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Competitive vs. Random Audit Mechanisms in Environmental Regulation: Emissions, Self-Reporting, and the Role of Peer Information

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Competitive vs. Random Audit Mechanisms in Environmental Regulation: Emissions, Self-Reporting, and the Role of Peer Information

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Abstract

In a simplifying analytical framework with endogenous levels of actual and self-reported emissions, we consolidate the existing literature into three main hypotheses about the relative merits, for a resource-constrained regulator, of random (RAM) and competitive (CAM) audit mechanisms in the presence or absence of peer information about actual emissions. Testing the three hypotheses in a quasi-laboratory experiment ($N = 131$), we find supportive evidence that CAM always induce more truthful reporting than RAM. Moreover, we provide the empirical validation of the theoretical prediction that CAM can succeed in aligning actual emissions more closely with the social optimum in the presence of peer information when RAM cannot. Behavioral mechanisms prevent reaching the first-best outcome.

Keywords: Environmental regulation; regulatory compliance; tournament theory; mechanism design; Laboratory experiment.

JEL classification: D62; H41; H83; L51; Q58.

1 Introduction

In many areas of economic life, regulated entities are obligated to self-report the level of a regulated activity to a regulator, broadly defined (Innes, 2017). Employees self-report task completion (Allen Jr and Bunn III, 2003) or workplace incidents (Probst and Estrada, 2010) to employers. Firms self-report emissions and release of regulated pollutants to environmental protection agencies (Malik, 1993; Helland, 1998). In several countries during the COVID19-pandemic, members of the public self-reported border crossings and compliance with quarantining regimes to public health authorities (Burns et al., 2020). Once obtained by the regulator, the reports can be used to determine the deviation of the entity's activity from a certain regulatory target and to implement, where appropriate, a reward or a penalty.

The economic literature has made considerable progress in its understanding of how to design efficient regulatory systems that harness the benefits of self-reporting while deterring misreporting through low-cost audit mechanism. Self-reporting acknowledges that the regulated entities tend to be better informed about their own activity levels than the regulator, who typically has to incur considerable monitoring costs in order to observe activity (Harford, 1987). It is vulnerable, however, to strategic misreporting (De Marchi and Hamilton, 2006). As a remedy, regulators can engage in costly audits to verify self-reported activity levels, but are constrained by limited auditing resources (Harford, 1987; Friesen and Gangadharan, 2013).

Progress has been especially pronounced in the context of environmental regulations where the activity in question is the emission of regulated pollutants, the regulated entities are firms, and fees are levied on the basis of self-reported emissions (De Marchi and Hamilton, 2006). There, the development of competitive audit mechanisms (CAM) (Gilpatric et al., 2011) has proven a particularly fruitful avenue for both theoretical and experimental research. This research shows that compared to the more conventional random auditing mechanism (RAM), CAM induces higher reported emissions and the same level of actual emissions with the same amount of auditing resources (Gilpatric et al., 2011; Cason et al., 2016). These findings underscore the potential of CAM to reduce misreporting of regulated entities. They also point towards the adoption of CAM as a partial remedy for dwindling auditing budgets available to regulatory agencies.

The present paper combines theory and experiments into a unified framework in order to examine more closely the impact of information structures between regulated entities on activity and reporting outcomes under the conventional RAM and the more sophisticated CAM. A focus on information structures is warranted both by empirical facts and by theoretical results. Empirically, even in seemingly similar settings information among regulated entities can differ substantially: Self-reporting employees may work side by side on the factory floor – or shirk in isolation in their home offices. Self-reporting polluters are as likely to be farmers cultivating adjacent fields as firms that know little interaction with each other's activities. The self-reporting citizens crossing a border may be members of a sports team – or complete strangers. While existing theory has modeled situations in which regulated entities are uninformed about the activity levels of their peers, situations in which the regulated entities are well informed are a common feature of the regulatory landscape. It is not immediately obvious which situation is more advantageous to the regulator and how the relative performance of RAM and CAM is affected by these differences in information structures among the regulated. For example, better peer information may well be used for collusive behavior that harms regulatory objectives (Gilpatric et al., 2011). However, a theoretical result shows that when firms have perfect peer information about each others' emissions, competitive auditing not only induces more reporting. It can, in fact, induce the socially optimal level of emissions, which the random audit mechanism fails to achieve (Oestreich, 2017). The finding that CAM can not only reduce misreporting (a secondary objective of regulation), but can in fact induce optimal emissions (a primary objective) is provocative and merits experimental scrutiny.

The paper makes two main contributions. First, it develops an analytical framework that unifies the theoretical contributions by Gilpatric et al. (2011), Cason et al. (2016), and Oestreich (2017). It does so with a view to deriving experimentally testable hypotheses about the comparative performance of CAM and RAM in terms of both activity levels and self-reporting in the presence and absence of peer information. As a measure of success in integrating these models, we demonstrate that the core findings of the literature can be replicated in this simplified setting: In the absence of peer information about activity levels, CAM induces the same level of actual activity as RAM, but leads to higher self-reported levels. In the presence of perfect information about each others' activity levels, CAM induces the socially optimal activity level while RAM does not. These findings constitute the core testable hypotheses that predict the presence and direction of differences in activity levels and reporting patterns between CAM and RAM depending on whether peer information is present or absent.

The second contribution is that we show in a quasi-laboratory experiment with 131 participants that all but one of the core hypotheses survive a test in a controlled setting. Participants play seven rounds of a game that mimics the unifying theoretical model. In each round, participants are randomly (re-)matched in groups of three and make two decisions individually:

their desired level of activity and the level of activity they wish to report. Each unit of activity reported incurs a fixed cost. Each unit of activity not reported incurs a penalty if the participant is audited. After each round, exactly one of the three participants is audited. In the RAM, the individual audit probability is fixed and uniform. In the CAM, the individual audit probability depends on the participant's report of activity level relative to the reports of the other two participants in the group. Each round is composed of 4 stages: a production stage, an information stage, a report stage and an audit stage. The game is parametrized such that the hypotheses developed in the analytical framework give rise to predictions of empirically distinguishable outcomes with respect to actual and self-reported activity levels.

Our experimental results show that in the absence of peer information, players' activity levels are statistically indistinguishable between both regimes: CAM and RAM lead to essentially the same activity levels. The self-reported activity levels differ, however: Under CAM, player self-report significantly higher activity than under RAM. As predicted, therefore, CAM outperforms RAM in terms of the secondary objective of truthful reporting. In the presence of peer information, CAM outperforms RAM also in terms of the primary regulatory objective: Activity levels under CAM are significantly lower than under the RAM while self-reported activity levels are significantly higher. This is the first experimental evidence that CAM succeeds in aligning activities levels closer with the social optimum, compared to RAM. We also find that there are behavioral forces that prevent a perfect alignment with the socially optimal activity level under peer information. These results respond to a call to provide an integrated experimental analysis of both activity level and self-reporting decisions (Cason et al., 2020), add evidence on the role of peer information for the regulatory performance of RAM and CAM, and provide an explanation for a deviation between theoretical predictions and experimental results in Cason et al. (2016).

In the following section, the paper develops the unifying analytical framework that culminates in the derivation of three testable hypotheses. The experimental design and its parametrization are presented in section 3 and lead to the concrete experimental predictions. Section 4 reports the results of the experiment and of our statistical tests. Section 5 discusses the experimental evidence and section 6 concludes with a summary and research outlook.

2 Theoretical Framework

Regulation. We consider a regulatory context with n regulated agents who choose a privately beneficial, but socially undesirable activity denoted by e_i. Agents accrue benefits from the activity captured by benefit function $g(e_i)$. This benefit function is assumed to be strictly concave with a maximum at e^0. Hence, in the absence of regulation, agents choose the maximum beneficial activity level, i.e. $e_i = e^0$, for $\forall i \in N$ where the marginal benefits are zero, that is $g'(e^0) = 0$.

Agents are supposed ot pay a linear fee t for every unit of the activity. We suppose that t is exogenously given; it is set by some higher-level authority. We think of t to induce the efficient activity level e^t if agents comply with it and choose the activity level according to $g'(e^t) = t$. For instance, in an environmental application, e^t would balance aggregated private marginal benefits from pollution and social marginal cost.

This paper focuses on the problem of the regulator who is in charge of enforcing the fee system. The regulator has to decide which of the n agents to audit given its limited audit resources. Accordingly, we define an audit mechanism as a strategy for the regulator to assign an audit probability p_i to every regulated agent i.

Regulator. The regulatory agency is charged with enforcing the fee system. It is at a disadvantage in comparison to the regulated agents as it can only observe the chosen activity level by agents after conducting a costly audit. Its operating budget is fixed including the resources allotted to conducting audits. Let K be the number of agents which the regulator can afford to audit, where $K \leq n$. Let $k \equiv K/n$ define the audit rate. If the regulator decides to increase the audit probability for one agent, it has to decrease the audit probability of at least one other agent in order to keep its budget at balance. Specifically, we have at all times that the assigned audit probabilities add up to the number of total audits: $\sum_{i=1}^{n} p_i = K$. Regulated agents pay fees on reported activity r_i. Let $\mathbf{r} = (r_1, ..., r_n)$ denote the vector of reported activity levels for the n agents. fees on reported activity levels may be potentially evaded by the agents. Thus, $e_i - r_i$ is the amount of potentially under-reported activity level by agent i.

The choice of the regulator is the announcement of an audit mechanism represented by function $p_i : (r_1, ..., r_n) \to [0, 1]^n \ \forall i \in N$, which maps the vector of activity-reports by the agents into probabilities for each agent of being audited. We assume that the regulator does know the unregulated activity level e^0 and can use it as reference value to compare activity reports to when designing the audit mechanism $p_i(\mathbf{r})$. After an audit, the regulator can perfectly observe the actual activity level chosen by the audited agents and potentially levy a linear penalty θ per unit of under-reported activity level, where $\theta > t$.

Information structure. The focus in this paper is on the performance of two different audit mechanisms under different information structures among regulated agents. Our theoretical framework captures two mutually exclusive assumptions about how much agents know about each others' activity levels:

Assumption 1a Agents have *no information* about each others activity levels.

Assumption 1b Agents have *perfect information* about each others activity levels.

Timing. An overview of the applied multistage game is as follows:

- In the *first stage*, the regulator announces an audit mechanism $p_i : (r_1, ..., r_n) \to [0, 1]^n$ which maps activity-reports into audit probabilities for each agent upon receiving the reports.
- In the *second stage*, agents choose the activity level e_i. Agents are not informed (Assumption 1a), or perfectly informed (Assumption 1b) about the activities of the other agents.
- In the *third stage*, agents choose activity reports r_i.
- In the *fourth stage*, some of the agents are audited according to the announced audit mechanism at the first stage. A fine θ is levied for every unit of under-reported activity levels $[e_i - r_i]$. This stage is automatic, that is there are no choices to make at this stage.

Problem of the agents. The problem of agent i is to choose activity level e_i and activity report r_i in order to maximize its expected profit:[1]

$$\max_{e_i \geq 0,\ r_i \leq e_i} \mathbb{E}\Pi_i(\mathbf{e}, \mathbf{r}(\mathbf{e})) = g(e_i) - tr_i - p_i(\mathbf{r}(\mathbf{e}))\theta[e_i - r_i]\ \forall i \in N, \tag{1}$$

where $\mathbf{e}$ denotes the vector of activity levels and $\mathbf{r}$ denotes the vector of reports chosen by all agents. Activity levels provide benefits to the agent through $g(e_i)$ and their cost is determined endogenously by the fee t on activity report r_i, the agent's individual audit probability p_i and penalty θ for potentially under-reported activity levels $[e_i - r_i]$.

[1] The agency does not reward over-reporting. If an agent is not audited, this agent pays $r_i t$ in fees. If an agent is audited this agent pays in addition $\max\{\theta(e_i - r_i), 0\}$. Since over-reporting is not rewarded, optimality implies that reported activity levels never exceed actual activity levels, that is $r_i \leq e_i$. Hence, without loss of generality, we can set $\max\{\theta(e_i - r_i), 0\} = \theta(e_i - r_i)$, and restrict the set of reported activity levels to be $r_i \leq e_i$.

Random audit mechanism. The random audit mechanism (RAM) is the common benchmark in the literature. The RAM allocates equal audit probabilities among all agents, regardless of the reports, formally: $p_i = k \ \forall i \in N$. We note that the RAM can fully enforce fees on the regulated activity if the expected marginal cost of under-reporting, $k\theta$ is larger than or equal to the fee rate, t. In that case, agents have no beneficial alternative but to truthfully report their activity levels. Knowing it is going to pay fees on all of its activity, an agent chooses socially efficient activity levels e^t. Thus, the regulator can fully enforce truthful reporting where $r_i = e_i$ and implement the socially efficient activity level $e_i = e^t \ \forall i \in N$, if the expected fine for under-reporting (audit rate times fine) is sufficiently large, $k\theta \geq t$.

To reflect the reality of many regulators (constrained auditing budgets and capped fines), we focus on cases where the relation between fee t and expected fine $k\theta$ does not lead to truthful reporting and socially efficient activity levels when the RAM is applied, that is $k\theta < t$. This focus sets the stage for the interesting case in which the RAM fails to implement efficient activity levels, because it is cheaper for the regulated agents to under-report activity levels (evade fees t) and rather face the expected penalty $k\theta$.

Proposition 1 *If $k\theta < t$, the RAM induces zero activity-reporting, i.e.: $r_i = 0 \ \forall i \in N$ and per-agent activity level $e_i = e^{k\theta}$, which is implicitly defined by:*

$$g'(e^{k\theta}) = k\theta \ \ \textit{for} \ \ \forall i \in N. \tag{2}$$

This result is independent of the information structure.

Since the RAM leads to zero activity-reporting and to more than socially optimal activity levels with capped fines and relatively low auditing budgets, the literature has pointed to more sophisticated audit mechanisms harnessing strategic interactions among the regulated agents to gain auditing leverage. We refer to these auditing strategies as *competitive audit mechanisms* (CAMs) in the following.

Competitive audit mechanism. The literature on CAMs is steadily growing. The main stylised facts on CAMs are as follows:

- CAMs are applied to regulated agents that self-report their activity level.
- CAMs *decrease* the audit probability of an agent, if the agent *increases* its reported activity levels: $\partial p_i(\mathbf{r})/\partial r_i < 0 \ \forall i \in N$,

- CAMs *increase* the audit probability of an agent, if another agent *increases* its reported activity level: $\partial p_i(\mathbf{r})/\partial r_j > 0 \; \forall j \neq i \in N$,
- CAMs keep the regulator budget balanced: If the regulator increases the audit probability for one agent, it has to decrease the audit probability of at least one other agent: $\sum_{i=1}^{n} \partial p_i(\mathbf{r})/\partial r_j = 0 \; \forall i \in N$.

We next propose a specific CAM which is in line with the features above. In addition, this CAM is able to induce the socially optimal activity level in equilibrium, where $e_i = e^t \; \forall i \in N$:

$$p_i(\mathbf{r}) = \begin{cases} 0 & \text{if } p_1 \leq 0, \\ 1 & \text{if } p_1 \geq 1, \\ k + \lambda \ln(\frac{(R_i)^{n-1}}{\prod_{j \neq i}^{n}(R_j)}) & \text{otherwise,} \end{cases} \tag{3}$$

where $R_i = e^0 - r_i$ and e^0 serves as a reference value for the regulator to compare reports against. Parameter λ determines the *degree of competitiveness* induced by the CAM. By *degree of competitiveness* we mean how quickly the audit probabilities per agent change in the reports. If $\lambda = 0$, random auditing results where $p_i = k \; \forall i \in N$. If $\lambda > 0$, the audit mechanism is competitive in that higher reports relative to other agents result in lower assigned audit probabilities. We will focus on the special case where $\lambda = (t/\theta - k)/((n-1)(2-N))$, and $N = \left(n - 2 + \sqrt{n^2 + 4n - 4}\right)/(2\,(n-1))$. We use this specific functional form for $p_i(\mathbf{r})$, because it can induce the optimal activity level e^t for all agents as shown below.

It is interesting to note that the smaller the relative audit budget of the regulator (measured by the difference between t/θ and k), the larger the degree of competitiveness induced by the CAM. In the event that the audit budget is sufficiently large ($t/\theta \leq k$) random auditing results and we recall from the analysis above that the RAM also implements the optimal activity level and truth-full reporting in that case. As before, we exclude such cases here with the assumption that $k\theta < t$ or $k < t/\theta$.

Illustrative example. In an attempt to illustrate the workings of the proposed CAM, Figure 1 illustrates the allocation of audit probabilities for a simple example with two agents ($n = 2$) when the regulator can afford to audit one of them ($K = 1$). In that case, the interior part of the audit function for agent 1 simplifies to:

$$p_1(r_1, r_2) = \frac{1}{2} + \lambda \ln(\frac{e^0 - r_1}{e^0 - r_2}),$$

with $\lambda = (t/\theta - 1/2)/((2 - \sqrt{2}))$. Figure 1 displays the audit rates p_1 and p_2 depending on reports r_1 and r_2. The report of agent 2 is fixed at the equilibrium value $r_2 = r_2^*$ and the report of agent 1 r_1 varies along the horizontal axis. When the reports coincide ($r_1 = r_2$), the audit probabilities also coincide ($p_1 = p_2 = 1/2$). If r_1 is increased, p_1 decreases and p_2 increases.

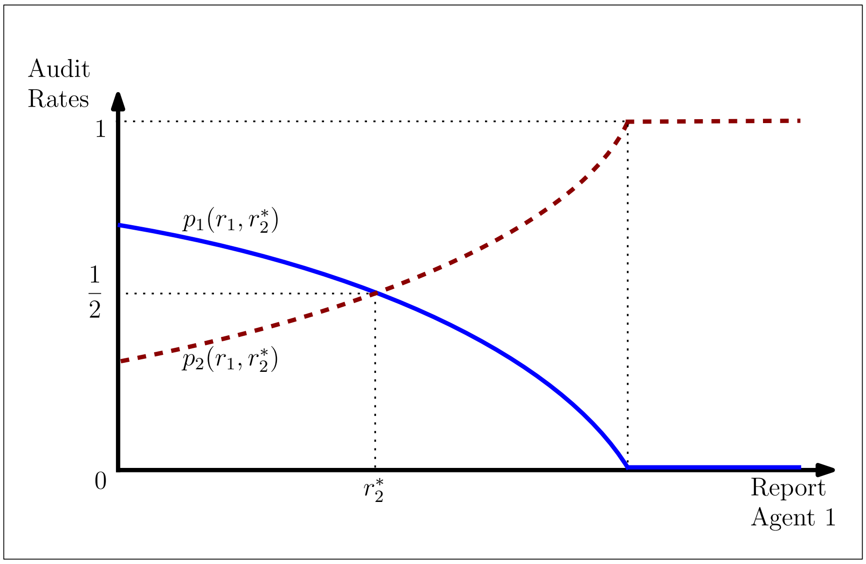

Figure 1: This Figure displays the audit rates p_1 and p_2 depending on reports r_1 and r_2 for the special case when $n = 2$ and $K = 1$. The report of agent 2 is fixed at the equilibrium $r_2 = r_2^*$ and report of agent 1 r_1 varies along the horizontal axis.

Equilibrium concept. Because agents are symmetric, we conjecture that there is a symmetric equilibrium in pure strategies, where $e_i = e_j$, $r_i = r_j$ and $p_i = k \; \forall j \neq i \in N$. The game is solved by way of backwards induction focusing attention on symmetric equilibria. Since stage 4 is automatic, we will next analyse stage 3.

2.1 Stage 3: Reporting equilibrium

At this stage agents simultaneously choose reports in order to minimize the total cost of their chosen activity level given the announced audit mechanism, their own activity level and the other agents' activity reports. Agents pay fees for their reported activity level and they face expected penalties for their unreported activity level.

Differentiating profit function (1) with respect to r_i yields the first-order condition (FOC) for an interior reporting solution $(\partial \mathbb{E}\Pi_i(\mathbf{e}, \mathbf{r}(\mathbf{e}))/\partial r_i = 0)$ – denoted by r_1^*. This FOC can be re-written as:

$$\underbrace{p_i\theta}_{\substack{\text{direct}\\\text{MB}}} + \underbrace{\lambda(n-1)\theta(\frac{e_i - r_i^*}{e^0 - r_i^*})}_{\substack{\text{indirect}\\\text{MB}}} = \underbrace{t}_{\text{MC}}, \; at \; r_i = r_i^* \in [0, e_i]. \tag{4}$$

Given the reporting choice is in the interior $(0 < r_i^* < e_i)$, the first-order condition (4) has a simple "marginal benefit = marginal cost" interpretation: The marginal cost (MC) of reporting is t, i.e. higher reporting results in paying higher fees. The marginal benefit (MB) of reporting has a *direct effect* and an *indirect effect* on the cost of the activity level. First, reporting one more unit of activity lowers the cost of activity *directly*, because the amount of under-reported activity levels decreases which lowers the expected fine by $p_1\theta$. Second, reporting more lowers the cost of activity levels *indirectly*, because the audit probability decreases which lowers the expected fine for the remaining under-reported activity levels by $-(\partial p_i/\partial r_i)\theta(e_i - r_i)$ and we note that $\partial p_i/\partial r_i = -\lambda(n-1)/(e^0 - r_i)$ under the proposed mechanism. It is the second indirect effect that may induce agents to report some of their activity level while they would report zero under the RAM, i.e.: when $\partial p_1/\partial r_1 = 0$.

Proposition 2

The competitive audit mechanism (3) induces a symmetric reporting equilibrium given by:

$$r_i^*(\mathbf{e}) = \frac{e_i^* - e^0(2-N)}{N-1} \; \forall i \in N, \tag{5}$$

where $N = \left(n - 2 + \sqrt{n^2 + 4n - 4}\right)/(2(n-1))$ *and* e_i^* *is the activity level in equilibrium. This result is independent of the information structure. The reporting equilibrium under the CAM is larger than under the RAM regardless of the information structure.*

We note that Proposition 2 is independent of whether agents have perfect information or no information about each others' activity levels. A condition for positive reporting levels is that the difference between the optimal activity level e^t and the unregulated activity level e^0 may not be too large. This can be guaranteed with the sufficient condition that $g'(e)$ is sufficiently steep. In that case, competitive auditing leads to higher activity reports than random auditing.

2.2 Stage 2: Activity equilibrium

At this stage agents simultaneously choose activity levels while considering how their choices translate into the reporting equilibrium at stage 3 given the audit mechanism $p_i(.)$ and the other agents' activity levels. We assume first that agents have perfect information about the other agents' activity levels (Assumption 1b) and subsequently derive the implications of no information about the other agents' activity levels (Assumption 1a) . To determine how activity levels change profit, we consider the total derivative of $\mathbb{E}\Pi_i(\mathbf{e}, \mathbf{r}(\mathbf{e}))$ with respect to e_i.[2] From the optimization at the reporting stage we know that $\partial\mathbb{E}\Pi_i/\partial r_i = 0$. Thus the effect of e_i on $\mathbb{E}\Pi_i$ through the agent's own reporting choice should be ignored (this is the envelope theorem).

Since we conjecture the existence of a symmetric equilibrium in pure strategies, the starting point of any deviation is $e_1 = ... = e_n$. Here we consider a deviation of agent i, so after this deviation we have $e_i \neq e_1 = .. = e_{i-1} = e_{i+1} = .. = e_n$. In this case, it must be true that the strategic effects of all other agents are identical. Thus, the first-order condition (FOC) in general form can be written as:

$$\frac{d\mathbb{E}\Pi_i}{de_i} = \underbrace{\frac{\partial E\Pi_i}{\partial e_i}}_{\substack{\text{direct}\\ \text{effect}}} + \underbrace{(n-1)(\frac{\partial E\Pi_i}{\partial r_j}\frac{\partial r_j}{\partial e_i})}_{\substack{\text{strategic}\\ \text{effects}}},\ \forall j \neq i \in N. \tag{6}$$

Using the particular profit function in (1), we can re-write the FOC as:

$$\underbrace{g'(e_i) - p_i\theta}_{\substack{\text{direct}\\ \text{effect}}} - \underbrace{(n-1)(\frac{\partial p_i}{\partial r_j}\frac{\partial r_j}{\partial e_i}\theta(e_i - r_i^*))}_{\substack{\text{strategic}\\ \text{effects}}} = 0,\ \forall j \neq i \in N. \tag{7}$$

By changing e_i, agent i has a *direct effect* on its own profit. For instance, higher e_i may have positive profit implications, if the benefits from increasing activity levels increase more quickly than the expected cost of e_i regardless of any strategic effects. The *strategic effect*

[2]The analysis follows closely Tirole (1988), p. 324.

comes from the fact that e_i not only changes the agent's own reporting behaviour, but also the other agents' reporting behaviour (by $\partial r_j/\partial e_i(n-1)$). The change in the other agents' reporting behaviour affects the audit probability of agent i, p_i, which in turn affects agent i's expected fine of unreported activity levels (in proportion to $(\partial p_i/\partial r_j)\theta(e_i - r_i^*)$). The total effect of e_i on $E\Pi_i$ is the sum of the direct and strategic effects.

At the point of symmetry ($e_i = e_j$ and $r_i = r_j$, $p_i = k$, $\frac{\partial p_i}{\partial r_i} = \frac{\partial p_j}{\partial r_j}$ and $\frac{\partial r_j}{\partial e_i} = \frac{\partial r_k}{\partial e_i}$), we can re-write the FOC as:

$$g'(e_i) = k\theta + \frac{\partial r_i}{\partial e_j}(t - k\theta), \text{ at } \forall j \neq i \in N. \tag{8}$$

We can learn from (8) that if $\partial r_i/\partial e_j = 1$ at $e_i = e_j$, then as a result we get $g'(e_i) = t$, i.e. a necessary condition for socially efficient activity levels in equilibrium holds. In other words, if an audit mechanism induces agent i to increase its report by one, when agent j increases its activity level by one, then this audit mechanism may implement efficient activity levels among all agents. This is precisely what the proposed CAM achieves under Assumption 1b.

Proposition 3 *Given that agents have perfect information about each other's activity levels (Assumption 1b), the competitive audit mechanism (3) induces socially efficient activity levels for all agents, i.e.: $e_i = e^t\ \forall i \in N$.*

A sufficient condition for the symmetric equilibrium to exist in pure strategies (Proposition 3) is that $g'(e_i)$ is sufficiently steep. That means, the marginal benefits from the activity have to decline sufficiently quickly. This is the case for instance for the parameters we choose for our experiment below.

In case agents have no information about each others' activity levels, the report of one agent cannot react to a change in the activity levels of the other agent. Thus $\partial r_j/\partial e_i = 0$ and $g'(e_i) = k\theta$ at equilibrium, i.e. the agent equalizes marginal benefits from activity levels $g'(e_i)$ to marginal cost, $k\theta$. In this setting (Assumption 1a), the RAM ($p_i = k$) induces the same activity level among the regulated agents as the CAM. Thus, we can establish the following proposition:

Proposition 4 *Given that agents have no information about each other's activity level (Assumption 1a), random auditing leads to the same per-agent activity level than competitive auditing:*

$$g'(e^{k\theta}) = k\theta \quad \textit{for} \quad \forall i \in N.$$

Activity levels are higher than the socially optimal activity level in that case.

3 Experimental Test and Hypotheses

3.1 Testable Hypotheses

We present below our main testable hypotheses derived from the theoretical framework.

Hypothesis 1. Given that agents have *no information* about each others activity level, the competitive audit mechanism leads to a) the same level of activity and b) a higher level of reported activity than the random audit mechanism.

Hypothesis 2. Given that agents have *perfect information* about each others activity level, the competitive audit mechanism leads to a) a lower level of activity and b) a higher level of reported activity than the random audit mechanism.

Hypothesis 3. Given that agents have *perfect information* about each others activity level, the competitive audit mechanism lead to the socially efficient level of activity.

3.2 Experimental Design

In order to test the aforementioned hypotheses, we designed a 2x2 experiment in which we manipulate the audit mechanism (random vs. competitive) and the information agents have about each other's level of activity (No Information vs. Perfect Information).

Participants play 7 rounds of a game that mimics the theoretical framework under a unique audit mechanism and a unique information structure. The unfolding of a particular round is displayed in Figure 2. In each round, participants are matched in groups of 3 and make two decisions individually: first, the level of activity they wish to produce, and second, the level of activity they wish to report. Reporting an extra unit incurs a fee t. Each unit of activity not reported costs θ if an audit reveals that the participant under-reported. Audits take place at the end of each round. Per round, exactly one participant in each group is audited. Under the random audit mechanism (RAM), the audit probability p^{RAM} is fixed and uniform. Under the competitive audit mechanism (CAM), the audit probability p^{CAM} depends on a participant's report, relative to the reports of the two other participants in the group. To ensure independence between each round, participants are re-matched every round following a perfect stranger matching procedure (i.e. a participant never encounters the same group member more than once). Each round is composed of 4 stages: a production stage, an information stage, a report stage and an audit stage.

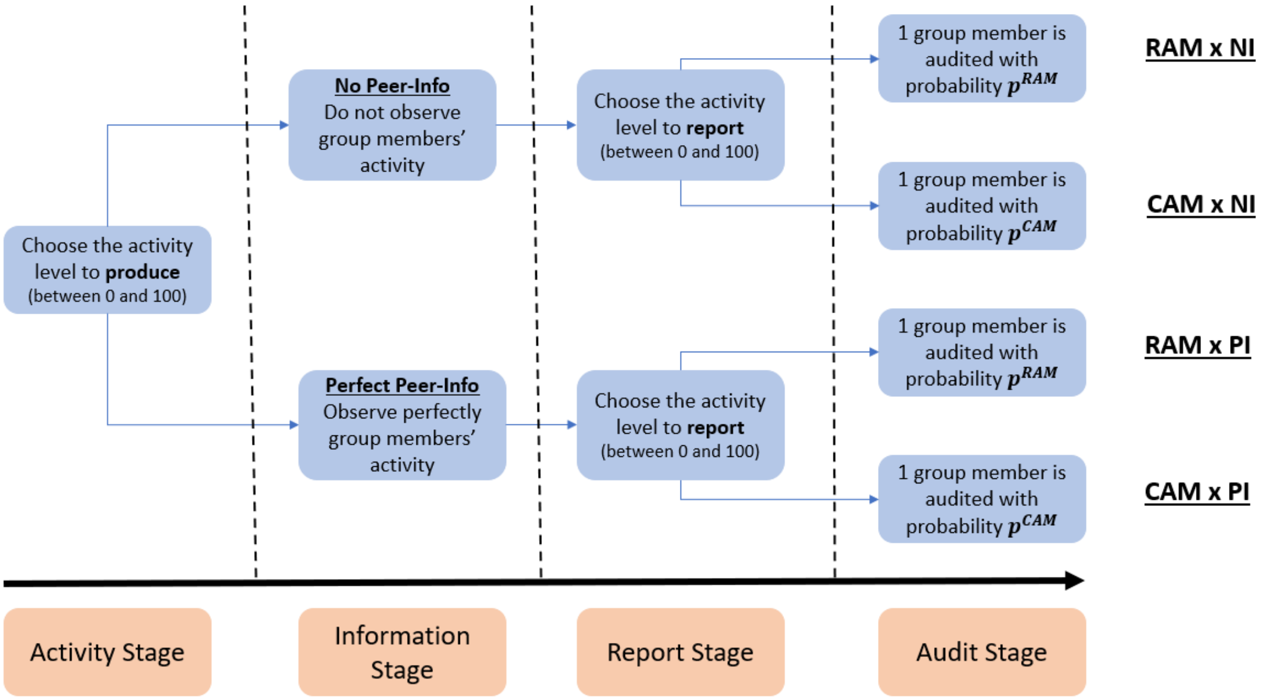

Figure 2: Unfolding of a round.

Production stage. Participants choose the level of activity to produce on a slider.[3] In addition, participants are asked to report their beliefs about the level of activity chosen by their fellow group members on two separate sliders. In the *Perfect Information* (PI) treatment, participants were asked to provide their beliefs about the *actual* activity level of each of the two other participants in their group. In the *No Information* (NI) treatment, participants are asked to provide their beliefs about the *reported* activity level of each of their group members.

To ensure that participants make informed decisions, information about the consequences of their choices are displayed on the screen. After choosing their activity level and indicating their beliefs about their group members, participants are informed about their own cost-minimizing report, their probability of being audited, their probability of not being audited, their payoff in each case as well as their expected payoffs for this round. In the PI treatment, participants are additionally informed about the cost-minimizing reports of their fellow group members. Participants can update their choice and beliefs and see how it affects the aforementioned

[3]All sliders range from 0 to 100 in increment of 1.

variables.

Information stage. In the PI treatment, participants are reminded of their chosen activity level and are informed about the chosen activity level of their fellow group members. In the NI treatment, participants do not receive any information about their fellow group members and are only reminded of their own activity level.

Report stage. Participants choose the activity level they wish to report on a slider.[4] In addition, they need to provide their beliefs about the reported activity level of each of the two remaining group members on a slider.[5] As in the production stage, participants are informed about the payoff-relevant consequences of their choice. In the NI treatment, participants are reminded of their own choice of activity level, their probability of being audited, their probability of not being audited, their payoff in each case and their expected payoff for this round. In the PI treatment, participants are additionally reminded of the actual activity level of their fellow group members. As in the production stage, participants can update their choice and beliefs and see how it affects the aforementioned variables.

Audit Stage. At the end of each round, one participant per group is selected for an audit according to the assigned audit probabilities by the audit mechanism. In the RAM treatment, each participant has a fixed probability of 1/3 of being audited regardless of their decisions or the decisions of their fellow group members. In the CAM treatment, the audit probability for a participant depends on her report relative to the reports of her fellow group members. The *higher* a participant's report relative to the reports of her fellow group members, the *lower* her probability of being audited. Conversely, the *lower* a participant's report relative to the reports of her fellow group members, the *higher* her probability of being audited. The exact audit probabilities are calculated according to the CAM algorithm presented in equation (3) in the theory section. Participants can see their final audit probability and conditional payoffs. In addition, information about the actual and reported activity level of every group member are displayed on the screen. This information is the same in all treatments.[6] By pressing a button, participants can see whether they have been audited and their earnings for this round. Before moving to the next round, participants are asked to report the information provided on the screen on their personal record sheet.

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[4]We set the slider default to the participant's cost-minimizing report.

[5]In the PI treatment, the slider default is set to the cost-minimizing reports of each of the two remaining group members. In the NI treatment, the slider default is set to the participant's beliefs indicated in the production stage.

[6]This feature of the design ensures that treatment differences are not driven by differences in learning.

Post-experimental Questionnaire. At the end of the session, participants are asked to report their age, gender and whether French is their native language. In addition, we elicit risk preferences following Dohmen et al. (2005) by asking participants to indicate how willing they are to take risks in general on a scale from 0 (not willing at all) to 10 (extremely willing).

Parametrization. Table 1 presents the functional forms and parameters chosen for each variable in the experiment. With these parameter values, a symmetric equilibrium in pure strategies exists under the CAM.

Table 1: Parameters of the experiment

Notation/ Functional form	Definition	Parameters
N	Number of participants per group	3
K	Number of audits per round	1
p^{RAM}	Random audit probability	0.33
e	Activity level	[0; 100]
r	Reported activity level	[0; e]
$g'(e) = 10 - 0.1e$	Marginal benefit from activity	
t	Fee on reported activity level	2.5
θ	Penalty on under-reported activity	3
e^0	Unregulated activity level	100
e^t	Optimal activity level	75

3.3 Procedure

The experimental design, hypotheses and procedure were pre-registered on the AEA RCT Registry.[7]

Participants. A total of 131 participants completed the experiment. Participants were recruited via Hroot (Bock et al., 2014) from a large pool of students, mainly from local engineering, business, and medical schools, who had previously registered to be potential participants in economics experiments at GATE-lab (Ecully, France). Overall, 57% of the participants were female and the average age was 23 years (SD = 3.99).

[7] RCT ID: AEARCTR-0004996

Procedure. The experiment was programmed using oTree (Chen et al., 2016) and conducted online in a highly controlled environment that mimics the conditions of the laboratory ("quasi-lab experiment"). The experiment was carried out over a series of 8 sessions varying between 15 and 21 participants during fall 2020. Digital copies of the instructions were provided to the participants, which were read aloud by the experimenter. To help facilitate learning, participants were asked to answer questions about two hypothetical scenarios related to the experiment. The experiment took an average of 1.75 hours. We pre-registered a sample size of 30 independent observations per treatment. With that sample size, the minimum detectable effect size with statistical power at the recommended .80 level is Cohen's d=0.74 for mean comparisons between treatments (Cohen, 2013).

Payment. Participants were paid the sum of their earnings for 4 randomly selected rounds in addition to a 2 euro show-up fee and 3 additional euro for completing the experiment. The average payoff was 24.71 euros (SD = 7.02). Participant earnings were denominated in ECU (experimental currency), which was exchanged for euros at the end of the session.[8] At the end of the session, participants were sent a link to electronically retrieve their payment via a third-party platform.

[8]In order to avoid large variations in payoffs between treatments, we use an exchange rate of 20 ECU equals 1 euro for the CAM treatments and 30 ECU equals 1 euro in the RAM treatments.

4 Results

4.1 Descriptive Statistics

Balance Check

Table 2: Summary of participants characteristics, by treatments.

Treatments	Cluster	% female	mean age	% French
RAM-NI	33	57.58%	23.73	90.91%
		(3.259)	(0.318)	(1.896)
RAM-PI	33	54.55%	23.88	84.85%
		(3.283)	(0.303)	(2.364)
CAM-NI	30	65.63%	23.5	84.38%
		(3.181)	(0.253)	(2.431)
CAM-PI	35	52.78%	22	88.89%
		(3.151)	(0.119)	(1.983)

Note: Table 2 displays the number of participants, the percentage of female, the mean age, and the percentage of French native speaker, by treatments. Standard errors in parentheses.

Table 2 summarizes participants characteristics in each treatment including the percentage of female, the average age, and the percentage of participants who indicated that French was their native language. Using one-way ANOVAs, we find no significant difference between treatments in the percentage of female ($F(3,130)=0.43$, $p=0.733$), age ($F(3,130)=1.67$, $p=0.177$) and the percentage of participants who indicated French as their native language ($F(3,130)=0.29$, $p=0.831$).

Data Overview

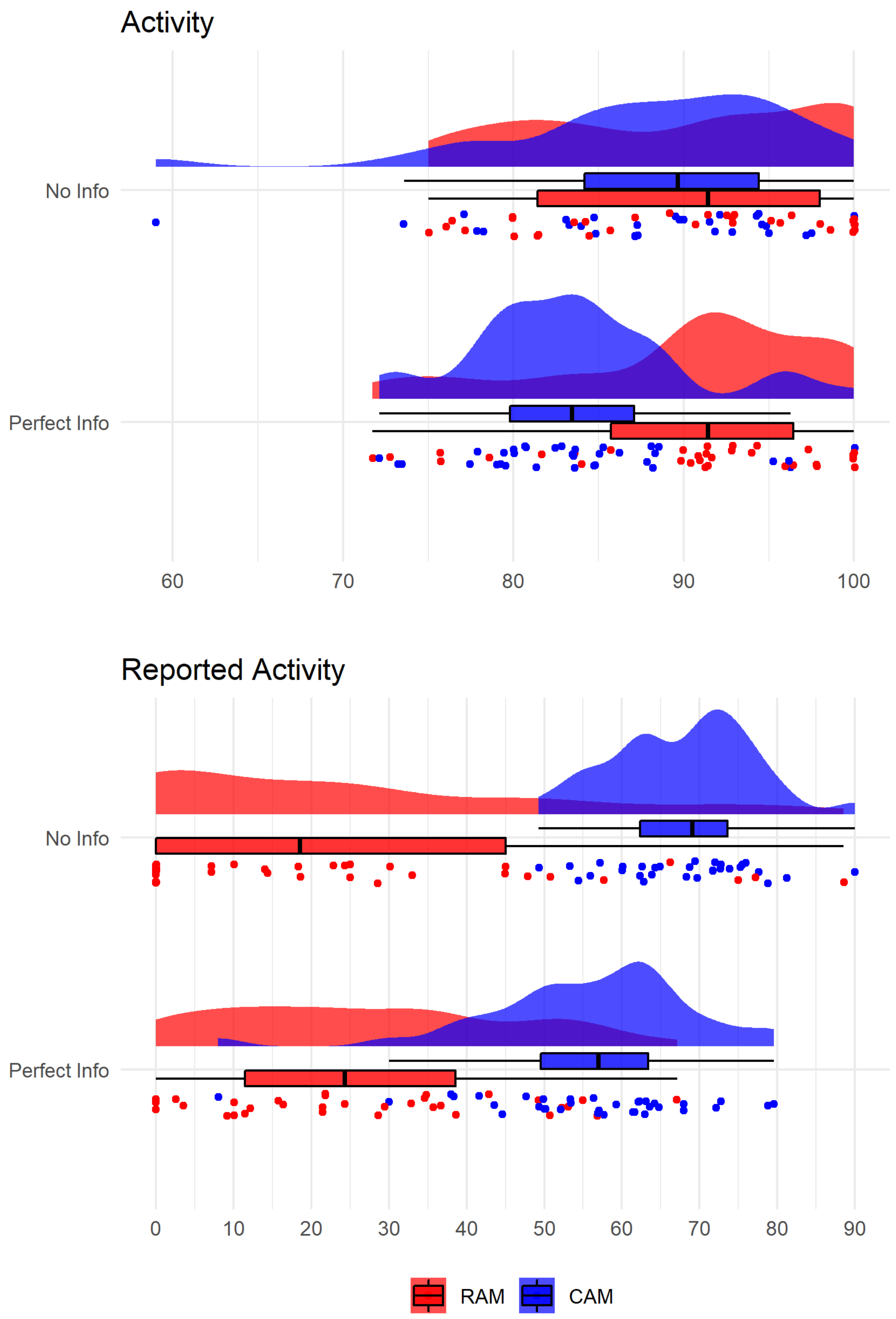

Figure 3: Distribution of actual and reported level of activity for both RAM (in red) and CAM (in blue), by information structures.

Figure 3 provides an overview of our experimental data. The top panel shows the distribution of the actual activity levels aggregated across rounds at the participants level for both RAM (in red) and CAM (in blue), by information structure. The lower panel displays the same information for the reported activity levels.

4.2 Comparative Statics

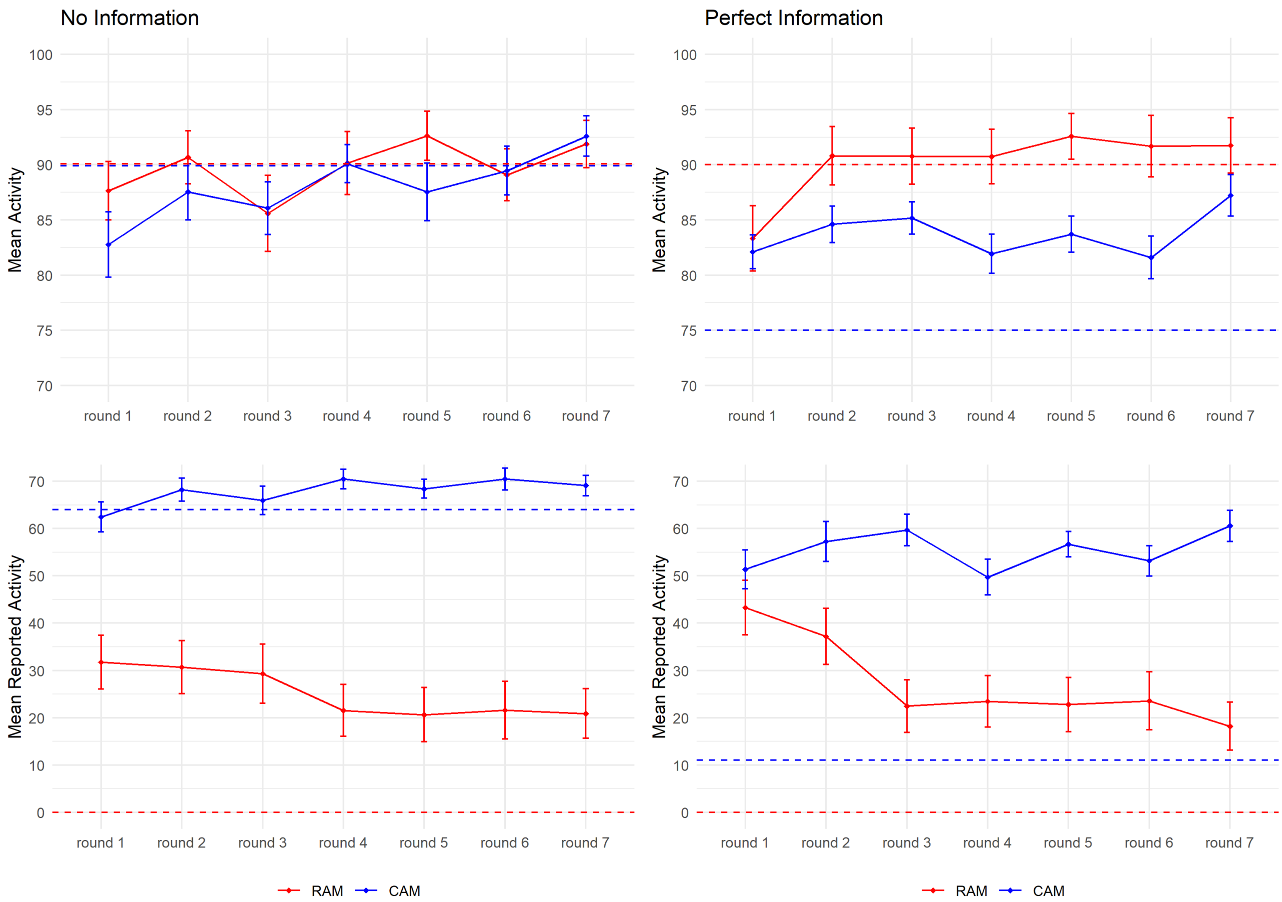

Figure 4: Evolution of the mean activity levels and mean reported activity levels for both RAM (in red) and CAM (in blue) across rounds, by information structures. Vertical bars indicate standard errors. Red dotted lines indicate the Nash Equilibrium for the RAM treatment. Blue dotted lines indicate the Nash Equilibrium for the CAM treatment.

Our main results are displayed in Figure 4. Figure 4 shows the evolution of the average levels of actual and reported activity in each round, under both the RAM (in red) and the CAM (in blue) both in the absence of peer-information (left panel) and when participants have perfect information about each other's activity level (right panel). Standard errors are represented with vertical bars. Red dotted lines indicate the Nash Equilibrium under the RAM, and blue dotted lines indicate the Nash Equilibrium under the CAM.

Consistent with our theoretical predictions, the top panel shows that the blue line is always below the red line when participants have perfect information about each other's actual activity level (right panel). In contrast, the blue line and the red line mostly overlap in the absence of peer-information (left panel). In terms of reporting, the bottom panel shows that the red line is always below the blue line under both information structures, which is also consistent with our theoretical predictions.

Analyses of mean

Table 3: Nash equilibrium (NE) and empirical means (EM) of actual and reported levels of activity, by treatments.

Activity level	RAM-NI		RAM-PI		CAM-NI		CAM-PI	
	NE	EM	NE	EM	NE	EM	NE	EM
Actual	90	89.66	90	90.25	90	88.01	75	83.77***
		(1.481)		(1.427)		(1.594)		(1.077)
Reported	0	25.20***	0	27.29***	64	67.88*	11	55.51***
		(4.520)		(3.291)		(1.676)		(2.376)
Obs.		33		33		30		35

Note: Table 3 displays the Nash equilibrium (NE) and empirical means (EM) of both actual and reported activity levels, by treatment. Standard errors in parentheses. Stars indicates differences from the equilibrium predictions using one-sample Wilcoxon sign-ranks test. Our unit of observation is the average across all rounds of a participant's level of activity. *p<0.05; **p<0.01; ***p<0.001.

Table 3 displays the Nash predictions derived from the model (NE) as well as the observed actual and reported activity levels (EM) by treatments. In terms of actual activity levels, we find no difference between the empirical means and the Nash Equilibria for the RAM under both information structures (two-sided Mann-Whitney tests:[9] RAM-NI: p=0.851; RAM-PI: p=0.376) and for the CAM under no information (MW test: p=0.367). In contrast, the CAM induces higher levels of activity than predicted by theory under perfect information (MW test: p<0.001).

[9]MW test, hereafter.

In terms of reported levels of activity, we replicate the well-established empirical finding that individuals self-reporting behavior typically deviates from pure payoff maximization (MW tests: RAM-NI: $p<0.001$; RAM-PI: $p<0.001$; CAM-NI: $p=0.035$; CAM-PI: $p<0.001$). While the rational economic model (Becker, 1968) assumes that people are dishonest whenever it is financially advantageous to do so, evidence suggests that people can also be influenced by intrinsic motivations which could include both moral and social considerations, such as lying-aversion (Gneezy, 2005).

To test our main hypotheses, we now turn to mean comparisons between both mechanisms, under each information structure. In the absence of peer-information, we find no significant differences in actual activity level between the CAM and the RAM (MW test: $p=0.495$) but significantly higher reported activity levels in the CAM than in the RAM (MW test: $p<0.001$), which support Hypothesis 1. When participants can perfectly observe each other's activity level, we find that CAM leads to significantly lower levels of activity (MW test: $p<0.001$) and higher levels of of reported activity than the RAM (MW test: $p<0.001$), which support Hypothesis 2. In contrast, we find that the CAM fails to achieve the socially optimal level of activity (MW test: $p<0.001$), which contrast with Hypothesis 3.

Table 4: Effect of the audit mechanisms on actual and reported levels of activity, by information structure.

Dep. var:	Actual level of activity				Reported level of activity			
	NI		PI		NI		PI	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CAM	-1.653	-0.442	-6.479***	-7.864***	42.67***	41.92***	28.22***	25.57***
	(2.175)	(2.037)	(1.787)	(1.676)	(4.823)	(4.932)	(4.058)	(4.212)
Round FE	X	X	X	X	X	X	X	X
Demographics		X		X		X		X
Const.	86.10	106.22	86.04	103.39	26.06	23.66	32.93	49.76
	(2.129)	(11.85)	(2.031)	(6.151)	(4.930)	(23.54)	(4.650)	(21.97)
Obs.	441	434	476	476	441	434	476	476
Clusters	63	62	68	68	63	62	68	68

Note: Table 4 displays the GLS coefficients of random effects regressions clustered at the participant level. Standard errors in parentheses. Stars indicates significant differences from the RAM. *$p<0.05$, **$p<0.01$, ***$p<0.001$.

To investigate the effect of the CAM relative to the RAM on the actual and reported level of activity under each information structure, we performed random-effects GLS regressions clustered at the participant level. The independent variables include a dummy variable equals to 1 if the participant was allocated to the CAM treatment and 0 otherwise; and rounds fixed effects. The GLS coefficients are displayed in columns (1) to (8) in Table 4. We use the actual activity levels as the dependent variable in columns (1) to (4). In contrast, we use the reported activity levels as the dependent variable in columns (6) to (8). Columns (1), (2), (5) and (6) show the results in the absence of peer-information. Columns (3), (4), (7) and (8) show the results when participants have perfect information about each other's activity levels. We control for participants demographics (gender, age, risk preferences and whether French is their native language) in columns (2), (4), (6) and (8).[10]

Consistent with our previous findings, columns (1) and (2) show no significant differences between RAM and CAM in activity levels in the absence of peer-information ($p=0.444$ and $p=0.828$, respectively). In contrast, CAM induces lower activity levels than RAM under perfect information and the results are significant at the 0.1% level ($p<0.001$ in both models). In terms of reporting, columns (5) to (8) show that CAM induces significantly higher levels of reported activity than the RAM, both in the absence of peer-information ($p<0.001$ in both models) and when participants have perfect information about each other's actual activity levels ($p<0.001$ in both models).

In summary, we find that the CAM never performs worse than the RAM. First, the CAM outperforms the RAM in terms of reporting under both information structures. Second, while the CAM fails to induce the socially optimal level of activity, it leads to lower activity levels when participants have perfect information about each other's activity levels.

Result 1: Given that agents have no information about each other's activity level, CAM lead to a) the same level of activity and b) a higher level of reported activity than RAM (support H1).

Result 2: Given that agents have perfect information about each other's activity level, CAM lead to a) a lower level of activity and b) a higher level of reported activity than RAM (support H2).

Result 3: Given that agents have perfect information about each other's activity

[10] The missing cluster in columns (2) and (6) is due to one participant leaving the experiment without completing the post-experiment questionnaire.

level, CAM does not lead to the socially optimal level of activity (does not support H3).

Analyses of variance

While our findings suggest that competitive audit mechanisms can be a beneficial alternative to random auditing, competitive audit mechanisms are more complex and rely on level-k reasoning. Thus, it is possible that while the data confirms our predictions at the aggregated level, the CAM may induce more heterogeneity in behavioral responses than the RAM. Higher variance in experiments involving tournaments is a common finding in the literature, to the exception of Gilpatric et al. (2011), who find that the competitive mechanism leads to less variance in reporting than random auditing. Figure 3 suggests that the CAM also induces less variance than the RAM in our setting, both in terms of activity levels and reporting.

Table 5: Effect of information structure and audit mechanism on actual and reported levels of activity.

Dep. var:	$(e_{ij} - \bar{e_j})^2$		$(r_{ij} - \bar{r_j})^2$	
	NI	PI	NI	PI
	(1)	(2)	(3)	(4)
CAM	-56.54	-115.08*	-874.12***	-600.29***
	(45.25)	(46.95)	(156.27)	(142.20)
round FE	X	X	X	X
Const.	266.15	237.36	1098.40	1124.11
	(53.85)	(51.07)	(128.68)	(117.36)
Obs.	441	476	441	476
Clusters	63	68	63	68

Note: Table 5 displays the GLS coefficients of random effects regressions clustered at the participant level. Standard errors in parentheses. Stars indicates significant differences from the baseline (RAM-NI). *p<0.05, **p<0.01, ***p<0.001.

To explore this issue further, we first investigate treatment differences in the variance of activity choices. To do so, we follow Gilpatric et al. (2011) by estimating random-effects GLS regressions of the squared deviation from the mean activity level, that is $(e_{ij} - \bar{e_j})^2$, where $\bar{e_j}$ is the treatment-specific mean level of activity in round j, on the treatment dummies. We control for rounds fixed effects and standard errors are clustered at the individual level. The GLS coefficients are reported in column (1) of Table 5. In addition, we also investigate treatment differences in the variance of reported activity. To do so, we estimate the same random-effects GLS regression as before, using the squared deviation from the mean reported activity level as the dependent variable, that is $(r_{ij} - \bar{r_j})^2$, where $\bar{r_j}$ is the treatment-specific mean reported level of activity in round j. The GLS coefficients are reported in column (2) of Table 5.

Column (1) in Table 5 shows no significant differences in variance between the CAM and RAM in terms of activity levels in the absence of peer-information (p=0.211). In contrast, column (2) shows that the CAM leads to significantly less heterogeneity in activity levels under perfect peer information (p=0.014). Second, we replicate Gilpatric et al.'s (2011) finding that the CAM leads to significantly less heterogeneity in reported activity levels under both information structures (p<0.001 in both cases), as shown in columns (3) and (4). These results suggest that, in contrast to experimental findings from previous studies investigating competitive incentives, our competitive audit mechanism actually leads to relatively less heterogeneity in individual behavior.

Result 4: The CAM does not induce more heterogeneity in actual nor reported activity choices.

5 Discussion and Conclusion

We examine the relative merits in terms of actual and self-reported activity levels of random (RAM) and competitive (CAM) audit mechanisms in a simplifying analytical framework. While RAM assign the same audit probability to each regulated agent, CAM assign a lower audit probability to the agents with higher self-reported activity levels relative to others. We first consolidate in a simplifying framework with endogenous levels of actual and self-reported activity the existing theoretical advances and extend it to situations in which peer information about activity levels is present or absent. Our theoretical model delivers three core predictions. First, in the absence of peer-information, CAM induce higher self-reported activity levels. Second, in the absence of peer-information, CAM induce the same actual activity levels as compared to RAM. These two results are isomorph to the main findings by Gilpatric et al. (2011) and Cason et al. (2016) respectively. Third, when agents have perfect information about each others' activity levels, CAM not only induce higher self-reported activity levels, but also induce lower activity levels. Given a particular design, CAM can even induce the socially optimal level of activity, while this is not feasible under RAM. This result is isomorph to the main finding by Oestreich (2017).

We then test these three predictions in a quasi-laboratory experiment with 131 participants, in which we manipulate the audit mechanism (RAM vs. CAM) as well as the information structure (no peer information vs. perfect peer information). Consistent with our theory, we find that the CAM never under-performs the RAM. First, we provide the first empirical validation of the theoretical prediction that CAM can align activity levels more closely with the social optimum in the presence of peer information than RAM. This is a relevant result for policy makers as in many applications, the chosen activity level is the primary objective of the regulator. In environmental regulations for instance, the regulator is typically more concerned about the emissions level and less concerned about the reporting levels. While CAM reduce the activity level, we provide evidence that behavioral mechanisms prevent reaching the first-best outcome. Finally, the prediction that CAM always induce more truthful reporting than RAM is also confirmed.

Two stylized facts that are not accounted for by the theoretical framework emerge from the experimental data. First, while the equilibrium under the CAM may be threatened by collusion, the collusive equilibrium of no reporting under the CAM is not observed in the data. In fact, we replicate the well-established finding that self-reporting is significantly higher than predicted by theory regardless of the information structure. This is consistent with the behavioral literature that people decisions can also be influenced by payoff-irrelevant motivations such as social considerations or lying-aversion (Gneezy, 2005). Second, we found that CAM can induce less heterogeneity in individuals' decisions, both in terms of actual and self-reported activity levels, which is consistent with (Gilpatric et al., 2011).

Concluding, our findings suggest that CAM can be a beneficial alternative to RAM for underfunded regulators. However, our paper focuses on the two limiting cases of the information structure (no information and perfect information). While some real-life applications could be sorted into one or the other limiting case, several others are likely to be somewhere in between (e.g. activity levels are only imperfectly observable or observable with some noise). Thus, future research might consider whether the advantages of the CAM would emerge in such context.

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