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AN EMPIRICAL EXAMINATION INTO THE PROPENSITY OF RECKLESS DECISION-MAKING WITHIN THE HIGH-PRESSURE ENVIRONMENT OF DEAL OR NO DEAL

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ABSTRACT

This paper discusses human attitudes towards risk and the development of expected utility models, laying the foundations for the creation of prospect theory in 1979. It proceeds to analyse the decisions of contestants on the popular TV game show Deal or No Deal to attempt to observe any evidence of differing levels of risk aversion under losses and gains as predicted by prospect theory. The results reveal some evidence of decreased risk aversion in the domains of losses and gains, with contestants displaying behaviour consistent with the break-even and house-money effects. We conclude there may be enough evidence of variable reference points to warrant further investigation, and propose suggestions for further research.

Key words: Decision making under uncertainty, behavioural economics, behavioural finance, biases & heuristics, Prospect Theory.

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I. INTRODUCTION

Human attitudes towards risk have always played their part in the decision-making process. The St. Petersburg paradox first described by Swiss mathematician Nicolas Bernoulli in 1713 arises when dealing with infinite expected monetary values, ultimately suggesting that expected-wealth maximising individuals would pay an infinite amount of money to take a gamble with a very low probability of receiving an infinite amount in return. The solution to this paradox led to the first formulation of expected utility theory (EUT) in 1738 by Nicolas' Cousin, Daniel Bernoulli (Bernoulli, 1954). The essence of Bernoulli's solution introduced the concepts of a utility function and of diminishing marginal utility, ensuring that even gambles with an infinite expected value have a finite expected utility.

The theory was used as the foundations for further research into attitudes towards gambles, leading to the development of the von Neumann-Morgenstern utility theorem in 1947 (von Neumann & Morgenstern, 1947). This formulation incorporated the inherent risk aversion typically exhibited by individuals and was adopted by economists.

Since then, the shortcomings of EUT have repeatedly been highlighted by various studies, with the use of linear probability weighting functions (Allais, 1953) and the inability of the theory to provide a plausible account of risk aversion over moderate stakes (Arrow, 1971) prompting criticism and development. The effects that framing can have on a decision-maker prove that individuals consider more than simply the objective features of a gamble (Tversky & Kahneman, 1981). Whilst EUT can explain some risk aversion over very large stakes, its scope is limited to these very specific scenarios.

The anomaly of risk aversion within the EUT framework has been studied in depth (Rabin & Thaler, 2001). It has been proposed that prospect theory (PT) better describes individuals' attitudes towards risk due to the incorporation of loss aversion (Kahneman & Tversky, 1979). Tests run within the paper show that individuals will often reject moderate stakes gambles when faced with an equal chance of winning £x or losing £x, implying the utility function of gains and losses is not symmetrical. Furthermore, the origin represents the reference point for an individual, the relative location of which varies over time and circumstance. PT incorporates these important differences into its model. In addition, this increased sensitivity to losses relative to gains can see an increase or decrease in risk-seeking behaviour when evaluating gambles, depending on the location of the individual's reference point.

This paper will study contestant decisions in Deal or No Deal, a popular TV game show. From here, it will attempt to identify any evidence of contestants exhibiting an increase in risk-seeking behaviour when operating in the domain of losses (DoL), and/or a decrease in risk-seeking behaviour when operating in the domain of gains (DoG). The definitions of each domain will be clearly defined in section IV of the paper. The paper proceeds as follows. Section II introduces the game show and will explore the findings of any similar studies. Section III expands on the nature and implications of prospect theory, as well as detailing the various underlying psychological biases applicable to this study. Section IV details the methodology and data analysed. In Section V contestants' utilities about different prize amounts are modelled, and various coefficients are developed in an attempt to quantify the risk of accepting a gamble. Section VI presents the results and analysis with reference to noticeable differences in behaviour between domains. Section VII concludes the paper.

II. DEAL OR NO DEAL AND SIMILAR STUDIES

Conceived in the Netherlands, Deal or No Deal's popularity has seen it spread to various countries around the world, although the format has remained largely the same. This paper will use the UK version of the game. Whilst various studies have used other game shows to measure risk attitudes (Beetsma & Schotman, 2001; Gertner, 1993; Hartley et al., 2013), Deal or No Deal is unique in terms of its structure and rules, and provides the perfect environment in which to examine decision-making under uncertainty. The lack of any quiz-type elements significantly reduces the effect intelligence has on the prosperity of a contestant's game, in turn increasing the significance of good fortune. It can be postulated that dealing with pressure and managing to overcome greed and psychological biases are the most important skills a contestant can have, to ensure a consistent and considered decision-making process is followed when required.

The standard[2] game consists of 22 numbered boxes, each with a value hidden inside, from 1p to £250,000. A contestant selects a box, which becomes their box for the rest of the game. They then proceed to open the remaining boxes one by one, thus eliminating values from the game. After five boxes have been opened, an individual known as "the banker" contacts the contestant and makes an offer for the contestant's box. The contestant can choose to accept (deal) or reject (no deal) this offer. The

[2] Whilst Deal or No Deal in the UK has a standard format outlined in this section, the show does occasionally see deviations from this format, often themed to coincide with various holiday seasons. For sake of consistency and accuracy, this paper will only use data from episodes that used the standard format.

banker will then make another offer after every three boxes opened thereafter. If the contestant removes high value boxes, the banker's offer decreases, reflecting a drop in the expected value of the contestant's box, and vice versa. As such a contestant wishes to open only low value boxes up until the point they choose the deal, and subsequently only open high value boxes. This ideal scenario sees the contestant choose to deal at the highest possible offer, before eventually with luck having an amount in their box lower than or equal to the value at which they dealt. If a player elects to stay in the game until the very end, they are presented with a final choice which is to "Swap" or "No Swap". This refers to swapping their box with the one remaining box left in play, claiming the contents of this box as a prize instead.

Various phenomena have been observed by a previous study conducted into decision-making within Deal or No Deal (Post et al., 2008). In this study, a contestant on the Dutch[3] edition of the show named Frank had a particularly unlucky run of boxes before removing the largest remaining value of €500,000. This saw the expected value of his box to drop from €102,006 to €2508. Frank went on to reject all subsequent offers, the last of which was 120% of the expected value. This increase in risk-seeking behaviour is consistent with the break even effect, with Frank attempting to recoup some of his losses. An elegant example of an increasing Risk appetite in loss.

The same paper explored the game of Susanne, a contestant on the German edition of the game. Susanne, contrary to Frank, had a particularly fortunate run of boxes and was left with €100,000 and €150,000 in play. She rejected an offer of €125,000, instead choosing to gamble on and ultimately won the larger amount of €150,000. This was despite the banker offer being 100% of the expected value, 2% higher than the average amount offered by the banker at the same stage of the game to other contestants categorised as "winners". This was behaviour representative of the house-money effect, or an increase in risk-seeking behaviour due to the sensation of playing with someone else's money. This is due to the fact that Susanne would still feel like a winner even if she won the minimum amount possible (€100,000).

The break-even effect exhibited by Frank is consistent with the predictions of Kahneman and Tversky, as if Frank's reference point had been the expected value of his box or the largest offer so far, removing the €500,000 would certainly place Frank in the domain of losses and would incite risk-seeking behaviour. Interestingly however, Susanne's display of risk-seeking behaviour is not in line with the predictions of prospect theory, which suggests increased risk aversion in the domain of gains. It is argued by the paper that both the break-even and house-money effects are examples of individuals failing to completely adapt to prior losses and gains. It

[3] The Dutch version of the show is different in that it is played over 9 rounds and there is considerably more money at stake.

may also be the case that Susanne is an extremely risk-seeking person, and when operating in the domain of gains at the end did display an increase in risk aversion, *relative to her behaviour in earlier rounds.*

It has been suggested that certain industries attract individuals with a higher risk tolerance (Nguyen & Leung, 2009). As such, contestants on Deal or No Deal, whilst heterogeneous about their specific risk preferences, can perhaps be assumed to be less risk-averse than their non-contestant counterparts. This may have important implications within the construct of this study, and as a result it will not necessarily be possible to generalise any findings of this study to individuals in the wider world.

III. PROSPECT THEORY AND PSYCHOLOGICAL BIASES

As touched on in section I, the introduction of prospect theory in 1979 introduced new concepts that are intuitively easy to understand yet could not be explained by EUT. The first of these was the idea that individuals evaluate their situation or choices around some reference point and do not associate utility with absolute values of wealth, but rather with gains and losses around this reference point. This reference point can be the status quo, but occasionally might be expected gains or losses. The idea of a variable reference point is described by the following example.

Two individuals, Alex and Beth, possess equivalent initial wealth. Alex takes a gamble with a 99% chance of winning £100,000 and a 1% chance of winning nothing. Beth takes a gamble with a 1% chance of winning £100,000 and a 99% chance of winning nothing. Both gambles are risk free, in that nothing can be lost. According to EUT, therefore, no utility can be lost, and everyone would be expected to take the gamble. If neither gamble wins however, it's fair to assume that Alex will be more disappointed than Beth. This is indicative of Alex effectively setting up a new reference point for himself due to the overwhelming odds of winning the gamble (Kahneman, 2011).

As such, a Deal or No Deal contestant's reference point may take on multiple values, not only between subjects but over the course of an individual's game. These values could match initial hopes/expectations, the highest offer received so far or the estimated expected value of the contestant's box. It could also be the case that as with the preceding example contestants doing particularly well or poorly tentatively set up new reference points for themselves according to how they think they're likely to do. The position of the reference point must be known to determine whether contestants are operating in the domains of losses and gains, and thus will be clearly defined in section IV.

Whilst prospect theory's contribution of evaluating gambles with regards to losses and gains about a reference point was undoubtedly an important one to the study of decision-making under uncertainty, the theory was not without its limitations. The original paper's choice problems posed to test subjects were hypothetical situations using moderate amounts in which no money was really ever going to be won or lost. Evidence since has shown that whilst risk aversion increases sharply as real potential gains or losses increase (Bosch-Domènech & Silvestre, 1999), the same cannot be said for hypothetical scenarios (Holt & Laury, 2002). Furthermore, psychological stress has been shown to impede the decision-making process (Keinan, 1987). With TV cameras, life-changing amounts of money, time constraints and the knowledge that a contestant probably has just one opportunity to play the game[4], there is strong evidence to support that Deal or No Deal is an extremely stressful environment.

With rational decision-making expected to be affected then, the importance and prominence of various psychological biases may enter into play. Biases can be categorised as either cognitive or emotional (Pompian, 2012). Cognitive biases are "basic statistical, information processing or memory errors that can deviate from rationality", whereas emotional biases are those that "arise spontaneously as a result of attitudes and feelings". Whilst many biases could perhaps be observed within the Deal or No Deal framework, the primary purpose of this paper is to identify any evidence of an increase or decrease in risk-seeking behaviour, and not to explain speculate on biases that may be driving these changes. As such, this section discusses only those biases that link strongly to the topics already discussed.

The gambler's fallacy is a cognitive bias which occurs as a result of individuals misunderstanding the nature of chance. It's been demonstrated that individuals who see a roulette wheel show red a few times sequentially erroneously believe that a black is due to show, and place an increased probability of this occurring (Tversky & Kahneman, 1974). A contestant on Deal or No Deal experiencing the same illusion may believe that an all-red round (unlucky) should be followed by a more forgiving round than perhaps the odds would dictate. A contestant with a strong enough conviction in this fallacy may have their decision affected when considering the banker offer. This is a key example of probability matching Koehler & James (2009).

The illusion of control bias is the notion that individuals like to believe they have more control over uncertain events than they actually do. This is shown by contestants regularly choosing boxes in some order that has some personal significance to them. Placing exaggerated importance on the order in which boxes are opened can place additional pressure on a contestant, and as discussed earlier, pressure most frequently has a negative impact on the decision-making process. A way to prevent this from

[4] Whilst unverified, no individuals ever played the UK version of the game show more than once, to the author's knowledge.

happening would be to choose a random order, or even just to open boxes sequentially.

IV. METHODOLOGY & DATA COLLECTION

The data examined has been obtained from two sources. The first dataset has been obtained from the official Deal or No Deal website, and contains very general information relating to the games of 1686 contestants from January 2006 to December 2011. The second dataset has been created by the author from detailed reports of the games of 20 random[5] individuals from the first dataset, and contains much more information relating to the paths taken by contestants through the game. These reports were available freely online via a website created by fans of the game show.

The first dataset is to be analysed to provide a general overview of the sample. This includes finding out various means and medians relating to the different variables, and establishing whether or not the majority of contestants *beat the banker*[6] or not. It will also be interesting to investigate whether the banker behaves consistently throughout the various seasons, with regards to the generosity of offers made.

The second dataset will be examined to ultimately answer the research question at hand. To do this, two models are developed to estimate the utility of wealth for any given contestant. From here, multiple risk coefficients can be produced to measure how risky gambling on would be at each banker offer. These risk coefficients vary in complexity and efficiency, with each being detailed thoroughly in the next section of this paper.

An extensive list of additional variables will also be collected for each contestant (see Table 1). These variables are for the most part the values of the boxes opened by the contestants in their correct orders, as any analysis needs to be path-dependent. This should highlight any evidence of the altering of reference points, in line with prospect theory. From here, all absolute monetary values will be transformed so that the utilities of these amounts can be worked with. At each banker offer stage, the various models will reflect the risk of continuing on, using the variables at that particular point in time. The steps within this section will be carried out for all 20 contestants in this dataset.

[5] A random number generator was used to ensure that any findings of this paper can reasonably be applied to the wider population.

[6] "Beating the banker" is a scenario in which a contestant accepts an offer from the banker of greater value than their box contents

The analysis of the second dataset will comprise of two subsections. The first will look at the sample as a whole, investigating which contestants accept/reject the most/least risky gambles, according to the models and risk coefficients devised. The average round in which contestants choose to accept the banker offer will also be established, as well as the range of maximum risk coefficients associated with each contestant's decision to not gamble further.

The second subsection of the analysis will attempt to answer the research question. As the research question centres on behavioural inconsistencies in the domain of losses and gains, these terms must be defined within the context of this study. The domain of losses will be characterised as seeing the banker offer reduce by a third or more from one round to the next. Similarly, the domain of gains will be characterised as seeing the banker offer increase by 50 percent (or more) from one round to the next. The scenarios that fit these criteria will be investigated, to analyse the contestants' decisions when facing gambles with the largest and smallest associated risk coefficients. These results will be compared with contestants' decisions when facing gambles with similar risk coefficients, though are said to be operating outside of any particular domain by the definition outlined in this section.

TABLE 1

Description of Additional Variables within the Detailed Dataset

Variable Name	*Type*	*Description*
PreviousContestantWinnings	Float	The amount won by the most recent contestant
Female	Binary	Indicates contestant's gender
B1	Float	Value of box opened 1st
B2	Float	Value of box opened 2nd
B3	Float	Value of box opened 3rd
B4	Float	Value of box opened 4th
B5	Float	Value of box opened 5th
B6	Float	Value of box opened 6th
B7	Float	Value of box opened 7th
B8	Float	Value of box opened 8th
B9	Float	Value of box opened 9th
B10	Float	Value of box opened 10th
B11	Float	Value of box opened 11th
B12	Float	Value of box opened 12th
B13	Float	Value of box opened 13th
B14	Float	Value of box opened 14th
B15	Float	Value of box opened 15th
B16	Float	Value of box opened 16th
B17	Float	Value of box opened 17th
B18	Float	Value of box opened 18th
B19	Float	Value of box opened 19th
B20	Float	Value of box opened 20th
B21	Float	Value of box opened 21st
BO1	Float	Amount of 1st banker offer
CD1	Binary	Indicates whether contestant dealt to 1st banker offer
BO2	Float	Amount of 2nd banker offer
CD2	Binary	Indicates whether contestant dealt to 2nd banker offer
BO3	Float	Amount of 3rd banker offer
CD3	Binary	Indicates whether contestant dealt to 3rd banker offer
BO4	Float	Amount of 4th banker offer
CD4	Binary	Indicates whether contestant dealt to 4th banker offer
BO5	Float	Amount of 5th banker offer
CD5	Binary	Indicates whether contestant dealt to 5th banker offer
BO6	Float	Amount of 6th banker offer
CD6	Binary	Indicates whether contestant dealt to 6th banker offer

V. MODELS & RISK COEFFICIENTS

To measure a contestant's aversion to risk, an accurate and consistent measure of the riskiness of rejecting a banker offer in favour of gambling must be modelled. An extremely basic model might determine this risk coefficient to be simply a function of the banker offer (o) over the expected value of the boxes remaining (μ).

$$r_1 = \frac{o}{\pi}$$

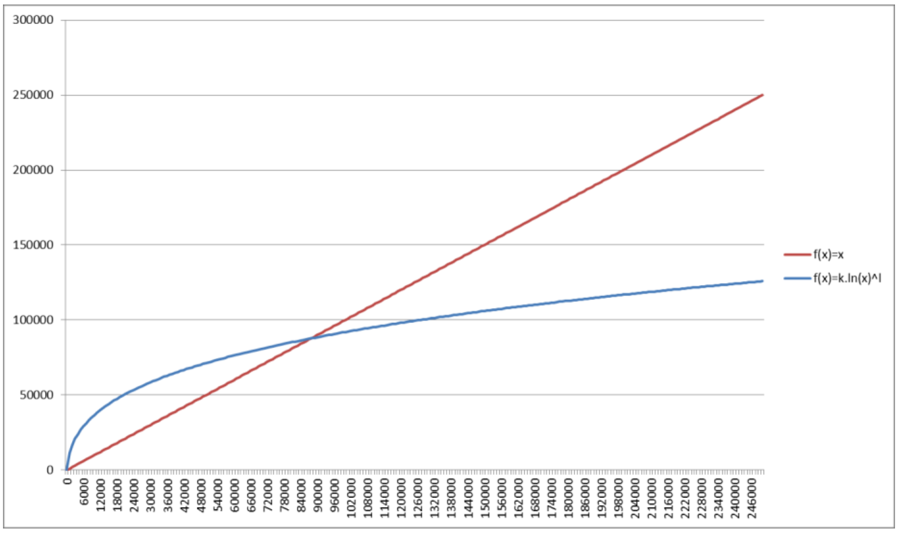
This approach however uses absolute monetary values in the equation. As it is not the true amounts at stake that are considered by contestants but rather the utility these amounts provide, a transformation must be incorporated into the model before any evaluation of risk can take place. Intuitive thinking tells us that an extra unit of wealth provides less additional utility to a rich individual than to a poor individual. This law of diminishing marginal utility was considered by Daniel Bernoulli who hypothesised that the utility of wealth (*u(x)*) can be expressed as a logarithm of the absolute monetary value.

$$u(x) = \log x$$

Contestants on Deal or No Deal can be assumed to gain more additional utility from £10,000 to £20,000 than from £100,000 to £110,000. Building on Bernoulli's hypothesis, a transformation function *f(x)* might look as follows:

$$f(x) = k.\ln(x)^l$$

Variables k and l are parameters and are arbitrary. Setting both to 4.1 produces the following curve:



With this transformation function, a new risk coefficient r_2 can be developed that successfully incorporates the law of diminishing marginal utility.

$$r_2 = \frac{f(o)}{f(\mu)}$$

At larger amounts, the rate of change in $f(o)$ and $f(\mu)$ decreases, and thus the incentive to gamble on also decreases, as contestants acknowledge that more utility can be lost from a decrease in some x than can be gained from an increase in the same x. This equation, whilst an improvement, still fails to model the evaluation of risk accurately under certain circumstances. For example, consider the following two choices:

50% chance of £90,000 and 50% chance of £110,000 OR £100,000 for sure (c1)

50% chance of nothing and 50% chance of £200,000 OR £100,000 for sure (c2)

The expected value of both gambles is the same, and the banker offer is the same. As a result the expected utilities are the same, and the respective r_2 coefficients for each choice are identical, implying that each gamble is as risky as the other. Most people would disagree with this suggestion, arguing that choice 2 is considerably riskier than choice 1, as a result of the standard deviation (σ) about the mean being much larger. The reason an increase in σ of the remaining boxes leads to a perceived increase in risk could be due to the tendency for individuals to naturally be more sensitive to losses than to gains, and thus increasing the stakes would increase the risk.

Whilst small losses have been shown to loom larger than small gains, larger amounts sees the effect exacerbated (Kahneman & Tversky, 1984). As the pain of leaving with nothing in choice 2 would be much greater than the increase in utility that could be gained from an extra £100,000. It would thus be safer to accept the sure thing in this instance. In choice 1 however, the utility provided by the worst possible outcome (£90,000) might offset any negative feelings experienced by losing the gamble, and hence the gamble is more likely to be taken. Indeed, an individual with immense wealth might see both choices as trivial. For the purposes of this study however, contestants are assumed to be homogenous with regards to their utilities of wealth.

To account for the effects a change in σ has on the evaluation of risk, a third risk coefficient r_3 is defined as follows:

$$r_3 = \frac{f(o)}{\sigma/\mu \cdot f(\mu)}$$

$$r_3 = \frac{\mu . f(o)}{\sigma . f(\mu)}$$

Incorporating the mean as a proportion of the standard deviation and multiplying this by *f(μ)* leads to a new risk coefficient that is altered by the spread of boxes still remaining in play. It is important to note that this model, when applied to the two choice problems above, give a larger risk coefficient to choice 1 (10) than to choice 2 (1). This is due to the extreme values presented in the choices, to illustrate a previous point. Choice 1 gives $\sigma/\mu = 0.1$ which causes such a high r_3, whereas in reality, σ/μ is never that low. In our dataset, the lowest value is 0.25, and only in 15 of 120 instances are the values lower than 1. The trend generally is that this component shrinks in magnitude throughout a contestant's game, leading to an enlarged (relatively speaking) r_3 as time continues. Any analysis will consider this limitation when dealing with standard deviation-to-mean ratios lower than 1.

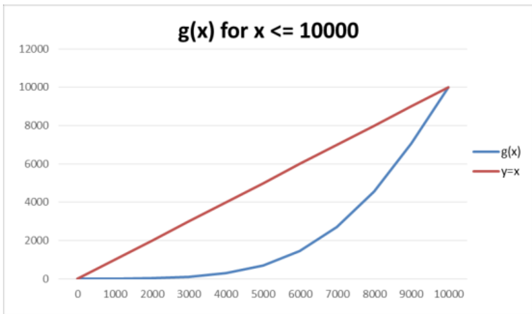
Though *f(x)* more accurately reflects the utility of wealth than *x*, it has severe limitations when dealing with small amounts. Though what is defined as a small amount will in practice vary between contestants, a general assumption can be made that contestants arrive on the game show with some reference point *r* in their minds. The current model has the steepest gradient near the origin, implying this is where the most utility is gained for an increase in *x*. I would argue that amounts smaller than the reference point are underweighted, or $u(x) < x$ for $x < r$. At *r,* the utility is accurately realised, or $u(x) = x$ at $x = r$. The utility at $x > r$ can still be essentially modelled by *f(x)*, only shifted horizontally by *r* and vertically by an arbitrary constant *c*.

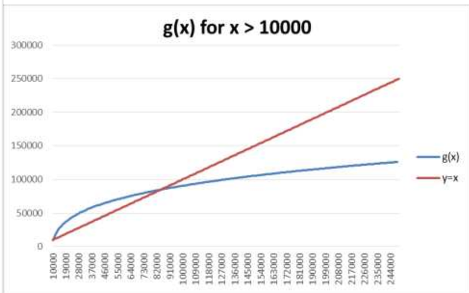
The new model *g(x)* can be defined as follows:

$$g(x) = \left\{\frac{2rx^3}{(x^3 - x + 2r)^3}\right\} \text{ for } x \leq r$$

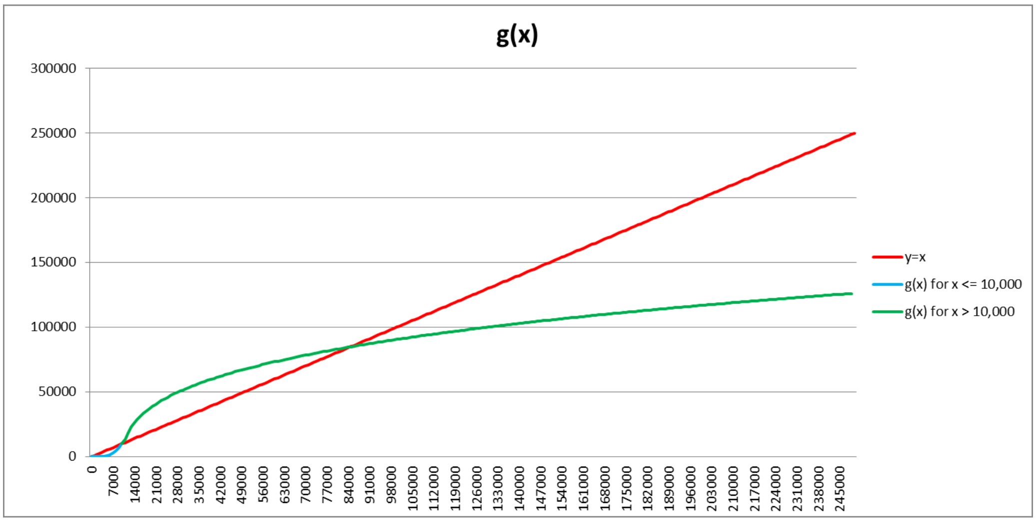
$$g(x) = \{k.\ln(x - r)^l + c\} \text{ for } x > r$$

Setting *r* to £10,000 seems like a reasonable reference point to define for any given contestant. This is due to numerous contestants stating their target amount of around this figure before the game has commenced, and the median prize money dealt to contestants from the general dataset being only slightly higher at £12,000. Setting *c* to 2000 prevents the gradient of the curve from increasing as *x* approaches £10,000, decreasing briefly from £10,000 to £11,000, before increasing again above £11,000, as there is no reason to assume that this would be the case. Keeping k and l at 4.1 produces the following plots:





When plotted on the same graph, the following curve is produced:



Substituting f(x) for g(x) in r_2 and r_3 creates two new risk coefficients, r_4 and r_5.

$$r_4 = \frac{g(o)}{g(\mu)}$$

$$r_5 = \frac{\mu . g(o)}{\sigma . g(\mu)}$$

The notion of an increasingly risky game has not yet been incorporated into any models, besides the gradually decreasing ${}^{\sigma}/_{\mu}$ (or increasing ${}^{\mu}/_{\sigma}$). As contestants are trying to avoid large values to maximise their offers and expected values, each low value box opened (relatively speaking) increases the chances of a high value box being opened next. Understanding the game in this way, the increased significance of later rounds is apparent, as there is a reduced chance of *not* finding the large values still left in play.

The models created to measure risk therefore must incorporate the time-sensitivity of the banker offer. A new variable t can be defined to measure how many boxes have been opened. Dividing t by 22 and multiplying this by r_3 and r_5[7] ensures the risk coefficients in earlier rounds are smaller than their time-insensitive counterparts. These new models, r_6 and r_7, are formally defined as follows:

$$r_6 = \frac{t.\mu.f(o)}{22.\sigma.f(\mu)}$$

$$r_7 = \frac{t.\mu.g(o)}{22.\sigma.g(\mu)}$$

The models developed in this section will be used to calculate a risk score at any banker offer of any contestant's game. This will be used to provide a general overview of how risk-seeking or risk-averse the individuals in the sample are, as well as to analyse any increased or decreased risk-seeking behaviour following certain events within the game.

VI. ANALYSIS

VI.1 General Dataset Analysis

TABLE 2
Description of Variables within the General Dataset

Variable Name	*Type*	*Description*
ContestantNumber	Integer	Chronological ordering of contestants
Dataset	Integer	1 = general dataset, 2 = detailed dataset
Series	Integer	The series in which the episode first aired
EpisodeDate	Date	The date on which the episode first aired
ContestantName	String	The contestant's name
PBA	Float	The amount in the contestant's box
MinOffer	Float	The minimum amount offered by the banker
MaxOffer	Float	The maximum amount offered by the banker
DealtWith	Float	The contestant's eventual winnings
DealtRed	Binary	Indicates whether winnings were at least £1000
PlayedUntilEnd	Binary	Indicates whether contestant played until the end

[7] Whilst one could multiply $t/22$ by all the risk coefficients up to this point to generate new coefficients, this wouldn't be useful as these coefficients were merely used to derive more complex models.

Swap[8]	Binary	Indicates whether contestant chose to swap their box with the one box remaining upon reaching the end of their game
BeatBanker	Binary	Indicates whether winnings were higher than PBA
PerfectGame	Binary	Indicates whether contestant won the maximum amount possible from their game

Table 2 lists the variables contained within the general dataset. Although this dataset cannot be analysed to provide an answer to the research question, preliminary analysis can be conducted to give a general overview of how contestants generally fare on the game show. Summarising the key variables (all those beneath the break in Table 2) and establishing various means will provide a reference point to help further understand any deviations from these values in the detailed dataset in the next section.

TABLE 3

Summary of Key Variables within the General Dataset

Variable	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*
PBA	1686	24669.14	53768.92	.01	250000
MinOffer	1686	2702.036	3375.875	-150	17500
MaxOffer	1686	26953.94	25579.39	250	172000
DealtWith	1686	15507.38	19617.08	.01	250000
DealtRed	1686	.8084223	.3936592	0	1
BeatBanker	1686	.4744958	.4994973	0	1
PerfectGame	1686	.2390273	.426616	0	1

The mean value contained with a contestant box was £24,669.14 over this period, whilst the average amount dealt to contestants was £15,507.38. Whilst this divide may initially appear to suggest that contestants often settle for considerably less than their box contains, the table also reveals that over 47% of contestants *beat the banker* during their games. The reason for this considerable divide is due to the fixed box values increasing exponentially, distorting the analysis and reducing the significance of using means. More useful is to look at the median values, to know where 50% of

[8] Although some data for this variable has been collected by the author, the dataset's lack of detail ensures it is not possible to identify occurrences of contestants choosing to swap and receiving *less* than their original box contents. For this reason, no extensive analysis will be conducted on this variable. As a result, there are expected to be a few records that are erroneously coded as PlayedUntilEnd=0, though this is not expected to be a large number and thus not anticipated to hinder any analysis.

the sample lies below and above, with regards to the player's box amount and eventual winnings.

TABLE 4

Detailed Summary of the PBA and DealtWith Variables

Percentiles		
%	*PBA*	*DealtWith*
1%	0.01	0.01
5%	0.1	1
10%	.5	20
25%	10	3000
50%	750	12000
75%	20000	20000
90%	75000	30000
95%	100000	44000
99%	250000	88000

Looking at the medians as opposed to the means tells a different story. In Table 4 it can be seen that 50% of contestants had £750 or less in their box (as expected), yet 50% of contestants won up to £12,000. Of these, half won at least £3000. At the other end of the scale, 10% of contestants had at least £75,000 in their box whereas only 5% won more than £44,000, with just 1% winning more than £88,000.

Examining only those contestants who *beat the banker* reveals that when this occurs, it's often quite a substantial gain. Table 4 shows that in over 96% of cases, the contestant won more than £1000, and the average winnings were nearly £18,000. This is compared with an average box value of little over £2500. As before, an examination of the median values should also be conducted for clarity.

TABLE 5

Summary of a Subset of Key Variables for BeatBanker = 1

Variable	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*
PBA	800	2597.436	7355.923	0.01	100000
DealtWith	800	17823.62	16821.97	0.04	250000
DealtRed	800	0.96125	0.193119	0	1
PerfectGame	800	0.40875	0.491911	0	1

TABLE 6

Detailed Summary of the PBA and DealtWith Variables for BeatBanker = 1

Percentiles		
%	*PBA*	*DealtWith*

1%	0.01	15.5
5%	0.01	1100
10%	0.1	3557.5
25%	1	8000
50%	100	15000
75%	1000	22475
90%	10000	31837.5
95%	15000	42000
99%	35000	80500

As displayed by Table 6, the values at the various percentiles support the arguments made by the mean values in Table 4. 75% of contestants who *beat the banker* had less than £1000 in their box, yet 95% left with more than £1100 in prize money.

Although analysis shows that contestants who *beat the banker* normally do very well, these individuals are just under half of the entire sample. Table 7 shows that the 478 contestants who won less than their box value received an average prize of just over £16,000. Although this figure is considerably less than the average PBA of nearly £75,000, it again must be noted that this figure may be distorted by the extremely high box values of a few contestants. Table 8 examines the values at various percentiles.

TABLE 7

Summary of a Subset of Key Variables for DealtWith < PBA

Variable	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*
PBA	478	74405.93	77482.38	0.1	250000
DealtWith	478	16607.46	14687.31	0.01	107031

TABLE 8

Detailed Summary of the PBA and DealtWith Variables for DealtWith < PBA

	Percentiles	
%	*PBA*	*DealtWith*
1%	1	0.01
5%	1000	9
10%	5000	750
25%	20000	6600
50%	50000	15000
75%	100000	22000
90%	250000	30000

95%	250000	44000
99%	250000	75000

50% of this subset may have been disappointed to discover their box contained more than £50,000. However, 75% still left with over £6600, and 50% left with over £15,000. Based on this data, although a significant decrease in prize money in real monetary terms is apparent for many contestants, the law of diminishing marginal utility ensures that many contestants would not be as disheartened as may have been expected.

It can be argued then, that accepting a banker offer, regardless of the ultimate box value, may not leave a contestant particularly susceptible to negative emotions following a game, if the amount dealt at provides a significant increase in utility. Many contestants may reach a point in which they know that the utility gained from accepting an offer will offset any amount of utility perceived to have been 'lost' by ultimately having a much higher amount in their box.

From this, it can be deduced that only the most risk-seeking contestants choose to play to the end, in an effort to maximise their utility by trying to win the highest amount possible[9]. These contestants averages are detailed in Table 9. The average prize of over £18,400 may seem to imply that playing until the end of the game is a wise thing to do. However, the table also shows that at least one individual won the largest prize of £250,000, and virtually half of this subset left with under £1000. The values at various percentiles are described in Table 10.

[9] This section refers to a contestant who continuously rejects offers deemed to provide significant utility, based on the transformation model g(x) defined in section V. A contestant that never has an offer of greater than £10,000 would not fit these criteria.

TABLE 9

Summary of a Subset of Key Variables for PlayedUntilEnd = 1 & MaxOffer > 10000

Variable	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*
PBA	246	15077.6	34630.89	0.01	250000
DealtWith	246	18422.7	38595.44	0.01	250000
DealtRed	246	0.5325203	0.4999585	0	1

TABLE 10

Detailed Summary DealtWith Variable for PlayedUntilEnd = 1 & MaxOffer > 10000

Percentiles	
%	*DealtWith*
1%	0.01
5%	0.01
10%	0.5
25%	10
50%	3000
75%	20000
90%	50000
95%	76000
99%	250000

As suspected, the mean is again a misleading statistic, with 75% of individuals who choose to play to the end receiving less than £20,000. Perhaps more concerning for risk-seeking contestants is that half of this group wins £3000 or less; amounts providing very little utility according to our model g(x), and highly unlikely to offset any utility potentially lost by setting up a new reference point at the highest offer received. Although large amounts can be won by playing until the end, larger amounts are won more frequently by contestants who choose to deal, as detailed by Table 11.

TABLE 11

Detailed Summary of the DealtWith Variable for MaxOffer > 10000 by PlayedUntilEnd

	DealtWith	
%	*PlayedUntilEnd = 0*	*PlayedUntilEnd = 1*
1%	0.26	0.01
5%	1100	0.01
10%	5000	0.5
25%	10000	10
50%	16500	3000
75%	24000	20000
90%	32000	50000
95%	42000	76000
99%	75000	250000
Max	110000	250000

The central 50% of those who choose to deal are considerably better off than their counterparts that elect to play until the end, accepting offers between £10,000 and £24,000. Those in this range who choose to gamble win between £10 and £20,000. The bottom 10% of the first group are also better off, accepting offers of up to £5000, compared to those in the second group who find a maximum of 50p in their boxes. The only percentile of contestants in the second group who win more than their group one counterparts are those in the top 10%, who luckily open their box to find values between £50,000 and £250,000. The top 10% of banker offers that are accepted, meanwhile, range from between £33,000 and £110,000.

VI.II. Detailed Dataset Analysis

As the r_7 model can be taken to be the most sophisticated measure of risk developed in this study, this is the metric we shall use throughout this section of the analysis. As such, we shall continue by using simply the notation r.

Comparing the largest risk coefficients associated with rejected banker offers by each contestant should give some indication as to how risk-seeking each contestant is. However, this will only reveal that a contestant's the tipping point[10] r is larger than this value. It is more useful to show these values alongside the r coefficient of the offer the contestant ultimately accepted, to display the bounds between which a

[10] Tipping point refers to the r coefficient that would lead to a contestant switching from "no deal" to "deal".

contestant's tipping point exists. This is of course not possible for the contestants who chose to play until the end. Table 12 displays the results.

TABLE 12
Comparing the largest risk coefficients associated with rejected banker offers

Contestant Number	***Obs***	***Max r***	***Deal r***
1	4	0.161805	0.181889
2	4	0.146163	0.070935
3	4	0.205801	0.285477
4	5	0.252832	0.509325
5	4	0.247141	0.317983
6	4	0.227189	0.232664
7	4	0.08178	0.163035
8	4	0.019661	0.216087
9	6	0.061469	N/A
10	6	0.350167	N/A
11	5	0.216245	2.727273
12	6	1.330767	N/A
13	6	0.637755	N/A
14	3	0.071456	0.118678
15	2	0.062228	0.106933
16	4	0.085566	0.17772
17	4	0.083327	0.260924
18	2	0.054084	0.079511
19	4	0.03801	0.478981
20	6	0.137844	N/A

According to the data here, contestants 12 and 13 are the most risk-seeking. Both contestants played until the end, though with different results, winning £250 and £35,000 respectively. When contestant 12 was facing the final offer with an r coefficient of 1.330767, the maximum that could be won was £250, and the minimum was £100. With this in mind, it is perhaps not so surprising that the contestant chose to gamble, and we should be cautious when stating that contestant 12 is the most risk-seeking of all the contestants. Contestant 13 meanwhile saw an ever-increasing list of offers that led to the final offer of £16,000. The remaining boxes contained £3000 and £35,000, and as such choosing to gamble can be seen as risk-seeking behaviour, given the non-linear nature of the utility function.

It is interesting that contestant 2 changes their risk preferences from one round to the next, based on our models. This could be due to initially taking a risk that would be outside their typical preferences, and following this round made a decision deemed to be more comfortable to them.

On the other end of the scale, the contestants deemed to be the most risk-averse are contestants 15 and 18. As well as dealing at the third offer, they also rejected gambles with a relatively low *r* coefficient. This could however be due to other reasons, such as having prior expectations or aims and sticking to them.

A look at the amount offered by the banker shows that on average banker offers increase as time goes on. Furthermore, the offers also increase as a percentage of the expected value of the contestant's box. As discussed by a previous paper the 'unfair' banker offers at earlier rounds could be to deter contestants from dealing too early, with offers becoming increasingly more generous as time goes on (Post et. al, 2008). The standard deviation of banker offers however increases considerably between offers 2 and 3, before becoming extremely large at offer 6. This suggests that although the average values offered are increasing, there is also an increasingly wider range of values from which the banker can make an offer.

TABLE 13
Summary of Banker Offers by Round

		Banker Offer				***Banker Offer as % of Expected Value***			
Off Num	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*	*Mean*	*Std. Dev*	*Min*	*Max*
1	20	5939.05	3979	500	13000	23.79	13.4	3.1	46.4
2	20	9040	4596	250	15000	36.31	17.1	2.8	67.6
3	20	10093.25	7262	15	30000	40.10	19	0.1	90
4	20	12270.75	8348	200	33000	46.88	19.9	6.26	90.1
5	20	13627.55	9095	600	35000	58.78	19.4	26.9	89.2
6	20	20420.89	31130	0.13	101000	72.56	20.5	32	100

Switching focus over to only those individuals deemed to be operating the domains of losses and gains (DoG/L) enables us to attempt to answer the research question. Due to each contestant only being able to deal once in a game, it isn't possible to say whether or not an individual operating in either domain is more or less risk-averse than they would be if they were operating normally[11]. It is possible however to study

[11] 'Normally', in this context, refers to an individual not said to be operating in the domain of losses or gains.

the *r* coefficient of gambles in different domains, and to analyse contestant decisions. Comparing these decisions with those made by contestants operating normally though facing similar prospects may lend credence to the argument that contestants are behaving in line with the predictions of prospect theory.

As defined previously, a contestant is said to be operating in the DoL if their current offer is worth no more than two-thirds of the previous offer. Likewise, the DoG is defined by seeing the offer increase by a minimum of 50% of the previous offer. This analysis will use the utilities of the banker offers as opposed to the absolute values, in line with the literature and arguments already made. A summary of banker offers and contestant decisions by domain is described by Table 14.

TABLE 14
Banker Offers & Contestant Decisions by Domain

	Normal		***Domain of Gains***		***Domain of Losses***	
	Offer	*Decision*	*Offer*	*Decision*	*Offer*	*Decision*
Obs	27	27	55.00	55.00	20	20
Mean	15010.3	0.2592593	9980.35	0.09	4815.75	0.15
St. Dev.	14703.59	0.4465761	6165.27	0.29	5465.832	0.366348
Min	700	0	500	0	15	0
Max	75000	1	30000	1	17500	1

The table displays a reduced proportion of individuals in the domains of gains and losses choosing to deal, relative to their normal counterparts. On average however, the banker offer was significantly lower than for normal individuals in these two domains, at two thirds the value in the DoG and one third the value in the DoL. As the utility gained from amounts under £10,000 is underweighted, it would be useful to see the same table for only offers of over this figure. This data is described by Table 15.

TABLE 15
Banker Offer & Contestant Decisions by Domain for Offer >= 10000

	Normal		***Domain of Gains***		***Domain of Losses***	
	Offer	*Decision*	*Offer*	*Decision*	*Offer*	*Decision*
Obs	18	18	25	25	5	5
Mean	20162.67	0.388889	15474.6	0.16	12700	0.2
Std. Dev	15507.87	0.501631	4512.721	0.374166	3734.97	0.447214
Min	10000	0	10000	0	10000	0
Max	75000	1	30000	1	17500	1

Again, fewer contestants choose to deal when operating the domains of losses and gains, though this should come as a surprise seeing as the banker offers are lower on average. As such, there is not enough evidence from this table to suggest an increase or decrease in risk aversion when operating in either domain. Furthermore, it is hard to draw any real conclusions about contestants operating in the domain of losses as the sample size of 5 is far too small.

As such, redefining the DoL may be necessary. The current definition compares the utilities of the current offer with the previous offer, implying any offers prior to that are not factored into a contestant's perception of their domain. It could be argued that a contestant would set their reference point at the highest offer received so far, and compare their current offer with that. We will maintain that to be classed as the DoL the current offer must be a maximum of two-thirds the value of the largest offer so far. Using this definition of DoL, Table 16 looks at banker offers, means and r coefficients for contestants who chose not to deal, by their respective domains.

TABLE 16

Banker Offer, Means & r-coefficients for Deal = 0 by Domain

	Normal			***Domain of Gains***			***Domain of Losses***		
	Offer	*Mean*	*r*	*Offer*	*Mean*	*r*	*Offer*	*Mean*	*r*
Obs	19	19	19	43	43	43	25	25	25
Mean	11488.3	29386.9	0.06	10327.16	26053.17	0.07	3936.64	12565.73	0.09
d. Dev	9108.2	13271.6	0.09	5864.86	10295.06	0.12	4127.27	10495.51	0.26
Min	700	10921.3	<0.01	500	11377.83	<0.01	15	175	<0.01
Max	35000	60650.2	0.25	30000	50005	0.64	17500	36170.01	1.33
	Offer as % of Mean			*Offer as % of Mean*			*Offer as % of Mean*		
Obs	19			43			25		
Mean	36.81			40.47			35.79		
d. Dev	23.67			18.03			21.55		
Min	5.01			3.13			0.05		
Max	90.05			84.21			85.71		

Here we see similar average r values, largest in the DoL. The r value in the DoG is slightly smaller, though is still larger than the values for contestants in neither domain. This implies that contestants in the DoG or losses on average accept more risky gambles than their normally-operating counterparts, with the results strongest in the DoL. Furthermore, the most risky gamble accepted by contestants in the normal domain had an r coefficient of 0.25, compared with values of 0.64 and 1.33 for contestants in the domains of gains and losses, respectively. If the 'fairness' of the banker offer is modelled as being a percentage of the expected value of the contestant's box, there is no real difference between the different domains, and in fact the banker's offers are slightly fairer in the Domain of Gains.

Switching our attention to the instances in which contestants choose to deal, as displayed by Table 17, we can see that it takes a much fairer offer on average to entice the contestant in the DoL to deal, and the average r coefficient for gambles considered too risky to continue were higher for the DoL and gains, with the case much more pronounced in the domain of losses. It is of course an important limitation of this study that these sample sizes are small and limited to a particular environment, prompting further research in the area.

TABLE 17

Banker Offer, Means & r-coefficients for Deal = 1 by Domain

	Normal			**Domain of Gains**			**Domain of Losses**		
	Offer	*Mean*	*r*	*Offer*	*Mean*	*r*	*Offer*	*Mean*	*r*
Obs	7	7	7	4	4	4	4	4	4
Mean	26357.14	49304.84	0.23	18125	33211.03	0.28	8187.5	13306.3	0.8
Std. Dev	21734.6	35784.49	0.15	3424.79	14650.72	0.13	6440.03	10959.18	1.29
Min	14000	22020.22	0.08	15000	21010	0.18	750	750	0.07
Max	75000	126500	0.51	23000	53201.1	0.48	16000	24013	2.73
	Offer as % of Mean			*Offer as % of Mean*			*Offer as % of Mean*		
Obs	7			4			4		
Mean	55.87			59.41			73.25		
Std. Dev	20.46			16.64			21.75		
Min	33.61			43.23			48.08		
Max	88.3			80.91			100		

VII. **CONCLUDING REMARKS**

By analysing contestants' decisions when operating in the domains of losses and gains this paper can conclude that there is evidence to suggest an increase in risk-seeking behaviour when operating in both domains. This is most notably the case when the reference point is estimated to be equal to the highest offer received up to that point. Under this definition, contestants are observed to accept riskier gambles when in the domain of losses than non-DoL contestants, and also require a fairer banker offer to entice them to deal. This is in line with the findings of other Deal or No Deal studies (Post et al, 2013), and contradicts prospect theory's prediction of increased risk aversion in the domain of gains.

However, a key limitation of this study is the quantity of data examined in detail. 20 contestants were assessed in detail allowing the analysis, the authors suggest further research based on the population of contestants.

Nevertheless, this paper contributes to the field of behavioural economics by potentially observing evidence of inconsistent risk preferences among individuals when faced with uncertain prospects. Further study into this area may reinforce the findings of this paper, and due to the ease of access to data and the ideal format of the game is greatly encouraged. As mentioned, a larger sample size would certainly assist when drawing conclusions, and further development of the coefficients associated with gambles may lead to a more accurate measure of the risks contestants face. Furthermore, the incorporation of probabilities into any models was omitted in this paper though should certainly be explored. This perhaps could include the overweighting and underweighting of low and high probabilities as described by a more recent development on prospect theory, cumulative prospect theory (Tversky & Kahneman, 1993).

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APPENDIX

A. Box Values

The 22 fixed prizes in Deal or No Deal (UK) are shown below in a similar style to that shown within the program. Red values indicate the largest 50%, whilst blue values indicate the smallest 50%.

1p	**£1,000**
10p	**£3,000**
50p	**£5,000**
£1	**£10,000**
£5	**£15,000**
£10	**£20,000**
£50	**£35,000**
£100	**£50,000**
£250	**£75,000**
£500	**£100,000**
£750	**£250,000**

B. Data

An example of some of the information collected about a contestant in the detailed dataset:

t	Box Opened	Value Eliminated (	f(VE)	g(VE)	Total Prize Remaining (TPR)
0					565666.61
1	B1	15000.00	43956.70	40207.54	550666.61
2	B2	0.01	#NUM!	0.00	550666.60
3	B3	1000.00	11325.71	2.92	549666.60
4	B4	1.00	0.00	0.00	549665.60
5	B5	75000.00	82906.10	118960.65	474665.60
6	B6	10000.00	36839.54	10000.00	464665.60
7	B7	0.50	#NUM!	0.00	464665.10
8	B8	20000.00	49603.84	55279.55	444665.10
9	B9	250.00	4520.70	0.04	444415.10
10	B10	50.00	1100.60	0.00	444365.10
11	B11	5.00	28.85	0.00	444360.10
12	B12	5000.00	26730.03	714.29	439360.10
13	B13	50000.00	71298.29	98683.59	389360.10
14	B14	100000.00	91969.79	134269.27	289360.10
15	B15	750.00	9513.08	1.18	288610.10
16	B16	35000.00	62142.96	81728.78	253610.10
17	B17	10.00	125.28	0.00	253600.10
18	B18	3000.00	20742.90	109.31	250600.10
19	B19	500.00	7341.42	0.34	250100.10
20	B20	100.00	2148.28	0.00	250000.10
21	B21	250000.00	125893.47	189803.10	0.10