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A Parametric Analysis of Choice Under Risk

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A PARAMETRIC ANALYSIS OF CHOICE UNDER RISK

by

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Accurate assessment of risk propensity is important because risky choices underlie a broad range of behavioral problems. The Balloon Analogue Risk Task (BART) is an assessment that measures propensity to engage in risky choice. While this is a useful assessment, the BART changes two variables that affect risky choice simultaneously, probability of an undesirable outcome and stake size, which cannot be separated within the context of the BART. The goal of this study was to evaluate the separate and combined effects of key factors that are likely to risky choice (Magnitude of payoff, probability of an undesirable outcome, and stake size) in the context of a new analog to risky choice: The Wheel of Choice Task. Adults between the ages of 18 and 25 (N = 23) were recruited to participate in this study. On each trial, participants chose between spinning the wheel or collecting their earnings. Spinning could result in a payoff or a loss of earnings, and as such constituted a risky choice. Risky choices increased as the probability of bankruptcy decreased, as the magnitude of reinforcement for the risky choice increased, and as stake size decreased. Effects of all three independent variables were systematic and robust. In addition to the main effects, interaction effects were observed between probability of a bankruptcy and magnitude, magnitude and stake size, and between all three variables, indicating complex but systematic interplay between these powerful determinants of risky choice. Future directions for this line of research include a further parametric analysis of stake size as well as the Wheel of Choice task's utility as a clinical or experimental tool.

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David William Sottile

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Introduction

The study of choice under risk cuts across scientific disciplines. ‘Choice under risk’ means that the probabilities of all relevant outcomes are known quantities that are less than 1.0, and at least one of these outcomes is undesirable to the individual making the decision (Angner, 2016). Examples of these kinds of choices include drug use, unsafe sex, and gambling. Often in the real world these risky choices do not have precise known probabilities but have been correlated with laboratory measures of choice under risk (Anderson & Mellor, 2008; Lejeuz et al., 2002). Choice under risk is a central focus of prospect theory, the dominant theoretical framework in behavioral economics. Prospect theory facilitates prediction of choice under risk by describing how the probability of an outcome relates to its subjective value. Similarly, ecological studies have identified variables that affect how organisms make decisions under risk. There have been efforts within behavior analysis to extend these findings to humans (e.g., Pietras & Hackenberg, 2001; Pietras, Locey, & Hackenberg, 2003). This work has significant translational potential. For example, assessing how people make choices under risk may allow health care professionals to make better treatment decisions. (Bowling & Ebrahim, 2001). There are several assessments that measure propensity to engage in risky behaviors which have been used in clinical settings with promising results (Harrison, Young, Butow, Salkeld, & Soloman, 2005). Improving our understanding of the factors that underlie risky choice could in turn yield better clinical assessment tools.

Factors that affect risky choice that have been identified in previous research include the magnitude of the outcome (Bornovalova et al. 2009), whether the payoff is variable or fixed (Bateson & Kacelnik, 1995; Meyer, Schley, & Fantino, 2011; O’Daly, Case, Fantino. 2006), the delay to reinforcement (Bateson & Kacelnik, 1995; O’Daly et al., 2006), the amount of opportunities or time to engage in risky choice (Goldshmidt & Fantino, 2004; Pietras &

Hackenberg, 2001; Pietras et al. 2003), level of deprivation (Barnard & Brown, 1984; Caraco, Martindale, & Whittam, 1980), gain versus loss and probability (Kahneman & Tversky, 1979; Kuhberger, 1998; Lattimore, Baker, & Witte, 1992). The diverse perspectives and expertise among the behavioral sciences investigating these phenomena are evident from the methodological heterogeneity that characterizes the field.

Within behavioral economics, hypothetical choice procedures are commonly used to investigate risky choice. Hypothetical choice experiments assess people's preferences by asking them what they would do in a proposed scenario. Hypothetical choices do not result in the actual consequences of that choice. Hypothetical choice experiments have been used by behavioral economists to discover links between preferences and variables such as probability of an outcome, framing of the outcome as a gain or loss, and delay of the outcome (Kahneman & Tversky, 1979; Myerson & Green, 1995). Hypothetical choices are limited in their usefulness. Hypothetical choice assessments are susceptible to endogeneity, when explanatory variables are correlated with the error term of an economic model (Guevara, 2015). This translates to difficulty in determining the causation of shifts in preferences. Within the context of clinical assessment, the inability to consistently identify the controlling variables of choice under risk limits the clinical utility of an assessment tool. This issue is overcome simply by using real consequences as part of the clinical assessment of risky choice.

Lejuez et al. (2002) is a study that evaluated the validity of an assessment of propensity to engage in risk taking behavior called the Balloon Analogue Risk Task (BART). The task involved pumping up a virtual balloon on a computer screen, with each balloon constituting a trial. Pumping either (1) increases the balloon size and adds cash value to a counter or (2) pops the balloon and resets the counter to zero. For any given trial, there is a maximum number of pumps, and a number within that range is randomly selected as the pump value that will cause the balloon to pop. At any time after the first pump, clients can press a collect button that moves the earnings on the counter to a balance that is not at risk, and ends the trial. The authors found that when the maximum number of pumps was 128 there were strong correlations between the number of pumps on unexploded balloons, other assessments of risk propensity, and actual risk taking behaviors. The BART procedure is similar to classic risky choice experiments conducted by behavior analysts. A risky choice experiment is a study of the conditions under which an organism will make a choice between a certain outcome and a probabilistic outcome. Each trial includes concurrently available response options that result in probabilistic and certain outcomes, respectively. In terms of the BART, the probabilistic choice is the pump, and the certain choice is the collect button. Interestingly, although the BART is well correlated with risk behaviors, typically participants do not engage in particularly risky behavior while engaged in the task.

Traditional conceptualization of risky behavior entail responding past the point of optimality. In terms of the BART, this means pumping a number of times that exceeds the number of pumps that is likely to yield the largest overall payoff. Interestingly, even “risky” respondents do not pump up to the point of optimal returns. This is a strange characteristic of a tool for assessing risky choice. It is perhaps the case that a more carefully selected set of assessment parameters would yield a wider range risk taking and serve as a more robust correlate of real-world risk propensity.

The BART also contains a confound that prevents the isolation of the specific controlling variables that underlie a person’s risky choices. Because each trial entails selection of a particular pump as the pump that pops the balloon, the probability that the next pump will pop the balloon increases across pumps. Similarly, with each passing pump, the amount of money being risked increases. This means that the probability of an undesirable event, and the magnitude of the potential loss (so-called “stake size”) co-vary and are confounded under the BART procedure. This is especially important in light of the fact that these two variables have been identified as factors that affect risky choice. In particular, the effect of probability is critical and is a central element of prospect theory. In contrast, stake size has been identified as a key variable of interest in risky choice but remains relatively understudied.

A study by Fehr-Duda, Bruhin, Epper, and Schubert (2010) offers the most robust evidence in support of the view that stake size is an important factor in risky choice. In their study, risky choice was analyzed in a hypothetical choice experiment for 153 students’ preferences for either a certain or probable outcome in a lottery. Probability and stake size were varied in different lotteries. Results show that risk aversion increases as stake size increases as well and demonstrates the previously discussed probability weighting effect, where small probabilities of gain are overweighted and large probabilities of gains are underweighted. However, this finding is derived from a variant of the hypothetical choice procedure. Whether stake size influences risky choices in procedures that involve repeated real choices is unknown. Importantly, previous studies that had evaluated this effect did not produce robust enough evidence to make claims due to inconclusive results, inappropriate experimental designs for the question or small sample sizes (Camerer, 1991; Etchart-Vincent, 2004; Kachelmeier & Shehata, 1992). Thus, more data is required to evaluate the role of stake size in risky choice.

The purpose of this study is to evaluate the role of the probability of an undesirable outcome, the magnitude of a desirable outcome, and stake size in the propensity to engage in risky choice. This will be accomplished by using the Wheel of Choice task. A similar task has been previously used to measure risk taking behavior with independently manipulated probability in a laboratory setting (Ernst et al., 2003; Rao, Sidhartha, Harker, Bidesi, Chen, & Ernst, 2011). This task is easily and quickly repeatable which is integral to obtaining a similar patterns of responding to those in the BART, and can easily be arranged to allow for isolation of variables confounded in the BART as described above. In order to best analyze these patterns of responding, a 3x3x2 ANOVA with repeated measurements will be used as the main data analysis. This will allow statements to be made regarding both the main effects of the variables of interest as well as the interaction effects between them.

Method

Setting and Materials

The study was conducted in a building on the campus of a large Midwestern university. Sessions were conducted in either of two adjacent small windowless rooms (3.66 m x 2.29 m). The rooms contained desktop PCs loaded with the Wheel of Choice software and a web browser. Opening the browser provided access to links to the study surveys. The surveys were delivered with Qualtrics (January-March, 2018; Qualtrics, 2018)). The Wheel of Choice task was created with Python 3.6.4 (3.6.4.; Python Software Foundation, 2018). The task itself was run on PyGame (1.9.3).

Subject Recruitment

Thirty participants were planned to be recruited in the study. This number of participants was determined by a statistical consultation. An interim data analysis determined that only 21 participants’ data were required to sufficiently account for a possible type II statistical error. 23 participants were recruited as two participant’s data was lost due to technical difficulties with the Python 3.6.4 software. Participants were recruited via flyers and classroom presentations. Flyers were approved by Student Activities and Leadership Programs then posted onto campus bulletin boards. Similarly, after course instructor's approval, a scripted presentation was delivered to a class. Permitting faculty member approval, extra credit was also offered to students in addition to remuneration.

To be included in the study participants were required to be between the ages of 18 to 25, be able to use a computer, and to demonstrate basic mathematical competency. The age criterion was selected to mimic the criterion used by Lejeuz et al. (2002), in order to facilitate comparisons between the two studies. The other criteria ensured that participants were able to engage appropriately with the study task. The math competency criterion was intended to ensure that participant choice was influenced by the independent variables manipulated in this study. The Math Ability Test was created to assess mathematical competency. If a participant answered five out the six questions on the test correctly, then they were eligible to participate in our study. There were no exclusionary criteria for this study.

Informed Consent Process

Graduate and undergraduate research assistants obtained informed consent and ran experimental sessions with participants in the experimental rooms. The computer was kept on a rolling desk to easily transport it from room to room as the availability requires.

The informed consent document was presented to participants via a video recording. This video recording was used to ensure consistency in the delivery of the information in the informed consent. The video displayed the text of the informed consent document as a recording of a member of the studying team reading the text was played. A study team member remained in the room to answer any questions. The video was paused prior to answering any questions to ensure that no pertinent information was missed. Once the video ended, the study team member prompted the participant to ask any questions regarding the informed consent prior to continuing to the informed consent quiz.

Participants took a quiz following the informed consent video on key information about the study. Participants were required to score at least a 70% on this quiz before beginning the session. If a participant scored lower than this, incorrect answers were reviewed with a study team member and then the quiz was retaken. The participant was not able to provide consent until they successfully passed the quiz. Participants could only take this quiz a maximum of three times.

The Math Ability Test was administered to participants following the informed consent quiz. Participants were required to answer five out of six questions correctly before moving forward. If a participant scored lower than this, incorrect answers were reviewed with a study team member and then the test was taken again. Participants could only take this test a maximum of three times. If the participant scored a five out of six or higher, the experimental procedures began immediately.

Surveys Related to Health Risk Behaviors

Participants took two surveys related to health risk behaviors: The Sexual Risk Survey or SRS (Turchick & Garske, 2009) and the drug use and alcohol use sections of the Addiction Severity Index – Lite or ASI – Lite (Caccicola, Alterman, McLellan, Lin, & Lynch, 2006). The SRS measures how frequently one engages in risky sex practices such as not using a condom during intercourse. A standardized overall score of sexual risk taking can be derived from this assessment (Turchick, Walsh, & Marcus, 2014). The drug use and alcohol use sections of the ASI – Lite are structured interviews that assess drug use and associated well-being. Composite scores can be derived from a participant's answers that indicate the severity of their drug and alcohol use problems.

Both surveys were delivered as self-paced computer-based interviews without assistance from the study team members. The study team member remained in the BERC lab room and was available for any questions or issues that arose during the interview process.

Wheel of Choice Task

After completing the health risk assessments, participants returned to the BERC lab room. The study team member then returned with them to the experimental room and opened the Wheel of Choice task. The display screen of the Wheel of Choice task features a segmented wheel with an arrow-shaped spinner, a button entitled "Spin", another button entitled "Collect", a display box entitled "Tokens", the exchange rate for tokens to USD, the current trial number (e.g. "Trial 1 of 180"), and a legend describing how many tokens will be earned if the spinner lands on one of the "win" colors. The wheel segments are always one of two colors on any given spin cycle. Some segments are black and landing on black will result in a reset of the current tokens to zero and an end of the trial. Other segments of the wheel are colored either green, blue, or yellow, depending on the trial. Colors represent the three incremental win sizes, with specific values available to participants onscreen (See Appendix B).

As the task window opens, the following message is displayed:

"In this task, you will spin a wheel to earn tokens. After the task, you will trade the tokens for real money. 3400 tokens are worth one dollar. If the wheel lands on green, blue, or yellow, you earn tokens. If the wheel lands on black you go bankrupt. Bankrupt means you lose all tokens won from that try. On any try, you can spin as many times as you want. Each spin has a chance of winning more tokens or going bankrupt. You can tell the chance of going bankrupt by

looking at the wheel. You can collect the tokens won at any time. The try ends when you collect the tokens or when you go bankrupt. Then you do another try and spin a new wheel. You will have a total of 180 trys. 36 out of these 180 trys will count toward your earnings. The rest will not count. Which ones count will be picked by the computer at random. Do your best on all the trys to get the most money. Press any key to begin."

After participants completed all 180 trials of the Wheel of Choice task, a debriefing screen appeared on the computer. This debriefing displayed the 36 trials that had been randomly selected for renumeration, the total number of tokens earned, and the total amount of money that this corresponded to. The study team member read this information out loud to the participant and thanked the participant for their time. This marked the end of the experimental session. Study participation was completed in a single session..

Experimental Design

A 3x3x2 within-subjects factorial experimental design was used for a total of 18 distinct experimental conditions.

Independent Variables. Participants experienced three different probabilities of going bankrupt, three different incremental values of winning, and two starting stake sizes, for a total of 18 conditions. One of each level of these variables was present throughout each spin cycle. The three probability conditions are categorized as high (probability of going bankrupt is set at .5), medium (probability of going bankrupt is set at .1), and low (Probability of going bankrupt is set at .01). The three different incremental values of winning are also categorized as high magnitude (a win earns 250 tokens), medium magnitude (a win earns 50 tokens), and low magnitude (a win earns 1 token). The starting stake size conditions correspond to the starting value of the tokens. All participants started each trial with 0 tokens or 250 tokens. Participants experience all levels of these variables at each of the levels of the other conditions ten times for a total of 180 trials per participant.

Dependent Variables. The primary dependent variable was the number of spins per trial. Participants were able to spin as many spins as they wanted on any given trial. The trial ended either when the participant went bankrupt or they pressed the collect button. The secondary dependent variables were the participant's scores on the SRS and ASI-Lite sections, whether a trial ended in a collection or a bankruptcy, the order number of the trial in the 180 trials, and the lag distance, which was defined as the trial distance between that trial and the most recent bankruptcy.

Data Analysis

Main Effects of the Primary Variables

Visual analysis. The primary visual display features aggregate data across three panels. The three panels correspond to the three levels of the probability of bankruptcy condition. Each panel has two data paths which correspond to the two levels of the stake size condition. Each data path will have three data points which correspond to the three levels of the magnitude condition. The data point will be the average number of spins for that specific combination of condition levels. An identical format is also used to show data from individual subjects.

ANOVA. The primary data analysis was a 3x3x2 ANOVA with repeated measurements for the independent variables of probability of bankruptcy, magnitude, and stake size on the dependent variable of number of spins per trial. This was conducted using the computer software Minitab 18.1.

Participants were exposed to ten trials of each experimental condition. Their scores on these trials were averaged together. This value was used as the dependent variable for the ANOVA. This analysis yielded seven different F statistics regarding the main effects and the interaction effects of each of these independent variables.

Order Effects

For order effect analysis, average number of spins was plotted as a function of ordinal trial number. One figure was created that sampled data from all experimental conditions. Another figure was created that sampled data from only conditions with a magnitude of one token. In addition, a Pearson correlation coefficient was calculated between the number of spins and order number of the trial in the 180 trials.

Local Effects of Bankruptcy

In order to detect whether a bankruptcy had temporally local effects on the number of spins in subsequent trials, two graphs were created. The first graph was the average number of spins by the lag distance for all trials in all conditions. The second graph was the average number of spins by the lag distance for all trials in the high magnitude, low probability of bankruptcy, 0 token stake size condition. This condition was selected because it had the highest variance of all condition as well as the highest average number of spins. In addition, a Pearson correlation coefficient was calculated between the number of spins and lag distance

Correlations with Self-Reported Risk Behaviors

Pearson correlation coefficients were calculated between the average number of spins across conditions and the composite scores of the SRS, the drug use section of the ASI – Lite, and the alcohol use section of the ASI – Lite. Additional correlations were calculated between the average number of spins in the condition with the most variance, number of days of any alcohol use in the past thirty days, number of days of alcohol use to intoxication in the past thirty days, number of days of marijuana use in the past thirty days and the previously analyzed composite scores.

Results

Main Effects of the Primary Variables

Visual analysis. Figure 1 shows the average number of spins for each experimental conditions for all participants.

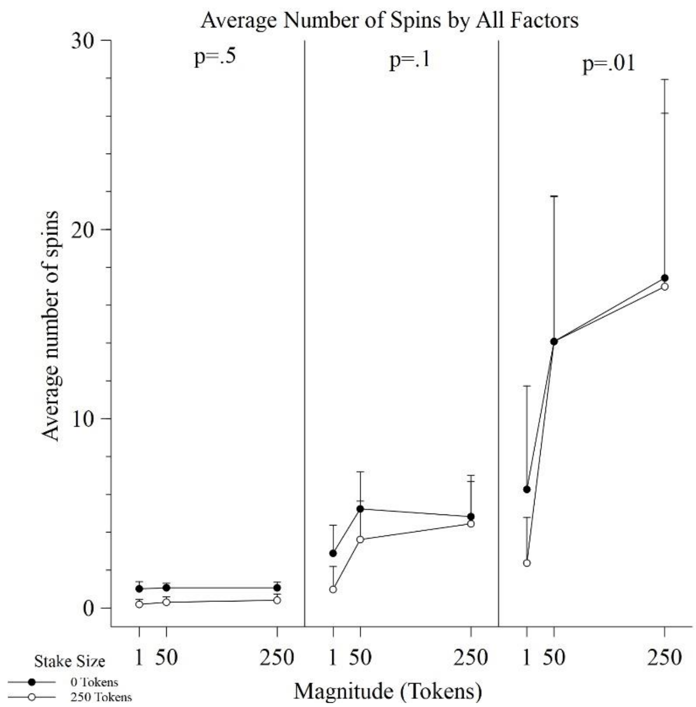

Figure 1. Aggregate Average Number of Spins by All Factors

From left to right, the panels indicate probability of bankruptcy condition changes from p = .5, to p = .1, to p = .01. The x-position of all three panels correspond to the three magnitude conditions (1, 50, and 250 tokens). The two separate data paths correspond to the two main stake size conditions: 0 tokens and 250 tokens. There are several important effects to note in this graph: First, as the probability of bankruptcy decreases, the average number of spins increases. Second, as the magnitude of a win increases, the average number of spins increases. However, this effect is only apparent in the p = .1 and the p = .01 conditions. The largest increase in the average number of spins occurs between a magnitude of one token and a magnitude of 50 tokens. Only a small increase in the average number of spins occurs between a magnitude of 50 tokens and a magnitude of 250 tokens. One data path decreases between these two points. In two panels, there is a clear separation of the two stake size data paths. This is most clear in the leftmost panel (p = .5) despite lower averages. In the rightmost panel (p = .01), it is unclear whether stake size had an effect.

All individual participants' data have been graphed in the same manner as Figure 1 (See appendix C). The presentation order of the figures corresponds to their overall similarity to the aggregate graph. In general, the relations between the independent and dependent variables that are apparent on the aggregate graph are also apparent of the large majority of the individual participant graphs. Specifically, the main effects of probability of bankruptcy, reinforcement magnitude, and stake size, are apparent in 20 (95%), 20 (95%), and 16 (76%) of cases, respectively. More detailed patterns described for the aggregate graph are also apparent in the large majority of individual graphs. The specific effects of stake size are the only exception, with 11 (52.4%) cases showing the stake size effect in the p = .5 condition, and seven (33.3%) cases showing the stake size effect in the p = .01 condition.

ANOVA. The ANOVA yielded seven different F statistics on the effects of magnitude, probability of bankruptcy, and stake size on number of spins. Generalized eta squared (η_G^2) was calculated for all these F statistics. Generalized eta squared is an effect size that permits comparison across different experimental designs (Olejnik & Algina, 2003). A generalized form of the equation was used in order to account for this repeated measures design.

Statistically significant main effects were detected for magnitude (η_G^2 = .27), probability of bankruptcy (η_G^2 = .62), and stake size (η_G^2 = .02). A statistically significant first order interaction was detected between magnitude and probability of bankruptcy (η_G^2 = .28). A statistically significant first order interaction was detected for magnitude and stake size (η_G^2 = .01). A statistically significant second order interaction was detected among all three independent variables (η_G^2 = .01). (See Tables 1-2; See Figure 2).

Table 1
Descriptive Statistics for Number of Spins by Experimental Condition

Factor	Level	N	Mean	SD
Magnitude	1 Token	126	2.282	3.22
	50 Tokens	126	6.395	7.25
	250 Tokens	126	7.526	9.09
Probability	.5	126	0.67	0.48
	.1	126	3.66	2.34
	.01	126	11.87	9.34
Stake Size	0 Tokens	189	5.98	7.34
	250 Tokens	189	4.82	7.24
	7000 Tokens	2	3.70	3.79

Table 2
Results of the 3x3x2 ANOVA

Source	*SS*	*df*	*MS*	*F*	*p*
Factor A	1919.6	2	959.79	47.03	< 0.01
Error A	816.2	40	20.41		
Factor B	8471.1	2	4235.55	63.48	< 0.01
Error B	2669.0	40	66.73		
Factor C	128.5	1	128.51	26.44	< 0.01
Error C	97.2	20	4.86		
AxB	2069.8	4	517.46	33.87	< 0.01
Error_{AxB}	1222.1	80	15.28		
AxC	52.7	2	26.34	13.73	< 0.01
Error_{AxC}	76.7	40	1.92		
BxC	8.6	2	4.31	1.02	0.37
Error_{BxC}	168.9	40	4.22		
AxBxC	56.4	4	14.09	5.85	< 0.01
Error_{AxBxC}	192.8	80	2.41		

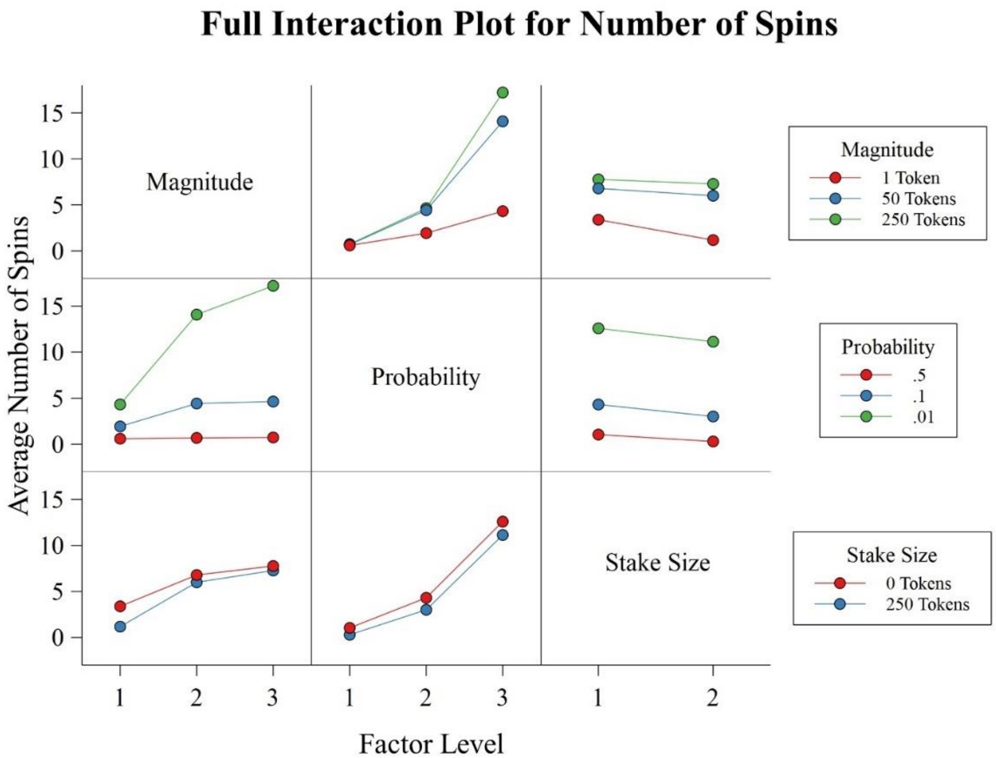

Figure 2. 3x3x2 ANOVA Full Interaction Plot

Order Effects

The average number of spins was graphed as a function of the ordinal value of the trial. Figure 4 contains data sampled from all experimental conditions. Figure 5 contains data sampled from experimental conditions with a magnitude of one token. Figure 4 shows a decreasing trend of spins as trial order increases. Figure 5 shows a larger decreasing trend of spins as trial order increases than Figure 4. A statistically significant Pearson correlation coefficient was calculated between the number of spins and order number of the trial in the 180 trials ($r = -.12$, $df = 3978$, $p < 0.01$).

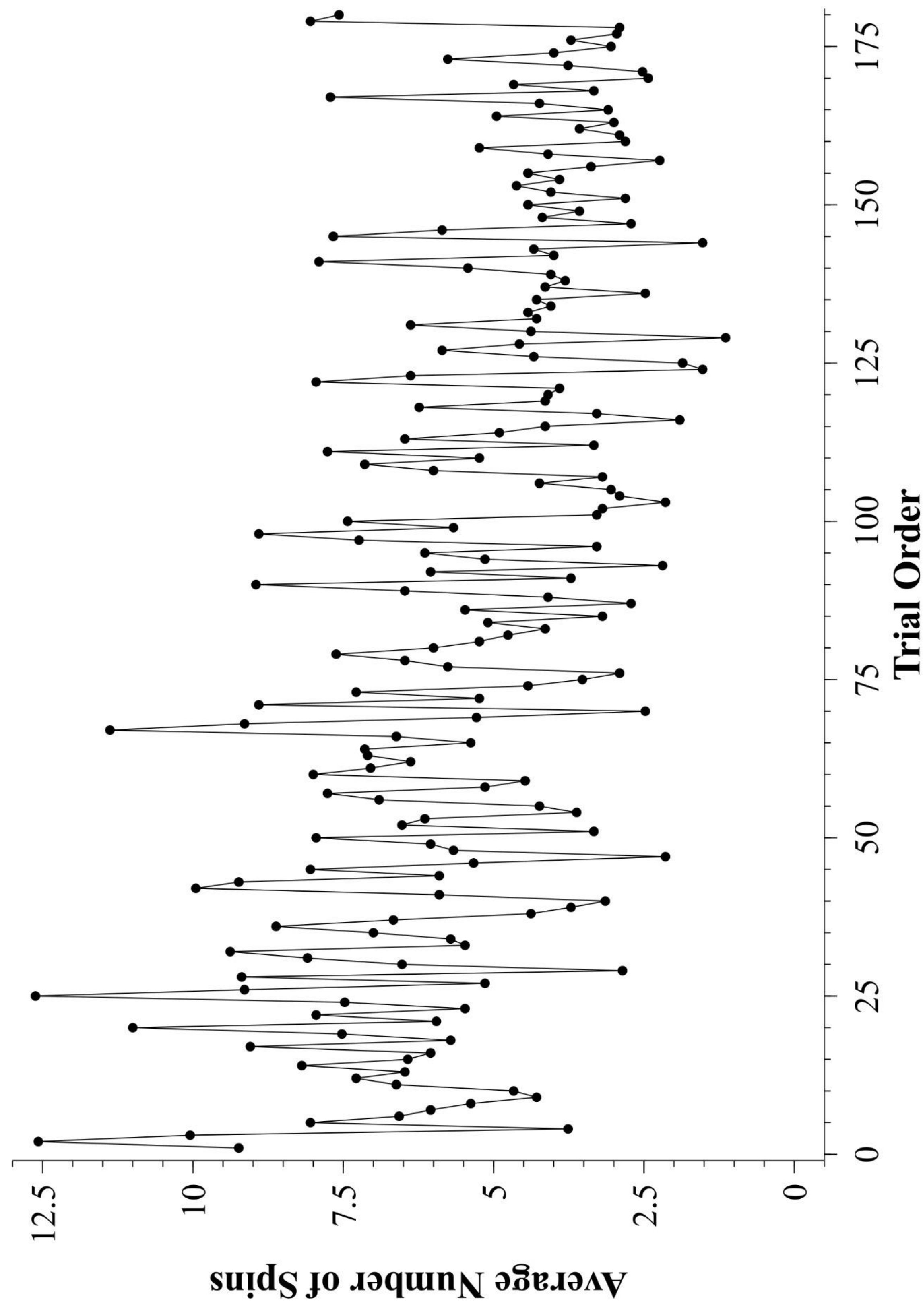

Figure 3. Average Number of Spins against Trial Order

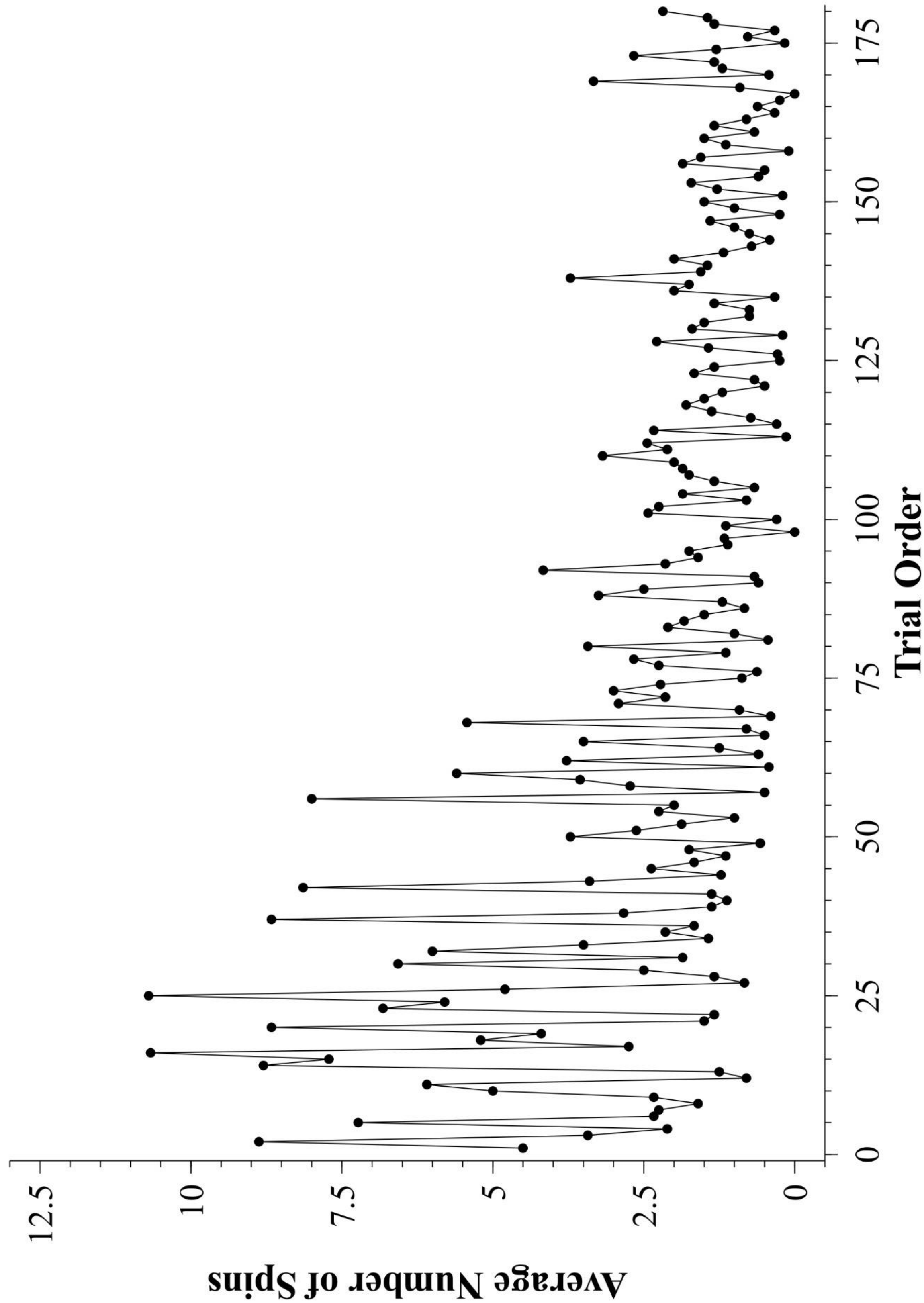

Figure 4. Average Number of Spins in One Token Magnitude Conditions against Trial Order

Local Effects of Bankruptcy

Lag distance was only graphed up to 11. A distance of 11 trials was chosen as the cutoff because less than 50% of participants experienced any trials that had a larger distance (See Figures 8 & 9).

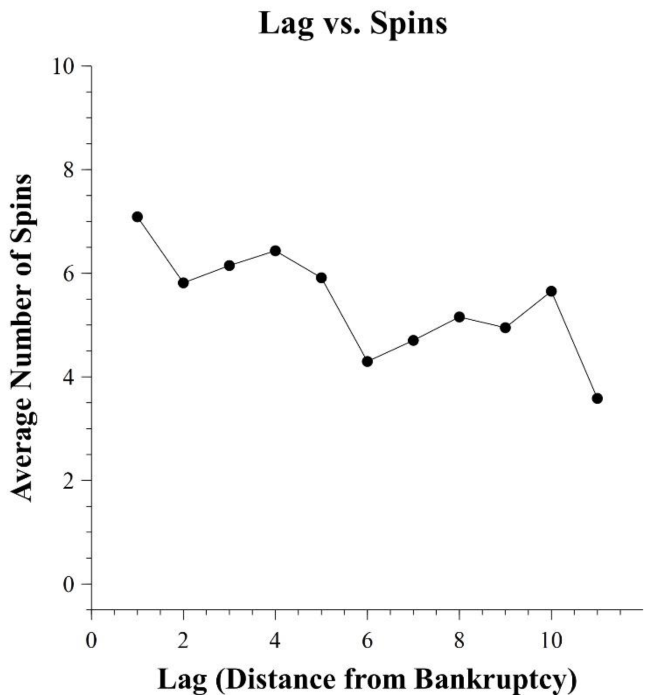

Figure 5. Lag vs. Average Number of Spins

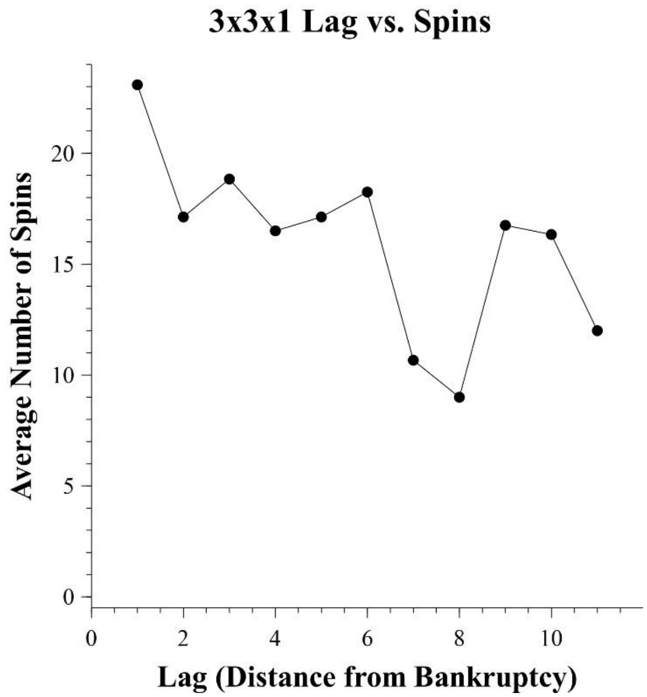

Figure 6. 3x3x1 Lag vs. Average Number of Spins

A decreasing trend in both graphs can be noted. This indicates that the average number of spins tends to decrease as the temporal distance from a bankruptcy increases. A statistically significant Pearson correlation coefficient was calculated between the number of spins and lag distance ($r = -.07$, $df = 3978$, $p < 0.01$)

Correlations with Self-Reported Risk Behaviors

Pearson correlations were calculated between participants' ASI-Lite composite score for drug use (M=0.02, SD=0.03), ASI-Lite composite score for alcohol use (M=0.07, SD=0.06), standardized score of the SRS (M=16.29, SD=12.91), and average number of spins during the Wheel of Choice task (M=5.40, SD=2.44) (See Table 3).

Table 3
Pearson Correlations between Risk Assessment Scores and Wheel of Choice Scores

	ASI-Alcohol CS	ASI-Drugs CS	SRS SS
ASI-Drugs CS	.35		
SRS SS	.50*	.33	
Average Spins	.03	.10	.38

** indicates that the correlation is statistically significant at the p<.05 level*

The only statistically significant correlation was between the ASI-Lite composite score for alcohol use and the standardized score of the SRS. Based on the results of this analysis, additional Pearson correlations were calculated. More specific measures of risk were selected including days of any alcohol use in the last 30 days (M = 4.52, SD = 3.89), days of alcohol use to intoxication in the last 30 days (M = 2.76, SD = 3.35), and days of marijuana use in the last 30 days (M = 3.48, SD = 8.00). These measures of risk were selected because they were the only ones that were reported somewhat frequently in the study sample. Additionally, an additional score from the Wheel of Choice task was selected for inclusion in the correlations. Specifically, the highest magnitude, lowest probability of bankruptcy, zero stake size or 3x3x1 condition (M = 17.44, SD = 10.50). This condition was selected because it had the greatest variance of all experimental conditions.

Table 4
Additional Pearson Correlations between Risk Assessment Scores and Wheel of Choice Scores

	ASI-Alcohol CS	ASI-Drugs CS	SRS SS	Alcohol (Any)	Alcohol (Intox.)	Marijuana
ASI-Drugs CS	.35					
SRS SS	.50*	.33				
Alcohol (Any)	.78*	.36	.45*			
Alcohol (Intox.)	.73*	.04	.45*	.80*		
Marijuana	.30	.96*	.31	.32	.04	
3x3x1 Spins	.11	.11	.56*	.09	.23	.08

** indicates that the correlation is statistically significant at the p<.05 level*

Three statistically significant correlations of note were detected in this analysis: A correlation between the SRS standardized score and past 30 days of any alcohol use, a correlation between the SRS standardized score and the past 30 days of any alcohol use to intoxication, and a correlation between the average number of spins in the 3x3x1 condition and the SRS standardized score.

Discussion

The results of this study show that probability of bankruptcy, magnitude of reinforcement and stake size all affect an individual's likelihood to engage in risky choice. Specifically, risky choices increase as the probability of bankruptcy decreases, as the magnitude of reinforcement for the risky choice increases, and as stake size decreases. The large changes in the mean amount of spins as probability of bankruptcy and magnitude change indicate that these variables are powerful determinants of choice under risk. The overall results of stake size show that it too may produce important effects on risky choice.

In addition to these main effects, there were three statistically significant interactions: An interaction between probability of bankruptcy and magnitude, an interaction between magnitude and stake size, and an interaction among all three independent variables. For the probability/magnitude interaction, magnitude had a greater positive effect on the number of spins at higher levels of probability of bankruptcy. For the magnitude/stake size interaction, stake size had greater negative effect on the number of spins at lower levels of magnitude. For the three way interaction, the effect of stake size was suppressed as a function of the probability/magnitude interaction.

The effects of probability of bankruptcy, the probability/magnitude interaction, and magnitude were large. It should be noted probability of bankruptcy had the largest effect by a difference of .32 to the second largest effect, probability/magnitude. The effects of stake size, the stake size/magnitude interaction, and the three-way interaction were small.

Probability of bankruptcy has a large impact on how the participants made risky choices. Its main effect as well as its interaction with magnitude make this evident. This is very consistent with the findings of previous studies of probability of an undesirable outcome's effect on risky choice (Kahenman & Tversky, 1979; Lattimore et al., 1992). These two studies used the decisions made by participants in hypothetical choice experiments in order to make statements about the effects of probability on risky choice. An integral aspect of prospect theory (Kahneman & Tversky, 1979) is the concept of probability weighting. Probability weighting is the tendency for humans to overweight the impact of small probabilities and underweight the impact of large probabilities. This effect is clear in the $p = .01$ condition of this study. The optimal number of spins for this condition is 50. Optimal in this circumstance is half of the number of spins before it becomes more likely for a bankruptcy to occur than not. The average number of spins in the $p =$

.01 was 11.87 which was far below the optimal number of spins. Even in the experimental condition that had the largest average number of spins (p =.01, magnitude of 250 tokens, and a stake size of 0 tokens) only had an average of 17.44 which was still far below the optimal number of spins. This can be interpreted as overweighting the small probability of going bankrupt during this level of the condition. By comparison, the optimal number of spins for the p = .1 condition was 5. The average number of spins in the p = .1 was 3.66. This difference indicates that the probability of .1 was not overweighted as much as the probability of .01 by the participants.

Magnitude's effect on risky choices in this study expands on the findings of Bornovalova (2009). Bornovalova et al. (2009) was a study of the effects of magnitude on risky choice in the context of the BART. This study used three different levels of magnitude: 1 cent, 5 cents, and 25 cents in USD. In order to make meaningful comparisons to this study, the corresponding value in cents for the magnitude conditions in Wheel of Choice task have been calculated. 1 token is equal to .03 cents, 50 tokens is equal to 1.47 cents, and 250 tokens is equal to 7.35 cents. Bornovalova et al. (2009) reported a decrease in risky choices as magnitude increased. However, the results of the Wheel of Choice task showed an increase in risky choices as magnitude increased. The largest increases in magnitude were noted between the 1 token and 50 tokens conditions. There are no corresponding values in this low part of the parameter space studied in Bornovalova et al. (2009). Smaller increases in the number of risky choices are detected between the 50 tokens and 250 tokens conditions at various levels of probability of bankruptcy and stake size. One decrease in the number of risky choices was detected between the 50 tokens and 250 tokens conditions when probability of bankruptcy is equal to .1 and stake size is equal to zero tokens. This indicates that increases in magnitude of a win at lower levels will increase the number of risky choices while the opposite effect will occur at higher levels of magnitude.

The results of Young, Webb, Rung, & McCoy (2014) may explain why this difference in the effect of magnitude has been found. Using a video game as an analog to choice under risk, the authors evaluated how long participants would wait before firing a weapon at an enemy. Waiting longer before firing the weapon would either increase the amount of damage caused or the probability the shot would hit the enemy depending on which experimental condition was in effect. Damaging the enemies in this analog was the desirable outcome. On average, participants in the increasing magnitude of damage condition did not wait as long as participants in the increasing probability of accurate hit condition. The authors propose that the effects of magnitude increase logarithmically: Larger increases in risk seeking behavior occur as magnitude increases in a lower space of parameter and small to no increases in risk seeking behavior occur as magnitude increases in a higher space of the parameter.

The effect of stake size a relatively understudied variable affecting risky choice. This study is the most robust evidence of the effect of this variable to date. A series of real risky choices were the dependent variable as opposed to hypothetical ones. The results of Fehr-Duda et al. (2010) also reported both the same main effect of stake size and interaction effect with probability on the number of risky choices. However, participants did not make as many risky choices in that study compared to this study. Additionally, the nature of the task was substantially different then the Wheel of Choice task. Participants in Fehr-Duda et al. (2010) filled out their preferences to accept a certain amount of amount over an uncertain amount of money. This type of decision making is potentially not as accurate of an analog to risky choice as the Wheel of Choice task.

There are several possible explanations for the effect of ordinal trial order on the number of spins. It is possible that the passage of time served as a motivating operation that increased the value of ending the experimental session. The experimental session ended after completing all 180 trials and participants were not required to spin on any trial. The motivating operation would also have a behavior altering effect of spinning less on later trials. Another possible explanation is that the outcomes of certain experimental conditions were not as reinforcing as others. Lower magnitude conditions could lead to such a small amount of tokens that a win did not constitute a reinforcing stimulus. The number of spins under these conditions would decrease following each exposure to them. This last explanation is supported by the larger decreasing trend in Figure 5.

The cause of the effect of temporal distance from a bankruptcy is unclear. Temporal distance from a bankruptcy had a small/medium correlation with the ordinal trial order ($r = .20$, $df = 3978$, $p < 0.01$). It is possible that the decreasing trend of the average number of spins is a function of ordinal trial order and not of lag. This limitation should be considered in the context of the following discussion of the effect of temporal distance from a bankruptcy on the number of spins. If a punisher is the consequence of a behavior, that behavior will decrease in future frequency. However, the average number of spins is at its highest in both graphs of lag versus spin at a temporal distance of one trial from a bankruptcy. This indicates that responding is at its highest at the shortest temporal distance and then decreases as distance increases. A possible explanation is that a recent bankruptcy is a motivating operation that affects the value of tokens. This motivating operation then also possesses the behavior altering effect of increasing the number of spins. As no bankruptcies occur and more tokens are acquired as a consequence of spinning the wheel, the motivating operation decreases (No bankruptcy trials were graphed in the visual analyses). An analysis that separately controls for temporal distance from a bankruptcy and trial order is required to make this distinction.

The correlational analysis of risk assessments detected that the number of spins in the experimental condition with the highest variance correlated with the standardized score of the sexual risk survey (SRS). This lends to support to the use of the Wheel of Choice task as an analog to real life risky choices that affect health. There were no similar correlations between the number of spins in this condition and either section of the ASI-Lite. A potential explanation for this is that scores on the both sections of the ASI-Lite were extremely low and there was little variance in these scores. This is not surprising considering that the study sample was drawn from a general population of college students, and not the population of individuals with substance use disorders the ASI-Lite was designed to assess. A degree of variance is necessary for any type of correlation to be detected between two variables, and in the present sample that level of variation is only observed in the measure of sexual risk.

Overall the results of this experiment are similar to the BART with some notable improvements. In this study and Lejuez et al. (2002), the condition with the lowest probability of an undesirable event elicited the highest number of risky choices. Participant’s scores on the BART were also correlated with measures of risk taking. The BART had significant correlations with more measures of risk taking than the Wheel of Choice task. This is potentially explained by the fact that the BART not only tested more of these relationships but also had a larger number of participants than this study. A larger number of participants means than the correlational analyses in this study were powered to detect smaller correlations than the current study’s analyses. There is evidence of probability weighting in both studies. With this evidence in mind, the Wheel of Choice task's capability to independently manipulate probability is potentially an advantage over the BART.

Limitations of this study include that while the 3x3x2 ANOVA was sufficiently powered to avoid a type II statistical error, the Pearson correlational analyses were not. A power analysis revealed that in order to detect a medium size correlation between our parameters, 84 participants' values would need to be used (G*Power 3.1.9.2). A larger study should be conducted to determine whether these risk assessments are in fact correlated with the average number of spins in the Wheel of Choice task.

The correlational analyses conducted among trial order, number of spins, and temporal distance from a bankruptcy may be autocorrelated. Autocorrelation refers to the increased likelihood that data is correlated when it is taken from the same participant. This reduces the power of the analysis. Future correlational analyses should control for this.

This study only used college students of a traditional age range as its participants. This was done to replicate the population used in Lejuez et al. (2002), but also reduces the generalizability of the results of this study to other populations. It is possible individuals that have been diagnosed with disorders of choice such as substance use disorder, alcohol use disorder, gambling disorder, or those that engage in risky sexual practices may respond different to the Wheel of Choice task. It is important to evaluate participants that fit these criteria in the context of the Wheel of Choice task to determine its potential utility as a clinical assessment of choice under risk.

In future studies, extra credit should not be used in addition to renumeration. It is possible that the extra credit was the controlling variable for participating in this study. This could be a confounding variable. A participant may make fewer risky choices throughout their participation because the experimental session would end earlier. This decision was made after one participant, WOF0021, did not respond differentially to any changes in experimental conditions.

Pleskac, Wallsten, Wang, and Lejuez (2008) propose that all sequential risk assessment tasks and the BART in particular are flawed due to the use of the adjusted mean score. This adjusted mean score is the average number of spins for all trials that did not end in a loss. The authors make an argument for the use of a different response mode where participants enter in the number of risky choices they would make at the beginning of the trial instead of actually making repeated risky choices. The authors termed this method the "automatic response mode."

This automatic response mode, while eliminating the bias of the adjusted mean score, introduces a different bias into how participants make risky choices. The consequences of any risky choice, whether that choice ends in a win or a loss, may affect the future risky behavior of that individual. By selecting the number of risky choices made in advance of the trial, the individual will not be affected by the consequences of each of these choices. Instead of using the automatic response mode or the adjusted mean score, it may be more useful to create a visual display of all trials and whether a bankruptcy occurred. Displaying whether any given trial ended in a loss and observing participant's data after this consequence may provide meaningful data on how these consequences affect the participant's behavior. The analysis of temporal distance from a bankruptcy indicates that this may potentially be the case. If a future analysis shows that temporal distance from a bankruptcy does have an effect, graphing the data instead of using a single average, as the BART uses, may be required to have an accurate analog to an individual's likelihood to engage in risky choice.

Future directions for this line of work include a broader parametric analysis of stake size. Stake size is still a relatively understudied phenomenon and only two levels of stake size were evaluated extensively in this study. Stake size has a clear effect on risk even if the stake size is relatively low (In this circumstance, equal to a single potential win). It is also possible that a larger interaction effect could be detected at larger levels of stake size between magnitude.

Further examinations of temporal distance and order should be conducted. There are multiple explanations for both of their respective effects on risky choice. These further examinations must control for both of these variables separately as they were partially conflated in this study. The task could be arranged in such a manner that a bankruptcy always occurred during certain trials in the order across all participants. The number of spins during the subsequent trials could be graphed against temporal distance as in Figure 4.

The Wheel of Choice task is potentially useful as an assessment of risk propensity. The task can change relevant factors that affect choice under risk without conflating other extraneous variables. This means that the task has greater control over the relevant factors than the BART. Anecdotally, participants reported that they enjoyed the task and appeared engaged throughout it. Shortening the task and the delivery time would enhance the value of this task as an assessment of risk taking. In its current form, an average session of the Wheel of Choice task takes approximately an hour and a half to complete. Thus, substantial resources are required to deliver this assessment. In order to decrease the delivery time, a future version of this task may only expose participants to a subset of the parameter values explored in the present study. Ideally, there would be a single set of parameter values that are most strongly correlated with risk propensity. Identifying and validating the set of parameter values that work best as an assessment of risk propensity is an important goal for future research.

In addition to clinical utility, the Wheel of Choice task is useful for conducting laboratory research on choice under risk. The ability to independently manipulate different aspects of risky choice is crucial to be able to conduct thorough experimental research. The task is also easily repeatable and potentially simple enough to use with children. In addition, participants earned an average of $8 USD and completed 180 trials with multiple risky choices made in the majority of these trials. This demonstrates that a large amount of data can be collected at a moderate cost when using this task.

The Wheel of Choice task is potentially useful for the experimental study of choice under risk. The greater control of probability of bankruptcy led to a different effect of magnitude than would have been predicted by previous studies using the BART. A further exploration of both of these parameter spaces is warranted and cannot be studied using the BART due to the conflation of these variables. The Wheel of Choice task also potentially has clinical utility as an assessment of risky choice. In order to determine whether or not it is of greater value than the BART, both further validation as a risk assessment as well as the usefulness of visual displays in risk assessments should be conducted.

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Appendix A

HSIRB Approval

WESTERN MICHIGAN UNIVERSITY

Human Subjects Institutional Review Board

Date: July 12, 2017

To: Anthony DeFulio, Principal Investigator
David Sottile, Student Investigator for Thesis

From: Daryle Gardner-Bonneau, Ph.D., Vice Chair Daryle J. Gardner-Bonneau

Re: HSIRB Project Number 17-07-02

This letter will serve as confirmation that your research project titled "A Parametric Analysis of the Effects of Stake Size, Magnitude, and Probability on Choice Under Risk" has been **approved** under the **expedited** category of review by the Human Subjects Institutional Review Board. The conditions and duration of this approval are specified in the Policies of Western Michigan University. You may now begin to implement the research as described in the application.

Please note: This research may **only** be conducted exactly in the form it was approved. You must seek specific board approval for any changes in this project (e.g., ***you must request a post approval change to enroll subjects beyond the number stated in your application under "Number of subjects you want to complete the study)."*** Failure to obtain approval for changes will result in a protocol deviation. In addition, if there are any unanticipated adverse reactions or unanticipated events associated with the conduct of this research, you should immediately suspend the project and contact the Chair of the HSIRB for consultation.

Reapproval of the project is required if it extends beyond the termination date stated below.

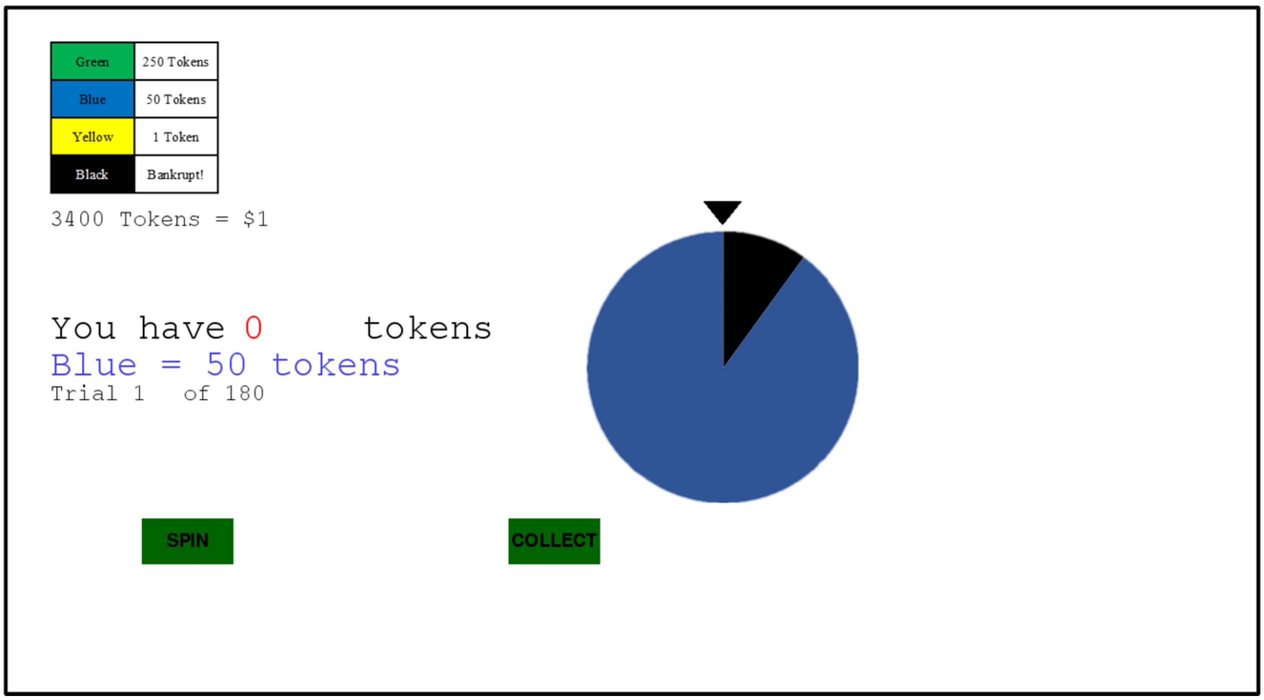
The Board wishes you success in the pursuit of your research goals.

Approval Termination: **July 11, 2018**

1903 W. Michigan Ave., Kalamazoo, MI 49008-5456
PHONE: (269) 387-8293 FAX: (269) 387-8276
CAMPUS SITE: 251 W. Walwood Hall

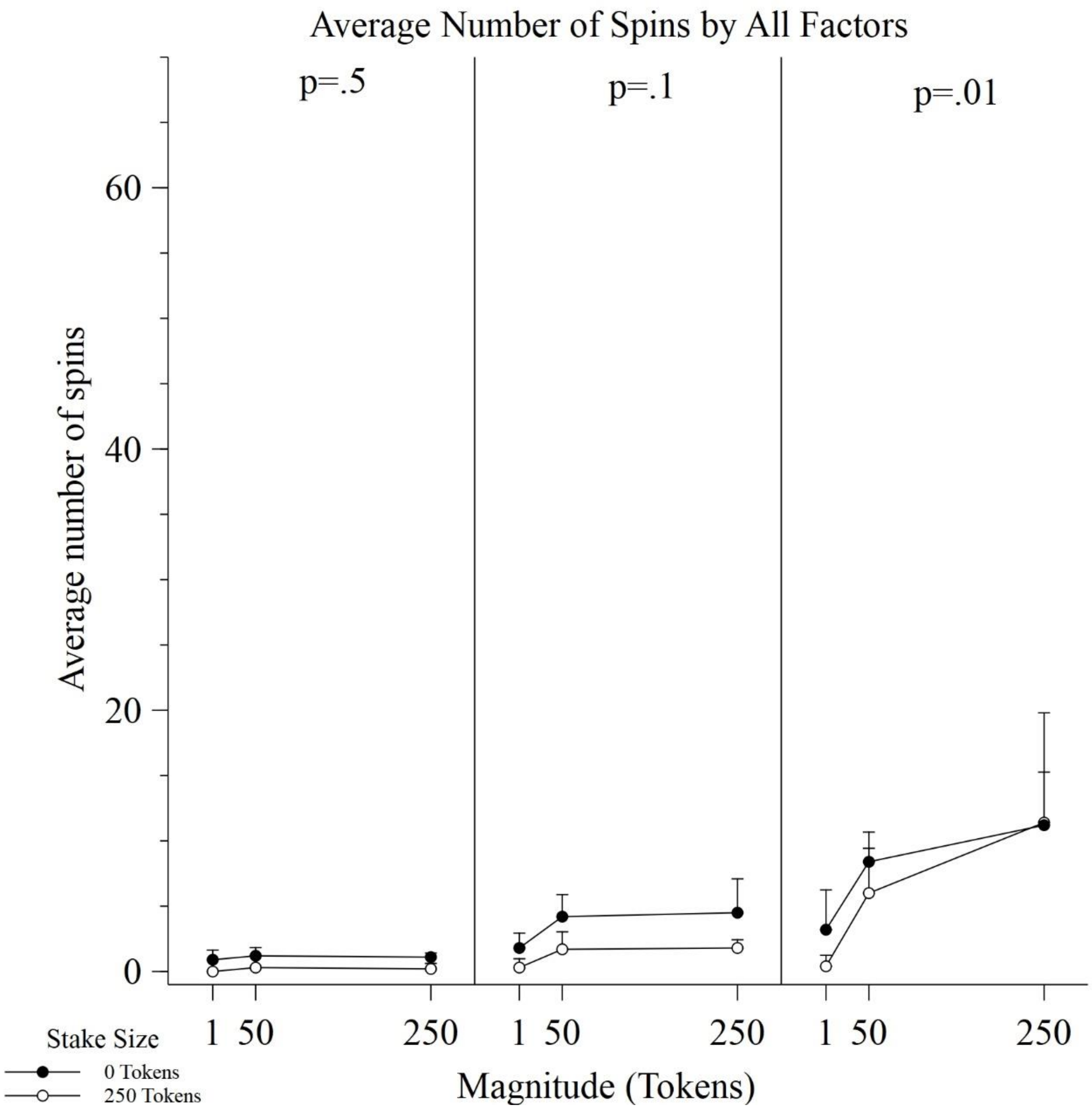
Appendix B

Wheel of Choice Main Screen

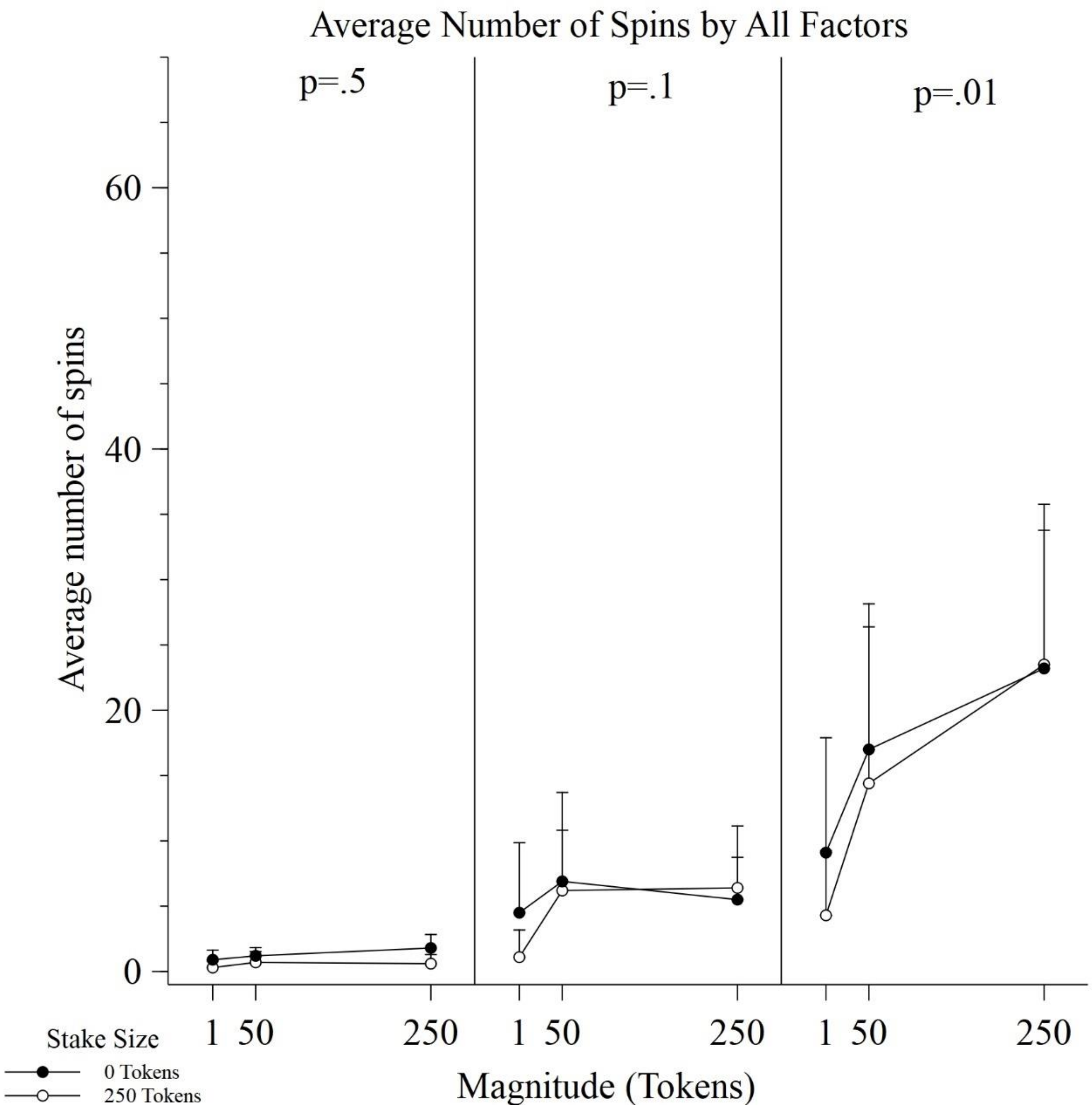

Green
250 Tokens
Blue
50 Tokens
Yellow
1 Token
Black
Bankrupt!
3400 Tokens = $1
You have 0 tokens
Blue = 50 tokens
Trial 1 of 180
SPIN
COLLECT

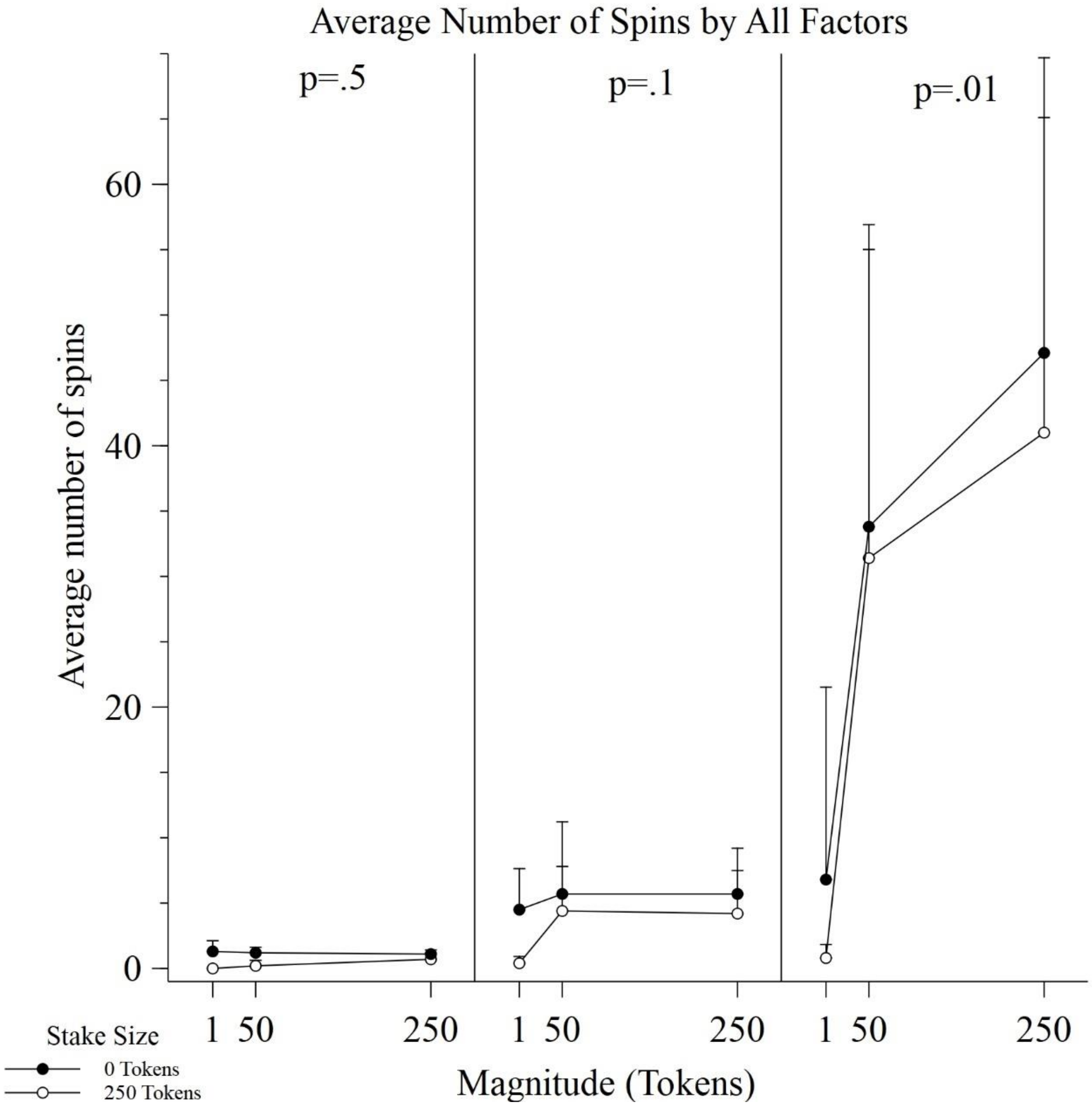
Appendix C

Individual Graphs of Average Number of Spins by All Factors

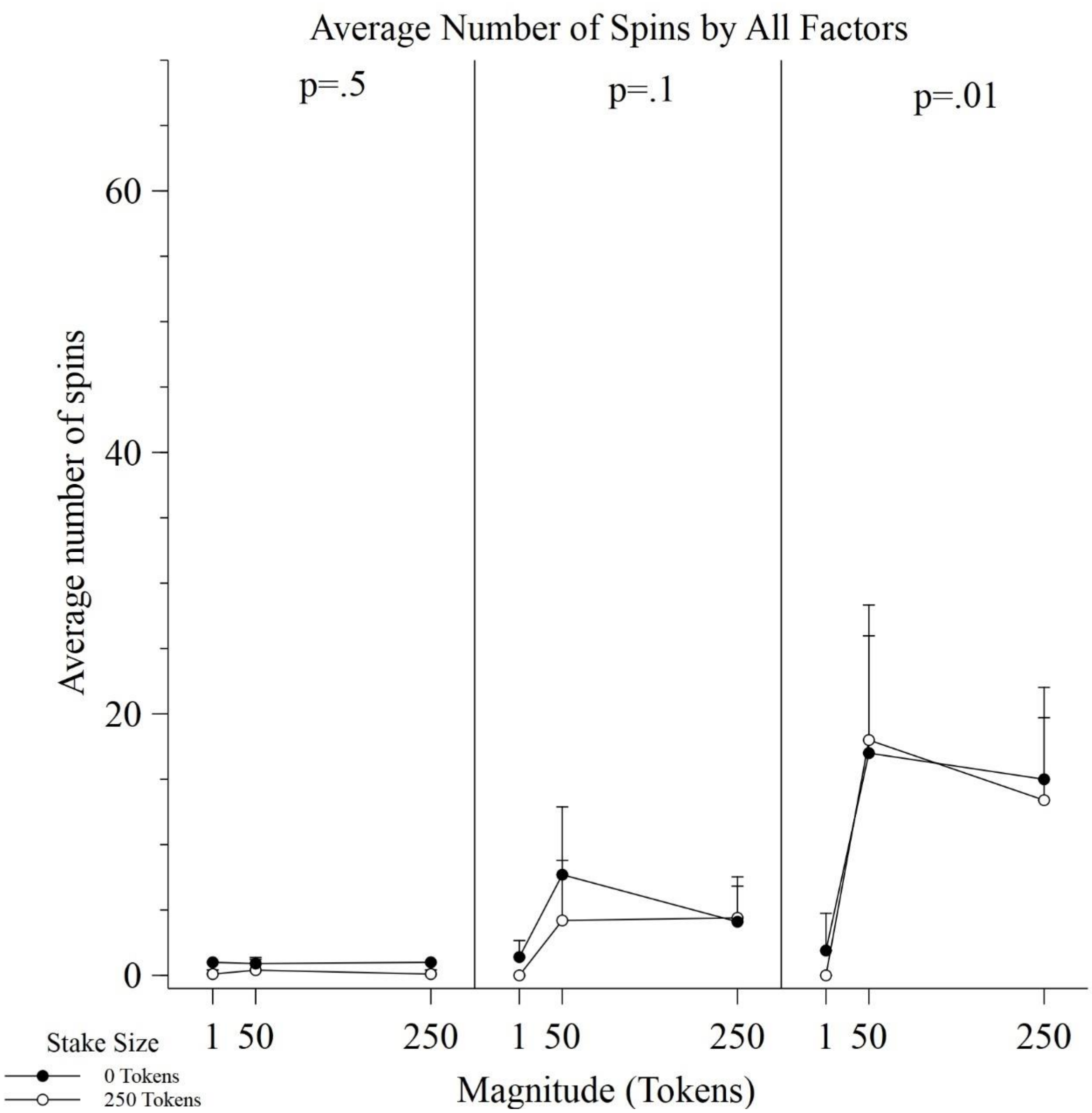


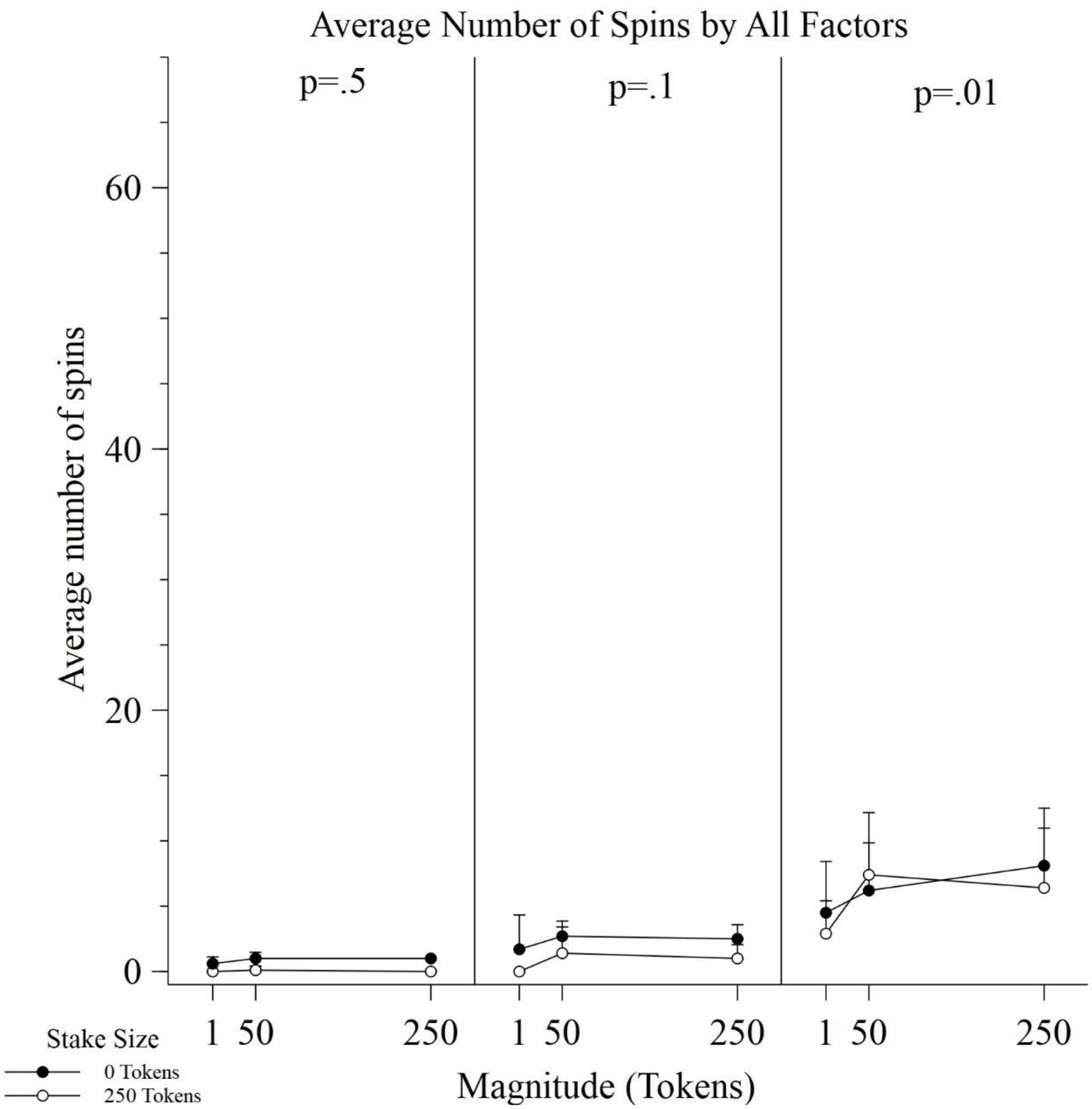
Average Number of Spins by All Factors
p=.5
p=.1
p=.01
60
40
20
0
Average number of spins
1 50 250
1 50 250
1 50 250
Magnitude (Tokens)
Stake Size
0 Tokens
250 Tokens


Average Number of Spins by All Factors
p=.5
p=.1
p=.01
Average number of spins
0
20
40
60
1 50 250
1 50 250
1 50 250
Magnitude (Tokens)
Stake Size
0 Tokens
250 Tokens



Average Number of Spins by All Factors
p=.5
p=.1
p=.01
Average number of spins
0
20
40
60
1 50 250
1 50 250
1 50 250
Stake Size
0 Tokens
250 Tokens
Magnitude (Tokens)


Average Number of Spins by All Factors
p=.5
p=.1
p=.01
60
40
20
0
Average number of spins
1 50 250
1 50 250
1 50 250
Magnitude (Tokens)
Stake Size
0 Tokens
250 Tokens


Average Number of Spins by All Factors
p=.5
p=.1
p=.01
Average number of spins
60
40
20
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1
50
250
1
50
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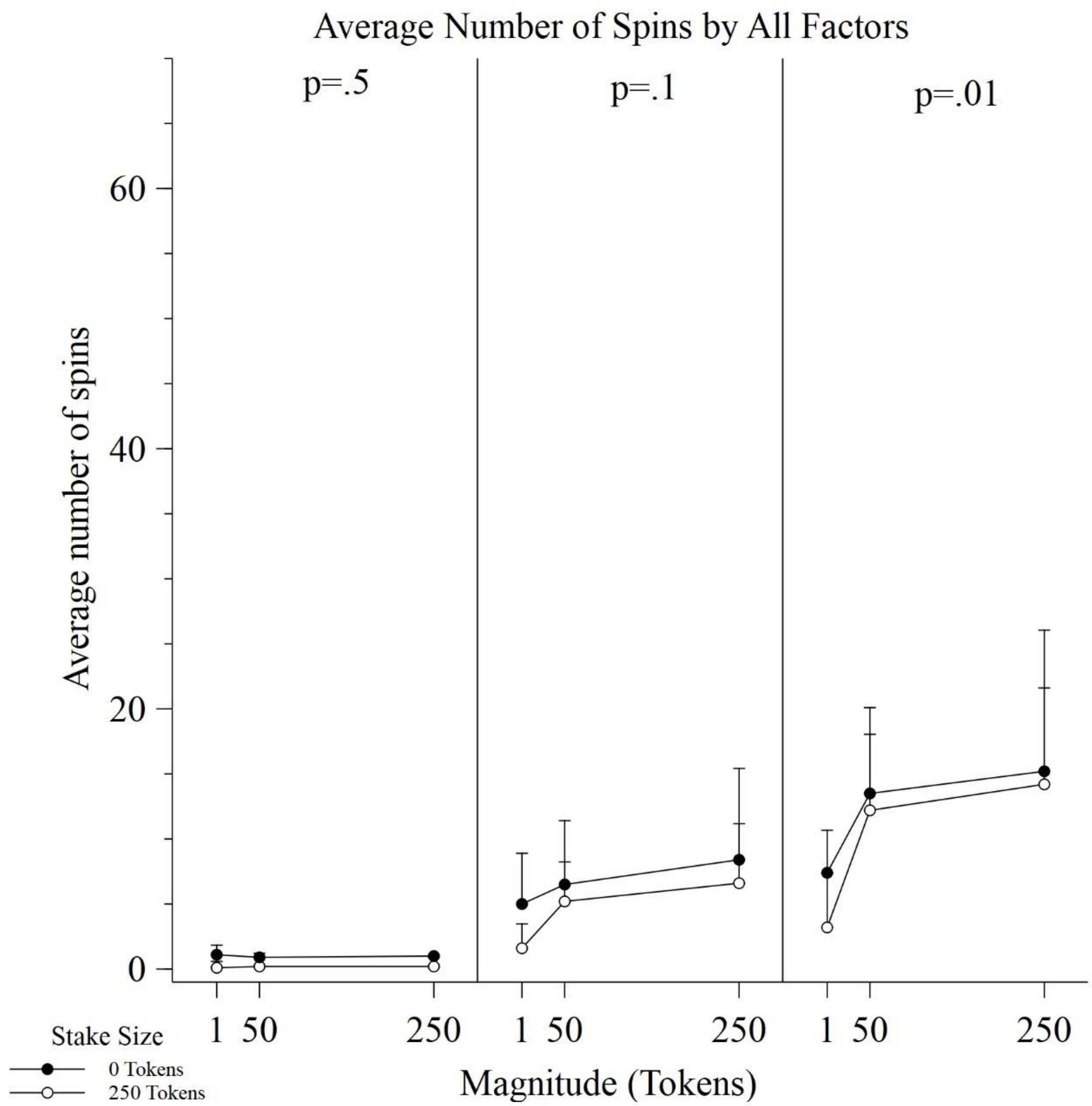
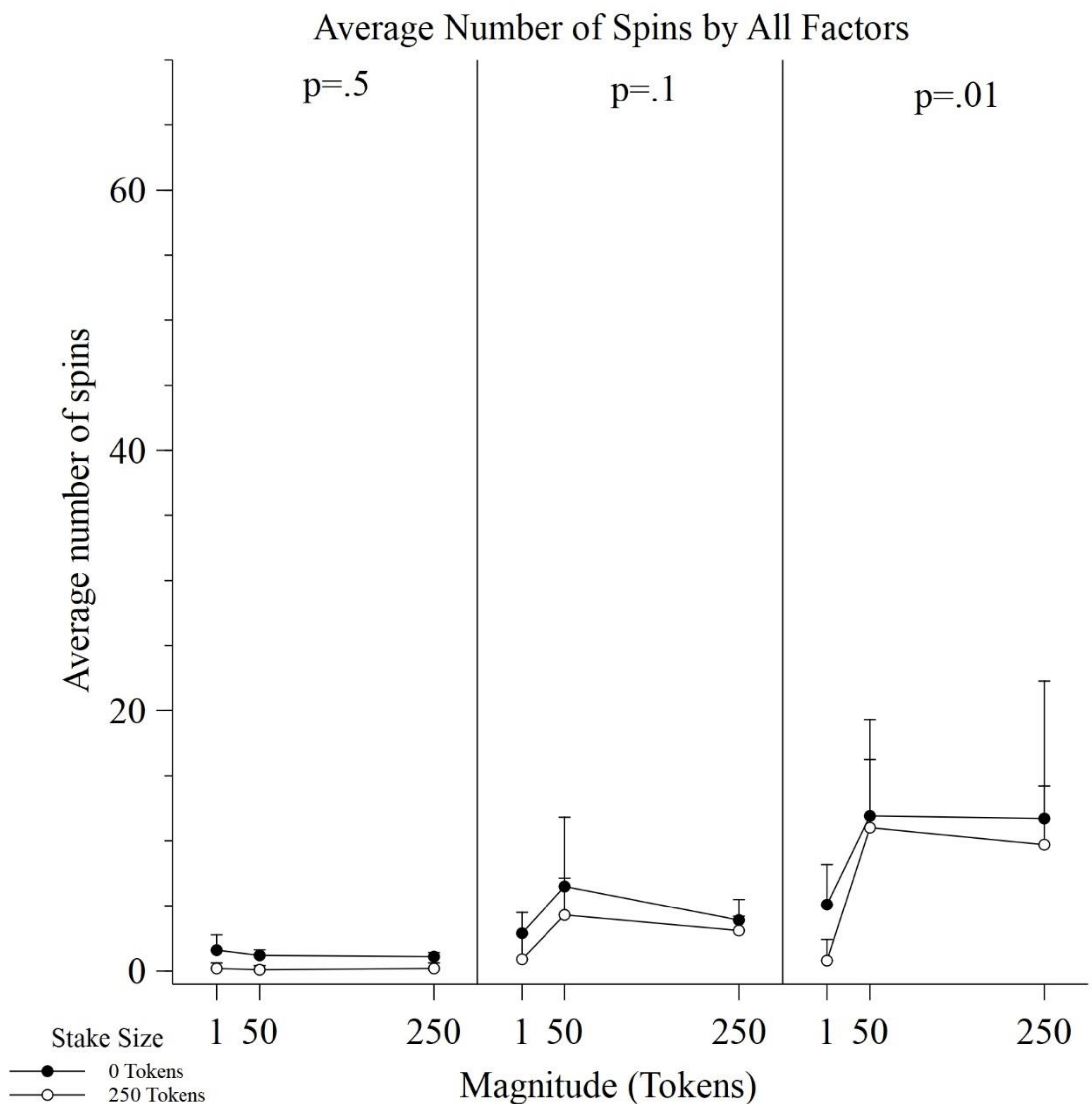
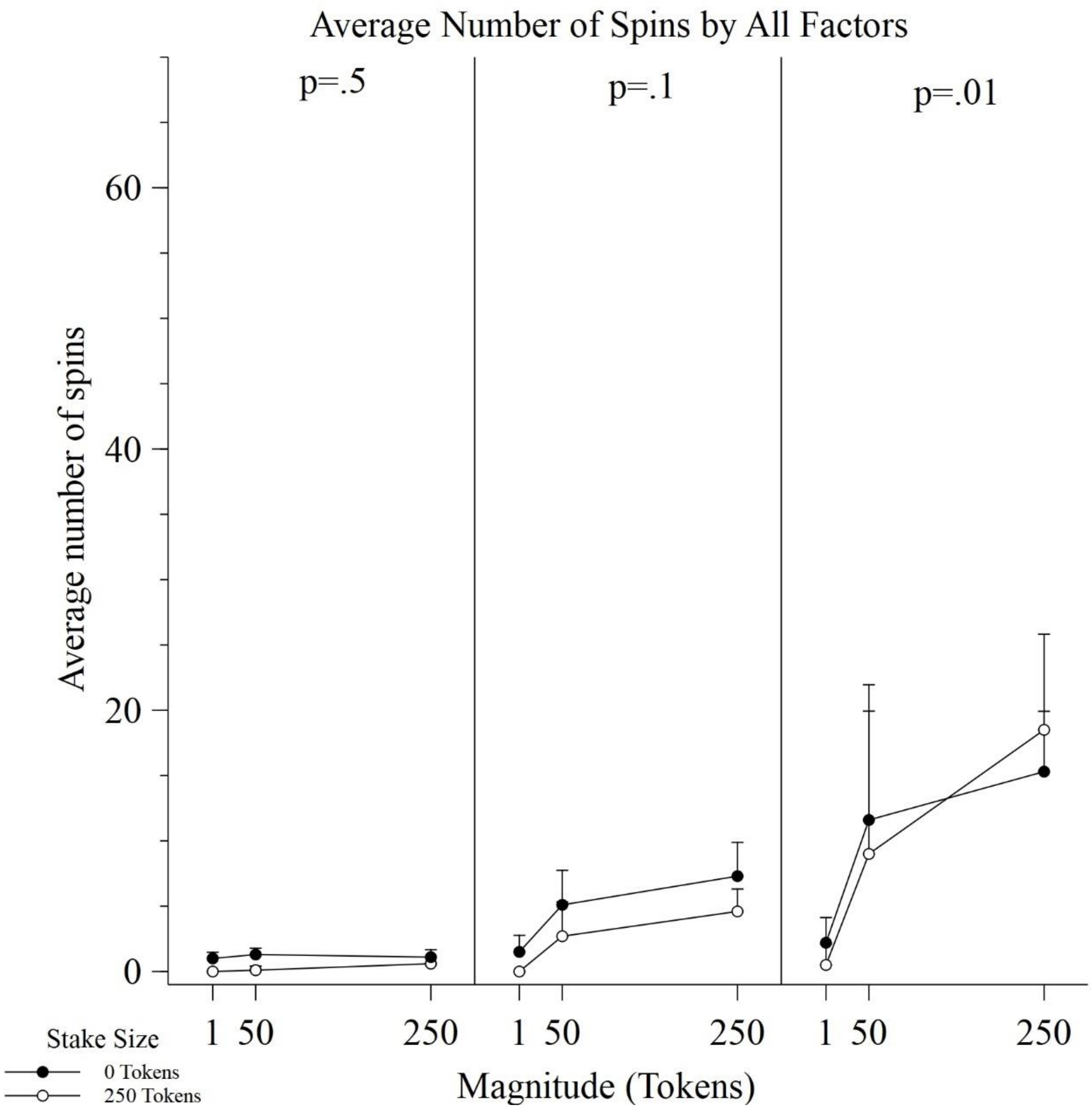
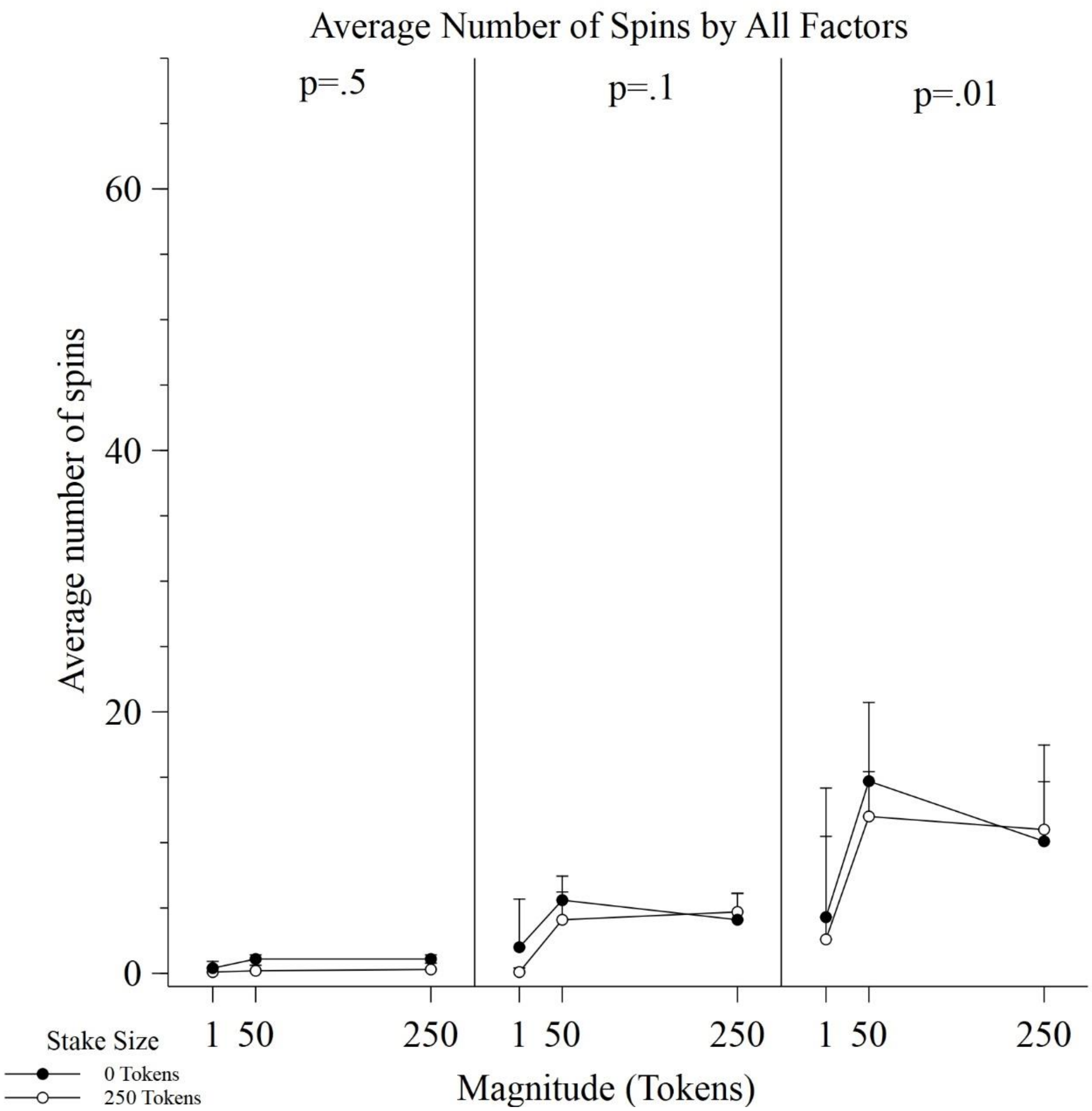
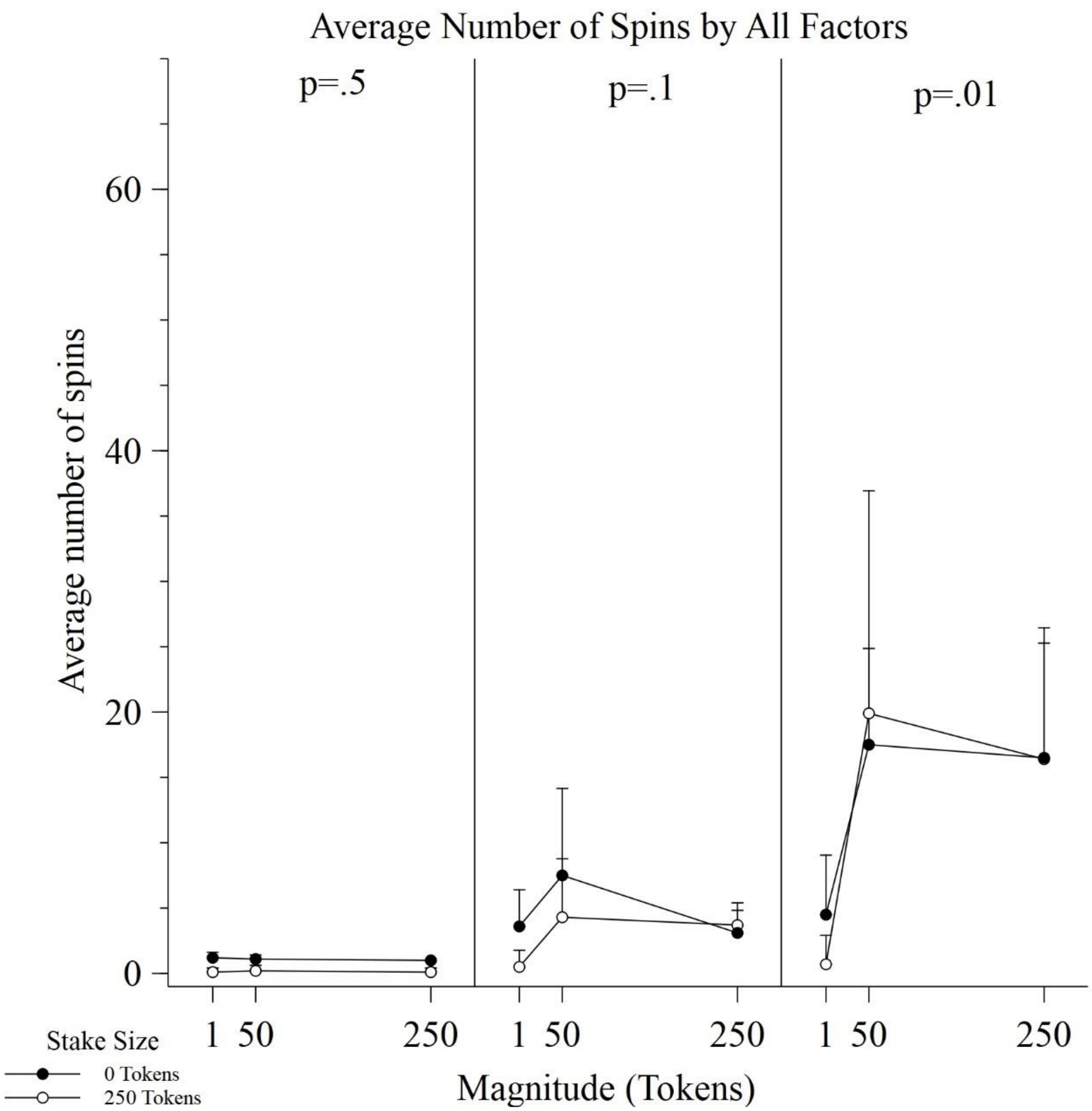
250
Magnitude (Tokens)
Stake Size
0 Tokens
250 Tokens

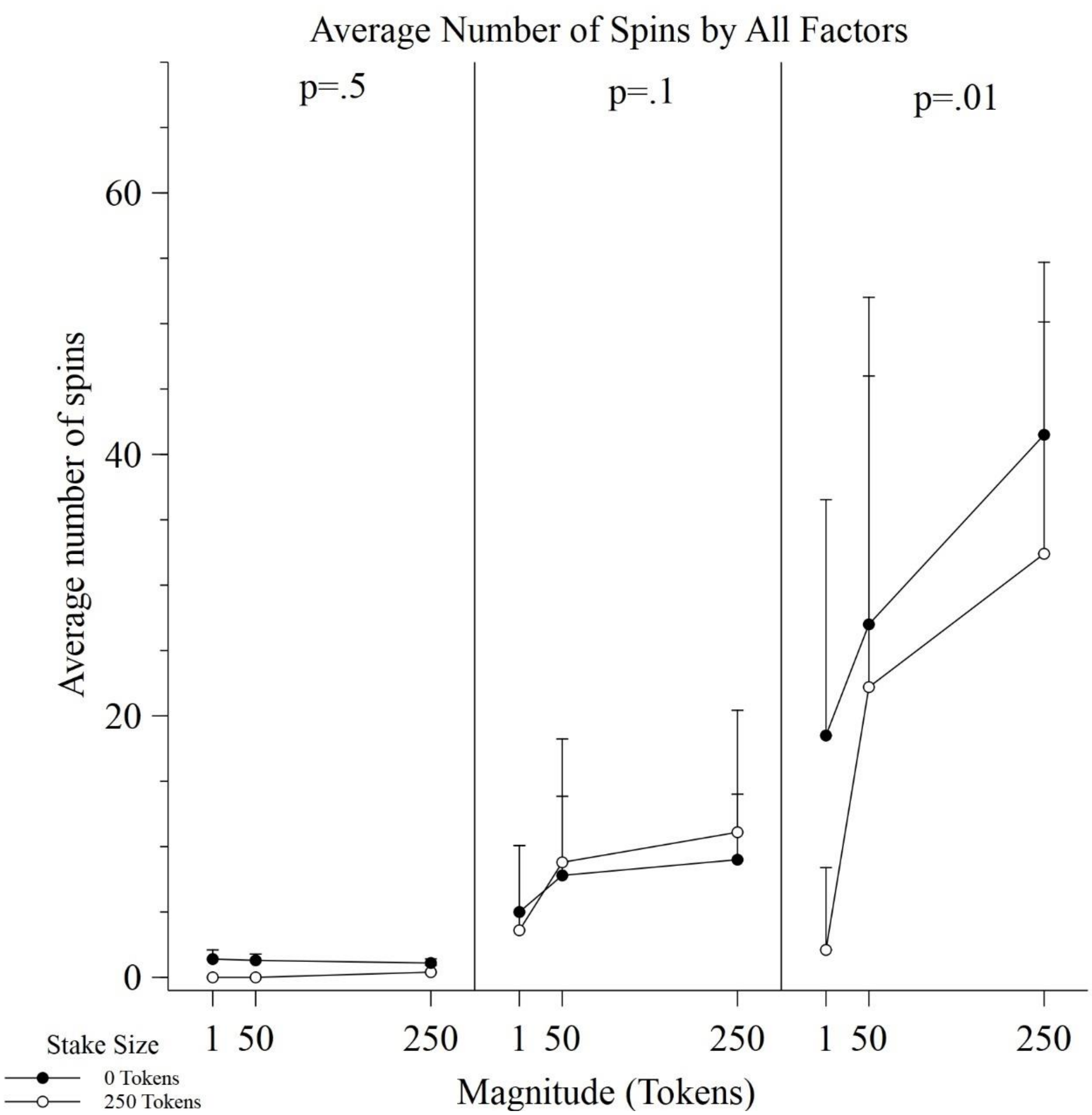

Average Number of Spins by All Factors
p=.5
p=.1
p=.01
Average number of spins
60
40
20
0
1 50 250
1 50 250
1 50 250
Stake Size
0 Tokens
250 Tokens
Magnitude (Tokens)

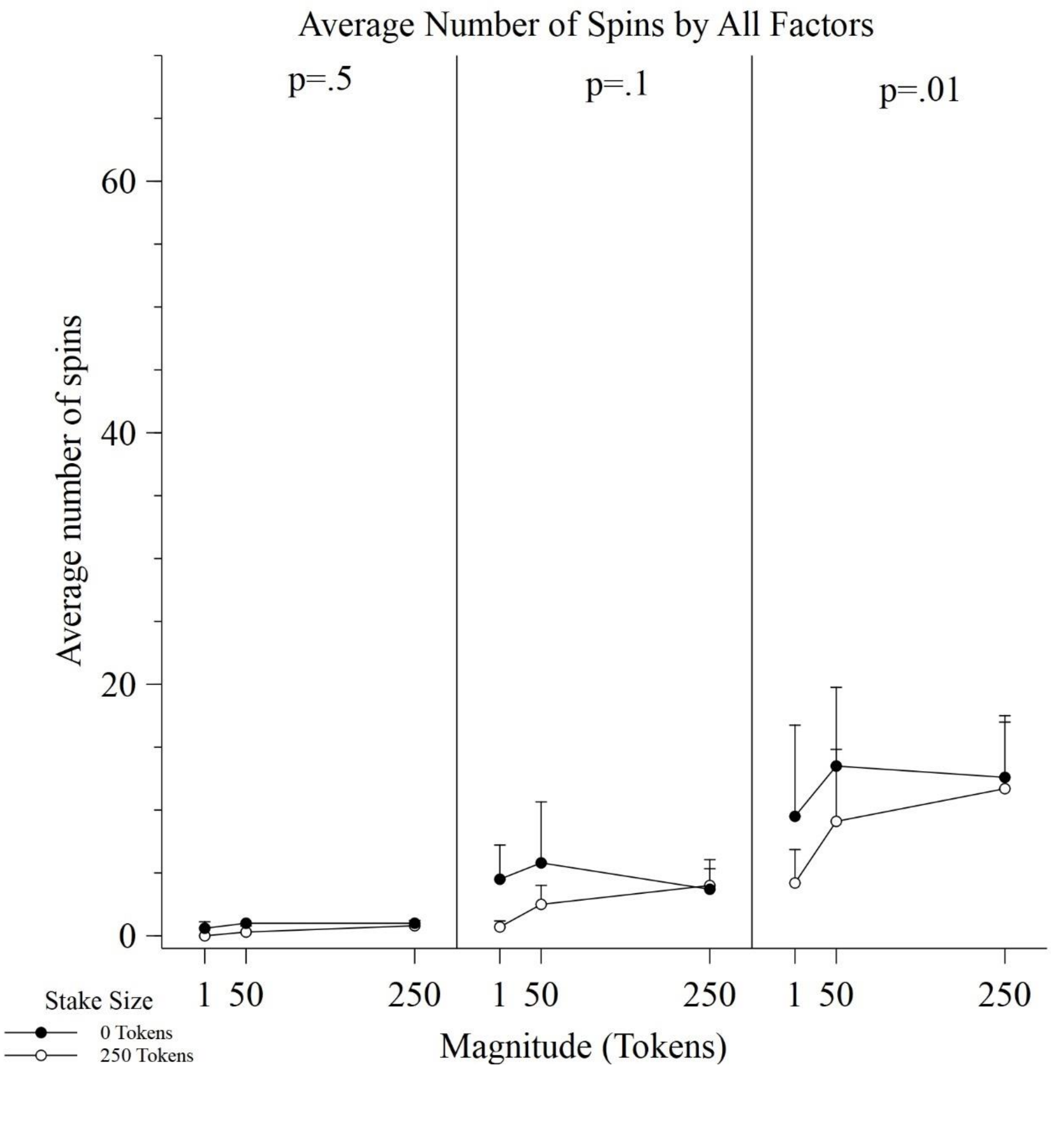

Average Number of Spins by All Factors
p=.5
p=.1
p=.01
Average number of spins
60
40
20
0
1
50
250
Stake Size
0 Tokens
250 Tokens
Magnitude (Tokens)


Average Number of Spins by All Factors
p=.5
p=.1
p=.01
Average number of spins
60
40
20
0
1 50 250
1 50 250
1 50 250
Magnitude (Tokens)
Stake Size
0 Tokens
250 Tokens

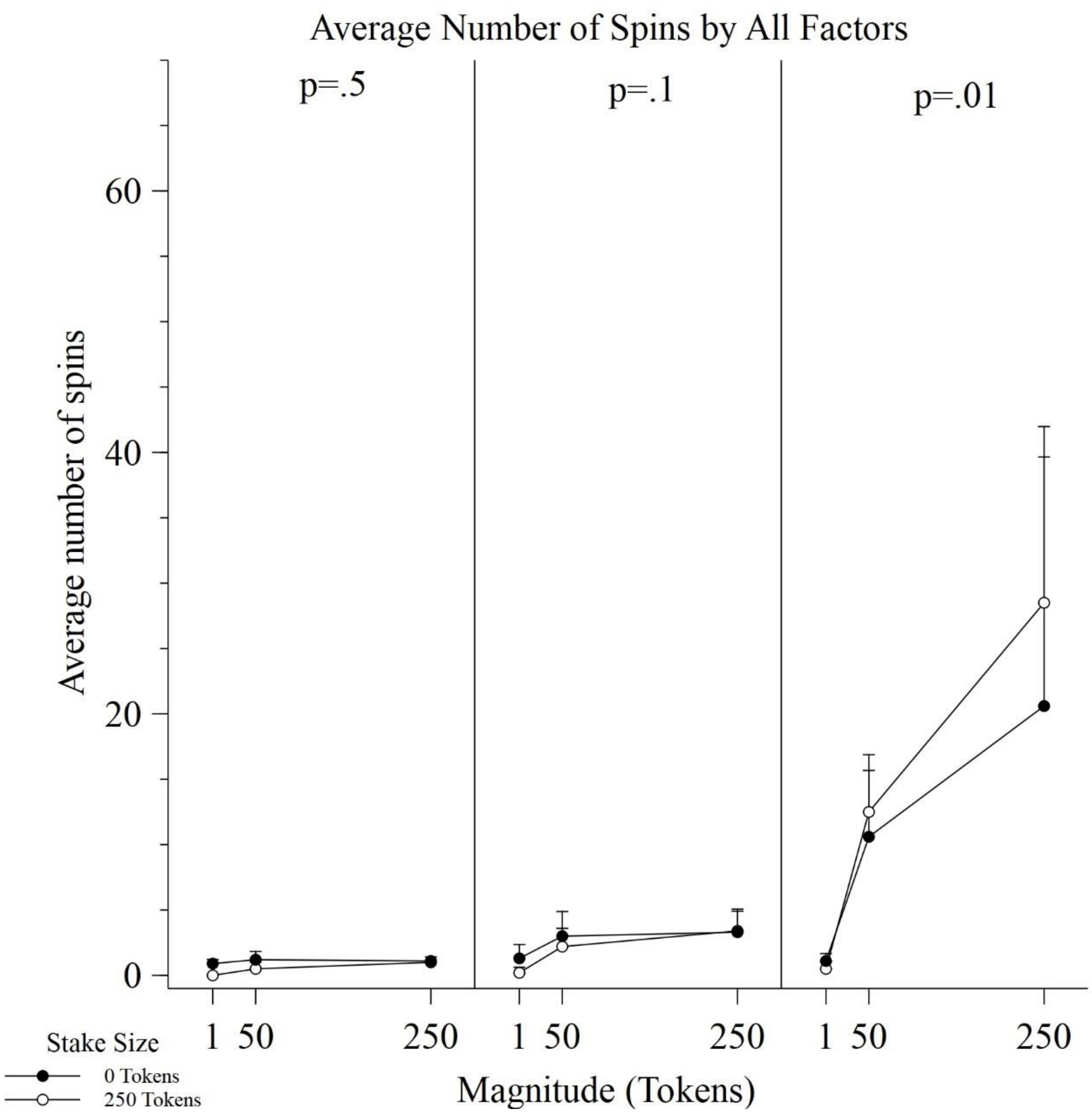

Average Number of Spins by All Factors
p=.5
p=.1
p=.01
60
40
20
0
Average number of spins
1
50
250
Stake Size
0 Tokens
250 Tokens
Magnitude (Tokens)


Average Number of Spins by All Factors
p=.5
p=.1
p=.01
Average number of spins
60
40
20
0
1
50
250
Stake Size
0 Tokens
250 Tokens
Magnitude (Tokens)

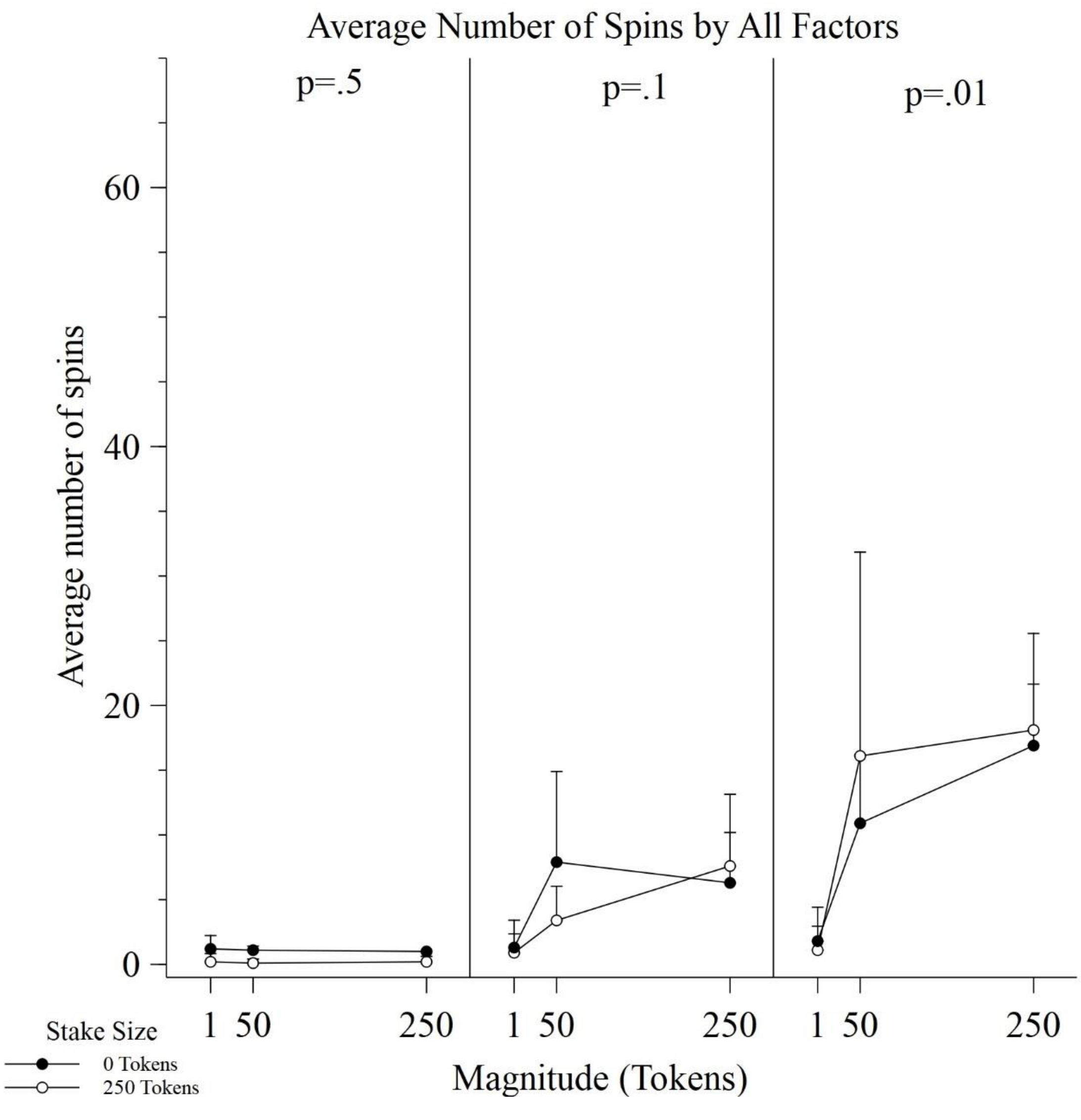

Average Number of Spins by All Factors
p=.5
p=.1
p=.01
Average number of spins
0
20
40
60
1
50
250
Magnitude (Tokens)
Stake Size
0 Tokens
250 Tokens



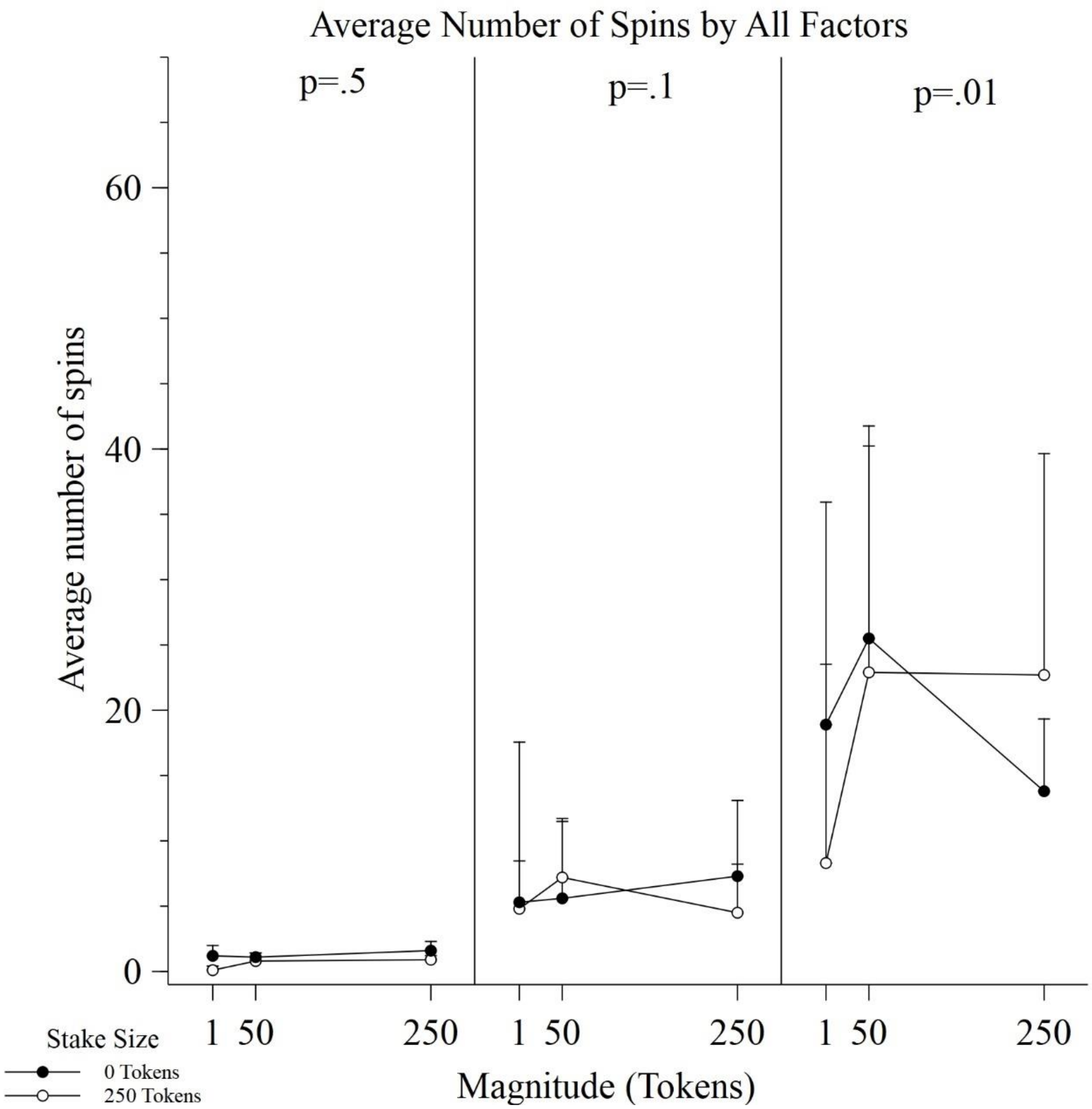
Average Number of Spins by All Factors
p=.5
p=.1
p=.01
Average number of spins
0
20
40
60
1 50 250
1 50 250
1 50 250
Magnitude (Tokens)
Stake Size
0 Tokens
250 Tokens

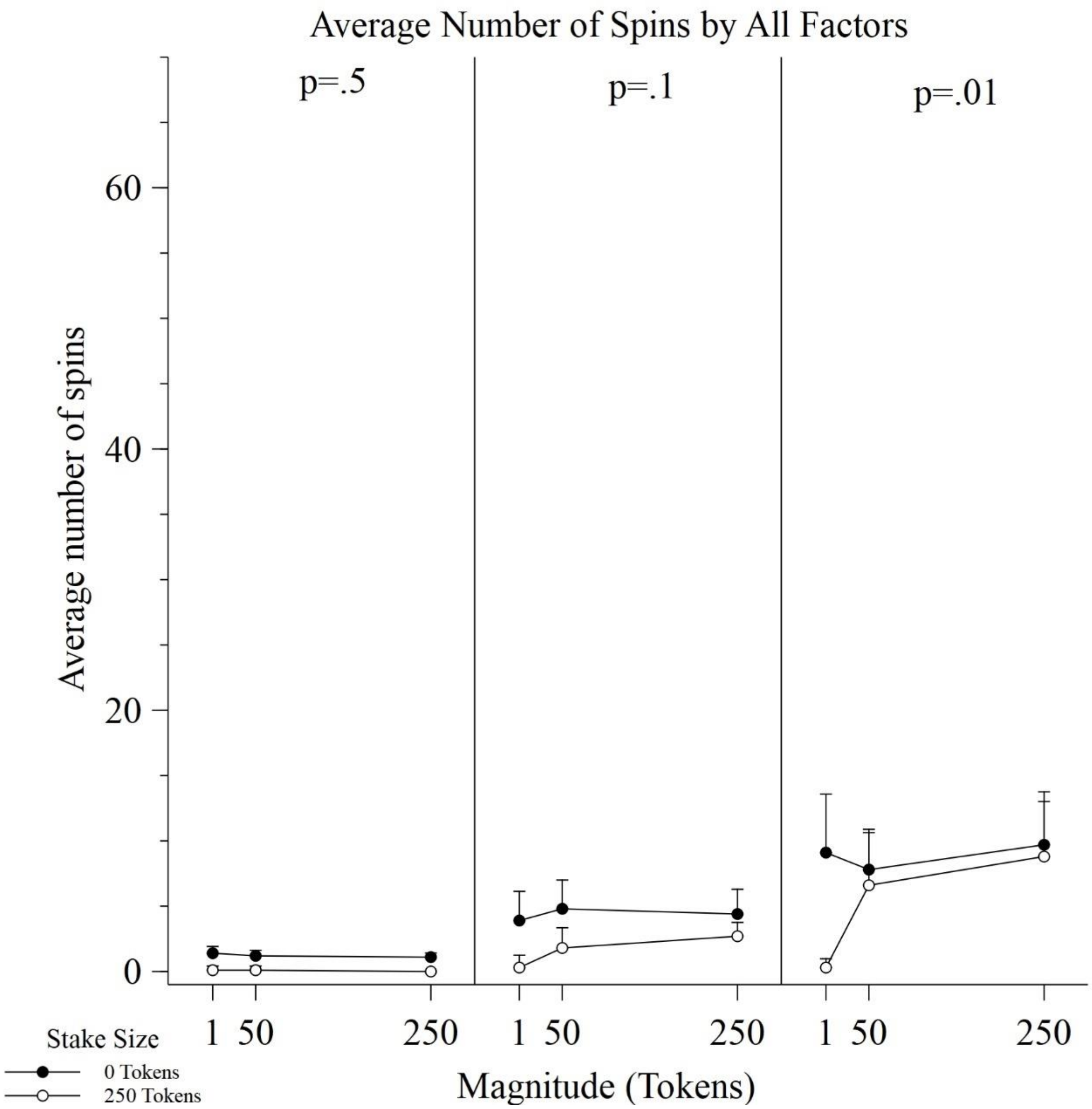


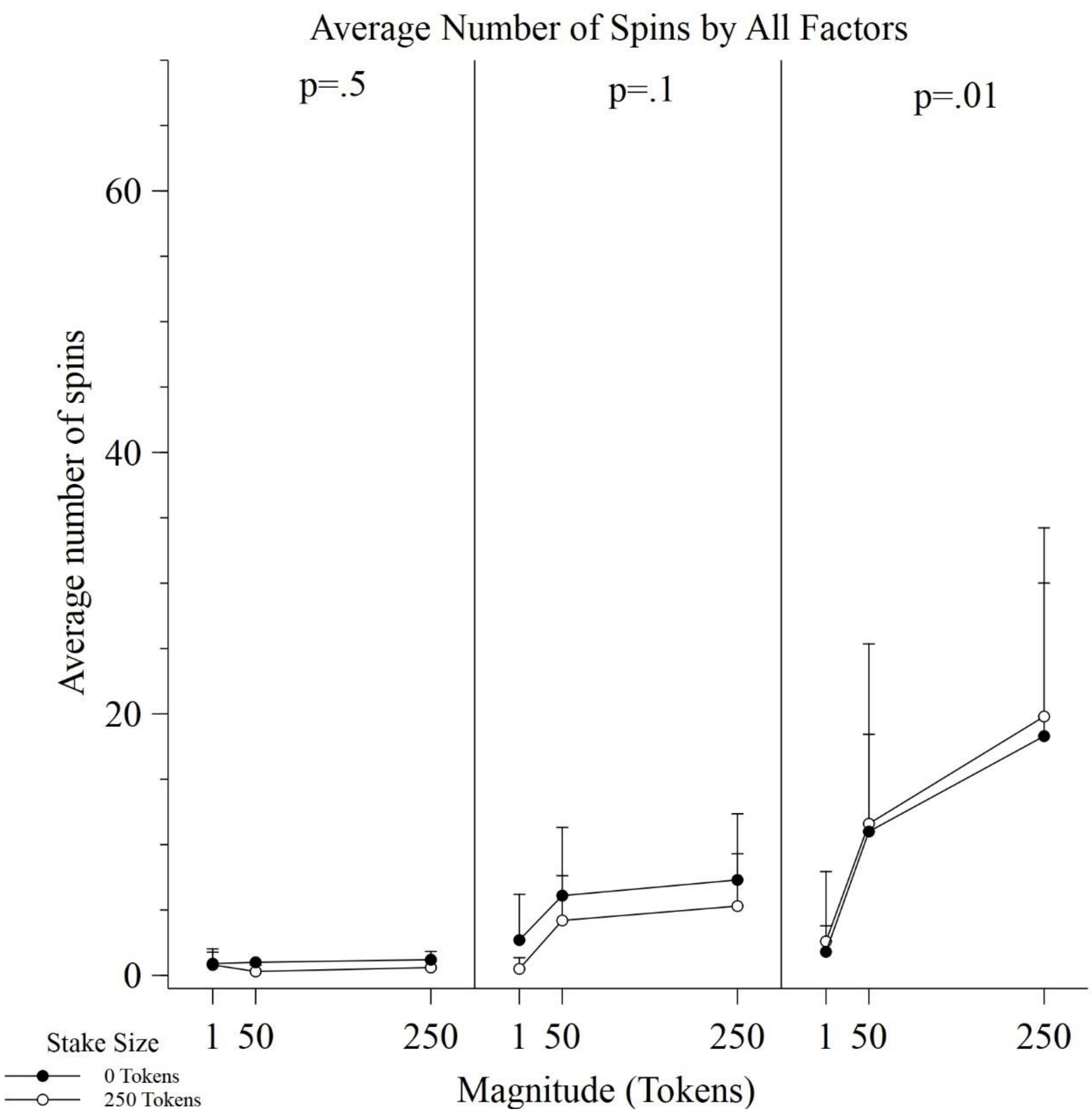
Average Number of Spins by All Factors
p=.5
p=.1
p=.01
Average number of spins
0
20
40
60
1
50
250
Magnitude (Tokens)
Stake Size
0 Tokens
250 Tokens

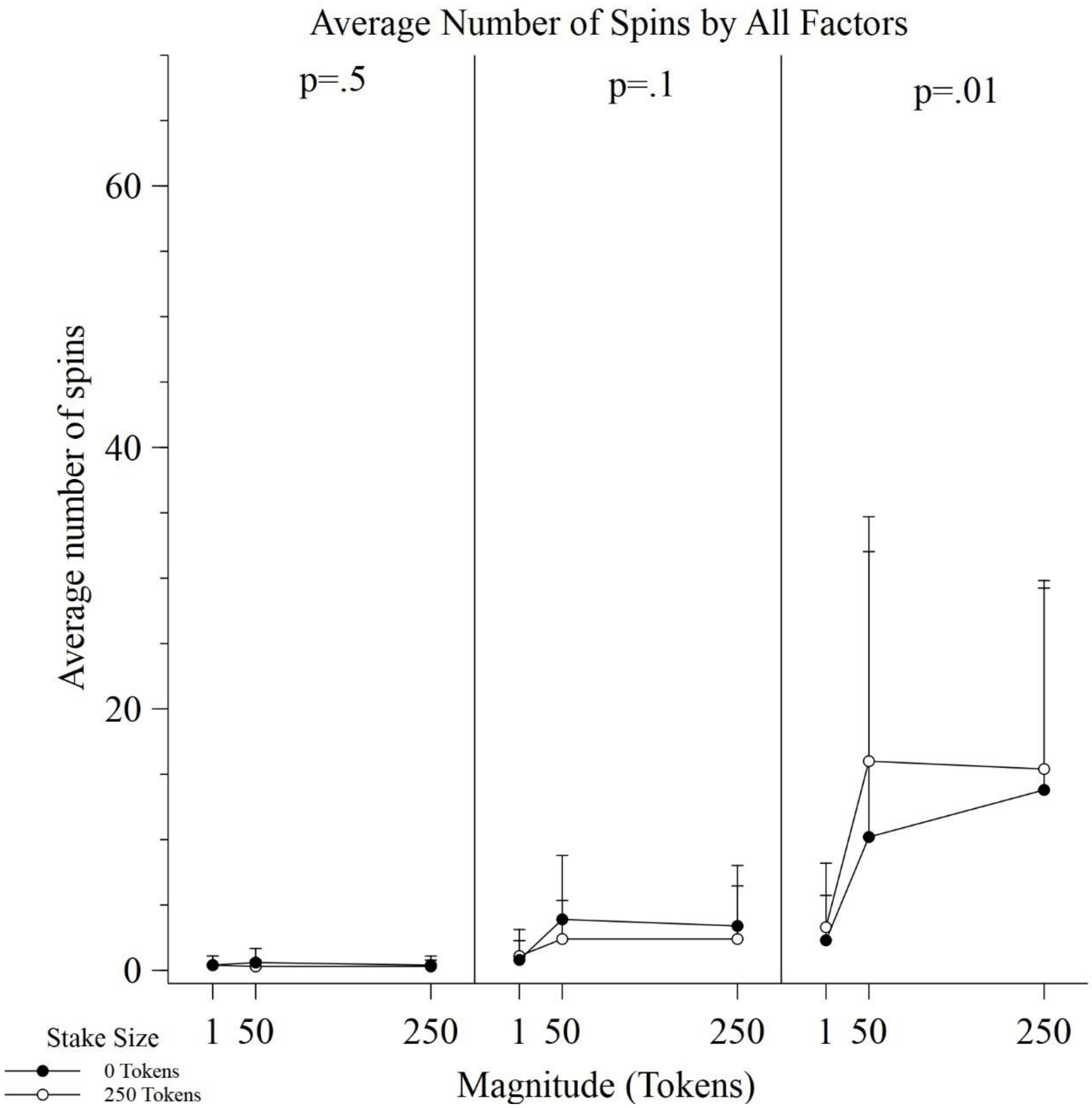


Average Number of Spins by All Factors
p=.5
p=.1
p=.01
60
40
20
0
Average number of spins
1 50 250
1 50 250
1 50 250
Magnitude (Tokens)
Stake Size
0 Tokens
250 Tokens

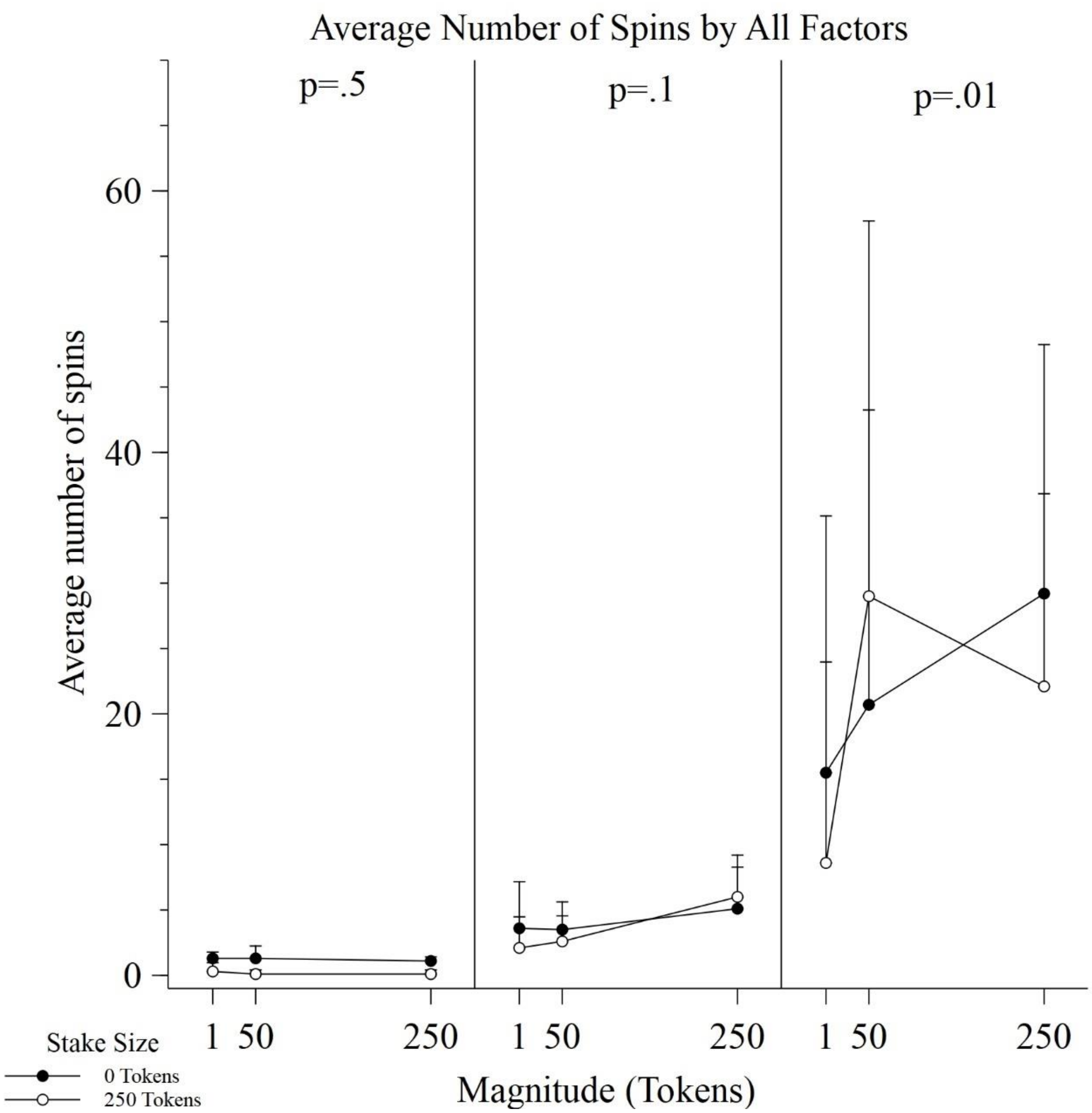

Average Number of Spins by All Factors
p=.5
p=.1
p=.01
60
40
20
0
Average number of spins
1 50 250
1 50 250
1 50 250
Magnitude (Tokens)
Stake Size
0 Tokens
250 Tokens

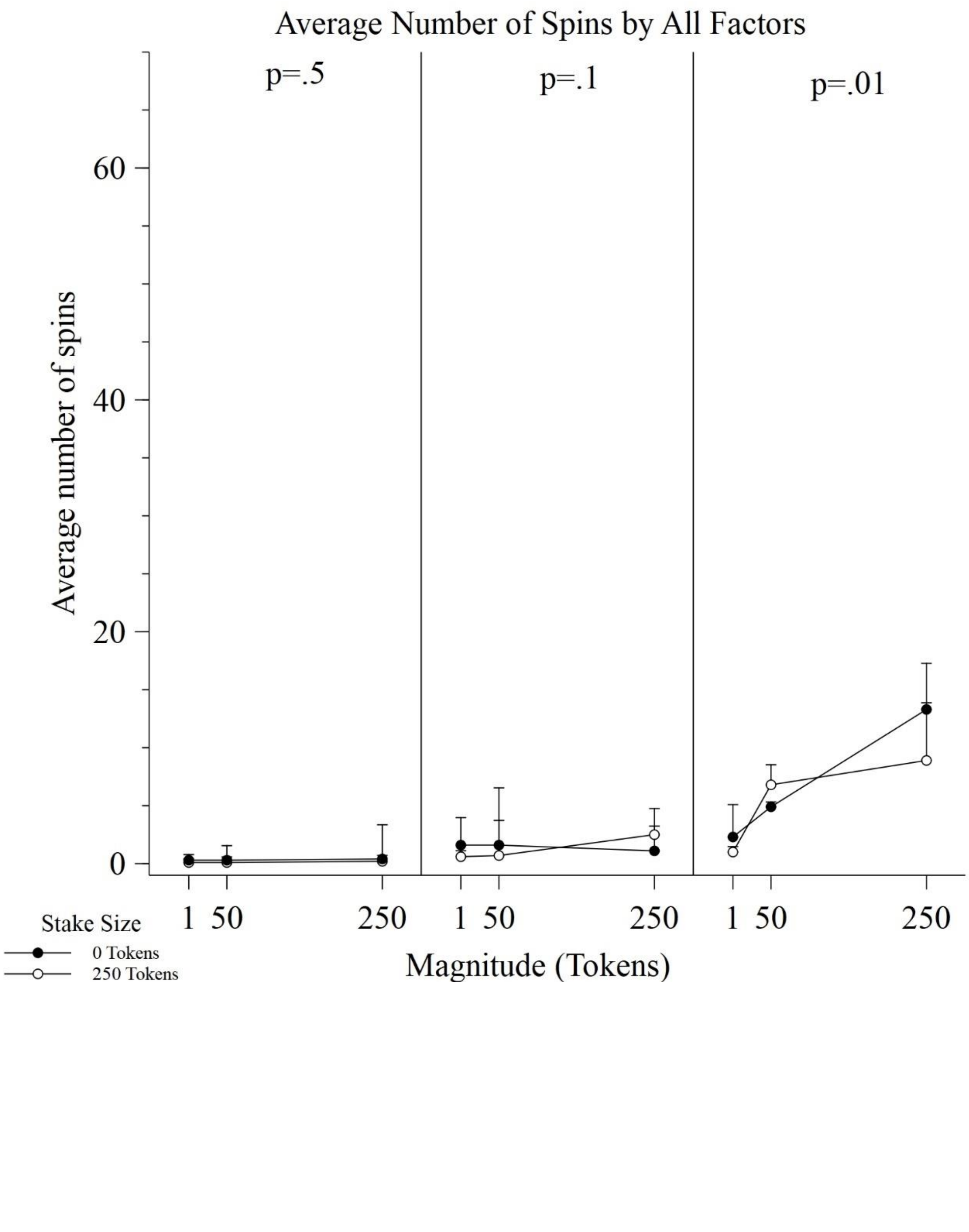

Average Number of Spins by All Factors
p=.5
p=.1
p=.01
Average number of spins
60
40
20
0
1 50 250
1 50 250
1 50 250
Magnitude (Tokens)
Stake Size
0 Tokens
250 Tokens


Average Number of Spins by All Factors
p=.5
p=.1
p=.01
Average number of spins
0
20
40
60
1
50
250
Magnitude (Tokens)
Stake Size
0 Tokens
250 Tokens

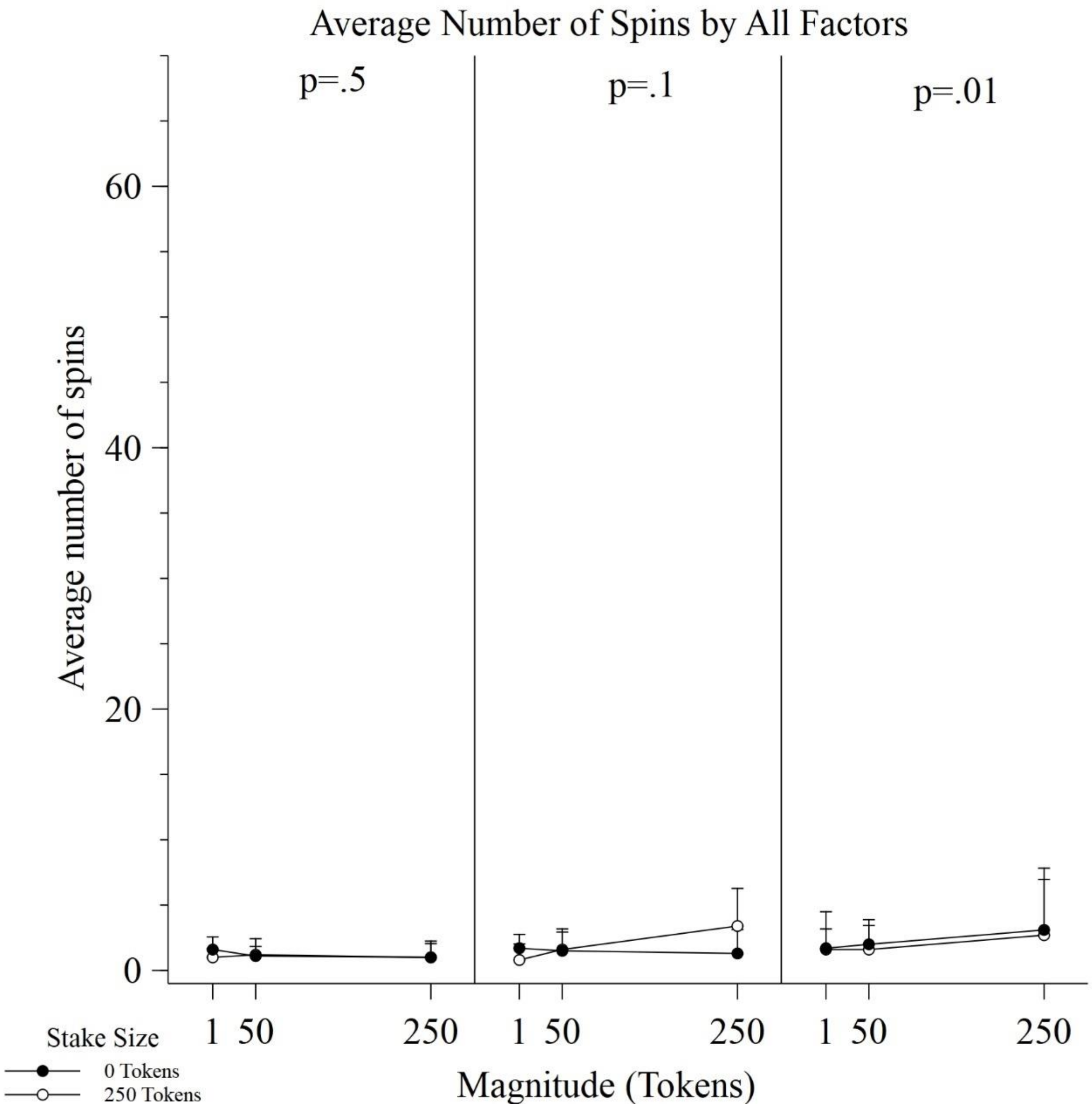


Average Number of Spins by All Factors
p=.5
p=.1
p=.01
Average number of spins
60
40
20
0
1 50 250
1 50 250
1 50 250
Magnitude (Tokens)
Stake Size
0 Tokens
250 Tokens


Average Number of Spins by All Factors
p=.5
p=.1
p=.01
Average number of spins
0
20
40
60
1
50
250
Magnitude (Tokens)
Stake Size
0 Tokens
250 Tokens



Average Number of Spins by All Factors
p=.5
p=.1
p=.01
Average number of spins
0
20
40
60
1 50 250
1 50 250
1 50 250
Magnitude (Tokens)
Stake Size
0 Tokens
250 Tokens


Average Number of Spins by All Factors
p=.5
p=.1
p=.01
Average number of spins
60
40
20
0
1 50 250
1 50 250
1 50 250
Magnitude (Tokens)
Stake Size
0 Tokens
250 Tokens