ISSN 1503-299X

WORKING PAPER SERIES

No. 19/2006

***JOKER*: CHOICE IN A SIMPLE GAME WITH LARGE STAKES**

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Joker: Choice in a simple game with large stakes*

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December 19, 2006

Abstract

This paper examines data from the Norwegian television game show *Joker*, where contestants make well-specified choices under risk. The game involves very large stakes, randomly drawn contestants, and ample opportunities for learning. Expected utility (EU) theory gives a simple prediction of choice under weak conditions, as one choice is always first-order stochastically dominating. We document frequent, systematic and costly violations of dominance. Most alternative theories fail to add explanatory power beyond the EU benchmark, but many contestants appear to have a systematic expectation bias that can be related to Tversky and Kahneman's (1973) "availability heuristic". In addition, there seems to be a stochastic element in choice that is well captured by the so-called Fechner model.

Keywords: Risky choice, stochastic dominance, choice models, stakes, game show.

JEL Classification: C9, C93, D81

*We thank Norsk Tipping and the Norwegian Gaming and Foundation Authority for providing data, especially Terje Helgesen and Kaare Sveen for answering our countless detailed questions. Thanks also to seminar participants at the First Nordic Behavioral and Experimental Economics Meeting and at the Norwegian University of Science and Technology for helpful suggestions.

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1 Introduction

Do people behave as rational (utility) maximizers when making risky choices? A battery of experiments in economics and psychology over recent decades suggest not.[1] Yet, economists seem reluctant to abandon the rational maximization model; it still occupies a core position in teaching and in research.

An important reason for the reluctance is a pronounced skepticism towards the generalizability of experimental findings to real-world decisions.[2] First, the stakes involved in the typical laboratory experiment are low, or even hypothetical. If stakes are trivial, the reasoning goes, experiments do not provide information about agents' behavior when faced with serious stakes in the "field". Second, the subject pool may be nonrepresentative of the populations of interest because of (self-)selection of participants. Students, for instance, are used extensively as subjects, and their behavior is not necessarily a good predictor of the way other groups choose. Third, in real life people will learn to avoid psychological biases, through repetition, observation and replication. (See Harrison and List, 2004 for an extensive discussion of these and other objections to experiments.)

This paper examines risky-choice data from the Norwegian television game show *Joker*, where all these issues can be addressed. It involves stakes of a magnitude that, to our knowledge, is unparalleled in previous literature. Actual bets in our sample involve an average stake of NOK289,000 (\$47,000 / €35,000 at the time of writing).[3] Next, participants are randomly drawn from a pool of up to five hundred thousand lottery players (of a total population of about 4.6 mill.). Finally, the game is very simple and provides ample opportunities for learning.

The standard expected utility (EU) framework gives a very strong and simple prediction of players' choices in this game. One of the choices always *first-order stochastically dominates* the alternative; hence we need not even assume risk aversion to predict choice within the standard framework (a positive marginal utility of wealth suffices). Despite the weak conditions under which EU should predict choices, and despite the stakes involved, one-third (or more in an alternative sample) of the contestants deviate from these predictions. The average cost of this "irrationality" exceeds NOK100,000 for these participants.

The violations of the EU predictions are systematically related to the state variables of the game. We utilize this nonrandomness and the stochastic properties of the game to search for alternative choice hypotheses that can better explain our data.

Modifying preferences in ways suggested by so-called non-EU theories does *not* help. The properties of our game are such that these models[4] make the same predictions as

[1] See, e.g., Camerer (1995) and Starmer (2000) for reviews of the descriptive limitations of expected utility theory.

[2] See Levitt and List (2006) for a comprehensive discussion of the generalizability of experimental results to the real world.

[3] We define "stake" as the difference in payoff between a winning and a losing bet. Average pretax wage income per person over 17 years was NOK188,300 in 2004. Lottery prizes are exempt from taxes.

[4] Our discussion on non-EU theories includes, but is not confined to, rank-dependent theory (Quiggin, 1982), regret theory (Loomes and Sugden, 1982), and cumulative prospect theory (Tversky and

EU of players' choices. We then investigate whether contestants are prone to some of the judgment biases discussed in the psychology literature (Kahneman *et al.*, 1982). We empirically test Rabin's (2002) "quasi-Bayesian" model of the "gambler's fallacy" but find that it adds no explanatory power to the standard predictions. It does seem, however, that many contestants have a systematic expectation bias that can be related to Tversky and Kahneman's (1973) "availability heuristic".

The expectation bias can only explain some of the anomalies in our choice data. As a final avenue of exploration, we discuss and test stochastic choice models. We find that the so-called Fechner model (Fechner, 1860/1966; Becker *et al.*, 1963) in *combination* with a systematic expectation bias gives a good account of our data. Hence, we need to incorporate both biased judgments and stochastic elements in choice to explain why people make nonoptimal choices in our simple game with large stakes.

Several authors have recently utilized television game shows to observe real decisions involving high stakes. List (2006) uses data from *Friend or Foe?* to explore strategic behavior in a natural prisoner's dilemma game. Similarly, Metrick (1995) uses data from *Jeopardy!* to analyze players' abilities to choose best strategic responses. Levitt (2004) tests theories of discrimination using evidence from *Weakest Link*. Berk *et al.* (1996) study contestants from *The Price is Right* to investigate bidding behavior in auctions. Related to our natural experiment, Gertner (1993), Beetsma and Schotman (2001) and Post *et al.* (2006) examine risky choices using data from *Card Sharks*, *Lingo* and *Deal or No Deal?*, respectively. All three papers suggest that the basic EU framework is inadequate to explain their data, but their main focus is still on estimating risk preferences within the standard framework. Our rejection of the EU predictions can in any case be viewed as an even stronger result, as neither *Card Sharks*, *Lingo* or *Deal or No Deal?* entails first-order stochastically dominant strategies. *Joker* is much simpler than the other three games. Finally, our paper differs from the others in that we test whether alternative theories of risky choice can better explain our data.

Although television shows provide an opportunity to study high-stakes decision making, it is important to bear in mind the caveats set out by List (2006). First, in common with controlled experiments, contestants in game shows are usually a selected group of individuals who may differ in important ways from the general population. This is much less of a problem in our case because, as mentioned above, contestants in the *Joker* bonus round are drawn randomly from several hundred thousand lottery participants. Second, television shows usually entail participants making their decisions in a TV studio in front of a large audience, which may itself bias the decisions in certain directions. Our contestants only appear on the show by phone, and there is no studio audience in *Joker*. Furthermore, we believe that, if anything, such "show effects" should lead to a bias towards acting in a manner consistent with the standard rational model. We find it very unlikely that contestants could improve on their future well-being by making nonrational choices. In this sense, our natural experiment offers a conservative test of the EU model and other models that share the EU predictions in our game.

The remainder of the paper is organized as follows. In the next section, we describe

Kahneman, 1992).

the game and our data. The predictions of the standard EU model are discussed in Section 3, and we contrast these predictions with the data. Section 4 explores systematic patterns among choices that deviate from the standard model. In Section 5, we examine the various alternative choice hypotheses against our data. We discuss our results and put forward some conclusions in Section 6.

2 *Joker*

In this section, we first explain how the bonus round of *Joker* is played and the underlying statistical properties of the game. Next, we discuss the information that is provided to the contestants and the possibilities for learning in the game. Finally, we provide a description of our data. Note that we provide an economic model of the game in Section 3.

2.1 Rules and statistical properties

The first prize winner on *Joker* is drawn from a pool of participants who have registered a game card number at "Norsk Tipping" (NT). One registration for one draw costs NOK20, but participants can pay for as many registrations as they like. Draws are conducted twice per week, on Wednesdays and Saturdays. In 2005, the average number of participants was about 400,000 (200,000) on Saturdays (Wednesdays), and the average bet was around NOK25 (1.25 registrations). According to a survey by NT, slightly more than one million Norwegians over the age of 15 had played *Joker* at least once in the last quarter of 2005. We remind the reader that Norway has a population of about 4.6 million. In case the first prize winner cannot be contacted by phone on the day of the bonus round, a computer plays the game on behalf of the contestant (more on games played by the computer below). Around 28 percent of the games in our sample were played by a computer.

The winner of the first prize is given a minimum amount that he or she cannot lose and then proceeds to a bonus round where the prize amount can increase in up to five discrete steps. In the bonus round, the players are presented with a row of five *open* discrete numbers between 0 and 9. The contestants' task is to guess, sequentially, whether numbers that are *hidden* to them are larger or smaller than the open number. If they guess larger, they choose to go "up" relative to the open number, while they choose "down" if they guess smaller. The hidden number is either a discrete number between 0 and 9 or a joker. If the hidden number is a joker, the contestant wins the top prize regardless of her choice, and the game is terminated. If a number is drawn and the contestant's guess was correct (wrong), her prize amount climbs one step up (down) the prize ladder.[5] Hidden number equal to the open number is regarded as a correct guess.[6]

[5] When at the bottom of the prize ladder (the minimum prize), the prize amount is not reduced in case of a wrong guess.

[6] Instead of making the guess, the contestant may choose to quit at any stage of the game, taking the prize amount he/she has won up to that point. In our sample of 356 human players, only one person

The *open* numbers are drawn (with replacement) from a symmetric probability distribution, with the highest probability of drawing a 4 or a 5.[7] On average, contestants thus often have to base their decisions on numbers for which the probability of guessing correctly is the smallest. More importantly, the sequence of *hidden* numbers is drawn from an *i.i.d.*, uniform distribution. Obviously, the probability that a given number or a joker is drawn depends on the number of jokers, and this is based on the following rule: If the top prize of the bonus round is less than NOK1 million the game is played without jokers. For games with a top prize between 1 and 2 million there is one joker among the hidden numbers, while there are two jokers if the top prize is above 2 million.

As mentioned above, some bonus rounds are played by a computer on behalf of the first prize winner. This computer is programmed to follow the expected prize-maximizing strategy of choosing "up" when the open number is less than 5 and "down" otherwise (see Section 3 below for more on payoff-maximizing choices). Note that computer-played bonus rounds are also shown on television, which may be important in allowing human contestants to learn the game.

2.2 Contestants' information

Fifteen to 20 minutes prior to recording the television show, the first prize winner is contacted by NT on the phone, and the basic rules of the game are explained to him or her. In addition, the contestant is presented with the row of five open numbers and the prize ladder for the game. Hence, these features are known prior to the recording of the show. In addition, contestants are informed that the hidden numbers are randomly drawn and may include jokers.[8] We note, however, that contestants are not explicitly informed that draws are *i.i.d.* events (i.e., that hidden numbers are drawn without replacement), or that hidden numbers have a uniform distribution. Moreover, they are not told how many jokers are present in their game, nor about the rules for the number of jokers.

Although these are potential deficiencies in a contestant's information set, the public nature of the game implies that these properties may have been learned over time. Moreover, in bonus rounds played by the computer, the host of the game show usually explains to the viewers that the computer always "chooses the most logical alternative". To the extent that human contestants trust this information, they thus may have observed a player who they know plays a sensible strategy.

utilized this option! Given the stakes involved in the game, this is indeed puzzling from an economist's point of view, as only extreme low risk aversion among contestants can be reconciled with such behavior. Estimation of risk aversion is not the topic of this paper, however, so we do not elaborate on this issue.

[7] The exact distribution from which the open numbers are drawn is $\Pr(5) = \Pr(4) = 0.15$, $\Pr(6) = \Pr(3) = 0.13$, $\Pr(7) = \Pr(2) = 0.1, \Pr(8) = \Pr(1) = 0.07$, and $\Pr(9) = \Pr(0) = 0.05$.

[8] The show is broadcast approximately one hour after it has been recorded. The contestant is not in a studio but participates by telephone. Unlike in many other game shows, there is no studio audience present.

2.3 Data description

Joker has been broadcast every Saturday from May 26, 2000 and every Wednesday from June 5, 2002 on the public Norwegian Broadcasting Corporation (NRK). According to NT's statistics, the TV show had an audience aged 12 and above of more than 800,000 (450,000) on average for Saturdays (Wednesdays) in 2005. We use data up to June 30, 2006, generously provided by the Norwegian Gaming and Foundation Authority and by the producer NT. The first source has protocols for most games and permitted us access to these protocols. The remaining data were obtained by watching videotapes and DVDs from NT. In all, we have information from 528 shows.[9] The number of decisions is much higher, of course, as each first prize winner makes up to five choices.

For each show, we recorded the date, the row of open numbers, the players' choices, the revealed hidden numbers, the prize ladder, the gender of the first prize winner, and whether the game was played by a human or the computer.[10] To give an impression of the stakes involved, Table 1 reports the average potential prizes for each step of the prize ladder. A bet on step 4 of the ladder has on average involved a potential gain of NOK$525,000$ for a correct guess, and a loss of 431,000 for an incorrect guess.

Table 1 here

In what follows, we will mainly analyze decisions made by the human contestants, and hence we divide our sample into games played by humans and those played by the computer. Unfortunately, we lack this information for 33 of the shows, leaving us with a sample of 495 shows for which we have information on all variables. Of these 495 bonus rounds, 139 (28 percent) were played by the computer and 356 by humans.

In Table 2, we report some summary statistics for the two subsamples. We notice that human contestants on average have won higher prize amounts than the computer, while the computer has climbed further up the prize ladder. These observations are reconciled by the fact that potential prizes have been somewhat smaller in the computer-played rounds.[11]

Table 2 here

3 A benchmark model

3.1 A model of *Joker*

Although the rules of the game were described above, it is helpful for the analyses that follow to recast the game by means of a formal model.

[9] This is all the shows broadcast over this period, except four: Saturday draws # 1, 2 and 20 and Wednesday draw # 162.

[10] In addition, we collected data on players' county of residence. We did not utilize this information.

[11] Recall that a computer plays when the first prize winner is unavailable on the phone, which happens most frequently during the summer holiday season. Because lottery participation and hence prizes are lower in this season, this largely explains the lower potential prizes under computer play.

Let $k = 1, 2, ..$ be an index for the sequence of bonus rounds in *Joker*. The decision maker in round k faces the same decision problem repeatedly, and we index the repetitions by $t = 1, .., 5$. At the start of each repetition, the decision maker can observe the state variable θ_t^k, which is drawn from a symmetrically distributed set $\Theta \equiv \{0, .., 9\}$. Upon observing θ_t^k, the decision maker makes the guess $y_t^k \in \{0, 1\}$, where $0 =$ is "down" and is $1 =$ "up".

The computer then makes a draw $d_t^k \in \{0, .., 9, J\}$, where J denotes a joker. The distribution of d_t^k is *i.i.d.* and uniform, but the probability that a given number or a joker is drawn depends on the number of jokers $m \in \{0, 1, 2\}$ in round k. We assume that the decision maker is generally unaware of the number of jokers in her game. The draw d_t^k generates one of four possible observable states of the world (referred to as "signals" below)[12] $s_t^k \in \{N, P, E, J\}$, where:

$$s_t^k = \begin{cases} N \text{ if } d_t^k < \theta_t^k \\ P \text{ if } d_t^k > \theta_t^k \\ E \text{ if } d_t^k = \theta_t^k \\ J \text{ if } d_t^k = J \end{cases} .$$

The contestants can thus observe a sequence of signals whose probability distribution depends on the underlying state but where the shock to the process d_t^k is *i.i.d.* Note that the probability of signal J or E is independent of the state variable θ_t^k, with $\Pr(J) = \frac{m}{10+m}$ and $\Pr(E) = \frac{1}{10+m}$. The probabilities of N and P are state dependent, however, and we have $\Pr(N|\theta_t^k) = \frac{\theta_t^k}{10+m}$ and $\Pr(P|\theta_t^k) = \frac{9-\theta_t^k}{10+m}$, respectively.

The payoff to the decision maker depends on her guess and the realized signal. Denote by $\pi(y_t^k, s_t^k)$ the payoff at trial t in round k when y_t^k is chosen and s_t^k is realized. The rules of *Joker* are such that at any trial t in any round k, payoffs can be ordered as follows:

$$\begin{aligned} \pi(0, P) &= \pi(1, N) < \\ \pi(0, N) &= \pi(1, P) = \\ \pi(0, E) &= \pi(1, E) \leq \\ \pi(0, J) &= \pi(1, J) \end{aligned} \tag{1}$$

Note that at most three different payoffs can materialize at any repetition. Note also the symmetry properties: the payoff is independent of choice if J or E is realized and is equal for correct or wrong guesses of N or P. The decision maker knows the payoff functions and their properties.

3.2 Choice: a benchmark

Let us assume initially that the contestant understands the structure of her decision problem (in particular, the *i.i.d* and symmetry properties of the underlying distribu-

[12] We use signal to avoid confusion between the "state variable" and the "state of the world". Moreover, past realized states of the world can serve as signals in the agent's decision problem, as we will discuss below.

tions). This would be the case if she either correctly interprets the information provided to her by NT or if she has understood ("learned") the game by watching earlier bonus rounds.

The natural benchmark for economists is to assume that players choose strategies to maximize expected (risk-adjusted) payoffs; i.e., that they act according to EU theory. A contestant facing the state variable θ_t^k would then choose $y_t^k = 0$, if:

$$\sum\nolimits_{s_t^k} \Pr(s_t^k|\theta_t^k)u(\pi(0, s_t^k) + W) > \sum\nolimits_{s_t^k} \Pr(s_t^k|\theta_t^k)u(\pi(1, s_t^k) + W),$$

and $y_t^k = 1$ otherwise. Here, $u(\cdot)$ is a utility function and W is the contestant's initial wealth. Given the properties of the payoff functions explained above, the choice criterion simplifies to:

$$[\Pr(N|\theta_t^k) - \Pr(P|\theta_t^k)]\,[u(\pi(0, N) + W) - u(\pi(1, N) + W)] > 0.$$

If we assume that $u'(\cdot) > 0$, the term in the last square brackets is positive. Hence, choice is determined by the sign of the first brackets. Now, because $\Pr(N|\theta_t^k) > \Pr(P|\theta_t^k)$ if and only if $\theta_t^k > 4.5$, the EU model predicts $y_t^k = 0$ if $\theta_t^k \in \{5, .., 9\}$ and $y_t^k = 1$ otherwise.

Note that this prediction requires only the assumption that there is a positive marginal utility of wealth. We do not even need to assume risk aversion. Choosing "down" ("up") is a *first-order stochastically dominating strategy* when $\theta_t^k \in (\notin)\{5, .., 9\}$.

3.3 The benchmark and the data

Given the weak conditions required for the simple decision rule in the benchmark model, the first question to be asked is whether deviations from this rule occur at all. The numbers reported in Table 3 show that significant deviations do indeed occur. First, as we can see from the second column, 32.6 percent of all human contestants make at least one dominated choice. Note that this includes contestants who drew a joker in repetition $t = 1, .., 4$, and thus made fewer than five choices. In the third column of Table 3, we report results for those contestants who made five choices. In this sample, 38.6 percent violated stochastic dominance at least once. Second, deviations from the benchmark are also highly significant if we examine individual choices. Around 11 percent of all choices violated stochastic dominance in our sample, a proportion that is clearly statistically significant.[13] This can also be illustrated by the fact that 57.2 percent (standard error 1.3 percent) of all choices were "up" in the full sample. By comparison, the EU model predicts a proportion of 51.0 percent making "up" choices in the same sample. These proportions are significantly different at all levels of interest. Table 3 shows that the same conclusion holds in the sample where all contestants make five choices.[14]

Table 3 here

[13] Note that Table 3 excludes choices based on $\theta_t^k = 0$ or 9. These open numbers really do not give the contestant any choice at all, because it is impossible to draw a hidden number lower than 0 or larger than 9. As a consequence, the host of the TV show often makes the "choice" for the contestant by telling him or her to go "up" or "down" when they face $\theta_t^k = 0$ or 9, respectively.

[14] Too many "up" choices indicates that deviations from rationality are systematically related to the state variable θ. We explore this relation in Section 4.1 below.

Do these deviations matter? In Table 4, we report the average prizes obtained for contestants who deviate from the rational benchmark. We also calculate what prizes these players would have realized *if* they had followed the EU model. Participants who do not draw a joker (third column) lose an average of NOK102, 000 by deviating from the rational benchmark. (The loss is somewhat lower when we include those who do draw a joker, because these contestants end up with the top prize regardless of choice.) The aggregate net loss of the players who violate stochastic dominance is more than NOK10.4 million.

Table 4 here

4 Patterns in dominated choices

The benchmark model does not square well with our data. There are frequent violations of stochastic dominance, and these violations are costly. Our next step is to explore if these "errors" are purely random or if they are systematically related to the state variables θ_t^k, the repetitions t, the sequence of bonus rounds k, stakes (prizes), or the gender of the contestants.

4.1 State variables, repetitions, and errors

In Table 5, we report the distribution of choices and deviations from the benchmark model conditional on the state variable θ_t^k. There are three noteworthy features of this distribution. First, there are generally more violations of stochastic dominance when dominance is less obvious, i.e., when the probability of guessing correctly is smaller. Whereas very few violate dominance at the tails of the state variable distribution, there is a significant proportion of dominated choices at the center. Second, the distribution of "errors" is centered around $\theta_t^k = 5$, rather than around the mean of 4.5. As many as 38 percent of choices conditional on $\theta_t^k = 5$ deviate from the rational choice of picking "up". Indeed, 55 percent of all errors in our sample are made when the open number is 5. Third, the distribution of errors is fairly symmetrical around 5. An implication of the last two observations is that there are substantially more dominated choices in the upper half of the state variable distribution ($\theta_t^k \in \{5, .., 9\}$), than in the lower half. Close to 80 percent of errors occur in the upper half. This explains the finding of too many "up" choices reported in Table 3 above.

Table 5 here

We next check if the propensity to make a dominated choice is related to the order of decision. In Table 6, we report the distribution of errors conditional on the repetition t. The table does not reveal any clear pattern in violations of dominance across repetitions. The error fractions appear somewhat higher at $t = 4$ and 5, but as shown in the lower row, statistically we cannot reject that the propensity to violate dominance is equal at all ts.

Table 6 here

4.2 Do stakes, learning or gender matter?

It has been claimed that the observed failures of rational choice models are attributable to costs of cognitive efforts and will thus disappear with proper incentives (e.g., Smith, 1985). Compared with the typical possibilities for gains and losses in controlled choice experiments, all bonus rounds in our data involve extremely high stakes, so the proper incentives should be present. Moreover, the simplicity of the game suggests that the costs of thinking should be moderate. Yet, as we have seen, there is a significant number of expensive deviations from the rational benchmark model. Our data allow us to push the role of stakes further. There is substantial variation in prizes among our bonus rounds. We measure the stake in a given bet as the difference between the prizes in the cases of correct and wrong guesses. In our sample with human contestants, the average size of this stake is just over NOK$289,000$. The standard deviation is $300,000$, while the minimum and maximum stakes are $26,000$ and $2,778,000$, respectively. This variation allows us to test if stakes matter for the probability of choosing rationally within our sample.

As we mentioned in Section 2.2, the public nature of the television show gives contestants the opportunity to learn how to make sensible choices. In particular, the fact that a rationally programmed computer plays a substantial fraction of the games should allow later human players simply to replicate the computer's choices. To check whether this type of learning takes place, we simply test whether the propensity to make irrational choices depends on the sequence k. Learning or replication would imply that the propensity to deviate from the benchmark model decreases as the history of the game show unfolds.

Certain laboratory experiments have found that female participants have a significantly higher propensity to deviate from the rational choice model than do male participants (see, e.g., Gal and Baron, 1996; West and Stanovich, 2003). Women comprise 48.7 percent of human bonus round players in our sample. We test if there are significant differences in deviation from rationality across genders in our natural experiment.

Table 7 here

In Table 7, we report probit estimates for the relationship between the probability of deviating from the benchmark model and stakes, the sequence k, and the gender of the contestant. In addition, the last column includes the state variables θ_t^k as control variables, but their inclusion has only minor effects on the estimates of the other coefficients. First, we see that the probability of picking the dominated option is unaffected by the stakes involved in the bet. Thus, despite a much larger variation in payoffs than previously examined, the adherence to rational choice seems to be unaffected by changes in stakes. Second, the gender variable is insignificant, so choices do not seem to differ between men and women. Third, the coefficient for the index for bonus round is highly significant. There are thus fewer errors over time in our sample, which could plausibly be because of learning. Note, however, that the magnitude of this effect is small. The estimated marginal effects from the probit model tells us that by adding an additional bonus round, the probability of making a nonoptimal choice decreases by 0.02 percentage points.

4.3 Choice reversal

One of the striking findings in controlled choice experiments is the phenomenon of "choice reversal". When confronted with exactly the same choice problem separated by a short time interval, the proportion who choose differently in the two cases has "often found to be of the order of 20 to 30 percent" (Loomes *et al.*, 2002). Our data permit us to investigate the degree of reversal under stochastic dominance and high stakes.

We consider contestants who have chosen at least twice based on the same state variable. We classify behavior into three categories: dominant, if choice obeys dominance in all identical situations; violation, if choice goes against dominance in all identical situations; and reversal, if the contestant switches alternatives at least once under identical circumstances. Table 8 reports the numbers and frequencies of the three categories.

Table 8 here

There are several noteworthy regularities in Table 8. First, the overall "error" proportion as evaluated against the benchmark model is higher than in the full sample (lower two rows); 14.8 percent of choices violate dominance in this sample. Second, the vast majority of dominated choices occur in conjunction with choice reversal. Only at the state variable $\theta_t^k = 5$ is there a significant proportion who consequently choose the dominated alternative. Third, when facing the state variable $\theta = 5$ more than once, there is a *minority* of contestants who obey dominance. Fourth, the overall reversal rate is 18.5 percent, but it varies considerably between θs. Except at the tails of the state variable distribution, where violations are rare anyhow, the rate is in line with reversal rates in controlled experiments. Note, however, that earlier experiments rarely operated with a stochastically dominating option. An exception is Loomes *et al.* (2002). Based on their Tables 2a and 2b (rows 41–45 and 86–90), we can compute a reversal rate of 2.6 percent in their dominance problems. In light of this and the high stakes involved, our rates of reversal stand out as high.

4.4 Summarizing the data

The findings above can be summarized as follows.

1. Contestants frequently violate first-order stochastic dominance in risky choices.
2. These violations are costly in terms of forgone prizes.
3. Stakes have no effect on the probability of following the prize-maximizing strategy.
4. The fraction of violations shows a significant but slow decline over time.
5. The propensity to choose dominated options is systematically related to the state variable θ.

6. The reversal rate of contestants' choices when facing two or more identical gambles is around 20 percent.

7. There is no obvious pattern in violations across repetitions for individual players.

The natural question that emerges from these findings is whether the observed choices can be reconciled with other plausible behavioral hypotheses.

5 Alternative choice hypotheses

We are obviously not the first to find that real-world decisions under risk deviate from the EU model, although high stakes and first-order stochastically dominating options perhaps make our results particularly noteworthy. As discussed in the Introduction, there is a large experimental literature in psychology and economics that demonstrates deviations from EU theory, and part of this literature proposes alternative hypotheses of choice under risk. In behavioral economics, deviations from EU predictions are ascribed to biases in people's probability judgments and/or to other preferences than the EU framework. A related but conceptually somewhat different approach is stochastic choice models, in which random "errors" are built into the process of choice. All three approaches may potentially better explain our data than EU, and so we discuss them in turn.

5.1 Non-EU preferences

Since the late 1970s, there has been an explosion of work on so-called non-EU theories that attempt to do a better job of matching experimental evidence. Indeed, a challenge in searching for alternative models that might better explain our data is that so many alternatives exist.[15] Starmer (2000, p. 332) starts his survey by informing readers that the "so-called non-expected utility models now number well into double figures". The number has risen further since the publication of Starmer's survey.

That said, the findings above and the statistical properties of *Joker* give clues to which models can potentially account for our data. Most importantly, the models must allow violation of stochastic dominance, as the frequent dominance violations are the most puzzling feature in our data. This permits us to exclude all models that Starmer (2000, Section 4.1) labels *conventional* non-EU theories; these are models that build on preferences that respect stochastic dominance. They include, but are not confined to, implicit EU (Chew, 1989), disappointment aversion (Gul, 1991), and rank-dependent expected utility theory (Quiggin, 1982). An important nonconventional contribution that can be excluded on the same basis is similarity-based theory (Rubinstein, 1988).

We now proceed to discuss two well-known non-EU models that in principle do allow for violations of stochastic dominance.

[15] In a recent discussion of behavioral economics, Fudenberg (2006) labels this phenomenon "choice overload in modeling choice".

5.1.1 Regret theory

One model that can potentially account for the choice of stochastically dominated options is regret theory (Loomes and Sugden, 1982). Consider a contestant facing the state variable $\theta_t^k = 5$. He/she would potentially experience "regret" if he/she chose "down", as the benchmark model predicts, and a signal $s_t^k = P$ is drawn. Rationally anticipating this possible regret, the contestant might prefer to go "up" instead. As we next show, however, the symmetrical properties of the payoffs in *Joker* rule out the possibility that regret theory can explain the violations of dominance observed in our data.

According to regret theory, a contestant facing the state variable θ_t^k would select $y_t = 0$ if:

$$\sum\nolimits_{s_t^k} \Pr(s_t^k|\theta_t^k)\psi[\pi(0, s_t^k), \pi(1, s_t^k)] > 0,$$

and $y_t = 1$ if this expression is negative. The function $\psi(\cdot,\cdot)$ is the regret/rejoice function, which, among other properties, is assumed to be skew symmetric. This means that $\psi(a, b) = -\psi(b, a)$ and $\psi(a, a) = 0$, for all a, b. Using the properties of the payoff functions in (1), the restriction above simplifies to:

$$\psi[\pi(0, N), \pi(1, N)] \left(\Pr(N|\theta_t^k) - \Pr(P|\theta_t^k)\right) > 0.$$

The regret/rejoice function is defined as:

$$\psi[\pi(0, N), \pi(1, N)] \equiv M[\pi(0, N), \pi(1, N)] - M[\pi(1, N), \pi(0, N)],$$

where $M(\cdot,\cdot)$ is increasing in its first argument and decreasing in its second. Because $\pi(0, N) > \pi(1, N)$, we thus have that $\psi[\pi(0, N), \pi(1, N)] > 0$. Hence, the lower inequality above holds for $\theta_t^k \in \{5, .., 9\}$. Although regret theory in principle allows for violations of stochastic dominance, it does *not* account for the deviations of the EU model that we observe in *Joker*.

5.1.2 Prospect theory

Of all non-EU models of choice under risk, Kahneman and Tversky's (1979) prospect theory is clearly the most widely discussed. In its original form, prospect theory models choice as a two-phase process. In the first phase, available options ("prospects") are possibly "edited" by one or more decision heuristics. We will return to possible decision biases due to editing below, but for now we assume that the contestant correctly evaluates the options available to her in *Joker*.

In the second phase of the decision process, choice is determined by a preference function that is quite different from EU preferences. The generalized version of this preference function (to handle gambles with more than two outcomes; Tversky and Kahneman, 1992), can be applied to *Joker* as follows. A contestant facing the state variable θ_t^k would choose $y_t^k = 0$ if:

$$\sum\nolimits_{s_t^k} \Pi[\Pr(s_t^k|\theta_t^k)]v[\pi(0, s_t^k) - \pi^*] > \sum\nolimits_{s_t^k} \Pi[\Pr(s_t^k|\theta_t^k)]v[\pi(1, s_t^k) - \pi^*], \qquad (2)$$

and $y_t^k = 1$ otherwise. In (2), $v[\cdot]$ is the "value function", which unlike an utility function, is defined over gains and losses relative to a reference point rather than over total wealth. In our setting, the reference point π^* is most naturally interpreted as the prize that the contestant has achieved up to repetition t. Note that, among other properties, $v[\cdot]$ is assumed to be strictly increasing. The function $\Pi[\cdot]$ is a transformation function from probabilities to decision weights. Again, various assumptions on the shape of $\Pi[\cdot]$ are imposed in the literature. For us, it is sufficient to note that the function is assumed to be strictly increasing.

The structure of the payoffs in *Joker* allows us to simplify considerably the choice rule in (2). Given the properties of (1), prospect theory predicts that contestant k will choose $y_t^k = 0$ at repetition t if:

$$\{\Pi[\Pr(N|\theta_t^k)] - \Pi[\Pr(P|\theta_t^k)]\} \{v [\pi(0,N) - \pi^*] - v [\pi(1,N) - \pi^*]\} > 0.$$

The term in the last braces is positive because $v[\cdot]$ is an increasing function. The first term is positive if $\theta_t^k \in \{5,..,9\}$ and negative otherwise. Hence, this version of prospect theory (i.e., without biases in the editing phase) gives the same predictions of choice as does the EU theory in our natural experiment and does not add explanatory power for our data.

Simply modifying preferences (or decision weights) in manners suggested by central non-EU models does not help in matching our evidence; they give the same predictions as EU in our game. We emphasize, however, with particular reference to prospect theory, that we have not allowed possible psychological biases to play a role so far. It is to such biases that we now turn our attention.

5.2 Biases in judgment

Psychologists have identified a number of biases that lead people to make errors in judgment under uncertainty. (See, e.g., the book-length overview in Kahneman *et al.*, 1982, or the surveys by Camerer, 1995 and Rabin, 1998). A broad discussion of all these possible biases is beyond the scope and beside the point in our context. Rather, we explore at some length two biases that we view as potentially relevant in matching our data.

5.2.1 The gambler's fallacy

One of the essential characteristics of the decisions in *Joker* is that they involve a few repeated choices. As we explained in Section 2.2, bonus round contestants are not *explicitly* informed that draws of d_t^k are independent. Moreover, even if they do understand that draws are independent, experiments in psychology and economics indicate that people exaggerate how likely it is that a small sample resembles the overall population from which it is drawn (see Rabin, 2002 for a review of the evidence). Tversky and Kahneman (1971) labeled this phenomenon the "belief in the law of small numbers". Rabin (2002) and Rabin and Vayanos (2005) model this belief by postulating that agents treat *i.i.d.* draws as draws without replacement, while updating as Bayesians in other respects.

Such agents are subject to the "gambler's fallacy", thinking that early draws of one signal increase the probability of next drawing other signals.

We consider two alternatives for modeling the gambler's fallacy in *Joker*. First, we assume that some contestants think that draws of d_t^k are not independent but rather are drawn from an urn without replacement. Second, we allow contestants to believe falsely that if $s_t^k = P$, it increases the probability that $s_{t+1}^k = N$ for a given state variable θ_{t+1}^k.[16] These approaches are clearly related, but as we will see, they have somewhat different empirical predictions.

Let us start with the former approach. We assume that a contestant does understand that his/her bonus round k *starts* with a full urn of hidden numbers but that numbers may not be replaced within his/her round. Following Rabin and Vayanos (2005), agents subject to the gambler's fallacy mistakenly believe that the repetitions $\{d_t^k\}_{t=1,..,5}$ are not *i.i.d.*, but follow the process:

$$\begin{aligned} d_t^k &= \widetilde{d}_t^k - \alpha \sum_{h=0}^{t-2} \delta^h d_{t-1-h}^k, \quad t = 2,..,5, \\ d_1^k &= \widetilde{d}_1^k. \end{aligned}$$

The sequence $\{\widetilde{d}_t^k\}_{t=1,..,5}$ is treated as *i.i.d.* by the contestants, but we allow for a biased expectation of this shock. Hence, players may enter the bonus round with the wrong prior on the expected value of hidden numbers, in addition to the wrong model for updating expectations. The parameter $\alpha \in [0,1)$ characterizes the strength of the belief in the gambler's fallacy. When $\alpha = 0$, the player correctly treats the sequence of hidden numbers as *i.i.d.* They may still deviate from the benchmark model if $E[\widetilde{d}_t^k] \neq 4.5$, however. The parameter $\delta \in [0,1)$ characterizes the duration of the gambler's fallacy. If $\delta = 0$, the player believes the hidden number d_t^k ought to counteract only the number from draw $t-1$. When $\delta \to 1$, the player believes that d_t^k will counteract the average of earlier drawings in round k.

Based on these premises, we can modify the benchmark model for player behavior in our game. Contestants who maximize the *perceived* expected prize will follow the decision rule:

$$y_t^k = \begin{cases} 0 \text{ if } E_{t-1}^k[d_t^k] < \theta_t^k \\ 1 \text{ if } E_{t-1}^k[d_t^k] > \theta_t^k, \end{cases},$$

where E_t^k is the contestant's k expectation at repetition t. If the contestant is subject to the gambler's fallacy, we can write this as:

$$\begin{aligned} y_t^k &= 0 \text{ if } E_{t-1}^k[\widetilde{d}_t^k] - \alpha \sum_{h=0}^{t-2} \delta^h E_{t-1}^k[d_{t-1-h}^k] < \theta_t^k, \quad t = 2,..,5, \\ y_1^k &= 0 \text{ if } E_0^k[\widetilde{d}_1^k] < \theta_1^k. \end{aligned}$$

[16] We thus assume that a signal $s_t^k = E$ does not affect contestants' probability assessment of s_{t+1}^k. Recall that the game is terminated if $s_t^k = J$ is realized, so this signal is irrelevant in terms of (non-Bayesian) updating.

With $\alpha = 0$ and a correct prior, we are back at the benchmark model. Because players treat the shock $\widetilde{d}$ as *i.i.d.* and past realizations of d are fully observable, the model yields the following testable restrictions on decisions for each repetition:

$$
\begin{aligned}
y_1^k &= 0 \text{ if } E^k[\widetilde{d}_1^k] < \theta_1^k \\
y_2^k &= 0 \text{ if } E^k[\widetilde{d}_1^k] - \alpha d_1^k < \theta_2^k \\
y_3^k &= 0 \text{ if } E^k[\widetilde{d}_1^k] - \alpha d_2^k - \alpha\delta d_1^k < \theta_3^k \\
y_4^k &= 0 \text{ if } E^k[\widetilde{d}_1^k] - \alpha d_3^k - \alpha\delta d_2^k - \alpha\delta^2 d_1^k < \theta_4^k \\
y_5^k &= 0 \text{ if } E^k[\widetilde{d}_1^k] - \alpha d_4^k - \alpha\delta d_3^k - \alpha\delta^2 d_2^k - \alpha\delta^3 d_1^k < \theta_5^k.
\end{aligned}
$$

The second approach to modeling the gambler's fallacy follows the same procedure but replaces lagged values of d_t^k with lagged values of realized signals s_t^k. If there are systematic effects of either lagged hidden numbers or signals, it could thus be interpreted as support of *Joker* contestants being subject to the gambler's fallacy.

A simple first way to investigate the empirical content of this hypothesis is to examine the distribution of dominated choices across repetitions $t = 1, .., 5$, as we did in Table 6. If the gambler's fallacy is important in explaining our data, we would expect to see variation in the propensity to choose nonoptimally across repetitions. However, as mentioned above, we cannot reject the hypothesis that "error" proportions are equal across ts; see the lower row of Table 6. Moreover, we see that violation of dominance is of the same order at $t = 1$, as for the later repetitions. Thus, we can clearly reject the hypothesis that contestants make their choices at $t = 1$, based on maximization with unbiased expectations.

We now proceed to explore in more detail the implications of the gambler's fallacy for repetitions $t = 2, .., 5$. If there is any empirical backing for the first model above, choices made at repetitions $t = 2, .., 5$ should be systematically related to the history of hidden numbers or signals for that round. In Table 9, we present the results from estimating a probit model with y_t^k as the dependent variable and the rational choice plus the sequence $\{d_{t-h}^k\}_{h=1,..,t-1}$ as explanatory variables, for $t = 2, ..5$. Only one of 10 estimated coefficients on lagged ds is statistically significant. Moreover, the χ^2-test of no effect on lagged hidden numbers cannot be rejected at any of the repetitions.

Table 9 here

In Table 10, we report results from similar estimations with the history of realized signals as explanatory variables. None of the estimated coefficients on lagged signals is even close to being significant. There is thus no evidence to support the gambler's fallacy story in our data.

Table 10 here

5.2.2 A focal point bias: Is 5 a "special number"?

One way to describe the contestants' task in *Joker* is that they should find the midpoint between 0 and 9. Once they realize that the midpoint is 4.5, the task of estimating whether the probability of drawing $d_t^k > \theta_t^k$ is larger than drawing $d_t^k < \theta_t^k$ should be manageable. However, the spike of errors at $\theta_t^k = 5$ reported in Table 5 indicates that many participants fail to calculate the midpoint correctly. Indeed, if *all* contestants erroneously believed that 5 is the midpoint, we should have observed a deviation rate of 50 percent at $\theta_t^k = 5$. Although the actual error rate of 38 percent (reported in Table 5) is significantly different from 50, it is certainly closer to to this rate than to the predicted rate of zero. Moreover, the large difference in error rates between $\theta_t^k = 4$ and 5 also indicates that something awkward is happening at 5. When facing a 4 or a 5, players are essentially facing identical choices between gambles, yet the error propensity is more than four times as high at $\theta_t^k = 5$.

One way to interpret this finding is that many contestants are subject to a "focal point bias". The digit 5 may stand out as the number that most easily comes to mind when one is estimating the midpoint between 0 and 9. Epstein (2006, p.360) claims that "the evidence that many individuals are misled by focal points in the simplest of calculations is conclusive", but he provides no references for this evidence. A focal point bias may be related to Tversky and Kahneman's (1973) "availability heuristic" whereby people disproportionately weight *salient* instances or associations in judgment, even if they have better sources of information.

In any case, we believe that some choice errors in our data are due to biased expectations among some of the contestants, falsely believing that $E[d_t^k] = 5$. If we impose this biased expectation on the standard model, it predicts a fraction of 58.8 percent of "up" choices in our sample of human contestants. This share is *not* significantly different from the actual "up" fraction 57.2 percent reported in Table 3.

In this sense, taking into account the focal point bias improves the overall match between the benchmark and our data. However, our focal point bias hypothesis can only explain the 55 percent of errors that occurs at $\theta_t^k = 5$. It does not explain the remaining 45 percent of deviations from the benchmark, nor does it explain the high rates of reversal in choice at other state variables than 5 (see Table 8). Hence, we now discuss models that can potentially account for these regularities.

5.3 Stochastic choice

Some decision theorists have traditionally studied choice behavior as a stochastic rather than as a deterministic phenomenon (e.g., Bush and Mosteller, 1955). Recently there has been a revival of interest among economists in modeling the stochastic element in decision making (see, e.g., Loomes *et al.*, 2002). Given the extensive violations of dominance and reversal in choice documented in Section 4.3, it is conceivable that stochastic choice models can add explanatory power to our data.

Three alternative approaches to the modeling of stochastic choice have been discussed in the recent literature. Harless and Camerer (1994) assume that any decision reveals true preferences (as defined by a deterministic theory) with probability $1-e$, but (because of, e.g., a lapse of concentration) there is some constant probability e that the individual chooses at random. This "constant error" model has been rejected in recent tests of stochastic choice models (Ballinger and Wilcox, 1997; Carbone, 1998). Moreover, the systematic pattern of dominance violations across state variables θ_t^k documented in Table 5 indicates that decision errors in our data are not due mainly to "trembles". Hence we do not follow this approach further.

A second approach to stochastic choice is the "random preference" model by Loomes and Sugden (1995). It assumes that there is a set of alternative preference relations for each decision maker and that he/she chooses based on one of these relations selected at random. A problem with this approach for our data is that choice is *not* stochastic in problems involving stochastic dominance; it predicts that the dominating option is chosen with probability one. The extensive violations of dominance in our data thus suggest that random preferences are not what is behind the results.

This leaves us with the third alternative of stochastic choice models, the "Fechner model" (Fechner 1860/1966; see also Becker *et al.*, 1963 and Hey and Orme, 1994). Following Hey and Orme, this model assumes that a contestant facing θ_t^k will choose $y_t^k = 1$ if:

$$V(1|\theta_t^k) - V(0|\theta_t^k) + \varepsilon_t^k > 0,$$

where $V(.|\theta_t^k)$ maps choices into values so that its specific form corresponds to a given deterministic theory. The error term ε is a continuous random variable, symmetrically distributed around zero. In general, the contestant may deviate from the predictions of the deterministic theory with a large enough draw of ε_t^k with the right sign. In particular, the smaller the difference in values assigned to the two choice options by the deterministic theory, the more likely it is that the predictions of this theory will be overturned by the error term. Hey and Orme (1994) interpret the randomness in this model as a type of *calculation error* by the decision maker.

Regardless of preferred deterministic core theory, the Fechner model can in principle explain several of the data regularities discussed in Section 4. It can accommodate both high rates of dominance violation and a high reversal rate if the variance of ε is sufficiently large.[17] Moreover, it generally implies more violations of dominance when the dominating alternative is less obvious. This is what we observed in Table 5 above. Finally, this model does not predict any particular systematic pattern of errors across repetitions; random calculation errors might as well occur at $t = 1$ as at $t = 5$. Again, this is what we saw in Table 6.

A simple empirical approach to the Fechner model in our game is to formulate the following linear model. Let the latent variable y_t^{k*} represent the perceived gain for contestant k if she chooses $y_t^k = 1$ at repetition t. In the Fechner model:

$$y_t^{k*} = \sum_{i=1}^{8} \alpha_i \theta_{it}^k + \varepsilon_t^k, \tag{3}$$

where $\theta_{it}^k = 1$ if $i = \theta_t^k$ and 0 otherwise, while ε_t^k is a standard normal variable assumed to be uncorrelated with the θ_{it}^ks. The expected gain for a given θ_{it}^k is accordingly $E[y_t^{k*}|\theta_{it}^k =$

[17] Loomes *et al.* (2002) and Loomes (2005) conclude that the Fechner model cannot explain the dataset in Loomes *et al.* because it contains high rates of reversal but low rates of dominance violation. Table 8 shows that these rates are of similar magnitude in our data, providing some support for the Fechner model.

$1] = \alpha_i$, $i = 1, .., 8$. The Fechner model thus implies that the index of the expected gain α_i is positive for $i \in \{1, .., 4\}$ and negative when $i \in \{5, .., 8\}$. Importantly, it also implies the following symmetry restrictions:

$$|\alpha_1| = |\alpha_8|\,,\ |\alpha_2| = |\alpha_7|\,,\ |\alpha_3| = |\alpha_6|\,,\ |\alpha_4| = |\alpha_5|\,. \tag{4}$$

Under the specified assumptions, the parameters can be estimated by a probit model corresponding to equation (6), with choice y_t^k as the dependent variable. The symmetry restrictions can be imposed and tested by means of a Wald test.

Table 11 here

Table 11 reports the estimated α_is for the general model. Wald test **a** gives the $\chi^2(4)$ test statistic for the restrictions in (4), and these are clearly rejected. This is not particularly surprising, given the much larger error fraction at $\theta_t^k = 5$ compared with the other values of state variable. Recall also our discussion above on the possibly biased midpoint estimates by the contestants. If players are prone to this bias, the Fechner model would predict that errors are symmetric around 5 rather than 4.5. Hence, a *combination* of the Fechner model and the focal point bias implies the joint restrictions:

$$|\alpha_2| = |\alpha_8|\,,\ |\alpha_3| = |\alpha_7|\,,\ |\alpha_4| = |\alpha_6|\,. \tag{5}$$

The Wald test **b** in Table 11 shows that we cannot reject these restrictions.

It thus seems that we need to rely on both a simple judgment bias and a stochastic element in choice to give a satisfactory account of our data. Many contestants seem to believe erroneously that 5 is the midpoint in the distribution of hidden numbers, and in addition, many violate dominance and reverse their choices in manners consistent with the Fechner model.

6 Discussion and conclusions

Around one-third of the participants in our natural experiment violate first-order stochastic dominance in large stake choices. Variation in stakes is unrelated to the propensity of violating dominance. When facing identical gambles (at least) twice, contestants choose differently in around 20 percent of the cases. Dominated choices are more likely to occur when dominance is less obvious, but there is a peculiar concentration of errors when the state variable takes the value 5. The fraction of violations of dominance shows a statistically significant but very slow decline over time.

With reference to a famous *Monty Python* sketch, Rabin and Thaler (2001) compare the issue of pointing out further failures of the expected utility model to beating a dead parrot (a “Norwegian Blue”). In their view, EU is an “ex-parrot”, far beyond the point of cure. In one way, our paper simply emphasizes Rabin and Thaler’s point. We have looked at a natural experiment where the amounts at stake are very large and the task is easy, yet even the most basic prediction of EU fails to give a satisfactory account of choice. The behavior of Norwegian lottery players seem to confirm that the Norwegian Blue is indeed dead.

On the other hand, the problem in explaining our choice data is not confined to the EU model. First, and fairly obviously, non-EU theories that respect stochastic dominance are not able to explain our data. Second, the simplicity of the game and symmetry of the payoffs implies that neither regret theory nor prospect theory can account for the frequent violation of stochastic dominance found in the data. Third, judgment bias in terms of "belief in the law of small numbers" framed as the "gambler's fallacy" does not seem to add explanatory power. Fourth, two versions of stochastic choice theories, the "constant error" and the "random preference" models, are also inconsistent with the patterns in our choice data.

In contrast, a third stochastic choice model, the Fechner model, augmented by a deterministic judgment bias in the expected median of our choice problem, matches our data quite well. Thus, the somewhat negative message from our natural experiment is that people seem to make rather crude and erroneous judgments of important parameters, even when the choice problem is simple and it involves large monetary stakes. It is tempting to argue that the extent of such judgment biases may be even more frequent in common economic situations with much more complicated choice problems.

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Table 1: Average potential prizes and stakes at different steps of the prize ladder.

Step, prize ladder	Average potential prize	Increase
0 (prize floor)	375,000	–
1	428,000	103,000
2	676,000	197,000
3	920,000	244,000
4	1,351,000	431,000
5 (top prize)	1,876,000	525,000

Note: Based on all 528 bonus rounds. Amounts in Norwegian kroner.

Table 2: Human- and computer-played rounds.

	Humans	Computer
Bonus rounds	356	139
Choices	1,549	614
Prize, average	1,310,000	1,256,000
Step, average	3.40	3.45

Note: Step, average shows the average final step on the prize ladder.

Table 3: Summary statistics, human contestants.

	Full sample	Sample with 5 repetitions
Bonus rounds	356	264
Players deviating from benchmark	116	102
Proportion (standard error)	32.6% (2.5%)	38.6% (3.0%)
Choices	1,375	1,176
Choices deviating from benchmark	149	133
Proportion (standard error)	10.8% (0.8%)	11.3% (0.9%)
Predicted "up" fraction	51.0%	50.5%
Actual "up" fraction (standard error)	57.2% (1.3%)	56.9% (1.4%)

Note: Full sample refers to all rounds played by human contestants. Sample with 5 repetitions excluding players who drew a joker on $t = 1, .., 4$. Predicted "up" fraction shows share of $y = 1$ choices if all players followed the benchmark model. Actual "up" fraction shows the actual shares of $y = 1$ choices in the two samples.

Table 4: Prizes for contestants who deviate from the benchmark.

	Full sample	Sample with 5 repetitions
Bonus rounds	116	102
Avg. realized prize	1,059,000	922,000
Avg. "optimal" prize	1,149,000	1,024,000
Avg. loss	90,000	102,000
Aggregate loss	10.4 mill.	10.4 mill.

Note: Avg. "optimal" prize shows the average take-home prize that players would have achieved by following the benchmark model.

Table 5: Deviation from benchmark model, human contestants.

θ	1	2	3	4	5	6	7	8	Sum
Choices	121	171	185	222	221	189	137	129	1,375
Deviations	2	2	8	19	84	20	9	5	149
Proportion	1.7%	1.2%	4.3%	8.6%	38.0%	10.6%	6.6%	3.9%	10.8%
Confidence	0.2%	0.1%	1.9%	5.2%	31.6%	6.6%	3.0%	1.3%	9.2%
interval	5.8%	4.2%	8.3%	13.0%	44.8%	15.9%	12.1%	8.8%	12.6%

Note: Choices are decisions based on θ by human contestants. Deviations are the numbers of decisions that do not follow the prediction from the benchmark model. Exact binomial confidence intervals.

Table 6: Deviation from benchmark at repetition t, human contestants.

t	1	2	3	4	5
Choices	315	294	274	259	233
Deviations	31	30	24	33	31
Proportion	9.8%	10.2%	8.8%	12.7%	13.3%
(s.e.)	(1.7%)	(1.8%)	(1.7%)	(2.1%)	(2.2%)
χ^2-test for proportions equal across ts: 4.52 (0.39)					

Note: s.e. is standard error. Number in parenthesis for χ^2-test is p-value.

Table 7: Effects of stakes, sequence and gender. Deviation from benchmark is dependent variable. Probit, marginal effects.

Stakes	0.000027	0.000026
	(0.000027)	(0.000021)
k (sequence #)	-0.000193	-0.000177
	(0.000059)**	(0.000048)**
Gender	-0.003521	-0.001532
	(0.017960)	(0.015158)
Controls for θ_t^k	No	Yes
Choices (obs.)	1371	1371
Pseudo R^2	0.013	0.202

Note: Robust standard errors in parenthesis, corrected for clustering at the level of individual players.
** denotes significance at 1%. Controls are state variables (θ).

Table 8: Decisions with two or more choices at the same state variable.

θ	1	2	3	4	5	6	7	8	Sum
Bonus rounds	17	28	27	44	46	29	17	14	222
Dominating at θ	15	28	22	34	20	23	13	13	169
proportion	88.2%	100%	81.5%	77.3%	43.5%	79.3%	76.5%	92.9%	75.7%
Violation at θ	0	0	0	1	10	1	1	0	13
proportion	-	-	-	2.3%	21.7%	3.4%	5.9%	-	5.9%
Reversal at θ	2	0	5	9	16	5	3	1	41
proportion	11.8%	-	18.5%	20.5%	34.8%	17.2%	17.6%	7.1%	18.5%
Choices at θ	34	58	59	93	95	63	35	29	466
Deviations	2	0	5	11	36	8	6	1	69
proportion	5.9%	-	8.5%	11.8%	37.9%	12.7%	17.1%	3.4%	14.8%

Note: Bonus rounds are those in which a human contestant chooses at the same θ at least twice. Choices at θ are the numbers of decisions at θ in those rounds.

Table 9: Gambler's fallacy I. Choice is dependent variable. Probit.

Repetition	$t = 2$	$t = 3$	$t = 4$	$t = 5$
Optimal choice	3.211	2.873	2.778	2.472
	(0.295)**	(0.214)**	(0.238)**	(0.211)**
d^k_{t-1}	0.008	0.005	0.023	0.024
	(0.033)	(0.036)	(0.038)	(0.036)
d^k_{t-2}		-0.006	-0.078	0.032
		(0.036)	(0.037)*	(0.034)
d^k_{t-3}			-0.014	0.017
			(0.036)	(0.036)
d^k_{t-4}				0.031
				(0.035)
Constant	-0.999	-1.313	-0.585	-1.422
	(0.186)**	(0.278)**	(0.288)**	(0.368)**
Choices	330	315	284	264
Pseudo R^2	0.62	0.61	0.54	0.50
χ^2-test, no effect	0.06	0.04	4.77	2.32
of lagged ds (p-value)	(0.81)	(0.98)	(0.19)	(0.68)

Note: Sample is all 356 rounds with human contestants. Robust standard errors in parentheses, corrected for clustering at the level of individual players. * denotes significance at 5%; ** at 1%.

Table 10: Gambler's fallacy II. Choice is dependent variable. Probit.

Repetition	$t = 2$	$t = 3$	$t = 4$	$t = 5$
Optimal choice	3.217 (0.289)**	2.860 (0.211)**	2.694 (0.235)**	2.562 (0.219)**
s_{t-1}^k	0.124 (0.215)	-0.153 (0.207)	0.010 (0.206)	0.086 (0.208)
s_{t-2}^k		0.008 (0.212)	-0.236 (0.206)	0.244 (0.208)
s_{t-3}^k			0.033 (0.209)	-0.010 (0.207)
s_{t-4}^k				0.393 (0.213)
Constant	-1.032 (0.172)**	-1.227 (0.278)**	-0.767 (0.221)**	-1.392 (0.294)**
Choices	330	315	284	264
Pseudo R^2	0.62	0.61	0.53	0.51
χ^2-test, no effect of lagged ds (p-value)	0.33 (0.56)	0.55 (0.76)	1.31 (0.73)	4.76 (0.31)

Note: Sample is all 356 rounds with human contestants. Robust standard errors in parentheses, corrected for clustering at the level of individual players. * denotes significance at 5%; ** at 1%.

Table 11: The Fechner model. Choice is dependent variable. Probit.

i	1	2	3	4	5	6	7	8
α_i	2.131 (0.278)	2.267 (0.271)	1.714 (0.160)	1.368 (0.123)	-0.305 (0.091)	-1.249 (0.130)	-1.509 (0.194)	-1.766 (0.202)
Wald test **a**: symmetry restrictions, Fechner (p-value): 61.91 (0.000)								
Wald test **b**: symmetry restrictions, biased midpoint (p-value): 3.79 (0.285)								

Note: Sample is all 356 rounds with human contestants. Robust standard errors in parentheses, corrected for clustering at the level of individual players. Wald tests **a** and **b** tests the restrictions given in equations (4) and (5), respectively.