Accident Analysis and Prevention 62 (2014) 63–78

Contents lists available at ScienceDirect

Accident Analysis and Prevention

journal homepage: www.elsevier.com/locate/aap

Estimating the subjective risks of driving simulator accidents☆

Vinayak Dixit[a,*], Glenn W. Harrison[b], E. Elisabet Rutström[c]

[a] School of Civil and Environmental Engineering, University of New South Wales, Sydney, Australia
[b] Department of Risk Management & Insurance and Center for the Economic Analysis of Risk, Robinson College of Business, Georgia State University, USA
[c] Dean's Behavioral Economics Lab, Robinson College of Business and Department of Economics, Andrew Young School of Policy Studies, Georgia State University, USA

ARTICLE INFO

Article history:
Received 18 May 2013
Received in revised form 29 July 2013
Accepted 22 August 2013

Keywords:
Experimental economics
Risk aversion
Subjective beliefs
Safety
Driver behavior

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.

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; 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 in 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; pp. 731–732) stated that "the question arises as to whether the driver has some knowledge of his ability and sets his critical

☆ We are grateful for the research support under grants from the Exploratory Advanced Research Program of the U.S. Federal Highway Administration.

* Corresponding author. Tel.: +61 2938 55381.
E-mail addresses: v.dixit@unsw.edu.au (V. Dixit), gharrison@gsu.edu (G.W. Harrison), erutstrom@gsu.edu (E.E. Rutström).

0001-4575/$ – see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.aap.2013.08.023

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; Greaves and Ellison, 2011). It has been shown that survey questions about intentions to act can result in biased measurements (Cummings et al., 1995; 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; Otsubo and Rapaport, 2008), route choice (Rapoport et al., 2006; Selten et al., 2007; Ramadurai and Ukkusuri, 2007; Daniel et al., 2009; Morgan et al., 2009; Hartman, 2012), 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. Fig. 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

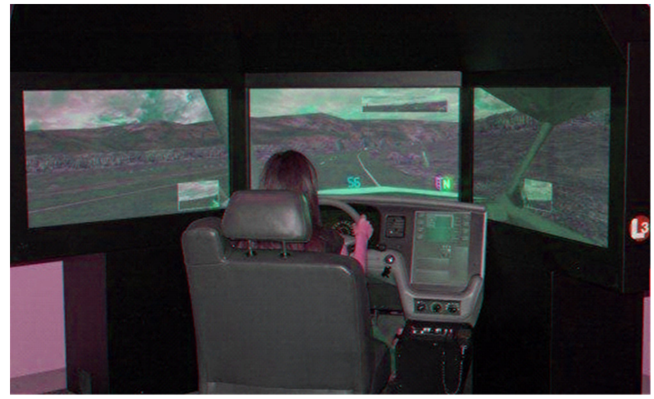

Fig. 1. Driving simulator.

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

Table 1
Gap sizes for Task 2, 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	