

**Experimental Economics in Transportation:
A Focus on Social Influences and the Provision of Information**

David Gaker
University of California at Berkeley
116 McLaughlin Hall
Berkeley, CA 94720-1720
gaker@berkeley.edu

Yanding Zheng
University of California at Berkeley
116 McLaughlin Hall
Berkeley, CA 94720-1720
yanding@berkeley.edu

Joan Walker
University of California at Berkeley
111 McLaughlin Hall
Berkeley, CA 94720-1720
joanwalker@berkeley.edu

corresponding author

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ABSTRACT

A major aspect of transportation planning is understanding behavior: how to predict it and how to influence it over the long term. Behavioral models in transportation are predominantly rooted in the classic microeconomic paradigm of rationality. However, there is a long history in behavioral economics of raising serious questions about rationality. Behavioral economics has made inroads in transportation in the areas of survey design, prospect theory, and attitudinal variables. Further infusion into transportation could lead to significant benefits in terms of increased ability to both predict and influence behavior. The aim of this research is to investigate the transferability of findings in behavioral economics to transportation, with a focus on lessons regarding personalized information and social influences. We designed and conducted three computer experiments using UC Berkeley students: one on personalized-information and route choice, one on social influences and auto ownership, and one combining information and social influences and pedestrian safety. Our findings suggest high transferability of lessons from behavioral economics and great potential for influencing transport behavior. We found that person- and trip-specific information regarding greenhouse gas emissions has significant potential for increasing sustainable behavior, and we are able to quantify this *Value of GREEN* at around \$0.24/pound of greenhouse gas avoided. Congruent with lessons from behavioral economics, we found that information on peer compliance of pedestrian laws had a stronger influence on pedestrian safety behavior than information on the law, citation rates, or accident statistics. We also found that social influences positively impact the decision to buy a hybrid car over a conventional car or forgo a car altogether.

INTRODUCTION

Behavioral economics draws influences from both psychology and economics with an objective to “figure out what really influences our decisions in daily life (as opposed to what we think, often with great confidence, influences them)” (1). The powerful tool of the field is its use of simple and cleverly designed experiments. These experiments are aimed at understanding behavior and often at exposing the irrationality of humans, and they are frequently successful. Even with high stakes and greater complexity (for example, marriage or entrepreneurs), behavioral economics uncovers many common biases (2).

Despite decades of research raising serious questions about rationality (3), the transportation profession is still too largely entrenched in the rational human paradigm. While there is ample evidence that people are irrational, behavioral economists have been successful at uncovering principles guiding these lapses. Armed with the knowledge of these techniques and principles, we can improve transportation planning, and this is the goal of this research. Note that we are not so much interested in proving so-called irrationality (which is debatable terminology), but in capturing significant drivers of transport behavior be they traditional or non-traditional factors.

INROADS OF BEHAVIORAL ECONOMICS IN TRANSPORTATION

Considering the volume of transport behavior literature, the infusion of behavioral economics into transportation has been relatively minimal. Further, the infusion has happened via a few primary avenues. One impact has been in the insights into survey research (for example, stated preference surveys), and in particular issues such as anchoring and framing (i.e., how responses are sensitive to how a situation is presented). See, for example, Gärling et al. (4), Louviere et al. (5), de Palma and Picard (6), Bonsall et al. (7), Ben-Elia et al. (8), and Rose et al. (9). Another avenue that has received considerable attention in transportation is prospect theory (10, 11), which focuses on decision-makers’ behavior under risk, including asymmetric perceptions of gains, losses, and probabilities. Example applications in transportation include Venter and Hansen (12), Nakayama and Kitamura (13), Avineri and Prashker (14), Zhang et al. (15), Han et al. (16), Avineri (17), Cantillo et al. (18), Elgar and Miller (19), Liu and Polak (20), and Puckett and Hensher (21). The final area of influence is a bit more indirect, but involves bringing the psychological (as well as sociological) theories that influence behavioral economics into transport behavioral studies. This includes theories regarding decision-making processes and the influences of factors such as attitudes, perceptions, and social influences. Examples of work in this area include Fuji and Gärling (22), Dugundji and Walker (23), Handy et al. (24), de Palma and Picard (25), Páez et al. (26), Schwanen and Mokhtarian (27), Axhausen (28), and Karash et al. (29). Despite these inroads, much more can be learned. Indeed, McFadden (30) emphasized the value of increased emphasis on behavioral science in transportation.

OBJECTIVES AND APPROACH

The aim of this research is to investigate the transferability of findings from behavioral economics to transportation, beyond the areas that have thus far been emphasized in the transportation literature as described above. While there are potentially dozens of other themes in behavioral economics from which the transport domain could benefit, we began this research by focusing on 2 themes: (1) information and feedback and (2) social influences. These two themes were selected as they are two of the most important drivers for behavioral modification mentioned by behavioral economists and they are highly relevant to transport behaviors.

Here we describe three experiments that focus on transportation issues, each inspired by research in behavioral economics. The methodological approach is to use behavioral economics as a driver for technique (experiments) and behavioral theories (irrationality), but do so with a strong eye on the needs for transportation. The transportation application areas we study are route choice, auto ownership, and pedestrian safety. The questions addressed in this paper are whether themes found in the experiments of behavioral economics hold under more realistic transportation choice environments, and whether we can learn valuable insights for transportation.

Employing one of behavioral economists’ most common experimental techniques, we conducted our experiments in Xlab (the “Experimental Social Science Laboratory”) at UC Berkeley. This is a computer laboratory for conducting human-subject experiments. The lab maintains a subject pool of over 2500 members, all of whom are UC Berkeley affiliates and most are undergraduate students. Xlab administration handles the recruiting and requires that researchers provide subjects with participation fees of around \$15/hour.

We programmed and conducted the experiments using the experimental economics software z-Tree (31), and we used the experimental design routines in SAS to develop the profiles presented to the subjects.

BEHAVIORAL ECONOMICS THEMES OF INFORMATION AND SOCIAL INFLUENCES

As discussed above, we focus on the two themes of information and social influences due to their prevalence in the behavioral economics literature as well as their potential for influencing behavior. Thaler and Sunstein (2) in their popular press review of behavioral economics, state that they have found “one of the most effective ways to nudge (for good or evil) is via social influence”. Here we highlight a few experiments particularly relevant to the task at hand.

One strong theme is the power of information and feedback. Schultz et al. (32) report a residential energy use study in California in which households were given information about their energy use relative to the average energy use for households in their neighborhood. They found that above average users reduced their energy consumption. However, below average users actually increased their energy use. To counteract this “boomerang” effect, above average users were given a frowning face emoticon with their report (causing them to decrease use even further), and below average users were given a smiley face emoticon (causing them to maintain their low level of energy use).

In the transport domain, Taniguchi et al. (33) examine the impact of a host of “travel feedback programs” instigated in Japan. These programs focus on working directly with households regarding goal setting (to more sustainable behaviors) and in providing personalized recommendations for modifying travel habits. Their meta-analysis indicates that these programs reduced car use by 7.3% to 19.1% and increased public transport use by 30.0% to 68.9% on average in residential areas of Japan. Gärling and Fuji (34) also conclude that programs focusing on personalized education and feedback can have large effects on transportation demand.

While personalized feedback is powerful, it is difficult for people to understand the direct and/or long-term implications of their actions. Therefore, anything that can be done to make the impacts more transparent helps. Thomson (35) reports an experiment with Southern California Edison customers aimed at reducing residential energy consumption. They provided two types of personalized feedback (to different groups). One was timely emails and text messages regarding energy use. The second was an ambient orb, which was placed in the house and glowed red during high energy use and green during low energy use. While the former did not lead to significant change in energy use, the latter led to a 40% reduction during peak periods.

A major theme in behavioral economics is the desire to conform to social norms. This is reflected in the studies above where comparison to ones neighbors influence behavior. There are also many other examples along these lines. For example, Coleman (36) reports a study aimed at increasing income tax compliance rates in Minnesota. Several strategies were used to attempt to increase voluntary tax compliance: (i) threats of increased examination and audit rates, (ii) redesign of the standard tax form, (iii) enhanced customer service, (iv) descriptions of the good works that taxes go towards, and (v) a statement that 90% of Minnesotans have already complied with the tax law. In this experiment, only the latter had a significant effect, demonstrating the power of informing people about what other people are doing.

Sometimes social influences are so strong that people blindly follow others without thinking on their own. The rationale is that others must know what they are doing or have some sort of private information. Behavioral economists talk of *information cascades* (37) and *social herding* (38), which is “a situation in which every subsequent actor, based on the observations of others, makes the same choice independent of his/her private signal”, possibly leading to “erroneous mass behavior” (39). This literature focuses on how such a phenomenon can lead to irrational or erroneous decisions, and there are many laboratory experiments along these lines. For example, using a simple gambling experiment, Çelen and Kariv (40) and Gale and Kariv (41) were able to show how subjects’ perceptions of probabilities were distorted away from reality when they were informed of others bets.

DESCRIPTION OF OUR EXPERIMENTS

As described above, our focus is on the themes of information and social influences. Therefore, we designed three experiments: the first focuses on information, the second on social influences, and the third combines the two.

The behavioral economics literature emphasizes the power of personalized feedback to impact one’s behavior. To test this, we designed a stated preference route choice experiment in which the relatively standard attributes of time and cost were provided for each alternative route. However, we also provided information on green-house gas emissions. While Ortúzar and Rodríguez (42) sought to find the willingness to pay for being exposed to less air pollution, we seek to find how people value reducing their own emissions. What we are testing is whether we can nudge people to more sustainable behavior if we provided trip-specific, personalized information on environmental impacts.

To test the social influences theme, we developed an “information cascade” experiment in an auto ownership setting. In an information cascade experiment in the lab, subjects make decisions in pre-determined order and their choices are broadcast to decision-makers who follow. Therefore, everyone but the first subject knows the

decision of some of the other people in the experiment before making their own decisions. Subjects were given a scenario involving a future job, a residential setting, a commute, and attributes of a conventional car and a hybrid car. They were then asked whether they would buy one of the cars or forgo owning a car. However, before making the decision, they were told the distribution of choices (buy conventional, buy hybrid, not have a car) of a certain number of other subjects participating in the experiment at the same time. We varied the scenario presented to each person and tested whether people were influenced by the reported decisions of others in the lab.

To test a combination of the themes of information provision and social influences, our third experiment mimicked the Minnesota tax experiment described above (36), but in a pedestrian safety context. We devised different types of information aimed to influence pedestrian jaywalking behavior, including information based on the law, based on accident and citation rates, and based on behavior of peers. We then presented each subject with only one of these pieces of information, and asked whether the subject felt that in the coming week he/she would cross against red lights more frequently, less frequently, or the same as the previous week. We tested whether, like the Minnesota tax experience, people are most impacted by the behavior of their peers or whether more traditional methods emphasizing the law or accidents would be more significant.

The details of each of the three experiments are described below. The results are presented in the next section.

Screen & Text for Experiment 1: Personalized-Information & Route Choice

FIGURE 1 provides an example screen from the route choice experiment. All subjects were given the same scenario, which was taking a trip with friends to a recreational area. They were presented three routes, each described by travel time, variation in travel time, toll cost, greenhouse gas emissions, and safety. Each respondent was presented 5 different sets of route choices and asked each time to select one of three provided routes.

Screen & Text for Experiment 2: Social Influences & Auto Ownership

FIGURE 2 provides an example screen from the auto ownership experiment. The setup described a future job and housing scenario. All respondents were presented the same job scenario, which is shown in FIGURE 2, where the key information is the salary of \$45,000/year. There were two residential land use scenarios: one suburban and one mixed-use. We were interested in seeing whether the social influences would override fairly strong initial land use triggers. FIGURE 2 displays the suburban scenario, and the mixed-use scenario is as follows:

Suppose you are graduating this semester and you have been offered an exciting job that will pay \$45,000 dollars per year. Considering all your options, you will most likely take this job. You have also been offered a great deal to live in an apartment in a mixed use neighborhood. The apartment is nice, although small. The neighborhood is fairly dense with retail and entertainment nearby and decent access to public transit. Driving from home to your job (one way) will take about 20 minutes and taking public transport will take about 35 minutes (also door to door, one way).

After the description of the job and residential scenario, we presented two auto purchase alternatives, one describing a conventional car and one describing a hybrid car. We provided attributes for each including purchase price, annual operating cost, and annual greenhouse gas emissions. The information cascade is presented with the auto descriptions, where respondents were told the choices of a certain number of their peers in the lab. We divided the subjects in any one lab (each lab had about 30 participants) into 4 groups, the first group had no information on peer decisions, and each following group had information on all preceding groups. The peer information did not roll over into the other lab sessions. Finally, the respondent was then asked to choose either to buy the conventional, to buy the hybrid, or to go without a car and rely on biking, walking and public transportation.

Screen & Text for Experiment 3: Information and Social Influences & Pedestrian Safety

In this experiment we examine how various types of information impact pedestrian behavior, in particular crossing against a red-light. FIGURE 3 shows a sample screen from the experiment. Each person was provided the introductory clarification of the subject area, shown at the top of the screen: "In the traffic laws, a red light indicates you are not supposed to start walking across the street. A flashing red light also means you are not supposed to start crossing the street. If the flashing red begins after you have already started to cross, you are supposed to finish crossing the street as quickly as possible." The control group (approximately 1/6th of the subjects) was only provided this introductory information. The remaining subjects were equally divided into five groups and each group was given one of the following five pieces of information (each is a true statement):

Accident statistics: “According to the Federal Highway Administration, approximately 250 pedestrians nationwide are killed or injured each day crossing illegally. This amounts to more than 1,100 deaths and over 150,000 injuries a year. The US Bureau of Transportation Statistics indicates that pedestrians struck by motor vehicles is the third most common cause of transportation fatalities and accounts for 10.7% of total transportation fatalities.”

The law, including the amount of a fine: “According to 2009 California Vehicle Code: Unless otherwise directed by a pedestrian control signal as provided in Section 21456, a pedestrian facing a steady circular red or red arrow signal shall not enter the roadway. By violating the red light, a pedestrian convicted of an infraction for a violation shall be punished by a fine not exceeding fifty dollars (\$50).”

Citation rates, including the amount of the fine: “According to the data from UC Berkeley Police Department, in Jan 2009, five students were convicted of a red light infraction and were punished by a fine of \$50 by the campus police around the campus.”

Peer behavior, positively stated: “An informal survey of students at Berkeley found that UC Berkeley students and staff cross legally at intersections 71.9% of the time.”

Peer behavior, negatively stated: “An informal survey of students at Berkeley found that UC Berkeley students and staff walk against the traffic signal 28.1% of the time.”

The peer behavior statistic was obtained simply by counting red-light violations at a variety of intersections around the campus.

RESULTS

We report here results from experiments conducted on 312 subjects in UC Berkeley’s Xlab between July and November, 2009. The demographics of our sample are as follows:

Number of respondents:	312
Age:	Median 20 (92% between 18-22)
Gender:	57% female
Have an auto in Berkeley:	22%
Not in the US for most of high school:	11% (82% of these were in Asia)
Vegetarian/Vegan:	6%

For the experimental results described below, we first state the key hypothesis being tested, then summarize our finding, and then present the details. After results on the key hypotheses from each experiment are described, we present some other interesting findings such as the *Value of GREEN*.

Results from Experiment 1: Personalized-Information & Route Choice

Hypothesis: We can nudge people towards more sustainable behavior by providing context- and person-specific information on the environmental impacts of their actions.

Findings: Results suggest this has great potential.

Recall in this experiment that each subject was presented three potential routes to take on a recreational trip with friends. The estimation results for the route choice model are shown in TABLE 1. These are panel data with 5 responses per person. We did not consider the panel in the estimation, and therefore the estimates are consistent but inefficient. Robust standard errors are used to obtain consistent estimates of the standard errors. The signs for all variables are correct and their significance high. In particular, to address the primary hypothesis of this experiment, the subjects were significantly swayed by the provision of information regarding greenhouse gases emitted for the route. As discussed more under “other findings” below, this model suggests a *Value of GREEN* of \$0.50 per pound. This and other statistics from the model (for example, an estimated value of time of \$6.51 per hour) will be discussed further after all estimation results are presented.

Our subjects are likely on the younger and more idealistic end of society (although they also, temporarily at least, are on the poorer side). However, the results are strong enough that they are worth pursuing on a broader scale. The results suggest that if people have better understanding of alternatives available and their relative impacts on the environment, they will take this into account and make choices that are more sustainable. With mobile-phone apps and greater understanding of related issues such as life-cycle costs and emissions modeling, the possibility of providing such personalized information (for example, in response to queries to a direction/mapping search engine) is real.

Results from Experiment 2: Social Influences & Auto Ownership

Hypothesis: Social influence in the form of an information cascade will impact whether a person buys a conventional car, buys a hybrid car, or forgoes having a car.

Findings: Our subjects were indeed influenced by the decisions of their peers.

Recall that in this experiment, the subjects were given a job and housing scenario, and then presented with a hypothetical conventional car and a hypothetical hybrid car. The choice was whether to buy one of the two cars or to forgo owning a car. Each subject had a different set of attributes presented to them (determined through experimental design); 17% of our subjects chose the conventional car, 49% chose the hybrid car, and 34% chose to go without a car. The social cascade twist was that subjects were told what other subjects in the same lab experiment chose to do.

The estimation results are shown in TABLE 2. The traditionally hypothesized and modeled influences of residential scenario (suburban versus mixed use) and costs (purchase price and operating cost) are highly significant with correct signs. Greenhouse gas emissions are significant (suggesting a *Value of GREEN* of \$0.37/annual pound when purchasing the vehicle and \$0.08/pound on an annual operating cost basis), and this is beyond the benefit of fuel cost savings as that is captured by the annual operating costs. The peer influence variable is the last parameter in the table where we include in each utility the fraction of peers reported to choose each of the three alternatives. It suggests that providing information on peer decisions impacts auto purchasing decisions. In terms of influencing sustainable behavior, it will depend on what the relative peer behavior is in terms of driving conventional or hybrid cars or not owning a car.

Results from Experiment 3: Information and Social Influences & Pedestrian Safety

Hypothesis: Providing information on social norms has a greater influence on pedestrian safety behavior than traditional information regarding accidents, citations, and fines.

Finding: Our results suggest that social norms do, indeed, have the most significant impact on behavior. Unfortunately, providing such behavioral statistics can degrade pedestrian safety due to the large percentage of the population that does not comply with the law.

Recall that in this experiment subjects were given varying types of information related to pedestrian safety. We had six different treatments and divided the subjects equally among them. After seeing one piece of information, the subjects were asked to state whether in the coming week they thought they would more frequently, less frequently, or not change their rate of walking against a red light relative to the previous week. Not surprisingly, most of our sample (66%) said our information would not influence their behavior. However, 27% stated they thought they would improve their pedestrian safety behavior. Unfortunately, 7% stated they would worsen their behavior.

The estimation results are shown in TABLE 3. The subjects provided their response in the form of a 7 point scale as shown in FIGURE 3. However due to the small percentage who reported a change in behavior, we modeled only 3 levels: change for the worse (more law breaking), no change, and change for the better (less law breaking). The first thing to note in the estimation results is that socio-demographics seemed to have the largest influence on the stated responses. In particular, we found that females were more likely to state they would improve their behavior, and subjects who spent most of their high school years outside the US were more likely to state they would change their behavior, either for the better or (more weakly) the worse. In terms of the effects of the information we provided, we estimated two parameters for each type of information: one for influencing a positive change in behavior, one for influencing a negative change in behavior. Both of these parameters are relative to no change and relative to the control group, which did not receive special information. The only significant parameter at the 95% level (or close to it) is that providing information on the percent of peers that cross illegally influences people to state they intend to worsen their pedestrian safety behavior. None of the other pieces of information were found to have a significant effect, either positive or negative.

Recall that the idea for this experiment came from the Minnesota tax compliance experiment where they found the social influence information to be the most effective in nudging desirable behavior. In our case there are indications that it could be influential (at least more so than accident rates and statements of the law), however it is influencing these subjects in the wrong direction: towards less desirable behavior. This is likely because our statistic is that their peers walk against red lights 28% of the time, which is high enough to make people feel it is okay to do. In the tax experiment, the compliance rate was 90%. Our result is along the lines of the “boomerang” effect described above in the context of the energy experiment. The lesson is that you don’t want to let people know they are behaving better than the norm.

Other findings: *Value of GREEN*, Power of FREE!, & Gains versus Losses

Other interesting findings from these results are presented in TABLE 4. The first is that because we have both price attributes and greenhouse gas attributes, we can estimate the *Value of GREEN*, and we can do so from both the route choice experiment and the auto ownership experiment. What is interesting and comforting is that the values of green from the two experiments are on the same order of magnitude: \$0.50/pound from route choice versus \$0.37/annual pound (purchase price) and \$0.08/annual pound (operating cost) in auto ownership. To test the hypothesis that the *Value of GREEN* does not significantly differ across the experiments, we used a joint estimator and applied a likelihood ratio test. This required assumptions as the auto ownership value is calculated in terms of annual pounds saved and the route choice experiment involves a trip with several friends so there may be cost sharing. We assume that two people in a car share the cost in the route choice experiment and purchasers of new cars expect to own the car 5.5 years. Making the appropriate unit conversions and estimating a single *Value of GREEN* using the data from both experiments, we found that our subjects value reducing their environmental impact at \$0.24/pound of greenhouse gas. Further, there was no statistical evidence to reject our null hypothesis (p-value of 0.63). We do not report the estimation results from the joint model; however, none of the other parameter estimates were significantly different from the separate models. Our evidence suggests that our respondents are able to understand and fairly consistently process their preferences in relation to greenhouse gas emissions in pounds, even though one experiment involved *tons per year* and one *pounds per trip*. The importance of these results in terms of sustainable behaviors is that there is a *Value of GREEN* and people (well, our young, poor, and idealistic undergraduates, at least) are willing to pay to reduce their impact on the environment.

Other interesting findings involve corroborating results from the behavioral economics literature. The first of these is the “power of FREE!” concept coined by Ariely (1), who points out that FREE! is an “emotional hot point... a source of irrational excitement... zero is not just another discount, it is a different place”. We test this by including a dummy variable in the route choice experiment when there was no toll on the route. This parameter is significant and suggests that people are willing to (irrationally) pay \$0.72 in order to avoid a toll or, equivalently, spend 8 more minutes traveling. In our experiment, this could partially be due to the desire to avoid stopping at a toll booth. The second behavioral phenomenon is at the heart of prospect theory which is that people are more risk averse than gain seeking. We see this in our results with the safety attribute in the route choice experiment. The results suggest subjects are willing to pay \$2.62 to avoid a route with below average safety, although they are only willing to pay \$0.43 to take a route with above average safety: a difference of over a factor of 6.

CONCLUSION

By applying simple lessons from behavioral economics to transportation, we have obtained several useful pieces of information regarding transportation behaviors. The strongest is that there is a *Value of GREEN* (estimated here to be \$0.24/pound); individual- and trip- (or choice-) specific information on environmental impact has the potential to significantly influence people towards more sustainable travel patterns. We also confirmed that social norms are amongst the most powerful influences of transport behavior. Whereas social norms have worked effectively in other settings to nudge behavior in a positive direction (such as the tax compliance example), they actually backfired in our pedestrian safety experiment because of the relatively high rate of jaywalking in the peer group. We also saw strong evidence that social influences impact auto ownership decisions, including whether to buy a car and what type (hybrid or conventional). In general, the results from our experiments are promising in terms of understanding and influencing transport behaviors. There is a lot more to learn by transferring lessons from behavioral economics to transportation, particularly in these areas of social influences and personalized-information. Critical questions include how other segments of society behave in these scenarios (we studied UC Berkeley students), how these transfer to real market situations (i.e., revealed preference settings), and whether the result is long-term behavioral shifts or merely short-term blips in behavior. We also need to think more comprehensively in terms of useful ways to nudge people towards more sustainable and safer behaviors and the implications that these behavioral findings have on our modeling and forecasting methods.

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Experiment 1
 Suppose you and a few friends are planning to take a daytrip to a nearby recreation area. You are going to drive (You'll borrow a car if you don't have one). There are a few routes available to you. We'll describe to you three alternative routes at a time, and ask you to select the route you would take given these options. Please analyze the attributes of each route thoroughly before making a decision. We'll run this experiment 5 times, each time describing 3 different routes from which you are to choose. This is the first stage of Experiment 1.

Explanations of attributes
 Time: One-way travel time from the origin to the destination.
 Time Variation: Standard deviation for the travel time. 95% of the values are within in two standard deviation of the mean.
 Toll: Toll for this route. (all the other costs are identical across three alternatives, such as gas)
 Greenhouse Gas Emission: Amount of greenhouse gas emitted for this route.
 Safety: Chance of accident. 3 denotes safer than normal condition. 2 denotes normal condition. 1 denotes less safe than normal condition.

Attributes	Route 1	Route 2	Route 3
Time (minutes)	70	90	90
Variation of Time (minutes)	12	18	5
Toll (dollars)	0.75	2.00	0.25
Greenhouse Gas Emission (pounds)	5	3	2
Safety	2	3	1

Please select one: Route1
 Route2
 Route3

FIGURE 1 Example screen from Experiment 1 (Route Choice).

Experiment 2
 Suppose you are graduating this semester and you have been offered an exciting job that will pay \$45,000 dollars per year. Considering all your options, you will most likely take this job. You have also been offered a great deal to live in a nice house in a suburban neighborhood, which you will also accept. The neighborhood is a typical residential area on the outskirts of the city, the house is nice size with a yard although you have limited walking access to retail and grocery stores. Driving from home to your job (one way) will take about 30 minutes and taking public transport will take about 60 minutes (also door to door, one way).
 Given this scenario, we ask that you consider your car purchase. If you own or have access to a car now, assume you will not take it with you. Two car options are described below. Please carefully evaluate the attributes and state whether you would buy one of these cars (and which one) or if you would not buy a car and rely on walking, biking, and public transportation.

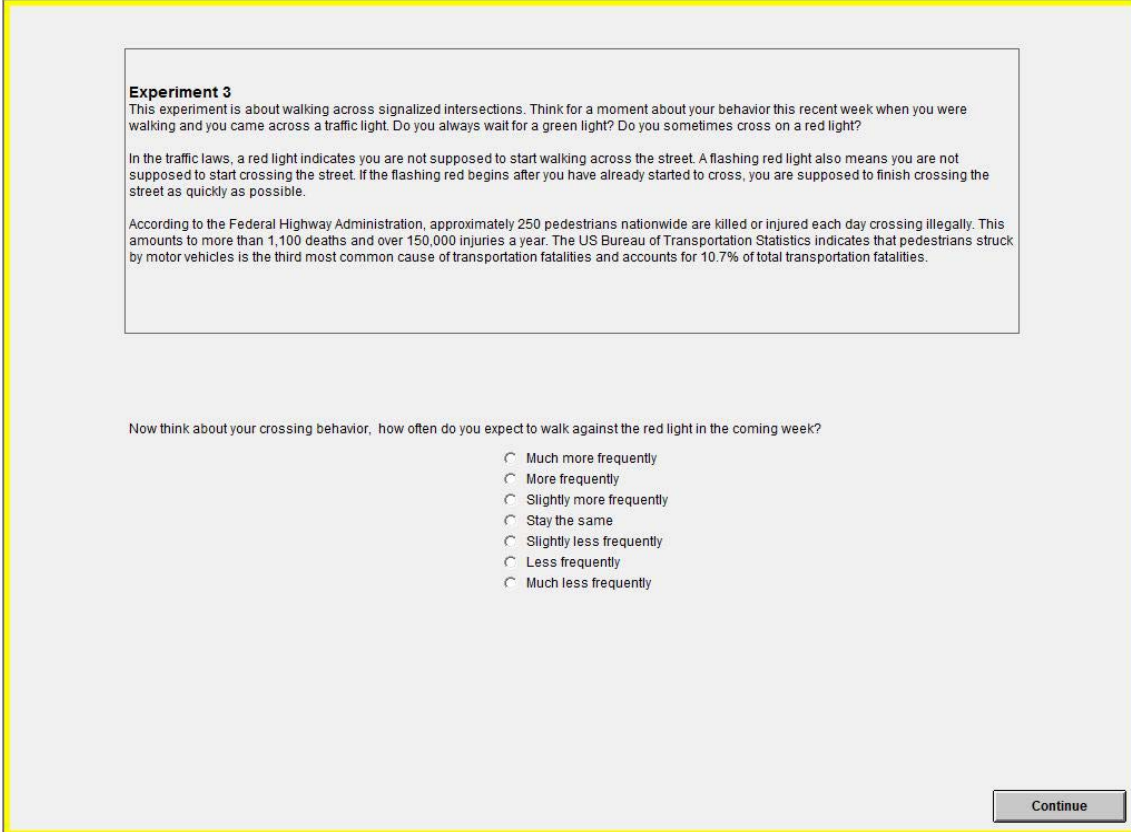
You may be interested in the choices made by some of your peers in the lab right now, which are displayed below:
 4 of you peers chose conventional.
 6 of you peers chose hybrid.
 2 of you peers chose not to buy a car.

Attributes	Conventional Vehicle	Hybrid Vehicle
Purchase Price (\$)	16000	22000
Annual Cost (\$/year)	5000	4300
Greenhouse Gas Emissions (tons/year)	3.2	3.0

Please Select One: 1 Conventional Vehicle as described above.
 2 Hybrid Vehicle as described above.
 3 Given these options, I will not buy a car.

Continue

FIGURE 2 Example screen from Experiment 2 (Auto Ownership).



Experiment 3
This experiment is about walking across signalized intersections. Think for a moment about your behavior this recent week when you were walking and you came across a traffic light. Do you always wait for a green light? Do you sometimes cross on a red light?

In the traffic laws, a red light indicates you are not supposed to start walking across the street. A flashing red light also means you are not supposed to start crossing the street. If the flashing red begins after you have already started to cross, you are supposed to finish crossing the street as quickly as possible.

According to the Federal Highway Administration, approximately 250 pedestrians nationwide are killed or injured each day crossing illegally. This amounts to more than 1,100 deaths and over 150,000 injuries a year. The US Bureau of Transportation Statistics indicates that pedestrians struck by motor vehicles is the third most common cause of transportation fatalities and accounts for 10.7% of total transportation fatalities.

Now think about your crossing behavior, how often do you expect to walk against the red light in the coming week?

- Much more frequently
- More frequently
- Slightly more frequently
- Stay the same
- Slightly less frequently
- Less frequently
- Much less frequently

[Continue](#)

FIGURE 3 Example screen from Experiment 3 (Pedestrian Safety).

TABLE 1 Estimation results from Experiment 1 (Route Choice)

Parameter	Estimate	t-test	p-value
Travel time (minutes)	-0.0596	-17.4	0.00
Standard deviation of travel time (minutes)	-0.0232	-3.9	0.00
Toll (\$)	-0.549	-14.9	0.00
Dummy variable if toll = \$0	0.393	3.7	0.00
Greenhouse gases (pounds)	-0.275	-10.1	0.00
Safety: below average (relative to average)	-1.44	-14.2	0.00
Safety: above average (relative to average)	0.236	3.8	0.00
Number of observations	312 subjects * 5 responses/subject		
Adjusted rho-square	0.308		

TABLE 2 Estimation results from Experiment 2 (Auto Ownership)

Parameter (& alternative to which it applies at right)	Conventional			Estimate	t-test	p-value
	Hybrid	No Car				
Constant (hybrid)	x			0.990	2.2	0.03
Constant (no car)		x		-10.1	-3.4	0.00
Suburban residential scenario (vs mixed use)			x	-1.76	-6.1	0.00
Purchase price (\$1000s)	x	x		-0.258	-4.7	0.00
Annual operating cost (\$1000s)	x	x		-1.27	-2.2	0.03
Greenhouse gas emissions (tons/year)	x	x		-0.192	-1.7	0.08
Fraction of peers who chose alternative	x	x	x	1.41	2.6	0.01
Number of observations				312		
Adjusted rho-square				0.173		

TABLE 3 Estimation results from Experiment 3 (Pedestrian Safety)

Parameter	improve	no change	worsen	Estimate	t-test	p-value
Constant - improve pedestrian safety behavior	x			-1.59	-4.0	0.00
Constant - do not change pedestrian safety behavior		x		0	fixed	
Constant - worsen pedestrian safety behavior			x	-3.56	-3.4	0.00
Female dummy - improve behavior	x			0.793	2.8	0.01
Female dummy - worsen behavior			x	-0.0530	-0.1	0.91
Outside US most of high school - improve behavior	x			0.940	2.3	0.02
Outside US most of high school - worsen behavior			x	0.928	1.4	0.15
<i>Information provided – improve behavior</i>						
Accident statistics	x			0.335	0.7	0.47
The law, including the amount of the fine	x			0.224	0.5	0.61
Citation rates, including the amount of the fine	x			0.378	0.8	0.42
Peer behavior, positively stated (X% obey law)	x			-0.495	-0.9	0.35
Peer behavior, negatively stated (X% break law)	x			-0.257	-0.5	0.63
Control group (no additional info given)	x			0	fixed	
<i>Information provided – worsen behavior</i>						
Accident statistics			x	0.716	0.6	0.57
The law, including the amount of the fine			x	1.38	1.3	0.21
Citation rates, including the amount of the fine			x	0.0749	0.1	0.96
Peer behavior, positively stated (X% obey law)			x	0.586	0.5	0.64
Peer behavior, negatively stated (X% break law)			x	2.57	2.4	0.02
Control group (no additional info given)			x	0	fixed	
Number of observations				312		
Adjusted rho-square				0.265		

TABLE 4 *Value of GREEN, Power of FREE!, Gains versus Losses*

<i>Value of GREEN</i>			
From route choice experiment <i>(GHG savings presented in pounds/trip)</i>	\$ 0.50	per pound	(\$ in terms of trip toll; per pound saved on the trip)
From auto ownership experiment <i>(GHG savings presented in tons/year)</i>	\$ 0.37	per pound	(\$ in terms of purchase price; per annual pound saved)
	\$ 0.08	per pound	(\$ in terms of operating cost; per annual pound saved)
Joint estimation: Constraining <i>Value of GREEN</i> to be equal across route choice and auto ownership experiments	\$ 0.24	per pound	(\$ per pound saved) Assumptions: Own car 5.5 years; Toll shared among 2 in car. There is no evidence to reject the null hypothesis that the <i>Value of GREEN</i> is the same (p -value = 0.63)
<i>Value of other things (all from the route choice experiment)</i>			
Travel time	\$ 6.51	per hour	
Travel time variance	\$ 2.54	per hour	
Avoiding a toll	\$ 0.72	- or -	7 minutes of travel time
Avoiding below average safety	\$ 2.62	- or -	24 minutes of travel time
Gaining above average safety	\$ 0.43	- or -	4 minutes of travel time