Title
Risk Aversion and Theft as a Source of Risk

Author
Booth, Nathan

Publication Date
2021-09-07

Undergraduate

Risk Aversion and Theft as a Source of Risk

Nathan Booth

Advisor: Ignacio Esponda

March 15, 2021

Abstract

This paper seeks to show that the potential to lose money as a result of theft has a different effect on an individual's risk aversion than the potential to lose money due to chance. This would indicate that an individual's risk aversion is inconsistent under different scenarios, contrasting current literature that assumes an individual's risk aversion is independent of the situation they are in. We attempt to show this through an experiment that frames loss in the form of theft. We use Amazon Mechanical Turk to gather responses to our experiment online. We find that our treatment has no statistical effect, that people do not act in a way that is inconsistent with their risk aversion simply because of the possibility of theft.

Introduction

In this paper, we will be investigating how people respond to differing sources of risk. Specifically, we want to look at whether or not there is a difference in decision making when the source of risk comes directly from another person, as opposed to a risk that is purely based on chance. Due to the difficult nature of interpreting an individual's actions, the best way to answer this question is in an experimental setting, where we can control for all outside variables that may affect an individual's risk preferences. We will be using Amazon's Mechanical Turk in order to perform an experiment that should help us investigate these actions.

In similar form to other research on behavioral economics, this experiment will aim to show the existence of a behavioral "paradox." This type of paradox consists of two situations which, when viewed through the existing theoretical framework, provide the exact same outcome. Thus, if the theory is correct, there should be no difference in action between the two situations. However, what makes these situations paradoxes is the fact that real people, when confronted with the two situations, choose contradictory actions in each situation. More information on these paradoxes will be discussed in the literature review section.

In this experiment, we will be looking at people's reaction to the possibility of deception. For an example, consider the process of investing money through a third party. It should be that the risks of the investment themselves are reasonably apparent. If this investment is, for example, a stock purchase, then the investing individual should be aware of the risk that the stock will fall. This is the sort of risk that is most carefully considered when an individual decides to invest, and rightfully so, as the result of their investment depends on it. However, there is another source of risk to the investing individual that is not related to the outcome of their investment at all. This is the risk of deception. Given the strict standards of accountability that most investment firms are held to, this is not a common issue for most individuals who choose to invest in the stock market through an investing firm. However, that does not mean that this risk is nonexistent. Even today, there are plenty of examples of people investing through a third party, only to later figure out that the third party investor has stolen from them and they have lost all of their money. The question that we will investigate through this experiment, is whether this risk of theft carries the same weight as the inherent risk of the investment. That is, the numerical result of the theft is the same as the result if the investment completely failed. In both cases, the investor is left with nothing. However, are both of these nothings the same to the investor? If they are not, then an individual might overreact to the possibility of theft, and in doing so, act in a way that is inconsistent with their normal risk preferences. The intuition behind this reaction stems from people's desire for things to be fair. It has been well-documented that people are willing to pay in order to punish someone who is acting in an unfair manner. This would indicate that they get some positive utility from ensuring that things are fair. Seen in another light, it seems that people would gain a disutility from things being unfair. In this situation, despite being well-informed of the probabilities, an individual may see this form of theft as an unfair treatment, which they would prefer to avoid. This is the reaction that we hope to uncover via this experiment.

While this paper will focus on the motivations and actions surrounding deception, it would also be interesting to consider how people react to a risk with a more positive outcome. If people indeed react disproportionately to the risk of dishonesty or getting scammed, then perhaps they will also react disproportionately to a chance for someone to act generously.

Literature Review/Theoretical Discussion

The common theory for discussing risk aversion comes from Bernoulli in 1738. He posits that people have an increasing but concave utility function of money. This explains why people will sometimes decline a gamble in favor of gaining money for sure, even if the gamble pays more on average. Based on this theory, the only thing that matters to an individual is their utility function of money, and they make decisions based on which alternative gives them more expected utility. It is from Bernoulli that we get our classic concept of risk aversion.

However, there have been developments in the field of risk aversion that question Bernoulli's theory. Specifically, Rabin (2001) discusses issues with Bernoulli's concept of risk aversion. In his paper, Rabin shows that even very moderate risk aversion under small gambles would imply that an individual is averse to gambles with almost infinite upside and comparatively little downside. In this paper, Rabin gives the example of an individual who is risk averse; that is, they would not accept a gamble in which they win $11 half the time and lose $10 half the time (even though on average this gamble pays $0.50). Then, if this individual follows expected utility maximization, they will also turn down a 50/50 gamble of losing $100 and gaining any amount (even if the potential gain is $2.5 billion). This points out a rather large flaw in the theory of using expected utility to analyze risk aversion. Despite this flaw, expected utility is still used as a common way of explaining and analyzing risk aversion due to a lack of a better alternative. Thus, in this paper, we will mostly use Bernoulli's concept of risk aversion due to expected utility maximization (though the amounts that we offer will be small in order to avoid this shortcoming of expected utility maximization).

In order to combat this issue with risk aversion that Rabin points out, the theory of loss aversion has been developed by Kahneman and Tversky (1979). In this refinement on risk aversion, we see that loss provides a much more significant effect than gain. Basically, the pain of losing any amount of money is greater than the joy of gaining that same amount of money. This concept of loss aversion can explain some of the issues with risk aversion. Consider the example from Rabin's paper above. In this case, the individual turns down the 50/50 gamble to gain $11/lose $10 not due to the concavity of their utility function, but rather because losing the $10 would have a greater effect than gaining the $11.

There have been further refinements to the concept of loss aversion. Karle et al. (2015) discuss how loss aversion is based on people's expectations. They found that when people are expecting a payoff, even that expectation is subject to loss aversion. Blavatskyy (2011) also shows that loss aversion can be applied to non-monetary losses. These include things such as loss of faith, loss of morale, and others. This leads to the possibility of applying the theory of risk aversion and loss aversion to analyze preferences over non-monetary goods. For instance, it may be that there is some sort of aversion to the feeling of being tricked or scammed that would affect the participants in our experiment.

For the literature on risk and loss aversion, all of the papers assume that an individual's preferences are fixed, and do not change from situation to situation. They assume that once we have revealed an individual's risk preferences, those risk preferences will not change over the course of their experiment. This is the area that we hope to shed some light on. If an individual's risk preferences truly are fixed, then their actions should not change if we give them a different scenario, as long as the numbers remain the same.

This concept of actions across different (but mathematically identical) scenarios is investigated by Tversky and Kahneman (1981). They look at what they call framing effects. In their paper, they produce two mathematically identical situations. However, they describe the situations differently to their subjects. Simply by changing the way that they describe the situations, they see a reversal in preferences from one situation to another. That is, in one situation people prefer an option A to an option B. But in the second situation people prefer an option D (which is the same numerically as option B) to option C (which is the same numerically as option A). This indicates that the way people understand a problem changes with how they are presented with the problem, not just the underlying numbers in the problem. This is the sort of result that we will be trying to replicate in our experiment.

Based on the current theory of risk aversion, we expect to see consistent risk preferences from any given individual. This experiment will look into whether these risk preferences really are consistent, or if there are moments in which people will contradict their own revealed preferences. We will analyze risk preferences from an expected utility maximization standpoint, despite the critiques that exist surrounding it.

As for the intuition that guides our hypothesis, we look at experiments on the Ultimatum Game. The Ultimatum Game is a scenario in which the subject is asked to split a certain amount of money between themselves and a second subject. Then, the second subject is asked to either accept or reject the split proposed by the first subject. If the offer is accepted, then both subjects walk away with the amount of money designated in the split. If the offer is rejected, then neither subject is paid. In theory, the second subject should accept any offer that is greater than zero, as their alternative pays them zero, and the first subject should never offer more than $0.01 to the second subject, as they will accept anything positive. However, the results of experiments run on the Ultimatum Game tell a different story. The first experiment using this game was run by Güth, Schmittberger, and Schwarze in 1982, and the results showed a divergence from what the theory suggests. The divergence from the theory can be explained by the issue of fairness. The recipient of the offer may reflect an offer that they deem unfair, and, anticipating this, the subject who chooses the offer may offer more than the bare minimum. In a later experiment by Kahneman, Knetsch, and Thaler in 1986 showed that a third party was willing to take a reduced payoff in order to punish an individual who offered an unfair split (Thaler). These results indicate that individuals derive some sort of utility from a sense of fairness, and consequently, should derive some sort of disutility if they believe that there is a lack of fairness. In our experiment, we anticipate that those who face the possibility of being stolen from will see this theft as a form of unfairness. We believe that they think the one who steals their money is not entitled to it and does not deserve it, thus making the theft unfair.

Experimental Design

In order to investigate this hypothesis, we design an experiment that will look for a framing effect. The experiment takes the form of a gamble, where the subject is given the odds of the gamble and then chooses how much they want to wager (the instructions issued to the subjects will be included in the appendix). For the experiment, we will be first giving each subject an initial endowment of five dollars. Then, they are instructed to choose how much of the endowment they want to wager on the gamble. The subjects will be allowed to keep whatever they do not wager on the gamble. This will allow us to obtain a quantitative measure of an individual's risk preferences. In essence, we are asking our subjects how much money they are willing to give up in order to have a chance at winning a larger sum of money. The gamble that we are offering has increasing expected payoff with respect to the amount wagered, therefore we should see even the most risk averse individuals wagering something on the gamble. Then, we expect to see the amount wagered increase for individuals who are less risk averse. By assuming that all subjects are expected utility maximizers, and using a utility function of money of $U(x) = \frac{x^{1-r}}{1-r}$ (From Holt and Laury 2002), we can use the amount that an individual wagers in order to determine their coefficient of relative risk aversion *r*.

The frame that we are presenting in this experiment is one where we frame a loss due to chance as a loss due to theft instead. We implement this frame via a compound lottery. We recognize that the use of a compound lottery may affect our results if the subjects are unable to properly understand how the compound lottery works, but using a compound lottery is necessary for providing a clear frame. In the first stage of the gamble, the subject has a 50% chance to move on to the second stage of the gamble. If the subject does not move on to the second stage of the gamble, then they lose their wager and their payoff is zero. The framing comes in this first stage of the gamble. For the control group, this loss will be explained as just losing the gamble due to chance. The subjects are told that the experimenter will choose a card from a stack of five red cards and five blue cards. If the card is red, then the subject loses, if it is blue, then the subject advances to the next stage of the gamble. For the treatment group, the consequence of drawing a red card is not simply losing the gamble. Instead, the treatment group will be told that a red card permits the administrator of the experiment to steal the subject's wager. This theft makes the subject ineligible for the second stage of the gamble, just as losing via a red card does for the control group. We are hoping that this frame of having their wager stolen, as opposed to just being lost to chance, will push subjects to think about how they feel about their money being stolen. If they feel that this theft is unfair, it should provoke them to try to avoid this unfair scenario, and the only way to make sure their wager cannot be stolen is to not wager anything in the first place.

After this first stage of the gamble is complete, the subjects who have advanced to the second stage will face the same gamble, regardless of whether they are in the control group or the treatment group. This second stage gives the subject a 66% chance of winning five times the amount that they wagered, and a 33% chance of losing, gaining nothing. This stage is entirely up to chance, and is explained to the subjects as a roll of a die.

All in all, for both the treatment and the control groups, the gamble offers a 33% chance of gaining five times the amount wagered, and a 66% chance of losing the wager, gaining nothing. Thus, an individual's expected payoff is $5 + \frac{2}{3}w$, where *w* is the amount wagered by the subject. Note that this expected payoff is indeed increasing with the amount wagered *w*, so the theory predicts that everyone will wager a non-zero amount.

The numbers in this part have been chosen in order to try to ensure a decent distribution of answers. Using the following table from Holt and Laury, specifically the column titled "Low real" under the "Proportion of Choices" column, we have determined that the median coefficient of relative risk aversion is about 0.3, with the average coefficient of risk aversion being 0.32.

TABLE 3—RISK-AVERSION CLASSIFICATIONS BASED ON LOTTERY CHOICES

Number of safe choices	Range of relative risk aversion for $U(x) = x^{1-r}/(1-r)$	Risk preference classification	Proportion of choices		
			Low real[a]	20x hypothetical	20x real
0–1	$r < -0.95$	highly risk loving	0.01	0.03	0.01
2	$-0.95 < r < -0.49$	very risk loving	0.01	0.04	0.01
3	$-0.49 < r < -0.15$	risk loving	0.06	0.08	0.04
4	$-0.15 < r < 0.15$	risk neutral	0.26	0.29	0.13
5	$0.15 < r < 0.41$	slightly risk averse	0.26	0.16	0.19
6	$0.41 < r < 0.68$	risk averse	0.23	0.25	0.23
7	$0.68 < r < 0.97$	very risk averse	0.13	0.09	0.22
8	$0.97 < r < 1.37$	highly risk averse	0.03	0.03	0.11
9–10	$1.37 < r$	stay in bed	0.01	0.03	0.06

[a] Average over first and second decisions.

Assuming that this distribution provided by Holt and Laury holds true for our experiment, we should see the median individual wagering $3.2 on the gamble in part 1, and the average individual wagering $3.05. This should help ensure that the responses we receive are not too skewed towards one extreme. However, we anticipate that our responses will be slightly skewed towards higher wagers. Since the gamble has a positive expected payout, we do not expect any of our subjects to wager $0, we expect wagers to all be non-zero. However, for any individual that is risk neutral or risk loving, the optimal strategy is to wager all $5. This means that we will not be able to differentiate between individuals who are risk neutral and risk loving We believe this is acceptable, as it would be too difficult to design a gamble that would both encourage those who are risk averse (which is a majority of the population according to Holt and Laury) to wager a non-zero amount, and provide a way for us to separate those who are risk loving from those who are risk neutral.

After the subject has completed this gamble, we will ask them a series of questions aimed at eliciting their risk aversion. To do so, we follow Holt and Laury (2002). In this second part of the experiment, we ask the subjects to choose from two options. The first option offers $2 in the case of a win, and $1.60 in the case of a loss. The second option offers $3.85 in the case of a win versus only $0.10 in the case of a loss. There are ten questions regarding these two gambles, with the chance of winning increasing each time. The following chart from Holt and Laury details the probabilities of winning for each of the ten questions:

TABLE 1—THE TEN PAIRED LOTTERY-CHOICE DECISIONS WITH LOW PAYOFFS

Option A	Option B	Expected payoff difference
1/10 of $2.00, 9/10 of $1.60	1/10 of $3.85, 9/10 of $0.10	$1.17
2/10 of $2.00, 8/10 of $1.60	2/10 of $3.85, 8/10 of $0.10	$0.83
3/10 of $2.00, 7/10 of $1.60	3/10 of $3.85, 7/10 of $0.10	$0.50
4/10 of $2.00, 6/10 of $1.60	4/10 of $3.85, 6/10 of $0.10	$0.16
5/10 of $2.00, 5/10 of $1.60	5/10 of $3.85, 5/10 of $0.10	−$0.18
6/10 of $2.00, 4/10 of $1.60	6/10 of $3.85, 4/10 of $0.10	−$0.51
7/10 of $2.00, 3/10 of $1.60	7/10 of $3.85, 3/10 of $0.10	−$0.85
8/10 of $2.00, 2/10 of $1.60	8/10 of $3.85, 2/10 of $0.10	−$1.18
9/10 of $2.00, 1/10 of $1.60	9/10 of $3.85, 1/10 of $0.10	−$1.52
10/10 of $2.00, 0/10 of $1.60	10/10 of $3.85, 0/10 of $0.10	−$1.85

Note that at the fifth question, it is numerically advantageous to choose option B, as its expected payoff is higher. However, as seen in the results from Holt and Laury, people do not immediately switch to option B once it becomes more profitable. Option A offers a lower expected payoff, but the minimum payoff of option A is much higher than the minimum payoff of option B. Thus those that are more risk averse will choose to pick option A for more than 5 questions; they are willing to accept a lower expected payoff in order to ensure that they get at least $1.60, as opposed to only earning $0.10 if they lose from option B.

Following Holt and Laury, we can use a subject's answers to this set of questions in order to infer a range that their coefficient of risk aversion *r* lies in. Then, we can use this range in order to see if the subject's choice in part 1 is consistent with the risk aversion that we elicit in part 2. This should allow us to both control for variances in risk aversion between our control and treatment groups, as well as letting us see how consistent the subject's risk preferences stay throughout the experiment.

We incentivize this experiment by offering payment based on the outcomes of the gambles that a subject participates in. We offer a $1 payment to all who complete the experiment.

Then, with probability 1/4, we pay the subject a bonus amount equal to the amount that they earned from the gamble in part 1. With probability 1/4, we pay the subject a bonus amount equal to the outcome of one of their choices from part 2. If this is the case, we randomly select one of the ten questions, and then compute the payoff of the subject's choice for that question. With probability 1/2, we offer no bonus payment to the subject. The potential to not receive any bonus payment brings the expected payoff of this experiment down to levels that are consistent with other tasks of similar length on Amazon Mechanical Turk. This randomized bonus payment structure should incentivize individuals to reveal their true risk preferences.

Data/Results

We use responses collected from survey responses distributed to subjects through Amazon's Mechanical Turk (MTurk). MTurk is a service offered by Amazon that connects requesters with workers. A requester can offer a task, and a reward for that task, and then a worker completes the task and claims the reward. In this experiment, the task offered was to complete a survey which held the experiment questions. For privacy concerns, we did not collect any demographic information about these subjects, and therefore cannot say how they represent the true population. However, care was taken to ensure that each subject could only submit one response, and the subject was randomly assigned to either the treatment group or the control group upon starting the survey. We received a total of 58 responses, with 40 of those responses belonging to the treatment group, and 18 responses belonging to the control group. Notably, this sample size limits the conclusions that we can draw from our results.

The reliability of data collected through MTurk has been widely discussed in recent years. Based on Buhrmester et al. and Berinsky et al, we do not expect our results to be inherently unreliable simply because they were collected through Amazon MTurk; however, there are aspects of the collected data that pose questions concerning the reliability of some of the responses. The most notable issue with the responses is the completion time. The median time in which the experiment was completed is just over two minutes. However, in total, the instructions given to the subjects are approximately 800 words long. Therefore we question whether those who completed the experiment very quickly were able to correctly read and understand what was asked of them in the experiment. Because of the structure of Amazon MTurk, the participants are not limited in the number of tasks they can complete, therefore the faster they complete each task, the more rewards they can claim. Thus it is likely that some of the responses were simply submitted in whatever fashion was fastest, with little regard given to answering the questions honestly. However, we also cannot claim that those who took more time offer more reliable results. Since it is not possible to monitor a subject's progress through the experiment, we cannot claim that those who spent more time on this task did so because they were carefully reading all of the instructions and thinking carefully about their responses.

In addition to the issues regarding completion time, we also observe 25 of our 58 responses having inconsistent responses in Part two. By inconsistent, we mean that the individual switched to option B, but then switched back to option A. The structure of the questions in Part two is such that once an individual switches to option B, they should not switch back. This could again indicate that the subjects were not reading the instructions carefully, and not thinking carefully about their responses. However, it could also mean that the instructions in Part two were unclear. Since we had no direct contact with the subjects, we cannot know which is the case. Therefore, for the responses from Part two, we simply take the total number of times the subject chose option A, and use that number for the number of safe choices that is listed in Table 1 from Holt and Laury, which does not produce a statistically significant change in our results.

Despite these questions about the reliability of our data, we present our results. Figures 1 and 2 below show the distribution of wagers for both the control group, and the treatment group.

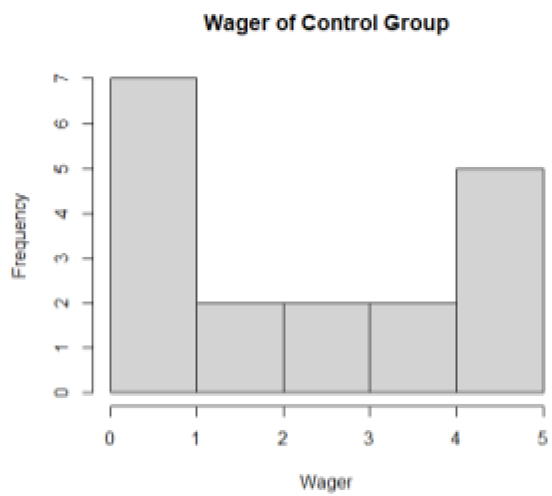

Figure 1: Histogram of Wagers from the Control Group

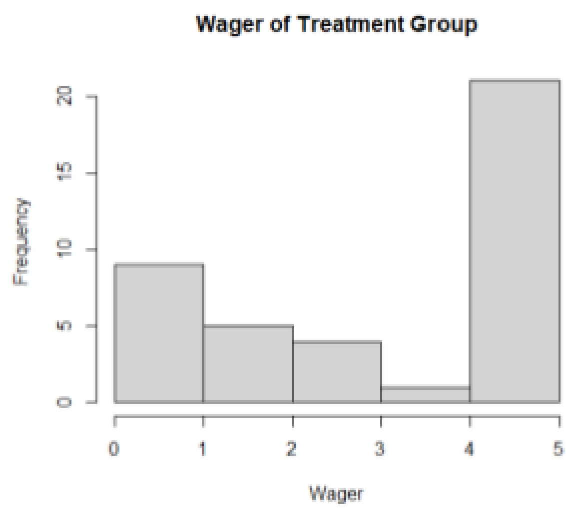

Figure 2: Histogram of Wagers from the Treatment Group

Then, figures 3 and 4 below show the number of safe choices made in Part two by subjects in both the control and the treatment group. Since we are looking at the number of safe choices, a

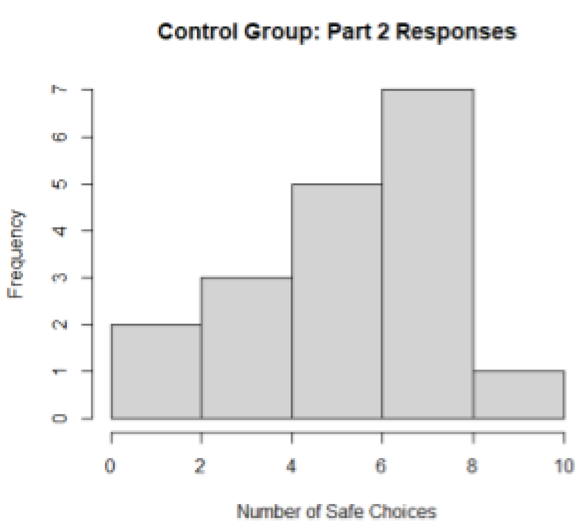

Figure 3: Number of Safe Choices Made in Part 2 by the Control Group

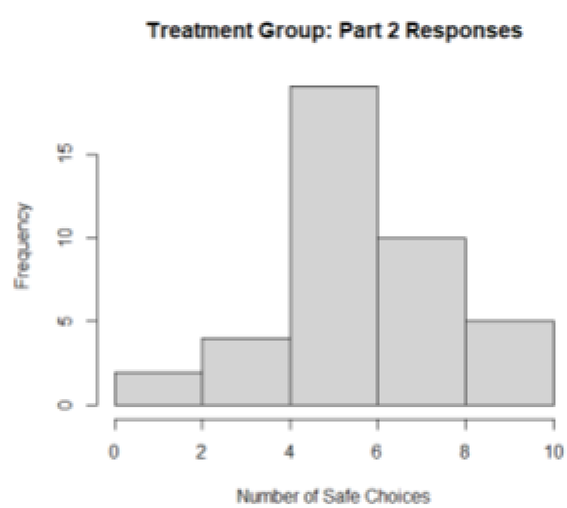

Figure 4: Number of Safe Choices Made in Part 2 by the Treatment Group

lower number of safe choices is associated with lower risk aversion, and less than four safe choices in total is associated with a subject being risk neutral or even risk loving.

Note that despite the visual differences in distribution, there is no statistical significance between either the wagers or the number of safe choices made by each group. A simple linear regression illustrates this. We regress the wager in Part one on a dummy variable for treatment, and control for risk aversion using the number of safe choices from Part two. Table 1 below shows the result of this linear regression.

Variable	Coefficient	Standard Error	T-statistic
Intercept	3.9280	0.7643	5.139
Treatment	0.8833	0.5449	1.621
Number of Safe Choices	-0.2422	0.1089	-2.224

Table 1: Linear Regression of Wager on Treatment, Controlling for Risk Aversion

We can see that the treatment has no statistically significant effect on an individual's wager, meaning that we have not found the framing effect that we were looking for.

Additionally, we look at whether our subject's choices are consistent over the entire experiment. We take the subject's response to part two as their true risk aversion. Using the number of safe choices from part two, we use the results from table 3 from Holt and Laury to assign each subject a range for their coefficient of risk aversion *r*. Then, we assume that individuals follow expected utility maximization with a utility function of money

$U(x) = \frac{x^{1-r}}{1-r}$Then, we can translate the range for the coefficient of risk aversion to a range of optimal wagers in the gamble from part one. The first order condition for expected utility gives us that the optimal wager for an individual with $r > 0$ is $w = \frac{5(2^{1/r} - 1)}{4 + 2^{1/r}}$. For individuals with $r < 0$, it is always optimal to wager the full $5. Then, we compare the range for an individual's optimal wager with their true wager from part one, finding the difference between the true wager and the range of their optimal wager. We find that for the control group, the average distance between their true wager and the theoretical optimal wager is 1.20; for the treatment group, the average distance between the true wager and the theoretical optimal wager is 1.73. These numbers are both statistically different from zero, but are not statistically different from each other. This indicates either a shortcoming of the theory of expected utility maximization, or potentially a misunderstanding of the gamble in part one. This inconsistency is interesting in that it supports the hypothesis that people do not have consistent risk aversion, however it does not support this specific hypothesis that the possibility of theft would inspire inconsistent behavior.

Conclusion

The design of this experiment was focused on finding whether simply introducing the possibility of loss resulting from theft could affect an individual's risk aversion. We have found, through a simple experiment conducted through Amazon MTurk, that framing a loss as the result of theft as opposed to a loss as the result of chance does not change an individual's risk aversion where that loss is a possibility. However, the frame of this experiment was very subtle. The only difference between the control group and the treatment group was where the control group lost money, the treatment group had that money stolen from them. In the end, both of these losses are the same numerically, and thus we see no difference in response. However, this experiment gives rise to other questions regarding risk aversion and theft. The greatest difficulty in this experiment was convincing the subjects that it was possible for actual theft to occur, without causing the subject to be skeptical of all information offered (namely the odds of winning the gamble). If the subject could be convinced that theft was a true possibility, but that all other parts of the scenario were legitimate, then we may see the treatment effect that we desired in this experiment. In addition to the difficulty of convincing the subject that the threat of theft is real, the anonymity of the internet played an important role in the results we received. An experiment that is conducted in person, where the subjects are able to see a tangible person who might be running off with their money would likely produce stronger results. All in all, the frame in this experiment was very weak, and so it is unsurprising that we found no significant results. If a future experiment with a stronger frame finds that the way in which one loses money affects an individual's risk aversion, then the classical concept of risk aversion may prove even weaker than it already is. We find evidence from our experiment that people do act with inconsistent risk aversions in the two parts of our experiment, but we cannot say whether this difference is due to misunderstandings during the experiment, or a deeper flaw in the theory of risk aversion.

References

Rabin, Matthew, and Richard H. Thaler. “Anomalies: Risk Aversion.” *The Journal of Economic Perspectives*, vol. 15, no. 1, 2001, pp. 219–232. *JSTOR*, www.jstor.org/stable/2696549. Accessed 11 Dec. 2020.

Kahneman, Daniel, and Amos Tversky. “Prospect Theory: An Analysis of Decision under Risk.” *Econometrica*, vol. 47, no. 2, 1979, pp. 263–291. *JSTOR*, www.jstor.org/stable/1914185.

Karle, Heiko, et al. “Loss Aversion and Consumption Choice: Theory and Experimental Evidence.” *American Economic Journal: Microeconomics*, vol. 7, no. 2, 2015, pp. 101–120. *JSTOR*, www.jstor.org/stable/24466990.

Blavatskyy, Pavlo R. “Loss Aversion.” *Economic Theory*, vol. 46, no. 1, 2011, pp. 127–148. *JSTOR*, www.jstor.org/stable/41485809.

Tversky, Amos, and Daniel Kahneman. “The Framing of Decisions and the Psychology of Choice.” *Science*, vol. 211, no. 4481, 1981, pp. 453–458. *JSTOR*, www.jstor.org/stable/1685855.

Thaler, Richard H. “Anomalies: The Ultimatum Game.” The Journal of Economic Perspectives, vol. 2, no. 4, 1988, pp. 195–206. JSTOR, www.jstor.org/stable/1942788.

Holt, Charles A., and Susan K. Laury. “Risk Aversion and Incentive Effects.” The American Economic Review, vol. 92, no. 5, 2002, pp. 1644–1655. JSTOR, www.jstor.org/stable/3083270.

Buhrmester, Michael, et al. “Amazon's Mechanical Turk: A New Source of Inexpensive, Yet High-Quality, Data?” Perspectives on Psychological Science, vol. 6, no. 1, 2011, pp. 3–5. JSTOR, www.jstor.org/stable/41613414. Accessed 9 Mar. 2021.

Berinsky, Adam J., et al. “Evaluating Online Labor Markets for Experimental Research: Amazon.com's Mechanical Turk.” Political Analysis, vol. 20, no. 3, 2012, pp. 351–368. JSTOR, www.jstor.org/stable/23260322. Accessed 9 Mar. 2021.

Appendix

Below are the instructions that were given to the experiment subjects. The difference between the control group and the treatment group is denoted by [brackets].

Page 1

The following experiment will contain two parts

You will be paid a base rate of $1 simply for completing this survey, and you have the chance to earn a bonus payment based on your responses to the two parts of the survey. Your bonus payment will be one of three amounts:

1. You will be paid a bonus equal to the amount of money you make in Part 1.
2. You will be paid a bonus equal to the amount of money you make in Part 2.
3. You will not be paid any bonus, you will only receive the $2 for completing the Survey

At the end of the experiment, the interface will randomly select which of the three amounts above determine your bonus.

Page 2

Consider the following scenario:

You are given $5. You may wager any portion of the $5 into the following gamble. Note that anything that you do not wager, you can keep. But the payoff of the gamble is dependent on how much you wager. The gamble is as follows:

- First, I will draw a card from a stack of ten cards. 5 of the cards are blue and 5 of the cards are red.
- If the card that I draw is red, then [you lose/I will steal your wager]: The payoff of your gamble will be zero and you will not progress to the second stage.
- If the card that I draw is blue, then you will progress to the next stage of the gamble:
    - In this Second stage, the interface will roll a 6-sided die
    - If the die lands on 1,2,3, or 4, you win, and the payoff of the gamble is five times the amount that you wagered
    - If the die lands on 5 or 6, you lose, and the payoff of your gamble is zero

Note that the amount of money you walk away with is:
$5 - however much you wager + the outcome of the gamble

Please enter how much you wish to wager:

Page 3

Part 2.

For each of the following 10 questions, you will be asked whether you prefer option A or option B. The options represent your chances at gaining money.

If this Part is selected for payment, I will randomly select one of the 10 questions below and you will be paid based on the outcome of the gamble that you selected.

1. Question 1
    a. 1/10 chance to receive $2.00, 9/10 chance to receive $1.60
    b. 1/10 chance to receive $3.85, 9/10 chance to receive $0.10
2. Question 2
    a. 2/10 chance to receive $2.00, 8/10 chance to receive $1.60
    b. 2/10 chance to receive $3.85, 8/10 chance to receive $0.10
3. Question 3
    a. 3/10 chance to receive $2.00, 7/10 chance to receive $1.60
    b. 3/10 chance to receive $3.85, 7/10 chance to receive $0.10
4. Question 4
    a. 4/10 chance to receive $2.00, 6/10 chance to receive $1.60
    b. 4/10 chance to receive $3.85, 6/10 chance to receive $0.10
5. Question 5
    a. 5/10 chance to receive $2.00, 5/10 chance to receive $1.60
    b. 5/10 chance to receive $3.85, 5/10 chance to receive $0.10
6. Question 6
    a. 6/10 chance to receive $2.00, 4/10 chance to receive $1.60
    b. 6/10 chance to receive $3.85, 4/10 chance to receive $0.10
7. Question 7
    a. 7/10 chance to receive $2.00, 3/10 chance to receive $1.60
    b. 7/10 chance to receive $3.85, 3/10 chance to receive $0.10
8. Question 8
    a. 8/10 chance to receive $2.00, 2/10 chance to receive $1.60
    b. 8/10 chance to receive $3.85, 2/10 chance to receive $0.10
9. Question 9
    a. 9/10 chance to receive $2.00, 1/10 chance to receive $1.60
    b. 9/10 chance to receive $3.85, 1/10 chance to receive $0.10
10. Question 10
    a. 10/10 chance to receive $2.00, 0/10 chance to receive $1.60
    b. 10/10 chance to receive $3.85, 0/10 chance to receive $0.10