Estimating the Subjective Risks

of Driving Simulator Accidents

by

Vinayak Dixit, Glenn W. Harrison and E. Elisabet Rutström[†]

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Abstract. We examine the subjective risks of driving behavior using a controlled virtual reality experiment. Use of a driving simulator allows us to observe choices over risky alternatives that are presented to the individual in a naturalistic manner, with many of the cues one would find in the field. However, the use of a simulator allows us the type of controls one expects from a laboratory environment. The subject was tasked with making a left-hand turn into incoming traffic, and the experimenter controlled the headways of oncoming traffic. Subjects were rewarded for making a successful turn, and lost income if they crashed. The experimental design provided opportunities for subjects to develop subjective beliefs about when it would be safe to turn, and it also elicited their attitudes towards risk. A simple structural model explains behavior, and showed evidence of heterogeneity in both the subjective beliefs that subjects formed and their risk attitudes. We find that subjective beliefs change with experience in the task and the driver's skill. A significant difference was observed in the perceived probability to successfully turn among the inexperienced drivers who did and did not crash even though there was no significant difference in drivers' risk attitudes among the two groups. We use experimental economics to design controlled, incentive compatible tasks that provide an opportunity to evaluate the impact on driver safety of subject's subjective beliefs about when it would be safe to turn as well as their attitudes towards risk. This method could be used to help insurance companies determine risk premia associated with risk attitudes or beliefs of crashing, to better incentivize safe driving.

Statement of Contribution/Potential Impact
This research utilizes methods from experimental economics to develop a controlled laboratory driving simulator experiment, to study the effects of risk attitudes and perceived beliefs on driver's choices and propensity to crash. Experimental economics provides a controlled, incentive compatible method to disentangle the complex interactions of driving skill, risk attitudes, and subjective perception and their impact on driving behavior. The study shows that it is critical to control for driver's risk attitudes when modeling driver behavior. We find that subjective beliefs change with experience in the task and the driver's skill. Though a significant difference was observed in the perceived probability to successfully turn among inexperienced drivers who did and did not crash, there was no significant difference in risk attitudes among these two groups. The main contribution is the application of incentive compatible methods from experimental economics to elicit risk attitudes and subjective beliefs in the context of driver behavior and safety.

Highlights
- The study uses methods from experimental economics to study driver behavior and safety
- The study demonstrates joint estimation of risk attitudes and subjective beliefs of drivers
- Subjective beliefs change with experience in the task and the driver's skill
- Drivers who crash had higher perceived probabilities to successfully complete the driving task
- There was no difference in drivers' risk attitudes among drivers who did and did not crash

Keywords: Experimental Economics, Risk Aversion, Subjective Beliefs, Safety, Driver Behavior

Driving is a risky activity. The time taken on a trip is not certain, the speed achieved on the trip is not certain, the chance of crashing is not certain, and each of these are outcomes that drivers will typically care about. Perception of risk has been shown to influence driving behavior (Ranney [1994], Deery [1999] and Chaudhary et al. [2004]). Dejoy [1989] found that there was significant optimism associated with judging accident risk, and concluded (p. 333) that "optimism arises because people persistently overestimate the degree of control that they have over events." This suggests the hypothesis that people recognizing themselves to be skillful in the driving task would underestimate the risk. Guppy [1993] found evidence that traffic offenders (speeders and drink-drivers) had a lower perceived probability of an accident than non-offenders. In addition, Deery [1999] identified risk acceptance as one of the characteristics that explain risk taking behavior of drivers. Risk acceptance is a matter of preference and is referred to as risk attitudes in the economics literature. The varying risk taking behaviors of drivers are frequently thought of as reflecting risk attitudes, but it is important to recognize that they also reflect subjective risk perceptions. Indeed, under the usual theories characterizing behavior in these settings, one has to think about risk attitudes and risk perceptions jointly. Both the risk attitude and the perception of the risk are subjective, and therefore likely to vary across individual drivers. Dixit [2013] used this paradigm to derive the two-fluid model for urban traffic, which is a model that captures driver aggressiveness (Dixit et al. [2012]), and crash likelihood (Dixit et al. [2011]). We demonstrate how it is possible to identify both risk attitudes and risk perceptions in drivers by the use of controlled experimental elicitation methods. We use driving simulators to induce a driving context on the decision environment. The use of a simulator allows us to have all of the controls that one might normally find a conventional laboratory experiment, but with "naturalistic" driving cues. The risky task we present to the participants is making a left hand turn when there is a cue of oncoming traffic generating a risk of crashing.

Apart from risk attitudes and perceptions, gap acceptance also depends on the driver's abilities

or skills.   Bottom and Ashworth [1978; p.731-732] stated that "the question arises as to whether the driver has some knowledge of his ability and sets his critical gap in the light of this or whether the critical gap is decided by the risk he is willing to take and the resulting variance is a function of the difficulty of the task he then sets himself. It is likely that the two factors interact and cannot be separated".   With our experimental design we can identify all three factors hypothesized to influence gap acceptance: risk attitudes, risk perceptions, and driving skill.

The lab environment gives us controls over the riskiness of the tasks and the experience drivers have with them, in ways that are not possible in the field.   The experiments reported here also use a salient monetary incentive, which sharpens the motivation for the participants to focus on those cues that are relevant for successfully completing the tasks.   Several studies have utilized survey based instruments to measure risk aversion (Machin and Sankey [2008]), risk perception (Rundmo and Iversen [2004]) and risky behaviors such as the propensity to speed (Corbett [2001], Hatfield et al. [2008] and Greaves and Ellison [2011]).   It has been shown that survey questions about intentions to act can result in biased measurements (Cummings et al. [1995] and Holt and Laury [2002]) and it is therefore important to also measure these factors in situations with salient motivations, as we do here. Survey instruments are usually associated with hypothetical bias which could be associated to strategic response, fear of being judged, or lack of sufficient incentives to state the truth.   Driving without crashing in the simulator requires some attention. Without proper incentives that mimic those in natural driving conditions, participants may be easily distracted by other aspects of the simulation or may simply not pay attention to the task at all.   Given these methodological strengths, experimental economics has been increasingly used to test theoretical predictions with regard to traffic equilibrium and departure time choice (Ziegelmeyer et al. [2008] and Otsubo and Rapaport [2008]), route choice (Rapaport et al. [2006]; Selten et al. [2007]; Ramadurai and Ukkusuri [2007]; Daniel et al. [2009]; Morgan et al. [2009] and Hartmann [2006]), as well as, public transit choice (Denant-Boemont and

Hammiche [2012]). Methods from experimental economics have also been used in transportation to study the impact of information (Denant-Boemont and Petoit [2003]) as well as risk aversion (Dixit et al. [2013]) on route choice.

In section 1 we describe the design of the simulator experiment, focusing on the risk of a crash in a naturalistic driving task. Section 2 describes the formal decision model which we estimate using full information maximum likelihood, so as to jointly estimate the latent parameters characterizing risk attitudes, risk perceptions and skill. Section 3 reviews our results, and Section 4 concludes.

1. Experimental Design

The experimental setup used a driving simulator to study behavior in a virtual experiment, as defined by Fiore et al. [2009]. The driving simulator is an MPRI PATROLSIM (http://www.mpri.com/driver/patrolsimiv.html), which has a 180° view using a three-channel plasma screen with an immersive driving environment. Figure 1 illustrates the typical setup.

The experiment consisted of seven tasks. As the participants arrived they were given instructions about each task. Special attention was given to the comfort and health of participants: they were allowed to leave with the fixed participation fee if they felt dizzy, nauseous or uncomfortable. We also ensured that drivers did not spend too much continuous time in the simulator, by interspersing driving tasks with non-driving tasks.

The subjects were given a fixed participation fee of $15, plus an initial endowment of $5 that would allow them to cover any losses incurred due to crashing in subsequent tasks. If they made no losses they kept the $5. The first task was to allow participants to gain familiarity with driving in a simulator and with the main features of the driving task. They were instructed to turn left at an empty intersection, for which they received $2 for a successful turn without crashing. Monetary incentives

in training tasks such as these motivate participants to pay attention to cues that are relevant to the task. This was followed by asking participants to fill out a demographics questionnaire, allowing them to rest from the simulator.

In the second task the participant's ability to judge the shortest and longest gaps was directly elicited. They were asked to drive up to the intersection and wait at the stop line and allow a vehicle stream with 11 cars to pass. The critical feature of the vehicle stream in this task is that the gap sizes between oncoming cars are random. These gap sizes are shown in Table 1. The participants were asked to report the gaps with the shortest gap size and longest gap size. They were first shown three simulated vehicle streams with 11 vehicles to familiarize themselves with the process, followed by the vehicle stream of 11 vehicles for which the responses were incentivized. Each correct answer about the shortest and longest gap size earned $1, so the subject earned $0, $1 or $2 from this task. The vehicle stream and the gap sizes used in this task were not the same as those in the core tasks. This task was intended only for identifying varying abilities to judge gap sizes, and was not intended to give subjects additional information about the later gap acceptance task. This task was then followed by another period away from the simulator, consisting of a questionnaire on a psychological construct known as the "locus of control."

In the third task the participants were initially shown the stream of vehicles that would later be used in the gap acceptance task, which is the task that is core to our research question. In the core driving tasks the participant was supposed to turn left between the vehicles in the oncoming stream for monetary consequences. The participants were instructed that they would be turning left at an intersection by accepting a gap through the stream of 11 vehicles with increasing gap sizes, so that there were 10 gaps of increasing size. Notice that, contrary to the earlier gap judgment task, the gap sizes are no longer random. The driving task was incentivized based on the order, and therefore the size of the gaps: the participant received $10 for successfully turning in gap #1 and the monetary

incentive was reduced by $1 for every increment in gap number. A driver who turned in gap #7, for example, would make $4 for a successful turn. The gap sizes for each gap are shown in seconds in Table 2. The participant lost $5 in the unfortunate event of a crash. Because of the presence of this possible loss the initial endowment of $5 was provided. The virtual environment for the driving task is shown from a "helicopter view" in Figure 2. The view for the participant was at street level, just as a driver would experience it.

Task three was again followed by a questionnaire in which the participants reported their belief about how many of 36 participants in an earlier driving study would either turn or not, and if turning, would make the turn successfully or crash at specific gap sizes. Table 3 shows the actual behavior observed in the earlier study, although this information was of course not given to the participants since they were asked to guess what it was. Each participant was paid $0.50 for each correct row and column that is shown in Table 3. Thus earnings from this task could range from $0 up to $3.50.

Task four was exactly the same as task three except that the participant first made three gap practice turns without any monetary consequences. The vehicle streams that were presented to the participants were the same in tasks three and four, as well as the three practice tasks. This was made clear to the participants before the three practice tasks and task four. The practice tasks allowed the participant to gain experience before driving again for monetary consequences. The fact that no monetary incentives were used here gave the participant an opportunity to undertake costless experimentation. The final drive was again incentivized and corresponds to our second core driving task. Just like after task three, the participants were then asked to report the number of outcomes for 36 participants, the correct row and column in shown in Table 4. The frequency of gaps chosen and crashed in for all the subjects in Task 3 and Task 4 are shown in Table 5.

In task five the participants were instructed to turn between pre-determined vehicles. This task was designed to measure differences in the driving skills of participants. The selection of the

gaps where participants had to turn was based on a draw from a deck of cards, each card representing a subset of the 10 gaps in the vehicle stream. All participants had to turn once in gap 1, once in either gap 2 or gap 3, once in any of gaps 4 - 7, and once in gaps 8 - 10. The participant had to turn in the gaps stated on the card, unless the card indicated a gap range already used, in which case a new card was drawn. In this task the driver had to drive four times, and received $5 for each successful turn and nothing if they crashed in each turn.

Task six was similar to task two in which the drivers had to identify the shortest and longest gap. However, in this case the vehicle stream that was presented to them was different from the one presented to them in task two, and is shown in Table 6. This task measures whether their ability to judge gap distance changes due to the experience gained.

In the final task seven the participants were presented with standard lottery choices, following Holt and Laury [2002], to determine their risk attitude. Each subject was presented with a choice between two lotteries, which we call A or B. Table 7 contains the basic payoff matrix presented to subjects. The first row shows that lottery A offered a 10% chance of receiving $5 and a 90% chance of receiving $4. The expected value (EV) of this lottery, EV_A, is $4.10. Similarly, lottery B in the first row has chances of payoffs of $10 and $0.25, for an expected value of $1.225. Thus the two lotteries have a relatively large difference in expected values, in this case $2.875. As one proceeds down the matrix, the expected value of both lotteries increases, but the expected value of lottery B eventually becomes greater than the expected value of lottery A.

The subject chooses A or B in each row, and one row is later selected at random for payout for that subject. Assuming local non-satiation, the last row is simply a test that the subject understood the instructions, and has no relevance for risk aversion at all. The logic behind this test for risk aversion is that only risk-loving subjects would take lottery B in the first four rows. A risk neutral subject should switch from choosing A to B when the EV of each is about the same, so a risk-neutral

subject would choose A for the first four rows and B thereafter. A risk-averse subject would switch from A to B after the fourth row.

Tasks three and four were designed to generate gap acceptance tasks that mimic lottery choices like those represented in Table 7. Table 8 presents the payoff consequences of task three as a lottery table similar to Table 7. A subject can choose to turn in any one of the 10 gaps, where the gaps are initially small (1.29 seconds between the oncoming vehicles) but increase over time until the maximum gap size of 1.85 seconds.

We also show in Table 8 an example of the probabilities of crashing that a subject may perceive for various gap sizes. We calculate the EV of choosing each gap for turning as the probability weighted average of the payments. If a subject is risk neutral she should simply choose to turn in gap size 1.81, since it gives her the highest EV. For illustrative purposes we also show in the final column that a risk-averse driver will base his choice on the Expected Utility (EU) rather than the EV, and here the risk-averse driver will delay his turn to a gap size of 1.85 compared to the risk neutral choice.[1]

A total of 132 participants were recruited from the student population of the University of Central Florida in 2009-2010. Each was given a $15 participation fee, and general instructions were given about the session. This fee is higher than for most other experiments conducted at the time since the participants had to come to an off-campus location where the driving simulator was located. Detailed instructions were provided prior to each task, and all instructions are provided in an appendix. The choices and earnings made by the participants were recorded as each task was completed, and the final payment made in cash at the end of the session. Each experiment lasted an average of 90 minutes.

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1 Section 2 explains the precise specification used for these predictions using EU.

2. Estimation

It is convenient to review the estimation of risk attitudes from the lottery defined over objective probabilities first, and then examine how that is extended to the driving lottery defined over subjective probabilities.

A. Risk Attitudes Over Objective Probabilities

Assume for the moment that utility of income is defined by the Constant Relative Risk Aversion (CRRA) function

$$U(x) = M^{(1-r)}/(1-r) \tag{1}$$

where M is the lottery prize and r≠1 is a parameter to be estimated. Thus r is the coefficient of CRRA: r=0 corresponds to risk neutrality, r<0 to risk loving, and r>0 to risk aversion. This functional form with r=0.9, is used in the numerical calculation of Table 8. Let there be two possible outcomes in a lottery. Under Expected Utility Theory (EUT) the probabilities for each outcome M_j, $p(M_j)$, are those that are induced by the experimenter, so expected utility is simply the probability weighted utility of each outcome in each lottery i:

$$EU_i = \Sigma_{j=1,2} \, [\, p(M_j) \times U(M_j) \,]. \tag{2}$$

The EU for each lottery pair is calculated for a candidate estimate of r, and the index

$$\nabla EU = EU_R - EU_L \tag{3}$$

calculated, where EU_L is the "left" lottery and EU_R is the "right" lottery as presented to subjects. This latent index, based on latent preferences, is then linked to observed choices using a standard logistic function $\Lambda(\nabla EU)$. This "logit" function takes any argument between ±∞ and transforms it into a number between 0 and 1 using the familiar sigmoid-shaped function in Figure 4. Thus we have the logit link function

$$\text{prob(choose lottery R)} = \Lambda(\nabla EU) \tag{4}$$

The cumulative normal distribution function is of course very similar, and leads instead to the "probit" specification. It will be useful later to note that (4) is formally identical to defining the latent index (3) by $\nabla EU = eu_R/(eu_L + eu_R)$, where $eu_i = \exp(EU_i)$ for i= {R, L}.

Even though Figure 4 is common in econometric texts, it is worth noting explicitly and understanding. It forms the critical statistical link between observed binary choices, the latent structure generating the index $y^* = \nabla EU$, and the probability of that index y^* being observed. In our applications y^* refers to some function, such as (3), of the EU of two lotteries. The index defined by (3) is linked to the observed choices by specifying that the R lottery is chosen when $\Lambda(\nabla EU) > \frac{1}{2}$, which is implied by (4).

Thus the likelihood of the observed responses, conditional on the EUT and CRRA specifications being true, depends on the estimates of r given the above statistical specification and observed choices. The "statistical specification" here includes assuming some functional form for the cumulative density function (CDF), such as one of the two shown in Figure 4. If we ignore responses that reflect indifference[2] the conditional log-likelihood would be

$$\ln L(r; y, \mathbf{X}) = \Sigma_i \, [\, (\ln \Lambda(\nabla EU) \times \mathbf{I}(y_i = 1)) + (\ln (1-\Lambda(\nabla EU)) \times \mathbf{I}(y_i = -1)) \,] \tag{5}$$

where $\mathbf{I}(\cdot)$ is the indicator function, $y_i =1(-1)$ denotes the choice of the Option B (A) lottery in risk aversion task i, and $\mathbf{X}$ is a vector of individual characteristics reflecting age, sex, race, and so on.

Harrison and Rutström [2008; Appendix F] review procedures and syntax from the popular statistical package *Stata* that can be used to estimate structural models of this kind, as well as more complex models.[3] None of the specific parametric assumptions used here are necessary for this

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[2] Harrison and Rutström [2008, p.48, 71] discuss the modeling of indifference.
[3] Extensions of the basic model are easy to implement, and is a major attraction of the structural estimation approach. For example, one can easily extend the functional forms of utility to allow for varying degrees of relative

approach.   Extensions to more flexible utility functions, or to Rank Dependent Utility or Prospect

Theory, can easily be undertaken, as long as the data can identify the necessary additional parameters.

It is a simple matter to correct for multiple responses from the same subject ("clustering"),[4] or

heteroskedasticity, as needed.

It is straight forward to generalize this Maximum Likelihood (ML) analysis to allow the core

parameter r to be a linear function of observable characteristics of the individual or task.   We would

then extend the model to be $r = r_0 + R \times X$, where r_0 is a fixed parameter and R is a vector of effects

associated with each characteristic in the variable vector X.   In effect the unconditional model

assumes $r = r_0$ and just estimates r_0.   This extension significantly enhances the attraction of structural

ML estimation, particularly for responses pooled over different subjects, since one can condition

estimates on observable characteristics of the task or subject.

An important extension of the basic model is to allow for subjects to make some errors.   The

notion of error is one that has already been encountered in the form of the statistical assumption that

the probability of choosing a lottery is not 1 when the EU of that lottery exceeds the EU of the other

lottery.   This assumption is clear in the use of a link function between the latent index ∇EU and the

probability of picking one or other lottery; in the case of the logistic CDF, this link function is $\Lambda(\nabla$EU)

and is displayed in Figure 4.   If there were no errors from the perspective of EUT, this function would

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risk aversion (RRA). Consider, as one important example, the Expo-Power (EP) utility function proposed by Saha
[1993]. Following Holt and Laury [2002], the EP function is defined as $U(x) = [1-\exp(-\alpha x^{1-r})]/\alpha$, where α and r are
parameters to be estimated. RRA is then $r + \alpha(1-r)y^{1-r}$, so RRA varies with income if $\alpha \neq 0$. This function nests CRRA
(as $\alpha \rightarrow 0$) and CARA (as $r \rightarrow 0$). The use of this EP specification is illustrated in Harrison, Lau and Rutström [2007].

[4] Clustering commonly arises in national field surveys from the fact that physically proximate households are
often sampled to save time and money, but it can also arise from more homely sampling procedures. For example,
Williams [2000; p.645] notes that it could arise from dental studies that "collect data on each tooth surface for each of
several teeth from a set of patients" or "repeated measurements or recurrent events observed on the same person." The
procedures for allowing for clustering allow heteroskedasticity between and within clusters, as well as autocorrelation
within clusters. They are closely related to the "generalized estimating equations" approach to panel estimation in
epidemiology (see Liang and Zeger [1986]), and generalize the "robust standard errors" approach popular in
econometrics (see Rogers [1993]). Wooldridge [2003] reviews some issues in the use of clustering for panel effects,
noting that significant inferential problems may arise with small numbers of panels.

be a step function, which is zero for all values of y*<0, anywhere between 0 and 1 for y*=0, and 1 for all values of y*>0.

The problem with this step function CDF is immediate: it predicts with probability one or zero. The likelihood approach asks the model to state the probability of observing the actual choice, conditional on some trial values of the parameters of the theory. Maximum likelihood then locates those parameters that generate the highest probability of observing all of the data. For binary choice tasks, and independent observations, we know that the likelihood of the sample is just the product of the likelihood of each choice conditional on the model and the parameters assumed, and that the likelihood of each choice is just the probability of that choice. So if we have any choice that has zero probability, and it might be literally 1-in-a-million choices, the likelihood for that observation is not defined. Even if we set the probability of the choice to some arbitrarily small, positive value, the log-likelihood zooms off to minus infinity. We can reject the theory without even firing up any statistical package.

An important behavioral error specification, due originally to Fechner and popularized by Hey and Orme [1994], posits the latent index

$$\nabla EU = (EU_R - EU_I)/\mu \qquad\qquad (3')$$

instead of (3), where μ is a structural "noise parameter" used to allow some errors from the perspective of the deterministic EUT model. As $\mu \rightarrow 0$ this specification collapses to the deterministic choice EUT model, where the choice is strictly determined by the EU of the two lotteries; but as μ gets larger and larger the choice essentially becomes random. When $\mu=1$ this specification collapses to (3), where the probability of picking one lottery is given directly by the difference of the EU of one lottery to the EU of the other lotteries. Thus μ can be viewed as a parameter that flattens out the link functions in Figure 4 as it gets larger. The likelihood function (5) can then be extended to include μ:

$$LL^{RA} = \ln L(r, \mu; y, \mathbf{X}) = \Sigma_i \, [\, (\ln \Lambda(\nabla EU) \times \mathbf{I}(y_i = 1)) + (\ln (1 - \Lambda(\nabla EU)) \times \mathbf{I}(y_i = -1)) \,] \qquad (5')$$

Thus we find estimates of r and μ that maximize the likelihood of the observed lottery choices.

An important contribution to the characterization of behavioral errors is the "contextual error" specification proposed by Wilcox [2008][2011]. It is designed to allow robust inferences about the primitive "more stochastically risk averse than." It posits the latent index

$$\nabla EU = ((EU_R - EU_L)/\nu)/\mu \qquad (3'')$$

instead of (3'), where ν is a new, normalizing term for each lottery pair L and R. The normalizing term ν is defined as the maximum utility over all prizes in this lottery pair minus the minimum utility over all prizes in this lottery pair. The value of ν varies, in principle, from lottery choice to lottery choice: hence it is said to be "contextual." For the Fechner specification, dividing by ν ensures that the *normalized* EU difference $[(EU_R - EU_L)/ \, \nu]$ remains in the unit interval.

B. Subjective Probabilities

In order to analyse the driving simulator data we have to estimate not only risk attitudes but also risk perceptions, or subjective probabilities. The outcomes, M_j, are now the earnings that can be made if making a successful turn or if crashing, conditional on which gap j is selected. The probabilities of crashing or turning successfully, $\pi_j(M_j)$, are those that are perceived by the subject. So EU is again just the probability weighted utility of crashing or turning successfully when choosing a specific gap j to turn in:

$$EU_j = \Sigma_{j=1,2} \, [\, \pi_j(M_j) \times U(M_j) \,]. \qquad (6)$$

The EU for each gap is calculated for a candidate estimate of r and $\pi_1(M_1)$, where event 1 refers to crashing, exploiting the fact that $\pi_2(M_2) = 1 - \pi_1(M_1)$. For simplicity, we will refer to π as a shorthand for $\pi_1(M_1)$. The problem with inferring the subjective probability π from gap choices is that the utility

function is a confound. This is where the experimental task with objective probabilities comes in, to identify the utility function from choices that do not involve the subjective probability π. Given the estimates of the utility function from those tasks with objective probabilities, we can use the choices over gaps defined in (6) to estimate and identify π.

A maintained assumption of our approach is that the utility function that we elicit from lottery choices over objective probabilities is the same utility function that characterizes the choices over lotteries defined on subjective probabilities and beliefs. This can be viewed as an identifying assumption, since one can then exploit the ability of an experimental design to recursively estimate utility from one task and then subjective beliefs and utility from another task. But it is a maintained assumption.[5]

In the driving task the participant makes a choice of one gap over a number of possible gaps. Let j index the gap, and define j ε {1, 2, ..., J}. In our case J=10. So the simple binary specification used for the lottery choices over objective probabilities must be extended to a multinomial specification. We define

$$eu_j = \exp[(EU_j/\nu)/\eta] \tag{7}$$

for any gap j, and for the behavioral error parameter η. We then define the latent index as

$$\nabla EU = eu_j/(eu_1 + eu_2 + \dots + eu_J) \tag{8}$$

for the specific gap j that the driver selected.[6] The end result is a log-likelihood for the driving choices

[5] Abdellaoui, Baillon, Placido and Wakker [2011] conclude that different probability weighting functions are used when subjects face risky processes with known probabilities and uncertain processes with subjective processes. They call this "source dependence," where the notion of a source is relatively easy to identify in the context of an artefactual laboratory experiment, and hence provides the tightest test of this proposition. Harrison [2011] shows that their conclusions are an artefact of estimation procedures that do not worry about sampling errors. A correct statistical analysis that does account for sampling errors provides no evidence for source dependence. Of course, failure to reject a null hypothesis could just be due to samples that are too small. In any event, we maintain the identifying assumption of source independence and there is no evidence to reject that assumption.

[6] With J=2 and η=μ, this is mathematically the same as the link function specification given by (3) and (4). There is no econometric reason why we have to use the same logit form to define the two components of the joint likelihood, although it does provide some consistency of interpretation across the two.

i defined by

$$LL^{DR} = \ln L(r, \pi, \eta; y, \mathbf{X}) = \Sigma_i [(\ln(\nabla EU) \times \mathbf{I}(y_i = 1)) + (\ln(1-\nabla EU) \times \mathbf{I}(y_i = -1))] \qquad (9)$$

The only differences from (5′) are that there are two core structural parameters here, r and π, instead of just r; that we use the behavioral error parameter η instead of μ; and that we do not explicitly specify the logistic function Λ in the log-likelihood (9) since it is implied by (7) and (8).

The use of a multinomial distribution is appropriate in our experiment, but would not generalize to all possible settings that may be of interest. In our experimental task the subjects are assumed to behave as if they decide which of the J gaps to take before they start driving. This is consistent with the experimental control we have, since the subject has been exposed to the precise vehicle flow and gap pattern they will encounter by task three and four *when they turn with real rewards*. To be precise, in task three they are told to observe the vehicle stream at the intersection, without turning, and then they are told to turn when we repeat exactly the same vehicle stream and they face real rewards. Prior to the paid turn in task four, they of course have three practice turns and are told that this is again exactly the same vehicle stream. This means that it is reasonable to assume that the subject behaves as if the choice of gap is made based on considering all gap size information simultaneously, and not sequentially, facilitating the analysis.

Of course, this is precisely where the controls of the laboratory are used to effect, since it would not be possible in the field to ensure exactly the same vehicle stream in terms of gap sizes. In that case, the driver has to make a decision based on the incoming traffic flow and judgment as to gap size. Hence, in that setting, one would want to use a distributional assumption that recognizes that once the driver turns in gap j it is impossible for there to be a turn in gap j+1, j+2, ..., J. This is a familiar problem of censoring that is found in survival analysis, and one would modify the likelihood function (9) in standard ways to account for this.

The joint estimation problem is to find estimates of r, π, μ and η so as to maximize the likelihood of the choices in *both* tasks: gap acceptance and lotteries. This makes good econometric sense, in the usual "full information" way. But it is also the structural model that flows from the theory of Subjective Expected Utility (SEU) due to Savage [1972]: one *jointly* infers the subjective probability *and* the utility function. This has an important implication, both theoretical and inferential. If we have a poor estimate of r, in the sense that it has a very large sampling error, we cannot, other than by statistical black magic, infer a precise estimate of the subjective probability of a successful turn π. This is not something one can avoid as a matter of theory, but of course one can seek to mitigate it by having reliable and transparent instruments to infer risk attitudes.

The implication is that we actually estimate the joint likelihood function defined for the choices in the risk aversion tasks and the choices in the driving tasks:

$$LL = LL^{RA} + LL^{DR} \qquad (10)$$

where LL^{RA} is defined by (5′) and LL^{DR} is defined by (9).

As discussed earlier with respect to r, we can extend the specification of the successful turn probability π to include covariates. In this case this is how we estimate subjective probabilities for turning gaps. Since the perceived probability of a successful turn is expected to be a function of the gap size we need to estimate a subjective probability distribution, and not just a single subjective probability. For this purpose we assume that the distribution follows the Weibull distribution as a function of x that denotes the actual gap size in seconds. Then we can estimate the two parameters of the Weibull Distribution λ and *k*:

$$\pi = 1 - \exp[-(x/\lambda)^k] \qquad (11)$$

The Weibull distribution was selected because it is flexible. Employing (11) we add the parameters λ and *k* to the likelihood function for driving behavior, so that we now have

$$LL^{DR} = \ln L(r, \pi, \eta, \lambda, k; y, \mathbf{X}) = \Sigma_i [(\ln(\nabla EU) \times \mathbf{I}(y_i = 1)) + (\ln(1-\nabla EU) \times \mathbf{I}(y_i = -1))] \qquad (9')$$

instead of (9). The joint likelihood (10) is defined as before, using this expression for LL^{DR}.

3. Results

Our main question is whether the propensity to crash is explained by the driver's risk attitude or risk perception, controlling for skill and experience. As discussed earlier, the variable for experience (*Task4*) is a dummy variable that takes a value of one for all choices made in the incentivized task 4, which allowed subjects to gain experience prior to making their final choice. The variable for skill (*Skill*) counts the number of successful turns in Task 6. In order to answer this question we first analyze turning choices as a function of risk attitudes and risk perceptions, since the propensity to crash is a consequence of the turning choice. Table 9 shows our initial estimation when we pool across all drivers. We jointly estimate risk attitudes and risk perceptions using data from both the lottery tasks and driving tasks three and four, controlling for driving skills as measured in task five. We quantify skill by counting the number of times, out of four possible chances that they do not crash in Task 5. Including data from tasks three and four allows us to investigate the effect of experience.

First, we find that subjects are risk averse. The coefficient for relative risk aversion has a point estimate of 0.51, with a fairly small standard error, indicating that the utility function is concave. Thus, our first conclusion is that modeling driving decisions assuming risk neutrality would be incorrect. Table 9 also shows the estimates for the Weibull parameters, *k* and λ, and Figure 5 illustrates the implied subjective probability of making a successful turn for any given gap size for the inexperienced drivers (i.e., Task 3 only). The subjective probability of making a successful turn is simply one minus the perceived risk of crashing. The model estimated assuming risk neutrality is shown in Table 10, and the dashed line in Figure 5 shows the implied subjective probability under the

risk neutrality assumption. The vertical lines in Figure 5 indicate the smallest and largest gap sizes

used in our simulator tasks, which ranged between 1.29 seconds and 1.85 seconds, and beyond that the

probabilities are predicted using the estimated Weibull function. The figure shows both the

distribution that corrects for risk aversion and the distribution resulting when incorrectly assuming

risk neutrality, in each case holding the variable *Skill* constant at its mean value. We can conclude

from Figure 5 that an assumption of risk neutrality would lead one to underestimate the perceived

probability of success for all gap sizes in Task 3. A similar conclusion would be drawn for Task 4. The

logic behind this conclusion is that since subjects are risk averse they generally choose to turn in a

larger gap size since that is less risky, than they would if they were risk neutral. Thus, if we

(incorrectly) assume that they are risk neutral then the choice of the larger gap size must be explained

by an increase in the perceived risk.

Table 9 also reports the effect of experience by including a dummy variable for *Task 4*. We

see that experience is (weakly) significant for k but not significant for λ. Figure 6 shows the implied

effect on the perceived success probability from this additional experience, again holding *Skill*

constant at its mean value. The main effect of experience is to increase the perceived probability in

smaller gaps and to decrease it in larger gaps. To understand how this inference follows from the

turning choices, Figure 7 shows the difference in cumulative frequencies of subjects turning for

different gap sizes: more drivers turn earlier in the smaller gaps when they have additional experience.[7]

The effect is consistent with subjects learning something about their own abilities.

We can also look at how beliefs differ by S*kill*, as measured by the number of times they do not

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7 We test whether this experience effect is due to an improved ability to judge the relative gap sizes by also estimating
the model including the variable *Gaplearn*. This variable is calculated based on behaviors in tasks two and six where
subjects are asked to state which gap is the smallest. We first calculate the deviation in gap size between the reported
gap and the actual smallest gap for each of tasks two and six. We then take the difference in this variable between the
tasks and interact with the task four dummy. This variable is not significant. For the sake of robustness the impact of
learning between tasks 3 and 4 on perceiving the longest gap was also tested but was not found to be significant.

crash in Task 5. Table 9 reports a significant effect on k and a weakly significant effect on λ, and Figure 8 shows the implication of the perceived success probability in Task 3. Figure 8 is constructed to show the effect of a shift in skill from those who only make one successful turn in Task 5 to those who make three successful turns. *Skill* shifts the cumulative density function to the right, implying that skilled drivers are more optimistic about their success in the smaller gaps. An interesting thing happens after subjects become more experienced, as shown in Figure 9. The inferred beliefs about success in turning for the skilled drivers change dramatically. Drivers who are both skilled and experienced are highly optimistic about their chances of success in the early, smaller gaps. In summary, we find that both experience (Figure 6) and skill (Figure 8 and 9) make drivers more optimistic about their chances of success.

We now turn to our core question of which type of drivers have a higher propensity to crash: those who are less averse to risk, or those who underestimate the risk? To answer this question we estimate the choice model separately for those who crashed and those who did not crash. Table 11 and Table 12 show these estimates for Task 3, and Table 13 reports a simple z-test between the coefficients in the two models (Paternoster et al. [1998]). We conclude that the estimated risk attitude parameter, r, is not significantly different across those who crashed or not. Risk attitudes therefore do not appear to play much of a role in explaining crash propensities. We therefore turn to look at the perception of risk as captured by the subjective probability of making the turn successfully.

We can see from Tables 11 and 12 that both k and λ are significant in determining the subjective success probability in Task 3, but they differ significantly across those who crashed and those who did not crash. Thus, while risk preference does not seem to be a characteristic that separates those who crash from those who do not, perception of the risk does. Figure 10 shows the subjective success probabilities separately for those who crashed and not, also controlling for skill level. We see that, independent of skill, those who crashed were more confident in their success than

those who did not crash. Among the high skilled drivers the biggest difference between those who crashed and not was in the optimism in the smaller gaps, while among the low skilled drivers it is in the optimism in the larger gaps. Not surprisingly, in the larger gaps the high skilled drivers both believed that they would be successful, and were successful at turning.

We conclude that while risk attitudes do not seem to explain who crashed or not, differences in the perception of the risk do.

These findings have important implications for road safety programs. For example, significant benefits could be generated by investing in training programs and education focusing on improving driver judgment of risks while driving. In-vehicle information about the level of risk, conditional on real-time traffic information derived from vehicle and road sensors, could also provide safety benefits by helping drivers' form more accurate risk perceptions. Apart from influencing policy, these findings should also influence the design of insurance mechanisms that promote safer driving behavior. Future research should quantify the benefits and costs of these and other programs, to rigorously evaluate what type of education and information that best improves the accuracy of risk perception among drivers.

4. Conclusion

We use methods from experimental economics to generate behavioral data in controlled, incentive compatible driving tasks implemented in a driving simulator. We ask whether the propensity to crash is due to risk attitudes or to risk perceptions, controlling for the skill of the driver. Incentive compatible methods reduce hypothetical bias, and reveal the true preferences and beliefs of individuals. The data is used to estimate structural decision models that rely on risk attitudes and subjective beliefs.

We find that it is critical to control for the risk attitude of drivers. Assuming risk neutrality

among drivers results in underestimation of the perceived probabilities of successfully turning in a given gap size.   However, we do not find that the propensity to crash is related to risk attitudes.   We do find, however, that the perception of the risk differs across those who crash and not.   Generally, those who crash are more optimistic about their success than those who do not crash.

Risk perception is also found to vary with experience and skill.   Skill defines better drivers and these drivers appear to know that they are better, as reflected in a higher degree of optimism about success.   Experience allows drivers to learn about themselves and therefore helps to standardize their perception of risks. This results in an increase in perceived probabilities of successfully turning at smaller gaps and a decrease in these probabilities for larger gaps.   Higher skilled drivers tend to also have a higher perceived success at shorter gaps, and lower perceived probability of success at longer gaps, compared to lower skilled drivers.   We also find that skilled drivers are less likely to crash than unskilled drivers.   Whether drivers are skilled or not, those who crash seem to do so because they underestimate the risk.

Table 1: Gap Sizes for Task Two, Showing the Shortest and Longest Gap

Between Vehicles	Gap Number	Gap Size (Seconds)	Shortest/ Longest
1-2	1	1.31	
2-3	2	1.18	Shortest
3-4	3	1.79	
4-5	4	1.9	Longest
5-6	5	1.68	
6-7	6	1.75	
7-8	7	1.65	
8-9	8	1.6	
9-10	9	1.58	
10-11	10	1.83	

Table 2: Gap Sizes for Task Three, the Three-Practice Tasks and Task Four

Between Vehicles	Gap Number	Gap Size (Seconds)	Earning if Successful
1-2	1	1.29	$10
2-3	2	1.45	$9
3-4	3	1.46	$8
4-5	4	1.58	$7
5-6	5	1.59	$6
6-7	6	1.60	$5
7-8	7	1.60	$4
8-9	8	1.81	$3
9-10	9	1.85	$2
10-11	10	1.85	$1

Table 3: Turning Characteristics Observed for 36 Subjects in Pilot Experiment in Task Three

	Gap 1 Vehicle 1-2	Gaps 2-3 Vehicle 2-4	Gaps 4-7 Vehicle 4-8	Gaps 8-10 Vehicle 9-11	No attempt	Sum
Successful	0	0	2	5	2	9
Crash	0	3	12	12	0	27
Total who will try	0	3	14	17	2	36

Table 4: Turning Characteristics Observed for 36 Subjects in Pilot Experiment in Task Four

	Gap 1 Vehicle 1-2	Gaps 2-3 Vehicle 2-4	Gaps 4-7 Vehicle 4-8	Gaps 8-10 Vehicle 9-11	No attempt	Sum
Successful	0	3	9	7	4	23
Crash	0	4	6	3	0	13
Total who will try	0	7	15	10	4	36

Table 5: Frequency of Gap Acceptance and Crashing, Pooled over All Subjects in Tasks Three and Four

Gap Number	Task 3		Task 4	
	#Choose	#Crash	#Choose	# Crash
1	1	1	6	3
2	3	3	24	1
3	4	4	16	5
4	9	9	4	0
5	7	6	4	2
6	11	10	3	0
7	14	10	7	1
8	13	9	8	3
9	13	12	3	2
10	11	5	8	2

Table 6: Gap Sizes for Task Six, Showing the Shortest and Longest Gap

Between Vehicles	Gap Number	Gap Size (Seconds)	Shortest /Longest
1-2	1	1.26	Shortest
2-3	2	1.29	
3-4	3	1.40	
4-5	4	1.97	Longest
5-6	5	1.56	
6-7	6	1.55	
7-8	7	1.65	
8-9	8	1.70	
9-10	9	1.67	
10-11	10	1.85	

Table 7: Lottery Choice Presented to Subjects in Task Seven

Decision	Option A	Option B	Your Choice (Circle A or B)	
1	$5.00 if throw of die is 1 $4.00 if throw of die is 2-10	$10.00 if throw of die is 1 $0.25 if throw of die is 2-10	A	B
2	$5.00 if throw of die is 1-2 $4.00 if throw of die is 3-10	$10.00 if throw of die is 1-2 $0.25 if throw of die is 3-10	A	B
3	$5.00 if throw of die is 1-3 $4.00 if throw of die is 4-10	$10.00 if throw of die is 1-3 $0.25 if throw of die is 4-10	A	B
4	$5.00 if throw of die is 1-4 $4.00 if throw of die is 5-10	$10.00 if throw of die is 1-4 $0.25 if throw of die is 5-10	A	B
5	$5.00 if throw of die is 1-5 $4.00 if throw of die is 6-10	$10.00 if throw of die is 1-5 $0.25 if throw of die is 6-10	A	B
6	$5.00 if throw of die is 1-6 $4.00 if throw of die is 7-10	$10.00 if throw of die is 1-6 $0.25 if throw of die is 7-10	A	B
7	$5.00 if throw of die is 1-7 $4.00 if throw of die is 8-10	$10.00 if throw of die is 1-7 $0.25 if throw of die is 8-10	A	B
8	$5.00 if throw of die is 1-8 $4.00 if throw of die is 9-10	$10.00 if throw of die is 1-8 $0.25 if throw of die is 9-10	A	B
9	$5.00 if throw of die is 1-9 $4.00 if throw of die is 10	$10.00 if throw of die is 1-9 $0.25 if throw of die is 10	A	B
10	$5.00 if throw of die is 1-10	$10.00 if throw of die is 1-10	A	B

Table 8: Abstraction of Driving Task as a Lottery Task

Gapsize	Probability of no crash $(1-p_{crash})$*	Pay if not crash	Probability of crash (p_{crash})*	Pay if crash	EV	EU for r=0.9**
1.29	0.063	$10	.937	-$5	-$4.06	-$10.21
1.45	0.187	$9	.813	-$5	-$2.38	-$7.22
1.46	0.199	$8	.801	-$5	-$2.41	-$6.96
1.58	0.383	$7	.617	-$5	-$0.40	-$2.59
1.59	0.403	$6	.597	-$5	-$0.57	-$2.19
1.60	0.422	$5	.578	-$5	-$0.78	-$1.83
1.69	0.611	$4	.389	-$5	+$0.50	+$2.45
1.81	0.844	$3	.156	-$5	+$1.75	+$7.59
1.85	0.900	$2	.1	-$5	+$1.30	+$8.47

* The probabilities in this table are based on our estimated Weibull model for a risk averse driver who are of lowest skill and drives in Task 3.

**A CRRA utility function was used to calculate the EU, as explained in the text.

Table 9: Model of Risk Attitudes (r) and Parameters (k, λ) of the Weibull Distribution

Parameters	Variables	Variable Description	Coefficient	Standard Error	p-value
r		Constant	0.51	0.05	0.00
k		Constant	10.42	3.70	0.00
	Task4	Task4=1 if experienced	-5.49	2.96	0.06
	Skill	Number of successful turns in task 5	-1.86	0.73	0.01
λ		Constant	1.67	0.07	0.00
	Task4	Task4=1 if experienced	0.23	0.18	0.19
	Skill	Number of successful turns in task 5	-0.06	0.03	0.10
μ_R		Fechner error associated with lottery task	0.10	0.01	0.00
μ_B		Log of the Fechner error associated with driving task	1.12	0.37	0.00

Table 10: Model for Risk Neutral Drivers

Parameters	Variables	Variable Description	Coefficient	Standard Error	p-value
k		Constant	10.36	1.87	0.00
	Task4	Task4=1 if experienced	-4.51	0.96	0.00
	Skill	number of successful turns in task 5	-1.58	0.58	0.01
λ		Constant	1.76	0.08	0.00
	Task4	Task4=1 if experienced	0.30	0.15	0.04
	Skill	number of successful turns in task 5	-0.02	0.04	0.68
μ_B		Fechner error associated with driving task	1.59	0.29	0.00

Table 11: Model for Task Three Drivers Who Crashed

Parameters	Variables	Variable Description	Coefficient	Standard Error	p-value
r		Constant	0.51	0.06	0.00
k		Constant	10.55	2.69	0.00
	Skill	number of successful turns in task 5	-1.97	0.88	0.03
λ		Constant	1.64	0.05	0.00
	Skill	number of successful turns in task 5	-0.09	0.03	0.00
μ_R		Fechner error associated with lottery task	0.11	0.01	0.00
μ_B		Fechner error associated with driving task	0.73	0.19	0.00

Table 12: Model for Task Three Drivers Who Did Not Crash

Parameters	Variables	Variable Description	Coefficient	Standard Error	p-value
r		Constant	0.54	0.08	0.00
k		Constant	4.21	2.12	0.05
	Skill	number of successful turns in task 5	1.57	1.19	0.18
λ		Constant	2.17	0.21	0.00
	Skill	number of successful turns in task 5	-0.15	0.06	0.01
μ_R		Log of the Fechner error associated with lottery task	0.08	0.01	0.00
μ_B		Fechner error associated with driving task	0.98	0.24	0.00

Table 13: z-test Between Coefficients for Model Comparing Those Who Crashed and Those That Did Not Crash

Parameters	Variables	z	p-value
r	Constant	-0.27	0.78
k	Constant	1.85	0.06
	Skill	-2.39	0.02
λ	Constant	-2.47	0.01
	Skill	0.94	0.34

FIGURE 1: Driving Simulator
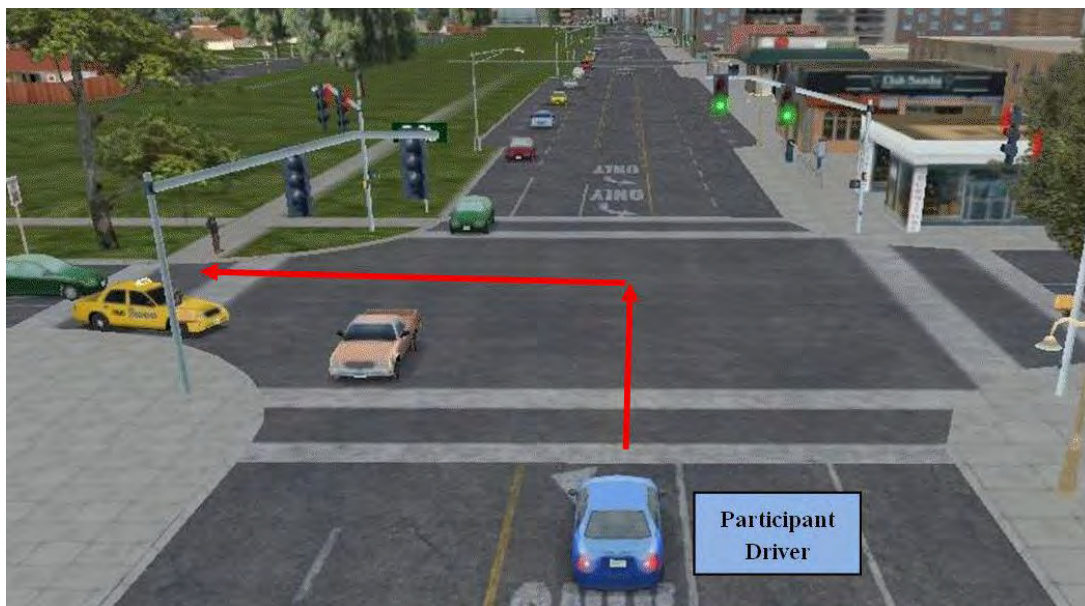
FIGURE 2: Helicopter View of the Driver Observing a Vehicle Stream
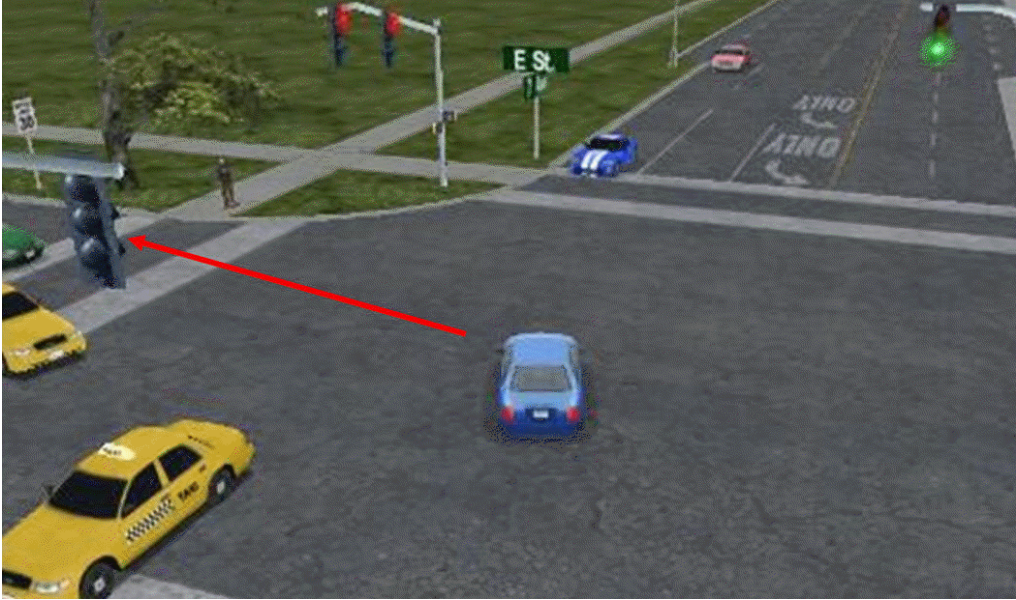
FIGURE 3: The Driver Accepting a Gap and Turning Left into Oncoming Traffic
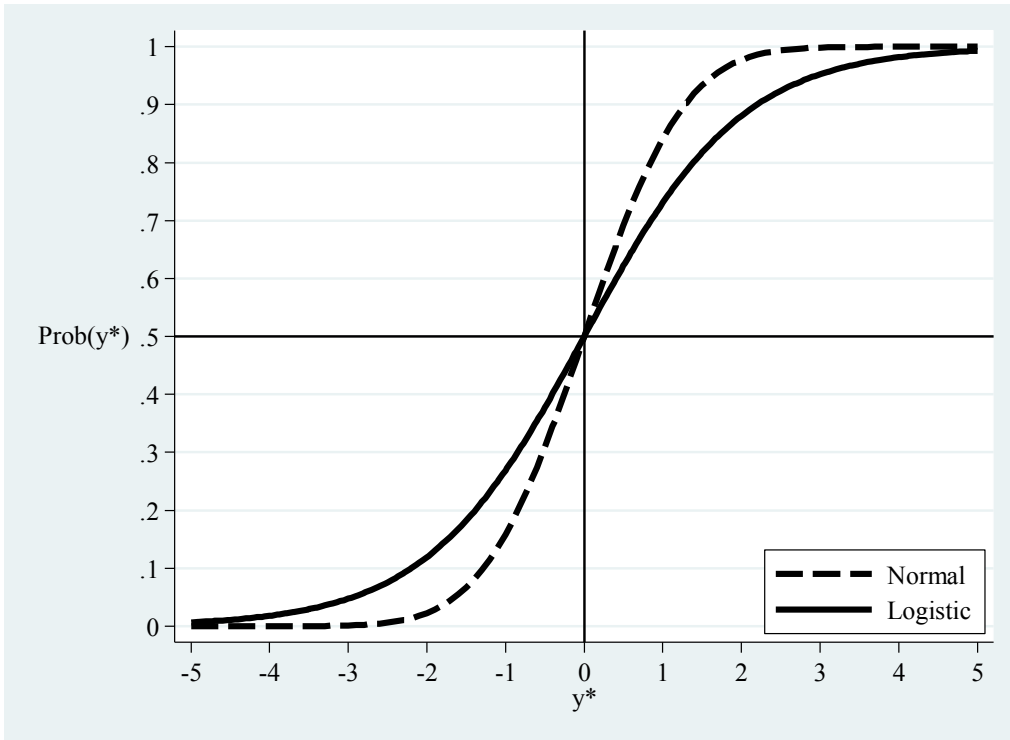
FIGURE 4: Normal and Logistic Cumulative Density Functions

NOTE: This graph is generated by setting the variable skill to its mean value.
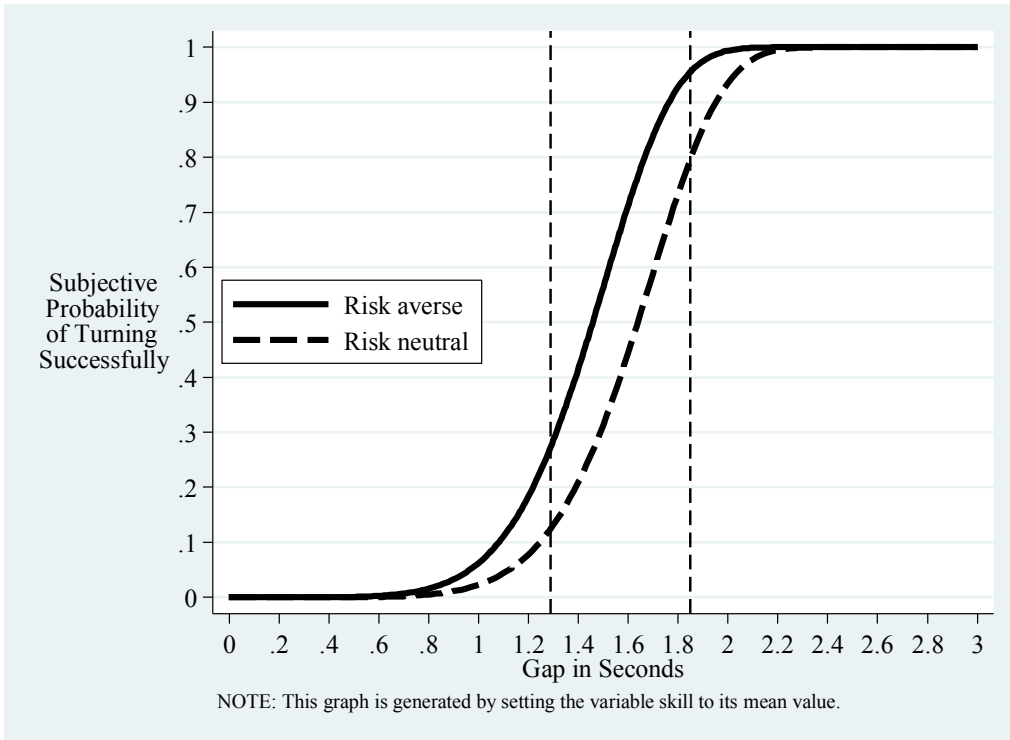
FIGURE 5: Effect of Controlling for Risk Attitudes in Inexperienced Drivers

NOTE: This graph is generated by setting the variable skill to its mean value.
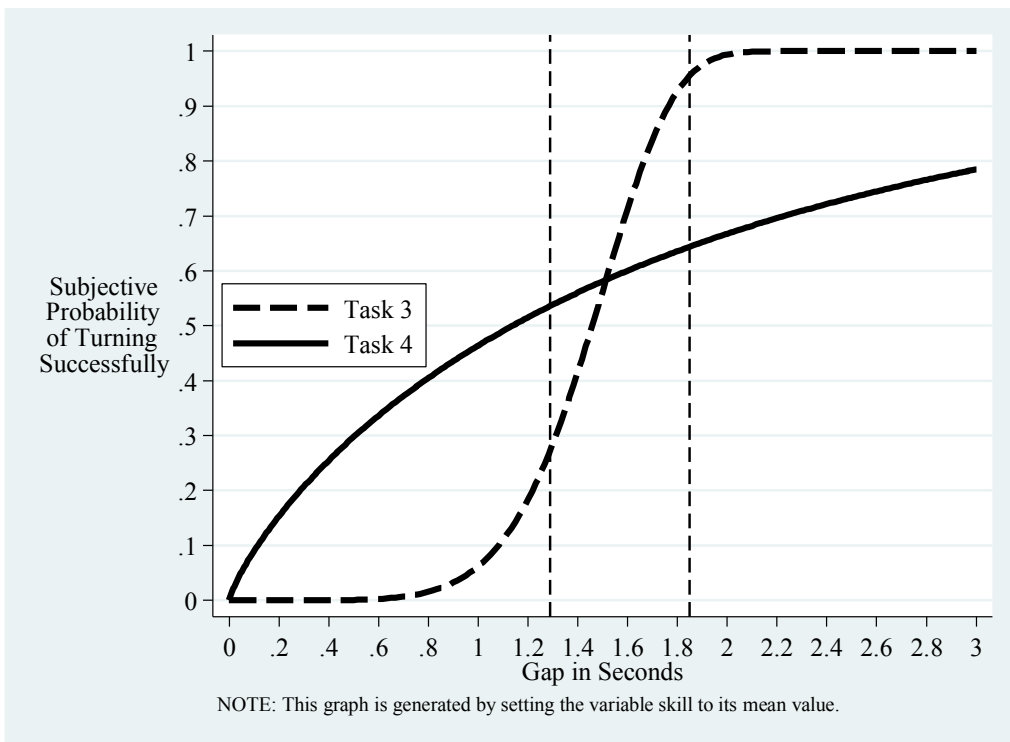
FIGURE 6: Effect of Experience on Perceived Probability of Success
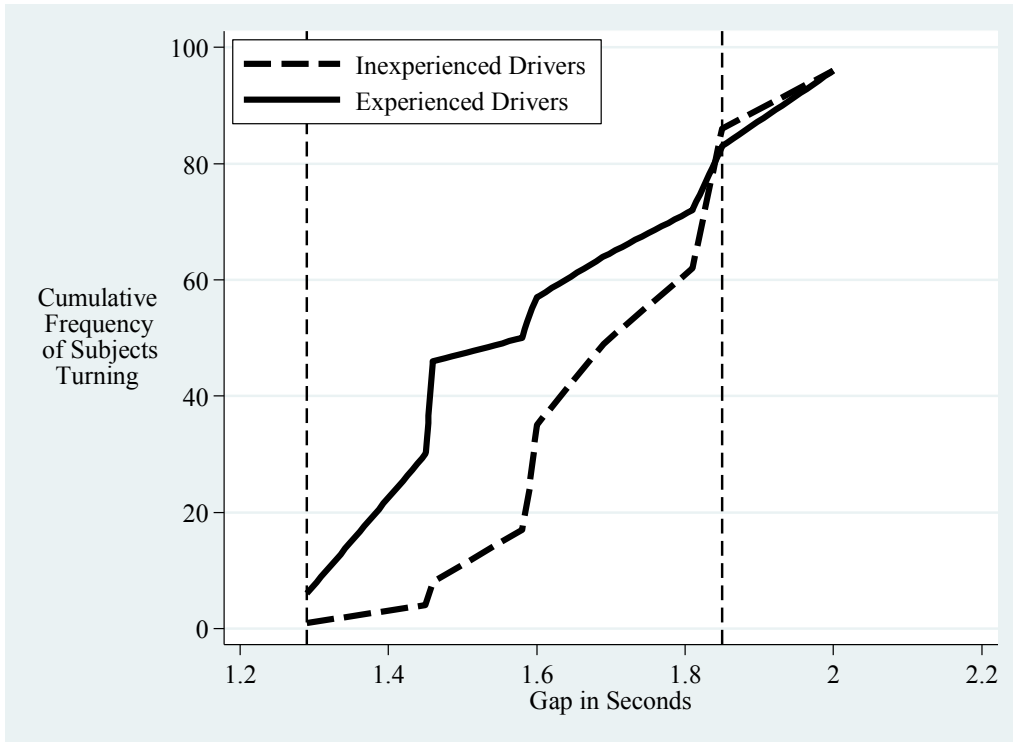
FIGURE 7: Frequency of Drivers Turning for Different Gap Sizes based on Experience

NOTE: Skill=1 are low skilled who make one successful turn in Task 5
Skill=3 are high skilled who make three successful turns in Task 5
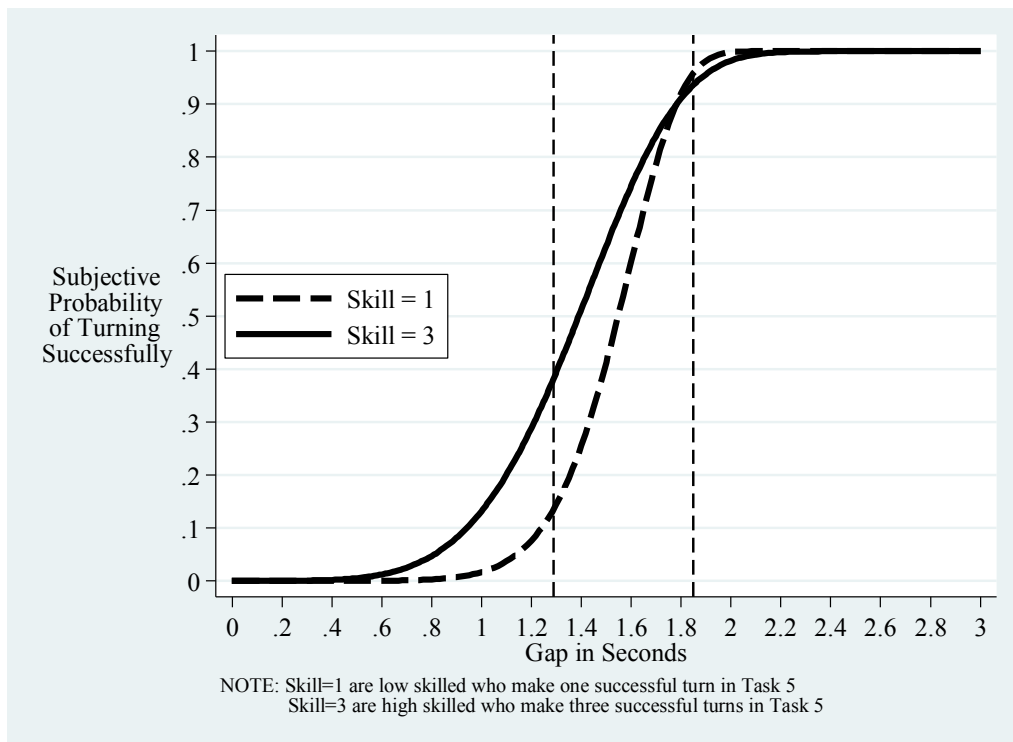
FIGURE 8: Effect of Skill on Perceived Probability of Success among Inexperienced Drivers
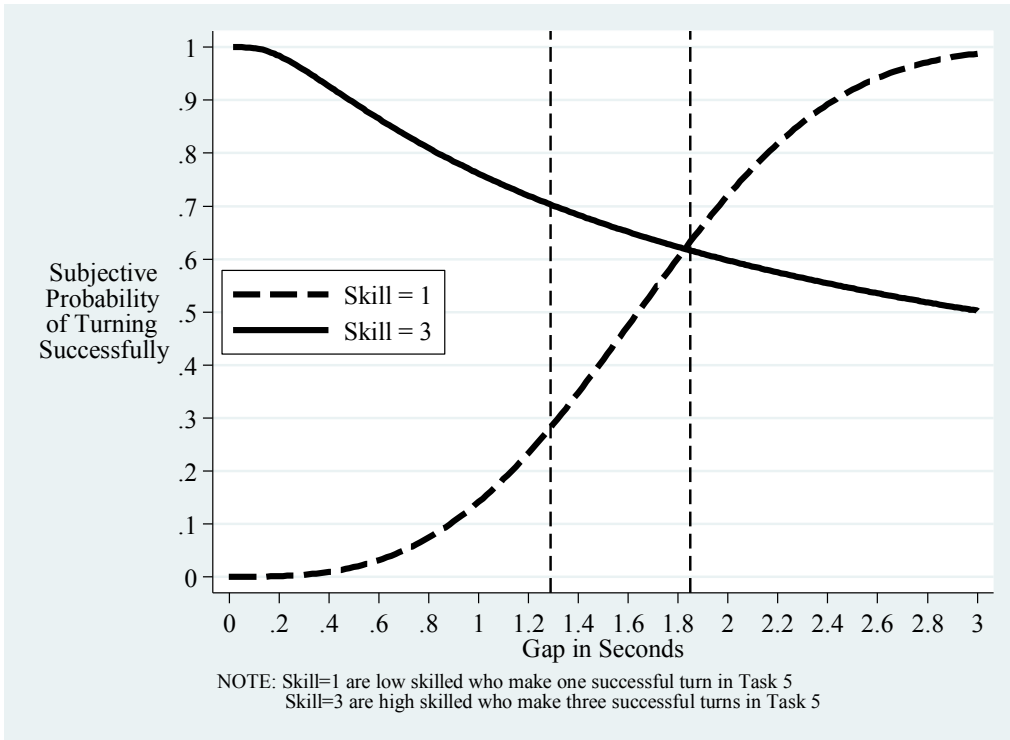
FIGURE 9: Effect of Skill on Perceived Probability of Success in Inexperienced Drivers
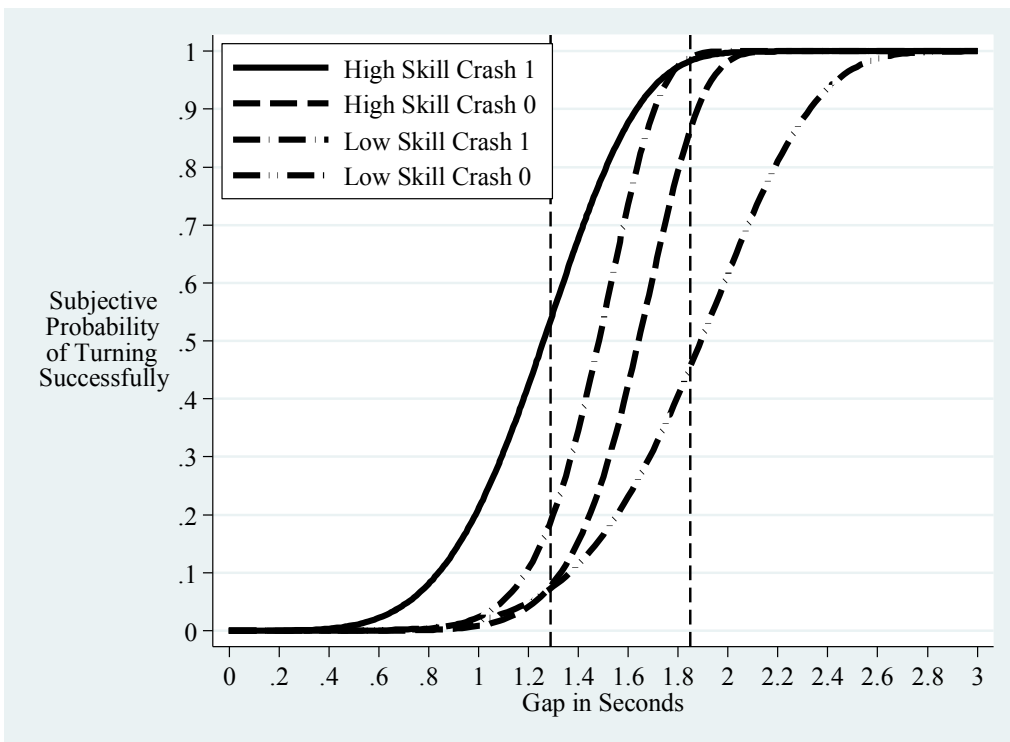
FIGURE 10: Differences in Perceived Probability of Success among Inexperienced Drivers Based on Skill and whether they Crashed or Not

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Appendix A: Instructions (<u>Not to be included for final publication</u>)

ID:

Welcome to the research study.

Please wait for an assistant to get you started.

ID:

This is a study of economic decision making.   We think you will find it interesting, you will be paid $15 for your participation, *and* you can earn additional money.   How much you earn will depend partly on chance but primarily on your own decisions. The instructions are simple and you will benefit from following them carefully.

In these tasks you should make any decisions that seem right to you.   The tasks give you the opportunity of earning money. You will be paid in cash today, at the end of the session.

The session will proceed in six parts.

In each part, except the last one, you will be making decisions in a simulated driving environment. You will have a chance to experience this environment before making decisions that have monetary consequences. In addition you will be given additional tasks: some are simple questionnaires, and others are choice tasks with monetary consequences that do not involve simulations.

The published results of our research will not identify you, or the choice you made in any way. Nor will we give this identifying information to anyone else. In fact, we will only identify you on these sheets by a numeric ID, and that ID will not appear on the sheet that has your name for our payment records.

We expect the entire task to take less than 60 minutes. You are free to leave at any time, but if you do not complete all tasks you will not receive the participation fee or your earnings.

If at any time you start feeling dizzy or nauseous, simply let us know so that you can take a break. If you feel too uncomfortable to continue you are, naturally, free to stop your participation. If you do, however, you will only receive the fixed participation fee and none of the other earnings.

In addition to the $15 participation fee, which is yours to keep, we are also giving you an initial $5 credit. This credit can be used to pay for losses you may incur, but if no losses are incurred you will be paid this $5 in addition to other earnings.

ID:

We would like to know how skilled you think you are as a driver. All drivers are not equally skilled. We want you to compare your own skill to the skill that you believe the other people who participate in this experiment have. We have recruited about 30 participants for this study, all from the UCF undergraduate student body. All participants have been recruited at the same time using the ExLab online recruitment database, the same way you were recruited.

By definition, there is one least skilled and one most skilled driver in this group of 30. We want you to indicate your own estimated position in this group. Of course, this is a difficult question since you do not know all the people in the group, or how skilled they are at driving. Nevertheless, we ask that you please make as accurate an estimate as possible.

In this table we have ranked groups of drivers from the lowest 10 percent to the highest. Please circle the range that you think you belong to.

Where do you place in terms of your skills as a driver?

Lowest   1-10%   11-20%   21-30%   31-40%   41-50%   51-60%

61-70%   71-80%   81-90%   Highest   91-100%

One aspect of skill as a driver is the safety of your driving. We also would like to know how safe you think you are as a driver. Again, we want you to compare how safe you are to how safe you believe the other participants in this experiment are as drivers.

In this table we have ranked groups of drivers from the lowest 10 percent to the highest. Please circle the range that you think you belong to.

Where do you place in terms of your safety as a driver?

Lowest   1-10%   11-20%   21-30%   31-40%   41-50%   51-60%

61-70%   71-80%   81-90%   Highest   91-100%

Please tell the lab assistant that you have finished.

ID:

PART 1 INSTRUCTIONS

In this part you will have a chance to drive in the simulator in a simplified environment. You will be sitting in a vehicle at an intersection and your task is to turn left. As you turn there will be cars on the street you turn onto, and there will also be a pedestrian waiting to cross the road. In a later part of the experiment you will be making a turn like this with monetary consequences. You will then be paid up to $10 for a successful turn in which you do not crash into any other cars or into the pedestrian. If you do not make the turn at all you will be paid nothing. If you turn and have an accident, either with other vehicles or with the pedestrian, you will have to pay $5 out of your initial credit.

You must obey normal traffic rules at all times. Thus, when turning left you must be placed in the left turning lane behind the white line, and you may not turn when the traffic light is red.

In part 1 you will have a chance to practice this turn 3 times. You will not be paid any money for these practice turns.

As you sit down in the simulator, please familiarize yourself with the controls of the vehicle before we start your first practice simulation. There is a red button on your right. Do not press this button because it stops the simulation and we would have to dismiss you without your earnings.

At any time, should you have any questions please do not hesitate to ask.

When you are ready, you will practice the turn 3 times. Immediately after these 3 practice turns, you will have one more chance to make the turn exactly the same way. In this fourth and final try you will get $2 for a successfully made turn, and $0 otherwise.

RECORD OUTCOME HERE:

Successful   ☐   **$2**

Unsuccessful   ☐   **$0**

Please return to the other room after the lab assistant has finished recording your outcome.

ID:

Some Questions About You

In this survey most of the questions asked are descriptive. We will not be grading your answers and your responses are completely confidential. Please think carefully about each question and give your best answers.

1. What is your AGE? _____ years

2. What is your sex? (Circle one number.)

   01   Male   02   Female

3. Which of the following categories best describes you?   (Circle one number.)

   01 White   06 Hispanic-American
   02 African-American   07 Hispanic
   03 African   08 Mixed Race
   04 Asian-American   09 Other
   05 Asian

4. What is your major? (Circle one number.)

   01 Accounting
   02 Economics
   03 Finance
   04 Business Administration, other than Accounting, Economics, or Finance
   05 Education
   06 Engineering
   07 Health Professions
   08 Public Affairs or Social Services
   09 Biological Sciences
   10 Math, Computer Sciences, or Physical Sciences
   11 Social Sciences or History
   12 Humanities
   13 Psychology
   14 Other Fields
   15 Does not apply

5. What is your class standing?   (Circle one number.)

   01 Freshman   04 Senior
   02 Sophomore   05 Masters
   03 Junior   06 Doctoral
   07 Does not apply

6. What is the **highest** level of education you expect to **complete**? (Circle one number)

   01 Bachelor's degree
   02 Master's degree
   03 Doctoral degree
   04 First professional degree
   05 High school diploma or GED
   06 Less than high school

ID:

7. What was the highest level of education that your **father** (or male guardian) **completed**? (Circle one number)

    01   Less than high school
    02   GED or High School Equivalency
    03   High school
    04   Vocational or trade school
    05   College or university

8. What was the highest level of education that your **mother** (or female guardian) **completed**? (Circle one number)

    01   Less than high school
    02   GED or High School Equivalency
    03   High School
    04   Vocational or trade school
    05   College or university

9. What is your citizenship status in the United States?

    01   U.S. Citizen
    02   Resident Alien
    03   Non-Resident Alien
    04   Other Status

10. Are you a foreign student on a Student Visa?

    01   Yes
    02   No

11. Are you currently...

    01   Single and never married?
    02   Married?
    03   Separated, divorced or widowed?

12. On a 4-point scale, what is your current GPA if you are doing a Bachelor's degree, or what was it when you did a Bachelor's degree? This GPA should refer to all of your coursework, not just the current year. Please pick one:

    01   Between 3.75 and 4.0 GPA (mostly A's)
    02   Between 3.25 and 3.74 GPA (about half A's and half B's)
    03   Between 2.75 and 3.24 GPA (mostly B's)
    04   Between 2.25 and 2.74 GPA (about half B's and half C's)
    05   Between 1.75 and 2.24 GPA (mostly C's)
    06   Between 1.25 and 1.74 GPA (about half C's and half D's)
    07   Less than 1.25 (mostly D's or below)
    08   Have not taken courses for which grades are given.

13. How many people live in your household? Include yourself, your spouse and any dependents. Do not include your parents or roommates unless you claim them as dependents.

    _____

ID: _____

14.   Please circle the category below that describes the total amount of INCOME earned in 2007
        by the people in your household (as "household" is defined in question 13).
        [Consider all forms of income, including salaries, tips, interest and dividend payments,
        scholarship support, student loans, parental support, social security, alimony, and child
        support, and others.]

        01      $15,000 or under
        02      $15,001 - $25,000
        03      $25,001 - $35,000
        04      $35,001 - $50,000
        05      $50,001 - $65,000
        06      $65,001 - $80,000
        07      $80,001 - $100,000
        08   over $100,000

15.   Please circle the category below that describes the total amount of INCOME earned in 2007
        by your parents.   [Consider all forms of income, including salaries, tips, interest and dividend
        payments, social security, alimony, and child support, and others.]

        01      $15,000 or under
        02      $15,001 - $25,000
        03      $25,001 - $35,000
        04      $35,001 - $50,000
        05      $50,001 - $65,000
        06      $65,001 - $80,000
        07      $80,001 - $100,000
        08   over $100,000
        09   Don't Know

16.   Do you work part-time, full-time, or neither? (Circle one number.)

        01   Part-time
        02   Full-time
        03   Neither

17.   Before taxes, what do you get paid? (fill in only one)

        01   _____ per hour before taxes
        02   _____ per week before taxes
        03   _____ per month before taxes
        04   _____ per year before taxes

18.   Do you currently smoke cigarettes? (Circle one number.)

        00   No
        01   Yes

        If yes, approximately how much do you smoke in one day? _____ packs

ID:

19.   How frequently do you drive?

        01   Almost every day
        02   Almost every week
        03   Several times a year
        04   Very rarely
        05   Not at all for more than one year

20.   How often do you play video games?

        01.   Almost every day
                    How many hours?_____
        02.   Almost every week
                    How many hours each time?_____
        03   Several times a year
        04   Very rarely
        05   Not at all for more than one year
        06   Never

Please tell the lab assistant that you have finished with the questionnaire.

PART 2 INSTRUCTIONS

In this simulation you will not be driving a vehicle but you will be viewing a simulation of the same intersection where you practiced turning in Part 1. The one difference from Part 1 is that there will be oncoming vehicles in the intersection. Later, when you will attempt to turn for money this is how the simulation will be. It will therefore be of some value to you to be able to judge the distance between vehicles in order to make a choice when to turn. In this part you will first view 3 simulations with 11 oncoming vehicles where the distance between them varies.

Each of the simulations you will view here will differ in terms of the distances between each of the vehicles.

After viewing these you will view one final simulation in which you are asked to guess which one of the gaps between the vehicles is the longest gap and which one is the shortest gap. For each gap you guess correctly you will be paid $1, so you can earn up to $2 in this task. If you are wrong you get no money for that guess.

I believe the shortest gap was gap number

1	☐	2	☐	3	☐	4	☐
5	☐	6	☐	7	☐	8	☐
9	☐	10	☐				

I believe the longest gap was gap number

1	☐	2	☐	3	☐	4	☐
5	☐	6	☐	7	☐	8	☐
9	☐	10	☐				

We will tell you the correct answer at the end of the session today.

Please let the lab assistant know when you are finished.

ID:

For the following questions, please circle one response that best matches your reaction to the statement.

1. "I believe that fate will mostly control what happens to me in the years ahead."

    | Strongly Disagree | Disagree | Slightly Disagree | Slightly Agree | Agree | Strongly Agree |

2. "I am usually able to protect my personal interests."

    | Strongly Disagree | Disagree | Slightly Disagree | Slightly Agree | Agree | Strongly Agree |

3. "When I get what I want, it's usually because I'm lucky."

    | Strongly Disagree | Disagree | Slightly Disagree | Slightly Agree | Agree | Strongly Agree |

4. "In order to have my plans work, I make sure that they fit in with the desires of people who have power over me."

    | Strongly Disagree | Disagree | Slightly Disagree | Slightly Agree | Agree | Strongly Agree |

5. "I have mostly determined what has happened to me in my life so far."

    | Strongly Disagree | Disagree | Slightly Disagree | Slightly Agree | Agree | Strongly Agree |

6. "Whether or not I get into a car accident depends mostly on the other drivers."

    | Strongly Disagree | Disagree | Slightly Disagree | Slightly Agree | Agree | Strongly Agree |

7. "Chance occurrences determined most of the important events in my past."

    | Strongly Disagree | Disagree | Slightly Disagree | Slightly Agree | Agree | Strongly Agree |

8. "I feel like other people will mostly determine what happens to me in the future."

    | Strongly Disagree | Disagree | Slightly Disagree | Slightly Agree | Agree | Strongly Agree |

9.   "When I make plans, I am almost certain to make them work."

| Strongly Disagree | Disagree | Slightly Disagree | Slightly Agree | Agree | Strongly Agree |

10.   "Getting what I want requires pleasing those people above me."

| Strongly Disagree | Disagree | Slightly Disagree | Slightly Agree | Agree | Strongly Agree |

11.   "Whether or not I get into a car accident depends mostly on how good a driver I am."

| Strongly Disagree | Disagree | Slightly Disagree | Slightly Agree | Agree | Strongly Agree |

12.   "Often there is no chance of protecting my personal interests from bad luck."

| Strongly Disagree | Disagree | Slightly Disagree | Slightly Agree | Agree | Strongly Agree |

13.   "When I get what I want, it's usually because I worked hard for it."

| Strongly Disagree | Disagree | Slightly Disagree | Slightly Agree | Agree | Strongly Agree |

14.   "Most of my personal history was controlled by other people who had power over me."

| Strongly Disagree | Disagree | Slightly Disagree | Slightly Agree | Agree | Strongly Agree |

15.   "Whether or not I get into a car accident is mostly a matter of luck."

| Strongly Disagree | Disagree | Slightly Disagree | Slightly Agree | Agree | Strongly Agree |

16.   "I think that I will mostly control what happens to me in future years."

| Strongly Disagree | Disagree | Slightly Disagree | Slightly Agree | Agree | Strongly Agree |

17.   "People like myself have very little chance of protecting our personal interests when they conflict with those of strong pressure groups."

| Strongly Disagree | Disagree | Slightly Disagree | Slightly Agree | Agree | Strongly Agree |

18.   "It's not always wise for me to plan too far ahead because many things turn out to be a matter of good or bad fortune."

Strongly Disagree	Disagree	Slightly Disagree	Slightly Agree	Agree	Strongly Agree

Please let the lab assistant know when you are finished.

ID:

PART 3 INSTRUCTIONS

In this part you will be making one left turn in the same intersection, but this time with oncoming traffic. The gaps between the oncoming vehicles will start out small and will increase as time passes.

You may not turn before the first oncoming vehicle.

You must turn before the last of the oncoming vehicles comes through the intersection in order to get paid. If you do not complete the turn you get no money. If you complete the turn with no accident you will be paid up to $10. If you have an accident you will be charged $5 out of your accumulated earnings.

A successful turn between the first two vehicles will pay you $10, but for every extra vehicle you delay the reward decreases by a dollar. So if you successfully turn between the 2nd and the 3rd vehicle you get $9, between the 3rd and the 4th $8, etc. until the last chance between the 10th and the 11th vehicle where you would be paid $1.

However, if you attempt a turn but have an accident, either with another vehicle or with the pedestrian, you will not get the reward but instead will have to pay for the accident. This accident cost is constant at $5 throughout the simulation. Therefore, it does not matter when you have an accident: if you have one it will cost you $5.

You will have a chance to view the pattern of the gaps between the vehicles one time before attempting the turn. Remember that they will be ordered from smallest to largest. Thus, we will play out the simulation one time completely first, and then you will be asked to make the turn the second time we play it out.

Do you have any questions?

Remember that if you do not turn before the last (11th) vehicle enters the intersection you will earn $0 for this part.

Are you ready to view the simulation one time now?

RECORD OUTCOME HERE:

Successful ☐ **gap number _____** **$_____**

Accident ☐ **gap number _____** **$- $5**

No turn ☐ **$0**

Please return to the other room after the lab assistant has finished recording your outcome.

ID:

We have run this experiment in the past with 36 participants. Each of them were given the exact same tasks in the exact same order. We would like to know how many of these 36 participants that you believe were able to turn without an accident in Part 3 that you just completed.

How many do you think attempted to turn between the vehicles indicated in each column of the table? Further, how many of these do you think were successful or crashed?

Please put a number in each cell to indicate the number of people you expect in that cell. Make sure that the number of people, when summed up over all cells, equals 36. There are 10 cells to fill in, apart from those for summations. The first column is for those you believe tried to turn in the first gap, between the 1st and 2nd vehicle. The second column is for those you believe tried to turn in either the second or the third gap, i.e. between the 2nd and 3rd or the 3rd and 4th vehicle. Similarly for the columns labeled "Gaps 4-7" and "Gaps 8-10". The column labeled "No attempt" is for those you believe never tried to turn at all. If you believe some people never tried you fill that number in only on the last row of that column. Make sure to check your sums.

	Gap 1 Vehicle 1-2	Gaps 2-3 Vehicle 2-4	Gaps 4-7 Vehicle 4-8	Gaps 8-10 Vehicle 9-11	No attempt	Sum
Successful						
Crash						
Total who will try						

For each of the 5 columns, and for each of the two rows, we will pay you 50 cents if you are correct. If you are correct in all cells you will therefore be paid $3.50. The experimenters will check your results while you complete the experiment and will let you know how you did at the end.

Please let the lab assistant know when you are finished.

ID:

PART 4 INSTRUCTIONS

In this part the driving scenario is exactly like last time, but now you will <u>not be paid for your turn or charged for any accidents</u>. This is a chance for you to practice the turn with no consequences. You will have a chance to <u>practice 3 times</u>. The gaps are exactly the way they were in the previous turn.

After you have finished your 3 practice turns <u>you will once again have a chance to make the left turn for money</u>. The situation is identical to Part 3.

RECORD PRACTICE OUTCOMES HERE:

Practice 1: gap number _____   Successful ☐   Accident ☐

Practice 2: gap number _____   Successful ☐   Accident ☐

Practice 3: gap number _____   Successful ☐   Accident ☐

You must turn before the last of the oncoming vehicles comes through the intersection in order to get paid. If you do not complete the turn you get no money. If you complete the turn with no accident you will get up to $10, but again this reward is decreasing as more and more cars pass by. If you have an accident at any time you will be charged $5 out of your accumulated earnings.

RECORD OUTCOME HERE:

Successful	☐	**gap number _____**	**$_____**
Accident	☐	**gap number _____**	**$- $5**
No turn	☐	**$0**	

Please return to the other room after the lab assistant has finished recording your outcome.

ID:

We will now ask you to guess how many of the 36 participants in our previous study you believe made this last turn successfully. Please put a number in each cell. Again, make sure that the number of people equals 36.

How many do you think attempted to turn between the vehicles indicated in each column of the table? Further, how many of these do you think were successful or crashed?

Please put a number in each cell to indicate the number of people you expect in that cell. Make sure that the number of people, when summed up over all cells, equals 36. There are 10 cells to fill in, apart from those for summations. The first column is for those you believe tried to turn in the first gap, between the 1st and 2nd vehicle. The second column is for those you believe tried to turn in either the second or the third gap, i.e. between the 2nd and 3rd or the 3rd and 4th vehicle. Similarly for the columns labeled "Gaps 4-7" and "Gaps 8-10". The column labeled "No attempt" is for those you believe never tried to turn at all. If you believe some people never tried you fill that number in only on the last row of that column. Make sure to check your sums.

	Gap 1 Vehicle 1-2	Gaps 2-3 Vehicle 2-4	Gaps 4-7 Vehicle 4-8	Gaps 8-10 Vehicle 9-11	No attempt	Sum
Successful						
Crash						
Total who will try						

For each of the 5 columns, and for each of the two rows, we will pay you 50 cents if you are correct. If you are correct in all cells you will therefore be paid $3.50. The experimenters will check your results while you complete the experiment and will let you know how you did at the end.

Please let the lab assistant know when you are finished.

ID:

PART 5 INSTRUCTIONS

In this part the driving scenario is exactly like last time, and you will again be paid for your turn. This time <u>we will tell you which gap you need to turn in to get paid</u>. We have here several cards and on each we have indicated a gap you will turn in. We will shuffle these card and then you will follow the gap instructions on each of them in the order they end up after shuffling. You will be turning 4 more times in this part. You will only turn once in Gap 1, once in either of Gaps 2-3, once in either of Gaps 4-7, and once in either of Gaps 8-10. If you pull a card that corresponds to a gap grouping that you have already turned in then you will pull another card.

If you successfully turn in the requested gap you will be paid $5. If you crash or if you do not turn you will get nothing for that attempt.

	Card 1	Card 2	Card 3	Card 4	Sum
Gap 1					
Gaps 2-3					
Gaps 4-7					
Gaps 8-10					
Success					
Crash					
Earnings					

Please return to the other room after the lab assistant has finished recording your outcome.

The experimenter will now score your guesses in tasks 3 and 4. You can then return to the simulator when it is available.

PART 6 INSTRUCTIONS

This time you will view a simulation of the intersection without turning. We again ask you to guess which one of the gaps between the oncoming vehicles is the shortest and which is the longest. The gaps will not be ordered from the shortest to the longest, but will appear in a random order. You will only view this one time and will guess immediately.

We will pay you $1 for each correct answer, i.e. you can earn up to $2.

I believe the shortest gap was gap number

1 ☐	2 ☐	3 ☐	4 ☐
5 ☐	6 ☐	7 ☐	8 ☐
9 ☐	10 ☐		

I believe the longest gap was gap number

1 ☐	2 ☐	3 ☐	4 ☐
5 ☐	6 ☐	7 ☐	8 ☐
9 ☐	10 ☐		

We will tell you the correct answer at the end of the session today.

Please let the lab assistant know when you are finished.

PART 7 INSTRUCTIONS

Your decision sheet on the next page shows ten decisions listed on the left. Each decision is a paired choice between "Option A" and "Option B." You will make a choice on each row and record these in the final column.

Here is a ten-sided die that will be used to determine payoffs. The faces are numbered from 0 to 9, and we will use the 0 face of the die to serve as 10. Look at Decision 1 at the top. Option A pays $5.00 if the throw of the ten sided die is 1, and it pays $4.00 if the throw is 2-10. Option B yields $10.00 if the throw of the die is 1, and it pays $0.25 if the throw is 2-10.

The other Decisions are similar, except that as you move down the table, the chances of the higher payoff for each option increase. In fact, for Decision 10 in the bottom row, the die will not be needed since each option pays the highest payoff for sure, so your choice here is between $5.00 or $10.00.

After you have finished making your choices, you will throw this die twice, once to select one of the ten decisions to be used, and a second time to determine what your payoff is for the option you chose, A or B, for the particular decision selected. Even though you will make ten decisions, only one of these will end up affecting your earnings, but you will not know in advance which decision will be used.

ID:

Decision	Option A	Option B	Your Choice (Circle A or B)
1	$5.00 if throw of die is 1 $4.00 if throw of die is 2-10	$10.00 if throw of die is 1 $0.25 if throw of die is 2-10	A B
2	$5.00 if throw of die is 1-2 $4.00 if throw of die is 3-10	$10.00 if throw of die is 1-2 $0.25 if throw of die is 3-10	A B
3	$5.00 if throw of die is 1-3 $4.00 if throw of die is 4-10	$10.00 if throw of die is 1-3 $0.25 if throw of die is 4-10	A B
4	$5.00 if throw of die is 1-4 $4.00 if throw of die is 5-10	$10.00 if throw of die is 1-4 $0.25 if throw of die is 5-10	A B
5	$5.00 if throw of die is 1-5 $4.00 if throw of die is 6-10	$10.00 if throw of die is 1-5 $0.25 if throw of die is 6-10	A B
6	$5.00 if throw of die is 1-6 $4.00 if throw of die is 7-10	$10.00 if throw of die is 1-6 $0.25 if throw of die is 7-10	A B
7	$5.00 if throw of die is 1-7 $4.00 if throw of die is 8-10	$10.00 if throw of die is 1-7 $0.25 if throw of die is 8-10	A B
8	$5.00 if throw of die is 1-8 $4.00 if throw of die is 9-10	$10.00 if throw of die is 1-8 $0.25 if throw of die is 9-10	A B
9	$5.00 if throw of die is 1-9 $4.00 if throw of die is 10	$10.00 if throw of die is 1-9 $0.25 if throw of die is 10	A B
10	$5.00 if throw of die is 1-10	$10.00 if throw of die is 1-10	A B

DECISION ROW CHOSEN BY FIRST THROW OF THE DIE: _____
THROW OF THE DIE TO DETERMINE PAYMENT: _____
EARNINGS: _____
Let the lab assistant know when you are done filling in the record sheet.