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Article (Accepted version)
(Refereed)

Original citation:
Foster, Gigi and Frijters, Paul and Schaffner, Markus and Torgler, Benno (2018) *Expectation formation in an evolving game of uncertainty: new experimental evidence.* Journal of Economic Behavior and Organization. ISSN 0167-2681

DOI: 10.1016/j.jebo.2018.07.013

Expectation Formation in an Evolving Game of Uncertainty: New Experimental Evidence

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September 18, 2018

Abstract

We examine the nature of stated subjective probabilities in a complex, evolving context in which participants are not told what the actual probability is: we collect information on subjective expectations in a computerized car race game wherein participants must bet on a particular car but cannot influence the odds of winning once the race begins. In our setup, the actual probability of the good outcome (a win) can be determined based on computer simulations from any point in the process. We compare this actual probability to the subjective probability stated by participants at three different points in each of six races. In line with previous research in which participants have direct access to actual probabilities, we find that the inverse S-shaped curve relating subjective to actual probabilities is also evident in our far more complex situation, and that there is only a limited degree of learning through repeated play. We show that the model in the inverse S-shaped function family that provides the best fit to our data is Prelec's (1998) conditional invariant model. We also find that individuals who report a greater degree of ambiguity are more pessimistic and less responsive to actual changes in real probabilities.

Keywords: behavioral economics, expected utility theory, experiments, expectations, probabilities
JEL classification: D40, L10

*We acknowledge the Australian Research Council (grant DP090987840), ORSEE, and the ASBLab at the University of New South Wales for enabling our experiments. Excellent research assistant work has been provided by Ho Fai Chan. We also thank two editors of JEBO and two anonymous referees for very helpful comments. This research has the approval of the UNSW Human Research Ethics Committee. All errors and viewpoints are our own.

Although its empirical picture has come into focus, the weighting function has remained a somewhat tricky object to analyze—at least in comparison with the utility function ... Overall, it does not look like a shape that one would draw unless compelled by strong empirical evidence. (Prelec 2000, p. 67)

1 Introduction

The quality of human judgment has been comprehensively explored in various disciplines, including psychology, management, and economics. The vast literature on non-expected utility theory (see Starmer 2000, Starmer 2004, for a review) originated in the persistent inability of rational models of behavior (von Neumann, J. & Morgenstern 1947) to predict choice behavior in experiments (Camerer & Loewenstein 2004) which spawned a cottage industry of experiments to tease out individuals' cognitive biases.

One prominent finding from this literature is that even when told the actual probabilities associated with outcomes, individuals behave as though other probabilities apply. Early experimental work by Preston & Baratta (1948), for example, identified an inverse S-shaped function in which subjective (psychologically-mediated) probabilities exceed objective (mathematical) probabilities, p, at low values of p, but fall short of objective probabilities at high values of p. Preston & Baratta's (1948) core proposal was that the crossing point in their experimental data—the point at which the subjective and objective probabilities were equal—was a function of an initial anchoring level, which itself may relate to inherent psychological or physiological attributes and an individual's initial position (p. 191-192). In their experiment, the inverse S-shape was not only visible in student data but also in data capturing the behavior of faculty of mostly professorial rank in the fields of mathematics, statistics, and psychology: participants who presumably were well-acquainted with probability theory. Subsequent work by Dale (1959) also reported that experimental participants tend to overestimate low probabilities and underestimate high probabilities.

Since then, a raft of theories—including prospect theory (Kahneman & Tversky 1979), rank-dependent utility theory (Quiggin 1982, Yaari 1987, Schmeidler 1989, Wakker 1994), adaptive probability theory (Martins 2006), and conditional small world theory (Chew & Sagi 2008)—have proposed specific cognitive decision rules regarding how subjective probabilities are derived from objective ones. Contrary to expected utility (EU) theory, however, these approaches treat actual probabilities as nonlinear inputs to subjective probabilities. Moreover, despite being axiomatically based, each has become associated with a particular probability-weighting function that relates the subjective probability p^s to the true probability p. These weighting functions can accommodate the psychophysics of diminishing sensitivity, wherein the marginal impact of a stimulus diminishes with increasing distance from a reference point (Tversky & Kahneman 1992, Camerer 1995, Fox & See 2003). They can also allow for affective aspects of the decision process, such as hope (when contemplating high-probability losses) or fear (when contemplating low-probability losses); emotionally richer decision-making settings, for example, may give rise to more pronounced inverse S-shapes (Rottenstreich & Hsee 2001, Trepel, Craig & Poldrack 2005).

1.1 Broader context and contribution

A key methodological divide in work examining subjective probability formation concerns whether participants have direct access to objective probabilities. One branch of literature aims to estimate a probability weighting function based on informing individuals of an outcome's true probability, and then observing their choice behavior (see, e.g., Abdellaoui, Baillon, Placido & Wakker 2011, Kilka & Weber 2001, Gonzalez & Wu 1999). Such studies were criticized by Fox & Tversky (1998): 'Although most empirical studies have employed risky prospects, where probabilities are assumed to be known, virtually all real-world decisions (with the notable exception of games of chance) involve uncertain prospects (e.g., investments, litigation, insurance) where this assumption does not hold. In order to model such decisions we need to extend the key features of the risky weighting function to the domain of uncertainty' (p. 880). In a similar vein, Abdellaoui et al. (2011) state,'[i]n many situations we do not know the probabilities of uncertain events that are relevant for the outcomes of our decisions' (p. 695). Simply put, in the real world people typically face decisions characterized by partial knowledge of the consequences of their actions (Tversky & Fox 1995). However, empirical tests in real-world situations are fraught with identification problems (Gilboa, Postlewaite & Schmeidler 2008). Lab experiments offer more control, though they have been criticized as somewhat artificial (Winkler 1991).

In this paper, we confront participants with scenarios whose complexity and uncertainty mimics those aspects of real-life decision-making contexts, in which the actual probability of success is not within individuals' feasible information set. We then estimate the probability weighting function using data drawn from repeatedly asking individuals for their estimates of the probability of a good outcome. While it is not impossible to correctly ascertain the actual probability of a good outcome, it is extremely difficult. Hence, as with many economic problems, probabilities are not truly given (see Gilboa et al. 2008). The objective probabilities we use are drawn from computer simulations of how each uncertain situation, on average, will play out from the point in time at which subjective probabilities are elicited.

The quality of people's assessments, their abilities, and the limits of their functioning in uncertain environments are all of theoretical and applied importance (Lichtenstein & Fischhoff 1977). We contribute to the literature examining people's intuitive judgements of likelihood (Gilovich, Griffin & Kahneman 2002), estimating the probability weighting function in the case of uncertainty (see, e.g., Tversky & Wakker 1995, Fox & Tversky 1998, Kilka & Weber 2001, Holt & Smith 2009, Wakker 2010, Abdellaoui et al. 2011, Baillon, Cabantous & Wakker 2012). We also contribute to a broader literature on the relationship between subjective probabilities and actual outcomes (see, e.g., Manski 2004, Hurd 2009, Carman & Kooreman 2014, Brenner, Koehler & Rottenstreich 2002). Overall, studies using survey data dominate this literature (de Palma, Andre, Brownstone, Holt, Magnac, McFadden, Moffat, Picard, Train, Wakker & Walker 2008). In our paper, by contrast, we construct an adaptation for the experimental laboratory of a race car game, in which participants must bet on the race's ultimate outcome, which cannot be influenced once the game is underway. We ask participants several times during each race what they think the odds are of their chosen car winning the race. Our set-up is thus dynamic—like the few existing papers (e.g. Cheung 2001) that examine dynamic, probabilistic processes over time—and allows us to monitor how agents update their probability expectations as a risky situation unfolds. This is an important feature of the study, as many interesting decision-making problems are dynamic in nature (Winkler 1991). Further, as Machina & Schmeidler (1992) point out (p. 746), "...real-world uncertainty seldom presents itself in terms of exogenously specified probabilities, but rather, as alternative 'events' or 'states of nature,' so that instead of well-defined objective probability distributions, the objects of choice are typically 'bets' or 'acts' ...". A bet on the outcome of an uncertain event—a choice that we examine in our study—is in other words a more typical object of choice in the real world than a choice between options that involve known objective probabilities.

The main novelty of our study compared to previous literature is in our repeated elicitation of subjective probabilities of a focal event dynamically, as the event draws closer, in a setting where the objective probability of the event is unknown to the participant but known to us as researchers. In this dynamic environment, we examine both the determinants of subjective probabilities and the relation of subjective probabilities to objective probabilities, sequentially fitting four different structural models of subjective probability formation that have been proposed in the literature—all of which accommodate the stylized inverse S-shape. We check the validity of our elicited subjective probabilities by comparing them against a set of incentivized choices made at the same moments that subjective probabilities are elicited. Participants may choose at these moments whether or not to pull out of the game, where pulling out involves recouping a fraction of their bet for sure rather than letting the race run its course and risking the loss of their whole bet. This check also allows us to determine whether stated probabilities have information value in terms of actual decisions featuring a trade-off between payoffs known now with certainty, versus risky future outcomes (de Palma et al. 2008). Such choices are exemplified in the TV game show *Deal Or No Deal*, in which the trade-off is between a safe option (receiving a sum of money for certain) and an opportunity to win more or less (e.g., Post, J. & Assem 2008, Bombardini & Trebbi 2012, Mulino, Scheelings, Brooks & Faff 2009, de Roos, N. & Sarafidis 2010, Deck, Lee & Reyes 2008, Botti & Conte 2008, Blavatskyy & Pogrebna 2008, de Palma et al. 2008, Andersen, Harrison, Lau & Rutström 2013). We avoid the danger that risk aversion will lead individuals to misrepresent their probability perceptions and therefore contaminate the data (Andersen, Harrison, Lau & Rutström 2010) by separating their choice behavior from their stated probabilities, and only incentivizing the former (for a recent evaluation of different belief elicitation methods, see Schlag, Tremewan & van der Weele 2015). Opinions differ on whether or not to use incentives for belief elicitation. We choose to keep decisions and evaluation processes as low as possible in cognitive load, noting that participants in our setting have no incentive to misreport their subjective probabilities.[1] The stability of the results we obtain over time, and the consistency of our results with other studies in other contexts, signal that misunderstandings or careless reporting are not first-order concerns in our context, despite the complexity of the task.

Our study design also includes a consideration of ambiguity, measured as the degree of confidence participants have in each of their stated subjective probabilities. This allows us to add to a growing literature that explores learning under ambiguity (Epstein & Schneider 2007) and that has called for more realistic models of the way beliefs are formed and the way they are

[1]Such incentives arise, for example, in experiments where participants can use stated beliefs to justify their (selfish) behavior (e.g., dictator games, public good games and trust games (Schlag et al. 2015)).

updated (Gilboa et al. 2008). There is a strong demand for experimental research in choice situations involving ambiguity (de Palma et al. 2008). By measuring the evolution of ambiguity, we are able to see the degree to which it changes, and how the relation between subjective and objective probability differs in situations with different levels of ambiguity.

Consistent with Baillon, Bleichrodt, Keskin, L'Haridon & Li (2013), we observe that with more information (e.g., more experience with the car race game, in our case), the probability weighting function becomes somewhat steeper over time, meaning that subjective probabilities at very low and very high levels become (marginally) closer to objective ones. This would be called in the literature a reduction in 'likelihood insensitivity' as experience increases. Research conducted in other, more static settings usually finds more likelihood insensitivity overall[2] in cases of uncertainty than in cases of risk (for a list of studies, see Baillon et al. 2013). Our experimental setting is uncertain, not rich in feedback, and initially unfamiliar to participants—which are also core features of many real situations in which people form judgements about the outcomes of uncertain events (Haltiwanger & Waldman 1985). In the lab setting, we can directly control participants' previous experience, while observing what happens to judgement, decisions, and perceived ambiguity as that experience increases.[3] We find that despite the significant complexity and dynamism of the scenario and the absence of direct information about actual probabilities, a model of S-shaped probability weighting fits the data remarkably well.

2 Experimental approach

To assess expectation formation during the unfolding of an uncertain event whose outcome matters, we use a novel experimental design featuring monetary payoffs whose scientific justification and relevant features are outlined here. Further details are available in the Appendix and upon request from the authors.

[2]For a formal definition and discussion of likelihood insensitivity (the nominal cause of the inverse-S shaped relation between objective and subjective probabilities), see Wakker (2010), chapter 7.

[3]Uncertainty due to imperfect foresight and humans' inability to solve complex problems has been at the core of revisions to the use of optimization strategies in understanding human actions (Alchian 1950). In fact, our setting in which betting on a simulated car race is the core choice is redolent of the original discussions about subjective probability that emerged many decades ago, where the analogy to (horse) races was drawn (de Finetti 1931, Anscombe & Aumann 1963, Heilig 1978).

2.1 Justification

Our setting is intentionally built to mimic a real-life situation, such as gambling or stock trading, in which the agent may observe initial information about statistical likelihoods or even provide input into the outcome generation process, but cannot perfectly anticipate a shock component present in the process before the outcome occurs. We empirically estimate the parameters of several non-expected utility models using our laboratory-generated data, as has been done in previous studies of similar real-life situations, with early research frequently using data from betting markets to explore the subjective and estimated objective winning probabilities (Griffith 1949, McGlothlin 1956, Weitzman 1965, Ali 1977) in, for example, horse races (see, e.g., Ali 1977, Jullien & Salanié 2000).

A disadvantage of most real markets is that there is no unambiguous 'true probability' to which behavior can be related, as the statistician only has access to realized events and not to the underlying true probabilities of these events. The results and limitations of earlier studies thus suggest the use of lab-based, real-life-mimicking experimental designs which have the advantages of conferring control over the risky data generating process (and hence allowing the researcher access to the objective probabilities); offering a richer set of variables capturing individual characteristics; and ensuring the absence of other potentially confounding factors, such as the presence of bankruptcy laws.

2.2 Design

In our experiment, participants were confronted with six animated race car games, where each participant's final payoff was linked to the outcome of one particular car.[4] In each game, the participant chose how to divide a fixed amount of money—earned previously in a real-effort task involving the completion of as many cross-sum calculations as possible in ten minutes (see Appendix A.3 for details)—into a wagered amount and an invested amount, where greater investment increased the chances that the participant's car would win (see Figure A.1 in the Appendix). Each race lasted for 10 laps and involved five cars in total (see Figure A.2), each performing according to a statistical process comprised of a random-walk component and an exogenous downward shifter, explained to participants as a temporary engine

[4]Each participant faced his own game involving competing cars controlled by the computer, with no interactions between the races or with the games of other participants. The experiment was programmed in an early version of CORAL (Schaffner 2013).

failure. The frequency of the incidence of this exogenous downward shock was reduced for the participant's car in proportion to the amount invested, explained to participants as investment into engine quality. Our choice to force participants either to bet or to invest their endowment was driven by two motivations. First, we wished to prevent participants from being able to merely hoard their endowment and thereby disengage monetarily (and arguably emotionally) from the outcome of the uncertain scenario. Second, we wished to increase the present salience of the opportunity cost of betting, such that participants would make a well-considered decision. Our choice to allow the initial endowment to vary depending on participants' effort was also intended to increase engagement.

Participants were offered the choice to withdraw from their bet at each of three pit stops (after laps 3, 6, and 9; see Figure A.2). If they elected to drop out at one of these points, then they would retain a fraction of the amount originally wagered. This fraction, respectively at each successive pit stop, was 40%, 25%, or 10% of the amount originally wagered. Upon a decision to drop out, the participant would see the race continue to completion on the screen, but would no longer have a monetary stake in its outcome. Participants' expectations about the likelihood of their car winning were elicited at the beginning of the race, and also at each of the three pit stops, by asking them how many times out of 1,000 they thought their car would win if the race were to continue 1,000 times from that point. The outcome of one of the six races, chosen randomly, was paid out in cash at the conclusion of the experiment.

To obtain data across different risk and endowment levels, we implemented four distinct treatments, each of which affected the way in which payoffs were structured. In the baseline treatment, participants received a $5 show-up fee plus five times the amount wagered in the event that their car won the race that was selected for payout. In the 'wealth' treatment, the payoffs from the races stayed the same, but the show-up fee was increased to $20. In the 'high-stakes' treatment, the show-up fee was again $5 but participants won 15 times the amount wagered if their car won the race that was selected for payout. Finally, in the 'low-stakes' treatment, participants received twice the bet if their car won, the exact amount wagered if their car came second, and half the wagered amount if their car came third.

In addition to gathering information about expectations and risk-taking in the race stage of the experiment, we asked participants to respond to several batteries of questions on their psychology and beliefs, and also collected standard demographic information. After the experiment had concluded, we used computerized repetitions of the data-generating process to simulate the actual likelihood for each race of the participant's car winning the race from the point of each pit stop, providing an objective picture of the future outcome against which we could compare participants' subjective expectations. In our context, as in many real-life scenarios, the true (mathematical) probability of winning changed as the race went on, because of changes in the observed positions of the cars. We therefore expected that subjective probabilities too would adjust as this new information became available, and the revelation of whether or not the participant's car would win grew ever closer.

At the start of the race, we informed each participant of the overall odds of his car winning the race, conditional on his choice of how much of his endowment to invest, and how much to wager. Crucial to our experiment however, and unlike the literature we build on, we did not tell participants the true (updated) mathematical expectation of winning when they arrived at the pit stops. We asked participants for their subjective probabilities sequentially as this complex situation unfolded, rather than backing them out of lottery choices at a point in time. Finally, every time we elicited a subjective probability, we also recorded the subject's degree of confidence in that answer, yielding a measure of perceived ambiguity that we discuss in greater detail later.

3 Simple statistics and model fit

A total of 239 participants took part in eight experimental sessions, all recruited using using ORSEE (Greiner 2004) via standard emails from the experimental participant pool at the ASBLab at the Australian School of Business within the University of New South Wales. The average participant age was 22 years, and 45.15% of participants were female. The large majority of participants are enrolled in commerce (including also economics and finance), engineering, and science. Only 6 percent of the participants are arts major which may indicate that there is substantial homogeneity in regard to familiarity with statistics. The average earnings in the real effort task, which as described above could then be split into a wagered and an invested amount, was \$24.42. The average bet was \$7.23, and there was a steep winning curve: payoffs were highly volatile, ranging from \$5 to \$105.20, with an average of \$23.62 across all four treatments. Full sample sizes by treatment, calculated at the levels of participant, participant-by-race, and participant-by-pit-stop are given in Table 1. In ensuing regression tables, these sample sizes fluctuate somewhat because of incomplete participant data on certain explanatory variables.

Table 1: Summary statistics

	Participants	Participant-Races	Participant-Pitstops
Sample sizes:			
Baseline Treatment	58	348	1044
Wealth Treatment	59	354	1062
High-Stakes Treatment	61	365[a]	1095
Low-Stakes Treatment	61	366	1098
TOTAL	239	1433	4299
Complete demographics[b]	233	1398	4194
Valid pitstops[c]	-	-	3925
Key variables:			
Pitstop expectations of winning	**5.21**	**5.21**	**5.21**
(standardized: times out of 10)	(.15)	(.08)	(.05)
Simulated chances of winning	**4.33**	**4.33**	**4.33**
(standardized: times out of 10)	(.13)	(.08)	(.05)
Ever dropped out of bet?	**50.63%**	**18.49%**	**14.63%**

Note: The top section of this table shows sample sizes, and the bottom section shows means of the key analysis variables, at each level of analysis. Expectations of winning, simulated chances of winning, and dropout behavior are all measured at the participant-pit-stop level. The bottom section of the table also shows the standard error of each mean.

[a] One participant experienced a computer problem during the final race. The observation has been excluded from the analysis, resulting in the total number of races of 365 for this treatment instead of 366.

[b] Six participants had missing or obviously wrong information in their demographics and were excluded from the respective analysis.

[c] Valid pitstops exclude all observations where participants had dropped out prior to the respective pitstop.

The key phenomenon to take from this descriptive table is the presence of aggregate over-optimism: participants report a belief that their car will win in 521 out of 1000 continuations, whereas the true number, found via our large-sample simulations, is 433 out of 1000. Subjective probabilities are thus around 9 percentage points higher than objective ones on average, and this difference is statistically significant, as can be seen from the small size of the associated standard errors.

Next, we look at the evolution of the raw relationship between the subjective probability and the objective probability of winning for each of the 6 races individuals faced, with a special focus on whether or not the match between subjective and objective probabilities improves as individuals learn more about the race. In the kernel plots shown in Figure 1, we see that for all six races a very similar inverse S-shaped curve emerges, and casual visual inspection does not indicate an obvious improvement in the fit as we move from Race 1 to Race 6. Still, the fitted regression slope is significantly steeper for the later races (4-6) than for the earlier ones (1-3). A particular feature evident in the plots for each race is that the subjective probability does not clearly converge to 1 even when the objective probability is very close to 1. Also, subjective probability remains above the objective probability until the objective probability reaches approximately 60%.

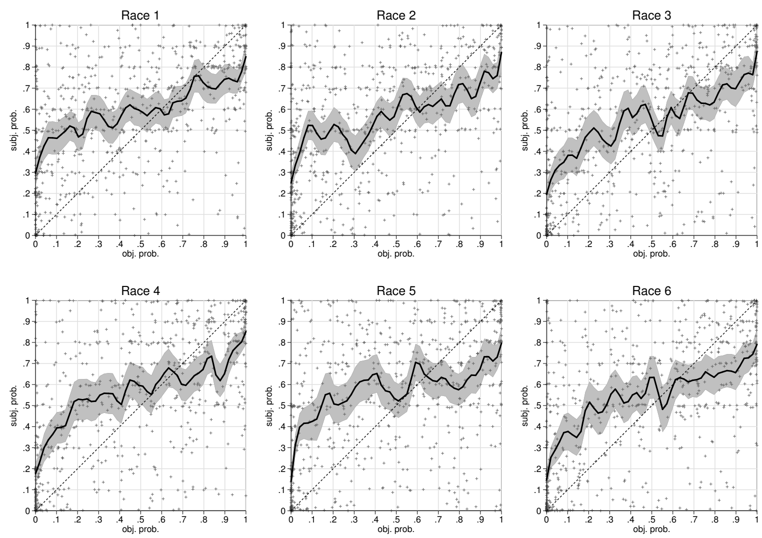

Figure 1: Kernel Plots by Race

3.1 Is there information in stated probabilities?

As discussed above, participants were given the choice at each pit stop to either withdraw from the race and receive a certain percentage of the bet, or let the game proceed further. The inclusion of this behavioral choice, presented at the same time that we elicit subjective probabilities, enables us to answer the preliminary question of whether stated probabilities contain information about choice behavior. Because the decision of whether to drop out involves the utility value of entertainment and excitement, we should expect choice behavior to relate not solely to subjective probability, but also to individual heterogeneity in entertainment value and a complicated option value of continuing.[5] Nevertheless, by examining whether subjective probabilities help explain choices, we can determine whether they contain any choice-relevant information over and above the effects of objective probabilities.

If we concentrate on the decision made at the last pit stop—when there are no future pit stops to anticipate—we can run more detailed specifications without being worried about the complication of the option value of future dropout opportunities. The optimal strategy in this situation, for a risk-neutral individual in any treatment except 'low stakes' who is interested only in monetary reward, is to drop out of the race if the probability of winning is below $\frac{10}{f}$ where f denotes the factor by which the wagered amount is multiplied if the participant's car wins (5 or 15 times, depending on the treatment) and the numerator captures the 10% fraction of the wagered amount that is paid out when dropping out at the final pit stop.

Table 2: Random Effects Probit coefficient estimates from the prediction of dropping out of a race

	All pitstops	**Final pitstop**					
Objective prob.	-3.197***	-3.176***	-3.975***				
	(0.442)	(1.002)	(1.187)				
Subjective prob.	-2.161***	-2.576***		-3.881***			
	(0.350)	(0.958)		(1.158)			
Obj. cutoff					1.625***	1.704***	
					(0.243)	(0.252)	
Subj. cutoff					0.750**		1.312***
					(0.316)		(0.322)
Chi^2	114.764	11.610	11.206	11.230	47.852	45.727	16.582
$Pr() > Chi^2$	0.000	0.003	0.001	0.001	0.000	0.000	0.000
N	3935	907	907	907	907	907	907
ll	-602.080	-120.133	-132.618	-135.097	-130.710	-133.266	-168.004

Significance levels: * 0.1; ** 0.05; *** 0.01. Standard errors clustered at the participant level in parentheses.
N = 3935 includes all valid pit stops for the entire sample with 265 (6.73%) observation where participants choose to drop out. N = 907 are all valid decisions at the third pit stop excluding the Low-Stakes treatment for a different payoff structure and with 45 (4.96%) choosing to drop out.

The first two columns of Table 2, where objective and subjective stated probabilities are used to predict dropout behavior either at all the pit stops (Column 1) or only at the final pit stop (Column 2), clearly illustrate that both real and stated probabilities affect the choice of whether to drop out. Compared to specifications with only one of the two types of probabilities included (shown in Columns 3 and 4 of Table 2), the specification that includes both has a superior fit to the data in terms of the standard information criteria (Bayesian, Aikake, and average likelihood ($\frac{-log(ll)}{N}$)).

[5] For the first two of three pit stops, the option of continuing includes the possibility of dropping out later.

Columns 5 to 7 then show the estimated effect on dropout behavior of the real or stated probability lying below the 10% cutoff described above. Comparing these results to the results in prior columns of Table 2 reveals that the contribution of subjective probabilities in explaining behavior is not fully captured in the cutoffs alone: the log likelihood associated with the model using only the cutoff dummies is substantially lower than that associated with the model that includes the continuous probabilities. This finding emphasizes that individuals do not make their choices purely on the basis of maximizing expected monetary returns.

In the first two columns of Table 2, where we include both the actual and stated probabilities, we find that the objective probability's estimated coefficient when predicting the latent variable related to the decision to drop out is 50% to 100% higher than that of the subjective probability, and both variables are highly significant in the equation. This intriguing finding indicates that participants use information reflected in the real probability that is not included in their stated probability.[6] In addition, the fact that there is additional cross-sectional variation in subjective probabilities that helps to explain behavior above and beyond the variability in objective probabilities supports the behavioral relevance and validity of our subjective probability measures.

3.2 Ambiguity

A more subtle dimension of expectations about the future in a setting like ours concerns an individual's perceived uncertainty, or the ambiguity of his belief, about the chances to win (see Manski 2004, Manski 2018, Giustinelli & Pavoni 2017). Ambiguity may be understood generally as the degree to which an individual believes he has the correct mental model of the phenomenon in question. We measure ambiguity at each pit stop, directly following the elicitiation of subjective probabilities, by asking participants the following question: "How confident are you that your guess is roughly right? (out of 100%)". This offers us a measure of the ambiguity level perceived by each participant in each decision-making situation.

The average level of ambiguity in our sample as measured this way is 0.29, with individual measures ranging across the full scale of 0 to 1 (1=highest ambiguity level, meaning zero confidence). Ambiguity is related to objective

[6] We do not explore this finding further here because there are many candidate explanations for it that fall outside our focus in this paper, including subliminal excitement due to unconscious awareness of additional information, and/or non-linearities in the decision making process.

and subjective probabilities, as shown in Figure 2, a heat map of the mean ambiguity levels for each 0.025x0.025 grid over the subjective and objective probability plane. Darker shades indicate higher average ambiguity levels.[7] Ambiguity levels tend to be high (low) for low (high) subjective probability values across the entire range of objective probability levels except for very low objective probabilities (lower than 15%). It is strikingly not the case that individuals who report low ambiguity also report subjective probabilities well-matched to objective ones, which would be indicated by lighter shading around the 45-degree line than elsewhere. Instead of this pattern, Figure 2 shows a cluster of low-ambiguity observations with objective probabilities near 1 but subjective probabilities around 0.2, indicating subjective beliefs far from reality and yet held with high confidence. Similarly, very low levels of ambiguity are present when subjective probabilities close to 1 are reported, regardless of what the objective probabilities are. The main stylised take-away from the heat map can be seen in its vertical patterns: when individuals have little confidence in their ability to read a situation, their default subjective expectation is overly pessimistic.

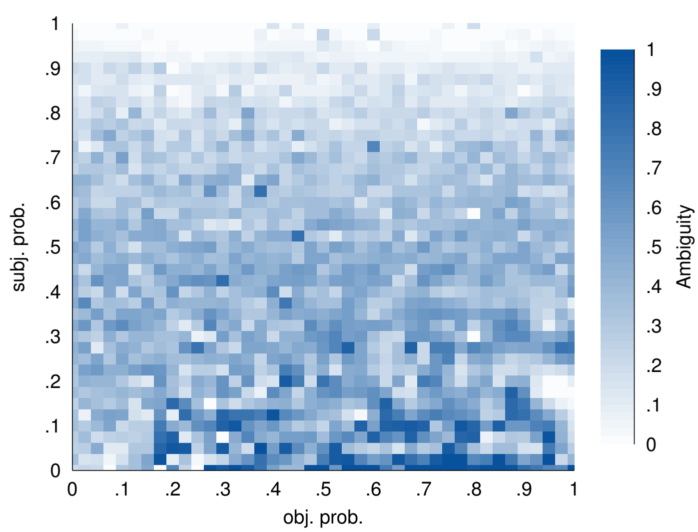

Figure 2: Mean Ambiguity across the Subjective and Objective Probability Plane

Figure 3 reports OLS estimates predicting our measure of ambiguity for

[7] Grids with no data points were interpolated using the thin-plate-spine method (Press, Teukolsky, Vetterline & Flannery 2007).

all six races using pit stop dummies, with pit stop 1 the reference group. Results indicate that belief ambiguity appears to decrease with time, evolving intuitively as the focal event draws closer, indicating some learning or adjustments of mental models throughout a race. Yet, even in the last pit stop of the last race, the level of ambiguity is still over 70% of that at the beginning (0.23 versus 0.32).

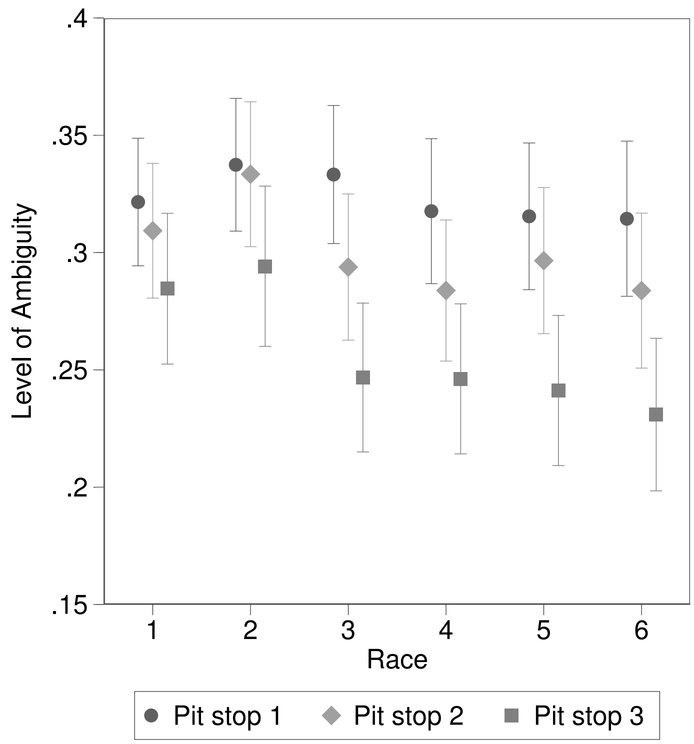

Figure 3: Ambiguity across pit stops

4 Reduced form and structural analysis

4.1 Reduced form

The conditional mean $E[p^s|p, X]$ of subjective probability is informative in its own right, in that under perfect rationality $E[p^s|p, X] = p$, meaning that deviations from this value throw light on the reduced-form divergence between stated beliefs and what the rationality assumption implies that beliefs 'should' be. In Table 3, we show these conditional means in the form of simple OLS regressions exploring the relationship between subjective probabilities, objective probabilities and ambiguity, with increasing arrays of characteristics (X variables) controlled.[8]

The results in the first four columns of Table 3 show that the coefficient on p in the regression predicting p^s hovers around 0.4 to 0.5, with a standard deviation of 0.02 to 0.03, implying that the coefficient is very significantly smaller than 1.[9] This finding is consistent with a systematic deviation from rationality as described above. It suggests that on balance, the net behavioral effect of increasing an event's probability when that probability lies in the middle range—analogous to a real world situation involving the odds of one of two major political parties winning the next election—will be much smaller than proportional to the actual change.

We do not measure the many mental models that individuals use to conceptualize and interpret the situation they confront in this experiment. However, we do conjecture that the more a person feels he has honed in on a particular mental model to think about the choice situation, the more likely that that model is useful in generating accurate subjective probabilities, i.e., more "correct". Consistent with this intuition, we observe that the relation between subjective and actual probability is moderated by the level of perceived ambiguity: the interaction between objective probability and ambiguity estimated in Table 3 indicates that subjective probabilities will track objective ones more strongly in settings that feature lower ambiguity.

The goal of adding sequentially more control variables to the specifications in Table 3 is to explore how much variation in subjective probabilities can be explained using observable factors. The variables included are almost surely endogenous to the processes that influence the formation of subjective probability—which is why we include them as proxies for these processes—but not to how objective probability is formed. We interpret the estimated effects of our individual control variables on subjective probability as capturing mainly the estimated influence of individual optimism, measured in different ways. Controlling for an array of potential sources of individual

[8] As detailed in Appendix B, our Introductory and Follow-up Questionnaires collected a vast array of information about participants. We selected the particular control variables to include in the models shown in Table 3 and Table 6 based on a combination of goodness-of-fit and coverage of the dimensions of the questionnaire (detailed estimation results for the controls are provided in Appendix C).

[9] Adding additional power terms of the objective probability to capture the non-linear relationship between it and subjective probability improves the model fit only marginally, generating a 2-3% increase in adjusted R^2.

Table 3: OLS regression results from predicting stated (subjective) probability

	(1)		(2)		(3)		(4)		Heteroskedasticity Model			
									Mean-shifter (β)		Variance-shifter (σ)	
Objectiv prob.	0.488***	(0.026)	0.429***	(0.023)	0.431***	(0.023)	0.570***	(0.033)	0.426***	(0.016)	-0.236***	(0.012)
Pitstop	-0.009**	(0.004)	-0.009**	(0.004)	-0.009**	(0.004)	-0.031***	(0.004)	-0.014***	(0.003)	0.003	(0.002)
Race Number (1-6)	-0.012***	(0.003)	-0.011***	(0.003)	-0.011***	(0.003)	-0.011***	(0.003)	-0.004**	(0.002)	-0.000	(0.001)
Amount wagered			-0.011***	(0.003)	-0.011***	(0.003)	-0.014***	(0.003)	-0.005***	(0.001)	0.000	(0.001)
Real-Effort Earnings			-0.001	(0.002)	-0.002	(0.002)	-0.000	(0.002)	0.001*	(0.000)	-0.002***	(0.000)
Amount to be won			0.001	(0.001)	0.001	(0.001)	0.001	(0.000)	0.000	(0.000)	0.000	(0.000)
High Treatment			-0.050	(0.046)	-0.076*	(0.045)	-0.048	(0.034)	0.001	(0.011)	-0.009	(0.009)
Low Treatment			-0.025	(0.039)	-0.040	(0.039)	-0.012	(0.032)	0.006	(0.010)	0.021***	(0.008)
Wealth Treatment			-0.047	(0.037)	-0.072*	(0.039)	-0.043	(0.028)	-0.010	(0.008)	0.001	(0.007)
Guess the winner			-0.037**	(0.017)	-0.036**	(0.017)	-0.041***	(0.015)	-0.023***	(0.005)	0.032***	(0.004)
Experiment experience			-0.001	(0.026)	-0.007	(0.027)	-0.037	(0.025)	-0.028***	(0.008)	0.001	(0.006)
Ambiguity							-0.124**	(0.050)	-0.432***	(0.024)	-0.291***	(0.014)
Ambig. X Obj. Prob.							-0.764***	(0.070)	-0.415***	(0.037)	0.301***	(0.028)
Demographic	No		No		Yes		Yes		Yes			
Psychological	No		No		No		Yes		Yes			
Physiological	No		No		No		Yes		Yes			
F	117.902		47.391		24.502		51.246					
$Pr() > F$	0.000		0.000		0.000		0.000		0.000			
N	4194		4194		4194		4193		4193			
$Adj.R^2$	0.298		0.327		0.365		0.546					
ll	-341.45		-250.95		-118.01		595.72		1135.76			
AIC	690.90		525.89		298.03		-1093.44		-2075.52			
BIC	716.27		601.99		494.61		-782.72		-1454.09			

Significance levels: * 0.1; ** 0.05; *** 0.01. Standard errors in parentheses. (I) denotes indexes built from sets of variables. See Appendix for further details on all control variables. The excluded reference categories are “Baseline Treatment”, “Australian Culture”, “Weekly Income None”, and “Wealth Level Above”.

optimism is of particular interest in our context because optimism (about a best outcome) or pessimism (about a worst outcome) influences risk-related behavior (Abdellaoui, L'Haridon & Zank 2010), perhaps via the mechanism of subjective probability formation. Our findings are generally in line with earlier research findings indicating that wealthier and healthier respondents tend to show more optimism in their stated probabilities. We find higher stated probabilities among participants who are younger, have higher weekly incomes, and/or are nonsmokers or vegetarians (see Appendix C for full estimation results).

In weighing alternatives to the assumption of rationality stated above, it is interesting to know not merely the conditional mean $E[p^s|p, X]$, but also the standard deviation of $[p^s - E[p^s|p, X]$, which can serve as a measure of how tightly the subjective probabilities are grouped around their conditional mean. The smaller the standard deviation, the more 'regular' the production of subjective probability. With this in mind, we estimate next a slightly expanded reduced-form model that allows for both heteroskedasticity and mean-level shifters. The main result of this heteroskedasticity analysis, shown in the final two columns of Table 3, is that the effect of race number (1 through 6) on the standard deviation has a coefficient of 0.002 ($sd = 0.001$), meaning that the standard deviation of the error term in the subjective probabilities does not fall between race 1 and 6. This indicates an absence of learning, which if present should produce a fall in the error over time as participants become more familiar with the race game. Indeed, the point estimate of the effect of race number is positive, not negative, although it is insignificant at all conventional levels. On the other hand, the coefficient of race number on the mean subjectivity probability is -0.013 ($sd = 0.002$) and significant at the 1 percent level, meaning that the average stated probability falls over time, drawing closer to the average true probability. Hence, while increasing experience with the game produces no learning in terms of a lowered spread of subjective probabilities, the mean prediction error does reduce.

4.2 Initial structural analysis

Although examining subjective probabilities in the above reduced-form manner is useful in drawing comparisons with what the rationality paradigm implies, the modelling exercises above cannot illuminate the deep structure of subjective probability formation. In this section, we consider in more technical detail the process by which objective probabilities are transformed into subjective ones. To identify which structure of subjective probability formation fits our data best, we horse-race four different theoretically-grounded subjective probability functions that have been proposed in the literature by fitting them to our data, using a simple maximum likelihood approach. We first seek the model that best explains our subjective probability data, and then proceed to estimate the determinants of the deep parameters of that best-fitting model.

The most standard type of probability weighting function is $p^s = \frac{(p)^\gamma}{\sum_j (p_j)^\gamma}$, where $\gamma < 1$ and j enumerates all possible outcomes an individual might consider. This function's most salient characteristic is that small probabilities are over-weighted and large probabilities are under-weighted, particularly if there is a large number of possible outcomes. The first two models we sequentially fit to our data are variations on this theme.

Our first model uses the set-up employed in Lattimore, Baker & Witte (1992) and Gonzalez & Wu (1999):

$$p^s_{it} = \frac{\alpha p^\gamma_{it}}{\alpha p^\gamma_{it} + (1 - p_{it})^\gamma} + v_{it} \tag{1}$$

Model (1), widely discussed in the literature, is a log-odds linear representation of the relation between p_{it} and p^s_{it}. Here, the parameter $\gamma < 1$ measures the change in sensitivity of the subjective probability to changes in the objective probability as the latter increases (i.e., γ controls curvature). α is primarily responsible for the curve's elevation, and measures the relative level of optimism (Bruhin, Fehr-Duda & Epper 2010). The weighting function becomes more elevated as α increases and more curved as γ decreases (Trepel et al. 2005). The error term v_{it} is standard normally distributed throughout, with unknown variance σ.

Our second model is taken from Wu & Gonzalez (1996):

$$p^s_{it} = \frac{p^\gamma_{it}}{[p^\gamma_{it} + (1 - p_{it})^\gamma]^\alpha} + v_{it} \tag{2}$$

Model (2) is a reduction of the Lattimore et al. (1992) model in the event that, in the prior model, $\alpha = 1$. Similar to the work by Camerer & Ho (1994) and Tversky & Kahneman (1992), Wu & Gonzalez (1996) estimate only one parameter of Model (2) (γ, with $\alpha = 1/\gamma$) instead of two. In a later article (Gonzalez & Wu 1999), the authors argue that curvature and elevation are two independent aspects of the function of interest and can be captured separately using two parameters, rather than represented by a single parameter as in Model (2).

The third model is Prelec's (1998) compound invariant model of p^s_{it} based on a particular axiomatic representation of choices between lotteries:[10]

$$p^s_{it} = \gamma \exp\left[-\beta(-\ln p_{it})^{\alpha}\right] + v_{it} \tag{3}$$

Model (3) allows for much flatter inverse S-shapes, and breaks away from the assumption that when p_{it} approaches 1, perceived and real probabilities must be the same (note in this function that when $p_{it} \downarrow 0$ then $p^s_{it} = 0$, but when $p_{it} = 1$, $p^s_{it} = \gamma$). As de Palma et al. (2008) point out, the parameter β reflects pessimism, whereas α reflects the degree to which the inverse S-shape is pronounced (p. 278).

The fourth model we estimate is Prelec's (1998) conditional invariant model of p^s_{it}:[11]

$$p^s_{it} = \gamma \exp\left[-\frac{\beta}{\eta}(1 - p^{\eta}_{it})\right] + v_{it} \tag{4}$$

Although the overall properties of Model (4) are similar to those of the compound invariant model near the extremities of the distribution, Model (4) allows for a slightly different shape. According to Prelec (2000), Models (3) and (4) offer two distinct advantages: they rationalize different classes of expected utility violations simultaneously, and they are tractable.

The results of sequentially fitting these models to our data are shown in Table 4, where models and parameters are identified by the model number and a shorthand abbreviation based on the names of the authors who proposed the model and—for the Prelec models—the model type. For Model (1) (the Lattimore et al. (1992) model), the log likelihood is -317.489 and the estimates for α and γ are both significantly different from 1, implying a strong aggregate inverse S-shape that deviates from rationality. For Model (2) (the Wu & Gonzalez (1996) model), although the fit is slightly superior to that of Model (1) (with a log likelihood of -314.372), the structural results are somewhat similar: the estimate for γ is 0.23 and significantly smaller than 1. Rationality is also violated in both the compound invariant and conditional invariant models (Prelec 1998), with all coefficient estimates significantly below 1, and with the stated probability in Model (4) only about

[10] The key preference axiom related to the compound invariant model is that, using (x_k, q_k) to denote a lottery in which the actual outcome x_k eventuates with probability q_k, it must hold that if $(x_1, q_1) \sim (x_2, q_2)$ and $(x_1, q_3) \sim (x_2, q_4)$ then $(x_3, (q_1)^M) \sim (x_4, (q_2)^M)$ implies $(x_3, (q_3)^M) \sim (x_4, (q_4)^M)$ with $M \geq 1$.

[11] The key axiom related to the conditional invariant model is that, with $0 < \lambda < 1$, it would have to hold that if $(x_1, q_1) \sim (x_2, q_2)$ and $(x_1, q_3) \sim (x_2, q_4)$, then $(x_3, \lambda q_1) \sim (x_4, \lambda q_2)$ implies $(x_3, \lambda q_3) \sim (x_4, \lambda q_4)$.

three-quarters ($\gamma = 0.74$) of the real probability when the real probability is at the limit of 1. The log likelihoods of Models (3) and (4) are -263.393 and -254.887, respectively, giving an early indication that Model (4) is superior.

Table 4: ML estimation of the functional form of subjective probabilities

	Model (1) [LBW]	**Model (2) [WG]**	**Model (3) [Pcomp]**	**Model (4) [Pcond]**
$\sigma(v_{it})$	0.261	0.261	0.258	0.257
	(0.003)	(0.003)	(0.003)	(0.003)
γ_{LBW}	0.233			
	(0.009)			
α_{LBW}	1.336			
	(0.026)			
γ_{WG}		0.203		
		(0.007)		
α_{WG}		0.739		
		(0.016)		
α_{Pcomp}			0.349	
			(0.018)	
β_{Pcomp}			0.517	
			(0.024)	
γ_{Pcomp}			0.882	
			(0.017)	
η_{Pcond}				0.223
				(0.020)
β_{Pcond}				0.326
				(0.018)
γ_{Pcond}				0.738
				(0.008)
N	4194	4194	4194	4194
ll	-317.489	-314.372	-263.393	-254.887
AIC	640.98	634.74	534.79	517.77
BIC	660.00	653.77	560.15	543.14

Standard errors in parentheses. $\sigma(v_{it})$ denotes the estimated variance of the errors in the given model.

We next statistically compare the results for each model using the three most commonly used criteria: Akaike's information criterion (AIC), the Bayesian information criterion (BIC), and the average log likelihood. We run these comparisons overall, and then after disaggregating the data into 'low' (below-median) and 'high' (above-median) ambiguity cases. We also present results excluding observations at the middle and endpoint of ambiguity—corresponding to reports of being 0%, 50%, or 100% confident that one's guess is roughly right—as the expectation literature has shown that respondents tend to use only a subset of focal values in a 0-100 scale, such as 0, 50, and 100 (for a discussion, see Bruine de Bruin, Fischbeck, Stiber & Fischhoff 2002, de Bruin, Fischhoff, Millstein & Halpern-Felsher 2000, Fischhoff & De Bruin 1999, Hill, Perry & Willis 2004, Hudomiet & Willis 2013,

Table 5: Likelihood comparisons across the four structural models

	LBW (1992)	WG (1996)	Prelec (1998) Comp. Inv.	Prelec (1998) Cond. Inv.
AIC	640.98	634.74	534.79	517.77
BIC	660.00	653.77	560.15	543.14
$-ln(L)/N$	0.0757	0.0750	0.0628	0.0608
Without mid- and endpoints				
AIC	490.70	484.68	341.29	299.54
BIC	509.23	503.21	366.00	324.24
$-ln(L)/N$	0.0682	0.0673	0.0469	0.0410
Low Ambiguity				
AIC	311.58	292.16	276.21	213.24
BIC	328.61	309.19	298.91	235.95
$-ln(L)/N$	0.0708	0.0663	0.0622	0.0476
High Ambiguity				
AIC	-318.14	-317.30	-469.32	-470.27
BIC	-301.28	-300.45	-446.85	-447.80
$-ln(L)/N$	-0.0796	-0.0794	-0.1172	-0.1174

AIC=2*k-2*ln(L); BIC=-2*ln(L)+k*ln(N). L=likelihood, N=number of observations, and k=number of estimated parameters.

Kleinjans & Soest 2014).[12] Table 5 shows that Prelec's (1998) conditional invariant model gives a superior fit by a large margin for the data overall and in two of the remaining three cases; for the data from the high-ambiguity setting used in the final rows of Table 5, the two Prelec models are clearly superior to the other two models, but have fit statistics that appear very similar to one another. Under particular conditions, the AIC is chi-square distributed, making the differences between models very significant not only in terms of sheer likelihood ratios, but also at the conventional 1% and even 0.01% levels of statistical significance.[13]

4.3 Extended structural analysis

Because Prelec's (1998) conditional invariant model delivers the best overall fit, we now parameterize its main components: σ, which captures the heteroskedasticity of the error term; γ, which can be interpreted as the subjective probability corresponding to objective certainty; and β, which corresponds to the sensitivity of the subjective probability to low values of p (i.e.,the higher is β, the steeper is the slope of p^s for low values of p, and the higher the value of p at which the subjective and objective probabilities cross). We perform this exercise based on the following extended structural model, where the δ's can be interpreted either as capturing the aggregate level of the associated deep structural parameter, or simply as best-fit coefficients capturing the influence on deep parameters of several variables at once: [14]

[12] We also plotted the relation between objective and subjective probabilities that we recover when fitting the four models to our data overall, and to the data subsets described here; see Figure C.1 in Appendix C.

[13] Since the models are non-nested and have different basic structures, there is no theoretically clear way to parameterize all four of them and then compare results. Indeed, for all these models, full parameterization engenders convergence issues because of the high degree of collinearity and the associated problems of a flat likelihood. Nevertheless, if we limit ourselves to structurally recovering only two parameters from the data for each model (including the variance of the error term), Prelec's (1998) conditional invariant model consistently delivers the best fit across all selections of parameter pairs (using the same variables from the data).

[14] We tried modelling all parameters of this model as functions of our data, but the collinearity in the parameters is too great to allow for this, meaning there is not enough variation in the data—rich as it is—to tease apart the determinants of all of the parameters separately.

$$
\begin{aligned}
p^s &= \gamma \exp\left[-\frac{\beta}{\eta}(1-p^\eta)\right] + v \\
\gamma &= x_{it}\delta_0 \\
v &\sim N(0,\sigma^2) = N(0,(p, x_{it}\delta_1)) \\
\beta &= x_{it}\delta_2
\end{aligned}
$$

To ensure γ, β, and σ are within their theoretical bounds, i.e., $0 < \gamma \leq 1$, $\beta > 0$ and $\sigma > 0$ (η is unconstrained), in the maximum likelihood model, we estimate ρ, ψ, and ϕ as free parameters such that γ is the inverse logit transformation of ρ, and β, and σ is the exponential form of ψ, and ϕ, respectively. The results of estimating the parameters of this extended structural model using our data are given in Table 6.

Table 6: Structural ML estimates of probability function parameters

	(1)		**(2)**		**(3)**		**(4)**	
ln(σ)								
Objectiv prob.	-0.144***	(0.032)	-0.124***	(0.040)	-0.260***	(0.042)	-0.251***	(0.044)
Pitstop	-0.017	(0.013)	-0.008	(0.014)	-0.002	(0.014)	0.002	(0.014)
Race Number (1-6)	0.019***	(0.006)	0.019***	(0.007)	0.019***	(0.007)	0.025***	(0.007)
Amount wagered			-0.016***	(0.004)	-0.015***	(0.004)	-0.022***	(0.005)
Real-Effort Earnings			-0.006***	(0.002)	-0.006**	(0.002)	-0.013***	(0.003)
Amount to be won			0.002***	(0.000)	0.000	(0.001)	0.002***	(0.001)
High Treatment			-0.075*	(0.041)	-0.040	(0.051)	-0.060	(0.055)
Low Treatment			-0.014	(0.036)	-0.004	(0.040)	0.223***	(0.045)
Wealth Treatment			-0.005	(0.034)	-0.031	(0.039)	-0.067	(0.045)
Guess the winner			0.035**	(0.014)	-0.000	(0.017)	0.052***	(0.020)
Experiment experience			0.128***	(0.032)	0.122***	(0.036)	0.070*	(0.037)
constant	-1.335***	(0.039)	-1.296***	(0.072)	-1.201***	(0.285)	-1.068***	(0.359)
ln(β)								
Pitstop	0.071*	(0.041)	0.052	(0.037)	0.070**	(0.032)	0.010	(0.030)
Race Number (1-6)	0.060***	(0.017)	0.058***	(0.015)	0.061***	(0.014)	0.071***	(0.011)
Amount wagered			0.035***	(0.007)	0.049***	(0.007)	0.026***	(0.008)
Real-Effort Earnings			0.027***	(0.005)	0.016***	(0.005)	0.006	(0.005)
Amount to be won			-0.002*	(0.001)	-0.002***	(0.001)	-0.001*	(0.001)
High Treatment			-0.011	(0.133)	0.411***	(0.115)	0.699***	(0.091)
Low Treatment			0.067	(0.078)	0.177**	(0.074)	0.662***	(0.079)
Wealth Treatment			0.103	(0.073)	0.338***	(0.079)	0.666***	(0.074)
Guess the winner			0.211***	(0.037)	0.155***	(0.041)	0.111***	(0.033)
Experiment experience			0.037	(0.070)	-0.079	(0.069)	-0.012	(0.065)
constant	-1.499***	(0.121)	-2.421***	(0.182)	-4.120***	(0.531)	-5.242***	(0.658)
logit(γ)								
Pitstop	0.215***	(0.040)	0.197***	(0.040)	0.186***	(0.038)	0.003	(0.035)
Race Number (1-6)	-0.010	(0.019)	0.006	(0.019)	-0.002	(0.019)	-0.033*	(0.018)
Amount wagered			0.091***	(0.019)	0.046**	(0.019)	-0.171***	(0.037)
Real-Effort Earnings			-0.001	(0.006)	-0.012*	(0.007)	0.017	(0.012)
Amount to be won			-0.001	(0.003)	0.006**	(0.003)	0.024***	(0.007)
High Treatment			0.038	(0.125)	-0.058	(0.149)	0.432*	(0.233)

Low Treatment		-0.363*** (0.111)	0.176 (0.126)	2.199*** (0.344)
Wealth Treatment		-0.210** (0.102)	0.054 (0.108)	0.795*** (0.145)
Guess the winner		0.002 (0.046)	-0.251*** (0.056)	-0.199** (0.078)
Experiment experience		0.101 (0.086)	-0.213* (0.120)	-1.193*** (0.170)
constant	0.629*** (0.110)	0.303 (0.195)	1.338 (1.130)	-8.647*** (2.196)
η				
constant	0.224*** (0.021)	0.259*** (0.030)	0.312*** (0.036)	0.407*** (0.070)
Demographic	No	No	Yes	Yes
Psychological	No	No	No	Yes
Physiological	No	No	No	Yes
N	4194	4194	4194	4194
ll	-215.895	-75.318	209.341	716.767

Significance levels: * 0.1; ** 0.05; *** 0.01. Standard errors in parentheses. (I) denotes indexes built from sets of variables. See Appendix for further details on all control variables.

One set of parameters of interest in Table 6 are the determinants of the heteroskedasticity in subjective probabilities, as these relate to whether or not the distribution of subjective probability becomes tighter as people acquire more experience. In our richest specification, shown in Column 4 of Table 6, the estimated coefficient on the race number (i.e., more experience with the race car game) is 0.025. Far from being negative, this coefficient implies an absence of learning across the six rounds of the experiment. The variable capturing prior experience as an experimental participant is also positive in predicting the variance of subjective probabilities, which we again take as evidence against learning effects. Higher race number is also estimated to have a positive rather than negative effect on β, the deep parameter for which a higher value indicates more curvature of subjective probabilities in relation to objective probabilities. We take this as further evidence that more experience with our race car game does not push our participants further toward accurate predictions about the game's outcome.

To gain more insight into the meaning of the large numbers of coefficients displayed in Table 6, we next show the frequency distributions of the three key parameters. Figure 4 shows the distribution of $\widehat{\beta} = x_{it}\widehat{\delta_2}$, Figure 5 the distribution of $\widehat{\gamma} = x_{it}\widehat{\delta_0}$, and Figure 6 the distribution of $\widehat{\sigma} = \sqrt{x_{it}\widehat{\delta_1}}$. We create these displays based on the results of our richest specification, to examine the range of possible values of each parameter. These frequency distributions show that the range of parameters across participants is very high.

Figure 4 shows us the wide range of values taken on by $\widehat{\beta}$. The mean of the estimated $\widehat{\beta}$s is around 0.62, implying that $\frac{\widehat{\beta}}{\widehat{\eta}}$ is close to 1.5 (since $\widehat{\eta} = 0.41$) which in turn implies that as p approaches zero, p^s approaches $\widehat{\gamma}e^{-1}$ which is roughly 0.185 at the mean of the $\widehat{\gamma}$'s. At the other end of

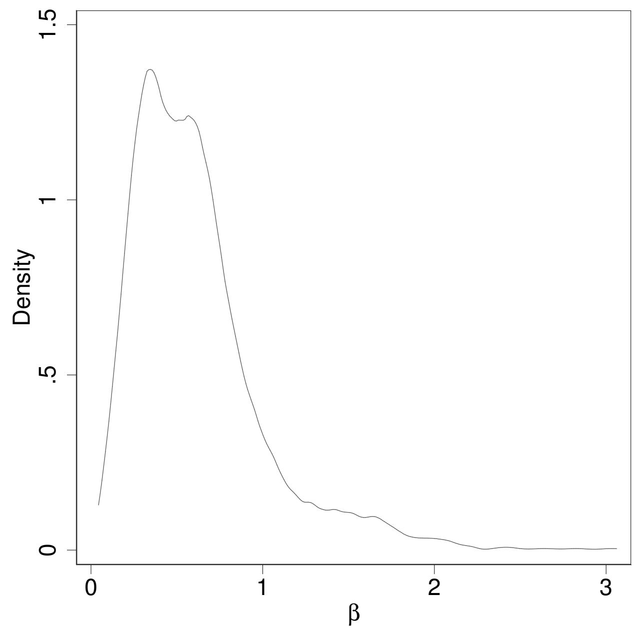

Figure 4: Distribution of $\widehat{\beta} = x_{it}\widehat{\delta_2}$

the range of objective probabilities, when p approaches one, p^s approaches $\widehat{\gamma}$, which equals roughly 0.83 at the mean of the $\widehat{\gamma}$'s. Hence, for the mean values of these coefficients, average subjective probability varies only between 0.185 and 0.83 as p varies over its entire range, from 0 to 1.

Similarly, looking at Figure 5, the distribution of $\widehat{\gamma}$ exhibits some mass near $\widehat{\gamma} = 1$, indicating that there is a substantial number of individuals for whom p^s approaches one as p approaches one.

Figure 6 shows that the distribution for $\widehat{\sigma}$ is somewhat erratic, with a mean around 0.21 but some individuals above 0.3 and a few below 0.1, from which we mainly deduce that almost no participants will have had a stable answering strategy that fits with the hypothesized subjective probability function.[15]

[15] One might object to this by noting that our use of an additive error term in the presence of a bounded subjective probability term almost 'forces' a low mean $\widehat{\gamma}$. This turns out not to be true: when one forces all observations to be fitted by only structural coefficients, thereby forcing an inverse S-shape to fit each combination of subjective probabilities with objective probabilities in the data, then given what is shown in Figure 1, one must conclude that for some people $\widehat{\gamma} = 0.1$ or even lower. Hence, in effect, having

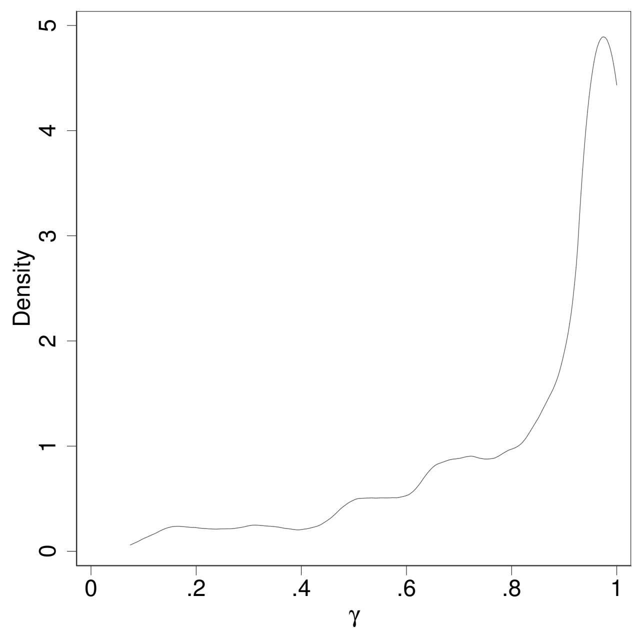

Figure 5: Distribution of $\widehat{\gamma} = x_{it}\widehat{\delta_0}$

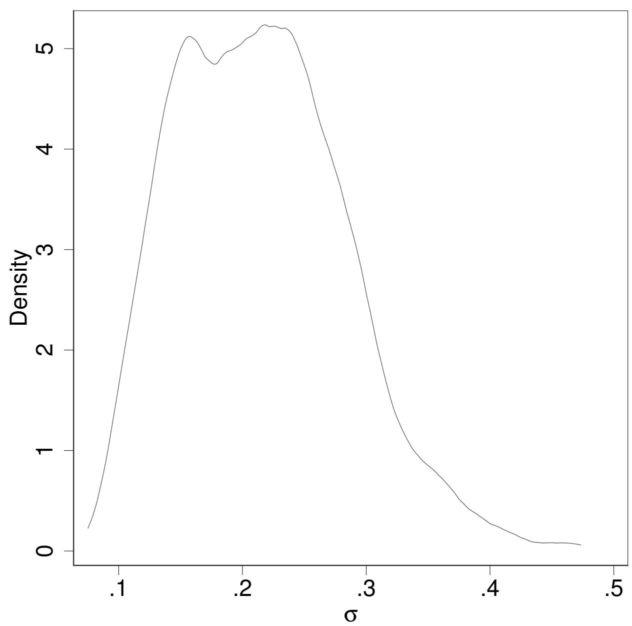

Figure 6: Distribution of $\widehat{\sigma} = \sqrt{x_{it}\widehat{\delta_1}}$

Finally, we show in the left panel of Figure 7 what the implied subjective probability function looks like for different archetypal individuals: for the average individual in the sample (for whom $x_{it} = \overline{x}$); for the individual with the highest estimated $\widehat{\gamma}$ given estimated $\widehat{\beta}$ is closest to 1 (whom one might label the 'most rational'); and for the individual with the highest estimated $\widehat{\sigma}$ (whom one might label the 'most erratic'). The person who displays near-rational behavior exhibits an almost 1-to-1 correspondence between real probabilities and subjective probabilities, bar a slight non-linearity near $p = 0$. The 'most erratic' person also displays almost the same subjective probability function as the 'most rational'. The person with the average values of observable characteristics displays a strong non-linearity very close to $p = 0$ and then a flattening out until $p = 1$. In the right panel of Figure 7, we graph the subjective probability function of the average individual from the subset of data that excludes reports of 0%, 50%, or 100% ambiguity, which is not noticeably different from the default shown in the left panel,[16] and then of the average individual from the subset of data featuring low ambiguity. The latter function lies above the former for the entire range of p, indicating more over-optimism in settings that are less ambiguous.

a linear error term 'merely' forces the estimated $\widehat{\gamma}$ to reflect the average sample behavior near $p = 1$ seen in Figure 1.

[16] Perhaps unsurprisingly, 80 percent of those participants who selected focal answers for ambiguity also selected focal answers for subject probabilities.

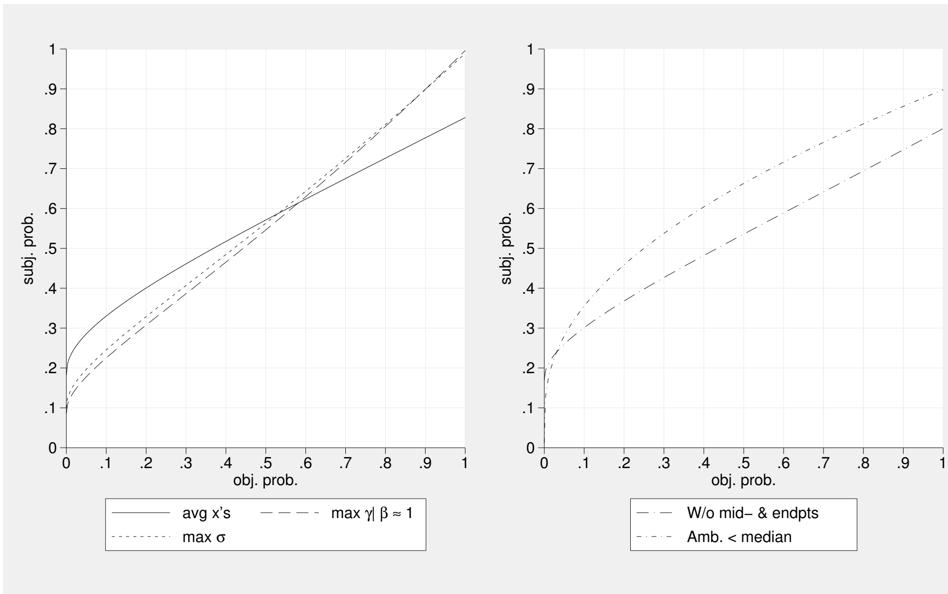

Figure 7: Graph of subjective versus objective probabilities under different settings

5 Discussion

The experimental approach in our paper is motivated by the fact that in most real-life choice situations, it is unrealistic to assume that individuals have access to the true probability of a good outcome. Whether it concerns corporate profits, movements in the price of goods, the arrival rate of potential marriage partners, the health of children and family, or the advent of a competitor, we have to guess the probabilities of good things eventuating based on limited information and with no credible outside source of truth. If even macroeconomists cannot accurately forecast inflation, and health economists cannot say with certainty how much disease reduction the extra dollar of health care buys, how can lesser-educated, 'ordinary' economic agents arrive at an estimate other than very imperfectly? Faced with the complex uncertainty of real life, are individual guesses about the probability of events remotely accurate and, if not, are they systematically wrong? By designing a lab-based choice situation that is complicated and cognitively taxing—but with the truth knowable to the researcher—we are able to explore the link between objective and subjective probabilities in a setting where the complexity level and the agent's access to information mimic reality.

Subjective probabilities, when plotted against objective probabilities, have been found by prior researchers to exhibit an inverse S-shape when experimental participants are told the true probabilities and their subjective probabilities are inferred from choices. We find that this inverse S-shape is also exhibited in our setting. Of the four models of subjective probability formation that we fit to our empirical data, Prelec's (1998) compound invariant model fits bets. Intriguingly, we see no evidence of learning: both the mean and the the variance of the error term (the deviation away from the inverse S-curve) are non-decreasing with the number of previous races experienced, both in reduced-form analysis and in structural modelling.

Examining the information about subjective probabilities in our data leads us to four additional observations. First, a 50 percent actual probability of a positive outcome (i.e., winning) was perceived by our participants as a 70 percent chance of winning. This suggests that in very complicated real-world situations, people make large over-estimates of middle-range probabilities of positive events. Second, we find severe under-estimation on average of the probability of events that in actuality are near certain to occur, with subjective probabilities no higher than 80% on average for events that will transpire with close to 100% certainty. Third, we find a large degree of individual heterogeneity in the relation between objective probabilities and subjective ones, with the extremities in the sample including near-rationality at the boundaries as well as extreme unresponsiveness to changes in actual probabilities in a middle range (i.e., flat inverse S-shapes). Thus, we find little evidence that 'one shape fits all'. Fourth, choice situations featuring high levels of perceived ambiguity tend to produce lower subjective probabilities which are also less sensitive to increases in objective probabilities, suggesting that ambiguity triggers a flight towards a particular default position, in this case pessimism.

In aggregate, our results suggest that individual decision-making in the presence of real-world complexity still conforms to the main tendencies observed in typical probability experiments: specifically, small probabilities are overestimated and large probabilities are underestimated. In terms of broad policy implications, this finding implies that aggregate behavior will not be proportionately reactive to changes in real probabilities in a middle range, and will be over-reactive to changes at the extremes. Our results in general, including our finding that ambiguity depresses response and encourages pessimism, also presage great difficulty in convincing individuals of the relevance of evidence-based projections and the legitimacy of optimism when a situation is dynamic, new, and very complicated.

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A Screenshots and experimental procedures

All experimental treatment protocols (baseline, “wealth", “high-stakes" and “low-stakes", as described in the text) consisted of six stages, as follows:

- An Introductory Questionnaire
- Relaxation, consisting of 5 minutes of relaxing beach sounds together with a voice-over of visualization guidance in a calm female voice
- Real Effort, consisting of cross sum calculations (adding up as many sets of 5-digit numbers as possible in a fixed time window), resulting in earned income
- A Test Race, consisting of 3 laps with labelled screens and a guiding voice-over in the same female voice used in the Relaxation stage
- 6 Real Races
- An incentivized “Guess the Winner" game
- A Follow-up Questionnaire focussing on demographics

Some participants wore heart rate monitors throughout the experiment, and all participants wore headphones from the start of the Relaxation stage until the end of the Real Races stage.

A.1 Introductory Questionnaire

In the Introductory Questionnaire, the participants were asked a set of standard questions regarding personality, locus of control, past/present/future savouring, and risk attitudes. These questions are reproduced in the next section.

A.2 Relaxation

The Relaxation stage was included to familiarize participants with a calm voice that would guide them through the car race set-up, and also to establish baseline readings for the heart rate monitors. Data from these monitors is not used in the present paper.

A.3 Real Effort

In the Real Effort stage, participants were presented with cross-sum problems for 10 minutes. The problems gradually became more difficult, and the participants receive a fixed amount per solved problem. A participant could opt to drop out of the solving process, and receive compensation for time foregone. Participants were able to earn up to 30 experimental dollars in this way.

A.4 Test Race

In the Test Race stage, participants were guided through the race process, with a voice-over explaining all the steps. Then a test race was shown, after which the participants had to answer a set of questions in order to proceed. The questions were explicitly designed so that they could not easily be solved by trial and error, and asking the experiment administrators in case of any question or confusion about the race procedure was explicitly encouraged.

A.5 Real Races

The Real Races stage confronted participants with 6 car races, in each of which participants could decide on how much of their earned income they would invest into their car and how much they would bet. Each race was independent of the others and one race would be paid out randomly in the end, so all of the earnings were available in each race. [17] The 6 cars would then race, and the advancement of each car was governed by the AR(1) process outlined in equation 5:

$$s_t = \theta s_{base} + (1-\theta) * (1 + U(-\gamma, +\gamma)) * s_{t-1} + D_t * f \tag{5}$$

where s_t is the advancement of the car between time $t-1$ and time t ($\delta t = 1/60 second$), and θ governs the importance of the base speed $s_{base} = 50$. θ was set to 0.02, with the remaining weight of .08 placed upon the speed at $t-1$ multiplied by one plus a uniform random change in speed of $\pm\gamma = 0.1$. Finally, with probability β, $D_t = 1$ and a shock of $f = -25$ was applied (in the other $1-\beta$ fraction of times, no shock was applied). This functional form was selected in order to give the race a natural appearance while allowing meaningful manipulation of the winning probability, through the raising or lowering of β.

[17] Participants were not allowed to retain any of the earnings: the full amount had to be split between investing and betting.

Compared to no investment, full investment in the car would change the rate of engine failures (β) from an expected 4 engine failures in 5 laps (the 'no investment' option, associated with almost zero % chance of winning) to a certain zero failures (the 'full investment' option, associated with an almost 100% chance of winning, but with no money left over to wager, and hence nothing to win). The other 4 cars would always have an expected rate of 2 engine failures in 5 rounds.

Figure A.1 shows the screen participants faced at the beginning of each race. As shown, they could choose the division of the money they had earned in the real-effort task into an amount bet on their car, and an amount invested in their car's engine. All the information about the possible outcomes of the race, including the amounts to be recovered by dropping out at each of the pit stops, was displayed and updated whenever the participant changed his proposed decision using the slider. Each participant could also choose the color of his car each race, which was of no consequence to the race outcome.

Figure A.2 shows the screen participants encountered at the first pit stop. This screen offers a choice of whether or not to drop out of the race, and shows the payoffs associated with dropping out and with not dropping out and experiencing either of two states of the world: that in which one's car wins, and that in which one's car does not win. The screens for the second and third pit stop were nearly identical, with simply a later dropout choice bolded.

At the pit stops, the key variable of participants' subjective expectation of winning was elicited by having the participant move a slider to answer the question: "If the race were to continue from this point randomly 1000 times, how often would your car come first?"

The "Amount wagered" analysis variable is simply the amount that the participant chose to bet on his car, which is equal to "Real-effort Earnings" minus the amount invested in the car's engine. The "Amount to be won" analysis variable is the maximum amount that could have been won in the given race, once the participant placed a bet—that is, the amount that would be won if the participant did not drop out of his initial bet and if, in addition, his car won.

A.6 Guess the Winner

In the incentivized "Guess the winner" game, which was played 6 times, participants were presented with a visual state of the race at a given pit stop (3,6, or 9) and had to bet on how often out of 1000 races their car would come first, conditional on the present position and race stage, by

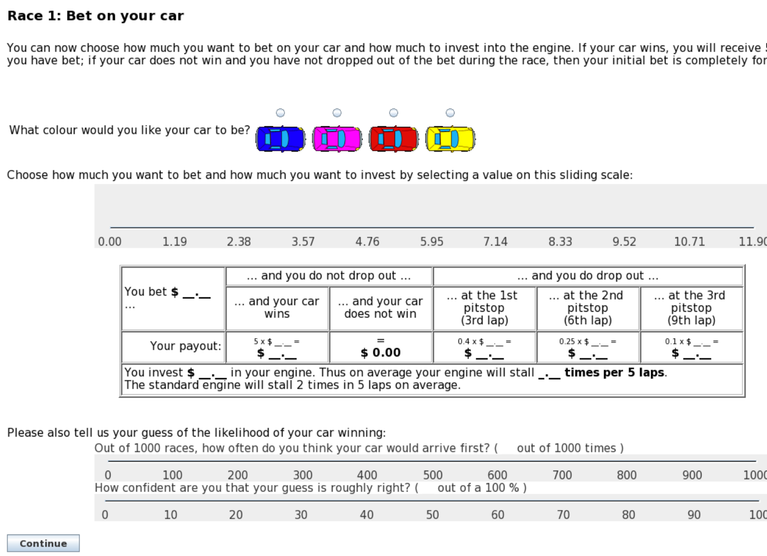

Figure A.1: Screenshot of the pre-race investment screen, with sliders for choosing the bet amount and entering expectations about race outcome.

specifying a point estimate and an interval. Participants were able to select an interval of between 2 and 200 times. The larger the interval they chose, the lower was the amount they would win if their interval contained the correct value. They amount they could win from this “Guess the winner" game was displayed when they moved the interval slider. The race was then simulated 1000 times from the given point by the computer, and if the number of times the participant’s car won fell into the prediction interval he had nominated, then the participant would receive \$ 0.10 plus \$ $x = ((200 - interval)/200)$. Participants’ winnings were summed up and paid out over the six “Guess the winner" games, and this total amount won was also used as the “Guess the winner" analysis variable, which is intended as an indicator of how well participants were able to predict the outcome of a race.

A.7 Follow-up Questionnaire

The Follow-up Questionnaire included questions on a variety of demographic characteristics. The variables on participant characteristics included in our analysis are constructed from these questions and the questions posed in the Introductory Questionnaire, which are provided in the next section.

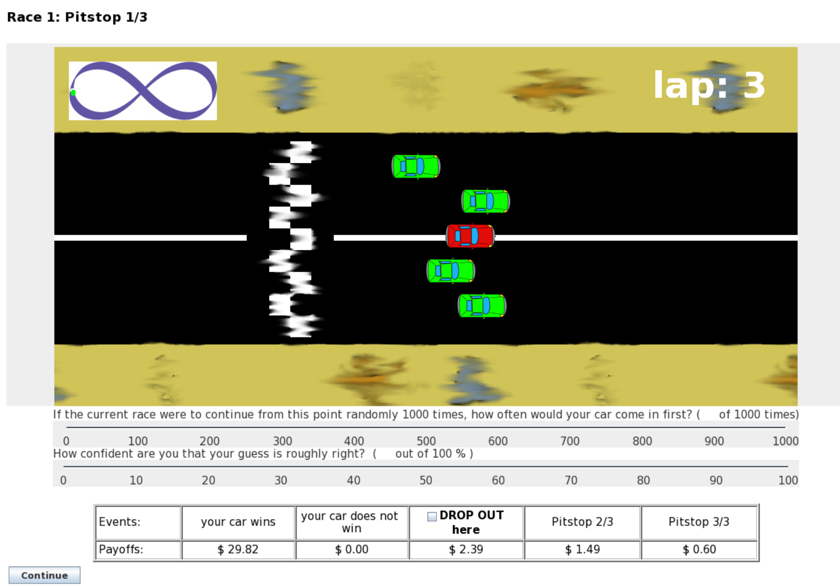

Figure A.2: Screenshot of the car race at the first pit stop, showing the positions of the cars and the payoffs for the respective events.

B Questionnaire Appendix

B.1 Self-esteem

The following statements posed to participants in the Introductory Questionnaire were coupled with scaled answer alternatives, ranging from Strongly Agree to Strongly Disagree. These items constitute a battery of self-esteem questions based on Rosenberg (1965). After reverse-coding questions 1, 3, 4, 7, and 10, we take the simple average of responses across all ten of these questions to construct our measure of self-esteem.

- On the whole, I am satisfied with myself.
- At times I think I am no good at all.
- I feel that I have a number of good qualities.
- I am able to do things as well as most people.
- I feel I do not have much to be proud of.
- I certainly feel useless at times.
- I feel that I am a person of worth, or at least on an equal plane with others.
- I wish I could have more respect for myself.
- All in all, I am inclined to feel that I am a failure.
- I take a positive attitude toward myself.

B.2 Optimism

The following questions, also answered on a Strongly Agree to Strongly Disagree scale, were used to capture participants' levels of optimism. The raw answers to item 4 below were used to create the analysis variable 'Disappointment', and those from item 6 were used to create the analysis variable 'Low Expectations'.

1. When I'm in a new and unfamiliar situation, I am always optimistic that things will work out for me (in other words, I feel and think that things will be OK).[18]

[18] This variable was excluded from the analysis due to insignificant results.

2. I often find myself doing things that I know, at the time I choose to do them, I will regret later.

3. When I expect that good things are going to happen to me in the future, I feel better about myself.[18]

4. When I get disappointed about something, it makes me feel that I'm to blame, because I should have known better in the first place and not expected as much.

5. I always try to be cautious when I approach new and unfamiliar situations, in case something goes wrong.[18]

6. I prefer to have low expectations of the future since that way I might be pleasantly surprised, and I'm protected from being disappointed.[18]

B.3 Locus of control

The following seven items, adapted from Rotter (1966) and answered on a Strongly Agree to Strongly Disagree scale, were used to measure locus of control. Answers to these questions (after appropriate reverse-coding) were averaged to obtain each participant's measure of locus of control.

- I have little control over the things that happen to me.
- There is really no way I can solve some of the problems I have.
- There is little I can do to change many of the important things in my life.
- I often feel helpless in dealing with the problems of life.
- Sometimes I feel that I'm being pushed around in life.
- What happens to me in the future mostly depends on me.
- I can do just about anything I really set my mind to.

B.4 Savoring

We also measured savoring, which we understand as individuals' capacity to enjoy good events in the past, present, and future, based on participants' answers to a battery of questions adapted from Bryant & Veroff (2006). The list of questions, each of which was answered on a Strongly agree to Strongly Disagree scale, is as follows:

1. Before a good thing happens, I look forward to it in ways that give me pleasure in the present.
2. It's hard for me to hang onto a good feeling for very long.
3. I enjoy looking back on happy times from my past.
4. I don't like to look forward to good times too much before they happen.
5. I know how to make the most of a good time.
6. I don't like to look back at good times too much after they've taken place.
7. I feel a joy of anticipation when I think about upcoming good things.
8. When it comes to enjoying myself, I'm my own 'worst enemy'.
9. I can make myself feel good by remembering pleasant events from my past.
10. For me, anticipating what upcoming good events will be like is basically a waste of time.
11. When something good happens, I can make my enjoyment of it last longer by thinking or doing certain things.
12. When I reminisce about pleasant memories, I often start to feel sad or disappointed.
13. I can enjoy pleasant events in my mind before they actually occur.
14. I can't seem to capture the joy of happy moments.
15. I like to store memories of fun times that I go through so that I can recall them later.
16. It's hard for me to get very excited about fun times before they actually take place.
17. I feel fully able to appreciate good things that happen to me.
18. I find that thinking about good times from the past is basically a waste of time.
19. I can make myself feel good by imagining what a happy time that is about to happen will be like.

20. I don't enjoy things as much as I should.
21. It's easy for me to rekindle the joy from pleasant memories.
22. When I think about a pleasant event before it happens, I often start to feel uneasy or uncomfortable.
23. It's easy for me to enjoy myself when I want to.
24. For me, once a fun time is over and gone, it's best not to think about it.

After reverse-coding questions 1, 3, 5, 7, 9, 11, 13, 15, 17, 19, 21, and 23, we take the average of responses to questions 1, 4, 7, 10, 13, 16, 19, and 22 to measure future-savoring ("SBI Anticipate" in the tables); the average of responses to questions 2, 5, 8, 11, 14, 17, 20, and 23 to measure present-savoring ("SBI Moment"); and the average of responses to questions 1, 6, 9, 12, 15, 18, 21, and 24 to measure past-savoring ("SBI Reminisce").

B.5 Non-incentivized risk aversion

To measure non-incentivized risk aversion, we used a standard (Holt & Laury 2002) lottery choice task in the Introductory Questionnaire, where the safe choices were \$20 and \$16 and the risky choices were \$40 and \$1 (roughly 5 times the values in the original paper (Holt & Laury 2002)). The following introductory text was used:

> For each of the nine pairs of lotteries listed below, please select your preferred lottery: either option A or option B. Each lottery is characterised by the probability of receiving one of two payoffs. (Probabilities are expressed as percentage chances of receiving this payoff, e.g. 20% = a chance of 2 out of 10 of receiving this payoff).

The participants then had to choose between the following options in each line, where on the participant's screen, the "–" was displayed as "chance of":

10% – $ 20	and	90% – $ 16	A	B	10% – $ 40	and	90% – $1
20% – $ 20	and	80% – $ 16	A	B	20% – $ 40	and	80% – $1
30% – $ 20	and	70% – $ 16	A	B	30% – $ 40	and	70% – $1
40% – $ 20	and	60% – $ 16	A	B	40% – $ 40	and	60% – $1
50% – $ 20	and	50% – $ 16	A	B	50% – $ 40	and	50% – $1
60% – $ 20	and	40% – $ 16	A	B	60% – $ 40	and	40% – $1
70% – $ 20	and	30% – $ 16	A	B	70% – $ 40	and	30% – $1
80% – $ 20	and	20% – $ 16	A	B	80% – $ 40	and	20% – $1
90% – $ 20	and	10% – $ 16	A	B	90% – $ 40	and	10% – $1

The number of safe choices (i.e., selections of option A) was used in the analysis as an indicator of risk attitude, with the variable label "Risk aversion (HL)", if participants exhibited a single switching point from A to B as they proceeded from the top of the table to the bottom. Participants with more than one switching point were classified as switching on the fifth line, corresponding to slight risk aversion. Exclusion of these latter participants did not alter the outcome.

B.6 Follow-up questionnaire

The following questions/statements were posed to participants in the Follow-up Questionnaire. Some questions required participants to type in answers in free-form; others were followed either by scaled answer alternatives, ranging from Strongly Agree to Strongly Disagree, or by appropriately populated arrays of answer alternatives. The exact mapping of the answers to these questions to variables used in our analysis is straightforward and available upon request.

- What is your year of birth?
- What is your month and day of birth?[19]
- Please indicate your gender.
- Please enter your nationality.[19]
- Please enter the country you were born.[19]
- Please enter the country whose culture you identify with most strongly. (This variable was used to create the Culture dummies in the regression, participants where put in three main categories, Australian, Asian and Other which is predominately USA or European.)

[19] This variable was excluded from the analysis due to insignificant results and/or collinearity issues.

- Do you speak English at home?
- Are you currently … (married, in a partnership, or single).[19]
- What is your current living situation?[19]
- Please enter the postcode of the area you live in.[19]
- Which degree program are you enrolled in (Economics; Commerce; etc.)?[19]
- When do you expect to graduate (month, year)?[19]
- Are you an international student?
- Have you ever participated in an experiment before?
- What is your weekly disposable income?
  (None or <\$100, \$100-\$199, \$200-\$299, \$300-\$399, \$400-\$499, >\$500 —This variable was encoded as "None", "Low", "Avg.", and "High", where no participant reported an weekly income above \$399)
- What was the highest year of school you completed?
- And how much schooling did your mother complete?
- And how much schooling did your father complete?
- Did you complete an educational qualification after leaving school? Please include any trade certificates, apprenticeships, diplomas, degrees or other educational qualifications.
- If yes, what was the highest type of qualification you obtained?
- Did your mother complete an educational qualification after leaving school? Please include any trade certificates, apprenticeships, diplomas, degrees or other educational qualifications.
- If yes, what was the highest type of qualification she obtained?
- Did your father complete an educational qualification after leaving school? Please include any trade certificates, apprenticeships, diplomas, degrees or other educational qualifications.
- If yes, what was the highest type of qualification he obtained?

- Please select the category or class of professions your mother's occupation falls into (even if she is unemployed).
- What is the full title of your mother's occupation?
- Please select the category of class of professions your father's occupation falls into (even if he is unemployed).
- What is the full title of your father's occupation?
- Are you a vegetarian?
- How tall are you, in centimetres?
- How much do you weigh in light clothing, in kilograms?
- Do you regularly smoke any tobacco product, such as cigarettes, cigars, or pipes?
- When you drink alcohol, on average, how many drinks do you have?
- Are you taking a prescribed medication?[19]
- Have you had any symptoms of or complaints about depression during the last month (30 days)?
- Which hand do you write with?
- What is your opinion of the following statement: 'Good luck charms sometimes do bring good luck.' (answer scale: Definitely not true, Probably not true, Don't know, Maybe, Probably true, Definitely true)[19]
- Do you have a lucky charm?
- Many people think there is someone watching out for them to make sure things go well. This someone cannot be directly seen. Is there someone, who cannot be seen by others, watching over you?[19]
- Apart from weddings, funerals and christenings, how often do you attend religious services these days?[19]
- How satisfied are you with your financial situation?[19]
- In political matters, people talk of "the left" and "the right". How would you place your views on this scale, generally speaking?[19]

- All things considered in your life, how happy would you say you are usually?
- Would you say that your family is ... (wealthier (Wealth Level Above), the same (Wealth Level Avg), or poorer (Wealth Level Poor) than others)?
- Overall, how would you rate your performance at university?
- Betting is justified.
- Gambling is justified.[19]

C Additional Results

Table C.1: OLS regression results from predicting stated (subjective) probability

	(3)		**(4)**		Heteroskedasticity Model			
					Mean-shifter (β)		Variance-shifter (σ)	
Objectiv prob.	0.431***	(0.023)	0.570***	(0.033)	0.426***	(0.016)	-0.236***	(0.012)
Pitstop	-0.009**	(0.004)	-0.031***	(0.004)	-0.014***	(0.003)	0.003	(0.002)
Race Number (1-6)	-0.011***	(0.003)	-0.011***	(0.003)	-0.004**	(0.002)	-0.000	(0.001)
Amount wagered	-0.011***	(0.003)	-0.014***	(0.003)	-0.005***	(0.001)	0.000	(0.001)
Real-Effort Earnings	-0.002	(0.002)	-0.000	(0.002)	0.001*	(0.000)	-0.002***	(0.000)
Amount to be won	0.001	(0.001)	0.001	(0.000)	0.000	(0.000)	0.000	(0.000)
High Treatment	-0.076*	(0.045)	-0.048	(0.034)	0.001	(0.011)	-0.009	(0.009)
Low Treatment	-0.040	(0.039)	-0.012	(0.032)	0.006	(0.010)	0.021***	(0.008)
Wealth Treatment	-0.072*	(0.039)	-0.043	(0.028)	-0.010	(0.008)	0.001	(0.007)
Guess the winner	-0.036**	(0.017)	-0.041***	(0.015)	-0.023***	(0.005)	0.032***	(0.004)
Experiment experience	-0.007	(0.027)	-0.037	(0.025)	-0.028***	(0.008)	0.001	(0.006)
Gender (female=1)	0.001	(0.027)	-0.015	(0.023)	-0.020***	(0.007)	0.007	(0.005)
Age	-0.037**	(0.017)	-0.028**	(0.012)	-0.018***	(0.005)	-0.007	(0.005)
Age^2	0.001**	(0.000)	0.000**	(0.000)	0.000***	(0.000)	0.000	(0.000)
Asian culture	0.069*	(0.041)	-0.004	(0.036)	-0.015	(0.011)	-0.032***	(0.012)
Other culture	0.096*	(0.057)	0.019	(0.043)	0.014	(0.020)	-0.043**	(0.018)
Weekly Income Low	-0.048	(0.036)	-0.035	(0.029)	-0.028***	(0.009)	0.055***	(0.007)
Weekly Income Avg.	0.068*	(0.036)	0.051*	(0.028)	0.026***	(0.008)	0.009	(0.006)
Weekly Income High	-0.045	(0.034)	-0.031	(0.026)	0.006	(0.009)	-0.009	(0.007)
Wealth Level Avg.	-0.053	(0.048)	-0.047	(0.035)	-0.001	(0.012)	0.045***	(0.010)
Wealth Level Poor	-0.020	(0.053)	-0.015	(0.039)	0.028**	(0.012)	0.040***	(0.010)
Performance at Uni	0.037**	(0.014)	0.014	(0.012)	0.011***	(0.003)	-0.013***	(0.003)
International Student	-0.002	(0.031)	0.031	(0.024)	-0.002	(0.007)	0.005	(0.006)
English speaker	0.019	(0.030)	-0.011	(0.023)	-0.021***	(0.007)	-0.000	(0.005)
Mum Schooled	-0.017	(0.040)	-0.057*	(0.034)	-0.037***	(0.009)	0.049***	(0.010)
Mum Qualified	-0.044	(0.037)	-0.022	(0.026)	-0.008	(0.009)	-0.032***	(0.008)
Mum Qual. Level	0.002	(0.027)	0.029	(0.022)	0.030***	(0.006)	0.007	(0.006)
Dad Schooled	0.087*	(0.048)	0.084**	(0.038)	0.035***	(0.010)	-0.045***	(0.010)
Dad Qualified	0.065*	(0.039)	0.014	(0.029)	-0.004	(0.008)	0.007	(0.007)
Dad Qual. Level	-0.032	(0.024)	-0.017	(0.018)	-0.010**	(0.005)	-0.025***	(0.004)
Risk-aversion (HL)			0.011**	(0.005)	0.010***	(0.002)	-0.009***	(0.001)
SBI: Reminisce (I)			0.020**	(0.010)	0.009***	(0.003)	-0.000	(0.002)
SBI: Anticipate (I)			-0.013	(0.011)	-0.003	(0.003)	-0.018***	(0.002)
SBI: Moment (I)			-0.012	(0.014)	-0.019***	(0.004)	0.024***	(0.004)
Optimism: Disapp.			0.011**	(0.005)	0.007***	(0.001)	0.002	(0.001)
Optimism: Low Exp.			-0.001	(0.005)	-0.001	(0.001)	0.002	(0.001)
Self Esteem (I)			0.008	(0.013)	0.016***	(0.004)	-0.003	(0.004)
Locus of Control (I)			0.004	(0.008)	-0.001	(0.002)	0.003**	(0.002)
Happiness			0.010	(0.012)	0.013***	(0.003)	-0.002	(0.004)
Lucky Charm			0.009	(0.008)	0.012***	(0.003)	0.000	(0.002)
BMI			0.007***	(0.002)	0.006***	(0.001)	0.001*	(0.000)
Lefthanded			0.029	(0.045)	0.042***	(0.013)	0.017	(0.011)
Vegetarian			0.077	(0.055)	0.077***	(0.020)	0.055***	(0.019)
Alcohol			-0.012	(0.022)	-0.016**	(0.006)	0.001	(0.005)
Smoking			-0.027	(0.020)	-0.038*	(0.020)	0.088***	(0.019)
Depression			-0.062*	(0.032)	0.004	(0.010)	-0.057***	(0.010)
Ambiguity			-0.124**	(0.050)	-0.432***	(0.024)	-0.291***	(0.014)
Ambig. X Obj. Prob.			-0.764***	(0.070)	-0.415***	(0.037)	0.301***	(0.028)

F	24.502	51.246	
$Pr() > F$	0.000	0.000	0.000
N	4194	4193	4193
$Adj.R^2$	0.365	0.546	
ll	-118.01	595.72	1135.76
AIC	298.03	-1093.44	-2075.52
BIC	494.61	-782.72	-1454.09

Significance levels: * 0.1; ** 0.05; *** 0.01. Standard errors in parentheses. (I) denotes indexes built from sets of variables. See Appendix for further details on all control variables. The excluded reference categories are "Baseline Treatment", "Australian Culture", "Weekly Income None", and "Wealth Level Above".

Table C.2: Structural ML estimates of probability function parameters reporting all the variables

	(3)		**(4)**	
ln(σ)				
Objectiv prob.	-0.260***	(0.042)	-0.251***	(0.044)
Pitstop	-0.002	(0.014)	0.002	(0.014)
Race Number (1-6)	0.019***	(0.007)	0.025***	(0.007)
Amount wagered	-0.015***	(0.004)	-0.022***	(0.005)
Real-Effort Earnings	-0.006**	(0.002)	-0.013***	(0.003)
Amount to be won	0.000	(0.001)	0.002***	(0.001)
High Treatment	-0.040	(0.051)	-0.060	(0.055)
Low Treatment	-0.004	(0.040)	0.223***	(0.045)
Wealth Treatment	-0.031	(0.039)	-0.067	(0.045)
Guess the winner	-0.000	(0.017)	0.052***	(0.020)
Experiment experience	0.122***	(0.036)	0.070*	(0.037)
Gender (female=1)	0.176***	(0.029)	0.214***	(0.032)
Age	-0.027	(0.021)	-0.008	(0.021)
Age^2	0.000	(0.000)	-0.000	(0.000)
Asian culture	0.018	(0.049)	0.283***	(0.052)
Other culture	0.116	(0.085)	0.167*	(0.093)
Weekly Income Low	0.198***	(0.036)	0.148***	(0.039)
Weekly Income Avg.	0.143***	(0.037)	0.044	(0.040)
Weekly Income High	-0.066	(0.049)	0.003	(0.048)
Wealth Level Avg.	0.014	(0.060)	-0.010	(0.063)
Wealth Level Poor	0.007	(0.064)	-0.042	(0.069)
Performance at Uni	0.009	(0.014)	-0.056***	(0.017)
International Student	0.156***	(0.036)	0.194***	(0.041)
English speaker	0.102***	(0.029)	0.040	(0.033)
Mum Schooled	-0.020	(0.046)	-0.147***	(0.054)
Mum Qualified	-0.073*	(0.044)	-0.152**	(0.062)
Mum Qual. Level	0.054	(0.033)	0.152***	(0.031)
Dad Schooled	0.164***	(0.050)	-0.058	(0.052)
Dad Qualified	-0.160***	(0.047)	0.119**	(0.052)
Dad Qual. Level	0.028	(0.028)	-0.100***	(0.029)
Risk-aversion (HL)			-0.012	(0.009)
SBI: Reminisce (I)			-0.054***	(0.016)
SBI: Anticipate (I)			-0.053***	(0.016)
SBI: Moment (I)			0.083***	(0.018)
Optimism: Disapp.			0.000	(0.007)
Optimism: Low Exp.			-0.011	(0.008)

Self Esteem (I)			-0.032	(0.020)
Locus of Control (I)			0.061***	(0.012)
Happiness			-0.029	(0.020)
Lucky Charm			-0.038**	(0.015)
BMI			-0.004	(0.003)
Lefthanded			0.057	(0.059)
Vegetarian			-0.050	(0.073)
Alcohol			0.076**	(0.033)
Smoking			-0.239***	(0.055)
Depression			-0.358***	(0.076)
constant	-1.201***	(0.285)	-1.068***	(0.359)
ln(β)				
Pitstop	0.070**	(0.032)	0.010	(0.030)
Race Number (1-6)	0.061***	(0.014)	0.071***	(0.011)
Amount wagered	0.049***	(0.007)	0.026***	(0.008)
Real-Effort Earnings	0.016***	(0.005)	0.006	(0.005)
Amount to be won	-0.002***	(0.001)	-0.001*	(0.001)
High Treatment	0.411***	(0.115)	0.699***	(0.091)
Low Treatment	0.177**	(0.074)	0.662***	(0.079)
Wealth Treatment	0.338***	(0.079)	0.666***	(0.074)
Guess the winner	0.155***	(0.041)	0.111***	(0.033)
Experiment experience	-0.079	(0.069)	-0.012	(0.065)
Gender (female=1)	0.163***	(0.058)	0.202***	(0.050)
Age	0.105***	(0.036)	0.309***	(0.034)
Age^2	-0.002***	(0.001)	-0.005***	(0.001)
Asian culture	0.001	(0.088)	-0.078	(0.085)
Other culture	-0.137	(0.154)	-0.551***	(0.145)
Weekly Income Low	0.064	(0.088)	0.303***	(0.067)
Weekly Income Avg.	-0.287***	(0.090)	-0.125*	(0.067)
Weekly Income High	0.431***	(0.098)	0.520***	(0.078)
Wealth Level Avg.	0.355***	(0.098)	0.021	(0.103)
Wealth Level Poor	0.282**	(0.113)	-0.156	(0.107)
Performance at Uni	0.085**	(0.033)	-0.035	(0.030)
International Student	-0.209***	(0.070)	-0.200***	(0.070)
English speaker	0.013	(0.066)	-0.146**	(0.063)
Mum Schooled	0.017	(0.080)	0.059	(0.083)
Mum Qualified	0.062	(0.089)	-0.101	(0.068)
Mum Qual. Level	0.075	(0.057)	0.048	(0.048)
Dad Schooled	-0.466***	(0.086)	-0.639***	(0.087)
Dad Qualified	0.503***	(0.093)	0.164**	(0.074)
Dad Qual. Level	-0.224***	(0.062)	0.028	(0.048)
Risk-aversion (HL)			0.002	(0.012)
SBI: Reminisce (I)			-0.183***	(0.024)
SBI: Anticipate (I)			0.032	(0.021)
SBI: Moment (I)			0.032	(0.033)
Optimism: Disapp.			-0.067***	(0.011)
Optimism: Low Exp.			0.024*	(0.013)
Self Esteem (I)			0.006	(0.036)
Locus of Control (I)			0.105***	(0.019)
Happiness			0.170***	(0.036)
Lucky Charm			-0.083***	(0.021)
BMI			-0.031***	(0.003)
Lefthanded			-1.067***	(0.194)
Vegetarian			-0.113	(0.109)
Alcohol			0.260***	(0.054)
Smoking			-0.111	(0.088)

Depression			0.374***	(0.098)
constant	-4.120***	(0.531)	-5.242***	(0.658)
logit(γ)				
Pitstop	0.186***	(0.038)	0.003	(0.035)
Race Number (1-6)	-0.002	(0.019)	-0.033*	(0.018)
Amount wagered	0.046**	(0.019)	-0.171***	(0.037)
Real-Effort Earnings	-0.012*	(0.007)	0.017	(0.012)
Amount to be won	0.006**	(0.003)	0.024***	(0.007)
High Treatment	-0.058	(0.149)	0.432*	(0.233)
Low Treatment	0.176	(0.126)	2.199***	(0.344)
Wealth Treatment	0.054	(0.108)	0.795***	(0.145)
Guess the winner	-0.251***	(0.056)	-0.199**	(0.078)
Experiment experience	-0.213*	(0.120)	-1.193***	(0.170)
Gender (female=1)	0.227**	(0.091)	0.211*	(0.113)
Age	-0.234**	(0.103)	0.051	(0.136)
Age^2	0.006***	(0.002)	0.001	(0.003)
Asian culture	0.487***	(0.119)	1.150***	(0.224)
Other culture	0.672	(0.428)	1.098**	(0.465)
Weekly Income Low	-0.280**	(0.117)	0.000	(0.205)
Weekly Income Avg.	-0.006	(0.126)	0.457***	(0.173)
Weekly Income High	0.343**	(0.151)	2.417***	(0.288)
Wealth Level Avg.	-0.047	(0.172)	-1.726***	(0.450)
Wealth Level Poor	-0.042	(0.196)	-0.966**	(0.412)
Performance at Uni	0.432***	(0.057)	-0.097	(0.065)
International Student	-0.454***	(0.092)	-0.364***	(0.121)
English speaker	0.065	(0.092)	-0.863***	(0.130)
Mum Schooled	-0.014	(0.112)	-0.913***	(0.172)
Mum Qualified	-0.251**	(0.113)	-0.575***	(0.185)
Mum Qual. Level	-0.109	(0.074)	0.392***	(0.105)
Dad Schooled	-0.183	(0.119)	-0.063	(0.266)
Dad Qualified	1.561***	(0.168)	1.011***	(0.254)
Dad Qual. Level	-0.466***	(0.101)	-0.571***	(0.127)
Risk-aversion (HL)			0.178***	(0.034)
SBI: Reminisce (I)			-0.047	(0.067)
SBI: Anticipate (I)			-0.463***	(0.058)
SBI: Moment (I)			0.289***	(0.082)
Optimism: Disapp.			-0.030	(0.019)
Optimism: Low Exp.			0.070**	(0.030)
Self Esteem (I)			-0.398***	(0.122)
Locus of Control (I)			0.337***	(0.038)
Happiness			0.874***	(0.135)
Lucky Charm			0.214***	(0.049)
BMI			0.285***	(0.043)
Lefthanded			-0.951***	(0.237)
Vegetarian			2.000***	(0.429)
Alcohol			0.326*	(0.170)
Smoking			-0.756***	(0.214)
Depression			0.690***	(0.263)
constant	1.338	(1.130)	-8.647***	(2.196)
η				
constant	0.312***	(0.036)	0.407***	(0.070)
N	4194		4194	
ll	209.341		716.767	

Significance levels: * 0.1; ** 0.05; *** 0.01. Standard errors in parentheses. (I) denotes indexes build from sets of variables. See Appendix for further details on all control variables. The excluded reference categories are "Baseline Treatment", "Australian Culture", "Weekly Income None", and "Wealth Level Above".

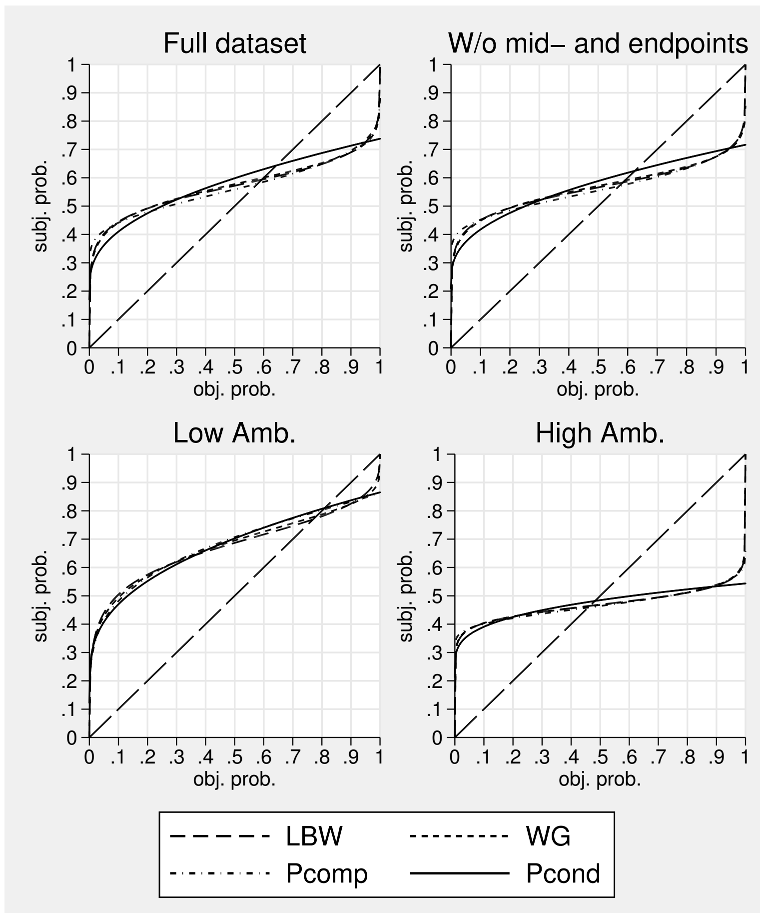

Figure C.1: Models fit under different levels of ambiguity