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ADAPTIVE UTILITY: OBSERVING THE RATE OF ADAPTATION IN HAPPINESS AS SHORT RUN SHIFTS REVERT TO LONG RUN AVERAGES

Cameron Bellamoroso
cbellamo@lion.lmu.edu

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Cameron Bellamoroso

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Faculty Advisor: Dr. Dorothea Herreiner

Abstract

In economics, human decision-making models are based on the utility, or happiness, a person experiences from the choices they make. Individual happiness is closely tied to societal and global well-being, a common political and and research goal. Psychological studies on happiness show that people generally return to an average level of happiness after experiencing a significant positive or negative change in their life, a process known as the "hedonic treadmill." Empirically, it is often difficult for people to predict the specific utility they will experience from a given choice, leading them to maintain constant preferences for only frequently experienced options. This study relies on recent utility models that describe the adaptive learning process observed in human behavior, where people become better over time at making accurate judgements for familiar choices. I study whether participants adhere to principles of an adaptive utility model in an economics lab experiment. Subjects rank many possible payoffs into four categories of desirability in repeated rounds, thereby determining thresholds of utility. The limitation of four categories forces participants to optimize how they distinguish between payoffs. Pairs of payoffs are randomly selected, and then the participant's ranking is used to determine which of the two payoffs is used for payment. Changing the frequency at which specific pairs are selected tests the rate of adaptation in participant rankings, thereby testing a core prediction of the model. Participants in the study adapt over the course of the game and get closer to the optimal strategy as they play. Results from this study suggest that people adapt typically only after several repeated rounds of information or after incurring a loss, and that receiving payoffs in one portion of their utility curve may result in adaptation in the rankings of both observed and unobserved payoffs with other amounts of utility.

1. Introduction

Economics traditionally studies scarcity and the choices made in response to said scarcity. Analyses conducted on both micro and macro levels require an in-depth understanding of human behavior. Expectations of risk and reward inform both individual and public decision-making as people attempt to maximize the benefit of each decision they make. Policy goals tend to include the maximization of individual or societal well-being. These attempts are made difficult, however, by the unpredictability of human behavior. Psychological studies on happiness show that people generally return to an average level of happiness after experiencing a significant positive or negative change in their life, a process known as the "hedonic treadmill." Empirical studies show that it is often difficult for people to predict their specific utility from a given choice, leading them to make mistakes in distinguishing options.

Robson and Whitehead (2019) propose a model based on these nuances of human behavior to provide a more descriptive quantitative basis from which to understand choice. They present a utility curve in the form of a stepwise function in which stimuli, or choices, are inputs that the individual places somewhere on the utility curve when making decisions. This model allows for adaptation by letting the curve to steepen or flatten in different regions as people adapt to their new surroundings. The curve becomes flatter when a step widens, and becomes steeper when the width of a step becomes narrower. It is based in part on an intersectionality of economics, psychology, and neuroscience, stemming from the idea that biological evolutionary properties affect how the brain processes information such that it ultimately minimizes the probability of an erroneous choice being made; people choose a less enjoyable option by mistake as infrequently as possible. Since people can store only a limited amount of information, they adapt to be most able to understand stimuli they frequently experience, while losing some ability to discern between less familiar stimuli. Minimization of error provides an instrumentally important aspect of adaptation over time. The assumptions of the model as presented by Robson and Whitehead have not previously been tested empirically.

This paper describes an economics lab experiment designed to test core assumptions and values used in the Robson-Whitehead model. The rate at which adaptation occurs is observed as participants play a repeated game in which they assign a large number of potential payoffs to a smaller number of possible ranks. This ranking system creates a limited range through which participants can choose to distinguish between payoffs. The resultant imprecision creates the necessity to adapt to choices in order to maximize accuracy levels (and maximizing reward) over the course of the experiment. Analysis of participant behavior in the experiment indicates that on average participants make changes to their strategies in 33% of rounds. No significant behavioral difference is observed in rounds after a tie occurs between selected

payoffs, but participants are more likely to make changes to their strategies in rounds immediately following a loss. In general people prioritize avoiding the lowest payoffs more than obtaining the highest payoffs. In most cases subjects identify the optimal strategy in conditions with even probabilities of selections but take longer to maximize their utility under conditions when they do not know the probabilities for selection. It is unclear if participants' would achieve the optimal rankings given a greater number of rounds, or if their adaptation is not sensitive enough to capture smaller marginal differences in expected utility. These results indicate the presence of an adaptive process similar to that described by the Robson-Whitehead model in which participants slowly adapt their strategies over time, resulting in a long-run difference in the valuation of various payoffs. The exact speed of this adaptive process occurs differently for each person and it is unclear from the results of this study if players would successfully adapt without the occurrence of negative reinforcement (losing a round).

2. Literature Review

Economic research has often focused on both the importance of happiness on an individual and global sense as well as understanding the many nuances in which people experience happiness. Some countries include national happiness as a primary goal in their policies and directives, such as Bhutan's gross national happiness index. Similarly, the Happy Planet Index and the Measurement of Economic Performance and Social Progress both incorporate subjective well-being into their statements on global well-being, a feature that is absent from the more popular Human Development Index. Hirschauer, Lehberger, and Musshoff (2015) analyze the potential role of happiness economics in organizing and preparing public policy. This theoretical paper compares various models of utility with observed phenomena such as the hedonic treadmill or the rat race. They posit that happiness provides a more important measure from which to interpret the value of a given policy or outcome, specifically noting that it provides a level of analysis which traditional utility models, both cardinal and ordinal, fail to capture.

In addition to its relevance in public policy, research in economics, psychology, and neuroscience work towards a common goal of interpreting how people experience happiness, as well as investigating manners in which happiness can be studied. Easterlin (2003) argues that adaptation of happiness depends on the nature or domain of the good in question, evidenced by self-reported data on happiness, health, and life satisfaction. They find that people adapt to significant life changes more in the pecuniary domain than the non-pecuniary domain. This paper relies on social comparison – how people are always aware of the possibility of having more in quantifiable domains – and adaptation to explain how the hedonic treadmill encapsulates the human experience after large changes in income but does so more poorly for non-pecuniary shifts such as divorce, moving one's home, or serious disability.

The notion of this adaptation of happiness pertains to several studies on significant changes in life, among which is Shkade and Kahneman's (1998) question on whether moving to California would significantly change people's reported happiness levels. Their efforts provide an empirical backing for the hedonic treadmill. They conducted a similar survey in both California and Michigan, questioning students on their happiness and expected happiness were they to move to California in the case of the Michigan students, and how Californian students would feel after moving to some new idealized paradise. The results of both expected happiness and reported current happiness were the same between schools. This experiment provides strong evidence that a disconnect exists between how people expect to like something and how much they actually enjoy it, and also exemplify one way in which the hedonic treadmill can be tested using methods of economic research.

Further work on the disconnect between expected enjoyment and actual happiness gained comes from Berridge, Robinson, and Aldridge (2009) in their study of the components of reward. They create a comparison between facial expressions and brain activations in both humans and animals to compare the occurrences of liking (experiencing a stimulus), wanting (desiring to experience a stimulus), and learning (changing the way they perceive a stimulus). They find that each of these processes link to different areas within the brain and do not always perfectly correlate in the way they occur; a stimulus with a larger "want" effect might have a lower "like" effect when consumed. This dissociation between processes may partially explain how people can incorrectly estimate how they will feel about certain life changes.

Oswald and Wu (2010) analyze national data to determine whether subjective, or self-reported, measures of happiness accurately represent real happiness. They compare data from the Behavioral Risk Factor Surveillance System with self-reported happiness surveys to find that the results correlate by state with $P<0.001$. This suggests that trends observed by various studies on happiness reflect the human experience and could be incorporated into future models of utility. The findings from this paper grant greater validity to previously mentioned papers as well as indicate a consistency in how people experience happiness. Jonathan W. Schooler and Iris B. Mauss (2009) present a slightly different perspective, arguing that being happy and having meta-awareness of happiness differ slightly. Specifically, they use neuroscientific evidence to support a philosophical claim that happiness is not always necessarily experienced consciously. This would suggest that there may be some level of disconnect between how people experience stimuli and how they think they experience stimuli.

2.2 Models of utility: The concept of utility holds a central role in economics, but many different individual studies have contributed different interpretations or revisions to the utility-based analysis of human behavior. Von Neumann and Morgenstern (1953) create the foundation of all modern

discussions of utility with their argument that human decision-making follows four axioms: (1) completeness – for all choices, some form of ranking exists– (2) transitivity – that if choice A is preferred to B, and B to C, then A is preferred to C–, (3) continuity–given those same rankings for A,B,C, there exists some value p where $pA + (1 - P)C$ is equally liked as B–, and (4) independence–if $A > B$, then $A + C > B + C$. This study provides the original framework of choice as a rational endeavor in which the actor seeks to maximize some form of utility when deciding between options. Debreu (1954) also discusses this theory and notes that items or bundles can be quantified into a numerical (rankable) system of choices. Utility connects subjective desires with a numerical system of analysis that are more easily applied to interpretations of behavior.

Kahneman and Tversky (1979) create prospect theory, the fact that people distinguish between an exact sum and the expected value of that same sum. They discover this nuance, along with observing that people misestimate small probabilities and weigh losses and gains differently, in a controlled lab experiment. Moreover, people tend to put greater weight on events with a small probability of occurring, and too low of a weight on events with high (but not guaranteed) likelihood of happening. This provides a critique of utility theory that suggests factors other than simple maximization of expected value affect decision making; people value different certainties, quantities, and cutoff points differently, and can also make "errors" in their valuations.

Karni, Edi, and Schmeidler (1986) propose a model that accounts for some irregularities in human behavior suggesting that what may seem like departures from rationality may have an evolutionary mechanism. They point out that, from a biological standpoint, people receive a significantly greater punishment from hitting zero (dying) than from a loss of a different degree. This explains some aspects of risk aversion and differing human preferences between the loss and gain domains. Furthermore, it provides a precedent for the methodology of modeling biological or psychological occurrences through economics. Robson (2001) also argues for the importance of biological history in the formation of utility and decision-making processes. They discuss evolutionary mechanisms and provide a series of examples of behavioral trends that stem from these mechanisms. Utility originates from a cost/benefit system that dates back to the origins of humanity. Subsequently, utility must evolve in a manner such that the probability of an error (a suboptimal choice) is as low as possible, resulting in a utility curve steepest at points of the largest number of stimuli. The Robson paper directly informs the model that will be tested in this study.

Rayo and Becker (2007) describe a utility curve with the feature that sometimes two stimuli will appear similar enough in how much an individual enjoys them that they will be unable to distinguish which one garners greater utility. This relates to how people distinguish visual stimuli not based on a fixed-point

system, but rather by a comparative process. Graphically, this new assertion results in flat sections on the utility curve where two choices seem to provide identical utility.

Netzer (2009) provides another lens of analysis for the Robson model with the use of a fitness criterion, or expected loss, as a motivator for the evolution of utility as opposed to the probability of error. This model creates a similarly shaped utility curve as the Robson model with the steepest section occurring in the region with the highest frequency of choices being made, however the model specializes to a slightly smaller degree. The less visited sections of the distribution remain steeper than the flatter corresponding areas on the Robson model.

Robson and Whitehead (2019) later expand upon the biology of human behavior in the specification of the model that motivates this experiment. They create a model designed to create an intersection between evolutionary biology and economic utility theories in an adaptive, hedonic, and cardinal model of utility. They propose a stepwise utility curve that relates directly to the firing of a neuron, or set of neurons, in response to stimuli. Furthermore, the model incorporates randomly generated noise which represents the inconsistency with which people make decisions. Subsequently, they will sometimes have an error when they choose a lesser (or better) option due to this noise. Additionally, their model includes an adaptation feature such that each stimulus observed causes the individual to adapt and become more able to distinguish that stimulus from other extremely close stimuli in utility, but also to observe the utility gained from that stimulus as closer to the mean. This accounts for the eventual desensitization observed in the hedonic treadmill. This model will be discussed in more detail later in this paper.

2.3 Utility in experiments: Games are often used in economic research to assess learning and preferences or utility. Learning through games has been visited several times in experimental economics. Erev and Roth (1998) challenge a base assumption of a rational strategy to show that people learn over the course of a game. Using a simple matrix with 100 periods in which the optimal equilibrium involves only mixed strategies, they find that people converge towards an equilibrium as they gain more information and reinforcement about the game they play. This shows that preferences may change over the course of a game as people become more aware of the results of their choices. Later, Camerer and Ho (1999) propose a variation on this reinforcement-based learning with “experience weighted attraction” in games with some form of uncertainty. They use varying discount rates on previous experience through rounds of a game to show that incorporating fictitious play creates a similar outcome to reinforcement-based learning.

Cooper and Kegel (2006) show that learning in one situation transfers to other similar situations. They let participants play in two different signaling games played sequentially. They observe a learning process within the first game that carries into the second game, as participants perform better in the

second game compared to unpracticed participants. This indicates that people can learn over a longer period of time and adapt to new games using information gained in previous iterations.

Charness and Levin (2005) show that people weigh experienced consequences differently from simple information when updating their knowledge to adapt to new occurrences. They conduct a lab experiment in which participants choose between two urns full of two colors of balls. Participants choose both with uncertainty and risk when making their choices as they know neither the ratio of balls nor which urn is which. Charness and Levin find that participants tend to make mistakes when it comes to guessing which urn holds the better payoffs. This effect is greater when they receive a good payoff from their first pick than when they receive only information by viewing a ball as if they had picked without receiving a reward. Similarly, Charness, Oprea, and Yukel (2018) test how people choose between and learn from biased information sources. They form an experiment in which people are rewarded for learning about a binary distribution and are given a series of information from different sources; they would see outcomes drawn from several different probability distributions without ever witnessing the underlying distributions. They find that people tend to over-emphasize information that aligns with their prior belief and actively pursue this strategy.

Bostian and others (2005) specifically test the potential of adaptive learning (people adapt in response to the results of their own previous behavior) in an experiment where participants choose the quantities of a good to bring to market, then learn some information about demand based on sales. They find that after starting at a relatively neutral position, people tend to move towards the optima but with a constant “pull towards center” effect that keeps them either just under or just over the optimal decision in the long run. The adaptive learning process allows participants to get close to the top solution, but that eventually a form of inertia sets in such that people stop adjustments once they grow suitable close to the correct distribution.

The multi armed bandit problem, as described by Farias and Madan (2011) provides context in which to view the trade-off between learning and earning. It forces participants to choose between a series of levers, each with a different set of payoff probabilities. They are unaware of the distributions of each lever initially, and thus must decide which lever to pull each subsequent round, to gather more information or to stick with the highest-paying lever found thus far. It creates a model in which direct knowledge becomes relevant for maximizing payoffs and people will retain the most knowledge about levers they pull frequently while remaining unable to distinguish clearly between less visited levers. Averbeck (2013) adds an evolutionary analysis to the way 3-armed bandit strategies can be played, relating it to foraging behavior. They note that knowledge of time horizon – or how long the game is to be played – is integral to

forming a strategy. In the short term taking higher probability options is more beneficial than finding the optimal strategy, whereas in the long run it is better to information sample.

The conventional application of utility for interpretation of lab behavior is challenged by Lichtenstein and Slavic (1971) in their discussion of preference reversals on gambles and bidding. They show that people show inconsistency in their behavior when presented with the same choices between gambles in different situations. The gamble that participants initially prefer often receives a lower bid in their lab experiment. This indicates that people value choices differently depending on the situation or manner in which they acquire them. This plays into the discussion on whether utility accounts for behavioral inconsistencies such as these or whether they represent error on the part of the participant.

Stauffer, Lak, and Schulzs' (2014) lab experiment featured monkeys who must decide between a series of gambles with rewards. They found that the neuronal firings within the monkeys' brains corresponded to what an idealized utility curve might look like. Furthermore, they witnessed neuronal firings that corresponded to learning as monkeys worked to correct errors made in their choices or beliefs. This provides neurobiological basis from which to observe the empirical observations made in economics experiments; liking, wanting, and learning occur at different times. This observation has been further described by Peciña (2008) in neural webs within human brains. They note that distinct regions of nucleus accumbens in neurons are responsible for liking and wanting. The activation of different regions of the nucleus suggests that the two processes are potentially dissociable.

Siri Leknes and Irene Tracey (2008) show that pleasure (positive stimulus) and pain (negative stimulus) are often considered and weighed on a single motivation-decision model. Effectively this argues that pain and pleasure are very closely related such the brain can implicitly compare the two; an increase in one will lead to a decreased hedonic experience of the other. They use molecular imaging on dopamine and opioid processing in the brain to support their claim that this decision-making process happens on a similar scale for both positive and negative stimuli. Tobler et. al. (2006) have participants make decisions involving both risk and varying payoff sizes while connected to fMRI machines. They found that the cerebral processes involved in observing risk/probability are distinct from those considering payoff sizes; people calculate how much they like an option separately from how they calculate how likely it is to occur.

In another study with monkeys in a lab, Stauffer, Lak, and Schulz (2014) used animal choices and brain scans to observe the relationship between various numerical observations (estimations of quantity, value, etc.) on the cerebral processes observed during decision-making. They varied risk, quantity, and time delay with rewards and found that similar dopamine neurons fired in response to all stimuli in a manner consistent with what a modelled utility curve would predict. This verifies people's assignation of some form

of value to drastically distinct decisions when making choices. Leibovich and others (2017) also compare the ways in which people process different kinds of information and show that people tend to rely on a continuous interpretation of magnitude when making decisions. Contrary to number sense theory, in which people are theorized to have an innate sense of numbers, their study shows that people learn and make decisions about magnitudes and numerosity holistically such that their decisions depend on information learned in the context of the choice: the values of nearby choices.

Grosskopf and Nagel (2007), raise an argument that the shift in strategies over time in beauty contest games represents adaptive behavior. They compare patterns in beauty contest games with varying numbers of players and varying rule sets. They find that the rate of adaptation people exhibited tended to closely mirror the conditions in which they played, as opposed to adhering to the game-theory equilibrium they might have discovered if they were consciously learning. This suggests that a primary motivator for behavior in economics experiments comes from adaptation to payoffs and previous strategies.

Freeman, Halevy, and Kneeland (2019) discuss the elicitation risk preferences, specifically the certainty equivalence, of players in an economics experiment by letting people use choice lists when deciding between gambles. They show that the manner in which this information is presented, a list or a single pair-wise choice, affects how people respond to these choices. Specifically, people become less risk averse when dealing with one certain outcome when their alternative is presented in a list. This provides further basis that preferences form depending on the context in which the decision is made. The amount of value people place on any given choice depends on things other than just the expected value of that choice.

Cardinal utility serves as a lens through which to analyze or interpret behavior within experimental economics. Polemarchakis and Rose (1984) show how cardinal utility can be derived based on behavior witnessed in asset demands. They provide a theoretical model and proof that consumer behavior can be interpreted in such a way that cardinal utility can be inferred. The relevance of cardinal and ordinal utility is discussed in Calvo, Emilio, and Peters (2005) paper on bargaining with different types of players. They note that traditionally bargaining has always been analyzed in the realm of cardinal utility but provide evidence that ordinal utility can also be used in an interpretation of bargaining strategies. Specifically, they show how a game with both ordinal and cardinal players might be solved.

Two studies look at the effectiveness of economics experiments conducted in an online environment. Anwyl-Irvine, A.L., Massonnié, J., Flitton, A. et al. (2020) describe the technological requirements involved in conducting an experiment online. They note that while many aspects of the experiment may remain the same, the level of technological connectedness required in these designs far surpasses previous systems. Participants must be connected to the server, often via multiple programs, and

have the potential to have other distractions present. Moreover, there can be timing issues due to server latency or slow connections. Additionally, subject recruitment may prove to be a challenge due to the limited capacity to screen participants in these conditions. Antonio A. Arechar, Simon Gächter & Lucas Molleman (2018) run a complicated experiment using Amazon's Mechanical Turk as a subject pool to see how data collected in this environment compares with data collected in an in-person lab. They find that in general people play in similar ways, but the dropout rate is significantly higher in online mediums. This suggests that online experiments are a logistical challenge, but that the results should not be biased since they found the drop-out rate to be uncorrelated with performance in the experiment.

3. Theoretical Framework

The economic experiment described in this paper is heavily informed by the theoretical model provided by Robson and Whitehead (2019). Their model accounts for empirical observations of nuances in human choice: randomness, reversals, learning, and long run adaptation. At its core, the model relates stimuli – all the experiences and choices a person can observe and make decisions between – and the neural firings in the brain. Whenever a person observes a stimulus, some number of "want" neurons fire in the brain. The number of neurons that fire guides the decision-making process for the individual. Because there is a distinction between how the brain processes "want" and "like" – i.e., desiring an outcome vs. actually experiencing said outcome – there is room for some inconsistencies or errors to occur. In this paper, the notion of error in choice refers to some of the potential outcomes of these inconsistencies. First, a stimulus might fire a different proportion of "want" neurons relative to "like" neurons, resulting in a person either over- or underestimating how much they will enjoy that stimulus. As a result of this occurrence, they might become unable to tell differently liked stimuli apart in terms of how much they want them, or they might mistakenly want the less-liked stimulus. Both cases result in a person mistakenly choosing a suboptimal outcome, or in other words making an error.

To motivate the adaptive properties of the model, it is assumed that cerebral processes necessitate a certain level of inaccuracy as people cannot possibly retain all information on all different stimulus in the short run. Nevertheless, it is possible to learn or adapt to certain stimuli to make it less likely an error occurs, but always at the cost of giving up some retained knowledge for a different, less frequently unobserved stimulus. The model then functions as a description of how a person behaves as they witness, decide between, and experience a series of stimuli. Long run adaptation occurs with the objective of eliminating as many short-term errors as possible and is based on information individuals receive as they make choices and experience stimuli.

The actual design of the model is conducted in several steps. First, it takes as an input some

stimulus $y \in [0,1]$. Then, $z = h(y) \in [0,1]$ denotes the "like" function, or rather the proportion of "like" neurons that fire in the brain. To capture the inconsistencies or randomness that occurs in choice, they add a noise function $\tilde{d}$. Then $\tilde{h}(y) = h(y) + \tilde{d}\delta$. This function maps $h : [0,1] \to \{0, \delta, 2\delta, 3\delta, ..., N\delta = 1\}$. $\tilde{d}$ is some integer $\in -D, ..., D$ where $\tilde{d} = 0$ with probability π_0, $\tilde{d} = \pm 1$ with probability π_1 and so forth. This creates a symmetrical noise function where $\pi_0 - \pi_1 > \pi_1 - \pi_2 > ... > \pi_{D-1} - \pi_D > \pi_D > 0$. The result of this "want" function is the step-function depicted in figure 1. The x-axis shows $h(y)$, and the y-axis shows $\tilde{h}(y)$. The noise function results in movements to the left or right where an observation will have a $\tilde{h}$ value different from its h value. If the noise would result in a stimulus appearing to be either less than 0 or greater than 1, then the noise is reset to 0.

The cutoff points for each step are then given a rank x_n, $n = 1, 2, ...N$ to denote the cutoff points, or end points for each step. Adaptation occurs as these cutoff points shift. The narrower the step, the less likely it is that an error occurs that involves the stimuli within that step. The cutoff points move based on the following function:

$$x_n^{t+1} = \begin{cases} x_n^t + \epsilon \text{ with probability } \xi & \text{if } h(y) + \tilde{d}\delta = n\delta \\ x_n^t - \epsilon \text{ with probability } \xi & \text{if } h(y) + \tilde{d}\delta = (n-1)\delta \\ x_n^t \text{ otherwise} & \end{cases} \tag{1}$$

Both ϵ and ξ are constant values that will affect the rate at which the utility curve adapts to observations. Effectively what this function states is that whenever a stimulus is observed, the step within which that stimulus falls (after noise is added) has the possibility of tightening by some small margin. As a person makes repeated choices, the steps with the most frequent observations will become very narrow, and the steps that are infrequently visited will widen. Since it is assumed that the frequency of past observation is a good indicator of future observations, this lowers the odds of an error occurring.

The hedonic treadmill effect also occurs as a result of this adaptive process. Since the height of the steps remains at a constant value of δ and the number of steps cannot change, the sections with the tightest steps, or the steepest curve, will gravitate towards a more central position on the Y-axis. This would explain how a person who initially experiences a significant change in their happiness level slowly returns to their average happiness level as the slower shifts in thresholds occur. These shifts explain how the way a person processes and thinks about different stimuli changes over time.

4. Experimental Design

4.1 Overview:

This paper documents the results of an economics lab experiment designed to test the manner in which people adapt as per the assumptions made in the Robson-Whitehead model. In an online lab environment accessible via web-browser, participants make choices in a repeated game with limited information. All subjects are provided with a guaranteed 5$ "show up fee" and are further compensated based on their decisions within the experiment. Earnings range from 9-21$, with an average of 15$[1]. Experimental sessions were conducted during the month of August of 2020 in an online format [2]. Subjects were recruited using ORSEE (Greiner 2015), the standard recruitment procedure used at Loyola Marymount University Economics Department's. Individuals learn about the system through various advertisements and, once registered with ORSEE, receive email-invitations to sign up for the individual experiments. Volunteer participants received an email in advance of the experiment containing a link to a Zoom conference call and to a weblink for a server hosted zTree client. Participants in the zoom call could see names of other participants in Zoom's participants tab, but could not unmute their microphones, chat universally, or turn on the video function. Experiment instructions were read to participants by the facilitator over Zoom and also given in writing in the zLeaf experimental program. Participants could also ask questions during the experiment by direct messaging the Zoom host. Informed consent and payment information were collected as the first stage in the zLeaf interface before the experiment began. People could choose between Venmo and a mailed check for payment[3].

After entering payment information and receiving instructions, participants are shown a series of 17 payoffs increasing in increments of 50 from 60-860. An experimental currency (ECU) is used with an exchange rate of 200 ECU/USD. Participants are then asked to rank each payoff from 1-4, with 1 being the least-preferred and 4 being the most-liked. Since there are 17 payoffs and only four categories, by necessity many payoffs must receive the same rankings. After all payoffs have been ranked, the experiment randomly selects two payoffs. All payoffs initially have equal probability of selection. Of the two payoffs randomly selected, the one the participant ranked more highly will be used for payment. If both selected payoffs have the same ranking, however, then one of the two will be selected at random for payment. Participants are shown which payoffs were selected and which one they received. They then return to the ranking page in which they may reassign rankings to the payoffs and the process repeats. A frequency table of which payoffs have been selected thus far by the computer is visible on their screen. Figures 1 and 2 below show the screens subjects see while making decisions.

[1]Funding comes from a Phi Beta Kappa research grant provided by the Loyola Marymount University chapter.
[2]Tests were run during the COVID-19 pandemic. Thus, all testing had to be done remotely.
[3]out of 67 subjects only four chose to be paid via a mailed physical check. The rest opted for Venmo

Figure 1: Example of a ranking screen in the experiment

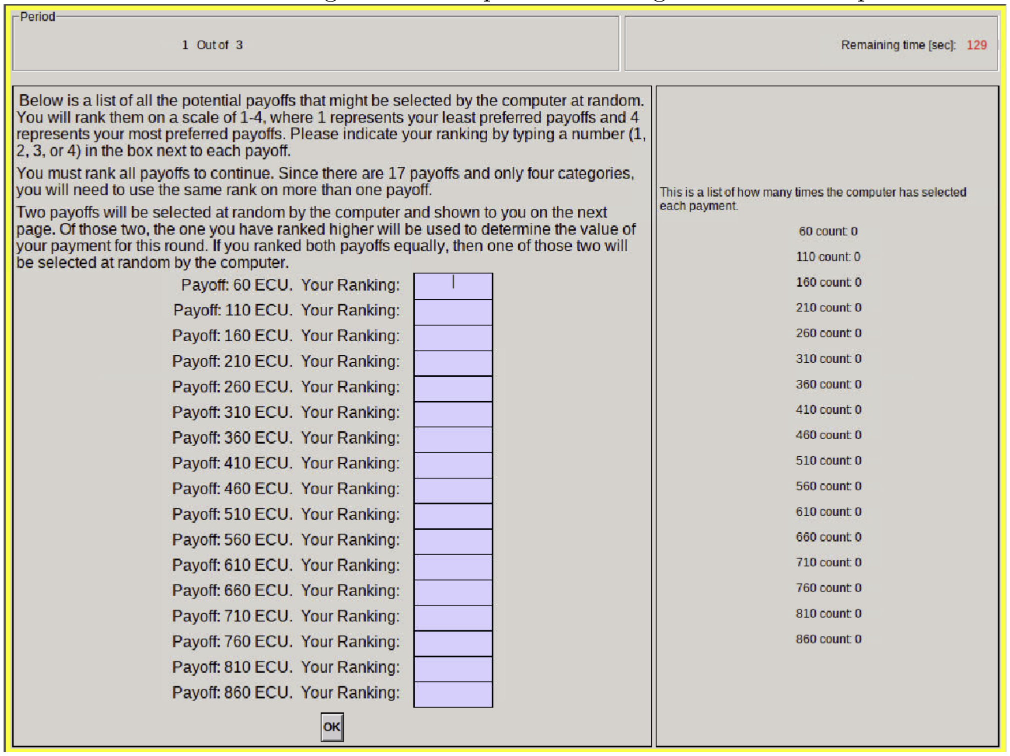
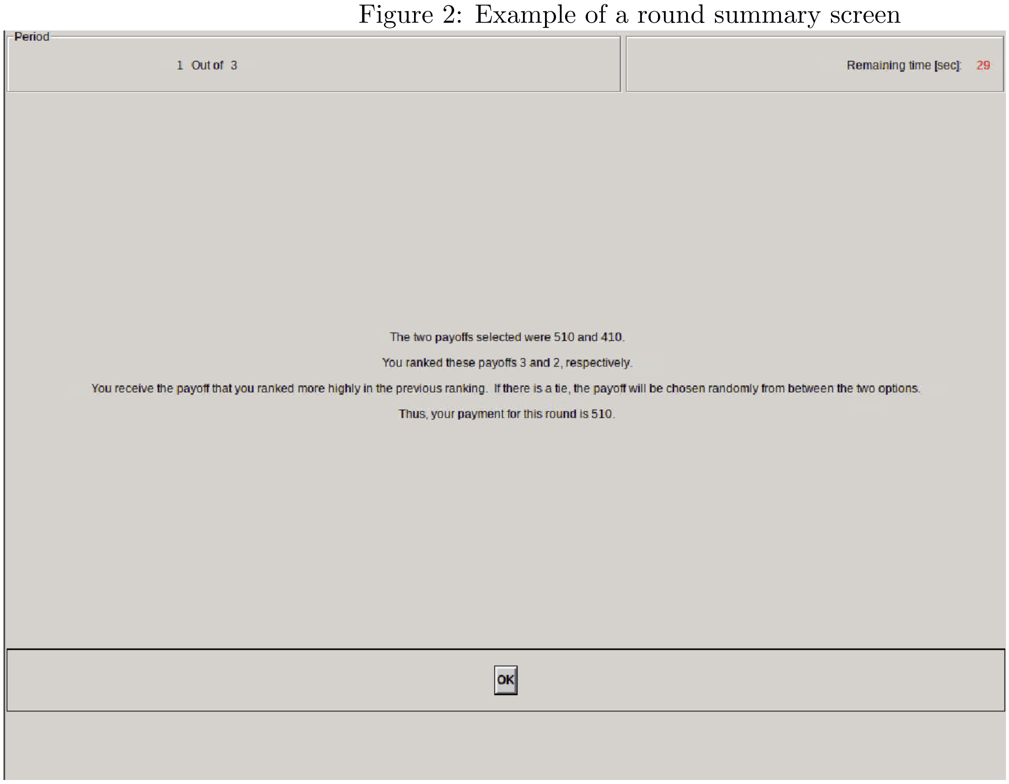
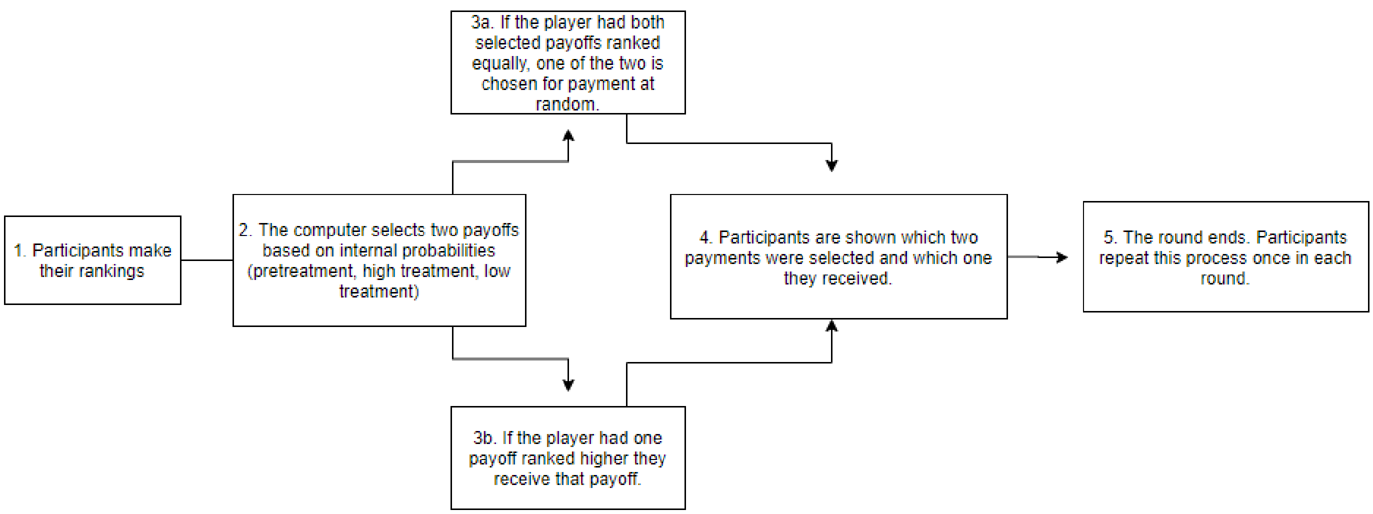


Figure 2: Example of a round summary screen



After 10 rounds of playing at these random probabilities, participants are asked to describe how they ranked the payoffs in the preceding rounds and why they chose those rankings. Participants are informed that the likelihood of which payoffs will get selected has changed such that it is no longer equal for all payoffs. The nature of this probability shift will depend on the treatment group of the subject. Subjects randomly assigned to the "low" treatment (treatmeant 0) group will face an increased probability that the lower valued payoffs will be selected. Subjects randomly assigned to the "high" treatment (treatment 1) will encounter more frequent selection of the higher valued payoffs. Subjects are not informed as to their assigned experimental treatment group nor the new probabilities they will experience. These shifts in probability simulate a significant life change for the worse or better, respectively; the majority of all choices and stimuli observed by an individual are different from the average stimulus witnessed previously. Participants play the game for an additional 25 rounds under the new conditions. At the end of all rounds, participants are asked again to describe their rankings and rationale for those rankings. After a short demographic survey, four rounds are randomly selected to be used for payment. The following flow chart describes the steps taken by each subject in each round.

Figure 3: Steps taken in each round



The main goal of this experiment is to observe patterns and trends with which people shift their rankings. The initial few rounds provide a baseline within which people learn the game and conform to any pre-existing preferences, such as aversions to specific ranges of payoffs. Subsequently, it can be observed how different conditions lead people to make changes in their rankings. The likelihood with which people change their rankings after a payoff is selected simulates the ξ value defined in the Robson-Whitehead model. We observe the likelihood with which people shift their rankings after each selection period, after

ties occur, and after specifically losing a tie.

4.2 Optimal play: Despite being unaware of the exact probabilities of selection, people may still optimize their play based on the information they witness. Within each round, two payoffs are selected. We will call the two payoffs i, j, where i, j refers to the ordinal value of the selected payoff with $i, j = 1$ referring to the lowest valued payoff, and $i \neq j$. Then P_i refers to the probability that payoff with ordinal value i is selected and P_j refers to the probability for payoff j. These probabilities are both given by the experiment and participants cannot affect them. The participants may, however, sort the payoffs into four categories, which we will call A, B, C, D, with A being the lowest and D being the highest. Then $|A| = X_A, |B| = X_B, |C| = X_C, |D| = X_D$. We can then write the total expected payoff of any strategy as:

$$E(x) = \sum_{i=1}^{17} \sum_{\substack{j=1 \\ j \neq i}}^{17} P_i P_j Y_{ijX_A X_B X_C}$$

This equation is the sum, for all pairs, of the probability of that pair being selected times the payoff that will be received based on the participant's rankings.

Participants maximize their expected payoff by trying, in general, to get higher Y values for pairs that have a heavier weight given by P_i, P_j. The only time it is possible to not receive the optimal payoff is when a tie occurs in the rankings, assuming all payoffs are ranked in an ordinally rational manner (i.e, no payoff receives a higher rankings than a higher valued payoff). Whenever this happens, there is a risk of receiving the lower of the two payments. Thus, the goal of the participants is to minimize both the probability and magnitude of errors occurring. With the pretreatment probabilities, the optimal strategy would be $X_A = X_B = X_C = X_D$, but since 17 cannot subdivide evenly by 4, one category arbitrarily receives an additional payoff. The optimal strategy with the high treatment probabilities is $X_A = 10, X_B = 3, X_C = 2, X_D = 2$, though it should be noted that participants are not explicity told the probabilities and thus cannot calculate this strategy. In the low treatment, the probabilities are inverted such that P_i in the high treatment equals P_{18-i} in the low treatment. The values of the payments remain unchanged. The optimal strategy depends on the probability of a tie occurring and the relative distance between the values of the different payoffs. Since the marginal change in value between payoffs is constant between all payoffs and the probability distribution in the low treatment is simply an inversion of that of the high treatment, the optimal strategy in the low treatment is the inverse of the high treatments': $X_A = 2, X_B = 2, X_C = 3, X_D = 10$.

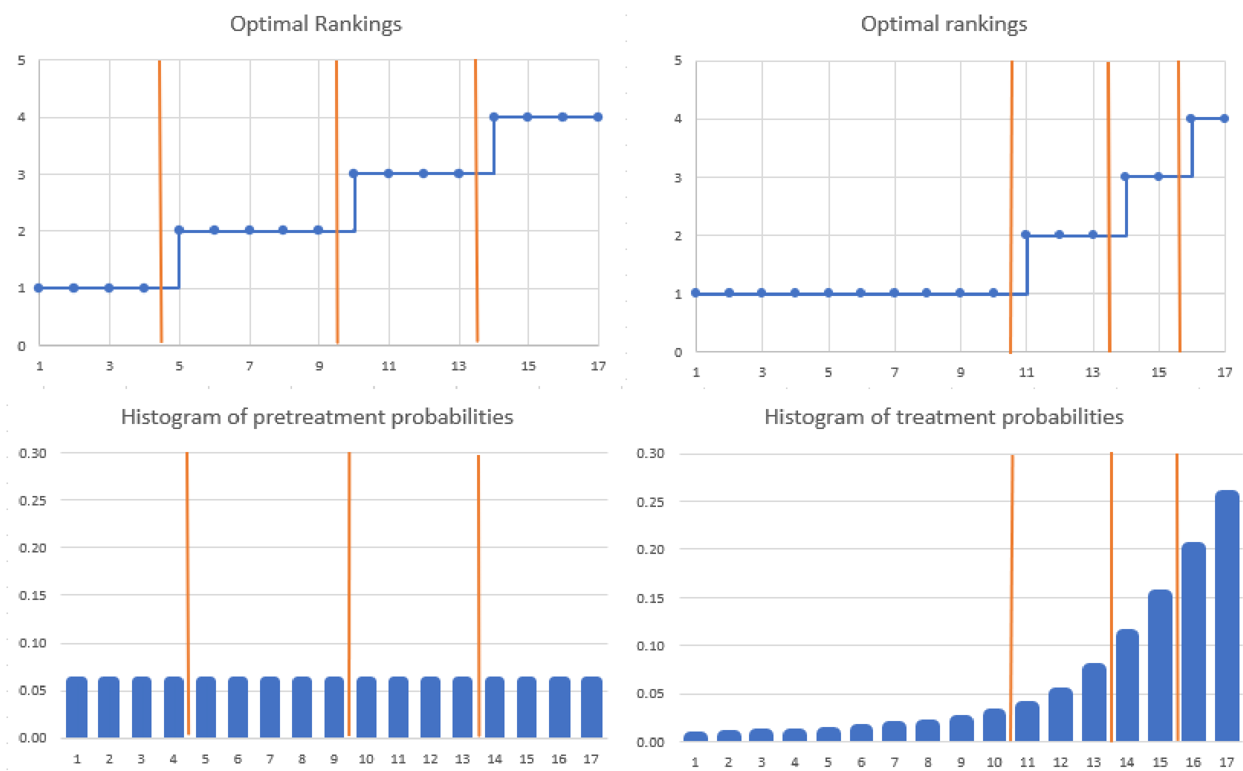
Table 1 compares the expected payoffs and probability of a tie occurring for different strategies a player might employ. Figure 4 shows the step utility function in both of these equilibria for the high

treatment. The graphs in figure 4 provide an example of what utility curve and distribution of payoffs look like in pretreatment and high treatment conditions.

Table 1: Expected value and tie probability in the high treatment

	Pretreatment, even-split strategy	Posttreatment, even-split strategy	Posttreatment, clustering in A
Expected Value	600.8 ECU	776.3 ECU	798.9 ECU
Probability of a tie	.206	.495	.201

Figure 4: Optimal play before and after treatment in the high treatment group



This optimal strategy can be found by considering the probability each pair of payoffs have of being selected multiplied against the outcome of what would happen if those payoffs were to be selected. Participants can arrange their rankings to minimize the probability of ties occurring and, subsequently, them receiving the lower of the two payoffs. It is important to note that players are highly unlikely to jump directly to a radically different new strategy, however. Instead, they are much more likely to slowly adjust the cutoff points similar to the shifts of x_n over time in the Robson-Whitehead model. If this is the case, then each shift must be considered as its own individual change in strategy. Players must be significantly motivated enough to continue to make small shifts until they reach an equilibrium

Let G_g be the utility gained by moving a payoff down from bin $g+1$, and let F_g be the utility gained by moving a payoff up from category g, where $g \in \{1,2,3\}$]. a_n refers to the nth payoff in bin A, and a, b, c are constants equal to the difference between two adjacent payoffs where $a = b = c$. The following

proof shows that at least one of the following G and F values must be positive in order for a shift in rankings to be beneficial to the player:

$$G_1 = aP_{b_1}[\textstyle\sum_{h=1}^{X_A} P_{a_h}(X_A + 1 - h)(-\frac{1}{2}) + \sum_{i=1}^{X_B} P_{b_i}(\frac{1}{2}(i-1))]$$

$$G_2 = bP_{c_1}[\textstyle\sum_{i=1}^{X_B} P_{b_i}(X_B + 1 - i)(-\frac{1}{2}) + \sum_{j=1}^{X_C} P_{c_j}(\frac{1}{2}(j-1))]$$

$$G_3 = cP_{d_1}[\textstyle\sum_{j=1}^{X_C} P_{c_j}(X_C + 1 - j)(-\frac{1}{2}) + \sum_{k=1}^{X_D} P_{d_k}(\frac{1}{2}(k-1))]$$

$$F_1 = aP_{a_X a}[\textstyle\sum_{h=1}^{X_A} P_{a_h}(X_A - h)(\frac{1}{2}) + \sum_{i=1}^{X_B} P_{b_i}(\frac{-1}{2}i)]$$

$$F_2 = bP_{b_X b}[\textstyle\sum_{i=1}^{X_B} P_{b_i}(X_B - i)(\frac{1}{2}) + \sum_{j=1}^{X_C} P_{c_j}(\frac{-1}{2}j)]$$

$$F_3 = cP_{c_X c}[\textstyle\sum_{j=1}^{X_C} P_{c_j}(X_C - j)(\frac{1}{2}) + \sum_{k=1}^{X_D} P_{d_k}(\frac{-1}{2}k)]$$

G_1 is the difference in utility that occurs from moving the lowest payoff in bin B into bin A. G_2 is the difference in utility that occurs from moving the lowest payoff in bin C into bin B. G_2 is the difference in utility that occurs from moving the lowest payoff in bin D into bin C.

F_1 is the difference in utility that occurs from moving the highest payoff in bin A into bin B. F_2 is the difference in utility that occurs from moving the highest payoff in bin B into bin C. F_3 is the difference in utility that occurs from moving the highest payoff in bin C into bin D.

An optimal strategy occurs when all of these G and F values are negative or equal to zero.

Proof:

Let $|A| = X_A$ and $|B| = X_B$, and let a_{x_a} be the highest gamble initially in bin A and b_1 be the lowest initially in bin B. Let P_{a_1} be the probability of gamble a_1 being chosen, and P_{b_1} be the probability of gamble b_1 being chosen.

We will show that the decision for moving a gamble is defined by the likelihood of that payoff being chosen and the number of other payoffs in that bin and adjacent bins.

Moving a payoff into a higher bin increases the odds of that payoff being selected, and the opposite is also true. The effect of switching the ranking of two payoffs relative to their value is to increase the probability of the lower gamble being chosen, which is never advantageous. Thus the ordinal ranking should always follow the values of payoffs.

Since payoffs should not be switched in order, for a payoff to be moved into a different bin it must be one of the cutoff values, otherwise it would result in a reversed ordering. For example, if gamble b_2 is

moved in to bin A then it would be ranked lower than gamble b_1, which is not advantageous. Thus, b_2 cannot move unless b_1 is moved first. We therefore only must check edge values between bins to determine if any gambles should be moved.

The overall payoff is determined as a series of weighted probabilities. For each pair of payoffs we multiple the probability of that pair being selected with the expected payoff for that pair. When shifting a payoff from one bin to another, the probability of that payoff being selected does not change. All that changes is the expected payoff that will occur if that pair is selected. Any pairs that do not include that payoff will not change in any way. When comparing strategies we must only do so for affected pairs; we compare only the pairs that include both the moved payoff and a payoff in either that original bin or the receiving bin for the moved payoff.

In an equilibrium state it must be not optimal to change the ranking for any payoff, i.e to shift any cutoff up or down. Since there are four bins, and therefore three cutoff points, and it must be checked in both directions, each equilibrium must therefore satisfy six conditions. Since the total payoff is calculated via the weighted probabilities of the payoffs given by any possible pair being chosen and the ranking's have no effect on probabilities, the only payoffs that change with a new ranking are those given by pairs in which one member has changed categories. This combined with the above statements let us develop the following payoff scheme differences:

Let G be the utility gained by moving d_1 into bin C. Equation 4 shows the different parts of this calculation:

$$4.1\text{: } G = [\frac{1}{2}P_{d_1}(P_{c_1}(c_1 + d_1) + P_{c_2}(c_2 + d_1) + ... + Pc_{X_C-1}(c_{X_C-1} + d_1) + P_{X_C}(X_{X_C} + d_1))]$$

$$4.2\text{: } +[P_{d_1}(P_{d_2}d_2 + ...P_{d_{X_D-1}}d_{X_D-1} + P_{d_{X_D}}d_{X_D})]$$

$$4.3\text{: } -[P_{d_1}d_1(P_{c_1} + Pc_2... + P_{c_{X_C-1}} + P_{c_{X_C}})]$$

$$4.4\text{: } -[\frac{1}{2}P_{d_1}(P_{d_2}(d_2 + d_1) + ... + P_{d_{X_D-1}}(X_{Dm-1} + d_1) + P_{d_{X_D}}(d_{X_D} + d_1))]$$

4.1 and 4.2 are the payoffs received by moving d_1 while 4.3 and 4.4 are the payoffs recieived by leaving d_1 in D.

4.1 is the sum of the expected payoffs given by d_1 and a payoff in C. It is the sum of the probability of each pair occurring multiplied by the average payoff given if that pair is selected.

4.2 is the sum of the pairs combining d_1 with a payoff in D. Each term is the probability of the pair being selected times the payoff they receive if this pair is selected.

4.3 is the comparison of d_1 with payoffs in C once more, but now for the strategy of leaving d_1 in D.

4.4 is the sum of d_1 and payoffs in D if d_1 is left in D.

If $G > 0$, then it as advantageous to put y_1 in the lower category, and if $G < 0$ it is advantageous to leave it in the higher category. Next, since the payoffs' values are evenly spaced such that $c_2 = 2c$, $c_3 = 3c$ and so forth, we can substitute these values to get all c and d values in terms of c.

Then, by substitution:

$$G = [\frac{1}{2}P_{d_1}(P_{c_1}c(X_C+2) + P_{c_2}c(X+C+3) + ... + P_{c_{X_C-1}}c(2X_C) + P_{c_{X_C}}(2X_C+1))]$$

$$+[P_{d_1}(P_{d_2}c(X_C+2) + ...P_{d_{X_D-1}}c(X_C+X_D-1) + P_{d_{X_D}}c(X_C+X_D))]$$

$$\text{-}\ [P_{d_1}c(X_C+1)(P_{c_1} + P_{c_2}... + P_{c_{X_C-1}} + P_{c_{X_C}})]$$

$$-[\frac{1}{2}P_{d_1}(P_{c_2}c(2X_C+3) + ... + P_{d_{X_D-1}}c(2X_C+X_D) + P_{d_{X_D}}c(2X_C+X_D+1))]$$

From here we can collect like terms and find the following equation:

G=

$$cP_{d_1}[P_{c_1}(\frac{n}{2}-n) + P_{c_2}(\frac{n}{2}-\frac{1}{2}-n) + ... + (-1)P_{c_{n-1}} + (-\frac{1}{2})P_{c_n} + \frac{1}{2}P_{d_2} + ... + P_{d_{m-1}}(\frac{m}{2}) + Py_m(-\frac{m}{2}+\frac{1}{2})]$$

This can be rewritten as G=$cP_{d_1}[\sum_{j=1}^{n} P_{c_j}(n+1-j)(\frac{-1}{2}) + \sum_{k=1}^{m} P_{d_k}(\frac{1}{2}(k-1))]$

The equation we derived above is what we can use to determine the six conditions needed to establish an equilibrium. First, we must create a slightly adjusted equation for moving a payoff up in ranking as opposed to down, which we will call F.

$$F = cP_{c_n}[\sum_{j=1}^{n} P_{c_j}(n-j)(\frac{1}{2}) + \sum_{k=1}^{m} P_{d_k}(\frac{-1}{2}k)]$$

This equation is derived the same way as G, except in this case c_{X_C} is the payoff that is shifting. Recall that c_{X_C} is the highest payoff in C, and that d_1 is the lowest payoff in bin D. Once again, if F is positive then c_{X_C} should be moved, whereas if it is negative then c_{X_C} should remain in C. This gives us our six equilibrium conditions, all of which should be less than or equal to 0 in an equilibrium. When we substitute in the probabilities used in this experiment for the values of P, we find the following optimal strategies. In each strategy payoffs are ranked such that no payoff receives a higher ranking than any higher payoff. The number of payoffs that must receive each ranking under each set of conditions are listed below with the format $[X_A, X_B, X_C, X_D]$:

Pre-treatment: [4-4-4-5], [4-4-5-4], [4-5-4-4], [5-4-4-4]

Post-treatment(high): [10-3-2-2]

Post-treatment(low): [2-2-3-10]

4.3 Hypotheses

Despite the presence of optimal strategies, it is unlikely for people to perfectly play these strategies, especially in later rounds where they lack knowledge of the exact probability distribution. The hypotheses are as follows:

1. Participants should gravitate to a roughly even split of payoffs in the pre-treatment rounds, with some occasional minor changes due to learning processes.

2. If people are responsive to entering the treatment phase, then they will shift their payoffs within the first five rounds of treatment conditions such that the most frequently selected payoffs have fewer other payoffs with the same rank.

3. If subjects respond more to ties than to information (observation of which payoffs have been selected with greater frequency), then they shift payoffs with greater frequency immediately after ties occur.

Data from this experiment reveal that in general participant behavior aligns with hypothesis 1, with a small deviation where people put slightly too many payoffs in the highest bin while shrinking the lowest bin in order to avoid receiving the lowest payoffs. Per hypothesis 2, almost all subjects began shifting rankings within the first three rounds post-treatment, but were significantly more likely to make changes after losing a round than when they continue to win rounds. Hypothesis 3 is not supported by the data as all regression models indicate that witnessing ties in rankings has a smaller, less significant effect on participant behavior than does losing a round or simple progression through the game.

5. Results

Data were analyzed using STATA. Analytic techniques included descriptive measures (means, range, etc), probit regressions, and fixed effects time analyses clustered across bundles of similar rounds. Variables of interest include the frequency and probability of changes to rankings, expected utility, tied rankings, losing a round, treatment group, player type, gender, college/major, and ethnicity. See appendix for log and .do files. New variables for “anychange”, “changesmade”, ”type2”, “tie”, and “roundlost” are generated. “anychange” evaluates to 1 in a round if at least one payoff holds a different ranking than it did in the previous round, and “changesmande” counts the total number of differences between the current and the previous round. “type2” divides players based on observed differences in their ranking methods after

data was collected and will be discussed more thoroughly later in this section.. "tie" is equal to 1 for a player in a round if the two payoffs selected in the previous round held the same ranking. "roundlost" equals 1 when the player received the lower of the two selected payoffs in the round previous.

Demographic information was gathered in a survey at the end of the experiment. Questions included gender, college/major, ethnicity, as well as a series of questions about their character, including perfectionism, life satisfaction, risk-taking, detail-orientation, preferential towards guaranteed sums than gambles, and desiring of a major life change were also evaluated. 95% of students came from Loyola Marymount University, which has its programs divided into six schools: liberal arts, communication and fine arts, business and administration, film and television, education, and science and engineering. Dummies for each of these schools were created and tested for significance in the models, omitting the school of film and television. An additional dummy is used to isolate math-based majors[4]. For the demographic questions were asked how well each trait described them and responded on an agreement scale that ranges from 1-4[5].

Of the ninety-two individuals who participated, sixty-seven showed up on time for the online experiment and sixty-five completed all stages of the experiment. Of the two subjects who did not complete the experiments and were thus omitted from some analyses, one disconnected within the first five minutes, and the other disconnected after the main stages of the experiment were completed but before the demographic survey.

Average duration for this experiment was forty-two minutes, with the longest session lasting fifty-three minutes and the shortest lasting thirty-four minutes. The number of subjects per session ranged from three to nine, with an average of six. The average earnings were $15, with a range of $9-21.2; earnings were, unsurprisingly, strongly correlated with the treatment group such that subjects randomly assigned to the "high" treatment group earned an average of $18.4 while those randomly assigned to the "low" treatment group earned an average of $12.1[6].

Age of participants ranged from 18 to 55, with 93 percent of subjects falling between 18 and 23 years of age. Fifty-seven percent of subjects were female. 7.8 percent of study participants self-identified as black, 25 percent Asian, 43 percent Caucasian, 14 percent Hispanic, 1.5 percent native American, and 7.8 percent "other". Compared to the general LMU student body, these demographics contain slightly more Asian students and slightly fewer Hispanic students. Subjects came from different academic backgrounds, with the largest portion (30 percent) coming from the school of business.

[4]Economics, applied/theoretical mathematics, business, physics, and engineering students are included in this group

[5]1=strongly disagree, 2=slightly disagree, 3=slightly agree, 4=strongly agree

[6]Participants who ended the experiment with less than $8 total earnings would be credited so their earnings would total $8, but all subjects already made more than this amount in the experiment.

The different demographic variables are analyzed for significance in the models and their relationship to other variables. The correlation table below[7] (3) shows the correlations between ethnicity and the primary variables of interest in the regression models. Though the coefficients might suggest that Asian or native American participants are less likely to be Type 2 players and Hispanic subjects are more likely to be Type 2 players, the small sample size represented in each of these categories makes it hard to draw any meaningful conclusions. Slightly more Asian and black participants are female. Additionally white participants make changes to their strategy less often and black students slightly more often, but both these coefficients are relatively small in scale. Additionally, Fischer exact tests failed to find significant relationships between these player-type, sex, college, or subjects' responses to questions on character. Ethnic and racial identities were not found to be significant in any of the regression models. These variables are thus omitted from later regressions in this paper due to small effects on R^2, low statistical significance, or minimal effects on other coefficients in the model. A regression table containing these models can be found in the appendix.

Table 2: Correlation table for racial identities

	anychange	female	type2	white	asian	black	hispanic	natamerican
anychange	1							
female	0.179***	1						
type2	0.161***	0.439***	1					
white	-0.0673**	-0.0120	-0.00307	1				
asian	0.0282	0.201***	-0.0893***	-0.497***	1			
black	0.0645**	0.131***	0.0475*	-0.251***	-0.165***	1		
hispanic	0.0187	-0.201***	0.104***	-0.349***	-0.229***	-0.116***	1	
natamerican	-0.0467*	-0.147***	-0.0864***	-0.109***	-0.0714***	-0.0361	-0.0501*	1
raceother	0.0113	-0.105***	0.00699	-0.277***	-0.182***	-0.0921***	-0.128***	-0.0399

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The data collected regarding the participant's college or field of study is analyzed by college for significant relationships with variables of interest. The table below (Table 4) shows the correlations between education and major model variables. Math majors are not individually found to have a strong relationship with the major variables of interest – namely "anychange" or Player type. Liberal arts majors are less likely to be in Type 2 and are slightly more likely to change their strategy in a given round. Liberal arts and School of Education are the only colleges whose effects are statistically significant on the regression models with the primary variables of interest. Note, however, that pseudo r^2 remains unchanged and these colleges had minimal effect on other coefficients. Most of the changes in other coefficients can be explained by the correlations between these colleges and both gender and Playtype. These models are available in the appendix.

[7] A full correlation table with all variables included in this study is available in the appendix. Smaller tables were used in the main paper for easier readability

Table 3: Correlation table for colleges and variables of interest

	anychange	female	type2	math	BCLA	SOE	CBA	CSE	CFA
anychange	1								
female	0.179***	1							
type2	0.161***	0.439***	1						
math	0.0302	0.0316	-0.0223	1					
BCLA	0.106***	-0.0855***	-0.236***	-0.0208	1				
SOE	0.0196	-0.147***	-0.0864***	-0.123***	-0.0925***	1			
CBA	0.0261	0.219***	0.0620**	0.726***	-0.257***	-0.0894***	1		
CSE	-0.0659**	-0.242***	-0.0210	0.00656	-0.226***	-0.0533*	-0.215***	1	
CFA	-0.0486*	0.166***	0.00699	-0.208***	-0.125***	-0.0399	-0.116***	-0.136***	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The following correlation table shows the relationship between the questions on participants character and other major variables of interest in the analytic model. None of these variables were statistically significant in the full regression models. Changes witnessed in other coefficients could be explained by the relationship held between these variables and gender, player type, or treatment. With a larger sample size these variables likely could have shown to have a greater effect. The regression models that include these variables can be found in the appendix.

Table 4: Correlation table for self-described characteristics

	anychange	female	type2	Wantchange	Perfectionist	Minval	Detailorient
anychange	1						
female	0.179***	1					
type2	0.161***	0.439***	1				
Wantchange	0.0874***	0.0458*	-0.000000188	1			
Perfectionist	0.109***	0.376***	-0.147***	0.269***	1		
Minval	0.128***	0.175***	0.0630**	0.299***	0.235***	1	
Detailorient	0.125***	0.305***	-0.00533	0.343***	0.534***	0.280***	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Three different patterns in participants' styles of play were identified. Type 1 players seemed to identify a general strategy that they adhered to closely within the first few rounds of the experiment. They are defined as individuals with an incorrect ordinal ranking in no more than three rounds. This group was characterized by actions such as maintaining an ordinally rational ranking (i.e., never ranking a lower payoff with a higher value than any higher payoff) and making fewer changes to their rankings on average per round than the other two groups; 35 people fall into this group. Type 2 players take a more "trial and error" approach when assigning rankings. They tend to change their rankings much more readily and sometimes, possibly as part of a trial and error process, make rank payoffs in an irrational manner (ranking at least one low payoff with a higher value than some higher payoffs). Type 3 players are defined as continuing to have key payoffs (the highest two in treatment 1, and the lowest two in treatment 0)

incorrectly ranked by the last three rounds without adaptation to their losses, or by making an average of 12 changes or more to their strategy per round over the course of the entire game. The third group comprised individuals that both often chose irrational rankings and did not adapt to occurrences in previous rounds. Participants in this latter group likely failed to understand some element of the game or were not motivated to maximize earnings. For this reason, group 3 was removed from all analyses; six subjects were in this third group type. These six were uncorrelated with ethnicity or major/education. Women were evenly distributed across type 1 and type 2, but men are much more likely to fall into type 1, with only two men in type 2. A Fischer exact test confirms the statistic significance of this distribution (p=.002). Table 6 (below) shows the number of rounds in which each player type behave irrationally.

Tables 9-11 (below) describe subject behavior over the course of the game and include the median rankings and the mean expected utility in each round[8]. The optimal strategy in the pretreatment round involves grouping payoffs evenly in each bin; for example, making the bin sizes 4-4-4-5 is optimal. During treatment, the optimal strategy changes such that the highest expected utility occurs with a ranking of 2-2-3-10 and 10-3-2-2 for the Low and High treatment groups, respectively. The horizontal divisions within each table indicates the optimal cutoff points for the rankings, and the colored areas indicate which payoffs are given which rankings on average by the participants. The maximum possible expected utility and the average expected utility of participants are both shown at the top. The red areas show payoffs that players assign the rank 4 on average, yellow shows the areas assigned rank 3 on average, green the rank 2 on average, and blue rank 1 on average. In optimal play it would be expected that the colored areas eventually line up with the horizontal divisions by the end of the game.

Type 1 players play close to theory, reaching the optimal strategy in the pretreatment rounds in one treatment group, and nearly reaching optimality in the other treatment group. In both treatments Type 1 players show some aversion to the lowest payoffs, giving fewer payoffs rankings of 1 and more payoffs rankings of 3 or 4. They rarely over-adapt in the treatment rounds; in only a few rounds do they reverse a shift they made in a previous round. By the end of the game they correctly rank the four most chosen payoffs but have not sufficiently fine-tuned their rankings after this point. The payoffs they correctly rank typically include the most commonly selected payoffs under treatment conditions. The greater selection rate of these payoffs means that they have a larger impact on the expected utility of the strategy than other less-chosen payoffs. As a result, Type 1 players still manage to capture most of the potential expected utility, missing, in total, only 6 ECU in the low treatment and 10 ECU in the high treatment compared to the optimal expected utility.

[8]A similar table that displays mean rankings can be found in the appendix. Median rankings are used for easier readability and elimination of noise caused by outliers in various rounds.

Table 5: Irrational round frequency table for type 1 players pretreatement

	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10
0	35	36	36	38	38	38	38	38	38	38
1	3	2	2	0	0	0	0	0	0	0

Table 6: Irrational round frequency table for type 1 players in treatment

	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10	c11	c12	c13	c14	c15	c16	c17	c18	c19	c20	c21	c22	c23	c24	c25
0	38	38	35	36	37	38	38	37	37	38	38	38	37	38	38	38	38	38	38	38	38	38	38	38	38
1	0	0	3	2	1	0	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0

Table 7: Irrational round frequency table for type 2 players pretreatment

	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10
0	11	12	12	10	11	11	12	12	12	14
1	10	9	9	11	10	10	9	9	9	7

Table 8: Irrational round frequency table for type 2 players in treatment

	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10	c11	c12	c13	c14	c15	c16	c17	c18	c19	c20	c21	c22	c23	c24	c25
0	14	15	14	11	11	11	9	6	8	8	7	7	6	7	6	5	5	5	4	4	4	4	4	4	4
1	7	6	7	10	10	10	12	15	13	13	14	14	15	14	15	16	16	16	17	17	17	17	17	17	17

Table 9: Average rankings in the high treatment for type 1 players

High treatment -- Type 1 median rankings n=19																																			
#	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35
MEU	601	601	601	601	601	601	601	601	601	601	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799
EU	572	588	589	594	593	595	597	597	597	597	774	775	776	777	780	780	780	779	780	782	783	783	786	786	786	786	786	787	787	788	788	788	788	788	789
MEU-EU	29	13	12	7	8	6	4	4	4	4	25	24	23	22	19	19	19	20	19	17	16	16	13	13	13	13	13	12	12	11	11	11	11	11	10
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
4	2	2	2	1	1	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
5	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
6	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
7	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
8	3	3	3	3	3	3	3	3	3	3	3	3	3	3	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
9	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	2	2	2	2	2	2	2	2	2	2	2	2	2
10	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
11	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
12	3	4	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
13	4	4	4	4	4	4	4	4	4	4	4	4	4	4	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
14	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
15	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	3	4	4	4	3	3	3
16	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
17	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4

Table 10: Average rankings in the high treatment for type 2 players

Low trea High treatment -- type 2 median rankings n=9																																			
#	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35
MEU	601	601	601	601	601	601	601	601	601	601	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799
EU	475	543	524	504	535	518	502	521	530	540	734	732	737	736	744	738	739	742	753	754	754	756	755	757	760	764	764	768	768	768	768	767	769	769	768
MEU-EU	126	58	77	97	66	83	99	80	71	61	65	67	62	63	55	61	60	57	46	45	45	43	44	42	39	35	35	31	31	31	31	32	30	30	31
1	1	1	1	2	1	2	2	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1
2	3	2	2	2	1	2	3	2	2	2	2	2	2	2	2	3	3	2	2	2	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1
3	2	2	3	3	1	2	3	2	2	2	3	3	3	3	3	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
4	3	2	3	4	3	3	3	3	3	3	3	3	3	3	3	2	2	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
5	3	3	3	3	3	3	3	2	2	2	2	2	2	2	2	3	3	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
6	3	2	2	3	2	2	3	3	3	3	2	2	2	2	2	3	3	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
7	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
8	3	4	4	4	4	3	3	4	3	3	3	4	3	3	3	3	3	2	2	2	2	3	3	3	3	3	3	3	3	3	3	3	2	2	2
9	3	3	3	3	3	4	4	3	4	4	4	4	4	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
10	3	3	3	3	3	3	3	3	3	3	4	4	4	4	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
11	3	3	4	3	3	3	3	3	3	4	4	4	4	4	4	4	4	4	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
12	3	3	4	4	4	3	3	4	4	4	4	4	4	4	4	4	3	4	3	3	3	3	4	4	3	3	3	3	3	3	3	3	3	3	3
13	3	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	3	3	3	3	3	3	3	3	3	3	3
14	3	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	3	3	3	3	3	3	3	3	3	4
15	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
16	4	4	4	4	4	4	3	4	4	4	4	4	4	4	4	4	4	4	4	4	4	3	3	3	3	3	4	4	4	4	4	4	4	4	4
17	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4

Table 11: Average rankings in the low treatment for type 1 players

Low treatment -- Type 1 median rankings											n=19																								
#	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35
MEU	601	601	601	601	601	601	601	601	601	601	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296
EU	577	587	589	590	590	591	597	598	598	598	283	284	283	286	287	289	289	289	290	290	289	289	291	291	291	291	291	291	291	291	291	290	290	290	290
MEU-EU	24	14	12	11	11	10	4	3	3	3	13	12	13	10	9	7	7	7	6	6	7	7	5	5	5	5	5	5	5	5	5	6	6	6	6
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
4	2	2	2	2	2	2	2	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
5	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
6	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
7	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
8	3	3	3	3	3	3	3	3	2	2	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
9	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
10	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
11	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
12	4	4	4	4	4	4	4	3	3	3	3	3	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
13	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
14	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
15	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
16	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
17	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4

Table 12: Average rankings in the low treatment for type 2 players

Low treatment -- Type 2 median rankings											n=12																								
#	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35
MEU	601	601	601	601	601	601	601	601	601	601	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296
EU	582	575	551	546	552	556	555	565	566	574	268	270	277	276	280	279	272	278	280	280	281	274	271	280	283	276	278	282	282	282	282	281	280	281	281
MEU-EU	19	26	50	55	49	45	46	36	35	27	28	26	19	20	16	17	24	18	16	16	15	22	25	16	13	20	18	14	14	14	14	15	16	15	15
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1.5	1.5	1	1	1	1	1	1	1	1	1	1	1	1	1.5	2	1.5	2	1	1.5	1.5	1	1	1	1	1	1	1	1	1	1	1	1
3	1	1	2	1.5	1	1	1	1	1	1	1	1	1	1	1.5	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
4	1	1.5	2	2.5	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2.5	2.5	2.5	2.5	2.5	2	2	2.5	2.5	2.5
5	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
6	2	2	2	2	2	2	2	2	2	2	2	2.5	2.5	2.5	3	3	3	3	3	3	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5
7	2	2	2.5	2.5	2.5	3	3	2.5	3	3	3	2.5	2.5	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
8	2	2	2.5	2	2	2.5	3	2	2.5	2.5	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
9	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
10	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3.5	3.5	3.5	3	3.5	3.5	3.5	3	3	3	3.5	3.5
11	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3.5	3.5	3.5	3.5	4	4	4	3.5	3.5	3.5	3.5	3.5
12	3	3	3	3	3	3	3	3	3	3	3	3	3	3.5	3	3	3.5	3.5	3	3	3	3	3	3.5	3.5	3.5	3.5	4	3.5	3.5	3.5	3.5	3.5	3.5	3.5
13	4	3.5	3	3	3	3	3.5	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
14	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
15	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
16	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
17	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4

The higher variation in the strategies of type 2 players can be seen in the overlapping spreads of values and preponderance of irrational rankings. Type 2 players require a longer learning period, for both high and low treatment groups, than type 1 players. In the High treatment, most type 2 players begin to create close to optimal rankings only after nearly 20 rounds and many continue to submit irrational rankings through the final rounds. Nevertheless, these players still exhibit many of the same trends witnessed in type 1 players. They initially prefer putting fewer payoffs in the lowest bins and instead opt to widen the upper bins. In the treatment rounds, they adapt more quickly than type 1 players to changes in probability, and, in several cases, over adapt, as can be seen in rounds 17-23 of the low treatment where they experiment with giving only one payoff the lowest ranking. Though they exhibit many fluctuations and irrationalities, they begin to learn and adjust rankings in areas where they witness frequent selections; the regions of the table that contain frequently selected payoffs begin to resemble optimality before the ranking areas that are infrequently selected. In the Low treatment they visually appear to arrive at a set of rankings closer to optimality than that reached by type 1, but the presence of several irrational rankings drags down their average expected utility. In total, they manage to capture all but 15 of the optimal ECU in the Low treatment and all but 31 ECU in the High treatment by the end of the game.

Tables 13 and 14 below shows the average number of changes in strategy exhibited by type 1 and type 2 players in each round. For both groups, the first three rounds display a greater amount of variance as people learn the rules of the game. In the open-ended question asked after the first ten rounds, several subjects identify some confusion with the ranking system that they held for the first two rounds. For this reason, the first three rounds are removed from regressions and analyses due to potential learning effects. There are observable trends in how type 1 and type 2 players change their rankings, and a t-test reveals a statistically significant difference in the two groups' average number of rank changes clustered in rounds 3-10, 11-24, and 25-35. Type 1 players adhere to their strategies much more consistently and show less variance of rankings across all 35 rounds. In 81% of all rounds type 1 players make no changes to their strategies with an average of .85 (t=11.83) changes and a standard deviation of 2.7 (p¡.001). Type 2 players are much more responsive and make more changes on average per round. In 66% of rounds type 2 players make no change, with an average of 1.31 (t=11.7) and standard deviation of 2.9. In both cases the rate at which players make changes to their strategies diminishes over the course of the game.

Table 13: Pretreatment average number of ranking changes

	rankingchanges_pretreat								
	r2	r3	r4	r5	r6	r7	r8	r9	r10
Type1_mean	2.7	.84	.97	.21	.68	.58	.45	.29	.16
Type1_sd	4.7	1.4	2.1	1.1	2.5	1.7	1.4	.69	.44
Type2_mean	5.4	3.9	3.3	3.1	3.1	1.8	2.6	1.8	1.2
Type2_sd	5.4	4	3.9	4	4.9	3	4.3	3.8	2.2

Table 14: Posttreatment average number of ranking changes

	r11	r12	r13	r14	r15	r16	r17	r18	r19	r20	r21	r22	r23	r24	r25	r26	r27	r28	r29	r30	r31	r32	r33	r34	r35
Type1_mean	.32	.18	.74	.61	.89	.5	.13	.24	.37	.34	.34	.079	.66	.26	.13	.13	.16	.13	.13	.29	.18	.13	.55	.053	.11
Type1_sd	1.1	.56	1.6	1.3	1.8	1.5	.34	.54	1.3	.88	1.5	.36	2.4	1	.47	.66	.97	.53	.47	1.3	.56	.81	1.4	.32	.65
Type2_mean	2	1.4	2	1.8	2.4	1.1	1.4	1.3	1.3	1	1.3	1.2	.48	1.2	.71	.76	.57	.48	1	.095	.48	.33	.43	.19	.095
Type2_sd	4	3.8	4.1	3.8	4.2	3.2	2.3	2.6	2.9	2.8	3	2.4	.87	2.4	1.2	1.2	1.1	1.6	2	.3	1.5	.8	.98	.51	.44

Participants' responses to receiving the lower of the two selected payoffs ("roundlost") is measured in fixed effects regressions shown in tables 15 and 16. Fixed effects are observed by subject id. Rounds are grouped before regressions are run based on where similar behavior is both predicted and observed. The first three rounds are omitted as a learning period for the game. Rounds 3-10 form the "earlyround" group and rounds 25-35 form the "lateround" group. The behavior of type 1 players was used to initially determine the cutoff point between middle rounds (11-24) and late rounds; there is a noticeable decrease in both the average number of changes and the standard deviation of that average after round 24 for these players. Three t-tests comparing means of changes made in these three groups show that all three groupings are significantly different from each other. In the early rounds, participants are aware that all payoffs have the same probability of selection and are still relatively new to the game; these rounds contain the highest number of changes in rankings. In the middle rounds, participants know that the probabilities have shifted but have played only a few rounds with the new conditions. In the late rounds, participants have a good idea of what payoffs are most frequently selected and are making final adjustments based on trial and error or fine tuning. The fewest average number of changes per round occur in this section.

Table 14 shows a fixed effects probit regression that uses a dichotomous outcome of whether any change was made in a person's rankings in a given round; overall players made no changes to their strategy in 77% of rounds. The model uses losing a round as the primary independent variable of interest; control variables include treatment, a tie occurring, gender, round number, and playtype. Type 3 players are omitted due to increased levels of irrationality observed with those players as are results from rounds 1-3 since in these rounds participants were still learning the basic game play, as evidenced by the disproportionately high number of errors in these rounds. Interaction terms are included to capture the relationship between type 2 players and both treatment and ties. The relationship between type 2 players and gender was also tested but it did not significantly impact the model.

In all regression columns losing a round has a statistically significant positive effect of between 65% and 82% on the probability of changing strategy. Participants lose rounds most often when ties occur, making these two variables strongly related. This makes it difficult to distinguish the effects of these variables. With the addition of the interaction term between tie and type2, tie gains statistical significance and the coefficient on roundlost decreases by about .05. This suggests that type 2 players respond less to ties than do type 1 players. The small increase in pseudo R^2 from .229 to .240 in regression 10 suggests that this difference in player types significantly affects the predictive ability of the model. Player type has a consistent positive coefficient but is not statistically significant nor does it hold a constant sign across the different regressions. Treatment is significant at the 90% level, indicating that people change strategies 130% more often in the high treatment. Gender is insignificant in the model, but this is expected due to

the correlation between player type and gender. Per regression 10, in early and late rounds people are 34% more and 50% less likely, respectively, to make changes to their rankings. The addition of the interaction term between treatment and type 2 player does not appear to impact the model in any meaningful way. An interaction between female and type 2 was tested on both this model and the following regression model (as shown in table 15) and was not found to have a significant effect in either case.

Table 15 shows a similar set of regressions to table 1, but with the outcome of the total number of changes made by an individual in each round. Additional controls are added in a stepwise fashion as before. The coefficient on "roundlost" is significant at all levels for all the modeled regressions; regression 10 suggests that losing the previous round leads to on average .97 more changes in strategy in the current round. The control variable for the round in which play occurs has a statistically significant impact with participants making .48 fewer changes during later rounds on average and .55 more changes in early rounds; the addition of the control variable for round resulted in one of the larger changes in R^2 from .176 to .216. Player type is not statistically significant in most of the regressions and has a sign that changes value several times between different regressions. Likewise, tie is never statistically significant and has very small effect sizes. Treatment is not statistically significant and has a coefficient of -.18 in regression 10, which notably of the opposite sign observed in the previous regression table. The interaction terms for tie and type2 affects the coefficients on tie and type 2 but does not otherwise impact the predictive power of the model nor does it achieve statistical significance. Likewise, the interaction between treatment and type 2 affects treatment and type 2 but otherwise does not impact the model.

Table 15: Probit regression on whether any change in rankings is made in a round

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	anychange	anychange	anychange	anychange	anychange	anychange	anychange	anychange	anychange	anychange	anychange
roundlost	0.685***	0.757***	0.673***	0.757***	0.673***	0.737***	0.737***	0.815***	0.729***	0.682***	0.682***
	(0.0733)	(0.0815)	(0.0967)	(0.0815)	(0.0967)	(0.102)	(0.102)	(0.0872)	(0.103)	(0.101)	(0.101)
tie			0.144		0.144	0.152	0.152		0.147	0.485***	0.485***
			(0.0836)		(0.0836)	(0.0884)	(0.0884)		(0.0885)	(0.113)	(0.113)
type2				0.303	0.286	0.428	-0.467	0.444	-0.798*	-0.502	0.829
				(0.347)	(0.351)	(0.386)	(0.326)	(0.379)	(0.367)	(0.375)	(0.429)
lateround						-0.595***	-0.595***	-0.595***	-0.581***	-0.593***	-0.593***
						(0.0861)	(0.0861)	(0.0864)	(0.0864)	(0.0870)	(0.0870)
earlyround						0.291***	0.291***	0.293***	0.306***	0.340***	0.340***
						(0.0855)	(0.0855)	(0.0861)	(0.0862)	(0.0880)	(0.0880)
treatment							0.895*		1.226*	1.355*	1.355*
							(0.382)		(0.532)	(0.545)	(0.545)
female								0.355	0.334	0.455	0.455
								(0.366)	(0.372)	(0.364)	(0.364)
tietype2										-0.736***	-0.736***
										(0.153)	(0.153)
treatmenttype2											-1.332*
											(0.557)
_cons	-0.920***	-1.287***	-1.316***	-1.287***	-1.316***	-1.445***	-1.445***	-1.761***	-1.781***	-2.063***	-2.063***
	(0.0359)	(0.275)	(0.278)	(0.275)	(0.278)	(0.313)	(0.313)	(0.478)	(0.485)	(0.499)	(0.499)
Fixed effects		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2065	1995	1995	1995	1995	1881	1881	1848	1848	1848	1848
pseudo R^2	0.039	0.175	0.177	0.175	0.177	0.230	0.230	0.227	0.229	0.240	0.240
chi2	87.41	312.0	327.4	312.0	327.4	395.3	395.3	376.7	386.6	393.5	393.5
p	8.84e-21	7.82e-37	3.10e-39	7.82e-37	3.10e-39	7.25e-51	7.25e-51	3.08e-48	1.17e-49	1.60e-50	1.60e-50

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 16: Regression table on whether the total number of changes made in a round

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	changesm	changesm	changesm	changesm	changesm	changesm	changesm	changesm	changesm	changesm	changesm
roundlost	1.197***	1.046***	1.161***	1.046***	1.161***	0.978***	0.978***	0.953***	0.989***	0.971***	0.971***
	(0.184)	(0.165)	(0.219)	(0.165)	(0.219)	(0.182)	(0.182)	(0.148)	(0.185)	(0.183)	(0.183)
tie			-0.187		-0.187	-0.0518	-0.0518		-0.0589	0.0445	0.0445
			(0.151)		(0.151)	(0.128)	(0.128)		(0.130)	(0.114)	(0.114)
type2				-0.262	-0.227	-0.317	-0.413*	-0.328	-0.0984	0.00528	0.528
				(0.319)	(0.317)	(0.321)	(0.179)	(0.322)	(0.301)	(0.308)	(0.565)
lateround						-0.475***	-0.475***	-0.470***	-0.475***	-0.476***	-0.476***
						(0.0867)	(0.0867)	(0.0873)	(0.0881)	(0.0881)	(0.0881)
earlyround						0.524***	0.524***	0.542***	0.537***	0.546***	0.546***
						(0.133)	(0.133)	(0.135)	(0.135)	(0.136)	(0.136)
treatment							0.0965		-0.218	-0.181	-0.181
							(0.344)		(0.441)	(0.450)	(0.450)
female								-0.325	-0.315	-0.265	-0.265
								(0.279)	(0.278)	(0.290)	(0.290)
tietype2										-0.275	-0.275
										(0.255)	(0.255)
treatmenttype2											-0.522
											(0.641)
_cons	0.564***	0.275	0.308	0.275	0.308	0.341	0.341	0.649	0.653	0.571	0.571
	(0.0430)	(0.302)	(0.300)	(0.302)	(0.300)	(0.321)	(0.321)	(0.423)	(0.422)	(0.438)	(0.438)
[1em] Fixed effects		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2065	2065	2065	2065	2065	1947	1947	1914	1914	1914	1914
R^2	0.043	0.175	0.176	0.175	0.176	0.216	0.216	0.216	0.216	0.217	0.217
F	42.32	4.984	4.967	4.984	4.967	4.745	4.745	4.815	4.796	4.957	4.957
p	9.70e-11	3.54e-30	1.89e-30	3.54e-30	1.89e-30	4.60e-29	4.60e-29	7.24e-29	4.32e-29	5.45e-31	5.45e-31

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6. Discussion

This experiment is the first to empirically test the Robson-Whitehead theoretical model (2019) and to have been run to simulate adaptive utility models in evolutionary game theory. This study observes the rate at which people shift their preferences as they receive information and are presented with different choices. Limiting the decision-making ability of participants forces them to model their choices as a step-function where the control they possess is shifting cutoff points. Most participants proved to be content to leave their rankings unchanged in most rounds, changing their strategies only after incurring a loss or after observing a significant change in probabilities over several rounds.

In the Robson-Whitehead model ξ refers to the likelihood with which people change their strategies after observing a set of selections. This value can be proxied in part by the effect of tie on anychange while controlling for roundlost. However, these regressions were not statistically significant, indicating that ξ depends heavily on other factors – such as round loss and learning effects. ϵ in the Robson-Whitehead model refers to the magnitude of the adjustments players make when they adjust strategies. This idea can be approximated by the average number of changes a player makes when making at least one change for their strategy – in other words, the average value of changesmade when anychange=1. This value is 3.94 in rounds 10-24 and 2.25 in rounds 25-30. This would imply that people change between 13% and 23% of their rankings when altering their strategies in this game.

It is important to note for both ξ and ϵ that the conditions of this experiment differ from that in the model in a few key ways. First, observations occur in pairs in this experiment, meaning that subjects always must react to a minimum of two observations instead of one. As such, isolating the effect a single observation has on a change in ranking is difficult, which may explain the insignificance observed on the tie variable. Second, the controlled environment limits the number of payoffs and ranking options, effectively forcing subjects to create a step-wise utility function with only four steps. This means that the magnitudes of the shifts likely will have different magnitudes under different conditions. One important note from the findings of these ϵ values is that people adjust not just the recently observed rankings when they change strategies. Observations of high-valued payoffs might result in a series of changes at multiple points along the utility curve.

Despite the controlled nature of the experiment, participants varied heavily in the ways they played the game. The demographic survey failed to find noticeable differences that correlated with how people played the game, though this likely relates to the small sample size. The only statistically significant observation lies in the relationship between gender and player type, with women evenly distributing across both player types and men predominantly falling into type 1. It is possible that with a larger sample size

specific fields of study (individual majors) might drive some of this division. The distinction between player types likely captures an understanding effect where type 1 players understand the full game much better than type 2 or type 3 players. This distinction allows us to potentially separate the more strategy-aware players that have comprehensive strategies from those who need positive or negative stimulus to determine good or bad strategies. Given enough time, it is likely that type 2 players would eventually reach similar patterns of play as type 1 players. It is worth noting, however, that by round 35 only four of of the type 2 players retained no irrational rankings. Specifically, the number of irrationalities actually increases as the treatment progresses. This number is driven by over adjustments as they focus on payoffs that were recently selected while ignoring other potentially selected pairs. Despite adapting considerably, these players seem to have never arrived at a comprehensive strategy or understanding of the game.

The success of individuals can be defined by how close they can come to the best rankings in rounds 1-10 and how well they shift from this strategy towards the optimal strategy in rounds 11-35. In the pretreatment round, many participants ranked the payoffs in a non optimal manner, even after identifying the correct strategy. The majority of participants showed greater levels of aversion towards the lowest payoffs than attraction towards higher payoffs. This trend in rankings suggests that people hold preferences in the game that are external to optimal play. In the open ended questions, several participants identify the correct strategy but also express their intention to avoid the lowest payoffs at all costs. Despite these initial preferences, participants nearly universally began changing their rankings once the treatment probabilities took place and the effect of the aversion to the lowest payments lessens.

The aversion many participants held towards the lowest payoffs presents a question towards individuals' ability to adapt better in the high or the low treatment. Although average expected utility is closer to optimal in the low treatment, most participants were predisposed to put fewer payoffs in the lower rankings. As such, it took a larger number of ranking changes to reach the optimal strategy in the high treatment than in the low treatment. No participants managed to reach a completely optimal set of rankings in the treatment rounds, but many managed to reach levels of expected utility within just a few cents of the maximum possible EU. Players consistently shifted the payoffs that are selected more frequently which also have the largest effect on expected utility when shifted. People seem to generally make broader or more impactful adjustments quickly but are either slow to make or simply never enact the smaller fine-tuning adjustments in strategy. An extended version of this game with more rounds would provide better insight into the long-term adaptability of players.

6.2 Limitations

This study was run as an undergraduate thesis and could not be extended in duration or funding

past what it accomplished. Nevertheless, the data reveal several meaningful trends in how individuals learn and craft strategies as they play a game. The use of fixed effects regressions allow for a larger number of observations from a smaller sample size, providing more insight into round to round behavior. A larger sample size for participants could give greater significance to analysis. Incentivizing participants with larger payoffs might incentivize faster or more precise adaptation over the course of the game.

The experiments were scheduled to run at the beginning of the Covid-19 pandemic, which necessitated a shift to online versions of all experimental software. Allowing participants to connect from their own homes posed a special set of challenges, as idle participants are much more difficult to reach in an online setting and the rate for no-shows and disconnects is much higher in an online format. Extending the playtime of the experiment was not possible due to the risk of subjects becoming bored or distracted over time. Repeating this experiment in a physical lab might provide different results and enable more flexibility in its structure and length.

Modifications on the experimental design in future studies could provide more information on participant behavior in these conditions. More treatment groups would allow for a wider variety of probability distributions to be used in order to test individual reactions to shifts towards average or other potential probability distributions. Additional tests that include changes in the quantity of both categories and payoffs would allow for a better understanding of ξ and ϵ values. The level of information given to participants could also be manipulated to see if more or less info on probability distributions affects how people adapt. Removing the frequency table for which payments have been selected thus far would test how well people learn when provided less information. Altering the level of punishment assigned to errors occurring would help identify the difference between the fear of tying and the general learning process. Finally, using some form of preference elicitation could provide greater insight into how susceptible individual utility is towards changes in the probabilities and create a structure closer to the one described in the Robson-Whitehead model.

7. Conclusions

This study finds that people adapt to new circumstances but respond most strongly to negative experiences. Adaptation occurs most strongly when the punishment for not adapting is strongest, but people are still able to capture very small changes in expected utility when facing a small probability of a loss. The change in participants' aversion to the low payoffs over the course of the game suggests that individual utility, or happiness, depends in part on their experiences in the game.

Despite the simplified nature of the experiment, the findings support the theoretical models

underpinning evolutionary game theory where individuals adapt their rankings to account for frequency of observation. Though based on empirical findings, the empirical models describe general trends in behavior without attempting to identify specific values or probabilities. As more specifics become known about these important values, it becomes possible both to verify the accuracy of adaptive utility models in general and to fine-tune them to give them more predictive capability. The results from this experiment indicate that the probability of changing strategy depends on learning effects and experiencing a loss, as well as that individuals make changes to multiple preferences after a single observation. People typically are content to leave their strategy unchanged unless motivated to change by either incurring a loss or repeatedly observing a trend in the selections over several rounds.

An understanding of adaptive utility provides more information on how individuals' well-being might change over time under different life conditions. Happiness often represents the ultimate goal of a policy or initiative; programs designed to increase the well-being of the populace may target aggregate individual happiness or quality of life. The greater the understanding of human happiness and, more importantly, how happiness levels respond to changes in life conditions the greater effectiveness that we can gain when setting goals for projects. These models, along with empirical findings, suggest that people's perception of happiness (or utility) at least partially depends on their environment, supporting the claim that people eventually return to average happiness levels after significant life changes. The findings of this study give insight as to the rate at which this adaptive process occurs and set the groundwork for further studies to be run investigating the conditions in which people's preferences adapt.

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Cameron Bellamoroso

Appendix A – Tables and figures

Senior Thesis

9/25/2020

Table 17: Correlation table with all variables

	Treatment	age	female	tie	type2	anychange	changes~e	irratio~t	BCLA	SOE	CBA	CSE	CFA	math	white	asian	black	hispanic	natamer~n	raceother	Wantcha~e	Perfect~t	Minval	Detailo~t
Treatment	1																							
age	0.124***	1																						
female	-0.0852***	0.0559**	1																					
tie	0.0845***	0.0282	0.00321	1																				
type2	-0.0457*	-0.143***	0.439***	0.0244	1																			
anychange	-0.0121	0.163***	0.179***	0.114***	0.161***	1																		
changesm~e	0.0359	0.408***	0.129***	0.0732***	0.0908***	0.657***	1																	
irration~t	0.0372	0.0744***	0.256***	0.00555	0.660***	0.240***	0.273***	1																
BCLA	-0.0397	0.142***	-0.0855***	0.022	-0.236***	0.106***	0.129***	-0.129***	1															
SOE	0.135***	-0.0113	-0.147***	0.0227	-0.0864***	0.0196	-0.0236	-0.0708***	-0.0925***	1														
CBA	-0.0753***	0.161***	0.219***	0.0281	0.0620**	0.0261	0.0548**	0.0753***	-0.257***	-0.0894***	1													
CSE	0.204***	-0.0483*	-0.242***	-0.00731	-0.021	-0.0659**	-0.0641**	-0.0955***	-0.226***	-0.0533*	-0.215***	1												
CFA	0.0246	0.00668	0.166***	0.000295	0.00699	-0.0486*	-0.0408	0.0102	-0.125***	-0.0399	-0.116***	-0.136***	1											
math	0.0142	0.111***	0.0316	0.0324	-0.0223	0.0302	0.0375	0.0691***	-0.0208	-0.123***	0.726***	0.00656	-0.208***	1										
white	0.0671**	-0.177***	-0.012	0.0307	-0.00307	-0.0673**	-0.0554**	0.0234	-0.0590**	0.144***	-0.0313	0.0596**	0.152***	0.0134	1									
asian	0.0441*	-0.0760***	0.201***	-0.0145	-0.0893***	0.0282	-0.0652**	-0.0106	-0.199***	-0.0714***	0.195***	-0.0457*	0.0645**	0.0802***	-0.497***	1								
black	-0.151***	0.0383	0.131***	0.000267	0.0475*	0.0645**	0.0730***	0.0245	0.269***	-0.0361	-0.0845***	-0.123***	-0.0921***	-0.0533*	-0.251***	-0.165***	1							
hispanic	-0.0137	-0.0265	-0.201***	-0.013	0.104***	0.0187	0.0104	0.00721	0.169***	-0.0501*	-0.193***	0.0760***	-0.128***	-0.0384	-0.349***	-0.229***	-0.116***	1						
natameri~n	-0.116***	-0.0393	-0.147***	0.000116	-0.0864***	-0.0467*	-0.0421*	-0.0916***	-0.0925***	-0.0156	0.175***	0.293***	-0.0399	0.127***	-0.109***	-0.0714***	-0.0361	-0.0501*	1					
raceother	0.0246	0.464***	-0.105***	-0.0157	0.00699	0.0113	0.130***	-0.0164	-0.0137	-0.0399	-0.00346	-0.136***	-0.102***	-0.101***	-0.277***	-0.182***	-0.0921***	-0.128***	-0.0399	1				
Wantchange	0.0327	0.126***	0.0458*	0.000981	-1.87E-07	0.0874***	0.0548**	0.0272	0.17***	0.132**	0.103**	-0.316**	0.0563*	0.0652*	-0.0329	0.151**	0.122***	-0.094***	-0.265***	-0.056**	1			
Perfecti~t	0.113***	0.102***	0.376***	0.0048	-0.147***	0.109***	0.0950***	-0.290***	0.121***	-0.00199	0.190***	-0.0948***	-0.00507	0.0797***	0.0503*	0.0647**	0.115***	-0.190***	-0.00199	-0.0599**	0.269***	1		
Minval	0.00933	0.250***	0.175***	0.0057	0.0630**	0.128***	0.175***	0.0550**	0.214***	0.0504*	-0.138***	0.0043	0.0589**	-0.208***	-0.0971***	0.0900***	0.116***	0.0449*	-0.113***	-0.0804***	0.299***	0.235***	1	
Detailor~t	0.0806***	0.000287	0.305***	0.0448*	-0.00533	0.125***	0.0975***	-0.0765***	0.161***	0.104***	0.0978***	-0.196***	-0.0469*	0.0953***	-0.00671	0.139***	0.104***	-0.137***	-0.0428*	-0.109***	0.343***	0.534***	0.280***	1

* p<0.05, ** p<0.01, p<0.001

Table 18: Average rankings in the high treatment for type 1 players

	High treatment -- Type 1 mean rankings n=19																																		
#	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35
MEU	601	601	601	601	601	601	601	601	601	601	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799
EU	572	588	589	594	593	595	597	597	597	597	774	775	776	777	780	780	780	779	780	782	783	783	786	786	786	786	786	787	787	788	788	788	788	788	789
MEU-EU	29	13	12	7	8	6	4	4	4	4	25	24	23	22	19	19	19	20	19	17	16	16	13	13	13	13	13	12	12	11	11	11	11	11	10
1	1.2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1.4	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1
3	1.4	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2
4	1.6	1.5	1.5	1.5	1.5	1.5	1.6	1.6	1.6	1.6	1.6	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.3	1.3
5	1.9	1.9	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.7	1.7	1.7	1.6	1.6	1.6	1.6	1.6	1.6	1.6	1.6	1.6	1.6	1.6	1.6	1.6	1.6	1.5	1.5	1.5	1.5	1.5	1.5
6	2.2	2.2	2.2	2.1	2.1	2.1	2.1	2.1	2.1	2	2	2	2	2	1.9	1.9	1.9	1.9	1.9	1.9	1.9	1.9	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.7
7	2.3	2.3	2.3	2.3	2.3	2.3	2.2	2.2	2.2	2.2	2.2	2.2	2.2	2.2	2.2	2.2	2.2	2.2	2.2	2.2	2.2	2.2	2.1	2.1	2.1	2.1	2.1	2	2	1.9	1.9	1.9	1.9	1.9	1.9
8	2.7	2.6	2.7	2.7	2.7	2.7	2.6	2.6	2.6	2.6	2.6	2.6	2.6	2.6	2.5	2.5	2.5	2.5	2.5	2.4	2.4	2.4	2.2	2.2	2.2	2.2	2.2	2.2	2.2	2.1	2.1	2.1	2.1	2.1	2.1
9	2.8	2.8	2.7	2.8	2.8	2.8	2.8	2.8	2.7	2.7	2.6	2.6	2.6	2.6	2.6	2.6	2.6	2.6	2.6	2.6	2.6	2.5	2.4	2.4	2.4	2.4	2.4	2.4	2.4	2.3	2.2	2.2	2.2	2.2	2.2
10	3.1	3.3	3.1	3	3	3.1	3.1	3.1	3.1	3.1	2.9	2.9	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.7	2.7	2.7	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5
11	3.2	3.4	3.4	3.1	3.1	3.2	3.1	3.1	3.1	3.2	3.1	3	3	3	3	2.9	2.9	2.9	2.9	2.9	2.9	2.8	2.7	2.7	2.7	2.7	2.7	2.6	2.6	2.6	2.6	2.6	2.6	2.6	2.5
12	3.3	3.5	3.5	3.4	3.4	3.4	3.3	3.3	3.3	3.3	3.4	3.4	3.4	3.4	3.2	3.2	3.2	3.2	3.2	3.2	3.1	3.1	3	3	2.9	2.9	2.9	2.9	2.9	2.9	2.8	2.8	2.8	2.8	2.8
13	3.6	3.8	3.8	3.8	3.8	3.8	3.8	3.7	3.7	3.7	3.7	3.7	3.6	3.6	3.4	3.4	3.3	3.2	3.2	3.2	3.2	3.2	3	3	3	3	3	3	3	2.9	2.9	2.9	2.9	2.9	2.9
14	3.7	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.8	3.6	3.6	3.6	3.6	3.6	3.5	3.5	3.5	3.4	3.5	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4
15	3.8	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.8	3.8	3.8	3.8	3.7	3.8	3.7	3.7	3.7	3.6	3.6	3.6	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5
16	3.8	4	4	4	4	4	4	4	4	4	4	4	4	4	4	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9
17	3.8	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4

Table 19: Average rankings in the high treatment for type 2 players

	High treatment -- type 2 mean rankings n=9																																		
#	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35
MEU	601	601	601	601	601	601	601	601	601	601	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799	799
EU	475	543	524	504	535	518	502	521	530	540	734	732	737	736	744	738	739	742	753	754	754	756	755	757	760	764	764	768	768	768	768	767	769	769	768
MEU-EU	126	58	77	97	66	83	99	80	71	61	65	67	62	63	55	61	60	57	46	45	45	43	44	42	39	35	35	31	31	31	31	32	30	30	31
1	2.2	1.9	2.1	2.1	1.7	2.2	2.2	1.8	1.8	1.7	1.6	1.5	1.6	1.5	1.6	1.9	2	1.8	1.6	1.6	1.6	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5
2	2.5	1.9	2.2	2.3	1.9	2	2.4	2.2	2.1	2	2	2.1	2.1	2.2	2.1	2.2	2.3	2.1	1.9	1.9	1.9	1.9	1.9	1.9	1.9	1.9	1.9	1.9	1.8	1.8	1.8	1.8	1.8	1.8	1.8
3	2.2	2.1	2.5	2.5	1.7	2.2	2.5	2.1	2.2	2.1	2.2	2.1	2.1	2	2.1	2	2.1	1.9	1.8	1.8	1.8	1.7	1.7	1.7	1.7	1.7	1.7	1.7	1.6	1.6	1.6	1.6	1.6	1.6	1.6
4	2.5	2.1	2.5	2.8	2.3	2.4	2.5	2.4	2.4	2.3	2.4	2.5	2.3	2.4	2.3	2	2	1.8	2	2	2	2	2	2	2	2	2	2	1.9	1.9	1.9	1.9	1.9	1.9	1.9
5	2.8	2.7	2.9	2.7	2.4	2.6	2.6	2.3	2.4	2.4	2.3	2.1	2.1	2	2.1	2.4	2.4	2.3	2	2	2	1.9	1.9	1.9	1.9	1.9	1.9	1.9	1.9	1.9	1.9	1.9	2	2	2
6	3.1	2.5	2.5	2.6	2.5	2.5	2.8	2.8	2.7	2.6	2.4	2.5	2.4	2.5	2.3	2.4	2.4	2.3	2.2	2.2	2.2	2.2	2.2	2.2	2.2	2.2	2.2	2.2	2	2	2	2	2	2	2
7	2.9	3	3.2	3	2.5	2.7	2.7	2.6	2.7	2.6	2.6	2.5	2.6	2.5	2.5	2.5	2.5	2.4	2.3	2.3	2.3	2.2	2.2	2.2	2.1	2.1	2.1	2.1	2.1	2.1	2.1	2.1	2.1	2.1	2.1
8	3.2	3.1	3.2	3.3	3.1	3.1	3	3.4	3.2	3.2	3	3.1	3	2.9	2.7	2.6	2.5	2.4	2.4	2.4	2.4	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.4	2.4	2.4	2.4	2.2	2.2	2.2
9	2.8	2.7	3	3	2.7	3.3	3.3	3.2	3.2	3.2	3.2	3.1	3.2	3	3.1	3.2	3.1	3	2.9	2.9	2.9	2.8	2.8	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.3	2.3	2.3
10	2.9	3.2	3.1	3.2	2.9	2.8	2.8	2.8	3.1	3.2	3.4	3.5	3.4	3.5	3.2	3.1	3.1	3	3	3	3	3	3	2.7	2.7	2.7	2.7	2.7	2.6	2.6	2.6	2.6	2.5	2.5	2.5
11	2.7	3.2	3.4	3.2	2.8	3.1	3.1	3	3.1	3.2	3.6	3.5	3.6	3.5	3.5	3.6	3.5	3.5	3.2	3.2	3.2	3.1	3.1	3.1	2.8	2.5	2.5	2.6	2.6	2.6	2.5	2.5	2.5	2.5	2.5
12	3	3.2	3.6	3.8	3.5	3.2	3.1	3.3	3.2	3.7	3.7	3.7	3.6	3.7	3.6	3.6	3.5	3.5	3.4	3.2	3.2	3.2	3.5	3.4	3.1	2.8	2.8	2.9	2.9	2.9	2.9	2.9	2.8	2.9	3
13	3.2	3.4	3.5	3.5	3.3	3.6	3.7	3.6	3.9	3.9	3.7	3.5	3.6	3.5	3.5	3.9	3.8	3.8	3.8	3.8	3.8	3.7	3.5	3.5	3.4	3.2	3.2	3.2	3.1	3.1	3.1	3.1	3.2	3.2	3.2
14	2.8	3.5	3.8	3.7	3.8	3.5	3.5	3.2	3.3	3.6	3.7	3.8	3.7	4	3.8	3.7	3.8	3.7	3.8	3.7	3.6	3.6	3.7	3.5	3.5	3.3	3.3	3.3	3.3	3.3	3.3	3.2	3.3	3.3	3.4
15	2.9	3.6	3.6	3.3	3.6	3.6	3.5	3.3	3.6	3.8	3.9	3.8	3.9	3.8	3.9	3.8	3.8	3.8	3.7	3.7	3.6	3.6	3.7	3.7	3.7	3.6	3.4	3.6	3.6	3.5	3.6	3.6	3.6	3.6	3.6
16	2.8	4	3.9	3.6	3.6	3.3	3.2	3.7	3.6	3.7	3.8	3.9	3.8	3.9	3.8	3.5	3.3	3.4	3.5	3.6	3.6	3.5	3.5	3.5	3.5	3.5	3.4	3.7	3.7	3.7	3.7	3.7	3.7	3.7	3.7
17	2.9	3.9	3.7	3.6	3.6	3.7	3.7	3.9	4	4	3.7	3.6	3.7	3.6	3.7	3.7	3.7	3.7	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4

Table 20: Average rankings in the low treatment for type 1 players

Low treatment -- Type 1 mean rankings											n=19																								
#	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35
MEU	601	601	601	601	601	601	601	601	601	601	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296
EU	577	587	589	590	590	591	597	598	598	598	283	284	283	286	287	289	289	289	290	290	289	289	291	291	291	291	291	291	291	291	291	290	290	290	290
MEU-EU	24	14	12	11	11	10	4	3	3	3	13	12	13	10	9	7	7	7	6	6	7	7	5	5	5	5	5	5	5	5	5	6	6	6	6
1	1.2	1.3	1.3	1.2	1.2	1.2	1.1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1.2	1.3	1.3	1.3	1.3	1.2	1.1	1	1	1	1	1	1.2	1.1	1.2	1.2	1.2	1.2	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.2	1.2	1.2	1.3	1.3	1.3	1.3	1.3	1.3
3	1.4	1.4	1.4	1.5	1.5	1.4	1.3	1.2	1.2	1.2	1.2	1.3	1.5	1.4	1.4	1.4	1.4	1.5	1.4	1.5	1.5	1.5	1.6	1.6	1.6	1.6	1.7	1.7	1.7	1.8	1.8	1.8	1.8	1.8	1.8
4	1.8	1.8	1.8	1.8	1.8	1.7	1.6	1.5	1.5	1.5	1.4	1.4	1.8	1.7	1.8	1.8	1.8	1.8	1.8	1.9	1.9	1.9	2	2	2	2	2.1	2.1	2.1	2.1	2.1	2	2.1	2.1	2.1
5	2.1	2.1	2	1.9	1.9	1.9	1.8	1.8	1.8	1.8	1.8	1.8	1.9	2	2.1	2.1	2.1	2.1	2.1	2.1	2.1	2.1	2.1	2.1	2.1	2.1	2.2	2.2	2.2	2.2	2.2	2.2	2.2	2.2	2.2
6	2.2	2.2	2.2	2.2	2.2	2.2	2.1	2	2	2	2.1	2.1	2.1	2.1	2.2	2.3	2.4	2.4	2.4	2.4	2.4	2.4	2.4	2.4	2.4	2.4	2.5	2.5	2.5	2.5	2.5	2.4	2.4	2.4	2.4
7	2.3	2.3	2.3	2.4	2.4	2.4	2.3	2.3	2.3	2.3	2.3	2.3	2.3	2.4	2.5	2.6	2.6	2.6	2.6	2.6	2.6	2.6	2.6	2.6	2.6	2.6	2.6	2.6	2.6	2.6	2.7	2.6	2.6	2.6	2.6
8	2.6	2.6	2.6	2.6	2.6	2.6	2.6	2.6	2.5	2.5	2.6	2.6	2.7	2.7	2.8	2.9	2.9	2.9	2.9	2.9	2.9	2.9	2.9	2.9	2.9	2.9	2.9	2.9	2.9	2.9	2.9	2.9	2.9	2.9	2.9
9	2.9	2.9	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.9	2.9	3	3.1	3.1	3.1	3.1	3.1	3.1	3.1	3.1	3.1	3.1	3.1	3.1	3.1	3.1	3.1	3.1	3.1	3.1	3.1	3.1
10	3.1	3.2	3.1	3.1	3	2.9	2.9	2.9	2.9	2.9	3	3	3.1	3.1	3.2	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.4	3.4	3.3	3.3	3.3
11	3	3.3	3.3	3.2	3.2	3.1	3.2	3.1	3.1	3.1	3.2	3.2	3.2	3.3	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.4	3.4	3.4
12	3.6	3.6	3.6	3.6	3.6	3.6	3.6	3.5	3.5	3.5	3.5	3.5	3.6	3.6	3.6	3.7	3.7	3.7	3.7	3.7	3.7	3.7	3.7	3.8	3.8	3.8	3.8	3.8	3.8	3.8	3.8	3.8	3.7	3.7	3.7
13	3.6	3.6	3.6	3.6	3.6	3.6	3.6	3.6	3.6	3.7	3.8	3.8	3.8	3.8	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9
14	3.8	3.9	3.9	3.9	3.9	3.8	3.8	3.8	3.9	3.9	3.9	3.9	3.9	3.9	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
15	3.7	3.9	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
16	3.7	3.9	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
17	3.6	3.9	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4

Table 21: Average rankings in the low treatment for type 2 players

Low treatment -- Type 2 mean rankings											n=12																								
#	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35
MEU	601	601	601	601	601	601	601	601	601	601	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296
EU	582	575	551	546	552	556	555	565	566	574	268	270	277	276	280	279	272	278	280	280	281	274	271	280	283	276	278	282	282	282	282	281	280	281	281
MEU-EU	19	26	50	55	49	45	46	36	35	27	28	26	19	20	16	17	24	18	16	16	15	22	25	16	13	20	18	14	14	14	14	15	16	15	15
1	1.1	1.1	1.5	1.6	1.6	1.6	1.6	1.3	1.3	1.3	1.3	1.3	1.1	1.1	1	1	1.2	1	1	1	1	1.1	1.2	1.1	1.1	1.1	1	1	1	1	1	1	1	1	1
2	1.3	1.1	1.6	1.6	1.7	1.7	1.6	1.4	1.4	1.4	1.4	1.3	1.4	1.5	1.6	1.5	1.6	1.7	1.6	1.6	1.5	1.6	1.6	1.5	1.4	1.6	1.6	1.5	1.5	1.5	1.4	1.4	1.4	1.4	1.4
3	1.4	1.4	1.9	1.9	1.7	1.7	1.6	1.4	1.4	1.4	1.4	1.5	1.5	1.6	1.7	1.8	1.9	2.1	2	2	1.9	1.9	1.9	1.8	1.7	2	2	1.9	1.9	1.9	1.7	1.7	1.7	1.7	1.7
4	1.7	1.8	2.1	2.1	2.1	2.1	2	2.1	1.9	1.9	1.8	1.8	1.9	2	2.1	2.1	2.1	2.1	2.2	2.3	2.2	2.3	2.3	2.3	2.3	2.4	2.4	2.3	2.3	2.3	2.2	2.2	2.3	2.3	2.3
5	2	2	2.1	1.9	1.9	2.2	2.1	2.1	2	2	2	2.1	2.1	2.1	2.2	2.2	2.2	2.2	2.3	2.1	2.1	2.2	2.2	2.2	2.2	2.2	2.2	2.2	2.2	2.2	2.2	2.1	2.1	2.1	2.1
6	2.1	2.1	2.1	2.4	2.4	2.4	2.4	2.4	2.4	2.3	2.3	2.5	2.5	2.5	2.7	2.7	2.6	2.6	2.7	2.7	2.6	2.7	2.7	2.7	2.6	2.6	2.7	2.7	2.6	2.6	2.6	2.6	2.5	2.5	2.5
7	2.3	2.4	2.5	2.5	2.5	2.7	2.7	2.5	2.7	2.7	2.7	2.6	2.6	2.7	2.8	2.8	2.7	2.7	2.8	2.9	2.8	2.9	2.9	2.9	2.7	2.7	2.8	2.9	2.9	2.9	2.7	2.7	2.8	2.8	2.8
8	2.6	2.7	2.7	2.5	2.6	2.7	2.8	2.5	2.7	2.7	2.7	2.7	2.7	2.7	2.7	2.7	2.7	2.8	2.9	2.9	2.9	2.9	2.9	2.9	2.9	2.8	2.9	2.9	2.9	2.9	2.8	2.8	2.8	2.8	2.8
9	2.6	2.7	2.7	2.6	2.7	2.6	2.7	2.7	2.7	2.7	2.7	2.7	2.7	2.8	2.9	3	2.9	3	3.1	2.9	2.9	2.9	2.9	3	3.1	2.9	2.9	3	2.9	2.9	2.8	2.8	2.8	2.8	2.8
10	3.1	3.1	3.1	3.1	3.1	3.1	3.3	3.2	3.1	3.2	3.2	3.1	3.1	3	3.3	3.2	3.3	3.3	3.4	3.2	3.1	3.1	3.1	3.3	3.3	3.3	3.2	3.3	3.3	3.3	3.2	3.2	3.2	3.3	3.3
11	3.3	3.3	3.3	3.4	3.4	3.3	3.4	3.4	3.4	3.4	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.4	3.4	3.4	3.4	3.5	3.5	3.5	3.4	3.4	3.5	3.5	3.5
12	3.3	3.2	3.1	3.1	3.1	3.1	3.1	3.1	3.1	3.2	3.2	3.3	3.4	3.5	3.4	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.4	3.3	3.3	3.3	3.2	3.2	3.2	3.2
13	3.7	3.6	3.3	3.3	3.3	3.4	3.5	3.5	3.5	3.6	3.5	3.5	3.5	3.4	3.5	3.5	3.5	3.5	3.6	3.5	3.6	3.6	3.6	3.8	3.8	3.7	3.7	3.7	3.5	3.5	3.5	3.5	3.5	3.5	3.5
14	3.9	3.7	3.5	3.5	3.7	3.9	3.9	3.7	3.7	3.8	3.7	3.7	3.6	3.6	3.6	3.9	3.9	3.9	3.7	3.6	3.5	3.3	3.3	3.7	3.7	3.7	3.7	3.7	3.5	3.5	3.5	3.5	3.5	3.6	3.6
15	3.9	3.9	3.6	3.8	3.8	3.8	3.8	3.8	3.8	3.9	3.8	3.8	3.7	3.5	3.7	3.6	3.7	3.7	3.8	3.7	3.8	3.6	3.6	3.8	3.8	3.8	3.8	3.8	3.7	3.8	3.8	3.8	3.8	3.9	3.9
16	3.9	3.9	3.8	3.5	3.6	3.7	3.7	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.7	3.6	3.9	3.9	3.9	3.9	3.9	3.8	3.8	3.8	3.7	3.7	3.7	3.7
17	4	3.9	3.8	3.7	3.8	3.9	3.9	3.9	3.8	4	3.9	3.9	3.9	3.7	3.9	3.9	3.7	3.9	3.8	3.7	3.7	3.5	3.5	3.9	3.9	3.9	3.9	3.9	3.7	3.7	3.7	3.8	3.8	3.8	3.8

Table 22: Probit regression on any changes being made with colleges as controls

	(1)	(2)	(3)	(4)	(5)
	anychange	anychange	anychange	anychange	anychange
roundlost	0.682***	0.682***	0.682***	0.682***	0.682***
	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)
type2	-0.502	-0.502	0.746	-0.281	0.746
	(0.375)	(0.375)	(0.399)	(0.497)	(0.399)
tie	0.485***	0.485***	0.485***	0.485***	0.485***
	(0.113)	(0.113)	(0.113)	(0.113)	(0.113)
tietype2	-0.736***	-0.736***	-0.736***	-0.736***	-0.736***
	(0.153)	(0.153)	(0.153)	(0.153)	(0.153)
lateround	-0.593***	-0.593***	-0.593***	-0.593***	-0.593***
	(0.0870)	(0.0870)	(0.0870)	(0.0870)	(0.0870)
earlyround	0.340***	0.340***	0.340***	0.340***	0.340***
	(0.0880)	(0.0880)	(0.0880)	(0.0880)	(0.0880)
female	0.455	0.455	0.455	0.455	1.013**
	(0.364)	(0.364)	(0.364)	(0.364)	(0.357)
Treatment	1.355*	2.688***	0.106	1.355*	1.440*
	(0.545)	(0.561)	(0.453)	(0.545)	(0.574)
BCLA		1.333***			1.112**
		(0.352)			(0.355)
SOE			1.248*		1.585*
			(0.536)		(0.626)
math				-0.221	
				(0.331)	
CBA					-0.221
					(0.331)
CFA					-0.380
					(0.323)
CSE					0.337
					(0.321)
_cons	-2.063***	-3.396***	-2.063***	-2.063***	-3.733***
	(0.499)	(0.515)	(0.499)	(0.499)	(0.609)
Fixed effects	Yes	Yes	Yes	Yes	Yes
N	1848	1848	1848	1848	1848
pseudo R^2	0.240	0.240	0.240	0.240	0.240
chi2	393.5	393.5	393.5	393.5	393.5
p	1.60e-50	1.60e-50	1.60e-50	1.60e-50	1.60e-50

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 23: Probit regression that includes self-identified characteristics

	(1) anychange	(2) anychange	(3) anychange	(4) anychange	(5) anychange	(6) anychange	(7) anychange	(8) anychange
roundlost	0.682***	0.682***	0.682***	0.682***	0.682***	0.682***	0.682***	0.682***
	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)
type2	1.754***	-0.470	1.198***	3.935***	1.754***	1.008**	1.754***	1.276*
	(0.377)	(0.599)	(0.320)	(0.970)	(0.377)	(0.321)	(0.377)	(0.597)
tie	0.485***	0.485***	0.485***	0.485***	0.485***	0.485***	0.485***	0.485***
	(0.113)	(0.113)	(0.113)	(0.113)	(0.113)	(0.113)	(0.113)	(0.113)
tietype2	-0.736***	-0.736***	-0.736***	-0.736***	-0.736***	-0.736***	-0.736***	-0.736***
	(0.153)	(0.153)	(0.153)	(0.153)	(0.153)	(0.153)	(0.153)	(0.153)
lateround	-0.593***	-0.593***	-0.593***	-0.593***	-0.593***	-0.593***	-0.593***	-0.593***
	(0.0870)	(0.0870)	(0.0870)	(0.0870)	(0.0870)	(0.0870)	(0.0870)	(0.0870)
earlyround	0.340***	0.340***	0.340***	0.340***	0.340***	0.340***	0.340***	0.340***
	(0.0880)	(0.0880)	(0.0880)	(0.0880)	(0.0880)	(0.0880)	(0.0880)	(0.0880)
female	1.788***	0.676	1.232***	0.698	-0.436	1.042**	0.296	1.758*
	(0.386)	(0.365)	(0.331)	(0.375)	(0.607)	(0.330)	(0.362)	(0.840)
treatment	-0.920**	-2.032***	-0.920**	-3.101***	-4.256***	-0.174	-0.920**	-1.587**
	(0.343)	(0.494)	(0.343)	(0.801)	(1.119)	(0.384)	(0.343)	(0.576)
Risktaking		1.112**						1.161*
		(0.355)						(0.475)
Minval			0.556**					0.438*
			(0.177)					(0.219)
Content				-1.090**				-1.657*
				(0.362)				(0.789)
Wantchange					1.112**			-0.925*
					(0.355)			(0.424)
Detailorient						0.746***		1.033
						(0.175)		(0.570)
Perfectionist							0.497***	-0.803
							(0.117)	(0.549)
_cons	-2.044***	-2.044***	-3.156***	2.317	-0.932*	-4.282***	-2.542***	0.488
	(0.450)	(0.450)	(0.685)	(1.319)	(0.433)	(0.829)	(0.512)	(1.502)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1848	1848	1848	1848	1848	1848	1848	1848
pseudo R^2	0.240	0.240	0.240	0.240	0.240	0.240	0.240	0.240
chi2	393.5	393.5	393.5	393.5	393.5	393.5	393.5	393.5
p	1.60e-50	1.60e-50	1.60e-50	1.60e-50	1.60e-50	1.60e-50	1.60e-50	1.60e-50

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 24: Probit regression on anychange with education/majors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
roundlost	0.682***	0.682***	0.682***	0.682***	0.682***	0.682***	0.682***	0.682***	0.682***
	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)
type2	1.754***	1.754***	1.754***	1.754***	1.754***	1.754***	1.754***	1.754***	1.754***
	(0.377)	(0.377)	(0.377)	(0.377)	(0.377)	(0.377)	(0.377)	(0.377)	(0.377)
tie	0.485***	0.485***	0.485***	0.485***	0.485***	0.485***	0.485***	0.485***	0.485***
	(0.113)	(0.113)	(0.113)	(0.113)	(0.113)	(0.113)	(0.113)	(0.113)	(0.113)
tietype2	-0.736***	-0.736***	-0.736***	-0.736***	-0.736***	-0.736***	-0.736***	-0.736***	-0.736***
	(0.153)	(0.153)	(0.153)	(0.153)	(0.153)	(0.153)	(0.153)	(0.153)	(0.153)
lateround	-0.593***	-0.593***	-0.593***	-0.593***	-0.593***	-0.593***	-0.593***	-0.593***	-0.593***
	(0.0870)	(0.0870)	(0.0870)	(0.0870)	(0.0870)	(0.0870)	(0.0870)	(0.0870)	(0.0870)
earlyround	0.340***	0.340***	0.340***	0.340***	0.340***	0.340***	0.340***	0.340***	0.340***
	(0.0880)	(0.0880)	(0.0880)	(0.0880)	(0.0880)	(0.0880)	(0.0880)	(0.0880)	(0.0880)
female	1.788***	0.676	1.788***	1.788***	1.788***	1.788***	1.078**	0.455	1.078**
	(0.386)	(0.365)	(0.386)	(0.386)	(0.386)	(0.386)	(0.369)	(0.364)	(0.369)
treatment	-0.920**	-2.032***	-0.920**	-0.920**	-2.253***	-0.920**	-0.920**	-2.253***	-2.253***
	(0.343)	(0.494)	(0.343)	(0.343)	(0.492)	(0.343)	(0.343)	(0.492)	(0.492)
BCLA		1.112**							1.112**
		(0.355)							(0.355)
SOE			2.256***						2.658***
			(0.523)						(0.622)
SFTV				-1.112**					
				(0.355)					
CBA					-1.333***				-0.221
					(0.352)				(0.331)
CFA						-1.492***			-0.380
						(0.350)			(0.323)
CSE							-0.710*		0.402
							(0.357)		(0.335)
math								-1.333***	
								(0.352)	
_cons	-2.044***	-0.932*	-2.044***	-2.044***	-0.711	-2.044***	-1.334**	0.622	-1.113*
	(0.450)	(0.433)	(0.450)	(0.450)	(0.432)	(0.450)	(0.436)	(0.648)	(0.548)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1848	1848	1848	1848	1848	1848	1848	1848	1848
pseudo R^2	0.240	0.240	0.240	0.240	0.240	0.240	0.240	0.240	0.240
chi2	393.5	393.5	393.5	393.5	393.5	393.5	393.5	393.5	393.5
p	1.60e-50	1.60e-50	1.60e-50	1.60e-50	1.60e-50	1.60e-50	1.60e-50	1.60e-50	1.60e-50

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 25: Probit regression on anychange including different race variables

	(1) anychange	(2) anychange	(3) anychange	(4) anychange	(5) anychange	(6) anychange
roundlost	0.682***	0.682***	0.682***	0.682***	0.682***	0.682***
	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)
type2	1.754***	0.642	0.521	1.754***	1.754***	1.633**
	(0.377)	(0.354)	(0.422)	(0.377)	(0.377)	(0.553)
tie	0.485***	0.485***	0.485***	0.485***	0.485***	0.485***
	(0.113)	(0.113)	(0.113)	(0.113)	(0.113)	(0.113)
tietype2	-0.736***	-0.736***	-0.736***	-0.736***	-0.736***	-0.736***
	(0.153)	(0.153)	(0.153)	(0.153)	(0.153)	(0.153)
lateround	-0.593***	-0.593***	-0.593***	-0.593***	-0.593***	-0.593***
	(0.0870)	(0.0870)	(0.0870)	(0.0870)	(0.0870)	(0.0870)
earlyround	0.340***	0.340***	0.340***	0.340***	0.340***	0.340***
	(0.0880)	(0.0880)	(0.0880)	(0.0880)	(0.0880)	(0.0880)
female	1.788***	0.676	1.788***	0.676	1.788***	0.676
	(0.386)	(0.365)	(0.386)	(0.365)	(0.386)	(0.365)
treatment	-2.412***	-0.920**	0.313	-0.920**	-0.920**	-2.291***
	(0.491)	(0.343)	(0.540)	(0.343)	(0.343)	(0.635)
asian	-1.492***					-1.961***
	(0.350)					(0.544)
white		1.112**				-0.469
		(0.355)				(0.419)
black			-1.233*			-0.590
			(0.557)			(0.532)
hispanic				-1.112**		-1.581**
				(0.355)		(0.547)
natamerican					0.363	-2.710***
					(0.541)	(0.761)
_cons	-0.552	-0.932*	-2.044***	-0.932*	-2.044***	1.028
	(0.432)	(0.433)	(0.450)	(0.433)	(0.450)	(0.698)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1848	1848	1848	1848	1848	1848
pseudo R^2	0.240	0.240	0.240	0.240	0.240	0.240
chi2	393.5	393.5	393.5	393.5	393.5	393.5
p	1.60e-50	1.60e-50	1.60e-50	1.60e-50	1.60e-50	1.60e-50

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 26: Probit regression on anychange with tie as the independent variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	anychange	anychange	anychange	anychange	anychange	anychange	anychange	anychange	anychange	anychange
roundlost	0.685***		0.673***		0.673***	0.737***	0.737***		0.729***	0.682***
	(0.0733)		(0.0967)		(0.0967)	(0.102)	(0.102)		(0.103)	(0.101)
tie		0.432***	0.144	0.432***	0.144	0.152	0.152	0.459***	0.147	0.485***
		(0.0696)	(0.0836)	(0.0696)	(0.0836)	(0.0884)	(0.0884)	(0.0744)	(0.0885)	(0.113)
type2				0.585	0.501	0.520	1.420***	0.629	1.420***	1.754***
				(0.312)	(0.314)	(0.346)	(0.373)	(0.334)	(0.373)	(0.377)
lateround						-0.595***	-0.595***	-0.532***	-0.581***	-0.593***
						(0.0861)	(0.0861)	(0.0853)	(0.0864)	(0.0870)
earlyround						0.291***	0.291***	0.294***	0.306***	0.340***
						(0.0855)	(0.0855)	(0.0854)	(0.0862)	(0.0880)
treatment							-0.900**		-0.898**	-0.920**
							(0.337)		(0.337)	(0.343)
female								1.733***	1.747***	1.788***
								(0.392)	(0.395)	(0.386)
tietype2										-0.736***
										(0.153)
_cons	-0.920***	-0.282	-0.255	-0.282	-0.255	-0.122	-0.122	-1.920***	-1.874***	-2.044***
	(0.0359)	(0.216)	(0.211)	(0.216)	(0.211)	(0.224)	(0.224)	(0.452)	(0.454)	(0.450)
Fixed effects		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2065	1995	1995	1995	1995	1881	1881	1848	1848	1848
pseudo R^2	0.039	0.153	0.177	0.153	0.177	0.230	0.230	0.202	0.229	0.240
chi2	87.41	305.1	327.4	305.1	327.4	395.3	395.3	360.9	386.6	393.5
p	8.84e-21	1.34e-35	3.10e-39	1.34e-35	3.10e-39	7.25e-51	7.25e-51	2.46e-45	1.17e-49	1.60e-50

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 27: Regressions on number of changes made with tie as the independent variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	changes	changesm	changesm	changesm	changesm	changesm	changesm	changesm	changesm	changesm
tie	0.324**	0.294**	-0.187	0.294**	-0.187	-0.0518	-0.0518	0.350***	-0.0589	0.0445
	(0.109)	(0.106)	(0.151)	(0.106)	(0.151)	(0.128)	(0.128)	(0.102)	(0.130)	(0.114)
roundlost			1.161***		1.161***	0.978***	0.978***		0.989***	0.971***
			(0.219)		(0.219)	(0.182)	(0.182)		(0.185)	(0.183)
type2				0.877	0.725	0.674	1.795***	0.827	1.795***	1.912***
				(0.649)	(0.623)	(0.607)	(0.497)	(0.629)	(0.497)	(0.517)
lateround						-0.475***	-0.475***	-0.444***	-0.475***	-0.476***
						(0.0867)	(0.0867)	(0.0879)	(0.0881)	(0.0881)
earlyround						0.524***	0.524***	0.538***	0.537***	0.546***
						(0.133)	(0.133)	(0.138)	(0.135)	(0.136)
treatment							-1.121**		-1.122**	-1.118**
							(0.370)		(0.370)	(0.368)
female								1.594**	1.524**	1.547**
								(0.584)	(0.554)	(0.558)
tietype2										-0.275
										(0.255)
_cons	0.680***	1.197**	1.223***	1.197**	1.223***	1.190**	1.190**	-0.458	-0.335	-0.399
	(0.0585)	(0.367)	(0.352)	(0.367)	(0.352)	(0.367)	(0.367)	(0.698)	(0.667)	(0.672)
Fixed effects		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2065	2065	2065	2065	2065	1947	1947	1914	1914	1914
R^2	0.005	0.147	0.176	0.147	0.176	0.216	0.216	0.191	0.216	0.217
F	8.897	6.155	4.967	6.155	4.967	4.745	4.745	4.855	4.796	4.957
p	0.00289	7.74e-41	1.89e-30	7.74e-41	1.89e-30	4.60e-29	4.60e-29	3.15e-29	4.32e-29	5.45e-31

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Periode

1 von 1

Verbleibende Zeit [sec]: 74

LOYOLA MARYMOUNT UNIVERSITY

Experimental Subjects Bill of Rights

Pursuant to California Health and Safety Code §24172, I understand that I have the following rights as a participant in a research study:

1.I will be informed of the nature and purpose of the experiment.

2.I will be given an explanation of the procedures to be followed in the medical experiment, and any drug or device to be utilized.

3.I will be given a description of any attendant discomforts and risks to be reasonably expected from the study.

4.I will be given an explanation of any benefits to be expected from the study, if applicable.

5.I will be given a disclosure of any appropriate alternative procedures, drugs or devices that might be advantageous and their relative risks and benefits.

6.I will be informed of the avenues of medical treatment, if any, available after the study is completed if complications should arise.

7.I will be given an opportunity to ask any questions concerning the study or the procedures involved.

8.I will be instructed that consent to participate in the research study may be withdrawn at any time and that I may discontinue participation in the study without prejudice to me.

9.I will be given a copy of the signed and dated written consent form.

10.I will be given the opportunity to decide to consent or not to consent to the study without the intervention of any element of force, fraud, deceit, duress, coercion, or undue influence on my decision.

OK

You will receive compensation for participating in this experiment.

How would you like to be paid?

- Venmo;
- Physical Check;

Please enter either your Venmo username or a physical address where you would like a check mailed.

OK

Informed Consent

TITLE: Economic Decision-making with Uncertainty

INVESTIGATOR: Cameron Bellamoroso, Economics Department, Bellarmine College of Liberal Arts, 360-350-2433

ADVISOR:Dorothea Herreiner, Phd, Economics Department, Bellarmine College of Liberal Arts, 310-338-2815

RISKS: There are no significant risks associated with this study. There will be no deception at any point during the experiment, which will help minimize any potential risks.

PURPOSE: You are being asked to participate in a research project that investigates human decision making. You will be asked to anonymously answer a series of questions on your computer. Each task will be explained to you before you begin that section. These questions will consist of different choices based on information you receive during the experiment. At the end, several optional demographic questions will be asked. You will not be photographed or video-recorded in any way. The session will last a maximum of 50 minutes.

BENEFITS: The benefits of the study include earning money and becoming more aware of decision-making principles which may inspire more interest in the field.

INCENTIVES: The decisions you make will determine your earnings. A $5 show-up fee is guaranteed, and your decisions will determine any further earnings. You will be paid through Venmo or by a mailed check once the experiment finishes.

CONFIDENTIALITY: You will be asked to provide limited demographic data such as class year, major, gender, and a few self-defined characteristics. The data will be stored anonymously such that you cannot be connected to it in any way, and your name will never be used in any dissemination of this research. All physical research materials and consent forms will be stored in a safe in the economics department. Payment information contains names but is kept separately from all other data such that they are unconnectable. Electronic data will be stored on an encrypted pin drive scrubbed of participants' names. When the research study ends, any identifying information will be removed from the data, or it will be destroyed. All the information you provide will be kept confidential.

RIGHT TO WITHDRAW: Your participation in this study is completely voluntary. You may withdraw your consent to participate at any time without penalty. Your withdrawal will not influence any other services to which you may be otherwise entitled, your class standing, or relationship with Loyola Marymount University. Upon withdrawal, you will receive the $5 show-up fee, but forfeit any other payment you might have received. Should you disconnect for any reason, you will receive just the $5 show-up fee.

SUMMARY OF RESULTS: A summary of the results of this research will be supplied to you after the completion of all elements of the study, at no cost, upon request. Phone: 310-338-2815. Email: dherreiner@lmu.edu

VOLUNTARY CONSENT:I have read the above statements and understand what is being asked of me. I also understand that my participation is voluntary and that I am free to withdraw my consent at any time, for any reason, without penalty. If the study design or use of the information is changed I will be informed and my consent reobtained. On these terms, I certify that I am willing to participate in this research project.

I understand that if I have any further questions, comments or concerns about the study or theinformed consent process, I may contact Dr.

RISKS: There are no significant risks associated with this study. There will be no deception at any point during the experiment, which will help minimize any potential risks.

PURPOSE: You are being asked to participate in a research project that investigates human decision making. You will be asked to anonymously answer a series of questions on your computer. Each task will be explained to you before you begin that section. These questions will consist of different choices based on information you receive during the experiment. At the end, several optional demographic questions will be asked. You will not be photographed or video-recorded in any way. The session will last a maximum of 50 minutes.

BENEFITS: The benefits of the study include earning money and becoming more aware of decision-making principles which may inspire more interest in the field.

INCENTIVES: The decisions you make will determine your earnings. A $5 show-up fee is guaranteed, and your decisions will determine any further earnings. You will be paid through Venmo or by a mailed check once the experiment finishes.

CONFIDENTIALITY: You will be asked to provide limited demographic data such as class year, major, gender, and a few self-defined characteristics. The data will be stored anonymously such that you cannot be connected to it in any way, and your name will never be used in any dissemination of this research. All physical research materials and consent forms will be stored in a safe in the economics department. Payment information contains names but is kept separately from all other data such that they are unconnectable. Electronic data will be stored on an encrypted pin drive scrubbed of participants' names. When the research study ends, any identifying information will be removed from the data, or it will be destroyed. All the information you provide will be kept confidential.

RIGHT TO WITHDRAW: Your participation in this study is completely voluntary. You may withdraw your consent to participate at any time without penalty. Your withdrawal will not influence any other services to which you may be otherwise entitled, your class standing, or relationship with Loyola Marymount University. Upon withdrawal, you will receive the $5 show-up fee, but forfeit any other payment you might have received. Should you disconnect for any reason, you will receive just the $5 show-up fee.

SUMMARY OF RESULTS: A summary of the results of this research will be supplied to you after the completion of all elements of the study, at no cost, upon request. Phone: 310-338-2815. Email: dherreiner@lmu.edu

VOLUNTARY CONSENT:I have read the above statements and understand what is being asked of me. I also understand that my participation is voluntary and that I am free to withdraw my consent at any time, for any reason, without penalty. If the study design or use of the information is changed I will be informed and my consent reobtained. On these terms, I certify that I am willing to participate in this research project.

I understand that if I have any further questions, comments or concerns about the study or theinformed consent process, I may contact Dr. David Moffet, Chair, Institutional Review Board, Loyola Marymount University, 1 LMU Drive, Los Angeles, CA 90045-2659 or by email at David.Moffet@lmu.edu.

Please type your name into the space to confirm you have received this information.

Date:

OK

Period

1 Out of 3

Remaining time [sec]: 52

WELCOME to today's experiment.

Your participation is anonymous.

All information is going to be saved under anonymous ID numbers.

You will be paid once the experiment concludes. You will be asked again at the end of the experiment to supply payment information, so please do not disconnect before you complete that step.

You are guaranteed a 5$ show up fee that will be sent to the address you provided. You will receive additional earnings for your participation upon completion of the rest of the experiment.

Please, switch off or mute your cell phone and any other mobile device so that it will not be a distraction during the experiment.

We ask that you also refrain from tabbing out, changing programs, or otherwise having distractions present while you take the experiment.

If you disconnect for any reasons you will have a small time window in which you can still reconnect by returning to this webpage.

OK

Period

1 Out of 3

Remaining time [sec]: 119

In this experiment, your decisions will affect the amount of an experimental currency you earn. The experiment is played in a series of rounds. In each round you will be asked to rank a list of experimental currency payments using a 4-point scale (1-4) to indicate how much you prefer one payment relative to the others, with 4 being the best and 1 being the worst. There will be 17 payments to rank in each round; the values of those payments will not change between rounds. You may not proceed to the next round until each potential payment has been ranked.

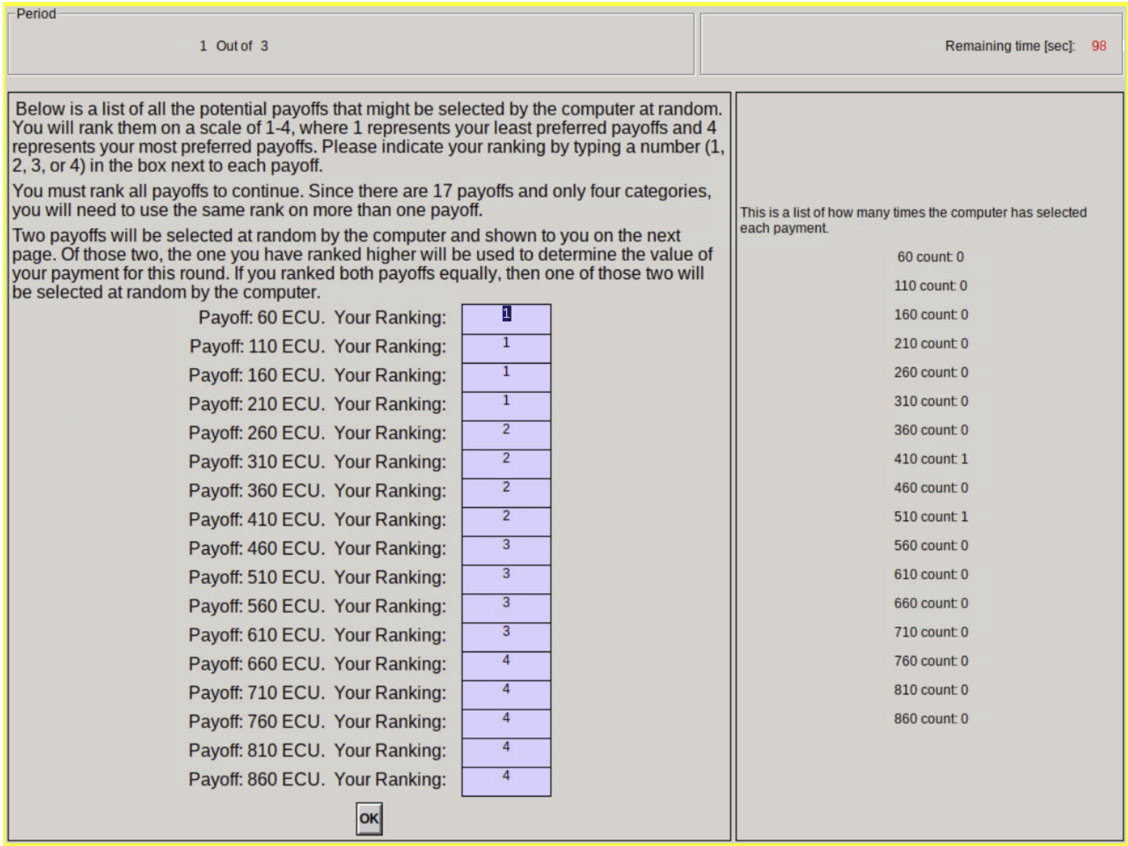
After you have submitted your rankings for each payment, two payments will be randomly selected by the computer. Your earnings in each round will be the payment that you had ranked highest of the two selected by the computer. If you had ranked the two selected payments equally, then the computer will randomly credit you with one of the payments before taking you to the next round.

At the start of each new round you will be shown the rankings you used in the immediately preceding round. You may choose to submit the same rankings in this new round as you did in the last round, or you may change your ranking for any or all of the payments. You will also be able to see how frequently each payment was selected by the computer up to that point in the experiment.

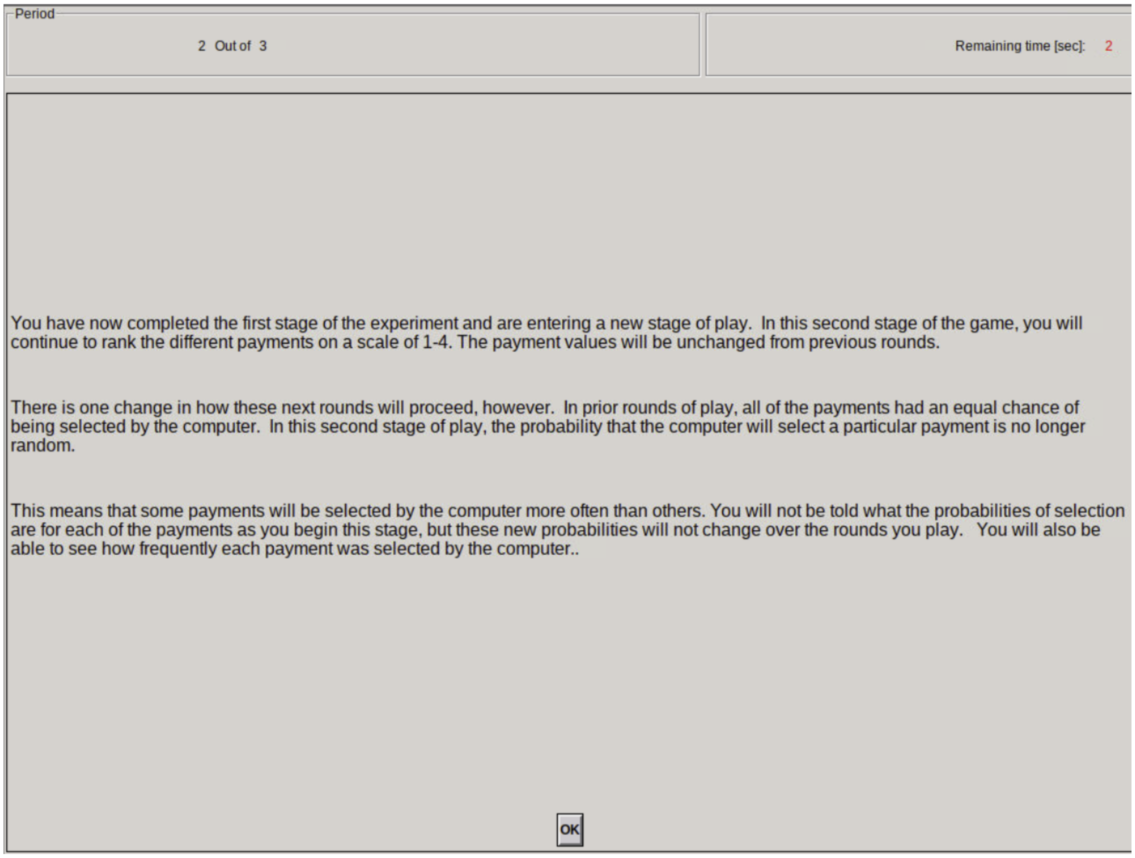
In the end, after all game rounds have been played, the program will randomly select four of your rounds and credit you with the sum of your earnings from those four rounds. Any four rounds might be selected.

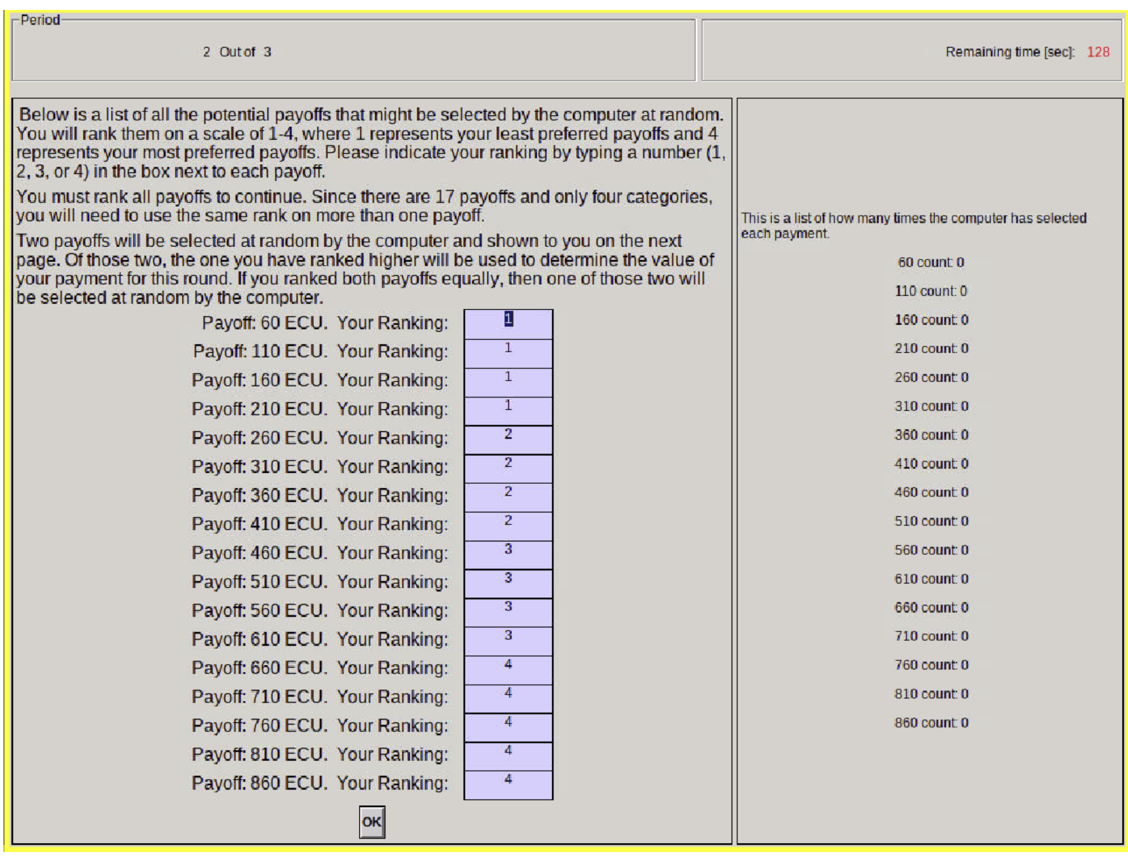
The experimental currency (ECU) converts to USD at a rate of 200 ECU/1 USD.

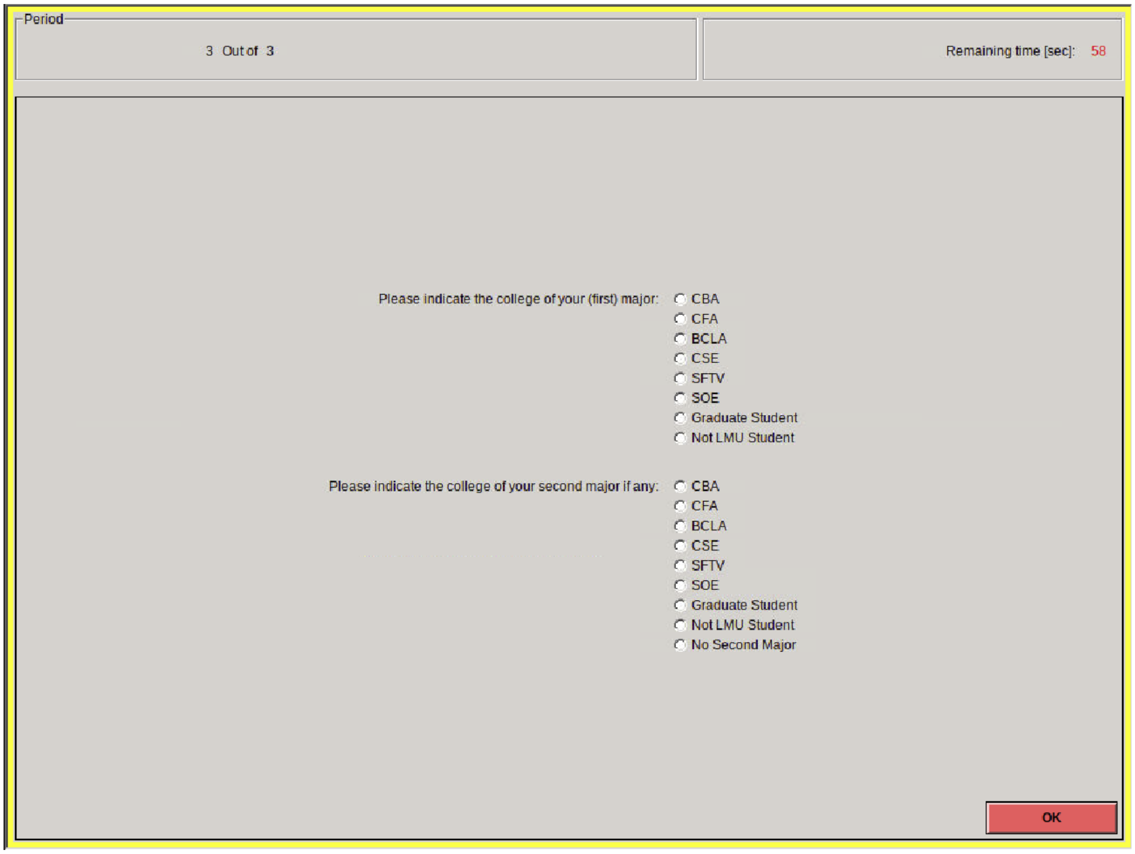
OK

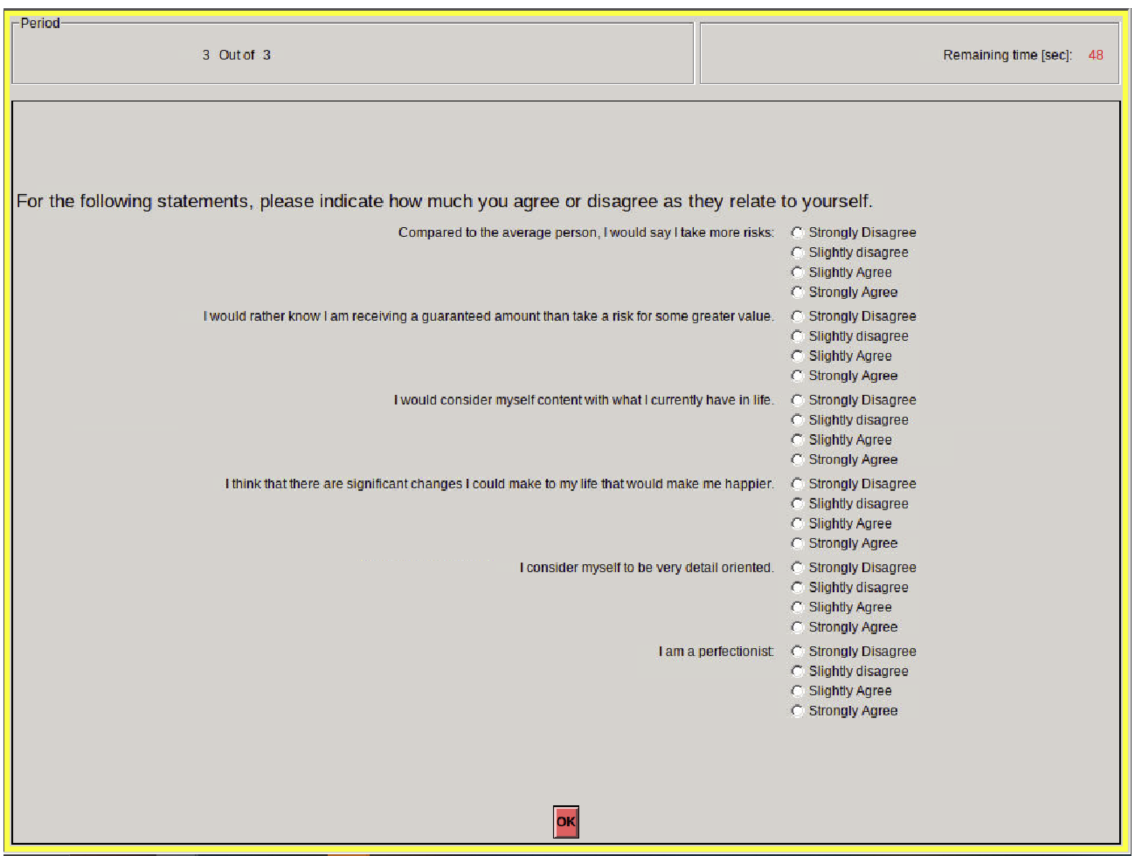

Period
1 Out of 3
Remaining time [sec]: 98
Below is a list of all the potential payoffs that might be selected by the computer at random. You will rank them on a scale of 1-4, where 1 represents your least preferred payoffs and 4 represents your most preferred payoffs. Please indicate your ranking by typing a number (1, 2, 3, or 4) in the box next to each payoff.
You must rank all payoffs to continue. Since there are 17 payoffs and only four categories, you will need to use the same rank on more than one payoff.
Two payoffs will be selected at random by the computer and shown to you on the next page. Of those two, the one you have ranked higher will be used to determine the value of your payment for this round. If you ranked both payoffs equally, then one of those two will be selected at random by the computer.
Payoff: 60 ECU. Your Ranking: 1
Payoff: 110 ECU. Your Ranking: 1
Payoff: 160 ECU. Your Ranking: 1
Payoff: 210 ECU. Your Ranking: 1
Payoff: 260 ECU. Your Ranking: 2
Payoff: 310 ECU. Your Ranking: 2
Payoff: 360 ECU. Your Ranking: 2
Payoff: 410 ECU. Your Ranking: 2
Payoff: 460 ECU. Your Ranking: 3
Payoff: 510 ECU. Your Ranking: 3
Payoff: 560 ECU. Your Ranking: 3
Payoff: 610 ECU. Your Ranking: 3
Payoff: 660 ECU. Your Ranking: 4
Payoff: 710 ECU. Your Ranking: 4
Payoff: 760 ECU. Your Ranking: 4
Payoff: 810 ECU. Your Ranking: 4
Payoff: 860 ECU. Your Ranking: 4
OK
This is a list of how many times the computer has selected each payment.
60 count: 0
110 count: 0
160 count: 0
210 count: 0
260 count: 0
310 count: 0
360 count: 0
410 count: 1
460 count: 0
510 count: 1
560 count: 0
610 count: 0
660 count: 0
710 count: 0
760 count: 0
810 count: 0
860 count: 0

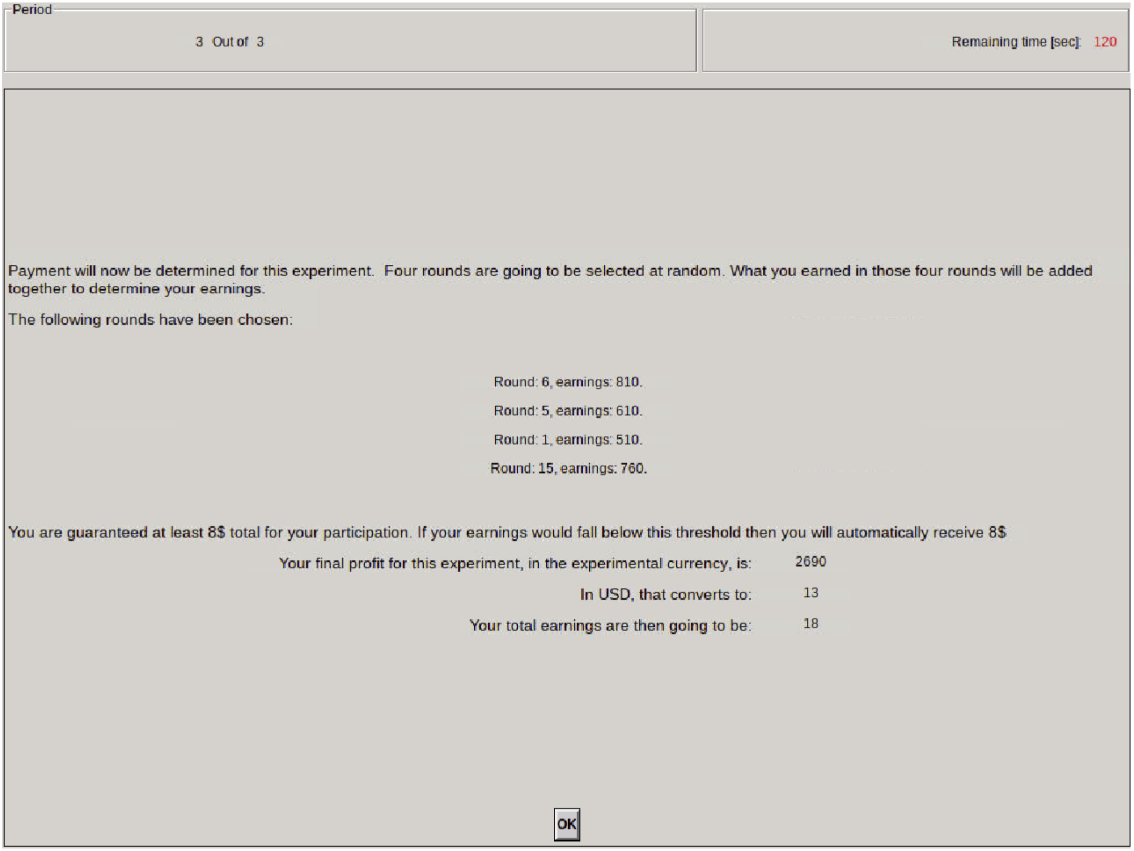

Period
1 Out of 3
Remaining time [sec]: 48
Please describe how you ranked the payoffs in the rounds.
What things did you consider while making your rankings?
(300 character limit)
OK

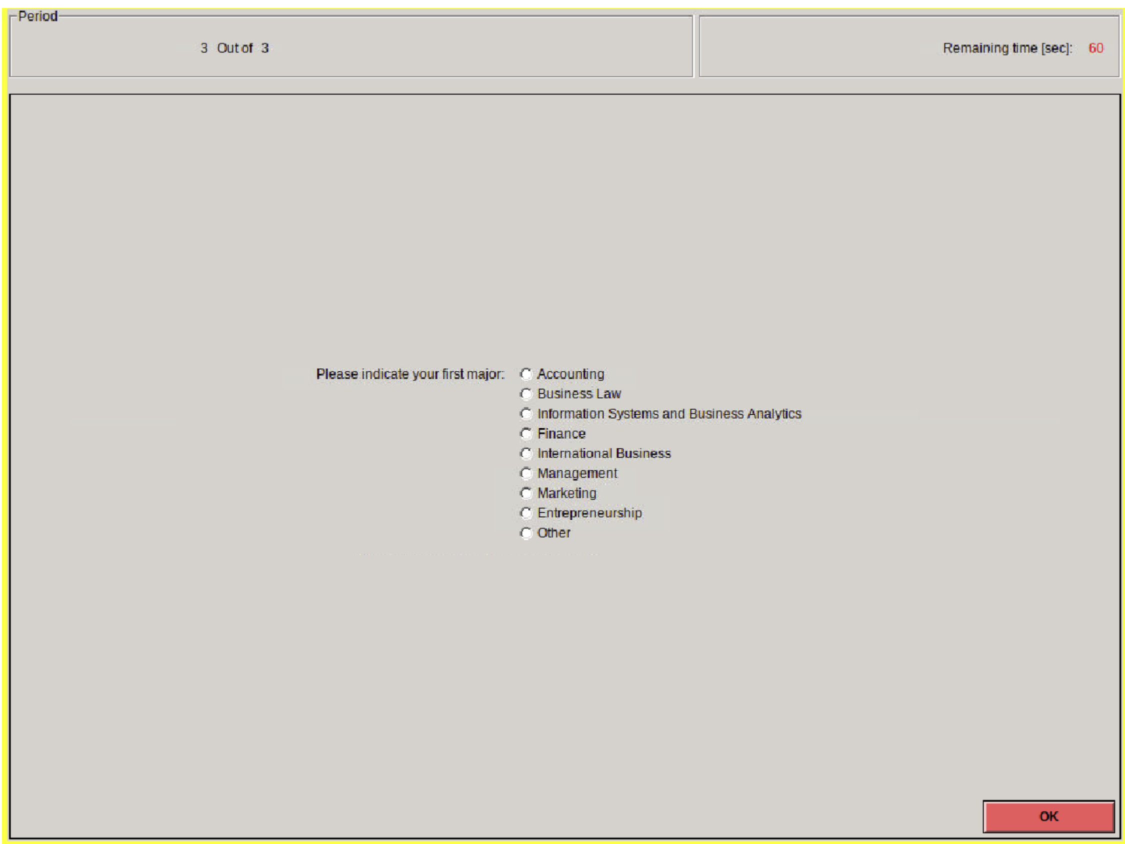

Period
2 Out of 3
Remaining time [sec]: 2
You have now completed the first stage of the experiment and are entering a new stage of play. In this second stage of the game, you will continue to rank the different payments on a scale of 1-4. The payment values will be unchanged from previous rounds.
There is one change in how these next rounds will proceed, however. In prior rounds of play, all of the payments had an equal chance of being selected by the computer. In this second stage of play, the probability that the computer will select a particular payment is no longer random.
This means that some payments will be selected by the computer more often than others. You will not be told what the probabilities of selection are for each of the payments as you begin this stage, but these new probabilities will not change over the rounds you play. You will also be able to see how frequently each payment was selected by the computer..
OK

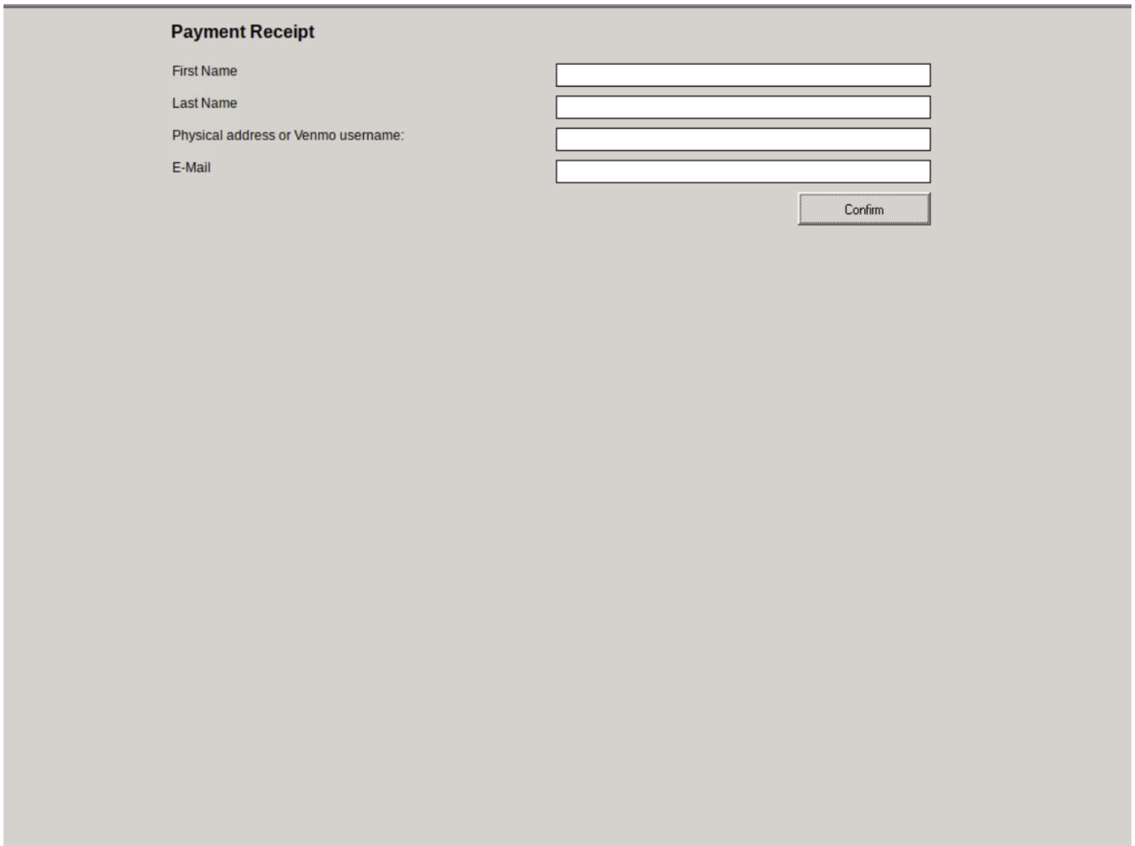

Period
2 Out of 3
Remaining time [sec]: 128
Below is a list of all the potential payoffs that might be selected by the computer at random. You will rank them on a scale of 1-4, where 1 represents your least preferred payoffs and 4 represents your most preferred payoffs. Please indicate your ranking by typing a number (1, 2, 3, or 4) in the box next to each payoff.
You must rank all payoffs to continue. Since there are 17 payoffs and only four categories, you will need to use the same rank on more than one payoff.
Two payoffs will be selected at random by the computer and shown to you on the next page. Of those two, the one you have ranked higher will be used to determine the value of your payment for this round. If you ranked both payoffs equally, then one of those two will be selected at random by the computer.
Payoff: 60 ECU. Your Ranking: 1
Payoff: 110 ECU. Your Ranking: 1
Payoff: 160 ECU. Your Ranking: 1
Payoff: 210 ECU. Your Ranking: 1
Payoff: 260 ECU. Your Ranking: 2
Payoff: 310 ECU. Your Ranking: 2
Payoff: 360 ECU. Your Ranking: 2
Payoff: 410 ECU. Your Ranking: 2
Payoff: 460 ECU. Your Ranking: 3
Payoff: 510 ECU. Your Ranking: 3
Payoff: 560 ECU. Your Ranking: 3
Payoff: 610 ECU. Your Ranking: 3
Payoff: 660 ECU. Your Ranking: 4
Payoff: 710 ECU. Your Ranking: 4
Payoff: 760 ECU. Your Ranking: 4
Payoff: 810 ECU. Your Ranking: 4
Payoff: 860 ECU. Your Ranking: 4
OK
This is a list of how many times the computer has selected each payment.
60 count: 0
110 count: 0
160 count: 0
210 count: 0
260 count: 0
310 count: 0
360 count: 0
410 count: 0
460 count: 0
510 count: 0
560 count: 0
610 count: 0
660 count: 0
710 count: 0
760 count: 0
810 count: 0
860 count: 0

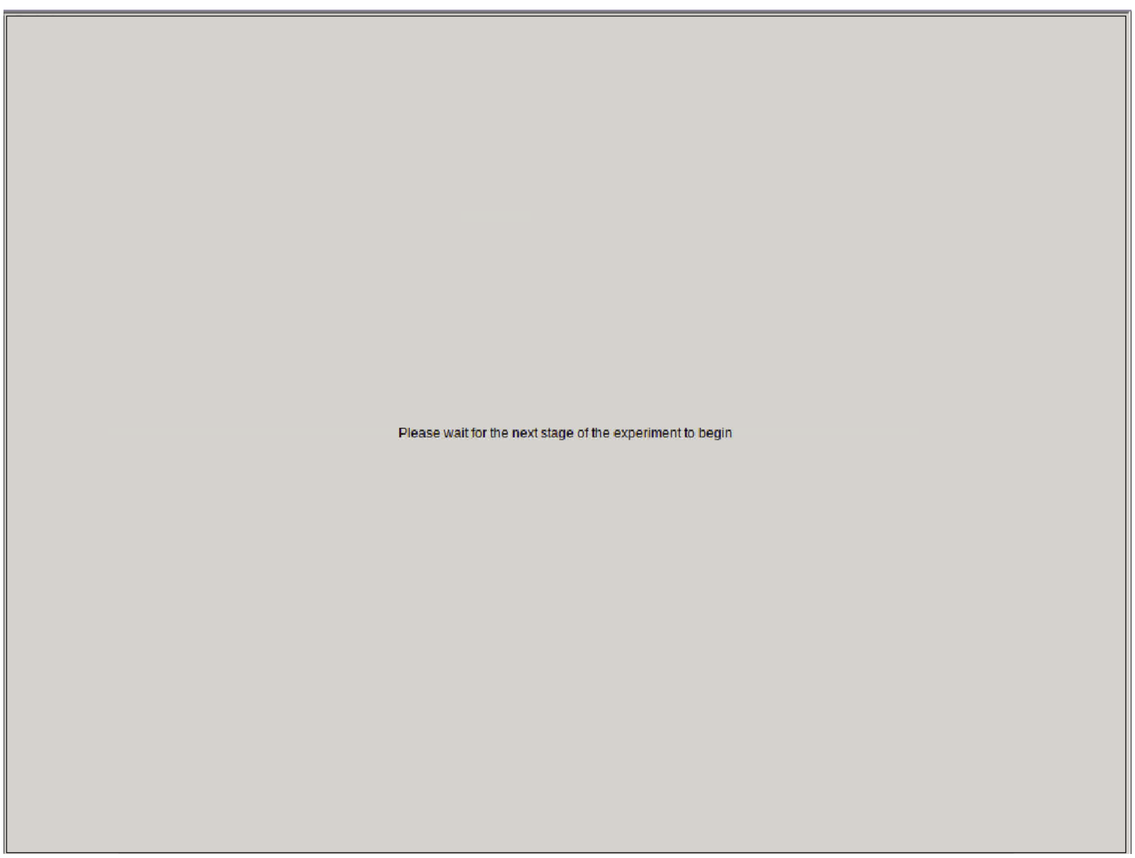

Period
3 Out of 3
Remaining time [sec]: 58
Please indicate the college of your (first) major:
CBA
CFA
BCLA
CSE
SFTV
SOE
Graduate Student
Not LMU Student
Please indicate the college of your second major if any:
CBA
CFA
BCLA
CSE
SFTV
SOE
Graduate Student
Not LMU Student
No Second Major
OK


Period
3 Out of 3
Remaining time [sec]: 48
For the following statements, please indicate how much you agree or disagree as they relate to yourself.
Compared to the average person, I would say I take more risks:
Strongly Disagree
Slightly disagree
Slightly Agree
Strongly Agree
I would rather know I am receiving a guaranteed amount than take a risk for some greater value.
Strongly Disagree
Slightly disagree
Slightly Agree
Strongly Agree
I would consider myself content with what I currently have in life.
Strongly Disagree
Slightly disagree
Slightly Agree
Strongly Agree
I think that there are significant changes I could make to my life that would make me happier.
Strongly Disagree
Slightly disagree
Slightly Agree
Strongly Agree
I consider myself to be very detail oriented.
Strongly Disagree
Slightly disagree
Slightly Agree
Strongly Agree
I am a perfectionist.
Strongly Disagree
Slightly disagree
Slightly Agree
Strongly Agree
OK


Period
3 Out of 3
Remaining time [sec]: 120
Payment will now be determined for this experiment. Four rounds are going to be selected at random. What you earned in those four rounds will be added together to determine your earnings.
The following rounds have been chosen:
Round: 6, earnings: 810.
Round: 5, earnings: 610.
Round: 1, earnings: 510.
Round: 15, earnings: 760.
You are guaranteed at least 8$ total for your participation. If your earnings would fall below this threshold then you will automatically receive 8$
Your final profit for this experiment, in the experimental currency, is: 2690
In USD, that converts to: 13
Your total earnings are then going to be: 18
OK


Period
3 Out of 3
Remaining time [sec]: 60
Please indicate your first major:
Accounting
Business Law
Information Systems and Business Analytics
Finance
International Business
Management
Marketing
Entrepreneurship
Other
OK


Payment Receipt
First Name
Last Name
Physical address or Venmo username:
E-Mail
Confirm


Please wait for the next stage of the experiment to begin

```
cap log close
clear

*********Appendix B
*********Do-file 1: summarizing statistics and initial organization

**** Cameron Bellamoroso
**** 9/18/2020
**** Senior Thesis

*This file cleans the data, generates new variables, and runs preliminary summary
*statistics and regressions. At the end it creates the data set used by do-file 2.

cd "D:\Work\Thesis\Data\Analysiscd"
log using ThesisAnalysis.txt, replace
use Datamaster_rebuilt1

**note that round 11 was skipped on accident in the code, and round 34 is then overwritten, meaning data from this round was manually repopulated using the GSF files from each experiment.

***Dropping useless variables:
cap drop Period
cap drop Group
cap drop test1
cap drop test2
cap drop test3

***Generating new useful variables

* Tie[period] is 1 if a tie occurred
forval k = 1/35{

cap drop tie`k'
gen tie`k' = 0
replace tie`k'=1 if tier1`k'==tier2`k'
local j=`k'+1
gen prevtie`j'=0
replace prevtie`j'=1 if tier1`k'==tier2`k'
}



* Earnings captured:
gen earnings = roundpay1+roundpay2+roundpay3+roundpay4+roundpay5+roundpay6+roundpay7+roundpay8+roundpay9+roundpay10+roundpay11+roundpay12+roundpay13+roundpay14+roundpay15+roundpay16+roundpay17+roundpay18+roundpay19+roundpay20+roundpay21+roundpay22+roundpay23+roundpay24+roundpay25+roundpay26+roundpay27+roundpay28+roundpay29+roundpay30+roundpay31+roundpay32+roundpay33+roundpay34+roundpay35
gen maxearnings = 0
forval i = 1/35{
replace maxearnings=maxearnings+activevar1`i' if activevar1`i'>activevar2`i'
replace maxearnings=maxearnings+activevar2`i' if activevar1`i'<activevar2`i'
}


cap drop endgameearnings
cap drop earningshare
cap drop earlygameearnings
cap drop endgamemax
cap drop earlygamemax
gen earningshare = earnings/maxearnings
gen endgameearnings = 0
gen earlygameearnings = 0
gen endgamemax=0
gen earlygamemax=0

forval i = 11/20{
replace earlygameearnings = earlygameearnings + roundpay`i'
replace earlygamemax=earlygamemax+activevar1`i' if activevar1`i'>activevar2`i'
```

```
replace earlygamemax=earlygamemax+activevar2`i' if activevar1`i'<activevar2`i'
}
forval i = 26/35{
replace endgameearnings = endgameearnings + roundpay`i'
replace endgamemax=endgamemax+activevar1`i' if activevar1`i'>activevar2`i'
replace endgamemax=endgamemax+activevar2`i' if activevar1`i'<activevar2`i'
}
replace earlygameearnings = earlygameearnings/earlygamemax
replace endgameearnings = endgameearnings/endgamemax

** dummy for losing the previous round

forval i=2/35{
gen lostround`i'=0
local j=`i'-1
replace lostround`i'=1 if activevar1`j'>=roundpay`j' & activevar2`j'>=roundpay`j'
}

*Generate changestrategy which logs how many changes people make in their rankings each round

forval i = 2/35{
cap drop rankingchanges`i'
gen rankingchanges`i'=0
local k = `i'-1
foreach j in A B C D E F G H I J K L M N O P Q{
replace rankingchanges`i'=rankingchanges`i'+1 if `j'Tier`i'!=`j'Tier`k'
}
}
*Creating a variable that shows the average number of times a person changes rank
gen avgrankchange_pretreat=0
forval i = 2/10{
replace avgrankchange_pretreat = avgrankchange_pretreat + rankingchanges`i'
}
replace avgrankchange_pretreat = avgrankchange_pretreat/9

gen avgrankchange_posttreat=0
forval i = 11/35{
replace avgrankchange_posttreat = avgrankchange_posttreat + rankingchanges`i'
}
replace avgrankchange_posttreat = avgrankchange_posttreat/25

*Generating a variable that counts how many payoffs have been given each ranking per round

forval i = 1/35{
cap drop binsize1`i'
cap drop binsize2`i'
cap drop binsize3`i'
cap drop binsize4`i'
gen binsize1`i'=0
gen binsize2`i'=0
gen binsize3`i'=0
gen binsize4`i'=0
foreach j in A B C D E F G H I J K L M N O P Q{
replace binsize1`i'=binsize1`i'+1 if `j'Tier`i'==1
replace binsize2`i'=binsize2`i'+1 if `j'Tier`i'==2
replace binsize3`i'=binsize3`i'+1 if `j'Tier`i'==3
replace binsize4`i'=binsize4`i'+1 if `j'Tier`i'==4
}
}



*Trying to identify types of players:
cap drop playtype
gen playtype=0

** coutning how many rounds of irrational play occur
cap drop irrationalroundcount
gen irrationalroundcount = 1
gen irrationalround1=0
```

```
forval i = 2/35{
gen irrationalround`i'=0
replace irrationalroundcount = irrationalroundcount+1 if ATier`i'>BTier`i' | BTier`i'>CTier`i'| CTier`i'>DTier`i' | DTier`i'>ETier`i' | ETier`i'>FTier`i' | FTier`i'>GTier`i' | GTier`i'>HTier`i' | HTier`i'>ITier`i' | ITier`i'>JTier`i'|JTier`i'>KTier`i' | KTier`i'>LTier`i' | LTier`i'>MTier`i'| MTier`i'>NTier`i' | NTier`i'>OTier`i' | OTier`i'>PTier`i' | PTier`i'>QTier`i'
replace irrationalround`i'=1 if ATier`i'>BTier`i' | BTier`i'>CTier`i'| CTier`i'>DTier`i' | DTier`i'>ETier`i' | ETier`i'>FTier`i' | FTier`i'>GTier`i' | GTier`i'>HTier`i' | HTier`i'>ITier`i' | ITier`i'>JTier`i'|JTier`i'>KTier`i' | KTier`i'>LTier`i' |LTier`i'>MTier`i'| MTier`i'>NTier`i' | NTier`i'>OTier`i' | OTier`i'>PTier`i' | PTier`i'>QTier`i'
}


* type 1 if the person always has a rational ranking system -- no reversals. Indicates a theoretical understanding of the game.
replace playtype=1 if irrationalroundcount<4

* Type 3s are excluded from many of the regressions -- they exhibit a lack of understanding and adaptation to the game throughout all rounds.  They are defined by having their lowest payoff ranked highly and their highest payoff ranked low in late rounds of the experiment.

replace playtype=3 if ATier35>1 & Treatment == 0

replace playtype=3 if QTier35 <4 & Treatment == 1

*reassigning outliers based on data trends and responses in chat
replace playtype=3 if avgrankchange_posttreat>9


*type 2 plays doesn't play universally rationally but does adapt and learn over the course of the game, either reaching a rational ranking or showing signs of responding to the trial and error approach.
replace playtype=2 if playtype==0



** general info:
replace sex = . if sex==0
replace ethnic = . if ethnic==0
replace age = . if age==0





*************************************************************

***Summarizing statistics




**looking at earnings based on player types
sum earlygameearnings if playtype==1
sum earlygameearnings if playtype==2
sum endgameearnings if playtype==1
sum endgameearnings if playtype==2
*note no difference seems significant


* generating a matrix that has the average rankings for each payoff in rounds 1-10
* The two tables seperate the player types
matrix pretreatsum1 = J(17,10,.)
matrix pretreatsum2 = J(17,10,.)
{
local col = 1
foreach i in 1 2 3 4 5 6 7 8 9 10{
local row = 1
foreach j in A B C D E F G H I J K L M N O P Q{
```

```
summarize `j'Tier`i' if playtype==1
mat pretreatsum1[`row',`col'] = r(median)
summarize `j'Tier`i' if playtype==2
mat pretreatsum2 [`row', `col'] = r(median)
local row = `row' + 1
}
local col = `col' + 1
}
matrix rownames pretreatsum1 = 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17
matrix colnames pretreatsum1 = r1 r2 r3 r4 r5 r6 r7 r8 r9 r10
matrix rownames pretreatsum2 = 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17
matrix colnames pretreatsum2 = r1 r2 r3 r4 r5 r6 r7 r8 r9 r10
}

* Generating tables that show the behavior in posttreatment rounds between playertypes and treatment groups.
{
matrix posttreatsum1_treat1 = J(17,35,.)
matrix posttreatsum2_treat1 = J(17,35,.)
matrix posttreatsum1_treat0 = J(17,35,.)
matrix posttreatsum2_treat0 = J(17,35,.)

local col = 1
forval i = 1/35{
local row = 1
foreach j in A B C D E F G H I J K L M N O P Q{
summarize `j'Tier`i' if Treatment & playtype==1, detail
mat posttreatsum1_treat1[`row',`col'] = r(mean)

summarize `j'Tier`i' if Treatment & playtype==2, detail
mat posttreatsum2_treat1[`row',`col'] = r(mean)

summarize `j'Tier`i' if !Treatment & playtype==1, detail
mat posttreatsum1_treat0[`row',`col'] = r(mean)

summarize `j'Tier`i' if !Treatment & playtype==2, detail
mat posttreatsum2_treat0[`row',`col'] = r(mean)

local row = `row' + 1
}
local col = `col' + 1
}

matrix rownames posttreatsum1_treat0 = 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17
matrix colnames posttreatsum1_treat0 = r1 r2 r3 r4 r5 r6 r7 r8 r9 r10 r11 r12 r13 r14 r15 r16 r17 r18 r19 r20 r21 r22 r23 r24 r25 r26 r27 r28 r29 r30 r31 r32 r33 r34 r35

matrix rownames posttreatsum1_treat1 = 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17
matrix colnames posttreatsum1_treat1 = r1 r2 r3 r4 r5 r6 r7 r8 r9 r10 r11 r12 r13 r14 r15 r16 r17 r18 r19 r20 r21 r22 r23 r24 r25 r26 r27 r28 r29 r30 r31 r32 r33 r34 r35

matrix rownames posttreatsum2_treat0 = 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17
matrix colnames posttreatsum2_treat0 = r1 r2 r3 r4 r5 r6 r7 r8 r9 r10 r11 r12 r13 r14 r15 r16 r17 r18 r19 r20 r21 r22 r23 r24 r25 r26 r27 r28 r29 r30 r31 r32 r33 r34 r35

matrix rownames posttreatsum2_treat1 = 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17
matrix colnames posttreatsum2_treat1 = r1 r2 r3 r4 r5 r6 r7 r8 r9 r10 r11 r12 r13 r14 r15 r16 r17 r18 r19 r20 r21 r22 r23 r24 r25 r26 r27 r28 r29 r30 r31 r32 r33 r34 r35
}

matrix posttreatmed1_treat1 = J(17,35,.)
```

```
matrix posttreatmed2_treat1 = J(17,35,.)
matrix posttreatmed1_treat0 = J(17,35,.)
matrix posttreatmed2_treat0 = J(17,35,.)

* Trying this again with medians
local col = 1

forval i=1/35{
local row = 1
foreach j in A B C D E F G H I J K L M N O P Q{
sort  Treatment playtype `j'Tier`i'

mat posttreatmed1_treat1[`row',`col'] = `j'Tier`i'[45]
mat posttreatmed1_treat0[`row',`col'] = `j'Tier`i'[10]
mat posttreatmed2_treat0[`row',`col'] = ((`j'Tier`i'[25]+`j'Tier`i'[26])/2)
mat posttreatmed2_treat1[`row',`col'] = `j'Tier`i'[59]
local row = `row'+1
}
local col= `col'+1
}
{
matrix rownames posttreatmed1_treat0 = 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17
matrix colnames posttreatmed1_treat0 = r1 r2 r3 r4 r5 r6 r7 r8 r9 r10 r11 r12 r13 r14 r15 r16 r17 r18 r19 r20 r21 r22 r23 r24 r25 r26 r27 r28 r29 r30 r31 r32 r33 r34 r35

matrix rownames posttreatmed1_treat1 = 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17
matrix colnames posttreatmed1_treat1 = r1 r2 r3 r4 r5 r6 r7 r8 r9 r10 r11 r12 r13 r14 r15 r16 r17 r18 r19 r20 r21 r22 r23 r24 r25 r26 r27 r28 r29 r30 r31 r32 r33 r34 r35

matrix rownames posttreatmed2_treat0 = 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17
matrix colnames posttreatmed2_treat0 = r1 r2 r3 r4 r5 r6 r7 r8 r9 r10 r11 r12 r13 r14 r15 r16 r17 r18 r19 r20 r21 r22 r23 r24 r25 r26 r27 r28 r29 r30 r31 r32 r33 r34 r35

matrix rownames posttreatmed2_treat1 = 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17
matrix colnames posttreatmed2_treat1 = r1 r2 r3 r4 r5 r6 r7 r8 r9 r10 r11 r12 r13 r14 r15 r16 r17 r18 r19 r20 r21 r22 r23 r24 r25 r26 r27 r28 r29 r30 r31 r32 r33 r34 r35
}
esttab matrix(posttreatmed1_treat1, fmt(%8.2g)) using treat1rankmed_type1.xls, title(Median Rankings) replace
esttab matrix(posttreatmed2_treat1, fmt(%8.2g)) using treat1rankmed_type2.xls, title(Median rankings) replace
esttab matrix(posttreatmed1_treat0, fmt(%8.2g)) using treat0rankmed_type1.xls, title(Median rankings) replace
esttab matrix(posttreatmed2_treat0, fmt(%8.2g)) using treat0rankmed_type2.xls, title(Median rankings) replace

** listing out the summary matrices

** making a matrix to summarize how many times people change rankings per round on average
matrix rankingchanges_pretreat = J(4,9,.)
gen avgrankchange110=0
local col = 1
foreach i in 2 3 4 5 6 7 8 9 10{
local row = 1
replace avgrankchange110=avgrankchange110+rankingchanges`i'
foreach j in 1 2{
summarize rankingchanges`i' if playtype==`j'
mat rankingchanges_pretreat[`row',`col'] = r(mean)
local row = `row' + 1
mat rankingchanges_pretreat[`row',`col'] = r(sd)
local row = `row'+1
}
local col = `col' + 1
}
```

```
replace avgrankchange110=avgrankchange110/9
matrix rownames rankingchanges_pretreat = Type1_mean Type1_sd Type2_mean Type2_sd
matrix colnames rankingchanges_pretreat = r2 r3 r4 r5 r6 r7 r8 r9 r10
gen avgrankchange1124=0
gen avgrankchange2535=0
matrix rankingchanges_posttreat = J(4,25,.)
local col = 1
forval i = 11/35{
local row = 1
replace avgrankchange1124=avgrankchange1124+rankingchanges`i' if `i'<25
replace avgrankchange2535=avgrankchange2535+rankingchanges`i' if `i'>24
foreach j in 1 2{
summarize rankingchanges`i' if playtype==`j'
mat rankingchanges_posttreat[`row',`col'] = r(mean)
local row = `row' + 1
mat rankingchanges_posttreat[`row',`col'] = r(sd)
local row = `row' + 1
}
local col = `col' + 1
}
replace avgrankchange1124=avgrankchange1124/14
replace avgrankchange2535=avgrankchange2535/11
matrix rownames rankingchanges_posttreat = Type1_mean Type1_sd Type2_mean Type2_sd
matrix colnames rankingchanges_posttreat = r11 r12 r13 r14 r15 r16 r17 r18 r19 r20 r21 r22
r23 r24 r25 r26 r27 r28 r29 r30 r31 r32 r33 r34 r35

matrix list pretreatsum1, format(%8.2f)
matrix list pretreatsum2, format(%8.2f)

matrix list posttreatsum1_treat1, format(%8.2f)
matrix list posttreatsum2_treat1, format(%8.2f)
matrix list posttreatsum1_treat0, format(%8.2f)
matrix list posttreatsum2_treat0, format(%8.2f)
matrix list rankingchanges_pretreat, format(%8.2f)
matrix list rankingchanges_posttreat, format(%8.2f)

ttest avgrankchange110==avgrankchange1124
ttest avgrankchange2535==avgrankchange1124
ttest avgrankchange110==avgrankchange2535

tab age
tab sex
tab ethnic

tab cfirstmajor
tab firstmajor
tab secondmajor

tab avgrankchange_posttreat playtype

tab sex playtype, exact
tab sex cfirstmajor, exact
tab cfirstmajor playtype, exact











esttab matrix(rankingchanges_pretreat, fmt(%8.2g)) using rankchange_pretreat.tex, title(
Pretreatment rankings) replace
esttab matrix(rankingchanges_posttreat, fmt(%8.2g)) using rankchange_posttreat.tex, title(
Pretreatment rankings) replace

esttab matrix(pretreatsum1, fmt(%8.2g)) using pretreatranksummary1.xls, title(Pretreatment
rankings for type 1) replace
```

```
esttab matrix(pretreatsum2, fmt(%8.2g)) using pretreatranksummary2.xls, title(Pretreatment rankings for type 2) replace


esttab matrix(posttreatsum1_treat1, fmt(%8.2g)) using treat1ranksum_type1.xls, title(Pretreatment rankings) replace
esttab matrix(posttreatsum2_treat1, fmt(%8.2g)) using treat1ranksum_type2.xls, title(Pretreatment rankings) replace
esttab matrix(posttreatsum1_treat0, fmt(%8.2g)) using treat0ranksum_type1.xls, title(Pretreatment rankings) replace
esttab matrix(posttreatsum2_treat0, fmt(%8.2g)) using treat0ranksum_type2.xls, title(Pretreatment rankings) replace



save "D:\Work\Thesis\Data\Analysiscd\Thesisdata2.dta", replace
```

```
cap log close
clear

*********Appendix B
*********Do-file 2: transposing data

**** Cameron Bellamoroso
**** 9/18/2020
**** Senior Thesis

*This file transposes the data to prepare it for fixed effects regressions and continues to sort and organize some variables. At
*the end it creates the data file called "Thesisdata3", which is used in do-file 3

cd "D:\Work\Thesis\Data\Analysiscd"
log using Thesisregressions.txt, replace
use Thesisdata2



** Making the data suitable to run the fixed effects regressions

gen id = _n
expand=35
sort id

set obs 2275
egen round = fill(1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35)

** this generates new variables as destinations as I transpose
foreach i in A B C D E F G H I J K L M N O P Q{
gen rank`i'=-1
gen selectedcount`i'=-1
}
gen roundearnings=-1
gen selectedpayoff1=-1
gen selectedpayoff2=-1
gen tieoccurs=-1
gen changesmade=-1
gen category1size=-1
gen category2size=-1
gen category3size=-1
gen category4size=-1
gen timerankround=-1
gen timepayround=-1
gen prevtieoccurs=-1
gen roundlost=-1
gen irraround=-1

** Moves all variables into columns instead of rows
gen rankingchanges1=0
forval i = 1/35{

foreach j in A B C D E F G H I J K L M N O P Q{
replace rank`j'=`j'Tier`i' if round==`i'
replace selectedcount`j'=`j'count`i' if round==`i'
}
replace roundearnings=roundpay`i' if round==`i'
replace selectedpayoff1=activevar1`i' if round==`i'
replace selectedpayoff2=activevar2`i' if round==`i'
replace tieoccurs=tie`i' if round==`i'
local j=`i'+1
replace prevtieoccurs=prevtie`j' if round==`j'
replace changesmade=rankingchanges`i' if round==`i'
replace category1size=binsize1`i' if round==`i'
replace category2size=binsize2`i' if round==`i'
replace category3size=binsize3`i' if round==`i'
replace category4size=binsize4`i' if round==`i'
```

```
replace irraround=irrationalround`i' if round==`i'
if `i'!=1{
replace roundlost=lostround`i' if round==`i'
}
}
replace prevtieoccurs=0 if round==1
replace roundlost=0 if round==1
forval i=1/10{
replace timerankround=TimeOKRankingRound`i'OK if round==`i'
replace timepayround=TimeOKRankingRound`i'OK if round==`i'
}
forval i=1/25{
replace timerankround=TimeOKTreatrank`i'OK if round==`i'
replace timepayround=TimeOKTreatpay`i'OK if round==`i'
}


** drops all the old variables
forval i=1/35{
foreach j in A B C D E F G H I J K L M N O P Q{
cap drop `j'Tier`i'
cap drop `j'count`i'
}
cap drop roundpay`i'
cap drop activevar`i'
cap drop activevar1`i'
cap drop activevar2`i'
cap drop tie`i'
cap drop rankingchanges`i'
cap drop binsize1`i'
cap drop binsize2`i'
cap drop binsize3`i'
cap drop binsize4`i'
cap drop tier1`i'
cap drop tier2`i'
cap drop TimeOKRankingRound`i'OK
cap drop TimeOKPayingRound`i'OK
cap drop TimeOKTreatrank`i'OK
cap drop TimeOKTreatpay`i'OK
cap drop prevtie`i'
cap drop irrationalround`i'
cap drop lostround`i'
}
cap drop A
rename tieoccurs tie


** generating a variable for the probabilities in treatment

gen treatpA = .004 if Treatment==1
gen treatpB = .005 if Treatment==1
gen treatpC = .006 if Treatment==1
gen treatpD = .007 if Treatment==1
gen treatpE = .009 if Treatment==1
gen treatpF = .012 if Treatment==1
gen treatpG = .014 if Treatment==1
gen treatpH = .017 if Treatment==1
gen treatpI = .021 if Treatment==1
gen treatpJ = .028 if Treatment==1
gen treatpK = .035 if Treatment==1
gen treatpL = .05 if Treatment==1
gen treatpM = .075 if Treatment==1
gen treatpN = .11 if Treatment==1
gen treatpO = .152 if Treatment==1
gen treatpP = .2 if Treatment==1
gen treatpQ = .255 if Treatment==1

replace treatpA = .255 if Treatment==0
replace treatpB = .2 if Treatment==0
replace treatpC = .152 if Treatment==0
```

```
replace treatpD = .11 if Treatment==0
replace treatpE = .075 if Treatment==0
replace treatpF = .05 if Treatment==0
replace treatpG = .035 if Treatment==0
replace treatpH = .028 if Treatment==0
replace treatpI = .021 if Treatment==0
replace treatpJ = .017 if Treatment==0
replace treatpK = .014 if Treatment==0
replace treatpL = .012 if Treatment==0
replace treatpM = .009 if Treatment==0
replace treatpN = .007 if Treatment==0
replace treatpO = .006 if Treatment==0
replace treatpP = .005 if Treatment==0
replace treatpQ = .004 if Treatment==0

gen pretreatp = 1/17

** generating the values of payoffs:
local i = 0
foreach j in A B C D E F G H I J K L M N O P Q{
gen `j'val = 0
replace `j'val = 60+50*`i'
local i = `i'+1
}

cap drop expectedutility
** generating a new variable to capture expected utility
gen expectedutility = 0
* each letter corresponds to a different payoff -- A is the lowest, Q the highest
foreach j in A B C D E F G H I J K L M N O P Q{
foreach i in A B C D E F G H I J K L M N O P Q{
** generate a local for whether a payoff combo has been used so far -- later we will make sure that payoffs are only used once in the sum
if `i'val != `j'val{
** these are the sum terms that check to see the ranking relationship that is present
** each if statement corresponds to a different possible state for each pair of rankings, then adds the sum
** rank`j' is the ranking a person assigned to payoff `j' in each given round
** treatp`i' is the probability of payment `i' to be chosen
** `i'val is the value of payoff `i'
replace expectedutility = expectedutility + (treatp`i'*treatp`j'/(1-treatp`i')*(`i'val+`j'val)/2) if rank`j'==rank`i'
replace expectedutility = expectedutility + (treatp`i'*treatp`j'/(1-treatp`i')*`j'val) if rank`j'>rank`i'
replace expectedutility = expectedutility + (treatp`i'*treatp`j'/(1-treatp`i')*`i'val) if rank`j'<rank`i'
** this records which pair was just used
** end of if "do" loop

** end of loop that checks if its the same payoff twice
}
** end of i loop
}
** end of j loop
}



** now repeated for the pretreatment rounds:
replace expectedutility=0 if round<11
foreach j in A B C D E F G H I J K L M N O P Q{
foreach i in A B C D E F G H I J K L M N O P Q{

** generate a local for whether a payoff combo has been used so far -- later we will make sure that payoffs are only used once in the sum
if `i'val !=`j'val{

** these are the sum terms that check to see the ranking relationship that is present
** each if statement corresponds to a different possible state for each pair of rankings, then adds the sum
```

```
** rank`j' is the ranking a person assigned to payoff `j' in each given round
** pretreatp is the probability of payment `i' to be chosen
** `i'val is the value of payoff `i'
replace expectedutility = expectedutility + (pretreatp*1/16*(`i'val+`j'val)/2) if rank`j'== rank`i' & round<11
replace expectedutility = expectedutility + (pretreatp*1/16*`j'val) if rank`j'>rank`i' & round<11
replace expectedutility = expectedutility + (pretreatp*1/16*`i'val) if rank`j'<rank`i' & round<11
** this records which pair was just used

** end of loop that checks if its the same pair twice
}
** end of i loop
}
** end of j loop
}
** note that maximum payout value for the high treatment is
** max payout low treatment is 295.6068
** max payout high treatment is 798.8611
** max pretreatment is 600.8091


* just fixing variable names to be more readable
cap drop tie
rename prevtieoccurs tie

*Turning everything into dummy variables
rename sex female
replace female=female-1


** generates round dummies divided 10 10 15
gen lateround=0
gen earlyround=0
replace lateround=1 if round>23
replace earlyround=1 if round<11

** Dummy for race/ethnicity
gen white=0
replace white=1 if ethnic==3
gen asian=0
replace asian=1 if ethnic==2
gen black=0
replace black=1 if ethnic==1
gen raceother=0
replace raceother=1 if ethnic>5
gen hispanic=0
replace hispanic=1 if ethnic==4
gen natamerican=0
replace natamerican=1 if ethnic==5

** dummies for school at lmu
gen CBA=0
replace CBA=1 if cfirstmajor==1|csecondmajor==1
gen CFA=0
replace CFA=1 if cfirstmajor==2|csecondmajor==2
gen BCLA=0
replace BCLA=1 if cfirstmajor==3|csecondmajor==3
gen CSE=0
replace CSE=1 if cfirstmajor==4|csecondmajor==4
gen SFTV=0
replace SFTV=1 if cfirstmajor==5|csecondmajor==5
gen SOE=0
replace SOE=1 if cfirstmajor==6|csecondmajor==6
gen othereduc=0
replace othereduc=1 if cfirstmajor>6|csecondmajor>6

**variable for math-based majors
gen math =0
```

```
replace math=1 if BCLA==1 & firstmajor==5
replace math=1 if CBA==1
replace math=1 if CSE==1 & firstmajor==1
replace math=1 if CSE==1 & firstmajor==7
replace math=1 if CSE==1 & firstmajor==8
replace math=1 if CSE==1 & firstmajor==10
replace math=1 if CSE==1 & firstmajor==11
replace math=1 if CSE==1 & firstmajor==13


** playtype as dummies
gen type2=0
gen type3=0
replace type2=1 if playtype==2
replace type3=1 if playtype==3

* probability of a change ocurring
gen anychange=0
replace anychange=1 if changesmade>0

**dummy to check for interaction between gender and playtype -- represents women
* who are type 2, making type 1 men the default group
cap drop playfemale
gen playfemale = female*type2

**interaction term for ties and type2s
cap drop tietype2
gen tietype2=tie*type2

**interaction term treatment and type2
gen Treatmenttype2 = Treatment*type2









order id round Treatment age female ethnic playtype cfirstmajor csecondmajor firstmajor
secondmajor Risktaking Minval Content Wantchange Detailorient, first
order Perfectionist changesmade tie roundlost expectedutility rankA rankB rankC rankD rankE
rankF rankG rankH rankI rankJ rankK rankL rankM rankN rankO rankP rankQ, after(Detailorient)

save "D:\Work\Thesis\Data\Analysiscd\Thesisdata3.dta", replace

```

```
cap log close
clear

*********Appendix B
*********Do-file 3: regressions and analysis

**** Cameron Bellamoroso
**** 9/18/2020
**** Senior Thesis

**This do file runs regression analysis, summarizes utility, and looks at the relationship between variables.
**Most tables are generated at the end of this do-file.

cd "D:\Work\Thesis\Data\Analysiscd"
log using ThesisAnalysis.txt, replace
use Thesisdata3

** generating tables that can show the expectedutility of people as they progress through the game:
matrix utilitytreat1 = J(3,35,.)
matrix utilitytreat0 = J(3,35,.)
local row=1
local col=1
forval i =1/35{
if `i'<11{
mat utilitytreat1[`row',`col'] = 600.8091
}
if `i'>10{
mat utilitytreat1[`row',`col'] = 798.8611
}
local row = `row'+1
sum expectedutility if Treatment==1 & type2 & round==`i'
mat utilitytreat1[`row',`col'] = r(mean)
local row = `row'+1
sum expectedutility if Treatment==1 & playtype==1 & round==`i'
mat utilitytreat1[`row',`col'] = r(mean)



local row = 1
if `i'<11{
mat utilitytreat0[`row',`col'] = 600.8091
}
if `i'>10{
mat utilitytreat0[`row',`col'] = 295.6068
}
local row = `row'+1
sum expectedutility if Treatment==0 & type2 & round==`i'
mat utilitytreat0[`row',`col'] = r(mean)
local row = `row'+1
sum expectedutility if Treatment==0 & playtype==1 & round==`i'
mat utilitytreat0[`row',`col'] = r(mean)
local row = 1
local col = `col'+1
}
matrix rownames utilitytreat1 = Max_expectedutility Type2Expectedutility Type1Expectedutility
matrix colnames utilitytreat1 = r1 r2 r3 r4 r5 r6 r7 r8 r9 r10 r11 r12 r13 r14 r15 r16 r17 r18 r19 r20 r21 r22 r23 r24 r25 r26 r27 r28 r29 r30 r31 r32 r33 r34 r35
matrix rownames utilitytreat0= Max_expectedutility Type2Expectedutility Type1Expectedutility
matrix colnames utilitytreat0 = r1 r2 r3 r4 r5 r6 r7 r8 r9 r10 r11 r12 r13 r14 r15 r16 r17 r18 r19 r20 r21 r22 r23 r24 r25 r26 r27 r28 r29 r30 r31 r32 r33 r34 r35

** making a table for irrational rounds:
tab irraround round if type2 & round<11, matcell(irraround2_pretreat)
tab irraround round if type2 & round>10, matcell(irraround2_posttreat)

tab irraround round if !type2 & !type3 & round<11, matcell(irraround1_pretreat)
tab irraround round if !type2 & !type3 & round>10, matcell(irraround1_posttreat)

```

```
** univariate models?
reg changesmade Treatment, r
reg changesmade female, r
reg changesmade type2, r

probit anychange Treatment, r
probit anychange female, r
probit anychange type2, r

** these are the regressions that use ties as the independent var -- not significant
{
* trying the same thing with roundlost as the independent var -- more statistical significance than with roundlost
reg changesmade tie if type3==0, r
eststo esty1
** adding fixed effects
reg changesmade tie i.id if type3==0, r
eststo esty2
** adding control for losing prev round
reg changesmade tie roundlost i.id if type3==0, r
eststo esty3
** adding control for player type
reg changesmade tie type2 i.id if type3==0, r
eststo esty4
** control for player type AND lost round
reg changesmade tie type2 roundlost i.id if type3==0, r
eststo esty5
** add controls for round clusters and removing the first couple rounds
reg changesmade tie type2 roundlost lateround earlyround i.id if type3==0 & round>2, r
eststo esty6
** control for gender (not statistically significant)
reg changesmade tie type2 roundlost lateround earlyround Treatment i.id if type3==0 & round>2, r
eststo esty7
** without losing a round
reg changesmade tie type2 lateround earlyround female i.id if type3==0 & round>2, r
eststo esty8
** with treatment control
reg changesmade tie type2 roundlost lateround earlyround female Treatment i.id if type3==0 & round>2, r
eststo esty9
**
reg changesmade tie type2 roundlost tietype2 lateround earlyround female Treatment i.id if type3==0 & round>2, r
eststo esty10
**
reg changesmade tie type2 roundlost tietype2 lateround earlyround female Treatment Treatmenttype2 i.id if type3==0 & round>2, r
eststo esty11


* now checking roundlosts occurring affecting the probit model
probit anychange roundlost if type3==0, r
eststo esti1
** adding fixed effects
probit anychange tie i.id if type3==0, r
eststo esti2
** adding control for losing prev round
probit anychange tie roundlost i.id if type3==0, r
eststo esti3
** adding control for player type
probit anychange tie type2 i.id if type3==0, r
eststo esti4
** control for player type AND lost round
probit anychange tie type2 roundlost i.id if type3==0, r
eststo esti5
** add controls for round clusters and removing the first couple rounds
probit anychange tie type2 roundlost lateround earlyround i.id if type3==0 & round>2, r
eststo esti6
** control for gender
```

```
probit anychange tie type2 roundlost lateround earlyround Treatment i.id if type3==0 & round>2, r
eststo esti7
** without losing a round
probit anychange tie type2 lateround earlyround female  i.id if type3==0 & round>2, r
eststo esti8
** with treatment control
probit anychange tie type2 roundlost lateround earlyround female Treatment i.id if type3==0 & round>2, r
eststo esti9
** no fixed effects
probit anychange tie type2 roundlost tietype2 lateround earlyround female Treatment i.id if type3==0 & round>2, r
eststo esti10


}



* trying the same thing with roundlost as the independent var -- more statistical significance than with roundlost
reg changesmade roundlost if type3==0, r
eststo esta1
** adding fixed effects
reg changesmade roundlost i.id if type3==0, r
eststo esta2
** adding control for losing prev round
reg changesmade roundlost tie i.id if type3==0, r
eststo esta3
** adding control for player type
reg changesmade roundlost type2 i.id if type3==0, r
eststo esta4
** control for player type AND lost round
reg changesmade roundlost type2 tie i.id if type3==0, r
eststo esta5
** add controls for round clusters and removing the first couple rounds
reg changesmade roundlost type2 tie lateround earlyround i.id if type3==0 & round>2, r
eststo esta6
** control for gender (not statistically significant)
reg changesmade roundlost type2 tie lateround earlyround Treatment i.id if type3==0 & round>2, r
eststo esta7
** without losing a round
reg changesmade roundlost type2 lateround earlyround female i.id if type3==0 & round>2, r
eststo esta8
** with treatment control
reg changesmade roundlost type2 tie lateround earlyround female Treatment i.id if type3==0 & round>2, r
eststo esta9
**
reg changesmade roundlost type2 tie tietype2 lateround earlyround female Treatment i.id if type3==0 & round>2, r
eststo esta10
**
reg changesmade roundlost type2 tie tietype2 lateround earlyround female Treatment Treatmenttype2 i.id if type3==0 & round>2, r
eststo esta11

* now checking roundlosts occurring affecting the probit model
probit anychange roundlost if type3==0, r
eststo est1
** adding fixed effects
probit anychange roundlost i.id if type3==0, r
eststo est2
** adding control for losing prev round
probit anychange roundlost tie i.id if type3==0, r
eststo est3
** adding control for player type
probit anychange roundlost type2 i.id if type3==0, r
```

```
eststo est4
** control for player type AND lost round
probit anychange roundlost type2 tie i.id if type3==0, r
eststo est5
** add controls for round clusters and removing the first couple rounds
probit anychange roundlost type2 tie lateround earlyround i.id if type3==0 & round>2, r
eststo est6
** control for gender
probit anychange roundlost type2 tie lateround earlyround Treatment i.id if type3==0 & round>2, r
eststo est7
** without losing a round
probit anychange roundlost type2 lateround earlyround female  i.id if type3==0 & round>2, r
eststo est8
** with treatment control
probit anychange roundlost type2 tie lateround earlyround female Treatment i.id if type3==0 & round>2, r
eststo est9
** no fixed effects
probit anychange roundlost type2 tie tietype2 lateround earlyround female Treatment i.id if type3==0 & round>2, r
eststo est10
**
probit anychange roundlost type2 tie tietype2 lateround earlyround female Treatment Treatmenttype2 i.id if type3==0 & round>2, r
eststo est11






** generating correlation tables for various collections of variables:

** main variables of analysis
estpost correlate Treatment age female tie type2 anychange changesmade irrationalroundcount, matrix
est store c1


**education w/ analysis vars
estpost correlate anychange female type2 math BCLA SOE CBA CSE CFA math, matrix
est store c2


** race/ethnic with analysis vars
estpost correlate anychange female type2 white asian black hispanic natamerican raceother, matrix
est store c3


** character w/ analysis vars
estpost correlate anychange female type2 Wantchange Perfectionist Minval Detailorient, matrix
est store c4

estpost correlate Treatment age female tie type2 anychange changesmade irrationalroundcount BCLA SOE CBA CSE CFA math white asian black hispanic natamerican raceother Wantchange Perfectionist Minval Detailorient, matrix
est store c5


******* This next section lookst at the significance of various relevant other variables
** testing for significance of race -- hispanic is the only one that appears to have an effect
probit anychange roundlost type2 tie tietype2 lateround earlyround female Treatment asian i.id if type3==0 & round>2, r
eststo rac1
probit anychange roundlost type2 tie tietype2 lateround earlyround female Treatment white i.id if type3==0 & round>2, r
eststo rac2
```

```
probit anychange roundlost type2 tie tietype2 lateround earlyround female Treatment black i.id if type3==0 & round>2, r
eststo rac3
probit anychange roundlost type2 tie tietype2 lateround earlyround female Treatment hispanic i.id if type3==0 & round>2, r
eststo rac4
probit anychange roundlost type2 tie tietype2 lateround earlyround female Treatment natamerican i.id if type3==0 & round>2, r
eststo rac5
probit anychange roundlost type2 tie tietype2 lateround earlyround female Treatment asian white black hispanic natamerican i.id if type3==0 & round>2, r
eststo rac6


**** Now checking on the demographic questions for significance -- note that in none of these does the r2 value change
probit anychange roundlost type2 tie tietype2 lateround earlyround female Treatment i.id if type3==0 & round>2, r
eststo ast
**Insignificant
probit anychange roundlost type2 tie tietype2 lateround earlyround female Treatment Risktaking i.id if type3==0 & round>2, r
eststo ast1
**insignificant
probit anychange roundlost type2 tie tietype2 lateround earlyround female Treatment Minval i.id if type3==0 & round>2, r
eststo ast2
** insignificant
probit anychange roundlost type2 tie tietype2 lateround earlyround female Treatment Content i.id if type3==0 & round>2, r
eststo ast3
** this one is significant -- check to see if relationship between Wantchange and type2?
probit anychange roundlost type2 tie tietype2 lateround earlyround female Treatment Wantchange i.id if type3==0 & round>2, r
eststo ast4
**this one is insignificant
probit anychange roundlost type2 tie tietype2 lateround earlyround female Treatment Detailorient i.id if type3==0 & round>2, r
eststo ast5
** insignificant
probit anychange roundlost type2 tie tietype2 lateround earlyround female Treatment Perfectionist i.id if type3==0 & round>2, r
eststo ast6
**now all of them together -- risktaking is now significant
probit anychange roundlost type2 tie tietype2 lateround earlyround female Treatment Risktaking Minval Content Wantchange Detailorient Perfectionist i.id if type3==0 & round>2, r
eststo ast7







** now checking for significance of major/school -- once again, most dont change the r2

** making a new regression table that looks at school in which people reside with similar controls as before

probit anychange roundlost type2 tie tietype2 lateround earlyround female Treatment i.id if type3==0 & round>2, r
eststo ist1
probit anychange roundlost type2 tie tietype2 lateround earlyround female Treatment BCLA i.id if type3==0 & round>2, r
eststo ist2
probit anychange roundlost type2 tie tietype2 lateround earlyround female Treatment SOE i.id if type3==0 & round>2, r
eststo ist3
probit anychange roundlost type2 tie tietype2 lateround earlyround female Treatment SFTV i.id if type3==0 & round>2, r
```

```
eststo ist4
probit anychange roundlost type2 tie tietype2 lateround earlyround female Treatment CBA i.id if type3==0 & round>2, r
eststo ist5
probit anychange roundlost type2 tie tietype2 lateround earlyround female Treatment CFA i.id if type3==0 & round>2, r
eststo ist6
probit anychange roundlost type2 tie tietype2 lateround earlyround female Treatment CSE i.id if type3==0 & round>2, r
eststo ist7
probit anychange roundlost type2 tie tietype2 lateround earlyround female Treatment math i.id if type3==0 & round>2, r
eststo ist8
probit anychange roundlost type2 tie tietype2 lateround earlyround female Treatment BCLA SOE CBA CFA CSE i.id if type3==0 & round>2, r
eststo ist9





** checking interaction with wantchange and type 2
gen wantchangetype2 = Wantchange*type2
probit anychange roundlost type2 tie tietype2 lateround earlyround female Treatment wantchangetype2 i.id if type3==0 & round>2, r


** this regression looks at how different the regression is omitting an additional three rounds -- lost significance on earlyround but all other coefficients unaffected
probit anychange roundlost type2 tie tietype2 lateround earlyround female Treatment i.id if type3==0 & round>5, r


** exporting all my matrices
esttab matrix(utilitytreat1, fmt(%8.2g)) using utilitytreat1.xls, title(Average Expected Utilities in Treatment 1) replace
esttab matrix(utilitytreat0, fmt(%8.2g)) using utilitytreat0.xls, title(Average Expected Utilities in Treatment 2) replace

esttab matrix(irraround1_pretreat, fmt(%8.2g)) using irraround1_pretreat.tex, title(Irrational round frequency table for type 1 players prettreatement) replace
esttab matrix(irraround1_posttreat, fmt(%8.2g)) using irraround1_posttreat.tex, title(Irrational round frequency table for type 1 players posttreatment) replace
esttab matrix(irraround2_pretreat, fmt(%8.2g)) using irraround2_pretreat.tex, title(Irrational round frequency table for type 2 players pretreatment) replace
esttab matrix(irraround2_posttreat, fmt(%8.2g)) using irraround2_posttreat.tex, title(Irrational round frequency table for type 2 players posttreatment) replace

esttab c5 using corrmat5.xls, unstack not noobs compress replace
esttab c4 using corrmat4.tex, unstack not noobs compress replace
esttab c3 using corrmat3.tex, unstack not noobs compress replace
esttab c2 using corrmat2.tex, unstack not noobs compress replace
esttab c1 using corrmat1.tex, unstack not noobs compress replace
esttab esti1 esti2 esti3 esti4 esti5 esti6 esti7 esti8 esti9 esti10 using "Regression1.tex", replace se scalars(chi2 p) r2
esttab esty1 esty2 esty3 esty4 esty5 esty6 esty7 esty8 esty9 esty10 using "Regression2.tex", replace se scalars(F p) r2
esttab esta1 esta2 esta3 esta4 esta5 esta6 esta7 esta8 esta9 esta10 esta11 using "Regression3.tex", replace se scalars(F p) r2
esttab est1 est2 est3 est4 est5 est6 est7 est8 est9 est10 est11 using "Regression4.tex", replace se scalars(chi2 p) pr2
esttab rac1 rac2 rac3 rac4 rac5 rac6 using "raceregressions.tex", replace se scalars(chi2 p) pr2
esttab ast ast1 ast2 ast3 ast4 ast5 ast6 ast7  using "characterraceregs_appendix.tex", replace se scalars(chi2 p) pr2
esttab ist1 ist2 ist3 ist4 ist5 ist6 ist7 ist8 ist9 using "majorregressions.tex", replace se scalars(chi2 p) pr2

```

```
cap log close
*********Appendix B
*********Do-file 4: data recreation

**** Cameron Bellamoroso
**** 8/30/2020
**** Senior Thesis

**Due to an error in coding, data for round 34 had to be manually repopulated using log files from the experiment.
**This do-file automates whatever information can be derived from info from other rounds.


cd "D:\Work\Thesis\Data\Analysiscd"
log using Thesisdatareplace, replace
use Datarecovered, replace


**Data for round 34 was overwritten in the original document. the variables for the rankings (A-Q)Tier34,
* roundpay34, activevar134, activevar234 were all manually brought in using the GSF file
* Further missing variables can be derived using these missing values

* Repopulating the missing tier values
local a=1
foreach i in A B C D E F G H I J K L M N O P Q {
replace tier134=`i'Tier34 if activevar134==(10+50*`a')

local a=`a'+1
}
local a=1
foreach i in A B C D E F G H I J K L M N O P Q {
replace tier234=`i'Tier34 if activevar234==(10+50*`a')

local a=`a'+1
}


*populating the counts for round 34 using info on what was picked each round.
local a=1
foreach i in A B C D E F G H I J K L M N O P Q {
replace `i'count34=`i'count33+1 if `i'count35==`i'count33+2 & missing(`i'count34)
replace `i'count34=`i'count33 if `i'count33==`i'count35 & missing(`i'count34)
replace `i'count34=`i'count33+1 if activevar234==(10+50*`a')|activevar134==(10+50*`a') & missing(`i'count34)
replace `i'count34=`i'count33 if missing(`i'count34)
local a=`a'+1
}
```