A Natural Experiment in "Jeopardy!"

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This paper uses the television game show "Jeopardy!" as a natural experiment to analyze behavior under uncertainty and the ability of players to choose strategic best-responses. The results suggest that, while most players bet in a rational manner, the failure rate for choosing best-responses increases as the betting problem grows more complex and that players' choices are affected by the "frame" of the problem. However, suboptimal betting tends to decrease as inferior players are driven from the game. The data also allow for estimation of the extent of risk aversion; the results imply near risk-neutrality. (*JEL* C72, C93, D81)

Since Maurice Allais's famous experiment (Allais and Ole Hagen, 1979), economists have documented considerable evidence on individual choice behavior under uncertainty. Yet, almost all of this evidence comes from laboratory experiments and involves the use of small or imaginary incentives.[1] This paper introduces evidence from a natural experiment of a large-stakes strategic decision problem. The natural experiment is the television game show "Jeopardy!" The cost, in prizes, of running an equivalent experiment in the laboratory would be over 5 million dollars.

Television game shows provide an interesting opportunity for economists. Many of these shows are structured so that, at some point, players face well-defined decision problems; often, these decision problems are in the form of strategic games.[2] On the show Jeopardy, three players compete by answering questions in various general-knowledge categories.[3] In the first two rounds, scores are accumulated through the answers to 60 different questions. Then, the first part of the game ends, and all players who have a positive score advance to the third and final round, called "Final Jeopardy." This round contains the strategic game studied in this paper.

In Final Jeopardy (FJ), players are shown a single category from which they will be asked one question. After seeing the scores of the other players and the category (but not the question), players are given several minutes to compute a bet on the success of

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[1]A survey of these results is contained in John D. Hey (1991).

[2]This is not the only attempt to tap this resource. A recent paper by Robert Gertner (1993) uses data from the game show "Card Sharks" to study risk aversion. His findings are discussed in Section III. Also, R. Tinberg (1988) studies the game show "The Price is Right." For other examples of natural experiments in decision theory, see Sarah Lichtenstein and Paul Slovic (1973) and Hans P. Binswanger (1980, 1981).

[3]As anyone who has watched the show is aware, Jeopardy contestants do not answer questions, they "question answers." All clues on the board are given in the form of statements (answers), and contestants who ring in must phrase their "answers" in the form of questions. In order to avoid confusing the reader, I use the conventional definitions of question and answer in the paper. My apologies to Jeopardy purists.

their answer. Players cannot bet more than their score or less than zero. Then, the question is revealed and players are given 30 seconds to write their answers. After time has elapsed, the answers and bets are revealed; correct answers are rewarded by adding the bet to the score, and incorrect answers are penalized by subtracting the bet from the score. At the end of this round, the player with the highest score is declared the winner. This player is allowed to keep her score in dollars and is invited back to play the next day. The second- and third-place players receive prizes but do not keep any of their score. In the event of a tie for first, all tied players get to keep the money and return the next day. If a player wins five consecutive games, then she is retired from the show but invited to the Tournament of Champions, for large cash prizes, at the end of the year.[4]

Since only the winner of the entire game gets to keep her prize, the FJ betting problem is crucial to the players. The large prizes coupled with subjects who are well informed about the rules make this an interesting game for study. The additional advantage of a market mechanism, in the form of champions returning to play again and poor players being "driven out," gives this problem further credibility as a natural experiment. The purpose of this paper is to use the data from this experiment to draw inference about risk attitudes and the ability of players to play best-responses in strategic situations. The main drawback of using a natural experiment is that there are many factors left uncontrolled. For this reason, the analysis in this paper is mostly descriptive, and my conclusions do not include any definitive tests of choice theories.

The paper is organized as follows: Section I gives the notation for the paper, presents some basic data, and describes the two classes of the FJ problem studied in the paper. Section II turns to the first of these two classes in order to analyze behavior under uncertainty. The "game" studied in this section is not really a game at all, since it will encompass only situations in which one player is so far ahead that she can guarantee victory. Her choice of actions in this context provides large-stakes evidence about risk aversion. The risk attitudes implied here show *less* risk-averse behavior than seen in the most comparable study. Section III studies a class of FJ in which the first- and second-place players bet against each other and can mostly ignore the actions of the third-place player. The objective here is to see whether the players are playing best-responses to the observed "empirical frequency" of strategies played by their opponents in my sample of similar games. I call such bets "empirical-best-responses."[5] The evidence shows that, for this class of games, first-place players almost all play empirical-best-responses. Conversely, there is strong evidence that second-place players do not choose empirical-best-responses, and in addition, there are indications that their choices are affected by the "frame" of the game. The difference in performance between the first- and second-place players seems to be the result of different levels of complexity in the strategic problems that they must solve before making their bets. Also, there is evidence that experienced players are more likely than nonexperienced players to play an empirical-best-response. Finally, Section IV provides a short discussion of the conclusions.

I. Setup and Basic Statistics

A. *Setup*

In the FJ problem, three players begin with scores earned in the previous two

[4]The rules of Jeopardy are described in detail in Alex Trebek and Peter Barsocchini (1990).

[5]This paper does not deal with any actual game-theoretic equilibria of the Final Jeopardy problem. Most possible solutions are very involved and quite far away from what is observed in the data. Interested readers may obtain a copy of a solution for a stylized version of the game from the author.

rounds of play. I rank these players by their scores and denote them as the initial endowment vector $\mathbf{X}=(x_1,x_2,x_3)$. Players are then presented with a category, and they must form an estimate of each player's probability of correctly answering a question in this category. There are eight possible combinations of correct/incorrect answers (states of nature) among the three players. Let $\mathbf{A}=(a_1,a_2,a_3)$ be the vector that represents correct/incorrect answers, with $a_i=1$ for correct answers and $a_i=0$ for incorrect answers, and let $P_i(\mathbf{A})$ be the ith-place player's subjective probability that state $\mathbf{A}$ will occur. From their initial scores, subjective probability distributions of the states, and beliefs about the bets of the other players, each player must choose some bet y_i, $y_i \leq x_i$, so as to maximize the expected utility of her winnings. Let $\mathbf{Y}=(y_1,y_2,y_3)$ be the vector of these bets. Final scores $\mathbf{Z}=(z_1,z_2,z_3)$, are calculated by $z_i=x_i+y_i$ if $a_i=1$ and $z_i=x_i-y_i$ if $a_i=0$. The winner is the player with the highest z_i. In the event of a tie, all tied players "win." The winner's prize is to keep her score in dollars. Second- and third-place players do not keep any of their score, although they do get prizes. These prizes are in the form of "goods," not money, with the second-place prize being more valuable. This difference is small, however, and in no case would it exceed a few hundred dollars in market price.

TABLE 1—FREQUENCY OF THE STATES FOR PLAYERS 1, 2, AND 3

State (a_1,a_2,a_3)	Number of observations	Frequency
(1,1,1)	75.0	$f(1,1,1)=0.20$
(1,1,0)	47.0	$f(1,1,0)=0.13$
(1,0,1)	43.5	$f(1,0,1)=0.12$
(1,0,0)	45.5	$f(1,0,0)=0.12$
(0,1,1)	26.5	$f(0,1,1)=0.07$
(0,1,0)	40.0	$f(0,1,0)=0.11$
(0,0,1)	26.5	$f(0,0,1)=0.07$
(0,0,0)	65.0	$f(0,0,0)=0.18$

Notes: A "1" indicates a correct answer for that player. Thus, all three players answered correctly in $f(1,1,1)=0.20$ of the games. Only games in which all three players made it to FJ are included. Fractional observations are due to some ties at the beginning of FJ. Observations from tied games are split between the two possible definitions for the state.

TABLE 2—FREQUENCY OF THE STATES FOR PLAYERS 1 AND 2

State (a_1,a_2)	Number of observations	Frequency
(1,1)	132.0	$f(1,1)=0.34$
(1,0)	93.0	$f(1,0)=0.24$
(0,1)	69.5	$f(0,1)=0.18$
(0,0)	98.5	$f(0,0)=0.25$

Notes: This table only includes the results for the first-place and second-place players. A "1" indicates a correct answer for that player. Thus, both players answered correctly in $f(1,1)=0.34$ of the games. Fractional observations are due to some ties at the beginning of FJ. Observations from tied games are split between the two possible definitions for that state.

B. *Data and Statistics*

The data used in this paper were taken from original Jeopardy programs broadcast between October 1989 and January 1992.[6] There are 393 total games yielding over 1,150 total decisions made by about 1,000 different subjects. Although I do not have hard data on the characteristics of Jeopardy contestants, it is likely that they are, in general, wealthier and better educated than the average person.[7] In Section II, I mention how this unrepresentativeness may affect the results.

For all 393 games, the number of outcomes in each state $\mathbf{A}$ is given in Tables 1 and 2. Table 1 includes only those games in which all three players had positive scores entering FJ. Table 2 includes data from all games, including the 24 in which player 3

[6] Data were collected using a VCR. No information was obtained directly from the Jeopardy production. A complete copy of the data set is available from the author upon request.

[7] The professions of contestants are announced at the beginning of the show, and they often discuss their hobbies or interests during a short on-air conversion between rounds.

TABLE 3—SAMPLE FREQUENCIES FOR W

W	Frequency
0	0.54
$0 < W \leq 10{,}000$	0.05
$10{,}000 < W \leq 20{,}000$	0.16
$20{,}000 < W \leq 30{,}000$	0.09
$30{,}000 < W \leq 40{,}000$	0.06
$40{,}000 < W \leq 50{,}000$	0.04
$W > 50{,}000$	0.06

Notes: W is the realized winnings of champions, subsequent to their first victory. To calculate this sample distribution, I use only the last 220 observations in the data. There are many gaps in the earlier observations due to preempting of the television show, and unbroken data are required for an unbiased sample.

was eliminated before FJ. In this case, the states are presented with a_3 ignored.

From these two tables, one can calculate the frequency that a player in the ith position answers correctly. These frequencies are $f(a_1 = 1) = 225/393 = 0.57$, $f(a_2 = 1) = 201.5/393 = 0.51$ and $f(a_3 = 1) = 171.5/369 = 0.46$. The fact that a player's position is a significant predictor of his success in FJ suggests that other statistics might matter as well. Surprisingly, if one controls for a player's position, then the score, x_i, has no predictive power. In a logit regression of FJ success (1 if right, 0 if wrong) on both position and score, the coefficient on position is positive and significant at the 5-percent level, while the coefficient on score is *negative* and insignificant. This implies that it is the relative position among the three players that predicts the probability of winning and that the amount they are ahead or behind adds little predictive power.

Since champions return to play again, players contemplating bets that give different probabilities of winning need to estimate the value of their future Jeopardy earnings. Since these estimates form an important part of the analysis in later sections, it is useful to look at some sample statistics. Defining W as the random variable representing future winnings for a first-time champion, the sample frequencies for various ranges are given in Table 3. The expected value of W is \$13,600 in this sample. Since estimates of future winnings of multi-game champions are similar, I will use the same W for all players.[8]

Overall, one can split FJ into two mutually exclusive types of games: in the first, player 1 is so far ahead of player 2 that $x_1 \geq 2x_2$. In this case, she can guarantee winning by betting $y_1 \leq x_1 - 2x_2$. The game is then reduced to a pure individual maximization problem, and one can analyze the implied risk attitudes given by player 1's choice of y_1. For my sample, 110 of the 393 games are of this type, and these games are studied in Section II. In the remaining 283 games, $x_1 < 2x_2$. Here, at the very least, player 2 can threaten player 1's lead by betting $y_2 = x_2$. In fact, it is this exact bet which player 1 most often "defends" against, since the most obvious betting regularity in these games is the tendency for the first-place player to bet just enough (by \$1) to "shutout" player 2 if both should answer correctly: $y_1 = 2x_2 - x_1 + 1$. This shutout bet is observed in almost half of the games, and when it is not made, the actual bet is usually quite close to it. Table 4 presents summary data on ranges of y_1 for the 283 games in which $x_1 < 2x_2$. To give a frame of reference, note that the average levels of x_1 and x_2 for these games are, respectively, \$8,120 and \$6,145.

Within the 283 games of this type, there is a subclass of 76 games in which both player 1 and player 2 have two main strategic options at their disposal and player 3's score is low enough so that his actions can be safely ignored. In Section III, I describe this subclass and analyze both players' specific betting choices.

II. Runaway Games: $x_1 \geq 2x_2$

A. *Preliminary Discussion*

The first class of games occurs when player 1 is so far ahead of player 2 in FJ

[8]Although the probability of winning the next game and of reaching the Tournament of Champions increases as championship tenure increases, the time remaining before forced retirement (after five wins) decreases. These two factors almost exactly cancel.

TABLE 4—BEHAVIOR OF PLAYER 1 WHEN $x_1 < 2x_2$

y_1	Number of observations	Frequency
$y_1 < 2x_2 - x_1$	8	0.03
$y_1 = 2x_2 - x_1$	26	0.09
$y_1 = 2x_2 - x_1 + 1$	135	0.48
$2x_2 - x_1 + 1 < y_1 \leq 2x_2 - x_1 + 100$	40	0.14
$2x_2 - x_1 + 100 < y_1 \leq 2x_2 - x_1 + 1{,}000$	40	0.14
$y_1 > 2x_2 - x_1 + 1{,}000$	34	0.12

that she can guarantee winning and advancing to the next game as champion. If $x_1 \geq 2x_2$, then, by setting any $y_1 \leq x_1 - 2x_2$, player 1 can ensure that she keeps at least $x_1 - y_1$, which wins regardless of player 2's bet. Of course, there is no reason why player 1 cannot bet more than $x_1 - 2x_2$, but she would then risk losing her bet *and* the full expected value of future winnings, while she could gain only the amount of her bet. In general, player 1 is faced with the simple problem of deciding how much to wager on the chance that she will answer the FJ question correctly. A typical example of this problem occurs if $X = (10{,}000, 2{,}000, 1{,}000)$. Here, player 1 can wager any $y_1 \leq 6{,}000$ and still be sure of winning. If one knew her subjective probability of answering correctly, then, as long as she chooses some $y_1 < 6{,}000$, it would be possible to form an estimate for her coefficient of absolute risk aversion. In this section, a related experiment is performed on the sample of 110 games which satisfy $x_1 \geq 2x_2$. Since I do not know any player's subjective probability of answering correctly, it is not possible to calculate specific risk parameters for any individual. Instead, I make several assumptions that allow for an estimate of the risk aversion of a representative player in the sample.

B. *Results*

Player 1's decision problem is modeled as

$$\text{(1)} \quad \max_{y_1} \left[pU(x_1 + y_1 + W_U) + (1-p)U(x_1 - y_1 + W_U) \right]$$

subject to

$$y_1 \leq x_1 - 2x_2 \qquad y_1 \geq 0$$

where x_1 and x_2 are known constants, p is her subjective probability of answering correctly [i.e., $p = P_1(a_1 = 1)$], and W_U is her certainty equivalent of W for utility function U.[9] I altered the true problem by adding in the constraint that y_1 must be small enough to ensure victory even if $a_1 = 0$. Since none of the 110 players faced with this decision violated this "constraint" and bet more than $x_1 - 2x_2$, this formulation is not inconsistent with the data. When the constraints do not bind, the first-order condition of (1) implies a solution for y_1. In the special case of constant absolute risk aversion, $U(x) = 1 - e^{-\alpha x}$,

$$\text{(2)} \qquad y_1 = \frac{\ln\left(\dfrac{p}{1-p}\right)}{2\alpha}.$$

From this equation, if I had uncensored y_1 for every player and knowledge of their private p, it would be possible to calculate an α for every individual. Since this information is not available, I instead estimate an α for the "representative" player, that is, the constant value of α that is most likely to result in the observed sample of bets (y_1) and correct/incorrect answers (a_1). To obtain this α, it is necessary to first make the assumption that there is no error in player 1's calculation of her optimal y_1. This

[9] I assume that W_U is invariant around the level of wealth changes which occur from correct or incorrect answers. This is done to avoid having to calculate a new certainty equivalent dependent on current-game winnings.

allows equation (2) to be written as

$$(2') \qquad p = \frac{\exp(2\alpha y_1)}{1+\exp(2\alpha y_1)}.$$

Since this is exactly the form of a logit regression, it is possible to calculate the maximum-likelihood level of α in a straightforward way; with a_1 as the dependent variable and y_1 as the independent variable, the slope coefficient is a consistent estimate of 2α.[10] This formulation also allows for a simple handling of the censoring on y_1. Since I am estimating the likelihood of correct answers (p) conditional on bets (y_1), any subset of the bets can be dropped without introducing bias. Therefore, I drop the two observations where $y=0$ and the four observations where $y_1 = x_1 - 2x_2$. This leaves 104 uncensored observations. Using this sample, the point estimate is 0.000066 for α, with a standard error of 0.000056. Since this estimate is not significantly different from 0, I cannot reject a null hypothesis that the representative player is risk-neutral.[11] Note that the model also implies that there is no intercept term in equation (2′). The evidence does not reject this implication; for the intercept, the point estimate is -0.179 with a standard error of 0.297.

To get a visceral sense for the risk attitudes implied by α, the point estimate can be translated into a certainty equivalent of 4,190 for the lottery (10,000, 0.5)—a lottery which gives a 50-percent chance at winning \$10,000 and a 50-percent chance at winning nothing. This certainty equivalent "seems" high; for example, Daniel Kahneman and Amos Tversky (1979) report that the majority of certainty equivalents for a (1,000, 0.5) lottery fall between \$300 and \$400. To go beyond a visceral sense for this result, it is necessary to look to related research.

Most other empirical studies of risk aversion focus on estimating the coefficient of relative risk aversion,[12] but since I lack data on wealth levels of the players, it is difficult to make useful comparisons with this literature. However, a recent paper by Gertner (1993) provides a remarkably similar data set. In this work, the author looked at choice behavior in the television game show "Card Sharks," where the "bonus" round of play provides a well-defined betting problem played for large stakes. He calculates a *lower* bound for α of 0.000310.[13] This is more than four standard errors above the estimate here of an α for the representative player. One possible partial explanation for this large disparity is that Jeopardy contestants are wealthier than those in Card Sharks, and my constant-absolute-risk-aversion specification has hidden the fact that absolute risk aversion actually declines with higher wealth levels. This explanation is not implausible. Another possibility is that players are overestimating their probability of success; if subjective estimates of p are systematically higher than the sample average, then players will appear less risk-averse

[10] I am grateful to Michael Boozer and Orley Ashenfelter for suggesting this logit estimation.

[11] There are several other reasonable approaches to the censoring problem; the approach used in the text leads to a comparatively high estimate for α. For example, out of 110 players in our sample, 20 chose to bet exactly $y_1 = x_1 - 2x_2 - 1$, or \$1 below the constraint used in the model. It is likely that most of these players chose this bet because they preferred to win outright rather than allow the possibility for a tie. Since I did not explicitly model this preference, the estimation treated these 20 players as unconstrained. If, instead, these observations are dropped from the sample, then one obtains a point estimate of 0.000037 for α, with a standard error of 0.000061. Also, it is possible to relax the assumption that player 1 correctly calculates y_1 and simultaneously model the censoring through a Tobit estimation of equation (2). Then, by making assumptions about the calculation error and the distribution of p in the sample, one can back out a value for representative α; for a wide range of reasonable assumptions, the resulting estimates for α are very similar to those obtained under the logit estimation of (2′). Details of these computations can be obtained from the author.

[12] The most extensive work in this area is by Kenneth R. MacCrimmon and Donald A. Wehrung (1986). See Ralph L. Keeney and Howard Raiffa (1976) for a survey of earlier studies. Other work has been carried out using stock-market data by researchers primarily interested in testing stock-market theories, but information about relative risk aversion is also estimated (Larry G. Epstein and Stanley E. Zin, 1991).

[13] Gertner (1993) also finds evidence that players do not bet according to expected utility theory. Because of this finding, his estimates of α should be viewed descriptively.

than they actually are. In Card Sharks, players deal with computable risks, and should not suffer from this bias. This "overestimation of success" could also explain some of the results of the next section.

III. Bet High or Low?

A. *Preliminary Discussion*

The example of "runaway games" is not a very interesting strategic problem. Player 1 has a decision to make, but as long as she does not violate the constraint that $y_1 \leq x_1 - 2x_2$, she need not concern herself with the behavior of the second- or third-place players. When $x_1 < 2x_2$, however, this is no longer the case. In these situations, player 2 can always challenge player 1 by betting, $y_2 \geq x_1 - x_2$, thus forcing player 1 to choose a bet based on her estimates of the probabilities of the final states. This strategic problem becomes more interesting as x_1 and x_2 grow closer together. This section studies games in which $3x_2 \geq 2x_1$ and $x_2 \geq 2x_3$. The first restriction, $3x_2 \geq 2x_1$, ensures that player 2 has at least two "interesting" strategies at his disposal. The second restriction, $x_2 \geq 2x_3$, simplifies the problem by making it possible to "ignore" the actions of the third player.

The importance of these restrictions is illustrated by the following example. Consider $\mathbf{X} = (10{,}000, 7{,}000, 1{,}000)$, and $P_i(a_1 = 1)$, $P_i(a_2 = 1)$ calculated from the sample frequencies in Table 2. One strong implication of the data, as will be seen, is that in these situations there is a focal-point bet of $y_1 = 4{,}001$. With this bet, player 1 seeks to "shut out" player 2 by making the smallest possible bet which ensures victory (*not* just a tie) if she answers correctly ($a_1 = 1$). In fact, this exact bet is played in over half of the games of this type. Overall, more than 90 percent of these games show player 1 playing some $y_1 > 4{,}000$. When $y_1 = 4{,}001$, then z_1 will be either 14,001 (if $a_1 = 1$) or 5,999 (if $a_1 = 0$). Player 2 has two main strategies at his disposal, although each strategy may be represented by many different bets. The first strategy is to play *Low*. "Low" strategies are represented by all bets such that $7{,}000 - y_2 \geq 5{,}999$. Any bet satisfying this restriction will win for player 2 whenever $a_1 = 0$. The simplest Low bet is $y_2 = 0$, but of course any $y_2 \leq 1{,}001$ will also do. The second strategy for player 2 is, not surprisingly, to play *High*. "High" strategies are represented by all bets $y_2 > 1{,}001$. When $y_1 = 4{,}001$, High bets only win when $a_1 = 0$ and $a_2 = 1$. By this strategy, player 2 is saying, "I will sacrifice my added probability of winning in return for a higher payoff when I do win." Given that player 2 only wins (and keeps his money) when his answer is right, the natural High bet is to bet everything, $y_2 = 7{,}000$. This intuition is reinforced by the fact that about 10 percent of first-place players bet exactly $y_1 = 4{,}000$ in these types of games. In this specific case, $y_2 = 7{,}000$ will tie when $a_1 = a_2 = 1$, whereas other High bets less than 7,000 will not. For this reason I give the bet of $y_2 = x_2 = 7{,}000$ a special name of *All*.

The importance of the restriction $3x_2 \geq 2x_1$ becomes clear if one limits attention to the focal bet. If, say, $\mathbf{X} = (10{,}000, 6{,}000, 1{,}000)$, then the focal bet for player 1 is $y_1 = 2{,}001$. Now, however, if $a_1 = 0$, then $z_1 = 7{,}999$, which is greater than x_2. In this case, player 2 does not have the option of a Low bet. Next, if $x_2 < 2x_3$, then the idea of a Low strategy is complicated by the presence of the third player. If $\mathbf{X} = (10{,}000, 7{,}000, 4{,}500)$, then $y_1 = 4{,}001$, $y_2 = 0$, $a_1 = 0$, will not win for player 2 if player 3 answers correctly and bets, say, $y_3 = 4{,}500$. Although these games are also interesting, their analysis is more complicated and not directly comparable to the cases where $x_2 \geq 2x_3$. Thus, in this section I restrict attention to an empirical investigation of the 76 games in which both of the restrictions, $3x_2 \geq 2x_1$ and $x_2 \geq 2x_3$, hold.[14]

[14] Within this subclass, the special case of $x_1 = x_2 + x_3$ has been excluded as well. In these games, player 1 has an extra incentive to bet exactly $2x_2 - x_1$, since any higher bet could possibly leave $z_1 < 2x_3$. The three occurrences of this special case are not included in the 76 games studied here.

TABLE 5—BEHAVIOR OF PLAYER 1

y_1	Number of observations	Frequency
$y_1 < 2x_2 - x_1$	2	0.03
$y_1 = 2x_2 - x_1$	7	0.09
$y_1 = 2x_2 - x_1 + 1$	44	0.58
$2x_2 - x_1 + 1 < y_1 < x_1$	22	0.29
$y_1 = x_1$	1	0.01

TABLE 6—BEHAVIOR OF PLAYER 2

y_2	Number of observations	Frequency
$y_2 \leq 3x_2 - 2x_1$	18	0.24
$3x_2 - 2x_1 < y_2 < x_2$	26	0.34
$y_2 = x_2$	32	0.42

B. *A Puzzle*

The behavior of players 1 and 2 in these games is shown in Tables 5 and 6, respectively. The importance of the specific ranges used in the tables will become clearer as the analysis progresses.

Note here that player 1 makes the focal bet of $2x_2 - x_1 + 1$ in over half of the games. In seven games she chooses to bet exactly $y_1 = 2x_2 - x_1$, thus allowing player 2 the possibility of tying the game. In only two games did player 1 bet below $2x_2 - x_1$, and in neither of these games was $y_1 < x_1 - x_2$. In one game player 1 bet $y_1 = x_1$. The remaining 22 bets were close to the focal bet, most within \$100 of it. The behavior of player 2 has been separated into three groups. The first group consists of bets $y_2 \leq 3x_2 - 2x_1$, the second group includes all other bets except $y_2 = x_2$, and the third group contains the bet $y_2 = x_2$. I refer to these groups as "Low," "High," and "All," respectively.

As mentioned in the Introduction, the methodology here is to determine whether the players are generally choosing to bet "empirical-best-responses." To do this, I assume that each player believes that her opponent is playing a mixed strategy equal to the above frequencies. Then, I compare the relative payoffs of different bets. This simplification precludes statements about the rationality of any one individual. Instead, I analyze behavior in the aggregate, assuming that players hold beliefs which are similar to the sample frequencies.

Consider first the behavior of player 2. Given the behavior of player 1, one can calculate the expected utility of a representative member of the Low, High, and All groups. For the Low group, $y_2 = 0$; for the High group, $y_2 = x_2 - 1$; for the All group, $y_2 = x_2$. These are the modal choices within each group, and a different representative member would not change the main results. If one substitutes the sample frequencies from Table 5 for player 2's beliefs about player 1's bet, then it is possible to calculate what the empirical-best-response would be for any utility function.[15] Under this framework, the expected utility of each of these bets is as follows.

(i) For $y_2 = 0$,

$$(3) \quad [P_2(0,1) + P_2(0,0)]U(x_2 + W_U).$$

In the 76 games of this type, the bet of $y_2 = 0$ would win whenever player 1 is wrong, since none of the games in the sample had player 1 bet $y_1 < x_1 - x_2$. Thus, the payoff to this bet is $x_2 + W_U$ in both states $(0,1)$ and $(0,0)$.

(ii) For $y_2 = x_2 - 1$,

$$(4) \quad [P_2(0,1) + 0.03P_2(1,1)]U(2x_2 - 1 + W_U) + 0.01P_2(0,0)U(1 + W_U).$$

The bet $y_2 = x_2 - 1$ always wins in state $(0,1)$, and also wins in state $(1,1)$ whenever $y_1 < 2x_2 - x_1$ (3 percent of the time, from Table 5) and in state $(0,0)$ when $y_1 = x_1$ (1 percent of the time). In the first two cases, the payoff is $2x_2 - 1 + W_U$, and in the third case the payoff is $1 + W_U$.

[15] I assume $U(x) > 0$ throughout this analysis.

(iii) For $y_2 = x_2$,

$$(5)\quad [P_2(0,1)+0.12P_2(1,1)]U(2x_2+W_U).$$

The bet $y_2 = x_2$ always wins in state $(0,1)$ and also wins in state $(1,1)$ whenever $y_1 \leq 2x_2 - x_1$ (12 percent of the time). The payoff in both of these states is $2x_2 + W_U$.

One can see from this analysis that the expected utility of $y_2 = x_2$ must be higher than the expected utility of $y_2 = x_2 - 1$ if beliefs are equal to the sample frequencies.[16] The bet of $y_2 = x_2$ has the possibility of tying at $z_2 = z_1 = 2x_2$ in state $(1,1)$. This can occur when player 1 bets $y_1 = 2x_2 - x_1$, which she did seven times in 76 games. By betting $y_2 = x_2 - 1$, player 2 gives up this chance to tie in return for the possibility of winning the game at $z_2 = 1$ in state $(0,0)$. This occurs if player 1 bets $y_1 = x_1$ or $y_1 = x_1 - 1$, which she did once in 76 games.[17] Also, the payoff at $z_2 = 2x_2$ is significantly higher than the payoff at $z_2 = 1$. To justify betting $x_2 - 1$ instead of x_2, player 2 would have to believe that player 1 was much more likely to play $y_1 = x_1$ than to play $y_1 = 2x_2 - x_1$. Given the sample frequencies, these beliefs do not seem likely, especially not by all 26 players who choose a High bet. Given any set of beliefs close to the sample frequencies, All is far superior to High. If we ignore issues of second-place and third-place prices, we can even say that the bet of $y_2 = x_2$ "first-order stochastically dominates" the bet of $y_2 = x_2 - 1$.[18] It is a puzzle why 26 players choose to make High bets such as $y_2 = x_2 - 1$.

Next, I analyze how players should choose between Low and All. From equations (3) and (5), one can see that $y_2 = 0$ will be preferred to $y_2 = x_2$ if

$$(6)\quad \frac{P_2(0,1)+P_2(0,0)}{P_2(0,1)+0.12P_2(1,1)} > \frac{U(2x_2+W_U)}{U(x_2+W_U)}.$$

Once again, I cannot say anything about whether or not (6) holds in any individual case. I can, however, analyze this inequality in several ways in order to understand better the decision facing the representative player. First, if players' beliefs about the probabilities of the states are the same as the sample frequencies in Table 2, then one can substitute $P_2(1,1) = f(1,1) = 0.34$, $P_2(0,1) = f(0,1) = 0.18$, and $P_2(0,0) = f(0,0) = 0.25$ and rewrite inequality (6) to show that $y_2 = 0$ will be preferred to $y_2 = x_2$ if

$$(7)\quad \frac{(0.18+0.25)}{(0.18+0.04)} = 1.95 > \frac{U(2x_2+W_U)}{U(x_2+W_U)}.$$

Even for very pessimistic estimates of W_U, (7) will hold for all but the most extreme

[16] Readers may wonder how these calculations would be changed if one tried to incorporate nonmonetary values into the utility functions. It is impossible to know the full extent of this distortion, but the most likely effect would be to throw more weight on W_U, since players are apt to place the most nonmonetary value upon winning the game and returning to play again.

[17] If all players are tied with 0 after FJ, then no one returns as champion.

[18] Trebek and Barsocchini (1990 p. 70) suggest that some players are motivated by the desire to finish in second place instead of third place because of the difference in prizes for these two final positions. However, even if one allows the difference in prizes to be worth \$500 (an upper bound; in many games the values are indistinguishable), then an increase of 15 percent in the chance of winning second place (another upper bound) for $y_2 = x_2 - 1$ over $y_2 = x_2$ would be worth \$75 in expected value. This is inconsequential compared to the other sums involved. In addition, several High bets are made in games where the third-place player has already been eliminated and player 2 is guaranteed at least second place. Hence, I ignore the issue of second place.

TABLE 7—DETERMINANTS OF PLAYER-2 BEHAVIOR

Explanatory variable	(i)	(ii)	(iii)	(iv)
Constant	−1.33 (1.37)	−1.44 (1.46)	−7.89 (2.79)	−7.73 (2.62)
$x_2/100$	0.00 (0.17)	−0.00 (0.04)	−0.02 (1.15)	−0.01 (0.71)
a_2	—	0.49 (0.84)	0.31 (0.50)	0.18 (0.28)
RATIO	—	—	9.13 (2.54)	8.02 (2.16)
CHAMP2	—	—	—	0.46 (1.88)
Pr(> Chi)	0.867	0.684	0.042	0.020

Notes: The table contains the results of four logit regressions with independent variable LOWYES2. LOWYES2 equals 1 if player 2 bet Low and equals 0 otherwise. The variable x_2 is player 2's score (in dollars); a_2 represents player 2's FJ answer (1 if correct, 0 if incorrect). RATIO is equal to x_2/x_1, the ratio of player 2's score to player 1's score. CHAMP2 is a discrete variable equal to the number of games that player 2 has previously won. Numbers in parentheses are asymptotic t statistics.

utility functions.[19] Thus, using sample frequencies of the states for beliefs indicates that Low should be chosen over All. The observed pattern, however, is that 32 players chose All and only 18 players chose Low. The preference for High over Low is even more difficult to justify.

Even if one drops the assumption that beliefs are close to the sample frequencies, it is still possible to draw testable implications from this framework. Returning to the inequality in (6), one can say for sure that, holding estimates of W_U constant, the size of x_2 should have an impact on the betting decision; if x_2 is relatively large, then player 2 would be more likely to forgo the increased chance of winning for a higher payoff today. To test this prediction, I regress a dummy variable, LOWYES2, which is set to 1 if player 2 played Low and 0 otherwise, on x_2 and other explanatory variables. In addition, players with relatively high expectations of success in answering correctly, $P_2(a_2 = 1)$, will place relatively more weight on the denominator of the left-hand side of (6) than on the numerator. This makes the inequality less likely to hold, and the player more likely to choose to play All over Low. One possible explanation for the modal choice of All over Low is that players who bet All have private information which makes their estimates of $P_2(a_2 = 1)$ significantly higher than the sample average. Lacking data on $P_2(a_2 = 1)$, I use player 2's realized success, a_2, as a proxy and include it as a regressor on LOWYES2.

Table 7 contains the results from four different logit regressions for LOWYES2. To interpret the coefficients, translate them into marginal probability effects by multiplying through by $p(1-p)$, where p is the probability that LOWYES2 = 1. In this case, the scaling factor is 0.18. In the first regression, when only x_2 is included as a regressor, its coefficient is insignificant and of the wrong sign to support the hypothesis that players are choosing empirical-best-responses. When the other regressors are added, the coefficient on x_2 is negative but insignificant at even the 25-percent level. I cannot reject the null hypothesis that the size of x_2 does not affect player 2's likelihood of betting Low. The use of a_2 allows a test of whether there is any difference be-

[19] In fact, it is difficult even to construct a case for which (7) does not hold. First, we note that if player 2 is risk-neutral, then (7) implies that Low is preferred to All if $19W_U > x_2$. Since the sample mean of W is \$13,600 and the maximum observed value of x_2 is \$11,800, it would be very surprising if any risk-neutral player did not satisfy $19W_U > x_2$. For risk-averse players, this inequality is even more extreme, and the necessary level of W_U drops to zero when $1.95 = U(2x_2)/U(x_2)$. Only risk-loving players might prefer All to Low. In this case, however, the certainty equivalent W_U, would be higher than its expected value, so that even pessimistic estimates of W_U would be high relative to x_2. Thus, in order for (7) not to hold, a player would need the unusual combination of risk-loving preferences and extremely pessimistic beliefs.

tween the betting behavior of players who eventually answered correctly and the behavior of players who did not. Equation (6) implies that the coefficient on a_2 should be negative. Regressions (ii), (iii), and (iv) find that the coefficient on a_2 is *positive* and insignificant. This finding also fails to support the hypothesis that players are choosing empirical-best-responses.

Using the same method, one can easily calculate that player 1 is making a bet close to the empirical-best-response in all but a few of the games. Since the vast majority of second-place players are choosing y_2 close to x_2, the best response for player 1 is to make the shutout bet. This fact is fairly intuitive, so there is no need to replicate the calculations that were performed for player 2. The two first-place players who bet less than the shutout bet may have made errors, or they may just have had very low private estimates of $P_1(a_1 = 1)$. Either way, one can safely conclude that, as a group, first-place players are having no problem finding their empirical-best-responses. This finding presents something of a puzzle. While a simple analysis of player 1's behavior indicates that players are betting close to optimally, the results for player 2 are difficult to explain if one believes that player 2 is correctly perceiving the strategic situation that he faces.[20] The next section attempts to explain why this anomaly might occur.

C. *Analysis of the Behavior*

Player 2 does not seem to play empirical-best-responses, if expected utility theory is his underlying decision criterion. This result would still hold under other axiomatic non-expected-utility functions.[21] Indeed, player 2 seems to violate dominance when he chooses a High bet, and this is a serious problem for every normative theory of choice. There are, however, several well-studied biases in probabilistic reasoning which can aid in explaining the results.[22] Unfortunately, there is no way of testing the validity of any of these explanations against each other. It is possible, however, to test for evidence of one specific decision-making bias: "framing."

Framing.—One possible explanation for player 2's difficulties relative to player 1 is that his strategic problem is more difficult; the calculation of a Low bet is "one-step" harder than the calculation of the shutout bet. Thus, one might expect player 2 to choose Low more often in games when the possibility of a Low bet is easier to compute. I attempt here to determine whether this type of framing matters. In Table 7, the third explanatory variable, RATIO, is a

[20]A previous version of this paper included data on a slightly more complex strategic situation for player 3. This situation is similar to that faced by player 2 in this section: a choice between High and Low strategies. This analysis found even stronger evidence that player 3 did not choose empirical-best-responses, and the types of deviations from the best-response were analogous to those found here.

[21]Most non-expected-utility theories were developed as a reaction to criticism of the independence axiom. Since most of the Jeopardy data consist of a single observation per player, axiomatic theories that rely on dropping or weakening the independence axiom will not explain the results. Another possibility, regret theory (David Bell, 1982; Graham Loomes and Robert Sugden, 1982), is an unlikely explanation because it would imply that the size of player 2's score, x_2, should have an even larger negative effect on his decision to play Low than is suggested by expected-utility theory. Table 6 shows no evidence that score matters at all.

[22]Biases that can help explain the results have the effect of overweighting the numerator and underweighting the denominator of the left-hand side of inequality (6). Examples of such biases are studied in Colin F. Camerer (1987) (ignorance or misapplication of Bayes' rule), Tversky and Kahneman (1974) and Hillel J. Einhorn and Robin M. Hogarth (1985) (anchoring and insufficient adjustment of probability estimates), Mark J. Machina (1982) and Soo Hong Chew and Epstein (1989) (nonlinear probability weights), and Daniel Ellsberg (1961) and Einhorn and Hogarth (1986) (ambiguity aversion). In addition, if players have a preference for betting "actively" (as discussed in Jack Ochs and Alvin E. Roth [1989]), then this would partially explain the results as well. I am grateful to an anonymous referee for bringing this last point to my attention.

ratio of x_2 to x_1. Given the actual behavior of player 1, there is no reason that a "closer" game, represented by a higher RATIO, should make it more likely that player 2 bets low. Nevertheless, the coefficient on RATIO is positive and significant at the 5-percent level. One intuitive reason for this result is that a closer game makes it simpler for player 2 to notice the possibility of making a Low bet. It is difficult to find an alternative explanation.[23]

Learning and Market Selection.—Next, I compare the betting behavior of experienced players ("champions") with that of inexperienced players ("non-champions"). In Table 7, the final regression includes CHAMP2, a discrete variable equal to the number of games that player 2 has previously won. CHAMP2 can take on possible values of 0, 1, 2, 3, or 4. When this variable is included as a regressor, its coefficient is positive and significant at the 10-percent level; champions are more likely to play Low than are non-champions. A translation of this coefficient implies an 8-percentage-point higher likelihood of playing Low for each additional game of championship tenure.[24]

This result is not surprising; one would expect experienced players to perform better than inexperienced players. But what causes this difference? Since there is no evidence that any relevant variables in inequality (6) are significantly different for champions and non-champions, one must turn to more "dynamic" explanations. The first possibility is that champions learn how to play Low from their experience in earlier games. However, looking at players with multiple experiences in games of the type studied in Section III, one finds that *no* repeat players switched to a Low bet after making a High or All bet in a previous game. Even if the study is expanded to include other similar situations, there is no evidence that learning explains any part of the positive coefficient on CHAMP2.[25]

Another possibility is that the market mechanism, in this case the rule that allows only winners to play again, is responsible for increasing the frequency of Low bets. Players who bet Low have a higher probability of winning the game and advancing to the next round. Therefore, one would expect market pressure, or "evolution," to favor these players. An analysis of the entire data set allows me to estimate the survival advantage to Low betting to be between 3 percent and 6 percent per game.[26] Then, simple simulations suggest that the fraction of the population that plays Low should be increasing at no more than 4 percentage points per game of championship tenure. In comparison, the survival advantage estimated by the coefficient on CHAMP2 indicated an 8-percentage-point difference. These simple calculations suggest that one can ascribe no more than half of the difference to the market pressure exerted by FJ betting behavior alone.

Another form of market pressure can appear by way of "correlated skills." If good Jeopardy players also tend to be good FJ bettors, then market pressures on good playing can affect the resulting fraction of

[23] In fact, a similar analysis for player 3 (not presented here) yields an even more highly statistically significant coefficient on RATIO, which is also used there as the "framing variable." It is also difficult to find any alternative explanations for this result.

[24] In the analysis of a similar strategic decision for player 3 (not presented here), the coefficient on the analogous CHAMP3 variable is significant at the 5-percent level. A similar translation of that coefficient implies a 9-percentage-point improvement for each additional game of championship tenure.

[25] It is possible to identify other subclasses of Final Jeopardy which give rise to the basic High versus Low problem. If these games are included, there is still no indication that a player has learned from a previous mistake. Also, since all taping for each televised week of play is done in a single day, and players may observe the other games from the studio audience, one might expect that players later in the "week" would be more likely to bet Low if they observed a Low bet in an earlier show. There no difference here as well.

[26] I estimate the lower bound by looking at as many games as I can identify when the Low/High decision is relevant and calculating the difference in winning percentage between the two strategies. I assume that all Low bettors in the sample would also bet Low whenever it was optimal in other contexts.

Low bettors in the population. Achieving a high score and placing oneself in a position to win are aided by sound strategy at many points during the game. FJ is the easiest part to study, but (betting) success here should not be uncorrelated with success in the earlier parts of the game. The evidence indicates that this may be the largest factor influencing the improvement in betting performance by champions.

IV. Conclusions

This paper has used a television game show as a natural experiment to study high-stakes decision-making. The results suggest two main themes about choice behavior: the first concerns "static" aspects, while the second concerns "dynamic" aspects.

1. *Although choices are not always optimal, they still tend to conform to patterns.* Many players overestimate their abilities or fail to notice that a specific option is available; in either case, however, the mistakes they make are not random, but seem to be similar across different individuals. This observation supports the existence of "stylized facts" of boundedly rational choice behavior.
2. *Suboptimal choice can persist despite the three mitigating factors of high stakes, an identifiable market mechanism, and an opportunity for players to learn.* In the case of Final Jeopardy, the most important of these mitigating factors is the market mechanism, and its role in driving out inferior players can be quantified. Nevertheless, since all three factors together are not sufficient to force "convergence" to optimal choices, the question remains: what would be sufficient? This question can only be answered by further empirical studies.

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