

**ELICITING RISK ATTITUDES FROM ROUTE CHOICES OVER SIMULATED
DRIVING CHOICES**

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ABSTRACT

Transportation planners and engineers alike have identified that drivers' risk attitudes have a significant effect on their route and departure time choices. We utilize methods from experimental economics to elicit risk attitudes through controlled incentivized experiments in driving simulators with actual monetary consequences. This last feature of our design can eliminate hypothetical biases observed in other studies that utilize purely hypothetical questions. We identify risk attitudes by defining simulated route choices as lotteries that may pay some money for sure or different monetary rewards with some uncertainty. We use structural estimation to estimate risk attitudes in our sample and allow for both Expected Utility theory and Rank-Dependent Utility theory. Our econometric approach applies the "contextual utility" correction by Wilcox (2011) to control for "size effects" that have been identified in the estimation of value of time and reliability. Our experimental design allows us to compare risk attitudes across two different regions in the US and study the demographic determinants of risk aversion. We find that, both under Expected Utility and Rank-Dependent Utility, risk attitudes are heterogeneous in our sample and largely explained by subjects' age and accumulated wealth during the experiment. Finally, we find no evidence of a structural difference between the two traffic regions used in this study.

KEYWORDS

DRIVING SIMULATORS, EXPERIMENTAL ECONOMICS, EXPECTED UTILITY THEORY, CONTEXTUAL UTILITY

1. INTRODUCTION

The literature demonstrates that risk attitudes (1-8) are important determinants of the valuation of travel time reliability. An important issue to study is the variability of risk attitudes across geographic traffic regions: If one can predict risk attitudes across regions with some degree of accuracy then it may not be necessary to conduct full scale measurements for every new policy evaluation in different geographic areas. In addition, finding simpler ways of eliciting risk attitudes, while maintaining the traffic context, can facilitate traffic policy evaluations. Here we present data from an experiment that elicits and compare risk attitudes from subjects recruited in the field both in Orlando, FL, and Atlanta, GA. Choices were framed in a driving context by generating simulated environments in driving simulators. We found that upon controlling for demographics there are no structural differences in risk attitudes among people living in the two regions from which we sampled from. Monetary incentives are presented to participants to incentivize responses rather than simply using hypothetical questions that rely on subjects truthfully revealing their preferences without any type of real incentive. Our approach is designed to avoid the hypothetical bias documented in the literature (9-11) and which is a critique to studies that use traditional surveys that do not provide incentives. The study uses methods from experimental economics to conduct controlled incentivized experiments to elicit risk attitudes (12) and uses structural econometrics to explicitly estimate them.

2. LITERATURE REVIEW

Studies that have investigated and modeled route and mode choices have relied on mean-variance models (13-18) that assume linear separability between the mean and variance in a linear utility model. Koster and Verhoeff (2012) (8) showed that under the assumption of independence between the mean and variance of travel time, the parameter estimates of variance under the linear separability assumptions (13-18) captures risk aversion with regard to departure time choice. Fosgerau (2010) (19) based on theory and field data showed that the mean and variance of travel time are in fact correlated, and undergo hysteresis, where in for the same mean travel time the variance of travel time is larger when recovering from congestion than when getting to it. Therefore, the parameter estimates could be biased. Consequently, it is critical to explicitly model risk attitudes in the utility function.

Typical studies (1-8, 10-18) that have evaluated value of time and value of reliability have relied on surveys with hypothetical questions, and therefore the resulting data are prone to hypothetical bias (7, 8, 9). To control for hypothetical bias, other studies have used revealed preference data or a combination of revealed and stated preference data (33-36). Methods from experimental economics are another way to control for hypothetical bias. A key characteristic of experimental economic methods is the use of incentive compatible instruments with actual monetary consequences for choices. The experimental instruments are based on the Induced Value Theory proposed by Smith (1974) for which he received the Nobel Memorial Prize in Economics in 2002 (20). Methods in experimental economics provide experimenters with insights about individuals' underlying preferences and with a wide range of laboratory and field tools while reducing hypothetical bias (11, 14). Using laboratory experiments to study driver behavior has proven to be informative to a number of questions such as studying equilibrium properties of

route choice and departure time choice (e.g., Rapoport et al., 2006 (21) and Selten et al., 2004(22)). Nielsen (2004) (23) studied individual travel behavior with regard to vehicle km travelled and estimated the value of time using actual incentives. Dixit et al. (24) and Mahmassani (2009) used actual incentives in controlled and interactive experiments to investigate travel behavior dynamics.

De Palma and Picard (2004) studied risk attitudes with hypothetical incentives for different user groups and across different *task domains*, i.e. for a financial portfolio choice and route choice in traffic (6). In the traffic context they studied choices across different routes with different expected travel times and different travel time variability. They found that absolute risk aversion was constant within a task domain, but was significantly different across domains. In addition Palma and Picard found that risk aversion was larger for transit users, blue collars and for business appointments, suggesting demographic effects on risk attitudes. The demographic effects on risk attitudes have been found to explain choice heterogeneity in lottery choice experiments as well (25, 26). From a policy perspective if risk attitudes are found to be heterogeneous across different traffic regions, this would mean that the policy agency would have to undertake these studies in each region. This motivates one of the first questions we ask in this study: Are risk attitudes different across individuals living in geographically different areas, while controlling for demographics?

Recent investigations (6, 7) have found “*size effects*” where the value of travel time savings has been found to increase with increments in travel time savings. Hjorth and Fosgerau (2011) found that this can be explained by “*reference dependence*” (7). They suggest using the ratio of difference in cost and travel time savings to estimate the value of travel time. A new utility paradigm proposed by Wilcox (2011) (27) called contextual utility was proposed to explain well-known violations of capability such as the Myers effect (Myers and Sadler, 1960) (28) in much the same way other heteroscedastic models such as decision field theory do (29). The final contribution of this paper is the use of “contextual utility” to control for this size effect. The advantage of using contextual utility is that it is strongly grounded in behavioral economics and has been found to get control for scale effects.

Our working hypothesis is that attitudes towards risk, as it is understood in the economics literature (e.g., Pratt, 1964 (12)), play a crucial role in driving route choices, therefore, our purpose is to study risk attitudes elicited from driving choices in driving simulation tasks. In particular, we study and compare choices from subjects recruited in the field both in Atlanta and Orlando.

To exemplify our approach suppose there are two routes a subject can take to go from home to work. One of those routes is a highway where the traffic flow is very predictable but the person has to pay a toll to use this route. The other route, where there is no toll, traffic can be very unpredictable. Thus, one could identify the highway route with a *safe bet* in the sense that a sufficiently risk averse individual would always choose the highway over the other route, even if that means to pay a toll, much like a person is willing to pay more for a financial asset that generates a safer stream of income. Similarly, one can identify the other route with a *risky bet* in the sense that a person that is very tolerant to risk might exhibit a strong preference for the

second route which has less predictable outcomes. We designed driving simulated environments that have monetary consequences and then we use experimental procedures and structural econometrics to elicit driving choices from subjects and estimate risk attitudes implied by those choices. We explain below in more detail the mapping from driving choices to monetary bets.

3. VALUATION TASKS

3.1 Valuation Tasks: Simulation Scenarios

Two simulation scenarios were developed for these experiments, both in the downtown area of the simulated world. Figure 1 shows a map of the downtown area, with the relevant streets marked in. In both scenarios, the driver's car is initially parked on B Street just south of the intersection with 6th Avenue (labeled home for illustration). The task is to drive from this point to the parking lot outside of a warehouse on F Street just north of 9th Avenue (labeled work for illustration). The drive takes 2 to 4 minutes, depending on which route they take and which scenario they are in. The driver can choose to take either 7th Avenue or 9th Avenue between B Street and F Street. No other options are allowed. Apart from the occasional random car that is modeled as a default in any scenario, some additional vehicles have been added to the simulation. This is partly to assist the driver in following the rules, such as speed limits, and partly for added realism.

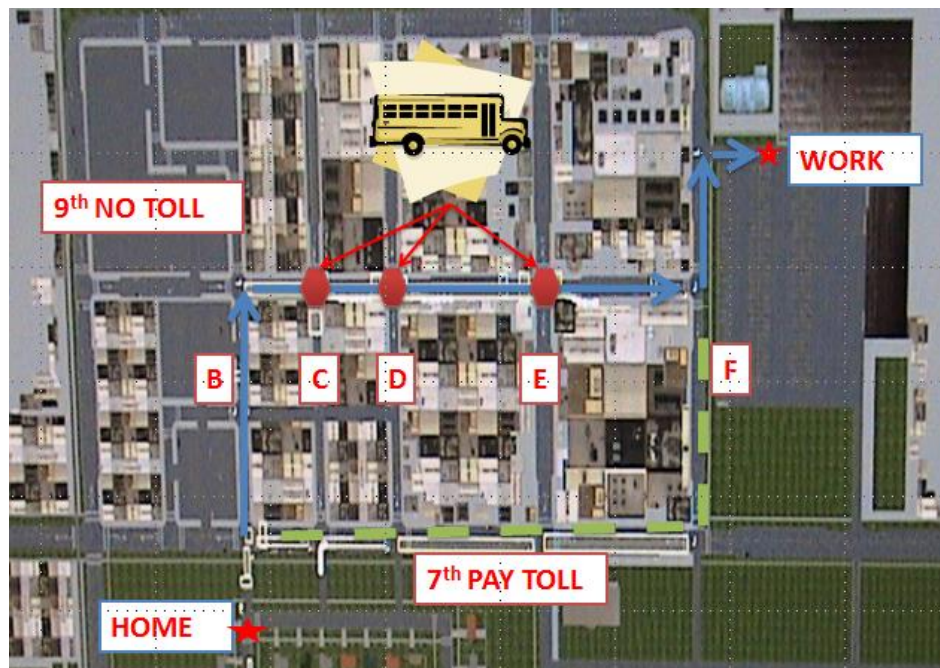


Figure 1: Downtown network with bus on 9th Avenue

As the driver reaches the intersection 7th Avenue and B Street the traffic light always turns red. This is to allow the driver some time to make the choice between turning right to get on 7th Avenue or continuing straight to take 9th Avenue.

The two scenarios differ only in one aspect: whether a school bus pulls up on 9th Avenue from C Street or not. When it does, it slows down the queue of vehicles traveling ahead of the participant vehicle on 9th Avenue.

Each participant drives six times in the simulator. The first three drives are practice drives and the second three drives are paid tasks. The driving tasks given to subjects are designed to elicit risk attitudes in the context of simulated drives. For this purpose the task was designed to mimic a standard risky choice task that is frequently used in the experimental economics literature. A participant is presented with a series of pairwise choices between prospects that differ in risk. In standard risky choice experiments it is common to give each participant a series of binary choices consisting of at least ten pairs, sometimes even as many as 100. Due to the time each drive takes in the simulator, and the risk of nausea, each driver only made three such pairwise choices.

Each pair of prospects consists of a choice between the 7th Avenue route and the 9th Avenue route. The former is the safer route because there is never a risk of a congestion delay due to a school bus. 9th Avenue is the risky route because there is a probability that drivers will encounter a school bus. This probability is explicitly told to subjects and varies across drivers and can be 0.3, 0.5 or 0.7. This is how travel time unreliability is induced. Each driver is also randomly assigned a wage which will be paid for each completed drive, and this wage can be \$4, \$5, or \$6. If the driver takes 9th Avenue and if there is no school bus, then this is the payment for that drive. However, if there is a bus the payment drops to \$0.25. This penalty for being late due to getting stuck behind a school bus is not related to the actual travel time in this task, but depends only on whether there is a bus or not. Each subject is randomly assigned a wage and a probability of a bus appearing on 9th Avenue by using a pseudo-random number generator. If the driver takes 7th Avenue there is a toll to be paid, and it is simply deducted from his wage. The toll varies across the three drives and is selected prior to the drives by the participant drawing a card from each of three decks. One of the drives has a toll from a deck with the low toll range, one drive has a toll from the medium range, and one has a toll from the high range (Table 1 shows wages and their corresponding toll ranges). The order in which drivers encounter the low, medium and high range is randomly determined by the participant rolling dice.

Table 1: Tolls and Wages in the Simulator Task

	Low Toll Range	Medium Toll Range	High Toll Range
Wage=\$4	\$0.5-\$1.50	\$1.60-\$2.50	\$2.60-\$3.50
Wage=\$5	\$0.5-\$1.80	\$1.90-\$3.20	\$3.30-\$4.50
Wage=\$6	\$0.5-\$2.80	\$2.20-\$3.80	\$3.90-\$5.50

To illustrate an implied pairwise route choice, Table 2 shows an example of the set of 3 choices a driver might face. In this example the probability of encountering a bus is 0.5, the wage is \$5, and the penalty for ending up behind a bus is \$4.75. This implies that the subject is facing a choice that pays \$5 with 50% chance and \$0.25 with 50% chance. On the contrary, the subject can earn \$5 for sure if he/she takes 7th Avenue but has to pay a toll to use this route. For any subject, these values are the same across the three drives except the value of the toll which is randomly determined. The last column shows that, for this example, the expected value of taking

7th Avenue exceeds that of taking 9th Avenue for the first two tolls, so a risk neutral driver would be expected to choose 7th Avenue for all but the highest of these three toll values (\$3.70). However, a sufficiently risk averse driver will choose to take 7th Avenue even when the expected value of taking 9th Avenue exceeds the expected value of taking the other route. By varying the tolls and the bus probabilities across drivers we can infer a characterization of the risk attitudes of the sample by pooling the observations across participants.

Table 2: Example of implied pairwise route choice

Probability of bus	Safe Option (7th Ave)	Risky Option (9th Ave) High Payoff	Risky Option (9th Ave) Low Payoff	Expected Value Difference
0.5	$\$5 - \$1.20 = \$3.80$	\$5	0.25	$\$3.80 - \$2.625 = \$1.18$
0.5	$\$5 - \$1.90 = \$3.10$	\$5	0.25	$\$3.10 - \$2.625 = 0.48$
0.5	$\$5 - \$3.70 = \$1.30$	\$5	0.25	$\$1.30 - \$2.625 = -\$1.325$
*Expected Value_{9th} = $0.5 * \\$5 + 0.5 * 0.25 = \\2.625				

3.2 Recruitment Process

Participants in Orlando, Florida, and Atlanta, Georgia, were recruited by invitation letters. Recipients were randomly selected from the United States Postal Service (USPS) mailing lists, with oversampling from mail carrier routes with median income levels below the state-wide median income level. Invitation letters directed recipients to our web page where they were instructed to create an anonymous Gmail account to use exclusively for our study to ensure strict privacy. Admission to participate in the study was contingent on respondents being at least 18 years old and holding a valid driver's license and valid vehicle insurance. Participants were informed that driving simulators are used in this study and were advised not to participate if they were sensitive to nausea. Four study sites were allocated for the study to receive participants from four regions: east Orlando, west Orlando, north-east Atlanta, and north-west Atlanta.

3.3 Participants and Sequence of Events

This study reports on 4 cohorts of subjects one in each of Atlanta and Orlando during summer 2011, one in each of Atlanta and Orlando during fall 2011. A total of 272 participants completed all tasks of this study. Participants' ages ranged from 18 years old to 75 years old of which 46.11% were male and 53.89% were female. It should be noted here that the 4 cohorts and tasks reported in this document are part of a larger study conducted by the authors (23).

Upon arrival to our study sites, research assistants welcomed participants and verified the validity of their drivers' license and car insurance. Then, an informed consent form (Per IRB of University of Central Florida and Georgia State University) was presented to the participants. The consent form explained briefly how the driving simulator operates and the general purpose of this study. Afterwards, participants were given instructions on the simulation via a short video and were then given three practice drives. Following the practice drives, subjects took a demographics questionnaire and then completed three drives for incentivized monetary payoffs. Participants earned \$25 dollars for participating in the session in addition to other earnings that

they accumulated from the three driving simulator tasks. Subjects were rewarded for every driving task (depending on the outcome) and research assistants carefully helped participants to track their accumulated income on record sheets. It should be noted here that this payment protocol is selected because it is designed to prevent choices being contaminated by multiple layers of randomizations implied by common protocols. It is a standard approach in the experimental economics literature to use the random incentive lottery mechanism (RILM) which chooses one task among many for payout. In theory, the RILM provides incentives to subjects to respond truthfully each task. However, Cox, Sadiraj and Smith (2011) and Harrison and Swarthout (2012) have pointed out potential contamination effects on choices of the RILM payment protocol (24, 25). By rewarding subjects for each task we avoid these potential confounds but we have to control in the econometric estimation for income accumulated during the experiment.

3.4 Apparatus

The driving simulator is PatrolSim by MPRI, a division of L3 communications. The software is installed on laptop computers (Asus G73JH-A1 and G73AW-A1) under a Windows XP operating system, which is the Windows platform used by PatrolSim. The computers are equipped with a Momo steering wheel and pedal kit for automatic transmission driving.

4. STRUCTURAL ESTIMATION

We emphasize that our purpose is simply to find a way of characterizing risk attitudes to illustrate our new approach of eliciting risk attitudes in simulated driving contexts and to make straightforward comparisons of risk attitudes in Atlanta and Orlando. We analyze two of the most prominent models of decision-making under risk and use them as latent choice models to characterize subjects' risk attitudes: the Expected Utility Theory (EUT) model and the Rank-Dependent Utility Theory (RDU) model. We explain first the case of EUT and extend our econometric methods to the RDU case at the end. For exposition purposes we assume for now the following constant relative risk aversion (CRRA) utility function

$$U(x) = \frac{x^{1-r}}{1-r} \quad (1)$$

Risk neutrality is characterized by r equal to zero, risk aversion is characterized by positive values of r and risk loving behavior by negative values of r . Our approach does not require the CRRA functional form; however, this is a standard assumption and we also analyze as a robustness check the case of CARA, $U(x) = 1 - e^{-rx}$.

The parameter in the utility function (1) can be estimated by using maximum likelihood estimators and a latent EUT structural model of choice. Let there be K possible outcomes in a binary choice; in our route choice task $K=2$. Under EUT the probabilities for each outcome k in the route choice task, p_k , are those that are induced by the experimenter, so expected utility is simply the probability weighted utility of each outcome in each binary choice i :

$$EU_{i,route} = \sum_{k=1,K} (p_k \times U_k) \quad (2)$$

In our environment this translates to,

$$\begin{aligned} EU_{i,7th} &= U(Wage - Toll) \\ EU_{i,9th} &= p(Wage - Bus_Penalty) + (1 - p)(Wage) \end{aligned}$$

We calculate the following latent index that reflects the difference in the subject's valuation of two alternatives in a given binary driving choice. This valuation reflects subject's preferences over reliable travel times (7th Avenue) versus unreliable travel times (9th Avenue)

$$\nabla EU_i = EU_{i,9th} - EU_{i,7th} \quad (3)$$

This latent index, based on latent EUT preferences, is then linked to observed choices using a function $\Phi(\nabla EU)$. We assume this to be a “probit” function that takes any argument between $\pm\infty$ and transforms it into a number between 0 and 1. Thus we have the probit link function,

$$\text{prob (choose 9th Avenue Route)} = \Phi(\nabla EU) \quad (4)$$

Even though this “link function” is common in econometrics texts, it forms the critical statistical link between observed binary choices, the latent structure generating the index ∇EU , and the probability of that index being observed. The index defined by (3) is linked to the observed choices by specifying that the risky route choice (9th Avenue route) is chosen when $\Phi(\nabla EU) > 1/2$, which is implied by (4). Therefore, the purpose of this link function is to model the possibility that the subject might commit errors when comparing the expected utility of any two given route choices. If there were no errors from the perspective of EUT, this function would be a step function equal to zero when $\nabla EU < 0$ and equal to one when $\nabla EU > 0$. Thus, if there were no errors, for any infinitesimal difference between the subject's expected utility evaluations of two given choices, the subject would be able to discern which of the two alternatives is better for him with complete certainty.

The likelihood of the observed responses, conditional on the EUT and the CRRA utility function specifications being true, depends on the estimates of r given the above statistical specification and the observed choices. The “statistical specification” here includes assuming some functional form for the cumulative density function (CDF). The conditional log-likelihood is then

$$\ln L(r, \alpha; y, \mathbf{X}) = \sum_i [(\ln \Phi(\nabla EU)) \times \mathbf{I}(y_i = 1) + (\ln (1 - \Phi(\nabla EU))) \times \mathbf{I}(y_i = -1)] \quad (5)$$

where $\mathbf{I}(\cdot)$ is the indicator function, $y_i = 1(-1)$ denotes that the subject chose the 9th Avenue (7th Avenue) route in driving task i , and \mathbf{X} is a vector of individual characteristics reflecting age, sex, race, and so on.

Harrison and Rutström (26) review procedures that can be used to estimate structural models of this kind, as well as more complex non-EUT models, with the goal of illustrating how to write

explicit maximum likelihood (ML) routines that are specific to different structural choice models. It is a simple matter to correct for multiple responses from the same subject (“clustering”), if needed.

It is also a simple matter to generalize this ML analysis to allow the core parameter r to be a linear function of observable characteristics of the individual or task. We extend the model to be $r = r_0 + R \times \mathbf{X}$, where r_0 is a fixed parameter and R is a vector of effects associated with each characteristic in the variable vector \mathbf{X} . In effect, the unconditional model assumes $r = r_0$. This extension significantly enhances the attraction of structural ML estimation, particularly for responses pooled over different subjects and treatments, since one can condition estimates on observable characteristics of the task or subject and control for heterogeneity.

An important extension of the core model is to allow for subjects to make some *behavioral* 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 route is not 1 when the EU of that choice exceeds the EU of the other choice. This assumption is clear in the use of a non-degenerate link function between the latent index ∇EU and the probability of picking a specific route choice as given in (4).

We employ the error specification originally due to Fechner and popularized by Hey and Orme (27). This error specification posits the latent index

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

instead of (3), where μ is a structural “noise parameter” used to allow some errors from the perspective of the deterministic EUT model. This is just one of several different types of error stories that could be used, and Wilcox (28) provides a review of the implications of the alternatives (Note that some specifications place the error at the final choice between one lottery or after the subject has decided which one has the higher expected utility; some place the error earlier, on the comparison of preferences leading to the choice; and some place the error even earlier, on the determination of the expected utility of each lottery). 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 route choice (lottery) is given by (4). Thus μ can be viewed as a parameter that flattens out the link functions as it gets larger. By varying the shape of the link function, one can imagine subjects that are more (or less) sensitive to a given difference in the latent index. Such informal intuition is not strictly valid, since we can choose any scaling of utility for a given subject, but it a suggestive motivation for allowing for structural errors, and why we might want them to vary across subjects or task domains.

An important contribution to the characterization of behavioral errors is the “contextual error” specification proposed by Wilcox (2012) (19). It is designed to allow robust inferences about the primitive “more stochastically risk averse than,” and posits the latent index

$$\nabla EU = ((EU_R - EU_L)/v)/\mu \quad (3'')$$

instead of (3'), where v is a new, normalizing term for each route choice pair. The normalizing term v is defined as the maximum utility over all prizes in this route choice pair minus the minimum utility over all prizes in this route choice pair. The value of v varies, in principle, from lottery choice pair to lottery choice pair: hence it is said to be "contextual." For the Fechner specification, dividing by v ensures that the normalized EU difference $[(EUR - EUL)/v]$ remains in the unit interval for each lottery pair. The term v does not need to be estimated in addition to the utility function parameters and the parameter for the behavioral error term, since it is given by the data and the assumed values of those estimated parameters. The contextual error specification is designed to control for possible errors in choices arising from facing different contexts. For example, suppose one binary choice is defined over a context that is in the level of hundreds of dollars, while the context of the other binary choice is in the level of millions of dollars. Even if the difference in EU of the alternatives is the same in both binary choices, a subject could be more prone to make errors in the second context because he is not used to deal with millions of dollars. This is just an illustrative example of a contextual error and therefore does not imply that they are more or less likely to occur at higher stakes.

As discussed in the literature review section "size effects" have been found to be an important issue in the estimations of Value of Travel Time Savings (VTTS), where the VTTS depends on the size of the difference between alternatives. This has been identified as an experimental artefact (6,7), and that it can be explained by "reference-dependence" (7). In general, these studies (6,7) have identified that estimating the coefficient on the marginal rate of substitution ($\Delta c/\Delta t$) between the difference in travel cost (Δc) and travel time (Δt), that results in an assumption that the error terms ($\underline{\varepsilon} = \varepsilon/\Delta t$) need to be scaled down by the difference in travel time reduced size effects, compared to traditional marginal utility models. Though these studies identify a method to reduce size effects, they have not been to provide a systematic theory for this. Contextual utility provides a foundational theory to reduce scale effects.

The specification employed here is the CRRA utility function from (1), the Fechner error specification using contextual utility from (3'), and the link function using the probit function from (4). The log-likelihood is then

$$\ln L(r, \mu; y, \mathbf{X}) = \sum_i [(\ln \Phi(\nabla EU)) \times \mathbf{I}(y_i = 1) + (\ln (1 - \Phi(\nabla EU))) \times \mathbf{I}(y_i = -1)] \quad (5')$$

and the parameters to be estimated are μ given observed data on the binary choices y and the vector of covariates \mathbf{X} .

The RDU model extends the EUT model by allowing for decision weights on lottery outcomes that can be different from probabilities. The specification of the utility function can be the CRRA function in (1) or the CARA function we will also use in the estimations. To calculate decision weights under RDU one replaces expected utility defined by (2) with RDU

$$RDU_{i,route} = \sum_{k=1,K} (w(k) \times U_k) \quad (2')$$

where

$$w(j) = \omega(p_j + p_{j+1} + \dots + p_J) - \omega(p_{j+1} + p_{j+2} + \dots + p_J)$$

for $j=1, \dots, J-1$, and

$$w(j) = \omega(p_j)$$

for $j=J$, with the subscript j ranking outcomes from worst to best, and $\omega(\cdot)$ is some probability weighting function. We adopt the simple “Prelec” probability weighting function proposed by Quiggin [1982], with curvature parameter γ :

$$\omega(p_j) = \frac{p_j^\gamma}{p_j^\gamma + (1 - p_j)^\gamma}$$

This function allows for the inverted-S shape found by Tversky and Kahneman (1992) in several experiments. The rest of the ML specification for the RDU model is identical to the specification for the EUT model except that the valuation of each lottery in the analysis must be calculated using (2') and that one has to estimate different parameters.

5. RESULTS

A total of 272 subjects completed the experiment. Most of the subjects completed the three drives for monetary outcome, although some choices from completed drives were lost due to encoding issues. Thus, a total of 803 data points were used in the estimation. Table 3 presents a summary of the data used in the estimation.

We control for subject heterogeneity in risk preferences by including a series of demographic variables as covariates in our estimation. The variable **female** is 1 for women, and 0 otherwise. **African American** is 1 based on self-reported ethnic status. **Hispanic** is also 1 based on self-reported ethnic status. We use three age dummies that are equal to 1 if the subject's age is in a given age interval and 0 otherwise: one dummy for subjects that are 30 years old or younger (**age_less30**), another dummy for people between 41 and 55 years old (**age41_55**) and a third dummy for people that are 56 years old or older (**age_over56**). **Income** is equal to 1, 2 or 3, depending on the self-reported income level intervals. Originally there were 9 brackets but we collapsed them into three brackets. **Education** is 1 if participants have a college degree or more and 0 if they are not college graduates. **CumulativeEarnBeforeTask** is the accumulated dollar amount participants have earned in all previous driving tasks. Since we are paying for all choices and it is possible that the amount of accumulated earnings might affect risk attitudes, we include this variable to control for the accumulated experimental income at the beginning of each driving task. We include the dummy **atl** which is 1 if the subject is from Atlanta and 0 if he/she is from Orlando. The estimated coefficient on the latter will allow us to test if there is a structural difference in risk attitudes between subjects in each of the two cities that is not captured by other observed demographic covariates.

Table 4 shows the estimates of the 4 structural models under consideration: i) EUT assuming a CRRA utility, ii) RDU assuming a CRRA utility and a Prelec probability weighting function, iii) EUT assuming a CARA utility and iv) RDU assuming a CARA utility and a Prelec probability weighting function. The results in the models are consistent. We cannot find a structural difference in risk attitudes between subjects in Atlanta and Orlando, and risk attitudes are affected by the earning accumulated in the experiment and, to certain extent, the age of subjects. We analyze first the case of EUT and then the case of RDU, focusing mainly on the results for

the case of CRRA utility and highlighting how they compare with the results of the case of CARA utility.

Table 3: Data summary

Variable	Group	Frequency	Percent	Cum. Percent
Age	18-21	261	31.44	31.44
	22-25	109	13.08	44.52
	26-30	94	11.35	55.87
	31-40	153	18.39	74.26
	41-55	154	18.58	92.84
	56-75	60	7.22	100.00
Gender	Female	447	53.89	53.89
	Male	383	46.11	100
Race	African American	187	22.54	22.54
	Hispanic	77	9.26	31.80
	White	397	47.78	79.58
	Asian	117	14.04	93.62
	Other	53	6.38	100
Income	\$15,000 or under	214	25.81	25.81
	\$15,001-\$25,000	120	14.48	40.29
	\$25,001-\$35,000	49	5.91	46.2
	\$35,001-\$50,000	69	8.36	54.56
	\$50,001-\$65,000	102	12.32	66.88
	\$65,001-\$80,000	74	8.96	75.84
	\$80,001-\$100,000	98	11.76	87.6
	\$100,000-\$200,000	77	9.28	96.88
Over \$200,000	26	3.12	100	
Education	Less than College	388	46.78	46.78
	College	442	53.22	100
Location	Atl	410	49.45	49.45
	Orl	420	50.55	100
Variable	Mean	Std. Deviation	Min.	Max.
CumulativeEarnBeforeTask	10.73	11.08	0	67.25

5.1 EUT Results

Figure 2 (first graph) shows the fitted distribution of the predicted CRRA risk aversion parameter using the values taken by the covariates for each subject. Thus, two subjects for whom the covariates take the same values will have the same predicted risk aversion parameter. The average predicted parameter r is equal to 0.29. These levels of estimated CRRA parameters are in the range of the same parameter estimated by Harrison, Lau and Rutström (26) for subjects

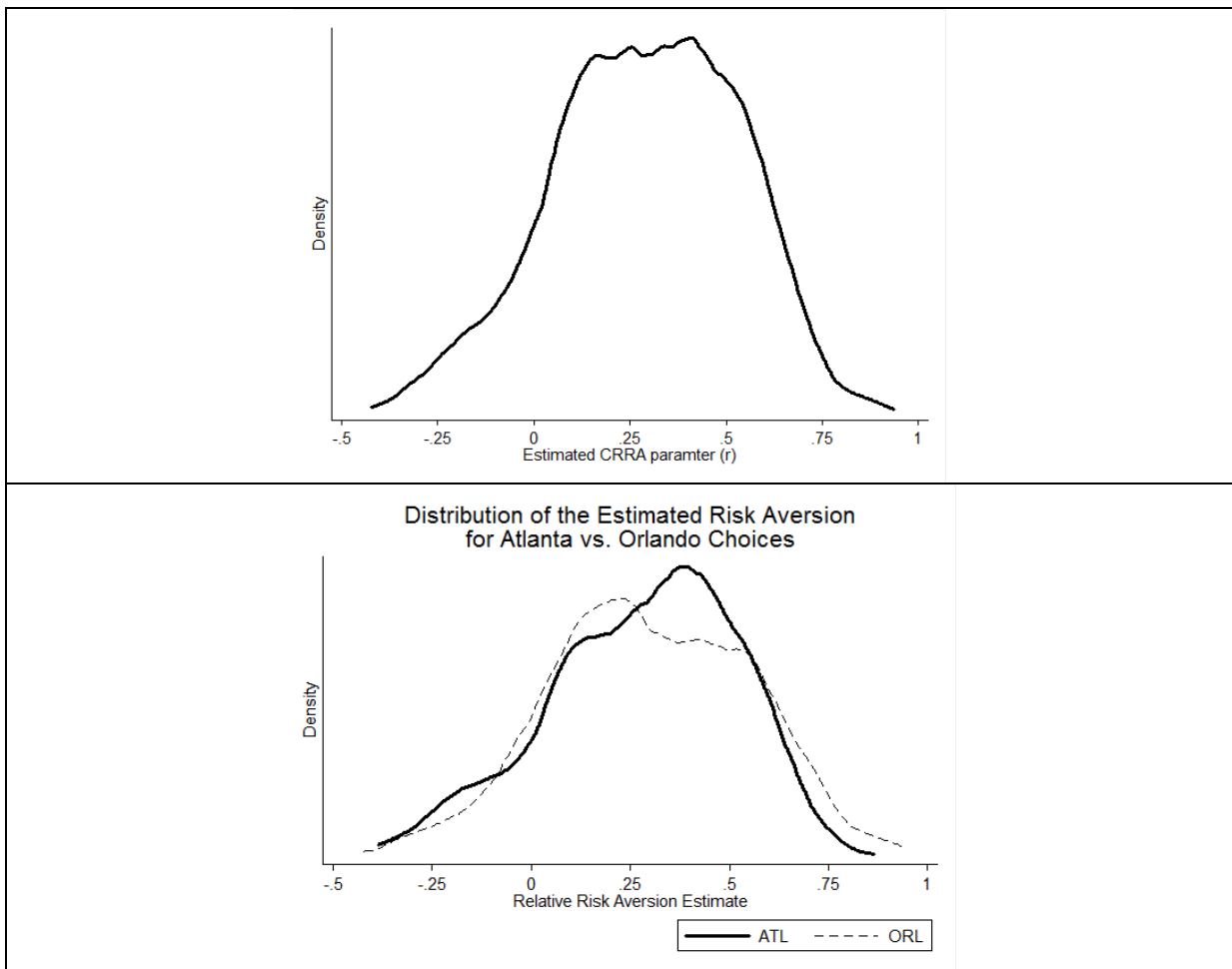


Figure 2: Fitted Distribution of Estimated Risk Attitudes under EUT

recruited in the field in Denmark. Age41_55, Age_over56, female, Income, Hispanic, Education and African American have no significant effect on risk attitudes (p -values 0.3150, 0.9540, 0.6190, 0.6890, 0.7050, 0.8110 and 0.2470, respectively).

We do not find evidence of a structural difference in risk attitudes between subjects in Atlanta and Orlando since the p -value of the estimated coefficient on atl is 0.7810. Figure 2 (second graph) illustrates the similarity in predicted risk attitudes in Orlando and Atlanta. Notice that any comparison of fitted distributions here are only for illustrative purposes since there is a statistical error compounding first at the level of the risk aversion parameter prediction and second at the level of distribution fitting.

CumulativeEarnBeforeTask has a significant effect on risk attitudes (coefficient=-0.0499, p -value =0.015). The negative estimated coefficient suggests that during the experimental session subjects were willing to take more risky route options the more they earned in previous driving tasks. This is evidence of the standard hypothesis in economics that risk aversion decreases when wealth increases.

Finally, the dummy *age_less30* has a *p*-value equal to 0.15 and an estimated coefficient equal to -0.3156. The sign of the estimate would suggest that younger people tend to exhibit less risk aversion than older individuals. Although not very significant in this model, this age dummy is informative when combined with the RDU model where we find a significant age effect on risk attitudes.

As a robustness check, we estimated the same model using the CARA utility function and we obtained basically the same qualitative results. In fact, all coefficients that we find significant with CRRA are also significant and of the same sign with CARA. It is worth noting that the coefficient on the dummy *age_less30* turns out to be significant and negative assuming CARA, giving further support to an age effect on risk attitudes.

5.2 RDU Results

The RDU model characterizes risk aversion as a combination of risk attitudes towards variation in prizes, captured by the concavity of the utility function, and attitudes towards probabilities, captured by the shape of the probability weighting function. For instance, suppose that an individual consistently underweight probabilities, which implies that the weighting function is convex. In Quiggin's (37) terms this is called *probability pessimism*; *probability optimism* can be similarly described by a concave probability weighting function. Notice that the same individual can also exhibit risk loving behavior towards prizes, characterized by a convex utility function, and still behave in a risk averse manner (e.g., choosing the safest lottery) if she also displays sufficient probability pessimism. Therefore, risk attitudes of subjects under the RDU model are characterized by the interaction of two components: how the subject feels about variation in prizes and the optimism/pessimism towards probabilities that the subject might display.

Figure 3 (first graph) shows the fitted distribution of the predicted CRRA risk aversion parameter. The average predicted CRRA parameter r is equal to -0.3048. This implies that on average individuals display risk loving behavior towards prizes. Nevertheless, the average predicted parameter γ of the probability weighting function is 0.5686 which implies that the function has an inverted-S shaped as found by Tversky and Kahneman (38) and that the individual on average exhibits probability pessimism for probabilities approximately above 31.7% and probability optimism below that. Figure 3 (second graph) shows the distribution for the probability weighting parameter across subjects.

Once again the dummy *atl* was not found to have a significant effect on risk aversion. The *p*-value of the coefficient of the *atl* dummy was 0.8130 in the equation for the utility parameters and 0.8600 in the equations for the probability weighting function parameter. This further suggested that people's preferences over risk were stable across the two geographic locations under consideration and variations could be explained by demographics.

CumulativeEarnBeforeTask still has an effect on risk attitudes, and interestingly only affects risk aversion towards variability in prizes since it has significant effect in the equation of the utility parameter (coefficient=-0.0720, *p*-value =0.014) and an insignificant effect in the equation of the probability weighting parameter (*p*-value = 0.5370). The negative estimated coefficient provides

further support to the hypothesis that risk aversion decreases as wealth accumulated in the laboratory increases.

Consistent with the findings under EUT, age has an effect on risk attitudes and it affects both the utility parameter and the probability weighting function parameter. In the case of RDU, this age effect is captured by the dummy variable *age_over56* as opposed to the EUT case in which it was captured by the dummy variable *age_less30*. The coefficient for the dummy *age_over56* is positive and equal to 0.5428 with a *p*-value of 0.0590, which implies that older people are more risk averse towards variability in prizes than younger individuals. This result mirrors the one under EUT which implies that younger individuals are less risk averse. The coefficient for *age_over56* in the equation for the probability weighting parameter is equal to 0.5165 with a *p*-value of 0.0160. Here the interpretation of the effect on attitudes towards probabilities is less straight forward. Suppose that two subjects have identical demographics except that one is older

than 56 and the other is younger. Suppose that the younger individual has a probability weighting parameter equal to the average (0.5686). The coefficient on *age_over56* would imply that the older individual would do little probability weighting since the probability weighting estimate would be 1.0851 (=0.5686+0.5165). However, if instead the younger individual had a probability weighting parameter greater than 1.5, this would imply that the older individual would exhibit probability pessimism over the whole unit interval.

Under RDU, African Americans were found to have exhibit more risk aversion towards prizes than non African Americans. The coefficient for this dummy was positive and equal to 0.7080 with a *p*-value of 0.0170.

Finally, we estimated the same model using the CARA utility function and found that *age_less30* was significant and consistent with the results under EUT. Also, the effect on the utility parameter of the African American dummy prevails, and the only significant covariate in the probability weighting parameter equation is the latter.

Table 4: Risk Aversion Estimates

	EUT with CRRA						EUT with CARA						RDU with CRRA						RDU with CARA					
	Robust Coef.	Std. Err.	z	P> z	95% C.I.		Robust Coef.	Std. Err.	z	P> z	95% C.I.		Robust Coef.	Std. Err.	z	P> z	95% C.I.		Robust Coef.	Std. Err.	z	P> z	95% C.I.	
r																								
atl	-0.058	0.209	-0.280	0.781	-0.468	0.352	-0.044	0.124	-0.350	0.727	-0.287	0.200	-0.097	0.410	-0.240	0.813	-0.900	0.706	-0.101	0.196	-0.520	0.605	-0.486	0.284
cumearnbeforetask	-0.050	0.021	-2.440	0.015	-0.090	-0.010	-0.024	0.010	-2.310	0.021	-0.045	-0.004	-0.072	0.029	-2.450	0.014	-0.129	-0.014	-0.019	0.022	-0.860	0.391	-0.062	0.024
age_less30	-0.316	0.219	-1.440	0.150	-0.746	0.114	-0.241	0.120	-2.010	0.044	-0.475	-0.006	-0.891	0.625	-1.430	0.154	-2.116	0.334	-0.429	0.179	-2.400	0.017	-0.780	-0.078
age41_55	0.162	0.162	1.000	0.315	-0.154	0.479	0.067	0.097	0.690	0.490	-0.124	0.258	0.418	0.345	1.210	0.226	-0.258	1.095	0.101	0.182	0.550	0.579	-0.256	0.458
age_over56	0.014	0.236	0.060	0.954	-0.448	0.475	-0.041	0.141	-0.290	0.770	-0.318	0.235	0.543	0.288	1.890	0.059	-0.022	1.107	0.201	0.134	1.490	0.136	-0.063	0.464
female	0.067	0.135	0.500	0.619	-0.198	0.332	0.009	0.074	0.130	0.899	-0.137	0.155	-0.272	0.303	-0.900	0.370	-0.865	0.322	-0.234	0.154	-1.520	0.128	-0.535	0.067
Income	-0.039	0.098	-0.400	0.689	-0.231	0.153	-0.057	0.064	-0.890	0.371	-0.182	0.068	0.059	0.157	0.380	0.708	-0.249	0.367	-0.051	0.078	-0.650	0.514	-0.204	0.102
hispanic	0.097	0.255	0.380	0.705	-0.404	0.597	0.013	0.125	0.100	0.919	-0.232	0.258	0.545	0.876	0.620	0.534	-1.172	2.261	0.153	0.191	0.800	0.424	-0.221	0.527
Educ	0.053	0.223	0.240	0.811	-0.384	0.490	0.005	0.138	0.030	0.973	-0.266	0.275	-0.237	0.472	-0.500	0.616	-1.163	0.689	-0.266	0.233	-1.140	0.253	-0.722	0.190
black	0.224	0.194	1.160	0.247	-0.155	0.604	0.147	0.115	1.270	0.202	-0.079	0.372	0.708	0.296	2.390	0.017	0.129	1.288	0.385	0.132	2.910	0.004	0.125	0.644
_cons	0.506	0.298	1.700	0.089	-0.078	1.091	0.420	0.179	2.340	0.019	0.069	0.771	0.001	0.687	0.000	0.998	-1.346	1.348	0.332	0.311	1.070	0.285	-0.277	0.941
gam																								
atl													0.021	0.117	0.180	0.860	-0.209	0.250	-0.028	0.124	-0.230	0.818	-0.271	0.214
cumearnbeforetask													-0.004	0.007	-0.620	0.537	-0.018	0.009	0.000	0.014	-0.010	0.991	-0.027	0.027
age_less30													-0.057	0.141	-0.400	0.689	-0.334	0.221	-0.093	0.092	-1.010	0.312	-0.274	0.088
age41_55													0.142	0.145	0.980	0.326	-0.142	0.426	0.080	0.142	0.560	0.573	-0.198	0.358
age_over56													0.517	0.215	2.410	0.016	0.096	0.937	0.452	0.335	1.350	0.178	-0.205	1.109
female													-0.087	0.080	-1.090	0.277	-0.244	0.070	-0.164	0.094	-1.740	0.082	-0.349	0.021
Income													0.038	0.043	0.900	0.369	-0.045	0.122	0.002	0.043	0.050	0.959	-0.083	0.087
hispanic													0.132	0.196	0.670	0.503	-0.253	0.516	0.123	0.108	1.140	0.255	-0.089	0.334
Educ													-0.056	0.128	-0.440	0.662	-0.307	0.195	-0.150	0.134	-1.120	0.263	-0.414	0.113
black													0.205	0.123	1.670	0.096	-0.036	0.447	0.262	0.108	2.420	0.016	0.049	0.474
_cons													0.435	0.201	2.160	0.031	0.041	0.830	0.629	0.199	3.160	0.002	0.239	1.020
mu																								
_cons	0.331	0.025	13.070	0.000	0.282	0.381	0.341	0.026	12.970	0.000	0.289	0.392	0.266	0.020	13.290	0.000	0.227	0.305	0.264	0.021	12.790	0.000	0.224	0.305
Number Of Observations	803						803						803						803					
Wald Chi2 (10)	13.72						13.87						26.69						23.76					
Prob>Chi2	0.1864						0.1789						0.0029						0.0083					

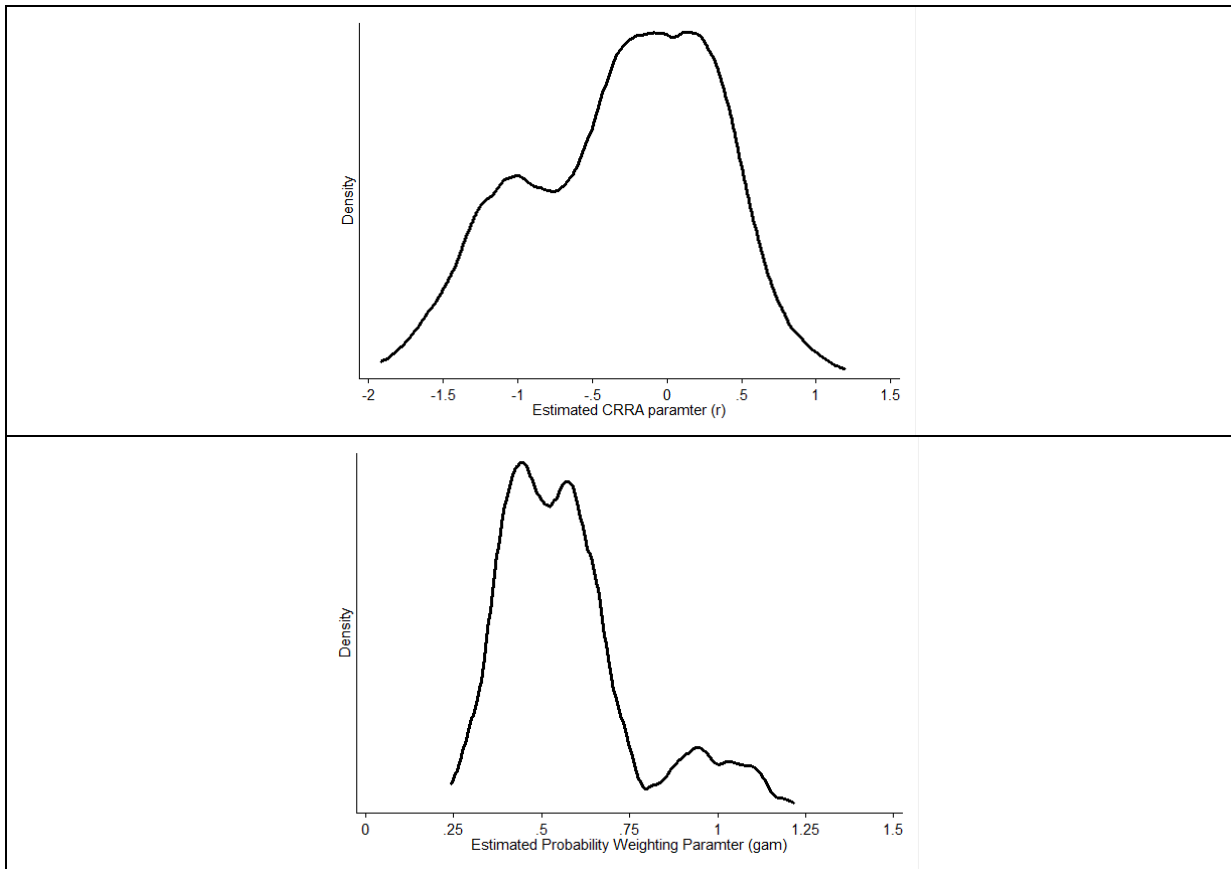


Figure 3: Fitted Distribution of Estimated Utility and Probability Weighting Parameters under RDU

6. CONCLUSIONS

In this study we utilize methods from experimental economics to elicit risk attitudes through controlled incentivized experiments in driving simulators with actual monetary consequences. Drivers made choices between two routes (7th Avenue and 9th Avenue). Each subject drove three times and hence made three route choices. Each route choice had different possible outcomes and probabilities of winning a monetary amount. In this sense the routes and the monetary rewards to subjects were designed to resemble lotteries that are normally used in economic experiments. These features allowed us to apply the tools that experimental economics has developed to identify risk attitudes but in the context of driving. The methods of experimental economics allow experimenters to develop a controlled environment, where the incentivized tasks are design to elicit the underlying preferences. This issue of incentivizing subjects with money in experiments has been found to significantly reduce hypothetical bias (11, 14).

We estimate risk attitudes with a structural estimation approach, in which we assume both the Expected Utility model and the Rank-Dependent Utility model as possible latent choice models. We allow for a CRRA and a CARA utility function, a Prelec probability weighting function, the

Fechner error specification, the contextual utility error correction, and a probit link function. The application of contextual utility to the field of transportation is another important contribution. The theory of contextual utility is strongly grounded in behavioral economics and psychology, and provides a systematic approach to control for behavioral errors arising from different cognitive abilities in different contexts.

We find that there is heterogeneity in the estimated risk attitudes across participants, which is consistent with earlier studies (6, 25, 26). Results suggest that there is an age effect on risk aversion and that wealth accumulated in the laboratory has a negative impact on risk aversion. It was encouraging to find that participants in the two geographic locations of our study, Orlando and Atlanta, did not exhibit structural differences in risk attitudes once demographic differences were controlled for in the estimation. This is encouraging from a policy perspective, since it indicates that it might not be required to conduct similar studies to evaluate risk attitudes in each region to assess the impact of risk attitudes on transportation choices. Future research may focus on examining the effect of risk attitudes across participants in the field and in multiple areas around the US. In addition, another interesting area of research would be to analyze previous stated preference studies and use contextual utility to control for scale effects and compare the estimated value of time and reliability. Finally, it is also relevant to study the external validity of simulated drives to analyze actual commuting choices.

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