Forthcoming in: *Management Science*

Explaining excess entry in winner-take-all markets*

Vincent Laferrière† David Staubli‡ Christian Thöni§

March 8, 2022

Abstract

We report experimental data from standard market entry games and winner-take-all games. At odds with traditional decision making models with risk aversion, the winner-take-all condition results in substantially more entry than the expected-payoff-equivalent market entry game. We explore three candidate explanations for excess entry: blind spot, illusion of control, and joy of winning, none of which receive empirical support. We provide a novel theoretical explanation for excess entry based on Cumulative Prospect Theory and test it empirically. Our results suggest that excess entry into highly competitive environments is not caused by a genuine preference for competing, but driven by probability weighting. Market entrants overweight the small probabilities associated with the high payoff outcomes in winner-take-all markets, while they underweight probable failures.

JEL-Classification: C92; D81; D91

Keywords: Winner-take-all market; Market entry game; Excess entry; Cumulative Prospect Theory; Probability weighting; Experiment

*We thank the editor, three anonymous referees, Adrian Bruhin, Helga Fehr-Duda, Urs Fischbacher, Thomas Fischer, Simon Gächter, Holger Herz, Matthias Krapf, Luís Santos-Pinto, Peter Wakker, Roberto Weber, and Christian Zehnder for helpful comments and suggestions. We also thank Lukas Haffert and Christoph Schleiffer for excellent research assistance. The project was funded by the Dr. h.c. Emil Zaugg-Fonds, grant no. B11162135 and the Swiss National Science Foundation, grant no. 100018_182185.

†University of Lausanne, FDCA, Quartier UNIL-Chamberonne, Bâtiment Internef, CH-1015 Lausanne; phone: +41 21 692 2809; email: vincent.laferriere@unil.ch

‡Swiss Federal Tax Administration, Eigerstrasse 65, CH-3003 Bern; phone: +41 78 760 0727; email: david.staubli@estv.admin.ch

§University of Lausanne, FDCA, Quartier UNIL-Chamberonne, Bâtiment Internef, CH-1015 Lausanne; phone: +41 21 692 2843; email: christian.thoeni@unil.ch; web: https://people.unil.ch/christianthoeni/; ORCID: 0000-0003-1190-8471

1 Introduction

Empirical research finds that most start-ups fail within a few years. Using data on the U.S. manufacturing sector, Dunne, Roberts, and Samuelson (1988) report that 61.5% of newly established plants exit the market after five years and 79.6% after ten years. Mata and Portugal (1994) confirm the high failure rates based on data of the Portuguese manufacturing industry. Hamilton (2000) finds the majority of people who enter self-employment to face lower expected earnings but higher variance than in a paid job. More recent evidence is barely more encouraging. According to the Small Business Administration Office of Advocacy's 2020 Frequently Asked Questions, the ten-year survival rate of new businesses is 33.6%, and the fifteen-year survival rate is 25.7%.[1]

This excess entry is at odds with early findings in the experimental literature. Standard experimental market entry games fail to find excess entry (see Sundali, Rapoport, & Seale, 1995; Rapoport, Seale, Erev, & Sundali, 1998). Instead, they find the number of market entrants to be in line with Nash equilibrium predictions. As Kahneman (1988) puts it, this tacit coordination towards the Nash equilibrium "looks like magic".

How come there is such a disconnect between empirical evidence from the laboratory and from the field? Entrepreneurship in the real world deviates in two main respects from the laboratory market entry game setting. First, in the real world successful market entry depends on entrepreneurial skills. Second, many markets in the real world feature winner-take-all characteristics, i.e., few competitors capture a very large share of the rewards and the remaining competitors are left with very little. Examples for the latter abound: network externalities create winner-take-all markets, namely in the IT industry, for example for social networks (e.g. Facebook, Twitter) or software (e.g. operating systems). Also industries with one or only few slots display winner-take-all characteristics. Examples are highly competitive environments like markets for CEOs or politicians. Finally, we see a particularly high concentration of rewards for a few competitors in the entertainment business such as performing arts (music, dance, etc.) or sports (tennis, football, boxing, etc.).

More recent research on market entry in competitive environments has focused on the role of beliefs about relative skill. Camerer and Lovallo (1999) report results from laboratory experiments showing that overconfidence can drive excess entry in a setting where market returns depend on skill. Moore and Cain (2007) build on Camerer and Lovallo (1999) and manipulate the difficulty of the task to determine skill levels. They find that skill-dependent market returns lead to excess entry only in the easy-task condition, but not in the difficult-task condition. Moore, Oesch, and Zietsma (2007), Dorfman, Bereby-Meyer, and Moran (2013), and Cain, Moore, and Haran (2015) confirm the finding that competitions over easy tasks are most likely to produce excess entry. Wu and Knott (2006) study aggregated market data on entry decisions of entrepreneurs and find excess entry in markets where there is a high degree of uncertainty about ability and low demand un-

[1] https://cdn.advocacy.sba.gov/wp-content/uploads/2020/11/05122043/Small-Business-FAQ-2020.pdf

certainty. Comparing the evolution of overconfidence between strategic and non-strategic environments, Brilon, Grassi, Grieder, and Schulz (2019) find that overconfidence persists when subjects can strategically send signals about their skill and opt out of competition (strategic). Overconfidence vanishes, however, when subjects are forced to compete with each other and cannot strategically send signals (non-strategic). Morgan, Orzen, Sefton, and Sisak (2016) allow subjects to make post-entry investment decisions to investigate the role of natural and strategic risk. They show that adding natural risk to market entry leads to a slight increase in the frequency of market entry and to a much higher post-entry investment.[2]

In Danz (2020) subjects have to choose between a piece-rate compensation and a competitive tournament after observing their competitors' past performances. By manipulating ex post information about their competitors' previous tasks, he shows that hindsight bias generates overplacement and increases subjects' valuations of tournament participation.

So far, the significant body of literature drawing on insight from behavioral economics to explore the roots of entrepreneurship is inconclusive. There is no clear "smoking gun" to account for the excess entry in the real world documented in the empirical literature (see Åstebro, Herz, Nanda, and Weber, 2014, for a review).

Closest to our work is Fischbacher and Thöni (2008) who modify the payout scheme to incorporate the winner-take-all characteristics of many real world markets. Deviating from standard market entry games, they do not distribute the market evenly among the entrants. Instead, they randomly determine a single winner who takes the entire market. In this winner-take-all setting they find excess entry well beyond Nash equilibrium predictions, absent any role for skill. However, since they do not contrast their results with an expected-payoff-equivalent standard market entry game, their setting cannot single out the winner-take-all feature as the cause of excess entry.

In this paper we fill this gap by running both a winner-take-all game (WTA) and an expected-payoff-equivalent standard market entry game (MEG). This allows us to isolate the effect of the winner-take-all feature. We find a large and statistically significant treatment effect: the WTA condition creates more market entry than the MEG condition. This treatment effect is puzzling. As market entry in the WTA condition offers the same expected payoff (henceforth, "expected payoff" always refers to "expected monetary payoff") but more variance than in the MEG condition we would expect just the contrary based on standard expected utility models with risk aversion.

We investigate a number of explanations for excess entry found in the literature. First, we rule out utility curvature as an explanation. To account for excess entry into WTA markets, convexity of utility functions would be required, which is incompatible with find-

[2]Experimental research has also found overbidding in rent-seeking contests (see Dechenaux, Kovenock, and Sheremeta, 2015, for a review). Cason, Masters, and Sheremeta (2020) show that efforts are consistently higher in winner-take-all contests compared to contests with proportional prizes. Sheremeta (2018) explores multiple behavioral explanations and finds impulsivity to be the primary driver of overbidding.

ings in the empirical literature. Then we find that neither wrong beliefs about other players' entry probability (henceforth, "blind spot", following Camerer and Lovallo, 1999), nor erroneous beliefs that one can influence random processes ("illusion of control", see Langer, 1975) can explain the treatment effect. Furthermore, we address the possibility that the competition-against-others structure of the WTA game provides an extra utility associated with successful market entry ("joy of winning"). Running two additional conditions that preserve the payoff consequences but eliminate the competitive element, we find that the treatment effect does not disappear when the competitive element is removed.

We finally investigate a new approach to understand excess entry through the lens of Cumulative Prospect Theory (CPT; Kahneman and Tversky, 1979, and Tversky and Kahneman, 1992). We show that—depending on the parameter specifications—CPT can be a powerful explanation for excess entry in winner-take-all markets. To explore the predictive power of CPT we ran an additional experiment where we estimate subjects' CPT parameters and relate them to their entry behavior. Our parameter estimates are in line with previous findings from the literature. We show that our pooled parameter estimates are consistent with the treatment effect. The driver of the effect is the inverse S-shaped weighting of cumulative probabilities. This translates into overweighting of small probabilities of winning large payoffs in the winner-take-all game. Further, we classify subjects as expected utility theory (EUT) types or CPT types using a finite mixture model approach. Relating this classification to market entry behavior, we are able to show that excess entry in the winner-take-all condition is primarily driven by CPT types.

Explaining excess entry by the biased perception of probabilities as described by the weighting of cumulative probabilities (henceforth "probability weighting") is promising for mainly two reasons. First, the inverse S-shaped weighting function is a well established finding of the behavioral economics literature (see G. Wu & Gonzalez, 1996; Fennema & Wakker, 1997; Abdellaoui, 2000; Harrison & Rutström, 2009; Bruhin, Fehr-Duda, & Epper, 2010a; Wakker, 2010; Fehr-Duda, Epper, Bruhin, & Schubert, 2011; Fehr-Duda & Epper, 2012; Bruhin, Santos-Pinto, & Staubli, 2018). Second, probability weighting offers a complementary explanation to overconfidence as a driving force behind excess entry. This is important because there are environments in which overconfidence is unlikely to arise (e.g. in competitions on difficult tasks).[3] We further show that the predictive success of probability weighting in a CPT framework extends to strategic situations. While there is a large number of experimental studies on CPT applied to individual choice problems, empirical research on CPT preferences in strategic contexts is surprisingly sparse.[4]

The remainder of the paper is organized as follows. The next section presents the

[3]Overconfidence about skill is far from being a ubiquitous phenomenon. It depends on subjects' characteristics (Schulz & Thöni, 2016), and whether the task is familiar or non-familiar to the subjects (Hoelzl & Rustichini, 2005).

[4]Ernst and Thöni (2013) show that behavior in all-pay auctions is consistent with reference-dependent utilities as proposed by CPT; Brünner, Reiner, Natter, and Skiera (2019) find evidence for CPT preferences in bidding behavior in online auctions; Nguyen, Villeval, and Xu (2016) relate prospect theory preferences to trust.

experimental design. Section 3 presents the main results. In Section 4 we investigate explanations for the treatment effect: blind spot, illusion of control, and joy of winning. In Section 5 we derive predictions for CPT and put the explanation to an empirical test. Section 6 concludes.

2 Experimental design

2.1 The game

In our game, n players decide simultaneously whether to enter a market ($Entry_i = 1$) or to stay out ($Entry_i = 0$). If a player decides to stay out, she gets a fixed payoff I. Staying out can be interpreted as earning a fixed payment for regular employment. In our setting, n is equal to 14 and I is equal to 45 experimental currency units (ECU). If a subject enters the market, her payoff depends on the number of market entrants ($E = \sum_{j=1}^{n} Entry_j$). The payoffs for entering the market follow the function described in Table 1, where E is the number market entrants, $\Pi(E)$ is the market payoff, and $\pi(E)$ is the market payoff divided by the number of entrants ($= \Pi(E)/E$).

Table 1: Payoff function for entrants, dependent on the number of entrants E

E	1	2	3	4	5	6	7	8	9	10	11	12	13	14
$\Pi(E)$	100	130	155	175	190	200	205	209	212	214	215	215	215	215
$\pi(E)$	100	65	51.7	43.8	38	33.3	29.3	26.1	23.6	21.4	19.5	17.9	16.5	15.4

In the market entry game (MEG) condition, each entrant earns a payoff $\pi(E)$. To illustrate, if five players enter the market, then the market payoff is 190 and each entrant earns 38. In the winner-take-all (WTA) condition the market payoff is randomly assigned to one entrant only. That is, one entrant earns $\Pi(E)$, while all other entrants earn zero. Each entrant receives the payoff of $\Pi(E)$ with probability $1/E$ and zero otherwise. To illustrate, if five players enter the market, then one randomly selected entrant gets the total market payoff of 190 and the four other players get a payoff of 0. Each entrant has a probability of 0.2 to be assigned the market payoff of 190. Consequently, given the number of entrants, the *expected* payoff for market entry is the same in both conditions.

Similarly to the payoff function in Fischbacher and Thöni (2008), $\Pi(E)$ is increasing and concave in E. In our case, however, $\Pi(E)$ flattens out at $E = 11$. In reality, total market returns may or may not be increasing in the number of competitors. As argued by Frank and Cook (1995), more competitors may increase the market value for several reasons: First, the winner in a competition with a large number of competitors will likely perform better than the winner in a competition with a small number of competitors. Thus, if not only relative but also absolute performance is rewarded, the winner's prize increases in E. This is plausible, for instance, in the music business or in sports with absolute performance measures (e.g. world records in athletics). Second, particularly in sports or the performing arts, more contestants increase public attention and media coverage, which in turn increases the rewards for the top performers. The marginal effect of an additional entry on market volume, however, is assumed to be decreasing. This gives rise to strictly decreasing expected payoffs *per entrant*, $\Pi(E)/E$, as the number of entrants increases. Due to limited potential market demand, an entrant therefore imposes an externality on other entrants by lowering their expected payoffs.

2.2 Nash equilibria

In this section we derive Nash equilibria in pure and in mixed strategies. We start with the simplest case assuming that players maximize their expected payoff. As the MEG and WTA conditions are equivalent under this assumption, the following analysis holds for both games. The pure-strategy Nash equilibria are straightforward. As long as there are less than three entrants, it is a best response to enter. When three other players enter the market, entry is no longer profitable, as a fourth entrant would forgo 45 and earn $\pi(4) = 43.8$. Any permutation of three players entering the market and the other 11 players staying out constitutes a Nash equilibrium in pure strategies. For the symmetric mixed-strategy Nash equilibrium, a player's entry probability, p^*, must satisfy:

$$\sum_{E=1}^{n} \binom{n-1}{E-1} {p^*}^{E-1} (1-p^*)^{n-E} v(E) = u(I), \tag{1}$$

where $v(E) = u(\pi(E))$ in the MEG condition and $v(E) = \frac{1}{E}u(\Pi(E)) + \frac{E-1}{E}u(0)$ in the WTA condition. The condition equates the value of staying out (right-hand side) to the value of entering the market if all *other* players enter the market with probability p^* (left-hand side). Assuming expected payoff maximization (linear $u()$, risk neutrality) and inserting the parameters of our experimental setting for n, I, $\Pi(E)$, and $\pi(E)$ yields $p^* = 0.25$. If all players enter with probability p^* and stay out with probability $1 - p^*$, the expected number of market entrants is 3.52. Besides the symmetric equilibrium there are numerous asymmetric equilibria in mixed strategies. They feature some players who always enter, some who always stay out, and some who randomize. In any Nash equilibrium the average number of entrants is between 3 and 3.80. The former corresponds to the equilibrium in pure strategies, the latter corresponds to an asymmetric Nash equilibrium in mixed strategies where four players enter with probability 0.95 and the other ten player stay out. Any mixed-strategy Nash equilibrium implies more market entrants than the pure-strategy equilibrium. This is because in our parameterization the third entrant in the pure-strategy equilibrium is clearly better off entering than staying out and the fourth entrant is almost indifferent between entering and staying out. For a detailed analysis of the Nash equilibria we refer the reader to Fischbacher and Thöni (2008).

The effect of risk preferences as explained by expected utility theory is straightforward. If we assume risk aversion (concave $u()$), then entry becomes less attractive in both the MEG and WTA conditions and the equilibrium is characterized by fewer expected entrants. The effect is, however, stronger for the WTA condition and the theory predicts more entrants in the MEG condition than in the WTA condition. The opposite is the case for convex utility. We will analyze the equilibria under richer preference assumptions in more detail in Section 5.

The asymmetric equilibria mentioned above are indicative for what happens if we assume heterogeneous agents. We restrict our attention to a model with two types of players and perfect information about the types. Consider a group with z risk neutral players (linear $u()$) and $14 - z$ risk averse players (concave $u()$). Because Equation (1) cannot be satisfied for both types of players at the same time, only one of the two types is willing to play a mixed strategy in equilibrium. If $z > 3$, then there is an equilibrium in which the z risk neutral players play a mixed strategy while the risk averse players do not enter. The expected number of entrants would then be equivalent to the game with only z players, and we can use Equation (1) to derive the entry probabilities. It turns out that the expected number of entrants is fairly insensitive to changes in group size (as long as $z > 3$), gradually decreasing from 3.80 for $z = 4$ to 3.52 for $z = 14$. If $z = 3$ then there is no mixed-strategy equilibrium, while for $z < 3$ there are mixed-strategy equilibria in which the risk neutral players always enter and (some of) the risk averse players use a mixed strategy. The same logic applies if the group contains z players with risk appetite (convex $u()$) and $14 - z$ risk neutral/averse players.

2.3 Experimental procedures

We repeat the game for 20 periods in groups of size 14. We use a partner matching, i.e., subjects are allocated to groups of 14 at the beginning of the session and interact only within this group during the session.[5] For all groups there are two phases, a phase of 20 periods in the WTA condition, and a phase of 20 periods in the MEG condition. To control for order effects, about half of the groups played the WTA condition first and the MEG condition second; for the remaining groups we reversed the order. In total we observe 6160 entry decisions from 154 subjects.

At the beginning of every period we elicit subjects' beliefs about how many other subjects would enter the market (hereafter we will refer to the entrants apart from the subject considered as "other entrants"). We incentivize truthful revelation of beliefs by rewarding a correct guess with five ECUs. Experimental research shows that belief accuracy increases when correct beliefs are rewarded (see Wright & Aboul-Ezz, 1988; Gächter & Renner, 2010). However, in order to keep subjects' focus on the main game, the reward for a correct belief is rather small compared to the payoffs of the game.[6] In the WTA condition we use the computer to generate a uniformly distributed random number between 0 and

[5] In the first session with 28 subjects we ran a stranger matching with two groups. The results are almost identical for the two matching protocols.

[6] The design of our belief elicitation stage is deliberately kept simple. Eliciting full probability distributions would require that subjects allocate probability mass across 14 outcomes (0–13 other entrants) in each round. This would distract subjects from the main task. The downside of our method is that we elicit only the mode of the distribution, which is consistent with a wide range of probability distributions. For a discussion of elicitation methods and their biases see Armantier and Treich (2013).

100 for each subject. Among the subjects who chose to enter the market, the one with the highest random number wins the winner-take-all competition and the corresponding payoff. All competitors learn their random number and the random number of the winner in their group at the end of each period. In both conditions subjects are also informed about the number of other entrants at the end of each period. The strategies "market entry" and "staying out" are neutrally denoted as "Alternative A" and "Alternative B".

Subjects were paid out the sum of the payoffs of the 40 market entry decisions as well as the rewards for the correct guesses on the number of other entrants. The accumulated earnings in ECU were converted to real money at the end of the experiment at an exchange rate of CHF 1.5 ($\approx$ USD 1.5) per 100 ECUs.

The sessions were run in the laboratory of the University of St. Gallen with undergraduate students recruited with ORSEE (Greiner, 2015). The experiment was programmed in z-Tree (Fischbacher, 2007). Subjects were randomly allocated to the sessions so that they could not infer with whom they would interact. Sessions lasted between 70 and 80 minutes with an average pay per subject of CHF 37 ($\approx$ USD 37).

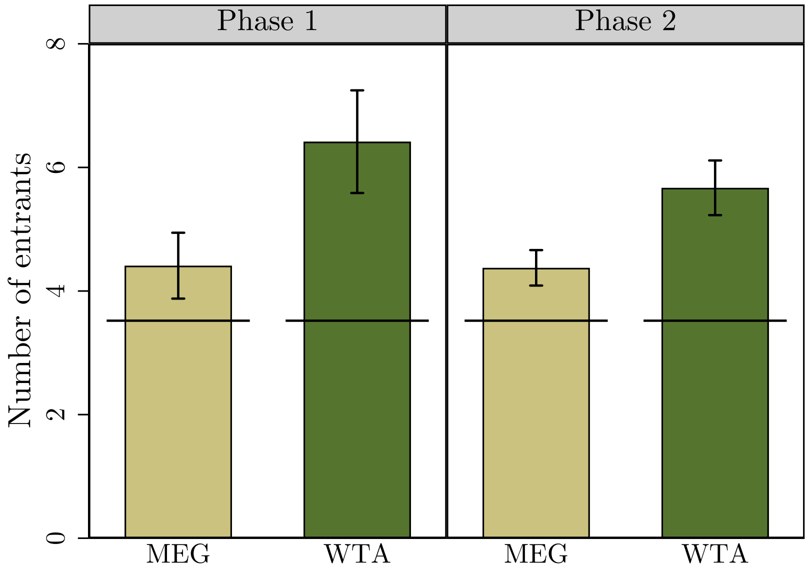
3 Results

Figure 1 shows that the WTA condition results in more market entry compared to the MEG condition. In phase 1 (phase 2) the average number of entrants across the 20 periods is 6.42 (5.67) in the WTA condition and 4.41 (4.38) in the MEG condition. The treatment effect is highly significant in both phases ($p = 0.008$, exact Wilcoxon-Mann-Whitney test using group averages as observations). Additionally, we can analyze the treatment effect within group. Pooling all groups across the two phases, the average number of entrants is 4.39 in the MEG condition and 6.08 in the WTA condition. An exact Wilcoxon signed-rank test on the within-group treatment effect yields a p-value of 0.002. Compared to the symmetric Nash equilibrium in mixed strategies (depicted by the horizontal lines in Figure 1) we observe excess entry in both conditions and in both phases.

Figure 2 shows market entry over time. It displays the average entry frequency across the 20 periods and both phases. The entry frequencies in both conditions become somewhat lower over time. While there is some indication that the MEG converges towards the predicted entry frequency, excess entry remains substantial in the WTA condition. In Table 2 we report linear probability models to test for time and order effects. Model (1) shows that both within phase and between phases we observe a significantly negative effect on entry. In Model (2) we interact period and the dummy for the second phase with the treatment dummy. The results suggest that the negative trend across the 20 periods within a phase is mainly driven by the MEG condition, whereas the reduction in entry frequency across phases is mainly driven by the WTA condition.

There is considerable heterogeneity in the entry behavior across subjects. The standard deviation of the individual number of entries over the 20 periods in the WTA condition is 6.41 (average individual number of entries is 8.68, data from both phases). About a

Figure 1: Number of entrants by treatment and phase



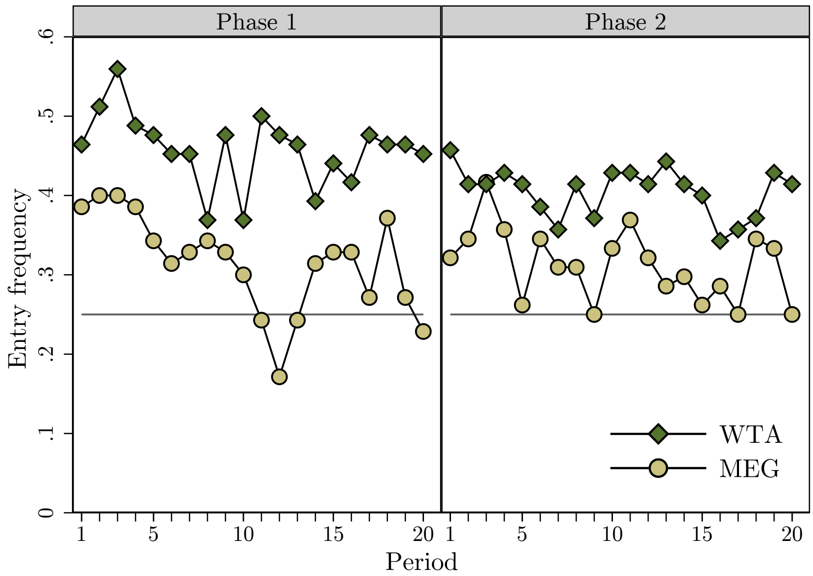
Notes. Average number of entrants in the two conditions per phase. The horizontal lines show the number of entrants predicted by the symmetric mixed-strategy Nash equilibrium with risk neutral players. Spikes show 95% confidence intervals, clustered on group.

quarter of the subjects enter two or fewer times during the 20 periods, while ten percent of the subjects enter in every period. In the MEG condition the standard deviation is somewhat lower (5.48), and 30 percent of the subjects enter two or fewer times, while only 2.6 percent enter in every period. For histograms of individual entry frequency see Figure B1 in the appendix.

Taken together, we observe excess entry relative to the Nash equilibrium in both conditions. In the MEG condition we observe a negative trend over time such that in the last periods the average number of entrants is no longer significantly different from the prediction ($p = 0.453$ in the final two periods, both phases). In the WTA condition, however, the corresponding difference remains highly significant ($p = 0.004$).

Our results on the WTA condition replicate and confirm the findings of Fischbacher and Thöni (2008), and our comparison with the expected-payoff-equivalent MEG condition allows us to identify the winner-take-all characteristics as the causal source of excess entry. This is puzzling because—for any number of other entrants—market entry in the MEG and WTA conditions offer the same expected payoff, but the latter comes with more variance. Thus, the results are at odds with legions of studies showing that subjects generally display risk averse behavior. Fischbacher and Thöni (2008) speculated that subjects either have "illusion of control" or that they gain extra utility from the thrill of competition in the WTA condition relative to the MEG condition. In the following we present additional data analyses and new experimental measures to investigate candidate explanations for the excessive entry behavior in the WTA condition relative to the MEG condition.

Figure 2: Entry over time



Notes. Frequencies of market entry in the two conditions per period across phase 1 and phase 2 (average over all periods in parentheses). The horizontal lines show the entry probability predicted by the symmetric mixed-strategy Nash equilibrium with risk neutral players.

Table 2: Linear probability models for entry

	Dependent variable: Entry	
	(1)	(2)
MEG	−0.118**	−0.116*
	(0.011)	(0.042)
Period	−0.003**	−0.002
	(0.001)	(0.002)
Phase 2	−0.028*	−0.053*
	(0.011)	(0.023)
MEG × Period		−0.003
		(0.003)
MEG × Phase 2		0.051
		(0.031)
Constant	0.482**	0.480**
	(0.021)	(0.036)
F-test	38.0	44.3
Prob > F	0.000	0.000
R^2	0.018	0.019
N	6,160	6,160

Notes: OLS estimates. Dependent variable is an individual entry decision; independent variables are dummies for the treatment (MEG) and phase 2, period, and interactions. Robust standard errors, clustered on matching group, in parentheses. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$.

4 Candidate explanations for excess entry

In this section we test the three hypotheses: blind spot, illusion of control, and joy of winning. For the first we make use of the beliefs elicited in the main experiment, for the second and third we present additional experimental measures.

4.1 Blind spot

In this section we address the blind spot explanation, that is, excess entry due to miscalibrated beliefs about other players' entry probability in the two conditions. Both conditions are strategic games: The fewer other players a particular player expects to enter, the more attractive market entry becomes. The treatment effect could be caused by biased beliefs. If players mistakenly belief that other players are less likely to enter in the WTA relative to the MEG condition, then the optimal response may be to enter more frequently in the WTA than in the MEG condition. This could arise from wrong beliefs about other players' risk preferences. As the WTA condition is subject to risk, overestimation of other players' risk aversion leads to underestimation of their entry probability.

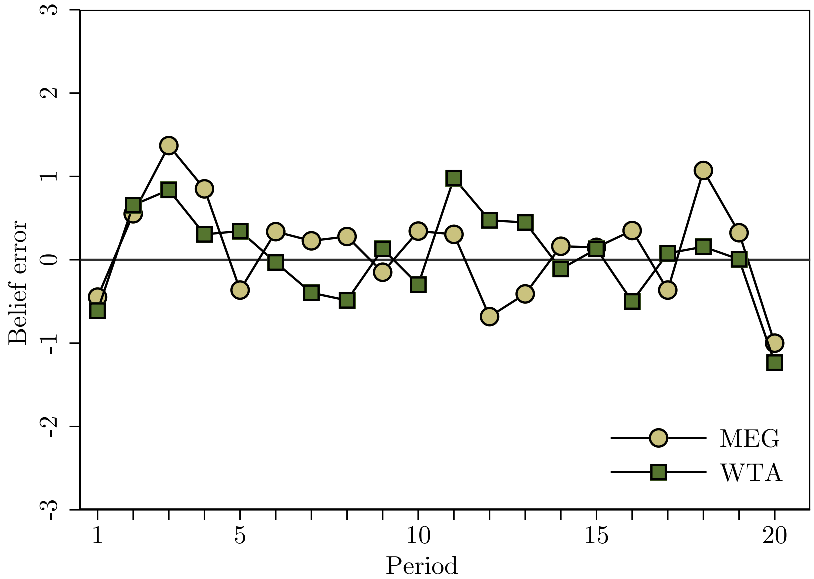
To address the blind spot explanation we elicited subjects' beliefs about the number of other entrants. We define the variable *Belief error* as the actual number of other entrants minus a subject's belief about the number of other entrants. It is thus a measure for the *underestimation* of the number of other entrants. Over the course of the 20 periods beliefs become more accurate and there is no systematic difference across conditions in terms of belief accuracy.[7] The blind spot explanation requires systematic underestimation in the WTA condition. Figure 3 shows the mean belief error across the 20 periods for the MEG and the WTA conditions. The mean belief error fluctuates around zero. That is, on average subjects' beliefs do not seem to be systematically biased.

Table 3 shows OLS regressions with the *Belief error* as the dependent variable. The estimate of the constant in Model (1) reflects the average *Belief error* across all subjects and all periods. The estimate indicates that subjects underestimate the number of other entrants by 0.095 which is not significantly different from zero. On average beliefs are therefore very accurate. The result in Model (2) indicates that subjects underestimate the number of other entrants somewhat less—by 0.102—in the WTA condition compared to the MEG condition (statistically insignificant). To provide evidence for the blind spot explanation, we would need subjects to underestimate the number of other entrants more strongly in the WTA condition. The negative sign of the coefficient estimate goes therefore against the blind spot explanation.

This does not suffice to rule out the blind spot explanation. The result in Model (2) is consistent with the following beliefs in the WTA condition: Those who enter frequently

[7] In the first five periods the absolute difference between the realized number of entrants and the belief is 2.08 on average, while in the last five periods the corresponding value is 1.64. If we regress the absolute belief error on period, a dummy for the WTA condition, and a dummy for the second phase, we observe a negative coefficient for period ($\beta = -0.028; p = 0.007$), while the other two coefficients are not significantly different from zero.

Figure 3: Belief errors over time



Notes. The figure shows the mean belief error in the MEG and the WTA conditions across the 20 periods (both phases). Positive (negative) values indicate that subjects underestimate (overestimate) the number of other entrants.

underestimate the number of other entrants and those who stay out overestimate the number of other entrants (thereby keeping average beliefs unbiased). We investigate this possibility by adding an interaction of the treatment dummy with the individual entry decision in Model (3).

Model (3) allows us to differentiate the effect of the beliefs by entry decision and condition. Table 4 provides the respective coefficient estimates. We find that subjects who enter in a given period display a positive belief error and subjects who do not enter in a given period display a negative belief error. To tackle the blind spot explanation we look at the difference in belief errors between the MEG and WTA conditions only for observations with $Entry = 1$. That is, we compare the lower-left cell and the lower-right cell of Table 4. The difference is equal to $\hat{\beta}_1 + \hat{\beta}_3 = -1.025$. This indicates that entrants underestimate the number of other entrants more strongly by 1.025 in the MEG condition compared to the WTA condition.

Again, the negative sign of the estimate, $\hat{\beta}_1 + \hat{\beta}_3$, goes against the blind spot explanation. To substantiate blind spot as an explanation for the treatment effect, we would need subjects to underestimate more strongly (or overestimate less strongly) the number of other entrants in the WTA condition compared to the MEG condition. Thus, the treatment effect cannot be explained by subjects erroneously underestimating the number of entrants in the WTA condition. On the contrary, if anything, subjects' beliefs strengthen the puzzle.

Table 3: Explaining belief errors

	Dependent variable: Belief error		
	(1)	(2)	(3)
WTA (β_1)		-0.102	0.265^{*}
		(0.060)	(0.084)
Entry (β_2)			1.606^{**}
			(0.177)
Entry $\times$ WTA (β_3)			-1.290^{**}
			(0.263)
Constant (β_0)	0.095	0.145^{*}	-0.358^{**}
	(0.055)	(0.060)	(0.054)
F-test	–	2.9	66.6
Prob $> F$	–	0.124	0.000
R^2	–	0.001	0.060
N	6,160	6,160	6,160

Notes: OLS estimates. Dependent variable is the belief error (number of other entrants – belief). Robust standard errors, clustered on matching group, in parentheses. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$.

Table 4: Mean belief error as a function of the WTA dummy and the Entry dummy

	WTA = 0	WTA = 1
Entry = 0	$\hat{\beta}_0 = -0.358^{**}$	$\hat{\beta}_0 + \hat{\beta}_1 = -0.093$
Entry = 1	$\hat{\beta}_0 + \hat{\beta}_2 = 1.247^{**}$	$\hat{\beta}_0 + \hat{\beta}_1 + \hat{\beta}_2 + \hat{\beta}_3 = 0.222^{+}$

Notes: $\hat{\beta}_j$ is the estimate of coefficient β_j from Model (3) of Table 3. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$.

4.2 Illusion of control

Subjects might believe they have some influence over the random process of the market payoff in the WTA condition. Such an "illusion of control" (IOC; Langer, 1975) might increase perceived profitability of market entry in the WTA condition. To investigate whether IOC drives the treatment effect, we introduce a measure for IOC and relate individual differences to market entry behavior.

We measure IOC with all participants after they completed the MEG and WTA phases. We identify IOC by the willingness to pay for a particular lottery ticket over other lottery tickets with the same objective winning probabilities. The 28 subjects in a session were presented with 28 symbols such as "%", "$", or "@". In the session we had an urn containing the complete set of symbols (28 cards), and subjects were told that two of the 28 symbols would be drawn at random. The two subjects with the respective symbols won additional CHF 50 (which is significantly more than the average earnings per subject in the main experiment).

After all subjects picked a symbol from the 28 symbols, they were informed that in order to have a one-to-one matching between symbols and subjects we would have to allocate the unchosen symbols to some of the subjects who chose the same symbols as others. Before subjects knew whether their preferred symbol was chosen more than once, all subjects had to indicate their willingness to pay to keep their symbol. Subjects were endowed with 800 ECUs. We explained to the subjects that there would be a sealed-bid second price auction for their symbol and they were asked to submit a bid. We explained to the subjects that in this auction format it would be optimal to bid exactly their willingness to pay.

Objectively, every symbol has the same probability to be chosen at random and subjects are aware of that. Consequently, there is no objective reason to pay to keep a particular symbol instead of being allocated another as yet unchosen symbol. If subjects nevertheless indicate a willingness to pay for their symbol, we interpret this as IOC.

On average subjects bid 114 ECUs with a standard deviation of 218. This implies that there is substantial variance: 43% of the subjects display no willingness to pay at all, 56% bid at most 5 ECUs, and 4% are willing to bid their full endowment of 800. Relative to the extra pay for winning the lottery (CHF 50 = 3333 ECUs), the vast majority of subjects have a rather low willingness to pay (see Figure B2 in the appendix for a histogram of the bids).

What matters for our purpose, however, is whether our measure for IOC has predictive power for excess entry. In Table 5 we use OLS regressions to investigate the effect on (1) the individual entry frequency in the WTA condition, and (2) the treatment effect (individual entry frequency in the WTA condition minus individual entry frequency in the MEG condition), both measured in percent. The results show that estimated coefficients in both models are close to zero and far from significant. These results suggest that illusion of control does not offer an explanation for excess entry.

Table 5: Excess entry and illusion of control

	Dependent variable: Entry frequency (in %)	
	WTA	WTA–MEG
Illusion of control	0.010	0.008
	(0.016)	(0.011)
Constant	42.290**	11.192**
	(1.899)	(1.568)
F-test	0.4	0.4
Prob > F	0.555	0.524
R^2	0.004	0.003
N	154	154

Notes: OLS estimates. Dependent variable is the individual entry frequency in WTA, or the treatment effect (frequency of entry in WTA minus frequency of entry in MEG). Both measures in percent. The independent variable is the bid in the auction for the symbol. Robust standard errors, clustered on matching group, in parentheses. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$.

4.3 Joy of winning

A main conjecture that Fischbacher and Thöni (2008) outline in their conclusion to explain excess entry is the thrill of winning a competition against others provided by the WTA condition. In the literature this phenomenon is often referred to as "joy of winning". The concept posits that winning a prize in a competitive environment generates more utility than winning the same prize in a simple lottery. Researchers have argued for the existence of joy of winning in contests and auctions. Studies include Goeree, Holt, and Palfrey (2002), Herrmann and Orzen (2008), Amaldoss and Rapoport (2009), Sheremeta (2010), Dohmen, Falk, Fliessbach, Sunde, and Weber (2011), Brookins and Ryvkin (2014), Herbst (2016).

In our setting the idea can be formalized by adding an extra payoff for the winner. This payoff represents the non-pecuniary joy of winning against the other market entrants. The mixed-strategy Nash equilibrium condition then writes:

$$\sum_{E=1}^{n} \binom{n-1}{E-1} {p^*}^{E-1} (1-p^*)^{n-E} \frac{1}{E} \left[\Pi(E) + jow\right] = I. \tag{2}$$

The main difference to Equation (1) is the term jow which is added to the winning payoff in the WTA condition. For simplicity, Equation (2) assumes linear utility functions. Predicting WTA entry probabilities in the range of 0.405 to 0.458 (see Figure 2) would require a jow term of about 80.

To address this potential explanation for excess entry, we run additional experimental sessions with two alternative conditions. The conditions are designed to preserve the monetary incentives of the WTA condition while eliminating the competitive element. We replace the strategic WTA game by a non-strategic individual choice problem, i.e., in both conditions a subject's payoff is independent of the decisions of the other subjects in the room. Instead, they depend on the frequency distribution of the number of market entrants as observed in the WTA condition in our main experiment (hereafter, "WTA condition" always refers to the WTA condition of the main experiment as described in Section 2.1).

The first treatment presents subjects with a situation where they have to form beliefs about the market entry behavior of the participants in the WTA condition in the past. We denote this treatment as AMB, for ambiguous winning probabilities. The second treatment goes one step further and presents the subjects with objective winning probabilities (OBJ) taken from the WTA condition.

In the AMB condition subjects decide in each of the 20 periods between Alternative A and Alternative B. The payoff function is identical to the WTA condition: Alternative B pays 45 ECUs for sure, while Alternative A pays either zero or a payoff which depends on the number of entrants according to Table 1. The number of entrants, however, is not decided in the game, but taken from the data of the WTA condition from the main experiment. More precisely, we allocate each subject to a particular group of 14 subjects from a session with the WTA condition. In each period in which the subject chooses Alternative A we replace one of the entrants in the original data by the subject in question to calculate the payoff in case of winning.[8] The feedback about the random numbers and the entry decisions is identical to the WTA condition, i.e., the AMB condition offers the same learning stimuli as the WTA condition. In addition, we also elicited beliefs. Because the subject in question is not an entrant, we elicit beliefs about the behavior of the group of 14 subjects from the WTA condition.

In the OBJ condition we go one step further towards individual choice and remove the belief element. Subjects again have to decide between Alternative A and Alternative B in 20 rounds, and the payoff for Alternative B remains 45 ECUs. The payoffs for Alternative A are still determined by entry behavior in the WTA condition, but we communicate the probability distribution of the entry behavior to the subjects. More precisely, in the OBJ condition we inform subjects about the absolute and relative entry frequencies in the WTA condition. The information shown in Table 6 is presented to subjects in the experimental instructions. It shows the absolute and relative frequencies of every possible number of market entrants observed in the WTA condition. The first row of the table shows the number of market entrants; the second row replicates the market payoff for each number of market entrants from Table 1. The interpretation is unchanged: If, for instance, five players enter the market, the market payoff is 190. The third row shows the number of times the respective number of market entrants was observed in the WTA condition. For instance, in 35 rounds the number of market entrants was five.[9]

Table 6: Information about the entry frequencies in the OBJ condition.

Number of participants who chose A	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Prize to win in ECU	100	100	130	155	175	190	200	205	209	212	214	215	215	215	215
Absolute number of rounds	1	0	1	8	20	35	51	30	15	13	2	4	0	0	0
Relative frequency in %	0.6	0	0.6	4.4	11.1	19.4	28.3	16.7	8.3	7.2	1.1	2.2	0	0	0

Notes. Information about the winning probabilities offered to the subjects in the OBJ condition. The table shows absolute and relative frequency of the number of entrants based on the entry decisions in the WTA condition in the main experiment. Alternative "A" stands for market entry.

The forth row shows the relative frequency with which the respective number of market entrants was observed in the WTA condition. For instance, in 19.4% of the rounds (=35/180) the number of market entrants was five. In the instructions the table was accompanied by a histogram showing the relative frequencies as a visual aid.

Thus, not only are payoffs for Alternative A independent of the decisions of the other

[8]In one group from the WTA condition data there was one period with no entry at all. We treated this case similar to the case with one entrant, i.e., the subjects who were allocated to this situation and chose Alternative A received 100 ECUs. This holds also for the OBJ condition.

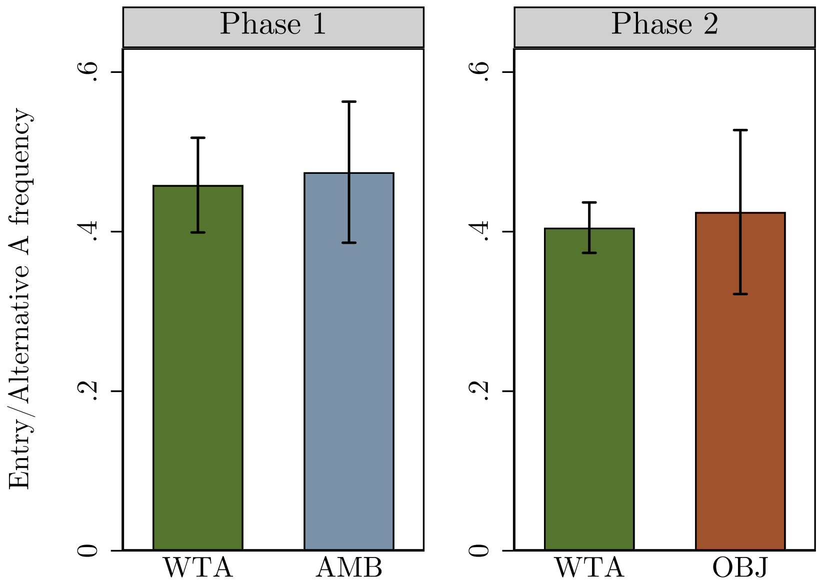
[9]The sum across all cells of the third row is 180 group/period outcomes. These stem from all sessions of the main WTA experiment except the one session where we used a stranger matching. We dropped the session with stranger matching because the instructions in the AMB and OBJ conditions explain that the data stems from experiments using a partner matching. See pages 14 to 20 of the appendix for the experimental instructions.

subjects in the session, in the OBJ condition subjects know the probability of each possible number of entrants and the probability of winning the market payoff given any number of entrants. This transforms the decision problem into a risky choice with complete information about all contingencies.

We conducted two sessions with a total of 53 subjects, none of which participated in the main experiment. All subjects had to read the original instructions of the WTA condition in order to have the same information about the game as the subjects from the main experiment. In addition, subjects received instructions detailing that they would not be in a strategic situation with the other subjects currently present in the laboratory. All subjects played 20 periods of the AMB condition followed by 20 periods of the OBJ condition. The average payoff per subject in the additional experimental sessions was CHF 31 (≈ USD 31).

The left panel of Figure 4 shows the frequency of Alternative A decisions in the AMB condition compared to the entry frequency observed in Phase 1 of the WTA condition. The frequencies are very similar, with 0.458 in the WTA condition and 0.475 in the AMB condition ($p = 0.741$). The right panel of Figure 4 shows the frequency of Alternative A decisions in the OBJ condition compared to the number of entrants in Phase 2 of the WTA condition. The entry frequency in the objective probability condition is 0.425, which is even somewhat higher than the 0.405 of the WTA condition ($p = 0.741$).

Figure 4: Ambiguous and objective winning probabilities



Notes. Left panel: Average entry frequency in phase 1 of the WTA condition and frequency of Alternative A decisions in the ambiguous probabilities condition (AMB). Right panel: Entry frequency in phase 2 of the WTA condition and frequency of Alternative A decisions in the objective probabilities condition (OBJ). Spikes show the 95% confidence intervals. In the WTA condition standard errors are clustered on group.

To sum up, we find no evidence that the risky alternative becomes less attractive if we eliminate the competitive element, and we conclude that "joy of winning" is unlikely to be a driver of excess entry.

5 Explaining excess entry with Cumulative Prospect Theory

After our unsuccessful empirical quest for the causes of excess entry we redirected our efforts to look for theoretical arguments that might help us understand why—contrary to our intuition—the winner-take-all feature renders market entry *more* attractive compared to the market entry game. This time we were successful: it turns out that Cumulative Prospect Theory (CPT; Kahneman & Tversky, 1979; Tversky & Kahneman, 1992) captures the differences between the MEG and WTA conditions surprisingly well. As a first step, we derive the Nash equilibria for CPT players. Next, we run new experimental sessions in which we elicit subjects' certainty equivalents for 40 two-outcome lotteries after they completed the MEG and WTA phases. This additional task allows us to estimate pooled CPT parameters. Finally, we compare actual entry decisions in both the MEG and the WTA conditions to theoretical predictions using our CPT parameter estimates. We show that our parameter estimates for the curvature of the utility function and the function to transform objective cumulative probabilities into subjective cumulative probabilities (henceforth "weighting function") can predict excess entry in the WTA condition. The decisive component is probability weighting.

The adequacy of linear probability weights has already been questioned by Allais (1953). Since then, a variety of non-linear functional forms for probability weights have been suggested in the literature (Quiggin, 1982; Goldstein & Einhorn, 1987; Lattimore, Baker, & Witte, 1992; Tversky & Kahneman, 1992; Prelec, 1998). We use probability weighting in the framework of CPT to make Nash equilibrium predictions in the MEG and WTA conditions.[10] To compute Nash equilibrium predictions under CPT we rewrite Equation (1) as:

$$\sum_{k=1}^{m} \omega_k u(x_k) = u(I). \tag{3}$$

The left-hand side describes the subjective value of market entry, where ω_k is the decision weight on outcome x_k, $u(x_k)$ is the utility associated with outcome x_k, and m is the number of possible outcomes for an entrant. In a mixed-strategy Nash equilibrium the expression on the left-hand side must be equal to the utility provided by staying out, $u(I)$. We use a two-parameter weighting function proposed by Goldstein and Einhorn (1987) and Lattimore et al. (1992):[11]

$$h(Q, \delta, \gamma) = \frac{\delta Q^\gamma}{\delta Q^\gamma + (1-Q)^\gamma}, \tag{4}$$

[10] For analysis of Nash equilibrium properties with (Cumulative) Prospect Theory decision making, see Goeree, Holt, and Palfrey (2003), Keskin (2016), or Metzger and Rieger (2019).

[11] The literature offers a wide range of specifications for the weighting function. We follow Gonzalez and Wu (1999), who argue that the evidence in the domain of gains favors a weighting function with two parameters.

where Q is the objective cumulative probability and the parameter γ governs likelihood sensitivity. If $\gamma \in (0,1)$, the function displays an inverse S-shaped pattern where small cumulative probabilities are upweighted and large cumulative probabilities are downweighted (likelihood insensitivity). If $\gamma > 1$, the function displays an S-shaped pattern where low cumulative probabilities are downweighted and high cumulative probabilities are upweighted (likelihood oversensitivity). Upweighting (downweighting) of small cumulative probabilities leads to overweighting (underweighting) of small probability extreme outcomes. The parameter δ governs the elevation of the weighting function (optimism/pessimism). If $\delta \in (0,1)$, the individual is pessimistic as she downweights the probability of high payoff outcomes and upweights the probability of low payoff outcomes. Conversely, if $\delta > 1$, the individual is optimistic as she upweights the probability of high payoff outcomes and downweights the probability of low payoff outcomes. When $\gamma = \delta = 1$ the weighting function is linear and the model boils down to expected utility maximization with $h(Q,1,1) = Q$.

The decision weights in Equation (3) are weighted cumulative probabilities on outcomes that are ordered by their payoff. If $x_1 \geqslant x_2 \geqslant \ldots \geqslant x_m$ holds for the set of possible realizations of X, then the subjective decision weights are:

$$\begin{aligned}
\omega_1 &= h(q_1) - h(0)\\
\omega_2 &= h(q_1 + q_2) - h(q_1)\\
&\vdots\\
\omega_k &= h(Q_k) - h(Q_{k-1})\\
&\vdots\\
\omega_m &= h(1) - h(Q_{m-1}),
\end{aligned}$$

where q_k denotes the probability that X is equal to x_k and $Q_k = \sum_{j=1}^{k} q_j$ denotes the cumulative probability, that is the probability that X is greater than or equal to x_k; $h(Q_k)$ is the weighting function as defined in Equation (4) applied to the cumulative probability Q_k. By setting $h(1)$ equal to one and $h(0)$ equal to zero we have the subjective decision weights sum up to one. To model utility curvature we use a constant relative risk aversion (CRRA) utility function:

$$u(x,\eta) = \begin{cases} \frac{x^{(1-\eta)}-1}{1-\eta}, & \text{for } \eta \neq 1 \\ \ln(x), & \text{for } \eta = 1 \end{cases} \tag{5}$$

where $x \geqslant 0$ is the payoff and η measures CRRA. The parameter η determines the curvature of the utility function: $\eta > 0$ corresponds to concave utility functions, $\eta = 0$ to linear utility functions, and $\eta < 0$ to convex utility functions.[12] Because negative payoffs

[12] In standard expected utility models risk preferences are directly related to the curvature of the utility function. In a CPT framework risk averse behavior can be attributed to the utility function and/or the probability weighting function. In what follows we will avoid the term risk aversion. Instead, we directly refer to the curvature of the utility function or to probability weighting. For a discussion on risk aversion in a CPT framework see e.g. Schmidt and Zank (2008).

are not possible in our games we only formulate the utility in the domain of gains.[13]

What does this imply for Nash equilibrium predictions in the MEG and WTA conditions? As market entry in the two conditions is subject to different levels of risk, the two conditions cease to be equivalent in terms of Nash equilibrium predictions. In the following we derive the symmetric mixed-strategy equilibria for the MEG and WTA conditions separately.

5.1 MEG condition

In the MEG condition the payoffs for market entry are determined by $\pi(E)$ according to Table 1. To compute the value of market entry we order all possible payoffs associated with market entry from the highest to the lowest:

$$\begin{aligned} X &= \{x_1, x_2, \ldots, x_{14}\} = \{\pi(1), \pi(2), \ldots, \pi(14)\} \\ &= \{100, 65, 51.7, 43.8, 38, 33.3, 29.3, 26.1, 23.6, 21.4, 19.5, 17.9, 16.5, 15.4\}. \end{aligned}$$

x_k is the payoff from entering the market if $k-1$ other players enter the market and $13-(k-1)$ other players stay out. Accordingly, q_k denotes the probability of winning the payoff associated with $k-1$ other players entering and $13-(k-1)$ other players staying out. Given the number of entrants, the payoff is non-random in the MEG condition, i.e., there is only strategic risk.

The probabilities $\{q_1, q_2, ..., q_{14}\}$ depend on the entry probability p of the other players. The probability that $k-1$ other players enter the market is:

$$q_k = \binom{13}{k-1} p^{k-1}(1-p)^{13-(k-1)}, \qquad k = 1, \ldots, 14. \tag{6}$$

To obtain the Nash equilibrium predictions we compute the decision weights ω_k associated with the probabilities q_k. The symmetric Nash equilibrium in mixed strategies is then the entry probability p^* that solves Equation (3). The predicted number of market entrants is obtained by multiplying the probability p^* with the number of players.

The first part of Table 7 shows the expected number of entrants for selected values of the three preference parameters. At the top left we start with the benchmark case of linear utility and linear probability weights, which results in 3.52 expected entrants (see Section 2.2). Increasing concavity of the utility function (η) has hardly any effect on entry, while increasing likelihood insensitivity (lowering γ) increases entry towards four entrants. Finally, lowering optimism (δ) reduces entry somewhat.

[13]In the instructions we frame the decision situation clearly as choice between a secure and a risky gain. Nevertheless, one could argue that the payoff from staying out (45) serves as a reference point, which would introduce the possibility for losses in both games. In Appendix A.1 we discuss the equilibria for a reference point of 45 and loss aversion. It turns out that loss aversion reduces the expected number of entrants very similarly to increasing concavity of the utility function. In the following we will restrict our attention to the gains only version in the main text.

Table 7: Predicted number of entrants in MEG and WTA

		MEG			WTA		
		$\eta = 0$	$\eta = 0.1$	$\eta = 0.2$	$\eta = 0$	$\eta = 0.1$	$\eta = 0.2$
$\gamma = 1$	$\delta = 1$	3.52	3.49	3.47	3.52	2.79	2.22
	$\delta = 0.8$	3.31	3.29	3.26	2.59	2.09	1.69
$\gamma = 0.75$	$\delta = 1$	3.74	3.70	3.66	6.14	4.38	3.05
	$\delta = 0.8$	3.47	3.43	3.39	4.08	2.84	1.99
$\gamma = 0.5$	$\delta = 1$	4.18	4.10	4.03	14.00	10.44	6.64
	$\delta = 0.8$	3.78	3.71	3.64	10.01	6.39	3.55

Notes. Expected number of entrants in the symmetric mixed strategy equilibrium with CPT preferences, for selected values of the three preference parameters η, γ, and δ.

5.2 WTA condition

In the WTA condition the payoff of market entry is subject to two kinds of risk: (i) strategic risk, originating from the behavior of other players, and (ii) natural risk, originating from the random draw of the winner among the entrants. In our main model we will assume that players do not distinguish between natural and strategic risk, but treat the two sources similarly and apply probability weighting to the compound objective probabilities.[14] Some support for combining the two sources of risk comes from our results from Section 4.3, where we report similar entry behavior in the OBJ condition compared to the WTA condition. We start by ordering the possible payoffs from the highest to the lowest to compute the value of market entry. The set of possible payoffs is:

$$X = \{x_1, x_2, \ldots, x_{15}\} = \{\Pi(14), \Pi(13), \ldots, \Pi(1), 0\}$$
$$= \{215, 215, 215, 215, 214, 212, 209, 205, 200, 190, 175, 155, 130, 100, 0\}.$$

Thereby, 215 is the winner's payoff for entering the market if 10, 11, 12, or 13 other players enter; 214 is the winner's payoff for entering the market if 9 other players enter. Zero is the payoff for entering the market with any number of other players if the player does not win the market payoff. The probabilities $\{q_1, q_2, ..., q_{15}\}$ associated with the set of payoffs are:

$$q_k = \begin{cases} \binom{13}{13-(k-1)} p^{13-(k-1)} (1-p)^{k-1} \frac{1}{14-(k-1)}, & \text{for } k = 1, \ldots, 14 \\ 1 - \sum_{j=1}^{14} q_j, & \text{for } k = 15. \end{cases} \quad (7)$$

Again, the symmetric Nash equilibrium in mixed strategies is the entry probability p^* that solves Equation (3). The right part of Table 7 shows the expected number of

[14]Alternatively one could assume that probability weighting applies to natural risk only. Our theoretical results would not differ much, because most of the predicted treatment effect originates from the natural risk part. Finally, probability weighting could only affect strategic risk. In this case (assuming linear utility) the model would not predict any difference between the WTA and the MEG conditions. Appendix A.2 provides a formal discussion on different variants of probability weighting.

entrants in the WTA condition. Starting with the 3.52 entrants in the benchmark case ($\eta = 0, \gamma = 1, \delta = 1$), we observe that the qualitative effects of the parameters are the same as in the MEG condition. However, the magnitude of the changes is much larger. For example, concavity of the utility function ($\eta > 0$) and pessimism ($\delta < 1$) reduce the number of entrants substantially. At the same time, likelihood insensitivity ($\gamma < 1$) results in substantial excess entry. Table 7 gives us a feel of the parameters we need to explain higher number of entrants in the WTA condition relative to the MEG condition. Without probability weighting ($\gamma = 1, \delta = 1$) the model reduces to standard expected utility and does not permit to explain the treatment effect (unless, of course, we were to assume convex utility, $\eta < 0$). Comparing the expected number of entrants across conditions shows that the model can explain the treatment effect if γ is sufficiently low, η is moderate, and δ is not too low. If we rule out (as most of the literature does) convex utility, then our theoretical results show that the explanation for excess entry within CPT must stem from probability weighting. Of the two parameters of the weighting function the main driver is γ. If $\gamma < 1$, then small probability events with very high and very low payoffs gain weight. In the WTA condition these are the high payoffs if one wins against many competitors. The worst outcome in the WTA condition (losing against any number of competitors) is underweighted, because it occurs with high probability. In the MEG condition, overweighting occurs for both the best and the worst outcomes of market entry, as both are small probability events.[15]

Thus, CPT can be a powerful explanation for excess entry into winner-take-all markets. Its predictive power, however, depends on the preference parameters. In order to explore the predictive power of CPT we ran new experiments. The experiments replicate the design of WTA and MEG conditions, followed by an elicitation of a series of certainty equivalents, which permits us to estimate CPT parameters. We compare our estimated parameters to previous estimates from the literature and use our estimates to evaluate the predictive power of CPT.

5.3 Experimental design

In a new experiment we elicit subjects' certainty equivalents for two-outcome lotteries (CPT task) after they completed the MEG and WTA phases. We will label these new observations as MEG_{CPT} and WTA_{CPT}, respectively. Both the MEG_{CPT} and WTA_{CPT} conditions are identical to the main experiment. Again, we run the MEG condition first in half of the sessions, reversing the order for the other half. We elicit subjects' certainty equivalents for 40 lotteries. Each lottery offers an amount x_1 with probability p and an amount $x_2 < x_1$ with probability $1-p$. Half of the lotteries were in the gain domain ($x_1 >$

[15] Alternatively, it would be possible to predict the treatment effect without inverse S-shaped probability weighting. In a model with $\gamma = 1$ combined with optimism ($\delta > 1$) players upweight the outcomes with high payoffs and downweight the outcomes with low payoffs. In the main text we emphasize the model with $\gamma < 1$ and $\delta < 1$, because there is substantial empirical support for these parameter ranges (see discussion in Section 5.4.1).

$x_2 \geq 0$) and the other half were corresponding lotteries in the loss domain ($0 \geq x_1 > x_2$). For each lottery in the loss domain, we endowed subjects with $|x_1| + |x_2|$. This ensures that subjects do not end up with a negative payoff and it equalizes the expected payoff of a lottery in the loss domain to its counterpart in the gain domain. At each screen subjects are presented with a lottery on the left and with 20 rows of equally spaced guaranteed outcomes ranging from x_1 to x_2 on the right. For each row we ask the subject if she prefers the lottery or the corresponding guaranteed outcome. We enforce monotonicity, i.e., subjects only choose the minimum certainty equivalent they prefer to a lottery and the computer fills in the remaining rows accordingly. A subject's elicited certainty equivalent for a lottery is the arithmetic mean of the lowest guaranteed amount preferred to the lottery and the highest guaranteed amount not preferred to the lottery.[16] Once a subject took the decisions on the 40 lotteries (they are allowed to go back and forth), a lottery and a row were randomly chosen by the computer and the subject's payoff is determined based on her decision for the randomly chosen lottery and row.

In addition to the show-up fee of CHF 5, subjects were paid for both phases as in the main experiment. Furthermore, subjects received the payment for the CPT task. Subjects received information about their payoff only after the CPT task. The exchange rate for this task was CHF 1 per 3 ECUs.

The sessions were run online with undergraduate students from the University of Lausanne and the EPFL (recruitment: ORSEE, Greiner, 2015; programming: oTree, Chen, Schonger, and Wickens, 2016). We ran ten sessions with a total of 134 subjects.[17] This gives us 5360 entry decisions and 5360 certainty equivalent elicitations. Sessions lasted between 47 and 100 minutes[18] with an average payoff per subject of CHF 43.

5.4 Results

Our new sessions replicate the findings on market entry behavior of the main experiment: In the first (second) phase we observe on average 6.49 (4.94) entrants in the WTA_{CPT} condition and 4.86 (4.18) entrants in the MEG_{CPT} condition. The treatment effect is significant ($p = 0.022$, exact Wilcoxon signed-rank test).

We use the CPT task to estimate the preference parameters. Following the estimation procedure for the single group case by Bruhin et al. (2010a), we estimate the CPT parameters based on the lottery decisions in the gain domain. This procedure uses maximum likelihood to estimate the parameters based on the elicited certainty equivalents. We account for two sources of heteroskedasticity in the error variances. First, the error

[16] See appendix Table B1 for the set of lotteries and pages 21–25 for screenshots.

[17] Due to no-shows and connection problems we did not always manage to get the desired group size. We had one session each with 11, 12, and 13, while the remaining seven sessions had 14 subjects. Such variations in group size are not a problem for our analysis because the equilibrium predictions of the expected number of entrants barely changes for group sizes between 11 and 14.

[18] The sessions' durations varied substantively because subjects could go at their own pace in the CPT task. Once a subject was done with this task, she would directly move to the final payment page. The payment was done by bank transfer within a week.

is proportional to the lottery's range $|x_1 - x_2|$, since subjects faced 20 equally spaced guaranteed outcomes for each lottery. Second, we account for heteroskedasticity between individuals, as subjects may differ with respect to previous knowledge, attention span, or ability.

We use the data elicited from the CPT task to perform parameter estimations. In a first step, we perform pooled estimations of CPT parameters. Assuming homogeneity across subjects, we confront market entry predictions using the parameters from the pooled estimations with the data on entry behavior in the MEG_{CPT} and the WTA_{CPT} conditions. In the second step, we relax the homogeneity assumption. We perform finite mixture model estimations to group subjects into types and test whether entry behavior is related to the type.

5.4.1 Pooled CPT estimations

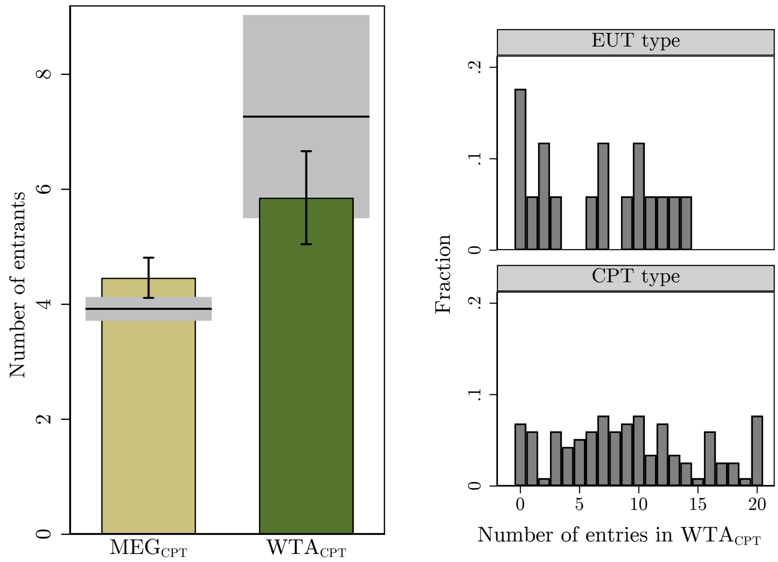
Using the full sample, we find the following point estimates (standard errors) for the CPT parameters: $\hat{\eta} = 0.131$ (0.031); $\hat{\gamma} = 0.517$ (0.023); $\hat{\delta} = 0.929$ (0.049). Our results are in line with previous estimates from the literature that use the same two-parameter specification for the weighting function (Fehr-Duda, De Gennaro, & Schubert, 2006; Bruhin et al., 2010a; Fehr-Duda et al., 2011; Bruhin et al., 2018). Overall the estimates in these studies point to a significantly inverse S-shaped weighting function and moderate pessimism. In terms of the utility function, most estimates indicate a curvature close to linearity, with moderate deviations in both directions.

Given our parameter estimates, CPT predicts 3.92 entrants in the MEG condition and 7.28 in the WTA condition in the symmetric mixed-strategy Nash equilibrium. We can use our estimates to illustrate why probability weighting produces such strong excess entry in the WTA condition, even with a concave utility function. In the equilibrium of the WTA game an entrant's probability of getting the highest prize (215, winning among eleven or more entrants) is 0.0055. The weight of these outcomes in the decision process is ten times higher (0.059). Conversely, the probability of getting zero is 0.863, while the decision weight attached to this outcome is downweighted to 0.736. In the MEG condition it is also the case that the best outcome (100, being the sole entrant) is strongly overweighted. However, in contrast to the WTA condition there is also substantial overweighting of the unprofitable outcomes of market entry (entry with six or more competitors). See Figure A1 in the appendix for an illustration.

To gain an idea on the error margin of the predicted number of entries we use a bootstrap approach. Based on 1000 bootstrap samples we estimate a distribution of CPT parameters, which we use to predict the corresponding entry probabilities. Using these probabilities allows us to derive a distribution of the expected number of entrants in the MEG and WTA conditions. The left panel of Figure 5 shows the results. The horizontal lines indicate the mean number of predicted entrants in the MEG_{CPT} and the WTA_{CPT} conditions, with the gray bands indicating the 95% confidence intervals. In the WTA_{CPT}

condition we observe a number of entrants below the point prediction, but still within the confidence interval. The low number of entrants in the WTA_{CPT} condition relative to the Nash equilibrium prediction is mainly due to the low entry frequency when played in the second phase. If we restrict the sample to the first phase, then the observed number of entrants in the WTA_{CPT} condition is substantially higher (see Figure B3 in the appendix). In the MEG_{CPT}, on the other hand, the observed number of entrants is above the Nash equilibrium prediction.

Figure 5: CPT preferences and entry



Notes. Left panel: Average number of entrants in the two conditions (bars with spikes indicating 95% confidence intervals); predicted number of entrants (horizontal bar) and corresponding 95% confidence interval (gray band). Right panel: Histogram of the number of entries during the 20 periods for subjects classified as expected utility maximizer (EUT) and Cumulative Prospect Theory (CPT) types.

5.4.2 Finite mixture model CPT estimations

The empirical literature on CPT preferences often finds evidence for substantial heterogeneity between subjects. However, CPT elicitation procedures like the one we use are too imprecise to provide reliable estimates on an individual level (Monroe, 2020).[19] To account for heterogeneity, we therefore identify types using a finite mixture model (FMM). Again, we follow Bruhin et al. (2010a) estimation procedure for the two-group case. As the authors explain, the idea is to assign an individual's risk taking choices to either the EUT group or the CPT group, each of the two groups being characterized by a distinct vector of parameters. The assignment of each subject to one of the two groups is based

[19]Table B2 in the appendix provides summary statistics of the individual CPT parameter estimates and Table B3 shows OLS estimates of entry frequency in WTA on the individual preference parameter estimates. All coefficient estimates have the expected sign: increasing utility curvature (η) or likelihood sensitivity (γ) leads to less entry in WTA and increasing optimism (δ) leads to more entry in WTA. However, none of the coefficients reach statistical significance.

on the posterior probability of type-membership.[20]

According to our FMM estimates, 117 out of the 134 subjects are classified as CPT types and the remaining 17 as EUT types. With 13 percent of the subjects being classified as EUT types, the estimated share of EUT subjects in our subject pool is somewhat lower than in Bruhin et al. (2010a) where the estimated share in the Zurich 2006 experiment is 22 percent.

The right panel of Figure 5 shows histograms of the number of times subjects of the EUT type (upper part) and the CPT type (lower part) enter in the WTA_{CPT} condition. The CPT types are less likely to enter very rarely (two or fewer times out of 20) and more likely to enter very often (15 times or more). In order to test whether the CPT types differ significantly from the EUT types, we regress the entry frequency (in percent) across the 20 periods of the WTA_{CPT} on the type dummy. Table 8 shows the two main results. First, even for EUT types we observe entry frequencies above Nash equilibrium predictions under the expected payoff maximizer assumption. Recall, while the predicted entry frequency under the expected payoff maximizer assumption is 25 percent, players of the EUT type who anticipate that the players of the CPT type enter more frequently should respond by refraining from entering in the winner-take-all game. Our results do not confirm this: The estimated entry frequency for EUT types (31.4 percent in Model 1) is even above the 25 percent. Second, the frequency at which CPT types enter is about 15 percentage points higher than for EUT types in the WTA_{CPT} condition. The effect is highly significant. In Model (2) we control for order effects, confirming the result that entry is less frequent when the WTA_{CPT} condition is played after the MEG_{CPT} condition. The dummy for CPT types remains highly significant. These results suggest that, in line with theory, excess entry is mainly driven by CPT types.

[20]We refer to Bruhin et al. (2010a, 2010b) for a detailed explanation of the estimation procedure. Figure B4 in the appendix shows an histogram of individuals' posterior probability of assignment and Table B4 shows the FMM estimates. We elicited certainty equivalents in both the gain and loss domains to keep the experimental design as close as possible to Bruhin et al. (2010a). For the parameter estimations, we only use the lotteries in the gain domain since we are interested in decision situations between a secure and a risky gain (see Footnote 13).

Table 8: Entry frequency and type.

	Dependent variable: Entry frequency (in %)	
	(1)	(2)
CPT type	14.170**	15.087**
	(4.314)	(4.591)
WTA in phase 2		−13.913*
		(4.558)
Constant	31.471**	36.381**
	(4.926)	(3.590)
F-test	10.8	6.4
Prob > F	0.009	0.019
R^2	0.027	0.083
N	134	134

Notes: OLS estimates. Dependent variable is the individual entry frequency in the WTA condition (in %). Independent variables are a dummy for the subject's type according to the finite mixture model, and a dummy for the WTA played after the MEG condition. Baseline case is the EUT type. Robust standard errors, clustered on group, in parentheses. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$.

6 Conclusion

In this study we systematically explore potential causes of excess entry into markets. Early experimental research showed that this phenomenon does not occur in standard market entry games. More recently, researchers have shown that overconfidence can create excess entry in games where the returns on market entry depend on skills. We provide experimental evidence that a market modeled as a winner-take-all game with a purely random determination of the winner creates strong excess entry relative to an expected-payoff-equivalent market entry game. This means that excess entry can occur even in environments where overconfidence in skills is irrelevant. We provide evidence that the explanation for excess entry is probability weighting. In environments where overconfidence about skill plays a role, the two biases—overconfidence and probability weighting—presumably reinforce each other.

It is clear that utility curvature, which underlies standard decision making models, is unlikely to explain excess entry. If subjects display concave utility functions, we would expect less rather than more entry in the winner-take-all condition compared to the market entry game. With additional data we explore and discard a number of explanations discussed in the previous literature. First, we show that wrong beliefs about the number of other players entering the market (blind spot) cannot account for the treatment effect. Second, we find no evidence that the treatment effect is driven by subjects who fall victim to the erroneous belief that they can influence random processes (illusion of control). Third, we find no evidence for explanations positing extra utility of winning in a competitive environment (joy of winning). To address this explanation, we ran an additional non-strategic condition which preserves expected payoffs and risk of the winner-take-all condition, but does not contain the competitive element. We find that the number of market entrants remains virtually unchanged. In an additional treatment we even provide objective probabilities associated to market entry and still find similar levels of excess entry. This latter result further strengthens the argument that it is not the additional complexity that comes with a strategic interaction that drives excess entry.

We identify probability weighting in accordance with Cumulative Prospect Theory as a powerful explanation for the treatment effect. We compute Nash equilibria of the standard market entry game and the winner-take-all condition. Under a broad range of realistic parameters, the model predicts more entry in the winner-take-all condition than in the market entry game. The effect is driven by the fact that the winner-take-all competition offers high stakes with low probabilities, while losing the competition is very likely. Typical parameters for the probability weighting function lead to overweighting of the profitable outcomes and underweighting of the bad outcome.

We ran an additional experiment, which allows us to estimate CPT parameters and relate these estimates to entry behavior. The calibrated predictions are consistent with observed entry behavior. In addition, the results of our finite mixture estimates suggests that excess entry is mainly caused by subjects that can be classified as CPT type. Taken together these results suggest that CPT is a useful descriptive theory not only for individual choice problems, but also in situations involving strategic risk. In addition, the fact that we observe very similar entry frequencies in our non-strategic conditions provides indicative evidence that CPT probability weighting may be similarly applied to both natural risk and strategic risk. In other words, moving from subjective belief based risk to objective probabilities (as in our OBJ condition) seems not to matter much for entry behavior and may be explained with the same underlying probability distortion.

Should regulators or nudgers care about excess entry in winner-take-all games? Our results provide a suggestive answer to that question. If excess entry was caused by non-standard preferences, such as high risk tolerance or strong non-monetary benefits from winning the competition against others (joy of winning), then there would be little ground for paternalistic interventions. Our results suggest that excess entry is not caused by such preferences, but by probability weighting. It is conceivable that subjects in our lab would not consciously choose to have decision weights that differ from objective probabilities and, if made somehow aware of the discrepancy, would prefer to use objective probabilities in their decision process. Thus, upcoming entrepreneurs or hopeful young athletes might enter winner-take-all markets not only because of overconfidence about their abilities, but also due to a systematic overestimation of the small winning probabilities. Consequently, a nudge to "objectify" probabilities might benefit would-be competitors. We leave for future research to investigate the design and effectiveness of such nudges. A much simpler policy conclusion is drawn by Frank and Cook (1995) who argue that progressive consumption taxation might be an effective measure to reduce the attractiveness of entry into winner-take-all markets.

For business executives who take investment decisions our findings can provide guidance. To gauge return prospects of an investment, anticipating the behavior of potential competitors is crucial. Biased probability perception can account for skew-seeking behavior and thus attraction to winner-take-all markets through optimism and likelihood-insensitivity. Åstebro, Mata, and Santos-Pinto (2015) have documented optimism and likelihood insensitivity both among college students and business executives. Based on our findings, markets with winner-take-all characteristics are likely to attract more competitors than the market volume warrants. As formalized in the Porter's Five Forces Framework (Porter, 1989), the threat of entry is an important determinant of the attractiveness of an industry in terms of its profitability. Our results suggest that an investment in a market where few competitors capture a large share of the rewards is less attractive compared to markets with a more equal share of rewards but the same expected return.

Finally, our results provide us with a testable conjecture for further research on market entry decisions: We compare two extreme payoff distributions—winner-take-all versus equal payoffs for all entrants—and show that, counter-intuitively, the riskier market attracts more entry. Consequently, in real market entry data one should find more excess entry in markets where the profits are skewed towards the top performers. In particular, excessive entry of new firms and high failure rates should be less prevalent in sectors where payoffs are relatively equal, arguably for example in hospitality, and more prevalent in sectors like information technology.

References

Abdellaoui, M. (2000). Parameter-free elicitation of utility and probability weighting functions. *Management Science*, *46*(11), 1497–1512.

Allais, M. (1953). Le comportement de l'homme rationnel devant le risque: Critique des postulats et axiomes de l'école americaine. *Econometrica*, *21*(4), 503–546.

Amaldoss, W. & Rapoport, A. (2009). Excessive expenditure in two-stage contests: Theory and experimental evidence. In I. N. Haugen & A. S. Nilsen (Eds.), *Game theory: Strategies, equilibra and theorems* (pp. 241–266). Nova Science Publishers.

Armantier, O. & Treich, N. (2013). Eliciting beliefs: Proper scoring rules, incentives, stakes and hedging. *European Economic Review*, *62*, 17–40.

Åstebro, T., Herz, H., Nanda, R., & Weber, R. A. (2014). Seeking the roots of entrepreneurship: Insights from behavioral economics. *Journal of Economic Perspectives*, *28*(3), 49–70.

Åstebro, T., Mata, J., & Santos-Pinto, L. (2015). Skewness seeking: Risk loving, optimism or overweighting of small probabilities? *Theory and Decision*, *78*(2), 189–208.

Brilon, S., Grassi, S., Grieder, M., & Schulz, J. (2019). Strategic competition and self-confidence. *GMU Working Paper in Economics No. 19-40.*

Brookins, P. & Ryvkin, D. (2014). An experimental study of bidding in contests of incomplete information. *Experimental Economics*, *17*(2), 245–261.

Bruhin, A., Fehr-Duda, H., & Epper, T. (2010a). Risk and rationality: Uncovering heterogeneity in probability distortion. *Econometrica*, *78*(4), 1375–1412.

Bruhin, A., Fehr-Duda, H., & Epper, T. (2010b). Supplement to "Risk and rationality: Uncovering heterogeneity in probability distortion". *Econometrica*, *78*(4), 1375–1412.

Bruhin, A., Santos-Pinto, L., & Staubli, D. (2018). How do beliefs about skill affect risky decisions? *Journal of Economic Behavior & Organization*, *150*, 350–371.

Brünner, T., Reiner, J., Natter, M., & Skiera, B. (2019). Prospect theory in a dynamic game: Theory and evidence from online pay-per-bid auctions. *Journal of Economic Behavior & Organization*, *164*, 215–234.

Cain, D. M., Moore, D. A., & Haran, U. (2015). Making sense of overconfidence in market entry. *Strategic Management Journal*, *36*(1), 1–18.

Camerer, C. F. & Lovallo, D. (1999). Overconfidence and excess entry: An experimental approach. *American Economic Review*, *89*(1), 306–318.

Cason, T. N., Masters, W. A., & Sheremeta, R. M. (2020). Winner-take-all and proportional-prize contests: Theory and experimental results. *Journal of Economic Behavior & Organization*, *175*, 314–327.

Chen, D. L., Schonger, M., & Wickens, C. (2016). Otree—an open-source platform for laboratory, online, and field experiments. *Journal of Behavioral and Experimental Finance*, *9*, 88–97.

Danz, D. (2020). Never underestimate your opponent: Hindsight bias causes overplacement and overentry into competition. *Games and Economic Behavior*, *124*, 588–603.

Dechenaux, E., Kovenock, D., & Sheremeta, R. M. (2015). A survey of experimental research on contests, all-pay auctions and tournaments. *Experimental Economics*, *18*(4), 609–669.

Dohmen, T., Falk, A., Fliessbach, K., Sunde, U., & Weber, B. (2011). Relative versus absolute income, joy of winning, and gender: Brain imaging evidence. *Journal of Public Economics*, *95*(3-4), 279–285.

Dorfman, A., Bereby-Meyer, Y., & Moran, S. (2013). When feeling skillful impairs coordination in a lottery selection task. *PLoS ONE*, *8*(6), 6–11.

Dunne, T., Roberts, M. J., & Samuelson, L. (1988). Patterns of firm entry and exit in U.S. manufacturing industries. *RAND Journal of Economics*, *19*(4), 495–515.

Ernst, C. & Thöni, C. (2013). Bimodal bidding in experimental all-pay auctions. *Games*, *4*(4), 608–623.

Fehr-Duda, H., De Gennaro, M., & Schubert, R. (2006). Gender, financial risk, and probability weights. *Theory and Decision*, *60*(2-3), 283–313.

Fehr-Duda, H. & Epper, T. (2012). Probability and risk: Foundations and economic implications of probability-dependent risk preferences. *Annual Review of Economics*, *4*, 567–593.

Fehr-Duda, H., Epper, T., Bruhin, A., & Schubert, R. (2011). Risk and rationality: The effects of mood and decision rules on probability weighting. *Journal of Economic Behavior & Organization*, *78*(1-2), 14–24.

Fennema, H. & Wakker, P. (1997). Original and cumulative prospect theory: A discussion of empirical differences. *Journal of Behavioral Decision Making*, *10*(1), 53–64.

Fischbacher, U. (2007). Z-tree: Zurich toolbox for ready-made economic experiments. *Experimental Economics*, *10*(2), 171–178.

Fischbacher, U. & Thöni, C. (2008). Excess entry in an experimental winner-take-all market. *Journal of Economic Behavior & Organization*, *67*(1), 150–163.

Frank, R. H. & Cook, P. J. (1995). *The winner-take-all society*. New York: The Free Press.

Gächter, S. & Renner, E. (2010). The effects of (incentivized) belief elicitation in public goods experiments. *Experimental Economics*, *13*(3), 364–377.

Goeree, J. K., Holt, C. A., & Palfrey, T. R. (2002). Quantal response equilibrium and overbidding in private-value auctions. *Journal of Economic Theory*, *104*(1), 247–272.

Goeree, J. K., Holt, C. A., & Palfrey, T. R. (2003). Risk averse behavior in generalized matching pennies games. *Games and Economic Behavior*, *45*(1), 97–113.

Goldstein, W. M. & Einhorn, H. J. (1987). Expression theory and the preference reversal phenomena. *Psychological Review*, *94*(2), 236–254.

Gonzalez, R. & Wu, G. (1999). On the shape of the probability weighting function. *Cognitive Psychology*, *38*(1), 129–166.

Greiner, B. (2015). Subject pool recruitment procedures: Organizing experiments with ORSEE. *Journal of the Economic Science Association*, *1*(1), 114–125.

Hamilton, B. H. (2000). Does entrepreneurship pay? An empirical analysis of the returns to self-employment. *Journal of Political Economy*, *108*(3), 604–631.

Harrison, G. W. & Rutström, E. E. (2009). Expected utility theory and prospect theory: One wedding and a decent funeral. *Experimental Economics*, *12*(2), 133–158.

Herbst, L. (2016). Who pays to win again? The joy of winning in contest experiments. *Working Paper of the Max Planck Institute for Tax Law and Public Finance*, *6*.

Herrmann, B. & Orzen, H. (2008). The appearance of homo rivalis: Social preferences and the nature of rent seeking. *CeDEx discussion paper series*.

Hoelzl, E. & Rustichini, A. (2005). Overconfident: Do you put your money on it? *Economic Journal*, *115*(503), 305–318.

Kahneman, D. (1988). Experimental economics: A psychological perspective. In R. Tietz, W. Albers, & R. Selten (Eds.), *Bounded rational behavior in experimental games and markets. Lecture notes in economics and mathematical systems, vol 314* (pp. 11–18). Springer.

Kahneman, D. & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*(2), 263–291.

Keskin, K. (2016). Equilibrium notions for agents with cumulative prospect theory preferences. *Decision Analysis*, *13*(3), 192–208.

Langer, E. J. (1975). The illusion of control. *Journal of Personality and Social Psychology*, *32*(2), 311–328.

Lattimore, P. K., Baker, J. R., & Witte, A. D. (1992). The influence of probability on risky choice: A parametric examination. *Journal of Economic Behavior & Organization*, *17*(3), 377–400.

Mata, J. & Portugal, P. (1994). Life duration of new firms. *Journal of Industrial Economics*, *42*(3), 227–245.

Metzger, L. P. & Rieger, M. O. (2019). Non-cooperative games with prospect theory players and dominated strategies. *Games and Economic Behavior*, *115*, 396–409.

Monroe, B. A. (2020). The statistical power of individual-level risk preference estimation. *Journal of the Economic Science Association*, *6*(2), 168–188.

Moore, D. A. & Cain, D. M. (2007). Overconfidence and underconfidence: When and why people underestimate (and overestimate) the competition. *Organizational Behavior and Human Decision Processes*, *103*(2), 197–213.

Moore, D. A., Oesch, J. M., & Zietsma, C. (2007). What competition? Myopic self-focus in market-entry decisions. *Organization Science*, *18*(3), 440–454.

Morgan, J., Orzen, H., Sefton, M., & Sisak, D. (2016). Strategic and natural risk in entrepreneurship: An experimental study. *Journal of Economics and Management Strategy*, *25*(2), 420–454.

Nguyen, Q., Villeval, M. C., & Xu, H. (2016). Trust under the prospect theory and quasi-hyperbolic preferences: A field experiment in vietnam. *Economic Development and Cultural Change*, *64*(3), 546–572.

Porter, M. E. (1989). How competitive forces shape strategy. In *Readings in strategic management* (pp. 133–143). Springer.

Prelec, D. (1998). The probability weighting function. *Econometrica*, *66*(3), 497–527.

Quiggin, J. (1982). A theory of anticipated utility. *Journal of Economic Behavior & Organization*, *3*(4), 323–343.

Rapoport, A., Seale, D. A., Erev, I., & Sundali, J. A. (1998). Equilibrium play in large group market entry games. *Management Science*, *44*(1), 119–141.

Schmidt, U. & Zank, H. (2008). Risk aversion in cumulative prospect theory. *Management Science*, *54*(1), 208–216.

Schulz, J. F. & Thöni, C. (2016). Overconfidence and career choice. *PLoS ONE*, *11*(1), e0145126.

Sheremeta, R. M. (2010). Experimental comparison of multi-stage and one-stage contests. *Games and Economic Behavior*, *68*(2), 731–747.

Sheremeta, R. M. (2018). Impulsive behavior in competition: Testing theories of overbidding in rent-seeking contests. *Available at SSRN 2676419*.

Sundali, J. A., Rapoport, A., & Seale, D. A. (1995). Coordination in market entry games with symmetric players. *Organizational Behavior and Human Decision Processes*, *64*(2), 203–218.

Tversky, A. & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, *5*(4), 297–323.

Wakker, P. P. (2010). *Prospect theory: For risk and ambiguity*. Cambridge University Press.

Wright, W. F. & Aboul-Ezz, M. E. (1988). Effects of extrinsic incentives on the quality of frequency assessments. *Organizational Behavior and Human Decision Processes*, *41*(2), 143–152.

Wu, B. & Knott, A. M. (2006). Entrepreneurial risk and market entry. *Management Science*, *52*(9), 1315–1330.

Wu, G. & Gonzalez, R. (1996). Curvature of the probability weighting function. *Management Science*, *42*(12), 1676–1690.

Appendix

A Cumulative Prospect Theory: Extensions

A.1 Loss aversion

Our main treatment of the WTA and MEG conditions with Cumulative Prospect Theory (CPT) assumes that players' reference points are zero and all payoffs in the game are perceived as gains. Alternatively we could assume that players have some reference point r, relative to which they evaluate the monetary payoff x using the utility function:

$$u(x,\eta) = \begin{cases} \frac{1}{1-\eta}\left((x-r)^{(1-\eta)} - 1\right), & \text{for } x \geqslant r \\ \frac{1}{1-\eta}\left(-\lambda(r-x)^{(1-\eta)} - 1\right). & \text{else} \end{cases} \tag{8}$$

For $0 < \eta < 1$ this function is concave in the domain of gains and convex in the domain of losses. We assume the CRRA parameter (η) is the same in both domains and we introduce a parameter for loss aversion (λ). Allowing for a different CRRA parameter in the domain of losses has very similar effects as variations in λ. In contrast to the solutions discussed in the main text, we now assume that the reference point is $r = 45$. Table A1 shows the predicted number of entrants for selected combinations of η, γ, and λ (with δ=1). The results for linear utility and $\lambda = 1$ are identical to the ones shown in Table 7. Increasing the CRRA parameter (η) while keeping $\lambda = 1$ reduces predicted entry in the WTA condition, but not as much as in Table 7. This is due to the fact that the utility function is convex in the domain of losses. Similarly to increasing the CRRA parameter, loss aversion substantially reduces the attractiveness of the WTA market, providing further support for the argument that probability weighting is the driver for the treatment effect.

Table A1: Predicted number of entrants, reference point at 45.

		MEG			WTA		
		$\eta = 0$	$\eta = 0.1$	$\eta = 0.2$	$\eta = 0$	$\eta = 0.1$	$\eta = 0.2$
$\gamma = 1$	$\lambda = 1$	3.52	3.47	3.42	3.52	3.12	2.81
	$\lambda = 1.2$	3.40	3.35	3.30	2.78	2.50	2.28
	$\lambda = 1.4$	3.30	3.25	3.19	2.29	2.09	1.93
$\gamma = 0.75$	$\lambda = 1$	3.74	3.67	3.60	6.14	5.02	4.14
	$\lambda = 1.2$	3.58	3.51	3.44	4.46	3.65	3.06
	$\lambda = 1.4$	3.45	3.37	3.30	3.32	2.77	2.36
$\gamma = 0.5$	$\lambda = 1$	4.18	4.08	3.97	14.00	11.93	9.22
	$\lambda = 1.2$	3.94	3.83	3.72	10.85	8.30	6.22
	$\lambda = 1.4$	3.74	3.63	3.52	7.88	5.80	4.22

Notes. Expected number of entrants in the symmetric mixed strategy equilibrium with CPT preferences with a reference point at 45, and for three levels of loss aversion (λ). We plot the entries for $\delta = 1$ and selected levels of η and γ.

A.2 Natural vs. strategic risk

In the main text we derive the CPT equilibria under the assumption that probability weighting applies to the combination of natural and strategic risk. Applying probability weighting only to one of the two sources of risk would change the prediction. As the empirical literature on CPT almost exclusively deals with natural risk it seems natural to apply probability weighting only to this source of uncertainty. In the following we discuss two methods:

WTA, N1: Weighting natural risk conditional on number of entrants. Here we simply assume that the player separates the strategic risk (ending up with $E-1$ competitors) from the natural risk conditional on the number of competitors ($q_E = \frac{1}{E}$). For $E = \{2, 3, \ldots, 14\}$ we use Equation (4) to transform the objective winning probabilities q_E into weights. The low probability high payoffs in the WTA markets have higher weights than the objective probabilities, which produces higher number of expected entrants relative to the case with linear probabilities. The left part of Table A2 shows the results. For comparison we also show the results of the MEG condition, which are not affected by probability weighting, because there is only strategic risk. Comparing the results to our model in the main text (Table 7) shows that the predicted number of entrants is very similar, suggesting that the inclusion of strategic risk is not a decisive factor when we explain the treatment effect.

WTA, N2: Decomposing natural and strategic risk. From Equation (7), we can write the cumulative probabilities of achieving an outcome at least equal to x_k:

$$Q_k = \sum_{j=1}^{k} \binom{13}{13-(j-1)} p^{13-(j-1)} (1-p)^{j-1} \frac{1}{14-(j-1)}, \quad \text{for } k = 1, \ldots, 14$$

and $Q_{15} = 1$ where $x_{15} = 0$ is the outcome when a player enters and loses.

If we multiply and divide Q_k by the objective probabilities of achieving an outcome at least equal to x_k, we can decompose natural and strategic in the following way:

$$Q_k = \left(\sum_{j=1}^{k} \binom{13}{13-(j-1)} p^{13-(j-1)} (1-p)^{j-1} \right) \left(\frac{\sum_{j=1}^{k} \binom{13}{13-(j-1)} \frac{p^{13-(j-1)}(1-p)^{j-1}}{14-(j-1)}}{\sum_{j=1}^{k} \binom{13}{13-(j-1)} p^{13-(j-1)} (1-p)^{j-1}} \right).$$

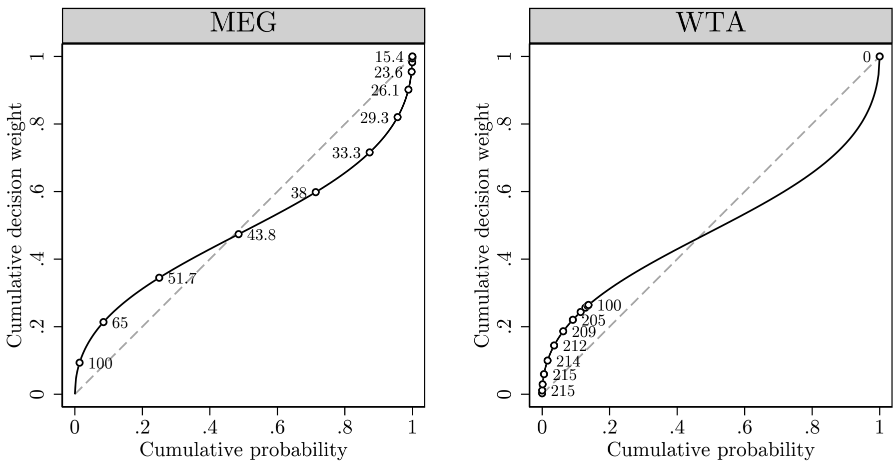
The first parenthesis on the RHS is the objective cumulative probability of facing at least $k-1$ competitors when entering. The second parenthesis is a weighted average of the risk component of each outcome larger or equal than x_k. If we apply equation Equation (4) only on the second parenthesis, then we can derive the decision weights only applying probability weighting on the risk components. The right part of Table A2 shows the results. Using this method, we find again very similar number of entrants compared to our model in the main text.

Table A2: Predicted number of entrants in WTA, weighting natural risk only.

		WTA, N1			WTA, N2		
		$\eta = 0$	$\eta = 0.1$	$\eta = 0.2$	$\eta = 0$	$\eta = 0.1$	$\eta = 0.2$
$\gamma = 1$	$\delta = 1$	3.52	2.79	2.22	3.52	2.79	2.22
	$\delta = 0.8$	2.71	2.21	1.80	2.61	2.10	1.70
$\gamma = 0.75$	$\delta = 1$	5.83	4.03	2.83	5.97	4.14	2.82
	$\delta = 0.8$	3.81	2.76	2.09	3.82	2.61	1.83
$\gamma = 0.5$	$\delta = 1$	14.00	10.26	5.83	14.00	10.36	6.11
	$\delta = 0.8$	9.78	5.51	2.84	9.89	5.77	2.45
MEG		3.52	3.49	3.47	3.52	3.49	3.47

Notes. Expected number of entrants in the symmetric mixed strategy equilibrium with CPT preferences and probability weighting applied to natural risk only, for selected values of the three preference parameters η, γ, and δ. WTA, N1 and WTA, N2 refer to the two variants of separating natural from strategic risk. If we weigh only strategic risk, the MEG predictions do not vary in γ and δ.

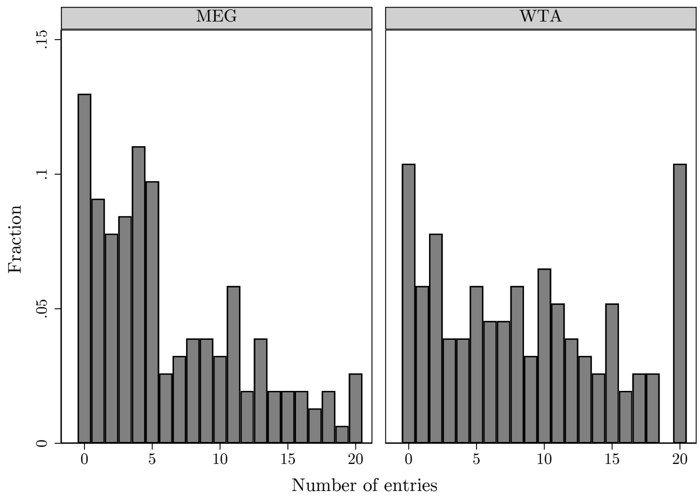
Figure A1: Probability weighting function and outcomes in the MEG and WTA conditions.



Notes. The solid line shows the CPT probability weighting function (see Equation 4), calibrated with our estimated parameters $\hat{\gamma} = 0.517$ and $\hat{\delta} = 0.929$. Dots indicate all possible outcomes for an entrant in the MEG condition (left panel) and the WTA condition (right panel). Due to space constraints not all dots are labelled with the respective payoff.

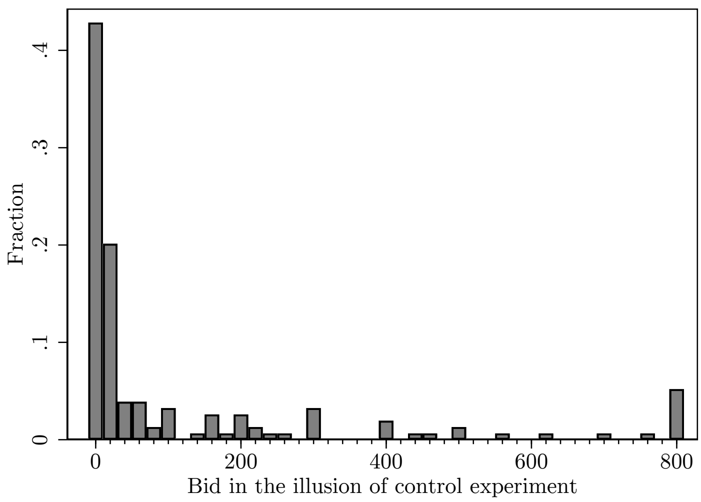
B Additional figures and tables

Figure B1: Histograms of individual entry frequency



Notes. Number of times a subject entered the respective market during the 20 periods, left panel for the MEG condition, right panel for the WTA condition. Data of both phases combined.

Figure B2: Histogram of bids



Notes. Histogram of individual bids in the second price auction of the illusion of control experiment. Bids are rounded up to multiples of 20.

Table B1: Lotteries in the gain domain $(x_1, p; x_2)$

p	x_1	x_2	p	x_1	x_2	p	x_1	x_2
0.10	20	10	0.95	40	10	0.50	10	0
0.50	20	10	0.05	50	20	0.50	20	0
0.90	20	10	0.25	50	20	0.05	40	0
0.05	40	10	0.50	50	20	0.25	40	0
0.25	40	10	0.75	50	20	0.95	50	0
0.50	40	10	0.95	50	20	0.10	150	0
0.75	40	10	0.05	150	50			

Notes. The outcomes are denominated in CHF. Each lottery has its counterpart in the loss domain. For example, the counterpart to the first lottery $(20, 0.10; 10)$ is $(-10, 0.10; -20; e = 30)$ where e is the endowment, which covers any losses and equalizes the expected payoffs in both domains. These lotteries are the same as used in Bruhin, Fehr-Duda, and Epper (2010a) for the Zurich 2006 sessions.

Table B2: Summary statistics of the individual CPT parameter estimates.

	Mean	Median	Std Dev	Min	Max
CRRA ($\hat{\eta}_i$)	-0.106	0.071	1.483	-8.998	4.947
Likelihood sensitivity ($\hat{\gamma}_i$)	0.685	0.588	0.565	0.000	5.251
Optimism/pessimism ($\hat{\delta}_i$)	1.115	0.915	1.109	0.000	9.984

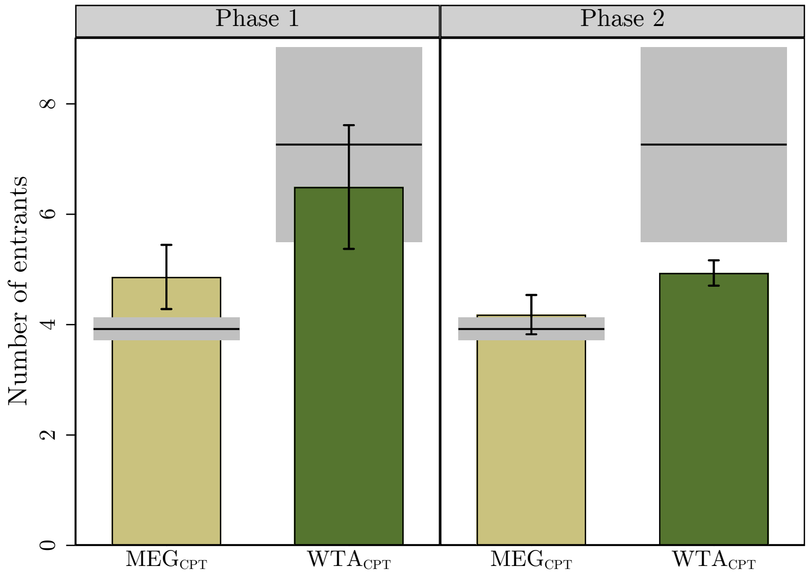
Number of observations = 134

Table B3: Entry frequency and individual CPT parameters.

	Dependent variable: Entry frequency (in %)	
WTA in phase 2	-14.020^{**}	-13.946^{**}
	(4.076)	(4.034)
$\hat{\eta}_i$	-1.682^{*}	-2.274
	(0.557)	(2.211)
$\hat{\gamma}_i$		-1.393
		(5.949)
$\hat{\delta}_i$		0.913
		(3.216)
Constant	49.419^{**}	49.263^{**}
	(3.833)	(4.888)
F-test	6.5	4.9
Prob > F	0.018	0.022
R^2	0.060	0.061
N	134	134

Notes: OLS estimates. Dependent variable is the individual entry frequency in the WTA condition (in %). Independent variables are a dummy for the WTA played after the MEG condition and the individual estimates for the three cumulative prospect theory parameters. Robust standard errors, clustered on group, in parentheses. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$.

Figure B3: Number of entrants by condition and phase in the CPT sessions



Notes. Average number of entrants by phase (bars with spikes indicating 95% confidence intervals) and 95% confidence interval of the predicted number of entrants (gray band).

Figure B4: Histogram of posterior probability of assignment to EUT type.

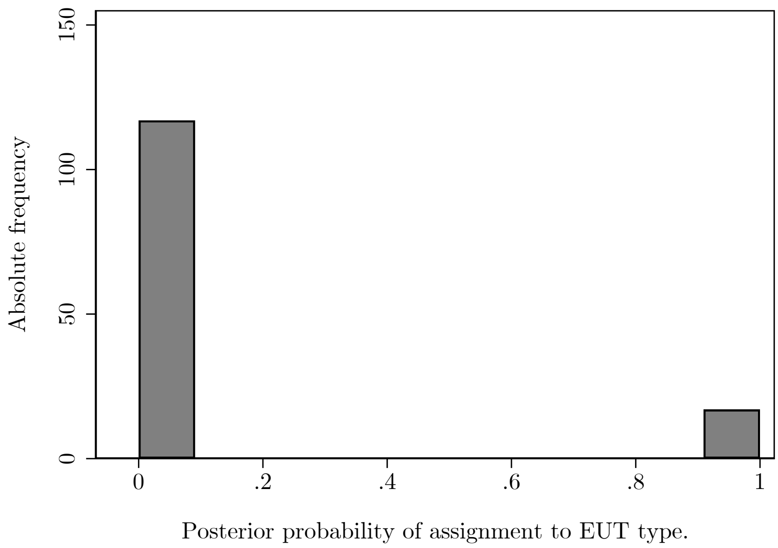


Table B4: Finite mixture model estimates.

	EUT type	CPT type
Relative size	0.127	0.873
	(0.029)	(0.029)
CRRA ($\hat{\eta}$)	0.080	0.141
	(0.013)	(0.034)
Likelihood sensitivity ($\hat{\gamma}$)		0.471
		(0.021)
Optimism/pessimism ($\hat{\delta}$)		0.930
		(0.055)
Number of subjects	134	
Number of observations	2680	
Log likelihood	-7875.8	
AIC	15765.6	
BIC	15806.9	

Notes: Robust standard errors, clustered on subjects, in parentheses.

C Experimental instructions

This appendix section shows a translated version of the experimental instructions that were handed out to subjects on paper (original instructions were in German). First we show the instructions of the main experiments (pages 41 to 49), followed by the instructions for the additional experiments described in section 4.3 (pages 50 to 56) and in section 5.3 (pages 57 to 61).

General instructions for the participants

You are about to participate in multiple economic experiments. **The experiments are independent of each other.** If you read the instructions carefully, you can, depending on your decisions, earn more or less money. It is therefore important to read the following instructions carefully.

The instructions you received from us are solely for your private information. Communication with other participants is **strictly forbidden** during the course of the experiment. Please ask an instructor in case of any questions. If you don't comply with those rules we will have to exclude you from the experiment including from any payments.

During the experiment, your income will not be computed in Swiss francs but in **points**. The points that you earn during the experiment will be converted to Swiss francs and paid out in cash. The following exchange rate applies:

1 point = 1.5 Swiss cents.

Instructions for experiment 1

For this experiment you receive an endowment of 800 points, which corresponds to 12 Swiss francs.

The experiment in which you are participating consists mainly of a lottery. The experimenter has a deck of 28 cards. On each of these cards there is one of the following 28 symbols:

#	E	*	+	€	J	%	$	O	?	Q	ö	¬	[
|	¦	§	=	¢	7	!	(	A	£	@	Y	S	1

The 28 symbols are now distributed to the participants. At the end of the experiment two cards will be drawn at random. The two participants with the corresponding symbols on their cards will receive **50 Swiss francs** in addition to the earned points that will be converted to Swiss francs.

To begin, you are prompted on the screen to choose one of those 28 symbols. Insert your choice and confirm with the OK-button.

The probability is pretty high, though, that more than one person chooses the same symbol. This problem will be addressed on the second screen.

In the cases where a particular symbol is chosen twice or more times we run an **auction**. The participant who wins the auction receives his or her desired symbol. To the other participants the computer will randomly assign another symbol which is not yet taken. For you to be able to participate in the auction we endowed you with 800 points. Though, the auction is not a "normal" auction where the participants progressively increase their bids. It works a bit differently:

The auction we perform is a so-called **second-price auction**. In this type of auction every participant can make exactly one bid which the other participants don't see. The bids are then compared with each other. As in "normal" auctions, the participant who made the highest bid gets the good, which in our case is the desired symbol. In contrast to "normal" auctions, however, the winner only pays the second highest bid. To illustrate, consider the following example:

Suppose there are three participants A, B, and C who take part in the auctioning of symbol X. They make the following bids:

- A bids x points
- B bids y points
- C bids z points

Let z be the highest bid and x be the lowest bid: $z > y > x$. C wins the auction and receives symbol X. He or she pays for it the second highest bid which is y points. A and B receive another symbol at random which is not chosen by any other participant. After the auction C's account balance will be 800 minus y points and the account balance of A and B is 800 points each.

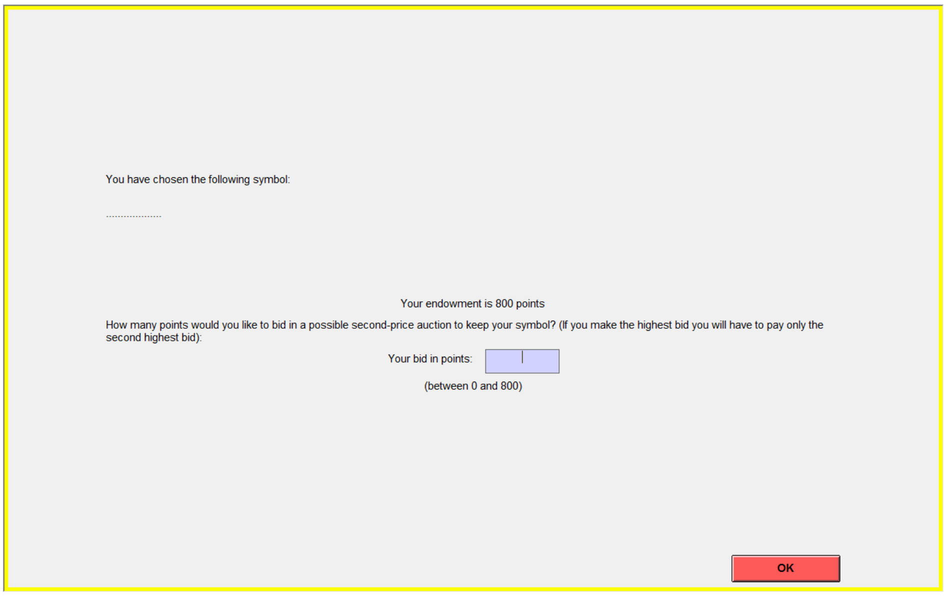
If two or more participants make the same bid, the computer will decide randomly who wins the auction. The winner will then pay exactly his or her bid as the second bid is the same.

The second-price auction has the following interesting property. **It is optimal for every participant to bid exactly as much as the good is worth to him or her.** The following example illustrates why:

> Suppose you are going to the sports store X to buy a skiing equipment set for a few hundred Swiss francs. You know exactly which one you want and you have already compared prices across different sports stores. Thus, you have already taken the decision to buy the skiing equipment set, that is, you will definitely buy it.
>
> Now, you are standing in front of the sports store and you see a crowd of people. A lady offers a voucher for sports store X with a value of 100 Swiss francs. Of course, she sells the voucher by means of a second-price auction. A few people are interested in the auction and the lady is distributing pieces of paper on which the bids should be written. How much should you bet now? Since you know that you are about to spend more than 100 Swiss francs in the sports store X, the 100 Swiss francs voucher is equivalent to 100 Swiss francs in cash. In a second-price auction it is therefore optimal for you to bid exactly 100 Swiss francs for the voucher. The explanation goes as follows:
>
> - If you bid less than 100 Swiss francs, say 90 Swiss francs, then someone who bids, for example, 91 Swiss francs will win the auction. But for 91 Swiss francs you would have been happy to buy the voucher. This reasoning holds for **any** bid below 100 Swiss francs.
> - If you bid more than 100 Swiss francs, say 105 Swiss francs, then you might end up paying too much for the voucher. For instance, if the second highest bid is 103 Swiss francs. This reasoning holds for **any** bid above 100 Swiss francs. It is never worth it to bit more than 100 Swiss francs. Not even if the second highest bid is less than 100 Swiss francs. In this case you could have bid just as well 100 Swiss francs to get the voucher at the same price as if you bid a higher price.

This line of reasoning holds independently of the number of people bidding for the voucher. **Thus, in a second-price auction it is always optimal to bid exactly as much as the good is worth to one.**

Back to the experiment: The assignment of symbols to participants for symbols that are chosen more than once will be settled by a second-price auction. To make sure that everyone is treated equally, **everyone** has to make a bid. The range of possible bids lies between 0 and 800. If you bid 0 you are, de facto, not participating in the auction. If your bid is above 0, you participate in the auction. This happens at a point in time where you don't know yet whether your symbol was chosen multiple times. After everyone has chosen a symbol in the first step, you are shown the following screen:



On the top of the page the symbol that you have chosen will be displayed. Below, you must indicate how much of your endowment of 800 points you bid, **if** a second-price auction takes place. The range of possible bids is between 0 and 800 points.

After inserting your bid, a screen will be displayed that informs you about the results. There are three possible cases:

a) **No one has chosen the same symbol as you.** In this case you will keep your chosen symbol and you will not participate in any auction. You will therefore keep your endowment of 800 points.

b) **Your symbol was chosen multiple times and your bid was the highest among all participants who have chosen the same symbol.** In this case you receive your desired symbol and you pay the second highest bid which was made for your symbol. In case somebody else with the same symbol has made the same bid you will pay exactly the amount that you have bid.

c) **Your symbol was chosen multiple times but your bid was not the highest.** In this case the computer will assign you randomly a symbol which is not yet taken. Since you didn't win the second-price auction, you keep your endowment of 800 points.

Memorize the symbol which you have chosen or the symbol which you were assigned, respectively. At the end of all experiments, there will be a random draw of a symbol to determine whether you win the lottery with your symbol.

Instructions for experiment 2

The new experiment is split into 20 rounds. At the beginning of the experiment, the participants are split into two equally sized groups. The group composition remains unchanged for the whole experiment. It is thus the same in every round.

Each member of a group has to make a choice between Alternative A and Alternative B at the beginning of each round. You can earn points depending on which alternative you choose and depending on the choices that the other participants of your group make. The rounds are identical and independent of each other throughout the experiment. That is, the number of points that you earn in a particular round depends only on the choices in this particular round. After the 20th round, all the points you earned during the experiment will be added up to your **total payoff.**

Computing the payoff in one round

In each round you must choose either Alternative A or Alternative B. If you choose Alternative A, your will participate in a prize competition with the participants of your group who also chose Alternative A. If you choose Alternative B you will not participate in the prize competition.

Your payoff if you choose Alternative A

All participants in a group who chose Alternative A participate in a prize competition where you have the chance to earn between 100 and 215 points.

Whether you win the prize competition is a matter of chance. A random number generator will assign to each participant a number between 0 and 100. For each participant, every number between 0 and 100 is equally likely. For the participants who have chosen Alternative A the random number will determine who wins the prize competition. The participant whom is assigned the *highest number* by the random number generator wins the prize competition. If you are the only participant of your group to choose Alternative A you win the prize competition in any case.

Your payoff in the price competition depends in particular on whether you win the prize competition. If you **don't win** the prize competition you get a payoff of zero points for this round. If you **win** the prize competition, then your payoff depends on how many competitors there are in the prize competition, that is, how many *other* participants also chose Alternative A. The more group members participate in the prize competition, the higher is the winner's payoff. The following Table summarizes the payoff as a function of the number of number of other participants who chose Alternative A:

Number of competitors in the prize competition	0	1	2	3	4	5	6	7	8	9	10	11	12	13
Payoff for the **winner** [in points]	100	130	155	175	190	200	205	209	212	214	215	215	215	215

If, for instance, you and four *other* participants chose A and you are assigned the highest random number, then you receive 190 points and the other 4 participants receive zero points.

Your payoff if you choose Alternative B

If you choose Alternative B you don't participate in the prize competition. You earn 45 points with certainty in the corresponding round.

Detailed procedures of a round

At the beginning of each round, you will see an input screen (Figure 1). On the left hand side of the header you see the number of the round you are currently in. On the right hand side of the header you see how much time you have left to make your choice.

Your task on this screen is to make your choice for Alternative A or Alternative B in this round.

Furthermore, you will be asked what choices you believe the **other members** of your group make. You are asked to indicate how many *other* members of your group you believe to choose Alternative A. Please note that you should indicate the number of **other** participants of your group who chose A, without counting yourself. If your estimate about the number of other group members to choose A turns out to be correct, you will get a bonus of **5 points** for the corresponding round. Apart from that, your indicated estimate is inconsequential for the further procedure of the round.

Once you have completed your inputs, please press the OK-button to confirm.

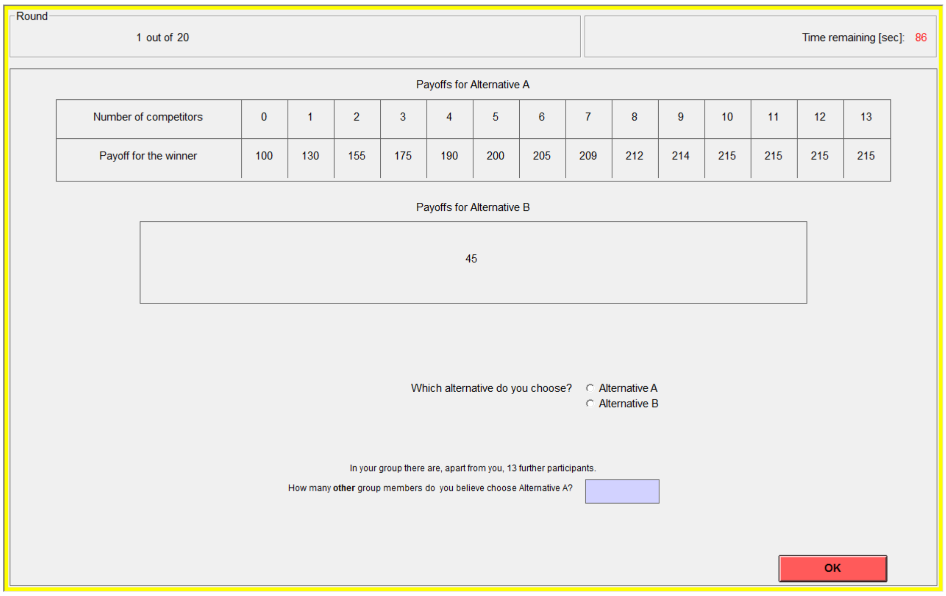


Figure 1: input screen

Subsequently, the computer generates for each participant a random number between 0 and 100. All numbers are equally likely. The participants who chose Alternative B will be assigned a random number as well which, though, is not consequential for any payoff.

For the participants who chose Alternative A, however, the random number determines whether you win the prize competition, that is, whether you earn a payoff between 100 and 215 points. Your random number will be displayed on the screen (Figure 2). Furthermore, it will be displayed how many participants chose Alternative A. Below you will see your payoff in this round and the indication, whether your estimate about the other group members' choices was correct. If this is the case, you receive 5 additional points.

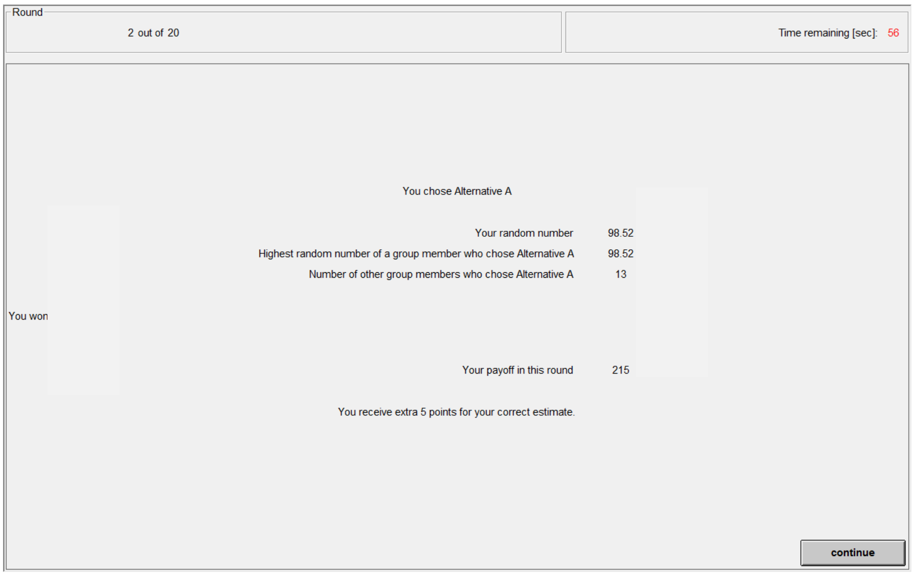


Figure 2: output screen.

Instructions for experiment 3

The third experiment is identical to the previous one in terms of the procedures. Again, there are 20 rounds to play. In each round you have to choose either Alternative A or Alternative B. The group composition is the same as in the previous experiment. The points you earn in this experiment will be added to the points that you earned in the experiments 1 and 3. The same exchange rate applies: 1 point will be converted to 1.5 Swiss cents and paid out at the end of the session.

There is one **important difference** to experiment 2:

The payoff for the participants who choose Alternative A are now determined in a different manner. There is **no** prize competition any more. Instead, everyone who chooses Alternative A receives the same number of points. As there is no prize competition anymore, there won't be random numbers either. But the number of points that you receive under Alternative A still depends on the number of other participants who also choose Alternative A. The payoffs are summarized by the following Table:

Number of other participants who choose A	0	1	2	3	4	5	6	7	8	9	10	11	12	13
Total payoff for **all** participants who choose A	100	130	155	175	190	200	205	209	212	214	215	215	215	215

If, for instance, you and four *other* participants choose Alternative A, then you get 175 points together. This payoff is equally distributed among those who choose Alternative A so that you receive a payoff of 43.75 (=175/4) points.

Everything else remains the same. The payoff possibilities of Alternative B remain at 45. Again, you can earn 5 points by give a correct estimate of the number of other participants to choose Alternative A.

Instructions for experiment 1

Welcome

Welcome to our economic experiment. If you read the instructions carefully, you can, depending on your decisions, earn more or less money. It is therefore important to read the following instructions carefully.

The instructions you received from us are solely for your private information. Communication with other participants is **strictly forbidden** during the whole experiment. Please ask an instructor in case of any questions. If you don't comply with those rules we will have to exclude you from the experiment including from any payments.

During the experiment, your payoff will not be computed in Swiss francs but in **points**. The points that you earn during the experiment will be converted to Swiss francs and paid out in cash. The following exchange rate applies:

1 point = 1.5 Swiss cents.

Instructions for experiment (i)

In this experiment we ask you to make choices between two alternatives, **Alternative A** and **Alternative B**. At the end of each round you receive a payoff (= a certain number of points) which depends on the alternative you choose.

You have to make this choice in a total of 20 consecutive rounds. Those 20 rounds are identical and independent of each other in terms of their procedure. Thus, your payoff in a particular round depends solely on your choice in this particular round. After the 20th round, all points that you received during the 20 rounds will be added to your total payoff.

Computing the payoffs in one round

In each round you must choose either Alternative A or Alternative B. If you choose Alternative A, your payoff will be subject to randomness. If you choose Alternative B you will receive a fixed payoff of 45.

If you choose Alternative A, then it will be determined randomly whether you receive a payoff which is higher than what you get under Alternative B or whether you receive a payoff of zero. The level and the probability of the possible payoffs are variable.

The payoffs are determined based on data of a completed experiment with another group of students. These students have already received their payoffs and they are not participating in today's experiment. To make sure you comprehend the decision situations of the participants of the completed experiment, we ask you to read the **instructions of the already completed experiment.** You find them in the attachment.

++

Please continue with the attachment (colored paper).

++

+++

Here we show the instructions for the WTA-condition of the main experiment

+++

+++

Please return now to the instructions of today's experiment (white paper).

+++

+++

After reading the attachment, please continue reading here.

+++

Today we are interested to know, what choices **you** would make in this situation. You will also face the choice between Alternative A and Alternative B.

In contrast to the completed experiment, however, your payoff for Alternative A will **not** depend on other participants' behavior in this room. Instead, we will use the **data of the completed experiment** to determine the level of your payoffs and their winning probabilities.

For this sake, during the experiment, you will be assigned a data set of a group from the completed experiment. If, in a given round, you choose Alternative A your payoff will be subject to randomness. It will be determined based on the number of participants who chose Alternative A in the corresponding round of the completed experiment. The choices of all participants will be replicated by the computer.

The prize is determined the same way as in the completed experiment:

Number of participants in the assigned group who chose A	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Payoff [in points]	100	130	155	175	190	200	205	209	212	214	215	215	215	215

Detailed procedures of a round

At the beginning of each round an input screen will be displayed (Figure 1). Your task on this screen is to choose either Alternative A or Alternative B for this round. Furthermore, you will be asked what choices you believe the participants of the completed experiment made. More concretely, you are asked to indicate how many of the 14 members of the group which you are assigned to choose Alternative A in the corresponding round. If your estimate regarding the behavior of the participants in the completed experiment is correct, you will get a bonus of 5 points for this round. Apart from that, your indicated estimate is inconsequential for the further procedure of the round.

Once you have completed your inputs, please press the OK-button to confirm.

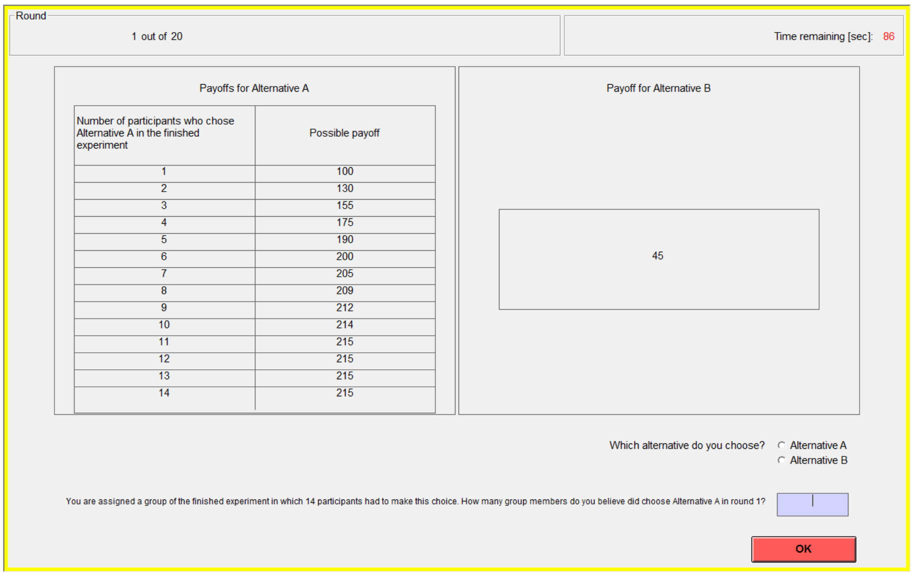


Figure 1: input screen

Subsequently, the computer will generate exactly as many random numbers as there are participants who chose Alternative A in this particular round of the completed experiment. You will be assigned one of those random numbers.

If you have chosen Alternative A, then this random number will determine whether you receive the prize, that is, whether you earn a payoff between 100 and 215 points. Is your random number the highest of all generated random numbers, then you receive a payoff of between 100 and 215 points. Otherwise you receive a payoff of zero.

If, for instance, you choose Alternative A in a given round and five participants of the completed experiment chose Alternative A in this particular round, then five random numbers will be generated. The random number that you are assigned to must be the highest for you to win the prize of 190.

The random numbers are also generated if you chose Alternative B. But they will be inconsequential for your payoff.

The results of these procedures will be displayed on the output screen (Figure 2).

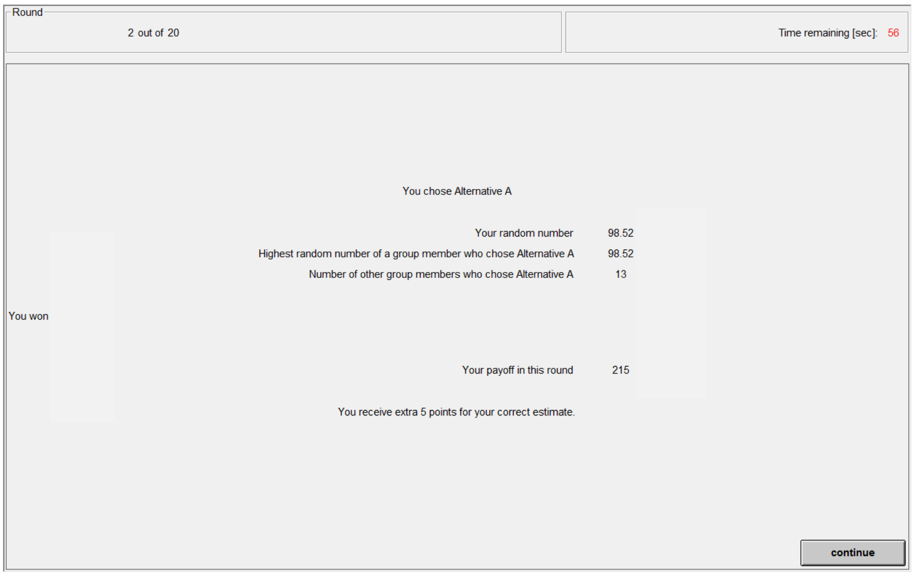


Figure 2: output screen

By clicking the „continue“-button, you get to the next round where you will face the same choice situation again.

Instructions for experiment (ii)

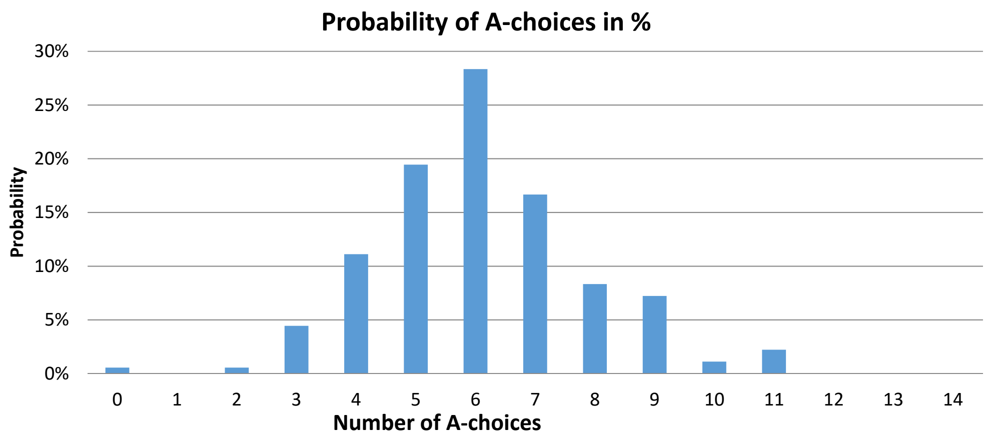
In this experiment you will face again choices between Alternative A and Alternative B. In this stage, however, we change the mechanism to determine your chances to win under Alternative A as well as your level of information.

Computing your payoff in one round

In each round you must choose either Alternative A or Alternative B. If you choose Alternative B, you will still get a payoff of 45. If you choose Alternative A you still get an uncertain payoff in the range of 0 to 215. Your winning chances are still based on the results of the already completed experiment.

In contrast to the previous experiment, you will not be assigned to a particular group for all rounds. Instead, in every round you will be randomly assigned any round of any group. Furthermore, you will learn the full statistical distribution of the A and B choices of the completed experiment.

Overall, 180 rounds were played in the completed experiment: Thereby the following distribution per round resulted:



Number of participants who chose A	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
Price to win in points	100	100	130	155	175	190	200	205	209	212	214	215	215	215	215
Absolute number of rounds	1	0	1	8	20	35	51	30	15	13	2	4	0	0	0
Relative frequency in %	**0.6**	**0**	**0.6**	**4.4**	**11.1**	**19.4**	**28.3**	**16.7**	**8.3**	**7.2**	**1.1**	**2.2**	**0**	**0**	**0**

Now, in every round, one of those 180 rounds will randomly be drawn as a basis to determine your payoff profile under Alternative A. If you happen to get a round where no participant chose Alternative A, you will get a payoff of 100 for this round.

Detailed procedures of a round

Again, at the beginning of each round an input screen will be displayed.

Your task is again to indicate for which of the two Alternatives A or B you choose in this round.

Furthermore, we will still ask you to indicate your beliefs about the behavior of the participants of the completed experiment. Now you have to indicate how many of the 14 group members chose Alternative A in the randomly drawn round. If your belief is correct, you get a bonus of 5 points.

Once you have completed your inputs, please press the OK-button to confirm.

Subsequently, the computer will again generate exactly as many random numbers as there are participants who chose Alternative A in this particular round of the completed experiment. You will be assigned one of those random numbers. If you have chosen Alternative A, then this random number will determine your payoff according to the same procedure as described above.

The results of these procedures will be displayed on the output screen. The screens correspond to the ones of the previous experiment.

Instructions CPT elicitation task

Instructions for experiment 3

In this last experiment, you do not interact anymore with the other participants. Your payoff for this experiment will only depend on your choices and luck.

Unlike the first two experiments, we won't use points but ECUs. The new exchange rate for this experiment is:

3 ECU = 1 CHF

You will face 40 situations of similar form and will have to take a decision for each of them.

You will have 40 minutes to take your decisions. During this time, you will be able to modify any decision at any time. Since you do not interact anymore with the other participants, the experiment will end up when you will be done with your decisions. You can move at your own pace. The 40 minutes should be more than enough to take your decisions.

Click on continue to see the next instructions

Continue

Instructions for experiment 3 (continued)

The 40 situations are independent from each other. For each situation, you have to choose between uncertain amounts of ECU (Option A) and certain amounts of ECU (Option B). The uncertain amount of Option A is randomly determined by the computer according to probabilities displayed on the screen.

There are two types of decisions. The amounts can either be positive (gain situation) or negative (loss situation). In loss situations, a specific amount of ECU is given to you (endowment) to compensate for any possible loss. This experiment cannot reduce the amount of money you have earned so far. For each situation, you receive the following information: the uncertain amounts of Option A and the probability attached to each amount, the certain amounts of Option B, and the endowment (only for loss situations).

After you validate your decisions, a situation is randomly drawn by the computer and your payoff will depend on your decision for this situation. Your payoff will be added to your payoff from the two previous experiments. Later, a screen will inform you on your total payoff for the 3 experiments and for each of them.

Click on continue to see an example of gain situation and one of loss situation.

Continue

Instructions for experiment 3 (continued)

Every situation will have a similar structure as the own showed on the right. The table contains 20 rows. Option A is the same for each row whereas Option B is different for each one.

Example of gain situation

In Option A, the gain is of 30.0 ECU with probability 25% and of 10.0 ECU with probability 75%.

In Option B, the certain gains range from 30.0 ECU to 11.00 ECU.

For each row, you have to choose if you prefer the corresponding certain gain (Option B) or if you prefer Option A.

To enter your decision, you will have to click on one of the gray buttons in the middle either in column A or column B. You do not have to enter your choice for each row because if you choose the Option B for a certain amount, then Option B is automatically chosen for all larger certain amounts. In other words, you have to choose from certain amount on you prefer Option B to Option A.

Click on Continue to see an example of loss situation.

n°	Option A	Your Choice		Option B A certain gain of ... ECU
1		A	B	30.0
2		A	B	29.0
3		A	B	28.0
4		A	B	27.0
5	Gain	A	B	26.0
6	of 30.0 ECU with	A	B	25.0
7	probability	A	B	24.0
8	25%	A	B	23.0
9		A	B	22.0
10	and	A	B	21.0
11		A	B	20.0
12		A	B	19.0
13	Gain	A	B	18.0
14	of 10.0 ECU with	A	B	17.0
15	probability	A	B	16.0
16	75%	A	B	15.0
17		A	B	14.0
18		A	B	13.0
19		A	B	12.0
20		A	B	11.0

Continue

Instructions for experiment 3 (continued)

Example of loss situation

In Option A, the loss is of 10.0 ECU with probability 75% and of 30.0 ECU with probability 25%.

In Option B, the certain losses range from 11.0 ECU to 30.00 ECU.

Contrary to a gain situation, you receive an endowment. This endowment ensures you do not lose money if the situation is chosen for the payment. The endowment is displayed at the top of the screen. Here, it is 40.0 ECU.

For each row, you have to choose if you prefer the corresponding certain loss (Option B) or if you prefer Option A.

Click on Continue to see how your payoff is determined.

Endowment: 40.0 ECU

n°	Option A	Your Choice				Option B A certain loss of ... ECU
1		A			B	-11.0
2		A			B	-12.0
3		A			B	-13.0
4		A			B	-14.0
5	**Loss**	A			B	-15.0
6	**of 10.0 ECU with**	A			B	-16.0
7	**probability**	A			B	-17.0
8	**75%**	A			B	-18.0
9		A			B	-19.0
10		A			B	-20.0
11	**and**	A			B	-21.0
12		A			B	-22.0
13	**Loss**	A			B	-23.0
14	**of 30.0 ECU with**	A			B	-24.0
15	**probability**	A			B	-25.0
16	**25%**	A			B	-26.0
17		A			B	-27.0
18		A			B	-28.0
19		A			B	-29.0
20		A			B	-30.0

Continue

Instructions for experiment 3 (continued)

Payoff determination (gain situation)

At the end of the experiment, a situation is drawn at random. Suppose that the situation on the right is drawn and that your choice is as shown. For the line n°10 and all of the above, you prefer Option B to Option A. In other words, for a certain gain larger or equal to 21.0 ECU, you prefer to get the certain amount of the row rather than to choose the uncertain Option A.

A row between 1 and 20 (first column) is then randomly drawn by the computer. In this example, suppose that row n°9 is randomly drawn. Because Option B was chosen for this line, your payoff would be the certain gain for this row (22.0 ECU). The payoff determination is similar for all the rows above row n°9 in this example. The payoff being always the certain amount of the randomly chosen row.

If row n°11 was randomly chosen, your payoff would depend on the outcome of Option A. In this case, you would win 30.0 ECU with probability 25% or 10.0 ECU with probability 75%. Again, the computer would determine which of the two amounts you would win. The payoff determination is the same for all lines below line n°11 in this example.

n°	Option A	Your Choice				Option B A certain gain of ... ECU
1		A		X	B	30.0
2		A		X	B	29.0
3		A		X	B	28.0
4		A		X	B	27.0
5	**Gain**	A		X	B	26.0
6	**of 30.0 ECU with**	A		X	B	25.0
7	**probability**	A		X	B	24.0
8	**25%**	A		X	B	23.0
9		A		X	B	22.0
10		A		X	B	21.0
11	**and**	A	X		B	20.0
12		A	X		B	19.0
13	**Gain**	A	X		B	18.0
14	**of 10.0 ECU with**	A	X		B	17.0
15	**probability**	A	X		B	16.0
16	**75%**	A	X		B	15.0
17		A	X		B	14.0
18		A	X		B	13.0
19		A	X		B	12.0
20		A	X		B	11.0

Continue

Instructions for experiment 3 (continued)

Payoff determination (loss situation)

Instead, suppose that the randomly chosen situation is the one on the right and that your choice is as shown. For the line n°13 and all of the above, you prefer Option B to Option A. In other words, for a certain loss smaller or equal to 23.0 ECU, you prefer to incur the certain loss of the row rather than to choose the uncertain Option A.

Now suppose that row n°12 is randomly drawn for the payment. Because Option B was chosen for this line, your payoff would be the certain loss for this row (22.0 ECU). The payoff determination is similar for all the rows above row n°12 in this example. The payoff being always the certain loss of the randomly chosen row.

If row n°14 was randomly chosen, your payoff would depend on the outcome of Option A. In this case, you would incur a loss of -10.0 ECU with probability 75% or -30.0 ECU with probability 25%. Again, the computer would determine which of the two losses you would incur. The payoff determination is the same for all lines below line n°14 in this example.

Your final payoff would be equivalent to the endowment (40.0 ECU) from which we substract the loss you incur. Remember, the endowment is always such that you cannot end up with a negative payoff.

Endowment: 40.0 ECU

n°	Option A	Your Choice				Option B A certain loss of ... ECU
1		A		X	B	-11.0
2		A		X	B	-12.0
3		A		X	B	-13.0
4		A		X	B	-14.0
5	**Loss**	A		X	B	-15.0
6	**of 10.0 ECU with**	A		X	B	-16.0
7	**probability**	A		X	B	-17.0
8	**75%**	A		X	B	-18.0
9		A		X	B	-19.0
10	**and**	A		X	B	-20.0
11		A		X	B	-21.0
12		A		X	B	-22.0
13	**Loss**	A		X	B	-23.0
14	**of 30.0 ECU with**	A	X		B	-24.0
15	**probability**	A	X		B	-25.0
16	**25%**	A	X		B	-26.0
17		A	X		B	-27.0
18		A	X		B	-28.0
19		A	X		B	-29.0
20		A	X		B	-30.0

Continue

Instructions for experiment 3 (continued)

Control questions

Please answer to the two following question to make sure you understood the instructions. Suppose your choice is as shown on the right.

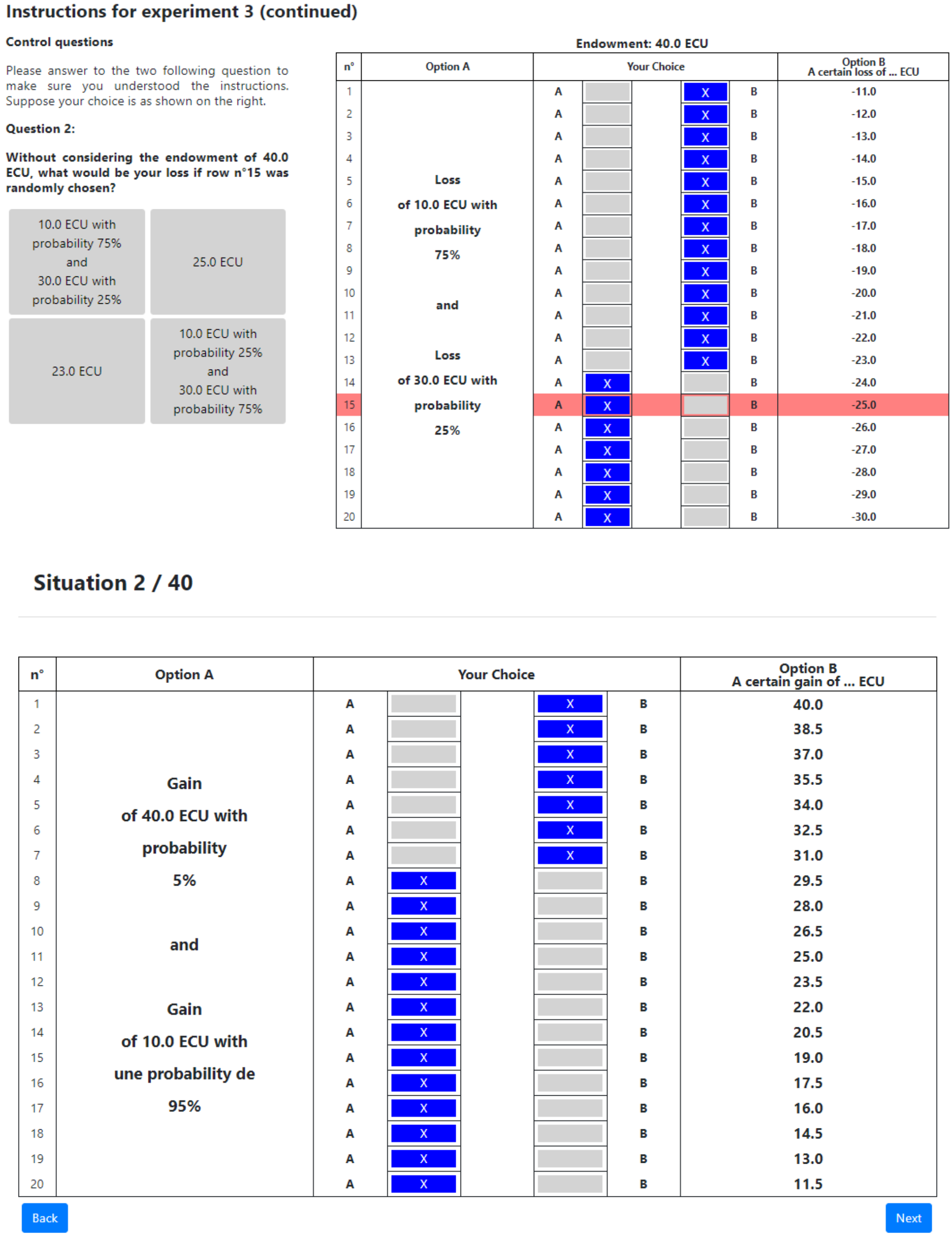
Question 1:

What is your payoff if row n°8 is randomly drawn for the payment?

30.0 ECU with probability 25% and 10.0 ECU with probability 75%	23.0 ECU
21.0 ECU	30.0 ECU with probability 75% and 10.0 ECU with probability 25%

n°	Option A	Your Choice				Option B A certain gain of ... ECU
1		A		X	B	30.0
2		A		X	B	29.0
3		A		X	B	28.0
4		A		X	B	27.0
5	**Gain**	A		X	B	26.0
6	**of 30.0 ECU with**	A		X	B	25.0
7	**probability**	A		X	B	24.0
8	**25%**	A		X	B	23.0
9		A		X	B	22.0
10	**and**	A		X	B	21.0
11		A	X		B	20.0
12		A	X		B	19.0
13	**Gain**	A	X		B	18.0
14	**of 10.0 ECU with**	A	X		B	17.0
15	**probability**	A	X		B	16.0
16	**75%**	A	X		B	15.0
17		A	X		B	14.0
18		A	X		B	13.0
19		A	X		B	12.0
20		A	X		B	11.0

Instructions for experiment 3 (continued)



Control questions

Please answer to the two following question to make sure you understood the instructions. Suppose your choice is as shown on the right.

Question 2:

Without considering the endowment of 40.0 ECU, what would be your loss if row n°15 was randomly chosen?

10.0 ECU with probability 75% and 30.0 ECU with probability 25%	25.0 ECU
23.0 ECU	10.0 ECU with probability 25% and 30.0 ECU with probability 75%

Endowment: 40.0 ECU

n°	Option A	Your Choice				Option B A certain loss of ... ECU
1	Loss of 10.0 ECU with probability 75% and Loss of 30.0 ECU with probability 25%	A		X	B	-11.0
2		A		X	B	-12.0
3		A		X	B	-13.0
4		A		X	B	-14.0
5		A		X	B	-15.0
6		A		X	B	-16.0
7		A		X	B	-17.0
8		A		X	B	-18.0
9		A		X	B	-19.0
10		A		X	B	-20.0
11		A		X	B	-21.0
12		A		X	B	-22.0
13		A		X	B	-23.0
14		A	X		B	-24.0
15		A	X		B	-25.0
16		A	X		B	-26.0
17		A	X		B	-27.0
18		A	X		B	-28.0
19		A	X		B	-29.0
20		A	X		B	-30.0

Situation 2 / 40

n°	Option A	Your Choice				Option B A certain gain of ... ECU
1	Gain of 40.0 ECU with probability 5% and Gain of 10.0 ECU with une probability de 95%	A		X	B	40.0
2		A		X	B	38.5
3		A		X	B	37.0
4		A		X	B	35.5
5		A		X	B	34.0
6		A		X	B	32.5
7		A		X	B	31.0
8		A	X		B	29.5
9		A	X		B	28.0
10		A	X		B	26.5
11		A	X		B	25.0
12		A	X		B	23.5
13		A	X		B	22.0
14		A	X		B	20.5
15		A	X		B	19.0
16		A	X		B	17.5
17		A	X		B	16.0
18		A	X		B	14.5
19		A	X		B	13.0
20		A	X		B	11.5

Back Next

Figure 1: Decision screen

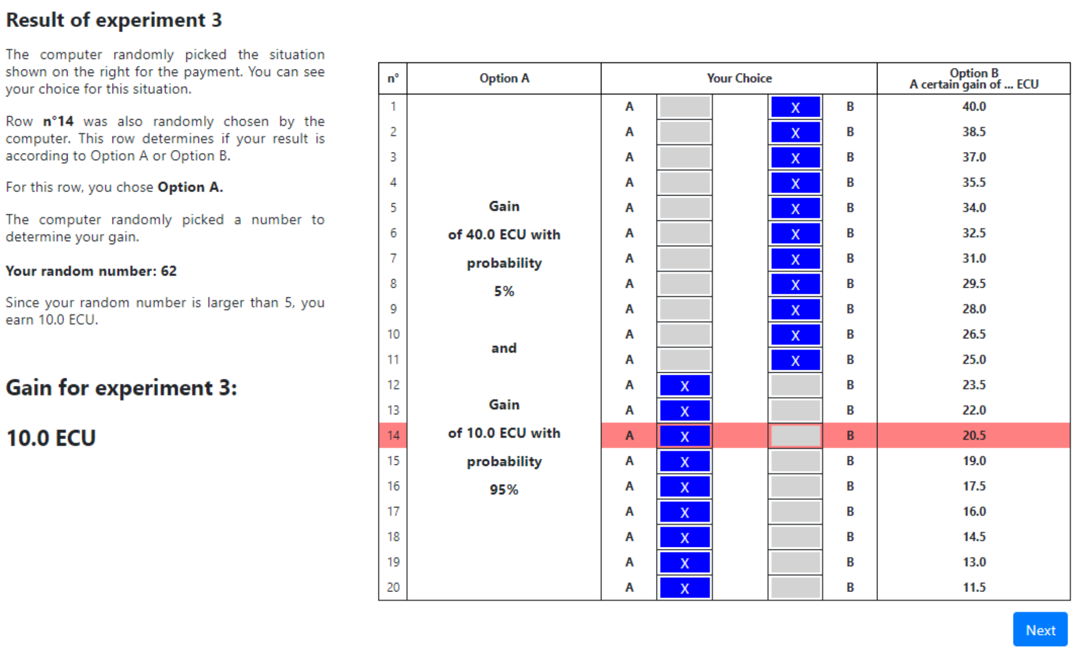


Figure 2: Result screen