Deal or No Deal?

Decision making under risk in a large-payoff game show

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Abstract

The popular TV game show "Deal or No Deal" offers a unique opportunity for analyzing decision making under risk: it involves very large and wide-ranging stakes, simple stop-go decisions that require minimal skill, knowledge or strategy, and near-certainty about the probability distribution. We examine the choices of 84 contestants from Belgium, Germany and the Netherlands. In contradiction with expected utility theory, choices can be explained in large part by the previous outcomes experienced by the contestants during the game. Most notably and consistent with the "break-even effect", risk aversion decreases strongly after earlier expectations have been shattered by unfavorable outcomes. Our results point in the direction of frame-dependent choice theories such as prospect theory and suggest that phenomena such as framing and path-dependence are relevant, even when large, real monetary amounts are at stake.

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The popular TV game show "Deal or No Deal" offers a unique opportunity for analyzing decision making under risk: it involves very large and wide-ranging stakes, simple stop-go decisions that require minimal skill, knowledge or strategy, and near-certainty about the probability distribution. We examine the choices of 84 contestants from Belgium, Germany and the Netherlands. In contradiction with expected utility theory, choices can be explained in large part by the previous outcomes experienced by the contestants during the game. Most notably and consistent with the "break-even effect", risk aversion decreases strongly after earlier expectations have been shattered by unfavorable outcomes. Our results point in the direction of frame-dependent choice theories such as prospect theory and suggest that phenomena such as framing and path-dependence are relevant, even when large, real monetary amounts are at stake.

I Introduction

THE THEORY OF RISKY CHOICE is one of the cornerstones of economics. Empirical research in this field is often plagued by problems of joint hypotheses and insufficient stimuli for the subjects. In order to circumvent these problems, some researchers analyze the behavior of contestants in TV game shows.

In everyday-life, people face many risky choice problems, often involving large stakes. Examples include choosing pension plans, home buying and selling, mortgage choice and buying insurance. Unfortunately, we generally do not directly observe risk preferences for these problems, because the true probability distribution is not known to the subjects and the subject's beliefs are not known to the researcher.

A large part of the empirical research therefore relies on laboratory experiments or classroom experiments. The main advantage of such experiments relative to real-life data is the possibility to control the probability distribution of the choice alternatives and to ensure that the distribution is known to the subjects. Nevertheless, experiments generally use hypothetical stakes or small real stakes, and subjects may not be sufficiently motivated to act optimally and reveal their true risk preferences. Some empirical studies try to deal with this problem by using small nominal amounts in relatively poor countries, so that the subjects face relatively large amounts in real terms.[1] Still, the stakes in these experiments are typically not larger than a monthly income and we may ask if the results are representative for larger amounts. Unfortunately, research budgets do not allow for using larger amounts in experiments.

Analyzing TV game shows is another approach. Examples of game show studies include the shows "Card Sharks" (Gertner, 1993), "Jeopardy!" (Metrick, 1995), "Illinois Instant Riches" (Hersch and McDougall, 1997), "Lingo" (Beetsma and Schotman, 2001), "Hoosier Millionaire" (Fullenkamp, Tenorio and Battalio, 2003) and "Who Wants to be a Millionaire?" (Hartley, Lanot and Walker, 2005).[2] The key advantage of game shows is that the decision problems are often simpler than real-life problems and the amounts at stake are larger than in experiments. Arguably, the behaviour of game show contestants may not be representative for behaviour outside the studio. Contestants may be influenced by e.g. social pressure from the audience, remarks and directions by the game show host and the unique event of appearing on national TV. Nevertheless, if the decision problems are sufficiently simple and the amounts at stake are sufficiently high, we may expect that the choices reflect the contestants' risk preferences.

Still, analyzing game show data is no panacea. In most game shows, the stakes are still modest. One noteworthy exception is "Hoosier Millionaire", where contestants can win $1,000,000. However, in this show, the stakes exhibit little variation across the different game rounds, making it difficult to estimate the risk attitudes of the contestants for a wide range of outcomes. Besides this, the $1,000,000 prize is paid out as a long-term annuity and therefore the present value is much smaller. Furthermore, many game shows involve skill (for example, guessing words in "Lingo"), knowledge (for instance, answering quiz questions in "Who Wants to be a Millionaire?", another high-stakes show), or strategy (for example, to beat opponents in "Jeopardy!"). This makes it difficult for contestants to assess the appropriate probability distribution and introduces a layer of uncertainty in addition to the risk of the game. The same is true for game option elements such as the "lifelines" in "Who Wants to be a Millionaire?", which are difficult to value.

In this study, we will analyze the decisions made in the main game of the international blockbuster show "Deal or No Deal". This show was developed by the Dutch production company Endemol and was first aired (in its current format) in the

Netherlands in December 2002. The game show soon became very popular and was exported to many other countries around the world.

For analyzing risky choice, “Deal or No Deal” has a number of favorable design features. The stakes are very high and wide-ranging: with a maximum prize of €5,000,000, a minimum of one cent and an average of roughly €400,000 (in the Netherlands), the game show can send contestants home as multimillionaires - or practically empty-handed. Unlike other game shows, “Deal or No Deal” involves only simple stop-go decisions that require minimal skill, knowledge or strategy. Also, the probability distribution is simple and known with near-certainty. Because of these features, the show seems well-suited for analyzing real-life decisions involving real and large risky stakes.

“Deal or No Deal” involves multiple game rounds, in each of which contestants must choose between a certain and an uncertain alternative. For this reason, the show seems particularly well-suited for analyzing path-dependence or the role of earlier outcomes. Thaler and Johnson (1990) conclude that risky choice is affected by prior outcomes in addition to incremental outcomes due to decision makers incompletely adapting to recent losses and gains. The contestants in “Deal or No Deal” never have to pay money out of their own pockets, but they still they can “lose”, because unfavorable outcomes can shatter their earlier expectations, and in addition, they have to sacrifice sure amounts in order to advance in the game.

We analyze all game rounds of 84 contestants from Belgium, Germany and the Netherlands in 2002-2006. We include various editions of the show in order to provide the opportunity to disentangle the effect of previous outcomes and the effect of the amounts at stake. Within all shows of the same edition, the two effects cannot be separated: unfavorable outcomes go hand in hand with lower stakes and *vice versa*. Using editions with a different average initial prize introduces variation in stakes that is not related to previous outcomes. Apart from the initial stakes, the game formats are comparable across the editions. Furthermore, the contestants from the three European countries are comparable in terms of their cultural and economic background.

We will analyze the contestants’ decisions using the classic expected utility theory (EUT), which doesn’t allow for path-dependence, as well as prospect theory (Kahneman and Tversky, 1979), in which prior outcomes may affect the subjective reference point that separates losses from gains.

Our EUT analysis estimates the Arrow-Pratt coefficient of relative risk aversion (RRA) using a constant relative risk aversion (CRRA) model. For each individual contestant, we infer a RRA estimate from his choices in the various game rounds. Next, we try to explain the cross-sectional differences in risk aversion with characteristics of the contestants and the history and current state of their game. This part of the analysis shows that large differences in risk aversion are needed in order to explain the observed choices and that risk aversion is highly affected by prior outcomes, contradicting EUT.

The analysis of prospect theory compares the actual choices with the choices predicted by the theory using various specifications for the subjective reference point. One of the specifications uses a sticky reference point and allows for incomplete adaptation to prior outcomes. This path-dependent specification gives the best fit to our data and seems able to explain the violations of EUT.

The remainder of this paper is organized as follows. In Section II, we describe the game show in greater detail. Next, Section III discusses our data material and Section IV explains our research methodology. In Section V, we present our empirical results. Finally, Section VI offers some concluding remarks and suggestions for future research.

II Description of the game show

The TV game show "Deal or No Deal" is developed by the Dutch production company Endemol and was first aired in the Netherlands in its current format in December 2002. The show soon became very popular and was exported to many other countries, including Belgium and Germany.[3] The following description applies to the Dutch episodes of "Deal or No Deal". Except for the prizes, the episodes from Belgium and Germany in our sample have a similar structure.

Each episode consists of two parts: an elimination game based on quiz questions in order to select one finalist from the audience and a main game in which "Deal or No Deal" is played by the finalist. Only the main game is subject to our research. Except for determining the identity of the finalist, the elimination game does not influence the course of the main game. The selected contestant has not won any prize before entering the final.[4]

The main game starts with 26 numbered briefcases containing hidden monetary amounts that are randomly drawn from a known, fixed set of prizes ranging from €0.01

to €5,000,000. One of the briefcases is selected by the contestant and this briefcase is not to be opened until the end of the game.

The game is played over a maximum of nine rounds and in each round a "banker" tries to buy the briefcase from the contestant by making him an offer. Prior to each bank-offer, the finalist obtains information about the unknown prize in his briefcase by choosing one or more of the other 25 briefcases to be opened. As more and more briefcases are opened and the prizes inside are revealed, the uncertainty regarding the prize in the contestant's own briefcase gradually disappears as the game progresses.

In the first round, the finalist selects six briefcases to be opened and subsequently a first bank-offer is made based on the remaining 20 prizes. If the contestant accepts the offer ("Deal"), he walks away with this sure amount and the game ends; if the contestant refuses the offer ("No Deal"), play continues and he enters the second round.

In this second round, the finalist has to open five more briefcases, followed by a new bank-offer. Once again, he has to decide to "Deal" or "No Deal". The numbers of briefcases to be opened in the nine rounds are respectively 6, 5, 4, 3, 2, 1, 1, 1, and 1, and so the number of remaining prizes decreases from 26 to 20, 15, 11, 8, 6, 5, 4, 3 and finally to 2. The remaining amounts and the current bank-offer are displayed on a scoreboard and need not to be memorized by the player. If the contestant rejects all offers he receives the prize in his own briefcase. Figure 1 illustrates the basic structure of the main game.

[INSERT FIGURE 1 ABOUT HERE]

To provide further intuition for the game, Figure 2 shows a typical example of how the main game is displayed on the TV screen. A close-up of the contestant is shown in the centre and the prizes in the 26 briefcases are listed to the left and the right of the contestant. Eliminated prizes are shown in a dark color and remaining prizes are in a bright color. The bank-offer is displayed at the top of the screen.

[INSERT FIGURE 2 ABOUT HERE]

Although the contestants do not know the exact bank-offers in advance, the banker behaves consistently according to a clear pattern. Not surprisingly, bank-offers generally are related to the average prize in the unopened briefcases: when the lower (higher) prizes are eliminated, the average remaining prize increases (decreases) and the banker makes a better (worse) offer. Furthermore, the banker becomes more generous as the game progresses and he typically compensates unfortunate contestants by making an above-average offer. Bank-offers are not informative, i.e. they cannot be used to determine which of the remaining prizes is in the contestant's briefcase.

We carefully selected the editions of "Deal or No Deal" included in our sample. Although the format generally similar across the world, there are some noteworthy differences. For example, in the daily editions from Italy, France and Spain, the banker knows the amounts in the briefcases and makes informative offers. This means that contestants are required to apply Bayesian updating, which complicates the analysis of their choices. In the daily edition from Australia, special game options known as "Chance" and "Supercase" are sometimes offered at the discretion of the producer after a contestant has made a "Deal". These options would complicate our analysis because the associated probability distribution is not known, which introduces a layer of uncertainty in addition to the pure risk of the game. The editions in our sample are chosen to maximize the differences in initial stakes, while minimizing the differences in the format of the game and the cultural and economical background of the contestants.

III Data

Our dataset includes all "Deal or No Deal" decisions of 84 contestants appearing in episodes aired in the Netherlands (40), Belgium (18) and Germany (26). Our sample represents the complete set of shows aired up to and including January 1, 2006.

The Dutch edition of "Deal or No Deal" is called "*Miljoenenjacht*". A key feature of the Dutch shows are the relatively high amounts at stake: the average initial prize is €391,411 and contestants may even go home with €5,000,000. The first Dutch episode was aired on December 22, 2002. The game show was aired 40 times, divided over six series of weekly episodes and three individual episodes aired on New Year's Day. The last Dutch episode in our sample dates from January 1, 2006. Part of the 40 shows are recorded on videotape by the authors; tapes of the remaining shows are obtained from the Dutch broadcasting company *TROS*.

The Belgian edition, also called "*Miljoenenjacht*", was aired 19 times, divided over two seasons of weekly episodes. The first series of 11 shows was launched on October 16, 2004; the second series of 8 shows started on October 15, 2005. The prizes are roughly five times smaller than the Dutch version: the maximum initial prize is €1,000,000 and the average amounts to €85,972. Copies of the Belgian shows are obtained from Endemol's local production company *Endemol België N.V*. The episode of November 26, 2005, is excluded from our sample, leaving 18 Belgian episodes. In this episode, contestant Andy eliminated all valuable prizes in the early rounds and received only insignificant bank-offers (≤ €360) thereafter. Although Andy's choices are consistent with our main findings – Andy is extremely unfortunate and rejects all offers – the episode is excluded because we may question if the choices reveal the true risk preferences when the stakes are small.

In Germany, the debut of "*Der MillionenDeal*" was on May 1, 2004. The first season consisted of 6 weekly episodes with an average mean initial prize of €237,565 and a maximum of €2,000,000. The show returned on TV on June 23, 2005 under a different name ("*Deal or No Deal - Die Show der GlücksSpirale*"), with less prizes on the board (20 instead of 26, so in fact the first round was skipped) and with decimated stakes: an average of €26,347 and a maximum of €250,000. Further, the elimination game was shortened considerably and instead of the regular number of one contestant per episode, two candidates played the final game sequentially. The German "small-stake" edition was broadcasted on a weekly basis and lasted for 10 episodes, yielding a total of 20 contestants in our sample. Copies of the German shows are obtained from TV station *Sat.1* and from Endemol's local production company *Endemol Deutschland GmbH*.

For every contestant we collect data on the eliminated and remaining briefcases, the bank-offers and the "Deal or No Deal" decisions in every game round, leading to a panel data set with a time-series dimension (the game rounds) and a cross-section dimension (the contestants). Furthermore, at the beginning of each main game, the game show host asks the contestant to introduce himself to the public. Based on this introduction talk and based on other conversations with the host during the course of the game we collect data on contestant characteristics such as age and education (more details are given in Section IV).

Table I shows summary statistics for our sample. Male and high-educated contestants seem somewhat overrepresented in the final game. This overrepresentation may, in part or in whole, result from the preceding elimination game. For example, the elimination game favors contestants with a relatively high level of general knowledge and/or computational skill. Although some questions require no more than ordinary luck, most questions do require some degree of knowledge and/or computational skill. Furthermore, at the end of elimination game, just before a last, decisive question, the two remaining contestants can avoid losing and leaving empty-handed by accepting a relatively small prize. Extremely risk averse contestants and/or contestants with a low level of general knowledge or computational skill are most likely to accept this offer. Nevertheless, we doubt there will be a decisive effect on our results. Our sample still includes many women and low-educated contestants and their RRA is not significantly different from the rest. Furthermore, the main finding of this study is the role of prior outcomes in explaining the relative differences in RRA; prior outcomes are random and therefore uncorrelated with contestant characteristics.

[INSERT TABLE I ABOUT HERE]

Table II shows summary statistics for the percentage bank-offers in our sample. Clearly, the banker becomes more generous as the game progresses. The offer typically starts at about six percent in the first round and approaches the average of remaining prizes in the later rounds. This strategy obviously serves to encourage contestants to continue playing the game and to gradually increase excitement. The premium offered to unfortunate contestants is illustrated by splitting the sample at $for_{i,r} = 0.5$, where $for_{i,r}$ measures the fortune of contestant i up to round r by dividing the average remaining prize in the relevant game round by the average of the initial prizes. The banker behaves in a similar way in all editions in our sample.[5]

[INSERT TABLE II ABOUT HERE]

IV Methodology

We first analyze the observed choices using expected utility theory. Our analysis uses a two-stage methodology that allows for heterogeneous risk attitudes. The first stage uses a backward induction method to estimate the Arrow-Pratt relative risk aversion (RRA) for every individual contestant based on the time-series of game rounds played by the contestant. In the second stage, we use multivariate regression analysis to explain the cross-sectional variation in the RRA estimates with characteristics of the contestants and the history and current state of their game. Subsequently, we move to prospect theory. The analysis then concentrates on the ability to explain the observed choices with various specifications for the reference point that separates losses from gains.

A. Individual RRA scores

The time-series of decisions to "Deal" or "No Deal" can be used to derive bounds on each contestant's RRA. In every game round, a unique RRA coefficient can be determined at which the contestant would be indifferent between accepting and rejecting the bank-offer. If the contestant accepts the offer, his RRA must be higher than this value; if the offer is rejected, his RRA must be lower. In turn, the bounds can be combined to arrive at a point estimate for the contestant's RRA.

To formalize this idea, we index contestants by $i = 1, \cdots, N$ and game rounds by $r = 1, \cdots, 10$, where r=10 refers to the opening of the contestant's own briefcase after rejecting the bank-offer in round 9. Furthermore, we use R for the round in which the game ends (i.e., the contestant accepts the bank-offer or, for R = 10, receives the contents of his own briefcase). In a given round r, the remaining prizes are denoted by x_r and the associated number of remaining briefcases by n_r. Given r = 1,…,9, x_{r+1} is a subset of n_{r+1} elements from x_r. The collection of all such subsets is denoted by X_r. Preferences are modeled using the CRRA utility function

$$u(x|\gamma, W) = \frac{(x+W)^{1-\gamma}}{1-\gamma} \tag{1}$$

with γ for the RRA coefficient and W for the contestant's initial wealth. We use $B(x_r)$ for the bank-offer as a function of the remaining prizes x_r. Since the bank-offers are highly predictable (see Section II), this function is treated as deterministic and known to the contestants.

The utility of accepting the current bank-offer ("Deal") is simply $u(B(x_r)|\gamma,W)$. Analyzing the expected utility of rejecting the offer ("No Deal") is complicated by the contestant's option to accept a bank-offer in a later round, similar to the "early-exercise option" of American-style stock options and real options in investment projects. Due to this option, the expected utility of a "No Deal" exceeds the expected utility of playing the game to the end. In the spirit of the decision-tree approach to valuing American-style options and investment projects, we can solve the dynamic programming problem by means of backward induction. Starting with the ninth round, we can determine the optimal "Deal"/"No Deal" decision in every game round, accounting for the possible scenarios and the optimal decisions in subsequent rounds. Given x_r, the statistical distribution of x_{r+1} is known:

$$\Pr[x_{r+1} = y|x_r] = \binom{n_r}{n_{r+1}}^{-1} = p_r \tag{2}$$

for any given $y \in X_r$, i.e., the probability is simply one divided by the number of possible combinations of n_{r+1} out of n_r. Thus, the expected utility of a "No Deal" is given by:

$$\underbrace{g(x_r,\gamma,W)}_{\substack{\text{expected utility of}\\ \text{continuing given the}\\ \text{prizes } x_r}} = \sum_{y\in X_r} \max\{\underbrace{u(B(y)|\gamma,W)}_{\substack{\text{utility of accepting}\\ \text{the offer given the}\\ \text{prizes } y}}, \underbrace{g(y,\gamma,W)}_{\substack{\text{expected utility}\\ \text{of continuing given}\\ \text{the prizes } y}}\} \times p_r \tag{3}$$

for $r = 1,\ldots,9$. When $r = 10$, only the contestant's own briefcase remains, so the "bank-offer" equals the prize in this last briefcase, i.e., $B(x_{10}) = x_{10}$, and the contestant need not make any further decisions. Thus,

$$g(x_{10},\gamma,W) = u(x_{10}|\gamma,W) \tag{4}$$

For a given contestant *i* and a given round *r*, we may compute the "switching value" or critical RRA value at which the contestant would be indifferent between stopping ("Deal") and continuing ("No Deal") in the following manner:[6]

$$\hat{\gamma}_{i,r}(W) = \left\{\gamma : g(x_{i,r},\gamma,W) = u(B(x_{i,r})|\gamma,W)\right\} \tag{5}$$

If the contestant accepts a bank-offer, then his certainty equivalent for continuing to play must be lower than the offer. In other words, his RRA will be higher than the switching value, so the switching value for round *R* provides a lower bound $\hat{\gamma}_i^{\mathrm{L}}(W) = \hat{\gamma}_{i,R}(W)$ to the contestant's RRA. Similarly, for earlier rounds ($r \leq R-1$) RRA will be lower than the switching values $\hat{\gamma}_{i,r}(W)$. Since the banker becomes more generous as the game progresses, the lowest upper bound is generally achieved in the penultimate round ($R-1$). More generally, we use $\hat{\gamma}_i^{\mathrm{U}}(W) = \min_{r=1,\ldots R-1}\{\hat{\gamma}_{i,r}(W)\}$ as the upper bound to the contestant's RRA.[7,8] To estimate the RRA coefficient, we use the arithmetic average of the two bounds:

$$\bar{\gamma}_i(W) = \tfrac{1}{2}\hat{\gamma}_i^{\mathrm{L}}(W) + \tfrac{1}{2}\hat{\gamma}_i^{\mathrm{U}}(W) \tag{6}$$

By construction, the upper and lower bounds are biased estimates, and by averaging, the positive and negative errors can be expected to cancel out, leading to a better estimate for the true RRA. Interestingly, the upper and lower bound show the same cross-sectional pattern in the second-stage regression. Thus, while the averaging is important for estimating the level of RRA, it does not materially affect our analysis of the drivers of RRA.

Initial wealth

When using the RRA estimator $\bar{\gamma}_i(W)$, we have to specify the appropriate initial wealth level (*W*). The higher we set the wealth level, the higher will be the RRA needed to explain a "Deal". As Rabin and Thaler (2001) note, expected utility theory says that risk attitudes derive from changes in lifetime wealth and people should not be averse to outcomes that do not significantly influence their lifetime wealth. We link our initial wealth levels to the median household income in Belgium, Germany and the Netherlands, roughly €25,000 for our sample period. Specifically, we consider wealth levels of €0 and €250,000. W = €0 can be interpreted as contestants not integrating their initial wealth with the outcomes during the game, an example of "narrow framing". W = €250,000 is the present value of a annuity that pays €25,000 annually using a 10% discount rate, a rough estimate of lifetime wealth.

Bank-offers

The results will also depend strongly on the bank function (B). The higher the expected offers, the more valuable the contestant's "early-exercise option" and the higher the RRA needed to explain a "Deal". Fortunately, the banker's behavior can be captured by simple rules of thumb, as discussed in Section II. For contestant i with remaining prizes $x_{i,q}$ and percentage bank-offer $b_{i,q}$ in game round $q = 1,\cdots,8$, we may capture this behaviour using the following model:

$$B(x_{i,r}) = b_{i,r} \times E[x_{10} | x_{i,r}] \quad (7)$$

$$b_{i,r} = b_{i,q} + (1 - b_{i,q}) \times \rho^{(10-r)/(r-q)} \qquad r = q+1,\cdots,9 \quad (8)$$

where $0 \le \rho \le 1$ determines the speed at which the percentage goes to 100%. Round q and 10 are not included, because the percentages for these rounds are known. The bank-offer for round q is shown on the scoreboard and the percentage in round 10 is always 100%.

By starting from the current percentage $b_{i,q}$, we capture the effect of high bank-offers to unfortunate contestants. Once the percentage is raised above 100%, it is expected to remain above 100% for the next rounds. At the surface, this approach may seem restrictive, because it assumes that an unfortunate contestant will receive generous offers also when his odds improve in later rounds. However, due to the skewed prize distribution, the contestant cannot return to his original situation once he has eliminated the big prizes, and to recover a material part of his losses, he will have to eliminate several low-valued briefcases and play until the late rounds, when the percentage bank-offer goes to 100%, irrespective of his fortune. Another possible objection is that the model accounts for generosity to unfortunate contestants only after the offer has already been raised. However, expected utility and our RRA estimates are determined mostly by the offers in good scenarios, and when the odds are still favourable, the precise offer in bad scenarios does not significantly affect our analysis. Accurate estimates for the offers in bad scenarios become relevant only when misfortune has already struck.

We estimate the relevant value of ρ by fitting the model for q=r-1 to the sample of bank-offers to all contestants in all relevant game rounds ($r = 2,\cdots,9$) using OLS regression analysis. The resulting estimate is $\rho = 0.80$ for the full sample. The model gives a remarkably good fit. It explains 84% of the total variation in the individual percentage-offers. The explanatory power is even higher for money-offers, with an R-squared of 97%.[9] Arguably, accurate money-offers are more relevant for accurate RRA estimates than accurate percentage-offers, because the favorable scenarios with high money-offers weigh heavily on expected utility. On the other hand, to analyze the risk behavior following losses, accurate estimates for low money-offers are also needed. It is therefore comforting that the fit is good in terms of both percentages and money amounts.

Since the principle behind the bank-offers is clear after seeing a few shows, we assume here that the contestants are familiar with this pattern. We use a deterministic bank function with percentage offers equal to those predicted by the above model.[10] Of course, for the contestants in the first shows, when the show had not been aired before, the pattern may not have been so obvious. Also, there remains some uncertainty about the bank-offer. Most notably, the bank-offer to the unluckiest contestants is relatively uncertain and ranges roughly speaking between 100 and 130 percent of the expected prize. Still, the bulk of the uncertainty comes from the uncertainty regarding the contents of the briefcases, especially if large amounts are at stake, and we therefore feel confident to assume a deterministic bank function. Using a stochastic bank function would introduce an extra layer of uncertainty, which would presumably yield RRA estimates for losers that are even lower than the values reported here, further strengthening the pattern reported in this study.

Example illustration

Table III illustrates our first-stage procedure for contestant Pieter, who appeared in the Dutch episode of December 12, 2004. For every game round, the table shows the remaining prizes, the average remaining prize, the bank-offer, the percentage bank-offer and the "Deal"/"No Deal" decision. Also shown are the switching values $\hat{\gamma}_{i,r}(W)$ that would make Pieter indifferent between the bank-offer and continuing play in a CRRA expected utility model assuming W = €0. Clearly, the switching values decrease monotonically with the game round number, reflecting the increasing percentage bank-offers. For round 1 to 4, the switching values must be higher than Pieter's actual RRA, because Pieter rejected the bank-offers in these rounds. The minimum of these four values is used as our RRA upper bound, i.e., $\hat{\gamma}_i^{\mathrm{U}}(W) = \hat{\gamma}_{i,4}(W) = 1.51$. Similarly, Pieter accepted the bank-offer in round 5, and hence the switching value for this round must be lower than the actual RRA. Thus, our RRA lower bound is $\hat{\gamma}_i^{\mathrm{L}}(W) = \hat{\gamma}_{i,5}(W) = 0.97$. Our RRA estimate is simply the average of the two bounds: $\bar{\gamma}_i(W) = 1.24$.

[INSERT TABLE III ABOUT HERE]

Myopic framing

Our RRA estimates assume that the contestants are fully rational and take into account all possible outcomes and decisions in all subsequent game rounds. This assumption can obviously be questioned because of the cognitive complexity involved. At the beginning of the game, in round 1, the contestant faces a highly complex decision problem, with 20 unopened briefcases and 8 more game rounds, yielding an overwhelming number of possible scenarios. Nevertheless, the complexity in most cases is lower than it seems at first sight. In the early game rounds, the percentage bank-offers are so low and increase so fast that almost all contestants reject the bank-offer and continue playing. The bank-offers become "competitive" in the middle rounds, when the number of remaining briefcases and game rounds is much smaller. In addition, the prize distribution is highly positively skewed and the contestant may focus on the largest remaining prizes and ignore the precise values of the smaller prizes without losing much information. For these reasons, the cognitive burden generally is lower than suggested by the initial number of briefcases and game rounds. Still, the contestants may employ a simplified version of the game to further reduce the complexity.

For example, contestants may use a "myopic" frame that compares the known current bank-offer with the unknown offer in the next round, ignoring the option to continue play after the next round. Using this frame, the expected utility of a "No Deal" is given by:

$$g(x_r, \gamma, W) = \sum_{y \in X_r} u(B(y) | \gamma, W) \times p_r \tag{3'}$$

The myopic frame ignores the option to continue play after the next round and hence lowers the value of a "No Deal" compared with the value in the model of full rationality. Nevertheless, the effect on our RRA estimates can be expected to be limited, because the estimates generally are derived from the last two game rounds played by the contestant. The continuation option becomes less valuable as the game progresses and in addition the decision to "Deal" reveals that the option value is limited.

We also considered a frame that focuses on the current bank-offer and the current set of remaining prizes, ignoring the option to accept a bank-offer in one of the subsequent game rounds. On the one hand, this "hyperopic" frame is appealing because all required information is shown on the scoreboard and the contestants don't have to memorize, estimate or compute it. On the other hand, the chronological order of the game suggests that contestants put less emphasis on a prize that can be taken home after nine rounds rather than on an offer that can be taken home in the next round. Despite the differences, the two frames give similar results for the unfortunate contestants, who drive our results. The unfortunate contestants generally continue playing to the late rounds, when the distribution of the offer in the next round and the distribution of the set of remaining prizes converge. In fact, in round 9, the two distributions are identical.

Hits and misses

Our first-stage analysis infers the risk attitude for every individual from his observed choices during the game. This approach allows for heterogeneous risk attitudes and gives EUT considerable freedom to fit to the data. Still, the model doesn't always give a perfect fit, because it may be impossible to explain all the choices of a given contestant with a single RRA value. Inconsistencies occur when the lower RRA bound exceeds the upper RRA bound, i.e., $\hat{\gamma}_i^{\mathrm{L}}(W) > \hat{\gamma}_i^{\mathrm{U}}(W)$; the model then can't explain why a contestant didn't stop in an earlier game round. We analyze the goodness of the model by comparing the actual choices with the predicted choices and analyzing the "hits" (correct predictions) and "misses" (incorrect predictions). To avoid "double-counting" of "No Deal" decisions, we focus on the last two game rounds of every contestant, typically a "No Deal" followed by a "Deal".[11] Later on, we will also analyze the goodness of EUT and prospect theory assuming homogenous preferences. Assuming homogeneity obviously will decrease the number of hits and increase the number of misses. The parameters will then be chosen by maximizing the total number of hits, or Maximum Score Estimation (Manski, 1975).[12]

B. Regression analysis

Having estimated the individual RRA scores $\bar{\hat{\gamma}}_i(W)$, $i = 1, \cdots, N$, we subsequently use multivariate regression analysis to explain the cross-sectional variation in the estimates. We will use the following linear regression model:

$$E[\bar{\hat{\gamma}}_i(W)] = \beta_0 + \sum_{j=1}^{K} \beta_j z_{i,j} \quad i = 1, \cdots, N \tag{9}$$

where $z_{i,j}$ is the value of the jth regressor, $j = 1, \cdots, K$, for the ith contestant, $i = 1, \cdots, N$. The unknown parameters are estimated by means of ordinary least squares (OLS) regression analysis.

Our regressors are discussed below. Particular care is given to the possibility of spurious regression. Specifically, our RRA estimates generally are obtained from the penultimate game round (R – 1) and the ultimate game round (R). Due to the increasing trend for the percentage bank-offer, the relevant round numbers will be negatively correlated with the RRA estimates. If the regressors are also determined by the round number, spurious regression may arise.

Contestant characteristics

At the beginning of "Deal or No Deal" the contestant is asked to introduce himself to the public. Based on this introduction and based on other conversations with the game show host during the course of the game, we are able to determine some characteristics. We include the following variables as regressors in our analysis:

- Age (years);
- Gender (female/male);
- Education (high/low).

In some cases, the contestant's age is not explicitly stated. In these cases we estimate the missing values based on the physical appearance of the contestant and other information revealed in the introduction talk, e.g., the age of children. Gender is obviously easy to determine, but it should be noted that usually, the contestant's spouse sits in the audience and is consulted on the decisions to "Deal" or "No Deal". Thus, decisions are often taken effectively by a male-female couple, which may obscure a possible gender effect. Although a contestant's level of education is usually not explicitly mentioned, it is often clear from the stated profession. We assign "high" to bachelor-degree level or higher (including students) and to equivalent work experience.

Stakes

We use a model of constant RRA, but RRA may actually change as the amounts at stake change, due to increasing relative risk aversion (IRRA). To analyze the effect of stakes, we include the natural log of the average remaining prize as a regressor in the model, a variable referred to as Log Stakes. Since our RRA estimate is the average of two bounds calculated from two different game rounds, we compute the average of the stakes in the same two rounds.[13]

Being the outcome of a random process, Log Stakes is obviously uncorrelated with contestant characteristics such as age and gender, which simplifies the disentangling of the various effects on RRA. Still, the variable is dependent on the game round number, because high and low values are more likely to occur in the later rounds, leading to possible spurious regression. However, a simulation study (not reported here) suggests that this effect is not strong in our study. The effect is most pronounced for the early rounds (rounds 1, 2 and 3), when the number of remaining briefcases is large (20, 15, and 11, respectively), and the late rounds (rounds 8, 9 and 10), when the number is small (3, 2 and 1, respectively). However, most contestants actually "deal" in the middle rounds (rounds 4, 5, 6 and 7), when number of unopened briefcases and the distribution is comparable (8, 6 and 5, and 4 cases, respectively).

The simulation results are confirmed by two robustness checks for our regression results. First, the results are not materially affected if we replace the average remaining prize with a variable that is constructed to be independent of the round number: the average prize of the initial 26 briefcases. Second, the results are robust to excluding the early and late rounds and focusing on the middle rounds.

Previous outcomes

As discussed in Section II, we measure the effect of prior outcomes by $for_{i,r}$, the average remaining prize in the current game round divided by the average of the original 26 prizes. Since our RRA estimate is the average of two bounds calculated from two different game rounds, we compute the average of the stakes in the same two rounds, a variable refereed to as Fortune or for_i. To distinguish between reactions to gains and reactions to losses, we introduce the dummy variable $loss_i = 1_{for_i \leq 1}$ that takes the value one for losses and zero for gains, and its complement $gain_i = 1 - loss_i$. The following two regressors are included:

- Prior losses: $(for_i - 1) \times loss_i$
- Prior gains: $(for_i - 1) \times gain_i$

Like Stakes, the fortune variables are uncorrelated with contestant characteristics, which simplifies our analysis. Still, within a given game format, the variables are highly correlated with Stakes, making it difficult to disentangle the two effects. This problem is however mitigated by the large differences in the initial stakes across the game formats, with a minimum of €26,000 for the German small-stakes show and a maximum of €391,000 for the Dutch large-stakes show. Furthermore, the variables are dependent on the game round number, because high and low values are more likely at the end of the game, leading to possible spurious regression. However, as for Stakes, this effect is limited because most contestants actually stop in the middle rounds. Indeed, the regression results are not materially affected if we replace Fortune with a regressor that is constructed to be independent of the round number or exclude the early and late rounds from the analysis.[14]

Shape of the distribution

To examine the role of the shape of the distribution of incremental outcomes, we include the following two shape parameters:

- Standard deviation of the remaining prizes, scaled by the average remaining prize
- Skewness of the remaining prizes

The mean of the remaining prizes is already included as Stakes. Higher-order statistics are not included, because mean, standard deviation and skewness almost completely describe the distribution. For example, skewness and kurtosis have an almost perfect correlation of 95 percent in this game.

Due to the structure of the game, the shape parameters are determined in large part by the round number. For example, during the course of the game, the contestants generally are confronted with a decreasingly skewed prize distribution, as a consequence of the falling number of remaining briefcases. In fact, in the ninth round, the distribution is perfectly symmetric, because the contestant then faces a 50-50 gamble between the two remaining briefcases. Thus, risk-averse contestants (high RRA), who stop early in the game, always face highly skewed gambles, while the more adventurous contestants (low RRA) choose to play the game until the later stages, when the skewness is low. Thus, we may find a correlation between RRA and skewness even if there is no causal relationship between the two. To avoid spurious regression, we use the shape parameters in deviation from the expected values for these parameters in the relevant game round. [15,16]

Interpreting the regression results

The risk attitude is likely to be explained, in part or in whole, by factors outside our second-stage regression model and we do not gauge EUT based on the explanatory power of the regression model. EUT is not necessarily wrong if two contestants with the same age, gender and education make different decisions for the same choice problem. The two persons may simply have different risk attitudes for reasons outside the model, e.g., their cultural or economic background. The litmus test for the theory is the ability to correctly predict the "Deal"/"No Deal" choices, as measured in by the number of "hits". The first-stage model allows for full heterogeneity of risk attitudes and therefore is likely to perform very well by this criterion. The purpose of the second-stage regression analysis is to investigate what drives this performance. In this respect, we may question EUT if our fortune variables, which according to the theory should be irrelevant, explain a sizeable part of the differences in risk attitude. This would also suggest that a path-dependent non-expected utility model will be relatively successful in explaining the observed choices.

C. Prospect theory

Besides EUT, we also analyze observed choice using cumulative prospect theory (CPT; Tversky and Kahneman, 1992). Unfortunately, we are not able to test CPT with the same rigor as EUT in this study. CPT involves several free parameters, and unlike our analysis of individual RRAs we cannot identify unique parameter values for every individual contestant. Furthermore, it is not clear how a CPT contestant would frame the decision tree in this game show, while the frame will undoubtedly have a decisive effect on the results. Finally, the theory doesn't forward the specification for the reference point or how the reference changes during the game. Still, we may investigate the explanatory power of CPT by using a single set of parameter values for all contestants and by using plausible specifications for the mental frame and the reference point.

We will again use the myopic frame that focuses on the current bank-offer and the unknown offer in the next round (see Section A above). Also, contestants are assumed to have a narrow focus and evaluate the outcomes during the game without integrating those with their initial wealth. Using this mental frame, the CPT value of the uncertain alternative ("No Deal") is:

$$CPT(x_r) = \sum_{y \in X_r} v(B(y))(w(P_r(y)) - w(P_r(y) - p_r)) \tag{10}$$

with $v(\cdot)$ for the value function and $w(\cdot)$ for the weighting function over cumulative rank-dependent probabilities $P_r(\cdot)$. The value function is given by

$$v(z) = \begin{cases} -\lambda(RP_r - z)^{\alpha^-} & z \le RP_r \\ (z - RP_r)^{\alpha^+} & z > RP_r \end{cases} \tag{11}$$

where $\lambda > 0$ is the loss aversion parameter, RP_r for the reference point that separates losses from gains, and $\alpha^- > 0$ and $\alpha^+ > 0$ measure the risk attitude in the domain of losses and gains, respectively. Cumulative rank-dependent probability is given by

$$P_r(y) = \begin{cases} \sum_{z \in X_r} 1_{B(z) \leq B(y)} \times p_r & B(y) \leq RP_r \\ \sum_{z \in X_r} 1_{B(z) \geq B(y)} \times p_r & B(y) > RP_r \end{cases} \tag{12}$$

These probabilities are transformed using the following probability weighting function:

$$w(P_r(y)) = \begin{cases} \dfrac{P_r(y)^{\beta^-}}{(P_r(y)^{\beta^-} + (1 - P_r(y))^{\beta^-})^{1/\beta^-}} & B(y) \leq RP_r \\ \dfrac{P_r(y)^{\beta^+}}{(P_r(y)^{\beta^+} + (1 - P_r(y))^{\beta^+})^{1/\beta^+}} & B(y) > RP_r \end{cases} \tag{13}$$

where $\beta^- > 0$ and $\beta^+ > 0$ measure the probability distortion in the domain of losses and gains, respectively.

We will use the Tversky and Kahneman (1992) estimates for the free parameters, as well as parameter values that are chosen by Maximum Score Estimation to give the best fit for our data set. Estimation of the free parameters is difficult because the CPT value is a complicated functional that cannot be included in standard estimation and optimization routines. Still, we may approximate the optimal parameter values using a grid search that searches over $\{0.5, 1, \cdots, 5\}$ for λ and $\{0.1, 0.2, \cdots, 1\}$ for the other four parameters.

Finally, we consider three plausible alternatives for the reference point. We first consider a zero reference, or $RP_r = 0$. In this case, the contestants never experience losses, because they never have to pay money from their own pockets. Of course, contestants may still experience "losses" if the outcomes shatter their earlier expectations. Our second specification therefore uses the current bank-offer as the reference, or $RP_r = B(x_r)$. The current bank-offer seems a plausible choice, because it is based on the average remaining prize, reflecting current expectations, and because the offer represents the riskless alternative and the opportunity cost of the risky alternative. The third reference is based on the maximum of the bank-offers to the contestant in the past rounds and the current round. This specification captures stickiness of the reference point after previous losses; when the offer increases after eliminating low-valued briefcases, the reference increases, but when the offer decreases after eliminating valuable briefcases, the earlier, higher offer remains the target. Sometimes, the highest offer is an unrealistic benchmark for the myopic contestant, because it can no longer be achieved with an offer in the next round, even if the contestant should eliminate the lowest remaining prize(s). In these cases, we use the highest bank-offer that can still be achieved. Thus, the third specification is $RP_r = \min\{\max_{s=1,\dots,r}\{B(x_s)\}, \max_{y \in X_r}\{B(y)\}\}$.

V Results

A. Individual RRA scores

Table IV summarizes our RRA estimates and the overall goodness of the EUT model. Panel A shows the results based on individual RRA estimates, allowing for heterogeneous risk preferences. Column 1 shows the results for the full sample, $W = €0$ and with rational framing. We find an average RRA of 1.15, a moderate degree of risk aversion. Furthermore, the degree of risk aversion differs widely across the contestants, some exhibiting strong risk aversion (RRA > 5) and others being risk seeking (RRA < 0). The model yields correct predictions for 85% of the Deal/No Deal decisions. Apparently, relatively few inconsistent choices occur and the lower RRA bound generally is lower than the upper RRA bound.

Not surprisingly, the RRA estimates increase if we raise the wealth level. As shown in Column 2, increasing the wealth level to €250,000 yields an average RRA of 6.68. This number is still modest compared with other studies that assume high wealth levels. Nevertheless, it illustrates that EUT needs high RRAs if lifetime wealth is included.

As discussed in Section IV, we may ask if the contestants are bounded rational in the sense that they adopt a "myopic frame" that focuses only on the current bank-offer and the offer in the next game round. Column 3 and 4 show that myopic framing leads to very similar results as rational framing, with slightly lower RRA estimates and identical hits percentages. Apparently, the continuation option has a relatively low value in the last rounds played by the contestant.

Column 5-6 shows separate results for the German small-stakes and Dutch large-stakes shows. Remarkably, the average RRA for the small-stakes show is 1.02, not far below the high-stakes average of 1.14, despite the sizeable differences in the initial stakes (1:15). This suggests that it will be difficult to explain a sizeable part of the differences in risk attitudes with the stakes.

Other game show studies found RRA estimates ranging from 0.64 (Fullenkamp, Tenorio and Battalio, 2003) to 6.99 (Beetsma and Schotman, 2001).[17] Our estimates are on the lower end of this range for low initial wealth levels and with myopic framing and at the higher end for high initial wealth levels and with rational framing. Thus, the level of RRA critically depends on the choices regarding initial wealth and mental framing. Still, as will be shown below, our main findings regarding the role of previous outcomes are robust to wealth and framing.

The results in Panel A allow for heterogeneous risk preferences. Panel B shows the results if we assume a uniform RRA for all contestants. Not surprisingly, the RRA values are similar to the means from Panel A. However, assuming homogenous preferences substantially reduces the overall fit; only 59%-63% of the observed choices are explained, depending on the precise specification, compared with 85-86% in Panel A. This means that substantial differences in RRA are needed in order to rationalize the bulk of the choices. Section B tries to explain these differences with contestant and game characteristics. Section C investigates if prospect theory with homogenous preferences fares any better in explaining the observed choices.

[INSERT TABLE IV ABOUT HERE]

B. Regression analysis

We now turn to explaining the cross-sectional differences in risk attitudes. Table V shows the OLS regression output. The first column contains the results for the full sample, W = €0 and with rational framing. Overall, roughly half of the variation in the RRA estimates can be explained by our model. Remarkably, the explanation is based on a single regressor: Prior Losses. The large positive coefficient of 1.45 suggests that the RRA strongly decreases following losses. In fact, the estimated coefficient implies that contestants become risk seeking (RRA < 0) after large reductions in the expected prize. This prediction is not based on extrapolation beyond the observed range; the most unfortunate contestants in our sample indeed exhibit risk-seeking behavior by rejecting bank-offers in excess of the average remaining prize. One such contestant, Frank, is discussed at the end of this section. Our data set of 84 contestants includes 8 or 10% of such cases.

Log Stakes has no significant explanatory power, consistent with the small differences in average RRA estimates between small-stakes and large-stakes shows in Table IV. The other regressors also don't have a significant effect. The contestant characteristics age, gender and education do not seem to affect the risk attitudes in this game. The shape of the prize distribution also doesn't play an important role. This finding may simply reflect that there is hardly any variation in the shape parameters after correcting for the effect of the game round number; apart from the mean, the distribution shape is determined in large part by the number of remaining briefcases (see Section IV-B).

As shown in the previous section, our conclusions regarding the *level* of RRA critically depend on the assumptions about initial wealth and mental framing. However, the conclusions regarding the relative *differences* in RRA and the *drivers* of these differences are more robust. Column 2 shows the effect of changing initial wealth to W = €250,000. Again, a large part of the differences in RRA can be explained by Prior Losses and the other regressors seem not relevant. However, for higher initial wealth levels, the differences in RRA are larger and a larger value of the regression coefficient for Prior Losses is needed to explain the differences. Furthermore, the goodness-of-fit falls for higher wealth levels. This suggests that a path-dependent non-expected utility model will be successful especially if we assume that the contestants do no integrate their initial wealth with the outcomes of the game.

Column 3 and 4 shows the results using a myopic frame. As in Table IV, the results are not significantly affected by framing. Column 5 and 6 show separate results for small-stakes and large-stakes shows. Since the fortune variables and Stakes cannot be disentangled if initial stakes are held constant, the regression now excludes Log Stakes. Again, the same pattern emerges: Prior Losses is the main driver of RRA.

[INSERT TABLE V ABOUT HERE]

The Prior Losses variable is independent of differences in stakes across editions. Still, it may capture the difference in stakes within editions and thus the Prior Losses effect may simply reflect IRRA. We may reject this interpretation for several reasons. First, in case of IRRA, we would also expect a significant effect for Prior Gains, but as shown above this variable doesn't play a significant role our analysis.

Second, IRRA does not explain why RRA becomes negative for the most unfortunate contestants. In the worst case, the contestant goes home empty-handed and returns to his initial wealth level. Thus, to assume that a negative RRA after large losses reflects IRRA, is to assume that contestants were risk seekers before they entered the game show—an implausible assumption. Related to this, the RRA increases so fast that even the Arrow-Pratt measure of *absolute* risk aversion increases in the domain of large losses (IARA). However, economic theory typically assumes decreasing ARA (DARA).[18]

Third, the effect of fortune, or stakes within editions, is stronger than the effect of stakes across editions. Thus, losers in large-stakes editions are predicted to be less risk averse than winners in small-stakes editions, if they face the same stakes. Table VI shows that this prediction is not based on extrapolation beyond the observed range. The table compares "losers" (Fortune $\leq$ 1) and "winners" (Fortune > 1) from the German small-stakes episodes with "losers" and "winners" from the Dutch large-stakes episodes. The differences in the initial stakes are so large that the Dutch losers on average still face larger stakes (roughly €135,000) than the German winners do (roughly €45,000). Still, confirming the explanatory power of Prior Losses in the regression analysis, the Dutch losers have lower RRAs than the German winners!

[INSERT TABLE VI ABOUT HERE]

Example illustration

Table VII illustrates our most striking finding, risk seeking following large initial losses, using the decisions by contestant Frank, who appeared in the Dutch episode of January 1, 2005. In round 7, after several unlucky picks, Frank opens the briefcase with the last remaining large prize (€500,000) and he sees the expected prize tumble from €102,006 to €2,508. The banker then offers him €2,400, or 96 percent of the average of remaining prizes. Frank rejects this offer and play continues. In the subsequent rounds, Frank deliberately chooses to enter unfair gambles, to finally end up with a briefcase worth only €10. Specifically, in round 8, he rejects an offer of 105 percent of the expected prize and in round 9 he rejects a certain €6,000 in favor of a 50-50 gamble between €10 and €10,000. We feel confident to classify such decisions as risk seeking behavior, because they involve single, simple, symmetric gambles with relatively large amounts at stake. Also, unless we are willing to assume that Frank would always accept unfair gambles of this magnitude, the only reasonable explanation for his choice behavior seems a reaction to his misfortune experienced during the game.

[INSERT TABLE VII ABOUT HERE]

C. Prospect Theory

The role of Prior Losses is obviously not consistent with EUT and our results point in the direction of frame-dependent choice theories such as prospect theory. Indeed, a lower risk aversion after eliminating valuable briefcases is reminiscent of the “break-even effect” (Thaler and Johnson, 1990): decision makers become more willing to take risk due to incomplete adaptation to previous losses. In prospect theory, this effect arises when the reference point sticks to the earlier, more favorable situation, placing relatively many remaining prizes in the domain of losses, where decision makers are risk-seeking. If contestants are sufficiently risk seeking in the domain of losses, they may even accept “unfair gambles” to escape these losses.

For example, Frank’s reference point in round 9 may well be the largest remaining prize of €10,000. In this case, Frank doesn’t compare a sure gain of €6,000 (the current bank-offer) with a 50-50 gamble between winning €10,000 and winning €10, but rather a sure loss of €4,000 (€6,000-€10,000) with a 50-50 gamble between losing €9,990 (€10-€10,000) and breaking even. If probability transformation and/or risk seeking is sufficiently strong for losses, CPT predicts that Frank would take the gamble.[19]

Table VIII shows the goodness of the CPT model for entire data set. The first three columns show the results using the Tversky and Kahneman parameter estimates. When the reference point equals zero, and contestants never experience losses, the model explains 57% of the choices. When gains and losses are measured relative to the current bank-offer, the percentage increases to 60%. This suggests that contestants do experience losses although they never have to pay money from their own pockets. The hits percentage increases to 65% if the reference equals the highest bank-offer, suggesting that incomplete adaptation to losses indeed helps to explain the observed choices. Among the new hits is Frank, who is predicted to stop in round 8 and 9 when using the other two specifications.

The hits percentage of 65% is substantially higher than the 59% for EUT with myopic framing and zero initial wealth (see Table IV, Panel B). When the CPT parameters are chosen to maximize the empirical fit, the goodness increases further, and the model with a sticky reference achieves a hits percentage of 68%. Compared with the Tversky and Kahneman parameter estimates, the improved fit is achieved without loss aversion ($\lambda = 1.00$), more curvature for the value function ($\alpha^- = 0.80$, $\alpha^+ = 0.70$) and less probability transformation ($\beta^- = 0.80$, $\beta^+ = 1.00$).

The CPT findings are consistent with our earlier results for EUT with heterogeneous preferences, where a high number of hits and a high explanatory power for Prior Losses are reported for the myopic model with zero initial wealth (see Table IV, Panel B, and Table V). Clearly, a dynamic but sticky reference point is a plausible explanation for the correlation between RRA and Prior Losses.

[INSERT TABLE VIII ABOUT HERE]

VI Conclusions

The popular TV game show "Deal or No Deal" seems particularly well-suited for analyzing decision making under risk, as it involves very large and wide-ranging stakes, simple stop-go decisions that require minimal skill, knowledge or strategy and near-certainty about the probability distribution.

We examine the observed choices of contestants in recent episodes from Belgium, Germany and the Netherlands. The degree of risk aversion differs strongly across the contestants, some demonstrating strong risk aversion and others exhibiting risk-seeking behavior. The differences can be explained in large part by the earlier outcomes experienced by the contestants in the previous rounds of the game. Most notably, risk aversion generally decreases after prior expectations have been shattered by eliminating valuable briefcases. Contestants facing a large reduction in the expected prize during the game may even become risk seeking; they reject bank-offers that exceed the expected prize and thus enter “unfair gambles”. This path-dependent pattern occurs in all editions of the game, despite sizeable differences in the initial stakes across the editions. Thus, “losers” seem less risk averse than “winners”, irrespective of the amounts at stake.

Path-dependence is not consistent with expected utility theory and points in the direction of frame-dependent choice theories such as prospect theory. Indeed, our findings seem consistent with the “break-even effect”: contestants become more willing to take risk after eliminating the valuable briefcases due to incomplete adaptation to losses or “stickiness” of the reference point that separates losses from gains. A simple version of prospect theory with a sticky reference point equal to the highest bank-offer yields surprisingly good predictions of the “Deal”/“No Deal” decisions in our sample. These results suggest that phenomena such as framing and path-dependence are also relevant when large, real monetary amounts are at stake.

This study has focused on episodes from the Netherlands, Belgium and Germany, because these episodes have a comparable game format and the three countries form a cultural and economical unity. For further research it would be interesting also to consider editions from developing countries (e.g., Mexico and India) in order to examine the role of the cultural and economical background of the contestants.

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Table I

Summary statistics

The table shows descriptive statistics for our sample of 84 contestants from Belgium, Germany and the Netherlands. Panel A shows summary statistics for our full sample. Statistics for contestants appearing in the second series of German episodes are shown in Panel B and statistics for the Dutch subsample are in Panel C. The contestants' characteristics age and education are revealed in an introduction talk or other conversations between the host and the contestant. Age is measured in years. Gender and education are defined as dummy variables, with values of 1 assigned to respectively females and contestants with a high level of education (bachelor-degree level or higher). The stop round is the round in which the bank-offer is accepted. For contestants that played the game to the end, the stop round is set equal to 10; figures from the second series of German episodes are adjusted by +1 to reflect the lower number of initial briefcases (corresponding to the omission of the first round). Prize won equals the bank-offer accepted or – for contestants who accepted all offers – the prize in the contestant's own briefcase. Prize in briefcase is the monetary amount in the contestant's own briefcase - the briefcase selected at the beginning of the main game.

A. Full Sample (*N* = 84)

	Mean	Stdev	Min	Median	Max
Age (years)	43.18	10.26	23.00	41.50	70.00
Gender (female=1)	0.31	0.47	0.00	0.00	1.00
Education (high=1)	0.49	0.50	0.00	0.00	1.00
Stop round	5.83	2.03	3.00	6.00	10.00
Prize won (€)	134,486.01	218,539.06	5.00	68,750.00	1,495,000.00
Prize in briefcase (€)	78,342.89	305,370.49	0.01	500.00	2,500,000.00

B. Small-stakes shows (Germany, *N* = 20)

	Mean	Stdev	Min	Median	Max
Age (years)	38.70	7.23	29.00	38.50	55.00
Gender (female=1)	0.40	0.50	0.00	0.00	1.00
Education (high=1)	0.55	0.51	0.00	1.00	1.00
Stop round	7.55	1.70	5.00	7.50	10.00
Prize won (€)	19,915.75	16,966.54	5.00	15,500.00	61,000.00
Prize in briefcase (€)	13,881.75	30,096.40	5.00	1,750.00	100,000.00

C. Large-stakes shows (Netherlands, *N* = 40)

	Mean	Stdev	Min	Median	Max
Age (years)	46.60	10.84	27.00	45.00	70.00
Gender (female=1)	0.28	0.45	0.00	0.00	1.00
Education (high=1)	0.55	0.50	0.00	1.00	1.00
Stop round	5.20	1.88	3.00	5.00	10.00
Prize won (€)	225,062.75	285,814.90	10.00	146,500.00	1,495,000.00
Prize in briefcase (€)	112,622.94	409,311.51	0.01	500.00	2,500,000.00

Table II

Bank-offers

The table shows summary statistics for the relative bank-offers in our sample of 84 contestants from Belgium, Germany and the Netherlands. Panel A shows summary statistics for our full sample. Statistics for contestants appearing in the second series of German episodes are shown in Panel B and statistics for the Dutch subsample are in Panel C. Game-round numbers for the second series of German episodes are adjusted by +1 to reflect the lower number of initial briefcases (corresponding to the omission of the first round). The average bank-offer as a fraction of the average of remaining prizes is reported for each game round. To illustrate the premium offered to unfortunate contestants, the sample is split at $for_{i,r} = 0.50$, where $for_{i,r}$ measures the fortune of contestant i up to round r by dividing the average remaining prize in the relevant game round by the average of the initial prizes. The number of observations is shown between parentheses; this figure is equivalent to the number of contestants rejecting all preceding bank-offers.

A. Full Sample

Round	Unconditional	$for_{i,r} < 0.50$	$for_{i,r} \geq 0.50$
1	0.06 (64)	0.06 (5)	0.06 (59)
2	0.14 (84)	0.17 (16)	0.14 (68)
3	0.36 (84)	0.44 (21)	0.33 (63)
4	0.57 (74)	0.65 (30)	0.51 (44)
5	0.69 (57)	0.76 (22)	0.65 (35)
6	0.83 (44)	0.92 (23)	0.72 (21)
7	0.95 (29)	1.02 (19)	0.81 (10)
8	0.95 (18)	0.95 (14)	0.94 (4)
9	0.98 (10)	0.99 (9)	0.89 (1)

B. Small-stakes shows (Germany)

Round	Unconditional	$for_{i,r} < 0.50$	$for_{i,r} \geq 0.50$
1	-	-	-
2	0.12 (20)	0.19 (2)	0.11 (18)
3	0.38 (20)	0.51 (3)	0.36 (17)
4	0.55 (20)	0.62 (7)	0.52 (13)
5	0.64 (20)	0.73 (6)	0.61 (14)
6	0.82 (18)	1.02 (5)	0.74 (13)
7	0.97 (13)	1.06 (7)	0.87 (6)
8	0.94 (10)	0.94 (6)	0.94 (4)
9	0.92 (6)	0.93 (5)	0.89 (1)

C. Large-stakes shows (Netherlands)

Round	Unconditional	$for_{i,r} < 0.50$	$for_{i,r} \geq 0.50$
1	0.06 (40)	0.06 (2)	0.06 (38)
2	0.14 (40)	0.17 (7)	0.14 (33)
3	0.35 (40)	0.44 (11)	0.32 (29)
4	0.63 (31)	0.72 (15)	0.54 (16)
5	0.78 (22)	0.79 (11)	0.77 (11)
6	0.90 (17)	0.91 (13)	0.87 (4)
7	1.00 (10)	1.03 (9)	0.79 (1)
8	0.96 (5)	0.96 (5)	-
9	1.06 (2)	1.06 (2)	-

Table III

Example "Pieter"

The table shows the gambles presented to a Dutch contestant named Pieter and the "Deal"/"No Deal" decisions made by him in game round 1 to 5. This particular episode was broadcasted on December 12, 2004. For each game round, the table shows the remaining prizes, the average remaining prize, the bank-offer, the percentage bank-offer, the "Deal"/"No Deal" decision and the switching values $\hat{\gamma}_{i,r}(W)$ used to compute the RRA estimate $\bar{\hat{\gamma}}_i(W)$ for Pieter. The switching values are based on W = €0.

	Game Round				
Prize (€)	1	2	3	4	5
0.01	X	X	X		
0.20					
0.50	X	X			
1	X	X	X	X	
5					
10	X	X	X		
20	X	X	X	X	X
50	X	X			
100	X				
500	X	X	X	X	X
1,000					
2,500	X	X	X	X	
5,000					
7,500	X				
10,000	X	X	X	X	X
25,000	X	X			
50,000	X	X	X		
75,000	X				
100,000					
200,000	X				
300,000	X	X	X	X	X
400,000					
500,000	X	X	X	X	X
1,000,000	X	X			
2,500,000	X				
5,000,000	X	X	X	X	X
Average (€)	483,534	459,205	533,003	726,628	968,420
Offer (€)	26,000	61,500	133,000	402,000	715,000
Offer (%)	5%	13%	25%	55%	74%
Decision	No Deal	No Deal	No Deal	No Deal	Deal
$\hat{\gamma}_{i,r}(0)$	6.84	2.76	1.53	1.51	0.97

Table IV

RRA Estimates

The table summarizes our estimates for the Arrow-Pratt coefficient of relative risk aversion (RRA) for our sample of 84 contestants from Belgium, Germany and the Netherlands. Panel A shows descriptive statistics for the heterogeneous estimates, obtained from the time-series of choices for each individual contestant. Descriptive statistics are shown for the upper bound $\hat{\gamma}_i^U(W)$, the lower bound $\hat{\gamma}_i^L(W)$ and the RRA estimate $\bar{\hat{\gamma}}_i(W)$, for various wealth levels (W = €0 and W = €250,000), mental frames (Rational and Myopic) and game show editions (All, Small and Large). A hit is defined as a correct prediction of a "Deal"/"No Deal" decision in the last two game rounds. Panel B shows the homogeneous estimates, i.e., uniform RRA estimates that apply for all contestants combined and are obtained by Maximum Score Estimation (Manski, 1975).

Panel A. Heterogeneous estimates

	Wealth	€0	€250,000	€0	€250,000	€0	€0
	Frame	Rational	Rational	Myopic	Myopic	Rational	Rational
	Edition	All	All	All	All	Small	Large
Lower bound	Mean	0.83	4.73	0.64	3.34	0.81	0.65
	Stdev	1.33	8.16	1.19	10.00	2.07	0.78
	Min	-1.33	< -20	-1.88	< -20	-1.33	-1.32
	Max	7.43	> 20	6.21	> 20	7.43	2.26
RRA estimate	Mean	1.15	6.68	0.95	5.59	1.02	1.14
	Stdev	1.14	8.03	1.03	8.67	1.61	0.96
	Min	-0.85	< -20	-0.84	< -20	-0.85	-0.84
	Max	5.93	> 20	5.08	> 20	5.93	3.72
Upper bound	Mean	1.46	8.64	1.26	7.85	1.24	1.62
	Stdev	1.17	8.39	1.06	9.26	1.32	1.27
	Min	-0.36	< -20	-0.56	< -20	-0.36	-0.36
	Max	5.21	> 20	4.67	> 20	4.43	5.21
	"No Deal" hits	89%	92%	89%	91%	88%	98%
	"Deal" hits	79%	79%	79%	79%	69%	90%
	Total hits	85%	86%	85%	86%	80%	94%
	N	84	84	84	84	20	40

Panel B. Homogenous estimates

Wealth	€0	€250,000	€0	€250,000	€0	€0
Frame	Rational	Rational	Myopic	Myopic	Rational	Rational
Edition	All	All	All	All	Small	Large
RRA	1.30	6.35	0.70	5.50	1.03	1.30
"No Deal" hits	52%	61%	64%	57%	42%	82%
"Deal" hits	74%	64%	53%	64%	75%	61%
Total hits	63%	63%	59%	60%	55%	71%
N	84	84	84	84	20	40

Table V

Regression results

The table shows regression results for our sample of 84 contestants from Belgium, Germany and the Netherlands. The dependent variable is the estimated contestant-specific RRA $\bar{\gamma}_i(W)$. Results are shown for various wealth levels ($W=€0$ and $W=€250{,}000$), mental frames (Rational and Myopic) and game show editions (All editions, Small only and Large only). Significance levels of 10%, 5% and 1% are denoted by *, ** and ***, respectively.

Wealth	€0	€250,000	€0	€250,000	€0	€0
Frame	Rational	Rational	Myopic	Myopic	Rational	Rational
Edition	All	All	All	All	Small	Large
Intercept	-0.05	21.19**	0.16	13.30	1.12**	1.82***
Age	0.02	0.03	0.01	0.04		
Gender (f)	-0.02	-2.48	0.02	-2.03		
Education (h)	-0.05	0.52	-0.02	-0.19		
Log Stakes	0.09	-1.04	0.07	-0.43		
Prior Losses	1.45***	15.48***	1.42***	14.86***	1.60**	1.63***
Prior Gains	0.24	-2.07	0.16	-2.73	1.86*	-0.04
Stdev/EV	-2.44	-21.47	-1.84	-28.56*		
Skewness	0.86	-6.36	0.90	-7.14		
R-sq.	0.48	0.26	0.48	0.24	0.57	0.39
Adj. R-sq.	0.43	0.19	0.43	0.16	0.52	0.35
N	84	84	84	84	20	40

Table VI

Fortune vs. Stakes

The table shows a comparison of "losers" from the second series of German episodes with "winners" from the Dutch large-stakes episodes. For each subset, the number of contestants (*N*), the mean of remaining prizes (stakes), the ratio of the mean of remaining prizes to the mean of all initial prizes (fortune) and the average estimated Arrow-Pratt coefficient of relative risk aversion (RRA) for both *W* = €0 and *W* = €250,000 and for both the rational (R) and the myopic (M) frame are shown.

	Small-stakes shows (Germany)		Large-stakes shows (Netherlands)	
	"Losers"	"Winners"	"Losers"	"Winners"
N	13	7	25	15
Stakes (€1,000)	12	45	135	699
Fortune	0.47	1.70	0.34	1.79
RRA (€0, R)	0.45	2.09	0.77	1.75
RRA (€250,000, R)	6.23	12.61	3.06	5.35
RRA (€0, M)	0.37	1.82	0.57	1.52
RRA (€250,000, M)	3.76	11.36	1.87	4.96

Table VII

Example "Frank"

The table shows the gambles presented to a Dutch contestant named Frank and the "Deal"/"No Deal" decisions made by him in game round 1 to 9. This particular episode was broadcasted on January 1, 2005. For each game round, the table shows the remaining prizes, the average remaining prize, the bank-offer, the percentage bank-offer, the "Deal"/"No Deal" decision and the switching values $\hat{\gamma}_{i,r}(W)$ used to compute the RRA estimate $\bar{\gamma}_i(W)$ for Frank. The switching values are based on W = €0. Frank ended up with a prize of €10.

	Game Round								
Prize (€)	1	2	3	4	5	6	7	8	9
0.01	X	X							
0.20	X	X							
0.50	X	X	X	X	X	X	X		
1	X	X	X	X	X				
5									
10	X	X	X	X	X	X	X	X	X
20	X	X	X	X	X	X	X	X	
50									
100									
500									
1,000	X								
2,500	X	X	X						
5,000	X	X							
7,500									
10,000	X	X	X	X	X	X	X	X	X
25,000	X	X							
50,000	X	X	X	X					
75,000	X	X	X						
100,000	X	X	X						
200,000	X	X	X	X					
300,000	X								
400,000	X								
500,000	X	X	X	X	X	X			
1,000,000	X								
2,500,000									
5,000,000	X								
Average (€)	383,427	64,502	85,230	95,004	85,005	102,006	2,508	3,343	5,005
Offer (€)	17,000	8,000	23,000	44,000	52,000	75,000	2,400	3,500	6,000
Offer (%)	4%	12%	27%	46%	61%	74%	96%	105%	120%
Decision	No Deal	No Deal	No Deal	No Deal	No Deal	No Deal	No Deal	No Deal	No Deal
$\hat{\gamma}_{i,r}(0)$	11.40	7.07	4.62	1.92	0.72	0.53	0.09	-0.05	-0.36

Table VIII

CPT results

The table shows the goodness of the cumulative prospect theory for our sample of 84 contestants from Belgium, Germany and the Netherlands.. Shown are the percentage of correct predictions ("hits") of "Deal"/"No Deal" decisions in the last two game rounds of all contestants in our sample. The first three columns are based on the Tversky and Kahneman (1992) parameter estimates for the value function and the weighting function. The parameter values in the other three columns are obtained by Maximum Score Estimation (Manski, 1975). Results are shown for three alternative specifications for the reference point: (i) zero, or no losses, (ii) the current bank-offer, B_i, and (iii) the highest bank-offer, $\min\{\max_{s=1,\cdots,r}\{B(x_s)\},\max_{y\in X_r}\{B(y)\}\}$.

Reference	€0	Current offer	Highest offer	€0	Current offer	Highest offer
Parameters	T&K	T&K	T&K	Optimized	Optimized	Optimized
λ	2.25	2.25	2.25	-	1.00	1.00
α^-	0.88	0.88	0.88	-	0.80	0.80
α^+	0.88	0.88	0.88	0.70	0.70	0.70
β^-	0.69	0.69	0.69	-	0.80	0.80
β^+	0.61	0.61	0.61	0.60	1.00	1.00
"No Deal" hits	46%	34%	53%	41%	27%	41%
"Deal" hits	71%	88%	79%	86%	90%	79%
Total hits	57%	60%	65%	62%	61%	68%
N	84	84	84	84	84	84

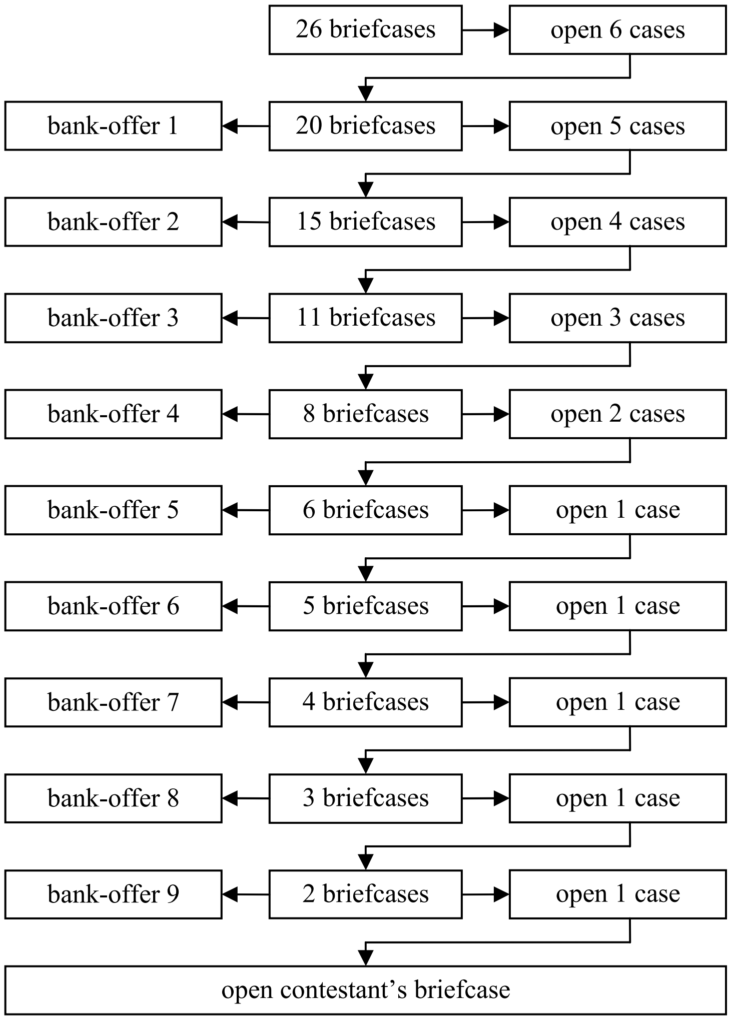

Figure 1: Flow chart of the main game. In every round, the finalist chooses a number of briefcases to be opened, each opened briefcase giving new information about the unknown prize in the contestant's own briefcase. After the prizes in the chosen briefcases are revealed, a "bank-offer" is presented to the finalist. If the contestant accepts the offer ("Deal"), he walks away with the amount offered and the game ends; if the contestant rejects the offer ("No Deal"), play continues and he enters the next round. If the contestant decides "No Deal" in the ninth round, he receives the prize in his own briefcase. The flow chart applies to the editions from the Netherlands and Belgium as well as the large-stakes edition from Germany. The small-stakes edition from Germany involves eight game rounds and starts with 20 briefcases.

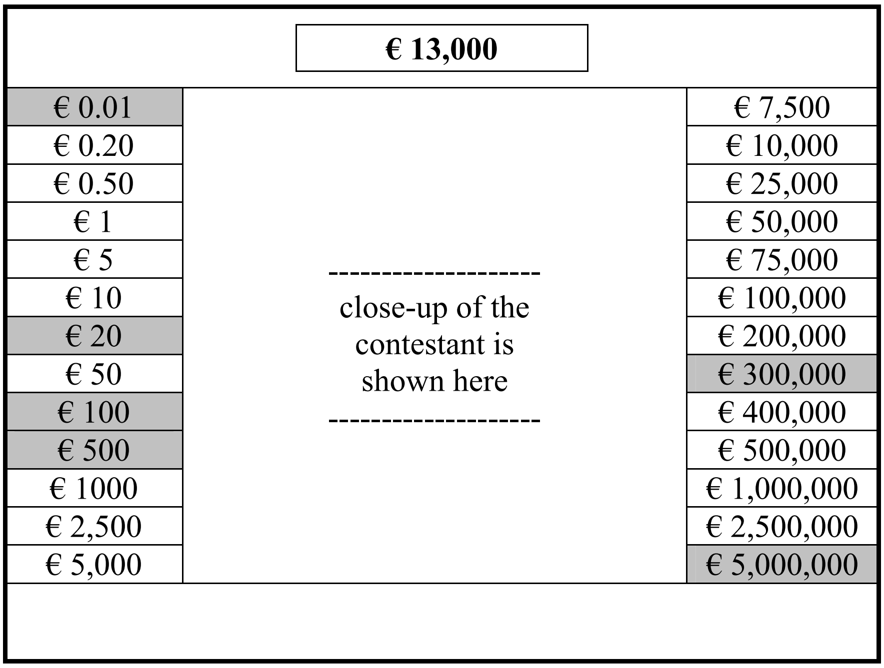

Figure 2: Example of the main game as displayed on the TV screen. A close-up of the contestant is shown in the centre of the screen. The possible prizes are listed in the columns to the left and right of the contestant. Prizes that are eliminated in earlier rounds are shown in a dark color and remaining prizes are in a bright color. The top bar above the contestant shows the bank-offer. This example demonstrates the two options open to the contestant after opening six briefcases in the first round: accept a bank-offer of €13,000 or continue to play with the remaining 20 briefcases, one of which is the contestant's own. This example reflects the prizes and the number of briefcases in the Dutch episodes.

Footnotes

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[1] See, for example, Binswanger (1980, 1981), Quizon, Binswanger and Machina (1984) and Kachelmeier and Shehata (1992).

[2] These studies analyze risk attitudes. Game shows are also analyzed for other purposes. For example, Levitt (2004) analyzes "The Weakest Link" to examine racial discrimination among contestants, List (2004) studies "Friend or Foe" to analyze the relationship between age and social preferences, and Bennett and Hickman (1993), Berk, Hughson and Vandezande (1996), and Tenorio and Cason (2002) examine "The Price Is Right" to study rational bidding and game theory.

[3] Other examples are Argentina ("*Trato Hecho*"), Australia, France ("*A Prendre ou à Laisser*"), Hungary ("*Áll az Alku*"), India ("*Deal Ya No Deal*"), Italy ("*Affari Tuoi*"), Mexico ("*Vas o No Vas*"), Spain ("*Allá Tú*"), Switzerland ("*Deal or No Deal - Das Risiko*"), Turkey ("*Trilyon Avı*"), the United Kingdom and the United States.

[4] Audience members have not been subject to an extensive selection procedure. For example, in the Netherlands, tickets are randomly distributed to players of the national lottery, which sponsors the shows. In some other countries the audience is selected less randomly. In the U.S. for example, people need to send in a personal videotape to be considered as a contestant, so selection is presumably based on "telegenic appearance".

[5] Indeed, a spokesman from Endemol, the production company of "Deal or No Deal", confirmed that the guidelines for bank-offers are the same for all editions included in our sample.

[6] Expected utility is a monotone decreasing and convex function of RRA and hence there exists a unique "switching value".

[7] When the amounts at stake become small, we may question if the contestant's decisions reveal his true risk preferences. We therefore require a minimum expected prize of €1,000 to compute bounds to the contestant's RRA and put the upper bound equal to the lowest switching value for all rounds $r \leq R$-1 satisfying this minimum expected prize criterion.

[8] For contestants who play the game until the end (R = 10), $\hat{\gamma}_{i,R}(W,B)$ is not a lower bound, because these contestants never accept an offer. For these contestants, we estimate the lower bound by the upper bound minus the average distance between the upper and lower bounds for the other contestants in the same game round or, for R=10, the previous game round. This approach is also used when the expected prize in round R is smaller than €1,000.

[9] Our analysis uses separate estimates for the four different editions included in our sample. The results are very similar for all editions: the German small-stakes, Belgian medium-stakes, German large-stakes and Dutch large-stakes editions involve estimates of $\rho = 0.84$, $\rho = 0.76$, $\rho = 0.80$ and $\rho = 0.81$, respectively.

[10] We have investigated various alternative models that link the offer to the game round, fortune, prior offers and the distribution of the remaining prizes. An extensive search over various specifications showed that only small improvements are possible relative to the model used here. These small improvements in our opinion do not outweigh the loss of parsimony and risk of data mining. Also, our RRA estimates are not materially affected by using a more sophisticated bank function.

[11] Our data set includes several "No Deal" choices for every contestant. Since the bank-offer generally becomes more generous as the game progresses, the early "No Deals" are simple to predict and including them would inflate the statistical goodness of the model and obscure the differences between the competing specifications. More worryingly, if the model errs for one of the early "No Deals", wrongly predicting a "Deal", then usually errors also occur for the following "No Deals". By contrast, we have at most one "Deal" for every contestant and hence optimizing over all game rounds would bias the results towards the "No Deal" predictions.

[12] Other estimation methods for discrete choice models include logit and probit estimation These methods yield similar results for our sample and are therefore not reported separately.

[13] Recall that for the contestants who play the game to the end or who face an expected prize smaller than or equal to €1,000, the lower RRA bound is not estimated using information from an actual game round. For these contestants, we simply used the Fortune and the Stakes values from the round that was used to compute the upper bound, recognizing that the game round number does not affect the expected prize.

[14] The relevant exogenous fortune variable is the probability of an average remaining prize that is lower than or equal to the actual value, given the number of remaining briefcases in the relevant game round.

[15] The expected values were estimated by means of Monte-Carlo simulation, using 1,000,000 random samples of n_r out of the 26 original prizes for every game round r=1,…,9.

[16] As for Log Stakes and Fortune, we use the average of the values for the two game rounds used to estimate RRA. If the lower RRA bound is not estimated using information from an actual game round, the missing values for the shape parameters are set equal to zero; after all, the expected deviation from the average is always zero.

[17] Apart from game show studies, the relative or absolute risk aversion coefficient has also been investigated using experimental studies (for example, Binswanger, 1981, and Levy, 1994), field surveys (Barsky, Juster, Kimball and Shapiro, 1997), portfolio allocation decisions (Friend and Blume, 1975) and macro data (see Kocherlakota, 1996, for a survey). Overall, the findings are mixed: some studies find decreasing absolute or relative risk aversion, others increasing absolute or relative risk aversion. Also, the range of estimated relative risk aversion is large; both single digit and double-digit coefficients are found.

[18] The argument is that wealthy individuals are not more risk-averse than poorer ones with regard to the same risk. Thus, as Arrow (1965) notes, DARA is necessary if risky assets are to be "normal goods", i.e., a rise in wealth leads to an increase in demand for them, whereas IARA implies they are an "inferior good".

[19] Accepting the current bank-offer leads to a CPT value of $-\lambda(4{,}000)^{\alpha_-}$. The 50-50 gamble yields a CPT value of $-w(0.5)\lambda(9{,}990)^{\alpha_-}$. Thus, CPT predicts that Frank would take the gamble if $w(0.5) \leq (0.4)^{\alpha_-}$.