When the Field Is Not Enough:

Using complementary field and lab experiments to investigate congestion pricing responses

by

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DBEL-WP 1402 March 2014

Abstract: We use data from a field experiment collecting route choices using GPS recorders and a lab experiment eliciting risk attitude characteristics of drivers. We find that drivers behave in predicted ways in response to variations in average travel times, and in response to manipulations of route pricing. Demand functions are downward sloping in tolls and in travel times. We do not find that drivers respond to variations in the unreliability of travel times, but this is not due to their risk attitudes. Almost all drivers are risk averse, and express a revealed preference in favor of the relatively safe route that is increasing in risk aversion. Because the alternate routes are located at some distance apart, we suspect that the lack of response to travel time unreliability is to be found in biases in drivers expectations of unreliability.

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Introduction

Traffic congestion is a rapidly growing concern in metropolitan areas worldwide. According to the 2012 Urban Mobility Report (Schrank, Eisele, and Lomax (2012)) in the US alone the estimated cost of excess travel time and wasted fuel consumption was $121 billion in 2011. The average annual delay per auto has increased from 16 hours in 1982 to 38 in 2011. About 2.9 billion gallons of fuel were wasted due to clogged highways, and the drivers experienced 5.5 billion hours of traffic delays. The report puts these costs in perspective and equates them to enough time for five vacation days, and the equivalent amount that Americans spend online shopping every year. As the volume of traffic increases, not only do average travel times increase but there is also an exponential increase in the variability of travel times, adding a great deal of uncertainty to travel and transportation services. With additional congestion the number of incidents will increase, and the delay caused by any one incident will be longer.

Important determinants to the welfare effects of congestion and congestion pricing are the reactions of the individual drivers. In this paper we provide evidence on how drivers respond to congestion and congestion pricing. We estimate responses and decision models based on data from complementary field and lab experiments. The field experiments are set in participants' natural traffic environment: common commuter corridors in two major cities: Orlando and Atlanta. Congestion conditions are therefore natural, generated by the traffic system that participants are familiar with. We measure these congestion conditions using GPS recorders in the participants' cars and are able to categorize travel routes by six timesofday intervals (3 during morning commutes and 3 during afternoon commutes), for each weekday, during 3 different time periods in 2011-2012. There is considerable variation in travel time across time, and we add to these natural variations experimental conditions that vary the monetary costs of choosing various routes. By basing our analysis on revealed preferences over route choices, using GPS recorders and real monetary route prices, we avoid the hypothetical biases that can be the result when using stated preference techniques.[1]

We do not find any significant influence from the unreliability of travel time on the route choices. However, this cannot be taken as evidence that our drivers are risk neutral since in the field data inferences of such preferences may be confounded by biases in the perceptions of travel time variations. Dixit, Harrison and Rutstrom (2013) demonstrate the importance of both risk perceptions and risk attitudes to choices made in a driving simulator experiment when there is an accident risk. In order to separate perceptions from preferences, we measure risk preferences in a lab task for the same participants, and find that these preferences correlate with route choice behavior in expected ways. We also find evidence that drivers reveal prefer the Expressway when it is faster on average, and when it has a lower relative price.

[1] Fifer, Rose and Greaves (2014) demonstrate significant hypothetical bias in stated choice data of responses to various driving charges.

Experimental Design

We collect data from a field driving task and from a stylized lab task involving lottery choices from the same subjects. We include two commuter corridors in Orlando, one on the east and the other on the west side of downtown, and two in Atlanta, one on the northeast and the other on the northwest side of downtown.

In the field driving part of the experiment the participants are paid to take certain trips, but they have a limited set of route and departure time choices. We only study drives during rush hours Monday – Friday 7 am – 9:30 am in the direction towards downtown and 4 – 8 pm in the opposite direction. Thus, trips that start before 7 am or 4 pm, or start after 9:30 am or 8 pm are not observed. We also include Saturdays 2 – 8 pm but those drives can be in either direction. Each route is approximately five miles long. Slight variations in the exact length of the route depend on availability of intersections and on-off ramps. These restrictions in time and location serve to limit the variability in traffic conditions and trip purposes so that drives are more comparable. The five mile segments were selected because they were highly congested, and because it was more likely that the recipients of our invitations frequently used these segments in full. This ensured that our study drivers were highly familiar with the routes and their congestion conditions. If we had used longer segments it would have increased the likelihood that many drivers would need to enter and exit the segments in their interiors, thus not making the routes comparable across drivers. To be observed, a drive must involve continuous travel on either of the two routes during the valid times. If the participant stopped or deviated in any way the drive would not be included as an observation. These segments also allowed us to present arterial and expressway route options that were reasonably close to each other and parallel so that they could serve as substitutes for the same trip purpose and be similar in access cost. If the two routes were too far apart, the distance to the start of one would be longer than the distance to the start of the other, and access cost on the former would be higher.

For participants on the west side of Orlando participant drivers can choose to take either SR408, the expressway, or SR50, the arterial. We observe route choices between Good Homes Road and John Young Parkway during these times. Figure 1 shows a map of these routes. The expressway has 2 or 3 lanes in either direction with a speed limit of 55 mph, whereas the local road has 2 or 3 lanes with a speed limit of 45 mph and 12 traffic signals. The two routes are 0.3 and 0.8 miles apart at the end points. Once the route is selected the participant cannot deviate from that route, so if the drive starts on SR408 in the morning rush hour traffic at Good Homes Road going towards downtown, a *valid* study drive must involve staying on SR408 the entire distance to John Young Parkway. Participants are not restricted to stay on the same route each time they travel but can vary their choice freely.

Drivers on the east side of Orlando travel either on SR408 or SR50 between Goldenrod and Mills Avenue where again SR408 is a tolled express way and SR50 is a local road. See Figure 1b for a map showing these routes. On the east side of Orlando, SR408 has 4 or 5 lanes in each direction with a speed limit of 55 mph and SR50 has 2 or 3 lanes in each direction, a speed limit of 45 mph and 15 traffic signals. The two routes are 1.2 and 2 miles apart at the end points. Drivers in north-east Atlanta travel either on the expressway SR400 or on the local road SR9. See Figure 1c for a map of these routes. SR400 has 4 lanes in each direction and a speed limit of 55 mph, and SR9 has 2 lanes in each direction plus a middle turning lane, a speed limit of 35 – 45 mph and 15 traffic signals. The two routes are 0.5 and 1.3 miles apart at the end points. Finally, drivers in north-west Atlanta travel either on the expressway I75 or on the local road SR41. See Figure 1d for a map of these routes. I75 has 5-7 lanes in each direction and a speed limit of 55 mph whereas SR41 has 2 lanes in each direction plus a center turning lane, a speed limit of 35 – 45 mph and 19 traffic signals. The two routes are 0.67 and 1 mile apart at the end points.

In the absence of attrition, each driver participates in three treatments of the field driving task. These treatments differ only in the relative price of the routes, due to the tolls charged by the study. In Orlando these tolls are in addition to the fixed tolls charged by the toll authority. A surcharge or subsidy is levied for either or both of the two routes, the expressway and the local road. The highest surcharge on the arterial is $1 and the highest surcharge on the expressway is $5.75, including the toll authority charges. The highest subsidy on the arterial is $0.50 and the highest subsidy on the expressway is $2.00. These surcharges and subsidies are assigned randomly to drivers, but each driver faces the same relative price for the full 20 drives of each 2 week long driving period. There are three driving periods, the first between the first and second meeting, the second between the second and third meeting, and the third driving period is between the third and the final meeting. The first driving period is the baseline no toll charges or subsidies are used. Drivers are simply paid a fixed $5 or $2.50 for each valid drive. This drive payment is the same for a driver for all three drive periods. During each of the subsequent two driving periods each driver is faced with a different set of toll charges or subsidies randomly selected from full range. Drivers do not know the exact charges or subsidies until the beginning of each two week driving period. All payment parameters are allocated randomly using a pseudo-random number generator.

Surcharges are collected individually from each participant and do not involve any toll agencies, except for the fixed tolls in Orlando that are collected directly by the toll authorities. Surcharges imposed by the study are simply deducted from the payment they get each time they drive in the study and are never higher than the initial drive payment, so drivers never pay out of pocket. If they are receiving a subsidy instead of a toll charge, this is added to the drive payment. Participants are informed about all earnings consequences of their route choices, including what the tolls are, in the meeting preceding each driving period. Tolls do not change during a driving period.

These variations in surcharges and subsidies, along with the naturally occurring variations in travel times, allow us to estimate parameters decision models that include the value of time and risk attitudes. For these purposes we assume a utility function of the following form:

$$(1) \qquad U_{it} = \beta_0 + \beta_T TD_{it} + \beta_M PD_{it} + \beta_V VTD_{it} + \alpha_i X_i + \gamma_i Z_i + \varepsilon_{it}$$

The utility (U) for each participant, *i,* in each drive, *t*, is a function of TD_{it}, the travel time difference between the arterial and the expressway, PD_{it} the difference in earnings across the arterial and the expressway, and VTD_{it}, the difference in the variance of travel times across the arterial and the expressway. In our estimations the three core parameters, $\beta_T, \beta_{M,}$ and β_V will be estimated as random coefficients. We predict that $\beta_T > 0, \beta_M > 0$ and $\beta_V < 0$ for risk averse expected utility maximizers. Further, X_i is a vector of participant specific demographic characteristics, and Z_i is a vector of drive characteristics. Table 1 lists all of these variables along with some descriptive statistics. This utility approach is similar to Small, Winston and Yan (2005).

Apart from inferring preference parameters from the driving data we also have the opportunity to include controls for risk attitudes as estimated from a separate lottery choice task. Next we will describe this task.

The lottery choice task

Each participant is presented with four lottery tasks. Each task is a binary choice between a safer and a riskier option, where each option has two possible outcomes. All outcomes are monetary and are fully known to the subject, as are all probabilities. Table 2 shows the set of all lottery prizes and probabilities used, and Figure 2 shows an example of what the computer screen looks like in the lottery task. The left lottery is always the relatively safe one, and the right lottery is always the relatively risky one. The same probability of getting the high prize is applied to both lotteries, but it varies across tasks. The lotteries are computerized and each participant first goes through a practice task. This practice task is the same for all participants and it has stakes that are very large to make it clear that it is just practice. No payments are made for the practice task. The program then randomly selects a combination of prizes and probabilities for each paid task from Table 2, thus varying these across participants and tasks. Each person responds to four lottery choices, thus encountering four cases from the set of prizes and probabilities. At the end of each lottery task the participant rolls dice to play out the selected lottery and the earnings are recorded, along with the cumulative earnings.

A subject's choice across the two lottery options in each task can be modeled using a variety of decision models. We illustrate here using the simple Expected Utility Theory (EUT) and assuming a Constant Relative Risk Aversion (CRRA) utility function. We first have the expected utility (EU_S) of the safe option

$$(2) \qquad EU_S = p\frac{{x_L}^{1-r}}{1-r} + (1-p)\frac{{x_H}^{1-r}}{1-r}$$

where p is the probability of a low prize, x_L, and therefore (1-p) is the probability of a high prize, x_H, and *r* is the coefficient of relative risk aversion. The parameter *r* in the utility function determines both the first- and second-order derivatives. When $r=0$ the utility function is linear, indicating risk neutrality. When $r>0$ the utility function is concave, commonly interpreted as risk aversion, and when $r<0$ the utility function is convex, or risk loving. Similarly we have the expected utility of the risky option:

$$(3) \qquad EU_R = p\frac{{y_L}^{1-r}}{1-r} + (1-p)\frac{{y_H}^{1-r}}{1-r}$$

with the same probability, p, of a low prize, y_L, and (1-p) of a high prize, y_H. A participant would then compare these expected utilities and employ some process for making the choice that allows for human errors, generally assumed to be random.

Participants and Data

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.[2] Admission to participate in the study was contingent on respondents being at least 18 years old and holding a valid driver's license and a vehicle with a valid insurance. Four study sites were selected: east Orlando, west Orlando, north-east Atlanta, and north-west Atlanta. The areas were selected because residents there were likely to commute on the study routes used in the larger set of experiments that include a field driving component. The selection of study routes was determined based on how closely substitutable a local road was to an express way. About 140,000 letters were sent out which resulted in 633 participants who showed up to the first meeting. Out of these 496 completed both the lottery and driving tasks analyzed here. The remaining subjects dropped out between the first and second session.

We collected choice data from 7 cohorts of field subjects: one in each of Atlanta and Orlando during each of June - July 2011, August - October 2011, and February – April 2012, and a final one in Atlanta during August – October 2012. Table 3 shows the distribution of participants across regions and cohorts, and Table 4 shows the distribution of the number of drives that each participant completed. The maximum number of drives were 60, but as is evident in this table, almost nobody completed that many. Across all cohorts and regions we observed a total of 15,427 drives.

To construct the variables that characterize the travel times on each of the routes we use the travel times recorded during these 18,543 drives. We calculate a mean and a variance for each of 6 time intervals for each weekday in each cohort. The weekday time intervals are 7-7:30 am, 7.30-8.30 am, 8.30-9.30 am, 4 – 5 pm, 5 – 6 pm, 6 – 8 pm. For the am drives the direction is always towards downtown and in the pm the direction is away from downtown, matching the direction of congestion. We also make observations on Saturdays. The time intervals on Saturdays are 2-5 pm, and 5-8 pm. Figure 3 shows the distributions of travel times by region and time of day, pooled across cohorts and weekdays, and Table 5 summarizes the means and standard deviations of the travel times. We can see that in all four regions, both in the AM and in the PM, the arterial route is about twice as slow as the expressway. Thus we would predict that adding road pricing on the

[2] While the Gmail requirement contributed to the low response rate, at the time we started recruitment this was a required privacy layer from the sponsor. An additional factor that reduced our response rate was that in the larger study we also used driving simulators and participants advised not to participate if they were sensitive to nausea. The data from the driving simulators is not analysed here.

expressway should shift drivers to the arterial. Generally the arterial route is also riskier than the expressway on a day to day basis, however, the pattern of risk has some additional interesting features. For example, Atlanta West experiences rare extreme events, increasing the risk, on both routes in the PM and on the arterial in the AM. Atlanta East also experiences rare extreme events on both routes, but that appears restricted to the PM. Finally, in Orlando East the expressway experiences rare extreme events in all timeslots, and the arterial in the two earlier PM timeslots. Once we add and subtract one standard deviation from each of the means, we find that the shortest traveltime is 3.1 minutes (3 minutes and 6 seconds) in the earliest morning timeslot on the Orlando East expressway, and the longest traveltime is 19.8 minutes (19 minutes and 48 seconds) on the Atlanta West arterial.

To get a sense for the magnitude of road pricing that should be acceptable given these travel time difference, let us do a quick calculation. Since the average travel time difference is about 5 minutes in all four regions, then if we assume an average value of time of $20 per hour, we would expect a willingness to pay to access the expressway of about $1.67 for risk neutral drivers.

Table 1 summarizes the characteristics of our participant pool across the four regions. While we see some representation of low income participants, the proportion is very low in the Atlanta east area, and instead we see a very high proportion of high income participants. In Orlando east on the other hand, almost 20% of the pool are from the lowest income groups. Similarly we see the highest participation rate of college graduates in Atlanta east and the lowest one in Orlando. Another difference between Atlanta and Orlando is that we have a much higher participation rate for younger drivers in Orlando. Commute times are longer in Atlanta, but the reported consequences of late arrival are less. In both Atlanta and Orlando, work related consequences are the most highly ranked ones.

Results

Descriptive findings

Figure 4 shows the aggregate frequency of expressway choices mapped against the difference in experimental earnings that was offered for the expressway and the arterial. The solid line is a plot of the raw frequencies, and the dashed line is a plot of the predicted choices based on a simple logit model that controls for several route characteristics and demographics. As is obvious from both, participants react to the changes in the relative prices offered for the alternate routes. We can see the drop in expressway selection from 80% when the relative earnings are the same on the routes, to 20% when there is a $4 difference in favor of the arterial. Disaggregating by region and cohort we find qualitatively similar responses to road pricing across all.[3] However, we see a wider confidence interval around the predicted responses in Orlando West Summer 2011 and Spring 2012, and in Atlanta West Spring 2012. There is no apparent explanation to the response variability in Orlando West other than the smaller sample size, however the Atlanta West Spring 2012 coincides with the introduction of the HOT lane on I85, a much publicized event, however not involving the Atlanta West route at all.

[3] The appendix includes figures with disaggregation of responses by region and cohort.

Figure 5 shows the aggregate frequency of expressway choices, and the prediction from a simple logit model, mapped against the difference in travel time characteristics of the routes. The horizontal axis measures the mean travel time on the arterial minus the mean travel time on the expressway calculated for the region, cohort, day of week, and time slot that the subject travels in, but pooled across all subjects and weeks for that cohort. Thus it is not a measure of the travel time at the moment that the subject is traveling but instead a characteristic that is more permanent than the instantaneous travel time. It should therefore not come as a big surprise that choices do not vary much across these travel time differences. Since participants are experienced in the traffic conditions on these routes they are likely to have adopted an optimal route choice before entering our study, and since our study is not manipulating the travel times, there is no reason for them to adjust. The lack of response to the travel time characteristics holds across all regions and cohorts. However, we do see some variability of the confidence intervals around the predictions. We see wider confidence intervals for all cohorts of Orlando East, and for Fall 2012 for both Atlanta East and West, as well as for Fall 2012 in Atlanta West.

Estimation results

We estimate the model in equation (1) using a mixedlogit formulation. We estimate the coefficients on the difference in average traveltimes (*TD*), the difference in variance of traveltimes (*VTD*) , and the difference in earnings (PD) as random coefficients. This allows us to investigate heterogeneity in responses to these variables by getting estimates of both the mean and the standard deviation of responses across individuals. The raw estimates are the parameters of the utility function, but we can also convert these estimates into effects on the propensity to choose the expressway.[4]

Table 6 shows our estimates pooled across all the four regions, along with separate models for each region. We see that for time slots in which the traveltime on the Arterial is higher than on the Expressway, the use of the Expressway is higher. The coefficient on the mean response to *TD* is positive and significant for all models. This implies that during times when the Arterial is generally slower, our drivers reveal a higher value for the Expressway. The corresponding choice propensities that are computed using the delta method show that the marginal effect of a minute time difference in about 4 percentage points for the pooled model. Since we estimate *TD* as a random coefficient we also have estimates on the heterogeneity of the responses to travel time differences is, and we do see significant effects from the standard deviation in the response *STD* in all of the four regions in Table 6. Figure 6 shows the distributions of responses based on the estimates of the mean and standard deviations in Table 6.

We do not see a significant mean marginal effect from the difference in the variance of travel times (*VTD)* our measure of unreliability. There is also no significant degree of heterogeneity in the effect, as seen by the insignificance of *SVTD* in all four regional models. The initial reaction by a

[4] We use the delta method to convert the estimated parameters of the utility function into marginal effects on the choice propensity, which allows us to compute point estimates, standard errors, significance levels, and confidence intervals of the latter. See Feiveson (1999) for a discussion of the delta method.

reader to this lack of effect may be to assume that it is due to very small values of VTD. However, that is not the case here. *VTD* is similar in magnitude to *TD*, for which we see significant effects in the utility model of Table 6.

An alternative hypothesis for explaining the lack of response to travel time unreliability is that our drivers are risk neutral, and do not care about unreliability. The problem with inferring risk attitudes from field travel times is that it is confounded by imprecisions and biases in the perceptions of travel times. We can, however, test the risk attitude hypothesis directly since we have an alternative measure of risk attitudes, estimated from the lottery tasks. We therefore include a variable that captures the risk attitudes expressed in the lottery task.[5] Figure 7 shows the distribution of the predicted *r* for each region. We can see that almost all drivers are risk averse by this measure, with an *r*-value greater than 0. We only see thin tails in the risk loving range with *r*-values below 0. In Table 6 we see that the coefficient on *r*, is positive and significant in two of our regions, Atlanta East and Orlando East, implying that those who are more risk averse are more likely to use the Expressway. This is an important finding because this could not be inferred from the field actions alone. We therefore conclude that the method suggested by Small, Winston and Yan (2005) to infer risk attitudes directly from field driving data would not work here. They correctly state that, theoretically, the ratio of the coefficients on travel time dispersion and road pricing identifies the subjective value of unreliability (as the marginal utility per dollar), however that assumes that the travel time dispersions that are measured for the routes are those that participants are perceiving. Our findings here indicate that, at least in this case where the routes are some distance apart, this assumption cannot be relied on.

We find evidence of significant reactions to our road price manipulations. We measure the road price manipulations as the difference in net earnings that are offered on the routes, *PD*. In Orlando we include the field tolls on the expressway in the net earnings calculations. We include also an interaction variable between the risk attitude of the driver and the earnings variable, *Pr*. In Atlanta West and Orlando East we find a strong positive influence on utility from increasing the earnings on the expressway in relation to that on the arterial, but this effect weakens with the degree of risk aversion. This is consistent with risk-averse individuals having a concave utility function and being at a relatively high point on the curve where the marginal utility is less than the marginal earnings, implying that they are discounting the utility of the additional earnings on the expressway. For Atlanta East and Orlando West we find the opposite pattern: there is no significant influence on utility from the earnings increase for drivers with a low degree of risk aversion, but this effect emerges for those who are risk averse. This is consistent with the drivers being at a point on the utility function where the marginal utility is greater than the marginal earnings, so that they are enhancing the utility of the additional earnings on the expressway.[6] Further, differences across

[5] We construct this variable from a Maximum Likelihood estimation model of Expected Utility, using a CRRA utility function, as shown in equations (2) and (3), controlling for a number of demographic characteristics. After estimating the ML model we predict the CRRA coefficient for each participant based on their actual demographics.

[6] The position on the utility function is only partially determined by the study earnings. Other earnings as well as the subjective value of time may also affect utility. Andersen, Cox, Harrison, Lau, Rutstrom, and Sadiraj (2013) demonstrate that subjects partially integrate experimental earnings with their other earnings.

regions could also reflect differences in the sensitivity of the behavioral response to variations in the expected utility, so called Fechner errors. There is also a very high degree of heterogeneity in these responses in all four regions, as shown by the significance for *SPD*. Figure 8 shows the distribution of responses to our road prices based on the mean and standard deviation estimates in Table 6. Based on these estimates we conclude that the demand curves are generally downward sloping in the relative road price of the routes, but that the strength of responses depends on risk attitudes and are heterogeneous.

We find only one demographic characteristic that has a consistent and significant effect in all four regions in Table 6 and that is the variable *Young*, capturing those participants who are younger than 31 years. Young drivers reveal significantly higher utility from driving on the expressway than other age groups. We also find that those drivers that appear more flexible in what departure time they use, as captured by the variable *TSused*, reveal less utility from using the expressway. These may be drivers who are taking more leisurely drives, rather than those who are commuting to work. We do not find that income matters for route choice in a systematic manner across the regions. Low income drivers reveal less utility from the expressway in Atlanta West, but more utility in Atlanta East and Orlando East. The latter is interesting since the Expressway in Orlando East has a $1 toll charge by the toll authority. One would expect that low income earners would be less willing to take a route that is priced. We also do not find that education matters in a systematic manner. Those who have graduated from college (*EducationHigh*) get more utility from the expressway in Atlanta East but less utility in Orlando East. Some adjustment of driving habits throughout a driver's participation in the study is evident in the significant effect that *DriveRecord* has: The utility of the expressway increases in Atlanta East and Orlando East, but decreases in Orlando West.

We also do not see any systematic effects across regions based on the variables that capture drive characteristics. Not surprisingly, Saturday drives (*DOW_D6*) are significantly different from other days in all four regions. On this day, the Expressway as relatively more attractive in Atlanta East and Orlando West, but relatively less attractive in Atlanta West and Orlando East. This likely reflects differences in the location of the destinations of Saturday drives in the various regions and serves to demonstrate that many motivators behind route choice are region specific. Morning drives reveal different utilities than evening drives, as captured by the variable *AM*. The sign is positive for Atlanta East, but negative for Atlanta West and Orlando West. Again, this could reflect differences in trip purposes across the regions. Notice, however, that almost none of the demographic or drive characteristics are significant once we convert the marginal effect on utility to marginal effect on the route choice propensity. The exception here is found in Atlanta East.

Conclusions

Using data collected via GPS recorders from drivers in Orlando, Florida, and Atlanta, Georgia, during 2011 – 2012 we investigate how drivers respond to variations in road pricing on congested roads. Using 18,547 observations we characterize travel times separately for each region, cohort, day of week, and time of day. We include a wide range of road pricing, applied independent of travel time, including both charges and subsidies.

We find that revealed preferences for the Expressway over the Arterial is expressed when the Arterial is relatively slower than the Expressway, and when the relative price of the Expressway is lower. On average the Arterial route takes twice as long as the Expressway, and our price differences between the Expressway and the Arterial range from $5.75 to -$2.00. We conclude that, despite the distance between the alternate routes, drivers respond to the time savings and the pricing. The degree of price response depends on the risk attitude of the driver.

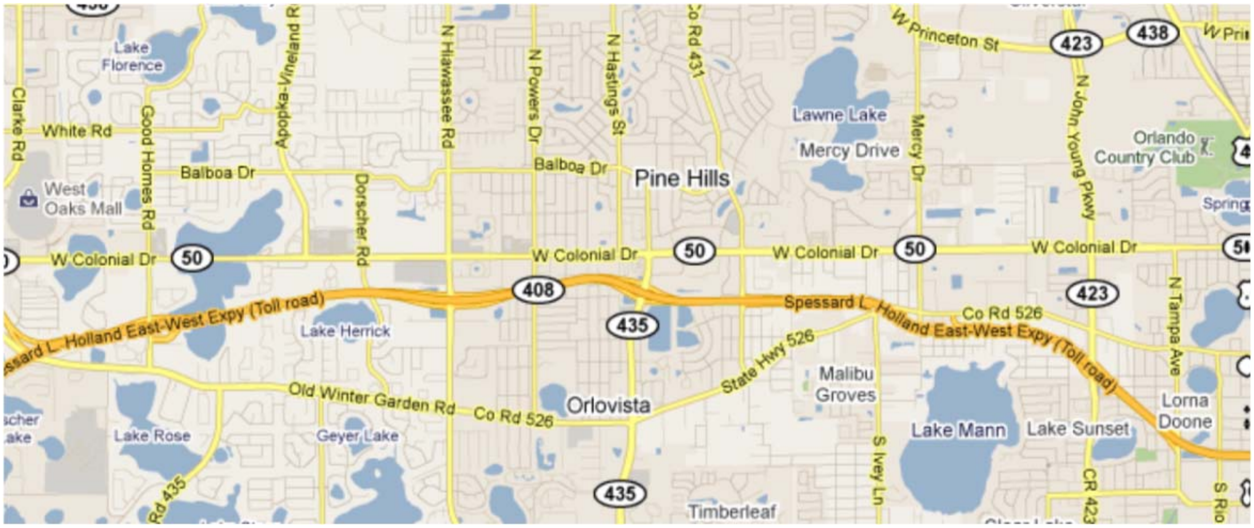
We do not find significant revealed preferences based on the unreliability in travel times, but this does not mean that drivers are risk neutral. Using complementary experimental tasks that elicit risk attitudes in the money domain, we find that risk-averse drivers have a revealed preference for the Expressway. The explanation to the lack of response to the travel time differences is not based on preferences, but more likely on perceptions of travel time variances. On a methodological note, we demonstrate that our experimental risk elicitation tasks generate measures that explain risk taking behavior in the field.

We do not find any support for differential revealed preferences over the routes based on income or education. We had expected low income drivers to have a revealed preference for the Arterial in Orlando, since even without our pricing drivers have to pay a toll to the toll authorities. In fact, we find that the low income drivers in Orlando East favor the Arterial over the Expressway. When interacting income with our road prices, we do find differences across income groups, although not always in the same direction. Drivers with a college degree favor the Expressway in Atlanta East, but favor the Arterial in Orlando East. Young drivers consistently favor the Expressway in all four regions.

There is some evidence that drivers have valuations over trip purpose and destinations that vary across regions. These type of variations in value imply that inferences regarding revealed preferences do not transfer across regions, even if driver characteristics are the same.

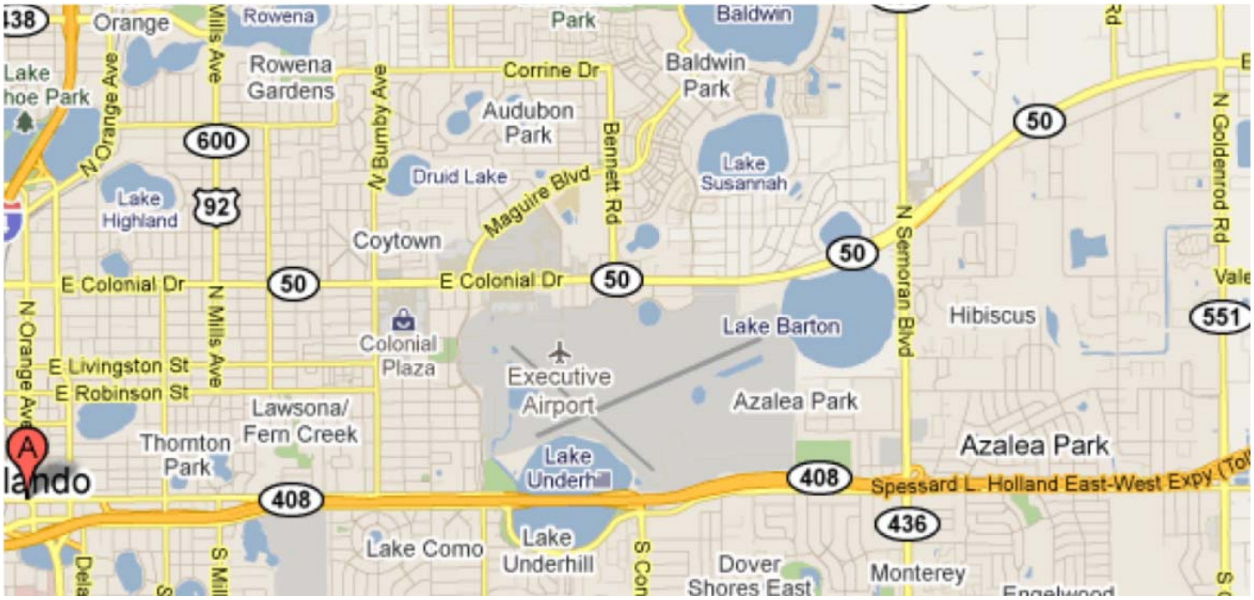
Figure 1: Maps of the four study corridors

Figure 1a: West Orlando



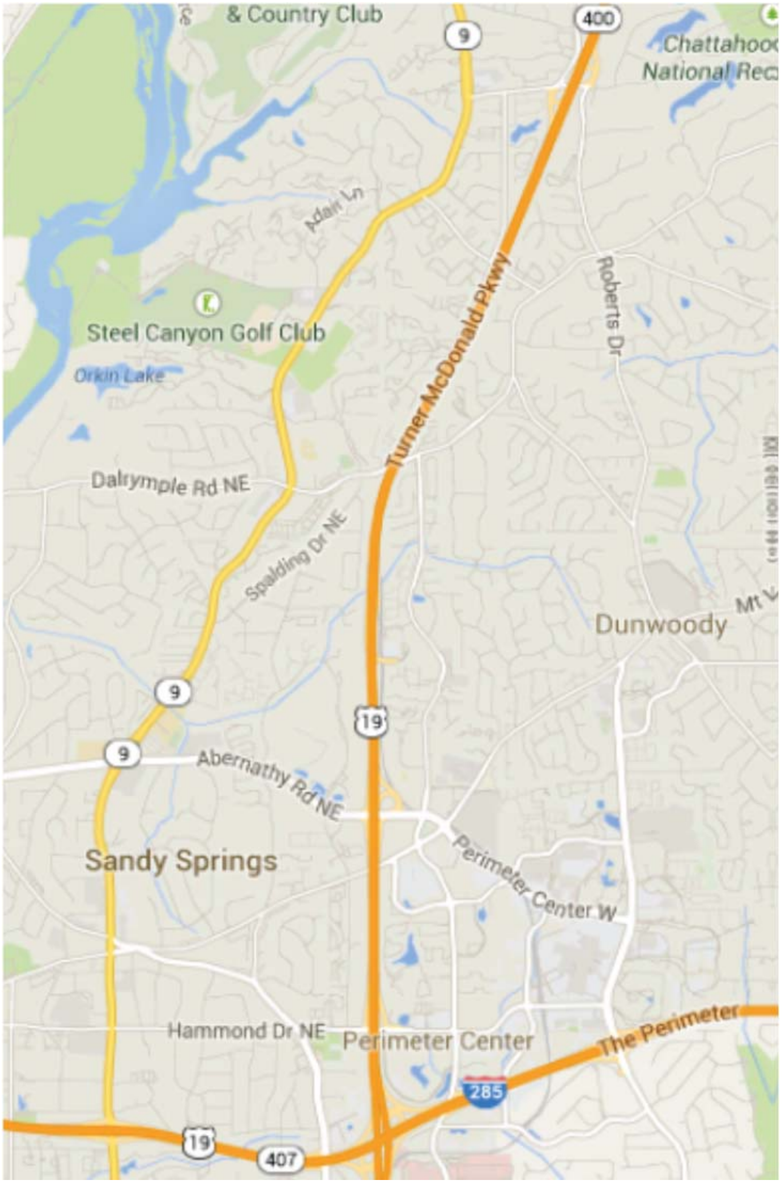
SR50 (Colonial Boulevard) and SR408, between Good Homes Road and John Young Parkway. SR408 has 2 lanes in each direction west of Hiawassee Road and 3 lanes east of this point. There are two toll gantries along this route, both with two express Epass lanes, the total toll at the time of the study was $1.75. SR50 has 12 traffic lights, 2 lanes and a turning lane west of Kirkman Road and 3 lanes and a median east of that point. At John Young Parkway the two routes are 0.8 miles apart and at Good Homes Road they are 1/3 mile apart.

Figure 1b: East Orlando



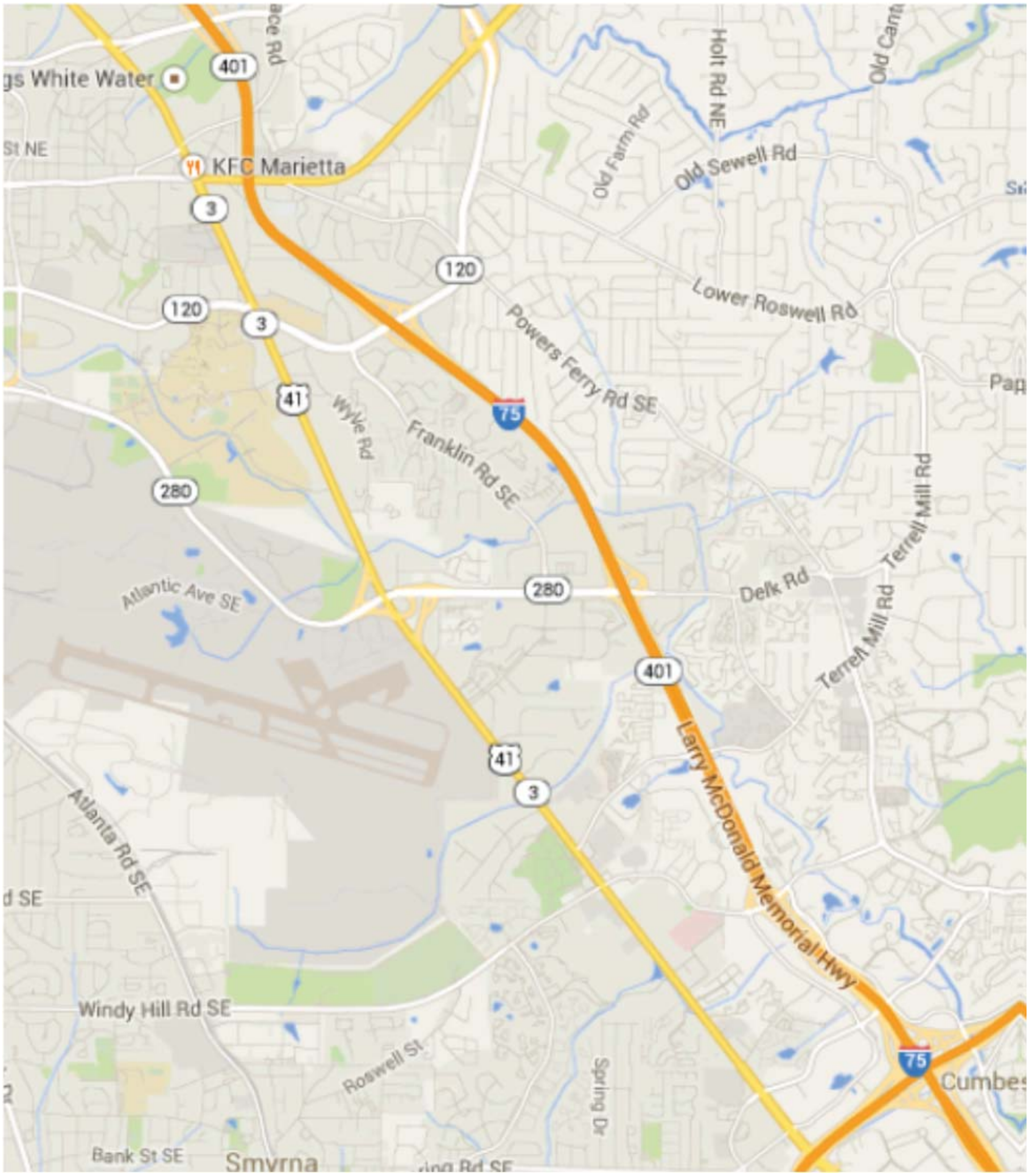
SR50 (Colonial Boulevard) and SR408 between Mills Avenue and Goldenrod Road. SR408 had 5 lanes west of Andes Road and 4 lanes east of that point, and there is one toll gantry with 3 express lanes at that same point. The toll was $1 at the time of the study. SR50 has 2 lanes and a center turning lane west of Bumby Street, 3 lanes with a median west of Semoran Boulevard and 2 lanes and a median east of that point. There are 15 traffic lights. At Goldenrod Road the two routes are 2 miles apart and at Mills Avenue they are 1.2 miles apart.

Figure 1c: North-East Atlanta



SR400 Expressway and SR9 between Northridge Road and I285. SR400 has 4 lanes in each direction. SR9 has 2 lanes in each direction plus a center turning lane and 15 traffic lights. At Northridge Road the two routes are 0.5 miles apart and at I285 the two routes are 1.3 miles apart.

Figure 1d: North-West Atlanta.



I75 Expressway and SR41 between North Marietta Parkway and I285. I75 has 5 lanes north of South Marietta Parkway, 6 lanes south of that point to Delk Road, and then 7 lanes. SR41 has 2 lanes in each direction plus a center turning lane and 19 traffic lights. At North Marietta Parkway the two routes are 2/3 mile apart and at I285 they are 1 mile apart.

Figure 2: Screen shot for practice lottery task

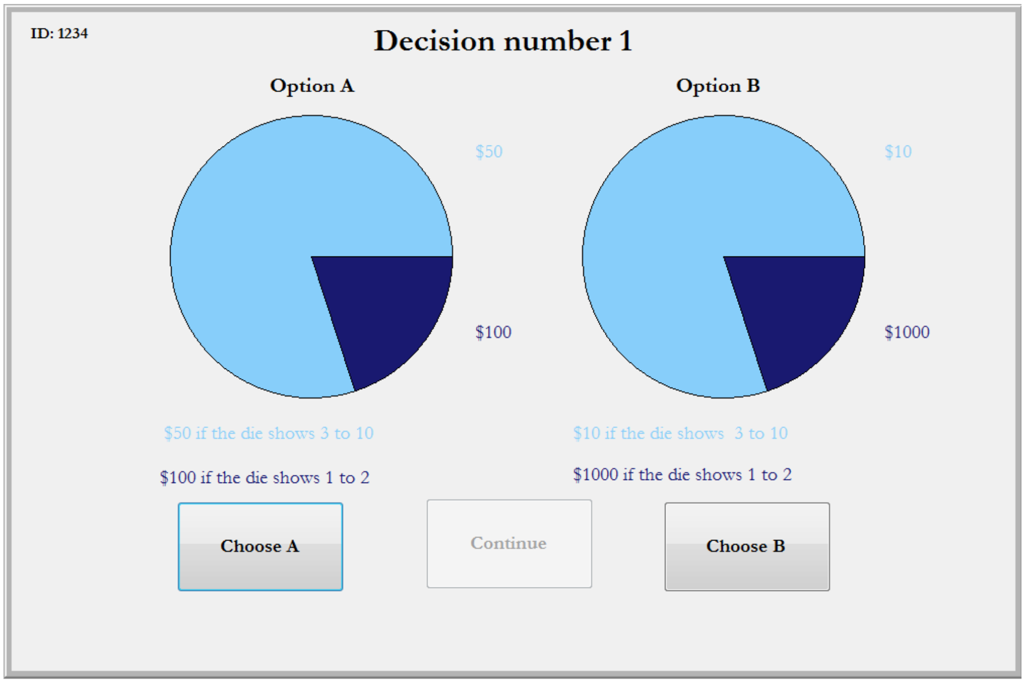
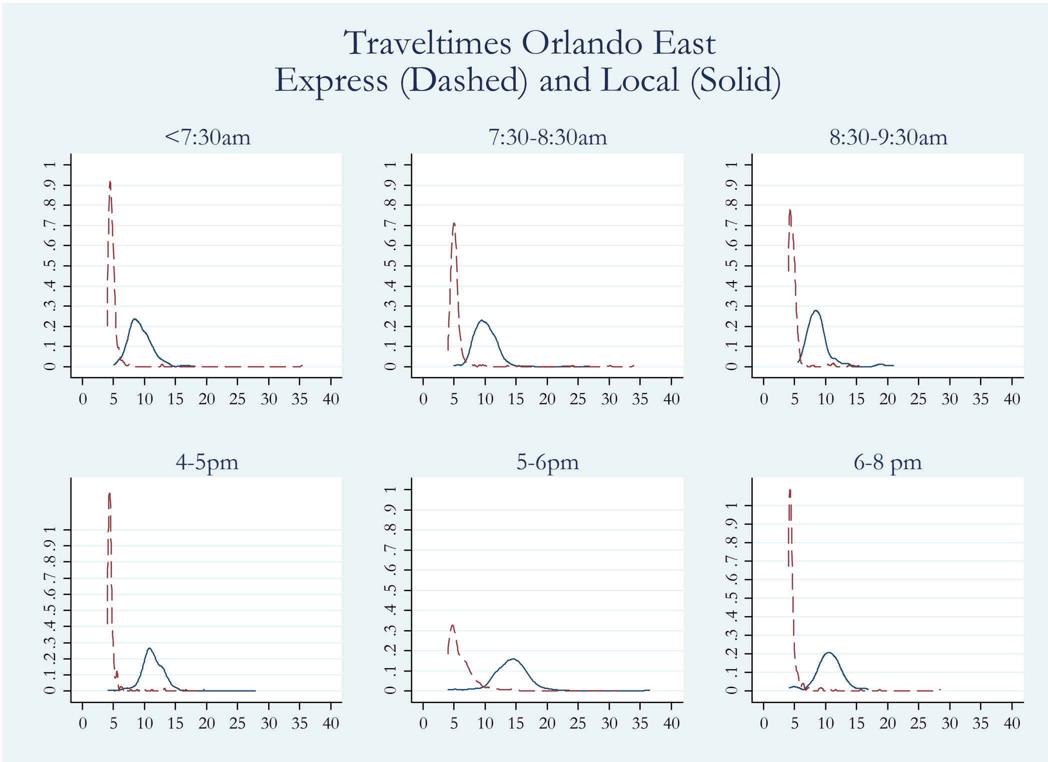


Figure 3: Travel time distributions on all four travel regions



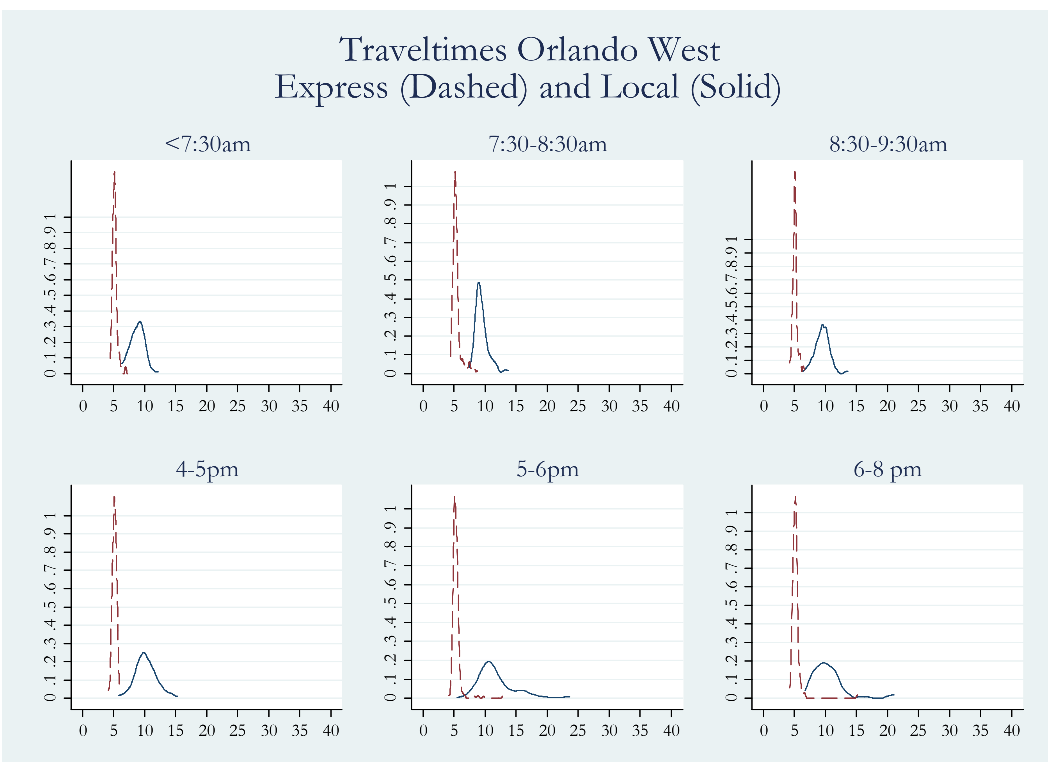
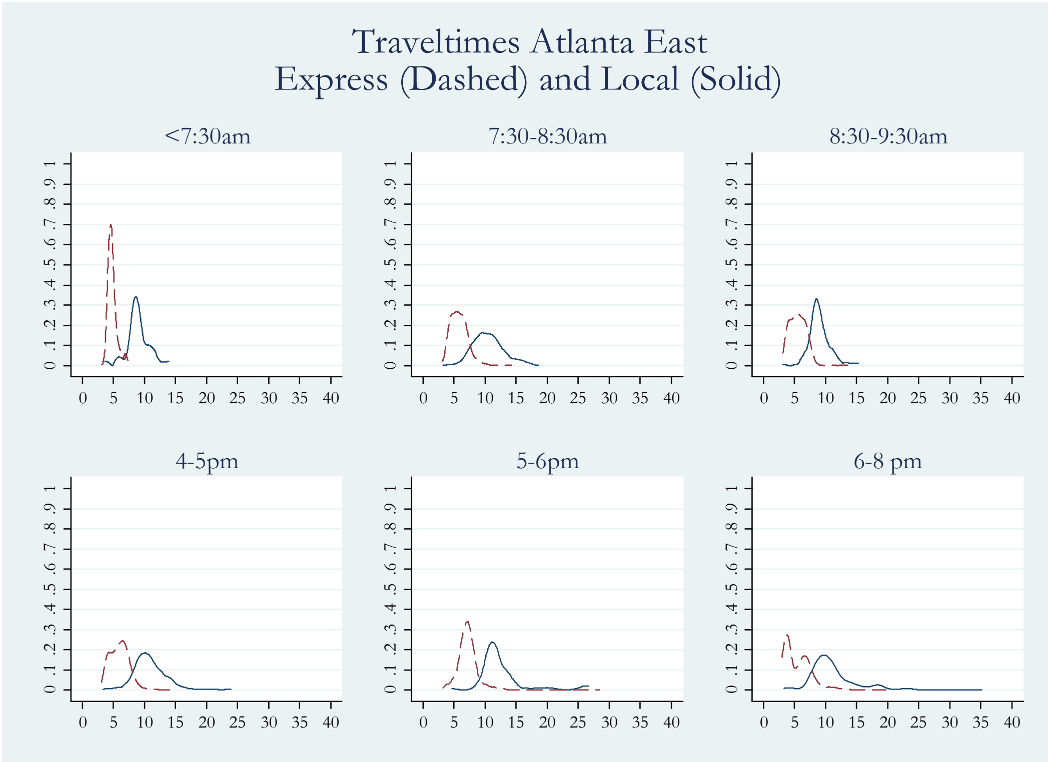


Figure 3 cont'd: Travel time distributions on all four travel regions



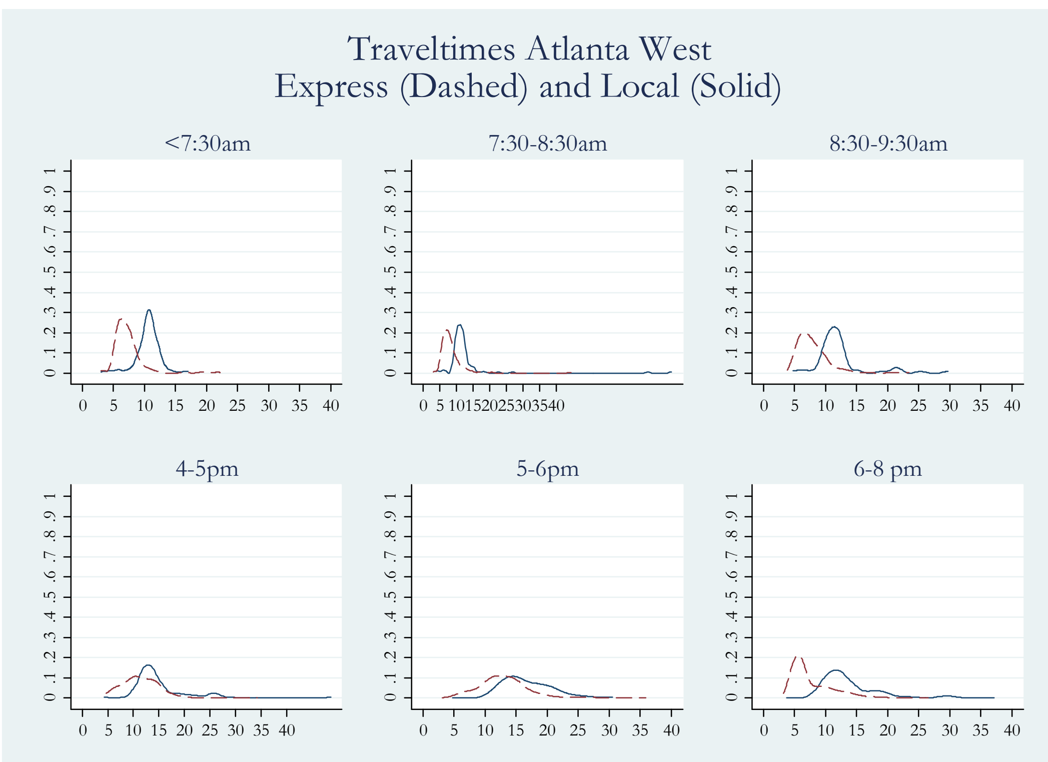


Figure 4:

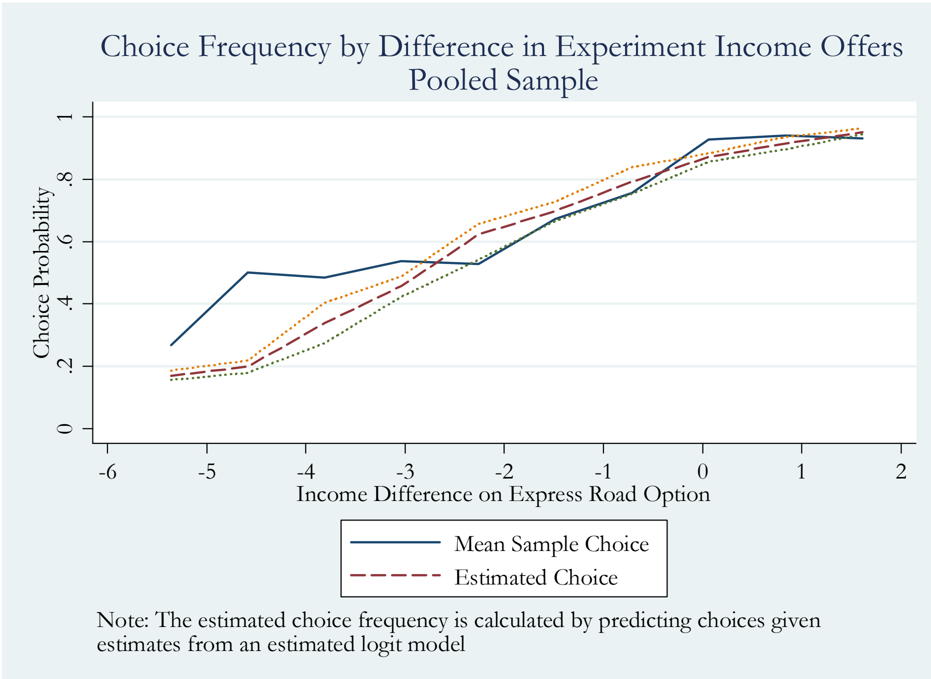


Figure 5:

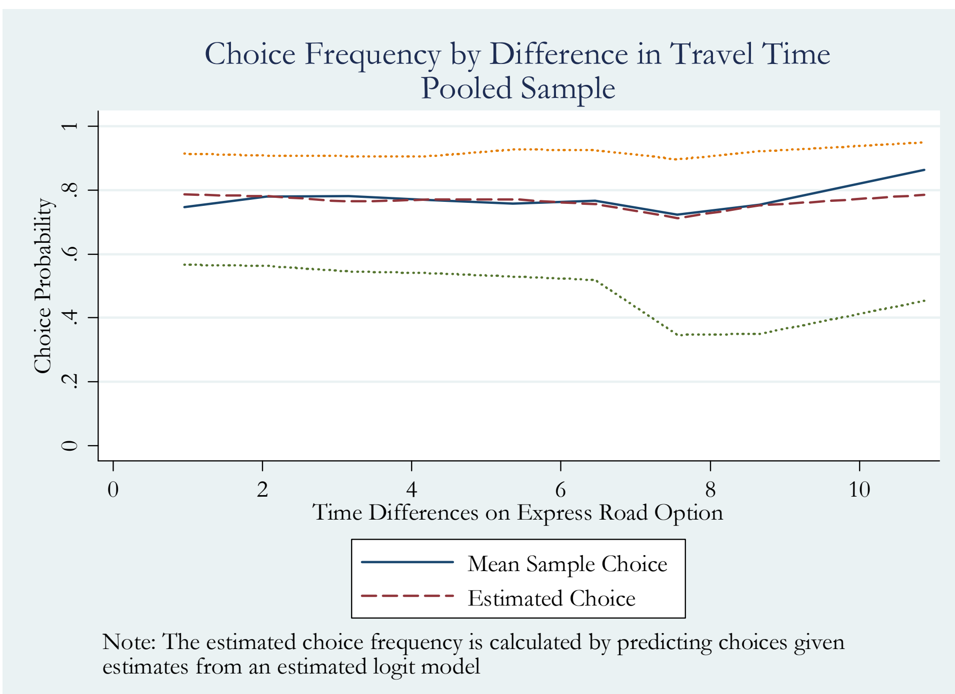


Figure 6: Distributions of Responses to Travel Time Savings

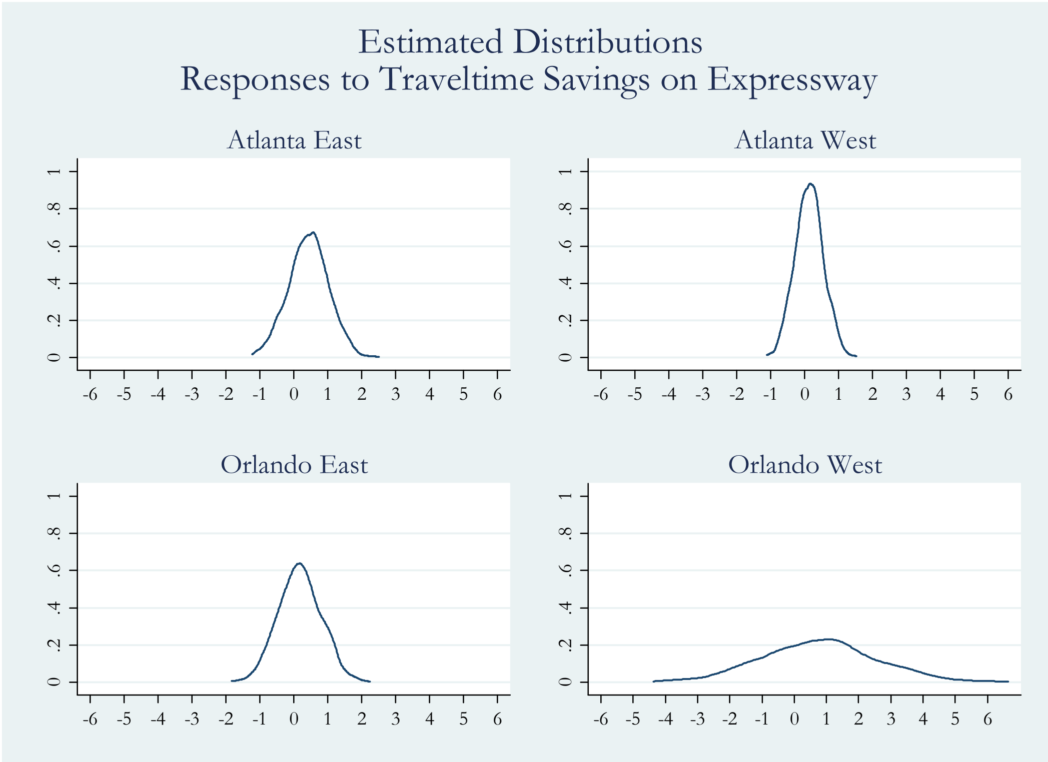
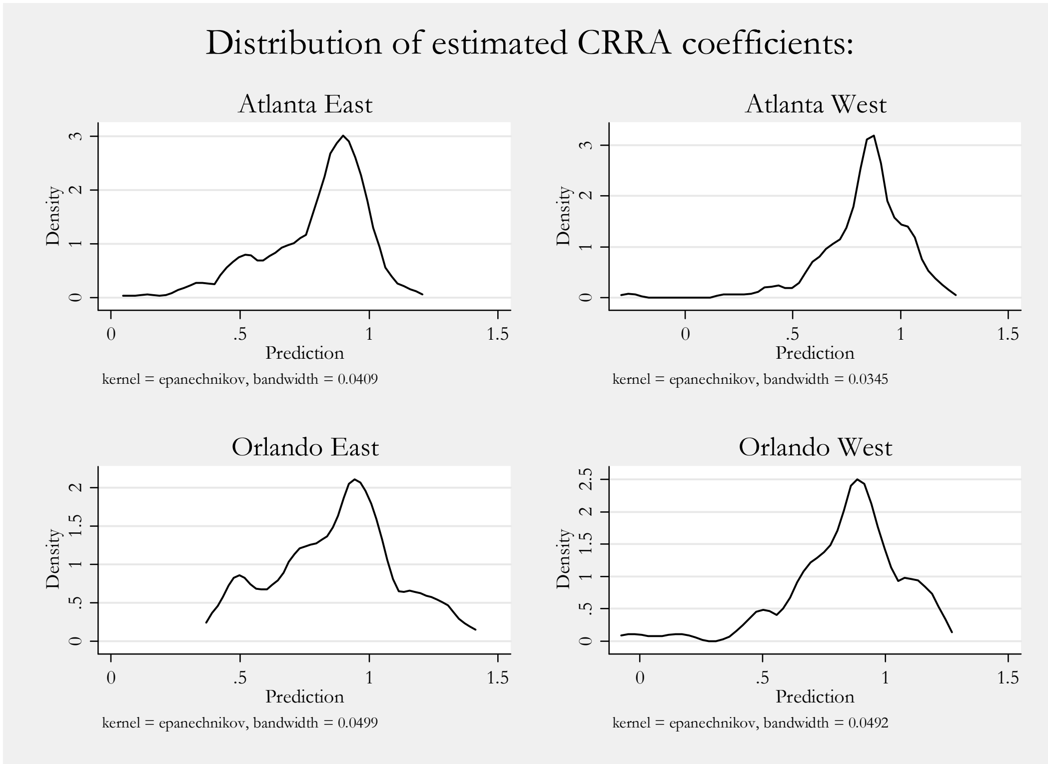


Figure 7: Distributions of CRRA coefficients by region



Distributions are predicted based on a model including the following demographics: Gender, Ethnicity, Age, Education, and Participant in Extreme Sports

Figure 8: Distribution of Responses to Road Pricing

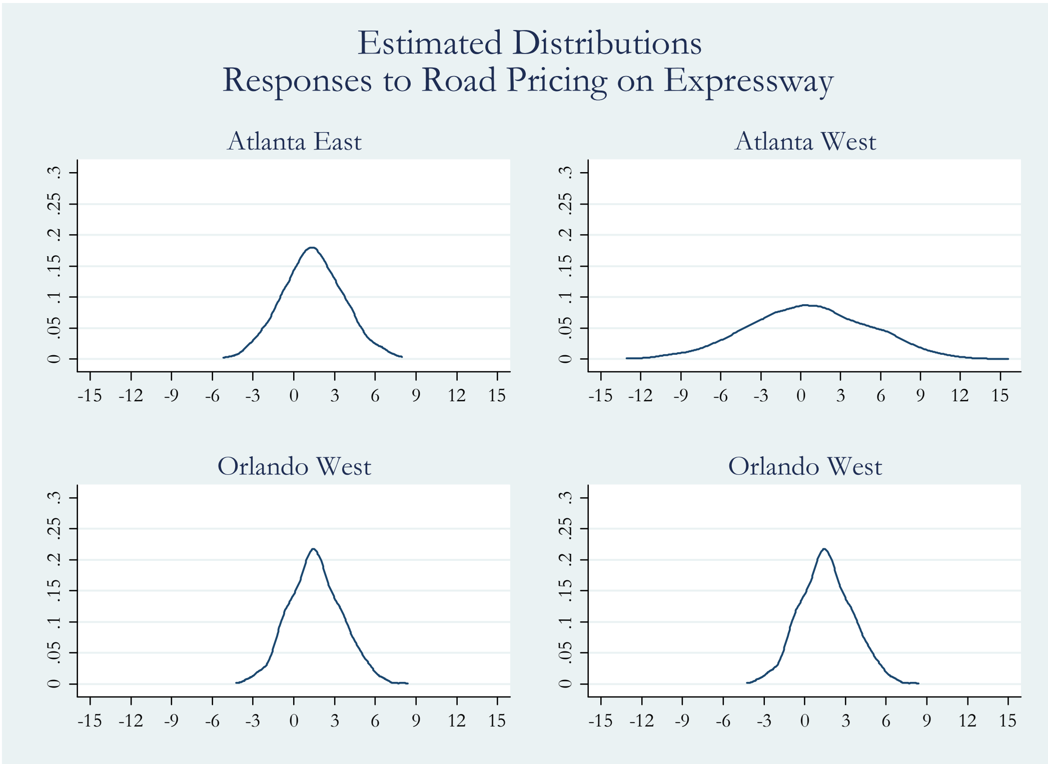


Table 1: Participant pool

	Atlanta East	Atlanta West	Orlando East	Orlando West
N	183	132	120	61
Female	50%	47%	46%	56%
Young (younger than 31 years)	11%	23%	35%	30%
Middle (between 31 and 55 years)	69%	61%	59%	62%
Old (older than 55 years)	19%	17%	6%	8%
IncomeLow ($35,000 or less)	4%	10%	19%	13%
IncomeMid (more than $35,001 - $80,000)	42%	45%	44%	44%
IncomeHigh ($80,001 -)	52%	42%	36%	43%
EducationHigh (college graduate or higher)	89%	80%	68%	69%
Smoking	8%	5%	11%	8%
ExtremeSports (often or every chance I get)	1%	4%	6%	2%
WorkDriving (is driving part of your job?)	19%	20%	18%	13%
ChoicePower (commute by own car)	93%	96%	98%	100%
CommuteTime (1=0-15 minutes 2=15-30 minutes 3=30-45 minutes 4=45-60 minutes 5= 60+ minutes)	3.2	3.6	2.6	2.6
PenaltyBoss (work related penalty)	29%	37%	44%	34%
PenaltyParking (parking related penalty)	15%	18%	37%	30%
PenaltyFamily (family related penalty)	9%	12%	18%	13%

Table 2: Prizes and probabilities in lottery task

Probability range	Safe Lottery Low Prize	Safe Lottery High Prize	Risky Lottery Low Prize	Risky Lottery High Prize
0.1 – 0.9	$2	$3	$0.25	$4
0.1 – 0.9	$2	$3	$0.25	$5
0.1 – 0.9	$2	$3	$0.25	$6
0.1 – 0.9	$4	$6	$0.50	$10

Table 3: Number of participants

	summer 2011	fall 2011	spring 2012	fall 2012	Sum
Atlanta East	44	54	20	64	182
Atlanta West	34	34	23	40	131
Atlanta sum	78	88	43	104	313
Orlando East	20	51	46		117
Orlando West	14	31	15		60
Orlando sum	34	82	61		177
Total	112	170	104	104	490

Table 4: Distribution of number of drives (recalculate the percentages)

	20 or more	30 or more	40 or more	50 or more	60
Atlanta East	75%	56%	30%	13%	0.5%
Atlanta West	66%	47%	27%	5%	0%
Orlando East	81%	66%	40%	20%	2.5%
Orlando West	72%	45%	25%	3%	0%

Table 5: Mean and Standard Deviation of travel times by region and am/pm

	Express AM	Arterial AM	Express PM	Arterial PM
Orlando East	5.1 (2.0)	9.6 1.9 (2.1)	5.4 (2.2)	12.2 2.25 (3.2)
Orlando West	5.3 (0.6)	9.3 1.75 (1.2)	5.3 (0.7)	10.9 2.1 (2.8)
Atlanta East	5.5 (1.4)	9.7 1.76 (2.2)	5.8 (2.0)	11.2 1.93 (3.6)
Atlanta West	7.9 (2.9)	11.6 1.5 (5.3)	10.4 (4.6)	15.01.4 (4.8)

Table 6: Mixed Logit estimates of mean-variance utility

	Pooled		Atlanta East		Atlanta West		Orlando East		Orlando West	
N	15,427		5,673		3,737		4,233		1,784	
	Coef.	*P>|z|*	*Coef.*	*P>|z|*	*Coef.*	*P>|z|*	*Coef.*	*P>|z|*	*Coef.*	*P>|z|*
cons	-1.83542	0.001	-1.42758	0.167	4.270307	0	-4.88762	0	-5.93119	0.016
CityD	4.592513	0								
CityD_West	-0.92792	0.011								
West	0.302978	0.307								
Wave2	0.719084	0	0.573021	0.056	0.81735	0.007	1.526649	0	5.25113	0
Wave3	0.257229	0.239	-0.2484	0.582	-0.48533	0.244	2.081225	0	2.648472	0.035
DOW_D1	0.028884	0.814	0.182281	0.44	0.238926	0.384	-0.34369	0.108	0.272524	0.559
DOW_D2	0.051064	0.657	0.231146	0.3	0.270236	0.238	-0.19128	0.341	-0.1815	0.657
DOW_D3	0.056441	0.627	0.259132	0.253	0.141566	0.532	-0.09879	0.62	0.194514	0.646
DOW_D5	0.163367	0.177	0.206455	0.361	0.462894	0.063	0.060692	0.771	-0.33594	0.436
DOW_D6	-0.10096	0.578	0.515433	0.059	-1.06346	0.011	-0.77839	0.027	2.170772	0.045
AM	0.027477	0.765	0.646461	0.001	-0.34528	0.04	-0.10953	0.545	-0.73285	0.028
TSused	-0.28872	0	-0.16152	0.054	-0.34095	0.002	-0.35054	0	0.35389	0.059
DriveRecord	0.014763	0.05	0.035951	0.011	-0.02031	0.14	0.045777	0.001	-0.06558	0.037
r	1.726673	0	2.205589	0.005	-0.3439	0.774	3.655288	0	1.05146	0.737
Female	-0.33933	0.017	0.209558	0.434	-0.3625	0.2	0.488904	0.051	0.137329	0.838
Young	2.17592	0	2.357235	0	3.318618	0	2.947029	0	1.492549	0.07
Old	0.449307	0.014	0.166101	0.553	0.01864	0.963	-0.33518	0.494	2.98011	0
IncomeLow	-0.773	0.002	2.049886	0.002	-2.6494	0	0.748847	0.029	-0.10371	0.918
IncomeHigh	-0.08159	0.598	0.654574	0.007	0.113371	0.749	0.269846	0.357	-1.02325	0.168
NotWorkActive	0.800213	0.151			7.389636	0	1.097271	0.759	-1.53573	0.158
Smoking	-0.38988	0.108	0.478559	0.364	-1.52826	0.058	-1.63631	0	4.233591	0.001
WorkDriving	-0.15007	0.409	-0.77119	0.007	0.94694	0.014	2.620073	0	-0.81754	0.357
EducationHigh	-0.44904	0.01	1.174141	0.001	0.011365	0.973	-0.72881	0.002	0.017574	0.976

Table 6 cont'd

	Pooled		**Atlanta East**		**Atlanta West**		**Orlando East**		**Orlando West**	
mean Pr	0.550008	0.04	1.221413	0.032	-2.57486	0.006	-1.28428	0.004	2.8236	0.097
mean PD	1.334387	0	0.595551	0.259	3.696966	0	2.749522	0	-0.02569	0.984
mean TD	0.319535	0	0.465426	0	0.143447	0.053	0.173482	0.048	0.758286	0
mean VTD	-0.00098	0.714	0.006546	0.57	0.000584	0.862	0.005067	0.598	-0.00664	0.415
STD	0.687603	0	0.590932	0	0.426393	0	0.621973	0	1.80303	0
SVTD	-0.0037	0.189	-0.0202	0.274	-0.00481	0.307	-0.00252	0.754	-0.00099	0.897
SPD	2.776732	0	2.743655	0	4.283931	0	2.503044	0	2.280813	0

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