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Ambiguity & Enforcement*

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Abstract

Law enforcement officials face numerous decisions regarding their enforcement choices. One important decision, that is often controversial, is the amount of knowledge that law enforcement distributes to the community regarding their policing strategies. Such decisions are complicated by the incentives that law enforcement agencies face, which could include enhancing public safety or enhancing agency revenues. Ultimately, though, the agency, with a publicly observable monitoring budget, must decide whether to announce or conceal their allocation of resources across multiple monitoring sites. In equilibrium, the decision is interesting only if criminals have non-neutral ambiguity preferences. Assuming the goal is to minimize criminal activity, a theoretical analysis suggests that agencies should reveal their resource allocation if criminals are uncertainty seeking, and shroud their allocation if criminals are uncertainty averse. We run a laboratory experiment to test our theoretical framework, and find that police behavior is approximately optimal given the uncertainty preferences of criminals.

Keywords: Law Enforcement, Strategic Uncertainty, Experimental Economics, Ambiguity Aversion

JEL codes: K42, C72, D81, D82

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1 Introduction

In the 18th century Jeremy Benthem proposed the *panopticon* as a mechanism for using monitoring uncertainty to influence the behavior of the monitored (Benthem, 1843). Benthem's panopticon was a circular penitentiary where a single centrally located observer could watch the inmates in each cell without themselves being observed by the inmates. Inmates would be unaware of when or if the observer was watching their cell and, Benthem argued, would therefore behave as if they were always being watched. Evaluating Benthem's hypothesis through the lens of modern utility theory, the success of the panopticon may depend on the uncertainty preferences of the monitored: an inmate who is sufficiently uncertainty averse might indeed behave as Benthem suggests, but an uncertainty seeking inmate might be relatively undeterred by an unknown probability of being monitored at any given instant.[1] If, instead, inmates were informed of the (truthful) instantaneous probability of being monitored the uncertainty seeking inmate may exhibit more compliant behavior because the revelation of the monitoring probability ameliorates some of the inmate's uncertainty.

Benthem's panopticon illustrates the central question of this paper: when should a monitor reveal, or shroud, their monitoring probabilities? The decision to reveal or shroud monitoring probabilities depends, not only on the uncertainty attitudes of the monitored, but is also affected by the incentives and motivations of the monitor. The monitor may seek to minimize non-compliant behavior, or they may seek to maximize the number of citations given for non-compliant behavior.[2]

The applications of strategic manipulation of monitoring uncertainty are varied, although we focus on law enforcement as our leading example.[3] Law enforcement officers weigh their primary

[1] Farago et al. (2008) find experimental evidence that criminals are more risk-taking than either students or entrepreneurs. Uncertainty aversion have been noted in Harel and Segal (1999), Lochner (2007) and DeAngelo and Charness (2012). However, Lochner (2007) notes that young males that are engaged in criminal behavior are responsive to law enforcement behavior in a manner that is consistent with expected utility theory. Finally, Mungan and Klick (2014) show theoretically that forfeiture of illegal gains generate behavior that is consistent with risk-aversion amongst would-be criminals.

[2] The latter incentive can be induced when the monitor has a citation quota or when the monitor shares in fine revenues, for example.

[3] The decision about whether to announce enforcement behavior is not unique to policing. Indeed, the IRS decides whether to provide information on auditing probabilities via the announcement of targeted sections of the tax code, while weighing the conflicting goals of incentivizing tax compliance and revenue recovery (Andreoni et al. (1998) provide an overview of the economics of tax compliance.) Several other examples of announced versus surprise monitoring environments exists. For example, a manager who supervises production at multiple plants, the Environmental Protection Agency air and water monitors, or the health department can choose whether to announce their planned inspection rate at each location, or not.

responsibility of "enforcing the laws that are enacted by elected officials . . . and . . . interpreted by the courts," with other important duties including crime prevention (USDOJ, n.d.). Common policing strategies may support one goal yet hinder others. For example, hidden speed traps or unmarked vehicles have the potential to detect individuals that are behaving recklessly without providing forewarning about the presence of enforcement but the use of signposted speed traps and marked patrol cars might allow the citizen to adjust their behavior to evade the law or even discourage individuals from breaking the law at all. To explore the relationship between the use of unmarked police vehicles and law enforcement revenues, we present Figure 1 which displays the relationship between the percentage of unmarked cars and the dependence of a location on revenues from law enforcement fines and fees.[4] Figure 1 shows a negative relationship between government dependence on law enforcement revenues and the use of unmarked police vehicles.

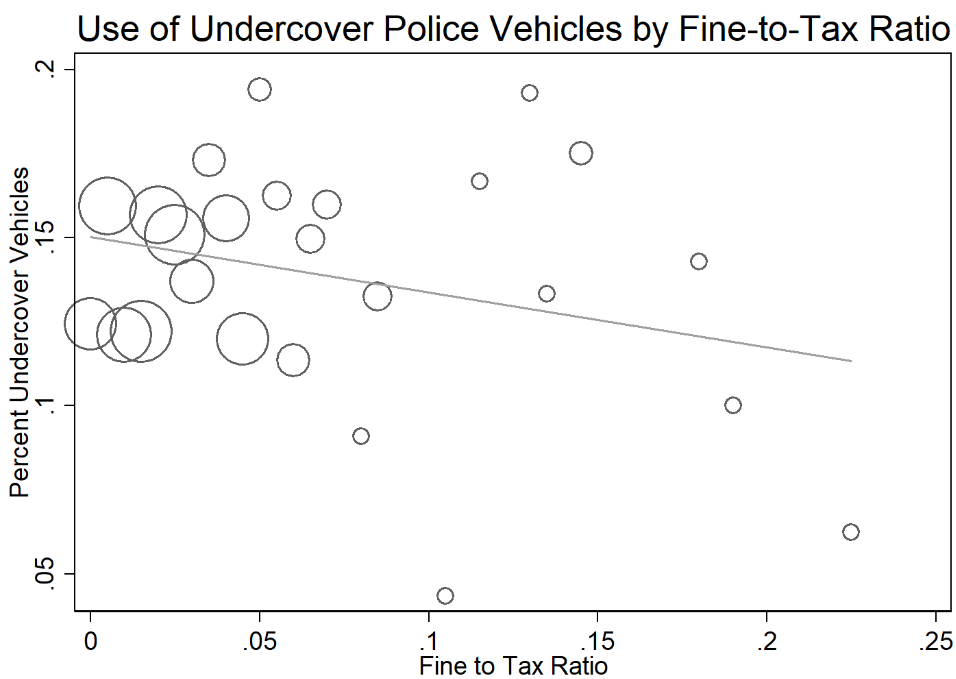


Figure 1: Share of Government Revenues from Law Enforcement Fines and Fees & the Use of Unmarked Police Vehicles. $N = 1606$, bubble size corresponds to the number of observations in each bin.

Figure 1 is consistent with the logic underlying Benthem's panopticon. When the fine-to-tax ratio is low, police officers are focused on crime prevention: the use of undercover vehicles increases

[4]The percentages of marked and unmarked police vehicles is sourced from the 2013 Law Enforcement Management and Administrative Statistics database, while revenues from taxes and law enforcement fines and fees were obtained from the 2013 US Census data on local and government finances about government revenues. In total, 1,606 cities are included in the data. The size of the bubbles in Figure 1 correspond to the number of observations.

uncertainty about the level of traffic monitoring which causes uncertainty averse citizens to behave more cautiously. In contrast, when the fine-to-tax ration is high, police officers have an incentive to write more citations: the use of marked vehicles reduces uncertainty about the level of traffic monitoring which may lead to more traffic violations and increased revenue. However, drawing causal inferences from this data is extremely challenging. In each jurisdiction, the decision of whether to reveal or shroud monitoring activities will depend on the cultural, historical, legal and institutional environment in which the decision makers are embedded.[5] Nevertheless, the data represented in Figure 1 is, to the best of our knowledge, the "best" observational data available on this topic. It is precisely because of the lack of data that allows for clean identification regarding the revelation of monitoring activities that we turn to a theoretical and experimental study of the question. We abstract away from the confounding factors mentioned above and use a unifying framework that can be broadly applied.[6] We build a theoretical model to identify the equilibrium effects of the revelation or shrouding of monitoring probabilities, and then test the equilibrium predictions in a laboratory experiment. Importantly our model does not assume expected utility, and our experimental results include evidence of non-neutral ambiguity preferences.

For concreteness, we present our model within the context of police monitoring and enforcement of speeding violations. We implement our model by positing that a driver has a choice of two roads, and that law enforcement may allocate their monitoring resources across both roads. The more resources placed on a given road, the greater the probability that a driver who speeds on that road will be caught and punished. The following describes the stages of the experiment:

- Stage 1 • Enforcement chooses monitoring probabilities m_A and m_B for the first and second road,
  • and chooses whether to reveal m_A and m_B or only reveal $m = m_A + m_B$
- Stage 2 • The driver decides to either speed on the first road (choice A), speed on the second
  • road (choice B) or not speed (choice C)
- Stage 3 • Enforcement and Driver payoffs are obtained

If a driver chooses A (B), then they earn a high payoff with probability $0.9 - m_A$ ($0.9 - m_B$) and earn 0 with probability $0.1 + m_A$ ($0.1 + m_B$). If the driver chooses C they receive a payment that induces an intermediate level of utility. The officer pays a constant marginal cost of monitoring

[5] For example, police monitoring varies across both geographic (signposted speed cameras in New South Wales, Australia and hidden speed cameras in Victoria, Australia) and temporal boundaries (hidden speed cameras were banned in Arizona in 2010).

[6] We focus on law enforcement monitoring as our leading example throughout the paper. However, in our experimental implementation we used a supervisor/worker framing to prevent subjects' existing preferences for breaking or abiding by laws from influencing our results. With only minor modifications, our model could easily be adapted to study the revelation of monitoring in other important and interesting environments, including auditing.

and can decide whether to reveal the monitoring probabilities (m_A and m_B) to the driver, or only reveal the total ($m_A + m_B$) monitoring probability.[7] We study two different payoff structures for the enforcement officer: one where the officer strictly prefers the driver to not speed and choose C (i.e. the officer wishes to minimize the number of speeding violations), and one where the officer's payoff is increasing in the monitoring probability on the road chosen by the driver (i.e. the officer earns revenue from catching a speeding driver).

This design allows us to address our central research questions. (1) How does monitoring uncertainty affect behavior? (2) Does an enforcer manipulate monitoring uncertainty to induce favorable behavior among the monitored? (3) Is there a distinction between enforcers with a revenue incentive and enforcers with a prevention incentive?

In addition, we vary whether drivers are paid in lotteries, or paid the expected value of the lottery induced by their strategy choice. When drivers are paid in lotteries they receive only a high prize or nothing and, therefore, their utility is independent of risk preferences. Any changes in behavior caused by the introduction of monitoring uncertainty must therefore be caused by ambiguity preferences, and not risk preferences.[8] When drivers are paid the expected value of the lottery induced by their choice then both risk preferences and ambiguity preferences determine the driver's response to monitoring uncertainty. The difference-in-difference comparison between the introduction of monitoring uncertainty across the lottery and expected value treatments reflect the effects of risk preferences.[9] We formally identify the effects of risk aversion and ambiguity aversion on driver behavior in Section 3.1.1.

Our key theoretical result is to identify when law enforcement should *shroud* monitoring activity and when law enforcement should *reveal* monitoring activity as a function of the underlying preferences of officers and drivers, which is summarized in Table 1. When the officer is motivated by revenue (prevention) incentives then, in equilibrium, they will reveal (shroud) their monitoring strategy when the driver is uncertainty averse and shroud (reveal) their monitoring when the driver

[7] We also study cases where the observability of monitoring is exogenously determined as a control.

[8] Further, we are able to rule out the possibility that the change in behavior is associated with any probabilistically sophisticated preference model. That is, we separate ambiguity preferences from both EU risk preferences and non-EU risk preferences (such as non-linear probability weighting).

[9] To clarify, we use the following terminology. A decision environment where probabilities are available is a risky environment, and a decision maker's attitude towards risk is their risk aversion. A decision environment where probabilities are not available is an uncertain environment, and a decision maker's attitude towards uncertainty in this environment is their uncertainty aversion. Ambiguity aversion is considered to be the difference in attitudes towards a risky environment and an (appropriately defined) uncertain environment. Relatedly, strategic uncertainty describes an environment where the source of uncertainty is the strategy choice of another person.

is uncertainty seeking. Intuitively, the officer discourages law breaking (by shrouding when facing an uncertainty averse driver) when motivated by prevention incentives but encourages law breaking (by shrouding when facing an uncertainty seeking driver) when motivated by revenue incentives. The more people who break the law, the more people that can be caught.[10]

	Revenue incentives	Prevention incentives
uncertainty aversion	**Reveal**	Shroud
uncertainty seeking	Shroud	**Reveal**

Table 1: Law enforcement choice to either reveal or shroud monitoring probabilities, in equilibrium, as a function of the officer's incentive structure (column) and the driver's uncertainty preferences (row). Bold entries indicate the modal behavior in our experimental implementation of the model.

Our experimental results are broadly consistent with our model's equilibrium predictions. Given the uncertainty preferences of drivers, the officers monitor at approximately optimal rates. We do find, however, a surprising pattern of driver uncertainty preferences. On aggregate, drivers exhibit uncertainty aversion when officers are motivated by enforcement incentives and exhibit uncertainty seeking when officers are motivated by prevention incentives. Given these preferences it is optimal for officers to always reveal their monitoring strategies, and officers do reveal their monitoring levels approximately 70% of the time.

This paper presents the first experimental evidence of human subjects manipulating the degree of uncertainty faced by their opponents in order to induce a desired behavior from their opponents. Subjects playing the role of officers recognize that shrouding their monitoring causes an undesirable response from drivers and therefore reveal their monitoring strategy to the drivers. This result follows naturally from previous research (discussed in more detail in Section 2) that demonstrated (1) subject behavior is affected by subject ambiguity preferences and exposure to strategic uncertainty, and (2) that subjects respond differently to ambiguity averse and ambiguity neutral opponents.

While our theoretical model is necessarily highly stylized the intuition behind the equilibrium is both intuitive and broadly applicable. When monitoring agents that are uncertainty averse (uncertainty seeking), increasing uncertainty in the level of monitoring at any given location or instant will cause the agents to undertake safer (riskier) actions. Knowing this, the level of monitoring uncertainty can be manipulated to induce favorable behavior from the monitored agents. While our theoretical results apply to a specific domain, our experimental results suggests that the underlying

[10]For clarity of argument we refer to the case where officers prefer to catch offenders, rather then prevent offenses from occurring, as the case where officers are seeking to maximize fine revenues. We recognize, but do not include in our model, that officers may have other non-pecuniary incentives that could generate a similar preference structure.

logic does indeed generalize to at least one related domain; specifically, the domain where utility maximizing agents are replaced with human decision makers.

The paper proceeds as follows. Section 2 identifies connections between our paper and previous work on monitoring and enforcement in the domains of law enforcement and auditing, as well as existing work on the role of strategic uncertainty. Section 3 describes our theoretical model and experimental design. Section 4 discusses the implementation of our experimental design. Section 5 presents the results of the experiment. Section 6 discusses our results in the context of previous research, as well as policy implications. Section 7 concludes the paper.

2 Literature Review

This research contributes to two distinct areas. As such, we outline the state of the literature in each of these research areas separately. We start by first discussing the literature on law enforcement, where we highlight various enforcement approaches that have been pursued in practice and those instances where these approaches have been examined within the lab. Second, we discuss the literature on ambiguity aversion and strategic uncertainty, focusing on the small experimental literature. We do not discuss the literature on the effects of risk aversion in games because the standard approach, to convert outcomes to utilities, is well understood.

2.1 Compliance and Enforcement Literature

Research using observational data highlights the tension for law enforcement agencies in deciding whether to announce their enforcement strategies. Namely, does announcing policing activities or shrouding them from citizens enhance the likelihood of deterring law violators? Announcing the locations of checkpoints or utilizing signage that indicates the heavy presence of law enforcement in certain regions has the potential to deter proscribed activities. Indeed, as noted by the National Highway Traffic Safety Administration, "although forewarning the public might seem counterproductive to apprehending violators, it actually increases the deterrent effect." Alternatively, many law enforcement agencies have opted to utilize unannounced law enforcement practices. Indeed, major law enforcement agencies such as the Los Angeles, New York and San Francisco police departments do not announce their checkpoints. Moreover, nearly 90% of law enforcement agencies in the U.S utilize unmarked law enforcement vehicles (Bureau of Justice Statistics, 2013).

The tension between whether announcing enforcement strategies or not is impacting public safety has received some attention. Lazear (2006) highlights the role of the cost of learning for citizens that are being monitored by law enforcement. In short, he notes that "for high cost learners, and when the monitoring technology is inefficient, it is better to announce what will be tested. For efficient learners, de-emphasizing the test itself is the right strategy. This is analogous to telling drivers where the police are posted when police are few. At least there will be no speeding on those roads. When police are abundant or when the fine is high relative to the benefit from speeding, it is better to keep police locations secret, which results in obeying the law everywhere."[11] Eeckhout et al. (2010) examine the use of arbitrary and publicized enforcement crackdowns (radar machines), noting that the marginal benefit of crackdowns is quite near to the marginal social cost. Banerjee et al. (2019) examine roadway checkpoints in India, and note that fixed location checkpoints are not advisable, as drivers learn about the locations of checkpoints and engage in strategic driving behavior to avoid checkpoints.[12] Lacey et al. (1999) examine a checkpoint program in Tennessee, whereby almost 900 checkpoints were well-advertised on the television, radio and in newspapers, finding that the checkpoints can be attributed to an over 20% reduction in drunk driving fatal crashes relative to locations where checkpoints are not utilized. However, and as noted above, there appears to be a trend amongst law enforcement agencies to withhold advanced, public knowledge about law enforcements' whereabouts, especially with regards to checkpoints.

The issue of alerting the public of the location of concentrated law enforcement or not has been further complicated by technological innovations. For example, radar detection technology has enabled drivers to identify when and where speed traps are being set up. And more recently, smartphones and apps such as *Waze*[13] have enabled drivers to real-time crowd-source information about the location of law enforcement activities - including DWI check points, speed traps, and speed cameras - to other individuals using the *Waze* app. In response to this functionality, the NYPD sent a cease-and-desist letter to *Google*, the parent company of $Waze$ that the functionality must be removed from the app immediately, as "individuals who post the locations of DWI checkpoints may be engaging in criminal conduct since such actions could be intentional attempts to prevent and/or impair the administration of the DWI laws and other relevant criminal and traffic laws."[14]

[11] Uncertainty over the application of the law could occur inadvertently, though. As DeAngelo and Owens (2017) note, changes in legal threshold result in disparate application of the laws, depending on officer experience, which could be generating further uncertainty about the application of laws.

[12] See also Olken and Barron (2009).

[13] `www.waze.com`

[14] In addition to $Waze$, other apps, such as *MrCheckpoint*, have also started appearing to notify the public of DWI checkpoints.

As adjustments to law enforcement decisions to announce or veil their checkpoint locations and timing, a common discussion relating to law enforcement decisions is whether they are being conducted for purposes of enhancing safety, revenues, or both. For example, Carpenter et al. (2015) discuss policing for profit with regards to civil asset forfeiture laws and the protection of personal property. Makowsky and Stratmann (2009, 2011) and DeAngelo et al. (2019) examine fiscal incentives of law enforcement agencies on public safety, finding that police are sensitive to principal-agent issues that can result in disproportionate law enforcement presence in regions that generate greater revenues to the principle. Recent lawsuits have been brought against the city of Buffalo and state of Missouri noting that, among other things, checkpoints aimed to generate revenues, not enhance safety. However, other analyses (e.g, DeAngelo and Hansen (2014)) have shown that roadway safety officers have considerable effects on public safety.

Regardless of the objective function of the law enforcement agency, agencies will aim to identify proscribed activities. The use of strategic uncertainty appears to be prevalent in recent years for large law enforcement agencies. However, it is also likely present in smaller law enforcement agencies, although less well-documented in media outlets. For example, as law enforcement agencies experience budget cuts, they could utilize strategic uncertainty so as to obscure knowledge of staffing cuts to the general public. Since perceptions of police presence matter for reducing crime (Vollaard and Hamed, 2012), it could be the case that strategic uncertainty can maintain higher levels of perception of police presence.

Although it is difficult to exclusively identify the effect of uncertainty using observational data, the role of uncertainty in legal issues has minimally been explored.[15] DeAngelo and Charness (2012) explore the role of uncertainty in enforcement, noting that subjects facing treatments with identical expected costs but containing uncertainty over the enforcement regime that will be faced are less likely to engage in proscribed behavior. Harel and Segal (1999) explore the role of uncertainty in the legal system by exploring conduct of defendants that face bench (certainty) versus jury (uncertainty) trials.[16] Finally, Grechenig et al. (2010) examine uncertainty pertaining to contributions to a public good, finding that subjects are willing to punish even when there is uncertainty about the degree of pro-social conduct of a person. Moreover, the punishment associated with the uncertainty does not support higher levels of cooperation and results in net welfare decreases. However, a void still remains in examining the choice to use uncertainty as an enforcement strategy.

[15] For example, Gee (2019) examines uncertainty through a large scale field experiment of job seekers by utilizing an uncertainty treatment where job seekers can and cannot observe the number of job seekers for a specific job position.

[16] See also Baker et al. (2004).

2.2 Strategic uncertainty literature

There is a small experimental literature on the role of ambiguity aversion and strategic uncertainty in games. Camerer and Karjalainen (1994) allows subjects to choose whether to play a matching pennies game against another person or against the flip of a coin. Subjects exhibit aversion to the uncertainty of another decision maker and prefer to play against the coin. Bohnet and Zeckhauser (2004) find that subjects are more trusting (i.e. willing to expose themselves to greater payoff uncertainty) in the trust game when their opponent's 'decision' is determined by an objective randomization device than when their opponent is actively choosing an action. In both cases, subjects exhibit uncertainty aversion in the face of strategic uncertainty.

In a series of papers, David Kelsey and Sara le Roux (Kelsey and le Roux, 2015, 2016, 2018) find that ambiguity preferences affect strategic behavior, that there is little difference in the amount of ambiguity perceived in the behavior of foreign versus domestic opponents, that ambiguity has a stronger effect on behavior in games than on behavior in ball-and-urn tasks, and that there is often little correlation between expressed ambiguity preferences across environments. Relatedly, Eichberger et al. (2008) establish that subjects find "grannies" to be a greater source of strategic ambiguity than game theorists.

Both Baillon et al. (Forthcoming) and Ivanov (2011) elicit beliefs over opponent's strategies and, using different theoretical underpinnings, use the reported beliefs to infer uncertainty preferences. In both cases they find evidence of ambiguity aversion in games. Calford (2019) elicits subject uncertainty preferences via ball-and-urn tasks and correlates uncertainty preferences with behavior in games, finding a correlation between uncertainty aversion and strategic behavior. In a separate treatment, Calford (2019) induces beliefs about an opponent's uncertainty preferences and finds that subjects best respond to their opponent's safe strategy more often when their opponent is uncertainty averse.

While it is clear that uncertainty preferences affect behavior in games, and Calford (2019) finds that subjects rationally change their behavior when faced with an uncertainty averse opponent, there is currently no experimental evidence regarding the decision to withhold strategic information from an opponent in order to manipulate the opponent's reaction to strategic uncertainty.

There is also a theoretical literature that studies equilibrium and solution concepts for games with ambiguity averse agents. These papers can be classified by their treatment of mixed strategies. Dow and Werlang (1994), Eichberger and Kelsey (2000), Eichberger and Kelsey (2014), Groes et al. (1998), Grant et al. (2016), Lo (2009) and Marinacci (2000) all restrict agents to playing only pure strategies while using a belief interpretation of mixing. On the other hand Azrieli and Teper (2011), Bade (2011), Lo (1996), Klibanoff (1996), and Riedel and Sass (2014) explicitly allow agents to play either mixed or ambiguous strategies. The chief difference between these two strands of literature is that in the latter strand agents may hedge against ambiguity given the availability of mixed strategies. Our experimental implementation, which allows only for pure strategies, is closer in spirit to the former strand.

3 Theory

We study a sequential game, with the officer moving first. First, the officer sets the monitoring levels across two roads, A and B, and then the driver chooses which road to speed on. We interpret a choice by the driver to travel on road C as being equivalent to a choice not to speed, and therefore, face no risk of being caught by the officer.

1. The officer sets $0 \leq m_A, m_B \leq 0.9$;
2. The driver chooses to implement either A, B or C.

We vary the observability of the officer's action, the officer's payoff incentives and the driver's payoff structure. In total, there are 12 variants of the game ($3 \times 2 \times 2$). Given the many similarities across variants, we analyse the 12 games using a common structure. It is important to note that the variant of the game being played at any given time is publicly observable. The differing payment schemes do not, therefore, induce a Bayesian game. Rather, the different payment schemes are different games that we analyze collectively for brevity.

The observability of the officer's action varies across treatments. There are three possible information structures:

1. The driver observes m_A and m_B, denoted as information scheme *Obs*;
2. The driver observes $m = m_A + m_B$ but not m_A or m_B, denoted as information scheme *Unobs*;
3. The officer chooses whether information scheme *Obs* or *Unobs* is used.

The driver faces one of two payment schemes. In the Probabilistic (*Prob*) treatment the driver is always paid either 100 or 0 points, with the probability of earning 100 points being determined by the officer and driver behavior. In the Expected Value (EV) treatment, the driver is paid the expected value of the lottery generated in the *Prob* treatment. The driver payoffs are displayed in Table 2.

	A	B	C
Probabilistic treatment	$\{100, 0.9 - m_A; 0, 0.1 + m_A\}$	$\{100, 0.9 - m_B; 0, 0.1 + m_B\}$	$\{100, 0.5; 0, 0.5\}$
Expected Value treatment	$100 \times (0.9 - m_A)$	$100 \times (0.9 - m_B)$	50

Table 2: Driver payoffs, in points. $\{x_1, p_1; x_2, p_2\}$ denotes the lottery which pays x_1 points with probability p_1 and x_2 points with probability p_2.

The officer also faces one of two payment schemes. Under each payment scheme there is a monitoring cost of $20(m_A + m_B)$. In the Revenue Maximization treatment (*RevMax*) the officer has an endowment of 20 points and earns an additional $100m_A$ in revenue if the driver chooses road A (and $100m_B$ in revenue if the driver chooses road B). In the Crime Minimization treatment (*CrimMin*) the officer has an endowment of 80 points and is penalized 40 points if the driver chooses either A or B. Officer payoffs are displayed in Table 3.

Revenue Maximization treatment	$20 + 100m_A\mathbb{1}(A) + 100m_B\mathbb{1}(B) - 20(m_A + m_B)$
Crime Minimization treatment	$80 - 40(\mathbb{1}(A) + \mathbb{1}(B)) - 20(m_A + m_B)$

Table 3: Officer payoffs, in points. $\mathbb{1}(A)$ is an indicator variable that equals 1 if the driver chooses road A, and 0 otherwise.

We proceed as follows to solve the game. First, we define the utility that the driver assigns, conditional on the observed level of monitoring, to each of their strategies. The driver's payoff is therefore fully specified at every information set and we then proceed to solve the game via backwards induction.

3.1 Driver preferences and best response

We impose as little structure on the preferences of the driver as possible, assuming only monotonicity, symmetry, non-triviality and continuity of the driver's utility function. Specifically, we do not assume expected utility and do not make assumptions about the nature of the driver's preferences over uncertainty. We write $U_t^I(X, m_A, m_B)$ to denote the driver's utility of choosing strategy $X \in \{A, B, C\}$ under information scheme $I \in \{\text{Obs}, \text{Unobs}\}$ in treatment $t \in \{\text{Prob}, \text{EV}\}$. We normalize $U_t^I(C, m_A, m_B) = 50$ for all m_A, m_B, I, t, and note that this normalization implies that utilities in the *Prob* and *EV* treatments are not directly comparable.

Definition 1 (Monotonicity)**.** $U_t^{\text{Obs}}(X, m_A, m_B)$ satisfies monotonicity if

- $m_A < m'_A \Rightarrow U_t^{\text{Obs}}(A, m_A, m_B) > U_t^{\text{Obs}}(A, m'_A, m_B)$ for all t and m_B; and
- $m_B < m'_B \Rightarrow U_t^{\text{Obs}}(B, m_A, m_B) > U_t^{\text{Obs}}(B, m_A, m'_B)$ for all t and m_A.

$U_t^{\text{Unobs}}(X, m_A, m_B)$ satisfies monotonicity if

- $m_A+m_B < m'_A+m'_B \Rightarrow U_t^{\text{Unobs}}(A, m_A, m_B) > U_t^{\text{Unobs}}(A, m'_A, m'_B)$ and $U_t^{\text{Unobs}}(B, m_A, m_B) > U_t^{\text{Unobs}}(B, m'_A, m'_B)$ for all t.

Definition 2 (Symmetry)**.** $U_t^{\text{Obs}}(X, m_A, m_B)$ satisfies symmetry if $U_t^{\text{Obs}}(A, m, m_B) = U_t^{\text{Obs}}(B, m_A, m)$ for all $m \in [0, 0.9]$, and $U_t^{\text{Obs}}(A, 0.4, m_B) = U_t^{\text{Obs}}(B, m_A, 0.4) = 50$ for all m_A, m_B.

$U_t^{\text{Unobs}}(X, m_A, m_B)$ satisfies symmetry if $U_t^{\text{Unobs}}(A, m_A, m_B) = U_t^{\text{Unobs}}(B, m'_A, m'_B)$ for all m_A, m_B, m'_A, m'_B such that $m_A + m_B = m'_A + m'_B$.

Definition 3 (Non-triviality)**.** $U_t^I(X, m_A, m_B)$ satisfies non-triviality if $U_t^I(A, 0, 0) > U_t^I(C, 0, 0)$ and $U_t^I(A, 0.9, 0.9) < U_t^I(C, 0.9, 0.9)$ for all I and t.

Notice that Non-triviality follows immediately from Monotonicity and Symmetry when $I = \text{Obs}$ but imposes weak additional restrictions when $I = \text{Unobs}$. Practically, Non-triviality ensures that when monitoring is maximal the driver always prefer C and when monitoring is minimal the driver will never prefer C. Further, continuity implies that there exists a value of $m_t^* \in (0, 0.9)$ such that $U_t^{\text{Unobs}}(A, m_A, m_B) = U_t^{\text{Unobs}}(B, m_A, m_B) = U_t^{\text{Unobs}}(C, m_A, m_B)$ whenever $m^* = m_A + m_B$. That is, there exists a level of monitoring that induces indifference in the driver.

We can now fully characterize the best response of the driver, under the assumption that the driver's preferences satisfy Monotonicity, Symmetry and Non-triviality. We denote the best response correspondence of the driver by $b_t^I(m_A, m_B)$.

Lemma 1. Assume that the driver's utility function satisfies Monotonicity, Symmetry, Non-triviality and is continuous in its second and third arguments. Then

$$b_t^{\text{Obs}}(m_A, m_B) = \begin{cases} C & \text{if } \min\{m_A, m_B\} > 0.4 \\ A & \text{if } m_A < 0.4, m_A < m_B \\ B & \text{if } m_B < 0.4, m_B < m_A \\ \{A, B\} & \text{if } m_A = m_B < 0.4 \\ \{A, C\} & \text{if } m_A = 0.4 < m_B \\ \{B, C\} & \text{if } m_B = 0.4 < m_A \\ \{A, B, C\} & \text{if } m_A = m_B = 0.4 \end{cases} \tag{1}$$

and

$$b_t^{\text{Unobs}}(m_A, m_B) = \begin{cases} C & \text{if } m_A + m_B > m_t^* \\ \{A, B\} & \text{if } m_A + m_B < m_t^* \\ \{A, B, C\} & \text{if } m_A + m_B = m_t^*. \end{cases} \tag{2}$$

Proof. For the case where $I = \text{Obs}$, the final row follows directly from symmetry. The three preceding rows each follow from the final row after applying monotonicity. The third row follows from rows four and six and monotonicity. The second row follows from rows four and five and monotonicity. The first row follows from rows five and six and monotonicity.

For the case where $I = \text{Unobs}$, the existence of m^* is guaranteed by non-triviality and continuity of the utility function. The first row then follows from the third row and monotonicity, and the second row follows from the third row, monotonicity and symmetry. $\square$

Note that m_t^* is a sufficient statistic for the uncertainty preferences of the driver, in the sense that the driver is not maximizing expected value if $m^* \neq 0.8$.

Definition 4 (Uncertainty preferences)**.** A driver has

- uncertainty neutral preferences if $m_t^* = 0.8$,
- uncertainty averse preferences if $m_t^* < 0.8$, and
- uncertainty seeking preferences if $m_t^* > 0.8$.

3.1.1 Relationship to common utility functions

Standard preference models have natural implications for uncertainty preferences in our environment. For example, under Expected Utility, risk preferences map directly onto the value of m^* in the *EV* treatment but have no influence on m^* in the *Prob* treatment. In the *Prob* treatment strategic uncertainty (uncertainty about the officer's choice of m_A and m_B) generates uncertainty about the *probability* with which the driver receives one of two fixed payments; because expected utility is linear in probability, risk preferences have no bearing on behavior. In the *EV* treatment, strategic uncertainty (uncertainty about the officer's choice of m_A and m_B) generates uncertainty about the *payment* that the driver receives, and expected utility risk attitudes do affect behavior.

Lemma 2. If a driver has Expected Utility preferences that satisfy Definition 2 then $m^*_{\text{Prob}} = 0.8$. If, in addition, the driver is

- risk neutral then $m^*_{\text{EV}} = 0.8$;
- risk averse then $m^*_{\text{EV}} < 0.8$;
- risk seeking then $m^*_{\text{EV}} > 0.8$.

Proof. The driver knows that $m_A + m_B = m$ and assume that the driver believes the distribution of m_A has probability density function $\mu(x)$. Further, suppose that the driver has expected utility preferences with Bernoulli utility function $u(\cdot)$. Definition 2 implies that $\mu(x)$ is symmetric (i.e. $\mu(x) = \mu(m-x)$ for $x \leq \frac{m}{2}$). Then, in the *Prob* treatment the expected utility of the driver playing A is given by:

$$\begin{aligned} EU(A) &= \int_0^m \big[u(100)(0.9-x) + u(0)(0.1+x)\big]\mu(x)dx \\ &= u(100)\Big[\int_0^m 0.9\mu(x)dx - \int_0^m x\mu(x)dx\Big] + u(0)\Big[\int_0^m 0.1\mu(x)dx + \int_0^m x\mu(x)\Big] \\ &= u(100)[0.9 - \frac{m}{2}] + u(0)[0.1 + \frac{m}{2}] \end{aligned}$$

where the third line has used the symmetry assumption. The expected utility of B is calculated similarly, and $EU(C) = \frac{u(100)+u(0)}{2}$. Clearly, $EU(A) = EU(B) = EU(C)$ when $m = 0.8$.

In the *EV* treatment, the expected utility of the driver playing A is given by:

$$EU(A) = \int_0^m u(100(0.9-x))\mu(x)dx$$

and note also that the expected value of playing A is given by $EV(A) = 100(0.9 - \frac{m}{2})$. If the driver is risk averse then $EU(A) \leq u(EV(A))$. At $m = 0.8$, $EV(A) = EV(C)$ and $u(EV(C)) = u(C)$ because C generates a fixed payment. Therefore, if the driver is risk averse then $EU(A) \leq u(C)$, so that $m^* \leq 0.8$. The opposite conclusion holds if the driver is risk seeking. □

To illustrate the distinct role of risk and ambiguity preferences across treatments we use the smooth ambiguity model as an example (Klibanoff et al., 2005). In the smooth ambiguity model preferences are represented by a double expectational form, where the inner expectation is taken with respect to objective uncertainty and the outer expectation with respect to subjective uncertainty. When m_A and m_B are observable to the driver, $I =$ Obs, there is no subjective uncertainty and the smooth ambiguity model collapses to expected utility. We therefore focus on the case where m_A and m_B are unobservable, $I =$ Unobs, where we can write the driver's utility from choosing A as

$$U(A) = \int \phi\Big(u(100)[0.9 - m_A] + u(0)[0.1 + m_A]\Big) d\mu(m_A)$$

in the *Prob* treatment where u is a Bernoulli utility function, $\mu(m_A)$ is the agent's subjective belief regarding the distribution of m_A, and ϕ is a mapping from $\mathbb{R}$ to $\mathbb{R}$ that encapsulates ambiguity preferences. The utility of choosing C can be expressed as

$$U(C) = u(100)[0.5] + u(0)[0.5]$$

because C involves no subjective uncertainty. Notice that normalizing $u(100) = 100$ and $u(0) = 0$ is consistent with our previous normalization that $U(C) = 50$. Applying this normalization to the utility of choosing A, $U(A)$, we have

$$U(A) = \int \phi\big(100[0.9 - m_A]\big) d\mu(m_A). \tag{3}$$

Equation 3 is independent of the curvature of the utility function, u. Intuitively utility in the *Prob* treatment is independent of risk preferences because there are only two possible outcomes. Uncertainty preferences in the *Prob* treatment are, therefore, entirely determined by the curvature of ϕ, the ambiguity preferences of the agent.

This does not hold in the *EV* treatment where the utility of choosing A is given by

$$U(A) = \int \phi\big(u(100[0.9 - m_A])\big) d\mu(m_A).$$

in this case, the utility of A, and aggregate uncertainty preferences are determined by both the curvature of u and ϕ.

The intuition outlined above regarding the relationship between ambiguity preferences and m^* is formalized in Lemma 3, and the relationship between risk preference, ambiguity preference, and aggregate uncertainty preferences are presented in Table 4 and Table 5. The uncertainty attitude of the driver can be summarized by the value of m^*, the level of total monitoring at which a driver is indifferent between choosing C and not choosing C.

Lemma 3. Assume that the driver has risk neutral "smooth" ambiguity preferences (Klibanoff et al., 2005) that satisfy Definition 2. If, in addition, the driver is

- ambiguity neutral then $m_t^* = 0.8$;
- ambiguity averse then $m_t^* < 0.8$;
- ambiguity seeking then $m_t^* > 0.8$.

for $t \in \{\text{EV}, \text{Prob}\}$.

Proof. The driver knows that $m_A + m_B = m$ and assume that the driver believes the distribution of m_A has probability density function $\mu(x)$. Further, suppose that the driver has smooth ambiguity preferences with Bernoulli utility function $u(c) = c$. Definition 2 implies that $\mu(x)$ is symmetric (i.e. $\mu(x) = \mu(m - x)$ for $x \leq \frac{m}{2}$). The utility of choosing A is therefore given by:

$$\begin{aligned} U(A) &= \int \phi\big(u(100)[0.9 - m_A] + u(0)[0.1 + m_A]\big) d\mu(m_A) \\ &= \int \phi\big(100[0.9 - m_A]\big) d\mu(m_A) \end{aligned}$$

Note that the expected value of playing A is given by $EV(A) = 100(0.9 - \frac{m}{2})$. If ϕ is linear (i.e. the driver is ambiguity neutral) then $U(A) = EV(A)$. If ϕ is concave (i.e. the driver is ambiguity averse) then $U(A) \leq EV(A)$ and if ϕ is convex (i.e. the driver is ambiguity seeking) then $U(A) \geq EV(A)$. At $m = 0.8$, $EV(A) = EV(C)$ and $U(EV(C)) = U(C)$ because C generates a fixed payment. Therefore, if the driver is ambiguity averse and $U(A) \leq EV(A)$ then $U(A) \leq U(C)$, so that $m^* \leq 0.8$. The opposite conclusion holds if the driver is ambiguity seeking. $\square$

		Ambiguity averse	(Expected Utility) Ambiguity neutral	Ambiguity seeking
		$\phi'' < 0$	$\phi'' = 0$	$\phi'' > 0$
Risk averse	$u'' < 0$	$m^* < 0.8$	$m^* = 0.8$	$m^* > 0.8$
Risk neutral	$u'' = 0$	$m^* < 0.8$	$m^* = 0.8$	$m^* > 0.8$
Risk seeking	$u'' > 0$	$m^* < 0.8$	$m^* = 0.8$	$m^* > 0.8$

Table 4: Characterization of the driver's indifference point, m^*, as a function of the driver's risk and ambiguity preferences in the *Prob* treatment.

		Ambiguity averse	(Expected Utility) Ambiguity neutral	Ambiguity seeking
		$\phi'' < 0$	$\phi'' = 0$	$\phi'' > 0$
Risk averse	$u'' < 0$	$m^* < 0.8$	$m^* < 0.8$	indeterminate
Risk neutral	$u'' = 0$	$m^* < 0.8$	$m^* = 0.8$	$m^* > 0.8$
Risk seeking	$u'' > 0$	indeterminate	$m^* > 0.8$	$m^* > 0.8$

Table 5: Characterization of the driver's indifference point, m^*, as a function of the driver's risk and ambiguity preferences in the *EV* treatment.

An implication of this analysis is that driver's ambiguity preferences can be identified by behavior in the *Prob* treatment and, under an auxiliary assumption that μ is constant across treatments, risk preferences can be identified by the difference in behavior between the *Prob* and *EV* treatments.

3.2 Officer behavior and equilibrium characterization

Given the simple cutoff rule best response behavior of drivers, the optimal strategy for the officer is the intuitive one: in the *CrimMin* treatment, monitor just enough to prevent speeding; in the *RevMax* treatment, monitor up to the maximal level such that the driver still speeds. Therefore, in equilibrium, no drivers speed in *CrimMin* and all drivers speed in *RevMax*, yet monitoring levels in the two treatments are indistinguishable.

Beginning with the *CrimMin* treatment, the officer strictly prefers to induce the driver to choose road C because the payoff penalty when a driver chooses roads A or B (40 points) is larger than the maximal monitoring cost (36 points). Therefore, given the driver's best response, $m_A, m_B \geq 0.4$ in the observed monitoring case and $m_A + m_B \geq m^*$ in the unobserved monitoring case. Because monitoring is costly, the officer wishes to minimize monitoring subject to this constraint. In the observed monitoring case we have an equilibrium at $m_A = m_B = 0.4$ where the driver chooses road C and in the unobserved monitoring case we have an equilibrium at $m_A + m_B = m^*$ where the driver chooses road C.[17]

In the *RevMax* treatment the marginal revenue from additional monitoring exceeds the marginal cost when the additional monitoring does not alter the driver's behavior. Therefore, the officer wishes to monitor up to the point where the driver switches to choosing road C. Therefore, in equilibrium $m_A, m_B = 0.4$ in the observed monitoring case and $m_A + m_B = m^*$ in the unobserved monitoring case.[18]

In the third information structure, where the officer can choose whether to fully reveal their monitoring strategy or not, the officer should reveal their monitoring if and only if their payoff is higher in the observed monitoring case. The payoff difference between the observed and unobserved case depends on whether m^* is greater or less than 0.8. In the *RevMax* treatment officer payoffs are increasing in m^*, and in the *CrimMin* treatment officer payoffs are decreasing in m^* – therefore the officer will reveal their strategy when $m^* < 0.8$ in the *RevMax* treatment and when $m^* > 0.8$ in the *CrimMin* treatment. Or, equivalently, the officer will reveal their strategy when drivers are uncertainty averse in the *RevMax* treatment and when drivers are uncertainty seeking in the *CrimMin* treatment.

We formalize the above intuition in Appendix A, and we summarize the full set of equilibrium predictions across all treatments in tables 6, 7 and 8.

		RevMax treatment	*CrimMin* treatment
uncertainty aversion	$m^* < 0.8$	$I = \text{Obs}$	$I = \text{Unobs}$
uncertainty seeking	$m^* > 0.8$	$I = \text{Unobs}$	$I = \text{Obs}$

Table 6: Officer's equilibrium choice of $I \in \{\text{Obs}, \text{Unobs}\}$ as a function of the officer's incentive structure (column) and the driver's uncertainty preferences (row).

[17] In the case of continuous monitoring the total monitoring level in equilibrium is unique. However, if the officers strategy space is discrete, as is the case in our experimental implementation, then there exists an equilibrium where the driver chooses A or B when $m_A + m_B = m^*$, and the officer chooses total monitoring to be one tick above m^*.

[18] In the case of continuous monitoring the total monitoring level in equilibrium is unique. However, if the officers strategy space is discrete, as is the case in our experimental implementation, then there exists an equilibrium where the drive chooses C when $m_A + m_B = m^*$, and the officer chooses total monitoring to be one tick below m^*.

	$I = \text{Obs}$	$I = \text{Unobs}$
Equilibrium monitoring level	$M = (0.8, 0.4, 0.4)$	$M = (m^*, m_A, m_B)$ with $m_A + m_B = m^*$

Table 7: Equilibrium monitoring levels as a function of the observable information structure. The same equilibrium monitoring levels hold in the case where the officer chooses I and the cases where I is fixed endogenously. $M = (m, m_A, m_B)$ indicates that the officer monitors road A with probability m_A, road B with probability m_B and that total monitoring is m.

	RevMax treatment	*CrimMin* treatment
Equilibrium on-path driver action	A or B	C

Table 8: Equilibrium driver action observed on the equilibrium path.

4 Experimental implementation

All experimental sessions were conducted at the Vernon Smith Experimental Economics Laboratory (VSEEL) at Purdue University, with subjects recruited via ORSEE (Greiner, 2015). The experimental interface was tested and refined using pilot sessions, and the data from the pilot sessions is not included in our analysis. The *Prob* treatment was conducted across 6 sessions using 110 subjects and the *EV* treatment was conducted across 4 sessions with 72 subjects. No subject participated in more than one session.

There were a few minor differences between the *Prob* and *EV* treatments. The *Prob* treatment consisted of 36 rounds, with subjects remaining in the same role (officer or driver) for the entire experiment, with an exchange rate of 100 points = \$1.20 and average earnings of \$24.63 (including a \$5 show up fee).[19] The *EV* treatment consisted of 48 rounds, with subjects switching roles after 24 rounds, an exchange rate of 100 points = \$0.90 and average earnings of \$25.21 (including a \$5 show up fee).[20] In both treatments opponents were randomly re-matched every period and subjects were paid the sum of their earnings across all rounds.

Within a session, subjects participated in 6 different games. Each of the games had one of the *CrimMin* or *RevMax* officer payoff schemes and one of the three information structures ($I = \text{Obs}, I = \text{Unobs}$ or endogenous I). Rounds were grouped into blocks of four rounds, with the game changing every block. The assignment of games to blocks varied across sessions, with the requirement that subjects played one block of $I = \text{Obs}$ and one block of $I = \text{Unobs}$ before playing

[19] Recall that the roles were described to the subjects as 'worker' and 'supervisor'.

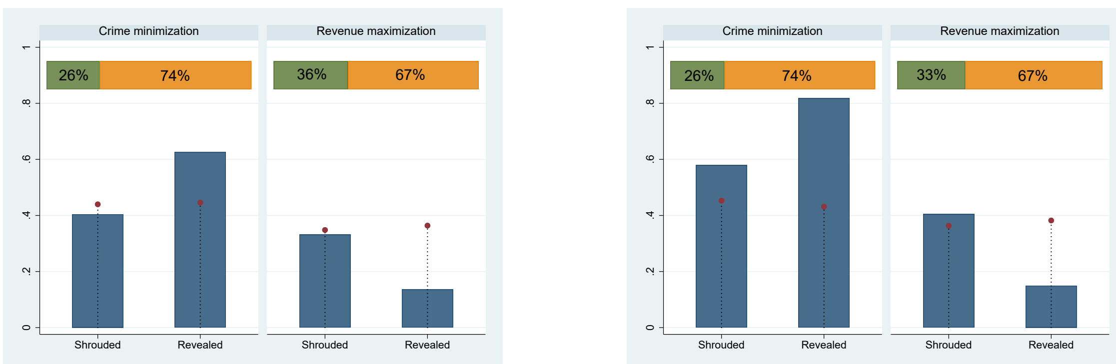
[20] We had subjects play both roles in the *EV* treatment to avoid concerns that subjects in the worker role may become bored and lose focus in the simpler environment.

a block with endogenous I.

The instructions, which are provided in an online appendix, were augmented with printed color-coded payoff tables. Subjects could use the tables to quickly look up payoffs given a conjecture of both their own and their opponents' actions.

5 Results

5.1 Data summary



(a) Probabilistic treatment

(b) Expected Value treatment

Figure 2: Summary of the complete dataset. Blue column heights represent the proportion of rounds in which the driver chose the safe option, C. Maroon dots represent the average level of monitoring across the two roads, $\frac{m_A+m_B}{2}$. Horizontal bars represent the proportion of rounds in which the driver chose to shroud (green) or reveal (orange) their monitoring strategy.

Figure 2 provides an overview of the entire dataset. Behavior is consistent across the *Prob* and *EV* treatments, and the data is broadly supportive of the theoretical predictions. In particular, in rounds where monitoring was observed, the average monitoring level is approximately 0.4 (denoted by the maroon dots), and the drivers choose C substantially more often in the *CrimeMin* treatments than in the *RevMax* treatments (denoted by the blue column heights). When monitoring is unobserved equilibrium monitoring depends on the driver's uncertainty preferences, and the data suggests that average monitoring is slightly lower in unobserved *RevMax* rounds and slightly higher in unobserved *CrimeMin* rounds (compared to the respective observed rounds). As we discuss in detail below, however, the distribution of monitoring is distinctly different in the two cases.

Of particular note is the decision by the officers to either reveal or shroud the level of monitoring. In the *CrimeMin* treatment, where the officer wishes to induce the driver to choose C, the drivers choose C more often when monitoring is revealed. In turn, the officers best respond to driver behavior and reveal their monitoring levels three quarters of the time. In the *RevMax* treatment, where the officer wishes to induce the driver to choose either A or B, the drivers choose C less often when monitoring is revealed. In turn, the officers best respond to driver behavior and reveal their monitoring levels two thirds of the time. Changing the observability of monitoring is costless, and induces large behavioral changes in the drivers.

The average behavior presented in Figure 2 masks much of the interesting variation in behavior across treatments, to which we now turn.

5.2 Driver behavior

The theoretical analysis and equilibrium predictions developed in Section 3 are deterministic. In order to bring the model to the data, we need to allow for stochastic choice. As an additional complication, the data reveals only the action chosen and not the strategy used by each subject. We therefore focus on modeling the probability, conditional on the observed monitoring strategy, that a driver chooses C. As a benchmark, we define the expected value function $V^I(m_A, m_B)$ to be

$$V^I(m_A, m_B) = \begin{cases} 100\max\{0.9 - m_A, 0.9 - m_B\} & \text{if } I = \text{Obs} \\ 100(0.9 - \frac{m_A+m_B}{2}) & \text{if } I = \text{Unobs.} \end{cases}$$

$V^I(m_A, m_B)$ implicitly leverages the drivers available information of both the monitoring probabilities and the payoff structure to assign a value, the expected value, to choosing optimally between A and B. We can then assign a utility to not choosing C as $U_t^I(\sim C, m_A, m_B) = \beta_0^I + \beta_1^I V^I(m_A, m_B)$ where β_0^I and β_1^I are parameters to be estimated, and recall that the utility of choosing C is normalized as $U_t^I(C, m_A, m_B) = 50$. Note that this utility function will satisfy Monotonicity if $\beta_1^I > 0$, satisfies Symmetry if $\beta_0^{\text{Obs}} + 50\beta_1^{\text{Obs}} = 50$, and Non-triviality if $\beta_0^I + 90\beta_1^I > 50$ and $\beta_0^I < 50$. The utility function that we take to the data is a special case of the general utility function in Section 3.1 when these restrictions hold.

To allow for choice errors, we assume that an individual i, in round r, will choose C if and only if

$$U_t^I(C, m_A, m_B) + \epsilon_{i,r}^I \geq U_t^I(\sim C, m_A, m_B)$$

where $\epsilon_{i,r}$ is an error term with a logistic distribution. We then estimate the latent variable logit model

$$y^I_{i,r,t} = \begin{cases} 1 & \text{if } 50 - \beta^I_{0,t} - \beta^I_{1,t} V^I_{i,r}(m_A, m_B) + \epsilon^I_{i,r} \geq 0 \\ 0 & \text{otherwise,} \end{cases} \tag{4}$$

where $y^I_{i,r}$ is an indicator variable equal to 1 if subject i chooses option C in round r under information scheme I and equal to 0 if the subject chooses options A or B. We estimate Equation 4 independently for the *Prob* and *EV* treatments and for rounds where the driver observes, or does not observe, the monitoring probabilities. Data from the crash minimization and revenue maximization treatments are pooled, and we estimate generalized estimating equation population averaged parameters (across subjects) with robust standard errors.

	EV treatment		Prob treatment	
	I = Obs	I = Unobs	I = Obs	I = Unobs
β_0	0.42	45.59	40.40	47.57
	(11.28)	(0.47)	(1.52)	(0.38)
β_1	0.99	0.10	0.21	0.06
	(0.23)	(0.01)	(0.03)	(0.01)
no. of obs	979	747	1115	865
$\beta_1 \leq 0$?	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$
Monotonicity satisfied?	Yes	Yes	Yes	Yes
$\beta_0 + 50\beta_1 = 50$?	$p = 0.159$		$p < 0.001$	
Symmetry satisfied?	Yes		No	
$\beta_0 + 90\beta_1 < 50$?	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$
$\beta_0 > 50$?	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$
Non-triviality satisfied?	Yes	Yes	Yes	Yes

Table 9: The top panel contains the population average GEE parameter estimates of equation 4, with robust standard errors. The bottom panel contains the p-values for tests of parameter restrictions associated with Monotonicity, Symmetry and Non-triviality.

Table 9 displays the estimated values of β_1 and β_0 for each treatment, and the lower panel of the table shows the results of tests for monotonicity, symmetry and non-triviality.[21] Monotonicity

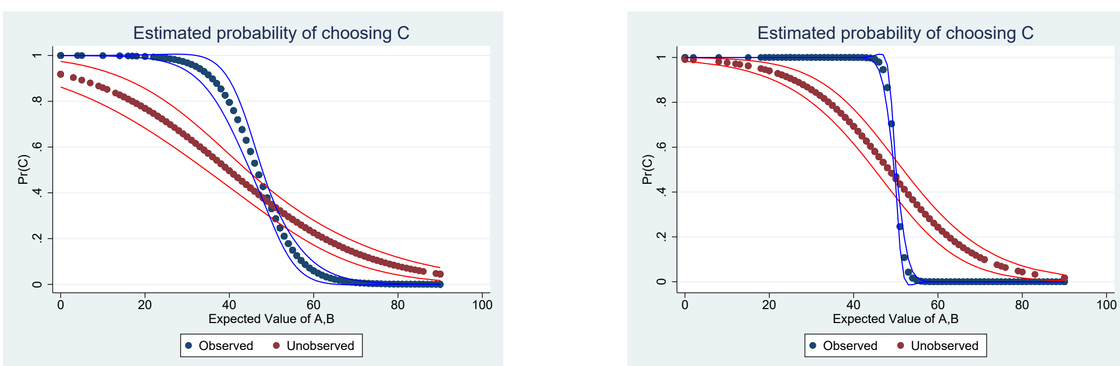
[21]For the *EV* treatment with observable monitoring we drop 2 out of 981 observations to ensure convergence of the GEE estimator.

and non-trivality are satisfied for each treatment, while symmetry is satisfied for the EV treatment but not the $Prob$ treatment.

Recall that the expected value of option C is always 50, so that the behavior of a rational decision maker with uncertainty neutral preferences can be characterized, up to an indifference, by choosing C if and only if $V(A, B) \leq 50$. The predicted probability of C being chosen is then given by

$$\Pr_t^I(C|V^I) = \frac{e^{50-\hat{\beta}_{0,t}^I-\hat{\beta}_{1,t}^I V^I(m_A,m_B)}}{1+e^{50-\hat{\beta}_{0,t}^I-\hat{\beta}_{1,t}^I V^I(m_A,m_B)}}. \tag{5}$$

Figure 3 plots the implied predicted choice probabilities as a function of monitoring levels with the data for the I = Obs case in blue and I = Unobs in red. In these figures symmetry implies that the blue curves should pass through the point $(50, 0.5)$ – this is true for the right panel but not the left panel. Even in the case where symmetry is rejected, the degree of asymmetry is small. Symmetry implies that a driver choose C with probability 0.5 when $V^{\text{Obs}}(m_A, m_B) = 50$, and in the $Prob$ treatment the estimated probability of choosing C is 0.5 when $V^{\text{Obs}}(m_A, m_B) = 46$.



(a) Probabilistic treatment

(b) Expected Value treatment

Figure 3: Estimated (logit) driver choice probabilities, with 95% confidence intervals.

In our model of stochastic choice, our identification of ambiguity and risk preferences (Section 3.1) also needs to be amended.

Definition 5. A driver is

- uncertainty neutral if $\Pr_{\text{EV}}^{\text{Obs}}(C|V^{\text{Obs}}) = \Pr_{\text{EV}}^{\text{Unobs}}(C|V^{\text{Unobs}})$;
- uncertainty averse if $\Pr_{\text{EV}}^{\text{Obs}}(C|V^{\text{Obs}}) < \Pr_{\text{EV}}^{\text{Unobs}}(C|V^{\text{Unobs}})$;
- uncertainty seeking if $\Pr_{\text{EV}}^{\text{Obs}}(C|V^{\text{Obs}}) > \Pr_{\text{EV}}^{\text{Unobs}}(C|V^{\text{Unobs}})$;

whenever $V^{\text{Obs}} = V^{\text{Unobs}}$.

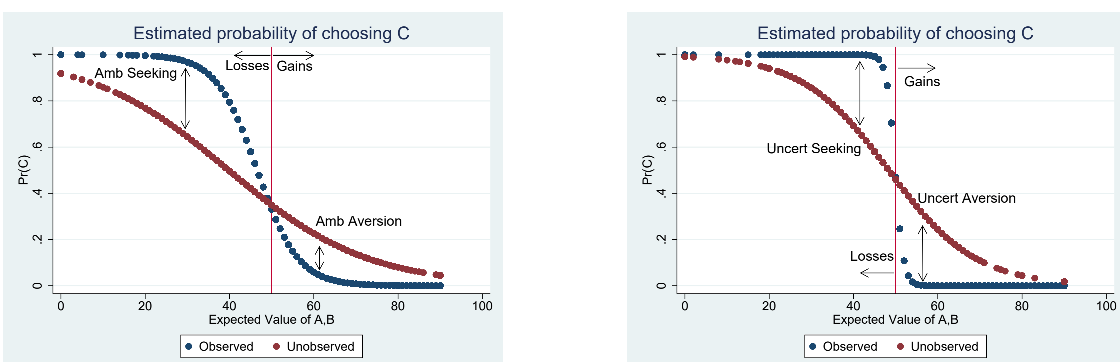
This definition is the natural one. When $V^{\text{Obs}} = V^{\text{Unobs}}$ then the expected value of choosing optimally between A and B is the same across the *Obs* and *Unobs* treatments and, therefore, the utility of choosing A or B must be equal for an uncertainty neutral driver. Equation 5 then implies that the choice probabilities across the two information structures must also be equal. Given our symmetry assumptions, the choice problem faced by a driver in the *Unobs* treatment is a mean preserving spread of the choice problem faced in the *Obs* treatment when $V^{\text{Obs}} = V^{\text{Unobs}}$: an uncertainty averse (seeking) driver dislikes the mean preserving spread and therefore chooses C more (less) often in the *Unobs* case.

In the *Prob* treatment we identify only the effect of ambiguity aversion, and not risk aversion, given that in all cases the only feasible payments are 0 or 100 points.

Definition 6. A driver is

- ambiguity neutral if $\Pr^{\text{Obs}}_{\text{Prob}}(C|V^{\text{Obs}}) = \Pr^{\text{Unobs}}_{\text{Prob}}(C|V^{\text{Unobs}})$;
- ambiguity averse if $\Pr^{\text{Obs}}_{\text{Prob}}(C|V^{\text{Obs}}) < \Pr^{\text{Unobs}}_{\text{Prob}}(C|V^{\text{Unobs}})$;
- ambiguity seeking if $\Pr^{\text{Obs}}_{\text{Prob}}(C|V^{\text{Obs}}) > \Pr^{\text{Unobs}}_{\text{Prob}}(C|V^{\text{Unobs}})$;

whenever $V^{\text{Obs}} = V^{\text{Unobs}}$.



(a) Probabilistic treatment (b) Expected Value treatment

Figure 4: Reference dependent uncertainty preferences.

Figure 3b shows the driver behavior for the *EV* treatment. When the monitoring probabilities are observed the predicted driver choice probabilities are nearly optimal: choosing C whenever $V(A, B) \leq 50$ and choosing A or B otherwise. This is not unexpected, given that drivers are choosing between three fixed payoffs and face no uncertainty. When monitoring probabilities are unobserved, options A and B are uncertain while option C pays a fixed 50 points.

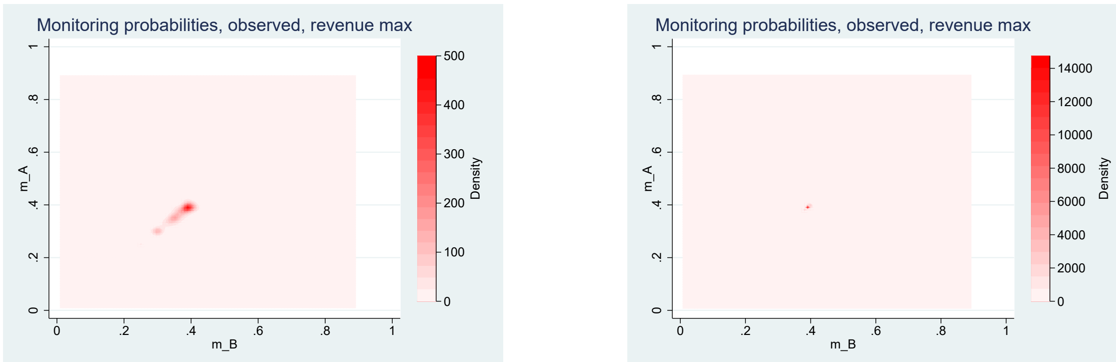
Figure 3a shows the driver behavior for the *Prob* treatment. When monitoring probabilities are observed each option pays 100 points with a known probability, and option C always pays 100 points with probability 0.5. When monitoring probabilities are unobserved, options A and B are ambiguous because they pay 100 points with an unknown probability, while option C pays 100 points with probability 0.5.

The most remarkable feature of Figure 3 is that, in both panels, we observe uncertainty seeking when $V(A, B) < 50$ and uncertainty aversion when $V(A, B) > 50$. Figure 4 emphasizes that uncertainty preferences are reflected around the reference point of $V(A, B) = 50$. The location of the reference point at $V(A, B) = 50$ is induced by the expected value of option C always being fixed at 50. While this behavior is consistent with prospect theory-like preferences for uncertainty (uncertainty aversion in the gains domain, and uncertainty seeking in the loss domain) we did not design our experiment to test for prospect theory and cannot, therefore, rule out alternative explanations. In particular, it may be the case that no individual driver exhibits reference dependence, yet aggregate preferences do generate reference dependent behavior. Uncertainty averse agents will be indistinguishable from uncertainty neutral agents when $V(A, B) < 50$, as both types will always choose C. Conversely, uncertainty seeking agents will be indistinguishable from uncertainty neutral agents when $V(A, B) > 50$, as both types will never choose C. Therefore, in aggregate, we see some uncertainty seeking when $V(A, B) < 50$ and uncertainty aversion when $V(A, B) > 50$.[22]

5.3 Officer behavior

Overall, the officer behavior approximates a best response to the driver behavior outlined in the previous section. For rounds where monitoring is observed, and driver behavior is close to the Nash equilibrium behavior, this implies that officer behavior is very close to the Nash equilibrium prediction ($m_a = m_b \in \{0.39, 0.4\}$ in the revenue maximization treatment and $m_a = m_b \in \{0.4, 0.41\}$ in the crash minimization treatment). Figures 5 and 6 show kernel density estimates of the probabil-

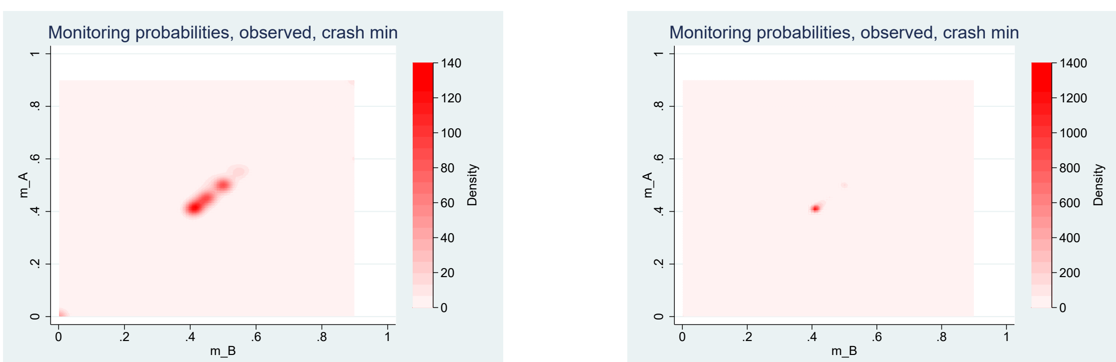
[22]It may also be that decision making simply becomes noisier in the face of uncertainty (i.e. choice probabilities biased towards 50% in the unobserved treatments). However, if decision noise were driving the effect, we would expect the red and blue curves in Figure 4 to intersect at the point where $\Pr(C) = 0.5$ (rather than at $V(A, B) = 50$ as predicted by prospect theory or the aggregation of heterogenous uncertainty preferences). For the EV treatment the point of intersection coincides with both predictions, but for the *Prob* treatment the point of intersection matches the prediction of prospect theory rather than the decision noise prediction.



(a) Probabilistic treatment

(b) Expected Value treatment

Figure 5: Officer monitoring probabilities, observed monitoring, revenue maximization treatment.

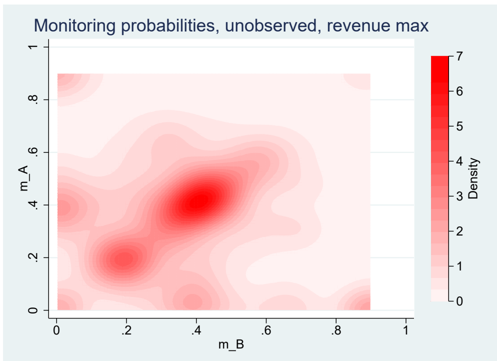


(a) Probabilistic treatment

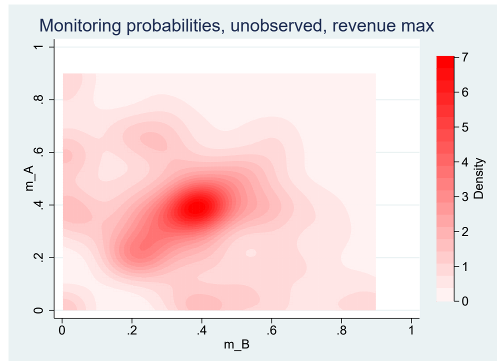
(b) Expected Value treatment

Figure 6: Officer monitoring probabilities, observed monitoring, crash minimization treatment.

ity density function of the officer's monitoring decision. The densities are remarkably high around the equilibrium monitoring probabilities – particularly in the revenue maximization EV treatment (Figure 5b). For comparison the expected officer payoffs, conditional on estimated driver choice probabilities, are shown in the appendix in figures 9 and 10.

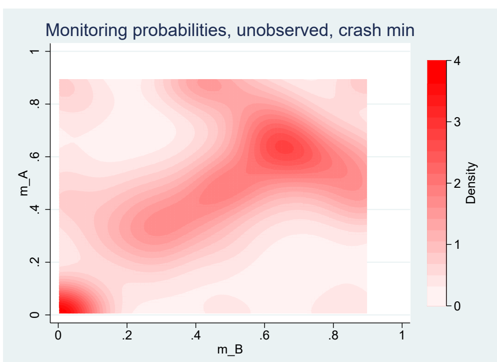


(a) Probabilistic treatment

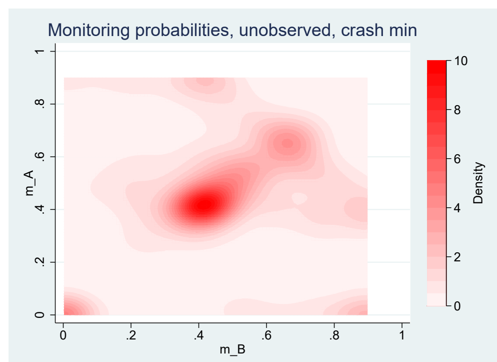


(b) Expected Value treatment

Figure 7: Officer monitoring probabilities, unobserved monitoring, revenue maximization treatment.



(a) Probabilistic treatment



(b) Expected Value treatment

Figure 8: Officer monitoring probabilities, unobserved monitoring, crash minimization treatment.

Figures 7 and 8 show kernel density estimates of the probability density function of the officer's monitoring decision for rounds where monitoring was observed by the driver. There is substantially more variation in the choice of monitoring levels when monitoring is unobserved, coupled with a substantial shift in mass towards lower monitoring for the revenue maximization case and a shift in mass towards greater monitoring for the crime minimization case. These changes in monitoring behavior, relative to the observed monitoring rounds, are a rational response to the uncertainty preferences of the drivers. In the revenue maximization case, where the equilibrium involves the officer inducing the driver to choose option A or B, we have $V(A, B) > 50$ and the reduction in monitoring is a rational response to the driver's uncertainty aversion in the gains domain. In the crash minimization case, where the equilibrium involves the officer inducing the driver to choose option C, we have $V(A, B) < 50$ and the increase in monitoring is a rational response to the driver's uncertainty seeking in the loss domain.[23] We also note that in the crash minimization rounds there are some officers who engage in zero monitoring. Setting $m_A = m_B = 0$ can, for example, be justified by an officer who exhibits a large amount of uncertainty aversion with respect to the driver's response to positive monitoring levels. For comparison the expected officer payoff, conditional on estimated driver choice probabilities, are shown in the appendix in figures 11 and 12.

Officers earn higher payoffs in rounds where drivers can observe the monitoring probabilities, under both the crash minimization and revenue maximization payment schemes. In the revenue maximization rounds the driver's uncertainty aversion in the gains domain implies that officers must lower their monitoring levels and therefore lower their fine revenue when monitoring is unobserved. In the crash minimization rounds the driver's uncertainty seeking in the loss domain implies that officers must increase their costly monitoring to prevent crashes when monitoring is unobserved. Given this we should expect the officer to reveal their choice of monitoring, under both payment schemes, when given the option. Table 10 demonstrates that the officers do, indeed, reveal their strategy more often than not.

	Revenue Max	Crash Min
Prob treatment	0.64	0.74
	[0.60, 0.68]	[0.71, 0.77]
EV treatment	0.67	0.74
	[0.63, 0.71]	[0.70, 0.77]

Table 10: Proportion of rounds in which the Officer revealed their monitoring strategy to the Drivers, with 95% confidence intervals in brackets.

6 Discussion

Various auditing, enforcement and monitoring policies have been examined extensively in the literature. The law enforcement literature, for example, typically revolves around policing for profit versus safety. While most of this research attempts to understand the effect of various law enforcement incentives (either endogenous or imposed) on public safety outcomes, observational studies

[23]This analysis holds irrespective of whether the driver behavior is caused by prospect theory style preferences or by some other phenomena.

struggle to understand the reason that one law enforcement strategy is more effective than another. Stated differently, the impact of a law enforcement strategy on public safety is a function of the law enforcer's incentives, the enforcement agency's decisions to announce or shroud their enforcement practices and the preferences (ambiguity and risk attitudes) of citizens. Given that, of these three factors influencing the effectiveness of law enforcement strategies, the law enforcement agency's decision to announce or shroud their enforcement practices is often the only observable behavior, empirical analyses using real-world data cannot fully determine the effectiveness of such law enforcement policies. While Figure 1 is suggestive of the relationship between fiscal incentives and law enforcement decisions to announce or shroud their strategies, Sha (2015) notes that "if you wanted to know if your local law enforcement was policing well or unfairly relative to other similar jurisdictions, there is little data available for you to assess that." Indeed, this is both because data on the reasons that law enforcement believe that they should engage in a particular enforcement strategy as well as citizen beliefs are unknown.

To overcome these issues, we utilize a lab environment to disentangle the impact of each of these three factors that influence the effectiveness of law enforcement strategies. In doing so, we identify how specific environments impact the decision to engage in riskier decisions by citizens. Simultaneously, we are able to identify the conditions that lead an enforcement agent to announce or shroud their intended enforcement practices. The nexus of these decisions yields important insights regarding issues of public safety that are ongoing. For example, California Vehicle Code 40802 does not permit "unjustified speed limit traps", which are defined as sections of highway with a lower speed limit that is not justified by a traffic survey conducted within the past five years. Hidden speed cameras were utilized in identifying speeding motorists in Arizona, but this was outlawed by the governor in 2010. Lastly, the Revised Code of Washington 46.08.065 prohibits the use of unmarked vehicles by public agencies, with exceptions only being made for Washington state patrol for general undercover or confidential investigative purposes, as approved by the chief of the Washington state patrol. These laws evolved out of concern that many communities and law enforcement agencies were conflicted about the use of marked or unmarked police cars.[24] The tension between using marked vehicles, or not, pertains to whether drivers are more responsive to the presence of a marked vehicle (risk; over time, with marked vehicles, the drivers learn the distribution of monitoring) or the concern that unmarked vehicles are patrolling (ambiguity; drivers cannot learn the distribution of monitoring). Our findings note that an agency concerned with increasing public safety should indeed reveal their enforcement activities (e.g. utilize marked vehicles) to deter ambiguity seeking citizens.

[24]See Preusser Research Group (2015) for a more in depth discussion of these trade-offs.

7 Conclusion

Citizens often comply with legal rules, but in the instances when they do not, we assign legal agents to identify and sanction non-compliance. The public service actors that we charge with the authority of managing such enforcement agencies can have incentives that could be conflicting, though. On the one hand, they aim to deter illegal activities and enhance public safety. Alternatively, they might desire to raise government revenues by establishing a monitoring environment that encourages the commission of illegal acts. Such a monitoring environment could include announcing or shrouding the presence of enforcement activities. Whether a monitoring environment deters or encourages citizens to commit proscribed activities depends on the ambiguity and risk attitudes of the citizens. While rich observational data of enforcement incentives and strategies are possible to obtain, in theory, an analysis that utilizes such data would suffer from selection effects in terms of the enforcement strategies deployed by agencies. Instead, we rely on a laboratory environment to overcome the endogeneity of the enforcement strategy while also being able to discern the ambiguity and risk attitudes of the enforced subjects. The results of our work display two unique equilibria for law enforcement: (1) revealing enforcement strategies when facing uncertainty averse citizens and revenue-enhancing incentives and (2) revealing enforcement strategies when facing uncertainty seeking citizens and safety-enhancing incentives. We note that these equilibria are consistent with an underlying prospect theory structure of uncertainty preferences among the representative citizen. When facing safety-enhancing incentives officers will, in equilibrium, monitor to such an extent that only uncertainty seeking citizens commit violations. Therefore, the choice to reveal monitoring is made to reduce violations among this subset of the population. On the other hand, when facing revenue-maximization incentives officers will, in equilibrium, monitor to such an extent that the marginal offender is uncertainty averse. Therefore, the choice to reveal monitoring is made to increase violations among this subset of the population.

A Complete equilbrium characterization

In this section we provide a complete equilibrium characterization.

A game consists of two players, an officer and a driver. For analytical convenience, we model the officer's strategy as a two stage decision. In the first stage, the officer chooses a total monitoring probability $m \in [0, 1.8]$ and a choice of information structure, $I \in \{\text{Obs}, \text{Unobs}\}$.[25] In the second

[25]In the case of exogenous information structure, the choice of I is trivial.

stage, the officer chooses m_A and m_B such that $m_A + m_B = m$. A complete strategy for the officer is therefore given by $(M, I) = (m, m_A, m_B, I)$, and each choice of m and I defines the start of a new subgame. A strategy for the driver is a pair of mappings from officer strategies to a choice of road $D^{\text{Obs}} : M \mapsto \{A, B, C\}$ and $D^{\text{Unobs}} : M \mapsto \{A, B, C\}$.[26] Payoffs for the officer are defined in Table 3. Utilities for the driver are given by the utility function $U^I(X, m_A, m_B)$ defined in Section 3.1. The driver moves after the officer's two stage decision and we solve the game using subgame perfect Nash equilibrium.

We impose the following conditions on the driver's strategy.

Assumption 1. *(a) Either the set* $\{(x, y) : D^{Obs}(m, x, y) = C\}$ *is closed, or the set* $\{(x, y) : D^{Obs}(m, x, y) \in \{A, B\}\}$ *is closed.*

(b) $D^{Unobs}(m, x, y) = D^{Unobs}(m, x', y')$ *for all* m*.*

Condition (a) rules out several pathological driver strategies including, for example, the case where $D(m, 0.4, y) = C$ if $y > 0.4$ is rational and $D(m, 0.4, y) = A$ if $y > 0.4$ is irrational. Condition (b) ensures that the driver cannot condition their decision on unobservable information in the unobservable treatment.

We first categorize the equilibrium in the case where I is exogenous.

Proposition 1. In the *CrimMin* treatment with $I = \text{Obs}$, if M and D^{Obs} form an equilibrium then $M = (0.8, 0.4, 0.4)$ and $D^{\text{Obs}}(0.8, 0.4, 0.4) = C$.

In the *RevMax* treatment with $I = \text{Obs}$, if M and D^{Obs} form an equilibrium then $M = (0.8, 0.4, 0.4)$ and $D^{\text{Obs}}(0.8, 0.4, 0.4) \in \{A, B\}$.

Proof. We begin with the *CrimMin* case. Subgame perfection requires that $D(m, m_A, m_B)$ is consistent with Equation 1. If, in addition, $D(0.8, 0.4, 0.4) = C$, then it follows immediately that the officer's best response is $M = (0.8, 0.4, 0.4)$. Therefore there exists an equilibrium with $M = (0.8, 0.4, 0.4)$ and $D(0.8, 0.4, 0.4) = C$. To show that there are no other equilibrium, we consider two cases. First, if the set of (x, y) values such that $D(m, x, y) = C$ is closed then any best response function for the driver satisfies $D(0.8, 0.4, 0.4) = C$. Second, if the set of (x, y) values such that $D(m, x, y) \in \{A, B\}$ is closed then the set of (x, y) such that $D(m, x, y) = C$ is open from below. There does not exist a best response for the officer who seeks to minimize $m_A + m_B$ subject to $D(m, m_A, m_B) = C$ and, therefore, no equilibrium exists.

[26] In the case of exogenous information structure, the driver's strategy is a single mapping from monitoring levels to a choice of road.

We continue with the *RevMax* case. Subgame perfection requires that $D(m, m_A, m_B)$ is consistent with Equation 1. If, in addition, $D(0.8, 0.4, 0.4) \in \{A, B\}$, then it follows immediately that the officer's best response is $M = (0.8, 0.4, 0.4)$. Therefore there exists an equilibrium with $M = (0.8, 0.4, 0.4)$ and $D(0.8, 0.4, 0.4) \in \{A, B\}$. To show that there are no other equilibrium, we consider two cases. First, if set (x, y) of values such that $D(x, y) \in \{A, B\}$ is closed then any best response function for the driver satisfies $D(0.8, 0.4, 0.4) \in \{A, B\}$. Second, if the set (x, y) of values such that $D(m, x, y) = C$ is closed then the set of (x, y) such that $D(m, x, y) \in \{A, B\}$ is open from above. There does not exist a best response for the officer who seeks to maximize $\min\{m_A, m_B\}$ subject to $D(m, m_A, m_B) \in \{A, B\}$ and, therefore, no equilibrium exists. □

Proposition 2. In the *CrimMin* treatment with $I =$ Unobs, if M and D^{Unobs} form an equilibrium then $M = (m^*, m_A, m_B)$ and $D^{\text{Unobs}}(m^*, x, y) = C$ with m^* as defined in Equation 2.

In the *RevMax* treatment with $I =$ Unobs, if M and D^{Unobs} form an equilibrium then $M = (m^*, m_A, m_B)$ and $D^{\text{Unobs}}(m^*, x, y) \in \{A, B\}$ with m^* as defined in Equation 2.

Proof. We begin with the *CrimMin* case. Subgame perfection requires that $D(m, m_A, m_B)$ is consistent with Equation 2. If, in addition, $D(m^*, m_A, m_B) = C$, then it follows immediately that the officer's best response is any m_A and m_B such that $m_A + m_B = m^*$. Therefore there exists an equilibrium with $M = (m^*, m_A, m_B)$ and $D(m^*, m_A, m_B) = C$. To show that there are no other equilibrium consider the case where $D(M, m_A, m_B) \in \{A, B\}$ so that the set of (x, y) such that $D(m, x, y) = C$ is open from below. There does not exist a best response for the officer who seeks to minimize $m_A + m_B$ subject to $D(m, m_A, m_B) = C$ and, therefore, no equilibrium exists.

We continue with the *RevMax* case. Subgame perfection requires that $D(m, m_A, m_B)$ is consistent with Equation 2. If, in addition, $D(m^*, m_A, m_B) \in \{A, B\}$, then it follows immediately that the officer's best response is any m_A and m_B such that $m_A + m_B = m^*$. Therefore there exists an equilibrium with $M = (m^*, m_A, m_B)$ and $D(m^*, m_A, m_B) \in \{A, B\}$. To show that there are no other equilibrium consider the case where $D(m^*, m_A, m_B) = C$ so that the set of (x, y) such that $D(m, x, y) \in \{A, B\}$ is open from above. There does not exist a best response for the officer who seeks to maximize $\min\{m_A, m_B\}$ subject to $D(m, m_A, m_B) \in \{A, B\}$ and, therefore, no equilibrium exists. □

Clearly in the case of endogenous information the officer will select $I \in \{\text{Obs}, \text{Unobs}\}$, conditional on the driver's uncertainty preferences, to maximize her payoff.

Proposition 3. In the *CrimMin* treatment, there are three classes of equilibrium:

- if $m^* < 0.8$, then $I = \text{Unobs}$ and $M = (m^*, m_A, m_B)$ and $D^{\text{Unobs}}(m^*, x, y) = C$ in every equilibrium.

- if $m^* = 0.8$, then $I = \text{Unobs}$ and $M = (0.8, m_A, m_B)$ and $D^{\text{Unobs}}(0.8, x, y) = C$ or $I = \text{Obs}$ and $M = (0.8, 0.4, 0.4)$ and $D^{\text{Obs}}(0.8, 0.4, 0.4) = C$ in every equilibrium.

- if $m^* > 0.8$, then $I = \text{Obs}$ and $M = (0.8, 0.4, 0.4)$ and $D^{\text{Obs}}(0.8, 0.4, 0.4) = C$ in every equilibrium.

In the *RevMax* treatment, there are three classes of equilibrium:

- if $m^* < 0.8$, then $I = \text{Obs}$ and $M = (0.8, 0.4, 0.4)$ and $D^{\text{Obs}}(0.8, 0.4, 0.4) \in \{A, B\}$ in every equilibrium.

- if $m^* = 0.8$, then $I = \text{Unobs}$ and $M = (0.8, m_A, m_B)$ and $D^{\text{Unobs}}(0.8, x, y) \in \{A, B\}$ or $I = \text{Obs}$ and $M = (0.8, 0.4, 0.4)$ and $D^{\text{Obs}}(0.8, 0.4, 0.4) \in \{A, B\}$ in every equilibrium.

- if $m^* > 0.8$, then $I = \text{Unobs}$ and $M = (m^*, m_A, m_B)$ and $D^{\text{Unobs}}(m^*, x, y) \in \{A, B\}$ in every equilibrium.

Proof. Follows immediately from Proposition 1 and Proposition 2. □

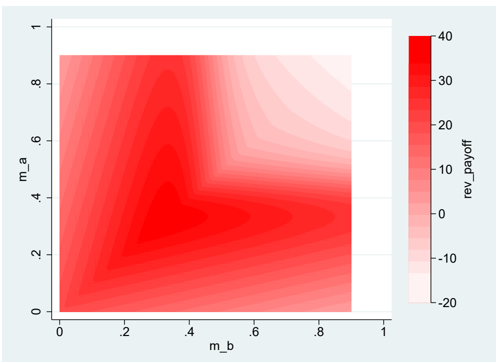
A.1 Discussion of equilibrium formulation

The structure of the game as defined in Appendix A is somewhat non-standard. For the special case of Expected Utility agents this structure is not necessary, and it would be more natural to formulate the game as a standard game of imperfect information and use sequential equilibrium as the solution concept. Under an assumption that the driver's beliefs are symmetric the resulting sequential equilibrium would be observationally equivalent to the equilibrium given in the text. Such an approach would, however, significantly complicate the analysis for non-EU agents.

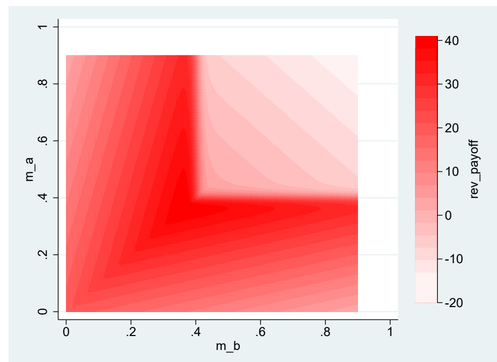
The general utility function developed in Section 3.1 assigns a utility value to each information set that could be faced by the driver without the need to specify the precise form of the beliefs of the agent nor the specific form of the agent's non-EU utility function. By suppressing beliefs, we circumvent the need to define a notion of belief consistency for non-EU agents. Small changes in the definition of belief consistency can radically alter the set of equilibrium, or even the existence of equilibrium, for games with non-EU agents (see the text following Definition 4 in Lo (2009) and section 3 of Eichberger and Kelsey (2014) for discussions). The approach taken here circumvents these technical issues and generates an equilibrium set that coincides with the 'intuitive' equilibrium of our game.

Our approach, which effectively fixes the utility of the player with the move at information sets immediately preceding terminal nodes, could be applied to any game of incomplete information with non-EU agents where the utilities at each information set have a natural structure.

B Officer empirical best response heat maps

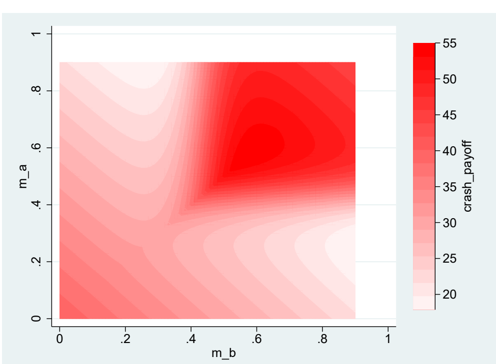


(a) Probabilistic treatment

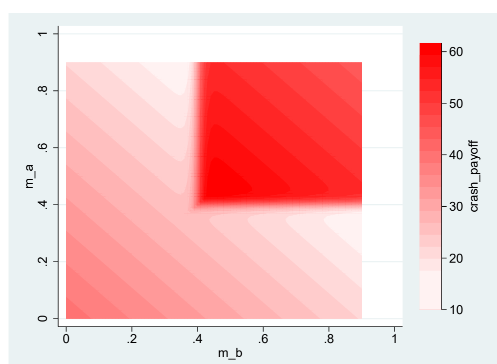


(b) Expected Value treatment

Figure 9: Officer empirical payoffs, observed monitoring, revenue maximization treatment.

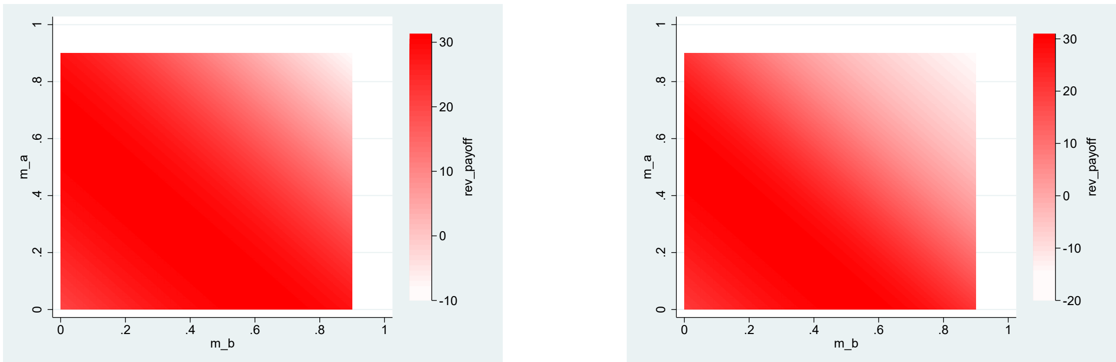


(a) Probabilistic treatment



(b) Expected Value treatment

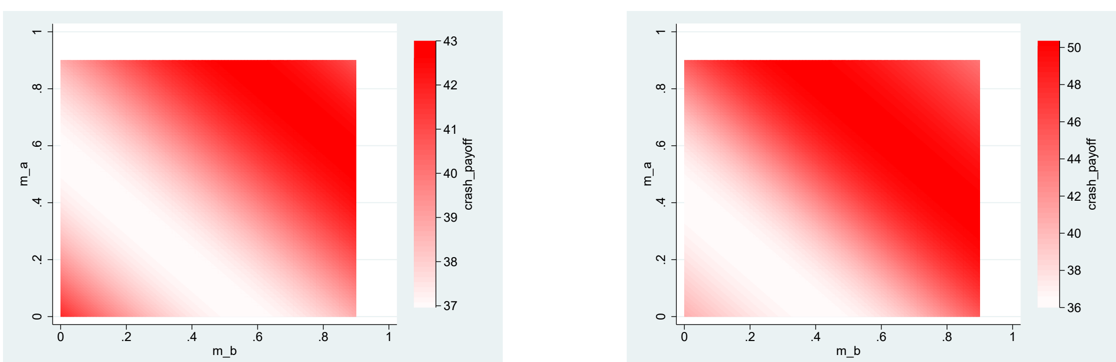
Figure 10: Officer empirical payoffs, observed monitoring, crash minimization treatment.



(a) Probabilistic treatment

(b) Expected Value treatment

Figure 11: Officer empirical payoffs, unobserved monitoring, revenue maximization treatment.



(a) Probabilistic treatment

(b) Expected Value treatment

Figure 12: Officer empirical payoffs, unobserved monitoring, crash minimization treatment.

C Instructions

The instructions for the Expected Value treatment are reproduced below, followed by the payoff guide provided to subjects.

Experimental Overview (V2)

You will be participating in an experiment on human decision making. There are two roles in the experiment: a Worker and a Supervisor. You will play one role for the first half of the experiment, and then the other role for the remainder of the experiment. Your computer screen indicates which role you will have in the first half of the experiment. Your computer screen will display useful information. Remember that the information on your computer screen is private. Please do not communicate with the other participants at any point during the experiment. If you have any questions, or need assistance of any kind, raise your hand and the experimenter will come and help you.

Please switch your phones off and place them away. The only materials you will need for this experiment are the computer and the calculator in front of you. We will also provide you with some paper if you wish to take notes.

This experiment will consist of multiple rounds. In each round there will be three tasks. The choice of the supervisor will affect the payoffs for each of the tasks. The worker will then decide which of the three tasks to implement. The points earned in each round will be added together and converted to USD at the end of the experiment at an exchange rate of 100 points = \$0.90. You will also receive, in addition, a \$5 show up fee.

Supervisor's decision

The supervisor will set the values of two variables, O_A and O_B. The supervisor will input their decisions using slider bars. To help fine tune your choice, you may click on the slider and then use the arrow keys to adjust your decision. While the Supervisor is making their decision, the Worker will see a wait screen. Each variable will take a value between 0 and 0.9, with increments of 0.01. The variables will affect the payoffs for each of task A, task B and task C as follows.

Effect on worker's payoffs

The worker will always earn 50 points if task C is implemented.

For task A, the worker's payoff will decrease as O_A increases. If $O_A = 0$, then the worker earns 90 points. If $O_A = 0.9$, the worker earns 0 points. The rate of decrease is linear, so that increasing O_A by 0.1 reduces the worker's payoff by 10 points. Equivalently, the formula is given by $W_A = 90 - 100O_A$, where W_A is the points earned by the worker.

For task B, the worker's payoff will decrease as O_B increases. If $O_B = 0$, then the worker earns 90 points. If $O_B = 0.9$, the worker earns 0 points. The rate of decrease is linear, so that increasing O_B by 0.1 reduces the worker's payoff by 10 points. Equivalently, the formula is given by $W_B = 90 - 100O_B$, where W_B is the points earned by the worker.

You may also view the supplemental payoff guide that was given to you as a visual representation of the payoffs.

Effect on supervisor's payoffs: Payment scheme 1

There are two payment schemes that will be used for the supervisor.

In payment scheme 1, increases in O_A will increase the supervisor's payoff for task A, but decrease their payoff for tasks B and C. Increases in O_B will increase the supervisor's payoff for task B, but decrease their payoff for tasks A and C. The formulas are given by:

$$S_A = 20 + 80O_A - 20O_B,$$

$$S_B = 20 - 20O_A + 80O_B$$

and

$$S_C = 20 - 20O_A - 20O_B$$

where S_A, S_B and S_C are the points earned by supervisor in each task.

Note that if O_A and O_B are each increased by the same amount, then the supervisor's payoff for task A and B increases, and their payoff for task C decreases.

You may also view the supplemental payoff guide that was given to you as a visual representation of the payoffs.

Effect on supervisor's payoffs: Payment scheme 2

In payment scheme 2, increases in either O_A or O_B will decrease the supervisor's payoff for tasks A, B and C with the payoff for task C always being larger than either tasks A or B.

$$S_A = 40 - 20O_A - 20O_B,$$

$$S_B = 40 - 20O_A - 20O_B$$

and

$$S_C = 80 - 20O_A - 20O_B$$

where S_A, S_B and S_C are the points earned by supervisor in each task.

You may also view the supplemental payoff guide that was given to you as a visual representation of the payoffs.

A picture of the Supervisor's decision screen is shown in figure 1.

The Worker's decision

In each round the Worker will choose either Task A, Task B, or Task C using a drop down menu. While the worker is making their decision, the supervisor will see a wait screen. The worker will only be able to see their payoffs, and not the supervisors payoffs, when making their decision (figure 2).

Information schemes

There will be three information schemes. The information scheme will affect what the worker can see when making their decision:

1. The Worker can see the exact payoffs of all outcomes at the time they make their decision.
2. The Worker can see only a range of possible payoffs, as described below.

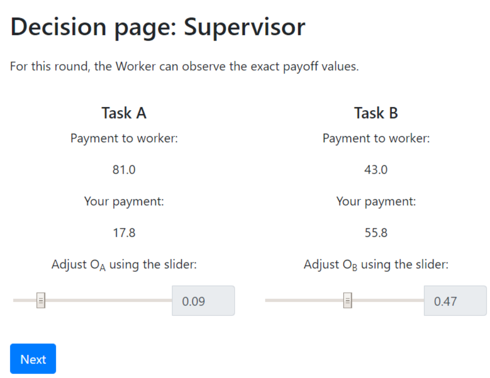


Figure 1: The Supervisor's decision screen

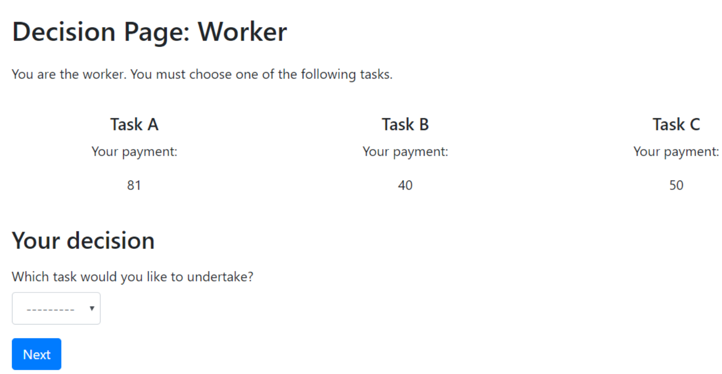


Figure 2: The Supervisor's decision screen

3. The Supervisor can decide whether the information scheme is number 1 or number 2.

In information scheme 2, the worker observes a range of possible payoffs for tasks A and B. The range will be presented as [min, max], where min is the smallest possible payoff and max is the largest possible payoff. The range shown will be the same for task A and task B, but the true payoffs may differ between task A and task B. **The sum of the true payoffs for task A and task B will always equal the sum of the minimum possible payoff plus the maximum possible payoff.**

The size of the range shown will depend on the sum of $O_A + O_B$. The supplemental payoff guide that was given to you shows how the range varies with O_A and O_B.

To illustrate an example, figure 3 shows the supervisor's screen under information scheme 2. The supervisor can see the exact payoff that the worker would receive, as well as the range of possible payoffs that will be shown to the worker. Note that the worker's payoff for task A, plus the payoff for task B, equals the sum of the minimum and maximum possible payoffs. Figure 4 shows the workers screen for the same round.

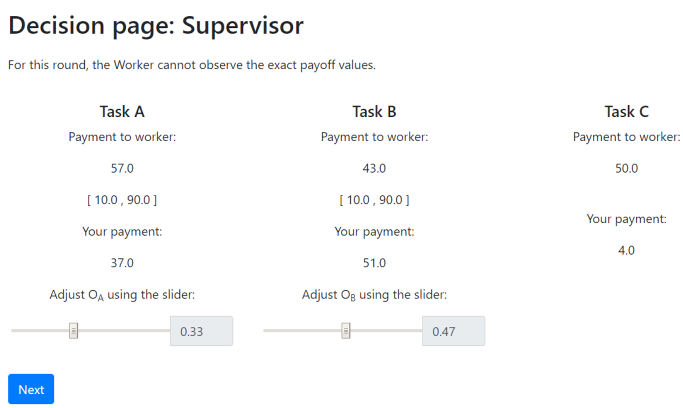


Figure 3: The Supervisor's decision screen

Rounds

There will be a total of 48 rounds. Each round you will be randomly and anonymously matched with another person in the room. You will maintain the same role (i.e. worker or supervisor) for

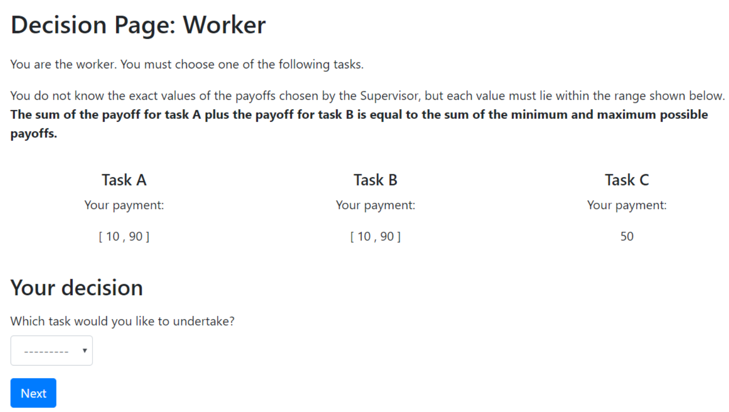


Figure 4: The Supervisor's decision screen

the first 24 rounds, and then switch to the other role for the next 24 rounds.

The first 12 rounds will be conducted using Payoff Scheme 1. Of these 12 rounds, the first 4 will use Information Structure 2, rounds 5-8 will use Information Structure 1, and rounds 9-12 will use Information Structure 3.

Rounds 13-24 will be conducted using Payoff Scheme 2. Of these 12 rounds, rounds 13-16 will use Information Structure 2, rounds 17-20 will use Information Structure 1, and rounds 21-24 will use Information Structure 3.

Rounds 25-36 will be conducted using Payoff Scheme 1. Of these 12 rounds, rounds 25-28 will use Information Structure 2, rounds 29-32 will use Information Structure 1, and rounds 33-36 will use Information Structure 3.

Rounds 37-48 will be conducted using Payoff Scheme 2. Of these 12 rounds, rounds 37-40 will use Information Structure 2, rounds 41-44 will use Information Structure 1, and rounds 45-48 will use Information Structure 3.

Feedback

At the end of each round, you will receive feedback on the round. The feedback for the supervisor will show the choice made by the worker and the payoffs of both parties. The feedback for the worker will include only the worker's payoff.

Note on earnings

Your total earnings will be the sum of your earnings in each round. It is possible to earn negative points in some rounds. In the unlikely event that someone has a negative points total after 48 rounds then their earnings will be set to 0 points.

Demographic survey

At the end of the experiment there will be a brief demographic survey. Please fill the survey in accurately. Once you have completed the survey your total earnings will be displayed. You should then sit quietly until an experimenter arrives at your terminal.

Summary

- In each round the Supervisor will select values for O_A and O_B.
- In each round the Worker will select one task; either A, B or C.
- In some rounds the Worker will be able to see their exact payoffs, in other rounds they will observe only a range of possible payoffs.
- The task chosen by the Worker will be implemented.
- Points will be summed across all rounds, and converted to dollars at the end of the experiment.
- Each round you will be randomly re-matched with another player in the room.

Supervisor Payoff Guide -- Scheme 1

Payoff for Task A		O_B									
		0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
O_A	0	20	18	16	14	12	10	8	6	4	2
	0.1	28	26	24	22	20	18	16	14	12	10
	0.2	36	34	32	30	28	26	24	22	20	18
	0.3	44	42	40	38	36	34	32	30	28	26
	0.4	52	50	48	46	44	42	40	38	36	34
	0.5	60	58	56	54	52	50	48	46	44	42
	0.6	68	66	64	62	60	58	56	54	52	50
	0.7	76	74	72	70	68	66	64	62	60	58
	0.8	84	82	80	78	76	74	72	70	68	66
	0.9	92	90	88	86	84	82	80	78	76	74

Payoff for Task B		O_B									
		0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
O_A	0	20	28	36	44	52	60	68	76	84	92
	0.1	18	26	34	42	50	58	66	74	82	90
	0.2	16	24	32	40	48	56	64	72	80	88
	0.3	14	22	30	38	46	54	62	70	78	86
	0.4	12	20	28	36	44	52	60	68	76	84
	0.5	10	18	26	34	42	50	58	66	74	82
	0.6	8	16	24	32	40	48	56	64	72	80
	0.7	6	14	22	30	38	46	54	62	70	78
	0.8	4	12	20	28	36	44	52	60	68	76
	0.9	2	10	18	26	34	42	50	58	66	74

Payoff for Task C		O_B									
		0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
O_A	0	20	18	16	14	12	10	8	6	4	2
	0.1	18	16	14	12	10	8	6	4	2	0
	0.2	16	14	12	10	8	6	4	2	0	-2
	0.3	14	12	10	8	6	4	2	0	-2	-4
	0.4	12	10	8	6	4	2	0	-2	-4	-6
	0.5	10	8	6	4	2	0	-2	-4	-6	-8
	0.6	8	6	4	2	0	-2	-4	-6	-8	-10
	0.7	6	4	2	0	-2	-4	-6	-8	-10	-12
	0.8	4	2	0	-2	-4	-6	-8	-10	-12	-14
	0.9	2	0	-2	-4	-6	-8	-10	-12	-14	-16

Supervisor Payoff Guide -- Scheme 2

Payoff for Task A					**O_B**					
O_A	**0**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
0	40	38	36	34	32	30	28	26	24	22
0.1	38	36	34	32	30	28	26	24	22	20
0.2	36	34	32	30	28	26	24	22	20	18
0.3	34	32	30	28	26	24	22	20	18	16
0.4	32	30	28	26	24	22	20	18	16	14
0.5	30	28	26	24	22	20	18	16	14	12
0.6	28	26	24	22	20	18	16	14	12	10
0.7	26	24	22	20	18	16	14	12	10	8
0.8	24	22	20	18	16	14	12	10	8	6
0.9	22	20	18	16	14	12	10	8	6	4

Payoff for Task B					**O_B**					
O_A	**0**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
0	40	38	36	34	32	30	28	26	24	22
0.1	38	36	34	32	30	28	26	24	22	20
0.2	36	34	32	30	28	26	24	22	20	18
0.3	34	32	30	28	26	24	22	20	18	16
0.4	32	30	28	26	24	22	20	18	16	14
0.5	30	28	26	24	22	20	18	16	14	12
0.6	28	26	24	22	20	18	16	14	12	10
0.7	26	24	22	20	18	16	14	12	10	8
0.8	24	22	20	18	16	14	12	10	8	6
0.9	22	20	18	16	14	12	10	8	6	4

Payoff for Task C					**O_B**					
O_A	**0**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
0	80	78	76	74	72	70	68	66	64	62
0.1	78	76	74	72	70	68	66	64	62	60
0.2	76	74	72	70	68	66	64	62	60	58
0.3	74	72	70	68	66	64	62	60	58	56
0.4	72	70	68	66	64	62	60	58	56	54
0.5	70	68	66	64	62	60	58	56	54	52
0.6	68	66	64	62	60	58	56	54	52	50
0.7	66	64	62	60	58	56	54	52	50	48
0.8	64	62	60	58	56	54	52	50	48	46
0.9	62	60	58	56	54	52	50	48	46	44

Worker Payoff Guide -- exact payoffs

Payoff for Task A

O_A \ O_B	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0	90	90	90	90	90	90	90	90	90	90
0.1	80	80	80	80	80	80	80	80	80	80
0.2	70	70	70	70	70	70	70	70	70	70
0.3	60	60	60	60	60	60	60	60	60	60
0.4	50	50	50	50	50	50	50	50	50	50
0.5	40	40	40	40	40	40	40	40	40	40
0.6	30	30	30	30	30	30	30	30	30	30
0.7	20	20	20	20	20	20	20	20	20	20
0.8	10	10	10	10	10	10	10	10	10	10
0.9	0	0	0	0	0	0	0	0	0	0

Payoff for Task B

O_A \ O_B	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0	90	80	70	60	50	40	30	20	10	0
0.1	90	80	70	60	50	40	30	20	10	0
0.2	90	80	70	60	50	40	30	20	10	0
0.3	90	80	70	60	50	40	30	20	10	0
0.4	90	80	70	60	50	40	30	20	10	0
0.5	90	80	70	60	50	40	30	20	10	0
0.6	90	80	70	60	50	40	30	20	10	0
0.7	90	80	70	60	50	40	30	20	10	0
0.8	90	80	70	60	50	40	30	20	10	0
0.9	90	80	70	60	50	40	30	20	10	0

Payoff for Task C

O_A \ O_B	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0	50	50	50	50	50	50	50	50	50	50
0.1	50	50	50	50	50	50	50	50	50	50
0.2	50	50	50	50	50	50	50	50	50	50
0.3	50	50	50	50	50	50	50	50	50	50
0.4	50	50	50	50	50	50	50	50	50	50
0.5	50	50	50	50	50	50	50	50	50	50
0.6	50	50	50	50	50	50	50	50	50	50
0.7	50	50	50	50	50	50	50	50	50	50
0.8	50	50	50	50	50	50	50	50	50	50
0.9	50	50	50	50	50	50	50	50	50	50

Worker Payoff Guide -- range

Range for Task A

O_A \ O_B	**0**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
0	[90,90]	[80,90]	[70,90]	[60,90]	[50,90]	[40,90]	[30,90]	[20,90]	[10,90]	[0,90]
0.1	[80,90]	[70,90]	[60,90]	[50,90]	[40,90]	[30,90]	[20,90]	[10,90]	[0,90]	[0,80]
0.2	[70,90]	[60,90]	[50,90]	[40,90]	[30,90]	[20,90]	[10,90]	[0,90]	[0,80]	[0,70]
0.3	[60,90]	[50,90]	[40,90]	[30,90]	[20,90]	[10,90]	[0,90]	[0,80]	[0,70]	[0,60]
0.4	[50,90]	[40,90]	[30,90]	[20,90]	[10,90]	[0,90]	[0,80]	[0,70]	[0,60]	[0,50]
0.5	[40,90]	[30,90]	[20,90]	[10,90]	[0,90]	[0,80]	[0,70]	[0,60]	[0,50]	[0,40]
0.6	[30,90]	[20,90]	[10,90]	[0,90]	[0,80]	[0,70]	[0,60]	[0,50]	[0,40]	[0,30]
0.7	[20,90]	[10,90]	[0,90]	[0,80]	[0,70]	[0,60]	[0,50]	[0,40]	[0,30]	[0,20]
0.8	[10,90]	[0,90]	[0,80]	[0,70]	[0,60]	[0,50]	[0,40]	[0,30]	[0,20]	[0,10]
0.9	[0,90]	[0,80]	[0,70]	[0,60]	[0,50]	[0,40]	[0,30]	[0,20]	[0,10]	[0,0]

Range for Task B

O_A \ O_B	**0**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
0	[90,90]	[80,90]	[70,90]	[60,90]	[50,90]	[40,90]	[30,90]	[20,90]	[10,90]	[0,90]
0.1	[80,90]	[70,90]	[60,90]	[50,90]	[40,90]	[30,90]	[20,90]	[10,90]	[0,90]	[0,80]
0.2	[70,90]	[60,90]	[50,90]	[40,90]	[30,90]	[20,90]	[10,90]	[0,90]	[0,80]	[0,70]
0.3	[60,90]	[50,90]	[40,90]	[30,90]	[20,90]	[10,90]	[0,90]	[0,80]	[0,70]	[0,60]
0.4	[50,90]	[40,90]	[30,90]	[20,90]	[10,90]	[0,90]	[0,80]	[0,70]	[0,60]	[0,50]
0.5	[40,90]	[30,90]	[20,90]	[10,90]	[0,90]	[0,80]	[0,70]	[0,60]	[0,50]	[0,40]
0.6	[30,90]	[20,90]	[10,90]	[0,90]	[0,80]	[0,70]	[0,60]	[0,50]	[0,40]	[0,30]
0.7	[20,90]	[10,90]	[0,90]	[0,80]	[0,70]	[0,60]	[0,50]	[0,40]	[0,30]	[0,20]
0.8	[10,90]	[0,90]	[0,80]	[0,70]	[0,60]	[0,50]	[0,40]	[0,30]	[0,20]	[0,10]
0.9	[0,90]	[0,80]	[0,70]	[0,60]	[0,50]	[0,40]	[0,30]	[0,20]	[0,10]	[0,0]

Payoff for Task C

O_A \ O_B	**0**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
0	50	50	50	50	50	50	50	50	50	50
0.1	50	50	50	50	50	50	50	50	50	50
0.2	50	50	50	50	50	50	50	50	50	50
0.3	50	50	50	50	50	50	50	50	50	50
0.4	50	50	50	50	50	50	50	50	50	50
0.5	50	50	50	50	50	50	50	50	50	50
0.6	50	50	50	50	50	50	50	50	50	50
0.7	50	50	50	50	50	50	50	50	50	50
0.8	50	50	50	50	50	50	50	50	50	50
0.9	50	50	50	50	50	50	50	50	50	50

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