

Economic and Intrinsic Motivations for Dishonesty: An Experimental Study

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Abstract

We study the role of economic versus intrinsic motivations for dishonesty in two different experimental tasks. In the theft task, participants have the opportunity to steal real physical money, by taking more than they have actually earned in the task. In the reporting task, we use a production task with self-reporting of accidents to study the fraudulent provision of information by individuals. Reporting was compulsory for some participants, but only voluntary for others. We find the incidence of dishonesty varies significantly across both the tasks and the type of reporting, demonstrating that intrinsic motivations can often override economic incentives.

Keywords: theft, deception, experiment, individual decision making, self-reporting, enforcement, intrinsic motivation

JEL Codes: C91, K42

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1. Introduction

Honest communication is an important part of many economic transactions. Examples include claims about insurance, product quality and labelling, and workplace theft and shirking. Honesty is also an important part of the regulatory framework with self-reporting being the cornerstone of enforcement of environmental and occupational safety and health regulations, among others. Nevertheless Mazar and Ariely (2006) claim that dishonesty is rife in all levels of U.S. society, and they provide evidence of the high financial costs to society of this pervasive dishonesty. This is also true in other countries, for example, fraud has been identified as the “most expensive crime category in Australia” (Lindley and Smith, 2011, p.5).

The Oxford English Dictionary defines dishonesty as a “disposition to deceive, defraud, or steal”.¹ Dishonesty therefore encompasses a broad range of acts from providing false information to more direct forms of theft such as physically stealing money and equipment. Dishonesty can be perpetrated against individuals (e.g. phishing scams, credit card fraud), businesses (e.g. employee theft and misuse of leave entitlements, false insurance claims), and government organisations (e.g. fraudulent social security claims, misuse of corporate credit cards).

The rational economic model (Becker, 1968) assumes that people are dishonest whenever it is financially advantageous to do so. To deter such acts therefore requires an increase in the financial disincentives such as the likelihood of detection and the amount of punishment when caught. At the other end of the spectrum to the rational economic actor, is someone who is always moral and never dishonest regardless of the financial incentive to do

¹ Online version March 2011. <<http://www.oed.com:80/Entry/54501>>; accessed 04 April 2011.

so.² Evidence suggests however that most people fall in-between these two extremes, being influenced by both economic incentives (e.g. Grogger, 1991) and intrinsic motivations which could include both moral and social considerations (e.g. Hurkens and Kartik, 2009).³ Indeed the behavioral approach to law and economics (Garoupa, 2003; McAdams and Ulen, 2008) has long challenged the standard neoclassical approach observing that “people exhibit bounded rationality, bounded self-interest, and bounded willpower” (Jolls et al., 1998, p.1471). Of particular relevance for our work are the role of bounded self-interest and the influence of social norms.

Our aim is to investigate the role of economic versus intrinsic motivations in promoting honest behavior. We use economic experiments to study two broad categories of dishonesty varying both the economic and potential intrinsic motivations across the tasks. In the *theft* task, subjects have the opportunity to steal real physical money, by taking more than they have actually earned in a mathematical task. This task corresponds to the more direct types of dishonesty such as employees stealing petty cash or equipment (e.g. computers or mobile phones), identity and credit card theft, and taking money from an “honesty” box or roadside stand. In the *reporting* task, we use a production task with self-reporting of accidents to study the fraudulent provision of information by individuals, either via actual lying or through withholding of relevant information. This reflects the potential for dishonesty in many areas such as social security claims, insurance claims, workplace expense claims, income tax returns, and financial reporting. All subjects participated in both types of

² Since our interest is in dishonesty associated with financial gain, this spectrum omits situations where it may be “moral” to lie (so-called “white lies”) to avoid hurting others. Additionally some people may get pleasure from lying (so-called “pathological liars”) but this should only be a small part of the population and not affect our results due to randomization of participants across treatments.

³ Intrinsic motivations have also been referred to as internal rewards (Mazar and Ariely, 2006) or moral rules (Shavell, 2002). For a survey of the literature on the role of intrinsic motivation in contexts other than dishonesty, see Fehr and Falk (2002). Benabou and Tirole (2003, 2006) provide a theoretical analysis.

tasks, however to explore how the type of reporting influences dishonesty, in the reporting task some participants faced compulsory reporting while for others it was voluntary.

Our approach is different to the existing experimental economics literature on dishonesty, which has exclusively used two-player communication games (Gneezy, 2005; Sánchez-Pagés and Vorsatz, 2007, 2009; Dreber and Johannesson, 2008; Hurkens and Kartik, 2009; Lundquist et al., 2009; Innes and Mitra, 2009). By using an individual decision-making context instead, we avoid potential confounds from social preferences and strategic behavior.⁴ The context is also closer to the types of “white collar” crimes we are interested in studying where the party being lied to or harmed by the dishonesty may be somewhat distant from, and possibly unknown to, the decision maker. In addition, in contrast to the literature, our design allows us to observe dishonesty in two distinct tasks hence improving our understanding of economic and intrinsic motivations in different situations. Our results may inform policymakers on how to deter dishonest acts, while also leading to a deeper understanding of economic decision-making in general.

Self-reporting is a common feature of many enforcement regimes, particularly for regulatory compliance. Under many regulations, firms must submit regular compliance reports to the enforcement agency. For example, occupational safety and health regulation requires annual reporting of workplace injuries and illnesses, with more prompt reporting required in the case of serious events. Under the Clean Water Act’s National Pollutant Discharge Elimination System, major point sources must submit monthly reports of their compliance with permit limits. It is claimed that self-reporting will both improve compliance

⁴ Hurkens and Kartik (2009) suggest that Gneezy’s (2005) results on the effect of incentives may be influenced by changes in social preferences. A second difficulty is whether the receiver believes the message sent to them, and whether senders anticipate this receiver scepticism. In this case, some messages will be strategic, further complicating interpretation of the results.

(i.e. safety and the environment in the above examples) and reduce enforcement costs (EPA, 1999, 2000). These benefits depend, in part, upon truthful reporting.⁵

More generally, self-reporting of crimes and violations is encouraged by offering lower penalties for those who voluntarily report offenses. The U.S. Federal Sentencing Guidelines Manual (USSC, 2010, §5K2.16), for example, allows penalty reductions in the case of voluntary disclosure of an offense that “was unlikely to have been discovered otherwise”, while the Department of Justice’s, Corporate Leniency Policy, reduces penalties for firms which voluntarily disclose antitrust violations.

Not all reporting regimes are the same, however. For example, as mentioned earlier, there are some environmental regulations with regular reporting requirements. On the other hand, many regulations contain no such requirements; instead, firms may be offered incentives to voluntarily disclose any violations that do occur (e.g. the EPA’s audit policy).⁶ One way to think about this difference is as compulsory versus voluntary reporting. Reporting by firms’ on corporate social responsibility is another example. Although reporting of this kind is voluntary in most countries, there are some arguments for it to be made compulsory (Overland, 2007). Theoretically, there should be no difference between compulsory and voluntary reporting, as long as the economic incentives coincide. Nevertheless, there seems a distinct difference between failing to voluntarily submit a report (an act of omission) and telling an outright lie (knowingly submitting a false report). We conjecture that this difference will matter, and that aversion to blatant lies could lead to greater reporting of violations in the compulsory self-reporting treatment than in the voluntary one. On the other hand, being compelled to submit a report could lead to crowding

⁵ Self-reporting is an important feature in other settings too. For example, the Australian medical pay-for-performance scheme for General Practitioners, relies on self-reports of the number of patients seen, tests completed, etc (Scott et al, 2009).

⁶ Firms are only eligible for the EPA’s audit policy if they disclose violations that would not otherwise be uncovered via mandatory monitoring (EPA, 2000).

out of the intrinsic motivation to voluntarily cooperate and therefore we may observe less reporting in the compulsory case.

We find that the incidence of dishonesty varies significantly across both the tasks and the treatments. While only one-third of subjects cheated in the theft task, of those who cheated, one-quarter took the maximum amount they could. In contrast, almost everyone was dishonest in the reporting task, with only 4% of subjects always reporting an accident, and around half of the subjects never reporting. Reporting of accidents was more frequent with compulsory reporting (20% of accidents) than with voluntary reporting (10% of accidents). We observe only a weak association of dishonesty across the two tasks, with those who cheated in the theft task less likely to report in the reporting task. Interestingly however, we find that those who cheated in the theft task were more likely to be influenced by the compulsory treatment, as we observe higher reporting levels in compulsory as compared to the voluntary treatment for this group.

Our results suggest that non-monetary factors such as intrinsic motivation can indeed be an important determinant of dishonesty, and can vary considerably with the type of dishonesty involved. In addition, the use of voluntary self-reporting could lead to less satisfactory compliance outcomes. Deterring dishonesty thus requires attention to both intrinsic motivation as well as economic incentives.

The paper proceeds as follows. Section 2 explains the experimental design and procedure. Section 3 presents the results, while Section 4 discusses explanations for our findings. Section 5 concludes by describing the broader policy implications and suggesting avenues for future research.

2. Experimental Design

2.1 Overview

All of the subjects participated in three different experimental tasks. The first task, the lottery task, involved a series of ten choices between two lotteries, designed to measure risk preferences. Second, they participated in the theft task, where they paid themselves according to their performance in the task, hence having an opportunity for dishonest gain. The third task was the reporting task, which involved a production decision, where production had a potential to cause an “accident” for which they could be penalised. Around half of the subjects experienced voluntary self-reporting, while the other half experienced compulsory self-reporting. That is, we use a between-subjects design for these scenarios.⁷ Following completion of the reporting task, subjects answered a few demographic questions, plus some questions about attitudes towards lying and their previous participation in dishonest behavior.⁸

Since our aim was to study different types of dishonesty and, in particular, to understand the role of economic versus intrinsic factors, we deliberately chose two very different tasks with a potential conflict between economic and intrinsic motivations. We discuss these design aspects and our research questions more fully in Section 2.4.

The lottery and reporting tasks were computerized using the software z-Tree (Fischbacher, 2007) while the theft task was conducted manually using pen and paper.⁹ We discuss the reasons for these design choices in the following section. In addition to a \$5 show-up fee, subjects were paid their earnings from one decision in the lottery task, and one round in the reporting task. Subjects paid themselves in the theft task. The experiment lasted

⁷ We only compare voluntary versus compulsory reporting in the reporting task and not in the theft task. This is because in the theft task, dishonesty takes the form of taking too much money, and while we do ask subjects to report the number of matrices they solved, false reporting here has no consequences. In the reporting task, false reporting is the only possible dishonest action.

⁸ These additional questions were adapted from Lundquist et al. (2009) and Nagin and Pogarsky (2003).

⁹ A copy of the experimental instructions is included in the appendix.

around 90 minutes, with average earnings being AU\$43 (approximately US \$40), of which \$7 on average came from the theft task.

The decision and round for payment in the lottery and reporting tasks respectively were selected at the end of the entire experiment, using physical randomization devices to enhance credibility. Specifically, a ten-sided dice (rolled twice) was used for the lottery task, and a bingo cage, containing the balls 1 to 30, for the reporting task. The experiments were held at the University of Queensland during 2010. There were 115 participants, with 59 participants in the voluntary treatment and 56 in the compulsory treatment. The participants were predominantly undergraduate students (90%), with around 60% being business and economics students.

2.2 The Theft Task

To measure dishonesty in an individual task we used the matrix task, a math test of sorts, devised by researchers in the marketing discipline (Mazar et al., 2008). Subjects were given a sheet of 20 matrices, where each matrix contains 12 three-digit numbers (e.g. 5.34). The task was to find a pair of numbers in each matrix that add up exactly to 10.00. A sample matrix is shown in Figure 1. The task is made more difficult because not all of the matrices have solutions, of which subjects were made aware. Subjects were given five minutes to solve as many matrices as possible and were told that they would earn \$1 for each correctly solved matrix.

After the five minutes was over, subjects were instructed to count the number of correctly solved matrices and record this number on their collection slip.¹⁰ We then collected the folded matrix sheets and placed them in a sealed envelope, emphasizing that we would

¹⁰ The collection slip read “I got _____ Boxes, which translates to \$ _____ (= \$1.00 per Box)”.

not open the envelope until everyone had left the lab. On each desk, we had already placed a small envelope containing 20 \$1 coins, and subjects were instructed to pay themselves using this money. Afterwards they were told to put their completed collection slip with any remaining money in the small envelope, seal the envelope, and leave it on their desk. Again, we emphasized that the envelope would not be collected until after everyone had left the lab.

We chose to do this part of the experiment manually to enhance credibility – specifically to convince subjects that their decisions were anonymous. We wanted to assure the subjects that we would not be deceiving them and checking up on them while they were still in the lab. We thought this would be more believable to subjects than if the task was computerised and the data immediately accessible to us.¹¹ We hoped to measure a baseline level of the dishonesty for each individual from this task, where the probability of detection was effectively zero. We cannot, of course, be certain that individuals viewed it this way however, we had to make some compromise to be able to collect individual level data on cheating.

From previous results in the literature, we believed that \$1 per matrix would be sufficient (i.e. salient) to encourage cheating. In addition, not all of the matrices had solutions, leaving considerable scope for cheating even for top performers. The total incentive to cheat ranged from \$10, for anyone who solved all ten matrices that had solutions, to \$20 for someone who solved none.

Mazar et al. (2008) note several advantages of using this task to measure dishonesty. First, subjects consider that the outcome is predominantly effort related rather than IQ related. Second, subjects can readily evaluate their own performance – they know if they

¹¹ This is also the reason why we do not control for order effects in the experiment. The participants may have been less likely to believe that they would not be checked up on if the theft task had followed the reporting task. In addition, we believed that experimenter demand effects could be stronger.

have the correct answer or not. This means that any dishonest gain can be reasonably interpreted as cheating, rather than as a genuine mistake. Note however, that in contrast to Mazar et al. (2008) who used a “recycle” treatment where subjects took their matrix sheet home with them, we collect individual level data and so are able to measure the degree (distribution) of dishonesty, as well as its existence.

2.3 The Reporting Task

In this task, subjects made a “production decision” where production activities can potentially cause an “accident”, but the probability of an accident can be lowered for a cost. There are 30 rounds of such decisions. In the first ten rounds, subjects face a conventional enforcement (CE) regime where there is some probability of being inspected (r) and a fine (f) for discovered accidents. These ten rounds allow subjects to learn about the task, and provide a baseline for comparison with their later decisions.¹²

In the following 20 rounds, subjects face one of two possible reporting regimes – either voluntary reporting or compulsory reporting. In voluntary, following an accident, subjects are given the binary choice: “Would you like to report the accident?” with response options of “Yes” or “No”. If they do report, then they pay a self-reporting fine (s), otherwise they face CE. In contrast, with compulsory, subjects *must* fill out a report, and are asked “What would you like to say in the report?” The response options are “I had an accident” or “I did not have an accident”. As with voluntary, a reported accident is assessed a fine of s , otherwise they face CE.¹³

¹² Prior to facing each regime subjects answered a series of quiz questions designed to assess their understanding of the instructions, and then participated in two practice rounds.

¹³ With compulsory reporting, subjects must file a report even if they do *not* have an accident however we did not permit them to file a false report in this case (i.e. reporting an accident when one did not occur). In the voluntary case, it did not make sense to ask the reporting question if no accident occurred.

The reporting task was framed using the language described here – i.e. we used the terminology of accident, inspection, and fine. While this is a deviation from the standard practice of using neutral language in economics experiments, since our aim was to understand attitudes towards dishonesty in a real-life situation of compliance with taxes, environmental, and health and safety programs, we used context specific language.

2.3.1 Theoretical Framework

The motivation behind the reporting task is the theoretical models of self-reporting developed by Malik (1993), Heyes (1996), and Innes (2001a), among others.¹⁴ We follow here the model and notation of Innes (2001a). Risk neutral firms choose an accident prevention effort or level of care (x), which determines the probability of an accident occurring: $p(x)$, where $p'(x) < 0$ and $p''(x) > 0$. Let F be the *expected* penalty if an accident occurs, which takes on the value s if the firm self-reports and rf if not. The firm's problem is to choose x to minimize its expected costs, $x + p(x)F \Rightarrow x^*(F)$. Assuming that in the case of indifference, firms will self-report, self-reporting occurs when $s \leq rf$. The enforcement agency will set $s = rf$ to economise on enforcement costs, without any loss of deterrence (because $x^*(s) = x^*(rf)$). A major advantage of self-reporting is the reduction in enforcement expenditures that arises because the agency need no longer inspect firms that self-report accidents. Instead, only non-reporters have to be inspected with probability r .¹⁵ This advantage however relies on truthful reporting of accidents.

A practical implementation of self-reporting however requires a strict incentive for self-reporting (i.e. $s < rf$), leading to a weakening of deterrence, and hence more accidents.

¹⁴ These models contrast with the more general crime model of Kaplow and Shavell (1994), who assume that potential offenders are heterogeneous and have a binary choice to commit a harmful act or not.

¹⁵ Additional potential benefits of self-reporting are earlier clean-up in the case of persistent pollutants (Heyes 1996), guaranteed remediation of damages (Innes 1999), and reduced firm expenditures on avoiding apprehension (Innes 2001b).

As a result, while self-reporting may generate enforcement economies, this may come at the expense of environmental protection, a concern expressed in the self-reporting literature (e.g. Innes, 2001a; Murphy and Stranlund, 2008).

Note that this model does not distinguish between compulsory and voluntary self-reporting, because theoretically there is no difference between the two (provided the monetary incentives are identical).¹⁶ Nevertheless, there are a number of behavioral reasons why we may observe a difference in the lab. For example, compulsory reporting may crowd out any intrinsic motivation to voluntarily report, leading to less reporting in the compulsory treatment. However an opposing force like aversion to lying can arise in this treatment as subjects who chose not to report have to explicitly send a false report (i.e. lie) and we may find this aversion increases reporting in the compulsory treatment. Thus, whether we observe higher levels of reporting in the compulsory treatment or in the voluntary treatment depends on the relative magnitude of these effects and cannot be stated a priori.

2.3.2 Lab Implementation

To implement this in the lab we made several adjustments to simplify the cognitive burden on subjects. The first was to have subjects directly choose the probability of an accident (p), rather than effort (x) itself. The second was to limit the number of choices available to subjects. The latter also enhanced salience, as it increased the difference between two options, and was acceptable because our main interest was in the reporting stage. We translated the problem into an equivalent maximization problem by including a fixed amount of revenue (R) each period. Then the problem becomes to choose p to maximize $R - x(p) -$

¹⁶ Few theoretical models make any distinction between voluntary and compulsory self-reporting, with most implicitly assuming the voluntary case, although this is rarely made explicit. An exception is Malik (1993) who models compulsory self-reporting, in which case a failure to report is interpreted as a violation.

pF .¹⁷ Subjects were told $R - x(p)$ which is described as their “trading profit”. The five options available to the subjects are shown in Table 1.

The production and enforcement parameters were held fixed across all rounds of both treatments. Random draws were conducted each round to determine whether an accident or inspection occurred.¹⁸ Subjects received their earnings from one randomly selected round from the 30 rounds.

Given our interest in studying the incentive (aversion) to lie we chose the enforcement parameters such that $s > rf$. In this case, all except the very risk averse will have a monetary incentive to lie therefore creating a potential conflict with one’s “moral incentive”. Alternatively, if we had set $s < rf$ then there would be no monetary gain from lying and all but the most risk loving would self-report.¹⁹ Hence in this case it would be difficult to isolate the impact of the monetary incentive from the moral incentive on dishonest behavior as both these effects would lead to less lying. A further constraint on our choices was the need to avoid bankruptcy in the experiment, which limits the upside for our fines and hence potential loss from being caught out.

The probability of inspection (r) was set at $\frac{1}{2}$ and the fine for a violation discovered via conventional enforcement (f) was set at \$15. The fine for a self-reported violation (s) was set at \$12. The expected fine under conventional enforcement is then \$7.50, so self-reporting

¹⁷ An interior solution requires that $x'(p) < 0$, while the second order condition for a maximum requires that $x''(p) > 0$. This is equivalent to an increasing (i.e. convex) cost of reducing accidents. The actual functions used were $R = 33.21$ and $x(p) = \frac{2}{0.05+0.3p}$.

¹⁸ To increasing comparability across sessions, we made the random draw prior to any sessions, and used the same random numbers in each session.

¹⁹ Note that an optimal self-reporting regime (from the theoretical literature) would set $s \leq rf$. Arguably however, the case of $s > rf$ is more realistic as we do not observe full (voluntary) self-reporting.

yields a fine that is higher by \$4.50, which should provide a sufficient monetary incentive to lie.²⁰

2.4. Research Questions

Since the purpose of our experiment was to study the influence of economic and intrinsic motivations on dishonest behavior, we deliberately chose two very different tasks, which allowed us considerable potential to vary these motivations across the tasks. Table 2 summarizes these differences between the theft and reporting tasks.

Consider first the economic or monetary incentive to be dishonest in each task. In the reporting task, the (expected) gain from dishonesty was constant at \$4.50 for all rounds and subjects. In contrast, the gain from dishonesty in the theft task was at least \$10, and usually higher, being inversely related to the number of matrices solved. Therefore, the economic incentive to be dishonest was higher in the theft task than in the reporting task. This difference was reinforced by the fact that the probability of detection was zero in the theft task, but positive in the reporting task.

The two tasks also differed in non-monetary aspects that may influence intrinsic motivations to be honest. In the reporting task, a number of factors may lead subjects to interpret the task as a “game” with fewer moral implications than in the theft task. These factors include the explicit statement of the probability of detection and punishment if caught, the computerization of the task making dishonesty at “arm’s length” from oneself compared with using real, physical money, and the use of “house money” rather than “earned money”.

²⁰ The *ex post* incentive to lie is obviously smaller than \$4.50 for the risk averse, and larger for risk lovers. Specifically for the risk averse, the gain from lying will decrease with the degree of risk preference and with the trading profit (lower accident probability). Using the constant relative risk aversion utility function with a coefficient of 0.5, we can compute the following *ex post gain from lying = certainty equivalent of lying – certain payoff if self report*. This gain ranges from \$3.77 when $p=100\%$, to \$3.41 when $p=40\%$, and \$1.06 when $p=20\%$ (the latter is rarely chosen).

The determinants of the final outcome also differ across tasks, for example, in the theft task the number of correct matrices solved depends solely on subjects' effort. In the reporting task however if an accident occurred, it could be due to less care taken by subjects' or due to bad luck. This perception of bad luck could lessen the moral imperative to be honest in the reporting task. Overall then, the intrinsic incentives predict that dishonesty should be more prevalent in the reporting task than in the theft task, while economic incentives predict the opposite. We investigate which of these incentives has a stronger influence on dishonesty.

We also consider the strength of different types of intrinsic motivations within the reporting task itself. Across the voluntary and compulsory treatments, the economic incentive to report is held constant, but differences in reporting could occur due to the explicit lie required with compulsory reporting or the crowding out of voluntary motivations to report.

3. Results

We present our results in the next three subsections. In each of the subsections, we begin with a discussion of descriptive aggregate statistics to highlight the effect of different tasks on dishonesty. We then report results from parametric regression models that can help disentangle the effects of different factors on dishonesty. Summary statistics for the variables discussed below are provided in Table 3a.

3.1 Are individuals dishonest?

Our experimental design allows us to measure dishonest behavior in different ways in the theft and reporting tasks. In the theft task, subjects are asked to pay themselves depending on how many of the 20 matrices they solved and leave the rest of the money in an envelope on the table. Given that subjects can readily determine their performance in the

matrix task, we can interpret dishonesty as a situation in which subjects take more money than they are entitled to. On average subjects correctly solved 4.5 matrices during the five minutes, with only two able to solve all ten, and six solving none. The average dishonest gain was \$2.43, far below the maximum possible gain, which was \$15.48 on average and ranged from \$10 to \$20.²¹

We construct three related but distinct measures of dishonesty using the above interpretation. Our first measure is a binary indicator of dishonesty – i.e. do they take more money than they are entitled to? Using this variable, we find that 33% of the subjects were dishonest in this task. That is, two-thirds of the subjects were willing to give up a gain of \$10 or more to be honest. The second measure is the magnitude of dishonesty, which is illustrated in Figure 2 where the size of the circles reflects the number of observations at each point. The larger circles along the diagonal show that most people are honest, with points above the diagonal representing subjects who took more than they had earned. Of the 33% who lie (38 subjects), 37% keep one dollar more than they should, 42% keep ten dollars or more than they should, and 18% of the subjects keep fifteen dollars or more. The figure also suggests that the dishonest were not just those who did poorly in the matrix task. The third measure is the percentage of maximum dishonest gain that is possible for each subject, given how many answers they get right in the task. We find that of those who are dishonest, 26% take the maximum amount possible.²²

²¹ The maximum possible dishonest gain equals \$20 minus the number of correctly solved matrices in Task 2.

²² We also constructed a measure of false reporting by comparing the number of matrices each subject reported solving with the actual number correctly solved. Honest subjects always correctly reported. Of the 38 dishonest subjects, six correctly reported the number of matrices they solved (but still took more money) while the other 32 overstated this. Interestingly of these 32, 27 filed a report to match what they took. It is also interesting to note that the majority of the dishonest (74%) also falsified their matrix sheet by ticking extra “Got It” boxes to match what they reported. Note however, there were no consequences to false reporting in this task as the probability of detection was implied to be zero.

In the reporting task, we can observe whether subjects reported an accident. Hence dishonesty in this task can be defined as the proportion of times they did not report an accident over 20 periods.²³ Only 15% of the accidents that occurred were reported, with 47% of the subjects never reporting an accident and only 4% of the subjects always reporting accidents.

A comparison of individual behavior across the theft and reporting tasks, indicates that those who were dishonest in the theft task reported less often in the reporting task (pairwise correlation; p value = 0.06). Investigating the correlation separately for the two types of reporting, we find that this correlation is only significant in the voluntary treatment (p value = 0.02) but not in the compulsory treatment (p value = 0.65), providing some early indicators of treatment differences.

Responses to our survey questionnaire give an alternative measure of participation in dishonest behavior and attitudes to lying. As reported in Table 3b, around one-third of respondents indicated they have lied in an application at least once, and a similar number have lied when selling something. About one-quarter of respondents reported having driven with an excess blood alcohol level, while only 8% have knowingly lied on their income-tax return. With regards to attitudes to lying, about half of the subjects agreed (either slightly or strongly) that “there are no degrees of lying”, and about three-quarters indicated responsiveness to the monetary incentives associated with lying.²⁴ Correlations between these survey responses and the measures of dishonesty in the theft and reporting tasks are reported in the final two columns of Table 3b. Attitudes towards lying show a significant correlation with behavior in the reporting task.

²³ With voluntary reporting, failing to report an accident is not technically dishonest, more like withholding of information; nevertheless, for ease of exposition we use the terminology “dishonesty” for failing to report an accident in either scenario.

²⁴ In contrast, only around 20% of the subjects in Lundquist et al. (2009) believed there are no degrees of lying, and only 4% of these strongly agreed.

Table 4 reports results from a parametric, multivariate regression, which can be useful to isolate the impact of different factors on dishonest behavior. The dependent variable is the magnitude of dishonesty in the theft task, and this is modelled using a Hurdle model, which is a generalization of the Tobit model in which the decision to cheat or not and the magnitude of the dishonesty are determined by different stochastic processes. The hurdle is crossed if an individual decides to cheat and take more than he is entitled to.²⁵ The independent variables include the proportion of accidents reported in the reporting task, and demographic variables like gender, age, and attitudes towards risk. To explain the decision to be dishonest or not, we also include the maximum possible gain from dishonesty as an explanatory variable to investigate how individuals respond to the economic incentives for dishonesty.

We present two different model specifications in Table 4. In our first specification (columns 1a and 1b), we only include the monetary incentive to be dishonest and decisions made in the reporting task as explanatory variables. In this specification, we want to explore if non-reporting subjects were also dishonest in the matrix task, both of which are incentivised tasks with monetary implications. In the second specification (columns 2a and 2b), we include the impact of demographic variables on dishonesty.

In both of the models, the decision to be dishonest is positively related to the potential gain associated with dishonesty, supporting the economic model. Each extra dollar of possible dishonest gain increased the likelihood of dishonesty by 3-4% on average. Our results suggest that the propensity to cheat in the theft task is approximately 40% lower for subjects who reported accidents more often in the reporting task however, this is not always

²⁵ The likelihood function for the hurdle model is given by the product of two separate likelihoods. First, the likelihood that a subject will cheat, captured by a standard Probit model, and second, the conditional likelihood of an individual cheating by a certain amount, estimated by using a truncated linear regression. The two parts of the hurdle-model are estimated separately (McDowell, 2003).

statistically significant. Dishonesty is more likely among men, older, and locally born subjects; but demographic variables explain little of the magnitude of dishonesty.^{26,27}

3.2 Does the proportion of reports submitted in the Reporting Task vary by treatment?

Figure 3a shows that the proportion of individuals who report accidents over the 20 periods is higher in the compulsory treatment as compared to the voluntary treatment. This difference is highest in the middle periods: periods 16-25 (9% in voluntary and 20% in compulsory). Figure 3b shows the distribution of the proportion of reports by treatment. The graph shows the mass shifts to the right (i.e. more reporting) when reporting is compulsory. It is also worth noting that all of the five subjects who always reported were in the compulsory treatment. Figure 4a presents the average proportion of reports submitted in the two treatments, averaged across periods and individuals. As is clear from this graph, the bar for the compulsory treatment is double that for the voluntary treatment (20% versus 10%, p value: 0.09, using a non-parametric ranksum test). This difference is also higher for subjects who were dishonest in the theft task (5% versus 18%, p value = 0.005), as illustrated in Figure 4b. For subjects who were not dishonest, there is no statistical difference in the proportion of reports across treatments though reporting is higher as a proportion of accidents in the compulsory treatment (13% versus 21%).

Table 5 reports estimates from a probit regression, which models the decision of the subject to report an accident. It accounts for individual specific heterogeneity by clustering

²⁶ The result that men were more likely to steal money than women, even after controlling for any differences in risk preference, is consistent with both Nagin and Pogarsky (2003) and Friesen (2009) who find women are significantly more compliant than men.

²⁷ These results are robust to different econometric specifications used, for example, a Tobit model of dishonesty gives similar results. Similarly, using the absolute amount of money taken (rather than a percentage of the maximum possible) in the second stage does not change our conclusions.

standard errors at the subject level.²⁸ We present different specifications to examine if reporting of an accident can be explained by the treatment subjects are in, the period in which they make their decision, the magnitude of dishonesty in the theft task, and demographic characteristics. The coefficient for the treatment variable is always statistically significant, with subjects in the compulsory treatment having about a 10% higher probability of reporting accidents in all specifications.

Subjects who cheated by a larger magnitude in the theft task, have a lower probability of reporting accidents, indicating some consistency of dishonest behavior across tasks.²⁹ In terms of demographics, older subjects have a higher probability of reporting, while those who answered more quiz questions correctly reported less often.³⁰ To control for the monetary incentive to report, across subjects, we include measures of the accident probability chosen, a measure of risk aversion, and the interaction between the two. Recall that the experimental parameters were set so that it was financially advantageous to *not* report, with the expected gain from *not* reporting equal to \$4.50. For risk averse subjects, the certainty equivalent of this gain from dishonesty decreases with their choice of accident probability and the degree of risk aversion. Nevertheless, this gain from dishonesty remains positive for all except the extremely risk averse who choose a low accident probability.³¹ Since the monetary incentive

²⁸ We also estimated random effects probit models for these specifications and the results are practically identical to the ones reported.

²⁹ Alternative definitions of dishonesty, for example, the percentage of maximum dishonest gain or a binary measure of dishonesty, give similar results.

³⁰ As noted earlier, quiz questions were used to assess subjects' understanding of the experimental instructions.

³¹ See footnote 20 for details.

is for everyone to be dishonest, there should be no relationship between these variables and the probability of reporting, and the results in Table 5 are consistent with this.³²

Overall, our results show that behavior is significantly different in the two treatments, with the propensity to report more in compulsory than in the voluntary treatment. We find this difference despite identical monetary incentives in the two treatments, indicating the important role of intrinsic incentives. We found that the lie aversion effect seems to be stronger than the crowding out of intrinsic motivation effect.

3.3 Additional Results

It is interesting to examine if individuals choose different levels of care (i.e., do they pay less to avoid an accident) across the voluntary and compulsory reporting treatments.³³ Figure 5 presents the five options individuals choose from in the two treatments, averaged over periods. We observe that in the compulsory treatment, options 2 (accident probability=80%) and 3 (accident probability =60%) were chosen more often than in the voluntary treatment, while options 1 (accident probability=100%) and 4 (accident probability =40%) were selected less often. Except for the change in option 3, these all reflect significant changes (p values < 0.02, rank sum test). Overall, these suggest a tendency away from the

³² Using a continuous measure of risk preference yields similar results. Including separate dummy variables for each level of ProbChoice and interacting these with Risk Averse showed that those choosing an accident probability of 40% (i.e. ProbChoice=4) had a 9% lower probability of reporting an accident, but other results remain unchanged. It is likely that subjects who have already paid a moderate amount to avoid an accident may feel that having an accident was unfair and may feel entitled to not report it. Note that the lowest accident probability (20%) was only rarely chosen.

³³ We also examined if individuals choose different levels of care in the self reporting regime than in the conventional enforcement regime. As explained above, in our experiment we set $s > rf$ to introduce a conflict between the monetary and moral incentives for self-reporting. Therefore, deterrence should not be weakened, but may instead be strengthened if subjects opt for self-reporting. Our results (based on a sign rank test and an ordered probit regression) suggest that, contrary to the economic incentives, introducing self-reporting actually weakened deterrence. This somewhat puzzling finding could have significant implications for regulators, as it suggests that self-reporting may affect behavior in a way that goes beyond changes in the economic incentives. On the other hand, our results may be potentially confounded by an order effect, as the self-reporting periods always followed the conventional enforcement periods, and this in itself might explain the results. Nevertheless, this is a worthy topic for further study.

extreme left of the distribution when we shift from voluntary to compulsory reporting. When we average across all five of the options, we find that the average level of care chosen in the compulsory treatment is marginally higher than the average level chosen in the voluntary treatment (2.32 versus 2.27).³⁴ This provides evidence that voluntary reporting can create incentives for individuals to exert less care and may need to be considered in field implementations of these regulatory policies.

4. Discussion

In this section, we discuss the possible reasons for our results, beginning first by summarizing our main findings, and then discussing explanations for the differences across tasks, followed by differences across treatments. Broader policy implications are in the next section.

4.1 Summary of Main Results

Our first main result pertains to the incidence of dishonesty and its magnitude. In the theft task, we found that around one-third of subjects took more money than they were entitled to, and within this around one-quarter took the maximum they could. On the other hand, a substantial majority of subjects (two-thirds) were completely honest in this task. This was despite no chance of detection, and for some of them who solved only one or two matrices, a potential dishonest gain of nearly \$20. Overall, we found that the average level of dishonesty was far below the maximum possible, a result consistent with Mazar et al. (2008). Since we collect individual level data on dishonesty, we can examine the reasons for this, and

³⁴ To examine this further, we estimate ordered probit models, where the dependent variable is the probability of choosing options 1 to 5. The estimates are consistent with the non-parametric results such that in the compulsory treatment, subjects choose higher levels of care, but this is not statistically significant. These results are not reported in the paper to save space.

conclude that rather than almost everyone being dishonest to a small degree, only a few are dishonest, some to a very large degree.³⁵

We reach a different conclusion from the reporting task, where we found that nearly everyone was dishonest at some point during the task. This is most striking in the compulsory treatment, where not reporting an accident required an outright lie. Only five subjects (9%) always reported an accident in this treatment. Thus dishonesty occurs much more frequently in the reporting task than in the theft task. In addition, we found that reporting occurred significantly more often in the compulsory reporting regime than with voluntary reporting, a result contrary to theoretical predictions.

On the other hand, correlations of dishonest behavior across the two tasks were relatively weak, and not always robust to changes in model specification. While a weak correlation is true in aggregate, the correlations were different in the two treatments, with a strong correlation in the voluntary treatment and a weaker relationship in the compulsory treatment, where the aversion to telling an outright lie caused a number of those who were dishonest in the theft task to report accidents.

4.2 Differences between the Tasks

The two tasks tell a different story about the incidence of dishonesty in the population, with dishonesty being endemic in the reporting task. Indeed, recall that we deliberately chose two very different tasks to measure dishonesty, with Table 2 summarizing the differences between the tasks. We found that dishonesty was less prevalent in the theft task despite the economic incentives being considerably larger than in the reporting task. Also, recall that our results (Section 3.1) showed that subjects were indeed sensitive to

³⁵ Recall that Mazar et al. (2008) did not have individual level data, because the matrix sheets were “recycled” (i.e. taken home) by participants. From the distribution of responses in a separate, general knowledge, task they concluded that most people cheat a little bit.

changes in the economic incentives in the theft task. Explanations for these differences between tasks must therefore turn to intrinsic incentives.

The fact that dishonesty increased after the introduction of explicit monetary *disincentives* in the reporting task, compared with the theft task with no explicit disincentives, is consistent with experimental findings in other settings that *explicit* penalties may crowd out intrinsic motivations and actually increase the very behavior they are trying to deter. For example, this has been observed in the context of common pool resources (Cardenas et al., 2000); corruption (Schulze and Frank, 2003); labor market gift exchange experiments (Fehr and Gächter, 2000); and fines for kindergarten pickups (Gneezy and Rustichini, 2000a). These researchers conjecture that this occurs because the nature of the (implicit) contract is changed by the introduction of monetary disincentives, which seems relevant here. In the theft task, with no explicit penalties given, subjects may rely on the general “social contract”, while in the reporting task, the specification of penalties may signal a different kind of contract, whereby “cheating” is acceptable as long as you are willing to pay the fine when caught.

There is also evidence that introducing monetary *rewards* for desired behavior can have perverse effects particularly if the rewards are only “small” (Frey and Oberholzer-Gee, 1997; Gneezy and Rustichini, 2000b). The implication in our setting is that you should only introduce enforcement if it is sufficiently large, to avoid it having a perverse effect. Mazar and Ariely (2006) also propose a non-monotonic relationship between economic incentives and dishonesty, resulting from an individuals’ need to maintain their self-concept as an honest person. They argue that small acts of dishonesty are easier to justify to oneself, generating an “activation threshold” level of dishonesty, below which the intrinsic rewards for honesty are not triggered and where dishonesty increases with economic incentives. However, once the threshold level is reached, dishonesty becomes unresponsive to changes in

economic rewards, until these rewards become sufficiently large to overwhelm intrinsic rewards, and once again, dishonesty increases with economic rewards. This “activation threshold” for intrinsic rewards can be moved, for example, the use of tokens instead of cash makes it easier to justify dishonesty to oneself, and may provide another explanation for why dishonesty was less frequent in the theft task, which involved real physical money.³⁶ Similarly, the perception that one has been unfairly affected by bad luck, as in the reporting task, could move this threshold, and justify dishonesty.

Overall, our results demonstrate that the type of dishonesty is an important determinant of behavior and that honesty is not a fixed character trait but rather influenced by the features of the situation. It also suggests that non-monetary factors matter along with traditional economic incentives.

4.3 Differences between Voluntary and Compulsory Reporting

In our experiment, we conjectured two intrinsic factors that might lead to a difference between reporting of accidents between the voluntary and compulsory regimes. First, we conjectured that compulsory reporting might create a crowding out effect: i.e., crowd out the intrinsic incentive to report that may exist in the voluntary reporting case, resulting in fewer reports of violations in the compulsory case than in the voluntary case.³⁷ Second, we conjectured that the aversion to lying would work in the opposite direction, with subjects being less willing to tell overt lies, and so reporting would be more frequent in the compulsory case. For example, Hurkens and Kartik (2009) found that people were less

³⁶ As noted earlier, the majority of those who were dishonest in the theft task tried to rationalise their lying by altering the matrix sheet to match their report, which provides evidence for the Mazar et al. (2008) theory about trying to maintain one’s self-concept as honest.

³⁷ Admittedly, the intrinsic motivation to voluntarily cooperate (report) is relatively weak both because of the lack of context (for example, saving the environment would be more likely to evoke moral feelings) and because it is not clear which other party is being harmed by the dishonest act (e.g. the “regulator” or experimenter). Yet previous experimental findings suggest that even in relatively neutral lab settings such effects can exist.

willing to tell “big” and “solemn” lies. Our results found that the aversion to lying effect was stronger than the crowding out effect.

An explanation for the aversion to lying can be found in the previously mentioned model of Mazar and Ariely (2006), where they argue that drawing attention to moral standards may lower the “activation threshold” for intrinsic rewards, making it harder to justify dishonesty to oneself. Applying this to our results might explain why dishonesty is more prevalent in the reporting task because it seems easier to justify to oneself a reporting mistake than outright stealing of money. Further, compulsory reporting makes lying harder to justify because, like a moral code, it draws attention to what you are doing.

A final explanation is related to status quo bias and the use of default options (Thaler and Sunstein, 2009). In both treatments, following an accident subjects had to select one of two options. However, with voluntary reporting subjects may interpret “not reporting” as the implicit default option and this potential inertia could lead to less reports being filed in the case of voluntary reporting.

5. Conclusion

Our results suggest that indeed we should be worried about dishonesty with almost everyone prone to dishonesty in certain situations. Dishonesty seems easier to justify to oneself, and so occurs more frequently, when the type of dishonesty is at “arm’s length” from the money being exchanged. Most “white collar” crimes, including regulatory compliance and filing false insurance claims, would fall into this category. Dishonesty is also more prevalent when the explicit disincentives crowd out intrinsic motives to be honest, this appears most likely when the monetary disincentives (or penalties) are relatively small, as is typically the case with much enforcement. These two factors do not bode well for regulatory enforcement.

As dishonesty is influenced by both the context and incentives in place, it suggests ways forward for enforcement agencies beyond simply increasing enforcement efforts. In particular, regulators should be cautious in using voluntary reporting instead of compulsory reporting, and this is even more so because those whose behavior changed the most with compulsory reporting were those who had been dishonest in the theft task. Anecdotally, the observation that compliance rates are considerably higher for major water dischargers than for toxic and hazardous waste regulation (Magat and Viscusi, 1990) is consistent with our conjecture, with the latter involving only voluntary reporting. More recently, Pfaff and Sanchiriro (2004) found that only relatively inconsequential violations are reported under the EPA's audit policy (voluntary reporting), compared with those uncovered with traditional enforcement procedures, and suggest that these could be "red herrings" to distract the agency from more substantial undisclosed violations.

However while the differences between tasks and treatments are clear, the explanations are less so. We find intrinsic motivations to be a significant factor influencing dishonesty, in many cases appearing to override economic incentives. Future work could focus on separating out the different explanations with a particular emphasis on when the introduction of explicit penalties crowds out the intrinsic incentives to be honest, and whether this reverses at sufficiently high penalty levels.

Table 1: Production Task Choices

Probability of Accident	Trading Profit
100%	27.50
80%	26.31
60%	24.51
40%	21.45
20%	15.03

Table 2: Differences between the Theft and Reporting Tasks

Type of incentive	Theft Task	Reporting Task	Prediction
<i>Economic</i>	No probability of detection or punishment	Explicit (known) probability of detection and fine	More dishonesty in the theft task.
	Monetary gain from dishonesty different across subjects (depending on their performance in the task), but minimum of \$10	Monetary gain from dishonesty was held constant across rounds and subjects at \$4.50 (expected value)	More dishonesty in the theft task.
<i>Intrinsic</i>	May rely on the “social contract”	Looks like a “game” situation so not viewed as “dishonesty” as such.	More dishonesty in the reporting task.
	Real, physical, cash	May be viewed as “tokens”	More dishonesty in the reporting task.
	Outcome determined by effort	Outcome determined by choice and luck	More dishonesty in the reporting task.

Table 3a: Summary Statistics

Variable	Task	Description	Mean	Std Dev	Min	Max
<i>Risk Averse</i>	Lottery	Switch to risky lottery after decision 5	0.77	0.42	0	1
<i>Correct Matrices</i>	Theft	Number of correctly solved matrices	4.52	2.56	0	10
<i>Dishonest</i>	Theft	Was subject dishonest or not	0.33	0.47	0	1
<i>Magnitude Theft Dishonesty</i>	Theft	Amount of extra money subjects keep	2.43	5.10	0	19
<i>Maximum Possible Theft Dishonesty</i>	Theft	Maximum dishonest gain possible	15.48	2.56	10	20
<i>% Max Dishonest</i>	Theft	Actual dishonest gain as % of maximum possible	0.15	0.32	0	1
<i>Period</i>	Reporting	Period of the reporting task	15.5	8.66	1	30
<i>Compulsory</i>	Reporting	Whether subject was in compulsory treatment	0.49	0.50	0	1
<i>Accident</i>	Reporting	Whether or not an accident occurred in a particular period	0.74	0.44	0	1
<i>Report</i>	Reporting	Whether an accident was reported or not in a particular period	0.15	0.36	0	1
<i>Proportion of accidents reported</i>	Reporting	Proportion of accidents that were reported	0.15	0.24	0	1
<i>ProbChoice</i>	Reporting	Accident probability option chosen (over 30 periods)	2.35	1.10	1	5
<i>ProbChoice100</i>	Reporting	Chose 100% accident probability (over 30 periods)	0.30	0.46	0	1
<i>ProbChoice80</i>	Reporting	Chose 80% accident probability (over 30 periods)	0.22	0.41	0	1
<i>ProbChoice60</i>	Reporting	Chose 60% accident probability (over 30 periods)	0.31	0.46	0	1
<i>ProbChoice40</i>	Reporting	Chose 40% accident probability (over 30 periods)	0.15	0.36	0	1
<i>ProbChoice20</i>	Reporting	Chose 20% accident probability (over 30 periods)	0.01	0.12	0	1
<i>Number correct quiz answers</i>	Reporting		7.17	1.09	2	8
<i>Total earnings</i>	n/a	Over all tasks	42.87	6.71	26.30	59.50
<i>Male</i>	n/a		0.61	0.49	0	1
<i>Business or Economics Major</i>	n/a		0.60	0.49	0	1
<i>Age</i>	n/a		19.45	2.35	17	33
<i>Born in Australia or NZ</i>	n/a		0.50	0.50	0	1

Table 3b: Responses to the Survey Questions

Question	Response Scale				Correlation with Extra Money Taken	Correlation with Prop. of Accidents Reported
	Strongly Disagree	Slightly Disagree	Slightly Agree	Strongly Agree		
I am more inclined to lie, the more I have to gain from the lie.	18%	20%	39%	23%	0.30***	-0.38***
I am less inclined to lie, the greater the risk of discovery	10	12	37	40	0.11	-0.19**
You either lie or you don't, there are no degrees of lying	23	23	23	30	-0.04	0.19**
	Never	Once	A Few Times	Many Times		
Have you ever lied in an application – in writing or in an interview – for example when applying for work, membership, school, or scholarships?	67%	14%	17%	2%	-0.01	-0.15
Have you ever lied when selling something?	66%	7%	21%	6%	0.04	-0.14
Have you ever consciously reported false information in your income-tax return?	93%	3%	3%	2%	0.10	-0.11
How many times have you received a speeding ticket?	85%	11%	2%	2%	0.07	0.04
How many times have you driven when you believe your blood alcohol content exceeded the legal limit?	75%	14%	10%	1%	0.13	0.04

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Hurdle Model of Dishonesty in the Theft Task

	(1a)	(1b)	(2a)	(2b)
	<i>Dishonest</i>	<i>% Max Dishonest</i>	<i>Dishonest</i>	<i>% Max Dishonest</i>
<i>Maximum dishonest gain possible</i>	0.035** (0.018)		0.037** (0.018)	
<i>Proportion of accidents reported</i>	-0.335 (0.213)	-0.650 (0.396)	-0.473** (0.239)	-0.641 (0.443)
<i>Male</i>			0.167* (0.089)	0.221 (0.159)
<i>Business or Economics Major</i>			0.011 (0.092)	0.029 (0.141)
<i>Age</i>			0.069*** (0.024)	0.014 (0.028)
<i>Risk averse</i>			-0.038 (0.110)	-0.006 (0.153)
<i>Number correct quiz answers</i>			0.014 (0.050)	0.012 (0.077)
<i>Born in Australia or NZ</i>			0.202** (0.102)	0.221 (0.165)
<i>N</i>	115	38	115	38
<i>Prob > Chi-squared^a</i>	0.0322		0.0073	
<i>Prob > F^b</i>		0.1095		0.3899

Dishonest is a binary measure of dishonesty in the theft task, *% Max Dishonest* is magnitude of dishonesty as a % of the maximum possible dishonest gain.

Marginal effects reported in the table for the probit regression, with standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

^a Result of Wald test of model significance; ^b Result of F-test of model significance.

Table 5: Probit Model of Reporting an Accident

	(1)	(2)	(3)
	<i>Report</i>	<i>Report</i>	<i>Report</i>
<i>Period</i>	-0.003** (0.001)	-0.004*** (0.001)	-0.004*** (0.001)
<i>Compulsory treatment</i>	0.096** (0.045)	0.089** (0.043)	0.081** (0.037)
<i>(Accident) Probability Choice</i>		-0.016 (0.024)	-0.019 (0.028)
<i>Risk averse</i>		0.027 (0.069)	0.026 (0.071)
<i>Prob Choice * Risk averse</i>		-0.014 (0.030)	-0.007 (0.032)
<i>Magnitude of dishonesty in theft task</i>		-0.010* (0.005)	-0.010* (0.005)
<i>Male</i>			0.018 (0.038)
<i>Age</i>			0.025*** (0.008)
<i>Business or Economics Major</i>			0.042 (0.035)
<i>Born in Australia or NZ</i>			0.070 (0.047)
<i>Number correct quiz answers</i>			-0.060*** (0.015)
<i>N</i>	1915	1915	1915
<i>Prob > Chi-squared^a</i>	0.0103	0.0007	0.0000

Marginal effects reported in the table; robust (clustered) standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

^a Result of Wald test of model significance.

Figure 1: Sample Matrix

3.91	0.82	3.75
1.11	1.69	7.94
3.28	2.52	6.25
9.81	6.09	2.46

Figure 2: Distribution of Magnitude of Dishonesty in the Theft Task

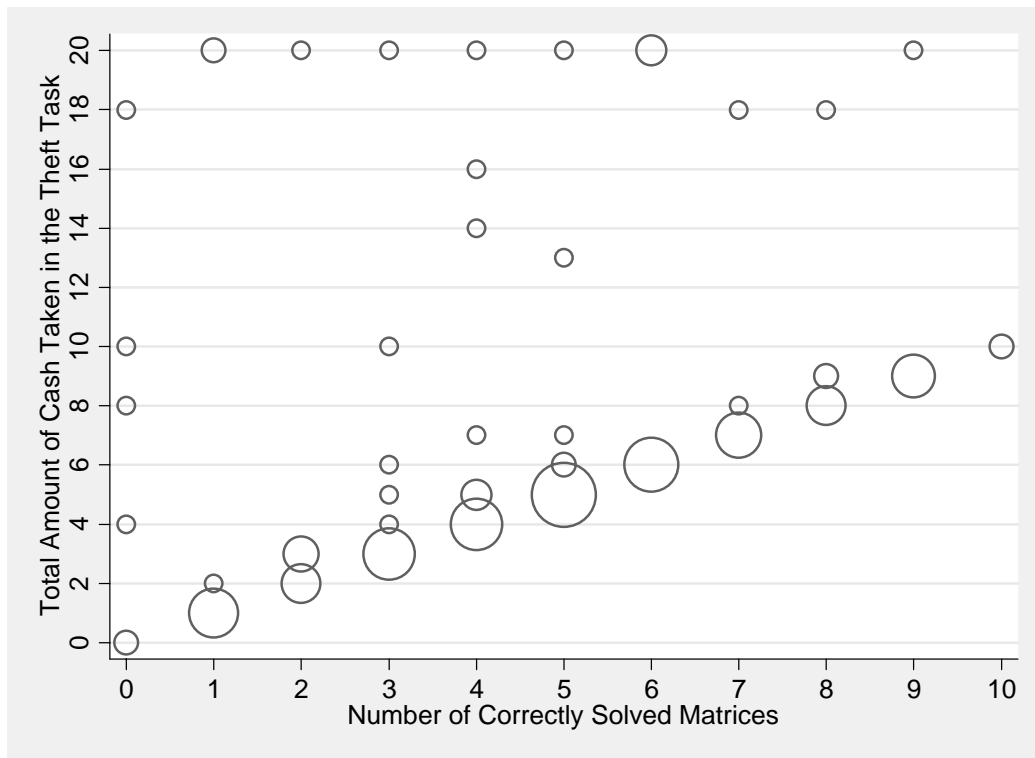


Figure 3a: Proportion of Individuals who Reported Accidents across Treatments

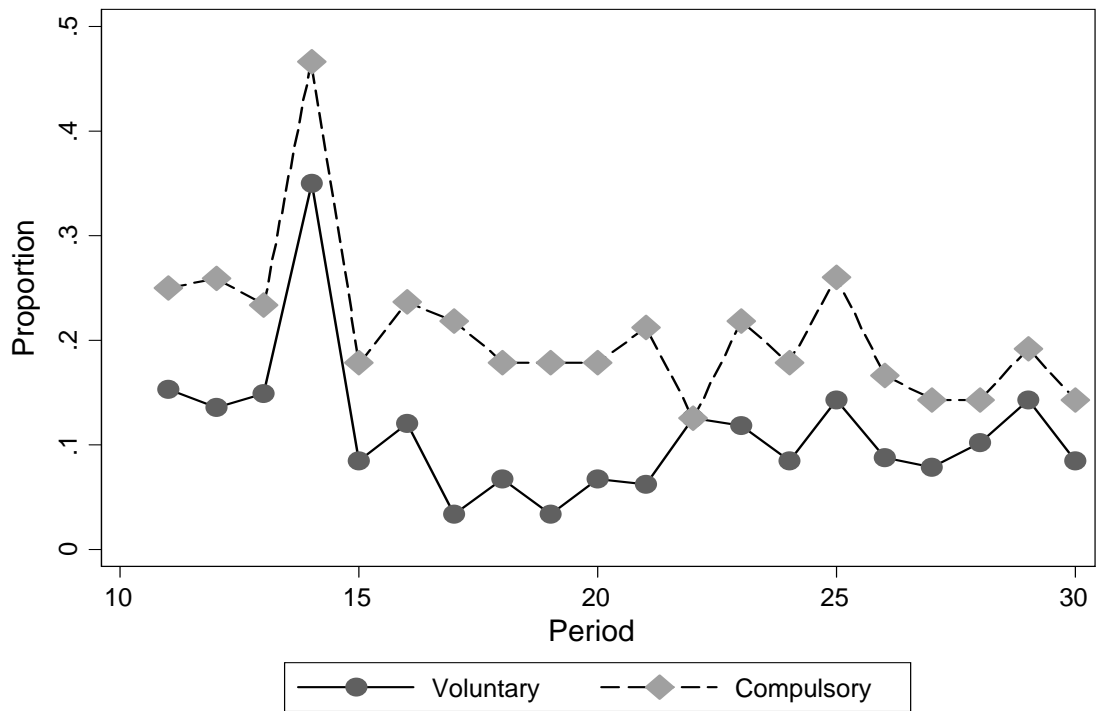


Figure 3b: Distribution of the Proportion of Accidents Reported by Treatment

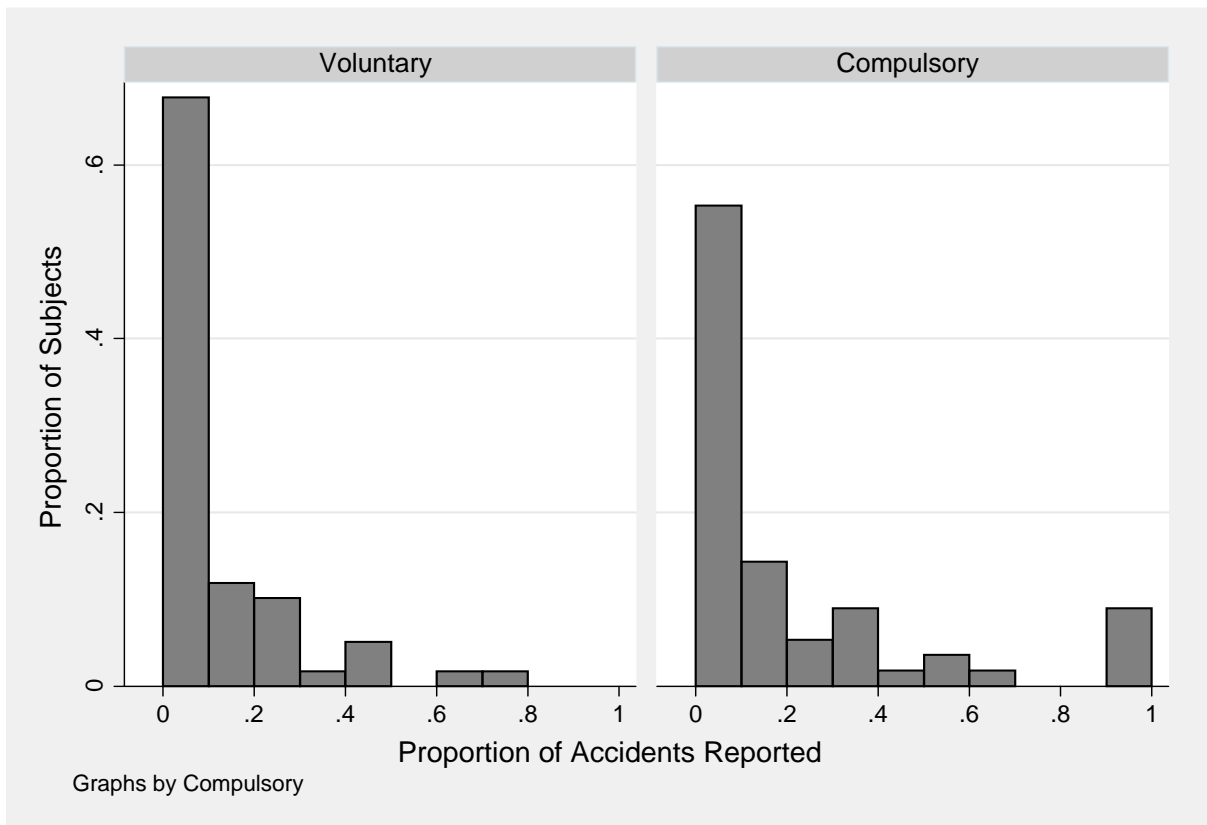


Figure 4a: Average Proportion of Accidents Reported by Treatment

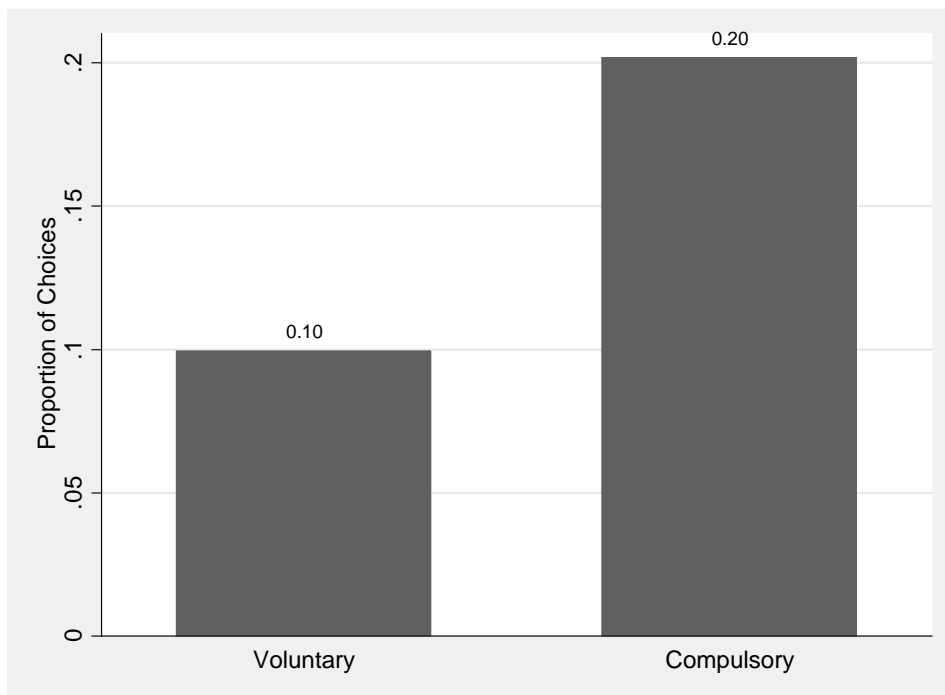


Figure 4b: Average Proportion of Accidents Reported by Dishonesty in the Theft Task and Treatment

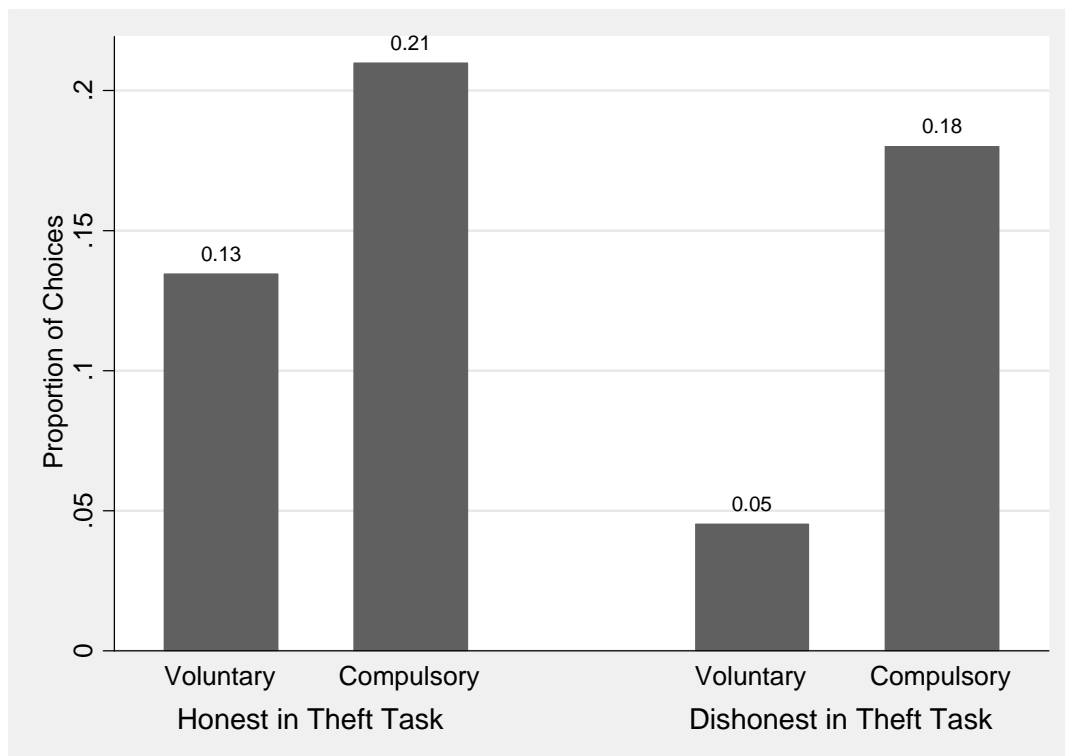
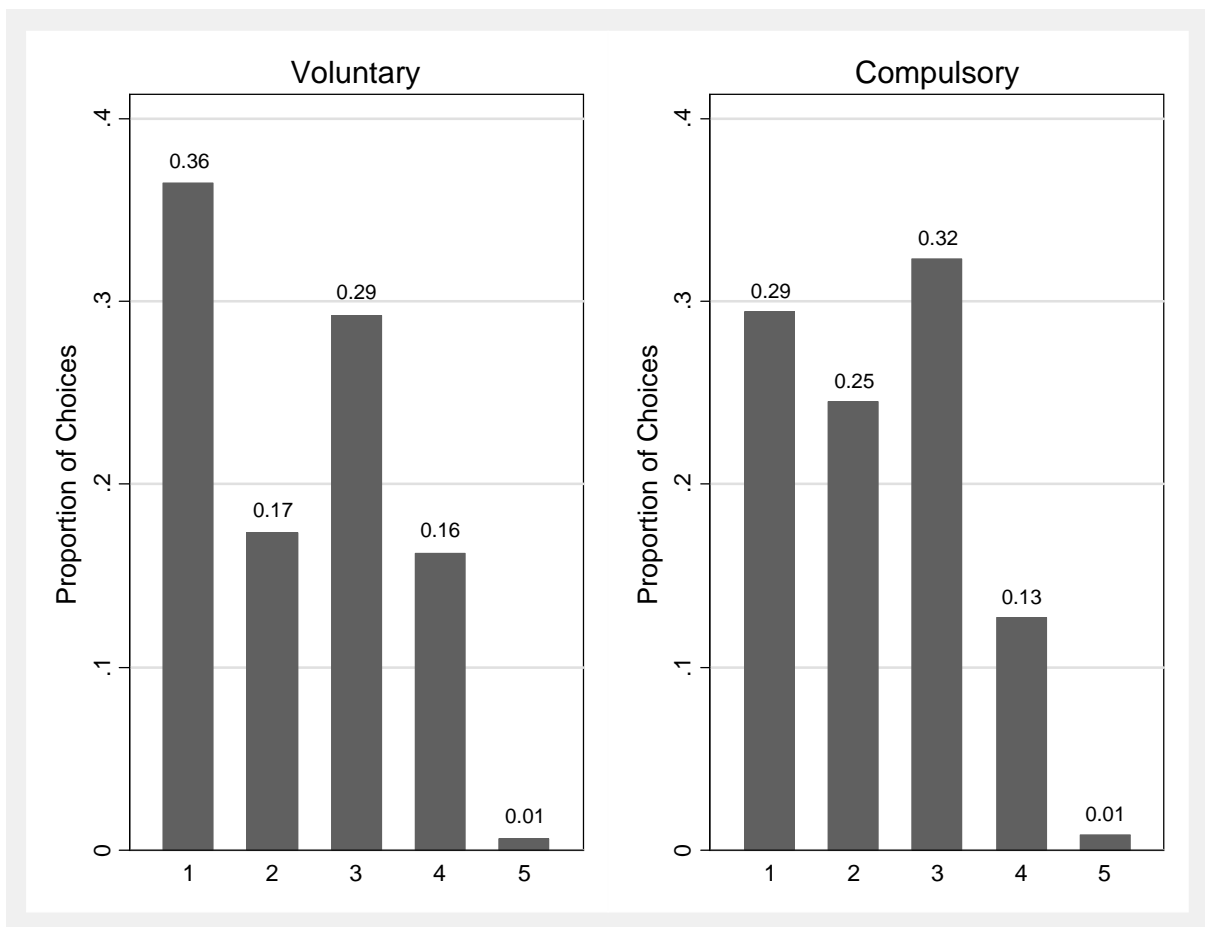


Figure 5: Choice of Probability of Accidents across Treatments



1: Accident probability = 100%; 2: Accident probability = 80%; 3: Accident probability = 60%; 4: Accident probability = 40%; 5: Accident probability = 20%

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Appendix: Experimental Instructions (Not for Publication)

Thank you for agreeing to take part in this study. Please read the following instructions carefully. A clear understanding of the instructions will help you make better decisions and increase your earnings.

The instructions which we have distributed to you are for your private information. Please do not communicate with the other participants during the experiment. Should you have any questions please ask us. Although there are many people participating in today's experiment, everyone is working independently. This means that your earnings are based entirely on your decisions and what others do has no effect on you.

At the end of the experiment we will give every participant 5 Australian Dollars in addition to the money that you will make in the experiment. You will participate in a number of tasks in this experiment and you will get information about each of these tasks one by one. Each task is independent and the decisions that you make in one task have no impact on your earnings in the other tasks.

All decisions that you make today are recorded only by an anonymous subject number and will only be used for research purposes. Your decisions will remain completely anonymous.

Task 1: Lottery Game

In this task, you will be asked to make a choice between two options - Option A or Option B – 10 times. The options differ in the following way:

OPTION A: pays \$7 in cash always.

OPTION B: has two possible payoffs, HIGH payoff = \$12 or LOW payoff = \$2

Whether Option B pays the HIGH or LOW payoff will be randomly determined in the following way:

At the end of the entire experiment, the experimenter will throw a ten-sided dice in front of you. The sides are numbered from 1 to 10 (the “0” face of the dice will serve as 10). If the number on the dice is associated with a HIGH payoff, then the payoff is \$12. If it is associated with the LOW payoff, then the payoff is \$2.

For example, you might be shown the following two options:

<p>OPTION A \$7 If the dice is 1 - 10</p>	<p>OPTION B \$2 - if the dice is 1 - 7 \$12 - if the dice is 8 - 10</p>
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In the above example, choosing OPTION A pays you \$7.00 no matter what the dice roll is. Choosing OPTION B will pay \$2.00 if the number rolled is 1, 2, 3, 4, 5, 6 or 7, and \$12.00 if the number rolled is 8, 9, or 10.

Actual Earnings in Task 1

This experiment will begin with your making choices between Option A and Option B on 10 different games (numbered Game 1 to Game 10, see the figure on the following page). Even though you will be asked to make a choice between Option A and Option B for 10 different games, your actual earnings in Task 1 will depend on your choice in only ONE of those games. At the end of the entire experiment the actual game that is played will be determined by rolling a ten-sided dice. The number rolled will be announced and then the dice will be rolled a second time to determine whether the payoff from Option B is HIGH or LOW.

For instance suppose the first time the experimenter rolls a dice, the number 5 comes up. This means that Game 5 will be used to determine your earnings for Task 1.

Next the experimenter will roll the dice again. If you chose Option A you will get \$7. If you chose Option B and the dice roll turns out to be 1,2,3,4 or 5 then you earn \$2 while if the dice roll turns out to be 6,7,8,9 or 10 then you get \$12.

Are there any questions?

Please proceed to Task 1.

In each of the 10 games below, please choose either Option A or Option B

Game 1	OPTION A \$7 If the dice is 1 - 10	OPTION B \$2 - if the dice is 1 - 9 \$12 - if the dice is 10	<input type="radio"/> OPTION A <input type="radio"/> OPTION B
Game 2	OPTION A \$7 If the dice is 1 - 10	OPTION B \$2 - if the dice is 1 - 8 \$12 - if the dice is 9 - 10	<input type="radio"/> OPTION A <input type="radio"/> OPTION B
Game 3	OPTION A \$7 If the dice is 1 - 10	OPTION B \$2 - if the dice is 1 - 7 \$12 - if the dice is 8 - 10	<input type="radio"/> OPTION A <input type="radio"/> OPTION B
Game 4	OPTION A \$7 If the dice is 1 - 10	OPTION B \$2 - if the dice is 1 - 6 \$12 - if the dice is 7 - 10	<input type="radio"/> OPTION A <input type="radio"/> OPTION B
Game 5	OPTION A \$7 If the dice is 1 - 10	OPTION B \$2 - if the dice is 1 - 5 \$12 - if the dice is 6 - 10	<input type="radio"/> OPTION A <input type="radio"/> OPTION B
Game 6	OPTION A \$7 If the dice is 1 - 10	OPTION B \$2 - if the dice is 1 - 4 \$12 - if the dice is 5 - 10	<input type="radio"/> OPTION A <input type="radio"/> OPTION B
Game 7	OPTION A \$7 If the dice is 1 - 10	OPTION B \$2 - if the dice is 1 - 3 \$12 - if the dice is 4 - 10	<input type="radio"/> OPTION A <input type="radio"/> OPTION B
Game 8	OPTION A \$7 If the dice is 1 - 10	OPTION B \$2 - if the dice is 1 - 2 \$12 - if the dice is 3 - 10	<input type="radio"/> OPTION A <input type="radio"/> OPTION B
Game 9	OPTION A \$7 If the dice is 1 - 10	OPTION B \$2 - if the dice is 1 \$12 - if the dice is 2 - 10	<input type="radio"/> OPTION A <input type="radio"/> OPTION B
Game 10	OPTION A \$7 If the dice is 1 - 10	OPTION B \$2 - \$12 - if the dice is 1 - 10	<input type="radio"/> OPTION A <input type="radio"/> OPTION B

Full-screen Snip

Once you have made all 10 choices please click on the OK button

OK

Task 2: Instructions

Please do not open the envelope. Wait for experimenter instructions!

In the large envelope on your desk you will find a sheet with 20 matrices like the one below:

Example		
3.91	0.82	3.75
1.11	1.69	7.94
3.28	2.52	6.25
9.81	6.09	2.46

In each matrix you should look for a unique set of numbers that **sum up exactly to 10**. In some matrices you may not have a solution.

When you find a set, circle the numbers, and mark the corresponding 'Got It' Box below, as in the example below:

Example		
3.91	0.82	3.75
1.11	1.69	7.94
3.28	2.52	6.25
9.81	6.09	2.46

Got it

For each matrix you solve, you will receive **\$1.00**. You have **5 minutes** for this task.

Once 5 minutes are up you have to do the following:

1. Count the number of correctly solved matrices and write down the number of correctly solved matrices on the green collection slip.
2. Fold your matrix sheet and place it in the envelope that we are going to bring to you. This envelope will remain sealed until after all participants have left the lab.
3. On your desk you will find a small envelope containing 20 \$1 coins. Now pay yourself with the money provided in the small envelope on your desk.
4. Fold the collection slip and put it into the envelope with the leftover money, seal the envelope, and leave it on the table. This will only be collected at the end of the experiment after all the subjects have left the lab.

All decisions that you make today are recorded only by an anonymous subject number and will only be used for research purposes. Your decisions will remain completely anonymous.

Task 3: Production Decision

In Task 3, you will make production decisions in 30 periods. This task has 2 parts and part 1 has 10 periods and part 2 has 20 periods. At the end of today's experiment we will randomly choose one of these periods using a bingo cage which contains balls numbered 1 to 30. You will receive your earnings from that chosen period.

Instructions for Part 1:

In this task you are responsible for making a production decision. When you produce, there is a chance that an accident will occur. Your production decision directly affects the probability of an accident. Reducing the probability of an accident is costly and will reduce your production earnings. Similarly increasing the probability of an accident will increase your production earnings.

You will receive your production earnings regardless of whether an accident occurs. However there is a chance that you will be inspected. If you are inspected and if an accident occurred, then you will incur a fine. The probability that you will be inspected is 50% and if an accident has occurred then you have to pay a fine of \$15.

The table below shows you the relationship between the probability of an accident and your production earnings. For example if you choose the probability of an accident to be 40%, then your production earnings are equal to \$21.45. If an accident occurs and you are inspected, you would have to pay a fine of \$15. Your earnings in this case would be $\$21.45 - \$15.00 = \$6.45$. This occurs 20% of the time ($0.4 * 0.5 = 20\%$). In the remaining 80% of the cases you would earn \$21.45.

Production decision

Please choose one of the following options:

- 100% accident probability and production earnings of \$27.50
- 80% accident probability and production earnings of \$26.30
- 60% accident probability and production earnings of \$24.50
- 40% accident probability and production earnings of \$21.45
- 20% accident probability and production earnings of \$15.05

You will pay a fine of \$15 if an accident occurs and if you are inspected. Otherwise you will not pay a fine and you will earn \$21.45.

Whether or not you have an accident will be determined by the computer in accordance with your chosen accident probability and is independent across periods. This means that whether or not you have an accident this period is not affected by what happened last period. Similarly whether you are inspected or not is also determined by the computer and is not affected by previous inspection outcomes.

You will participate in 2 practise periods before the actual task begins. The earnings that you obtain in the practice periods will not count towards your final earnings. The practice periods are intended to help you understand how to make your decisions in this task. We will also ask you to answer some questions to check your understanding of the instructions.

Instructions for Part 2: [voluntary treatment]

In this part 2, you will make the same production decision as in Part 1. In addition, you have an option to report whether an accident has occurred or not (see an example below). If you report that you had an accident, you will pay a self reporting fine of \$12. If you do not submit a report, you will be inspected with 50% probability and fined \$15 if an accident did occur.

You chose: 100% accident probability, which gives you \$27.50 in production earnings.

You DID have an accident.

Would you like to report the accident? Yes
 No

You will participate in 2 practise periods before the actual task begins. The earnings that you obtain in the practice periods will not count towards your final earnings. The practice periods are intended to help you understand how to make your decisions in this task. We will also ask you to answer some questions to check your understanding of the instructions.

Instructions for Part 2: [compulsory treatment]

In this part 2 you will make the same production decision as in Part 1. In addition, you will be asked to fill in a report about whether an accident has occurred or not (see an example below). If you report that you had an accident, you will pay a self reporting fine of \$12. If you report that you have not had an accident, you will be inspected with 50% probability and fined \$15 if an accident did occur.

You chose: 100% accident probability, which gives you \$27.50 in production earnings.

You DID have an accident.

You will need to fill out a report. What would you like to say in the report? I HAD an accident
 I DID NOT have an accident

You will participate in 2 practise periods before the actual task begins. The earnings that you obtain in the practice periods will not count towards your final earnings. The practice periods are intended to help you understand how to make your decisions in this task. We will also ask you to answer some questions to check your understanding of the instructions.