

An Examination of Traveler Responses to Real-time Bus Arrival Information Using Panel Data

Feng Zhang

School of Architecture, Planning, and Preservation
University of Maryland, College Park
College Park, Maryland, USA
Tel: 301-405-8858, Fax: 301-314-9583
Email: fzhang@umd.edu

Qing Shen

School of Architecture, Planning, and Preservation
University of Maryland, College Park
College Park, Maryland, USA
Tel: 301-405-6797, Fax: 301-314-9583
Email: qshen@umd.edu

Kelly J. Clifton,

School of Architecture, Planning, and Preservation
University of Maryland, College Park
College Park, Maryland, USA
Tel: 301-405-1945, Fax: 301-314-9583
Email: kclifton@umd.edu

Submitted for presentation at the 87th Annual Meeting
of the Transportation Research Board, and
Publication in Transportation Research Record
November 2007

Word count = 6330 + 4 tables = 7330

Abstract

In recent years, a considerable amount of money has been spent on ITS projects for public transportation, most notably real-time transit information systems. Strikingly few studies to date have been completed to investigate empirically the effects of deploying such a system. This paper examines the effects of real-time transit information on travelers' behavior and psychology. The 2006-07 University of Maryland campus transportation panel survey data are used to examine how travelers responded to ShuttleTrac, a newly implemented real-time bus arrival information system for the university's shuttle service. Two fixed-effects models and five random-effects ordered probit models are estimated to sort out causal relations between ShuttleTrac information use and two behavioral and five psychological indicators respectively. We find real-time information use significantly increased rider's feeling of security about riding bus after dark and boosted their overall satisfaction level. However, it is not found to significantly increase traveler's shuttle trip frequency, at least in the short term, perhaps due to the lack of enough adjusting time. These results suggest that although transit agencies and scholars should not be too optimistic about achieving immediate ridership increase by providing real-time information to travelers, they can expect positive psychological responses from transit riders.

AN EXAMINATION OF TRAVELER RESPONSES TO REAL-TIME BUS ARRIVAL INFORMATION USING PANEL DATA

INTRODUCTION

Public transit is widely recognized as an environmentally sustainable transportation mode. However, in the U.S. where low-density suburban expansion has prevailed for decades, transit's market share of urban travel has been continuing to fall, as it often fails to compete with the automobile which offers great convenience and flexibility. U.S. transit market share dropped to 1.51 percent of the total in 2005 [1]. Facing the great challenge of providing adequate transit service in American cities, transportation researchers and policymakers in this country have shown an increasing interest in learning from international experiences and exploring innovative approaches. One of the new strategies for high-quality transit service is the development of real-time transit information systems. These systems provide timely and accurate information to current and potential riders to enable them to make better pre-trip and en-route decisions. The most frequently provided real-time transit information includes vehicle arrival times, service disruptions and delays.

A considerable amount of money is being spent on real-time transit information systems [2]. The underlying reasons for deploying this kind of system include both economic and social considerations. Transit agencies expect these systems to boost the ridership, and hence revenues, by attracting more passengers. From transit users' perspective, the time saved by real-time transit information is certainly an economic benefit. Besides, transit agencies may boost their public images by making such visible efforts to improve their service. Perhaps a deeper social consideration is that social inequity in American cities, worsened by suburbanization and segregation, may be narrowed to some extent by improving transit service for the disadvantaged population who are largely captive transit riders.

One pertinent question regarding the effectiveness of real-time transit traveler information systems is how trip makers respond to the real-time information provided to them. Whereas drivers' behavior under Advanced Traveler Information System (ATIS) has gained tremendous academic attention [3], knowledge about effects of real-time transit information on transit riders is sparse.

This paper aims to address the question of how travelers respond to real-time transit information by using panel survey data to model the effects of real-time information usage on people's behaviors and perceptions regarding transit service. University of Maryland has deployed a real-time information system named ShuttleTrac for its extensive, campus-oriented shuttle service. The data used in this analysis are extracted from a pair of campus-wide transportation surveys among university members for both pre- and post-deployment time periods. This study contributes to the existing literature by 1) using revealed-preference surveys to find out actual effects of real-time bus arrival information, 2) applying panel models to micro-level panel data to sort out causal effects, and 3) looking at both behavioral and psychological changes of individual travelers.

PREVIOUS RESEARCH

Traveler's behavior under auto-oriented ATIS has been studied for about two decades. A thorough review by Lappin and Bottom [3] collected more than 180 papers published as of mid-2001 on the topic of traveler response to real-time traveler information. These papers examined the consequences at both the individual and the network levels. When it comes to real-time transit information, however, there exist only a small number of studies.

From the traveler's perspective, several interrelated questions concerning real-time transit information have been asked by scholars: What kind of transit information is useful and attractive to users? What determines travelers' use of real-time information? What is the value, measured by traveler's willingness-to-pay, of this kind of information? And how travelers would actually respond to real-time transit information behaviorally and psychologically? Of particular interest to this paper is the last question. Previous studies addressing this question can be classified into two categories – effectiveness evaluation and modeling study.

The first category is the empirical evaluation of transit rider reactions to real-time transit information systems. Typically both a before survey and an after survey among transit users were carried out by transit agencies to obtain information on individual characteristics, use of and attitude toward transit service, and use of and attitude toward real-time information, and statistical comparisons of before-and-after aggregated indicators are performed.

For example, the landmark survey that measured people's reactions to the London Countdown system was reported by Smith et al [4]. This survey covered perhaps the most complete set of issues related to real-time information, including system reliability, bus service reliability, ergonomics, passenger behavior at stops, passenger perceptions and valuation of Countdown, and ridership and revenue generation. Several frequently cited key findings are 1) video survey and interview of passenger behavior at stops suggested much reduced stress; 2) the average perceived waiting time dropped from 11.9 minutes to 8.6 minutes; and 3) passenger valued Countdown at an average of 31cents.

Two well-known examples in the U.S. are Transit Watch (TW) in Seattle, Washington, and Transit Tracker in Portland, Oregon [5-6]. The agencies responsible for these systems both carried out surveys to evaluate system effectiveness. One of the important findings from the TW satisfaction evaluation survey was that although TW and the improved information is perceived as a real benefit by its users, the users did not seem to think that it increased their overall satisfaction with the transit experience. Likewise, the Transit Tracker survey found no significant difference between satisfaction ratings before and after Transit Tracker was in place. It could be attributed to the fact that riders were already very satisfied before the deployment of Transit Tracker. In terms of ridership, the study found no changes in nighttime ridership at the bus stops as a result of deploying Transit Tracker.

A more recent study focused on psychological effects of real-time train arrival information [7]. The authors collected a panel sample of travelers (N=53) for before-and-after time points. They found the perceived wait time decreased by 20 percent, while no effects on perceived security and ease of use were identified.

The advantages of this type of studies are that they use empirical data and often look at both behavioral and psychological responses. However, these practice-oriented evaluation studies rarely apply sophisticated modeling techniques to empirical data. Therefore, one could hardly infer the causal effects of real-time information on the behavior or perception.

The second category is modeling study. Stated-preference survey or simulation was often applied to model the effects of real-time information on transit passengers at individual level. For example, two studies utilized stated-preference surveys to explore potential impacts of advanced transit information on mode preference [8-10]. Travelers were asked how likely they would consider transit use given certain advanced transit information. Both studies found promising potential of advanced transit information (real-time schedule information in second case) in increasing the preference for transit.

Another rider behavior that was researched was passenger path choice with real-time transit information. Hickman and Wilson [11] developed one of the first dynamic path choice frameworks that take into account information on bus arrival at stops and its accuracy. It was assumed that the strategy of passengers to board a vehicle is to minimize total expected travel time, which can be informed to passengers through real-time information. To evaluate path choices and travel time benefits resulting from the information, the model was applied to a case study corridor, using a computer simulation to model vehicle movement and passenger path choice. The results suggest that real-time information yields only very modest improvement in passenger service measures such as the travel time and the variability of trip times, but significant changes in path assignments. Further they found improving information accuracy has only a slight effect in improving travel times.

The study by Mishalani, Lee, and Mccord [12] is unique in that it took passenger utility as the dependent variable. The utility is assumed to be a function of the difference between the estimated waiting duration acquired by the passenger upon arriving at the bus stop and the actual time that passenger waits for the bus. Then passenger arrivals and transit bus operations were simulated as a stochastic system. Passenger utilities under different real-time information provision scenarios were computed based on simulation. The problem of this study is the vague definition of utility and unconvincing utility function. It is not clear as why utility was defined based solely on the consistency of predicted and actual waiting time.

A recent study by Chorus et al [13] first presented a theoretical model of travel information use and effect by incorporating Bayesian updating into a regret-based framework of travel choice, and used numerical simulation to model non-habitual car drivers' mode choice with presence of real-time transit information. Their results showed that even in the case where transit information is acquired, and the message is favorable to transit, its impact on mode choices will be limited. Thus the study suggested conservative estimates of the impact of transit information provision on modal shifts.

With generally sound theoretical frameworks and sophisticated modeling techniques, these modeling studies have provided useful insights about how travelers would respond to real-time transit information. The major weakness of this kind of studies is that they used stated-preference and simulation methods rather than revealed-preference data, which is likely due to the lack of real-world cases of this emerging technology application. The stated preference approach is characterized by the hypothetical nature of the exercise. Respondents are placed in unfamiliar situations in which complete information is not available. In reality, travelers would not necessarily respond in the stated or simulated ways.

The literature has painted a somewhat mixed picture. On the one hand, stated-preference and simulation studies generally found positive influences of real-time information on mode shift. On the other hand, real-world applications have not provided definitive evidence of increase in ridership due to real-time transit information, although positive psychological responses were usually detected. Therefore, the small volume of empirical research completed to date and the

disparities among the findings point to the necessity for further study. This study attempts to fill some of the gaps by modeling behavioral and psychological effects of real-time transit information using revealed-preference data.

SURVEY AND DATA

University of Maryland, College Park operates a Shuttle-UM system with a 60-vehicle fleet, serving College Park campus and commuters from nearby communities. During summer 2006, the University's Department of Transportation Services (DOTs) started to implement a GPS-based Real-Time Passenger Information System, named ShuttleTrac. The ShuttleTrac system is composed of five components – 30 touch-enabled BusFinder terminals at select stops, a large display screen at an activity center, an Interactive Voice Response (IVR) system for telephone inquiry, a website for Internet inquiry, and a website for WAP-enabled handheld inquiry¹. Therefore, travelers can acquire real-time shuttle arrival information (estimated arrival times of buses scheduled to arrive at that stop within the next 30 minutes) via various media before or during a trip. This system represents the-state-of-practice of real-time transit passenger information system.

After the GPS devices were installed during the summer of 2006, timing/schedule adherence data was gathered on each route throughout the fall semester and first half of the spring semester. This extensive data gathering and fine tuning of the route schedules allow the system to be highly accurate with its arrival predictions. Although since December 2006 ShuttleTrac has been accessible via Internet and telephones, it has been fully functional only since the early April of 2007. An extensive marketing of this system was conducted during April 2007.

To examine travelers' responses to this new ShuttleTrac system and evaluate its effectiveness, DOTs sponsored a study which consists of three pairs of surveys – a panel online campus transportation survey, a panel one-day travel diary survey and a repeated cross-sectional shuttle onboard survey, all designed and administered by the authors of this paper. Data used in this paper were extracted from the first pair of surveys. Note that the surveys were conducted within an academic year and there was no other major change regarding shuttle service such as scheduling or routing. This makes the surveys more valuable in sorting out the effects of ShuttleTrac.

The Campus Transportation Survey was conducted for both pre- and post-ShuttleTrac periods. Wave 1 started on September 13, 2006 and ended on October 12, 2006. Wave 2 started on April 19, 2007, two weeks after campus-wide marketing of ShuttleTrac, and ended on May 13, 2007. The purpose of the before-and-after survey is to explore potential shuttle trip increase, and overall attitude/perception change because of real-time shuttle arrival information. Questions in the online questionnaires for both waves asked about four types of information 1) commuting pattern, 2) use and perceptions of shuttle, 3) attitudes, and 4) personal characteristics. Additional questions about awareness and use of ShuttleTrac were presented in wave 2 questionnaire.

The sampling strategy is as follows: in wave 1, online recruiting methods were used targeting the entire university community, including 1) recruiting emails sent to various campus email-lists three times, 2) recruiting message published on campus-wide daily online FYI system twice, and 3) advertisement on DOTs website. To ensure adequate presence of shuttle riders

¹ See <http://www.transportation.umd.edu/GPS/index.html>

grouping the sample, some supplementary recruiting methods were used, including 1) posters at two campus shuttle shelters, 2) fliers handed out at a major shuttle hub, and 3) advertisement on shuttle onboard survey forms. In wave 2, we sent out emails directly to the respondents of wave 1 survey three times, trying to recruit them for wave 2 survey. Meanwhile, new participants were recruited using similar methods as in wave 1. Because it was impossible for us to keep the record of the number of people who received the recruiting message, there is no way to calculate the response rate.

The sample size of wave 1 is 1679, and wave 2 sample size is 1306. Out of 1679 wave 1 respondents, 623 (37%) participated in wave 2 survey. A large number of wave 1 respondents did not participate in wave 2 survey because they were not required to make the commitment of doing it again. We assume that the attrition from the study was random.

This panel dataset was used for analysis in this paper. Panel data analysis becomes more and more popular in transportation research because of its advantages over cross-sectional data. Not only panel data are particularly useful in answering questions about the dynamics of change, but also they provide stronger evidence for causal inference than cross-sectional data because unobserved heterogeneity was controlled for.

A concern of wave 2 survey is that it started only two weeks after extensive marketing of the ShuttleTrac service and insufficient time had passed adequately to test the impact of the intervention. Some components of ShuttleTrac had already been functional and available to the public before the marketing of ShuttleTrac. For instance, phone numbers and Internet had worked since the beginning of the spring semester. But it was not until early April that the busfinders were deployed and extensive marketing was run. Therefore, travelers may not have enough time to adjust their behaviors and perceptions. Nonetheless, we consider wave 2 survey data as an adequate empirical basis for understanding how travelers respond to the ShuttleTrac system.

The full panel dataset (N=623) was used to estimate behavioral models. In survey questionnaires, non-shuttle riders are allowed to skip questions about perceptions on shuttle service. Therefore, to ensure conceptual validity and avoid missing data, we extract a shuttle-rider panel dataset from the full dataset to estimate psychological models. The shuttle-rider panel dataset (N=482) excludes respondents whose monthly shuttle trip count is zero for both waves. Descriptive statistics for both datasets are presented in Table 1 and Table 2.

VARIABLES AND HYPOTHESIZED RELATIONSHIPS

In the surveys, respondents answered questions about their use and perception of shuttle for pre- and post-ShuttleTrac periods. Therefore, it is possible for us to examine both behavioral and psychological effects of ShuttleTrac using the panel datasets.

In the survey respondents rated their frequency of shuttle use to take part in different activities by choosing among 6 options: “never”, “less than once a month”, “less than once a week”, “1-2 days a week”, “3-4 days a week”, and “5 or more days a week”. Based on their answers, a continuous variable named “monthly frequency of shuttle use” was generated by assuming a middle value for each category and aggregating trip counts for all purposes.

It is generally hypothesized that real-time bus arrival information will entice drivers away from their cars and encourage patrons to ride buses more. In our case, we hypothesize that ShuttleTrac would increase university travelers’ monthly frequency of shuttle use and attract new riders.

In addition, we further hypothesize that the number of campus-based shuttle trips will increase because the ShuttleTrac system mainly serves the campus. More specifically, with real-time arrival information, university students or faculty/staff members may use shuttle more to engage in campus-based non-mandatory (maintenance or discretionary) activities such as going shopping, meeting friends, having meal, etc. Therefore, trip counts for those activity purposes (shopping, personal business, meal, social and recreational) were aggregated to generate a new dependent variable named “monthly campus-based shuttle trip frequency.” Note that shuttle trips for maintenance or discretionary activities are not necessarily campus-based. One can of course take the shuttle from an off-campus site to another for maintenance or discretionary purposes. But it rarely happens because all shuttle routes start from the campus and it is not convenient to travel between two off-campus sites unless they are on the same route.

The five psychological dependent variables are feeling of security about riding shuttle during the day time, feeling of security about riding shuttle at night, perception of shuttle on-time performance, general anxiety level while waiting for shuttle, and overall satisfaction level of shuttle service. They represent shuttle riders’ general perception on shuttle service. In survey questionnaires, questions for the first four of these variables were presented using 5-point likert scales with only the lowest and highest points labeled. Question for overall satisfaction level was presented using a 10-point likert scale. For the sake of comparability, we collapsed satisfaction ratings into 5 levels. Another transformation is the order reverse of waiting anxiety level. Originally, 1 means “not anxious at all” and 5 “extremely anxious”.

Our principle interest is in the effect of using ShuttleTrac. A dummy explanatory variable was extracted from the survey to indicate whether or not the shuttle rider has used one of the devices of the new ShuttleTrac system. Although respondents told us how many times they have used ShuttleTrac, the frequency of ShuttleTrac usage was not directly incorporated to avoid potential endogeneity, which is caused by reverse causality – more shuttle trips cause more ShuttleTrac use.

A number of individual characteristics were incorporated into regression models as independent variables. Variables that do not vary between two surveys are time-invariant variables, which in our case are sex (male=1), race (white=1), and citizenship (foreign=1). As shown later in the discussion of model specification, time-invariant variables will be canceled out in fixed-effects models. Age is dropped too because everyone has the same one year increment. Age square was included in five psychological models to capture possible non-linear effect of age on psychological dependent variables.

Three vehicle-related variables indicate whether a respondent has a valid driver license, regular car access, and a campus parking permit. All three are hypothesized to be negatively related to number of shuttle trips. Correlation tests show that they are not highly correlated. In addition, model sensitivity test further proves that there does not exist the problem of multicollinearity among them.

Based on the question of “how far is where you live from the nearest shuttle stop”, we derived three dummy variables to indicate their accessibility to shuttle service – “less than 5 min walk”, “5-10 min walk”, and “10-20 min walk”. The baseline category is “more than 20 min walk” and “don’t even know”, indicating the shuttle is not accessible from where respondent lives. Presumably, nearer to shuttle stops, more shuttle trips.

Another important locational variable is whether a respondent live on campus or off campus. On-campus students very likely ride shuttle more often than off-campus commuters, especially for various non-mandatory activities. One more locational characteristic is the number

of commuting-to-campus days in past week for commuters, ranging from 0 to 7. More commuting days possibly bring more shuttle commuting trips. But more likely, since all shuttle lines are campus-based, more commuting days mean more days on campus and consequently more shuttle use. Because students living on campus skipped this question, a reasonable transformation is to consider them commuting to campus 7 days a week. This way we did not have to lose a large number of cases of on-campus students. This variable is dropped in the psychological models because of the problem of multicollinearity.

METHODOLOGY

Two behavioral dependent variables, total number of shuttle trips and number of campus-based shuttle trips, were transformed by adding .5 to all scores and then taking the natural logarithm. This transformation was chosen because it both reduced the skewness of the distribution of trip counts and ensured that the model did not predict trip counts less than zero. An alternative approach would be to assume that Y_{it} has a Poisson distribution. This was not chosen because results from the Poisson analysis and the log-linear OLS analysis were virtually identical in the two-period case [14].

For each time point, we have one linear equation for a sample of individuals labeled $i=1, \dots, n$. In our case, we have following two-equation model:

$$\ln Y_{i1} = \mu + \gamma W_{t1} + \beta Z_i + \alpha_i + \varepsilon_{i1} \quad (1)$$

$$\ln Y_{i2} = \mu + \delta X_i + \gamma W_{t2} + \beta Z_i + \alpha_i + \varepsilon_{i2} \quad (2)$$

Here, Z is a vector of measured explanatory variables that are constant over time (time-invariant variables), W is a vector of measured explanatory variables that vary with time, and β and γ are vectors of coefficients. Our principle interest is in δ , which may be regarded as the effect of the event X , which, in our case, represents the use of ShuttleTrac. Some of these individuals experience the event (use of ShuttleTrac) between two measurements ($X_i=1$), other do not ($X_i=0$). The ε s are time-specific random disturbances that are assumed to be independent of the explanatory variables, and of α_i^2 . The α_i s represent unobserved differences across individuals (unobserved heterogeneity) that are constant over time.

The main reason for collecting panel data is to deal with the unobserved heterogeneity α_i . One approach, called within transformation, is to time-demean the data. Specifically, we average equations 1 and 2, subtract the averaged equation from equation 1 and 2, and obtain two equations as follows:

$$\ln Y_{i1} - \overline{\ln Y_i} = -0.5\delta X_i + \gamma(W_{i1} - \overline{W_i}) + (\varepsilon_{i1} - \overline{\varepsilon_i}) \quad (3)$$

$$\ln Y_{i2} - \overline{\ln Y_i} = 0.5\delta X_i + \gamma(W_{i2} - \overline{W_i}) + (\varepsilon_{i2} - \overline{\varepsilon_i}) \quad (4)$$

Consequently, time-constant unobserved heterogeneity α_i was cancelled out and no longer a problem. Then equations 3 and 4 can be pooled to estimate coefficients δ and γ with the OLS estimator. The OLS estimator with time-demeaned data is normally called fixed-effects (FE) estimator or within estimator. One character of the within transformation is that all time-invariant variables Z are canceled out too.

An alternative to fixed-effects model is random-effects (RE) model. It is assumed that α_i is random variables and is not correlated with any independent variable (i.e. W , Z and X). Here α_i

² It is permissible for ε_1 to be correlated with ε_2 in our two-period case (16). Therefore, no autocorrelation test is necessary here.

is no longer a problem, but serial correlation is. A pooled GLS estimator, namely random-effects estimator, can be used to deal with serial correlation.

We chose the FE estimator over the RE one based on the theoretical considerations and the statistical test. RE estimator demands the assumption that unobserved heterogeneity is uncorrelated with explanatory variables. In randomized experiments, the possibility of correlation between treatment and unobserved heterogeneity is reduced by random assignment. In that case, RE estimator is appropriate. In non-experimental scenarios, however, the possible biasing effects of “unmeasured selectivity” could be a serious problem. It is commented by many scholars that the fixed-effects estimator is nearly always preferable for estimating causal effects of events with non-experimental data. Essentially our data is non-experimental in that the treatment (ShuttleTrac use) is not randomized among riders. Therefore, theoretically the FE estimator is preferable in our case. Moreover, we performed the Hausman specification test and the result suggested that the RE estimator was biased.

The five psychological dependent variables consist of discrete values, and therefore the OLS estimation is not appropriate. Furthermore, because these variables are all ordered responses, a good approach is to estimate ordered probit or logit models. Parallel to above discussion, the fixed effects estimator is preferable to the random effects estimator in our panel dataset. However, fixed-effects ordered logit/probit model is not commonly used because of its estimation difficulty. In psychology and economics literature (e.g. [15]), random effects ordered probit model is commonly utilized to explain categorical dependent variables with natural order in panel data. Hence we used this type of model to examine ShuttleTrac’s effect on shuttle riders’ perceptions on Shuttle-UM.

The random-effects ordered probit model can be described as follows:

$$y_{it}^* = \beta X_{it} + \epsilon_{it}, \quad i = 1, \dots, N, t = 1, 2$$

$$\epsilon_{it} = \alpha_i + \varepsilon_{it}, \quad Var(\epsilon_{it}) = \sigma_\alpha + \sigma_\varepsilon = \sigma_\alpha + 1, \quad Corr(\epsilon_{i1}, \epsilon_{i2}) = \rho = \frac{\sigma_\alpha}{1 + \sigma_\alpha}$$

$$y_{it} = \begin{cases} 1 & \text{if } y_{it}^* \leq \mu_1 \\ 2 & \text{if } \mu_1 < y_{it}^* \leq \mu_2 \\ 3 & \text{if } \mu_2 < y_{it}^* \leq \mu_3 \\ 4 & \text{if } \mu_3 < y_{it}^* \leq \mu_4 \\ 5 & \text{if } \mu_4 < y_{it}^* \end{cases}$$

Where, y_{it}^* is an unobserved latent variable, and y_{it} is the observed ordered categories in the data; μ_j is the J-th cut-off point for the categories; X_{it} are observable explanatory variables; ε_{it} is a time-varying error term, normally distributed, uncorrelated with X_{it} ; and α_i is the unobserved individual heterogeneity, normally distributed, constant over time and uncorrelated with X_{it} (assumption of random-effects). The cross-period correlation of ϵ_{it} is ρ . If ρ is significantly different from 0, it indicates there is cross-period correlation with respect to ϵ_{it} [16]. Readers are referred to Frechette [17] for details of estimation process. We used “reoprobit” command in Stata 9, written by Frechette, to estimate coefficients.

The estimated coefficients for the independent variables in seven models are displayed in Table 3 and 4, along with their significance levels. Note that a dummy variable indicating wave 2 was included in all seven models to capture the possible trendy shift.

EMPIRICAL RESULTS

Results for two behavioral models (Model 1 and 2) using traveler panel dataset are displayed in Table 3. Since the fixed-effects estimator was chosen, four time-invariant variables are dropped, including age, gender, race, and foreign citizenship. The variable of primary interest, ShuttleTrac use dummy variable, has positive signs in both models as expected. However, both effects are not statistically significant. This seems to suggest that travelers may not increase their shuttle trips because of use of real-time bus arrival information. An apparent explanation is that our wave 2 survey was only a couple of weeks (less than a month) after the extensive marketing, there was not enough time for many travelers to adjust their travel behavior.

In Model 1, three variables are significantly related to the number of shuttle trips. The effect of obtaining a campus parking permit is to decrease the shuttle trip count by 61%. The magnitude of this effect is rather large. With one more day commuting to campus a week, the number of monthly shuttle trips increase by about 6.7%. Although the number of commuting days is correlated with on-campus dummy, sensitivity test shows there is no multicollinearity problem between them in Model 1. Another significant variable is “<5 min walk to nearest shuttle stop”. It suggests that moving from a place where shuttle is not accessible by walk to one where nearest shuttle stop is less than five minutes away increases the shuttle riding frequency by 41.9%, another huge effect. In Model 2, two statistically significant variables are on-campus dummy and 5-10 minute walk to stop dummy. If one moves from an off-campus place to an on-campus one, his campus-based shuttle trips nearly double (increase by about 92%).

Results for five psychological models (Model 3-7) using shuttle-rider panel dataset are in Table 4. First we examine the effects of ShuttleTrac use. The ShuttleTrac use dummy shows positive signs as expected in all models except for Model 6. And only in Model 2 and Model 5 the coefficients are statistically significant. In Model 2, the positive effect of ShuttleTrac use on feeling of security about riding shuttle is significant at the 0.1 level. On the contrary, it has no significant effect on feeling of security at day. A plausible explanation is that daytime safety is not as a serious problem as nighttime safety and hence there is room for improvement for the latter. Meanwhile, our estimation results show that ShuttleTrac use has no significant effect on perceptions on shuttle on-time performance (it just misses the .1 significance – the p value is 0.108) and waiting anxiety level. More specifically, with ShuttleTrac use, shuttle riders do not tend to feel the shuttle on-time performance is better or feel less anxious while waiting for the bus. It may be attributed to relatively few times of ShuttleTrac use. People need more experience to evaluate their experiences.

Results of Model 7 show that ShuttleTrac use has significantly positive effects on shuttle riders' overall satisfaction level at the 0.05 confidence level. In ordinal models, magnitude of coefficients only has meaning for the latent variable. To interpret the coefficient of ShuttleTrac use, we predict probabilities for different situations. Other variables kept constant at mean values, ShuttleTrac use decreases the probability of one rating satisfaction level 4 (7 or 8 in original coding) by 0.003 (from 0.558 to 0.555), while increases the probability of rating 5 (9 or 10 in original coding) by 0.071 (from 0.195 to 0.266). As the literature on psychology of waiting service suggest, overall satisfaction stands on the highest level, and changes in other affective reactions (in this case, anxiety level and feeling of security) would contribute to changes in overall satisfaction level [18]. ShuttleTrac use can positively influence nighttime waiting safety feeling, then part of ShuttleTrac use's significantly positive effect on overall satisfaction level can be attributed to that indirect path. A more direct path is that after experiencing the new ShuttleTrac system, one or more times, shuttle riders feel more satisfied with Shuttle service, not

because they feel safer or less anxious while waiting or feel buses more on-time, but because they appreciate the agency's effort of trying to improve shuttle service.

Coefficients of wave 2 dummy show that in general people felt less safe about riding shuttle during the day and less anxious while waiting in wave 2 than in wave 1. And they thought shuttle had better on-time performance in wave 2. Findings for other variables are presented as follows. Age has significant effects on feeling of security at day and night. Men feel safer while waiting for shuttles at day and at night than women. Race also showed significant differences. White people feel safer at night than non-white. Meanwhile, whites feel less anxious while waiting for shuttles and have a higher overall satisfaction level about shuttle service. For shuttle on-time performance, students feel worse than faculty and staff members. A consistent result is that students feel less satisfied with Shuttle service. Some interesting findings are about shuttle accessibility variables. People who live within 5 min walk to a nearest shuttle stop feel safer about riding the shuttle at day but think shuttle service is less punctual. Those who live 5-10 minute walk to a stop have the same negative feeling about shuttle on-time performance.

CONCLUSION

This paper analyzed the relationships between real-time passenger information use and traveler shuttle trip frequency and shuttle riders' perceptions on shuttle service. Two behavioral models and five psychological models were estimated using the fixed-effects OLS estimator and the random-effects ordered probit estimator respectively. Dependent variables measuring traveler behavior changes are the number of monthly shuttle trips and the number of monthly campus-based shuttle trips. Indicators considered in psychological models are feeling of security during the day and after dark, perception of shuttle on-time performance, waiting anxiety level, and overall satisfaction level about shuttle service.

ShuttleTrac use was found significantly correlated with two psychological variables out of five examined here – feeling of security about riding shuttle after dark and overall satisfaction level. However, ShuttleTrac use does not show significant effects on shuttle trip frequency. We may interpret these findings with consideration of the timing of wave 2 survey. It seems to suggest that shuttle riders may need more time to adjust their behavior in response to real-time information. What is encouraging is that, real-time bus arrival information seems to help address the issue of night-time safety and in general make travelers feel more satisfied with shuttle service.

A possible implication of these findings is that we should be conservative in predicting transit ridership increase immediately after the deployment of real-time transit information system. A stated-preference survey in Chicago shows that about 67% of all respondents said that they would increase transit usage when provided with real-time transit information, 60% for current users and 70% for non-current users [19]. In light of our results, such stated preference may need to be considered with reservation.

Our results also suggest that other approaches (e.g. building more on-campus student housing, rerouting lines or rearranging stops to make shuttle within walking distance for more students, or increasing the price of a campus parking permit) would increase shuttle usage significantly. This is consistent with previous study [20]. Universities may consider such approaches, along with other proven policies (e.g. unlimited access [21] and promoting non-motorized mode [20]), if they want to achieve goals such as increased transit ridership and promote sustainability in campus community.

Further research on long-term effects of real-time transit information system is necessary to understand how travelers may gradually change their behaviors and perceptions as they make more use of real-time transit information. The Wave 3 online survey targeting previous participants is actually being conducted during November 2007. In addition, with the diary data and onboard data we have collected through our surveys, we will be able to investigate trip-specific travel behaviors and psychology regarding shuttle service, such as trip-specific departure time choice and mode choice.

REFERENCE

1. U.S. Urban Personal Vehicle & Public Transport Market Share from 1900. <http://www.publicpurpose.com/ut-usptshare45.htm>. Accessed July 10, 2007.
2. Cham, L., Darido, G., Jackson, D., Laver, R. and Schneck, D. . Real-time Bus Arrival Information Systems Return-on-Investment Study. Final Report, U. S. Department of Transportation. Oct 2006.
3. Lappin, J. and J. Bottom. Understanding and Predicting Traveler Response to Information: A Literature Review. Washington, DC, Office of the Metropolitan Planning, Federal Highway Administration. 2001.
4. Smith, R., S. Atkins, and R. Sheldon, "London Transport Buses: ATT in Action and the London Countdown Route 18 Project," Proceedings of the First World Congress on Applications of Transport Telematics and Intelligent Vehicle-Highway Systems, Paris, France, November 30-December 3, 1994, pp. 3048-3055.
5. TransitWatch: Bus Status Video Monitors in Seattle - Customer Satisfaction Evaluation. Draft Report, Science Applications International Corporation, McLean, Va., August 31, 1999.
6. Transit Tracker Evaluation Final Report, Tri-County Metropolitan Transportation District of Oregon (TriMet) Marketing Information Department, June 2002
7. Dziekan, K. and A. Vermeulen. Psychological Effects of and Design Preferences for Real-Time Information Displays. *Journal of Public Transportation*, Vol. 9, No. 1, 2006, pp. 71-89.
8. Abdel-Aty, A., R. Kitamura, and P. Jovanis. "Investigating Effect of Advanced Traveler Information On Commuter Tendency to Use Transit." in *Transportation Research Record: Journal of the Transportation Research Board*, No. 1550, TRB, National Research Council, Washington, D.C. 1996, pp. 65-72.
9. Abdel-Aty, A. Using Ordered Probit Modeling to Study the Effect of ATIS on Transit Ridership. *Transportation Research Part C* 9(4), 2001, pp.265-277.
10. Reed, T. B. and J. C. Levine. Changes in Traveler Stated Preference for Bus and Car Modes Due to Real-Time Schedule Information: A Conjoint Analysis. *Journal of Public Transportation*, 1(2), 1997, pp.25-47.
11. Hickman, M. D. and N. H. M. Wilson. Passenger Travel Time and Path Choice Implications of Real-Time Transit Information." *Transportation Research Part C* 3(4), 1995, pp. 211-226.
12. Mishalani, R. G., S. Lee, and M. McCord. Evaluating Real-Time Bus Arrival Information Systems. in *Transportation Research Record: Journal of the Transportation Research Board*, No. 1550, TRB, National Research Council, Washington, D.C., No. 1731, TRB, National Research Council, Washington, D.C., 2000, pp. 81-87.
13. Chorus, C., E. Molin, B. Van Wee, T. Arentze, and H. Timmermans. Responses to Transit Information among Car-drivers: Regret-based Models and Simulations. *Transportation Planning & Technology*, Vol. 29 No. 4, 2006, pp. 249-271.
14. Allison, P.D. Using Panel Data to Estimate the Effects of Events. *Sociological Methods & Research* 23, 1994. pp. 174-199.
15. Karni, E., T. Salmon, and B. Sopher. Individual Sense of Fairness: An Experimental Study. *Experimental Economics*, upcoming.
16. Greene, W. H. *Econometric Analysis*. 5th ed. Upper Saddle River, NJ: Prentice Hall, 2002.
17. Frechette, G. R. Random-effects ordered probit. *Stata Technical Bulletin* 59, 2001, pp. 23-27.

18. Taylor, S.A., Fullerton, G. Waiting for service: perceptions management of the wait experience. in T.A. Swarz, D. Iacobucci, Services Marketing and Management, Sage publications. 2000, pp. 171-190.
19. Tang, L. and P. Thakuriah. An Analysis of Behavioral Responses to Real-Time Transit Information Systems. Presented in the Association of Collegiate Schools of Planning annual meeting. Fort Worth. 2006.
20. Toor, W. and S. Havlick. Transportation and sustainable campus communities: issues, examples, solutions. Island Press, 2004.
21. Brown, J., D. Hess and D. Shoup. Fare-free Public Transit at Universities: An Evaluation. Journal of Planning Education and Research, 23(1), Fall 2003, pp. 69-82.

Table 1 Descriptive statistics of full panel dataset for wave 1 and wave 2

Table 1 Descriptive statistics of full panel dataset										
	Wave 1 (before)					Wave 2 (after)				
Variables	N	Min	Max	Mean	SD	N	Min	Max	Mean	SD
Use of ShuttleTrac	N/A					623	0	1	0.412	0.49
# of shuttle trips a month	623	0	116	10.91	17.82	623	0	154	10.33	17.8
# of campus-based shuttle trips	623	0	94	2.85	7.21	623	0	94	2.68	7.06
Age	610	16	72	30.94	11.94	610	17	73	31.94	11.9
Male	615	0	1	0.4	0.49	time-invariant				
White	614	0	1	0.68	0.47	time-invariant				
Foreign citizen	618	0	1	0.17	0.37	time-invariant				
Student	622	0	1	0.64	0.48	619	0	1	0.63	0.48
New to school	623	0	1	0.21	0.41	623	0	0	0	0
Driver license	616	0	1	0.94	0.24	612	0	1	0.95	0.21
Car access	623	0	1	0.76	0.43	620	0	1	0.78	0.42
campus Parking permit	623	0	1	0.56	0.5	620	0	1	0.56	0.5
Live on campus	623	0	1	0.15	0.36	623	0	1	0.15	0.36
# days of commuting to campus a week	623	0	7	5.09	1.49	623	0	7	5.08	1.61
<5 min walk to nearest stop	623	0	1	0.37	0.48	623	0	1	0.37	0.48
5-10 min walk to stop	623	0	1	0.1	0.3	623	0	1	0.09	0.29
10-20 walk to stop	623	0	1	0.07	0.26	623	0	1	0.06	0.24

Table 2 Descriptive statistics of shuttle-rider panel dataset for wave 1 and wave 2

Table 1 Descriptive statistics of shuttle-rider panel dataset										
Variables	Wave 1 (before)					Wave 2 (after)				
	N	Min	Max	Mean	SD	N	Min	Max	Mean	SD
Use of ShuttleTrac	N/A					482	0	1	0.51	0.5
feeling of security at day	453	1	5	4.813	0.516	460	1	5	4.751	0.55
feeling of security at night	414	1	5	3.988	1.029	429	1	5	4.063	1.02
perception of on-time performance	422	1	5	3.618	0.785	419	1	5	3.773	0.61
waiting anxiety level	436	1	5	3.138	1.106	448	1	5	3.002	1.1
overall satisfaction level	465	1	5	3.789	0.944	478	1	5	3.897	0.88
Age	475	16	72	28.682	10.75	475	17	73	29.68	10.7
Age square	475	256	5184	937.94	797.1	475	289	5329	996.3	818
Male	478	0	1	0.423	0.494	time-invariant				
White	477	0	1	0.66	0.474	time-invariant				
Foreign citizen	479	0	1	0.196	0.398	time-invariant				
Student	481	0	1	0.723	0.448	479	0	1	0.716	0.45
Driver license	478	0	1	0.923	0.268	477	0	1	0.941	0.24
Car access	482	0	1	0.689	0.463	480	0	1	0.717	0.45
campus Parking permit	482	0	1	0.479	0.5	480	0	1	0.471	0.5
Live on campus	482	0	1	0.187	0.39	482	0	1	0.187	0.39
<5 min walk to nearest stop	482	0	1	0.436	0.496	482	0	1	0.446	0.5
5-10 min walk to stop	482	0	1	0.116	0.321	482	0	1	0.108	0.31
10-20 walk to stop	482	0	1	0.083	0.276	482	0	1	0.064	0.25

Table 3 Estimated coefficients of behavioral models

	Model 1	Model 2
	Ln(# monthly shuttle trips)	Ln(# montly campus-based shuttle trips)
wave 2	-0.041	-0.042
ShuttleTrac use	0.063	0.056
Age	dropped	dropped
Male	dropped	dropped
Foreign citizen	dropped	dropped
White	dropped	dropped
Driver license	-0.465	-0.232
Car access	0.121	-0.213
Campus Parking permit	-0.61***	-0.213
Live on campus	-0.148	0.916***
# commuting days a week	0.067*	-0.004
Student	0.032	-0.16
<5 min walk to nearest stop	0.419**	-0.013
5-10 min walk to stop	0.065	-0.399**
10-20 walk to stop	0.284	-0.083
_cons	1.265***	0.721*
within R_sq	0.0447	0.0466
Overall R_sq	0.3605	0.2368
# obs	1196	1196
# groups	606	606

* Significant level: * 0.1 **0.05 ***0.01

* Full dataset has 623 individual participants (N=623), which makes 623*2= 1246 observations in panel models supposedly. Because of missing variables, the number of observations in Model 1 and 2 is 1196, and the number of individuals who have at least one observation in models is 606. Therefore, dataset used in Model 1 and 2 is an unbalanced panel dataset.

Table 4 Estimated coefficients of psychological models

	Model 3	Model 4	Model 5	Model 6	Model 7
	feeling of security at day	feeling of security at night	On-time performance	waiting anxiety	overall satisfaction
wave 2	-0.426***	-0.054	0.255*	0.222**	-0.010
ShuttleTrac use	0.177	0.261*	0.274	-0.054	0.378**
Age	0.133**	0.083*	-0.047	0.016	-0.062
Age square	-0.00136**	-0.00084	0.00075	0.00007	0.00105*
Male	0.476***	0.715***	-0.191	0.139	0.018
White	-0.016	0.361**	-0.215	0.38***	-0.481***
Driver license	-0.099	0.013	0.059	0.082	-0.005
Car access	-0.127	-0.116	-0.086	-0.16	-0.234
Campus Parking permit	-0.076	-0.211	0.063	0.12	0.234
Live on campus	0.034	0.134	-0.34	-0.147	-0.078
Student	0.232	0.006	-0.405*	-0.263	-0.451**
Foreign citizen	0.057	0.093	0.133	0.157	0.166
<5 min walk to nearest stop	0.455**	0.281	-0.443**	0.094	0.092
5-10 min walk to stop	0.33	-0.211	-0.528**	-0.165	-0.131
10-20 walk to stop	0.491	0.08	-0.123	0.379*	-0.35
_cut1	-1.016	-1.343	-4.774***	-1.125	-4.866***
_cut2	-0.751	-0.113	-3.683**	0.288	-3.758***
_cut3	-0.0812	1.196	-2.312	1.503**	-2.593***
_cut4	1.454	2.571***	1.426	2.826***	-0.0949
rho	0.502***	0.616***	0.569***	0.496***	0.618***
Cragg-Uhler Pseudo R ²	0.063	0.063	0.077	0.066	0.055
# obs	886	818	817	860	870
# groups	469	445	450	461	461

* Significant level: *0.1 **0.05 ***0.01

* Rider dataset has 482 individual participants (N=482). Because of missing variables, the numbers of observations in Model 3-7 vary between 817 and 886, and the numbers of individuals who have at least one observation in models vary between 450 and 469. Therefore, datasets used in Model 3-7 are all unbalanced panel ones.