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# Loss Aversion and lying behavior: Theory, estimation and empirical evidence

Ellen Garbarino<sup>a</sup>, Robert Slonim<sup>b</sup>, Marie Claire Villeval<sup>c</sup>

July 18, 2017

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We theoretically show that loss-averse agents are more likely to lie to avoid receiving a low payoff after a random draw, the lower the *ex-ante* probability of this bad outcome. The *ex-ante* expected payoff increases as the bad outcome becomes less likely, and hence the greater is the loss avoided by lying. We demonstrate robust support for this theory by reanalyzing the results from the extant literature and with two new experiments that vary the outcome probabilities and are run double-anonymous to remove reputation effects. To measure lying, we develop an empirical method that estimates the full distribution of dishonesty.

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## 1. Introduction

Dishonesty is pervasive and deters economic growth and development.<sup>1</sup> Going beyond the initial economics-of-crime approach (Becker, 1968), economists have broadened their study the behavioral determinants of dishonesty. This emerging literature shows that the extent to which individuals are or are not willing to follow the moral course of action can be affected by ethical values, social preferences, institutions, and norms (*e.g.*, Gneezy 2005; Ariely 2012; Gächter and Schultz 2016; Mann *et al.* 2016).<sup>2</sup> Whereas the effect of the level of incentives (*i.e.*, the financial benefit) and of the nature of incentives (*e.g.*, individual, team-based or competitive) on dishonesty has received substantial attention,<sup>3</sup> little is known theoretically or empirically about the impact of the probability of payoffs on dishonesty. This is surprising, as economists have intensively explored how individuals take actions to avoid unlikely low payoffs (*e.g.*, by investing in effort, buying insurance or protection, *etc.*). It is likely that some people also use dishonest actions with the same objective (*e.g.*, exaggerating insurance claims after an accident, cheating to get a bonus, *etc.*). To fill this gap, our first two contributions are to theoretically and empirically study the role of payoff probabilities on dishonesty. Our third main contribution is to introduce an econometric method to estimate the full distribution of dishonesty in the most common context used to study dishonesty: when agents privately observe the outcome of a random process but can report a different outcome.

Theoretically, we explore a determinant of dishonesty that is predicted by loss aversion and which operates through the *probability* of the privately observed outcomes that people can either report on honestly or dishonestly. Specifically, we show that loss aversion predicts that the extent to which individuals behave dishonestly is sensitive to the probability of observed outcomes because this probability affects the payoff that is expected to be observed, and the expected payoff in turn affects the loss-averse utility of the honest and dishonest reports. If individuals suffer more from losses than they enjoy equivalent gains, as loss aversion contends (Kahneman and Tversky 1979; 1992), then individuals gain more utility from being dishonest the further the realized outcome is

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<sup>1</sup> For example, the overall gross tax gap estimate by the IRS in the U.S represents about 16% of estimated actual tax liability. The global hidden financial assets in offshore tax havens represent up to \$280 billion in lost income tax revenues. These unpaid taxes limit the resources available to invest in public services. The World Bank Institute estimates that corruption is equal to about 2% of global GDP. Corruption and embezzlement deter investment, and therefore hinder growth.

<sup>2</sup> For recent surveys on the experimental economic literature on dishonest behavior, see Rosenbaum *et al.* (2014), Irlenbusch and Villeval (2015), and Abeler *et al.* (2016).

<sup>3</sup> Studies examining the level of incentives on dishonesty include Fischbacher and Föllmi-Heusi (2013) and Kajackaite and Gneezy (2017). Studies examining the nature of incentives on dishonesty include Jacob and Levitt (2003), Conrads *et al.* (2013), Danilov *et al.* (2013), Charness *et al.* (2014) and Faravelli *et al.* (2015).

below the payoff that they expected to observe. That is, the less likely a bad payoff outcome is expected to occur, the more this bad outcome will be below the expected outcome, and thus the greater the loss that is avoided by lying.

Only a few studies have experimentally investigated the role of loss aversion in cheating, and none theoretically (Shalvi 2012; Cameron and Miller 2013; Grolleau *et al.* 2016; Schindler and Pfattheicher 2016; Balasubramanian *et al.* 2017). Most studies manipulate the endowment to vary the reference state; in particular, subjects can receive from \$0 to \$X with no endowment (the gain frame) or receive from -\$X to \$0 plus an \$X endowment (the loss frame). They generally find support for greater dishonesty in the loss than gain frame.<sup>4</sup> In contrast, we analyze the variation in the reference state resulting from differences in the probabilities of the privately observed outcomes. In our model, a dishonest report causes a gain in utility from the payoffs occurring in both the loss and gain domains, where variations in the probability of the outcomes affects the relative size of the gains and losses that occur between reporting honestly and dishonestly. Hence, our model provides a formal theoretical relationship between loss aversion and lying.

Our second main contribution is empirical and experimental. We first test the theoretical implications of our model by re-examining the extensive experimental literature on dishonesty in which the outcome of a random draw that is observed only by the subject is reported to the experimenter. In this literature, the probabilities of the outcomes and the rate of lying vary dramatically across studies, allowing us to test the implications of our model. We then further test the theoretical implications by conducting two new experiments in two distinct contexts that control for all factors other than the probabilities of the payoff outcomes that subjects can observe.

Empirically studying the likelihood that individuals cheat requires a valid statistical measure of dishonesty. Because statistics on fraud in natural settings focus on people who have been detected, which introduces a selection bias, researchers have increasingly turned to running experiments with participants who might be more representative of the general population with regard to the likelihood to commit fraud. The most common technique to detect cheating involves subjects generating an outcome from a random device (*e.g.*, flipping a coin, rolling a die, drawing a ticket) where the

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<sup>4</sup> Using real-effort tasks, Cameron and Miller (2013) and Grolleau *et al.* (2016) find that individuals misreport their performance more in a loss than in an equivalent gain frame. Schindler and Pfattheicher (2016) also find, using both a die-rolling task and a coin-tossing task, that more people cheat in a loss than gain frame. In contrast, Blanco *et al.* (2017) find that people cheat in a gain frame, but not in a loss frame. In a different approach, Shalvi (2012) examines lying to affect the odds of winning and shows that individuals dishonestly increase the likelihood of winning by turning negative gambles into positive gambles. Finally, Balasubramanian *et al.* (2017) consider instead a reference point related to expected daily income on MTurk and find reduced dishonesty at higher incentive levels driven by those subjects who have already exceeded their stopping point.

outcome can only be observed by the subject (e.g., Fischbacher and Föllmi-Heusi 2013; Shalvi *et al.* 2011). If a subject privately observes an outcome with a payoff that is less than the maximum possible payoff, then he has a financial incentive to lie by dishonestly reporting a higher payoff outcome than observed.<sup>5</sup>

Virtually every paper using this technique compares the proportion of each reported outcome with the theoretical proportion if subjects reported truthfully. While this approach indicates whether the proportion of subjects reporting any particular outcome differs from the expected proportion if all subjects reported honestly, it does not describe the distribution of the proportion of subjects that behaved dishonestly. This limitation makes it difficult to compare the extent of lying across studies beyond indicators for when dishonesty does and does not significantly occur.<sup>6</sup> This limitation motivates our econometric contribution, the provision of a technique to estimate the full distribution of the proportion of individuals who lie. By estimating this full distribution, our technique provides a precise estimate not only of the mean and confidence intervals (indicating lower and upper bounds on the proportion of people lying), but also for any other statistical inference that can be inferred from the full distribution. The technique uses the information on the distribution of possible outcomes individuals can observe to infer the PDF and CDF of dishonesty. We have developed a software to implement our technique that is freely available at the following address: <http://lyingcalculator.gate.cnrs.fr>. In addition to allowing researchers to estimate the distribution of lying for their data, the calculator provides a trivial method to perform power calculations to determine appropriate sample sizes for each treatment.

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<sup>5</sup> The artificiality of the laboratory may, however, affect behavior. Reassuringly, the literature shows that dishonesty in the lab correlates with dishonesty in the field (Hanna and Wang 2013; Barfort *et al.* 2015; Cohn and Maréchal 2015; Cohn *et al.* 2015; Dai *et al.* 2017; Potters and Stoop 2016). Moreover, several modifications have been tried to reduce the risk of scrutiny. For example, the die can be put in a cup to make more salient the fact that only the subject can observe the realization of the die roll (Shalvi *et al.* 2011). In “mind games,” as used in this paper, subjects have to predict the realization of an outcome prior to acting and report whether their prediction was correct or wrong (Shalvi 2012; Jiang 2013; Barfort *et al.* 2015; Kajackaite and Gneezy 2017; Potters and Stoop 2016). This method guarantees to subjects that a lie can never be detected.

<sup>6</sup> Abeler *et al.* (2016) advance the analysis by using a simple formula to report a proxy for the mean lying percent. Their formula indicates that the percent of subjects that lie equals  $(r-p)/(1-p)$  where  $r$  is the percentage of subjects that report the higher payoff and  $p$  is the likelihood of observing this good outcome. For instance, in a coin toss ( $p=50\%$ ), if  $r=60\%$ , then this formula implies that on average 20%  $\{(0.6-0.5)/0.5\}$  would have lied. There are, however, limitations to this formula. First, it does not provide the distribution, confidence intervals or any other statistic. Second, the statistic may not correctly measure the mean. This can most easily be seen if we look at when  $r=50\%$ , in which case this formula indicates that on average 0% of subjects  $\{(0.5-0.5)/0.5\}$  would have lied. However, this ignores the distribution of possible outcomes that the subjects could have observed that includes less than 50% observing the higher payoff outcome who then report dishonestly. Our approach addresses these limitations by providing the entire CDF and PDF of lying including the correct mean of the distribution.

We first apply our technique to empirically test our theory on the extant lying literature. We estimate the mean percent of individuals reporting dishonestly from all studies exploring lying using random devices we were able to obtain data from. We started from the list of studies surveyed by Abeler *et al.* (2016) and added a few additional studies. Our review includes 81 studies representing 389 treatments and 36,668 individuals from 44 countries.<sup>7</sup> Controlling for several variables that can affect the decision to lie (*e.g.*, monetary stakes, laboratory setting, etc.), we find a highly significant and robust negative correlation, ranging from -0.42 to -0.52 depending on the specifications, between the probability of observing a low payoff outcome and the mean lying propensity. This between-study correlation indicates, as predicted by loss aversion, that the mean proportion of individuals that behave dishonestly to avoid a low payoff outcome is higher when this outcome is less likely.<sup>8</sup>

While the evidence is consistent with the loss aversion hypothesis, concerns about one's reputation effects might also lead to similar results. Reputation concerns, as modeled in Dufwenberg and Dufwenberg (2016) or Gneezy *et al.* (2016) predict an equilibrium in which individuals are more likely to lie to get a higher payoff the less likely the claim for a higher payoff might be perceived as lying by observers (*e.g.*, the experimenter). In the context of probability tasks, we trivially show theoretically that reputation concerns predict that people will lie more when there is a higher probability of a good outcome because success will look less suspicious to the potential observers. Thus, both reputation concerns and loss aversion may be influencing the relationship we observe in our analysis of the literature.

We address the potentially confounding reputation and loss aversion explanations for the relationship between dishonesty and the likelihood of the outcome in two ways. First, we further examine the existing data from the literature to test whether the impact of the probability of the bad outcome persists once we control for reputation. To control for reputation, we include proxies for the level of observability of the subject's identity when making reports; for example, a subject who has to report face to face with the experimenter would be categorized as highly observable. Unsurprisingly, we find support for a main effect of reputation; subjects are less likely to lie in

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<sup>7</sup> The objectives of the two reviews are different: while Abeler *et al.* (2016) try to identify the individual, economic and methodological determinants of misreporting, we focus on the impact of the distribution of probabilities of the low and high outcomes on the mean lying rate, a dimension that they do not consider. Another difference is that our analysis is conducted at the treatment level while theirs is at the level of individual decisions.

<sup>8</sup> For example, subjects lie more in a die task where only one value earns zero payoff (like in Fischbacher and Föllmi-Heusi (2013) in which the mean lying rate to avoid the zero payoff is 61%) than when five out of six sides earn zero (like in Kajackaite and Gneezy (2017) in which the mean lying rate is only 15%). Our results hold regardless of whether we define a bad payoff outcome as the lowest possible outcome or all outcomes except the highest one.

treatments with moderate and high observability than in treatments with low observability. However, we find no significant interaction effect between observability and the probability of the bad outcome; that is, regardless of level of reputation, the relationship between the probability of the bad outcome and lying remains significant. Thus, reputation concerns cannot explain the relationship between the probability of the bad outcome and lying.

Second, to further test the loss aversion lying hypothesis, to remove across experiment differences in the extant literature, and to minimize the potentially confounding influence of reputation, we designed two novel experiments using a “mind coin-tossing game” in which we vary only the likelihood of the various outcomes. To remove reputation, both experiments were run online and double-anonymous (*i.e.*, with no chance of any observers). In both experiments, individuals have to predict the outcome of a coin toss before tossing a coin in private. This task is repeated three times and then subjects have to report the number of correct predictions, which determines their payoff. Across subjects and in two different contexts, we vary the number of correct predictions required to earn a fixed amount of money, which makes the probability of the undesired outcome (earning \$0) vary from 12.5% to 50% to 87.5%. In study one, involving 978 subjects on MTurk, the beneficiary of a lie is oneself and the subject can earn either \$0 or \$2. In study two, involving 422 different MTurkers, the beneficiary is a cause that the subject either supports or opposes (either the Democratic National Party or the Republican National Party in the U.S.) and the subjects can earn either \$0, \$1 or \$8 for the party they are randomly assigned to.

We use our econometric approach to demonstrate that, consistent with our loss aversion prediction, people lie more often to avoid the undesired outcome when the probability of this undesired outcome is lower. When the outcome of the task benefits the subject directly, on average 75.88% of the subjects lie to get a \$2 rather than \$0 payoff when the likelihood of getting the low payoff is 12.5%, whereas 66.26% lie when the likelihood of the low payoff is 50% and only 44.18% lie when the likelihood is 87.5%. The same qualitative finding is observed when the beneficiary of a lie is either a cause that the individual supports or a cause that he opposes. On average, 77.65% of subjects lie to avoid giving \$0 to a cause they support and 59.62% lie to avoid giving the highest possible payoff (\$8) to a cause they oppose when the likelihood of these outcomes is 12.5%. The respective mean percentages decrease to 21.24% and 33.79% when the probability of those outcomes is 50%, and further decreases to 7.61% of supporters that lie to give \$8 to their party and 4.25% of subjects that lie to give \$0 to the party they oppose when the likelihood of a bad outcome is 87.5%.



Overall, we show that loss aversion predicts that the probability of observing each payoff outcome affects the level of dishonesty. Our review of the extant literature and our two experiments confirm that individuals are more likely to lie when the undesired outcome is more unlikely, and this follows theoretically from the implications of loss aversion. This has important practical implications in terms of policy making; in particular, it suggests to focus audits and controls on settings with low probability of occurrence.

The remainder of this paper is organized as follows. Section 2 presents the theory. Section 3 details our econometric technique to estimate the distribution of the percentage of subjects who misreport. Section 4 applies this method to the existing literature while Section 5 presents our two new experiments. Section 6 discusses our results and concludes.

## 2. A theory of Loss Aversion and the probability of outcomes on lying

This section shows theoretically that agents with loss averse preferences who privately observe the low payoff outcome will be increasingly likely to lie the smaller the *ex-ante* probability of observing this low outcome. To show this, we examine the comparative static effect of changing the probability of observing the low payoff on the difference in the utility of the agent dishonestly reporting the not-observed high payoff vs. honestly reporting the observed low payoff. Given the potential importance of reputation effects (*e.g.*, Abeler *et al.* 2016; Dufwenberg and Dufwenberg 2016; Gneezy *et al.* 2016; Khalmetski and Sliwka 2017), our theoretical model includes adverse utility effects for reputation that can also be affected by the probability of observing the low payoff.

Let  $x_1$  and  $x_2$  ( $x_2 > x_1$ ) be an agent's monetary payoffs if he reports the low and high payoff outcomes, respectively, where the *ex-ante* probability of observing  $x_1$  and  $x_2$  is  $p$  and  $1-p$ . In this context, the *ex-ante* expected observed payoff is  $x_e = px_1 + (1-p)x_2$ ; *i.e.*,  $x_e$  is the expected observed realization before observing how the random event is resolved. We show that if an agent has loss-averse preferences (Kahneman and Tversky, 1979; 1992) and uses the *ex-ante* expected observed payoff  $x_e$  as his reference point,<sup>9</sup> then after observing the low payoff outcome he will be increasingly

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<sup>9</sup> An alternative model for the reference point would be to allow it to be endogenously determined (in a manner similar to Koszegi and Rabin 2006) by subjects who anticipate with some probability  $q$  that they might report dishonestly if they observe the bad outcome. Intuitively, allowing for endogenous reference point formation should not change any of the comparative static predictions that we derive so long as  $q < 1$  and the endogenous adjustment of the reference point keeps the reference point proportional to the probability of the bad outcome, though it could weaken the magnitude of the loss aversion effect. However, for subjects where  $q=1$  (that is, for subjects who intend to lie for sure if they get the bad outcome regardless of the probability of getting the bad outcome  $p$ ), then the loss aversion prediction would no longer hold. A formal extension to allow for endogenous reference point formation is beyond the scope of this paper, and we thus leave this for future research.

more likely to dishonestly report the high payoff than to honestly report the low payoff the less likely the *ex-ante* probability of observing the low payoff outcome (*i.e.*, the smaller  $p$  is). Intuitively, as the likelihood of observing the low payoff decreases, the *ex-ante* expected observed outcome (the reference point) increases, so the sense of loss related to honestly reporting increases. As the probability of the low payoff decreases, the person expects an increasingly higher payoff and so increasingly suffers a greater loss if he reports the low payoff, and hence is more inclined to dishonestly report the higher outcome to avoid that loss. As the likelihood of observing the *ex-ante* low payoff decreases, the gain in utility for a loss-averse agent who reports dishonestly to avoid the loss increases, increasing the benefits of a dishonest vs. honest report. We now formally show this.

We assume an agent's utility is a function of the moral cost of dishonesty  $m()$ , reputation  $r()$ , and the reference-dependent loss-averse utility  $g()$  and  $h()$  of the monetary payoff:

$$U(x_R | x_O) = g(x_2 - x_e) * I(x_R \geq x_e) - h(x_e - x_1) * I(x_R < x_e) - m(x_R - x_O) * I(x_R \neq x_O) - r(p, b) * I(x_R = x_2) \quad (1)$$

where  $I()$  is an indicator function that equals 1 if true and 0 if false, and  $x_R$  and  $x_O$  are the agent's reported and privately observed outcomes, respectively. As theorized in recent research notably by Dufwenberg and Dufwenberg (2016) and Gneezy *et al.* (2016), we include reputational disutility for making a report to earn the high payoff,  $x_R = x_2$ ,  $r(p, b)$ ;  $r(p, b)$  represents the potential loss in reputation from reporting the high income which may seem suspicious of lying to other subjects or the experimenter who observe the report.  $b$  captures the observability of the report by others. We assume that  $r()$  is increasing in  $p$  to capture that the more likely the bad outcome should have occurred, the more suspicious the report of a higher payoff will appear dishonest, and hence the greater the loss in reputation. We assume that  $r(0, b) = 0$  for all  $b$ ; if there is no chance to observe a low payoff, then there is no suspicion that the agent was behaving dishonestly. We further assume that  $r(p, b)$  is an increasing function of the observability  $b$ ; if no one can observe the report (or identify the person making the report), then there is no loss of reputation (*i.e.*,  $r(p, 0) = 0$ ), and as more people can observe the agent making the report, the greater the possible suspicion.

The functions  $m()$ ,  $r()$ ,  $g()$  and  $h()$  are continuous and twice differentiable;  $m()$  is the moral cost of reporting an outcome that was not observed by the agent, and  $g()$  and  $h()$  are the utility of gains and losses, respectively. We assume:

$$m'(x) \geq 0 \text{ and } m''(x) \geq 0 \quad (2)$$

Assumption (2) reflects the (weakly) increasing moral cost of lying as a function of the gain from misreporting. For instance, Mazar *et al.* (2008), Lundquist *et al.* (2009), and Fischbacher and

Föllmi-Heusi (2013) find evidence consistent with  $m'(x) > 0$ , while Kajackaite and Gneezy (2017) cannot reject that  $m'(x) = 0$ .

If the agent observes the low payoff outcome (*i.e.*,  $x_O = x_1$ ), then he has a monetary incentive to dishonestly report observing the higher payoff,  $x_R = x_2$ . It follows from equation (1) that when observing the low payoff outcome, the agent's utility if he reports the low or high payoff, respectively, will be:<sup>10</sup>

$$U(x_1 | x_1) = -h(x_e - x_1) \quad (3)$$

$$U(x_2 | x_1) = g(x_2 - x_e) - m(x_2 - x_O) - r(p, b) \quad (4)$$

It follows that the difference in utility  $U(d)$  between dishonestly reporting observing the high payoff ( $x_2$ ) and honestly reporting observing the low payoff ( $x_1$ ) is:

$$U(d) = U(x_2 | x_1) - U(x_1 | x_1) = g(x_2 - x_e) + h(x_e - x_1) - m(x_2 - x_1) - r(p, b) \quad (5)$$

Equation 5 highlights how the utility gained from the higher payoff by an agent with reference-dependent loss-averse preferences when reporting dishonestly *vs.* honestly can be decomposed into two components. First, he gains utility from the monetary gain above the reference point,  $g(x_2 - x_e)$ , and second, he gains utility from avoiding the monetary loss below the reference point  $h(x_e - x_1)$ .

Substituting for  $x_e = px_1 + (1-p)x_2$  and rearranging, the difference in utility between dishonestly reporting observing the high payoff ( $x_2$ ) and honestly reporting observing the low payoff ( $x_1$ ) is:

$$U(d) = g(p^*(x_2 - x_1)) + h((1-p)^*(x_2 - x_1)) - m(x_2 - x_1) - r(p, b) \quad (6)$$

Differentiating  $U(d)$  with respect to the probability of the low outcome ( $p$ ), we have:

$$U'(d) = (x_2 - x_1)[g'(p(x_2 - x_1)) - h'((1-p)(x_2 - x_1))] - r'(p, b), \text{ and} \quad (7)$$

$$U''(d) = (x_2 - x_1)^2[g''(p(x_2 - x_1)) + h''((1-p)(x_2 - x_1))] - r''(p, b) \quad (8)$$

It immediately follows from (7) that as the likelihood of the bad outcome  $p$  increases, agents lose increasingly more utility through reputation effects. To examine the effect of a change in  $p$  on reporting, we isolate the three distinct forces driving their overall comparative static effects. First, we isolate the effect of reputation assuming no reference dependence or loss aversion. Second, we

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<sup>10</sup> Given our assumption that if an agent observes the high outcome,  $x_O = x_2$ , then it is trivial to show that he will always receive higher utility honestly reporting the high payoff outcome ( $x_R = x_2$ ) than dishonestly reporting the low payoff outcome ( $x_R = x_1$ ). Among others, Houser *et al.* (2012), Fischbacher and Föllmi-Heusi (2013), Cohn *et al.* (2015), and Dai *et al.* (2017) acknowledge that downward lying may occur because of altruism towards the experimenter or because subjects fear of being identified as cheaters, but they assume that this behavior is extremely unlikely. In all of the 389 treatments we have examined, we have found only one treatment (Utikal and Fischbacher 2013) in which subjects report the low payoff outcome statistically more often than the expected frequency of the true distribution they should have observed. This has been observed with a very specific population: nuns. Moreover, in their Observed treatments, Gneezy *et al.* (2016) have identified only one subject out of 602 who underreports. See also evidence in footnote 14. Thus, we do not theoretically examine the possibility of lying in the case where subjects observe the higher payoff outcome.

isolate the effect of loss aversion by assuming no reputation effects and linear marginal utility over gains and losses. Third, we isolate the reference-dependent effect of diminishing marginal utility of losses and gains by assuming no reputation effects and the utility of losses and gains are identical (*i.e.*,  $g(x) = h(x)$ ). These cases provide the intuition for the forces of reputation, loss-aversion and reference-dependent preferences on reporting dishonestly rather than honestly as the probability of observing the bad outcome changes. Then, we examine their combined impact.

*Case 1: Reputation effects without loss aversion or reference dependence*

To isolate the reputation effect, we assume:

$$\begin{aligned} g(x) &= kx \quad (k > 0) \\ h(x) &= g(x) \end{aligned} \tag{9}$$

$g(x)$  and  $h(x)$  are linear utility functions (*i.e.*, no diminishing marginal utility) and  $g(x) = h(x)$  (*i.e.*, no loss aversion). In this case, the marginal utility of reporting dishonestly vs. honestly is:

$$U'(d) = k(x_2 - x_1) - k(x_2 - x_1) - r'(p, b) = -r'(p, b) \leq 0 \tag{7'}$$

It thus follows that agents will (weakly) be more likely to dishonestly report the higher outcome the less likely the bad outcome may occur. However, note that if no one observes the report (*i.e.*,  $b=0$ ), then there is no effect on reputation and  $U'(d) = -r(p, 0) = 0$ . We return to this observation in the discussion of the empirical analysis (section 4) and our experimental design (section 5) to isolate loss aversion and reference dependence from reputation effects.

*Case 2: Loss Aversion without reputation and reference-dependent diminishing marginal utility:*

To isolate the loss aversion effect, we assume:

$$\begin{aligned} g(x) &= kx \quad (k > 0) \\ h(x) &= (1+a)g(x) \quad \text{and } a > 0. \\ r(p, b) &= 0 \end{aligned} \tag{10}$$

$g(x)$  and  $h(x)$  are linear utility functions (*i.e.*, no diminishing marginal utility) and with  $a > 0$   $h(x)$  is steeper than  $g(x)$ , reflecting loss aversion. The marginal utility of reporting dishonestly is:

$$U'(d) = k(x_2 - x_1) - (1+a)k(x_2 - x_1) - r'(p, b) = -ak(x_2 - x_1) < 0 \tag{7''}$$

Intuitively, as the probability of observing the bad payoff increases, the increase in utility in the gain domain,  $k(x_2 - x_1)$ , is always less than the decrease in utility in the loss domain,  $(1+a)k(x_2 - x_1)$ . This follows immediately from the steeper slope of losses than gains assumed with loss-averse preferences. Thus, as the probability of observing the bad payoff increases, the net gain in utility from the payment falls through the loss aversion, and may fall below the moral cost of lying, at

which point the agent will have overall greater utility from reporting honestly. For a decrease in the probability of observing the bad payoff, therefore, we have our main result:

**Theoretical Result 1** (*Loss aversion effect on reporting dishonestly*): As the probability of observing the bad payoff outcome decreases, increasing utility will be received from reporting dishonestly than honestly.

Note that loss aversion and reputation make the identical prediction as the probability of the bad outcome changes so long as agents are observed by others ( $b > 0$ ). To address this concern empirically, we employ two strategies. First, when we examine the previous literature, we explore the effects of changes in  $p$  overall and in the interaction with different degrees of observability (various  $b$ ). If reputation is the ONLY effect driving the relationship between  $p$  and dishonest reports, then we would anticipate the effect of  $p$  varying with observability; seeing the smallest (or no) effect when there is no or low observability and the largest effect when observability is high. Second, we present evidence from two new experiments where there is no ability to observe subjects (*i.e.*,  $b = 0$ ) and where subjects know they cannot be observed.

*Case 3: Reference-dependence and diminishing marginal utility without reputation and loss aversion:*

To isolate the reference-dependent diminishing marginal utility effect, we assume that (a) there is no observability, (b) the utility of losses and gains are identical for the same absolute size of the gain and loss, and (c) the utility of gains and losses exhibit diminishing marginal utility the further payoffs are from the reference point:

$$g(x) = h(x), g'(x) > 0, g''(x) < 0 \text{ and } r(p, b) = 0. \quad (11)$$

In this case, we have:

$$U'(d) = (x_2 - x_1)[g'(p(x_2 - x_1)) - g'((1-p)(x_2 - x_1))], \text{ and} \quad (7''')$$

$$U''(d) = (x_2 - x_1)^2[g''(p(x_2 - x_1)) + g''((1-p)(x_2 - x_1))] \quad (8')$$

Given diminishing marginal utility,  $g''(x) < 0$ , it immediately follows that  $U''(d) < 0$  for all  $p$ .

Further, equation (7''') indicates that if  $p = 0.5$  then  $U'(d) = (x_2 - x_1)[g'(.5(x_2 - x_1)) - g'(.5(x_2 - x_1))] = 0$ .

Thus, given  $U''(d) < 0$  for all  $p$  and  $U'(d) = 0$  when  $p = 0.5$ , it immediately follows that:

$$\begin{aligned} \text{For } p < 0.5: U'(d) > 0; U''(d) < 0 \\ \text{For } p = 0.5: U'(d) = 0; U''(d) < 0 \\ \text{For } p > 0.5: U'(d) < 0; U''(d) < 0 \end{aligned} \quad (11)$$

Intuitively, when  $p$  is less than 0.5, the reference point  $x_e$ ,  $x_e = px_1 + (1-p)x_2$ , is closer to the higher payoff  $x_2$  than the lower payoff  $x_1$ , *i.e.*,  $|x_2 - x_e| = p(x_2 - x_1) < |x_1 - x_e| = (1-p)(x_2 - x_1)$ , and thus we are on the steeper part of the utility function in the domain of gains than in the domain of losses due to the assumed diminishing marginal utility; thus, as  $p$  increases, more utility is gained in the gain domain than is lost in the loss domain, and thus  $U'(d) > 0$ . In contrast, when  $p$  is greater than 0.5, the reference point  $x_e$  is now closer to the lower payoff  $x_1$  than the higher payoff  $x_2$ , *i.e.*,  $|x_1 - x_e| = (1-p)(x_2 - x_1) < |x_2 - x_e| = p(x_2 - x_1)$ , and thus we are on the steeper part of the utility function in the domain of losses rather than in the domain of gains; thus, in this case due to the assumed diminishing marginal utility, as  $p$  increases, more utility is gained in the loss domain than is lost in the gain domain, and thus  $U'(d) < 0$ . This provides our second theoretical result:

**Theoretical Result 2** (*Reference-dependence and diminishing marginal utility*): As the probability  $p$  of observing the bad payoff outcome decreases, increasingly more utility will be received from reporting dishonestly than honestly when  $p$  is greater than 0.5, and less utility will be received from reporting dishonestly than honestly when  $p$  is less than 0.5.

*General Case: Reference-dependence and Loss Aversion:*

Both reference dependence and loss aversion predict that as the probability  $p$  of observing the bad outcome decreases, increasingly more utility will be received from reporting dishonestly than honestly when  $p$  is greater than 0.5. However, when  $p$  is less than 0.5, loss aversion continues to predict that as  $p$  decreases, utility will be increasing when reporting dishonestly; in contrast, reference dependence predicts that utility of reporting dishonestly than honestly will be decreasing. Given that loss aversion predicts a linearly decreasing effect of  $p$  on the utility of reporting dishonestly than dishonestly (eq. 7') whereas reference dependence predicts a diminishing positive effect (eq. 7''), and given  $U'(d) = 0$  at  $p = 0.5$ , continuity implies that there exists a  $p^*$  ( $0 \leq p^* < 0.5$ ) such that for all  $p > p^*$  the loss aversion effect is greater than the reference dependence effect.

To explore where the loss aversion effect is greater than the reference-dependent diminishing marginal utility effect,  $p^*$ , we consider the functional form of utility where agents have CRRA preferences, *i.e.*,  $g(x) = x^{(1-r)}/(1-r)$  where  $r$  is the coefficient of relative risk aversion. We examine CRRA given the extensive experimental economics literature that has estimated this functional form. To address loss aversion, we assume  $h(x) = (1+\alpha)g(x)$ , with  $\alpha > 0$ . With these preferences, it is easy to show that  $p^* = 1 / [(e^{\ln(\alpha)/r}) + 1]$ . This result indicates that as the degree of loss aversion  $\alpha$  increases, *ceteris paribus*  $p^*$  decreases and the range in which the loss aversion effect is greater than the reference dependent effect increases. This result also shows that as the relative degree of risk

aversion  $r$  increases (*i.e.*, agents have greater diminishing marginal utility), *ceteris paribus*  $p^*$  increases and the range in which the reference dependent effect is greater than the loss aversion effect increases. Note that adding reputation concerns ( $b > 0$ ) should also reduce  $p^*$ , restricting the interval in which reference dependence dominates.

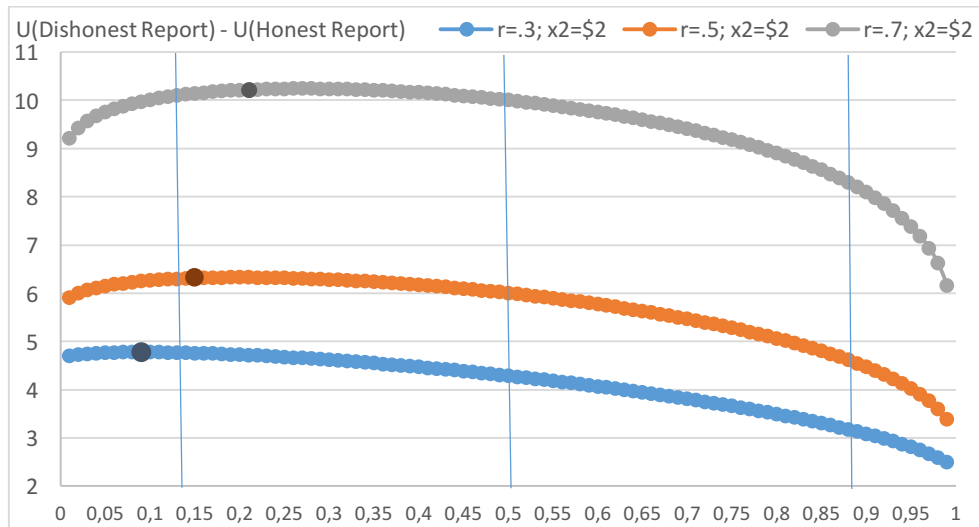
Figure 1 provides a graphical example of the difference in utility from reporting dishonestly vs. honestly,  $U(d)$ , for an agent with CRRA utility (and when  $b=0$  for the sake of simplicity). We assume that losses are twice as steep as gains ( $\alpha=2$ ) as is commonly estimated (*e.g.*, Kahneman and Tversky 1992; Abdellaoui *et al.* 2007). We consider  $r = 0.3$ ,  $r = 0.5$  and  $r = 0.7$ , within the range commonly estimated in the literature (*e.g.*, Holt and Laury 2002; Eckel and Grossman 2008). Figure 1 shows that  $p^*$  is greater for agents with greater relative risk aversion; for example,  $p^* = 0.09$ ,  $0.20$  and  $0.27$  for  $r = 0.3$ ,  $0.5$  and  $0.7$  respectively. Consistent with Results 1 and 2 (and Result 3 below), Figure 1 also shows that as  $p$  decreases from 1 to  $p^*$  the agent receives increasingly more utility from reporting dishonestly than honestly, and that as  $p$  further decreases below  $p^*$  the relative benefits of reporting dishonestly start to decrease.<sup>11</sup> Finally, if we assume the CRRA functional form of utility and standard values for relative risk aversion and loss aversion, then the loss aversion effect will dominate the diminishing marginal utility effect for values of  $p > p^*$  in the range of  $0.09 \leq p^* \leq 0.25$ .

The combined theoretical prediction for agents that have reference-dependent loss-averse preferences with diminishing marginal utility is summarized as follows:

**Theoretical Result 3** (*Reference-dependence and loss-aversion with diminishing marginal utility*): As the probability  $p$  of observing the low payoff outcome decreases, increasingly more utility will be received from reporting dishonestly than honestly when  $p$  is greater than  $p^*$ . Moreover,  $p^*$  will decrease the more loss averse and the less risk averse the agent is. Adding reputation concerns would decrease  $p^*$  even further.

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<sup>11</sup> Note that in our experiments, we examine values of  $p = 0.125$ ,  $p = 0.5$  and  $p = 0.875$ ; for these values of  $p$ , indicated with vertical lines, Figure 1 shows that for these common values of loss aversion and risk aversion, the utility of reporting dishonestly vs. honestly is strictly greater as  $p$  decreases:  $U(d|p=0.125) > U(d|p=0.5) > U(d|p=0.875)$ .



**Figure 1:** Utility of reporting dishonestly vs. honestly (*d*) as a function of the probability of the low payoff outcome

Note: Utility functions of losses and gains assume CRRA utility with losses twice as steep as gains, assuming the low payoff is \$0 ( $x_1=\$0$ ) and the high payoff is \$2 ( $x_2=\$2$ ). Vertical lines represent the values of  $p$  (0.125, 0.5, 0.875) used in the experiments reported in section 5.

### 3. A precise estimate of the full distribution of dishonesty in experiments

This section presents our technique to estimate the full distribution of the percent of subjects lying. We first explain our method in the case of two payoffs and then generalize to the case of  $m$  payoffs.

#### *Two payoffs*

Consider  $N$  subjects who privately observe the outcome of a random device (*e.g.*, die rolls, coin tosses) and report one of two possible payoffs:  $x_1$  and  $x_2$  ( $x_1 < x_2$ ) that map directly from the random device (*e.g.*, Tails pays \$0, Heads pays \$5; 1-5 on the die pays \$0, 6 pays \$2). Outcomes  $x_1$  and  $x_2$  occur with probabilities  $p$  and  $1-p$ , respectively. If  $R$  subjects ( $0 \leq R \leq N$ ) report the higher outcome  $x_2$ , we want to know the probability distribution of the percent of subjects who observed the low outcome  $x_1$  but reported dishonestly the high outcome  $x_2$ .

As is common in the literature, we assume that any subject who reports the low outcome  $x_1$  reports truthfully.<sup>12</sup> Letting  $T$  be the number of subjects that observed the high outcome, there are

<sup>12</sup> Rigdon and d’Esterre (2015) have unpublished data in which they were able to observe the true outcome subjects observed (unbeknownst to the subjects) along with the reported outcome. In personal correspondence (March 2017), the authors informed us that not a single subject lied when reporting the lower monetary outcome. Kröll and Rustagi (2016) asked 72 milkmen to roll a die 40 times using a Bluetooth enabled die that transmits the actual outcome of each roll to the smartphone of the experimenter, subjects being unaware of this. In personal communication (June 2017), they



R+1 different possible numbers of subjects that could have observed the high outcome (*i.e.*,  $0 \leq T \leq R$ ). For each possible T, the percent of subjects who lied is:

$$L_{T,R,N} = [R-T] / [N-T] \quad (12)$$

where the numerator is the difference between the number of subjects who reported the high outcome and the number of subjects that observed the high outcome (*i.e.*, the number who were dishonest), and the denominator is the difference between the number of subjects in the experiment and the number that observed the high outcome (*i.e.*, the number who could have been dishonest).

To examine the probability of each possible realization of T, note that  $Q_{T,N,p} = [(N! / (T!(N-T)!)] * p^T * (1-p)^{(N-T)}$  is the *unconditional* probability that T subjects would observe the high outcome if we allowed all possible observations for T from T = 0 to N. However, since we assume no subject is dishonest to report the low outcome if he observed the high one, there are at least N-R subjects that observed the low outcome, and thus the unobserved number of subjects T that observed the high outcome cannot exceed R. Thus, the probability that T subjects would have observed the high outcome when R subjects reported the high outcome is:

$$P_{T,N,R,p} = \frac{Q_{T,N,p}}{\sum_{k=0}^R Q_{k,N,p}} \quad \text{for all } T = 0 \text{ to } R \quad (13)$$

where the numerator is the probability of the realization of T based on the binomial distribution with N observations, R successes and probability  $p$ . The denominator adjusts up these probabilities by the cumulative likelihood that between 0 and R subjects observed the high outcome.<sup>13</sup>

The PDF that  $y = L_{T,R,N}$  subjects were dishonest when R subjects reported the high outcome is:

$$\Pr(y = L_{T,R,N}) = P_{T,N,R,p} \quad (14)$$

The CDF that  $L_{T,R,N}$  or more subjects lied follows directly by summing over the PDF:

$$\Pr(y \geq L_{T,R,N}) = \sum_{k=0}^T (P_{k,R,N,p}) \quad (15)$$

The expected percent of subjects who lied,  $E_{N,R,p}$ , is the sum (over all possible observations T given R subjects reported the high outcome) of the percent of subjects who were dishonest weighted by the probability that T subjects observed the low outcome:

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informed us that underreporting occurred in only 9 cases out of 2880 (0.3% of all observations); in 8 out of the 9 cases, under-reporting was by 1 point and in the ninth case it was by 2 points.

It is also possible to relax our assumption (*e.g.*, we could allow for decision error so that with probability  $\epsilon_{ij}$  reports an outcome that he did not intend to report). While we expect decision errors are unlikely given the simplicity of the task and would likely be symmetric, we cannot rule out that no errors occur but leave this for future research.

<sup>13</sup> In personal correspondence, David Hugh-Jones notes that our adjustment of the denominator can over-estimate the percent of lying when the sample is small and when the true percent of subjects who lie is also small. A Bayesian approach and Maximum Likelihood estimation may correct this bias, but is beyond the scope of this paper.

$$E_{N,R,p} = \sum_{T=0}^R (P_{T,R,N,p} * L_{T,R,N}) \quad (16)$$

Finally, the lower bound for the Confidence Interval (CI, hereafter) ( $p$  value) that  $y$  subjects were dishonest is simply the minimum value of  $L_{T,R,N}$  such that:

$$p/2 < \Pr(y \geq L_{T,R,N}), \quad (17)$$

and the upper bound for the CI ( $p$  value) that  $y$  subjects were dishonest is simply the maximum value of  $L_{T,R,N}$  such that:

$$\Pr(y \geq L_{T,R,N}) < 1-p/2 \quad (18)$$

### *More than two payoffs*

In some experiments there are more than two payoffs (*e.g.*, across die outcomes or multiple coin tosses). Consider  $m$  distinct outcomes  $x_1, \dots, x_m$  with probability  $p_1, \dots, p_m$ , respectively, with  $x_1 < x_2 < \dots < x_m$ . The question we address is what percent of subjects who observe an outcome below some threshold  $x_k$  ( $1 < k \leq m$ ) are dishonest and report an outcome equal to or above  $k$ .<sup>14</sup> To examine the expected percent of subjects who act dishonestly to avoid the worst  $k-1$  outcomes to obtain one of the best  $m-k$  outcomes, let  $p = p_1 + \dots + p_{k-1}$  and then follow the procedure for two outcomes.

Bifurcating the data into two payoff groups might be interesting in a variety of cases. For instance, if payoffs are similar for the lowest  $k-1$  outcomes and distinctly higher and similar for the top  $m-k$  outcomes, or as we are interested in this paper, to study whether subjects want to either avoid the lowest possible outcome ( $k=2$ ) or obtain the highest possible outcome ( $k=m$ ).

### *Implementation*

Using the full distribution of possible outcomes, we can directly calculate the expected percent of subjects who were dishonest conditional on having received the low payoff outcome(s) ( $E_{N,R,p}$ ), and the PDF ( $P_{T,N,R,p}$ ) and CDF ( $\Pr(y \geq L_{T,R,N})$ ). Using the CDF, we can also estimate the confidence interval for any level of significance to determine the minimum and maximum percent  $y$  who were dishonest. Thus, we are able to examine not only whether subjects were dishonest, but also (a) the mean expected percent who were dishonest, (b) the minimum and maximum percents we can be confident were dishonest (the lower and upper bounds on the CI), and (c) using the CDFs, whether two (or more) treatments significantly differ for any statistic of interest including for instance at the means, medians, quantiles and over the full distribution, using non-parametric tests.

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<sup>14</sup> Researchers may also be interested in partial lying (*e.g.*, to examine how many subjects lie from one outcome  $x_k$  to  $x_j$  ( $k < j$ )) to measure small vs. big lies. We believe the techniques to estimate partial lies can be developed from the methods presented in this paper, but leave it for future work as it requires technical sophistication beyond the scope of this paper.

In Appendix 1, Table A1 provides a few examples with  $N=100$  subjects and  $R=60$  subjects who report the high outcome, and different values of  $p$  and of the CI. In the same Appendix, Figure A compares our measures with those used in Abeler *et al.* (2016).

#### 4. Re-examination of the existing literature

To test the prediction of loss aversion on lying, we first apply our technique to estimate the mean percent of individuals reporting dishonestly across previous studies. Specifically, the objective is to test the hypothesis that there will be a negative correlation between the likelihood of a low payoff outcome and the percent of dishonest reports.

To create our dataset, we started from the 72 studies identified in Abeler *et al.*'s (2016) meta-analysis and we added more recent studies. We retained the same inclusion criteria they used. Specifically, we include studies in which subjects have to report the private realization of a random device (a die, a coin, a ticket or a card) that is unobservable to the experimenter, and without any risk of detection during or after the experiment. We include 'mind games' in which subjects report the number of times they were able to correctly predict (to themselves) the outcome of a random device. We exclude studies in which the subject's payoff depends on strategic interactions with other players, but we retain those in which the report may affect other people. We exclude the treatments in which there is no variation in the monetary incentives associated with all possible realizations of the random device. When the data to calculate the mean lying rates were not available in the paper, we contacted the authors and included all of the studies in which the authors provided us with this additional information.

In total, our analysis includes 81 studies and 389 treatments, involving 36,668 individuals from 44 countries and representing 257,682 decisions (see Appendix Table A2).<sup>15</sup> Seventy-one percent of these studies have been conducted by a team involving at least one economist; 53% of the treatments have been run in a standard laboratory setting with standard student-subjects pools; 13% are from artefactual field experiments conducted as in a lab setting but involving atypical subjects.

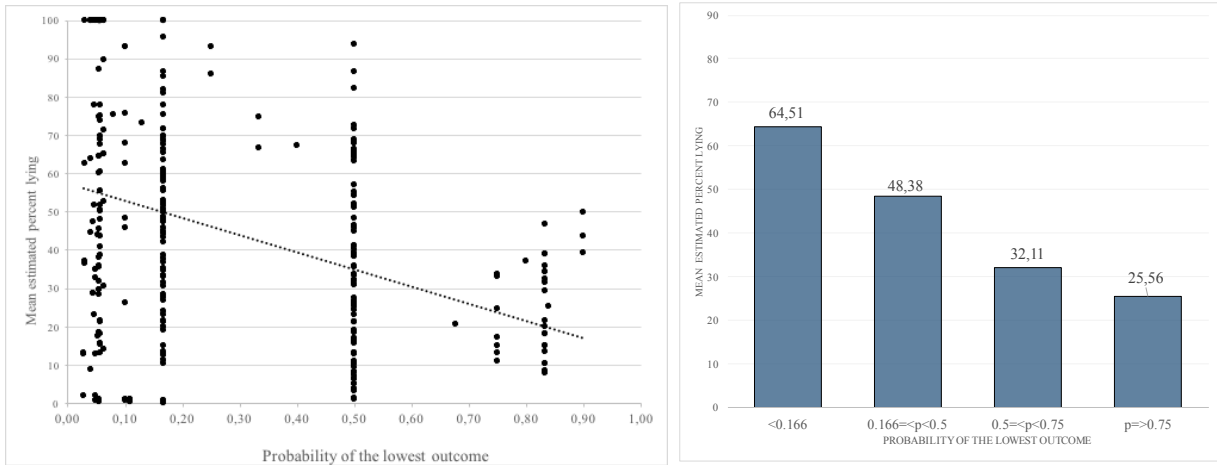
When there are only two possible outcomes (for example in a single coin tossing task or when there are only two payoffs for all possible die rolls) we calculate the percent of subjects who lie to get the high payoff when they observed a low outcome. This calculation requires only knowing the total number of subjects, the number of subjects reporting the high outcome, and the probability of

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<sup>15</sup> We include 69 of the 72 studies of Abeler *et al.* (2016) and add 12 new studies. Three of their studies were not included because the data available did not allow us to measure the lying rates.

getting the low outcome. When there are more than two possible outcomes, we estimate two statistics: first, the percent of people who lied to avoid the lowest payoff, and second, the percent who lied to get the highest payoff, *i.e.* framing all payoffs, except the highest one, as bad outcomes. In the case of repeated decisions (up to 20 coin tosses or card draws and up to 75 die rolls), we define the lowest and the highest outcomes as those associated with the bottom 5% and the top 5% outcomes of the theoretical distribution, respectively.<sup>16</sup>

Figure 2 displays our estimated mean percent of subjects lying to avoid the lowest payoff in the reviewed studies as a function of the likelihood of the lowest outcome. In panel A, the *x*-axis represents the probability of the lowest outcome and the *y*-axis represents the mean percent lying. Each treatment in every study gives one observation. Panel B aggregates this information for various probability intervals. In Figure 3, we consider instead the relationship between the estimated mean percent of subjects lying to avoid the low payoff, when the latter is defined as any payoff except the highest one, and the likelihood of not getting the highest outcome.

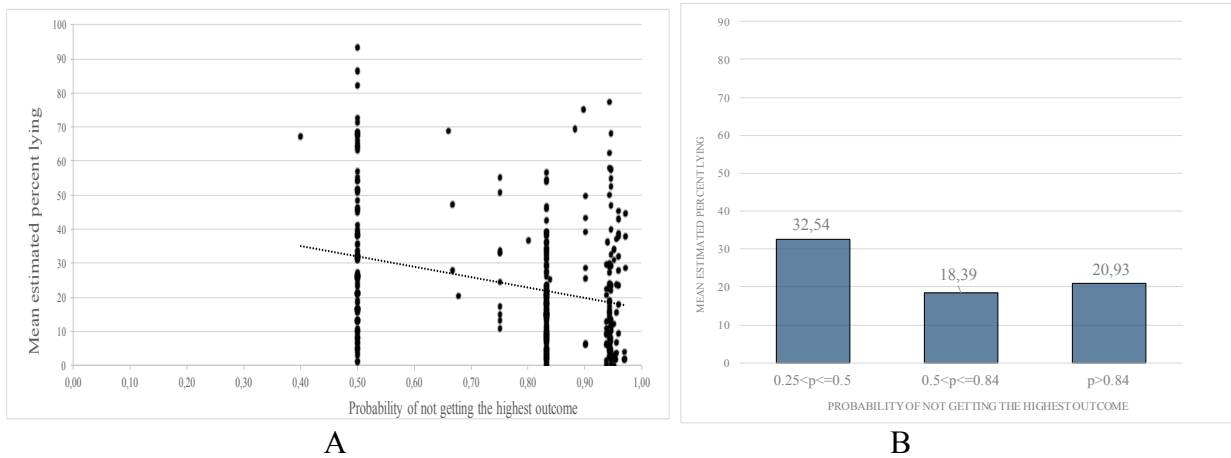


A B

**Figure 2: Mean estimated percent of subjects lying to avoid the lowest payoff by the likelihood of the lowest outcome, literature review**

*Note:* In Panel B, the bar with  $p < 0.166$  corresponds to 139 treatments and 11,270 subjects, the bar with  $0.166 \leq p < 0.5$  corresponds to 102 treatments and 12,129 subjects, the bar with  $0.5 \leq p < 0.75$  corresponds to 107 treatments and 7,399 subjects, the bar with  $p \geq 0.75$  corresponds to 37 treatments and 4,502 subjects. In total, we have 385 treatments instead of 389 in this figure because in one study information was not available at the treatment level.

<sup>16</sup> For example, when subjects have to predict the outcome of 20 coin tosses and earn money that monotonically increases with the number of correct predictions, the bad (good) outcome is defined as getting at most 6 (at least 14, resp.) correct guesses (with  $p=0.057$ ). The 5% threshold is arbitrary, but it allows us to avoid studying extremely rare events such as  $2^{-20}$  in the case of predicting all 20 coin tosses incorrectly or  $1-2^{-20}$  in the case of predicting all 20 coin tosses correctly.



**Figure 3:** Mean estimated percent of subjects lying to avoid a low payoff by the likelihood of not getting the highest outcome, literature review

Note: In Panel B, the bar with  $0.25 < p \leq 0.5$  corresponds to 107 treatments and 7,395 subjects, the bar with  $0.5 < p \leq 0.84$  to 141 treatments and 15,656 subjects, the bar with  $p > 0.84$  to 141 treatments and 13,617 subjects.

Consistent with loss aversion, these figures show a clear negative relationship between the estimated mean lying rate and the likelihood of the bad outcome, regardless of whether it is defined as the lowest outcome or any outcome except the highest.

Due to the large variance in lying across studies for a given probability, we have further analyzed the data using linear regressions in which the dependent variable is the mean estimated lying rate with each treatment serving as one observation. Robust standard errors are clustered at the study level and sample weighting allows us to control for the large diversity of sample sizes across studies.<sup>17</sup> In models (1) to (3) in Table 1, the bad outcome is defined as the lowest payoff outcome, whereas in models (4) to (6) it is defined as any outcome except the highest.

Our main independent variable of interest is the probability of the bad outcome that aims at capturing the effect of loss aversion. However, one potential additional explanation for the effect of the probability of the bad outcome on lying, as discussed in the theory, could be reputation concerns: when the probability of a bad outcome is higher, subjects may feel more worried about appearing to have lied if they report the higher outcome. To control for the reputation effect in order to isolate the effect of loss aversion, we define three categories of observability of subjects' behavior in the experiments: "low observability" characterizes treatments in which there is no interaction between the subject and the experimenter (studies conducted online, or in a laboratory setting but with a double-blind procedure or using mind games without verbal reporting); "high observability"

<sup>17</sup> Note that we also estimated regressions with bootstrapping (allowing for up to 500 replications), instead of introducing weights. The results remain qualitatively similar.

characterizes treatments in which the subjects are observed by another subject or where they have to verbally report the outcome to an experimenter (either in the laboratory or in the field, face-to-face or on the phone); “moderate observability” characterizes the intermediate cases (studies conducted in the field or in the laboratory without double anonymity and without verbal reporting). 42% of the treatments (162) have low observability, 49% (193) have moderate observability and 9% (34) have high observability. In all models, in addition to the probability of the bad outcome, the independent variables include the degree of observability (with low observability as the omitted reference category) and interaction terms between the probability of the bad outcome and the degree of observability. If reputation is solely driving the causal effects of  $p$  on lying and loss aversion is not playing a role, then we would expect that  $p$  would have the lowest or no impact on lying in the low observability condition and the highest impact in the high observability condition.

Models (2) and (5) augment models (1) and (4) by including the expected values of the lowest/bad outcome and of the good/highest outcome, converted from local currencies to US Dollars by 2015 Purchasing Power Parities.<sup>18</sup> They also include a control for conducting the experiment in a standard university lab setting and a dummy variable indicating whether the study has been conducted by a team involving economists, as opposed to studies conducted by other social scientists. In models (3) and (6) we add country dummies.

Consistent with Figures 2 and 3, all specifications reported in Table 1 show that the mean lying rate increases significantly (most of the time at the 1% level of significance) when the likelihood of the bad outcome decreases. This effect is robust to either measure of lying (to avoid the lowest payoff or to get the highest payoff). Moreover, the magnitude of the estimated effect is substantial; for instance, if we compare a die roll with a 5/6 chance to observe the bad outcome to a coin toss with a 50% chance to observe the bad outcome, *ceteris paribus*, the estimate with all the controls (Model 6) predicts 14.47 percentage points ( $[(5/6)-(1/2)]*0.434$ ) more subjects will lie in the coin toss condition.<sup>19</sup>

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<sup>18</sup> For example, suppose a die task in which each dot pays \$1, except when the subject rolls a 6. Conditional on getting the lowest outcome, the expected value of this lowest outcome is \$0, while the expected value of a good outcome is \$3. Conditional on getting the highest outcome, the expected value of the highest outcome is \$5, while the expected value of a bad outcome is \$2.

<sup>19</sup> We re-estimated the six models in Table 1 adding the square of the probability of the lowest (or bad) outcome to test for evidence of the reference dependence diminishing marginal utility implication that an increase in the probability could have a positive effect for low values of  $p$  (see Figure 1). However, in these regressions (available upon request) the squared term is never significant. This suggests that either  $p^*$  is close to zero, we do not have enough observations with low enough values of  $p$ , the loss aversion effect dominates the reference dependence effect for the lowest values of  $p$  we observe, we do not have enough power to detect this effect, or the implication is incorrect. Experiments could easily be designed to test the reference dependence implication, but in this study we focus on the loss aversion hypothesis.

**Table 1.** Likelihood of the bad outcome as a determinant of the mean lying rate

Dep. Variable:	Lying to avoid the lowest outcome			Lying to avoid a bad outcome		
	(1)	(2)	(3)	(4)	(5)	(6)
Mean lying rate						
Probability of the lowest outcome	-0.488*** (0.092)	-0.524*** (0.089)	-0.499*** (0.075)	-	-	-
Probability of a bad outcome	-	-	-	-0.418** (0.166)	-0.425** (0.189)	-0.434*** (0.152)
Moderate observability	-0.017 (0.073)	-0.136** (0.067)	-0.177*** (0.060)	0.352 (0.246)	0.202 (0.226)	-0.115 (0.160)
High observability	-0.299** (0.125)	-0.402*** (0.112)	-0.392*** (0.112)	-0.161* (0.092)	-0.235** (0.090)	-0.187** (0.077)
Probability of the lowest outcome*	0.161 (0.169)	0.186 (0.133)	0.116 (0.103)	-	-	-
Moderate observability						
Probability of the lowest outcome* High observability	0.084 (0.334)	0.265 (0.282)	0.287 (0.305)	-	-	-
Probability of a bad outcome* Moderate observability	-	-	-	-0.420 (0.303)	-0.361 (0.283)	0.017 (0.193)
Probability of a bad outcome* High observability	-	-	-	-0.136 (0.276)	0.002 (0.235)	-0.040 (0.236)
EV of the lowest outcome	-	0.007 (0.006)	0.005 (0.004)	-	-	-
EV of a good outcome	-	-0.001 (0.001)	-0.001 (0.001)	-	-	-
EV of a bad outcome	-	-	-	-	0.010** (0.004)	0.011** (0.005)
EV of the highest outcome	-	-	-	-	-0.003** (0.001)	-0.003** (0.001)
Laboratory	-	0.136*** (0.50)	0.175*** (0.52)	-	0.126*** (0.036)	0.132*** (0.033)
Economics affiliation	-	0.102** (0.041)	0.033 (0.041)	-	0.070 (0.050)	0.027 (0.029)
Country dummies	No	No	Yes	No	No	Yes
Constant	0.647*** (0.053)	0.577*** (0.055)	0.659*** (0.082)	0.593*** (0.112)	0.546*** (0.138)	0.565*** (0.132)
Nb observations	385	385	385	389	389	389
Nb clusters	81	81	81	81	81	81
R <sup>2</sup>	0.242	0.309	0.492	0.298	0.386	0.590

*Note:* Table 1 reports OLS estimates with robust standard errors (in parentheses) clustered at the study level and sample weighted. Each treatment gives one observation. 4 observations are missing in models (1) to (3) because information on lying to avoid the lowest outcome was not available at the treatment level in one study. \*\*\*, \*\*, and \* indicate significance at the 0.01, 0.05 and 0.10 level, respectively.

Table 1 also indicates that reputation plays a role: moderate and high observability lead to less lying than low observability, consistent with the concern for appearing dishonest being greater when the subject is more observable. But importantly, there is no significant interaction effects between

observability and the probability of the bad outcome in any model. This indicates that reputation concerns alone cannot explain the relationship between the probability of the bad outcome and lying.

The regressions also show that the expected values have an impact consistent with expected utility maximizers with increasing marginal utility over money; in particular, as the expected value of the bad payoff increases (so the marginal utility of an extra dollar if lying is smaller), more subjects lied; and as the expected payoff of the highest outcome increases (so there is a greater increase in payoffs to lie), less subjects lied. These results are directional in the analysis of lying to avoid the lowest payoff, and significant in the analysis of lying to get the highest payoff. However, when we replace the Expected Values with alternative definitions of the payoffs, we do not find significant effects, thus in general we find little evidence the size of the monetary stakes had a robust effect on lying, consistent with Abeler *et al.* (2016).<sup>20</sup>

Overall, the findings from our analysis of the extant literature supports our Theoretical Result 1 about the role of loss aversion in lying. Our second approach to isolate the effect of loss aversion from potential reputation effects is to run new experiments where we eliminate as much as possible the possibility of reputation effects. We now present these experiments.

## **5. Two within-study tests of loss aversion and lying**

In this section, we test whether the relationship between the probability of observing the bad outcome and the percent of subjects lying holds when we directly manipulate the probability of the outcomes, remove the variations in conditions that exist between studies in the literature (*e.g.*, different recruitment, subjects, tasks and payoffs), and eliminate as much as possible potential reputation concern effects. In our first experiment, we vary the probability distribution of outcomes, *ceteris paribus*, to earn a fixed payoff for oneself. In our second experiment, we test the robustness of this relationship in a setting where the beneficiary of the lie is not the subject, but a cause that the subject either supports or opposes.

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<sup>20</sup> In alternative specifications (available upon request), we replaced the expected values by the maximum and the minimum payoffs. These variables were never significant, except the lowest payoff in model (6), with a positive sign. We also replaced the expected maximum payoff with the difference in the expected payoffs from reporting the maximum and minimum payoffs. Again, these variables were never significant. Since the  $R^2$  is not higher in these alternative specifications, we omit reporting them.



### 5.1. Study 1: Lying for self

#### *Experimental design and procedures*<sup>21</sup>

This experiment is based on a mind coin tossing game.<sup>22</sup> Subjects have the opportunity to earn money for themselves depending on their ability to predict the outcome of three coin tosses. They are instructed to toss a coin three times, but before each toss they have to predict which side of the coin will be face-up. They have to report only the number of correct guesses. Thus, they can inflate their actual success by misreporting the number of correct guesses. The major advantage of the mind game process is that the subjects know that their outcome cannot be scrutinized: the experimenter cannot observe the prediction or the actual outcome of the coin toss. To eliminate reputation concerns, the experiment was also run online and double-anonymous; it was common knowledge that the experimenter never knew the identity of the subjects. Therefore, individuals should have no reason to disguise a lie to maintain a positive image with other subjects or the experimenters.<sup>23</sup>

The study involves three between-subject treatments that vary the probability of observing the lowest and the highest payoff. In the “0002” treatment, subjects earn \$0 if they report 0, 1, or 2 correct guesses and they earn \$2 if they report 3 correct guesses. The probability of observing the low payoff is 87.50% and the probability of observing the high payoff is 12.50%. In the “0022” treatment, subjects earn \$0 if they report 0 or 1 correct guess and they earn \$2 if they report 2 or 3 correct guesses. Here, the probability of observing the low payoff or the high payoff is 50%. Finally, in the “0222” treatment, subjects earn \$0 if they report 0 correct guesses and they earn \$2 if they report at least one correct guess. Here, the probability of observing the low payoff is 12.50% and the probability of observing the high payoff is 87.50%. Procedures and payoffs are common knowledge.

The experiment was run using Amazon MTurk with 978 U.S. participants.<sup>24</sup> We varied the number of participants across treatments based on a preliminary statistical power analysis, with the objective of getting approximately the same number of likely opportunities to get the \$0 payoff in

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<sup>21</sup> The full instructions for both experiments are available in the online Appendix. Web link accessible as of 18/07/2017 [https://az1.qualtrics.com/ControlPanel/?ClientAction=EditSurvey&Section=SV\\_b19Z03D013uo61v&SubSection=&SubSection=&PageActionOptions=&TransactionID=1&Repeatable=0](https://az1.qualtrics.com/ControlPanel/?ClientAction=EditSurvey&Section=SV_b19Z03D013uo61v&SubSection=&SubSection=&PageActionOptions=&TransactionID=1&Repeatable=0)

<sup>22</sup> Mind games have been used mainly with a die (Jiang 2013; Shalvi and de Dreu 2014; Barfort *et al.* 2015; Kajackaite and Gneezy 2017; Potters and Stoop 2016), rarely with coin tosses (Shalvi 2012).

<sup>23</sup> Kajackaite and Gneezy (2017) find that some people may not lie in non-mind games such as Fischbacher and Föllmi-Heusi (2013) because they want to disguise a lie due to concerns with scrutiny.

<sup>24</sup> The use of MTurk ensures a double anonymous procedure reinforcing the lack of observation by others. It also enables the collections of a large number of short duration observations from a broad demographic pool. Given the simplicity of the task, we feel confident that participants understood the instructions. Moreover, studies have shown that the quality of data and behavior on MTurk do not differ from that of other sources (*e.g.*, Paolacci *et al.* 2010; Horton *et al.* 2011; Suri and Watts 2011).

each treatment, and hence the same number of respondents with a financial motive to lie. 80 persons participated in the 0002 treatment, 327 in the 0022 treatment and 571 in the 0222 treatment. After the task was explained (see the online instructions for full details), they tossed a coin and reported the number of correct predictions. We also collected a number of socio-demographic characteristics (including age, gender, highest educational attainment, category of household annual pretax income, mean weekly expenditures).<sup>25</sup> A summary of our subjects' characteristics by treatment and the effects of these characteristics on payoffs can be found in Appendix Tables A3 and A4.<sup>26</sup> On average, the experiment lasted 7 minutes 45 seconds (S.D.= 8 minutes and 24 seconds) and subjects earned \$3.27 (S.D.= 0.64) which included a \$1.50 participation fee.

### *Results*

Our model predicts that subjects will be more likely to lie to avoid earning \$0 in the 0222 treatment than in the 0022, and more likely to lie in the 0022 treatment than in the 0002 treatment. The data confirm these two predictions, as summarized in our first result:

**Result 1.** Consistent with the loss aversion model presented above, individuals lie more on average to increase their own payoff when observing the low payoff is more unlikely.

*Support for Result 1.* Table 2 displays summary statistics by treatment, including the distributions of reported outcomes, the  $p$ -values of  $\chi^2$  goodness-of-fit tests comparing the empirical distributions of reports with the theoretical distribution, the  $p$ -values of binomial tests comparing each category of reported outcome with its theoretical relative frequency, the mean estimated lying rates using our technique, and the associated 95% confidence intervals.

Table 2 shows that the percentage of reports paying \$0 is 2.98% in the 0222 treatment, 16.82% in the 0022 treatment and 48.75% in the 0002 treatment, while the theoretical percentages should be 12.50%, 50% and 87.50%, respectively. Binomial tests and  $\chi^2$  goodness-of-fit tests show that the reports deviate significantly from the theoretical distribution. Our estimation based on the full

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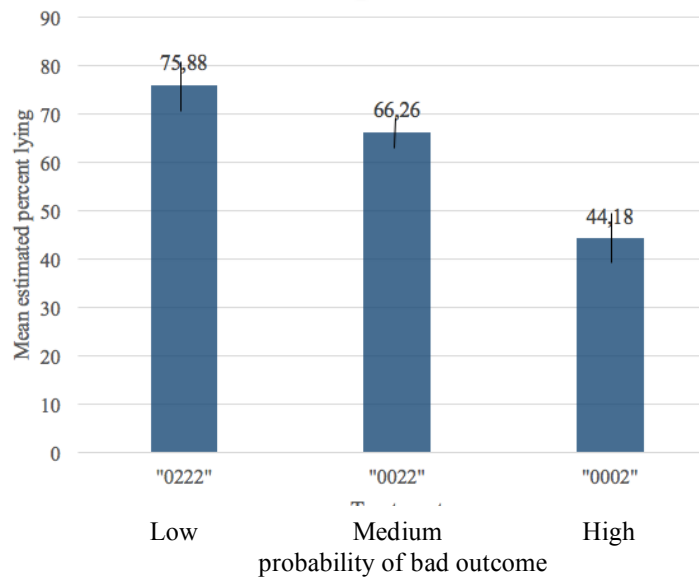
<sup>25</sup> We also collected beliefs about the social appropriateness of reporting different outcome combinations using a procedure inspired from Krupka and Weber (2013), and we elicited the person's belief in good luck using a twelve-item questionnaire from psychology (Darke and Freedman 1997). Since neither of these potential moderators had substantial or consistent effect, they have been removed from the remaining analyses.

<sup>26</sup> The various demographics are randomly dispersed across conditions. In study 1, pairwise tests show no significant differences between conditions on gender ( $p>0.14$ ), age ( $p>0.14$ ), education ( $p>0.90$ ), income ( $p>0.07$ ), or weekly spending ( $p>0.80$ ). We cannot estimate lying at the individual level, so to test the effects of covariates we used the participant's payout as a proxy for lying, since those who lied receive the larger payout. The demographic and attitudinal variables have little effect on the participant's payout. Only age consistently reaches the 0.05 level of significance, such that younger people get higher payouts. Additional analyses find no significant interactions of the covariates with the conditions (all  $p$ -values  $> 0.05$ ), demonstrating that none of the covariates moderate the effects of treatment on payout.

distribution of reports (assuming that nobody lies downwards) shows that on average 44.18% of participants who had a financial motive to lie lied in the 0002 treatment, 66.26% in the 0022 treatment, and 75.88% in the 0222 treatment. Pairwise comparisons indicate that the differences between the three treatments are significant at the  $p < 0.01$  level, as there is no overlap between the 95% confidence intervals. Figure 4 illustrates these findings.<sup>27</sup>

**Table 2.** Summary statistics, Study 1

Treatments	0222	0022	0002
<i>Number of reported correct guesses</i>			
0	17 (2.98%)	13 (3.98%)	3 (3.75%)
1	165 (28.90%)	42 (12.84%)	11 (13.75%)
2	308 (53.94%)	221 (67.58%)	25 (31.25%)
3	81 (14.19%)	51 (15.60%)	41 (51.25%)
N	571 (100%)	327 (100%)	80 (100%)
<i>p-values from <math>\chi^2</math> goodness-of-fit tests</i>			
	<0.001	<0.001	<0.001
<i>p-values from two-sided Binomial tests</i>			
0 correct guess	<0.001	<0.001	0.016
1 correct guess	<0.001	<0.001	<0.001
2 correct guesses	<0.001	<0.001	0.299
3 correct guesses	0.229	0.094	<0.001
Percent who earned \$0	2.98%	16.82%	48.75%
Expected percent if no lying	12.50%	50.00%	87.50%
<i>Mean percent of subjects lying</i>			
	75.88	66.26	44.18
<i>Confidence Interval, 95%</i>			
	70.03-80.62	62.40-69.73	39.39-48.63



**Figure 4.** Mean estimated percent of subjects lying, by treatment, Study 1

<sup>27</sup> Our findings are consistent with those of Abeler *et al.* (2016) who also report the results of an experiment in which they shift the distribution of true states. Subjects have to draw one chip out of 50 chips that pay either 4 or 10 GBP. In one treatment, there are 5 chips paying GBP 10 and in the second treatment there are 30 chips paying GBP 10. They find that people cheat significantly more in the second condition.

## 5.2. Study 2: Lying to support or avoid supporting an organization<sup>28</sup>

To test the robustness from our first experiment, we ran a second experiment using a 2x2 between-subject and within-subject design. The within-subject manipulation varies the likelihood of observing the worst and best outcomes and includes an intermediary outcome in the payoff distribution. The presence of three outcomes lets us test whether subjects are more willing to lie to avoid the worst outcome (in order to get the intermediary or best outcome) or to get the best outcome (in order to avoid the worst or intermediary outcome). The second dimension varies the beneficiary of the reported outcome between subjects. The beneficiary is no longer the individual but a cause that the individual either supports or opposes.<sup>29</sup> This experiment thus gives us two distinct robustness tests: whether subjects lie more as the probability of the bad outcome decreases when (1) lying will *benefit* a cause they support (by lying either to avoid reporting the bad outcome, or by lying to report the best outcome) and (2) lying will *avoid benefiting* a cause they oppose (by lying either to avoid reporting the best outcome, or by lying to report the worst outcome).<sup>30</sup>

### *Experimental design and procedures*

The second experiment is also based on a mind game. Subjects complete two sets of three coin tosses, each set with a different incentive structure. In the “0018” treatment, reporting zero or one correct guess pays nothing, while reporting two correct guesses pays \$1 and reporting three correct guesses pays \$8. In this treatment, the probability of observing the lowest payoff outcome is 50% and the probability of observing the highest payoff outcome is 12.5%. In the “0188” treatment, reporting zero correct guesses pays nothing, reporting one correct guess pays \$1, and reporting two or three correct guesses pays \$8. In this treatment, the probability of observing the lowest payoff

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<sup>28</sup> Stimuli available at this address. Web link accessible as of 18/07/2017

[https://az1.qualtrics.com/ControlPanel/?ClientAction=EditSurvey&Section=SV\\_ac4TD3rGA3HZALr&SubSection=&SubSection=&PageActionOptions=&TransactionID=1&Repeatable=0](https://az1.qualtrics.com/ControlPanel/?ClientAction=EditSurvey&Section=SV_ac4TD3rGA3HZALr&SubSection=&SubSection=&PageActionOptions=&TransactionID=1&Repeatable=0)

<sup>29</sup> This constitutes another originality of our study. In the previous literature, when the report of the subject impacts another entity, this entity is usually another subject in the experiment and the deciding player’s payoff is also affected (e.g., Conrads *et al.* 2013; Shalvi and de Dreu 2014; Meub *et al.* 2015; Muehlheusser *et al.* 2015; Weisel and Shalvi 2015; Amir *et al.* 2016; Banerjee *et al.* 2016; Cadsby *et al.* 2016). We are aware of only one other study where the beneficiary of a lie is a nonprofit organization (Lewis *et al.* 2012).

<sup>30</sup> This design also gives information on whether people are willing to lie when their payoff is not affected. On the one hand, the moral cost of lying is not compensated with a personal monetary benefit, which should discourage lying. Conversely, the moral justification of donating or avoiding donating to a cause you either support or oppose may encourage lying. Moreover, the design lets us test whether subjects are more willing to lie to help a cause they support vs. to avoid helping a cause they oppose. We have no *a priori* hypothesis nor know of any literature that suggests whether lying to support or lying to not help support will be stronger.

outcome is 12.50% and the probability of observing the highest payoff outcome is 50%. We balanced the order between the two incentive structures across individuals.

Depending on the condition, the beneficiary of the reported outcome is either the Republican National Party (RNP) or the Democratic National Party (DNP) in the U.S.<sup>31</sup> All participants earn a fixed payoff (\$1.50) for themselves that is independent of their reported outcome. At the beginning of the session, we asked subjects to indicate their agreement with the goals of, and desire to help, both the RNP and DNP. We included these questions not only to measure their partisanship, but also to induce them to think about their support or opposition before deciding whether to report honestly or not. Subjects were then matched randomly with one party and were informed that their reported outcome could generate a donation to this party.

This experiment included 422 (different) MTurkers residing in the US. After the decision task, we elicited each subject's political affiliation to identify whether the party he was assigned is one he supports or opposes. In particular, we assume that if a subject states an affiliation with the Democratic (Republican) party, then he would support the cause of the DNP (RNP) and oppose the cause of the RNP (DNP).<sup>32</sup> If a participant states no affiliation with either the Democratic or Republican party (they indicated any other party or no affiliation with any party), we assume they neither support nor oppose either party. After reporting the number of correct predictions in the two decisions, subjects also had to decide whether the experimenter would add \$2, subtract \$2 or not change the total donation made for each party. At the end of the experiment, one of the four monetized decisions (the two mind games "0018" and "0188" and the two decisions to either add, subtract or leave unchanged) was chosen at random to be carried out. Overall, 181 (42.89%) subjects reported an affiliation with the Democratic Party and 80 (18.96%) with the Republican Party, and 151 (35.78%) self-reported as Independent. Given the importance of (mis-)matching the political affiliations, we retain for the analysis only those who stated a Democrat or Republican affiliation. This left 115 subjects assigned to potentially help their own party and 146 assigned to potentially help the party they oppose.

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<sup>31</sup> The studies were run in April 2016 during the primary season before either party's nominee had been determined.

<sup>32</sup> We use the stated political party affiliation in the analysis because it is the identity reported by the subject, but note that this variable is consistent with our other measures. Those subjects who stated an affiliation with the Democratic party report a mean agreement with the DNP goals of 31.76 (S.D.=16.73; range -50 - +50) but an agreement of -32.92 (S.D.=19.10; range -50 - +50) with the goals of the Republican party. Conversely, those affiliated with the Republican party, agree with the RNP goals (mean 26.71; S.D. = 18.16; range -50 - +50) and disagree with the DNP goals (mean -27.39; S.D.=21.79). In contrast, independents show limited agreement with either party's goals (DNP: mean -0.37; S.D.=25.90 and RNP: mean -13.41; S.D.=24.87).

We elicited beliefs and socio-demographic variables as in the first study and we additionally collected a scale measure of guilt proneness (Cohen *et al.* 2011) and religiosity (Huber and Huber 2012) to proxy internal moral costs (see Appendix 2 and Tables A3 and A5 in Appendix 3).<sup>33</sup> After all subjects completed the experiment, the final payoffs to each party were determined and a single payment was made. On average, the experiment lasted 13.02 minutes (S.D.=11.31). Subjects earned a flat fee of \$1.50 and generated an average of \$2.84 for the party they were partnered with.

### Results

Table 3 displays summary statistics about the results of Study 2, for each treatment and for three categories of subjects (those who were matched with the party they support, those matched with the party they oppose, and those who reported no affiliation to either the DNP or RNP). It also includes the distributions of reported outcomes, the  $p$ -values of  $\chi^2$  goodness-of-fit tests and binomial tests, the mean estimated lying rates, and the associated 95% confidence intervals.

**Table 3.** Summary statistics, Study 2

	0018 Treatment			0188 Treatment		
	Support	Oppose	Other	Support	Oppose	Other
<i>Number of reported correct guesses</i>						
0	5 (4.35%)	21 (14.39%)	18 (11.18%)	3 (2.61%)	23 (15.76%)	20 (12.42%)
1	40 (34.78%)	59 (40.41%)	66 (40.99%)	30 (26.09%)	75 (51.37%)	60 (37.27%)
2	48 (41.74%)	59 (40.41%)	54 (33.54%)	64 (55.65%)	41 (28.08%)	68 (42.24%)
3	22 (19.13%)	7 (4.79%)	23 (14.29%)	18 (15.65%)	7 (4.79%)	13 (8.07%)
N	115 (100%)	146 (100%)	161 (100%)	115 (100%)	146 (100%)	161 (100%)
<i>p-values from <math>\chi^2</math> goodness-of-fit tests</i>						
	0.121	0.046	0.608	<0.001	<0.001	0.322
<i>p-values from two-sided Binomial tests</i>						
0 correct guess	0.004	0.454	0.721	<0.001	0.258	1
1 correct guess	0.565	0.494	0.371	0.012	0.001	1
2 correct guesses	0.386	0.494	0.329	<0.001	0.021	0.222
3 correct guesses	0.046	0.002	0.475	0.321	0.002	0.095
Percent earn worst	39.13%	4.79%	NA	2.61%	32.87%	NA
Expected percent	50.00%	12.50%		12.50%	50.00%	

<sup>33</sup> There are no significant differences between conditions on gender ( $p > 0.69$ ), age ( $p > 0.05$ ), education ( $p > 0.90$ ), income ( $p > 0.46$ ), weekly spending ( $p > 0.34$ ), political affiliation ( $p > 0.38$ ). As expected, there is a significant difference between agreement with the political goals of the party the participant is donating to, based on whether the person was in the support or oppose condition ( $ps < 0.001$ ). The demographic and attitudinal variables have little effect on the participant's payout. We again see some effect of age, although less consistently strong here, and in the opposite direction as in study 1, with older respondents reporting higher payouts. Additional analyses find no significant interactions of the covariates with the supporting and opposing conditions (all  $p$ -values  $> 0.05$ ), demonstrating that the covariates do not moderate the effects of treatment on payout.

Percent earn not best	80.87%	45.20%	NA	28.70%	84.24%	NA
Expected percent	87.50%	50.00%		50.00%	87.50%	
<i>Mean percent of subjects lying to avoid</i>						
- the worst outcome	21.24	59.62	8.33 <sup>a</sup>	77.65	33.79	5.16 <sup>a</sup>
* lower bound CI	6.43	37.86	0	63.59	22.13	0
* upper bound CI	34.35	74.00	27.15	86.47	43.76	14.93
- any bad outcome	7.61	10.71	7.32 <sup>b</sup>	42.10	4.25	2.00 <sup>b</sup>
* lower bound CI	1.70	0	0	30.47	0	0
* upper bound CI	13.69	22.94	18.30	51.84	9.47	6.07

*Notes:* For Support conditions, the ‘worst’ outcome is to give \$0 and a ‘bad’ (or not best) outcome is to give less than \$8. For Oppose conditions, the ‘worst’ outcome is to give \$8 and a ‘bad’ outcome is to give anything greater than \$0. For the Other category (“independents” and “others”), there is no obvious best or worst outcome. Thus, we estimate the mean percent of subjects lying as follows: <sup>a</sup> lying to avoid giving \$8 to a party, <sup>b</sup> lying to avoid giving anything to a party.

Although not central to our core loss aversion prediction, we first test whether lying is higher amongst people who support or oppose a cause than amongst those who are not affiliated with either party to assess whether people lie for or against a cause they care about. This is confirmed by the  $p$ -values from  $\chi^2$  goodness-of-fit tests and by the lower bounds of the 95% confidence intervals in Table 3: for the independent subjects, the empirical distribution of reports almost never differs significantly from the theoretical distribution. In contrast, the reports of partisans differ from the distribution expected if subjects reported honestly in a majority of cases.<sup>34</sup>

Our model predicts that people who support the party they are matched with will be more willing to lie to avoid earning \$0 for this party in the 0188 treatment than in the 0018 treatment; and that people who oppose the party they are matched with will be more willing to lie to avoid giving \$8 in the 0018 treatment than in the 0188 treatment. The data confirm this prediction.

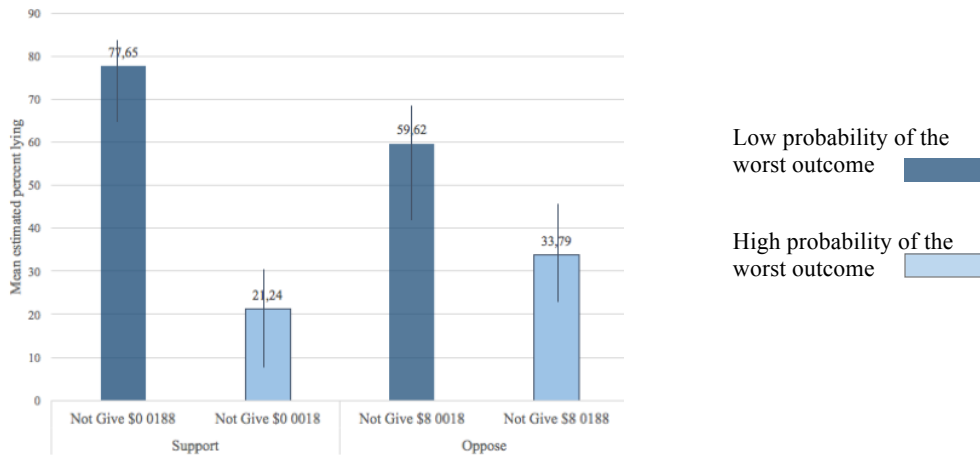
**Result 2.** Consistent with our loss aversion model, individuals lie more to support a cause when the less desired outcome is more unlikely. The same directional effect is found when they oppose a cause.

*Support for Result 2.* As a complement to Table 3, Figures 5A and 5B show the mean estimated lying rates and confidence intervals when lying to avoid the worst outcome (*i.e.* giving \$0 to the party one supports or \$8 to the party one opposes) and when lying to avoid a bad outcome/get the best outcome (*i.e.* giving \$8 to the party one supports, or \$0 to the party one opposes), respectively. The right two bars show the lying rate when subjects are paired with the party they oppose and the left two bars

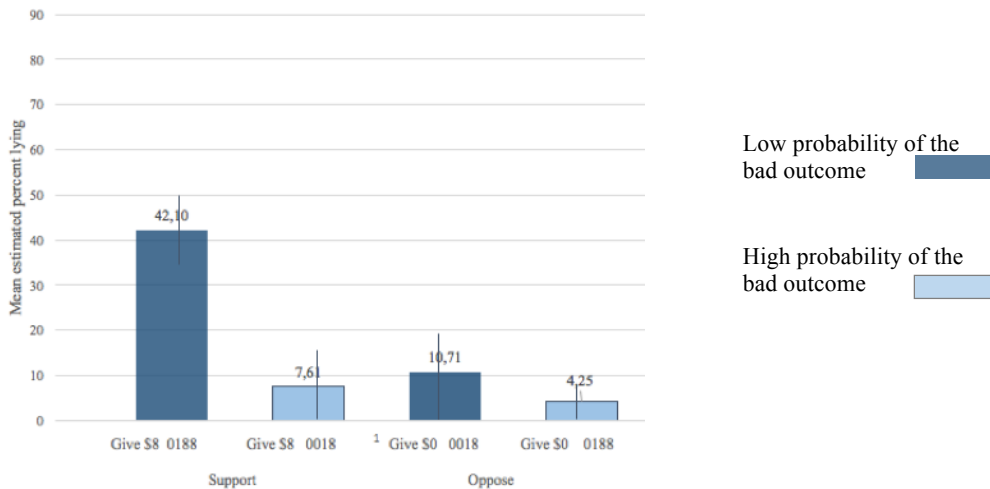
<sup>34</sup> Note that we also do not find any significant difference in the reported number of correct predictions between the subjects who declare an affiliation to the Democratic party and those who declare an affiliation to the Republican party (Kolmogorov-Smirnov tests of equality of distribution of reported outcomes, 0018 treatment:  $p = 0.951$  when subjects are matched with their preferred party and  $p = 0.780$  when they are mismatched; 0188 treatment:  $p = 0.675$  when subjects are matched with their preferred party and  $p = 0.987$  when they are mismatched).

show the lying rate when subjects are paired with the party they support. The light bars represent the case when the worst outcome is likely and the dark bars the case when the worst outcome is unlikely.

Table 3 and Figures 5<sub>A&B</sub> show that for those subjects who support the party they are matched with, the estimated lying rate is significantly higher when observing the worst or a bad outcome is more unlikely (77.65% and 42.10%, respectively) than when it is more likely (21.24% and 7.61%, respectively). That is, there is approximately a 56 percentage point increase in lying when observing the worst outcome is more unlikely than when observing it is more likely (77.65% - 21.24%) and a 35% percentage point increase in lying when the bad outcome is more unlikely than when it is more likely (42.10% - 7.61%). These differences are significant at least at the  $p < 0.05$  (1-0.975\*0.975) level since at least 97.5% of the two distributions in each comparison do not overlap.



**Figure 5A.** Mean estimated percent lying to avoid the worst outcome, Study 2



**Figure 5B.** Mean estimated lying rates to avoid a bad outcome/get the best outcome, Study 2



For those who were paired with the party they oppose, the lying rate is again higher when the worst or a bad outcome is more unlikely (59.62% and 10.71%, respectively) than when it is more likely (33.79% and 4.25%, respectively). There is approximately a 26 percentage point increase in lying when the worst outcome is more unlikely than when it is more likely (59.62% - 33.79%) and a 6% percentage point increase when the bad outcome is more unlikely than when it is more likely (10.71% - 4.25%). When the worst outcome is more unlikely (EV=59.62), the lower bound on the 90% confidence interval is 43.36% and when it is more likely (EV=33.79%) the upper bound on the 90% confidence interval is 42.49%. This difference is significant at least at the  $p < 0.10$  (1-0.95\*0.95) level since 95% of the two distributions do not overlap. However, we cannot reject that there is no statistical difference when the bad outcome is more unlikely (EV=10.71%) than when it is more likely (EV=4.25%) since even the tails of the 60% confidence intervals overlap each other.

### *Robustness checks*

Overall, consistent with loss aversion, these results support our main hypothesis that people will lie more the when they expected to get a good outcome (*i.e.*, when there is a low probability of a bad outcome, even in the absence of the possibility for external reputation effects. They also suggest that people are slightly less sensitive to the outcome's likelihood when lying to avoid giving money to a cause they oppose than when giving to a cause one supports.<sup>35</sup>

To explore the robustness of the results, we first test whether subjects who think the study is about lying or dishonesty behave differently, as this awareness could generate some external pressure even in the absence of observability. In a post-experimental questionnaire, we asked subjects what they believed the aim of the experiment was in an open-ended question. Of the 235 subjects who responded, 35% (in both mismatched and matched conditions) mentioned something related to honesty (*e.g.*, lying, honesty, morality, cheating, ethics, etc.). The subject's beliefs about the purpose of the study does not correlate with their earnings, which would be expected if people were acting

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<sup>35</sup> A Kolmogorov-Smirnov test concludes that the distribution of reported outcomes differs between subjects who support the party they are paired with in the 0188 treatment and the subjects who oppose the party they are paired with in the 0018 treatment ( $p=0.045$ ). A Mann-Whitney rank-sum test shows that the reports are higher when subjects support than when they oppose ( $p =0.024$ ) the party they are paired with. In contrast, both a Kolmogorov-Smirnov test and a Mann-Whitney test indicate that there is no difference in reports between subjects who support the party they are paired with in the 0018 treatment and the subjects who oppose the party they are paired with in the 0188 treatment ( $p=0.950$  and  $p=0.702$ , respectively). To compare the values between supporters and opponents in these tests, we transform the reports of the subjects who oppose the party they are matched with (for example, 0 reported correct prediction in 0188 for opponents is coded 4, so that it can be compared to 3 correct predictions by supporters in the 0018 treatment).

based on their fear of suspicion. The salience of our interest in lying is not changing behavior, and thus it is unlikely that a fear of behaving suspiciously would explain the results.<sup>36</sup>

However, even if we remove the potential influence of others knowing you are lying, one could still worry about internal moral cost (*i.e.*, being concerned about feeling guilty or less morally upright if lying) playing a role in the relationship between the probability of the bad outcome and lying behavior. We offer three tests of the potential influence of internal moral cost: the size of the lie, individual guilt proneness and personal religiosity. If internal moral cost is driving lying rates we might expect smaller lies to be less costly and hence more common than larger lies. In Study 1, getting \$2 requires predicting at least one coin toss correctly in the 0222 treatment, hence a subject who predicted no coin toss correctly would have to report an outcome that is just one more correct prediction than he observed in order to receive the \$2. If size of the lie matters, we should observe a concentration of reports in the category that is just sufficient to earn \$2. In fact, in the 0222 treatment, 29% report 1 correct guess (instead of the expected 37.5%), whereas 54% report 2 correct guesses (instead of 37.5%), and 14% report 3 (instead of 12.5%). Thus, we do not see a disproportionate percent of subjects reporting one correct prediction, the minimum additional correct predictions to receive the \$2.

If internal moral cost were explaining our findings, we should expect that those who experience little internal moral cost will show little or no responsiveness to the probability of the bad outcome. In our post-experimental questionnaire, we elicited (a) the guilt proneness of our subjects using the Cohen *et al.*'s (2011) 6 item survey questions and (b) their religiosity using the Huber and Huber's (2012) 4 item survey questions. We consider a sub-sample consisting of the third of subjects who exhibit the lowest level of guilt proneness (those who should experience the least internal moral cost), regardless of whether they are matched with their favorite party or not (N=95). We find that the mean lying rate is 63.48% (CI: 37.57-78.96) when the probability of the bad outcome is 12.5%, 42.54% (CI: 29.71-53.10) when the probability is 50%, and 12.06% (CI: 5.25-18.54) when the

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<sup>36</sup> In study 1, 47.06% of the subjects in the 0222 treatment believe that the experiment is about lying and 21.69% that it is about luck (the other interpretations are too diverse to be categorized on a single denomination). The respective percentages are 47.33% and 26.33% in the 0022 treatment, and 47.37% and 21.05% in the 0002 treatment. Pairwise comparisons show that these percentages do not differ significantly ( $p > 0.1$ ). We also estimated a logit model in which the dependent variable is the high payoff and the independent variables include the beliefs about the aim of the experiment (studying lying, the role of luck, and others). We find that the belief that the experiment is about lying is not significantly correlated with earnings. Similarly, in study 2, 34.9% (34.8%) of participants in the match (mismatch) condition believe the experiment is about lying and 20.5% (21.7%) believe it is about politics. These beliefs do not differ significantly across treatments. Multinomial logit analyses show that whether people thought the study was about lying, politics or something else had no significant effect on the payout to the parties. Details are available upon request.

probability is 87.5%.<sup>37</sup> This result is quite similar to the lying rates in the overall sample similarly collapsed (68.10% probability of the bad outcome is 12.5%, 26.60% probability is 50%, and 5.65% probability is 87.5%), and show a strong effect of outcome probability on lying, thus the tendency to experience guilt is not driving the difference in lying based on probability of outcome.

We repeat the same procedure focusing on the subjects with the third of the sample with the lowest levels of religiosity, again regardless of whether matched or not with their preferred party, since we expect that these subjects experience the least internal moral cost (N=77). Again, we still find that lying is more likely when the probability of the bad outcome is lower. The mean lying rate is 65.51% (CI: 38.70-81.43) when the probability of the bad outcome is 12.5%, 43.77% (CI: 21.11-60.29) when it is 50%, and 9.46% (CI: 2.26-16.70) when it is 87.5%.

These additional analyses indicate that even for those subjects who should feel the least moral pressure the probability of the bad outcome has a negative impact on lying, and the effect of the probability of the bad outcome on lying is not dissimilar to those in the overall sample. These additional results support that internal moral cost is unlikely to explain the effect of the probability of the bad outcome on lying, hence loss aversion remains the most plausible explanation of our findings.

## 6. Discussion and conclusion

Loss aversion predicts that the probability of observing each payoff outcome affects the level of dishonesty. In this paper, we demonstrate theoretically that as the likelihood of observing an *ex-ante* low payoff outcome decreases, the gain in utility for a loss-averse agent who reports dishonestly to avoid the loss increases. We also develop a simple econometric technique to estimate the full distribution of dishonesty, which gives us a precise estimate of the mean lying rate, confidence intervals and any other statistic one can obtain from the CDF. We use this technique to analyze data from the extant literature and two new experiments. We confirm that individuals lie more to avoid the undesired outcome when this undesired outcome is more unlikely to be observed.

Several extensions of our study might further extend our understanding. For example, regarding the measurement of lying behavior, we could also consider a Bayesian approach and allow for priors, which may tighten the distribution of dishonesty. We could also allow for decision errors, which

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<sup>37</sup> The probability of the bad outcome is 12.5% in the 0018 (0188, respectively) treatment for subjects who oppose (support, resp.) and lie to avoid giving 8 (0, resp.). It is 50% in the 0188 (0018, respectively) treatment for subjects who oppose (support, resp.) and lie to avoid giving 8 (0, resp.). It is 87.5% in the 0188 (0018, respectively) treatment for subjects who oppose (support, resp.) and lie to give 0 (8, resp.).

would add more noise. To further test the theoretical model, new experiments could measure each subject's degree of loss and risk aversion to more directly investigate the relationship between loss aversion and lying.<sup>38</sup>

The role of loss aversion and reference-dependence does not exclude the influence of other factors that may motivate people to lie more when a bad payoff outcome is more unlikely. Recent models consider how decision makers derive disutility based on the degree to which they are perceived to be cheaters by others (*i.e.*, reputation concerns), and even in their own eyes. In particular, if subjects perceive potential suspicion by the experimenter, they may be more likely to cheat when the bad outcome is rare than when it is more likely. Although we cannot exclude that some participants have a distaste for being perceived as acting suspicious in the extant literature, we found no interaction effect between the degree of observability of subjects in this literature and the impact of the probability of the bad outcome. Even in studies where observability is very limited or nonexistent, lying is less likely when the bad outcome is more likely. Being conducted online and double-anonymous, our own experiments exclude any direct contact with, and any possibility of being observed by, the experimenter to minimize the salience that could possibly generate suspicion or risk of negative reputation if lying. Moreover, using a mind game guarantees that a lie cannot be detected at the individual level even if someone was observing the subject. Thus, concerns about external reputation do not drive the results. The evidence from study 2 also refutes the explanation of internal moral cost driving the results; even subjects who have a lower guilt proneness or are less religious are less likely to cheat when the probability of the bad payoff outcome is higher. Thus, there is consistent evidence that loss aversion is influencing lying.

Our study has a number of implications, both for academics and for policy-makers. Regarding academic implications, future studies can use our statistical method to estimate the full distribution of lying to more accurately assess the rate of lying. Our analysis reveals the importance of controlling for the probability of low payoff outcomes when studying lying behavior. Finally, it suggests that if experimentalists want to study situations where dishonesty might not otherwise be too high, they should use a large sample and set a low probability for the bad outcome. Regarding policy implications, our results suggest that to limit lying, choices should be framed to increase the

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<sup>38</sup> We did not measure risk and loss aversion because, first, the length of our study was already approaching the average time for running MTurk studies, and to appropriately estimate loss aversion would go beyond the upper limits of an MTurk study. Second, we estimate lying at the treatment level, thus we would need many more observations per subject to estimate lying at the individual level. Third, we were concerned that measuring loss or risk aversion before our lying task might affect behavior and that performing the lying task first might affect the measure of risk and loss aversion.

perceived likelihood of the undesired outcome. They also suggest that costly efforts of detection should be concentrated on situations in which the likelihood of a bad outcome is relatively low.

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# Supplementary Materials for:

Loss aversion and lying behavior: Theory, estimation and empirical evidence

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(web link accessible as of 18/07/2017

[https://az1.qualtrics.com/ControlPanel/?ClientAction=EditSurvey&Section=SV\\_bi9ZO3D013uo61v&SubSection=&SubSubSection=&PageActionOptions=&TransactionID=1&Repeatable=0](https://az1.qualtrics.com/ControlPanel/?ClientAction=EditSurvey&Section=SV_bi9ZO3D013uo61v&SubSection=&SubSubSection=&PageActionOptions=&TransactionID=1&Repeatable=0) )

Experiment 2: Lying to support or avoid supporting an organization instructions

(web link accessible as of 18/07/2017

[https://az1.qualtrics.com/ControlPanel/?ClientAction=EditSurvey&Section=SV\\_ac4TD3rGA3HZALr&SubSection=&SubSubSection=&PageActionOptions=&TransactionID=1&Repeatable=0](https://az1.qualtrics.com/ControlPanel/?ClientAction=EditSurvey&Section=SV_ac4TD3rGA3HZALr&SubSection=&SubSubSection=&PageActionOptions=&TransactionID=1&Repeatable=0) )

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## Appendix 1. Illustrations of the method of estimation of the percent of lying

Table A1 provides a few examples with N=100 subjects and R=60 subjects who report the high outcome, and different values of  $p$  and of the CI. When  $p = 50\%$ , we can reject that all subjects were honest at the 90<sup>th</sup> and 95<sup>th</sup> percent CI, but not at the 99<sup>th</sup> percent. At the 90<sup>th</sup>, 95<sup>th</sup> and 99<sup>th</sup> percent CI, we can be confident that at least 7.0%, 4.5% and 0.0% of subjects were dishonest, respectively, and at most 32.0%, 33.7% and 36.9% were dishonest. If the likelihood of the high outcome was lower, falling from 60% to 50%, to 40%, to 10%, to 3%, we would be 95% confident that at least 0.0%, 0.0%, 21.3%, 52.5% and 57.3% were dishonest, respectively, and at most 22.3%, 36.9%, 42.9%, 58.3% and 60% were dishonest.<sup>39,40</sup>

**Table A1. Illustration of the method of estimation of the percent of dishonest subjects**

Example	Inputs				Outputs		
	N	R	$p$	CI	EV	Lower bound	Upper bound
1	100	60	50%	95%	19.63%	4.45%	33.72%
2	100	60	50%	90%	19.63%	6.98%	31.95%
3	100	60	50%	99%	19.63%	0.0%	36.91%
4	100	60	40%	95%	7.88%	0.0%	22.31%
5	100	60	60%	95%	32.88%	21.25%	42.85%
6	100	60	90%	95%	55.51%	52.51%	58.32%
7	100	60	97%	95%	60.00%	57.31%	60.00%

Notes: N = number of subjects; R = number who report the higher outcome;  $p$  = probability of the lower outcome; CI = confidence interval; EV = expected value; lower and upper bound of the CI.

The following Figures A compare measures using our lying calculator with the alternative method used by Abeler *et al.* (2016) in three examples. In Abeler *et al.*, the percent of subjects that lie equals  $(r-p)/(1-p)$  where  $r$  is the percentage of subjects that report the higher payoff and  $p$  is the likelihood of observing this good outcome. We have made simulations with N=600 subjects. The x-axis represents the number of subjects  $r$  who report the good outcome and the y-axis represents the estimate of the mean rate of lying. The top left panel corresponds to a coin toss with 50% chance to observe the bad outcome. The top right panel corresponds to a die roll with 5/6 chance to observe the bad outcome. The bottom panel corresponds to a die roll with 1/6 chance to observe the bad outcome. Our method has the advantage of providing confidence intervals. The main differences are concentrated around the range of observations close to the true value (for example, when N is between 250 and 320 for the case in which  $p=0.5$ ; see the top left panel). More generally, our method indicates a higher lying rate around the truth.

<sup>39</sup> Given R=60 subjects out of the N=100 subjects reported the higher outcome, we assume that the highest possible percent who could have been dishonest is 60%.

<sup>40</sup> Following from footnote 7, Abeler *et al.*'s (2016) approach would indicate 20% lying in examples 1-3 of Table A1, and 0%, 33.3%, 55.6% and 58.8% for examples 4 through 7. Thus, their formula gives a reasonable approximation (within 2%) of the true expected percent that lied in six of the seven cases, but is off by 8% in example 4.

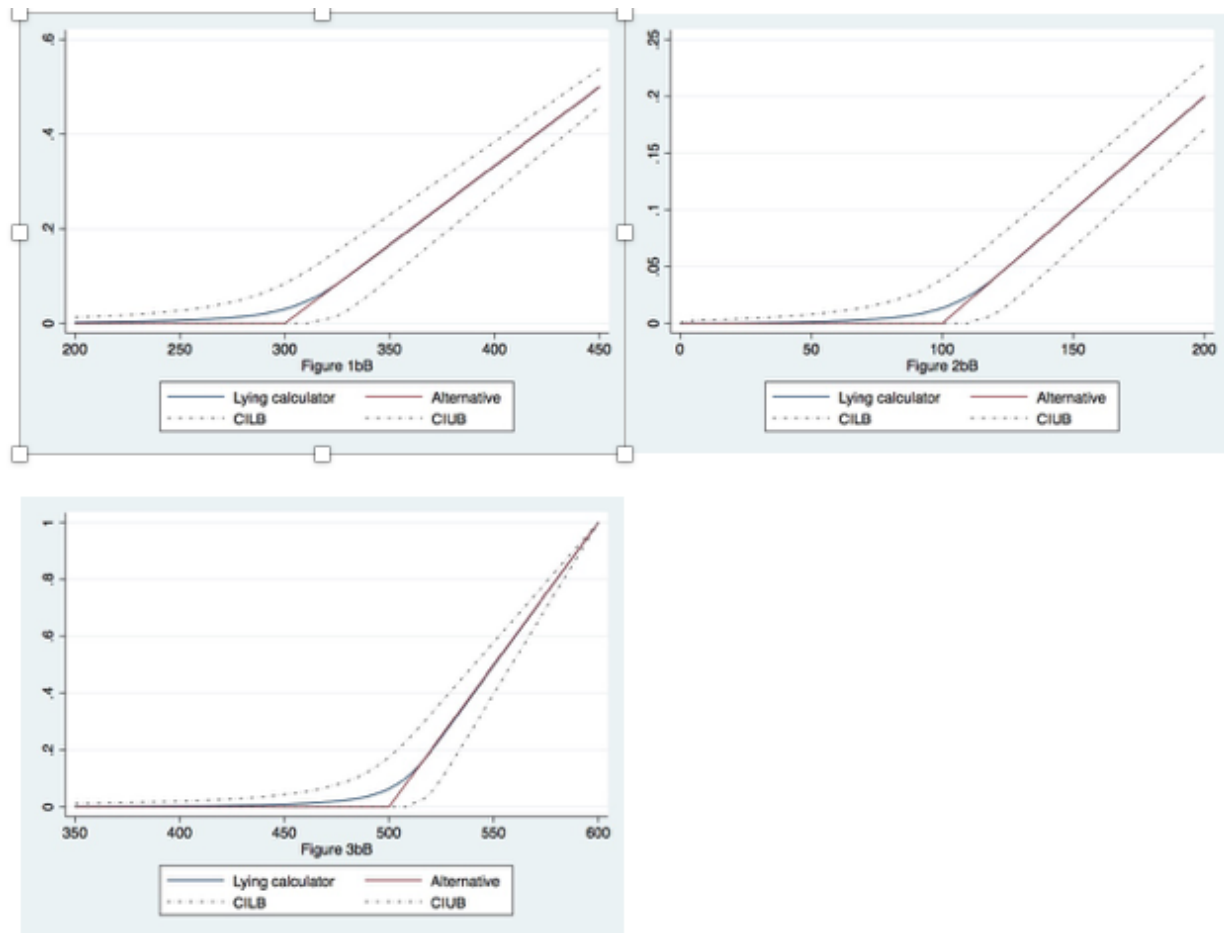


Figure A. Comparisons between our method and the method proposed in Abeler *et al.* (2016)

## **Appendix 2. Instructions**

### **Instructions for Experiment 1: Lying for self**

#### *Overview:*

In addition to your normal pay for completing the task, you can get additional money for yourself. At the completion of this experiment, we will bonus you for any additional money you make. While the base pay for completing the task is modest, you might potentially get significant extra money.

#### *How you will generate extra money:*

The task involves predicting coin flips. The results of this coin flip will determine your extra pay.

#### *Coin toss task:*

You will be asked to toss a coin three times. If you do not have a coin at this time, please get a coin before proceeding to the next page.

#### *Tossing the coin:*

When you toss the coin, let it land on a flat surface so that one side of the coin is clearly facing-up and the other side is clearly facing-down.

#### *Predicting the outcome of each coin toss:*

Before each toss, predict which side of the coin will be face-up. To make your prediction, we would like you to make your prediction out loud before each coin toss. Thus, you can make just one of two possible predictions:

“I predict Heads will be face-up” Or  
“I predict Tails will be face-up.”

#### *Recording the outcome of your prediction:*

In this task you will toss a coin a total of three times and report how many times you correctly predicted the coin toss. If you correctly predict the coin toss all three times, then report 3. If you correctly predict the coin toss twice, then report 2. If you correctly predict the coin toss just once, then report 1. And if you do not correctly predict any of the three coin tosses, then report 0.

Note that it does not matter in which order you make correct or incorrect predictions. For instance, if you correctly predicted the first toss only, or the second toss only, or the third toss only, then in all these cases you would report 1.

#### *Valuing each correct prediction:*

Depending on the outcome of your coin tosses you can get a \$2 bonus payment.

The page will indicate how much you can get for each correct prediction. There will be an amount listed for getting 0 correct predictions, 1 correct prediction, 2 correct predictions and 3 correct

predictions. You will indicate your number of correct predictions by clicking on the appropriate option.

On this page we show you an example of how you will record the number of correct predictions. The payout schedule is shown below. This is only an example, the actual payout schedule may be different.

*Example:*

Click on the number of correct coin toss predictions

Payout Schedule:

- 0 correct prediction - Gain \$0 additional reward
- 1 correct prediction - Gain \$0 additional reward
- 2 correct predictions - Gain \$2 additional reward
- 3 correct predictions - Gain \$2 additional reward

You will thus only click on the number of correct predictions, and then click next to move to the next page.

*Getting started:*

If you have not done so yet, please get a coin. We would like you to not take any breaks while completing the rest of the task, so when you are ready, please continue to the prediction page and additional survey questions.

Prediction page differed between subject conditions

*Prediction Page (0002 condition):*

Please complete your three coin tosses now and click on the number of correct coin toss predictions. Depending on your outcome, you will receive payment of the amount listed.

- 0 correct prediction - Gain \$0 additional reward (1)
- 1 correct prediction - Gain \$0 additional reward (2)
- 2 correct predictions - Gain \$0 additional reward (3)
- 3 correct predictions - Gain \$2 additional reward (4)

*Prediction Page (0022 condition):*

Please complete your three coin tosses now and click on the number of correct coin toss predictions. Depending on your outcome, you will receive payment of the amount listed.

- 0 correct prediction - Gain \$0 additional reward (1)
- 1 correct prediction - Gain \$0 additional reward (2)
- 2 correct predictions - Gain \$2 additional reward (3)
- 3 correct predictions - Gain \$2 additional reward (4)

*Prediction Page (0222 condition):*

Please complete your three coin tosses now and click on the number of correct coin toss predictions. Depending on your outcome, you will receive payment of the amount listed.

- 0 correct prediction - Gain \$0 additional reward (1)
- 1 correct prediction - Gain \$2 additional reward (2)
- 2 correct predictions - Gain \$2 additional reward (3)
- 3 correct predictions - Gain \$2 additional reward (4)

Before we move on to the attitude and demographic questions, we would like to give you one more chance to earn more money for yourself. Like you, other participants in this study are reporting the outcomes of coin



tosses to earn money. We would like you to evaluate whether reporting more, less or the actual amount of money earned is “socially appropriate” and “consistent with moral or proper social behavior,” or are “socially inappropriate” and “inconsistent with moral or proper social behavior.” By socially appropriate, we mean behavior that most people agree is the “correct” or “ethical” thing to do. Another way to think about what we mean is that if the participant was to select a socially inappropriate choice, then someone else might be judgmental of this person for doing so. Please answer each question as accurately as possible, based on your opinion of what constitutes socially appropriate or socially inappropriate behavior. At the end of the experiment, we will randomly select one participant and one of the four questions below. If you are chosen and gave the same response to the question that is most frequently given by all other participants, then you will receive an additional \$100 as a bonus to your MTurk account.

How socially appropriate or inappropriate is it to report...

	Very Socially Inappropriate (1)	Somewhat Socially Inappropriate (2)	Somewhat Socially Appropriate (3)	Very Socially Appropriate (4)
an outcome that earns \$0 when the prediction would earn \$0 (4)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
an outcome that earns \$2 when the prediction would earn \$0 (1)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
an outcome that earns \$2 when the prediction would earn \$2 (2)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
an outcome that earns \$0 when the prediction would earn \$2 (7)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Before we finish, please complete the following set of questions about your experience, your views and yourself.

What type of coin did you use for the coin toss?

- Quarter (1)
- Dime (2)
- Nickel (3)
- Penny (4)
- Other (5)

If you predicted three coins tosses correctly, how much extra money would you have earned?

- \$1 (1)
- \$2 (2)
- \$4 (3)
- \$8 (4)
- \$10 (5)

If we asked 1000 people to toss a coin three times, how many of them do you think would toss three heads?  
\_\_\_\_\_ Please move the slide to your response (2)

How would you classify your political affiliation?

- Republican (1)
- Democratic (2)
- Independent (3)
- Other (4)

How much do you agree with the goals of the Republican National Party?  
\_\_\_\_\_ Please move the slide to your response (1)

How much do you agree with the goals of the Democratic National Party?  
\_\_\_\_\_ Please move the slide to your response (1)

How often do you vote in national elections (including Senate, House of Representative, and Presidential elections)?

- I never vote in national elections (1)
- I occasionally vote in national elections (2)
- I sometimes vote in national elections (3)
- I frequently vote in national elections (6)
- I usually vote in national elections (4)
- I always vote in national elections (5)

Please indicate your level of agreement with the following statements (1=Strongly disagree, 7=Strongly agree).

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Luck plays an important part in everyone's life. (1)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Some people are consistently lucky, and others are unlucky. (2)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I consider myself to be a lucky person. (3)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I believe in luck. (4)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I often feel like it's my lucky day. (5)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I consistently have good luck. (6)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
It's a mistake to base any decisions on how lucky you feel. (7)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Luck works in my favor. (8)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I don't mind leaving things to chance because I'm a lucky person. (9)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Even the things in life I can't control tend to go my way because I'm lucky. (10)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
There is such a thing as luck that favors some people, but not others. (11)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Luck is nothing more than random chance. (12)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

And finally a few questions about yourself... What is your gender?

- Male (1)
- Female (2)

What is your highest educational degree obtained?

- Primary school (1)
- Less than high school (2)
- High school diploma or equivalent (3)
- Undergraduate degree (4)
- Post-graduate degree (5)

What year were you born (e.g., 1980) (Dropdown box)

What is your approximate household annual pretax income?

- Less than \$10,000 (1)
- Between \$10,000 and \$20,000 (2)
- Between \$20,000 and \$30,000 (3)
- Between \$30,000 and \$50,000 (4)
- Between \$50,000 and \$70,000 (5)
- Between \$70,000 and \$90,000 (6)
- Between \$90,000 and \$110,000 (7)
- Between \$110,000 and \$130,000 (8)
- Between \$130,000 and \$150,000 (9)
- More than \$150,000 (10)

How much money do you spend in a typical week (this should be your daily expenses e.g., food, travel, mobile charges, purchases; but excluding rent, mortgage, educational fees, work expenses)?

- \$0-\$29 (1)
- \$30-\$49 (2)
- \$50-\$79 (3)
- \$80-\$119 (4)
- \$120-\$174 (5)
- \$175-\$249 (6)
- \$250-\$350 (7)
- More than \$350 (8)

What do you think we are trying to assess with this study? (open-ended)

## **Instructions for Experiment 2: Lying to support or avoid supporting an organization**

### *Overview:*

In this experiment, you will generate money for a political party. At the completion of this experiment, we will make a donation through the party's online donation page. The amount we will donate will be the sum of the amount that was generated by all participants who completed the study for the same political party. In a few pages, we will tell you which party you will be generating money for. First we will explain how you will generate money for the political party.

### *Generating money for the political party:*

There will be 4 tasks that will affect the outcome. The first two task pages will involve predicting coin flips and the last two task pages will involve simple decisions. One of these four tasks will be randomly chosen to determine your donation. Each task is equally likely to be chosen. At the end of the study, we will show you which task was chosen and what your outcome was for that task, this will determine your individual donation. We will add all participants' outcomes at the end of the experiment and make a total donation.

### *Coin toss task:*

On the following pages you will be asked to toss a coin three times. If you do not have a coin at this time, please get a coin before proceeding to the next page.

### *Tossing the coin:*

When you toss the coin, let it land on a flat surface so that one side of the coin is clearly facing-up and the other side is clearly facing-down.

### *Predicting the outcome of each coin toss*

Before each toss, predict which side of the coin will be face-up. To make your prediction, we would like you to make your prediction out loud before each coin toss. Thus, you can make just one of two possible predictions:

“I predict Heads will be face-up” Or  
“I predict Tails will be face-up.”

### *Recording the success of your prediction:*

You will toss the coin a total of three times for each of the following pages, and on each page you will report how many times you correctly predicted the coin toss. If you correctly predict the coin toss all three times, then report 3. If you correctly predict the coin toss twice, then report 2. If you correctly predict the coin toss just once, then report 1. And if you do not correctly predict any of the three coin tosses, then report 0.

Note that it does not matter in which order you make correct or incorrect predictions on each page. For instance, if you correctly predicted the first toss only, or the second toss only, or the third toss only, then in all these cases you would report 1.

### *Value of each correct prediction:*

You will earn money for one of two political parties by correctly predicting the coin tosses. Each page will indicate how much you earn for each correct prediction. There will be an amount listed for getting 0 correct predictions, 1 correct prediction, 2 correct predictions and 3 correct predictions. You will indicate your number of correct predictions by clicking on the appropriate option.

On this page we show you an example of how you will record the number of correct predictions. The payout schedule is shown below. This is only an example, the actual payout schedule will be different for each task.

Each page is for a separate set of three coin tosses. The donation amounts may vary between the two pages and for the number of correct predictions.

*Example*

Click on the number of correct coin toss predictions

*Payout Schedule:*

- 0 correct prediction - Earn \$0 for the party for this page
- 1 correct prediction - Earn \$3 for the party for this page
- 2 correct predictions - Earn \$3 for the party for this page
- 3 correct predictions - Earn \$6 for the party for this page

You will thus only click on the number of correct predictions, and then click next to move to the next page.

DNP 0018/0188 condition (DNP 0188/0018 condition same with the order of the prediction pages switched)

*Political party you will generate money for:*

You will either be randomly assigned (with equally probability) to generate money for the Democratic National Party or the Republican National Party.

The Democratic National Party's purpose is to advance the Democratic agenda and support Democratic candidates running for office. If you would like to learn more about this organization, please click on the following link that will open a new page on their home page  
<https://www.democrats.org/about/our-party>

The Republican National Party's purpose is to advance the Republican agenda and support Republican candidates running for office. If you would like to learn more about this organization, please click on the following link that will open a new page on their home page <https://www.gop.com/platform/>

You have been randomly assigned to generate money for the Democratic National Party.

How do you feel about the Democratic National Party? (sliding scales from -50 - +50)

\_\_\_\_\_ How much do you agree with the goals of this party? (1)

\_\_\_\_\_ How much do you want to help this party achieve their goals? (2)

How do you feel about the Republican National Party? (sliding scales from -50 - +50)

\_\_\_\_\_ How much do you agree with the goals of this party? (1)

\_\_\_\_\_ How much do you want to help this party achieve their goals? (2)

*Summary:*

In this experiment, you will have two prediction pages each with three coin tosses. On each prediction page, you will toss a coin three times and make a prediction before each toss as to the outcome of the toss. You will then record how many tosses you correctly predicted of the three tosses. The page will also indicate how much will be donated to the Democratic National Party based on the number of correct predictions. The two coin toss tasks will be followed by the two decision tasks. One of these four tasks will be randomly selected with equal probability to determine the donation. At the end of the experiment, we will add or subtract the amount of money you have generated to the total money that we will send based on the outcome of all participants in this experiment.

*Getting started:*

If you have not done so yet, please get a coin. We would like you to not take any breaks while completing the two prediction pages, so when you are ready, please continue to the prediction pages.

*Prediction Page 1:*

Please complete three coin tosses now and click on the number of correct coin toss predictions. If this is the task selected for you, we will add the amount listed to the donation to the Democratic National Party.

- 0 correct prediction - Earn \$0 for the Democratic National Party (1)
- 1 correct prediction - Earn \$0 for the Democratic National Party (2)
- 2 correct predictions - Earn \$1 for the Democratic National Party (3)
- 3 correct predictions - Earn \$8 for the Democratic National Party (4)

*Prediction Page 2:*

Please complete three coin tosses now and click on the number of correct coin toss predictions. If this is the task selected for you, we will add the amount listed to the donation to the Democratic National Party.

- 0 correct prediction - Earn \$0 for the Democratic National Party (1)
- 1 correct prediction - Earn \$1 for the Democratic National Party (2)
- 2 correct predictions - Earn \$8 for the Democratic National Party (3)
- 3 correct predictions - Earn \$8 for the Democratic National Party (4)

*Decision Task 1 (Democratic National Party):*

If this page is randomly selected, based on your choice below we will either add or subtract money from the donation to be made at the end of the study to the Democratic National Party.

- Add \$2 to the total donation to the Democratic National Party (1)
- Add nothing to the total donation to the Democratic National Party (2)
- Subtract \$2 from the total donation to the Democratic National Party (3)

*Decision Task 2 (Republican National Party):*

If this page is randomly selected, based on your choice below we will either add or subtract money from the donation to be made at the end of the study to the Republican National Party.

- Add \$2 to the total donation to the Republican National Party (1)
- Add nothing to the total donation to the Republican National Party (2)
- Subtract \$2 from the total donation to the Republican National Party (3)

RNP 0018/0188 condition (RNP 0188/0018 condition same with the order of the prediction pages switched)

*Political party you will generate money for:*

You will either be randomly assigned (with equally probability) to generate money for the Democratic National Party or the Republican National Party.

The Democratic National Party's purpose is to advance the Democratic agenda and support Democratic candidates running for office. If you would like to learn more about this organization, please click on the following link that will open a new page on their home page <https://www.democrats.org/about/our-party>

The Republican National Party's purpose is to advance the Republican agenda and support Republican candidates running for office. If you would like to learn more about this organization, please click on the following link that will open a new page on their home page <https://www.gop.com/platform/> You have been randomly assigned to generate money for the Republican National Party.

How do you feel about the Democratic National Party?

- \_\_\_\_\_ How much do you agree with the goals of this party? (1)
- \_\_\_\_\_ How much do you want to help this party achieve their goals? (2)

How do you feel about the Republican National Party?

- \_\_\_\_\_ How much do you agree with the goals of this party? (1)
- \_\_\_\_\_ How much do you want to help this party achieve their goals? (2)

*Summary:*

In this experiment, you will have two prediction pages each with three coin tosses. On each prediction page, you will toss a coin three times and make a prediction before each toss as to the outcome of the toss. You will then record how many tosses you correctly predicted of the three tosses. The page will also indicate how much will be donated to the Republican National Party based on the number of correct predictions. The two coin toss tasks will be followed by the two decision tasks. One of these four tasks will be randomly selected with equal probability to determine the donation. At the end of the experiment, we will add or subtract the amount of money you have generated to the total money that we will send based on the outcome of all participants in this experiment.

*Getting started:*

If you have not done so yet, please get a coin. We would like you to not take any breaks while completing the two prediction pages, so when you are ready, please continue to the prediction pages.

*Prediction Page 1:*

Please complete three coin tosses now and click on the number of correct coin toss predictions. If this is the task selected for you, we will add the amount listed to the donation to the Republican National Party.

- 0 correct prediction - Earn \$0 for the Republican National Party (1)
- 1 correct prediction - Earn \$0 for the Republican National Party (2)
- 2 correct predictions - Earn \$1 for the Republican National Party (3)
- 3 correct predictions - Earn \$8 for the Republican National Party (4)



*Prediction Page 2:*

Please complete three coin tosses now and click on the number of correct coin toss predictions. If this is the task selected for you, we will add the amount listed to the donation to the Republican National Party.

- 0 correct prediction - Earn \$0 for the Republican National Party (1)
- 1 correct prediction - Earn \$1 for the Republican National Party (2)
- 2 correct predictions - Earn \$8 for the Republican National Party (3)
- 3 correct predictions - Earn \$8 for the Republican National Party (4)

*Decision Task 1 (Republican National Party):*

If this page is randomly selected, based on your choice below we will either add or subtract money from the donation to be made at the end of the study to the Republican National Party.

- Add \$2 to the total donation to the Republican National Party (1)
- Add nothing to the total donation to the Republican National Party (2)
- Subtract \$2 from the total donation to the Republican National Party (3)

*Decision Task 2 (Democratic National Party):*

If this page is randomly selected, based on your choice below we will either add or subtract money from the donation to be made at the end of the study to the Democratic National Party.

- Add \$2 to the total donation to the Democratic National Party (1)
- Add nothing to the total donation to the Democratic National Party (2)
- Subtract \$2 from the total donation to the Democratic National Party (3)

Before we move on to the attitude and demographic questions, we would like to give you one more chance to earn more money for yourself. Like you, other participants in this study are reporting the outcomes of coin tosses to earn money for a political party. We would like you to evaluate whether reporting more (or less) money earned than actually occurred is “socially appropriate” and “consistent with moral or proper social behavior,” or are “socially inappropriate” and “inconsistent with moral or proper social behavior.” By socially appropriate, we mean behavior that most people agree is the “correct” or “ethical” thing to do. Another way to think about what we mean is that if the participant was to select a socially inappropriate choice, then someone else might be judgmental of this person for doing so. Please answer each question as accurately as possible, based on your opinion of what constitutes socially appropriate or socially inappropriate behavior. At the end of the experiment, we will randomly select one participant and one of the four questions below. If you are chosen and gave the same response to the question that is most frequently given by all other participants, then you will receive an additional \$100 as a bonus to your MTurk account.

How socially appropriate or inappropriate is it to report...

	Very Socially Inappropriate (1)	Somewhat Socially Inappropriate (2)	Somewhat Socially Appropriate (3)	Very Socially Appropriate (4)
an outcome that earns \$0 for a political party you strongly support when the prediction would earn \$0 (4)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
an outcome that earns \$8 for a political party you strongly support when the prediction would earn \$0 (1)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
an outcome that earns \$8 for a political party you strongly oppose when the prediction would earn \$8 (2)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
an outcome that earns \$0 for a political party you strongly oppose when the prediction would earn \$8 (3)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Before we finish, please complete the following set of questions about you experience, your views and yourself.

What type of coin did you use for the coin toss?

- Quarter (1)
- Dime (2)
- Nickel (3)
- Penny (4)
- Other (5)

What organization were you partnered with for the coin toss donations?

- American Red Cross (1)
- Democratic National Party (4)
- Republican National Party (5)

How many sets of coin tosses did you complete?

- I completed 1 set of 3 coin tosses (1)
- I completed 2 sets of 3 coin tosses (2)
- I completed 10 sets of 3 coin tosses (3)
- I completed 20 sets of 3 coin tosses (4)

How will the amount of your donation determined?

- The sum of the outcomes from all four tasks will be added together (1)
- One of the four pages will be randomly chosen and the outcome from that page will be used. (2)
- The political party will be given a set amount of money regardless of what I did. (5)

We would like to know more about your political ideology. Please indicate how much you identify yourself as being politically liberal or conservative in general.

- 1 (very liberal) (4)
- 2 (5)
- 3 (6)
- 4 (7)
- 5 (8)
- 6 (9)
- 7 (very conservative) (10)

Please indicate how much you identify yourself as being politically liberal or conservative in economic issues

- 1 (very liberal) (4)
- 2 (5)
- 3 (6)
- 4 (7)
- 5 (8)
- 6 (9)
- 7 (very conservative) (10)

Please indicate how much you identify yourself as being politically liberal or conservative on social issues.

- 1 (very liberal) (4)
- 2 (5)
- 3 (6)
- 4 (7)
- 5 (8)
- 6 (9)
- 7 (very conservative) (10)

How would you classify your political affiliation?

- Republican (1)
- Democratic (2)
- Independent (3)
- Other (4)

How often do you vote in national elections (including Senate, House of Representative, and Presidential elections)?

- I never vote in national elections (1)
- I occasionally vote in national elections (2)
- I sometimes vote in national elections (3)
- I frequently vote in national elections (6)
- I usually vote in national elections (4)
- I always vote in national elections (5)

Please indicate your level of agreement with the following statements (1=Strongly disagree, 7=Strongly agree).

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Luck plays an important part in everyone's life. (1)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Some people are consistently lucky, and others are unlucky. (2)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I consider myself to be a lucky person. (3)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I believe in luck. (4)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I often feel like it's my lucky day. (5)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I consistently have good luck. (6)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
It's a mistake to base any decisions on how lucky you feel. (7)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Luck works in my favor. (8)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I don't mind leaving things to chance because I'm a lucky person. (9)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Even the things in life I can't control tend to go my way because I'm lucky. (10)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
There is such a thing as luck that favors some people, but not others. (11)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Luck is nothing more than random chance. (12)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

In this set of questions you will read about situations that people are likely to encounter in day-to-day life, followed by common reactions to those situations. As you read each scenario, try to

imagine yourself in that situation. Then indicate the likelihood that you would react in the way described.

	very unlikely (1)	unlikely (2)	slightly unlikely (3)	about 50% likely (4)	slightly likely (5)	likely (6)	very likely (7)
After realizing you have received too much change at a store, you decide to keep it because the salesclerk doesn't notice. What is the likelihood that you would feel uncomfortable about keeping the money? (1)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
You give a bad presentation at work. Afterwards your boss tells your coworkers it was your fault that your company lost the contract. What is the likelihood that you would feel incompetent? (2)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
At a coworker's party, you spill red wine on their new cream colored carpet. You cover the stain with a chair so that nobody notices. What is the likelihood that you would feel that the way you acted was pathetic? (3)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
You lie to people but they never find out about it. What is the likelihood that you would feel terrible about the lies you told? (4)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
You successfully exaggerate your damages in a lawsuit. Months later, your lies are discovered and you are charged with perjury. What is the likelihood that you would think you are a despicable human being? (5)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
You make a mistake at work and find out a coworker is blamed for the error. Later, your coworker confronts you about your mistake. What is the likelihood that you would feel like a coward? (6)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Please answer regarding your frequency of the following:

	never (1)	rarely (2)	occasionally (3)	often (4)	very often (5)
How often do you think about religious issues? (1)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
How often do you experience situations in which you have the feeling that God or something divine intervenes in your life? (2)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
How often do you take part in religious services? (3)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
How often do you pray? (4)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

To what extent do you believe that God or something divine exists?

- not at all (1)
- not very much (2)
- moderately (3)
- quite a bit (4)
- very much so (5)

And finally a few questions about yourself... What is your gender?

- Male (1)
- Female (2)

What is your highest educational degree obtained?

- Primary school (1)
- Less than high school (2)
- High school diploma or equivalent (3)
- Undergraduate degree (4)
- Post-graduate degree (5)

What year were you born (e.g., 1980) (Drop Down)

What is your approximate household annual pretax income?

- Less than \$10,000 (1)
- Between \$10,000 and \$20,000 (2)
- Between \$20,000 and \$30,000 (3)
- Between \$30,000 and \$50,000 (4)
- Between \$50,000 and \$70,000 (5)
- Between \$70,000 and \$90,000 (6)
- Between \$90,000 and \$110,000 (7)
- Between \$110,000 and \$130,000 (8)
- Between \$130,000 and \$150,000 (9)
- More than \$150,000 (10)

How much money do you spend in a typical week (this should be your daily expenses e.g., food, travel, mobile charges, purchases; but excluding rent, mortgage, educational fees, work expenses)?

- \$0-\$29 (1)
- \$30-\$49 (2)
- \$50-\$79 (3)
- \$80-\$119 (4)
- \$120-\$174 (5)
- \$175-\$249 (6)
- \$250-\$350 (7)
- More than \$350 (8)

In the last four years, how many times have you donated money to a political party?

- 0 (1)
- once (2)
- 2-3 times (3)
- 4-5 times (4)
- 6-10 times (5)
- More than 10 times (6)

In the last four years, how much money have you donated to a political party?

- \$0 (1)
- \$1-20 (2)
- \$21-50 (3)
- \$51- 100 (4)
- \$101-250 (6)
- More than \$250 (7)

In the last four years, how many times have you donated your time to a political party?

- 0 (1)
- once (2)
- 2-3 times (3)
- 4-5 times (4)
- 6-10 times (5)
- More than 10 times (6)

In the last four years, how much time have you donated to a political party?

- 0 hours (1)
- 1-20 hours (3)
- 21-50 hours (4)
- 51-100 hours (6)
- 101 - 250 hours (7)
- More than 250 hours (8)

What do you think we are trying to assess with this study? (open-ended)

**Appendix 3. Tables**

**Table A2. List of studies included in the review**



Authors (Year)	Nb treatments	Nb subjects	Country	Lab	Students	Nb coin tosses	Nb die rolls	Nb other devices	Observability
1. Abeler <i>et al.</i> (2014)	4	1102	Germany	Lab+telephone	Both	1 and 4	-	-	1/2
2. Abeler (2015)	1	60	China	Lab	Yes	-	-	1 ticket/10	1
3. Abeler <i>et al.</i> (2016)	8	1098	UK	Lab	Yes	-	-	1 chip/50	1/2
4. Amir <i>et al.</i> (2016)	11	403	Israel	Online	Yes	20	-	-	0
5. Anthony <i>et al.</i> (2016)	2	200	Germany	Lab	Yes	-	1	-	1
6. Arbel <i>et al.</i> (2014)	2	399	Israel	Lab	Yes	-	1	-	1
7. Ariely <i>et al.</i> (2014)	2	188	Germany	Art. field	No	-	40	-	0
8. Aydogan <i>et al.</i> (2015)	2	120	Germany	Lab	Yes	2	-	-	1
9. Balasubramanian <i>et al.</i> (2017)	10	320	India	Online	No	6	-	-	0
10. Banerjee <i>et al.</i> (2016)	8	1344	India	Art. Field	No	-	1	-	1
11. Bar-El and Tobol (2017)	4	358	Israel	Lab	Yes	-	1	-	1
12. Barfort <i>et al.</i> (2015)	1	862	Denmark	Online	Yes	-	4*10	-	0
13. Beck <i>et al.</i> (2016)	6	191	Germany	Lab	Yes	-	1	-	1
14. Blanco and Cardenas (2015)	2	103	Colombia	Lab	Yes	-	1	-	1
15. Braun and Hornuf (2015)	7	342	Germany	Lab	Yes	-	40	-	0
16. Bryan <i>et al.</i> (2013)	7	238	USA	Lab + online	Both	10	-	1 nb/10	0/2
17. Bucciol and Piovesan (2011)	2	160	Italy	Art. field	No	1	-	-	1
18. Cadsby <i>et al.</i> (2016)	1	90	China	Lab	Yes	-	1	-	1
19. Charness <i>et al.</i> (2017)	2	173	Spain	Lab	Yes	-	1	-	1
20. Chylitova and Korbel (2014)	3	444	Czech Rep.	Art. field	Yes	-	1	-	2
21. Clot <i>et al.</i> (2014)	2	98	Madagascar	Lab	Yes	-	1	-	1
22. Cohn <i>et al.</i> (2014)	8	435	Switzerland	Art.field+ online	Both	10	-	-	0
23. Cohn and Marechal (2015)	1	162	Switzerland	Art. field	No	10	-	-	1
24. Cohn <i>et al.</i> (2015)	4	285	Switzerland	Art. field	No	10	-	-	1
25. Conrads <i>et al.</i> (2013)	4	554	Germany	Lab	Yes	-	1	-	1/2
26. Conrads and Lotz (2015)	4	246	Germany	Lab + tel+ online	Yes	4	-	-	0/1/2
27. Dai <i>et al.</i> (2017)	2	471	France	Art. field+lab	Both	-	1; 3-sided	-	1
28. Dato and Nieken (2015)	1	288	Germany	Lab	Yes	-	1	-	1
29. Dieckmann <i>et al.</i> (2015)	5	1015	Multiple	Online	No	1	-	-	0
30. Diekmann <i>et al.</i> (2015)	6	466	Switzerland	Lab	Yes	-	1	-	1
31. Di Falco <i>et al.</i> (2016)	1	1080	Tanzania	Lab	Yes	1	-	-	1
32. Djawadi and Fahr (2015)	1	252	Germany	Art. Field	Both	-	-	1 chip	1
33. Drupp <i>et al.</i> (2016)	4	164	Germany	Mail	Both	4	-	-	0
34. Duncan and Li (2016)	1	203	USA	Online	No	-	1	-	0
35. Effron <i>et al.</i> (2015)	6	1704	USA	Online	No	13 and 20	-	-	0
36. Fischbacher and Föllmi-Heusi (2013)	7	1347	Switzerland	Lab	Yes	-	1	-	0/1
37. Foerster <i>et al.</i> (2013)	2	28	Germany	Lab	Yes	-	6; 8-sided	-	1
38. Fosgaard <i>et al.</i> (2013)	4	209	Denmark	Lab	Yes	1	-	-	1
39. Gächter and Schultz (2016)	23	2568	Multiple	Lab	Yes	-	1	-	1
40. Gneezy <i>et al.</i> (2016)	3	314	Germany	Lab	Yes	-	-	1	1
41. Halevy <i>et al.</i> (2013)	1	51	Netherlands	Lab	Yes	-	60	-	1
42. Hanna and Wang (2013)	2	826	India	Art. field+lab	Both	-	42	-	1
43. Hilbig and Hessler (2013)	6	765	Germany	Lab	Yes	-	1	-	1
44. Hilbig and Zettler (2015)	6	549	Germany	Lab+Online	Both	2 and 10	1	-	0/1/2
45. Houser <i>et al.</i> (2016)	4	249	USA	Art. field	No	2	-	-	1/2
46. Hruschka <i>et al.</i> (2014)	8	223	Multiple	Art. field	No	30	-	-	1

Authors (Year)	Nb treatments	Nb subjects	Country	Lab	Students	Nb coin tosses	Nb die rolls	Nb other devices	Observability
47. Hugh-Jones (2016)	30	1475	Multiple	On line	No	1	-	-	0
48. Jacobsen and Piovesan (2016)	3	149	Denmark	Art. field	No	-	1	-	1
49. Jiang (2013)	2	39	Netherlands	Lab	Yes	-	20	-	0
50. Jiang (2015)	4	216	Multiple	Lab	Yes	-	20	-	0
51. Kajackaite (2016)	1	91	Germany	Lab	Yes	-	-	1 ticket/100	1
52. Kajackaite and Gneezy (2017)	17	1303	USA, Germ	Lab	Yes	-	1	1 ticket/10	0/1
53. Kroher and Wolbring (2015)	6	382	Germany	Lab + online	Yes	-	1	-	0/1/2
54. Mann <i>et al.</i> (2016)	10	2179	Multiple	Art. field+lab	Both	-	20	-	1
55. Maréchal <i>et al.</i> (2017)	5	301	Switzerland	Lab	Yes	-	10	-	1
56. Meub <i>et al.</i> (2015)	2	94	Germany	Lab	Yes	-	1	-	1
57. Muehlheusser <i>et al.</i> (2015)	1	108	Germany	Lab	Yes	-	1	-	1
58. Munoz-Izquierdo <i>et al.</i> (2014)	3	270	Spain	Art. field	Yes	1	-	-	1
59. Pascual-Ezama <i>et al.</i> (2015)	48	1440	Multiple	Lab+verbal+no contact	Yes	1	-	-	0/1/2
60. Ploner and Regner (2013)	6	316	Germany	Lab	Yes	-	1	-	1
61. Potters and Stoop (2016)	2	102	Netherlands	Lab	Yes	-	-	20 cards	0
62. Rauhut (2013)	3	240	Switzerland	Lab	Yes	-	4*12	-	1
63. Ruffle and Tobol (2014)	1	427	Israel	Art. field	No	-	1	-	2
64. Ruffle and Tobol (2015)	1	156	Israel	Art. field	No	-	1	-	2
65. Schindler and Pfattheicher (2017)	4	386	Multiple	Lab+on-line	Both	1	75	-	1
66. Shalvi (2012)	2	178	Netherlands	Lab	Yes	20	-	-	0
67. Shalvi <i>et al.</i> (2011)	2	129	USA	Lab	Yes	-	1	-	1
68. Shalvi <i>et al.</i> (2012)	4	144	Israel	Lab	Yes	-	1	-	1
69. Shalvi and Leiser (2013)	2	126	Israel	Lab	Yes	-	1	-	1
70. Shalvi and de Dreu (2014)	8	120	Netherlands	Lab	Yes	10	-	-	0
71. Shen <i>et al.</i> (2016)	1	205	Singapore	Lab	Yes	-	1	-	1
72. Skoda (2013)	3	90	Czech Rep.	Lab	Yes	-	1	-	1
73. Suri <i>et al.</i> (2011)	3	674	India, USA	Online	No	-	1	-	1
74. Thielmann <i>et al.</i> (2016)	1	152	Germany	Online	No	2	-	-	0
75. Utikal and Fischbacher (2013)	2	31	Germany	Art. field+lab	Both	-	1	-	0
76. van 't Veer <i>et al.</i> (2014)	2	173	Netherlands	Lab	Yes	-	1	-	1
77. Waubert de Puiseau and Glöckner (2012)	4	407	Germany	On-line	Both	5	-	-	0
78. Weisel and Shalvi (2015)	1	36	Germany	Lab	Yes	-	20	-	1
79. Wibral <i>et al.</i> (2012)	2	91	Germany	Lab	Yes	-	1	-	1
80. Zetler <i>et al.</i> (2015)	1	134	Germany	Online	No	2	-	-	0
81. Zimmerman <i>et al.</i> (2014)	1	189	Israel	Online	Yes	20	-	-	0
Total	389	36668	44	53% of lab treatments	68.5% of treatments	48% of treatments	47% of treatments	5% of treatments	Mean: 0.67

**Appendix Table A3. Exogenous characteristics of participants**

Experimental treatments	Study 1: Lying for oneself			Study 2: Lying for a cause <sup>a</sup>	
	0002	0022	0222	Supporting	Opposing
N	80	327	571	115	146
% Females	57.5	48.3	52.7	45.2	42.5
Mean (SD) age	36 (11.7)	38 (12.0)	38 (12.1)	35 (10.6)	38 (11.3)
Education (in %)					
- Less high school	0	.6	.5	.9	.7
- High school	28.7	29.2	31.0	39.1	39.3
- Undergraduate	58.8	57.1	49.5	50.4	49.7
- Post-graduate	12.5	13.2	19.0	9.6	10.3
Income (in %)					
< \$30k	35.0	24.6	25.9	33.9	31.3
\$30k - \$50k	16.3	26.5	24.3	27.8	20.1
\$50k - \$70k	12.5	22.1	21.0	16.5	18.1
\$70k - \$90k	15.0	10.4	10.7	7.8	11.1
> \$90k	21.2	16.4	18.1	13.9	19.4
Spending (in %)					
< \$50	15.0	15.7	16.1	20.8	10.3
\$50 - \$79	15.0	13.8	11.5	19.1	14.5
\$80 - \$119	23.8	21.3	23.3	14.8	21.4
\$120 - \$174	15.0	20.7	19.3	20.9	20.7
\$175 - \$249	15.0	13.5	14.0	18.3	14.5
> \$250	16.3	15.1	15.9	10.5	18.6
Affiliation (in %):					
- DNP				72.2	67.1
- RNP				27.8	32.9
Agreement w/ goals of party donating to					
Dem - Dems(s)/Reps(o)				33.1(13.7)	-32.5(20.0)
Rep - Reps(s)/Dems(o)				27.9(16.6)	-29.3(19.2)

*Notes:* DNP: Democratic National Party; RNP: Republican National Party. “Income” is percentage of people in income categories. “Spending” is percentage of people in weekly spending categories. “Affiliation” percentage of people state either Democratic or Republican affiliation. “Agree with goals” is the mean response to the question about how much the subject agrees with the goals of the party they were assigned to donate to, on a continuous scale between -50 and +50 (included); for example, how much did a Democrat assigned to donate to the DNP agree with the goals of the DNP (support), or how much did a Democrat assigned to donate to the RNP agree with the goals of the RNP (oppose). <sup>a</sup> Only people who stated their party affiliation as Democrat or Republican are included since these allow for matching or mismatching.

The various demographics are randomly dispersed across the conditions. In study 1, pairwise testing show no significant differences between conditions on gender ( $ps > 0.14$ ), age ( $ps > 0.14$ ), education ( $ps > 0.90$ ), income ( $p > 0.07$ ), or weekly spending ( $ps > 0.80$ ). In study 2, there are no significant differences between conditions on gender ( $p > 0.69$ ), age ( $p > 0.05$ ), education ( $p > 0.90$ ), income ( $p > 0.46$ ), weekly spending ( $p > 0.34$ ), political affiliation ( $p > 0.38$ ). As expected, there is a significant difference between agreement with the political goals of the party the participant is donating to, based on whether the person was in the support or oppose condition ( $ps < 0.001$ ).

**Appendix Table A4: Study 1 Logistic Regression: Influence of Possible Covariates on Payout**

DV: Participant Payout Beta(SE)	Study 1: Lying for oneself			
	Overall	0002	0022	0222
N	927	78	304	545
Females	0.020(0.21)	0.387(0.51)	-0.120(0.33)	-0.304(0.52)
Year born	0.027(0.01)***	0.048 (0.02)**	0.037(0.01)***	0.037(0.02)**
Education	-0.242(0.15)	-0.601(0.43)	0.640(0.26)**	0.389(0.38)
Income	0.094(0.06)	0.060(0.14)	0.229(0.10)**	0.029(0.14)
Spending	0.000(0.06)	-0.159(0.18)	0.023(0.10)	0.092(0.15)
Luck Beliefs				
- Luck exists	0.021(0.09)	0.079(0.25)	-0.019(0.13)	0.149(0.20)
- I am lucky	0.002(0.10)	0.290(0.25)	0.143(0.14)	0.216(0.27)

*Notes:* The current technique does not allow for regression-based analysis, so to test the effects of covariates we have used the participant’s payout level as a proxy for lying, since those who lied will have gotten the larger pays. “Income” is percentage of people in income categories. “Spending” is percentage of people in weekly spending categories. Factor analysis of the belief in luck scale (Darke and Freedman 1997) forms two factors representing a belief that there is such a thing as ‘luck’ and a belief that the respondent is lucky. \*\*\* and \*\* indicate significance at the 0.01 and 0.05 level, respectively. Note that the number of observations in this Table is slightly lower than the total number of participants since some subjects did not complete the demographic questionnaire.

As can be seen in Table A4, the demographic and attitudinal variables have little effect on the participant’s payout. Only age consistently reaches the traditional significance cutoff in study 1, such that younger people get higher payouts. Additional analyses (not shown) find no significant interactions of the covariates with the conditions (all  $p$ -values > 0.05), demonstrating that none of the covariates moderate the effects of treatment on payout.

**Appendix Table A5: Study 2 Ordinal Logistic Regression: Influence of Possible Covariates on Payout**

DV: Participant Payout Beta(SE) N	Study 2: 0018 Treatment			Study 2: 0188 Treatment <sup>a</sup>		
	Overall	Supporting	Opposing	Overall	Supporting	Opposing
	244	107	137	244	107	137
Females	0.103(0.26)	0.088(0.40)	0.335(0.38)	0.109(0.27)	0.121(0.49)	-0.052(0.36)
Year born	-0.026(0.01)**	-0.018(0.02)	-0.043(0.02)**	-0.015(0.01)	-0.031(0.03)	-0.032(0.02)
Education	-0.096(0.19)	0.133(0.29)	-0.280(0.27)	-0.024(0.19)	-0.206(0.36)	0.067(0.25)
Income	0.120(0.07)	0.182(0.11)	0.092(0.10)	-0.040(0.07)	0.025(0.13)	-0.074(0.09)
Spending	-0.058(0.08)	-0.135(0.12)	0.063(0.12)	-0.049(0.08)	-0.040(0.15)	0.021(0.10)
Luck Beliefs						
- Luck exists	-0.004(0.11)	-0.203(0.15)	0.175(0.17)	0.138(0.11)	-0.208(0.17)	0.249(0.16)
- I am lucky	0.191(0.12)	0.275(0.18)	0.168(0.19)	-0.057(0.13)	0.365(0.21)	-0.095(0.19)
Religiosity	-0.027(0.15)	0.046(0.26)	-0.139(0.21)	0.232(0.15)	0.060(0.31)	0.190(0.19)
Guilt Prone	-0.390(0.14)***	-0.512(0.21)**	-0.086(0.20)	-0.100(0.14)	0.194(0.24)	-0.057(0.19)
Democratic	-0.152(0.31)	-0.459(0.51)	0.050(0.41)	-0.359(0.31)	-0.617(0.60)	-0.075(0.39)

*Notes:* The current technique does not allow for regression-based analysis, so to test the effects of covariates we have used the participant’s payout level as a proxy for lying, since those who lied will have gotten the larger pays. “Income” is percentage of people in income categories. “Spending” is percentage of people in weekly spending categories. Factor analysis of the belief in luck scale (Darke and Freedman 1997) forms two factors representing a belief that there is such a thing as ‘luck’ and a belief that the respondent is lucky. Religiosity and guilt proneness are composite measure created from Huber and Huber’s 5 item religiosity scale (2012) and Cohen *et al*’s 6 item guilt proneness scale (2011), respectively. ‘Democratic’ tests whether Democrats get higher or lower payout than Republicans. <sup>a</sup>Only people who stated their party affiliation as Democrat or Republican are included since these allow for matching or mismatching. \*\*\* and \*\* indicate significance at the 0.01 and 0.05 level, respectively. Note that the number of observations in this Table is slightly lower than the total number of participants since some subjects did not complete the demographic questionnaire.

As can be seen in Table A5, the demographic and attitudinal variables have little effect on the participant’s payout. We again see some effect of age, although less consistently strong here, and in the opposite direction as in study 1, with older respondents getting higher payouts. As in Study 1 Additional analyses (not shown) find no significant interactions of the covariates with the supporting and opposing conditions (all *p*-values > 0.05), demonstrating that the covariates do not moderate the effects of treatment on payout.