Risk Attitudes in Large Stake Gambles: Evidence from a Game Show

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Abstract

This paper estimates the degree of risk aversion of contestants appearing on *Vas o No Vas*, the Mexican version of *Deal or No Deal*. We consider both dynamic agents who fully backward induct and myopic agents that only look forward one period. Further, we vary the level of forecasting sophistication by the agents. We find substantial evidence of risk aversion, the degree of which is more modest than what is typically reported in the literature.

Keywords: Risk attitude; Uncertainty; Expected utility theory; Game show
JEL classification: D8, C9

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I. Introduction

Attitudes toward risk play significant roles in explaining a vast range of individual choice and behavior. Therefore economists have long attempted to elicit the degree of risk aversion from naturally occurring data sources as well as surveys and experiments in the laboratory and field. Empirical findings are surprisingly dispersed. From a field experiment in India, Binswanger (1981) finds that when payoffs are small, about 50% of individuals are fairly risk averse while a third of subjects are risk neutral or risk loving over small stakes. Using financial market data, Hansen and Singleton (1982) find that the coefficient of relative risk aversion is near 1. In a laboratory experiment, Holt and Laury (2002) find that 81% of subjects are risk averse, while 13%-29% are risk neutral and 6% are risk loving. For about 60% of their subjects, the coefficient lies between 0.15 and 0.97. Chetty (*forthcoming*) infers risk preferences from labor supply behavior and finds the coefficient of relative risk aversion ranges from 0.15 to 1.78 with an average of 0.71. Using a set of hypothetical lottery questions in the Health and Retirement Study, Barsky, Juster, Kimball, and Shapiro (1997) also find substantial heterogeneity in risk tolerance. Using similar questions in the German Socio-economic Panel, Dohmen, Falk, Sunde, Schupp, and Wagner (2005) estimate the constant relative risk aversion coefficient and find that it mostly lies between 1 and 10 but there is a non-negligible mass for higher values up to 20.

A variety of game shows also provide natural experiments on risk attitudes; refer to Gertner (1993) for *Card Sharks*, Metrick (1995) for *Final Jeopardy!*, Hersch and McDougall (1997) for *Illinois Instant Riches*, Beetsma and Schotman (2001) for *Lingo*, Fullenkamp, Terino, and Battalio (2003) for *Hoosier Millionaire*, Hartley, Lanet, and Walker (2005) for *Who Wants To Be A Millionaire* (2005). Despite of the possibility that participants in these game shows are not representative of population, the advantage of using data from game shows is that we can recover risk preferences more accurately because they are not only comparable to a well-controlled laboratory environment but involve large stakes (Kachelmeier and Shehata 1992). These game show studies also find a relatively wide range of risk preferences.

This paper provides further information regarding risk preferences by examining individuals' gambling decisions in a popular Mexican television game show, *Vas o No*

Vas.[1] This game show is well-suited to our agenda due to its simple and clean setting. The show is particularly attractive because it is the game of pure luck and individual decisions that solely depend on contestants' preferences while other shows somehow require intellectual ability. The remainder of the paper proceeds as follows. In Section II we briefly explain the game show. Section III presents our estimation strategy to recover risk preference parameters in standard utility functions. Section IV discusses our findings and compare with previous findings, including concurrent papers that examine variants of the game in other countries. Section V concludes.

II. The Game Show

Our data are from "Vas o No Vas", the Mexican version of the television program "Deal or No Deal" which airs in many countries around the globe. The format of the show is similar in each market, but there are slight variations. In the Mexican version, once a contestant is selected from the audience, 26 models appear with identical briefcases. Each briefcase contains a sheet specifying an amount of Pesos. The distribution of amounts is common knowledge, but the contestant, host, and models do not know the contents of any briefcase. Table 1 gives the denominations in the briefcases. At the first stage the contestant selects a single brief case which is set aside. This is the only briefcase from which the contestant can collect the amount of money inside. The game then proceeds to a series of rounds. In the first round, the contestant selects six of the remaining 25 briefcases. These six briefcases are opened, revealing the amounts inside which the contestant will not collect. At this point the "bank", who also does not know the contents of any briefcase, makes an offer.[2] The contestant can decide to end the game and take the offered amount or continue playing the game. If the contestant chooses to continue, another five briefcases are selected, their contents revealed and a new offer is generated. This process continues with the revelation of four then three then two briefcases. Beginning in the sixth round a single briefcase is selected each round. In the

[1] A variant of this show is now airing in the U.S. under the name *Deal or No Deal*.

[2] The only one who knows the contents of each briefcase is the government official who was in charge of filling the briefcases and he plays no role in the show. This is an important feature of the game because the bank can strategically make offers if it knows the value of the held briefcase and contestants should take it into account for their decisions. Without this kind of complication it is easier to elicit risk aversion from participants' decisions in the Mexican show.

ninth round, there are only two active briefcases, the original one set aside and one other. If the contestant rejects the bank's offer, the original briefcase is opened and the contestant's payment equals the amount revealed. Regardless of outcome, the show concludes with the contestant being presented an oversized check.[3]

The data were collected from the television network's website.[4] In most cases the show summary provides a complete description of the peso amount revealed and the offers made each round. However, in some cases a complete record is not provided and those episodes are omitted from our analysis.

III. Data Analysis

To determine the optimal choice, consider the decision a contestant would face in the final round. Let the value if each briefcase be denoted B_1, B_2 …, B_{26}, where $B_1 = 1$, $B_2 = 5$ and so on from Table 1. In the ninth and final round only two briefcases, *i* and *j*, remain active. A contestant must compare the utility of the offer $u(O_{ij})$ and the lottery of $u(B_i)/2+u(B_j)/2$, where $u(O_{ij})$ is the offer made when briefcases *i* and *j* remain active. In the eighth round the contestant has three active briefcases, B_i, B_j, and B_k, and a certain offer of O_{ijk}. At this stage the contestant must compare $u(O_{ijk})$ and the expected utility of continuing to the final round given by:

$$E[u(continuing \mid i,j,k)] = \frac{1}{3}\int \max[u(O_{ij}), \frac{u(B_i)}{2} + \frac{u(B_j)}{2}] f(O_{ij}) dO_{ij} + \frac{1}{3}\int \max[u(O_{ik}), \frac{u(B_i)}{2} + \frac{u(B_k)}{2}] f(O_{ik}) dO_{ik} + \frac{1}{3}\int \max[u(O_{jk}), \frac{u(B_j)}{2} + \frac{u(B_k)}{2}] f(O_{jk}) dO_{jk} \quad (1)$$

where $f(O_{ij})$ denotes the probability distribution of the offers that would be made if briefcases *i* and *j* are the only active briefcases. Likewise, in the seventh round, the expected utility of continuing is given by:

[3] This feature differs from some other contests where the recipient only receives the large novelty check for winning large prizes. Fullenkamp et al. (2003) point out that such a presentation may influence behavior.

[4] The show summaries can be viewed at www.esmas.com/vasonovas. The data was collected from the first 62 shows televised in Mexico in 2005 and 2006. As seen in Table 1, during this time, the format of the show changed with respect to the money amounts in the 26 briefcases. The analysis considers this formatting change to be exogenous. The data used in the analysis are available from the authors upon request.

$$
\begin{aligned}
E[u(continuing \mid i,j,k,l)] = &\frac{1}{4}\int \max\{u(O_{ijk}), E[u(continuing \mid i,j,k)]\} f(O_{ijk})dO_{ijk} \\
&+\frac{1}{4}\int \max\{u(O_{ijl}), E[u(continuing \mid i,j,l)]\} f(O_{ijl})dO_{ijl} \\
&+\frac{1}{4}\int \max\{u(O_{ikl}), E[u(continuing \mid i,k,l)]\} f(O_{ikl})dO_{ikl} \\
&+\frac{1}{4}\int \max\{u(O_{jkl}), E[u(continuing \mid j,k,l)]\} f(O_{jkl})dO_{jkl}
\end{aligned}
\tag{2}
$$

Iterating this process gives the comparison faced by a participant at any round. In analyzing behavior we consider four types of participants that differ along two dimensions. The first dimension pertains to how the participant believes the offers are generated in future rounds, these beliefs are either sophisticated or naïve. Those we term "sophisticated" participants anticipate that the future offer is based not only upon the expected value of the active briefcases, but the variance. In addition, we assume that they know that the offer depends on round since the broadcasters and advertisers want the game to last for the entire time slot building suspense as it goes and, as a result, the offer is pretty small in the earlier phase. We assume that sophisticated participants estimate the following double-log offer function for forecasting:

$$
\ln O_n = 0.99 + 1.23 \cdot \ln \overline{B}_n - 0.31 \cdot \ln SD_n - 0.09 \cdot n - 0.002 \cdot n^2 \tag{3}
$$

$R^2 = 0.93$ Number of observations = 411

where $\overline{B}_n$ and SD_n denote average and standard deviation of the monetary values in the n active briefcases. We assume that participants estimate the natural logarithm of offer to ensure that the predicted offer is positive. The sample includes all the offers made at every round in the shows we examine except for one show in which an exceptionally generous offer was made at Christmas. All the estimates of this sophisticated offer function are significant at the 5 percent significance level. The high R^2 reflects the notion that the offer is quite predictable. The estimates are consistent with our expectation. The offer is higher when the expected value of the remaining briefcases is higher and/or when the standard deviation is lower. The offer also increases when there are fewer briefcases left. Figure 1 plots the predicted and actual log offers.

We also assume that sophisticated contestants know the uncertainty regarding their point prediction. To account for this, we assume that they use the prediction error from the estimation to determine the distribution of offers, the $f(\cdot)$ in equation (1) and (2). Assuming that the error term related to equation (3) follows a normal distribution, we estimate its standard deviation. For computational convenience, we discretize the support of the distribution of the predicted offer, symmetrically around the mean, into seven intervals and assign the cumulative probability to the corresponding point in each interval.[5] On the other hand, we assume that "naïve" participants simply expect that future offers will be the average of the values in the active briefcases, that is $O_n = \overline{B}_n$.

The second dimension is the degree to which participants are forward looking. The "dynamic" participant reasons through the ramifications of a decision to the game's end, as we described in equation (1) and (2). On the other hand "myopic" participants only look one period ahead, treating the next period's offer or distribution of offers depending on sophistication as the value of arriving at that stage of the game. In the example for the seventh round, this simply amounts to replacing $\max\{u(O_{ijk}), E[u(continuing \mid i, j, k)]\}$ with $u(O_{ijk})$ in equation (2).

By seeing if a person chose to continue or stop the game, we observe only a bound on their risk attitude. In general, though not always, offers are below expected value of the remaining briefcases. Therefore, generally speaking if a person opts to continue they are not too risk averse and, if they opt to stop, they are not too risk loving. Hence, for individuals who do not go all the way, we can estimate both the upper and lower bound on their risk preferences, while we only know the upper bound for those who go all of the way.[6] We consider two standard forms for the utility function: Constant Relative Risk Aversion (CRRA) and Constant Absolute Risk Aversion (CARA). CRRA is modeled as $u(x) = \frac{(x+W)^{1-r}}{1-r}$ where W is initial wealth. CARA is modeled as $u(x) = \frac{1}{-\sigma} e^{-\sigma x}$. Our estimation technique essentially takes a value of the risk parameter for the given utility function and asks "is the choice that we observed consistent with someone who has this

[5] The support is divided into two 5%, two 10%, two 20%, and one 30% intervals.

[6] For example, Krahnen, Rieck, and Theissen (1997) show that it is misleading to estimate the degree of risk aversion by a single stage procedure.

risk value?"[7] For a person to be considered consistent with a particular parameter value, each decision that person made had to be consistent with that value. For computational simplicity we only consider behavior from round 4 with 8 briefcases or later. Even in round 4 there are 10,080 possible ways that briefcases can be eliminated, all of which must be considered in determining the optimal decision for a dynamic sophisticated person with a given parameter value. In the earlier rounds offers are very low presumably in an effort to keep the show going which evidently was successful as no one ever chose to take the offer in the first three rounds.

IV. Behavior in High Stakes Lotteries

This section presents a discussion of our findings. Using our methodology we have four categories of contestants. The first category includes those who accept an offer and have bounded risk preferences. The second includes those who are not consistent with any risk parameter value. That is, these subjects accept an offer indicating that they are more risk averse than a previous rejection that has indicated that they must be less risk averse than. The third category includes contestants that never accepted an offer and thus could be extremely risk loving. The fourth group includes those we cannot identify as being in one of the first two groups due to computational limits and the possibility that their behavior is consistent at extreme parameter values beyond our parameter range.

In general we observe similar levels of risk aversion as those reported in previous studies. While we find considerable variation in risk attitude boundaries, many of the participants behaved in a manner consistent with mild risk aversion. It is encouraging to note that only for a small fraction of people could their behavior not be explained by some level of risk aversion. We first present the results for CRRA and then present the results for CARA. A comparison with previous work is then offered.

The Level of Risk Aversion with CRRA.

To estimate the degree of relative risk aversion, initial wealth levels have to be specified. Given that data are not available for the wealth of each participant, we estimated risk attitudes at various wealth levels. Specifically, we used W_L = \$89,121

[7] A copy of the computer code is available from the authors upon request.

(low), W_H = \$209,902 (high), and $W_A = (W_L+W_H)/2$ (average), all in Mexican pesos.[8] For the exposition we focus on W_A, but where appropriate we include results for the other wealth levels in the accompanying tables.

The baseline case we present is for sophisticated dynamic agents. For 36 of the 52 participants we could estimate both lower and upper bounds on their risk parameters r, of which four were inconsistent. Fourteen of the contestants never accepted an offer and only for two of the subjects no bounds could be identified. This information is presented in Table 2 for all three wealth levels. Table 3 and Figure 2 provide the basic results for the 46 usable contestants (i.e. those for whom we could identify two consistent bounds and those that never accepted an offer). Table 3 presents the mean, maximum, minimum, standard deviation, and number of observations for the upper bound, the lower bound conditional on being observed, and the midpoint conditional on being observed. Figure 2 plots the possible range of r for each participant.

The highest possible value of r that any of these participants could have is 3.905. In fact only four participants (9%) could have $r \geq 2$, suggesting that we do not see much evidence of "extreme" risk aversion. On the other hand we do see evidence that at least a few subjects are extremely risk loving. The lowest upper bound we identify is -4.675 and five contestants (11%) must have $r < 0$. For the 32 participants that we could identify consistent upper and lower bound, the average midpoint of the parameter interval is 0.475, indicating that overall there is a mild degree of risk aversion. 26 of these 32 contestants (81%) must be risk averse, as indicated by intervals that lie completely above $r = 0$ in Figure 2, while only 1 must be risk loving. For the 14 with no observed lower bound, four (29%) must be risk loving. Following Bombardini and Trebbi (2005), if one assumes that risk parameters are normally distributed the maximum likelihood estimate of the mean based on the bounds of the 46 usable participants is 0.608. However this estimate is not statistically different from zero at the 10 percent significance level.

As mentioned earlier we relax the assumption of sophisticated dynamic contestants in two ways. One is what we term "myopic," in which the subjects only look one period into the future. The other is what we term naïve in which case the expected offer is

[8] W_L is computed using the 2002 GDP per capita from the OECD converted into pesos by using the official exchange rate data from the Central Bank of Mexico for that year. W_H is extracted from Loyola (2002).

simply the expected value of the contents of the active briefcases. This would suggest that we are considering four models; however, as it turns out the naïve offers are such that a dynamic person who can consider the possibility of continuing past the next period anticipates stopping next period to be optimal and thus is indistinguishable from a myopic naïve agent. Therefore, we have only two alternative specifications; sophisticated myopic and naïve.

As indicated by Table 2, allowing agents to be myopic and at the same time sophisticated in their offer beliefs is unappealing. With this specification we find that 11 subjects are not consistent with any value of r and we cannot determine consistency for 22 others. Essentially with this specification in early rounds where there is considerable variation, the participants expect low offers given their level of sophistication but do not consider the better future offers that will subsequently result as the variance decreases. When these participants continue it seems as though they are forgoing a relatively good offer in exchange for something they expect to be bad indicating risk loving preferences. Stopping suggests that the subjects are not too risk seeking, but given our computational limits we are unable to determine if the behavior is inconsistent or these participants have consistent preferences.[9]

Assuming that agents are naïve, there are 8 unidentified contestants but only 1 that is clearly inconsistent, as shown in Table 2. Under this model, we see a marked increase in the amount of risk aversion. Of those from whom we observe upper and lower bounds, the average midpoint increases to 2.636, see Table 3. The maximum r that we observe could be as high as 13.98, and 10 of the 43 usable contestants (23%) are sufficiently risk averse such that $r > 2$. In fact, as shown in Figure 3, all of the contestants could have a positive r. For this specification the maximum likelihood estimate of the mean of r is 1.076, which is statistically different from zero at the five percent confidence level.

The effect of our wealth choice is also demonstrated in Tables 2 and 3. By definition, increasing wealth makes a person making the identical decision appear more relatively

[9] The maximum prize is 5,000,000 and thus $r < -12$ results in the need to compute $(5{,}000{,}000+W)^{13}$, which creates an overflow error. Therefore, it could be that stopping indicates a constant's r is below -13.5, which is consistent with previous decisions indicting that r is less than -12 or it could be inconsistent with previous decisions indicating r is above -13.

risk averse. But it does not appear that the wealth assumption changes the results substantially.

The Level of Risk Aversion with CARA.

The results for CARA are summarized in Tables 4 and 5 and Figures 4 and 5. The basic conclusions are similar to the CRRA case. Again we find evidence of mild risk aversion in our sophisticated dynamic specification. The average midpoint for contestants for whom we could identify both bounds in 6×10^{-7}, see Table 5. Twenty six of the 46 usable contestants (57%) must be risk averse, while only one must be risk loving, see Figure 4. From Table 5, the highest possible σ we observe is 1.98×10^{-5} and the lowest σ that at least one contestant must have is -5.9×10^{-6}.[10]

As evidenced in Table 4 by the large number of inconsistent and unidentified contestants, the myopic sophisticated model is again unappealing.[11] However, the naïve model is reasonable. With this specification, the contestants appear more risk averse as a group, with the average midpoint shifted up to 4.8×10^{-6}. The maximum possible σ becomes 7.35×10^{-5} and 31 of the 49 usable contestants (63%) must be risk averse. With this specification, five of the contestants (10%) must be risk seeking, see Figure 5. It is interesting to note that this is greater than the percentage of contestants who must be risk loving in the sophisticated dynamic model.

Comparison with Other Studies.

As mentioned earlier, there are four concurrent studies using data from *Deal or No Deal* in different countries: Bombardini and Trebbi (2005) using data from Italy; Mulino, Scheelings, Brooks, and Faff (2006) and De Roos and Sarafidis (2006) using data from Australia; Post, and Van den Assem, Baltussen and Thaler (2006) using data from Belgium, Germany, and the Netherlands. In this section we compare our results and methodology with those from these studies. But first, we note some of the differences in show formats. In both the Australian and Italian shows, potential payoffs include non-

[10] The CARA utility function is not defined when σ is zero, so a maximum likelihood estimation based on normal distribution is not applicable.
[11] With CARA, computational limits do not allow us to evaluate values of σ below -7×10^{-5}.

cash prizes such as a car or a year's supply of soap.[12] In the Australian show, contestants may have supplementary rounds like "Chance" or "SuperCase" in which contestants can play another bonus round even if they accept the current offer. In the Italian show, contestants may have an option to "Change" allowing them to swap the held briefcase with any one of the remaining briefcases. This ability is non-trivial as the bank knows the amount of money held in each briefcase and thus the offers may be informative.

Analytical methodologies differ across studies in several ways. Mulino et al. assume that contestants look forward only one round as in our myopic model, but they assume participants compare the current offer with the expected utility of the remaining briefcases. In addition to a myopic or static model, the other three papers, like ours, attempt to fit data to the framework in which contestants compute all possible paths and solve a dynamic decision-making problem by using backward induction. A static model is defined differently though. Bombardini and Trebbi and De Roos and Sarafidis employ a myopic model similar to that of Mulino et al. while Post et al. assume that myopic contestants would stop by accepting an offer in the very next round as do we. But Post et al. do not consider the uncertainty or forecasting errors associated with future offers.

There are also differences in how contestants form expectations of future offers in the dynamic model. Post et al. estimate an offer function where future offers are a percentage of expected value dependent upon the current offer and round. However, they assume that future offers are predictable without error. Bombardini and Trebbi face a more difficult problem in that offers are potentially informative as the banker knows the contents of the briefcase and therefore, they consider both informative and uninformative offers. Like Post et al., Bombardini and Trebbi calculate the empirical distribution of offers as a percentage of expected value for each round.[13] As in our model, Bombardini and Trebbi assume that contestants take forecasting errors into account. However, they do not assume that contestants do not take into account the variance of the active briefcases, which we have found to be a significant factor impacting offers. Similar to our approach, De Roos and Sarafidis employ a regression approach to describe how contestants predict future offers. They assume that contestants base their forecasting on the mean and the

[12] The Mexican show introduced non-monetary payoffs after our sample period.

[13] In the case of informative offer, the empirical distribution is specific to the rank of the held briefcase among the active briefcases as well as round.

standard deviation of the remaining briefcases for each round, but they do not consider forecasting errors.[14]

Despite the differences in methodologies and show formats, it is interesting to compare the results across studies.[15] Mulino et al. find that participants in the Australian show are overall risk loving; in their myopic model, the CRRA coefficient estimate at the zero wealth level is -0.31 to -0.26 and significantly less than zero.[16] They find 24 inconsistent cases (about 26%). However, using data from the same Australian show, De Roos and Sarafidis find that the coefficient at the zero wealth level is between 0.16~0.24 (myopic) and 0.46~0.66 (dynamic) and all their estimates are significantly larger than zero. They find that, when evaluated at a higher wealth level (annual income), the estimates are larger (about 0.6 for the static model and 1.8~3.2 for the dynamic model). Trying to bound risk preferences, both studies ignore an extra incentive from "Chance" or "SuperCase" which is a special feature of the Australian show. Also both include "inconsistent" contestants for estimation.

Bombardini and Trebbi find that, for the Italian show participants, the CRRA coefficient is typically between 3.41 (static) and 3.15~4.03 (dynamic) when annual labor income multiplied by 10 is used for the initial wealth. The estimates are quite sensitive to the wealth level; under the dynamic model, they find 0.43~0.51 at the zero wealth and 1.08~1.37 with the wealth being the annual income. Despite the fact that the coefficient is on average significantly larger than zero, Bombardini and Trebbi find a large degree of heterogeneity in risk preferences. They also report that 4%-6% of participants are inconsistent, a slightly smaller percentage then we observed.

The results of Post et al. are most comparable to ours because of the similarity in show formats and similarities in methodological approaches. They find that the CRRA

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[14] Instead, De Roos and Sarafidis employ a random utility model including contestant-specific random effects.

[15] Cultural differences across countries could also explain some of the variation. However such a comparison should be done within a unified analytical framework, which is somehow infeasible due to the differences in show formats.

[16] This framework is exactly equivalent to the static model of Bombardini and Trebbi. They found that the estimated CRRA coefficients from the myopic model are lower than those from the dynamic model. This suggests that Mulino et al. estimate lower bounds on risk attitudes. On the other hand, as they explain in their paper, the presence of the Chance and SuperCase supplementary rounds makes contestants more likely to accept low offers. Ignoring in the analysis as they do would lead to overestimating the risk aversion coefficient. It is not clear which of these effects dominates.

coefficient ranges from 1.15 (wealth = 0) to 6.68 (wealth = annual income), which are higher than our estimates. The estimates become slightly lower under the myopic model. Like the other studies, they also find a non-ignorable mass of inconsistent behaviors (15% of participants).

Only two other studies estimate the CARA parameter. Mulino et al. present the average minimum upper bound of the CARA parameter, that is -7.8×10^{-6}. De Roos and Sarafidis find that the coefficient is between 6×10^{-6} (static) and 6×10^{-5} (dynamic), which again confirms that ignoring the possibility of backward induction and dynamic decision-making makes contestants appear less risk averse. Again except Mulino et al. our estimates are on average lower.

V. Conclusions

Risk attitudes are an integral part of the economy, which explains why they have been studied in may contexts. However, there is surprising little agreement on the degree of risk aversion in the population.[17] Game shows can provide a natural experiment for measuring risk. Unlike laboratory experiments in which the prize amounts are typically small, game shows typically involve substantial amounts of money.[18] *Deal or No Deal* offers a clean data set for evaluating people's risk attitudes in high stakes lotteries. In the Mexican version of the show that we analyze, the top price is 5,000,000 pesos (approximately US$442,000). Complete information is provided regarding the possible prizes, the offers the contestant faces, and the actual decisions of the contestant. The ability to cleanly observe behavior in high stakes situations, explains why several researchers are focusing on this game shows.

In general, we find substantial evidence of risk aversion in both the CRRA and CARA specifications. However, the degree of risk aversion is typically more modest than what has been reported by previous researchers. One possible explanation for this

[17] In fact, based upon laboratory experiments, Isaac and James (2000) conclude that the same individual exhibits different risk preferences in different decision problems.

[18] The relatively high stakes in the experiments of Holt and Laury (2002) involved a maximum prize of US$346.50. The ability to offer such large prizes on game shows is derived from the television network's ability to sell advertising space to large viewing audience which may impact behavior. Laboratory experiments by Dufwenberg and Muren (forthcoming) show that an audience can impact behavior in two person games. Of course, none of the models of risk aversion specify a minimum magnitude threshold below which risks are viewed differently.

difference is that Mexico is a developing country and economic development may change people's risk attitudes through various channels from life expectancy at the micro level to economic vulnerability at the macro level. We hope our study encourage more cross-culture comparative studies. We also find a considerable variation in risk attitudes, with a few people being extremely risk averse while others are risk loving. Ultimately, only a small percentage of people were found to be inconsistent with any reasonable level of risk aversion in either the CRRA or CARA specifications. More studies are required to determine if these inconsistent behaviors are simply random mistakes or due to the analytical limitation of the classical expected-utility framework.

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Table 1. Denominations in the 26 Briefcases

Format 1		Format 2	
$1	$20,000	$1	$7,500
$5	$25,000	$5	$10,000
$10	$50,000	$10	$25,000
$15	$75,000	$15	$50,000
$20	$100,000	$20	$75,000
$50	$200,000	$50	$100,000
$100	$300,000	$100	$200,000
$200	$400,000	$200	$300,000
$500	$500,000	$500	$400,000
$1,000	$750,000	$1,000	$500,000
$2,000	$1,000,000	$2,000	$1,000,000
$2,500	$2,500,000	$2,500	$2,500,000
$5,000	$5,000,000	$5,000	$5,000,000

Note: 36 shows follow "Format 1" and 16 follow "Format 2". The only change is the distribution of the payoffs, the mechanics of the game are the same.

Table 2. Distribution of Findings CRRA

	CRRA (W_A)	CRRA (W_L)	CRRA (W_H)
	Sophisticated Dynamic		
Upper and Lower bounds	32	33	30
No Lower bound	14	14	15
No Results	2	2	3
Inconcistencies	4	3	4
	Sophisticated Myopic		
Upper and Lower bounds	9	9	10
No Lower bound	10	11	10
No Results	22	20	23
Inconcistencies	11	12	9
	Naïve		
Upper and Lower bounds	31	32	31
No Lower bound	12	11	12
No Results	8	8	8
Inconcistencies	1	1	1

Notes: W_A (average), W_L (low) and W_H (high) denote the different levels of wealth considered in the study. W_L=$89,121, W_H = $209,902, and $W_A = (W_L+W_H)/2$.

Table 3. Summary of Results for CRRA Utility Function

	Sophisticated Dynamic			Sophisticated Myopic			Naïve		
	Lower Bound	Upper Bound	Average	Lower Bound	Upper Bound	Average	Lower Bound	Upper Bound	Average
				CRRA (W_A)					
Mean	0.008	0.676	0.475	-0.604	1.061	0.296	1.388	3.804	2.636
Max	1.870	3.905	2.060	0.750	3.900	1.920	3.470	13.980	5.730
Min	-4.695	-4.675	-3.995	-2.685	-1.810	-2.128	-3.180	0.045	0.855
Std. Dev.	*1.413*	*1.483*	*1.054*	*1.303*	*1.523*	*1.292*	*1.356*	*2.451*	*1.300*
No. Obs.	*32*	*46*	*32*	*9*	*19*	*9*	*31*	*43*	*31*
				CRRA (W_L)					
Mean	0.102	0.573	0.403	-0.514	0.566	0.204	1.004	2.966	2.074
Max	1.545	3.000	1.762	0.655	3.000	1.630	3.200	9.460	4.437
Min	-3.045	-2.925	-2.593	-2.190	-4.605	-1.828	-4.300	0.035	-0.490
Std. Dev.	*0.992*	*1.092*	*0.841*	*1.106*	*1.705*	*1.109*	*1.434*	*1.779*	*1.135*
No. Obs.	*33*	*47*	*33*	*9*	*20*	*9*	*32*	*43*	*32*
				CRRA (W_H)					
Mean	0.344	0.843	0.799	-0.416	1.298	0.539	1.529	4.391	2.994
Max	2.175	5.020	2.347	2.080	5.150	2.202	4.450	18.405	6.723
Min	-3.180	-4.550	-0.315	-3.180	-2.145	-2.420	-3.180	0.060	0.950
Std. Dev.	*0.859*	*1.697*	*0.595*	*1.662*	*1.791*	*1.486*	*1.444*	*3.167*	*1.503*
No. Obs.	*30*	*45*	*30*	*10*	*20*	*10*	*31*	*43*	*31*

Notes: W_A (average), W_L (low) and W_H (high) denote the different levels of wealth considered in the study. W_L=\$89,121, W_H= \$209,902, and $W_A = (W_L+W_H)/2$.

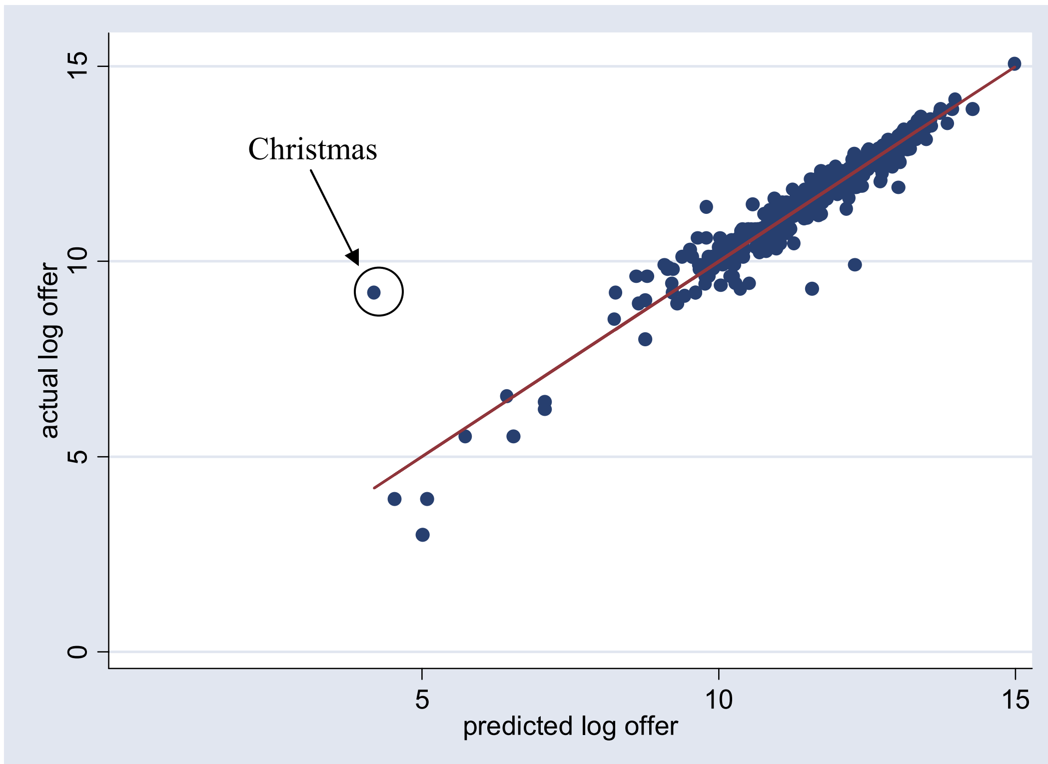
Table 4. Distribution of Findings CARA

Sophisticated Dynamic	
Upper and Lower bounds	32
No Lower bound	14
No Results	1
Inconsistencies	5
Sophisticated Myopic	
Upper and Lower bounds	16
No Lower bound	0
No Results	22
Inconsistencies	14
Naïve	
Upper and Lower bounds	35
No Lower bound	14
No Results	2
Inconsistencies	1

Table 5. Summary of Results for CARA Utility Function

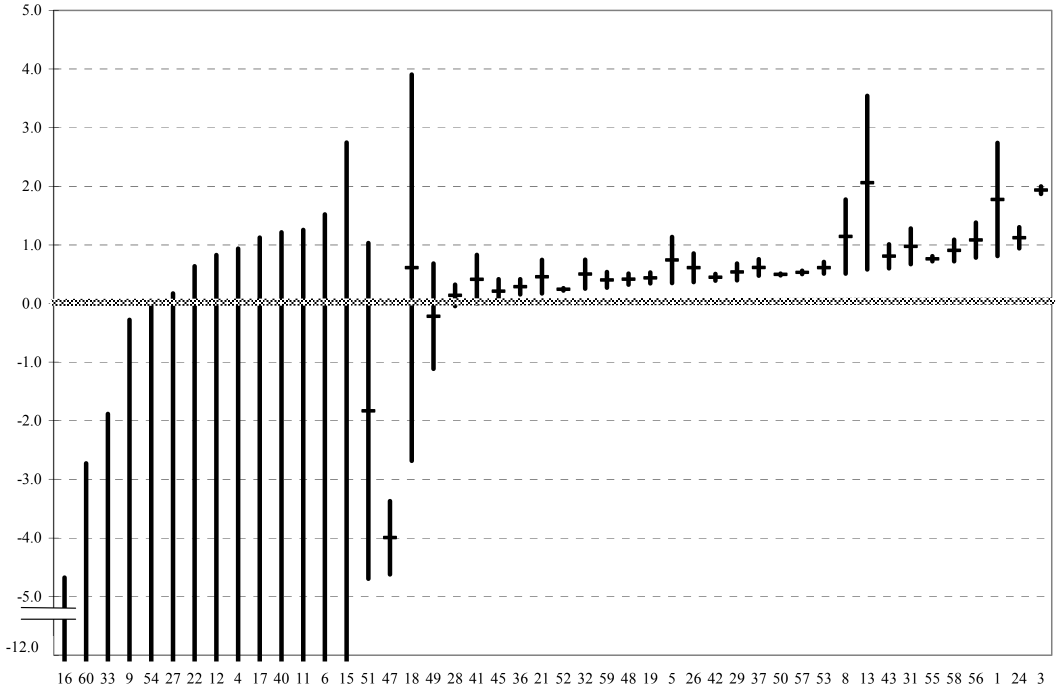
	Sophisticated Dynamic			Sophisticated Myopic			Naïve		
	Lower Bound	**Upper Bound**	**Average**	**Lower Bound**	**Upper Bound**	**Average**	**Lower Bound**	**Upper Bound**	**Average**
Mean	-0.0000013	0.0000026	0.0000006	0.0000006	0.0000048	0.0000027	0.0000010	0.0000081	0.0000048
Max	0.0000047	0.0000198	0.0000059	0.0000045	0.0000198	0.0000100	0.0000162	0.0000735	0.0000231
Min	-0.0000269	-0.0000059	-0.0000132	0.0000001	0.0000003	0.0000002	-0.0000269	-0.0000294	-0.0000228
Std. Dev.	*0.0000069*	*0.0000037*	*0.0000040*	*0.0000011*	*0.0000047*	*0.0000024*	*0.0000078*	*0.0000150*	*0.0000080*
No. Obs.	*32*	*47*	*32*	*16*	*17*	*16*	*35*	*49*	*35*

Figure 1. Predicted versus Actual Log Offers



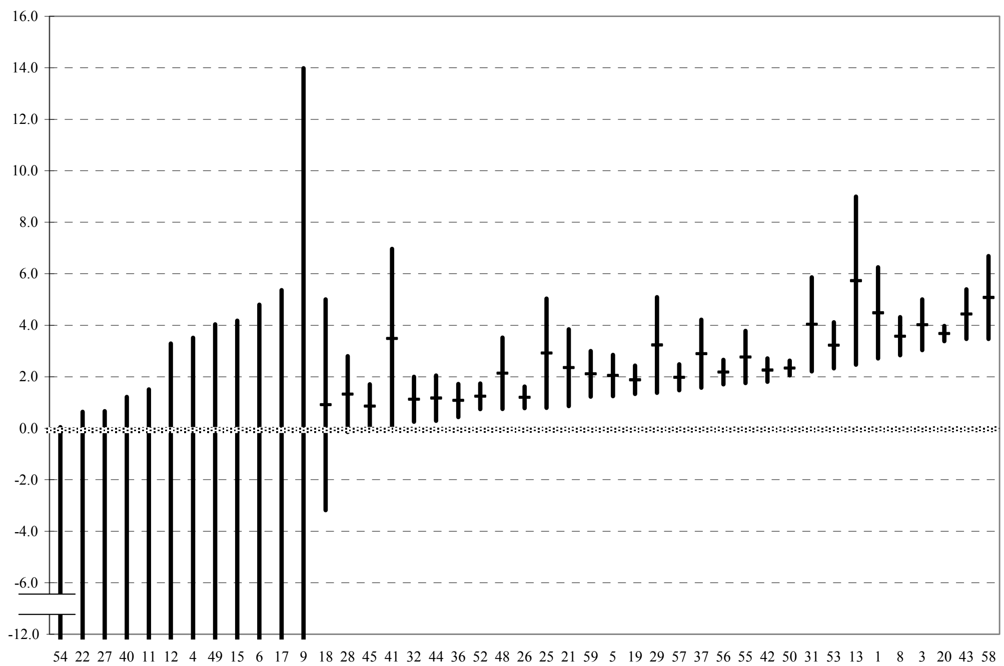
Notes: The outlier (Christmas offer) is not used for estimation.

Figure 2. Risk Aversion Estimates for Usable Contestants under CRRA with Sophisticated Dynamic Specification



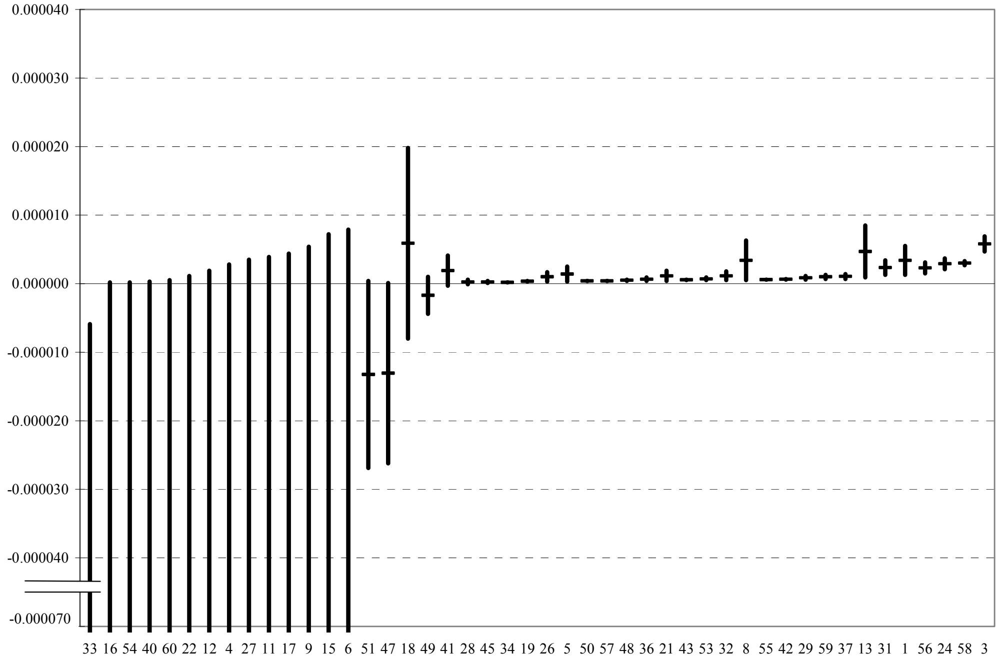
Notes: Mid points are removed for the shows that went all the way or for which we do not find a lower bound (show 17).

Figure 3. Risk Aversion Estimates for Usable Contestants under CRRA with Naïve Specification



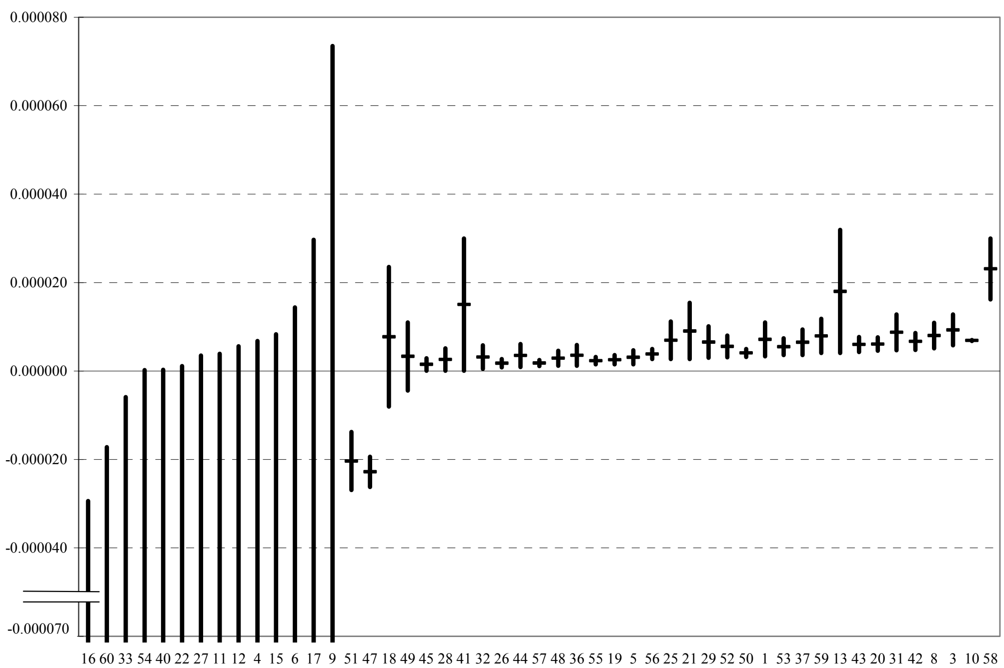
Notes: Mid points are removed for the shows that went all the way or for which we do not find a lower bound (shows 49 and 17).

Figure 4. Risk Aversion Estimates for Usable Contestants under CARA with Sophisticated Dynamic Specification



Notes: Mid points are removed for the shows that went all the way or for which we do not find a lower bound (show 17).

Figure 5. Risk Aversion Estimates for Usable Contestants under CRRA with Naïve Specification



Notes: Mid points removed for the shows that went all the way or for which we do not find a lower bound (show17).