Risky Decision Making on Catch 21

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Abstract

I describe whether high stakes risky decisions in the game show Catch 21 are more consistent with expected utility theory or prospect theory. The show permits for an analysis of two distinct decisions: the card placement decision and the stop/continue decision. I find evidence of reference dependence in both the card placement decision and the stop/continue decision. These findings suggest that the decisions on Catch 21 may be better explained by prospect theory than expected utility theory, which is consistent with the conclusions of other studies that use game show data.

I. Introduction

In this paper, I examine how well economic choice models of expected utility theory and prospect theory explain the risky decision making of contestants in the game show Catch 21. This game show allows for the analysis of risky decision making where the potential monetary payoff is large, which has been difficult in other behavioral studies. Difficulty arises because economists conduct most of their experiments on college campuses. The participants are usually college students and the monetary payoffs are usually small (Kahneman and Tversky, 1981), (Hardies, Breesch and Branson, 2013), (Peng and Miao, Xiao, 2013). Game shows offer scenarios in which the financial stakes are high and the probability of outcomes are known. Therefore, researchers have used game shows to analyze individual risky decision making (Gertner, 1993), (Post, van den Assem, Baltussen and Thaler, 2008).

The television game show Catch 21 provides a scenario in which the stakes are large and outcome probabilities are well defined. In the Catch 21 bonus round, one contestant is initially dealt three hands of cards. A dealer then reveals one card at a time from a standard deck and the contestant seeks to add the card to one of the three hands. The goal is to end up with a score of 21 in all three hands, using standard blackjack rules. Catch 21 provides two platforms to analyze risky decision making, as contestants first decide where to place each dealt card (henceforth, card placement decision), and then must decide whether to stop or to continue playing the game after each card is dealt (henceforth, stop/continue decision). I study whether decisions in the bonus round may be more consistent with a model of expected utility theory or prospect theory.

The answer to this question is valuable in application. Knowledge of how individuals make risky choices is critical for the analysis of financial investment practices, retirement savings strategies and lottery activities, among others. It is also important for the analysis of policy making under uncertainty. In addition, my findings will contribute to the growing economic literature that uses data from game shows.

Traditionally, economists have relied on expected utility theory to explain how individuals make choices under uncertainty (von Neumann and Morgenstern, 1944). More recently, behavioral economists have developed prospect theory as an alternative model of individual decision making (Kahneman and Tversky, 1979). Prospect theory, unlike standard formulations of expected utility theory, allows for reference dependent choices. Consider the following example: Larry begins with $150,000 and loses $50,000. Nathan begins with $50,000 and gains $50,000. Now, Larry and Nathan both have $100,000. Assuming monetary wealth is the only argument of the utility function, expected utility theory implies that Larry and Nathan have equal utility. Prospect theory, in which utility also depends on a point of reference, implies that Larry and Nathan may not necessarily have equal utility, as Larry's loss and Nathan's gain are significant.

I analyze the decisions in the bonus round of Catch 21 in several different ways. I find evidence of reference dependence in the card placement decision. That is, contestants that are dealt lucky behave differently than those that are unlucky, all else equal. Also, I find evidence of reference dependence and path dependence in the stop/continue decision. Lucky contestants may be more risk seeking while unlucky contestants may be more risk averse. Both of these results suggest that prospect theory may better explain risky decisions in the bonus round of Catch 21 than expected utility theory.

The rest of this paper proceeds as follows. Section 2 describes the rules of the bonus round of Catch 21, as well as related literature. Section 3 describes the data. Section 4 provides an analysis of the card placement decision and Section 5 provides an analysis of the stop/continue decision. Section 6 presents theoretical framework for maximum likelihood estimation of the two choice models and Section 7 concludes.

II. Background and Related Literature

A. Background

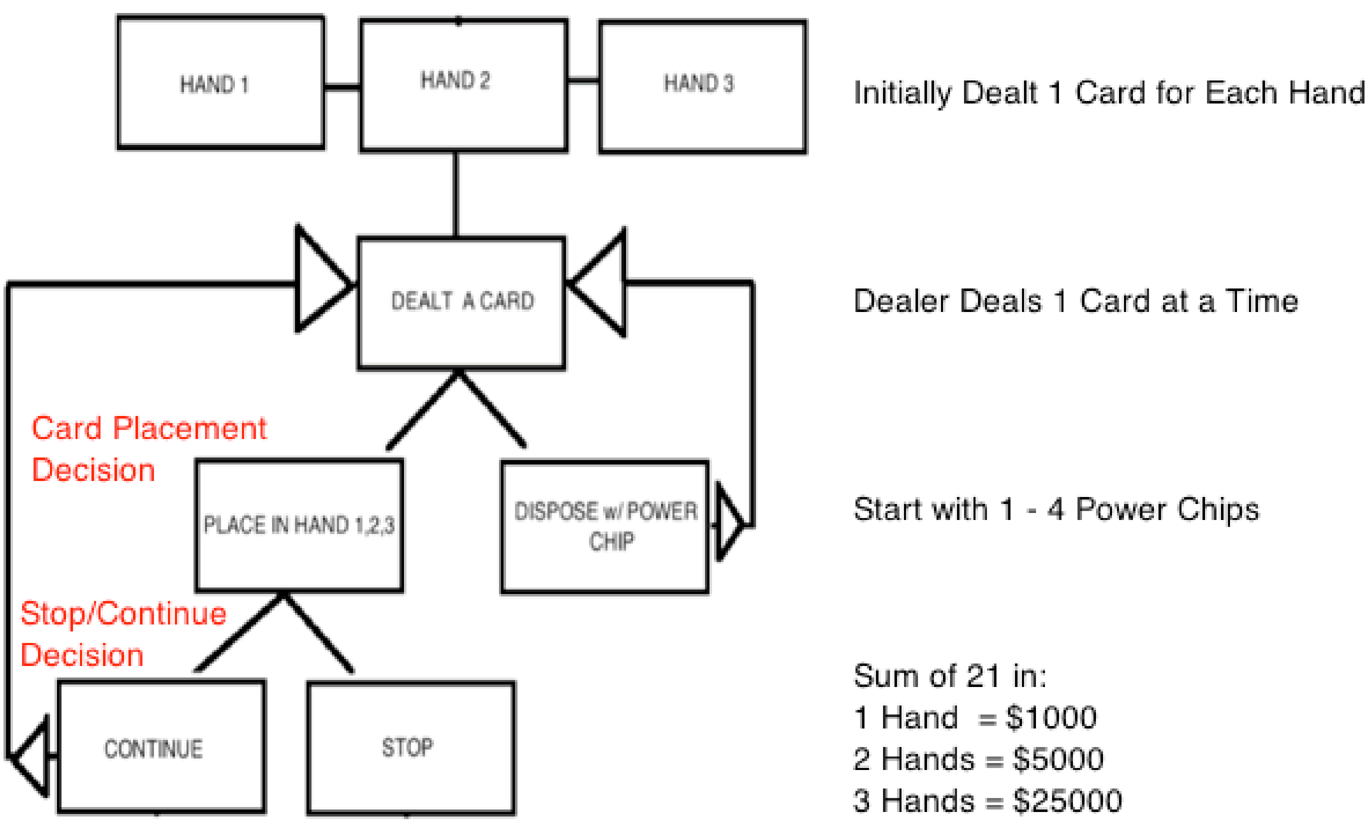
Game Show Network aired 300 episodes of Catch 21 in the United States from 2008-2011. One contestant competes for a maximum prize of $25,000 in the bonus round. A contestant reaches the bonus round after competing against two other contestants in three earlier rounds. The earlier rounds consist of a combination of popular culture trivia and a card game similar to blackjack. The contestant is awarded $1000 for reaching the bonus round and keeps this money regardless of the bonus round results.

Figure 1 shows a game diagram for the bonus round. The contestant simultaneously controls three hands of cards. They are initially dealt one card for each hand. A dealer reveals a card from a shuffled, standard deck and the contestant must decide between adding the card to one of their three hands, and if so, to which hand. Contestant can also discard an unwanted card by using what is called a Power Chip. Contestants begin the bonus round with up to four Power Chips, depending on their success in the earlier rounds.[1]

[1] Starting in Season 2, contestants began the Bonus Round with a minimum of 2 Power Chips

The game uses standard blackjack point values for the cards, in which all numbered cards have a value of their number, face cards have a value of 10 and an ace has a value of either 1 or 11. The goal of the game is to reach a sum of 21 in each of the three hands. The contestant wins $1,000 for reaching a sum of 21 in one hand, $5,000 for reaching a sum of 21 in two hands and $25,000 for reaching a sum of 21 in all three hands. However, the contestant loses all of their winnings if they reach a sum of over 21 in any hand. A contestant faces the decision to stop or continue playing the game only after a card is placed in a hand. This is the stop/continue decision.

Figure 1- CATCH 21 GAME DIAGRAM



B. Related Literature

The analysis of risky choice is important to almost every field of economics. The two most prevalent models to explain risky decision making are expected utility theory and prospect theory. Expected utility theory, the traditional model, predicts that individuals make decisions by weighing outcomes of possible choices according to their probability of occurrence. The choice with the maximum expected utility is selected (von Neumann and Morgenstern, 1944). Expected utility theory assumes that judgment is in reference to a fixed asset position. More recent research has documented many examples of behavior that violates expected utility theory. Kahneman and Tversky (1979) proposed prospect theory as an alternative choice model. Prospect theory defines outcomes as gains or losses relative to a reference point, rather than as states of wealth in expected utility theory.

There is a large literature that empirically investigates how individuals make risky decisions. Many researchers have used the expected utility model to estimate a risk aversion parameter (Gertner, 1993), (Jiankopolos and Bernasek, 1998). Others have used expected utility theory to examine the properties of constant relative risk aversion (CRRA) or constant absolute risk aversion (CARA) (Palsson, 1996). It has been difficult to test these hypotheses since most researchers are constrained by small budgets. Using data from game shows is one method to circumvent this issue (Gertner, 1993), (Hartley, Lanot and Walker 2006). Conducting experimental work in developing areas to create high stake scenarios is another method, since low nominal payoffs hold greater real value in developing regions. In such studies, Binswanger (1980) and Kachelmeir and Shehata (1992) found that risk aversion tends to increase as payoffs increase. Thus, Holt and Laury (2002) developed a flexible expo-power utility function to allow for non-constant relative risk aversion and absolute risk aversion. Even so, Holt and Laury's model may not be best at explaining risky decisions since, unlike models of prospect theory, it does not include a parameter for reference point.

The paper I follow most closely is Post et al. (2006), which tests data from the game show “Deal or No Deal” for consistency with a model of expected utility theory and an alternative model based on prospect theory. Their main finding is the importance of reference dependence. They conclude that a model of prospect theory with a sticky reference point explains contestant decisions on “Deal or No Deal” much better than a model of expected utility theory in the spirit of Holt and Laury (Post, ven den Assem, Baltuseen and Thaler, 2006, pg. 67).

Following Post et al. (2006), I analyze decisions fro ma different game show- Catch 21. The Catch 21 data offer a few advantages relative to the “Deal or No Deal” data. Most notably, Catch 21 allows for the analysis of two distinct decisions for path dependence and reference dependence, whereas “Deal or No Deal” only permits the analysis of one. Also, while Post et al. are not able to predict the payoff outcome of the stop/continue decision in “Deal or No Deal” with certainty, the payoffs of the stop/continue decision in Catch 21 are known to the contestant and the viewer. This allows for improved accuracy. Additionally, the “Deal or No Deal” data contain contestant decisions from similar game shows filmed in three different countries. The authors model decisions from the three countries separately. This paper will analyze twice as many decision nodes as the “Deal or No Deal” paper, and all are from the same country. The larger sample size should permit more precise estimates. While the stakes are lower than in “Deal or No Deal,” Catch 21 is a useful platform for analyzing high stakes decisions since the potential payoff is much greater than in most economics experiments.

III. Data

I examine decisions from 294 bonus rounds of Catch 21, a United States game show. The data contains the card placement and stop/continue decisions from every episode of the show ever produced, except for 6 episodes that introduced slightly different game rules. The 294 episodes aired between July 2008 and July 2011 on "Game Show Network." Every episode features a new contestant in the bonus round. Scott Sternberg, one of the producers, explained that contestants are selected after meeting with the producers and simulating game play. He also said, "[contestants] were cast as reality contestants are typically- based on who the producers felt would perform well and be entertaining on the show." Thus, it is clear that the sample is not a random sample from the general population. However, this threat to external validity is common to all research based on data from game shows, and completely analogous to similar concerns that apply to data generated by laboratory experiments.

I collected a variety of information for each contestant. I assembled data on each contestant's gender, education level and occupation. Education and occupation are generally revealed to the audience when the contestant is introduced at the beginning of the episode[2]. Zero cards dealt indicates the initial three cards dealt to a contestant. Each additional card dealt defines a new card placement decision. I note the number of Power Chips that each contestant began with and the amount of money that they won in the bonus round. I organize these observations as a panel dataset. I observe 1819 card placement decisions and 673 stop/continue decisions made by a total of 294 different contestants.

Table 1 provides summary statistics the 294 contestants. There are only 206 observations of BachDegree because 88 contestants do not share their education or occupation. Hands of 21

[2] When education level is not shared, it is often evident from their stated occupation.

indicates the total number of hands in which a contestant reached a sum of 21[3]. Following Post et al. (2006, pg. 44-45) I do not condition on gender or education in my analysis[4].

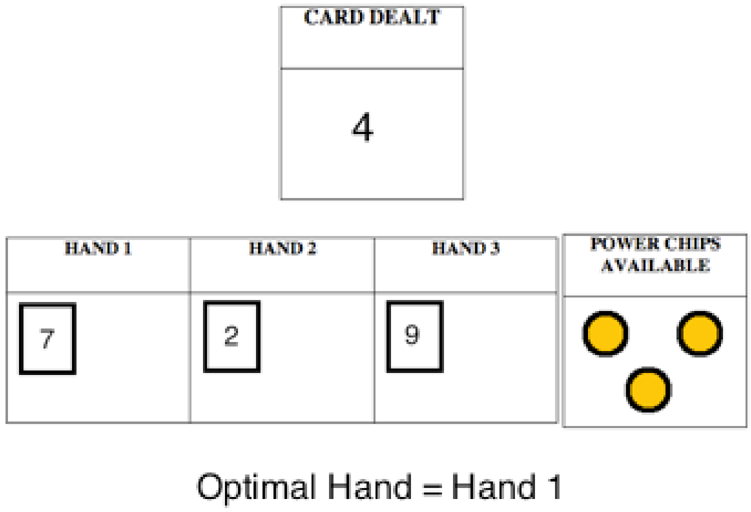
IV. Card Placement Decision

A. Preliminary Analysis

When dealt a card in the Bonus Round of Catch 21, contestants must decide whether to place it in one of their three hands or to discard it with a Power Chip. I assume that contestants are myopic, in that they make decision with respect to outcomes of the next dealt card[5]. Card placement that maximizes the chance to reach the next prize level is a critical part of the strategy of the game. Therefore, I define the optimal card placement decision as that which maximizes the probability of reaching a sum of 21 in a hand on the next dealt card. Henceforth, P(21) is the probability of reaching a sum of 21 in a hand on the next card dealt. Consider the following game scenario in which John is dealt a 4 as his first card:

[3] This does not necessarily correspond to Amount Won. Consider the following: A contestant reaches a sum of 21 in 2 hands, but proceeds to bust in their third hand. In this case, Hands of 21 is equal to 2 but Amount Won is equal to 0.
[4] As in "Deal or No Deal," the contestant often receives advice from the live studio audience and is allowed to consult with friends/family while making a decision, thus mitigating the role of gender and education.
[5] The cognitive difficulty of considering outcomes several cards ahead likely prevents contestants from thinking in this manner. In addition, the host of the game show often encourages contestants to only think dealt card ahead. Lastly, Post et al. (2006), who adopted the frame of myopia, performed a replication of their analysis without this assumption as a robustness check. They found that their estimates did not change significantly when using a model of backward induction.

Figure 2 – Illustration of P(21)



Placing the 4 in Hand 1 results in P(21) equal to 0.333[6]. Placing it in Hand 2 results in P(21) equal to 0, since there is no single dealt card can lead to a sum of 21 in a hand. Placing the 4 in Hand 3 results in P(21) equal to 0.0833[7]. Using one of the three available power chips results in P(21) equal to 0. Therefore, the optimal card placement decision is Hand 1 and I denote the P(21) associated of the optimal placement as P(21)*. While John's decision is straightforward, I show that the observed card placement decisions are not always optimal.

A contestant has made the optimal card placement decision if the observed decision is the same as the optimal decision[8]. Otherwise, if a different placement decision would have resulted in a higher P(21), then the contestant has not made the optimal decision. My sample consists of

[6] 16 out of the remaining 48 cards (four 10 cards, four Jacks, fours Queens & four Kings) will results in a sum of 21 on the next dealt card

[7] 4 out of the remaining 48 cards (all 4 8s)

[8] If placing in Hand 1 or Hand 2 lead to equal P(21), both of which are greater than the P(21) of placing in Hand 3 or using a Power Chip, then the contestant has made the optimal decision if they choose either Hand 1 or Hand 2. Likewise for similar scenarios.

2,113 card placement decision nodes[9]. Table 2 shows the summary statistics for this analysis. Opt Placement is binary, coded as 1 if the observed card placement decision is optimal. The first row of Table 2 shows that only 45.5% of the card placement decisions were optimal. This raises the question of the magnitude of the non-optimal decisions.

Refer back to Figure 2, in which the optimal card placement decision of Hand 1 results in P(21)*= 0.333. If John chooses Hand 3 then P(21) is equal to 0.0833. At each card placement decision node, I define the deviation from the optimal decision as the difference:

$$\text{Dec\_Dev\_Opt} = P(21)^* - P(21)_{observed} \quad (1)$$

If John chooses Hand 3 then Dec_Dev_Opt is equal to 0.2497. If he correctly chooses Hand 1, then Dec_Dev_Opt is equal to 0. Therefore, Dec_Dev_Opt = 0 indicates that a contestant made the optimal card placement decision. A large value of Dec_Dev_Opt represents a poor placement. The 3rd row of Table 2 shows that, on average, each observed placement decision reduced the chance of reaching a higher prize level on the next dealt card by 4.13 percentage points, relative to the optimal placement. Conditional on being non optimal, the average value of Dec_Dev_Opt is 7.5 percentage points (n=1,152). The distribution of Dec_Dev_Opt, conditional on being nonzero, is depicted in Figure 3.

Examining the card placement decisions throughout a contestant's entire play in the bonus round is telling as to whether certain individuals simply make worse placements than others. Cont_Dev_Opt is the average reduction in P(21) relative to the optimal placement for

[9] I do not include every card placement decision in this sample. The following scenarios are not included: (1) if the placement results in a contestant winning $25,000, (2) if the placement forces a contestant to bust and (3) if the contestant chooses to stop playing the game after placing the card. In case (1) the placement decision is trivial. In case (2), the placement decision is not economically relevant. In case (3), the contestant does not attempt to make the optimal choice, rather they just make any decision that does not result in a bust.

each contestant (row 4 in Table 2)[10]. Each observation of Cont_Dev_Opt corresponds to one of the 294 contestants. Cont_Dev_Opt = 0 indicates that the contestant made the optimal placement for each dealt card. There are three contestants for whom this is the case. Figure 4 shows the distribution of Cont_Dev_Opt for the other 291 contestants. This distribution suggests that there is not a clear distinction between good and bad card placement decision makers.

It seems possible that the amount of prize money that a contestant has won may affect the card placement decision. Perhaps after the excitement of winning $5000, a contestant's perception of probability is skewed. I find that the proportion of optimal placements when a contestant's current prize is $0 is significantly different than when their current prize is $1000. Contestants placed optimally more often when they have not won any money yet relative to when they won $1000. However, I do not find a significant difference between the proportion of optimal placements made between other prize levels (Table 3).

Perhaps contestants who appear in the first 100 episodes of Catch 21 are at a disadvantage relative to those in the last 100 episodes. That is, perhaps there is a learning effect in which contestants make better placement decisions if they are given the opportunity to learn from the mistakes of others. I observed 724 card placement decisions in the first 100 episodes and 694 in the last 100. 45.7% of the card placement decisions made in the earlier episodes were optimal and 45.8% of those in the later episodes were optimal. There is not a significant difference between the proportion of optimal placements in the first and last 100 episodes (Table 4). I also examine the 393 and 376 non-optimal placement decisions made in the first 100 episodes and last 100 episodes respectively. I again find that there is no significant difference in

[10] If I observe 5 card placement decision nodes for a contestant, then their Cont_Dev_Opt is (1/5) times the sum of each Dec_Dev_Opt for their 5 observed decisions

Dec_Dev_Opt between placements made in the first and last 100 episodes. Therefore, I find no evidence of a learning effect, both in terms of how the proportion of optimal placements and the magnitude of non-optimal decisions.

The card placement decision is important because of its financial implications. Refer back to Figure 2, in which John's current prize is $0. If he makes the optimal placement in Hand 1, the expected payoff of the next dealt card is $333[11]. However, if he instead places the card in Hand 3, the expected payoff of the next card is only $83.3[12]. I define ΔExp_Pay_X as the difference between the expected payoff of the optimal placement decision and that of the observed placement, given current prize level X (rows 5-7 in Table 2) [13]. In John's case, ΔExp_Pay_0 is equal to $249.7[14]. That is, making the non-optimal placement reduces John's expected payoff of the next card by $249.7. Note that the value of ΔExp_Pay_X is exactly zero if the optimal placement decision is made.

Figures 5-7 show the distribution of ΔExp_Pay_X for non-optimal placements at each prize level. I observe 568 such decisions when the prize level is $0, 455 at $1000 and 129 at $5000. The median decrease in expected payoff for a non-optimal placement was $83.33 at prize level $0, $416.67 at prize level $1000 and $2,173.91 at prize level $5000. Therefore, contestants that do not place optimally lower their expected payoff of the next card by large amounts.

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[11] 0.333*$1000 + 0.666*$0 = $333
[12] 0.0833*$1000 + 0.9167*$0 = $83.3
[13] 996 card placement decisions are observed at prize level = $0, 875 at prize level = $1000 and 242 at prize level = $5000
[14] $333 – $83.3 = $249.7

The card placement decision has a real economic impact on the amount of money that a contestant wins in the bonus round. The next section examines if reference dependence is evident in the card placement decision.

B. Empirical Strategy- Card Placement Decision

A contestant experiences good luck or bad luck based on the cards that they were dealt. Luck is exogenous from decisions made by the contestant. Under the assumption of myopia, I define $\Delta P(21)$ as:

$$\Delta P(21) = P(21)^* - P(21) \qquad (2)$$

where

$P(21)$ = the probability of reaching a sum of 21 in a hand on the next card **before** the next card is dealt

$P(21)^*$ = the probability of reaching a sum of 21 in a hand on the next card **after** the card is dealt and **if** the dealt card is placed optimally

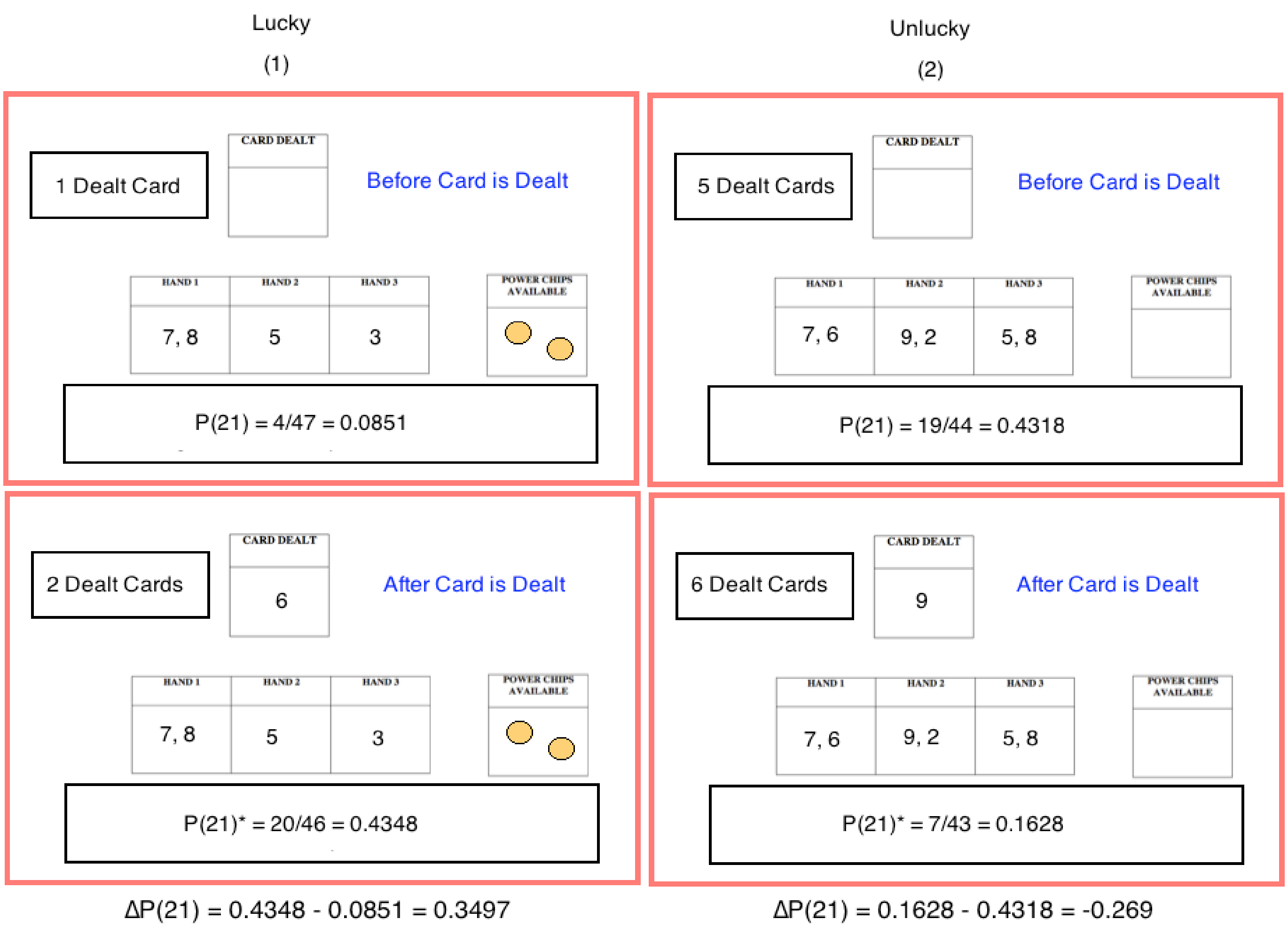
Consider the example depicted in Figure 8 to be understand the definition of $\Delta P(21)$. As shown in the first column, before the card was dealt the contestant only had an 8.51% chance of earning $1000. That is, $P(21) = 0.0851$. The contestant was ecstatic when a 6 was dealt. Their chance of reaching a higher prize level on the next card increased to almost 44% after the card was dealt, if they optimally placed the 6 in Hand 2. That is, $P(21)^* = 0.4348$. Therefore, $\Delta P(21)$ is large and positive, equal to 0.3497 for the lucky contestant.

In contrast, the second column of Figure 8 shows an unlucky contestant. With no abailable power chips, the contestant has a good chance of reaching the $1000 level before the card is dealt ($P(21) = 0.4318$). Unfortunately, they are dealt a 9 and if they place optimally in

Hand 2, their chance of reaching $1000 on the next hand reduces to P(21)* = 0.1628. Therefore, ΔP(21) is small and negative, equal to -0.269.

Therefore, a large value of ΔP(21) indicates that a contestant was dealt a favorable card that exceeded their expectations for reaching a higher prize level. Similarly, a small, negative value of ΔP(21) suggests that a contestant was dealt an unfavorable card that lowered their expectations for earning a higher prize. That is, a large value of ΔP(21) suggests that a contestant was lucky and a small value suggests that a contestant was unlucky.

Figure 8- Lucky and Unlucky Contestants



In order to test for reference dependence, I examine if luck plays a role in the card placement decision. That is, if contestants with equal P(21)* but different ΔP(21) behave differently. If reference dependence is not evident, then being lucky should not have an effect on whether a card is placed optimally.

My sample consists of 1819 observed card placement decision nodes.[15] Table 6 shows summary statistics for this sample. For individual i and number of dealt cards t, the following model tests whether luck plays a role in the card placement decision:

$$\text{(3)} \qquad \text{Opt Placement}_{i,t} = \beta_0 + \beta_1(P(21)^*_{i,t}) + \beta_2(\Delta P(21)_{i,t}) + \gamma_1(X_{i,t}) + \mu_{i,t}$$

where Opt Placement is binary, equal to 1 if the contestant made the optimal placement and X is a vector of various game scenarios, including prize level, number of cards dealt and number of available Power Chips.[16] A coefficient of ΔP(21) that is significantly different from zero indicates that being luck has an effect on whether a card is placed optimally. This also begs the question of whether the effect is different for lucky and unlucky contestants.

I define a contestant as lucky if ΔP(21)≥0, like in column 1 of Figure 8, and unlucky if ΔP(21)<0, like in column 2 of Figure 8. I observe 1515 lucky decision nodes and 305 unlucky

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15 I exclude placement decisions for which I do not observe a previous placement. That is, I exclude observations where the number of cards dealt is less than 2.

16 As a robustness check, I distinguished between decision nodes where the contestant reaches a sum of 21 in a hand on the previous dealt card and those that did not. This did not alter the significance or magnitude of the regression estimates. Therefore, I only provide the results of the simpler model.

decision nodes, as seen in Table 6.   For individual i and number of dealt cards t, the following model estimates the individual effects of being lucky and unlucky on the card placement decision:

(4) $\text{Opt Placement}_{i,t} = \beta_0 + \beta_1(P(21)^*_{i,t}) + \beta_2(\Delta P(21)_{i,t}{*}\text{Lucky}_{i,t}) + \beta_3(\Delta P(21)_{i,t}{*}(1 - \text{Lucky}_{i,t})) + \gamma_1(X_{i,t}) + \mu_{i,t}$

where Lucky is a dummy equal to 1 if the contestant was lucky and zero otherwise. In this model, a significant difference between β_2 and β_3 suggests that being lucky and unlucky have different effects at to whether a card is placed optimally.

C. Results- Card Placement Decision

Table 7 provides regression estimates for model 3, which examines if lucky plays a role in the card placement decision. Column 1 shows the results for the base specification that does not control for game scenarios. I find a significant and negative coefficient of $\Delta P(21)$, which suggests that the luckier a contestant is, the less likely they are to make the optimal placement, all else equal. This provides initial evidence of reference dependence.

I control for various game scenarios in columns 2 and 3 to ensure that I isolate the impact of being lucky or unlucky. It seems very important to account for prize level, since that determines the number of hands a contestant can place a card between. When controlling for prize level, I again find a negative and significant coefficient of $\Delta P(21)$ (column 2 of Table 7). It is less clear on theoretical grounds if the number of cards a contestant has been dealt or the number of power chips available for use is important to the card placement decision. Nonetheless, I control for these games scenarios and again find a negative and significant coefficient of ΔP(21) (column 3 of Table 7). Therefore, there is evidence of reference dependence in the card placement decision since the effect of being lucky or unlucky on placing a card optimally is significantly different from zero.

Table 8 provides regression estimates for model 4, which examines the individual effects of being lucky and unlucky on the card placement decision. In the base specification, I find a significant and negative coefficient of ΔP(21) for lucky contestants but the coefficient of ΔP(21) for unlucky contestants is not significant (column 1 of Table 8). The same holds true when I control for prize level (column 2) and control for all game scenarios (column 3). In all three cases, I find that there is a significant difference between the effect of being lucky and unlucky in the card placement decision (Table 9). Therfore, lucky contestants are less likely to place optimally than unlucky contestants, all else equal. Contestants that arrived at equal P(21)* in different ways behave differently.

There is evidence of reference dependence in the card placement decision, and, specifically, evidence that being dealt a good card has a significant effect on whether that card is placed optimally. Unlike expected utility theory, prospect theory accounts for reference dependence in decision making. Prospect theory assumes that decision makers evaluate outcomes as gains and losses relative to a reference point. Contestants appear to frame the card placement decision differently if they are lucky or unlucky. Therefore, prospect theory may better explains the observed card placement decisions than expected utility theory. This conclusion is consistent with Post et al.'s (2006) study of Deal or No Deal.

Future research may want to consider a nonlinear specification to test for reference dependence in the card placement decision. I divided my sample of 1819 decision nodes into 15 segments based on the value of P(21)*. Figure 9 shows the mean proportion of optimal placements for the first 5 segments (smallest values of P(21)*) and similarly for Figures 10 and 11. It appears that a nonlinear model would better explain the relationship between Opt Placement and P(21)*.

V. Stop/Continue Decision

A. Empirical Strategy

After placing a card in one of the three hands, contestants must decide whether to stop or continue play in the bonus round. I again assume that contestants are myopic. Table 10 reports summary statistics for the 673 stop/continue decisions observed in the sample[17]. Stop is binary equal to 1 if the contestant chose to stop play in the bonus round. Note that a contestant faces no risk before winning $1000, so all further analysis will only use a sample of contestants who have won at least $1000.

I use the same definitions of P(21), P(21)*, and ΔP(21) as before so that ΔP(21) quantifies the luck that comes with a dealt card. Moreso than in the card/placement decision, it seems very important in the stop/continue decision to distinguish between contestants that reached a higher prize level with the previous dealt card and those that did not in the stop/continue decision. Perhaps reaching a higher prize level makes a contestant less inclined to stop gameplay because of the "house money" effect. That is, contestants may feel that they are

[17] Contestants who do not face the stop/continue decision are not included here (i.e. contestants who used a Power Chip to discard the previous card)

gambling with money that does not belong to them and therefore are more risk seeking. In contrast, maybe reaching a higher prize level makes a contestant more likely to stop gameplay because they wish to safely secure their earnings and are more risk averse. Therefore, I differentiate between contestants that reached a sum of 21 in a hand with the previous dealt card and those that did not for this analysis.

For individual i and number of dealt cards t, the following model estimates the effect of luck on the stop/continue decision:

$$(5) \quad Stop_{i,t} = \beta_0 + \beta_1(P(21)_{i,t}) + \beta_2(\Delta P(21)_{i,t} * (1 - 21\ Previous_{i,t})) + \beta_3(21\ Previous_{i,t}) + \gamma_1(X_{i,t}) + \mu_{i,t}$$

where 21 Previous is binary, equal to 1 if the contestant reached a sum of 21 in a hand with the previous dealt card. X is a vector that controls for various game scenarios, including prize level, power chips and cards dealt.

I observed 147 stop/continue decisions at the $5000 prize level and 32.7% of them chose Stop. In contrast, I observed 526 stop/continue decisions at the $1000 level and only 15.4% of them chose Stop. This difference is likely due to the unique nature of decision making in the Catch 21 Bonus Round[18]. Therefore, the distinction between stop/continue decisions made at the $1000 and $5000 levels seems to be very important. It is less clear, however, whether there are theoretical grounds for other game scenarios affecting the stop/continue decision. The number of power chips available and the number of cards dealt to a contestant may or may not be important to the stop/continue decision. Therefore, I control for these game

[18] A player can not possibly reach the $5000 prize level without first choosing Continue at the $1000 level.

scenarios in some models, but it is uncertain whether the models that control for these game scenarios are as important in interpretation.

A significant β_3 in model 5 is evidence of path dependence, since it indicates that contestants who reached a higher prize level with the previous card, all else equal, behave differently than those who did not. In addition, given that a contestant did not reach a higher prize level with the previous card, a significant β_2 in model 5 indicates that luck plays a role in the decision to end gameplay in the bonus round. This evidence of reference dependence would beg the question of the individual effects of being lucky and unlucky.

I define lucky and unlucky contestants in the same way as the card placement decision, where positive or zero values of $\Delta P(21)$ indicate a lucky contestant and negative values indicate an unlucky contestant. For individual i and number of dealt cards t, the following model estimates the individual effects of being lucky and unlucky on the stop/continue decision:

$$\text{(6)} \quad Stop_{i,t} = \beta_0 + \beta_1(P(21)_{i,t}) + \beta_2(\Delta P(21)_{i,t} * Lucky_{i,t} * (1 - 21\ Previous_{i,t})) + \beta_3(\Delta P(21)_{i,t} * (1 - Lucky_{i,t}) * (1 - 21\ Previous_{i,t})) + \beta_4(21\ Previous_{i,t}) + \gamma_1(X_{i,t}) + \mu_{i,t}$$

where Lucky is a dummy equal to 1 if the contestant was lucky and zero otherwise. In this model, a significant difference between β_2 and β_3 would suggest that being lucky and unlucky have different effects on the stop/continue decision.

B. Results- Stop/Continue Decision

Table 11 provides regression estimates for model 5, which tests the effect of luck on the card placement decision. Column 1 shows the results for the base specification, which does not control for game scenarios. I find a significant and negative coefficient on ΔP(21)*(1 – 21 Previous) which indicates that the luckier a contestant is, the less likely they are to stop game play in the bonus round, given they did not reach a higher prize level with the previous dealt card, all else equal. I again find that this coefficient is negative and significant when I control for prize level (column 2).[19] Luck plays a role in the stop/continue decision, since contestants not only frame their decision based on their current chances of reaching a higher prize level but also on whether they arrived at these chances by being lucky or unlucky. This is evidence of reference dependence.

I also find a significant and negative coefficient on 21 Previous in both the base specification and when controlling for prize level (columns 1&2 of Table 11). This provides evidence of path dependence. Contestants that arrive at the stop/continue decision after winning more money with the previous card, all else equal, behave differently than those that did not. Specifically, a contestant who reached a higher prize level with the previous dealt card is less likely to stop gameplay than one who did not, all else equal. This may support the house money effect, since a contestant who just won more money appears to be less risk averse than those who did not.

Table 12 shows the regression estimates for model 6, where I distinguish between the effects of being lucky and unlucky. When prize level is controlled for, the coefficient of ΔP(21)*(1 – 21 Previous) is negative and significant for lucky contestants, yet is positive and significant for unlucky contestants (column 2). Additionally the second row of Table 13 shows that, when prize level is controlled for, the coefficient of ΔP(21)*(1 – 21 Previous) is

[19] The coefficient of ΔP(21)*(1 – 21 Previous) is not significant when I control for other game scenarios (column 3). As discussed earlier, though, it is not clear on theoretical grounds whether there is an economic rationale to include these controls.

significantly different for lucky contestants and unlucky contestants. This indicates that being dealt a lucky card decreases the likelihood of a contestant ending game play while being dealt an unlucky card increases it, all else equal.[20]

It is clear that reference dependence is evident. If reference dependence was not important to the stop/continue decision, then we would expect contestants with the same prize level and the same P(21) to behave similarly. However, the random draw of a card appears to change a contestant's reference point and alter the way that they frame the stop/continue decision. If the card is lucky, then contestants are more likely to continue playing the game. They may be more risk seeking. However, if the card is unlucky, contestants are more likely to end game play. They may be more risk averse. Therefore, whether the stop/continue decision is framed as a gain or a loss relative to chances before a card was dealt is significant.

Evidence of reference dependence and path dependence suggest that the observed stop/continue decisions may be more consistent with prospect theory than expected utility theory. A model of prospect theory would likely account for the differences in the stop/continue decision between those who experience good and bad luck. In contrast, a model of expected utility theory may not be flexible enough to explain these differences, since it assumes that decision makers evaluate outcomes without respect to prior gains or losses.

Future research may want to consider using a nonlinear specification to examine the stop/continue decision. Just as in the card placement decision, I divided my sample of 673 decision nodes into 15 segments based on the value of P(21). Figure 12 shows the mean proportion of stop decisions for the smallest five segments and similarly for the middle and

[20] Again, I find that controlling for cards dealt and power chips changes these results. However, I emphasize that it is unclear whether or not there is a theoretical basis for including them. There is a well defined reason to control for prize level, though, so I focus on those results.

largest 5 segments in Figures 13 and 14. It appears that a nonlinear model would better explain the relationship between Stop and P(21).

In addition to using nonlinear model, future work may want to adopt Post et al's (2006) framework, which would permit a more detailed analysis of risk aversion in the stop/continue decision. I tailor their framework for using maximum likelihood to estimate two choice models to Catch 21 in the next section.

VI. Framework for Maximum Likelihood Estimation

A. Expected Utility Theory

While previous tests provide convincing evidence of reference dependence in the stop/continue decision, applying the framework of Post et al. (2006) to Catch 21 could provide greater insight as well as a detailed analysis of risk aversion. Post et. al use the Holt and Laury (2002) expo-power model of expected utility theory:

(6) $$u(x) = \frac{1-e^{-\alpha(W+x)^{1-\beta}}}{\alpha}$$

There are three unknown parameters in this utility function: the coefficients of risk aversion α and β, and an initial wealth parameter W[21].

Post et al. (2006) define the likelihood function in terms of a stop value and continuation value. The stop value is the utility of a contestant's current prize. The continuation value is the expected utility of a contestant's unknown prize with the next dealt card if they choose Continue. Let x represent a contestant's current prize.

[21] Since lifetime wealth is unobservable, Post et al. (2006) include the free parameter of initial wealth. However, it may be better to let W depend on education or occupation, since it is surely different for each individual.

The stop value is:

(6) $$sv(x) = u(x)$$

Let $X(x)$ denote the set of possible payoffs (either \$0, \$1000, \$5000 or \$25,000) for dealt card $t+1$ and p_y be the probability of $y \; \forall \; y \epsilon X(x_t)$. As previously mentioned, a key assumption is that contestants are myopic, and only consider outcomes one dealt card ahead. Thus, the continuation value is defined as:

(7) $$cv(x_t) = \sum_{y \epsilon X(x_t)} u(y) p_y$$

The stop/continue decision for individuals $i = 1, \ldots, N$ with dealt card $t = 1, \ldots, T$ is based on the difference between the continuation value and the stop value plus an error term (Becker et al., 1963), (Hey and Orme, 1994). The errors are independent, normally distributed random variables with a mean of zero and standard deviation $\sigma_{i,t}$. To control for the fact that the standard deviation is likely greater for more difficult decisions than for easier ones, an indicator of decision difficulty is used:

(8) $$\delta(x_{i,t}) = \sqrt{\sum_{y \epsilon X(x_{i,t})} (u(y) - cv(x_{i,t}))^2 p_y}$$

The standard deviation of the error is assumed to be proportional to the indicator of difficulty, such that $\sigma_{i,t} = \delta(x_{i,t})\sigma$ with σ being a constant parameter.

Therefore, given these assumptions, the likelihood of the stop/continue decision is:

(9) $$l(x_{i,t}) = \begin{cases} \Phi\left(\frac{cv(x_{i,t}) - sv(x_{i,t})}{\delta(x_{i,t})\sigma}\right) & \text{if "Continue"} \\ \Phi\left(\frac{sv(x_{i,t}) - cv(x_{i,t})}{\delta(x_{i,t})\sigma}\right) & \text{if "Stop"} \end{cases}$$

where $\Phi(.)$ is the cumulative normal distribution function.

Post et al. (2006) estimate the four parameters, α, β, W and σ by maximum likelihood. I comment on Post et al.'s estimation in Appendix A.

B. Prospect Theory

Using the same data, Post et al. estimate the parameters of a model based on prospect theory. All assumptions and definitions are the same, except a prospect theory value function is used instead of the expo-power utility function. The value function is defined by:

(10) $$v(x|RP) = \begin{cases} -\lambda(RP - x)^{\propto} & x \leq RP \\ (RP - x)^{\propto} & x \geq RP \end{cases}$$

There are three unknown parameters in this model. λ>0 is a loss aversion parameter, RP specifies the reference point that distinguishes gains from losses and α > 0 measures the value function's curvature. Post et al. (2006) estimate these parameters and the constant parameter σ using the same maximum likelihood procedure as earlier.

VII. Conclusion

It is clear that the choices made on Catch 21, are not representative of most high stakes risky decisions. Individuals do not make choices about an investment strategy or plan savings for retirement in front of a live audience or under the pressure of a production crew. Unlike laboratory experiments, though, contestants receive consultation from the host and discuss options with family and friends before making their decision. Contestants likely contemplate a strategy for the stop/continue decision well before the game begins. In this regard, decisions in Catch 21, may be surprisingly similar to other high stakes risky decisions.

The findings in this paper are consistent with the study of “Deal or No Deal” in Post et al. (2006). I find evidence of reference dependence in the card placement decision and the stop/continue decision, as well as path dependence in the stop/continue decision. Both of these results suggest that risky decision making on Catch 21 may be better explained by prospect theory than expected utility theory.

The limitations of this paper are clear. My analysis of the card placement and stop/continue decisions are purely descriptive. A more accurate claim as to which choice model the Catch 21 decisions are more consistent with could be made by following the Post et al. (2006) framework and using maximum likelihood to estimate a model of expected utility theory and an alternative model of prospect theory.

Future research may also want to study a relationship between the card placement and stop/continue decisions. Perhaps contestants who do not make the placement decision optimally are less inclined to continue play in the Bonus Round. Lastly, it would be interesting to test for path dependence and reference dependence in a Catch 21 laboratory experiment, where participants are drawn from a random sample.

VIII. References

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Appendix A- Maximum Likelihood Estimation for Post et al. (2006)

I replicated the estimation of the expected utility model of Post et al. (2006) for the United States. Using publicly available data from the authors, I performed their estimation of the expected utility model using 349 stop/continue decisions from 53 episodes of "Deal or No Deal" aired in the United States. I use the same likelihood function defined in the previous section to estimate the same four parameters: α, β, W and σ. The Post et al. published results are shown in the first column of Table 14. In addition to the parameters estimates, the authors report the mean log-likelihood (MLL) and the hit percentage, defined as the number of correctly predicted "Deal" decisions. They find that $\alpha = 4.18 * 10^{-5}$ and can not reject the hypothesis that α=0, which indicates a model of constant relative risk aversion. Additionally, they find that $\beta = 0.171$, and are able to reject the hypothesis that β =0, which would have suggested that contestants exhibit constant absolute risk aversion.

Similar to most maximum likelihood procedures in economics, I seek to find parameters that minimize the negative of the likelihood function[22]. Figures 15-18 show the behavior of the likelihood function when three of the parameters are fixed to the estimated values published by Post et al. (2006, Table 6). All four of these figures show smooth, convex curves that have a local minimum. When the problem is restricted to estimating only one parameter at a time, I am able to replicate the results of the authors.

Although the 1-parameter problem shows that the published parameter values likely result in a local minimum, the result of the 2-parameter problem (second column of Table 14) creates doubt that the published estimates are the global minimum of the likelihood function. I

[22] This section will thus report the negative values for log-likelihood and all figures will display the negative of the mean log-likelihood

restrict the problem to 2 parameters by estimating only α and β, while fixing W and σ to their published values. I find that the MLL is minimized when $\alpha = 4.99 * 10^{-6}$ and $\beta = 4.01 * 10^{\wedge}(-12)$. These estimates result in a mean log-likelihood equal to the published MLL of 0.259979, which is less than the published value. Figure 19 shows the behavior of the likelihood function over different values of α, with $\beta = 0.171$. Similarly, Figure 20 shows the behavior of the likelihood function over different values of α, with $\beta = 0$. W and σ are fixed to the published estimates in all three figures. While the global minimum is unclear, it is clear that there is more than one local minimum of the likelihood function which both have reasonable economic interpretations.

The 3-parameter problem provides greater insight into whether the published value is the global minimum of the likelihood function. I fix β to its published value and minimize the likelihood function with respect to the other three parameters. The third column in Table 14 shows the resulting estimates. Only the estimate for σ matches the published value. While there is no true upper bound on W, its estimate in this case may have an implausible economic interpretation. The estimate $W = 3{,}800{,}056$ is likely not a reliable estimate for a contestant's initial wealth[23].

Estimating all 4 parameters confirms suspicions that while the published value is a local minimum, it is likely not the global minimum. The fourth column in Table 14 shows the results of this estimation. As expected from the results of the 2-parameter problem, I estimate [$\alpha = 4.97 * 10^{\wedge}(-6), \beta = 1.41 * 10^{\wedge}(-10)$] as well as a value of W with what seems to be a

[23] Although estimating initial wealth as constant across all contestants is likely not reliable to begin with. As mentioned earlier, a better estimate could be found by conditioning on education or occupation.

plausible economic interpretation[24]. The mean log-likelihood is 0.259975, which is again less than the published value.

The conclusion of this replication exercise is that the likelihood function is very flat, and there are many estimates that result in an MLL very close to 0.260. I do not claim that I have found a global minimum, only that it that there are many local minimums close together. However, it is apparent that published estimates are not the global minimum.

[24] I have not calculated the standard errors for these parameter estimates and therefore cannot speak to the implications of absolute and relative risk aversion from my estimates.

Appendix B- Tables and Figures

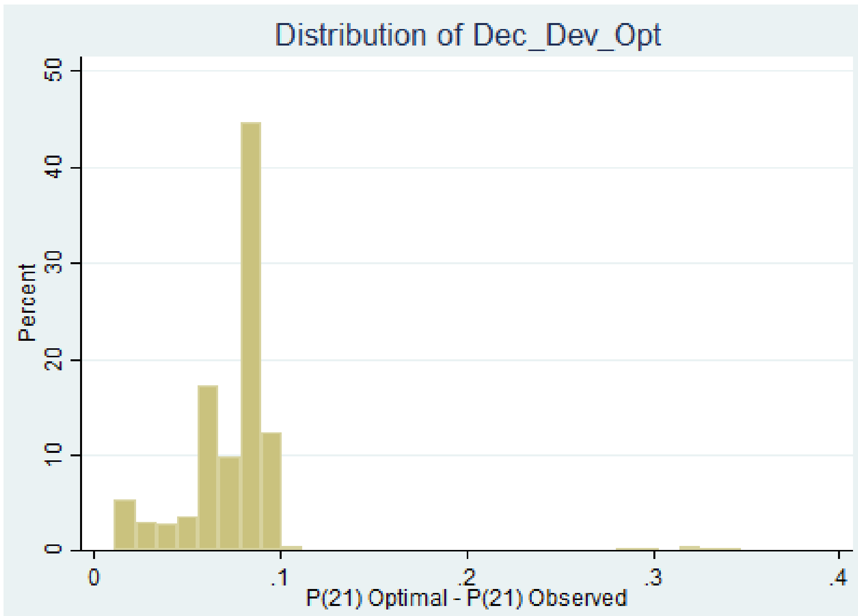
Table 1- *Summary Statistics of Contestants*

Variable	Obs	Mean	Std. Dev.	Min	Max
Female	294	.4387755	.4970835	0	1
BachDegree	206	.592233	.4926166	0	1
Cards Dealt	294	8.268707	1.639708	4	13
Initial Power Chips	294	2.860544	.7137898	1	4
Hands of 21	294	1.489796	.7782657	0	3
Amount Won	294	4163.265	6045.381	0	25000

Table 2- *Summary Statistics for all Card Placement Decision Nodes*

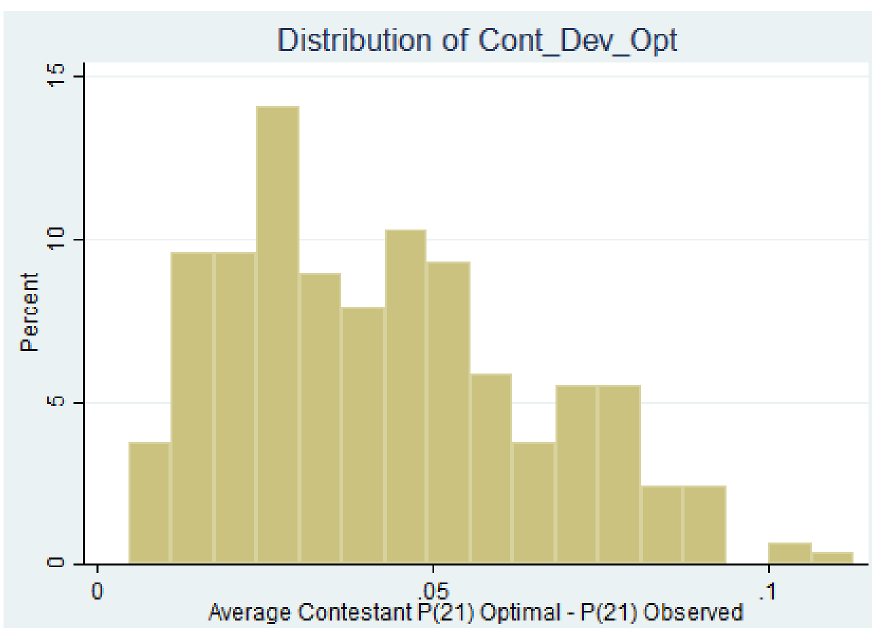
Variable	Obs	Mean	Std. Dev.	Min	Max
P(21)	2113	.1915596	.1315455	0	.8
Opt Placement	2113	.4548036	.498071	0	1
Dec_Dev_Opt	2113	.0413184	.0442887	0	.3478261
Cont_Dev_Opt	294	.0419724	.0227959	0	.1129777
∆Exp_Pay_0	996	41.35553	39.06084	0	105.4579
∆Exp_Pay_1000	875	202.372	238.0854	0	1739.13
∆Exp_Pay_5000	242	1105.425	1288.505	0	8536.585

Figure 3- *Distribution of nonzero Dec_Dev_Opt (reduction in P(21) relative to the optimal card placement decision)*



N=1152

Figure 4- *Distribution of nonzero Cont_Dev_Opt (average Dec_Dev_Opt by Contestant)*



N=291

Table 3- *t-Test of Proportion of Optimal Card Placement Decisions at different prize levels*

H_0 : Proportion of Optimal Card Placement Decisions at Prize Level X = Proportion of Optimal Card Placement Decisions at Prize Level Y

Prize Levels	t-Statistic	Degrees of Freedom	p-Value
Prize = 0, 1000	-2.1815	1869	0.0293
Prize = 0, 5000	-1.0467	1236	0.2954
Prize = 1000, 5000	0.3596	1115	0.7192

Table 4- *t-Test of Proportion of Optimal Placements between first 100 and last 100 episodes*

H_0 : Proportion of Optimal Card Placement Decisions in first 100 episodes = Proportion of Optimal Card Placement Decisions in last 100 episodes

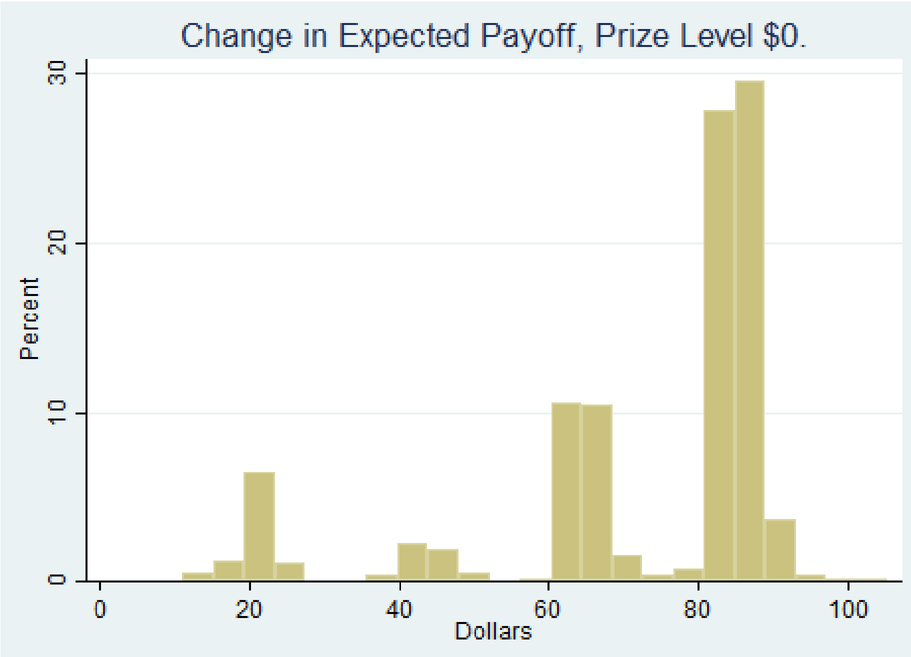
Sample	t-Statistic	Degrees of Freedom	p-Value
First 100 eps (724 decisions) Last 100 eps (694 decisions)	-0.0389	1416	0.9690

Table 5- *t-Test of Dec_Dev_Opt between non-optimal decisions in the first 100 and last 100 episodes*

H_0 : Dec_Dev_Opt in first 100 episodes = Dec_Dev_Opt in last 100 episodes

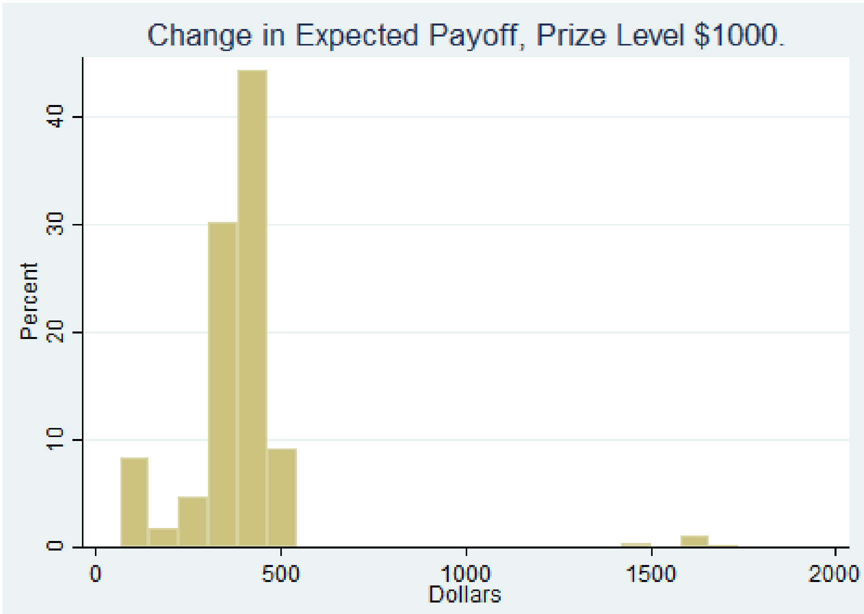
Sample	**t-Statistic**	**Degrees of Freedom**	**p-Value**
First 100 eps (393 decisions) Last 100 eps (376 decisions)	-0.0482	767	0.9616

Figure 5- *Distribution of ΔExp_Pay_0*



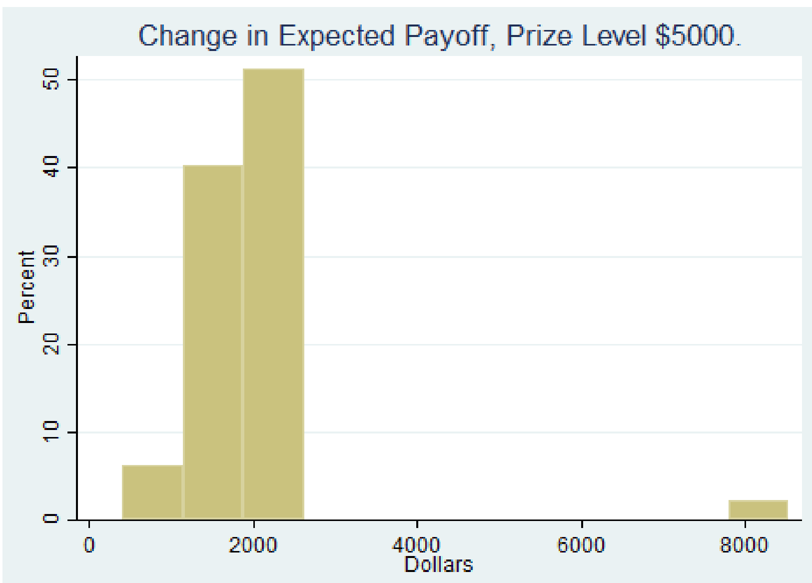
N = 568

Figure 6- *Distribution of ΔExp_Pay_1000*



N=455

Figure 7- *Distribution of ΔExp_Pay_5000*



N = 129

Table 6- *Summary Statistics for Regression Analysis of Card Placement Decision*

Variable	Obs	Mean	Std. Dev.	Min	Max
Opt Placement	1819	.4947774	.5001102	0	1
P(21)	1819	.1941586	.1344161	0	.8
P(21)*	1819	.2326742	.1242394	0	.8
ΔP(21)	1819	.0385156	.1187539	-.4153846	.6521739
$1000 Prize	1819	.4612424	.4986327	0	1
$5000 Prize	1819	.1330401	.3397115	0	1
Cards Dealt	1819	4.819131	2.098705	2	12
Power Chips	1819	1.948873	.5107455	0	4
Lucky ΔP(21)	1514	.073792	.0826739	0	.6521739
Unluck ΔP(21)	305	-.1365939	.1155744	-.4153846	-.0110993

Table 7- *Regression Estimates for the Card Placement Decision, Model 3- Effect of Luck*

	Opt Placement (1)	Opt Placement (2)	Opt Placement (3)
P(21)*	0.53007 (0.09391)***	0.43883 (0.09967)***	0.31431 (0.10145)***
ΔP(21)	-1.36948 (0.10123)***	-1.41380 (0.10275)***	-1.27963 (0.09854)***
$1000 Prize		-0.04784 (0.02456)*	-0.12998 (0.02495)***
$5000 Prize		-0.10561 (0.03667)***	-0.28098 (0.03736)***
Cards Dealt			0.06987 (0.00567)***
Power Chips			0.00250 (0.02127)
R^2	0.09	0.09	0.17
N	1,819	1,819	1,819

** p<.10; ** p<.05; *** p<.01*

Table 8- *Regression Estimates for the Card Placement Decision, Model 4- Lucky vs. Unlucky*

	Opt Placement (1)	Opt Placement (2)	Opt Placement (3)
P(21)*	0.67878 (0.09429)***	0.64145 (0.10220)***	0.47150 (0.10260)***
ΔP(21)*Lucky	-2.50774 (0.17201)***	-2.50343 (0.17324)***	-2.04740 (0.17591)***
ΔP(21)*(1 – Lucky)	-0.07442 (0.16576)	-0.11806 (0.17220)	-0.41368 (0.15629)***
$1000 Prize		-0.02426 (0.02443)	-0.10078 (0.02504)***
$5000 Prize		-0.03701 (0.03808)	-0.20669 (0.03964)***
Cards Dealt			0.05891 (0.00571)***
Power Chips			0.00946 (0.02081)
R^2	0.14	0.14	0.18
N	1,819	1,819	1,819

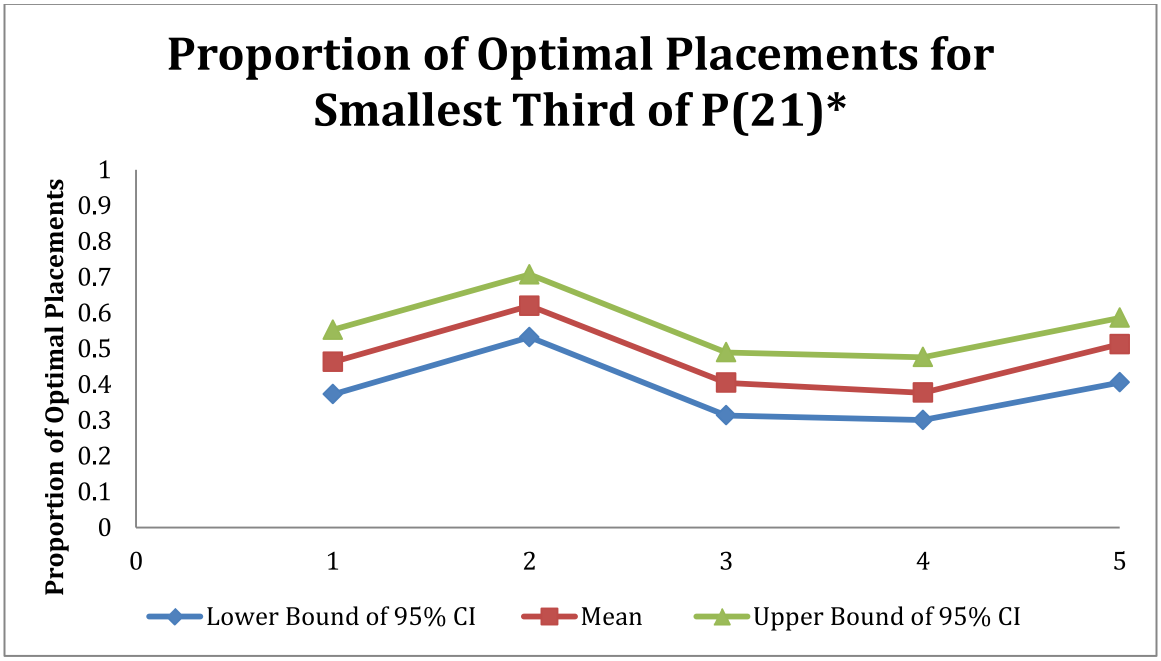
** p<.10; ** p<.05; *** p<.01*

Table 9- *F-Test that the Coefficient of ΔP(21) is equal for lucky and unlucky contestants, Card Placement Decision*

	F-Value	p-Value
Base Specification (1)	82.78	0.00***
Controls for Prize Level (2)	75.91	0.00***
Controls for all Game Scenarios (3)	37.11	0.00***

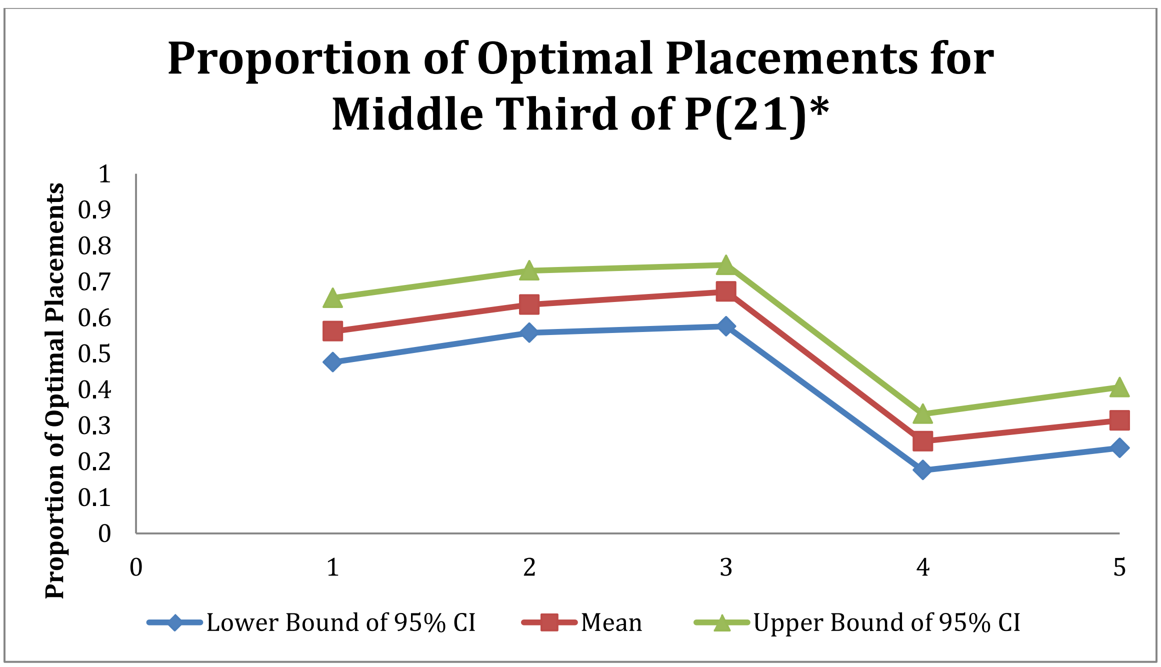
** p<.10; ** p<.05; *** p<.01*

Figure 9- *Proportion of Optimal Placements for Smallest Third of P(21)**



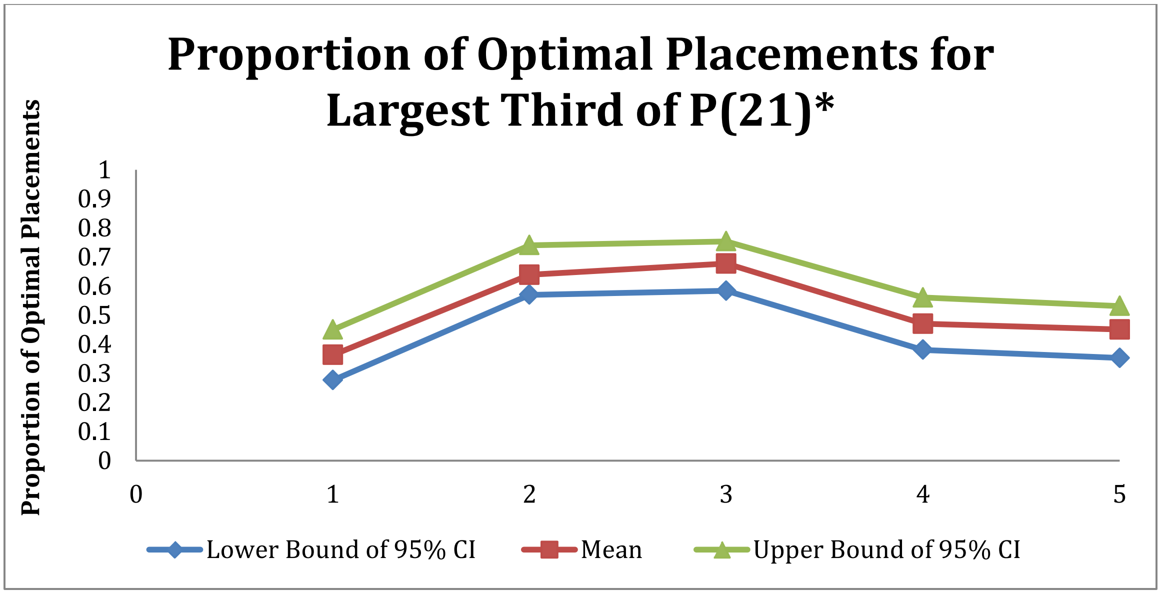
N=121per segment

Figure 10- *Proportion of Optimal Placements for Middle Third of P(21)**



N=121per segment

Figure 11- *Proportion of Optimal Placements for Largest Third of P(21)**



N=121per segment

Table 10- *Summary Statistics for Stop/Continue Decision Sample*

Variable	Obs	Mean	Std. Dev.	Min	Max
Stop	673	.191679	.3939147	0	1
P(21)	673	.189713	.1452222	0	.7804878
P(21)*	673	.1969699	.1207663	0	.8
∆P(21)	673	.0072568	.1310906	-.3643411	.4634147
$5000 Prize	673	.218425	.4134846	0	1
Cards Dealt	673	5.197623	2.008433	2	12
Power Chips	673	1.97474	.4764867	0	4
Lucky ∆P(21)	492	.0652214	.0781047	0	.4634147
Unluck ∆P(21)	181	-.1503044	.1156237	-.3643411	-.0124113

Table 11- *Regression Estimates for the Stop/Continue Decision, Model 5- Effect of Luck*

	Stop (1)	Stop (2)	Stop (3)
P(21)	0.14306	0.28206	0.08947
	(0.12576)	(0.12477)**	(0.11452)
ΔP(21)*(1 – 21 Previous)	-0.69511	-0.59014	-0.09458
	(0.23899)***	(0.23909)**	(0.18471)
21 Previous	-0.15176	-0.19289	-0.04114
	(0.03797)***	(0.03928)***	(0.03644)
$5000 Prize		0.20268	0.07617
		(0.04160)***	(0.04178)*
Cards Dealt			0.08702
			(0.00814)***
Power Chips			-0.05178
			(0.02752)*
R^2	0.03	0.07	0.24
N	673	673	673

* $p<0.1$; ** $p<0.05$; *** $p<0.01$

Table 12- *Regression Estimates for the Stop/Continue Decision, Model 6- Lucky vs Unlucky*

	Stop (1)	Stop (2)	Stop (3)
P(21)	0.16873 (0.12617)	0.31274 (0.12579)**	0.10356 (0.11661)
ΔP(21)*Lucky*(1 – 21 Previous)	-0.85576 (0.25742)***	-0.76715 (0.25647)***	-0.16957 (0.20027)
ΔP(21)*(1-Lucky)*(1 – 21 Previous)	0.72590 (0.53031)	0.99143 (0.48234)**	0.52965 (0.45615)
21 Previous	-0.16997 (0.03915)***	-0.21377 (0.04056)***	-0.05086 (0.03858)
$5000 Prize		0.20579 (0.04141)***	0.07862 (0.04195)*
Cards Dealt			0.08619 (0.00822)***
Power Chips			-0.05168 (0.02756)*
R^2	0.04	0.08	0.25
N	673	673	673

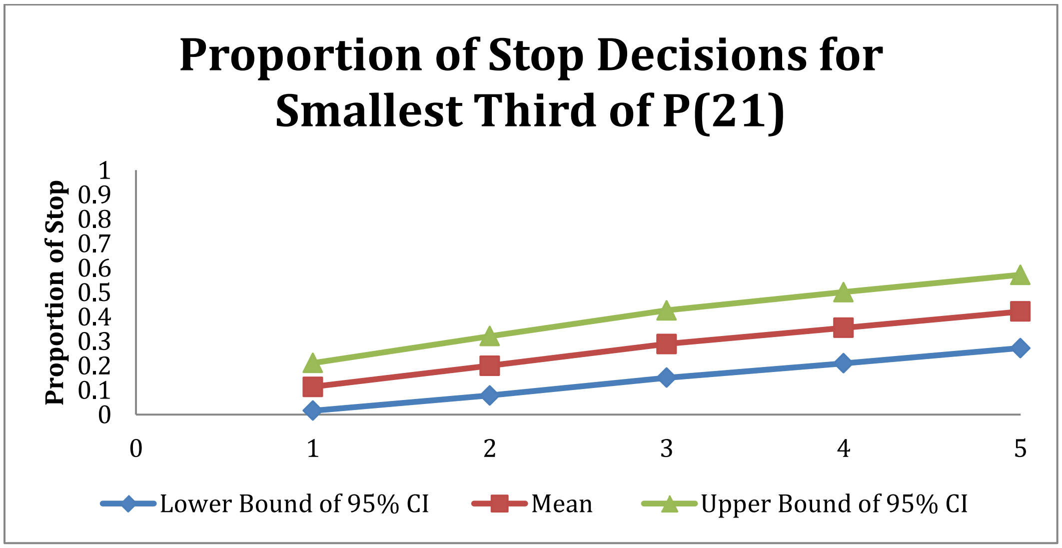
* p<0.1; ** p<0.05; *** p<0.01

Table 13- *F-Test that the Coefficient of ΔP(21) is equal for lucky and unlucky contestants, Stop/Continue Decision*

	F-Value	p-Value
Base Specification (1)	6.82	0.0092***
Controls for Prize Level (2)	9.71	0.0019***
Controls for all Game Scenarios (3)	1.86	0.1728

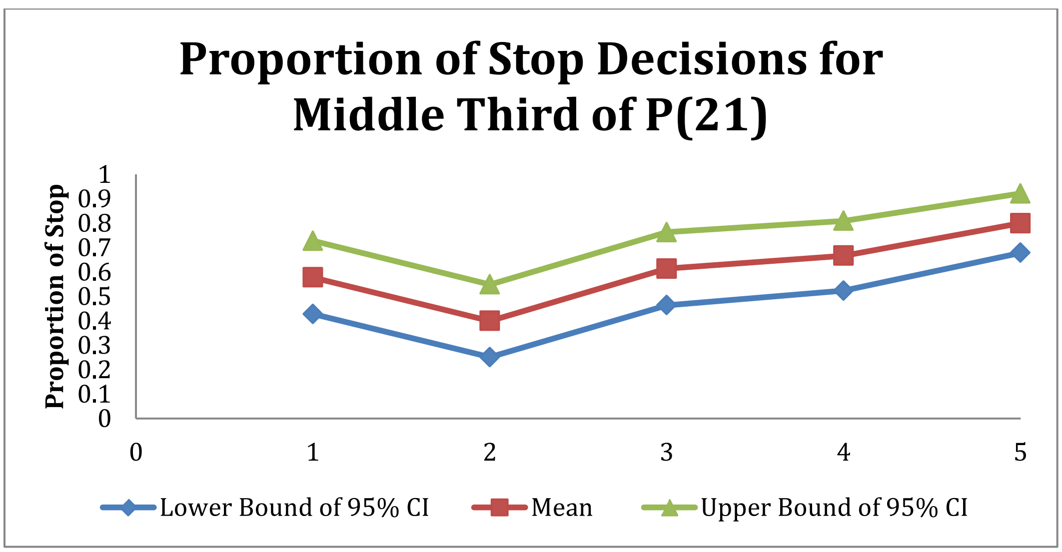
- *p<.10; ** p<.05; *** p<.01*

Figure 12- *Proportion of Stop Decisions for Smallest Third of P(21)*



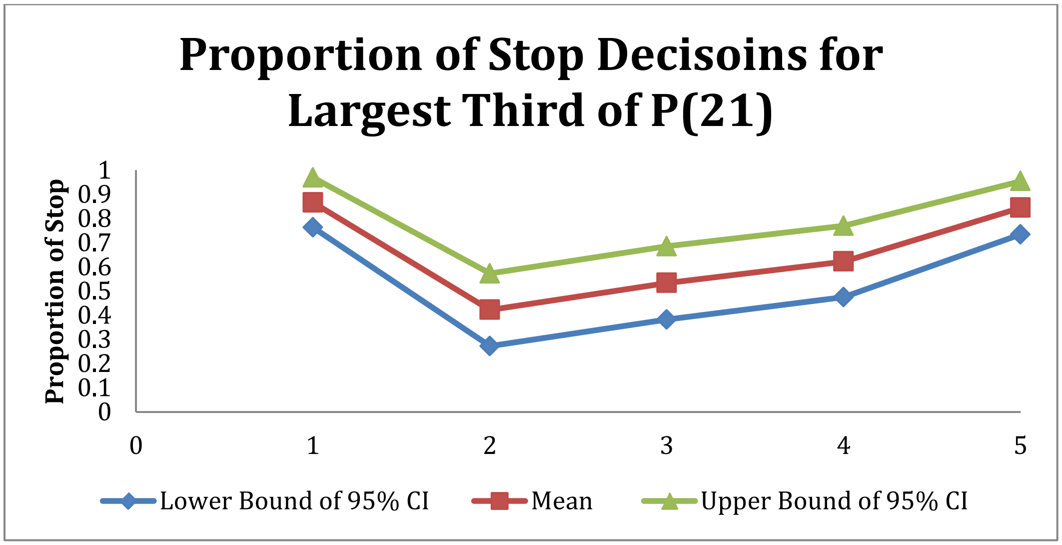
N=45 per segment

Figure 13- *Proportion of Stop Decisions for Middle Third of P(21)*



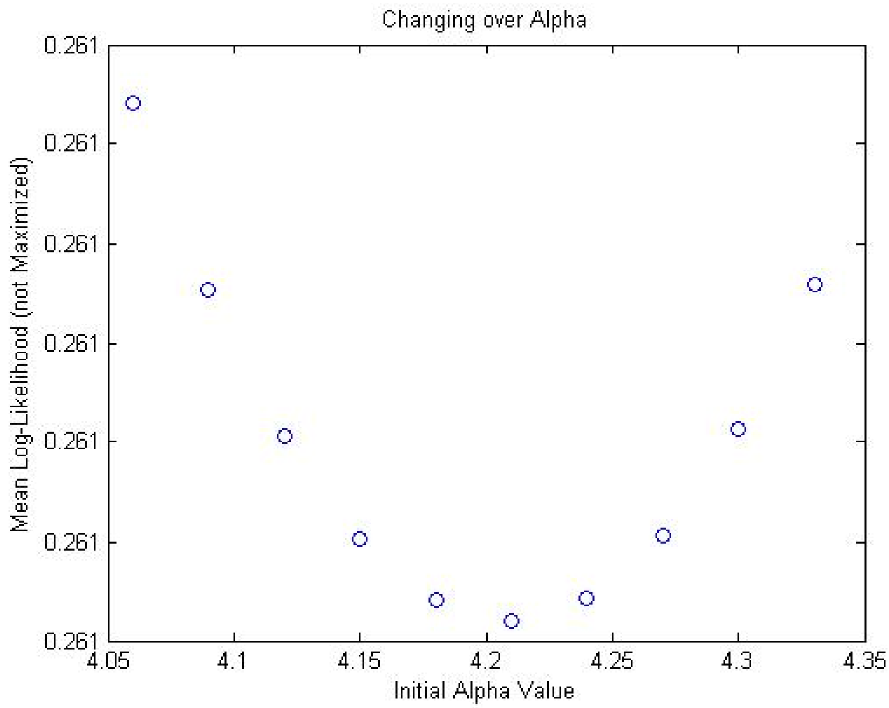
N=45 per segment

Figure 14- *Proportion of Stop Decisions for Largest Third of P(21)*



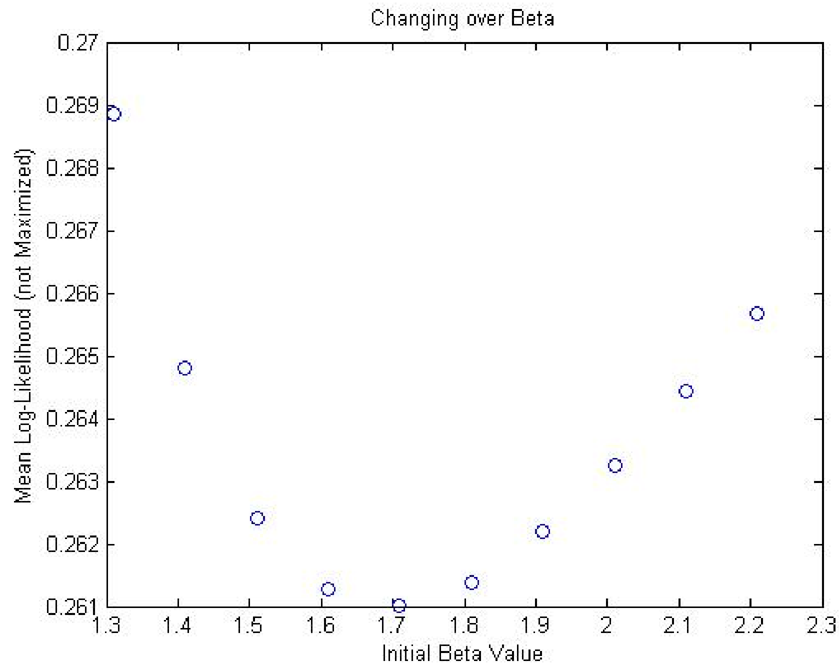
N=45 per segment

Figure 15



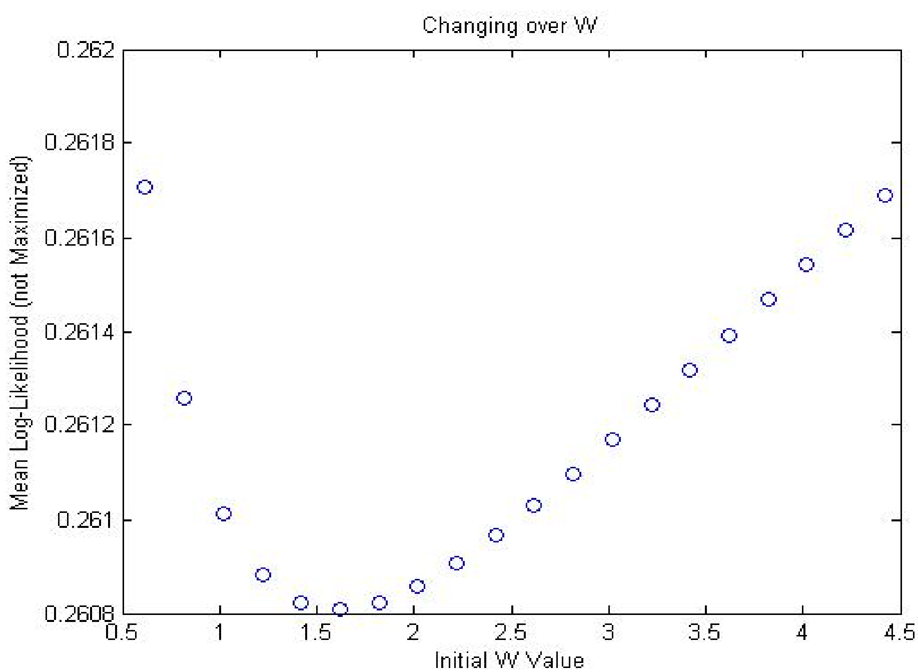
Note: Alpha is scaled by 10^(-5)

Figure 16



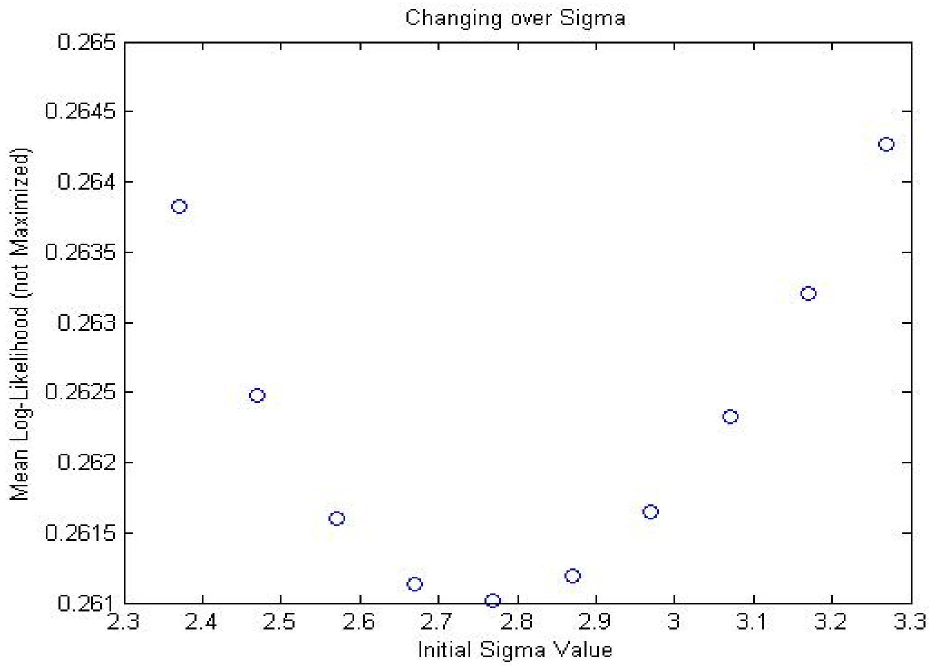
Note: Beta is scaled by 10^(-1)

Figure 17



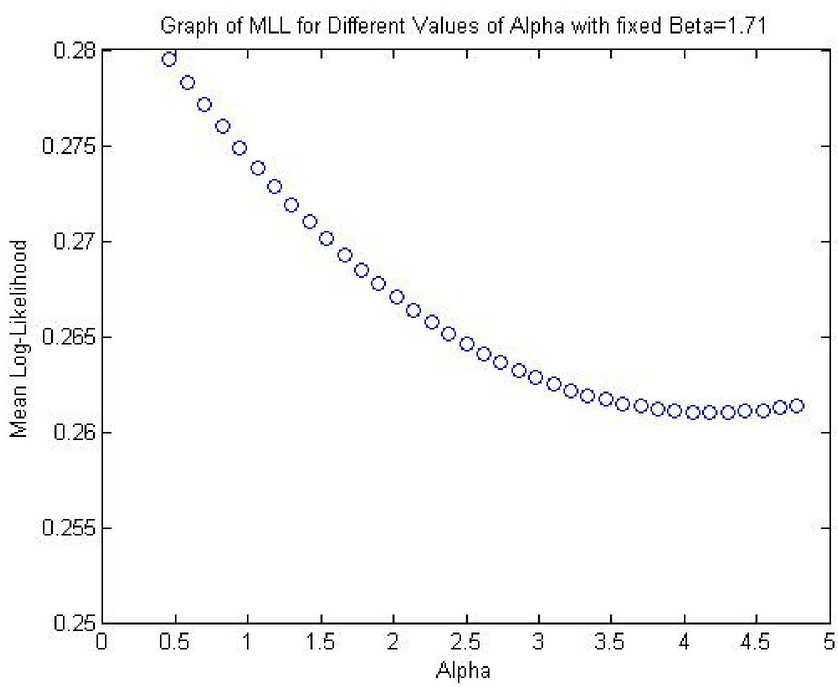
Note: W is scaled by 10^5

Figure 18



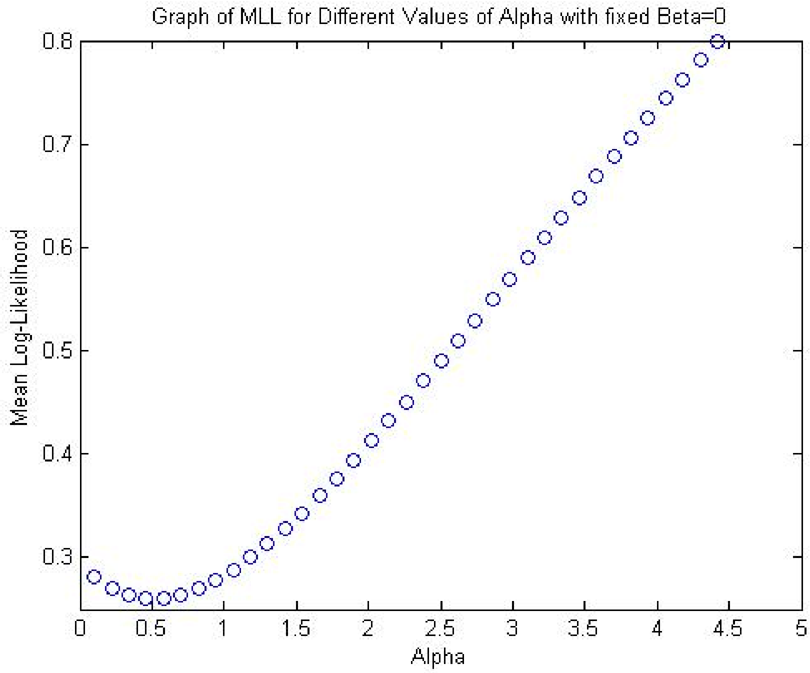
Note: Sigma is scaled by 10^(-1)

Figure 19



Note: Alpha is scaled by 10^(-5)

Figure 20



Note: Alpha is scaled by 10^(-5)

Table 14- *Deal or No Deal Replication Estimates*

Estimate	Published in Post et al. (2006)	2 Parameter (W & σ fixed)	3 Parameter (β fixed)	4 Parameters
	(1)	(2)	(3)	(4)
α	4.18*10^(-5) (0.000)	4.99*10^(-6)	6.86*10^(-5)	4.97 * 10^(-6)
β	0.171 (0.000)	4.01*10^(-12)	0.171	1.41*10^(-10)
W	101,898 (0.782)	101,898	3,800,056	204,804
σ	0.277 (0.000)	0.277	0.277	0.279
MLL	-0.261012	-0.259979	-0.260577	-0.259975
Hit %	88.8%	88.3%	89.1%	87.9%

Note: Standard Errors for columns (2) – (4) need to be calculated in order to draw conclusions about risk aversion