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Income and choice under risk*

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Abstract

This paper studies the relationship between income and risky choice in a field experiment where stakes are of first-order importance to the subjects' living standards. We combine observations of stopping decisions in a Norwegian game show with reliable data on each subject's income. Participants in the experiment are randomly drawn from a large subject pool that is representative of the Norwegian population. Our results clearly indicate that people are risk-averse in making large-stake choices and that decision makers with high income are more willing to accept financial risk.

JEL Classification: C9, C93, D81

Keywords: Risky choice; Field experiment

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1 Introduction

The relationship between the economic resources of a decision maker, such as wealth or income, and his attitudes towards risk is fundamental in theories of choice under uncertainty.[1] Such theories are, in turn, central in many economic models that influence economic policy. In spite of this, there are only a few empirical investigations of the relationship between risky choice and the affluence of the decision maker. An important reason for the limited amount of research is a lack of fully adequate data for the task. Ideally, the data should contain (*i*) observations of choices between well-defined risky options, (*ii*) a credible measure of the decision makers' income or wealth, (*iii*) choice outcomes that have a substantial effect on the subjects' financial situation, and (*iv*) a representative subject pool.

This paper contributes to the empirical literature on choice under risk by collecting and analyzing a data set that can meet these four criteria. We combine choice data from a framed field experiment (according to the taxonomy of Harrison and List, 2004) with reliable data on each subject's income. The field experiment is the Norwegian game show *Millionsjansen* ("The Million Chance"). This game show meets the first criterion because contestants face a straightforward choice between taking home a sure prize or accepting a gamble with a simple probability distribution. We fulfill the second criterion by collecting tax register data on each contestant's income (and a measure of financial wealth) prior to their participation on the show. The financial outcomes in the experiment are of first-order importance to the subjects' living standards; hence, the third criterion is easily met. The average stake in the gambles we observe is 647,000 Norwegian kroner ($113,000/€87,000 at the time of writing), with a median of 600,000. In comparison, the average annual pre-tax income of the contestants was 311,000 kroner before their participation in the lottery. Our experiment thus offers a rare opportunity to analyze how people's willingness to risk large amounts of real money depends on their income level. Finally, the last criterion is also satisfied by our data set because participants on the game show are randomly drawn from a very large pool of candidates that is representative of the adult Norwegian population.

We are agnostic about the underlying risk preferences of our subjects, and hence we do not make any choice-theoretic assumptions in our analysis. Rather, we use a reduced form approach to estimate how the propensity to accept a given gamble depends on the decision maker's income and other characteristics. Naturally, the reduced form approach precludes us from estimating parameters associated with a particular type of utility function. However,

[1] According to expected utility theory, for instance, a central property of risk preferences is the relationship between the decision maker's wealth or income and his risk aversion. Similarly, prospect theory is characterized by its insistence on a reference level of income or wealth as a main determinant of risky (financial) choices.

our modest sample size would require strong assumptions to fully identify a structural model. We believe our reduced form estimates are more transparent and empirically credible.

We uncover three interesting patterns in the data. First, people are generally risk-averse in making high-stake choices: participants reject gambles with positive expected payoff when the risk becomes sufficiently high. Second, risk tolerance increases with income: the higher a subject's income is, the more likely he or she is to accept a given gamble. Third, in contrast with much of the earlier research on individual risk attitudes, we do not find statistically significant effects on choice of the gender or age of the decision maker.

1.1 Related literature

Previous empirical research on how risk attitudes vary with income or wealth can be divided into three different branches.[2] The first branch uses data on individual asset holdings to analyze how portfolio composition varies with individual wealth. When combined with a theoretical portfolio choice model, this variation can be used to deduce the subjects' risk aversion. This approach is thus fundamentally structural. The results from these studies are somewhat mixed. Using cross-sectional data, Friend and Blume (1975) do not reject constant relative risk aversion across US households, while Morin and Fernandez Suarez (1983) and Guiso and Paiella (2008) find evidence of decreasing relative risk aversion across Canadian and Italian households, respectively.[3] Moreover, the theoretical model on which these studies base their estimates has been seriously challenged by empirical research in finance (see, e.g., Campbell, 2003), calling into doubt the robustness of these findings. It thus seems worthwhile to supplement the asset holdings approach with more direct observations of risky financial choices, as we do in this paper.

A second type of study uses survey questions to measure risk attitudes. These analyses often include explorations of the relationship between income and/or wealth and risk attitudes among the respondents. Notable examples of such explorations include Barsky et al. (1997), Donkers and Melenberg (2001), and Dohmen et al.(2011). Again, the reported results are somewhat conflicting: using the expected utility model as their basis, Barsky et al. (1997) find a U-shaped pattern between risk preferences and income/wealth in their survey of US households; risk tolerance decreases for low income and wealth values and then increases. On

[2] Our literature review focuses on contributions that contain analyses of the relationship between risk preferences and income or wealth. We do not attempt to give a comprehensive survey of the large body of literature that estimates risk preferences because most of this research is silent on how their subjects' incomes affect the choices under investigation.

[3] Chiappori and Paiella (2011) note that cross-sectional portfolio analyses suffer from an identification problem if true preferences are heterogeneous. To remedy this weakness, they use panel data from Italian households and find a small but significant negative correlation between wealth and risk aversion across households.

the other hand, Donkers et al. (2001) and Dohmen et al. (2011) find a positive relationship between income/wealth and the willingness to take risks in surveys of Dutch and German households, respectively. A general concern about using surveys to elicit risk preferences is the tendency of surveys to rely on hypothetical choice situations. In particular, the financial stakes involved are usually imaginary, raising the question of whether the results can be generalized to the real world.[4] In contrast, our field experiment involves choices with stakes that have a significant impact on the subjects' standards of living.

Finally, there are a few field experiments, prior to ours, that shed light on the relationship between financial resources and risk preferences.[5] One important contribution comes from Harrison et al. (2007), who estimate risk attitudes using a controlled field experiment on a representative sample of Danes. They do not find any effect of household income on structural utility parameters across their subjects. We note that Harrison et al. use the household income category (high or low) as the measure of income for their subjects, whereas we have income data on each individual subject. Moreover, the financial stakes involved in their experiments are modest. Indeed, in a related paper (Andersen et al. 2008a, p. 591), the same authors are careful to emphasize that they do not claim global validity for their estimates if stakes were reduced or increased substantially. In a related study on a representative sample of Dutch respondents, von Gaudecker et al. 2011) find an ambiguous association between structural utility risk parameters and the income and wealth category of respondents. Finally, our paper is related to the study by Bombardini and Trebbi (2012). Like us, they analyze choice data from a television show with high stakes and investigate how choices relate to, among other variables, the income of the decision maker. Bombardini and Trebbi estimate a highly structural model, assuming that preferences have constant relative risk aversion. Their estimate of this constant is clearly heterogeneous across their subjects, but they do not find that this parameter is related to the measure of individual income. Our approach differs from that of Bombardini and Trebbi (2012) in that we do not assume a specific functional form of preferences. In addition, Bombardini and Trebbi *estimate* the income of their subjects (based on occupation and city/region of residence), while we have

[4]Dohmen et al. (2011) make a serious attempt to meet the generalizability concern by running a complementary experiment with a representative subject pool and real stakes. Their experiment confirms the validity of the risk willingness measure used in the survey, but they do not report on whether the relationship between income/wealth and risk attitudes is comparable in the experiment and the survey. Moreover, although the financial stakes in their experiment are non-negligible, they are an order of magnitude smaller than in our natural experiment.

[5]Experiments of risky choice conducted in the lab commonly use college students as subjects (Harrison and List, 2004), and may thus be of limited value in identifying the relationship between risk preferences and income or wealth. Field experiments such as ours attempt to overcome this drawback by using samples from populations with wider demographics.

actual income data on each individual.[6]

We are by no means the first to use data from television game shows to study risk preferences; see Andersen *et al.* (2008b) for a comprehensive survey of the early literature on estimating risk aversion in game shows.[7] We believe, however, that our particular show has some important advantages compared to those previously studied: first, the weekly contestant in our show is randomly drawn from a large subject pool. In most other game shows, such as *Deal or No Deal* (analyzed by Post et al. 2008, among many others) and the Italian *Affari Tuoi* (analyzed by Bombardini and Trebbi 2012), contestants must pass a pre-qualification or an interview. Participants are thus a selected group of individuals who may differ in important ways from the general population (see List, 2006). This type of selection problem is much smaller in *Millionsjansen*. Second, in previously analyzed television shows participants make their decisions in a TV studio in front of an audience, which in itself may bias the decisions in certain directions (see again List 2006). Our contestants only appear on the show by phone and there is no studio audience. Third, *Millionsjansen* arguably cultivates the risk preference aspect of choice to a larger degree than most previously analyzed shows. Bombardini and Trebbi (2012) argue that in shows such as *Jeopardy*, *Card Sharks*, and *Lingo* (employed to elicit risk preferences by Metrick 1995, Gertner 1993, and Beetsma and Schotman 2001, respectively) the ability to calculate fairly complicated odds or one's probability of correctly answering questions of knowledge might interfere with risk preferences and bias estimates of risk aversion. We analyze a straightforward stopping problem where the contestant's choice is between taking home a sure prize and accepting a gamble with a simple probability distribution.

The remainder of the paper is organized as follows. In Section 2, we explain how *Millionsjansen* is played and some basic statistical properties of the game. The data are discussed in Section 3, while Section 4 presents key properties of the gambles played and of the players' response to them. In Section 5 we present and discuss our regression results, and then we conclude in Section 6.

[6] Note also that having "average income" was one of the criteria for being selected to participate in the show analyzed by Bombardini and Trebbi (2012). As commented by the authors themselves (p.1357), this limits the extent to which they can compare risk attitudes across income levels.

[7] The strengths of game show data are well known, and these are shared by our experiment: choice options are well-defined, stakes are real and large, the tasks are repeated in the same manner from contestant to contestant, and samples are drawn from populations with a wider set of demographics than in the typical lab experiment.

2 *Millionsjansen*

We now briefly discuss the central properties of *Millionsjansen* and the information available to the participants in the game.

2.1 The rules of the game and the drawing procedure

Millionsjansen was broadcast weekly on the public service channel NRK1 (Norway's largest TV channel) between February 2007 and December 2011. The single weekly contestant in the game was randomly drawn among those who had bought tickets in a traditional lottery (called *Lotto*) that week. Approximately 1.5 million Norwegians buy *Lotto* tickets weekly, out of a current total adult population of just under 3.9 millions.[8] The cost of participating in *Lotto* is low; currently the price of a one-week ticket is 40 kroner. The TV producer attempted to contact the player that was drawn to play *Millionsjansen* approximately 30 minutes before the show was recorded. If the player could not be reached by phone, a computer played on behalf of this individual. In our sample, 59 percent of the games were played by the computer.[9] To those who could be reached, the rules and procedures of the game were explained during the telephone conversation.

The structure of the game is as follows: The player is presented with seven numbered balls hiding the six monetary prizes (in thousand kroner) $\{400, 500, 600, 700, 800, 1000\}$ and one "bandit". He/she iss then invited to sequentially and *without replacement* pick one ball at a time to reveal the hidden prize. The player wins the accumulated prizes hidden by his/her selected balls. If he/she picks the ball hiding the bandit the game is terminated and the player wins the default prize of 500,000.

Crucially, between each ball selection, the player can choose to stop the game and take home the prize money accumulated to that point. It is these stopping problems that allow us to analyze the risk attitudes of the contestants: choosing to stop gives a sure monetary prize while choosing to continue is risky and involves a high-stake monetary gamble. We note that each player in principle could select up to six balls, depending on when he/she chooses to stop and on whether the bandit is drawn. We will refer to the ball selection opportunities as the six rounds of the game but observe that the stopping problem begins in round two because contestants must select a ball in round one. We also note that in rounds 2-5, choosing to continue gives a probability distribution of monetary prizes and, if the bandit is not drawn,

[8]The total population in Norway is just above 5 million, but only adults (18 years and above) are allowed to participate in the lottery.

[9]This fraction includes winners that chose to have the computer play the game for them and gives rise to a potential sample selection problem. We return to this issue in the next section, where we also discuss the strategy played by the computer.

an *option* to choose in the next round.

2.2 The contestants' information

The simple sequential game structure explained above was, in all likelihood, well understood by the contestants, arguably at least as well as in the typical lab experiment. As mentioned above, the rules of the game were explained to the subjects 30 minutes in advance of their play. This is akin to the experimental instructions given to subjects in controlled experiments. In addition, the public nature of the game implies that contestants had an easy way to observe how the game works. The game was broadcast in prime time on Saturday nights as part of a program with very high ratings.[10]

3 Data and sample properties

3.1 The data

We have data from all the 251 recorded episodes of the show. As mentioned above, in 59 percent (147 episodes) of the programs, a computer made the choices on behalf of the winner. For our purposes, it is the choices made by the remaining 104 human contestants that are of interest, and, with the exception of the sample selection discussion in Section 3.2 below, our analysis uses this sample only. For each episode, we have recorded how the game evolved (i.e., the contestant's choices and the realized prizes) and the player's name, gender, and place of residence.[11] We used the contestant's name and residence in the publicly available tax return statistics to identify his/her birth year and taxable income and wealth in the calendar year prior to the person's appearance on the show. This procedure allowed us to identify the age, income, and taxable wealth for all 104 contestants.

Taxable income in the Norwegian tax system is an informative and reliable measure of the tax players' true income: deductions are few and standardized, different sources of income (e.g., labor, capital, and pension income) are generally uniformly treated, and income providers (e.g., employers, banks, and the social security administration) report to tax authorities the income paid to every individual. Unfortunately, similar reliability does not apply to taxable wealth, which is a highly imprecise measure of individuals' true (financial) wealth. In particular, the combination of widespread house ownership and very low tax valuation of

[10] Rating numbers from are in the range of 600,000-900,000 viewers 12 years and above. This is similar to the ratings for the main Saturday evening news on NRK1.

[11] These observations were collected partly from logbooks that the Norwegian Gaming and Foundation Authority and the producer Norsk Tipping generously gave us access to and partly from watching the programs.

Table 1: Descriptive statistics for experimental subjects and the adult Norwegian population

	Mean income	Median income	Mean wealth	Average age	Male fraction
Subjects ($N = 104$)	323.0	268.3	345.6	52.7	0.606
(St.dev.)	(228.8)		(906.7)	(13.5)	(0.489)
Adult population	286.9	233.4	233.3	47.5	0.498

Data for the adult population are from Statistics Norway. Income (wealth) is annual taxable income (wealth) in thousand 2010 kroner. Mean income and wealth, and median income for adult population is for those aged 17 and older in 2010 (N = 3,870,146). Average age and male fraction is calculated for those aged 18 and above as of 31 December 2011 (N = 3,867,645).

houses imply that many individuals have zero[12] taxable wealth (tax value of house less size of mortgage) even if the market value of their housing wealth is substantial. For this reason, income is our preferred measure of the subjects' economic resources, but we will make use of the wealth variable in robustness checks of our baseline analysis.

3.1.1 The contestants

Table 1 provides descriptive statistics for the individual specific variables and compares our sample to 2010 data for the adult Norwegian population. To make the subjects' income comparable to the 2010 national data, we inflate income from prior years by the change in the consumer price index from the year in question to 2010.

The table shows that on average, our subjects are richer than the general population. The mean (median) income of our subjects is 12.4 percent (14.9 percent) higher than in the population at large, while average taxable wealth is 48.8 percent higher among subjects. This is not a surprising pattern given that, as seen in the last two columns of Table 1, our subjects are slightly older and have a higher share of men than in the adult population. It is well known that men, on average, have higher incomes than do women. Moreover, the share of young people (i.e., below 30) in the sample is much lower than that in the general population, while the share of middle-aged subjects is higher; this also contributes to higher income and wealth levels in the sample.

These caveats notwithstanding, the contestants in our game seem to comprise a fairly representative cross section of the adult Norwegian population. A null hypothesis of equality between mean income among subjects and the adult population cannot be rejected (t-statistic = 1.614; p-value = 0.109). The difference between the mean taxable wealth in the sample and that of the adult population is clearly not significant given the large standard deviation of this variable. Similar hypotheses for the average age and for the male fraction in the sample are rejected; i.e., our sample is, on average, significantly older and consists of significantly more men, but it is income that is our primary variable of interest. Recall also that our sample captures a wider set of demographics than that used in a typical lab experiment and

[12]Taxable wealth is truncated at zero.

Table 2: Number of contestants, stop choices and bandits drawn in the different rounds of the game

	Round 1	Round 2	Round 3	Round 4	Round 5
Contestants	104	90	74	39	4
Stop choices	-	3	26	34	4
Bandits drawn	14	13	9	1	-

that the random draw of the contestants avoids some of the sample selection issues that may be present in other game shows.

3.1.2 Exits, prizes, and stakes

Players exit the game if they choose to stop or if they draw the bandit. Table 2 shows how the number of contestants declines between rounds. Among the 104 contestants that entered the game, 14 drew the bandit in round one while 90 survived until the stopping problem began in round two. Among these 90 players, 23 exited the game because they drew the bandit between rounds two and four, and the remaining 67 chose to stop at some point between rounds two and five. We note that none of the contestants chose to proceed or survived to the final round six of the game.

Figure 1 shows the distribution of the take-home prizes among the 104 contestants. The average prize is close to 1.3 million kroner, more than four times the mean annual income reported in Table 1. The median prize is even higher at 1.5 million. The prize distribution is skewed to the right due to the high fraction of participants that won the minimum prize after drawing the bandit.

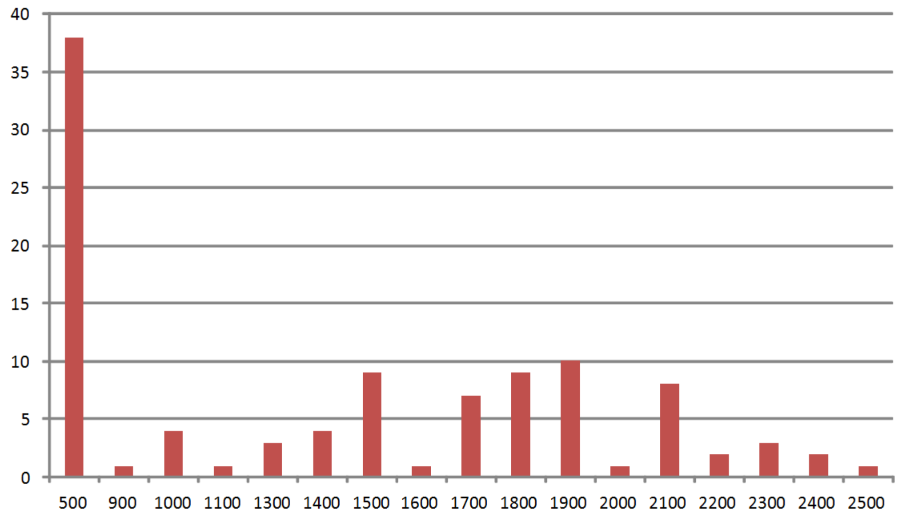
We are primarily interested in the stopping problems faced by players from round two onwards. When choosing in these rounds, each player has accumulated a certain prize amount in the earlier round(s). If the contestant chooses not to stop, he or she risks losing this amount less the default prize of 500,000. The difference between the accumulated prize and the default prize is thus a natural measure of the stake faced by contestants in a given gamble. Figure 2 shows the distribution of stakes in our sample.

Our observations cover 207 stopping problems (gambles), with an average stake of close to 648,000 kroner. This is more than twice the mean annual income reported in Table 1. The median gamble involved a stake of 600,000. We note that the stake can be negative; this happened in round two when the players drew 400,000 in round one.

3.2 Sample selection issues

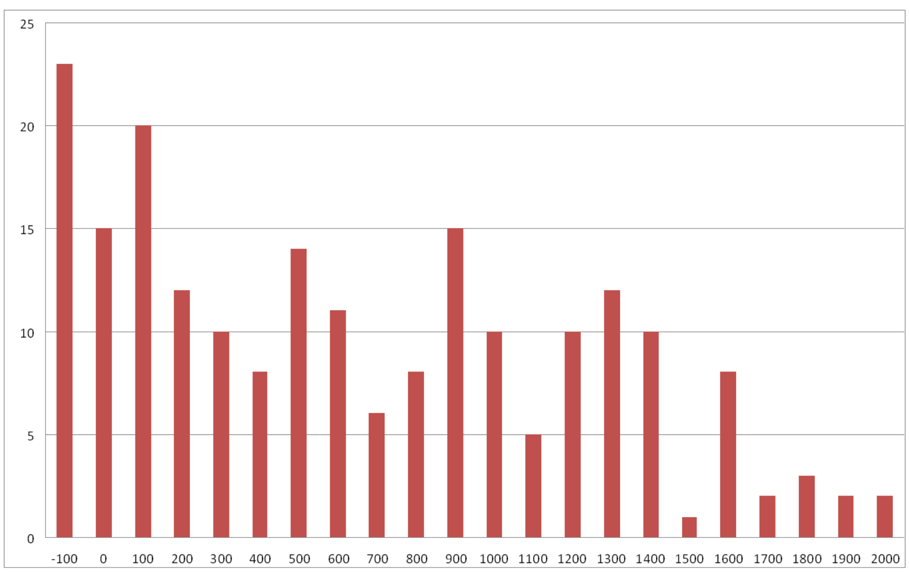
The preceding subsection documented that our subjects, in terms of observable individual characteristics, constitute a fairly representative sample of the population. Still, there are

Figure 1: Distribution of prices won



Amounts on horizontal axis are in thousands nominal kroner. The mean (median) of the distribution is 1,289,423 (1,500,000), and the standard deviation is 671,315.

Figure 2: Distribution of stakes in gambles faced by contestants from round two onwards ($N = 207$)



Amounts on horizontal axis are in thousands nominal kroner. The mean (median) of the distribution is 647,343 (600,000), and the standard deviation is 573,678.

sample selection issues that need to be addressed when evaluating the validity of our results.

3.2.1 Lottery players as the subject pool

Our subject pool consists of people who buy lottery tickets, and their risk preferences may be different from those of the population in general. However, as reported in Section 2.1, every week approximately 40 percent of the adult Norwegian population buys these lottery tickets. Together with the random selection of contestants, the mere size of the sampled population should go some way in meeting concerns about external validity. The random selection of contestants also implies that internal validity should be of less concern than in earlier studies of high-stakes game shows, where contestants must actively apply and pass tests or interviews before appearing on the show.

3.2.2 Opting out and self selection

A potentially more serious concern about our sample is related to the fact that a computer plays on behalf of the winner in 59 percent of the episodes. In a majority of these episodes, the producer is simply unable to contact the contestant who is selected to play (recall that the contact attempt takes place only 30 minutes before the show is recorded). However, the producer estimated to us that in approximately 40 percent of the episodes played by the computer (55-60 shows), the producer did make contact, but the contestant chose to have the computer play on his or her behalf. Opting out of the game could be correlated with risk preferences and is thus a source of a potential bias in our analysis.

To refrain from choosing is puzzling in its own right, as the contestants would not know the computer's choices in advance. The computer was programmed to not stop until the accumulated prize money had reached at least two million kroner, and this was carefully explained to the contestants. However, the structure of the game was such that two million could be reached through various paths with different associated risks. A priori, players would thus not know if the computer's choices would be consistent with their risk preferences.

A more plausible explanation of opting out is that these winners remained anonymous to the public; the name of the winner in the computer played rounds was not announced on the show. It is unclear how a desire to remain anonymous relates to risk preferences, but we have attempted to investigate how anonymous winners differ from those who participated on the show according to observable characteristics. From the producer's logbooks, we could identify 96 (out of 147) of the winners in the computer played rounds. We do not have information to distinguish between winners where the producer was unable to obtain contact and winners who refrained from participating.

Table 3: Comparison of participants and non-participants

	Participants ($N = 104$)	Non-participants ($N = 96$)	Test statistic for equality in samples
Mean income	323.0	264.5	2.052[a]
(St.dev. / p-value)	(22.5)	(17.9)	(0.041)
Mean age	52.7	58.3	-2.798[a]
(St.dev. / p-value)	(1.3)	(1.5)	(0.006)
Male fraction	0.606	0.531	1.07[b]
(p-value)			(0.285)

Income is annual taxable income in thousands 2010 krone.
Statistics marked [a] and [b] denote t- and z-tests, respectively.

Figure 3: The age distribution among out subjects ($N = 104$) and non-participants ($N = 96$)

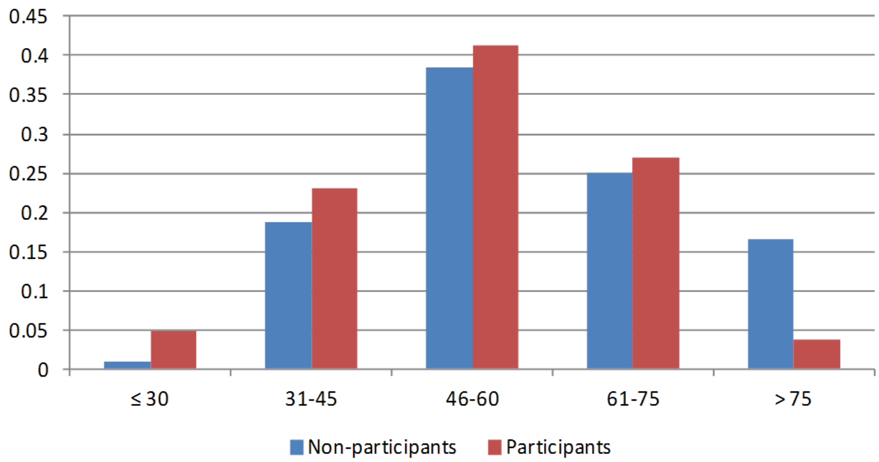


Table 3 compares the observable characteristics between those who participated on the show with the 96 identifiable non-participants. The table shows that our subjects on average have higher income than non-participants. The significantly higher age of the non-participants is an important reason for the difference in income. Table 3 shows that the average age is approximately 5.5 years higher among non-participants. As seen from Figure 3, this difference is due to a higher share of those older than 75 years (i.e., retirees) among the non-participants. We recall from Section 3.1 that the average age of our subjects is higher than that of the general population - the average age of the non-participants is thus even further from the population average. The gender distribution among the non-participants is, on the other hand, closer to the population distribution, but the male fraction is not significantly different between the two samples.

Our data does not permit strong conclusions about the sample selection issues created by the computer played rounds. The fact that some participants refrain from choosing despite the fact that the riskiness of computer's strategy is unknown may in itself be of interest for understanding risk preferences, but the data does now allow us to pursue this issue further. On the other hand, our sample is arguably at least as representative of the adult population as is the non-participants, lending some credence to the generalizability of our results.

4 The gambles

Our primary interest is the relationship between income and risk preferences, but our data also allow us to test whether, after controlling for the decision maker's income, gender and age systematically affect risk tolerance. To explore these linkages, we need to control for the characteristics of the gambles that the contestants are invited to accept or reject. To help us identify the relevant gamble characteristics, we now provide a formal description of the subjects' decision problem, and then use these characteristics to identify the key properties of every gamble that was played in our sample.

Consider an arbitrary contestant, whose income, age, and gender are observable attributes. In round $t = \{2, .., 6\}$ of the game, the player has drawn some combination n_t of prizes in previous rounds, and has at his/her disposal the accumulated prize x_t, equal to the sum of the elements in n_t. By wagering (investing) x_t, the player participates in a gamble whose statistical properties are *uniquely identified* by n_t.[13] The gamble yields a random immediate monetary payoff plus, in rounds $\{2, .., 5\}$, a possible option of participating in further gambles. Given n_t, the immediate random payoff is specified by a simple distribution $p(x_{t+1}; n_t)$, where x_{t+1} is the player's accumulated prize after the gamble.

This description highlights the wagered amount x_t, the probability distribution p_t, and the imbedded option of more gambles as the key characteristics of gamble n_t. Among these properties, analyzing the option value is the most complicated. Because the game involves multiple rounds, the value of gamble n_t, $t = \{2, .., 5\}$, should in principle account for both the probability distribution over immediate payoffs, p_t, and the optimal decisions in later rounds. In theory, we can solve the entire dynamic optimization problem by means of backward induction. This approach, however, requires knowledge of the contestants' stopping rule (derived from, e.g., a utility function), and assumes that players take into account all possible outcomes and decisions in all subsequent game rounds. Our goal, however, is to characterize the relationship between risk preferences and income without imposing a structural choice model. Moreover, experimental studies of backward induction indicate that subjects generally take only one or two steps of strategic reasoning and ignore further steps of the process (see, e.g., Johnson et al., 2002). For these two reasons, we follow Post et al. (2008) and initially assume that contestants ignore the option to continue play after the current round t. However,

[13] We note that it is the combination, and not the sum or permutation, of previous prizes that identifies the gamble. For example, the gamble available in round 3 to a player that has drawn $(500, 1000)$ is identical to the gamble faced by a player who has drawn $(1000, 500)$ (the permutation is irrelevant), but it is different from gamble faced by a player who has drawn $(700, 800)$ (x_t does not identify the gamble).

we will perform a robustness analysis to determine whether our estimates may be biased due to this assumption.

In principle,

$$\sum_{t=2}^{6} \binom{6}{t-1} = 62$$

different gambles could occur in *Millionsjansen*, but 19 of these were not played (by people) in the history of the game show.[14] Table 4 reports the investment, x_t, the first four moments of the probability distribution, p_t, and the number of plays with acceptance rates for the 43 gambles that were actually played. There are several noteworthy patterns in this table: the expected *net* payoff from the gambles (fourth column) generally declines as the game proceeds from one round to the next. This is because the required investment to participate in the gamble (second column) increases faster in t than the expected gross payoff (third column). On the other hand, the standard deviation of the payoff (fifth column) increases sharply with t. This implies that, if one is willing to equate risk with the variance or standard deviation, the risk-return trade-off of the gambles deteriorates quickly as the game moves from one round to the next.

A broader concept of risk would take into account higher moments of the payoff distribution. The sixth and seventh columns of Table 4 show that all gambles played in Millionsjansen exhibit negative skew and positive excess kurtosis. It is common in economics to assume that agents dislike negative skew (e.g., Kraus and Litzenberger, 1976). There is less discussion in the literature about preferences for kurtosis, but Dittmar (2002) put forward the intuitive hypothesis that people dislike (positive) excess kurtosis because they are averse to extreme outcomes.[15] We note from Table 4 that, unlike for the mean and the standard deviation, there is no clear pattern between the skewness or kurtosis and the round of the game.

The last column of Table 4 reports the number of offers and acceptance rates for each gamble played. The acceptance rate declines quickly as the game proceeds from one round to the next: in round two, 87 out of 90 gambles (96.7 percent) offered were accepted; in round three, 48 out of 74 gambles (64.9 percent) were accepted; in round four, 5 out of 39 gambles (12.8 percent) were accepted, while none of the four gambles offered in round five were accepted.

The data in Table 4 also allow us to make some initial observations about risk attitudes among our subjects. For this purpose, we categorize the exits of the 90 players that faced at least one gamble along two dimensions: exit due to rejection of gamble or drawing the

[14] The non-occurring gambles are two (out of 20 feasible) in round four, 11 (out of 15 feasible) in round five, and all six possible gambles in round six.

[15] Higher kurtosis means that more of the variance in a distribution is the result of infrequent extreme deviations, as opposed to frequent modestly sized deviations.

Table 4: Gambles played by human contestants

Gamble n_t (prizes in previous rounds)	Investment (x_t)[a]	Expected payoff (mean of p_t)[b]	Expected net payoff[c]	Standard dev. of p_t[d]	Skewness of p_t[e]	Kurtosis of p_t[f]	Plays (share) accepts)
Round 2							
400	400	1,017	617	306	-0.80	1.27	23 (1)
500	500	1,083	583	349	-0.85	0.82	15 (1)
600	600	1,150	550	383	-0.89	1.02	20 (1)
700	700	1,217	517	412	-1.00	1.65	12 (1)
800	800	1,283	483	436	-1.20	2.51	10 (1)
1,000	1,000	1,417	417	471	-1.97	4.23	10 (0.70)
Round 3							
{400, 500}	900	1,440	540	546	-1.82	3.69	8 (0.88)
{400, 600}	1,000	1,500	500	587	-1.73	3.26	4 (0.75)
{400, 700}	1,100	1,560	460	623	-1.71	3.30	5 (0.80)
{400, 800}	1,200	1,620	420	653	-1.76	3.61	4 (1)
{400, 1,000}	1,400	1,740	340	702	-2.1	4.50	6 (0.50)
{500, 600}	1,100	1,560	460	631	-1.63	2.77	6 (1)
{500, 700}	1,200	1,620	420	665	-1.63	2.93	2 (1)
{500, 800}	1,300	1,680	380	694	-1.70	3.30	3 (0.67)
{500, 1,000}	1,500	1,800	300	742	-2.02	4.20	5 (0.20)
{600, 700}	1,300	1,680	380	701	-1.60	2.94	5 (0.60)
{600, 800}	1,400	1,740	340	730	-1.68	3.31	9 (0.78)
{600, 1,000}	1,600	1,860	260	777	-2.01	4.20	2 (1)
{700, 800}	1,500	1,800	300	762	-1.72	3.54	3 (0)
{700, 1,000}	1,700	1,920	220	807	-2.05	4.37	6 (0.33)
{800, 1,000}	1,800	1,980	180	835	-2.14	4.65	6 (0.33)
Round 4							
{400, 500, 600}	1,500	1,875	375	925	-1.89	3.66	2 (0)
{400, 500, 700}	1,600	1,925	325	964	-1.83	3.44	3 (0.67)
{400, 500, 800}	1,700	1,975	275	998	-1.82	3.49	2 (0)
{400, 500, 1,000}	1,900	2,075	175	1,053	-1.96	3.88	3 (0)
{400, 600, 700}	1,700	1,975	275	1,005	-1.76	3.15	2 (0.5)
{400, 600, 800}	1,800	2,025	225	1,037	-1.76	3.28	3 (0.33)
{400, 600, 1,000}	2,000	2,125	125	1,090	-1.92	3.73	1 (0)
{400, 700, 800}	1,900	2,075	175	1,072	-1.75	3.31	1 (0)
{400, 700, 1,000}	2,100	2,225	125	1,170	-1.79	3.41	2 (0)
{500, 600, 700}	1,800	2,025	225	1,047	-1.68	2.82	3 (0)
{500, 600, 800}	1,900	2,075	175	1,078	-1.70	3.01	6 (0)
{500, 600, 1,000}	2,100	2,175	75	1,130	-1.87	3.52	3 (0)
{500, 700, 1,000}	2,200	2,225	25	1,162	-1.88	3.61	1 (0)
{500,800,1,000}	2,300	2,275	-25	1,190	-1.94	3.77	1 (0)
{600, 700, 800}	2,100	2,175	75	1,147	-1.68	3.15	3 (0)
{600, 700, 1,000}	2,300	2,275	-25	1,195	-1.88	3.63	1 (0)
{600, 800, 1,000}	2,400	2,325	-75	1,223	-1.94	3.80	1 (0)
{700, 800, 1,000}	2,500	2,375	-125	1,253	-1.98	3.92	1 (1)
Round 5							
{400, 500, 600, 700}	2,200	2,233	33	1,504	-1.70	n/d	1 (0)
{400, 500, 600, 800}	2,300	2,267	-33	1,537	-1.66	n/d	1 (0)
{400, 500, 700, 800}	2,400	2,300	-100	1,572	-1.61	n/d	1 (0)
{400, 600, 700, 800}	2,500	2,333	-167	1,607	-1.55	n/d	1 (0)

[a] Investment is the prize accumulated in previous rounds, thousands kroner.

[b] Expected payoff is the expected prize of choosing "accept" once, in thousands kroner. It ignores the option value of further gambles that may materialize by choosing to accept in rounds {2,..,5}.

[c] Expected net payoff is expected payoff minus investment.

[d] Standard deviation is the standard deviation of the gamble when choosing "accept" once, thousands kroner.

[e] Skewness is the skewness of the gamble when choosing "accept" once.

[f] Kurtosis is the excess kurtosis of the gamble when choosing "accept" once. Not defined in round 5 because of too few outcomes in the probability distribution.

Table 5: Type of exits from the game

	Rejected gamble	Drew bandit
Expected net payoff > 0	61	22
Expected net payoff < 0	6	1

bandit (cf. Table 2), and exit at a positive or negative net expected payoff gamble. Table 5 reports the number of contestants in each category. Sixty-one players exited the game by rejecting a positive net expected payoff gamble. Such a choice is consistent with risk aversion, and it contradicts risk neutrality or risk-seeking behavior. The six players that exited the game by rejecting a negative expected net payoff gamble had all accepted positive expected net payoff gambles in earlier rounds. The behavior of these players is thus both consistent with risk aversion, and not contrary to risk neutrality, or indeed, (mild) risk seeking. A similarly ambiguous conclusion applies to the 22 players that were ejected by the bandit after accepting a positive expected net payoff gamble. There is only one observation in our data that contradicts risk aversion: the player who drew the bandit after accepting the negative expected payoff gamble $(700, 800, 1000)$. In summary, a hypothesis of risk aversion is unambiguously supported by the behavior of 61 out of 90 subjects, while the hypothesis is contradicted for only one subject. For the remainder 28 subjects, choices are consistent with risk aversion, but not uniquely so.

5 Results

We are now in a position to estimate how the propensity to accept identical gambles depends on the income, age, and gender of the decision maker. We estimate various versions of the linear probability model[16]

$$s_{il} = \alpha + \beta y_i + \theta m_i + \phi a_i + \boldsymbol{\tau'}_l \boldsymbol{\kappa} + \epsilon_{il}, \tag{1}$$

where the dummy variable s_{il} equals 1 if contestant i rejects gamble l. The coefficients β, θ, and ϕ give the effects of income y_i, gender ($m_i = 1$ if the contestant is male), and age a_i, respectively. The vector $\boldsymbol{\tau}_l$ contains the gamble controls and consists of moments of the distribution that characterizes gamble l. As usual, α is a constant term while ϵ_{il} is the error term.

The empirical literature discussed in Section 1.1 does not give a clear cut hypothesis of the sign of β. However, theoretical models are often based on the intuitively appealing

[16] We have also estimated the model as a logit, and this yields similar results. Because the LPM-coefficients are easier to interpret, we report only these estimates.

assumption that the richer the decision maker, the more gambles expressed in absolute dollars he or she would be willing to accept.[17] This points to a positive relationship between income and risk tolerance; i.e., a negative β. As regards the effect of the decision maker's gender, it appears to be something of a consensus in psychological research that males are more likely to take risks than females (see, e.g., the meta study by Byrnes, Miller, and Schafer 1999). Our hypothesis is thus that θ is also negative. Eckel and Grossman (2008) conclude, however, that even though most studies find that women are more risk averse than men, there is enough counter-evidence to warrant caution. In particular, they emphasize that many studies of gender differences in risk attitudes may be biased due to omission of variables such as individual wealth. Hence, it should be of interest to analyze if women are less willing to take large financial risks when controlling for individual income. There is less research on how risk tolerance varies with age, but Jianakoplos and Bernasek (2006) find that risk taking decreases with age and conclude that this supports the "conventional wisdom" about risk tolerance and age. We might thus hypothesize that ϕ is positive. The vector $\boldsymbol{\tau}_l$ includes the statistical moments reported in Table 4 above. The probability of accepting a gamble is obviously expected to be increasing in its net expected payoff and decreasing in its variance. As discussed above, economic theory also suggests that the propensity to accept a gamble increases in its skewness and decreases with its kurtosis.

5.1 Baseline results

The results from our base model are reported in Table 6. In Column (A) we include all three individual characteristics and the full set of gamble controls (statistical moments) as explanatory variables. The estimated coefficient on income has the hypothesized negative sign and is significant at the 10 percent level. Taken at face value, the coefficient implies that the effect on the probability of gamble acceptance of an increase in annual income by 100,000 is to increase the probability by 2.1 percentage points. Column (B) shows that the effect of income is little affected by the inclusion of the subject´s gender and age in the regression. From columns (A) and (C) we see that the coefficient on the male dummy variable is negative as expected. On average, men are thus more willing than women to accept the high financial risk involved in our gambles. This is consistent with the gender differences generally found in the literature on risk taking, but we note that the effect is imprecisely estimated and insignificant at conventional levels. By comparing columns (A) and (C), we see that the point estimate on the male dummy decreases (in absolute value) when we control for the income of the decision maker. This could indicate that some of the much discussed

[17] In expected utility theory, this corresponds to the notion of decreasing absolute risk aversion.

Table 6: Baseline results

	(A)	(B)	(C)	(D)
Income	-0.000208*	-0.000230*		
	(0.000118)	(0.000121)		
Male	-0.0391		-0.0591	
	(0.0447)		(0.0449)	
Age	0.000105			0.000150
	(0.00137)			(0.00138)
Expected net	-0.000248	-0.000284	-0.000218	-0.000264
payoff	(0.000675)	(0.000680)	(0.000710)	(0.000718)
Variance	6.69e-07***	6.55e-07***	6.74e-07***	6.55e-07***
	(2.32e-07)	(2.36e-07)	(2.42e-07)	(2.45e-07)
Skewness	0.100	0.0890	0.102	0.0908
	(0.174)	(0.170)	(0.165)	(0.168)
Kurtosis	0.0777	0.0722	0.0830	0.0776
	(0.0575)	(0.0549)	(0.0530)	(0.0543)
Observations	203	203	203	203
R-squared	0.519	0.518	0.511	0.508

The accept/ reject dummy, s_{il}, is the dependent variable.
Robust standard errors (clustered at individual participants) in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

difference in risk attitudes between the sexes reflects income differences, but our estimates are too imprecise to draw firm conclusions on this issue. Finally, we see from columns (A) and (D) that there is no relationship between the age of the subject and his or her risk taking in our data.

Turning to the gamble controls, Table 6 shows that the propensity of gamble rejection decreases in the mean net payoff, while it increases in the variance and the kurtosis of the payoff, as hypothesized. (Only the coefficient on the skewness of the payoff distribution has an unexpected sign.) We note that only the coefficient on the variance is statistically significant. However, this should not necessarily be taken as evidence of no effect of the other moments. Closer inspection of these variables reveals that they are highly correlated across gambles, making it difficult to distinguish the effects they have on the acceptance decision. Because we are mainly interested in the impact of individual characteristics, we present robustness checks using different specifications of the gamble controls below.

5.2 Robustness

The baseline results suggest that higher income individuals are more tolerant of the high financial risks involved in our game. We now check the robustness of this conclusion by changing the base model in three directions. A first concern is that, as mentioned above, the high correlation between the gamble characteristics makes it difficult to identify separate effects of these characteristics. Because of this, columns (A) and (B) in Table 7 report results using a more restrictive specification, where we use the coefficient of variation as the only variable characterizing the gamble faced by the contestant. This single variable represents

Table 7: Alternative gamble controls

	(A)	(B)	(C)	(D)
Income	-0.000214*	-0.000245**	-0.000139	-0.000165
	(0.000119)	(0.000119)	(0.000094)	(0.000101)
Male	-0.0595		-0.0480	
	(0.0468)		(0.0437)	
Age	0.000289		-0.000603	
	(0.00144)		(0.00170)	
Coefficient of variation	3.936***	3.914***		
	(0.3163)	(0.3267)		
Fixed effects	No	No	Yes	Yes
Observations	207	207	207	207
R-squared	0.481	0.477	0.681	0.679

The accept/ reject dummy, s_{il}, is the dependent variable.
Robust standard errors (clustered at individual participants) in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

in a simple way the trade-off between risk and return in a given gamble. The results in column (A) and (B) show that the estimated effect of the coefficient of variation is positive, as expected, and highly statistically significant. By comparing with Table 6, we see that the effect of income on the decision to accept the gamble is unaffected.

A second concern about the baseline results is that we have ignored the continuation value embedded in the gambles. For reasons discussed in Section 4, we have assumed that the subjects think only one step ahead when they decide whether to accept or reject the gamble. However, if the degree of such myopia varies between subjects and if it is systematically related to income, ignoring the continuation value can bias our estimates of the income coefficient. A flexible way to check if exclusion of the continuation value affects our estimates is to include gamble fixed effects in the model. We define and include dummy variables for all gambles n listed in Table 4, and thus our identification is based on variation in income, age, and gender between subjects confronting identical gambles. The results from this estimation are reported in columns (C) and (D) in Table 7. The income coefficient is somewhat lower in absolute value, and it is no longer statistically significant (absolute t-value of 1.63). A decrease in the income coefficient could be due to a relationship between income and degree of myopic behavior. We notice that taking into account the continuation value, makes all gambles more valuable and it should thus, ceteris paribus, increase the propensity to accept. For the continuation value to explain the lower income coefficient, it must be the case that low income subjects are less myopic than high income subjects. Although possible, we find this rather implausible. A more likely explanation for the smaller effect of income is that the variation remaining in the income variable in the fixed effects specification is simply too low to identify the effect with any precision. Furthermore, as is well known, introducing fixed effects generally increases the errors in variables problem and likely leads to bias towards zero in estimated effects.

Table 8: Regressions including taxable wealth

	(A)	(B)
Income	-0.000214*	-0.000231*
	(0.000122)	(0.000127)
Positive wealth	-0.0589	-0.0590
(dummy)	(0.0475)	(0.0448)
Male	-0.0309	
	(0.0446)	
Age	0.000587	
	(0.00141)	
Myopic expected	-0.000232	-0.000269
payoff	(0.000674)	(0.000679)
Myopic variance	6.80e-07***	6.66e-07***
	(2.31e-07)	(2.35e-07)
Skewness	0.105	0.0869
	(0.181)	(0.176)
Kurtosis	0.0785	0.0703
	(0.0594)	(0.0569)
Observations	203	203
R-squared	0.523	0.522

The accept/ reject dummy, s_{il}, is the dependent variable.
Robust standard errors (clustered at individual participants) in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

As a final specification check, we include an indicator of taxable wealth in the model. As discussed in Section 3.1, taxable wealth is a highly imperfect measure of the subjects' true wealth, but given the crucial role assigned to wealth in models of risky choice, we nevertheless wish to investigate if controlling for taxable wealth changes the income effect. Among our 104 subjects, 53 had zero taxable wealth in the calendar year prior to their appearance on the game show. In Table 8, we therefore present results from a model where a dummy variable equals one if the subject had positive taxable wealth.[18] Although imprecisely estimated, the coefficient on wealth has the expected negative sign. On average, subjects with taxable wealth are more likely to accept a given gamble. This supports our baseline finding of a higher risk tolerance among rich subjects. Comparing the results in Table 8 with those in Table 6 show that the effect of income is largely unaffected.

6 Conclusions

We have examined the connection between income and risky choice with a sample of individuals representative of the general Norwegian population. We find that risk aversion best characterizes behavior when people face gambles with payoffs that significantly impact living standards. We also find considerable support for an increase in risk tolerance as the (pre-gamble) income of a person increases. On the other hand, we find only a weak, statistically

[18] We have also tested specifications where the amount of taxable wealth is included directly. The results from these specifications are similar, but less precisely estimated.

insignificant effect of gender on risk attitudes and no effect of age. Our findings imply that welfare evaluations of government policies that have real effects on living standards should assume that people are risk averse and that poor people are less willing to carry risk.

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