1 Background

Lying can taint research, unnecessarily raise the cost of goods, and lead consumers to make sub-optimal decisions. While traditional economic theory would suggest that agents will lie when given an incentive to do so, people are frequently honest despite an incentive to behave otherwise. Much recent research in the field has considered the notion of a "moral cost" of lying that overrides small incentives for lying and leads to the observed prevalence of honest behavior. In light of Kahneman and Tversky's (1979) theory that "losses loom larger than gains," a worthwhile question is whether potential losses are more convincing incentives to lie than gains. Unfortunately, there is currently disagreement in the literature concerning the impact of losses on lying behavior. A hallmark of scientific research is the ability to reproduce results and methods in a variety of contexts, a feat that has yet to be accomplished in considering the intersection of loss and lying.

There are three paradigms that have been used most frequently by economists to study deceptive behavior: the coin-toss paradigm (Bucciol & Piovesan, 2011), the die-roll paradigm (Fischbacher & Föllmi-Heusi, 2013), and the matrix task (Mazar et al., 2008). In the coin-toss paradigm, participants are informed that their payout is determined by the outcome of a coin toss (Bucciol & Piovesan, 2011); they privately flip a fair coin and report the observed result. Because the experimenters do not observe the coin toss or the outcome, there is no way of knowing whether an individual subject was honest or not in reporting their observation. The result of the coin-toss paradigm is a dichotomous outcome: participants receive a full amount for observing the "correct" outcome and nothing otherwise. Consequently, participants also face a binary decision and cannot choose to lie sub-maximally (meaning that there is not an opportunity to misreport the outcome so that the participant receives less than the maximum payout). In their meta-analysis of experimental deception paradigms, Gerlach et al. (2019) argue that the dichotomous nature of the coin-toss paradigm may decrease the rate of lying relative to other paradigms (namely, the die-roll paradigm) due to the high moral cost of maximal lying.

Similarly to the coin-toss paradigm, the die-roll paradigm (Fischbacher & Föllmi-Heusi, 2013) relies on subjects privately observing a random outcome. Participants are given a six- (Fischbacher & Föllmi-Heusi, 2013) or ten-sided (Charness et al., 2019) die, and there is a different payoff for each possible outcome. Unlike in the coin-toss paradigm, subjects in the die-roll paradigm are able to observe outcomes that result in payoffs less than the maximal amount but greater than zero. As a result, subjects have the option to lie along a scale (sub-maximally) instead of only choosing between maximal lying and not lying at all. This feature of the die-roll paradigm adds complexity to the decision and, as Gerlach et al. (2019) note, generally produces a higher rate of lying than observed in coin-toss experiments.

In recent years, there has been a growing literature concerning the influence of loss aversion (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992) on dishonest behavior. Unfortunately, the variety of possible paradigms for studying dishonesty intersected with the different methods for framing outcomes as losses has yielded ambiguity and conflicting results. While (Charness et al., 2019; Ezquerra et al., 2018) use the die-roll paradigm and are unable to show results indicative of the effects of loss aversion, numerous publications (Garbarino et al., 2019; Duc Huynh, 2020; Gneezy et al., 2018) using the coin-toss paradigm and matrix activity (Grolleau et al., 2016) have offered evidence of loss aversion increasing deceptive behaviors. Notably, Charness et al. (2019) use a different method for framing outcomes as losses than Garbarino et al. (2019) do. This discrepancy raises the question of whether the lack of loss aversion effects in Charness et al. (2019) were the product of the experimental paradigm or the loss framing method.

Under the Charness et al. (2019) design, players are assigned to either a money manipulation (MM) or no money manipulation (NMM) treatment arm. From there, they are either assigned to a loss frame (MM-L, NMM-L) or a gain frame (MM-G, NMM-G). In the NMM treatment arm, outcomes in both loss and gain domains are not realized until after the experiment; NMM-L (NMM-G) participants are told that they will receive a fixed payout (nothing), minus (plus) whatever they "lose" ("gain") in the game. Conversely, both sets of players in the MM treatment arm receive physical cash before playing the game. MM-G players receive an empty envelope for their earnings as well as a full envelope of bills containing their potential earnings, while MM-L players receive a full envelope for their earnings and an empty envelope for money they will return to the experimenters.

While one of the anonymous referees for Charness et al. (2019) expressed concern that the NMM condition represented a gain domain and the MM condition represented a loss frame, the results within the MM are significantly different. Namely, Charness et al. (2019) show that while MM-G participants demonstrated dishonest behavior (albeit at a somewhat lower level than both groups of NMM players), MM-L participants did not behave significantly differently from players in the baseline group, who appear to have behaved honestly. Charness et al. (2019) consider that giving the participants money could have implicitly imparted a burden of trust onto the players, making those in the MM treatment arm want to behave more honestly.

Garbarino et al. (2019) describe a model for loss aversion in risky situations and validate their model using the probability of a "good" outcome as the instrument for framing an outcome as a gain or loss. The model put forth by Garbarino et al. (2019) asserts that for a given lottery of possible outcomes, agents set the lottery's expected value as their reference point. Under this design, an agent facing a low probability of a high payoff and a high probability of a low payoff would have a relatively low reference point. Thus, receiving the low payoff would be a loss, but the loss experienced after having a high *ex-ante* probability of a high payoff and receiving a low payoff would be substantially greater in magnitude.

To validate their model, Garbarino et al. (2019) conduct an experiment using the coin-toss paradigm in which players flipped a coin four times and received payment based on the number of correct (*ex-ante*) guesses they made about the outcome of the coin toss. While the sequence of four coin tosses introduces the possibility of designing a game in which players can lie at sub-maximal levels, Garbarino et al. (2019) maintain the dichotomous structure of the typical coin-toss paradigm. In the high-probability treatment (H), players earned $2 if they correctly guessed the outcome at least twice and nothing otherwise. In the low-probability treatment (L), players earned $2 if they correctly guessed the outcome at least three times and nothing otherwise.

A possible concern related to the Garbarino et al. (2019) experiment is that payoffs were dependent on players' *guesses* about the observed outcome of the coin flip. While the correctness of a guess is determined randomly in reality, it is possible that subjects perceive it as a measure of skill. A meta-analysis of deception paradigms shows that participants are less likely to lie in games when they view their payout as the result of skill (Gerlach et al., 2019). In light of the literature concerning skill-based payoffs in dishonesty activities, it seems likely that the Garbarino et al. (2019) design would decrease deceptive behavior, so we would expect to see more dishonesty if the perceived skill component was removed.

The goal of this research is to address the discrepancy in the methodological literature studying the impact of loss aversion on dishonesty.

2 Method

There will be 500 participants obtained from the Emory University student population and Amazon's Mechanical Turk. 400 participants will come from MTurk, and the remaining 100 will come from Emory University.

Participants will be randomly assigned to one of five treatment arms: probability loss (PL), probability gain (PG), manipulated loss (ML), manipulated gain (MG), or no incentive (control, C).

Participants will receive information about their treatment arm (see below).

Participants will complete the activity on a computer via Qualtrics, where they will view their private instructions[1] and a digital six-sided die. Subjects will be told to "roll" the die as many times as they would like but to record only the first number they see (1, 2, 3, 4, 5, or 6) in the online survey. There will be one practice round during which subjects will be asked to record the first observed number and what their payoff would be (based on their treatment arm).

Probability Loss: Subjects are told that they will receive a payoff according to the table below.

	Die roll value					
	1	2	3	4	5	6
Payoff	\$0.00	\$1.00	\$3.00	\$4.50	\$6.00	\$7.50

Probability Gain: Subjects are told that they will receive a payoff according to the table below.

	Die roll value					
	1	2	3	4	5	6
Payoff	\$0.00	\$1.00	\$2.00	\$3.00	\$6.00	\$7.50

Manipulated Loss: Subjects are told that they are endowed with \$5.00 and will lose an amount according to the table below.

	Die roll value					
	1	2	3	4	5	6
Losses	\$5.00	\$4.00	\$3.00	\$2.00	\$1.00	\$0.00

Manipulated Gain: Subjects are told that they will receive a payoff according to the table below.

	Die roll value					
	1	2	3	4	5	6
Payoff	\$0.00	\$1.00	\$2.00	\$3.00	\$4.00	\$5.00

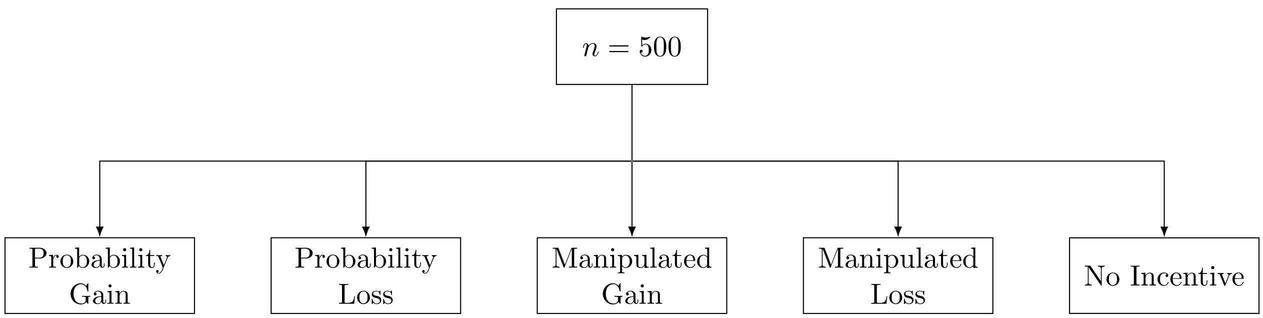
No Incentive: Subjects are not given any additional instructions and are paid \$2.50 for showing up, regardless of what they roll.

[1] To read the current draft of the instructions and surveys, click here

After participants have rolled the die and recorded the outcomes, they will be given a survey asking about demographics, risk attitudes and behaviors, and questions designed to take attention away from risk attitudes questions. After completing the survey, a random 50% of all participants will be paid according to their reports.

2.1 Treatment arms

Figure 1: Treatment visualization



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