establishment) Act. The Battery Control Regulations codify many of the techniques described in the Standard Operating Procedure; this is no coincidence, since the Nigerian regulatory bodies worked closely with an author of the Standard Operating Procedures in designing these regulations.

A workshop has been convened among regulators from five Sub-Saharan African countries to discuss the new Nigerian regulations. The intention is to roll these regulations out across the other nations in attendance. My hypothesis is that this would place each of those countries in a position where $Q_{j,c} > Q^*_{j,c}$, i.e., the number of regulations Q on industry j in country c exceeds the optimum. To test this hypothesis, I will need to collaborate with these regulators.

The ideal experiment with which to test the model and its predictions is, for a given industry, randomly assign the number of regulations contained in the law governing that industry across countries. This is obviously infeasible. Instead, I hope to proxy for $Q_{i,c}$ by varying the number of regulations for which a firm's compliance is considered to be within the purview of regulating officer i in country c. For example, one of the clauses in the new Battery Control Regulations is that "The Polluter-Pays-Principle shall apply to every facility." On its surface, this clause is grounds for a Pigouvian tax; however, for the time being, the Nigerian government does have the capacity to measure the quantity of pollution emitted by any individual recycling facility. However, as part of an intervention, we might be able to make available a monitoring device that the regulators could be trained to use and would be able to measure pollution, making this clause observable. Another clause that is similarly unenforceable at the moment reads, "A person who operates a used battery recycling plant shall carry out blood lead test[s] on the facility workers at least twice every year."

My proposed intervention is as follows. First, I will identify five regulations that are not currently being enforced (due to lack of funding, appropriate equipment, etc.), feasible to enforce given the budget constraints of the intervention, and hypothesized to have a significant impact on pollution. Officer i will be randomly assigned a subset of these five for which to be responsible, where Q_i denotes the number of regulations which officer i is tasked to enforce. For simplicity, let's assume there are only three possibilities: $Q_i \in \{1, 5, Q_{\text{total}}\}$ for all i, where Q_{total} represents the total number of regulations in the law. If $Q_i = 1$, then i will be given one specific regulation to enforce; we'll call this "narrow enforcement." If $Q_i = 5$, then i is tasked with enforcing all five regulations; we will call this "wide enforcement." If $Q_i = Q_{\text{total}}$, then i will not be given any direction on which regulations from the law ought to be enforced; we'll call this "control."

Officers in all three arms — narrow, wide, and control — will be given appropriate training to be able to enforce all five regulations. Further, for any special equipment that is required to be able to measure compliance on these regulations, officers across all three groups will have equal access. If, for example, an officer in the control group were to choose to measure compliance on fume hood suction, they would be able to access the windmeter necessary for that test just as easily as an officer in the treatment groups would.

In short, the only difference between officers in the two treatment arms and the control arm is the mandate: the regulations on which the officers are explicitly told (by their boss) to be checking compliance.

3 Data

The most important data to collect will be on pollution. The plan is to roll out a network of low-cost remote particulate matter (PM2.5) monitors across relevant areas of participating countries. This will allow us to measure pollution — and, therefore, the effectiveness of any actions taken to abate it — across firms and across time.

Although pollution is ultimately the object in which the policymakers ought to be most directly interested in the context of this particular industry, more proximate outcomes may be of more general interest.[2] For example, actions taken by the regulatory officer — e.g., taking and recording measurements of firm compliance on particular regulations, informing firms of violations, recommending fines or sanctions to superiors — more directly capture corruption itself. The pollution response captures the "reduced form" measure of the overall impact of the intervention as a whole — which is valuable *per se* — whereas the actions of the regulator capture the "first stage" measure of the effect of the intervention on corruption.

Therefore, to the extent possible, we will collect data on actions taken by the officer before, during, and after an inspection. In order to be able to say something about corruption, it may be necessary to compare some of these actions to an objective benchmark. For example, if an officer reports that a firm is testing its workers for blood lead, it would be necessary to verify this claim — either by "auditing the auditor" as done in Duflo et al. (2013), or by bringing in a third party to do so — in order to be able to determine whether the officer is behaving corruptly.

Furthermore, it may be possible to collect data on the actions taken by the firm itself, e.g., the purchase of new equipment, hiring new employees or retraining existing employees, etc. These sit somewhere between officer actions and pollution along the causal chain, so one might consider these to be part of the mechanism that would explain any reduced form response. If these changes are made in direct response to an officer's regulatory actions, then they are valid measures of the effect of the intervention on regulatory enforcement and, presumably, corruption.

Finally, it will be necessary to collect some data on the output level of the firms; pollution levels may increase or decrease mechanically as a result in changes in output, which would confound our measurement of the effect of the intervention. This is an especially large concern given the size of the industry and, therefore, the potential for spillover effects. Suppose that, for example, that the intervention causes firms that receive treatment inspections to be regulated more stringently than firms that receive control inspections. If the firms respond to this by simply lowering output and therefore pollution in order to comply, then firms that receive control interventions may benefit from this reduced competition and therefore increase their market share. This does not doom the intervention — it still was effective at increasing regulatory effectiveness — but it does mean that the net effect of the intervention is ambiguous, as the control group is no longer a valid counterfactual for the treatment group (i.e., the parallel trend assumption is violated), at least in terms of pollution.

[2] We may also be concerned, given how downstream pollution is from the intervention, about a lack the power to be able to detect a pollution response.

4 Empirical Strategy

In Section 3, I discussed the array of outcomes that I intend to collect, and the reasons for which these may be necessary. For ease of exposition, in this section I ignore that nuance, and proceed as if there were only one outcome of interest: pollution.

Consider the purpose of regulation enforcement in this context: correct the externality of pollution. In the absence of enforcement, firms would maximize profits without taking into account the harm caused by the pollution as a result of their production.

Given the generally lax enforcement of the (quite stringent) Battery Control Regulations in Nigeria up till now, it is not unreasonable to assume that firms will not voluntarily come into compliance; rather, they will wait until forced to do so. Therefore, we should not expect to see a large change in firm behavior except in response to an observable, credible threat of enforcement: e.g., an inspection, a fine, a sanction, etc. Suppose that for firms in this industry, seeing is believing: they do not respond unless an enforcement officer shows up at their factory and conducts an inspection.

Assume for now that this response is instantaneous. This lends itself to the following empirical strategy, where, because treatment is randomly assigned, a simple comparison of means would be valid, but a two-way fixed effects model may be more effective at purging the regression of counterproductive variation:

$$y_{it} = \alpha_0 I_{it} + \alpha_1 \text{NARROW}_{it} \times I_{it} + \alpha_5 \text{WIDE}_{it} \times I_{it} + \delta_t + \gamma_i + \varepsilon_{it}, \tag{1}$$

where y_{it} is pollution for firm i at time t, I_{it} is an indicator variable that is equal to 1 if firm i is inspected at time t, NARROW_{it} is an indicator variable that is equal to 1 if the inspection of firm i at time t was conducted by an officer tasked with enforcing the narrow set of regulations, WIDE_{it} is equal to 1 if tasked with enforcing the wide set of regulations, δ_t is time fixed effects, γ_i is firm fixed effects, and ε_{it} is an error term.[3]

The coefficients of interest are α_1 and α_5, with which we can test the null hypotheses that $\alpha_1 \geq 0$ and $\alpha_5 \geq 0$. If the former is rejected, then wide enforcement is more effective at causing firms to reduce pollution than undirected enforcement — noting that, because y measures pollution, a negative coefficient implies *more* effective enforcement. If the latter is rejected, the preferred interpretation is that narrow enforcement is more effective at causing firms to reduce pollution than undirected enforcement. A third null hypothesis is that $\alpha_1 \geq \alpha_5$. If this is rejected, then narrow enforcement is more effective than wide enforcement.

In the context of the model, we can interpret the coefficients of interest as identifying

[3]One might be tempted to include officer fixed effects, but because treatment is randomized at the inspector level, this would be colinear with treatment.

the optimal number of regulations Q^*. If $\alpha_1 < \alpha_5 < 0$, then $Q^* < 5$, i.e., *fewer* regulations bring *more* enforcement. If $\alpha_5 < 0$ but $\alpha_1 \geq 0$, then $Q^* \in [5, Q_{\text{total}})$ and is closer to 5 than to Q_{total}, i.e., there are too many regulations, but not *way* too many. If $\alpha_1 \geq 0$ and $\alpha_5 \geq 0$, then $Q^* \geq 5$ and is closer to Q_{total} than to 5, i.e., there may not be too many regulations.

Now we consider the more realistic scenario where firms do not respond instantaneously to an inspection. This requires an event study approach, which is a generalization of Equation 1 where the coefficients of interest are allowed to evolve over several time periods.

$$y_{it} = \sum_{\tau} (\beta_{0,\tau} I_{i,t+\tau} + \beta_{1,\tau}\text{NARROW}_{i,t+\tau} \times I_{i,t+\tau} + \beta_{5,\tau}\text{WIDE}_{i,t+\tau} \times I_{i,t+\tau}) + \delta_t + \gamma_i + \varepsilon_{it}, \quad (2)$$

where τ denotes event time, and the β_τ coefficients indicate the response of the firm τ periods after the intervention. Suppose, for illustrative purposes, that we decide to include three leads and three lags in the model. Then we define the "event" (the inspection) to be occurring at $\tau = 0$ and estimate the model by summing from $\tau = -3$ to $\tau = 3$ (excluding $\tau = 0$). The coefficient $\beta_{0,t+3}$, for example, is the pollution response of a firm three periods after a control group inspection, while $\beta_{1,t+1}$ is the pollution response of a firm in the period immediately before a narrow enforcement inspection. The coefficients of interest are $\beta_{1,t+\tau}$ and $\beta_{5,t+\tau}$ for $\tau > 0$, i.e., the difference in post-inspection pollution response between narrow enforcement inspections and control inspections, and between wide enforcement inspections and control inspections.

The lags are important to include in the regression because if, for example, compliance requires the purchase of a new piece of equipment, retraining of employees, or hiring of new employees, then a firm response to enforcement will take time. The leads are also important, e.g., to capture pretrends that differ across control and treatment (wide or narrow) inspections.

Differential pretrends could happen here for two reasons. The first is that if firms catch wind of an upcoming inspection, they may change their behavior in anticipation; if this differs across control and treatment — if, for example, officers are easier to bribe if they have a wider mandate — then the leads will capture this.

The second is that, even though treatment status is randomly assigned, it is done so at the level of the officer, which opens the door to selection into treatment at the firm level. To illustrate, suppose that officers have some discretion in which firms they choose to inspect, and that, for example, treatment officers always choose to inspect the firms that they know to be out of compliance on the regulations they are tasked with enforcing. If firms are naturally converging toward the same level of compliance over time (even absent any intervention), then the leads will show the firms receiving treatment inspections to be on a different pretrend than those receiving control inspections.

In the (unlikely) scenario that this study involves multiple countries, then it may be necessary to generalize Equation 2 to allow coefficients on the interaction terms to differ by country. The regression would then be given by

$$y_{ict} = \sum_{c}\sum_{\tau}(\mu_{0,c,\tau}I_{i,c,t+\tau} + \mu_{1,c,\tau}\text{NARROW}_{i,c,t+\tau} \times I_{i,c,t+\tau} + \mu_{5,c,\tau}\text{WIDE}_{i,c,t+\tau} \times I_{i,c,t+\tau}) + \delta_t + \gamma_i + \varepsilon_{it}, \tag{3}$$

where the coefficients of interest, $\mu_{1,c,\tau}$ and $\mu_{5,c,\tau}$ for $\tau > 0$, give the difference in post-inspection pollution response between narrow enforcement inspections and control inspections in country c.

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