Information Disclosure by Enforcement Objective*

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Abstract

When governing entities levy financial penalties for rule violation, they may aim to maximize compliance or revenues. Agents may be uncertain of these objectives; further they may also not know enforcers' detection ability for rule violation. Utilizing a framework of verifiable disclosure game, we investigate how rule enforcers leverage the options to hide or reveal their privately-informed detection ability and how agents respond. Our model derives multiple equilibria. To examine the selection among those equilibria, we conduct laboratory experiments where the enforcer's objective is known to the agent in transparent treatments, but unknown to the agent in the opaque treatment. In transparent treatments, unraveling occurs. However, under the opaque treatment, only compliance-maximizing enforcers with strong detection ability reveal their detection ability, and agents violate the rule when enforcers hide. Our results outline that when the enforcement objective is opaque to agents, strategic withholding information related to the detection ability benefits revenue-maximizing enforcers.

Keywords: Enforcement Objective, Experiments, Information Disclosure, Transparency.

JEL Codes: C72, D82, K42.

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1 Introduction

Governing entities make numerous decisions related to rule enforcement. Among those decisions, one important choice is whether or not to disclose verifiable information on her detection ability to agents. This choice is relevant in various real-world examples: a police department may provide public notice to drivers that speed limits are enforced by aircraft or automatic traffic cameras; a homeowner association (HOA) can reveal how often a community is inspected for potential rule violations; and the Internal Revenue Service (IRS) may post the frequency of auditing tax reports on the website.

However, rule enforcement may serve under two different extremes of objectives: some rule enforcers may aim to achieve *compliance maximization*, while others may seek to achieve *revenue maximization*. Under the former, the enforcer aims to deter rule violations. Under the latter, the enforcer implicitly encourages rule violations because her revenue increases through fines collected upon detecting the agent's violation of the rule. Compliance maximization and revenue maximization are fundamentally different enforcement objectives. It is crucial to understand how different objectives affect both the enforcer's decision of disclosing private information on her detection ability and how the agent responds by either complying with or violating the rule.

Furthermore, the enforcer's exact objective may not always be transparent to the agent. The opaqueness of enforcement objective adds an additional layer of private information to the enforcer, alongside her detection ability. Therefore, it may also affect equilibrium strategies of both the enforcer and the agent. There has been scant research into different enforcement objectives despite the significance. Utilizing a theory-based laboratory experiment, this paper provides the first attempt to study the role of enforcement objectives in a game featuring asymmetric information.

We begin with a theoretical framework involving two risk-neutral players, an enforcer and an agent. The enforcer's detection ability is determined by her fixed resources in the short run. Thus, we model the enforcer's detection ability as her exogenous and verifiable private information. The detection ability of an enforcer can be either strong or weak: knowing that the enforcer is of strong (resp. weak) detection ability, the agent should comply with (resp. violate) the rule. The enforcer decides between revealing the detection ability to the agent at a small cost or hiding the information. The agent, after observing the enforcer's action, chooses whether to comply with the rule or violate it. Enforcers of different objectives are endowed with different payoff structures. While the enforcer always knows her own objective, her objective may be transparent or opaque to the agent. The enforcer's exact objective is modeled as public information if it is transparent to the agent. If the enforcer's exact objective is opaque to the agent, it is modeled as a second dimension of the enforcer's private information.

Our theory shows that equilibrium strategies differ under different extremes of enforcement objectives. With a transparent enforcement objective, there is always an unraveling equilibrium: concealing the enforcer's detection ability does not lead an agent to choose a different action from what he would do when the detection ability was revealed. This is because only the enforcer with advantageous private information is willing to pay a small cost to showcase her detection ability. Hence, hiding information signals disadvantageous private information. For a compliance-maximizing (resp. revenue-maximizing) enforcer, strong detection ability (resp. weak detection ability) is advantageous, because it deters violation (resp. induces violation). Therefore, if a compliance-maximizing (resp. revenue-maximizing) enforcer hides, the agent fully infers that the enforcer is of weak (resp. strong) detection ability and will violate the rule (resp. comply with the rule). Under different parameter specifications, there are also other equilibria that do not involve full unraveling. For instance, when the agent believes that a revenue-maximizing enforcer's detection ability is sufficiently likely to be weak, there is an equilibrium where both types of enforcer hide the detection ability, and the agent violates the rule when the enforcer hides.

When the enforcement objective is instead opaque to the agent, we derive multiple equilibria under a wide range of parameters. Those equilibria can be distinguished by how the agent respond when the enforcer hides. In the pure-strategy equilibrium where the agent violates upon the enforcer's action of hiding, only the compliance-maximizing enforcer whose detection ability is strong reveals. In contrast to the transparent objective scenario's unraveling equilibrium, the current equilibrium favors the revenue-maximizing enforcer without compromising the compliance-maximizing one. So we call this equilibrium the "revenue-optimal equilibrium." Another pure-strategy equilibrium is called the "compliance-optimal equilibrium", where only the revenue-maximizing enforcer with weak detection ability reveals, and the agent complies with the rule if the enforcer hides. This equilibrium benefits the compliance-maximizing enforcer without hurting the revenue-maximizing one when compared with the transparent objective's unraveling equilibrium. There is also a mixed-strategy equilibrium where only (1) the compliance-maximizing enforcer with strong detection ability and (2) the revenue-maximizing enforcer under weak detection ability will reveal with positive probability, and the agent mixes upon the enforcer's action of hiding. In all three equilibria, the agent can no longer perfectly infer the enforcer's detection ability upon the enforcer's action of hiding. As a consequence, the additional private information on enforcement objective dissolves the unraveling result.

Enforcement objective is usually not reported in observational data. Even so, it is challenging to make enforcers credibly report their true objective in surveys or questionnaires. To examine the selection among multiple equilibria and study different environments, we conducted two series of laboratory experiments, Study 1 and Study 2, with a total of four between-subjects treatments. In both studies, subjects are randomly assigned a role, either an enforcer or an agent.[1] Study 1 utilizes between-subjects treatments to compare equilibrium behavior between two different enforcement objectives: compliance maximization versus revenue maximization. The two treatments in Study 1 vary by the enforcement objective, represented by the enforcer's payoff structure. Under the compliance treatment, the enforcer derives a higher payoff if the agent chooses to comply with the rule. Under the

[1]To avoid the concerns of using loaded terms in laboratory experiments, neutral language is used throughout the entirety of experiment. Section 4 provides the details of the experimental design.

revenue treatment, instead, an agent's violation behavior will make the enforcer better-off.

In Study 2, we examine two additional between-subjects treatments: transparent objective and opaque objective. The objective is randomly assigned to each enforcer, and can be either compliance maximization or revenue maximization. The enforcer's exact objective is known to the agent in the transparent treatment, but unknown to the agent in the opaque treatment. This makes the transparent treatment a "combination" of the two treatments in Study 1, although subjects need to comprehend both enforcement objectives instead of only one. Our between-subjects design in Study 2 provides a direct comparison between transparent and opaque enforcement objectives.

Our results in Study 1 show that the unraveling equilibrium is selected as the actual play in both the compliance treatment and the revenue treatment. In Study 1, we focus on two main outcome variables, the enforcer's hiding behavior and the agent's compliance behavior when the enforcer hides. Consistent with the prediction from the unraveling equilibrium, there is no significant difference between overall hiding behavior across the two treatments. Among enforcers with strong (resp. weak) detection ability, the compliance-maximizing enforcers hide less (resp. more) often than revenue-maximizing ones; agents, upon observing the enforcer's action to hide, violates more often under the compliance treatment than the revenue treatment. Our results provide supportive evidence that the unraveling equilibrium is selected under both enforcement objectives and thus, hiding the detection ability does not benefit the enforcer as long as her exact objective is transparent to the agent.

Regarding Study 2's experimental results, we find that the opaque enforcement objective generates stark differences from the transparent enforcement objective. Compared to the unraveling equilibrium under transparent objective, we predict that the opacity in enforcer's objective is overall beneficial to the enforcer. As we compare the enforcer's payoffs between transparent and opaque treatment, we observe a significantly higher payoff under the opaque treatment. In particular, the payoff of revenue-maximizing enforcers is significantly higher under the opaque treatment. Meanwhile, we find no significant difference across treatments in terms of compliance-maximizing enforcers' payoffs. Those observations, together with the result that a majority of agents choose to violate the rule upon observing the enforcer's action to hide, support that the equilibrium being played out is the revenue-optimal equilibrium. Hence, the opacity in enforcer's objectives benefits the revenue-maximizing enforcers.

Our study highlights the role of enforcer's different objectives. There has been growing attention to the revenue-maximizing motive in real-world scenarios, even though such a motive is rarely studied in the literature.[2] These different motives lead to distinct strategic outcomes. When the enforcement objective is transparent, we show that the enforcer only showcases her favorable private information, which means that the compliance-maximizing enforcer with high detection ability or a revenue-maximizing enforcer with low detection ability reveals. The agent can infer the enforcer's unfavorable private information when the enforcer hides her detection ability.

Moreover, agents are often left to speculate about the true motive of the enforcer. In this case, it is not immediately clear how the agent should interpret the enforcer's action of hiding her detection ability. As part of the actual play, only the compliance-maximizing enforcer with high detection ability reveals; when the enforcer hides, the agent violates the rule. Compared to the unraveling equilibrium in the transparent objective scenario, this equilibrium leads to a strictly higher payoff to the revenue-maximizing enforcers. As a result, we reach the conclusion that rule enforcers may leverage concealing the detection ability to affect the agent's behavior only when her objective is opaque to the agent.

From a theoretical perspective, this paper contributes to the voluntary disclosure literature by introducing two dimensions of private information to the sender. Canonically, the sender (i.e., the enforcer) has only one dimension of private information (i.e., the detection ability) and decides whether to reveal this information to the receiver (i.e., the agent). The equilibrium result involves unraveling, i.e., the receiver essentially perfectly observes/infers

[2]See https://www.nytimes.com/2021/10/31/us/police-ticket-quotas-money-funding.html for a recent New York Times news report that is related to enforcer's objective of revenue maximization. A summary of current literature is available in Section 2.

the sender's private information and leaves no information rent to the sender. However, this paper includes a new dimension of private information (i.e., the enforcer's objective) that cannot be credibly disclosed but affects the incentives of players. The new dimension provides a natural channel to break down the unraveling result, which is further validated by our laboratory experiment.

The remainder of the paper is organized as follows. Section 2 reviews related literature. Section 3 presents our theoretical framework. Section 4 describes the experimental design and procedures. Section 5 summarizes our testable hypotheses. Section 6 provides our experimental results. Section 7 concludes.

2 Related Literature

This paper contributes to two strands of the literature. The first strand is on the broad literature of rule enforcement. Motivated by Becker (1968), classic theories of crime and deterrence assume that the authority's enforcement effort is perfectly-observed (Polinsky and Shavell, 2007) or at least unbiased to potential defenders (Bebchuk and Kaplow, 1992; Garoupa, 1999). Previous literature documents that the uncertainty from detection probability has an positive impact on reducing crime rate in non-strategic environments, either due to risk aversion (Paternoster, 1987; Apel and Nagin, 2011; Apel, 2013; Chalfin and McCrary, 2017) or ambiguity aversion (Harel and Segal, 1999; Snow and Warren, 2005; D'Antoni, 2018).

While theory predicts that embedding uncertainty over enforcement probability reduces apprehension rate, experimental evidence from previous literature is relatively mixed. DeAngelo and Charness (2012) provide experimental evidence about uncertainty related to regimes in a non-strategic decision environment. They find that with identical expected costs, subjects facing uncertainty about the enforcement regime are less likely to engage in prohibited behavior. In terms of uncertainty that originates from ambiguity aversion, Baker et al. (2003)

show that using an ambiguous environment to induce detection probability reduces crime, while Salmon and Shniderman (2019) find minimal support that ambiguity in detection probabilities increases compliance level.[3]

Various studies have examined the agency's incentive to reveal information about its enforcement policy publicly to agents (Apel and Nagin, 2011; Apel, 2013; Chalfin and McCrary, 2017). One important aspect missing from those studies is that the interaction between enforcers and agents is strategic. We model the detection ability as verifiable information, which differentiates our model from the cheap talk game assuming that the enforcer can lie about her enforcement probability (Baumann and Friehe, 2013). A recent theory paper by Buechel et al. (2020) studies the optimal enforcement effort level by dividing agents into two types: sophisticated and naive. We adopt a different theoretical approach by assuming that detection ability is regarded as short-run constraints. Besides, to the best of our knowledge, no study has yet incorporated philosophically-different enforcement objectives to a Bayesian-Nash framework.

A few empirical studies have examined the fiscal incentives of law enforcement agencies with real world data (Makowsky and Stratmann, 2009; Carpenter et al., 2015; Harvey and Mungan, 2019). Meanwhile, other related works (e.g, DeAngelo and Hansen (2014)) found that roadway safety officers have considerable effects on public safety. Comparison between the two enforcement objectives, compliance maximization and revenue maximization, have been investigated in terms of individual decision-making (Makowsky et al., 2019) and games of complete information (Calford and DeAngelo, 2023). Specifically, Calford and DeAngelo (2023) investigate law enforcement schemes in a game with uncertainty-averse players in a laboratory experiment. Different from Calford and DeAngelo (2023)'s theoretical framework, our paper models the game in an asymmetric information framework — the enforcer's detection ability and objective can both be the enforcer's private information. Moreover, we

[3]Uncertainty from fine size is another important factor that affects apprehension behavior. The effect of uncertain fine size has been covered in various experimental studies, including DeAngelo and Charness (2012) and Feess et al. (2018) for uncertainty with known probability distributions (i.e., risk), and Agranov and Buyalskaya (2021) for uncertainty with unknown probability distribution (i.e., ambiguity).

find the optimal enforcement strategies depend on both the enforcer's detection ability and enforcement objective.

There are other research areas that study information disclosure related to enforcement effort. For instance, the crackdown literature assumes that authorities determine the enforcement effort and then choose whether to reveal it to agents or not (Lazear, 2006; Eeckhout et al., 2010; Dur and Vollaard, 2019). Those studies find that revealing is optimal only when many potential offenders perceive a low probability of apprehension. Similarly, literature related to tax avoidance also studies when it is optimal to reveal a chosen enforcement effort to taxpayers (Andreoni et al., 1998; Hallsworth, 2014; Mascagni, 2018; Slemrod, 2019). Different from all above papers, the timeline of the current game is different: the enforcer's detection ability here is modeled as a private information and the enforcer can only choose to reveal it or hide it. We adopt this simplification assumption to make the analysis of opaque objectives tractable.

The second strand of literature is about signaling and verifiable disclosure games. Initial signaling games by Spence (1973) are tested in classic laboratory experiments such as Brandts and Holt (1992) and Brandts and Holt (1993). Recent developments of signaling game with unknown priors focus on the belief formation in the long run under repeated plays (Brandts and Holt, 1996; Drouvelis et al., 2012; Possajennikov, 2018; Szembrot, 2018; Vinogradov and Makhlouf, 2021). In the signaling game literature, limited attention has been drawn to the heterogeneity of sender's objective functions, and how the private information of a sender's objective function affects equilibrium.

The current paper joins the growing literature on unraveling and voluntary information disclosure (Viscusi, 1978; Grossman and Hart, 1980; Grossman, 1981; Milgrom, 1981; Milgrom and Roberts, 1986). Under the canonical setup, the sender's action of disclosure is represented by an interval that contains the true state (see Dranove and Jin (2010) for a survey of literature). The unraveling result in theory is consistent with not only the notable experimental work by Jin et al. (2021), but also earlier investigations (Forsythe et al., 1989;

King and Wallin, 1991; Dickhaut et al., 2003). Previous literature has also investigated various factors that may break down the unraveling under voluntary information disclosure, including commitment (Fréchette et al., 2022), competition between senders (Sheth, 2021; Penczynski et al., 2022), receiver's naivete (Hagenbach and Koessler, 2017; Deversi et al., 2021; Montero and Sheth, 2021),[4] strategic reasoning (Li and Schipper, 2020), and the complexity of information structure (Jin et al., 2022). Our paper adds new insights to the literature by incorporating enforcer's conflicting objectives to the literature and this channel dissolves unraveling.

3 Theory

3.1 Setup

There are two players in the game: an enforcer (she) and an agent (he). Both players are assumed to be risk neutral.[5] The enforcer is privately informed of a fixed amount of resources to enforce a rule in the short run: when the agent violates the rule, the enforcer detects it with probability $\theta \in \Theta = \{\underline{\theta}, \bar{\theta}\}$ where $0 \leq \underline{\theta} < \bar{\theta} \leq 1$. Thus, we let θ capture the enforcer's private information on her detection ability, i.e., her type, and $p \in [0, 1]$ be the agent's prior probabilistic belief that the enforcer's type is $\bar{\theta}$. The enforcer has two possible actions after privately observing θ: to hide (H) her type from the agent or to reveal (R) her type to the agent. The enforcer will incur a small cost if she chooses to reveal a verifiable evidence about her detection ability θ. For instance, it is costly for police to alert drivers of red light cameras ahead. After observing the enforcer's action, the agent has two possible actions: to comply (C) with the rule or violate (V) it.

We normalize the agent's payoff to 0 if he chooses to "violate" and ends up being detected,

[4]In line with Buechel et al. (2020)'s approach to characterize how agent naivete distorts sequential equilibrium, Deversi et al. (2021), and Montero and Sheth (2021) both find that agent's naivete shapes the unraveling equilibrium.

[5]Same qualitative results hold if players are not excessively risk averse or risk seeking.

and normalize his payoff to 1 if he chooses to "violate" without being detected. The agent receives $\lambda \in (0,1)$ if he chooses to "comply." For the problem to be interesting, we impose the assumption $1-\bar{\theta} < \lambda < 1-\underline{\theta}$ so that the agent behaves differently if he knows whether the enforcer is of type $\bar{\theta}$ or $\underline{\theta}$.

As our main innovation, we explore two distinct objectives that the enforcer may follow: one, to maximize the agent's compliance levels, and two, to maximize revenue through fines imposed for violations. Different objectives are associated with different payoff structures of the enforcer. We aim to study the following research questions: (1) what happens if the enforcer's objective is publicly known as compliance maximization vs. revenue maximization, (2) what happens if the enforcer's private objective is transparent to both parties before the enforcer takes an action vs. remains opaque to agent when the latter takes the action.

We denote the enforcer's objective as $g \in G = \{com, rev\}$. When the enforcer's objective is compliance maximization, i.e., if $g = com$, he receives payoff $\underline{b}$ if the agent chooses to "violate" and $\bar{b}$ if the agent chooses to "comply", where $0 < \underline{b} < \bar{b} \leq 1$. When the enforcer's objective is revenue maximization, i.e., if $g = rev$, the enforcer benefits from the agent's violation of the rule. In particular, a strong (i.e., type-$\bar{\theta}$) enforcer receives $\bar{\bar{r}}$ if the agent chooses to "violate", a weak (i.e., type-$\underline{\theta}$) enforcer receives $\bar{r}$ if the agent chooses to "violate", and both types of enforcer receive $\underline{r}$ if the agent chooses to comply. We assume that $0 < \underline{r} < \bar{r} < \bar{\bar{r}} < 1$, because a strong enforcer has a higher probability of detecting violation and collecting fines. We also assume that the enforcer's cost to reveal her detection ability $c \in (0, \min\{\underline{b}, \frac{(\bar{b}-\underline{b})(\bar{r}-\underline{r})}{(\bar{b}-\underline{b})+(\bar{r}-\underline{r})}\})$, so that we can reduce the number of equilibria without compromising the existence of separating ones.

3.2 Compliance Maximization vs. Revenue Maximization

We first analyze the scenarios when the enforcer has a publicly known objective, which is to maximize compliance or to maximize revenue. Given a publicly known enforcement objective, the timeline of the verifiable disclosure game is simple. The informed enforcer chooses to hide her detection ability or reveal it at a small cost first. The agent decides whether to comply with or violate the rule after observing the enforcer's action. The analysis here serves as a benchmark for analysis in Section 3.3.

The equilibrium notion we adopt is the perfect Bayesian equilibrium (PBE) (Fudenberg and Tirole, 1991), which involves three components: the enforcer's strategy, the agent's strategy, and the agent's belief about the enforcer's detection ability. However, in our description of equilibria, we only specify the agent's belief and action when the enforcer hides, as his belief and action would be trivial otherwise. We say the agent unravels if on the equilibrium path, whenever the enforcer chooses to hide her detection ability, the agent's belief degenerates and imposes probability 1 on the true detection ability of the enforcer.

Denote $p^* \equiv \frac{1-\underline{\theta}-\lambda}{\bar{\theta}-\underline{\theta}}$ the cutoff belief such that the agent is indifferent between complying and violating, i.e., $\lambda = p^*(1-\bar{\theta}) + (1-p^*)(1-\underline{\theta})$. We now describe in Propositions 1 and 2 equilibria of the two games when $p < p^*$, which is the parameter range that we use for our experiment design. The description of equilibria under the full parameter range is given in Appendix A.

When it is common knowledge that the enforcer aims to maximize compliance, the disclosure game of verifiable information admits a fully separating equilibrium. Type-$\underline{\theta}$ enforcer's private information is disadvantageous for compliance maximization purpose and thus she hides to avoid incurring a cost. A type-$\bar{\theta}$ enforcer incurs a small cost to reveal her type. When the enforcer hides, the agent infers that the enforcer's type is $\underline{\theta}$ and violates the rule. It is easy to show that this is the unique equilibrium, and we omit the proof.

Proposition 1. *When $p < p^*$ and it is public information that the enforcer aims to maximize compliance, there is a unique equilibrium. In this pure-strategy equilibrium, only the type-$\bar{\theta}$ enforcer reveals; when the enforcer hides, the agent unravels and violates the rule.*

When the enforcer aims to maximize revenue, the disadvantageous type becomes $\bar{\theta}$. Because if the agent knows that the enforcer's detection ability is strong, he will comply with the rule, which leads to the lowest payoff to the enforcer. There is still an equilibrium where only the disadvantageous-type enforcer hides and the agent unravels. However, there are two additional equilibria. We provide the economic intuition for the pooling equilibrium below, where the enforcer always hides and the agent violates when the enforcer hides. This is driven by the assumption that $p < p^*$. In this case, if the agent takes the enforcer's favorable action (i.e., to violate) when the enforcer hides, then the enforcer has no incentive to exert a cost to reveal her detection ability. Knowing that both types of enforcer hide, the agent will choose to violate because $p < p^*$.

Proposition 2. *When $p < p^*$ and it is public information that the enforcer aims to maximize revenue, there are three equilibria. In one pure-strategy equilibrium, only type-$\underline{\theta}$ enforcer reveals; when the enforcer hides, the agent unravels and complies with the rule. In the other pure-strategy equilibrium, both types of enforcer hide; the agent does not update his belief and violates the rule when the enforcer hides. In the mixed-strategy equilibrium, only type-$\underline{\theta}$ enforcer reveals with positive probability; when the enforcer hides, the agent mixes between complying and violating.*

We leave the full description of the mixed strategy equilibrium to Appendix A. All three equilibria satisfy the intuitive criterion proposed by Cho and Kreps (1987). Since the theory does not predict a unique equilibrium, a controlled laboratory experiment is crucial to find out the actual play.

3.3 Transparent vs. Opaque Enforcement Objective

We now modify the timing of the game by adding an earlier stage where the agent does not know the enforcer's exact objective. The agent's prior for the objective to be compliance maximization is $\gamma \in [0, 1]$. We assume that the distributions of θ and g are independent.

In one scenario discussed in the current section, the enforcement objective is transparent to both parties before the enforcer makes the decision. Thus, the enforcer's private information is an element in Θ. In the second scenario, the objective becomes known to the enforcer before she takes the action but remains opaque to the agent when he takes an action. Thus, the enforcer's private information can be summarized as an element in $\Theta \times G$.

Given Propositions 1 and 2, the analysis regarding the transparent scenario is trivial. We omit the description of the three equilibria, as each one essentially involves two groups of g-contingent strategy profile and belief profile, with one group described in Proposition 1 and one group described by one equilibrium in Proposition 2. We call the equilibrium an unraveling equilibrium, when the strategy profile and belief profile condition on $g = com$ correspond to the one in Proposition 1, and those condition on $g = rev$ corresponds to the first equilibrium in Proposition 2.

The analysis is more complicated if the enforcement objective is now opaque to the agent. We cannot follow the argument in the transparent scenario to show the existence of an unraveling equilibrium. Recall the intuition behind the unraveling equilibrium: the rule enforcer only hides information that is disadvantageous, but showcases information that is advantageous, and thus the agent can perfectly infer the enforcer's type when she chooses to hide information. Whether $\bar{\theta}$ is advantageous or disadvantageous depends on the enforcer's objective — it is advantageous if the enforcer is a compliance maximizer, and it is disadvantageous if the enforcer is a revenue maximizer. In the opaque scenario, the agent does not know the enforcer's exact objective, and thus cannot make a perfect inference.

In the main text, we only include the description of the equilibria under the parameter range used for experiment design. The full description of the equilibria under all parameters is relegated to Appendix A.

Proposition 3. *If $p < p^*$ and $\gamma < \gamma^*(p) \equiv \frac{p(1-p^*)}{p^*(1-p)}$, there are three equilibria. In one pure-strategy equilibrium, only the compliance-maximizing type-$\bar{\theta}$ enforcer reveals; when the enforcer hides, the agent violates the rule. In the other pure-strategy equilibrium, only the revenue-maximizing type-$\underline{\theta}$ enforcer reveals; when the enforcer hides, the agent complies with the rule. In the mixed-strategy equilibrium, only the compliance-maximizing type-$\bar{\theta}$ enforcer and the revenue-maximizing type-$\underline{\theta}$ enforcer reveal with positive probability; when the enforcer* *hides, the agent mixes between complying and violating.*

There are three equilibria when the enforcement objective is opaque to the agent. They differ by the agent's actions (i.e., to violate, to comply, or to mix between violating and complying) when the enforcer hides. In the equilibrium where the agent violates when the enforcer hides, both types of revenue-maximizing agent can obtain their highest payoff by hiding, and thus we call this equilibrium the "revenue-optimal PBE."[6] In this equilibrium, the compliance-maximizing type-$\underline{\theta}$ enforcer also hides, because revealing incurs a cost and cannot change the agent's behavior, but the compliance-maximizing type-$\bar{\theta}$ enforcer reveals to deter violation. In the equilibrium where the agent complies when the enforcer hides, both types of compliance-maximizing agent can obtain their highest payoff by hiding. Thus, we call this equilibrium the "compliance-optimal PBE." In this equilibrium, the revenue-maximizing type-$\bar{\theta}$ enforcer also hides, because revealing incurs a cost and cannot change the agent's behavior, but the revenue-maximizing type-$\underline{\theta}$ enforcer reveals to induce violation.

We leave the full description of the mixed-strategy equilibrium to Appendix A. Note that all three equilibria satisfy the intuitive criterion of Cho and Kreps (1987). Besides, all three equilbria in the opaque scenario attain a higher overall payoff (across the space of $\Theta \times G$) on the enforcer's end than the unraveling equilibrium in the transparent scenario: the revenue-optimal PBE benefits the revenue-maximizing enforcer without hurting the compliance-maximizing one, the compliance-optimal PBE benefits the compliance-maximizing enforcer without hurting the revenue-maximizing one.

4 Experimental Design and Procedures

The purpose of our controlled, laboratory experiment is twofold. First, we would like to examine the selection among equilibria characterized in Section 3. Second, the direct comparison of different enforcement objectives calls for a controlled environment.

[6]See Appendix A for a formal definition of the revenue-optimal PBE, as well as the compliance-optimal PBE which we describe later.

In our experiment, each participant was involved in only one the two studies: Study 1 or Study 2. Study 1 contains two treatments: compliance maximization objective ("Compliance" treatment) and revenue maximization objective ("Revenue" treatment). Study 2 also includes two treatments: transparent objective ("Transparent" treatment) and opaque objective ("Opaque" treatment). The experiment utilizes a between-subjects design so each subject is assigned to only one of the four treatments.

For both studies' sessions, we recruited an even number of subjects. To avoid loaded terms such as "crime", "enforcer", or "compliance", we use neutral language throughout the whole experiment. Specifically, one subject will be the "Red Player" (Enforcer) and one subject will be the "Blue Player" (Agent).[7] Subjects keep their role throughout the entire experiment. The Red Player will be of two types, either a "Type A" (Strong detection ability) or a "Type B" (Weak detection ability), with equal chance. This setup induces $p = 0.5$ to subjects. Each Red Player will be randomly assigned to one of the two types, and will then keep the same type throughout the entirety of the experiment.

The game is played for twenty rounds. At the beginning of each round, new groups of two subjects will be formed. The Red Player decides between two options, "Option R" and "Option H." If the Red Player chooses Option R, the Blue Player is informed of the Red Player's type. If the Red Player chooses Option H, the Blue Player is not informed of the Red Player's type. That means, "Option R" is equivalent to the case when the enforcer reveals her detection ability to the agent, while "Option H" mimics the case when the enforcer hides her detection ability to the agent. The Blue Player will be informed of the Red Player's choice, and then chooses between two options, "Option C" and "Option V." Option C corresponds to the agent's action of complying with the rule, while Option V is in line with the action that the agent violates the rule. Once both players have made their decisions, each participant will be informed of his/her individual earnings for the round. Participants will not be informed of the earnings of other participants.

[7] The use of "Red Player" and "Blue Player" is inspired by experimental instructions from Jin et al. (2021) and Jin et al. (2022).

	Study 1		Study 2	
	Compliance	Revenue	Transparent	Opaque
Rule I	✓		✓	✓
Rule II		✓	✓	✓
Randomly assigned?			✓	✓
Exact rule known to the blue player?	✓	✓	✓	

Table 1: Description of between-subjects treatments in the experiment.

There are two different compensation rules for the Red Player, either Rule I (Compliance maximization) or Rule II (Revenue maximization). Table 1 summarizes all four treatments in the between-subjects experiment. In Study 1, there is only one compensation rule for the Red Player (either Rule I or Rule II), and that's the same within each treatment. The Red Player's compensation rule is common knowledge in Study 1, but the compensation rule is different across the two treatments.

In Study 2, the Red Player's compensation rule ("Rule I" and "Rule II") will be randomly determined at the beginning of the experiment. After that, Red players also keep their compensation rule throughout the entirety of the experiment. Each Red Player always knows his/her type and his/her compensation rule. The two treatments in Study 2 differs in terms of whether the Red Player's exact compensation rule is known or unknown to the Blue Player. Under the transparent treatment, the Blue Player will be also informed of Red Player's exact compensation rule. Under the opaque treatment, the Blue Player does not know the exact compensation rule of the Red Player. Instead, the blue player only knows that it is equally likely for a Red Player's compensation rule to be "Rule I" or "Rule II." As a consequence, our design induces $\gamma = 0.5$ as well.

Figure 1 presents the payoff table when Red Player's compensation rule is Rule I. Figure 2 provides the payoff table when Red Player's compensation rule is Rule II. The numbers are in points, with the exchange rate of 10 points =\$1.[8] We parameterized the experiment to

[8] With this exchange rate, we are actually expanding all the parameters used in Section 3 by 10. This expansion does not affect the nature of equilibria characterized in Section 3. The purpose is to avoid subjects' confusion from calculating payoffs with decimals. This setup also provides reasonable amount of payments to subjects under the paying for one random period (RPS) mechanism (Azrieli et al., 2018).

match the interesting cases of multiple equilibria under both revenue maximization objective and under the opaque objective, more specifically, $p < p^*$ and $\gamma < \gamma^*$.[9]

Here are some explanations on how the parameters used in the experiment are tied with theory described in Section 3. Rule I resembles the case of compliance-maximizing enforcement objective. When the Red Player's compensation rule is Rule I, the Red Player obtains a higher payoff when the Blue Player chooses Option C. If the Red Player chooses Option R, she receives a 5-point lower payoff than Option H, holding the Blue Player's action constant. That coincides with the theoretical framework that revealing the detection ability makes the enforcer incur a positive but minimal cost. If the Blue Player chooses Option C, she receives a sure payoff of 50 points. If the Blue Player chooses Option V instead, her payoff depends on the Red Player's type, i.e., the detection ability of the enforcer. Under type A, the detection ability is strong, so if the Blue Player chooses Option V, she will receive a payoff of 30 points, which is lower than the sure payoff of 50 points. Under type B, the Blue Player's payoff from Option V is 80 points, higher than what he receives from choosing Option C.[10]

Rule II resembles the case of revenue-maximizing enforcement objective. As shown in Figure 2's payoff table, the Red Player receives the lowest payoff when the Blue Player complies, i.e., choosing Option C. For a revenue-maximizing enforcer under $\bar{\theta}$, she is more likely to detect the agent's rule violation behavior than a weak enforcer and thus, is more likely to increase her revenue due to the agent's violation of the rule. That makes the expected payoff of a revenue-maximizing enforcer gets higher under $\bar{\theta}$. Thus, as shown in Figure 2, a type-A Red Player receives a higher payoff than a type-B Red Player if a Blue

[9] For the curious reader: We adopt the following parameters in our theory for experimental design: $\bar{\theta} = 0.7$, $\underline{\theta} = 0.2$, $\lambda = 0.5$, $\bar{b} = 0.7$, $\underline{b} = 0.5$, $\bar{r} = 0.75$, $\bar{r} = 0.5$, $\underline{r} = 0.4$, and $c = 0.05$. With those parameters, we can get $p^* = 0.6$ and $\gamma^* = \frac{2}{3}$. So our parameters allow for a unique separating equilibrium under the compliance treatment, while multiple equilibria under other treatments.

[10] We used the expected payoff of an agent's violation in the experiment. Recall that we selected $\bar{\theta} = 0.7$ for strong enforcers (i.e., type A in the experiment). The agent's payoff is 0 if his violation behavior is detected by the enforcer, and 100 points when he violates and is not detected. That makes the agent's expected payoff as $(1 - 0.7) \times 100 + 0.7 \times 0 = 30$ points. Similarly, for weak enforcers (i.e., type B in the experiment), we used $\underline{\theta} = 0.2$ for the experiment, so the agent's expected payoff from violation is 80 points according to Section 3.

Payoffs (Red Player, Blue Player)	The blue player chooses Option C	The blue player chooses Option V
The red player is Type A, and the red player chooses Option R	65, 50	45, 30
The red player is Type B, and the red player chooses Option R	65, 50	45, 80
The red player is Type A, and the red player chooses Option H	70, 50	50, 30
The red player is Type B, and the red player chooses Option H	70, 50	50, 80

Figure 1: Payoff table for rule I (Compliance maximization) used in the experiment.

Payoffs (Red Player, Blue Player)	The blue player chooses Option C	The blue player chooses Option V
The red player is Type A, and the red player chooses Option R	35, 50	70, 30
The red player is Type B, and the red player chooses Option R	35, 50	45, 80
The red player is Type A, and the red player chooses Option H	40, 50	75, 30
The red player is Type B, and the red player chooses Option H	40, 50	50, 80

Figure 2: Payoff table for rule II (Revenue maximization) used in the experiment.

Player chooses Option V.

After all twenty rounds elapsed, subjects filled out a questionnaire consisting of demographics information, their description of strategy used in the experiment, a non-incentivized risk-preference test similar to Eckel and Grossman (2008), a non-incentivized ambiguity-preference test with two Ellsberg (1961) questions, and a Cognitive Reflection Test (CRT) (Frederick, 2005). After finishing the questionnaire, the session is over and subjects will be informed of his/her earnings of the experiment privately. One of the twenty rounds will be randomly selected and participants will be privately paid based on that round in addition to their $10 show-up bonus. The average payment is $15.89.

Subjects for this experiment were 224 undergraduate students at Texas A&M University, recruited using the econdollars.tamu.edu website, a server based on ORSEE (Greiner, 2015). Sixteen sessions took place at the Economic Research Laboratory at Texas A&M University from March to August 2023, with four sessions for each treatment, and fifty-six subjects within each treatment. The experiment was programmed and conducted with the software z-Tree (Fischbacher, 2007). Every session lasted less than 90 minutes, including instructions, comprehensive quiz questions, and payment procedures.

Instructions and interfaces used in experiments are available as supplemental materials.

5 Testable Hypotheses

In this section, we summarize our five testable hypotheses for the experiment. These hypotheses are based on our model described in Section 3 and the experimental design characterized in Section 4.

Hypothesis 1 and Hypothesis 2 examine different equilibrium behavior under different treatments in Study 1 (compliance maximization vs. revenue maximization). Recall from Section 3 that in the compliance maximization treatment, there is a unique equilibrium. Type-$\bar{\theta}$ enforcer will reveal, while type-$\underline{\theta}$ enforcer hides. As a compliance-maximizing enforcer's hiding behavior signals weak detection ability, it is optimal for an agent to violate the rule conditional on "Hide." In the revenue maximization treatment, there are multiple equilibria, and we establish our hypothesis based on the unraveling equilibrium. Specifically, since the enforcer aims to maximize revenue by detecting agent's violation behavior, type-$\bar{\theta}$ enforcers hides her detection ability to agents, while a type-$\underline{\theta}$ enforcer reveals her detection ability to agents. Under this unraveling equilibrium, as the enforcer's hiding behavior signals $\bar{\theta}$, it is optimal for the agent to comply with the rule, making the enforcer being unable to increase her revenue from the agent's violation by hiding $\bar{\theta}$.

Based on the two unraveling equilibria under two treatments, we expect no difference between the overall frequency of enforcer's hiding behavior because $p = 0.5$ is induced in our experiment. If we examine the enforcer' behavior by type, we expect a significantly higher level of hiding under $\underline{\theta}$ than $\bar{\theta}$ for the compliance treatment. On the contrary, we hypothesize that hiding level is higher under $\bar{\theta}$ than $\underline{\theta}$ for the revenue treatment. On the agent's end, conditional on "Hide", a higher compliance level under the revenue treatment is expected.

Recall from Section 3 that we derived multiple equlbria when the enforcement objective is revenue maximization. In the pooling equilibrium, both types of enforcer hide. In the mixed-strategy equilibrium, type-$\bar{\theta}$ enforcers always hide, while type $\underline{\theta}$ enforcers play a mixed strategy by placing probability $\frac{2}{3}$ to hide. The agent's best response is to mix between "Comply" and "Violate" with equal probability conditional on "Hide."[11] A falsification of only Hypothesis 1 leads to supporting evidence of the mixed-strategy PBE under revenue maximization objective. Falsifications of both Hypothesis 1 and Hypothesis 2 imply supportive evidence for the pooling PBE under revenue maximization objective.

Hypothesis 1. *There is no significant difference in overall hiding levels across treatments in Study 1.*

Hypothesis 2. *Conditional on "Hide", the compliance level is higher under the revenue treatment.*

Hypothesis 3-5 investigate whether or not the opaqueness of enforcement objective benefits the enforcer when she hides her detection ability to the agent. Those hypotheses are built upon the assumption that the unraveling equilibria defined in Section 3.3 is selected under the transparent treatment, although more rounds may be needed for subjects to understand the optimal strategies of both enforcement objectives. As long as the unraveling equilibrium is played under the transparent treatment, the enforcer's payoff of opaque treatment is predicted to be significantly higher than the transparent treatment.

Based on parameters described in Section 4, there are two pure-strategy PBEs and one mixed-strategy PBE under the opaque treatment. Under the mixed-strategy equilibrium, a compliance-maximizing enforcer with strong detection ability is assigning probability 0.5 to both "Reveal" and "Hide". The agent best responds by complying with probability 0.6 when the enforcer hides, while placing probability 0.4 to "Violate" when the enforcer hides.

[11] See Appendix A for a full characterization of this mixed-strategy equilibrium.

Hypothesis 4 and Hypothesis 5 imply that under the opaque treatment, the revenue-optimal equilibrium is selected among multiple equilibria. The increase in enforcer's payoff comes from revenue-maximizing enforcers instead of compliance-maximizing enforcers. If the compliance-optimal PBE is the actual play, we expect to observe a significant higher payoff of enforcers only for compliance-maximizers, but not revenue-maximizers. If the revenue-optimal PBE is the actual play, we should observe a significant higher payoff of enforcers only for revenue-maximizers, but not compliance-maximizers. Finally, we should observe a significantly higher payoff of enforcers under both enforcement objectives if the mixed-strategy PBE is the actual play under the opaque treatment. As a consequence, we can see that falsifications of both Hypothesis 4 and Hypothesis 5 support the compliance-optimal equilibrium. A falsification of only Hypothesis 4 leads to supportive evidence of the mixed-strategy equilibrium under the opaque treatment.

Hypothesis 3. *The enforcer's payoff is higher under the opaque treatment than the transparent treatment in Study 2.*

Hypothesis 4. *There is no significant difference between compliance-maximizing enforcer's payoffs across the transparent and the opaque treatment in Study 2.*

Hypothesis 5. *In Study 2, the opaque treatment generates a higher payoff for revenue-maximizing enforcers than the transparent treatment.*

6 Results

6.1 Results from Study 1

Table 2 provides summary statistics for the main outcome variables used in Study 1. We find no significant difference of enforcer's overall hiding levels across different types between the compliance treatment and the revenue treatment ($p \approx 0.169$). If we examine the data by separating the enforcer's type, we observe a significantly higher level of hiding under

Treatment	Compliance mean (std deviation)	Revenue mean (std deviation)
Hiding Rate		
Full Data	0.680	0.707
	(0.467)	(0.455)
Strong Enforcer	0.446	0.921
	(0.498)	(0.270)
Weak Enforceer	0.914	0.493
	(0.280)	(0.501)
Enforcer's Payoff (In Points)	59.58	48.40
	(9.25)	(12.92)
Compliance Rate Conditional on "Hide"	0.423	0.604
	(0.495)	(0.490)
Pairs	28	28
Subjects	56	56
Sessions	4	4

Table 2: Summary statistics of main outcome variables by Study 1's treatment (standard deviations in parentheses).

the revenue treatment for strong enforcers ($p < 0.001$), while significantly higher level of hiding under the compliance treatment for weak enforcers ($p < 0.001$). Furthermore, we also performed Ordinary Least Squares (OLS) regression analysis based on the enforcer's overall hiding behavior. Table 3 shows that there are no significant treatment effects across Study 1's treatments. Adding period effects and survey control variables (risk attitudes, ambiguity attitudes, CRT responses, and subjects' demographics) does not change the result. Hence, Hypothesis 1 holds.

To investigate whether each type of enforcer behaves as the equilibrium predictions, we also performed Wilcoxon-Mann-Whiteney non-parametric tests (Siegel and Castellan Jr., 1988). Table 4 demonstrates those results. Rounds 16-20 are used for main tests, while full data is regarded as robustness checks. A large fraction (95%) of compliance-maximizing enforcers hide under $\underline{\theta}$, while 28% under $\bar{\theta}$ hides in rounds 16-20. When it comes to the last 5 rounds of the experiment, 99% of type-$\bar{\theta}$ revenue-maximizing enforcers hide, while less than $\frac{1}{3}$ of type-$\underline{\theta}$ revenue-maximizing enforcers hide. That means, enforcers tend to reveal their detection ability to agents as predicted in theory — when they are either compliance-

Variables	(1) Hiding Rate	(2) Hiding Rate	(3) Hiding Rate
Revenue Treatment	0.027	0.027	0.030
	(0.080)	(0.078)	(0.074)
Constant	0.680***	0.788***	0.758***
	(0.046)	(0.063)	(0.190)
Period Effects?	N	Y	Y
Survey Controls?	N	N	Y
Observations	1120	1120	1120
R-squared	0.001	0.020	0.027

*** p<0.01, ** p<0.05, * p<0.1

Table 3: OLS regressions of the treatment effect on enforcer's hiding behavior over time in Study 1. Robust standard errors clustered at the session level in parentheses, using bootstrapping for 1000 times.

	Enforcer		Agent
	Hide|Strong mean	Hide|Weak mean	Comply|Hide mean
Rounds 16-20	0.28 vs 0.99	0.95 vs 0.32	0.33 vs 0.67
	(0.000)***	(0.000)***	(0.000)***
Full Data	0.45 vs 0.92	0.91 vs 0.49	0.42 vs 0.60
	(0.000)***	(0.000)***	(0.000)***

Table 4: Relative frequency and comparison tests in Study 1. Results of the compliance treatment is on the left, while results of the revenue treatment is on the right. p-values in parentheses. * means significant at the 10% level. ** means significant at the 5% level. *** means significant at the 1% level.

maximizers with $\bar{\theta}$, or when they are revenue-maximizers under $\underline{\theta}$.

One potential concern is the possibility of mixed strategies equilibrium in the revenue treatment. Under the mixed-strategy equilibrium of revenue maximization objective, type-$\underline{\theta}$ enforcer should mix by assigning probability $\frac{2}{3}$ to hiding her detection ability, while the agent assigns probability 0.5 to complying with the rule. Table 4 also examines such behavior for both type-$\underline{\theta}$ enforcers and agents. For both full data and last 5 rounds, the proportion of behavior observed in data is significantly different from the predicted probability under the mixed-strategy equilibrium.

Figure 3 plots the time trend of hiding behavior for both types of enforcers in each treatment. There is clear evidence that subjects gain more experience as the number of

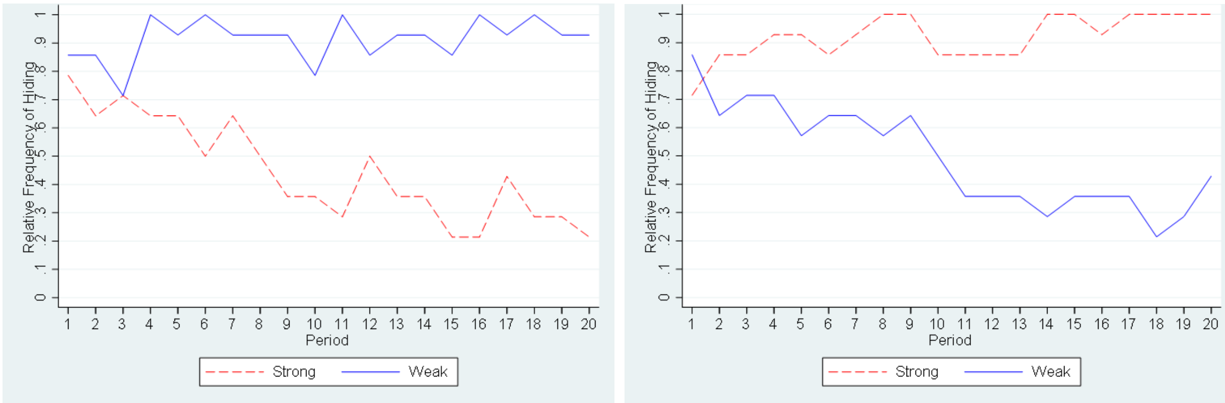

Figure 3: Relative frequency of hiding behavior by the enforcer's detection ability of compliance treatment (left) and revenue treatment (right).

rounds increase.[12] Under the compliance maximization objective, a strong enforcer's hiding behavior decreases as rounds increase, while nearly all weak enforcers hide. On the contrary, we observe opposite results when the enforcement objective is revenue maximization. Those observations support that the enforcer's behavior is in line with the unraveling equilibrium under both treatments in Study 1.

Result 1. *There is no difference in overall hiding levels across the two treatments in Study 1. For a strong enforcer, the level of hiding is higher under the revenue treatment. For a weak enforcer, the level of hiding is higher under the compliance treatment.*

While most revenue-maximizing enforcers hide when they are strong and the frequency of weak enforcer's hiding behavior decreases significantly as rounds increase, the proportion of hiding is still not close to zero for weak enforcers.[13] Therefore, following the description in Section 5, we examine agents' behavior to rule out the possibility of mixed-strategy PBE under the revenue treatment.

We find consistent evidence that Hypothesis 2 holds. We calculate the relative frequency that agents choose to comply with the rule conditional on "Hide". Those results are also shown in Table 4. The relative frequency of compliance conditional on "Hide" under com-

[12]Figures A.2-A.5 examines the possibilities of mixed strategies. The proportion of behavior deviates from the predicted mixed-strategy probability significantly.

[13]Table A.2 provides details on how the enforcer's hiding behavior evolve across time by detection ability.

Variables	(1) Compliance Rate|"Hide"	(2) Compliance Rate|"Hide"	(3) Compliance Rate|"Hide"
Revenue Treatment	0.181**	0.180**	0.191*
	(0.089)	(0.104)	(0.104)
Constant	0.423***	0.389***	0.646***
	(0.071)	(0.072)	(0.170)
Period Effects?	N	Y	Y
Survey Controls?	N	N	Y
Observations	777	777	777
R-squared	0.033	0.035	0.078

*** p<0.01, ** p<0.05, * p<0.1

Table 5: OLS regressions of the treatment effect on agent's behavior conditional on the enforcer's hiding behavior over time in Study 1. Robust standard errors clustered at the session level in parentheses, using bootstrapping for 1000 times.

pliance treatment is 0.42 for full data, and 0.33 for the last 5 rounds. Under the compliance treatment, the compliance level conditional on "Hide" is significantly lower than the compliance level conditional on "Hide" under the revenue treatment ($p < 0.01$ for both full data and last five rounds' data).[14]

Table 5 examines the determinants of agent's compliance behavior conditional on observing "Hide." Column 1 depicts an OLS regression of agent's compliance rate conditional on "Hide." The treatment effect is positive — the revenue treatment generates a 18.1% higher level of compliance, conditional on the enforcer's hiding behavior, than the compliance treatment. Columns 2 and 3 add periods effects and survey controls to the regression and the initial result still holds. Those results demonstrate clear differences between agents' behavior under different enforcement objectives, conditional on the enforcer's hiding behavior.

Result 2. *Agents' compliance level conditional on "Hide" is significantly higher under the revenue treatment.*

What also matters is how overall equilibrium outcomes evolve across time, since after

[14]Before the first round of the game, subjects are required to answer several comprehensive quiz questions so that they can understand the payoff tables for both players. A subject's role is assigned only after all subjects complete all comprehensive quiz questions. Sample screenshots are available in Figure A.8 and A.14. Besides, as a comprehensive check, we also looked at whether agents choose a lower payoff when the enforcer's type is revealed. Only 10 out of 1120 agent observations in Study 1 chose dominated options, and the proportion of such irrational behavior decreased to zero in rounds 16-20.

each round, each subject receives feedback about the enforcer's detection ability and both players' decisions in her pair. We would also like to understand that whether the compliance treatment generates the unique equilibrium predicted in Section 3. To achieve this goal, we consider paired outcomes of one enforcer and one agent in a round. Following Propositions 1 and 2, we divide observed outcomes into two different categories for the compliance treatment, while three categories for revenue maximization. For the compliance treatment, we classify a pair of enforcer-agent outcome as "separating equilibrium" if one of the following two cases are satisfied: (1) a type-$\bar{\theta}$ enforcer reveals and the paired agent complies; or (2) a type-$\underline{\theta}$ enforcer hides and the paired agent violates. All other cases are classified as "others."

When it comes to the revenue treatment, there are instead three different outcomes for an enforcer-agent pair. An enforcer-agent pair is classified as "separating equilibrium" if one of the following two cases are satisfied: (1) a type-$\bar{\theta}$ enforcer hides and the paired agent complies; or (2) a type-$\underline{\theta}$ enforcer reveals and the paired agent violates. An enforcer-agent pair is classified as "pooling equilibrium" if the enforcer hides regardless of her type and the paired-agent violates the rule. All other outcomes are documented as "others."[15]

Table 6 shows the percentage of equilibria under both treatments in Study 1. The percentage of separating equilibrium increases over time as we regard each five rounds as a block. The percentage of the unique separating equilibrium increases from 37.86% in rounds 1-5, to 66.43% in rounds 16-20 under the compliance treatment. The percentage of separating equilibrium under revenue treatment also increases over time as we regard each five rounds as a block, from 32.86% in rounds 1-5, to 67.14% in rounds 16-20. In the mean time, the percentage of pooling equilibrium decreases from 42.86% in rounds 1-5 to 21.43% in rounds 16-20.[16] Those percentages also confirms that the separating equilibrium are the

[15]One potential concern from Table 6 is the possibility of mixed-strategy equilibrium pairs. By OLS regression results from Study 1, we have already provided sufficient supportive evidence that the separating equilibrium is selected based on the enforcer's hiding behavior and the agent's compliance behavior conditional on "Hide." Also, the purpose of counting equilibrium pairs is to guarantee that the compliance treatment generates a majority of the unique, separating equilibrium in the experiment.

[16]If a subject plays randomly by assigning equal chance to the two actions, the proportion of separating equilibrium is 25% in each treatment–significantly lower than the proportion of separating equilibrium observed in Study 1's data.

Compliance Maximization				
Equilibrium	Rounds 1-5 Number (Percentage)	Rounds 6-10 Number (Percentage)	Rounds 11-15 Number (Percentage)	Rounds 16-20 Number (Percentage)
Separating	106 (37.86%)	146 (52.14%)	164 (58.57%)	186 (66.43%)
Others	174 (62.14%)	134 (47.86%)	116 (41.43%)	94 (33.57%)
Total	280 (100%)	280 (100%)	280 (100%)	280 (100%)
Revenue Maximization				
Equilibrium	Rounds 1-5 Number (Percentage)	Rounds 6-10 Number (Percentage)	Rounds 11-15 Number (Percentage)	Rounds 16-20 Number (Percentage)
Separating	92 (32.86%)	142 (50.72%)	178 (63.57%)	188 (67.14%)
Pooling	120 (42.86%)	84 (30%)	50 (17.86%)	60 (21.43%)
Others	68 (24.28%)	54 (19.28%)	52 (18.57%)	32 (11.43%)
Total	280 (100%)	280 (100%)	280 (100%)	280 (100%)

Table 6: Percentage of equilibrium outcomes under different treatments in Study 1.

majority under both treatments in Study 1.

To sum up, our results support both Hypothesis 1 and Hypothesis 2. That means, we find that the unraveling equilibrium is played when the enforcement objective is transparent to agents.[17] Conversely, we find no support of the pooling equilibrium or the mixed-strategy equilibrium under the revenue treatment.

Result 3. *Our data support the unraveling equilibrium being the actual play in both treatments in Study 1.*

6.2 Results from Study 2

The main takeaway of Study 1's result is that transparent enforcement objectives lead to unraveling equilibria. Hence, we learn that the strategy of concealing detection ability does

[17]We are aware that enforcers' irrational behavior that deviates from equilibrium strategies may affect the treatment effect. Hence, we conducted additional OLS regressions with two different subsets of Study 1's data. The first focuses on enforcer-optimal pairs (pairs with the enforcer's action coincides with the equilibrium prediction in Section 3), following Deversi et al. (2021). Table A.4 shows that by eliminating those irrational enforcers who deviated from equilibrium, we observe a significant treatment effect of 21.9% on agent's compliance level conditional on "Hide."

Treatment	Transparent mean (std deviation)	Opaque mean (std deviation)
Hiding Rate		
Full Data	0.736	0.779
	(0.441)	(0.415)
Compliance-Strong	0.479	0.429
	(0.501)	(0.496)
Compliance-Weak	0.943	0.907
	(0.233)	(0.291)
Revenue-Strong	0.907	0.993
	(0.291)	(0.084)
Revenue-Weak	0.614	0.786
	(0.489)	(0.411)
Enforcer's Payoff (In Points)	54.44	55.74
	(12.75)	(12.90)
Compliance Rate Conditional on "Hide"	0.466	0.452
	(0.499)	(0.498)
Pairs	28	28
Subjects	56	56
Sessions	4	4

Table 7: Summary statistics of main outcome variables by Study 2's treatment (Standard deviations in parentheses).

not benefit the enforcer. Then, we would also like to understand whether the opaqueness of enforcement objectives can help the enforcer leverage the option of concealing her detection ability. For that purpose, we compare the two treatments in Study 2, i.e., transparent and opaque enforcement objectives.

Table 7 provides summary statistics for the main outcome variables of the experiments in Study 2. We observe a slightly higher level of hiding under the opaque treatment ($p \approx 0.095$), even though the level of significance is not high. Such a difference is driven mainly by the revenue maximizers whose detection ability is weak ($p \approx 0.002$). In terms of compliance level when the enforcer hides, we find no significant difference across the two treatment ($p \approx 0.679$). Another main outcome variable for Study 2 is the enforcer's payoff. In line with Hypothesis 3, a higher overall payoff of enforcer is observed under the opaque treatment ($p \approx 0.083$), as also shown in Table 8.

	Full Data mean	Compliance Maximization mean	Revenue Maximization mean
Enforcer's Payoffs	54.44 vs 55.74 (0.083)*	59.05 vs 59.55 (0.639)	49.82 vs 51.92 (0.079)*

Table 8: Enforcer's payoffs in Study 2. Results of the transparent treatment is on the left, while results of the opaque treatment is on the right. p-values in parentheses. * means significant at the 10% level. ** means significant at the 5% level. *** means significant at the 1% level.

Result 4. *In Study 2, the enforcer's overall payoff is higher under the opaque treatment than the transparent treatment.*

Our hypotheses in Study 2 are based on unraveling equilibria under transparent objectives. Thus, we examine the data from transparent treatments first, and then compare it with the opaque treatment since the only difference is whether the enforcement objective is common knowledge or the enforcer's private information. Table 9 presents the percentage of equilibria under the transparent treatment. The definitions of equilibrium pairs are the same as what has been used in Table 6. The proportion of the unique PBE under compliance maximization is consistent with what we have observed in Study 1's data. The proportion of separating PBE under revenue maximization is significantly lower (from 35.71% in rounds 1-5 to only 47.14% in rounds 16-20), but it is still the majority of all enforcer-agent pairs. All in all, even though Study 2 already imposes higher cognitive requirements to subjects, the transparent treatment's data still support the claim that unraveling equilibrium is played more often than other equilibria.

We also need to verify Hypothesis 4 and Hypothesis 5 to determine the actual play under the opaque treatment. Therefore, we compare the enforcer's payoff between transparent and opaque treatment. Table 8 demonstrates such results. The enforcer's overall payoff under the opaque treatment is significantly higher than the transparent treatment ($p \approx 0.083$), even though the difference is only 1 point in total. As demonstrated in Table 9, the smaller-than-expected payoff difference is due to a larger proportion of irrational behavior that deviates

Compliance Maximization				
Equilibrium	Rounds 1-5 Number (Percentage)	Rounds 6-10 Number (Percentage)	Rounds 11-15 Number (Percentage)	Rounds 16-20 Number (Percentage)
Separating	72 (51.43%)	76 (54.29%)	76 (54.29%)	86 (61.43%)
Others	68 (48.57%)	64 (46.71%)	64 (46.71%)	54 (38.57%)
Total	140 (100%)	140 (100%)	140 (100%)	140 (100%)

Revenue Maximization				
Equilibrium	Rounds 1-5 Number (Percentage)	Rounds 6-10 Number (Percentage)	Rounds 11-15 Number (Percentage)	Rounds 16-20 Number (Percentage)
Separating	50 (35.71%)	56 (40%)	62 (44.29%)	66 (47.14%)
Pooling	50 (35.71%)	48 (34.29%)	52 (37.14%)	46 (32.85%)
Others	46 (28.58%)	36 (25.71%)	26 (18.57%)	28 (20%)
Total	140 (100%)	140 (100%)	140 (100%)	140 (100%)

Table 9: Percentage of equilibrium outcomes under the transparent treatment in Study 2.

from equilibrium predictions under the transparent treatment.[18] To be specific, in Study 2's transparent treatment, fewer subjects play the unraveling equilibrium than in Study 1's revenue treatment.

As we examine the enforcer's objective separately, we find no significant difference in payoffs between compliance-maximizing enforcers. A significant higher payoff of enforcers is also generated under the opaque treatment for revenue-maximizing enforcers ($p \approx 0.079$). Those comparison of enforcer's payoff confirms our prediction that the opaqueness of enforcement objective benefits the revenue-maximizing enforcer. Thus, we conclude that both Hypothesis 4 and Hypothesis 5 hold.

Result 5. *In Study 2, there is no significant difference between compliance-maximizing enforcer's payoffs across the two treatments.*

Result 6. *In Study 2, the opaque treatment generates a higher payoff for revenue-maximizing enforcers than the transparent treatment.*

[18]Recall that if the equilibrium unravels under transparent objectives, the expected payoff for compliance-maximizers is 57.5 points, while 42.5 points for revenue-maximizers.

In addition to our verification of Hypothesis 4 and Hypothesis 5, we also adopt two additional approaches to further validate our predictions related to equilibrium selection under opaque enforcement objectives.

The first approach is to look at the compliance behavior conditional on "Hide" under the opaque treatment, as the main difference between the two pure-strategy PBEs are whether subjects comply with or violate the rule conditional on "Hide." The percentage of compliance is 45.18% for full data, while 38.89% for the last 5 rounds. Recall from Table 4 that the compliance rate conditional on "Hide" is 42% under the compliance treatment while 69% under the revenue treatment in Study 1.

One may wonder why we find no significant difference in compliance rates when the enforcer hides across the opaque and transparent treatments. We provide our conjecture here. From the agent's perspective, the transparent treatment essentially combines two games together which requires the agent to reason separately contingent on the compliance-maximizing objective and the revenue-maximizing objective, while the opaque treatment contains only one game and does not require the agent to make contingent reasoning. To make our comparison like-for-like, in our analysis of the agent's compliance behavior, we go back to Study 1's data and compare the two treatments in Study 1 which do not require contingent reasoning, with the opaque treatment. As demonstrated in Table 10, the compliance rate conditional on "Hide" is significantly lower than the revenue treatment ($p < 0.001$) while slightly higher than the compliance rate than the compliance treatment, but not significant ($p \approx 0.235$).[19]

The second approach is to examine equilibrium pairs under the opaque treatment, and see how the behavior evolves over time. Hence, we classify an enforcer-agent pair based on the equilibrium characterizations following Proposition 3. To be specific, we classify a enforcer-agent pair as "Revenue-Optimal PBE" if an enforcer reveals only when she is a compliance-maximizing $\bar{\theta}$ type, while an agent violates when the enforcer hides. Conversely,

[19]Recall from Section 3 that if the agent mixes, she will place probability 0.6 to "Comply." Figure A.6 and Figure A.7 plot the agent's compliance conditional on "Hide" under the opaque treatment.

Full Data	Comply|Hide mean
Compliance vs. Opaque	0.423 vs 0.452 (0.235)
Revenue vs. Opaque	0.603 vs 0.452 (0.000)***

Table 10: Relative frequency and comparison tests between the opaque treatment and the two treatments in Study 1. Results of the transparent treatments in Study 1 are on the left, while results of the opaque treatment are on the right. p-values in parentheses. * means significant at the 10% level. ** means significant at the 5% level. *** means significant at the 1% level.

Equilibrium	Rounds 1-5 Number (Percentage)	Rounds 6-10 Number (Percentage)	Rounds 11-15 Number (Percentage)	Rounds 16-20 Number (Percentage)
Revenue-Optimal	114 (40.72%)	154 (55%)	138 (49.29%)	152 (54.29%)
Compliance-Optimal	92 (32.85%)	60 (21.43%)	110 (38.28%)	72 (25.71%)
Others	74 (26.43%)	66 (23.57%)	32 (11.43%)	56 (20%)
Total	280 (100%)	280 (100%)	280 (100%)	280 (100%)

Table 11: Percentage of equilibrium outcomes under the opaque treatment in Study 2.

an enforcer-agent pair is classified as "Compliance-Optimal PBE" if an enforcer reveals only when she is the revenue-maximizing $\underline{\theta}$ type, while an agent complies when then enforcer hides. Table 11 presents such results. The percentage of Revenue-Optimal PBE pairs increases from 40.72% in rounds 1-5, to 54.29% in rounds 16-20. Besides, the proportion of revenue-optimal pairs dominate all other possibilities.

In summary, with all those examinations from both strategies and enforcer's payoffs' perspectives, we find that agents violate the rule when the enforcer hides under the opaque treatment. With that, we confirm that the opaqueness of enforcement objective breaks down unraveling and benefits the revenue-maximizing enforcers by generating higher payoffs, without hurting compliance-maximizing enforcers.

Result 7. *Our data supports the "Revenue-Optimal" PBE as the actual play. That means, agents violate the rule conditional on "Hide" under the opaque treatment.*

7 Conclusion

In this paper, we investigate whether a rule enforcer has the incentive to voluntarily disclose her private information on detection ability to the agent through a theory-driven laboratory experiment. In particular, we connect this voluntary disclosure problem with two conflicting enforcement objectives, i.e., compliance maximization and revenue maximization. Our goal is to understand when an enforcer will choose to hide her privately-informed detection ability, and how an agent will respond, under each enforcement objective. Moreover, when the enforcement objective is also the enforcer's private information, we examine whether or not the enforcer can take advantage of the opaqueness in her enforcement objective.

Our theoretical analysis provides a full characterization of all equilibria. Under a wide range of parameters, we derive multiple equilibria in the game. Those equilibria can be differentiated by whether an agent complies, violates, or mixes between "Comply" or "Violate" when the enforcer hides her detection ability. A controlled, laboratory experiment is the appropriate method to examine the selection among multiple equilibria as well as to compare different environments directly.

Our experimental results show that when the enforcer's objective is transparent to the agent, the enforcer cannot affect the agent's compliance behavior by strategically withholding information about her detection ability. This is because unraveling happens for both enforcement objectives as long as the exact objective is common knowledge: the agent can fully infer the enforcer's undisclosed information. However, the opaqueness in enforcement objectives breaks down unraveling, and thereby allowing the enforcer to leverage the strategy of hiding information. Overall, compared to the equilibrium played under transparent objectives, the equilibrium played under opaque enforcement objectives benefits enforcers. In particular, the opaqueness strictly improves revenue-maximizing enforcers' payoff without hurting compliance-maximizing enforcers.

The game structure and findings in our study are not only relevant to rule enforcement.

Instead, they can be adapted to other contexts involving conflicting motives. For example, suppose a firm can incur a small cost to obtain evidence about the quality of a new product developed by an entrant firm. When the entrant firm plays this disclosure game, not revealing the verifiable quality information can be perceived by a customer as bad news about the quality of this new product. On the contrary, when the incumbent firm plays this game, no news can be perceived as good news. In both cases, unraveling occurs. However, if both the entrant and incumbent play this disclosure game and remain silent, the interpretation of silence becomes a nontrivial question.

We conclude our paper by providing several promising avenues for further research. The first intriguing task may be considering the possibility of allowing the enforcer choose whether or not to disclose her enforcement objective to the agent. Another possible extension is to extend the theoretical framework by adding reputation effects to the enforcer's objective. That means, the revenue-maximizing enforcer prefers to be perceived as a compliance maximizer by agents. Last but not least, future work could connect opaque enforcement objectives to other environments related to asymmetric information. Potential examples include partially-verifiable disclosure (Glazer and Rubinstein, 2004), cheap talk (Crawford and Sobel, 1982), and Bayesian persuasion (Kamenica and Gentzkow, 2011). Studying the role of opaque enforcement objectives in those games can be challenging yet rewarding tasks.

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Supplementary Appendix: Not Intended for Publication

A Theory Appendix

We now characterize the set of equilibria in Sections 3.2 and 3.3 almost everywhere in the parameter space $p \in [0, 1]$ and $\gamma \in [0, 1]$.

It is useful to recall that $p^* \equiv \frac{1-\lambda-\underline{\theta}}{\bar{\theta}-\underline{\theta}}$ from the main text. We also define $\gamma^*(p) \equiv \frac{p(1-p^*)}{p^*(1-p)}$, $\gamma^{**}(p) \equiv 1 - \frac{1}{\gamma^*(p)} = \frac{p-p^*}{p(1-p^*)}$, and $\gamma^{'}(p) = \frac{p(1-p^*)}{p^*+p-2pp^*}$. It is easy to show that all three functions are weakly increasing, $\gamma^{**}(p) < 0 < \gamma^{'}(p) < \gamma^*(p) < 1$ for all $p \in (0, p^*)$, and $0 < \gamma^{**}(p) < \gamma^{'}(p) < 1 < \gamma^*(p)$ for all $p \in (p^*, 1)$.

A.1 Omitted Details in Section 3.2

We only construct the mixed strategy equilibrium in Proposition 2 as the other parts in the proof of Proposition 2 are straightforward.

Mixed Strategy in Proposition 2

In the mixed strategy equilibrium, type-$\bar{\theta}$ enforcer hides and the type-$\underline{\theta}$ enforcer adopts strategy $(\sigma_1[\underline{\theta}](R), \sigma_1[\underline{\theta}](H)) = (1 - \gamma^*(p), \gamma^*(p))$. When an enforcer hides, the agent's belief of the enforcer's type is $(\pi_H(\bar{\theta}), \pi_H(\underline{\theta})) = (p^*, 1 - p^*)$ and he adopts the strategy $(\sigma_2[H](V), \sigma_2[H](C)) = (1 - \frac{c}{\bar{r}-\underline{r}}, \frac{c}{\bar{r}-\underline{r}})$.

Proof. We first observe that the type-$\bar{\theta}$ enforcer hides with probability 1, because revealing incurs a cost and makes the agent comply, which is the worst outcome for the revenue-maximizing enforcer. Hence, only type-$\underline{\theta}$ enforcer mixes.

Since the agent is indifferent between complying and violating, the belief on $\bar{\theta}$ upon observing hiding must satisfy $\pi_H(\bar{\theta}) = p^*$.

By Bayes' rule, inducing this posterior p^* requires

$$\frac{p}{p + (1 - p)\sigma_1[\underline{\theta}](H)} = p^* \implies \sigma_1[\underline{\theta}](H) = \gamma^*(p).$$

On the other hand, the agent mixes such that type-$\underline{\theta}$ enforcer is indifferent between revealing and hiding. This requires that

$$\bar{r} - c = \bar{r}\sigma_2[H](V) + \underline{r}(1 - \sigma_2[H](V)) \implies \sigma_2[H](V) = 1 - \frac{c}{\bar{r} - \underline{r}}.$$

To this end, we have constructed this mix-strategy equilibrium. □

Counterparts of Propositions 1 and 2 Under $p > p^*$

We now characterize equilibria when $p > p^*$ in all of the games discussed in Section 3.2. We first establish the counterpart of Proposition 1.

Proposition 4. *When $p > p^*$ and it is public information that the enforcer aims to maximize compliance, there are three equilibria. The first pure-strategy equilibrium is described in Proposition 1. In the other pure-strategy equilibrium, both types of enforcer hide; the agent does not update his belief when an enforcer hides, and thus, complies with the rule. In the mixed strategy equilibrium, type-$\underline{\theta}$ enforcer hides, type-$\bar{\theta}$ enforcer adopts strategy $(\sigma_1[\bar{\theta}](R), \sigma_1[\bar{\theta}](H)) = (\gamma^{**}(p), 1-\gamma^{**}(p))$; when an enforcer hides, the agent's belief of the enforcer's type is $(\pi_H(\bar{\theta}), \pi_H(\underline{\theta})) = (p^*, 1-p^*)$ and he adopts the strategy $(\sigma_2[H](V), \sigma_2[H](C)) = (\frac{c}{\bar{b}-\underline{b}}, 1 - \frac{c}{\bar{b}-\underline{b}})$.*

Proof. Again, we only establish the mix-strategy equilibrium. First, notice that the type-$\underline{\theta}$ enforcer has no incentive to reveal. Hence, only the type-$\bar{\theta}$ enforcer mixes to make the agent indifferent between complying and violating upon observing the action to hide. This requires that $\pi_H(\bar{\theta}) = p^*$.

By Bayes' rule, inducing this posterior requires

$$\frac{p\sigma_1[\bar{\theta}](H)}{p\sigma_1[\bar{\theta}](H) + (1-p)} = p^* \implies \sigma_1[\bar{\theta}](H) = \frac{1}{\gamma^*(p)} = 1 - \gamma^{**}(p).$$

On the other hand, the agent mixes such that type-$\bar{\theta}$ enforcer is indifferent between revealing and hiding. This requires that

$$\bar{b} - c = \sigma_2[H](C)\bar{b} + (1 - \sigma_2[H](C))\underline{b} \implies \sigma_2[H](C) = 1 - \frac{c}{\bar{b} - \underline{b}}.$$

To this end, we have constructed this mix-strategy equilibrium. □

We present the counterpart of Proposition 2 and omit the proof.

Proposition 5. *When $p > p^*$ and it is public information that the enforcer aims to maximize revenue, there is a unique equilibrium. In this pure-strategy equilibrium, only type-$\underline{\theta}$ enforcer reveals; when an enforcer hides, the agent unravels and complies with the rule.*

A.2 Omitted Details in Section 3.3

It is easy to show that the following pure equilibria exist in their respective parameter range. We thus omit the proofs.

Compliance-Optimal PBE: For $\gamma < \gamma^*(p)$, there exists an equilibrium where only the revenue-maximizing type-$\underline{\theta}$ enforcer reveals; when the enforcer hides, the agent complies with the rule because he updates his belief to $(\pi_H(com,\bar{\theta}),\pi_H(com,\underline{\theta}),\pi_H(rev,\bar{\theta}),\pi_H(rev,\underline{\theta}))$ $=(\frac{p\gamma}{1-(1-p)(1-\gamma)},\frac{\gamma(1-p)}{1-(1-p)(1-\gamma)},\frac{p(1-\gamma)}{1-(1-p)(1-\gamma)},0)$.

Revenue-Optimal PBE: For $\gamma > \gamma^{**}(p)$, there exists an equilibrium where only the compliance-maximizing type-$\bar{\theta}$ enforcer reveals; when the enforcer hides, the agent violates because he updates the belief to

$$(\pi_H(com,\bar{\theta}),\pi_H(com,\underline{\theta}),\pi_H(rev,\bar{\theta}),\pi_H(rev,\underline{\theta}))=(0,\frac{\gamma(1-p)}{1-p\gamma},\frac{p(1-\gamma)}{1-p\gamma},\frac{(1-\gamma)(1-p)}{1-p\gamma}).$$

The following two mixed-strategy equilibria exist in their respective parameter range.

PBE-3: For $\gamma'(p) < \gamma < \gamma^*(p)$, there exists a mixed-strategy equilibrium where the revenue-maximizing type-$\underline{\theta}$ enforcer reveals for sure and the compliance-maximizing type-$\bar{\theta}$ enforcer plays mixed strategy $(\sigma_1[com,\bar{\theta}](R),\sigma_1[com,\bar{\theta}](H))=(\frac{1}{\gamma}-\frac{1}{\gamma^*(p)},\frac{1}{\gamma^*(p)}-\frac{1}{\gamma}+1)$; when the enforcer hides, the agent updates his belief to
$(\pi_H(com,\bar{\theta}),\pi_H(com,\underline{\theta}),\pi_H(rev,\bar{\theta}),\pi_H(rev,\underline{\theta}))=(p^*-\frac{1-\gamma}{\gamma}\gamma^*(p)p^*,1-p^*,\frac{1-\gamma}{\gamma}\gamma^*(p)p^*,0)$ and adopts mixed strategy $(\sigma_2[H](V),\sigma_2[H](C))=(\frac{c}{\bar{b}-\underline{b}},1-\frac{c}{\bar{b}-\underline{b}})$.

Proof. Denote $\tau\equiv\sigma_1[com,\bar{\theta}](H)$. Notice that compliance-maximizing type-$\underline{\theta}$ and revenue-maximizing type-$\bar{\theta}$ enforcer have a strict incentive to hide. We begin with assuming that revenue-maximizing type-$\underline{\theta}$ reveals for sure. Then the agent updates his belief to

$$\begin{aligned}&(\pi_H(com,\bar{\theta}),\pi_H(com,\underline{\theta}),\pi_H(rev,\bar{\theta}),\pi_H(rev,\underline{\theta}))\\=&(\frac{p\gamma\tau}{p\gamma\tau+(1-p)\gamma+p(1-\gamma)},\frac{\gamma(1-p)}{p\gamma\tau+(1-p)\gamma+p(1-\gamma)},\frac{p(1-\gamma)}{p\gamma\tau+(1-p)\gamma+p(1-\gamma)},0).\end{aligned}$$

To make the agent indifferent between violating and complying, τ must satisfy

$$1-p^*=\frac{\gamma(1-p)}{p\gamma\tau+(1-p)\gamma+p(1-\gamma)}\implies\tau=\frac{1}{\gamma^*(p)}-\frac{1}{\gamma}+1.$$

To show that $\tau>0$ and $1-\tau>0$, we must require that $\gamma'(p)<\gamma<\gamma^*(p)$.

We plug the above τ into the vector of π_H to establish the belief and follow the argument of Proposition 4 to derive the mixed strategy played by the agent to make compliance-maximizing type-$\bar{\theta}$ enforcer indifferent between revealing and hiding. At last, the fact that the revenue-maximizing type-$\underline{\theta}$ enforcer has the incentive to reveal is guaranteed by the assumption that $c<\frac{(\bar{b}-\underline{b})(\bar{r}-\underline{r})}{(\bar{b}-\underline{b})+(\bar{r}-\underline{r})}$. □

PBE-4: For $\gamma^{**}(p) < \gamma < \gamma'(p)$, there exists a mixed-strategy equilibrium where the compliance-maximizing type-$\bar{\theta}$ enforcer reveals for sure and revenue-maximizing type-$\underline{\theta}$ enforcer plays mixed strategy $(\sigma_1[rev,\underline{\theta}](R),\sigma_1[rev,\underline{\theta}](H))=(\frac{1}{1-\gamma}-\gamma^*(p),\gamma^*(p)-\frac{\gamma}{1-\gamma})$; when the enforcer hides, the agent updates his belief to $(\pi_H(com,\bar{\theta}),\pi_H(com,\underline{\theta}),\pi_H(rev,\bar{\theta}),\pi_H(rev,\underline{\theta})) = (0,\frac{\gamma(1-p^*)}{(1-\gamma)\gamma^*},p^*,1-p^*-\frac{\gamma(1-p^*)}{(1-\gamma)\gamma^*})$ and adopts mixed strategy $(\sigma_2[H](V),\sigma_2[H](C)) = (1-\frac{c}{\bar{r}-\underline{r}},\frac{c}{\bar{r}-\underline{r}})$.

Proof. Denote $\eta = \sigma_1[rev,\underline{\theta}](H)$. We begin with assuming that the compliance-maximizing type-$\bar{\theta}$ enforcer reveals for sure. It is easy to see that compliance-maximizing type-$\underline{\theta}$ enforcer and the revenue-maximizing type-$\bar{\theta}$ enforcer have no incentive to reveal.

When the enforcer hides, the agent updates the belief to

$$\pi_H(com,\bar{\theta}) = 0, \pi_H(com,\underline{\theta}) = \frac{\gamma(1-p)}{1-p\gamma-(1-p)(1-\gamma)(1-\eta)},$$
$$\pi_H(rev,\bar{\theta}) = \frac{p(1-\gamma)}{1-p\gamma-(1-p)(1-\gamma)(1-\eta)}, \pi_H(rev,\underline{\theta})) = \frac{(1-\gamma)(1-p)\eta}{1-p\gamma-(1-p)(1-\gamma)(1-\eta)}.$$

To make the agent indifferent between violating and complying, η must satisfy the following indifference condition

$$p^* = \frac{p(1-\gamma)}{1-p\gamma-(1-p)(1-\gamma)(1-\eta)} \implies \eta = \gamma^*(p) - \frac{\gamma}{1-\gamma}.$$

The requirement that $\eta > 0$ and $1-\eta > 0$ leads to $\gamma^{**}(p) < \gamma < \gamma'(p)$.

We plug this value of η into the vector of π_H to establish the belief and follow the argument of Proposition 2 to derive the mixed strategy played by the agent. At last, the fact that the compliance-maximizing type-$\bar{\theta}$ enforcer has the incentive to reveal is guaranteed by the assumption that $c < \frac{(\bar{b}-\underline{b})(\bar{r}-\underline{r})}{(\bar{b}-\underline{b})+(\bar{r}-\underline{r})}$. □

In sum, we have established the following result to complete the parameter range of Proposition 3. Figure A.1 provides a graphical illustration of parameters range supporting different PBEs.

Proposition 6. *If $\gamma < \gamma^{**}(p)$, there exists a unique equilibrium: Compliance-Optimal PBE. If $\gamma^{**}(p) < \gamma < \gamma'(p)$, there exist three equilibria: Compliance-Optimal PBE, Revenue-Optimal PBE, and PBE-4. If $\gamma^{'}(p) < \gamma < \gamma^*(p)$, there exist three equilibria: Compliance-Optimal PBE, Revenue-Optimal PBE, and PBE-3. If $\gamma > \gamma^*(p)$, there exists a unique equilibrium: Revenue-Optimal PBE.*

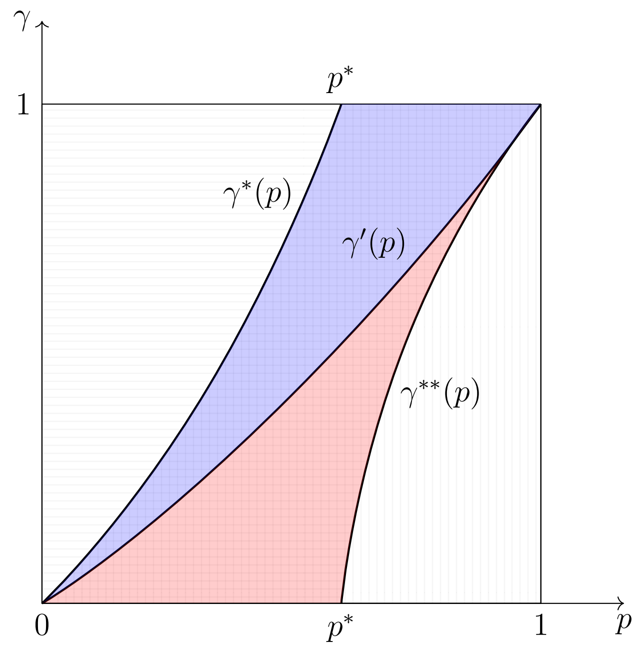

Figure A.1: Parameters range supporting compliance-optimal PBE (Vertical Pattern) , revenue-optimal PBE (Horizontal Pattern), PBE-3 (Blue), and PBE-4 (Red) in the game with opaque enforcement objectives.

B Additional Results

Treatment (no. of sessions, subjects)	Female mean (std deviation)	Correct Responses in CRT mean (std deviation)	Risk mean (std deviation)	Ambiguity mean (std deviation)	From Texas? mean (std deviation)
Compliance	0.589	1.304	2.554	0.554	0.679
(4 sessions, 56 subjects)	(0.492)	(1.085)	(1.281)	(0.497)	(0.467)
Revenue	0.571	1.250	2.429	0.643	0.625
(4 sessions, 56 subjects)	(0.495)	(1.057)	(1.362)	(0.479)	(0.484)
Transparent	0.571	1.357	2.821	0.571	0.607
(4 sessions, 56 subjects)	(0.495)	(1.156)	(1.403)	(0.495)	(0.489)
Opaque	0.553	0.964	2.446	0.500	0.554
(4 sessions, 56 subjects)	(0.497)	(1.101)	(1.322)	(0.500)	(0.497)

Table A.1: Summary statistics for control variables by treatment. Note that the variable ”Ambiguity” is recorded in a binary way–1 means a subject is ambiguity averse, while 0 means other circumstances.

Compliance Maximization				
Detection Ability	Rounds 1-5 mean (std deviation)	Rounds 6-10 mean (std deviation)	Rounds 11-15 mean (std deviation)	Rounds 16-20 mean (std deviation)
Strong ($\bar{\theta}$)	0.686	0.471	0.343	0,285
	(0.468)	(0.503)	(0.478)	(0.455)
Weak ($\underline{\theta}$)	0.871	0.941	0.941	0.957
	(0.337)	(0.282)	((0.282)	(0.204)

Revenue Maximization				
Detection Ability	Rounds 1-5 mean (std deviation)	Rounds 6-10 mean (std deviation)	Rounds 11-15 mean (std deviation)	Rounds 16-20 mean (std deviation)
Strong ($\bar{\theta}$)	0.857	0.929	0.914	0.986
	(0.352)	(0.259)	(0.282)	(0.120)
Weak ($\underline{\theta}$)	0.7	0.6	0.343	0.329
	(0.462)	(0.493)	(0.478)	(0.473)

Table A.2: Relative frequency of enforcer's hiding behavior across treatments in Study 1.

Treatment	Rounds 1-5 mean (std deviation)	Rounds 6-10 mean (std deviation)	Rounds 11-15 mean (std deviation)	Rounds 16-20 mean (std deviation)
Compliance	0.486	0.412	0.443	0.333
	(0.502)	(0.495)	(0.500)	(0.474)
Revenue	0.450	0.607	0.716	0.674
	(0.500)	(0.491)	(0.454)	(0.471)

Table A.3: Relative frequency of agent's compliance behavior conditional on enforcer's hiding behavior in Study 1.

Variables	(1) Compliance Rate|"Hide"	(2) Compliance Rate|"Hide"	(3) Compliance Rate|"Hide"
Revenue Treatment	0.193*	0.197*	0.219*
	(0.096)	(0.088)	(0.100)
Constant	0.410***	0.336***	0.508***
	(0.084)	(0.083)	(0.182)
Period Effects?	N	Y	Y
Survey Controls?	N	N	Y
Observations	652	652	652
R-squared	0.036	0.042	0.077

*** p<0.01, ** p<0.05, * p<0.1

Table A.4: OLS regressions of the treatment effect on agent's behavior conditional on the enforcer's hiding behavior over time in Study 1 for enforcer-optimal subject pairs. Robust standard errors clustered at the session level in parentheses, using bootstrapping for 1000 times.

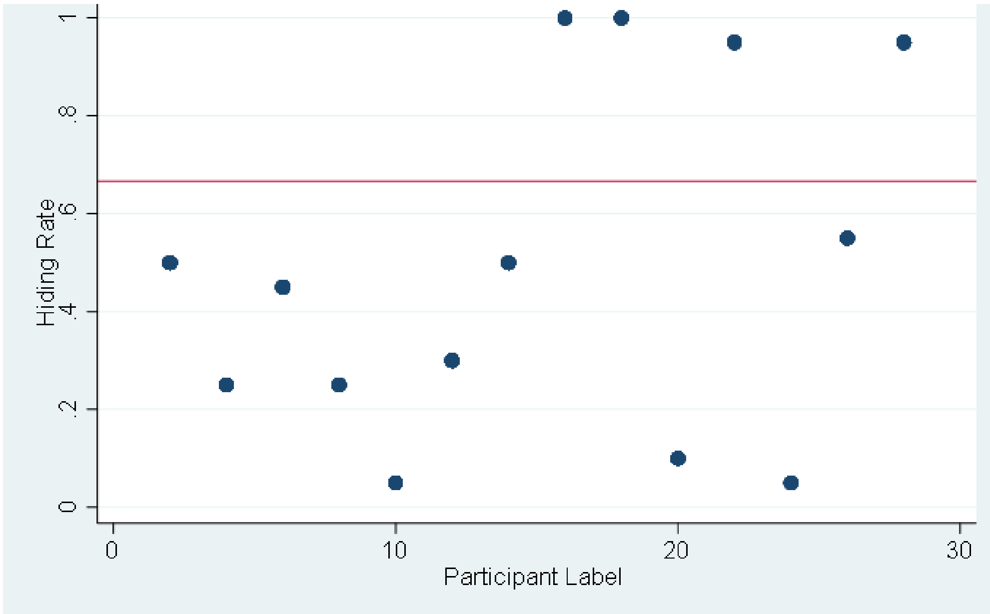

Figure A.2: Weak enforceer's hiding behavior in full data, under the revenue treatment. The proportion that satisfies the mixed-strategy equilibrium (the weak enforcer hides with probability $\frac{2}{3}$) is marked by the red solid line.

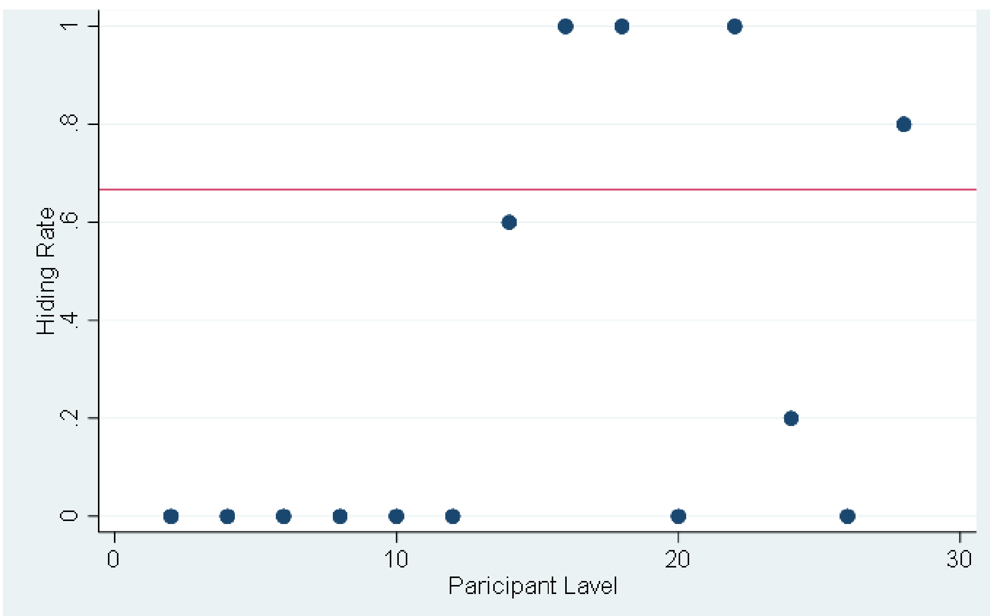

Figure A.3: Weak enforceer's hiding behavior in the last five rounds, under the revenue treatment. The proportion that satisfies the mixed-strategy equilibrium (the weak enforcer hides with probability $\frac{2}{3}$) is marked by the red solid line.

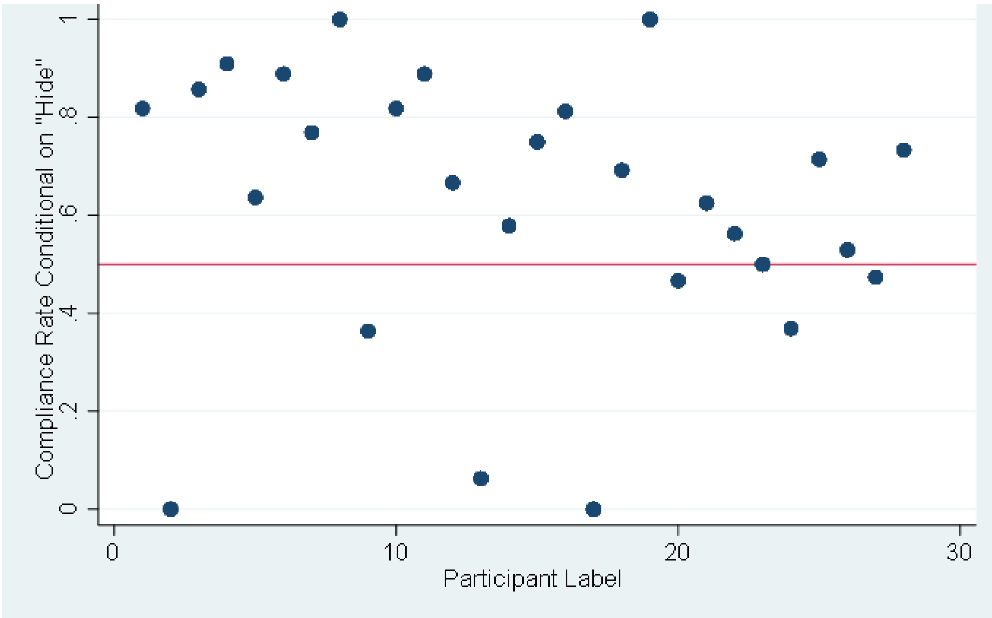

Figure A.4: Agent's compliance behavior conditional on "Hide", under the revenue treatment. The proportion that satisfies the mixed-strategy equilibrium (the agent complies with probability $\frac{1}{2}$) is marked by the red solid line.

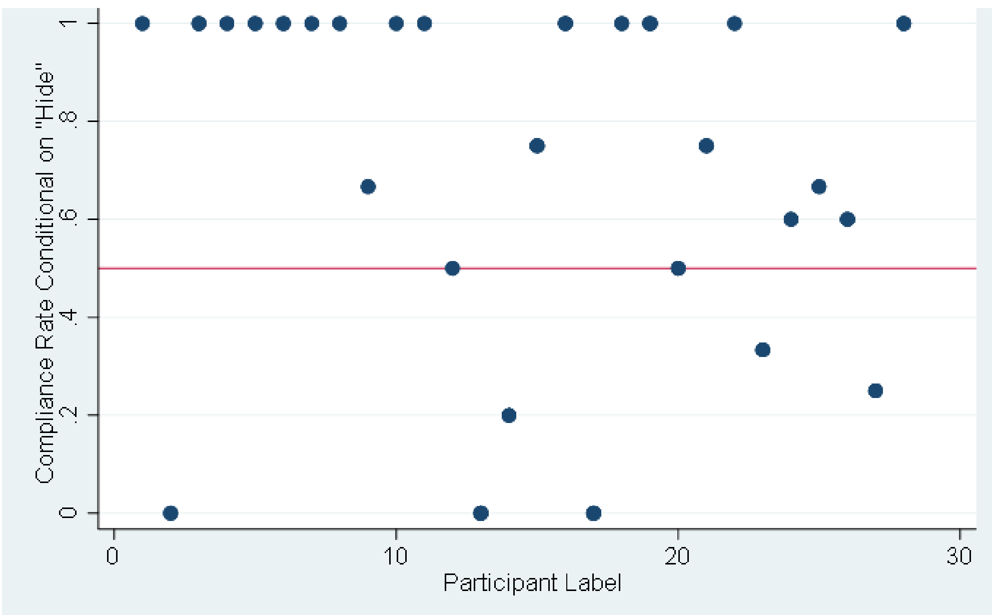

Figure A.5: Agent's compliance behavior conditional on "Hide" in the last five rounds, under the revenue treatment. The proportion that satisfies the mixed-strategy equilibrium (the agent complies with probability $\frac{1}{2}$) is marked by the red solid line.

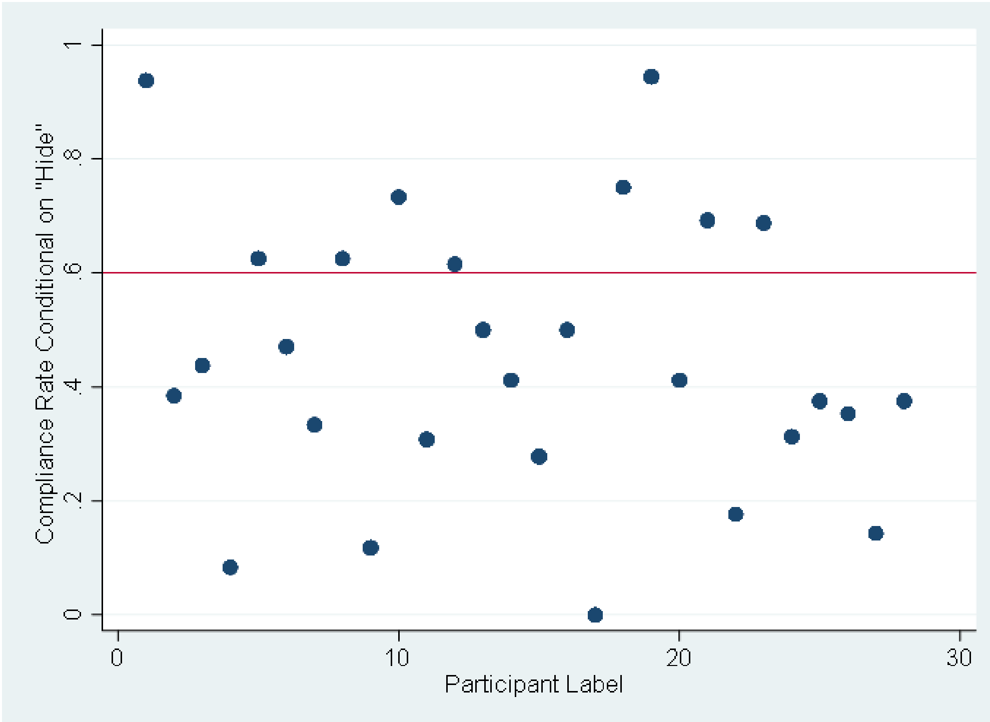

Figure A.6: Agent's compliance behavior conditional on "Hide", under the opaque treatment. The proportion that satisfies the mixed-strategy equilibrium (the agent complies with probability $\frac{3}{5}$ conditional on "Hide") is marked by the red solid line.

Transparent Treatment				
Enforcer's Payoff	Rounds 1-5 mean (std deviation)	Rounds 6-10 mean (std deviation)	Rounds 11-15 mean (std deviation)	Rounds 16-20 mean (std deviation)
Compliance-maximizer	58.857	58.643	59.071	59.643
	(9.562)	(9.283)	(9.375)	(8.941)
Revenue-maximizer	48.714	48.929	50.786	50.857
	(13.901)	(13.723)	(14.133)	(14.595)

Opaque Treatment				
Enforcer's Payoff	Rounds 1-5 mean (std deviation)	Rounds 6-10 mean (std deviation)	Rounds 11-15 mean (std deviation)	Rounds 16-20 mean (std deviation)
Compliance-maximizer	59.357	59	61.786	58.071
	(9.777)	(9.616)	(8.724)	(8,859)
Revenue-maximizer	49.714	55.143	50.143	52.714
	(13.933)	(15.902)	(13.646)	(15.101)

Table A.5: Enforcer's Payoff across treatments in Study 2.

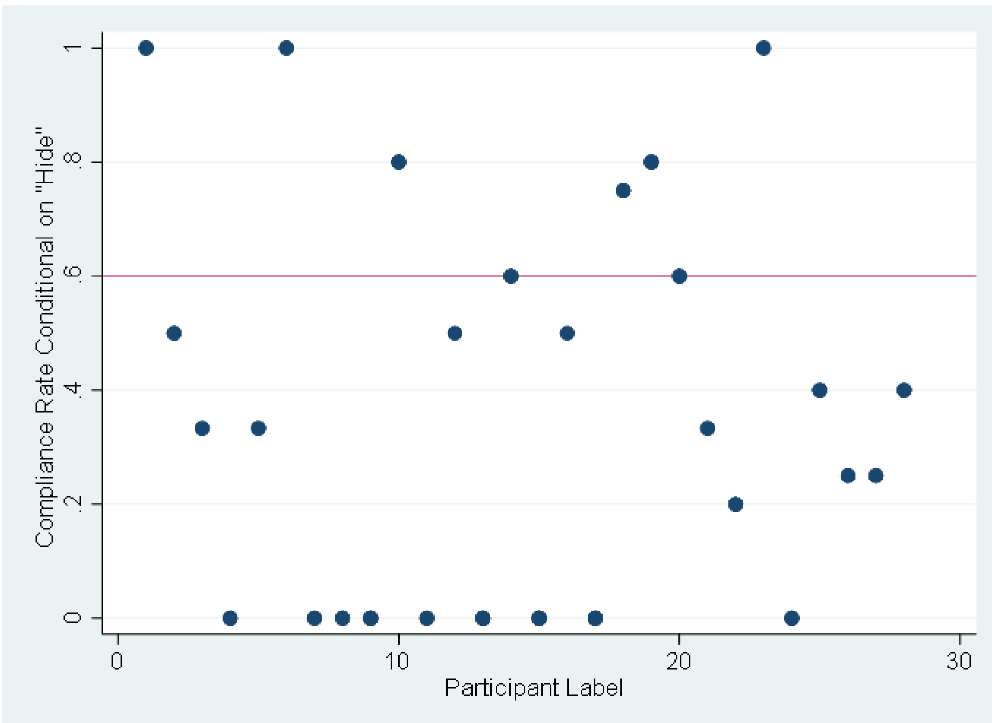

Figure A.7: Agent's compliance behavior conditional on "Hide" in the last five rounds, under the opaque treatment. The proportion that satisfies the mixed-strategy equilibrium (the agent complies with probability $\frac{3}{5}$ conditional on "Hide") is marked by the red solid line.

C Instructions

C.1 Compliance Treatment

Thank you for participating in our study. Please turn off your electronic devices and put them away. It is very important that you remain silent and do not talk to others.

This is an experiment in decision-making. The earnings you make today will be determined by your decisions and the decisions of others. If you pay close attention to the instructions, you have the opportunity to make money during this experiment. The earnings will be paid in addition to your payment for participating in this study. Earnings during the experiment will be denominated in points, with the following exchange rate: 1 point =10 cents. All of your earnings will be paid to you in private at the end of the experiment.

If you have questions or need assistance during the experiment, please raise your hand and one of the experimenters will quietly answer your question.

Description

The experiment consists of a game played with a group of two participants. One participant will be the "red player" and one participant will be the "blue player". The game will be played for 20 rounds. Participants that are red players will always be red players. Participants that are blue players will always be blue players. However, in each round, the matching of red player and blue player is random. It is very unlikely that you are paired up with the same participant in two consecutive rounds.

Each red player has a randomly-determined type, either "Type A" or "Type B". The type of a red player is **equally likely** to be "Type A" or "Type B". At the beginning of the experiment, the type of each red player will be randomly determined. Each red player will then keep the same type throughout the entirety of the experiment.

The red player will decide between two options, "Option R" and "Option H". If the red player chooses Option R, the blue player is informed of the red player's type. If the red player chooses Option H, the blue player is not informed of the red player's type. The blue players will decide between two options, "Option C" and "Option V".

The timing of events in each round is as follows:

1. The computer randomly matches participants in pairs.
2. The red player decides between Option R and Option H.
3. The blue player is informed of the red player's decision.
4. The blue player decides between Option C and Option V.

5. Each participant will be informed of his/her individual earnings for the round. Participants will not be informed of the earnings of other participants.

The earnings of a red player will be determined by the red player's type, the red player's decision, and the blue player's decision. The earnings of a blue player will be determined by the red player's type and the blue player's decision.

All information about possible payoffs is provided in the Table 1 below. In each cell of the table, the payoff for the red player is on the left, and the payoff for the blue player is on the right.

For each participant, in addition to their $10 participation payment, one round from round 1 to round 20 will be randomly selected and participants will be paid based on that round.

Payoffs (Red Player, Blue Player)	The blue player chooses Option C	The blue player chooses Option V
The red player is Type A, and the red player chooses Option R	65, 50	45, 30
The red player is Type B, and the red player chooses Option R	65, 50	45, 80
The red player is Type A, and the red player chooses Option H	70, 50	50, 30
The red player is Type B, and the red player chooses Option H	70, 50	50, 80

Table 1

C.2 Revenue Treatment

Thank you for participating in our study. Please turn off your electronic devices and put them away. It is very important that you remain silent and do not talk to others.

This is an experiment in decision-making. The earnings you make today will be determined by your decisions and the decisions of others. If you pay close attention to the instructions, you have the opportunity to make money during this experiment. The earnings will be paid in addition to your payment for participating in this study. Earnings during the experiment will be denominated in points, with the following exchange rate: 1 point =10 cents. All of your earnings will be paid to you in private at the end of the experiment.

If you have questions or need assistance during the experiment, please raise your hand and one of the experimenters will quietly answer your question.

Description

The experiment consists of a game played with a group of two participants. One participant will be the "red player" and one participant will be the "blue player". The game will be played for 20 rounds. Participants that are red players will always be red players. Participants that are blue players will always be blue players. However, in each round, the matching of red player and blue player is random. It is very unlikely that you are paired up with the same participant in two consecutive rounds.

Each red player has a randomly-determined type, either "Type A" or "Type B". The type of a red player is **equally likely** to be "Type A" or "Type B". At the beginning of the experiment, the type of each red player will be randomly determined. Each red player will then keep the same type throughout the entirety of the experiment.

The red player will decide between two options, "Option R" and "Option H". If the red player chooses Option R, the blue player is informed of the red player's type. If the red player chooses Option H, the blue player is not informed of the red player's type. The blue players will decide between two options, "Option C" and "Option V".

The timing of events in each round is as follows:

1. The computer randomly matches participants in pairs.
2. The red player decides between Option R and Option H.
3. The blue player is informed of the red player's decision.
4. The blue player decides between Option C and Option V.
5. Each participant will be informed of his/her individual earnings for the round. Participants will not be informed of the earnings of other participants.

The earnings of a red player will be determined by the red player's type, the red player's decision, and the blue player's decision. The earnings of a blue player will be determined by the red player's type and the blue player's decision.

All information about possible payoffs is provided in the Table 1 below. In each cell of the table, the payoff for the red player is on the left, and the payoff for the blue player is on the right.

For each participant, in addition to their $10 participation payment, one round from round 1 to round 20 will be randomly selected and participants will be paid based on that round.

Payoffs (Red Player, Blue Player)	The blue player's chooses Option C	The blue player's chooses Option V
The red player is Type A, and the red player chooses Option R	35, 50	70, 30
The red player is Type B, and the red player chooses Option R	35, 50	45, 80
The red player is Type A, and the red player chooses Option H	40, 50	75, 30
The red player is Type B, and the red player chooses Option H	40, 50	50, 80

Table 1

C.3 Transparent Treatment

Thank you for participating in our study. Please turn off your electronic devices and put them away. It is very important that you remain silent and do not talk to others.

This is an experiment in decision-making. The earnings you make today will be determined by your decisions and the decisions of others. If you pay close attention to the instructions, you have the opportunity to make money during this experiment. The earnings will be paid in addition to your payment for participating in this study. Earnings during the experiment will be denominated in points, with the following exchange rate: 1 point =10 cents. All of your earnings will be paid to you in private at the end of the experiment.

If you have questions or need assistance during the experiment, please raise your hand and one of the experimenters will quietly answer your question.

Description

The experiment consists of a game played with a group of two participants. One participant will be the "red player" and one participant will be the "blue player". The game will be played for 20 rounds. Participants that are red players will always be red players. Participants that are blue players will always be blue players. However, in each round, the matching of red player and blue player is random. It is very unlikely that you are paired up with the same participant in two consecutive rounds.

Each red player has a randomly-determined type, either "Type A" or "Type B". The type of a red player is **equally likely** to be "Type A" or "Type B". At the beginning of the experiment, the type of each red player will be randomly determined. Each red player will then keep the same type throughout the entirety of the experiment.

There can be two possible compensation rules for the red player, either "Rule I" or "Rule II". The compensation rule of each red player is equally likely to be "Rule I" or "Rule II". At the beginning of the experiment, the compensation rule of each red player will be randomly determined. Each red player will then keep the same compensation rule throughout the entirety of the experiment. The red player's compensation rule is **always known** to the blue player.

The red player will decide between two options, "Option R" and "Option H". If the red player chooses Option R, the blue player is informed of the red player's type. If the red player chooses Option H, the blue player is not informed of the red player's type. The blue players will decide between two options, "Option C" and "Option V".

The timing of events in each round is as follows:

1. The computer randomly matches participants in pairs.

2. The red player decides between Option R and Option H.

3. The blue player is informed of the red player's decision.

4. The blue player decides between Option C and Option V.

5. Each participant will be informed of his/her individual earnings for the round. Participants will not be informed of the earnings of other participants.

The earnings of a red player will be determined by the red player's type, the red player's decision, and the blue player's decision. The earnings of a blue player will be determined by the red player's type and the blue player's decision.

All information about possible payoffs is provided in tables below. Table 1 provides possible payoffs when the red player's compensation rule is Rule I. Table 2 provides possible payoffs when the red player's compensation rule is Rule II. In each cell of the table, the payoff for the red player is on the left, and the payoff for the blue player is on the right.

For each participant, in addition to their $10 participation payment, one round from round 1 to round 20 will be randomly selected and participants will be paid based on that round.

Payoffs (Red Player, Blue Player)	The blue player chooses Option C	The blue player chooses Option V
The red player is Type A, and the red player chooses Option R	65, 50	45, 30
The red player is Type B, and the red player chooses Option R	65, 50	45, 80
The red player is Type A, and the red player chooses Option H	70, 50	50, 30
The red player is Type B, and the red player chooses Option H	70, 50	50, 80

Payoffs (Red Player, Blue Player)	The blue player chooses Option C	The blue player chooses Option V
The red player is Type A, and the red player chooses Option R	35, 50	70, 30
The red player is Type B, and the red player chooses Option R	35, 50	45, 80
The red player is Type A, and the red player chooses Option H	40, 50	75, 30
The red player is Type B, and the red player chooses Option H	40, 50	50, 80

C.4 Opaque Treatment

Thank you for participating in our study. Please turn off your electronic devices and put them away. It is very important that you remain silent and do not talk to others.

This is an experiment in decision-making. The earnings you make today will be determined by your decisions and the decisions of others. If you pay close attention to the instructions, you have the opportunity to make money during this experiment. The earnings will be paid in addition to your payment for participating in this study. Earnings during the experiment will be denominated in points, with the following exchange rate: 1 point =10 cents. All of your earnings will be paid to you in private at the end of the experiment.

If you have questions or need assistance during the experiment, please raise your hand and one of the experimenters will quietly answer your question.

Description

The experiment consists of a game played with a group of two participants. One participant will be the "red player" and one participant will be the "blue player". The game will be played for 20 rounds. Participants that are red players will always be red players. Participants that are blue players will always be blue players. However, in each round, the matching of red player and blue player is random. It is very unlikely that you are paired up with the same participant in two consecutive rounds.

Each red player has a randomly-determined type, either "Type A" or "Type B". The type of a red player is **equally likely** to be "Type A" or "Type B". At the beginning of the experiment, the type of each red player will be randomly determined. Each red player will then keep the same type throughout the entirety of the experiment.

There can be two possible compensation rules for the red player, either "Rule I" or "Rule II". The compensation rule of each red player is equally likely to be "Rule I" or "Rule II". At the beginning of the experiment, the compensation rule of each red player will be randomly determined. Each red player will then keep the same compensation rule throughout the entirety of the experiment. The red player's compensation rule is **unknown** to the blue player.

The red player will decide between two options, "Option R" and "Option H". If the red player chooses Option R, the blue player is informed of the red player's type. If the red player chooses Option H, the blue player is not informed of the red player's type. The blue players will decide between two options, "Option C" and "Option V".

The timing of events in each round is as follows:

1. The computer randomly matches participants in pairs.

2. The red player decides between Option R and Option H.

3. The blue player is informed of the red player's decision.

4. The blue player decides between Option C and Option V.

5. Each participant will be informed of his/her individual earnings for the round. Participants will not be informed of the earnings of other participants.

The earnings of a red player will be determined by the red player's type, the red player's decision, and the blue player's decision. The earnings of a blue player will be determined by the red player's type and the blue player's decision.

All information about possible payoffs is provided in tables below. Table 1 provides possible payoffs when the red player's compensation rule is Rule I. Table 2 provides possible payoffs when the red player's compensation rule is Rule II. In each cell of the table, the payoff for the red player is on the left, and the payoff for the blue player is on the right.

For each participant, in addition to their $10 participation payment, one round from round 1 to round 20 will be randomly selected and participants will be paid based on that round.

Payoffs (Red Player, Blue Player)	The blue player chooses Option C	The blue player chooses Option V
The red player is Type A, and the red player chooses Option R	65, 50	45, 30
The red player is Type B, and the red player chooses Option R	65, 50	45, 80
The red player is Type A, and the red player chooses Option H	70, 50	50, 30
The red player is Type B, and the red player chooses Option H	70, 50	50, 80

Payoffs (Red Player, Blue Player)	The blue player chooses Option C	The blue player chooses Option V
The red player is Type A, and the red player chooses Option R	35, 50	70, 30
The red player is Type B, and the red player chooses Option R	35, 50	45, 80
The red player is Type A, and the red player chooses Option H	40, 50	75, 30
The red player is Type B, and the red player chooses Option H	40, 50	50, 80

D Interfaces

D.1 Sample Screenshots in Study 1

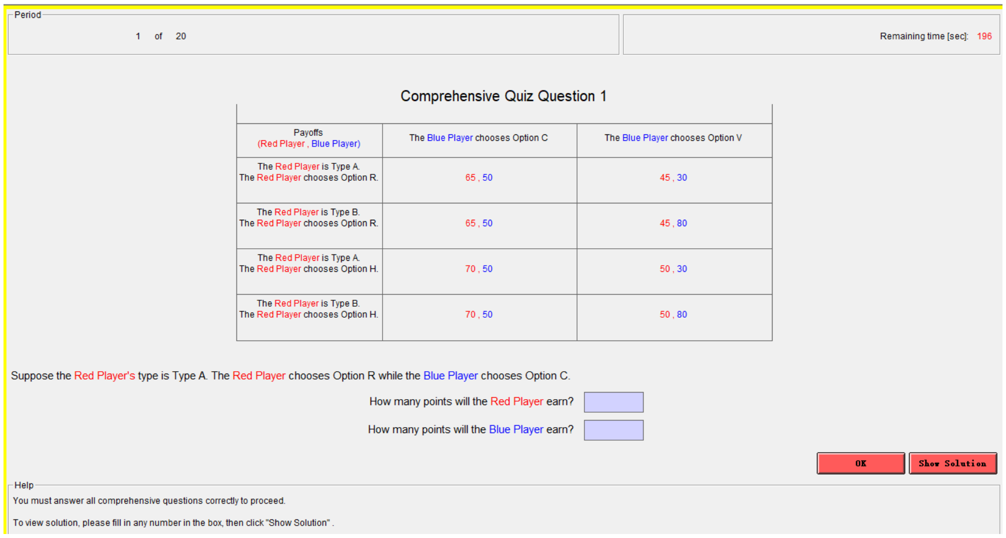

Figure A.8: Example screen for comprehensive quiz questions in Study 1.

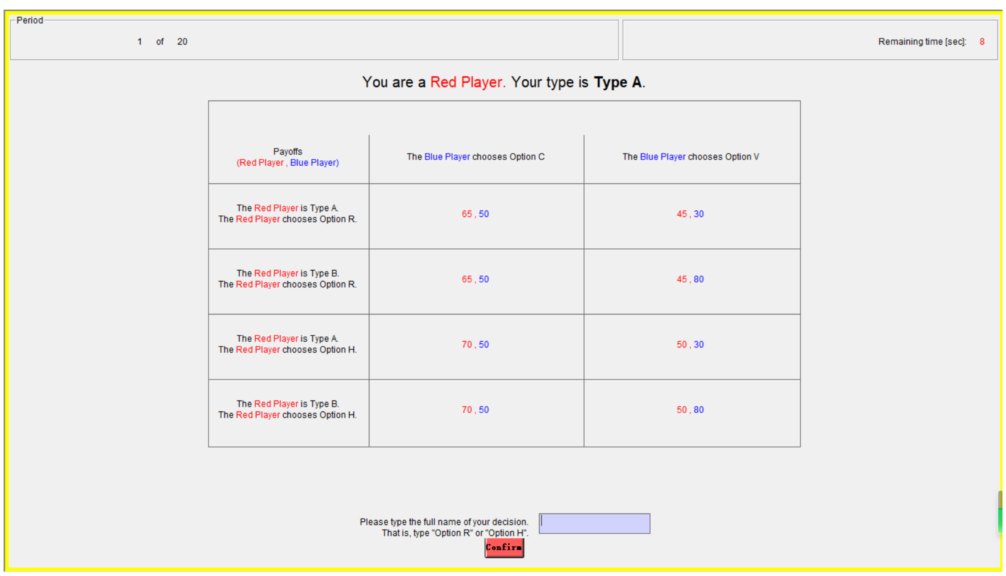

Figure A.9: Example screen for the red player's decision under compliance treatment in Study 1.

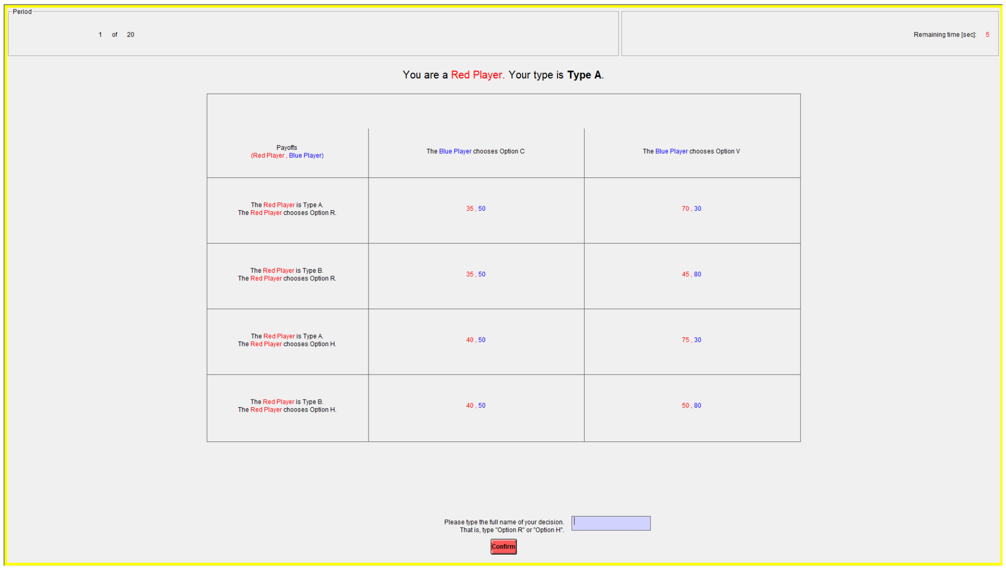

Figure A.10: Example screen for the red player's result under revenue treatment in Study 1.

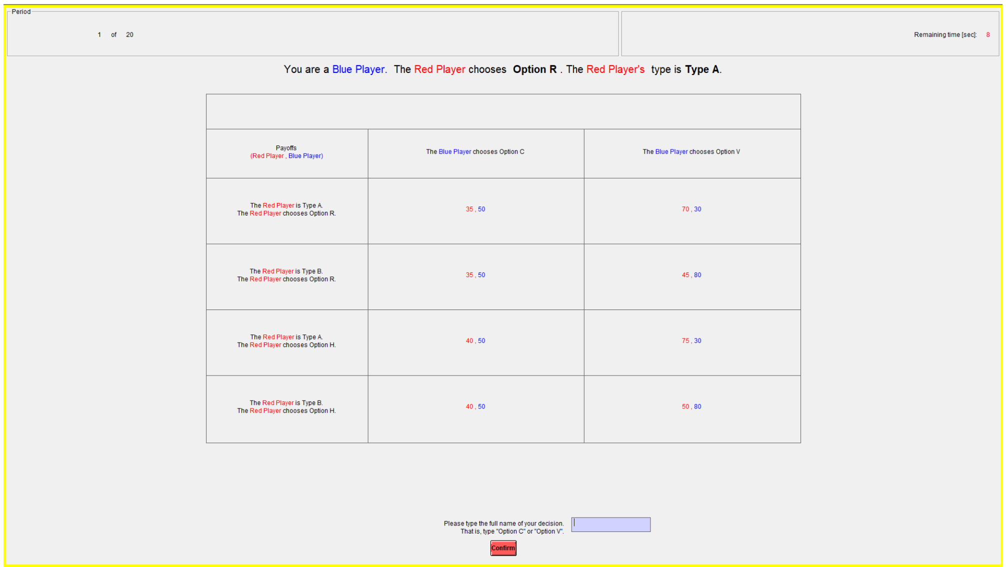

Figure A.11: Example screen for the blue player's result in Study 1.

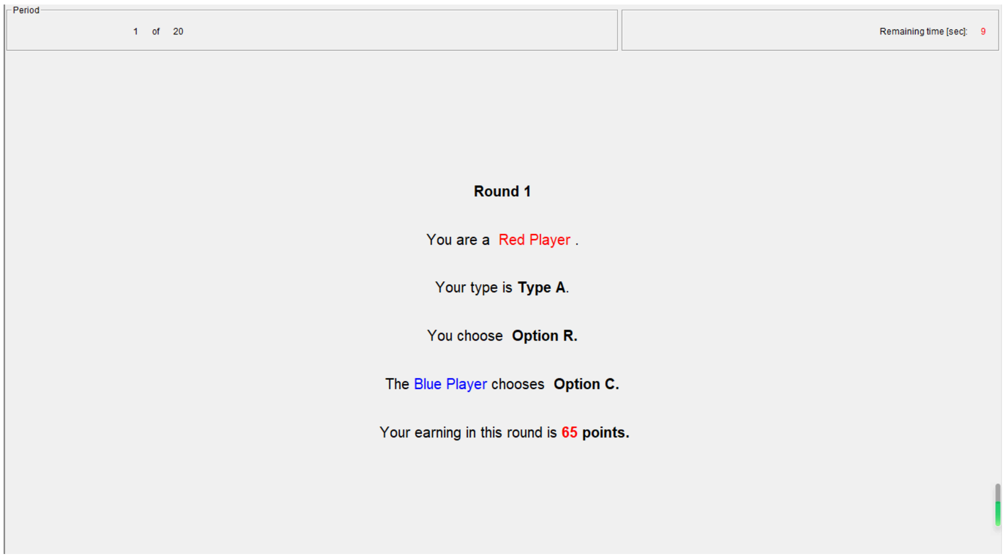

Figure A.12: Example screen for the red player's result in Study 1.

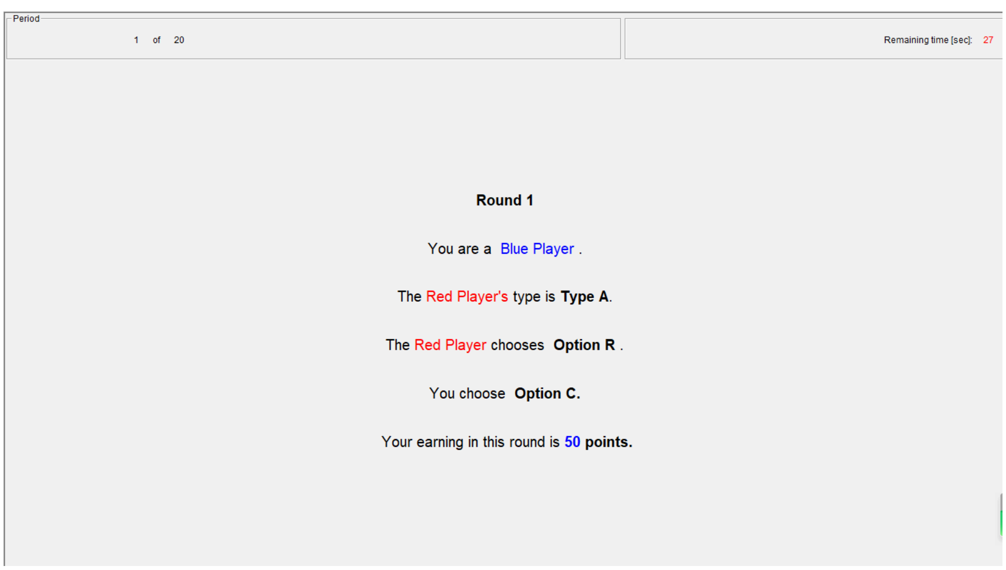

Figure A.13: Example screen for the blue player's result in Study 1.

D.2 Sample Screenshots in Study 2

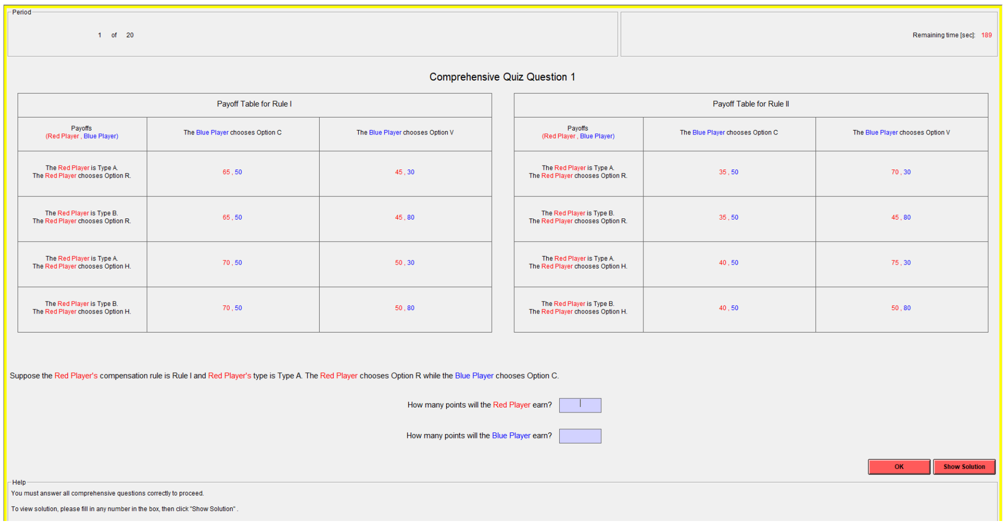

Figure A.14: Example screen for comprehensive quiz questions in Study 2.

Figure A.15: Example screen for the red player's decision under in Study 2. This screen is the same across the two treatments.

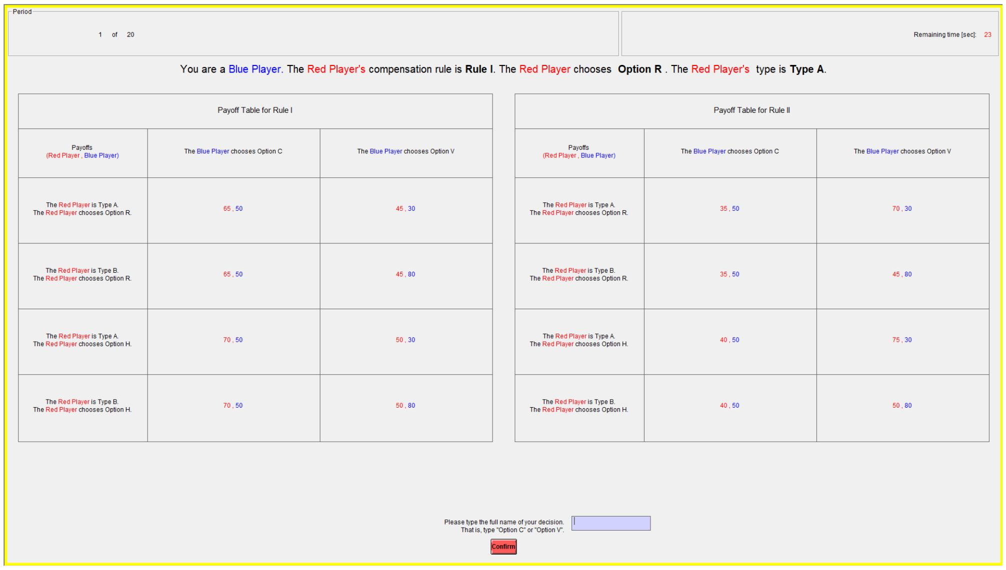

Figure A.16: Example screen for the blue player's decision under transparent treatment in Study 2.

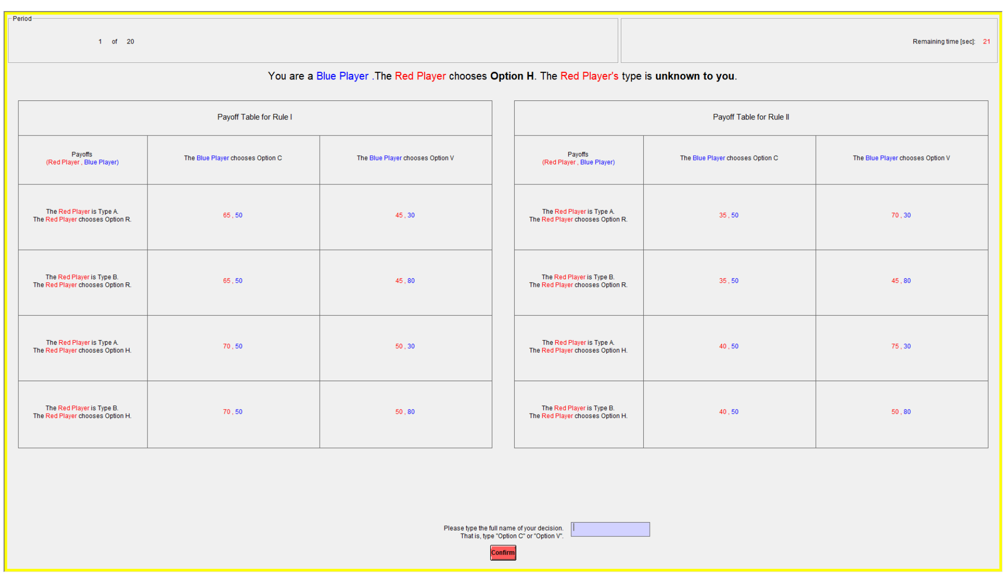

Figure A.17: Example screen for the blue player's decision under opaque treatment in Study 2.

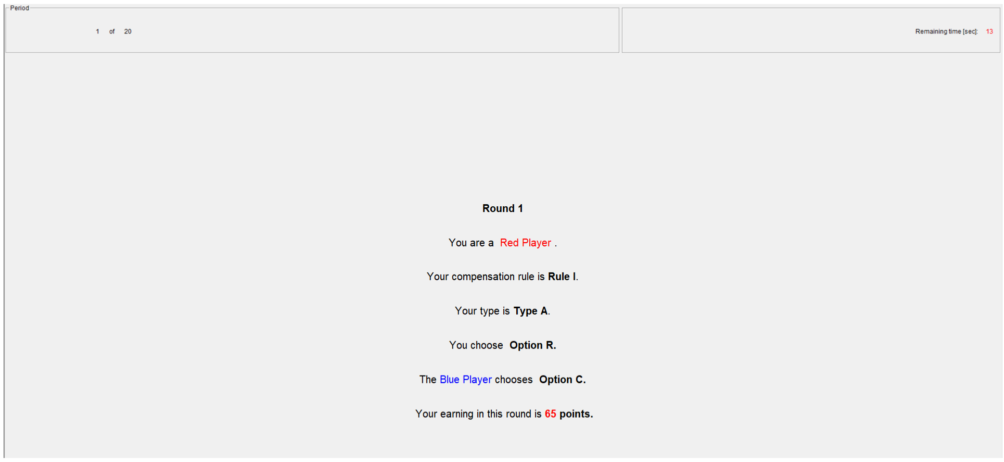

Figure A.18: Example screen for the red player's result in Study 2.

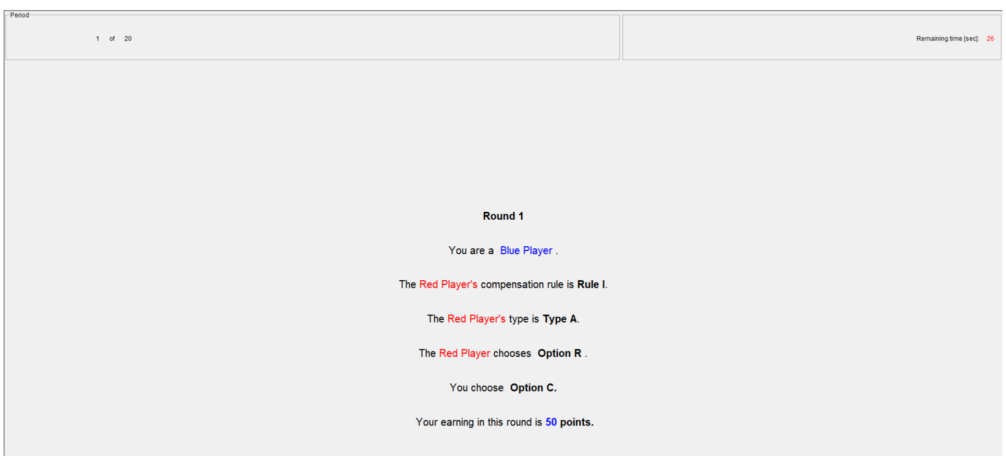

Figure A.19: Example screen for the blue player's result in Study 2.