# Modeling the Timing of User Responses to a New Urban Public Transport Service

## Application of Duration Modeling

Kiron Chatterjee and Kang-Rae Ma

**When a new service is introduced into the transport market (or an existing service is modified), the timing and nature of the responses of individuals can be expected to vary considerably. The aggregated responses of individuals will determine overall usage of the service. This paper reports how a panel survey was used to obtain information on the timing and nature of responses to a new public transport service. The survey results indicate how awareness, perceptions, and usage of the service change over time. Duration modeling was applied to analyze the factors that influenced the time taken to use the new service. It indicates that being younger, being from a household without a car, gaining a bus service that is physically closer to the home than services previously available, and using buses frequently before the new service was introduced all reduce the time taken to use the new service. The duration modeling provides useful results for operators to consider in marketing new transport services. For forecasting the overall usage of a new service, predicting new users and their frequency of usage need to be considered. It is anticipated that this type of analysis will lead to better understanding of the impacts of transport policy interventions and to improved transport forecasting tools.**

When a new service is introduced into the transport market (or an existing service is modified), the timing and nature of the responses of individuals can be expected to vary considerably. Some individuals may switch immediately from another service to the new one, others will take some time before they use the new service, and others will never use the service. Some may use the new service only once, others may use it regularly each week, and others may use it increasingly over time. The growth in usage of a new service (or what can be referred to as its dynamic demand profile) depends on the aggregation of individual responses.

Conventional methods of travel demand analysis (based on cross-sectional travel data and on equilibrium principles) are static and are not able to forecast the dynamic demand profile of a new transport service. They assume that travel demand will attain a new level after the service is introduced but they do not indicate any timescale for when this level of demand will be reached. The dynamic demand profile will determine the consequences of a new transport service for public welfare (user benefits, societal costs) and business viability (revenue streams), so efforts should focus on forecasting dynamic behavioral responses.

Douglas (*1*) analyzed the patronage growth for 13 new or upgraded rail schemes from around the world and estimated an average ramp-up factor of 79% for the first year of operation, 95% for the second year of operation, and steady-state patronage after 3 years. However, there was considerable variation in growth across the schemes. Douglas noted that demand stemming from induced demand may take longer to ramp up than diverted demand. He considered that ramp-up may arise due to the learning curve, travel habits, operational "teething" problems, and marketing deficiencies. The ramp-up factors provide useful figures indicative of average growth in demand across the schemes studied but are not able to indicate the growth in demand that can be expected for a specific scheme. The research described here sought to understand the responses of travelers to a new transport service, recognizing that it could help in forecasting dynamic demand profiles. It involved a four-wave panel survey and various statistical analyses of the data. A paper presented at the 2006 International Conference on Travel Behaviour Research describes the survey methodology in detail and provides descriptive statistics on the survey data (*2*).

The next section of this paper considers behavioral explanations for dynamic responses and what is known about them. The third section summarizes the panel survey used to obtain information on the behavioral responses of residents to a new bus service. In the fourth section, changes in travel perceptions and behavior across the waves are presented before the application of duration modeling to the data is introduced and reported. The paper concludes by considering further areas for research and reflecting on the insights gained in the reported analysis.

## EXISTING KNOWLEDGE

The timing of user responses to a new transport service may be influenced by various behavioral factors. Longer times of responses may be expected when

- Habit prevents any conscious deliberation about behavior,
- Time is required to become aware of change and to acquire and process information about it,
- A period of experimentation is required with alternative behaviors,
- A gradual modification of behavior is made toward preferred behavior,

Centre for Transport and Society, University of the West of England, Bristol BS16 1QY, United Kingdom. Current affiliation for K.-R. Ma, Department of Urban and Regional Planning, Chung-Ang University, Anseong-si, Gyeonggi-do, South Korea. Corresponding author: K. Chatterjee, Kiron.Chatterjee@uwe.ac.uk.

*Transportation Research Record: Journal of the Transportation Research Board, No. 2010,* Transportation Research Board of the National Academies, Washington, D.C., 2007, pp. 62–72.
DOI: 10.3141/2010-08

- Long-term commitments exist toward current travel behavior (e.g., season tickets), and
- An option is tried only after sufficient time to develop a positive attitude toward it.

Shorter response times may be expected when

- Conscious deliberation occurs because of goals not being achieved (e.g., roadworks) or because of decision context changing (e.g., change of residential location),
- Awareness takes place in advance of the change and preparation is made for it, and
- Variety in behavior is sought.

Despite behavioral change being of major interest to transport planners, there is relatively little understanding about the importance of these factors and how they affect the timing of responses to a change in the travel environment (*3*). In recent years, travel behavior researchers have focused considerable attention on habit. The role of habit has been conceptualized (*4, 5*) and empirical investigations have sought to identify the importance of habit while providing insights into some of the other behavioral factors identified previously. For example, Fujii and Kitamura (*6*) looked at the effect of providing subjects with a 1-month free bus pass and compared behavior immediately before, immediately after, and 1 month after the experiment. They found an increase in positive attitudes toward bus and use of bus, and they found a decrease in habitual car use after the experiment, which was sustained to some degree 1 month later.

The stability of travel behavior has been explored with citizen panel surveys. Dargay and Hanly (*7*) used 11 years of data from the British Household Panel Survey to analyze stability of car ownership and commute mode. They used random effects models (ordered probit), which take into account heterogeneity, to show that state dependence (last year's behavior) is an important determinant of both car ownership and commute mode behavior, after taking into account other determinants such as household income and fuel prices. Thørgersen (*8*) used three waves of travel data (between 1998 and 2000) to study public transport use for a random sample of participants in Denmark and found that current behavior is strongly conditional on past behavior but is mediated by current attitudes and perceived behavioral control. Thørgersen also found that current behavior determines future attitudes and perceived control. Simma and Axhausen (*9*) used panel data from Germany and the Netherlands to examine the relationship within period and between period of travel commitments (car ownership and public transport season tickets) and mode usage and found that commitments in one period affect mode usage in the next.

Although the preceding studies have provided useful insights into the role of past behavior and habit in determining current behavior, they did not specifically examine the timescale of behavioral responses (the subject of this paper). Substantial research has been carried out on the dynamic travel decisions of motorists, which has involved measuring route and departure time choices. A number of studies have used travel diaries and laboratory simulations to collect data and estimate models for the day-to-day decision making of motorists (*10–12*). Although these studies are informative about the timing of motorists' responses to information, they do not offer insights into travelers' mode choices and how these choices are affected by interventions designed to change the relative attractiveness of different modes. Mode choice is an aspect of travel behavior in which there are major barriers to change (as listed at the beginning of this section) and change tends to take longer to occur.

An important reason for the limited knowledge on the timescale of transport mode behavioral responses is difficulty in obtaining suitable data. Bradley (*13*) looked at the effect on mode choice of a new rail commuter line between Almere and Amsterdam. Before-and-after data were collected for 475 commuters and Bradley specified and estimated dynamic logit models accounting for response lags and state dependence. He found improved model estimation for dynamic model specifications, and he found that forecasts are quite different if dynamic specifications are used instead of static specifications. He concluded, though, that to understand and model the effects of changes in the travel environment "multiple 'after' periods are necessary to determine whether policies grow, diminish, or remain stable over time." To improve the potential for identifying causal impacts, three or more time occasions are necessary to monitor the sequence of changes that occur in variables.

Hensher (*14*) studied the switching of motorists from free highway routes to a new urban toll road in Sydney, Australia. Data were available on the precise date of switching to the toll road for 170 motorists and they were used to estimate a duration model to identify the factors influencing the time of switching to the toll road. This is a rare example in which the challenge of measuring, understanding, and predicting the timescale of behavioral responses has been addressed.

The review highlights that information is lacking on the timing and nature of behavioral responses to new transport services. The work described next involved the design and implementation of a survey to capture such information to analyze the timing of behavioral change.

## RESEARCH METHOD

### Fastway Case Study

The Fastway bus system began operating in the Crawley and Gatwick Airport area in the county of West Sussex, southern England, in September 2003 (*15*). It is intended to be a modern, high-quality public transport system that provides a frequent, reliable service and offers a real alternative to the car. The Fastway buses travel in dedicated lanes and guideways along significant parts of their routes and also benefit from barrier-controlled bus gates and priority at signal-controlled junctions. Real-time information is provided at bus stops and on the Internet and the buses are a modern fleet of high-specification vehicles with low-floor access, comfortable and modern interiors, and low-noise and low-emission engines.

The Fastway system supplements existing bus services within the area and is designed to provide more direct public transport services than are otherwise available connecting residential areas with key employment sites such as Gatwick Airport. The first Fastway service (Route 10) experienced steady growth in passengers from 4,000 passengers per day in September 2003 to 6,000 in May 2005, and the second service (Route 20) was introduced in August 2005. The route maps are presented in Figure 1. The Route 20 service provides the case study for this paper.

### Panel Survey

Longitudinal data are required to study temporal change in behavior. Event history data recording travel behavior in continuous time

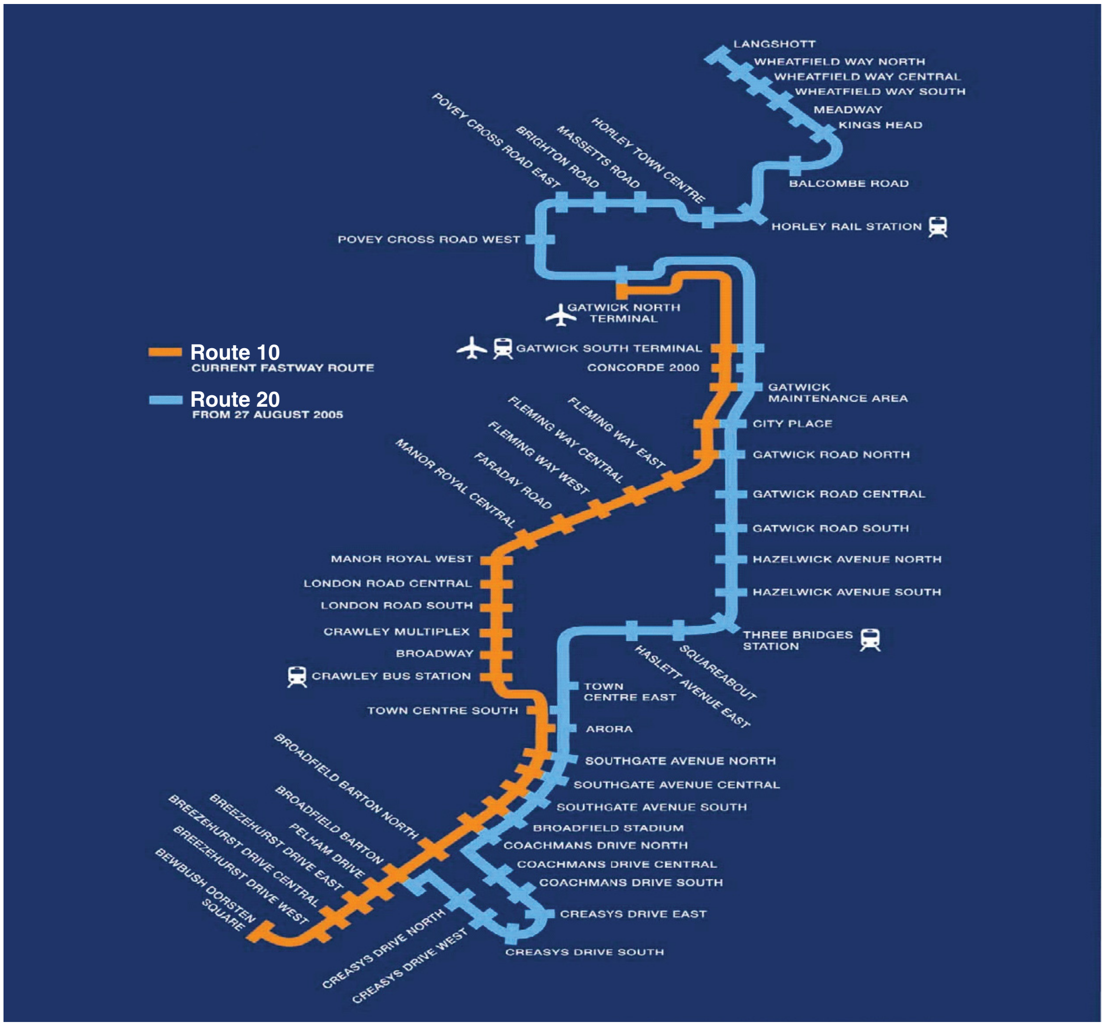


**FIGURE 1 Fastway routes (www.fastway.info).**

were not feasible to obtain; instead, a classic panel survey was conducted. A classic panel study involves the same respondents being surveyed at different times. Survey approach, design, and issues are discussed in detail by Chatterjee and Ma (*2*) and an overview is provided next.

Douglas (*1*) identified an average of 79% ramp-up 1 year after a rail scheme introduction or upgrade. This suggests that most, but not all, responses take place within a year. For a new bus service the timescale of responses is likely to be shorter than for a new rail service, as it will be used for local journeys and is likely to be more readily known to potential users. The Fastway panel study involved four waves, with Wave 1 taking place 1 month before the introduction of the Route 20 service, Wave 2 taking place 1 month after the introduction of the service, and Waves 3 and 4 taking place at subsequent 2-month intervals. The overall length of the panel study of 7 months aimed to span a period sufficient for behavioral responses to take place and to start to diminish.

The target population for the panel survey was residents living close to the new Route 20 service and not living close to the Route 10 service. This resulted in residents in the following two areas being targeted:

- Broadfield (south). Residents living near the Coachmans Drive and Creasys Drive bus stops indicated in Figure 1.
- Three Bridges (east). Residents living near the Haslett Avenue East, Squareabout, Three Bridges Station, Hazelwick Avenue, and Gatwick Road South bus stops indicated in Figure 1.

Characteristics of the two targeted areas are presented in Table 1. The electoral register used to identify residents in the target areas provided names and addresses of approximately 2,500 residents. The panel survey used self-administered postal questionnaires as the survey instrument. Well-known difficulties with panel studies are sample aging, attrition, and response contamination (*16*). Sample aging concerns the sample becoming unrepresentative over time as it ages. Given the limited overall duration of the panel study (7 months), it is not a serious issue. Attrition involves losing respondents over the course of survey waves, and it needs to be minimized in any panel study to avoid the composition of the sample changing over the course of the study. The first wave of the postal survey (in August 2005) achieved a 22% response rate (554 responses), which is typical of experience with a self-completion postal questionnaire; 361 respondents said they

**TABLE 1 Characteristics of Broadfield South and Three Bridges Electoral Wards**

| Characteristic | Broadfield South | Three Bridges | Crawley |
|---|---|---|---|
| Location | Edge of town neighborhood | Inner town neighborhood | — |
| Public transport (before Fastway Routes 10 and 20 introduction) | One bus service to town center | National rail station and various bus services (mostly on boundary of neighborhood) | — |
| Index of multiple deprivation[a] | 3 of the 4 ward subareas are ranked in the top decile of deprived subareas in the county of West Sussex | None of the subareas within ward are ranked in the top decile of deprived subareas in the county of West Sussex | 7 subareas within town are ranked in the top decile of deprived subareas in the county of West Sussex |
| Percentage of population aged 65 and older[b] | 5.2 | 20.7 | 14.7 |
| Mode share percentages for travel to work[b] | | | |
| Car | 69.6 | 60.5 | 67.5 |
| Train | 3.1 | 8.0 | 6.2 |
| Bus | 11.7 | 2.1 | 6.3 |
| Walking | 4.8 | 14.4 | 7.8 |
| Percentage with distance to work less than 2 km[b] | 7.1 | 38.8 | 19.3 |
| Percentage of households without car[b] | 22.4 | 22.1 | 20.4 |

[a]Office of the Deputy Prime Minister English Index of Multiple Deprivation 2004, which is a measure of multiple deprivation at the small area level and is an index based on seven domains of deprivation.
[b]From 2001 Census.

were willing to participate further in the study. They were sent the second questionnaire and 220 responses were received (in October 2005). To maximize subsequent participation a £20 ($34.40 in 2005 U.S. dollars) incentive was offered to those participating in the final two waves; 254 responses were received for Wave 3 (in December 2005) and 247 responses were received for Wave 4 (in March 2006).

No attempt was made to refresh the sample during the course of the study because there was no further source of participants. This can be justified as it was not the expressed aim of the panel study to obtain a representative sample of the population of interest. Instead of seeking statistical generalizations, the study intended to develop greater understanding of dynamic behavioral responses.

Response contamination concerns behavior or its reporting being affected by panel membership and the quality of information provided decreasing (or increasing) over the course of the study. The survey was presented to the residents as a general travel survey instead of as a survey focusing on the new bus service. Providing information about the new Route 20 service was avoided. To maintain quality of response through the survey, the questionnaire was designed to be as simple as possible and emphasized the importance of providing complete responses even if that involved repeating information provided in a previous questionnaire.

The structure and design of the questionnaire were similar in each wave to ensure as far as possible that responses were directly comparable. Respondents were asked to provide information on the following:

- Views and perceptions of local transport and travel;
- Weekly frequency of use of different transport modes;
- Travel to work details;
- Leisure travel details;
- Shopping travel details;
- Awareness, perceptions, attitudes, and use of bus services; and
- Personal and household information.

### Response Sample

For analyzing the timing of behavioral responses, the focus is on those respondents whose residential circumstances did not change during the survey period and who participated in at least Waves 1 and 3. This results in a sample of 247 respondents; 187 residents participated in all four waves of the questionnaire. Table 2 compares the characteristics of the sample of 554 Wave 1 respondents, the 187 all-wave respondents, and the Crawley population in general. It indicates that car ownership was higher for the survey samples than for the Crawley population in general and that differences between the Wave 1 respondents and all-wave respondents are relatively small and therefore that attrition does not adversely affect the sample characteristics.

## RESULTS AND ANALYSIS

### Changes in Awareness, Perceptions, and Usage of Route 20

To enable direct comparison, results are reported with respect to the 187 residents who participated in all four waves of the questionnaire. Of the 187 all-wave respondents, 60% were aware of the new Fastway service 1 month before it was introduced and 76% were aware of it 1 month after it was introduced. Respondents were not asked about general awareness of the Route 20 service after Wave 2, as it was

TABLE 2 Characteristics of Survey Samples

| Characteristic | Crawley Population (from Census 2001) (%) | Wave 1 ($N = 554$) (%) | All-Wave ($N = 187$) (%) |
|---|---|---|---|
| Female | 51 | 55 | 56 |
| Aged younger than 35 (and >16) | 34 | 27 | 19 |
| Aged 65 and older | 19 | 19 | 18 |
| Full-time employed | Not known | 52 | 49 |
| Part-time employed | Not known | 13 | 16 |
| Households without car | 20 | 9 | 10 |
| Used route 10 service | Not applicable | 29 | 32 |
| Intending to use new fastway service | Not applicable | 27 | 26 |

assumed that most would have become aware of the service. They were asked about awareness of specific Route 20 service characteristics in Waves 2, 3, and 4. The change in awareness over the three waves is indicated in Figure 2, which shows that greater awareness existed about where to catch the bus service than about destinations served, timetable, and fares. Awareness of each of the service characteristics consistently increased over time.

Figure 3 shows how agreement with the statements "It is easy for me to reach my nearest bus service in terms of distance and convenience" and "Buses provide a realistic option for most of my journeys in Crawley" changed over the course of the survey. It also shows the numbers of respondents who had used the Route 20 service in the different waves. Figure 3 shows small increases in positive perceptions toward bus services through the survey period. The number of residents who used the Route 20 service increased from 34 in Wave 2 to 61 in Wave 4.

## Timing of Responses to Route 20 Introduction

The timing of responses to the introduction of Route 20 is shown in Figure 4 in terms of new users of the service. This refers to the sample of 247 respondents. Residents were asked in Waves 2, 3, and 4 to indicate whether they had used the service and in which preceding week they had first used it. Respondents will not always have recollected this information accurately, but it can be expected that they will be accurate to within at least 4 weeks given the 2-month intervals between survey occasions. The number of new users is largest in the first week after introduction of the new service and tends to decline over time. Spikes in new users occur in Weeks 10–13 and in Week 21. These weeks correspond to times when questionnaires were returned and may reflect some survey subjects indicating the current week as the first week they used Route 20 when actual first use occurred earlier.

Table 3 compares how the percentage of residents using Route 20 by the end of the survey period (March 2006) varies according to resident characteristics.

## Duration Modeling

Attention now turns to analyzing the factors influencing the elapsed time after Route 20 introduction until residents first use or adopt the service. Event history (or duration) data are available from the panel study. If a resident started to use the Route 20 service, a date was obtained (estimated by participant to the nearest week) when the event took place. It is preferable to model the duration of the event instead of modeling usage with a dichotomous or ordinal indicator variable for state of usage at the three postintroduction observation periods (using a logit or probit model). Analyzing durations allows

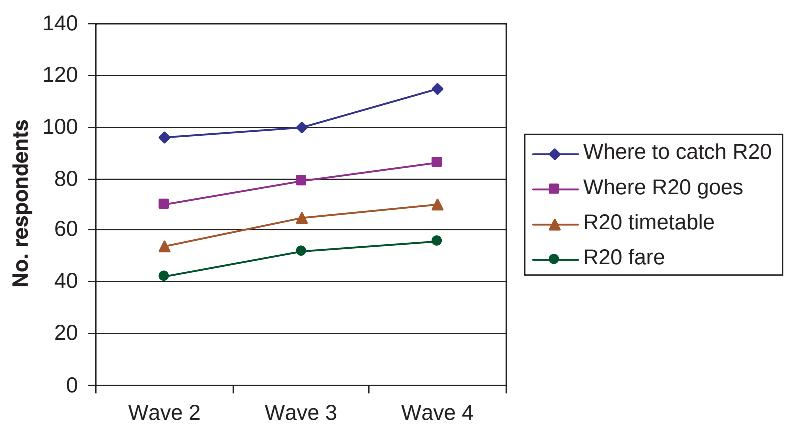


FIGURE 2 Awareness of Route 20 characteristics.

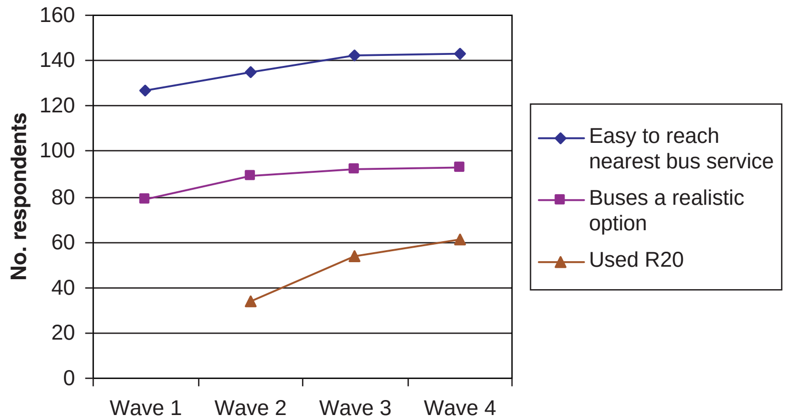


FIGURE 3 Perceptions and use of Route 20.

the full information available on duration times to be used, and, as Petersen (*17*) noted, an indicator variable at discrete points cannot capture the range of variability in duration times. In policy terms, the duration analysis is intended to shed light on how characteristics of travelers and their trip making influenced responsiveness to the new service.

An excellent introduction to duration modeling is provided by Box-Steffensmeier and Jones (*18*). Bhat (*19*) and Washington et al. (*20*) noted that there have been surprisingly few applications of duration modeling in the transport field but that they have been increasing recently. In recent years, there have been increasing applications of duration modeling with many of them in the field of activity-based modeling and concerning the time devoted to activities and the time interval between activities. At the 2006 International Conference on Travel Behaviour Research, two papers used duration modeling to examine time lags of behavior. Chen and Chen (*21*) analyzed the duration of time until a significant increase in time allocation to discretionary activities and related that to a change in job or home location. Beige and Axhausen (*22*) analyzed the duration of car ownership and public transport season ticket ownership and related that to change in residential location and other factors. This study is interested in the time to adoption or first use of a new public transport system and an approach is followed in duration modeling similar to that used by Hensher (*14*) when he studied the elapsed time until motorists switched to a new toll road.

The first important concept in duration (or survival) modeling is the survivor function, $S(t)$, which expresses the probability, $P$, that the duration, $T$, has survived beyond or has not ended at time $t$.

$$S(t) = P(T \geq t) \tag{1}$$

In modeling the duration of time until adoption of Route 20, each resident still using Route 20 at time $t$ would be considered a survivor. The second important concept in duration modeling relates to the occurrence of an event (in this case, Route 20 adoption) and is the probability density function ($f$) of an event occurring.

$$f(t) = \lim_{\Delta t \to 0} \frac{P(t + \Delta t > T \geq t)}{\Delta t} \tag{2}$$

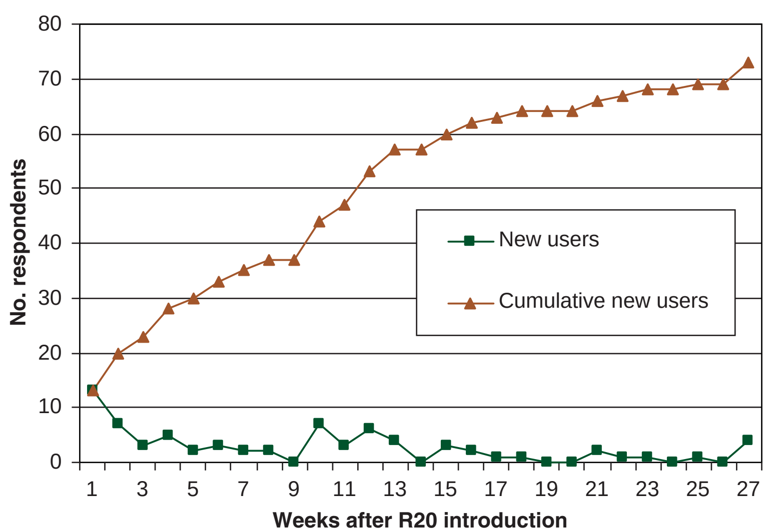


FIGURE 4 Number of new users of Route 20 in weeks after its introduction.

**TABLE 3 Variation of Route 20 Use by Resident Characteristics**

| Resident Characteristic | | Total Number of Respondents | Percentage Used Route 20 |
|---|---|---|---|
| Analysis sample | | 247 | 30 |
| Gender | | | |
| Male | | 111 | 27 |
| Female | | 136 | 32 |
| Residential area | | | |
| Broadfield | | 98 | 50 |
| Three Bridges | | 149 | 16 |
| Age | | | |
| Younger than 25 | | 20 | 45 |
| 25–34 | | 33 | 30 |
| 35–44 | | 56 | 32 |
| 45–54 | | 51 | 29 |
| 55–64 | | 46 | 20 |
| 65 and older | | 41 | 29 |
| Driving license | Yes | 211 | 26 |
| Employment status | Full-time employed | 129 | 29 |
| Children in household | Yes | 54 | 33 |
| Cars in household | | | |
| 0 car in household | | 24 | 88 |
| 1 car in household | | 121 | 25 |
| 2 cars in household | | 102 | 22 |
| Bus pass | Yes | 29 | 29 |
| Car use frequency at Wave 1 | | | |
| Not at all | | 44 | 57 |
| Less than once per week | | 12 | 42 |
| 1 to 2 days per week | | 32 | 34 |
| 3 to 4 days per week | | 33 | 21 |
| 5 days a week or more | | 126 | 20 |
| Bus use frequency at Wave 1 | | | |
| Not at all | | 156 | 11 |
| Less than once per week | | 40 | 53 |
| 1 to 2 days per week | | 27 | 52 |
| 3 to 4 days per week | | 13 | 77 |
| 5 days a week or more | | 11 | 100 |
| Route 10 used at Wave 1 | Yes | 73 | 73 |
| Route 20 awareness at Wave 1 | Yes | 146 | 25 |

This can be interpreted as the instantaneous probability of occurrence of event $T$ at time $t$. The cumulative distribution function ($F$) of the duration may be expressed as follows:

$$F(t) = \int_0^t f(t)dt \tag{3}$$

The third important concept is the hazard rate, $h(t)$, which can be expressed as follows:

$$h(t) = \lim_{\Delta t \to 0} \frac{P(t + \Delta t > T \geq t | T \geq t)}{\Delta t} \tag{4}$$

The hazard rate specifies the rate at which a duration ends in the interval $[t, t + \Delta t]$ given that the duration has not terminated at the start of this interval. This hazard rate is usually used for modeling duration data, but there are direct relationships between the survivor function, the duration density, and the hazard rate (*18*).

This study is interested in the elapsed time until use of the Route 20 service and not the length of time in which use of Route 20 continues. It would be difficult to define what is meant by continued use of Route 20. So, here there is a binary state single-episode situation in which the time is observed until Route 20 is used. Figure 5 presents four observed event histories. Observation 1 has a duration of zero, which in this case implies starting to use Route 20 as soon as it is introduced. It is shown that usage of Route 20 is sustained through the period of monitoring, although that is not of concern in this analysis. Observations 2 and 3 have durations measured within the period of monitoring; Observation 4 is not observed within the period of monitoring, although it is shown to occur shortly afterward. There is no left censoring of the duration data in this study, as usage of the Route 20 service was monitored as soon as it was introduced. It is assumed that individuals who have not used Route 20 may do so beyond the period of monitoring and therefore allowance is made for right censoring.

The Stata program (*23*) is used to fit hazard-based duration models of the conditional probability of a time duration (period of not using

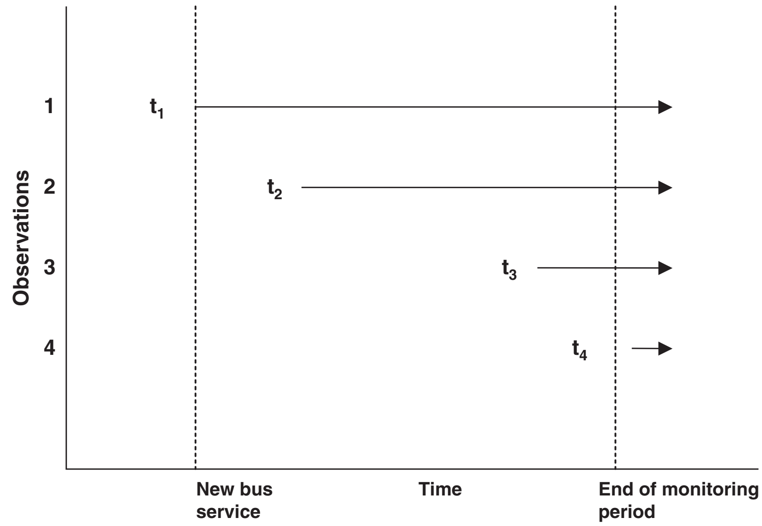


FIGURE 5 Illustration of duration data.

Route 20) ending at time *t*, given that duration has continued until time *t*. As well as accounting for duration dependence, hazard-based duration models can also account for the effect of exogenous variables on the conditional probabilities. One key difference to the analysis of Hensher is that here the effect of a variety of exogenous variables is tested, whereas he tested the effect of only two exogenous variables. The exogenous variables tested include those listed in Table 3 plus seven variables for perceptions toward local transport and travel at Wave 1, some additional variables for travel behavior at Wave 1, and three calculated variables for walking access times to Route 20 bus service. Time-varying exogenous variables have not been tested. Perception variables, for example, were measured not just at Wave 1 but at each wave and they could be tested as time-varying exogenous variables in the same way Hensher proposed.

Cox and Oakes (*24*) suggested visually inspecting plots of the survival and hazard distributions obtained by using nonparametric methods to guide selection of a parametric distribution. This confirmed a monotonically decreasing hazard function. The Weibull distribution was selected for the survival and hazard functions. The specifications of the Weibull hazard rate and survivor functions are as follows:

$$h(t) = (\lambda\alpha)(\lambda t)^{\alpha-1} \tag{5}$$

$$S(t) = \exp(-\lambda t)^{\alpha} \tag{6}$$

where

$t$ = time,
$\alpha$ = shape parameter, and
$\lambda$ = scale parameter.

If parameter $\alpha$ is greater than 1, then the hazard is monotone increasing in duration (positive duration dependence); if it is less than 1, then it is monotone decreasing in duration (negative duration dependence); and if it is equal to 1, then the hazard is constant in duration. The proportional hazard approach is used, which assumes that covariates act multiplicatively on the underlying hazard function through the function $g(X)$.

$$h(t) = h_0(t)g(X) \tag{7}$$

$$g(X) = \exp(X\beta) \tag{8}$$

where $X$ represents a vector of covariates and $\beta$ is a vector of estimable parameters.

Comparisons of different parametric distributions showed the Weibull distribution to be an appropriate selection. Model fit was judged by using the Akaike information criterion (AIC) as recommended by the Stata manual (*23*) and showed that selection of the lognormal or log-logistic distribution produced model fits and parameter estimates very similar to the Weibull distribution. Testing the presence of unobserved heterogeneity (using gamma distribution and inverse-Gaussian distribution) was also found on the basis of AIC not to produce better model fit. A more general model specification was tested, allowing the shape parameter $\alpha$ to differ according to area (Broadfield and Three Bridges), but it was not found to improve model fit.

Empirical results are presented in Table 4 for three duration models. Model 1 contains objectively measured variables only, Model 2 also contains subjectively measured variables for perceptions, and Model 3 also contains variables for past behavior (state dependence variables).

The shape parameter, $\alpha$, is close to 1 for each model, which suggests that the hazard rate is close to a constant rate over time after accounting for explanatory variables. Model 1 indicates that the likelihood of using Route 20 sooner increases if a resident lives in Broadfield, is younger, lives in a house with fewer cars, has a bus pass (which provides free bus travel to those aged 60 and over or disabled who apply for the pass), and experiences a decreased walking time to access bus services. Specifically, the last item measures the reduction in walking time at the home end of the journey to access bus services to Gatwick Airport (which is a representative location in the area) resulting from the Route 20 service. This was calculated from the postcodes of the residents and the Transport Direct journey planner website (*25*).

With Model 1, it is implied from the survivor function that, for a sample of Broadfield residents with characteristics similar to the mean (aged 40, household with one car, without a bus pass, reduction in walk access time of 6 min), 50% of them will not have used Route 20 after 29 weeks. For a similar sample of Three Bridges residents, 50% of them will not have used Route 20 after 108 weeks.

In Models 2 and 3 an attempt is made to capture the effect of perceptions and past behavior. In Model 2 it was found that adding two

TABLE 4 Hazard Model Parameter Estimates

| Independent Variable | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Constant | −3.47 (−5.67) | −3.84 (−4.19) | −6.17 (−8.49) |
| Area (0 = Three Bridges, 1 = Broadfield) | 1.11 (4.16) | 1.16 (4.20) | 0.64 (2.05) |
| Age (continuous) | −0.014 (−1.53) NS | −0.011 (−1.19) NS | −0.001 (−0.06) NS |
| Car ownership (0 = none, 1 = 1, 2 = 2 or more) | −0.77 (−4.22) | −0.54 (−3.18) | −0.46 (−2.63) |
| Bus pass (0 = none, 1 = bus pass) | 1.16 (3.02) | 0.82 (2.08) | −0.02 (−0.05) NS |
| Reduction in walk access time (in minutes) to nearest bus stop for travel to Gatwick Airport | 0.081 (2.72) | 0.066 (2.20) | 0.028 (0.89) NS |
| The car is the only realistic option for most of my journeys in Crawley (1 = strongly agree, . . 5 = strongly disagree) | | 0.29 (2.60) | |
| Buses provide a realistic option for some of my journeys in Crawley (1 = strongly agree, . . 5 = strongly disagree) | | −0.35 (−2.66) | |
| Bus use frequency at Wave 1 | | | 0.54 (4.33) |
| Used fastway Route 10 at Wave 1 (0 = no, 1 = yes) | | | 1.64 (5.27) |
| α (shape parameter) | 0.85 | 0.91 | 1.07 |
| No. of cases | 247 | 247 | 247 |
| Log likelihood | −214.9 | −201.1 | −176.3 |
| Akaike information criterion | 443.9 | 420.3 | 370.7 |

*z*-statistics in parentheses.
NS = nonsignificant at 5% significance level.

of the seven perception variables improved model fit and the objective variables remained statistically significant (except for age). In Model 3 model improvement was enhanced further by including variables for past behavior. More frequent users of bus at Wave 1 and users of Route 10 at Wave 1 were found to use Route 20 earlier. The frequency of use of modes other than bus had no significant effect after accounting for car ownership and bus use frequency. The effect of Route 10 usage can be explained by Route 10 serving Broadfield before the introduction of Route 20 and for the residents in Broadfield targeted in this study by Route 20 providing a more directly accessible service with shorter walking distances.

These results indicate that including state dependence variables (in this case, past bus use) significantly improves the explanatory power of the duration model and is a consistent finding with that of other work using panel data to estimate travel choice models (*7–9, 13*). However, a note of caution should be expressed about including these variables. Unobserved heterogeneity is captured in the parameter estimates of the state dependence variables (and quite possibly the perception variables included in Model 2). Washington et al. (*20*) noted that a solution to this problem is to instrument state dependence variables by regressing them against exogenous variables and using the regression-predicted values as variables in the duration model. Results are presented for Models 2 and 3 to illustrate the potential increased explanatory capability of including perceptions and state dependence variables, but Model 1 is proposed as the preferred model.

Figure 6 compares how many predicted numbers of residents (from the sample 247) used the Route 20 service in the first 6 months after its introduction from the observed data and the three duration

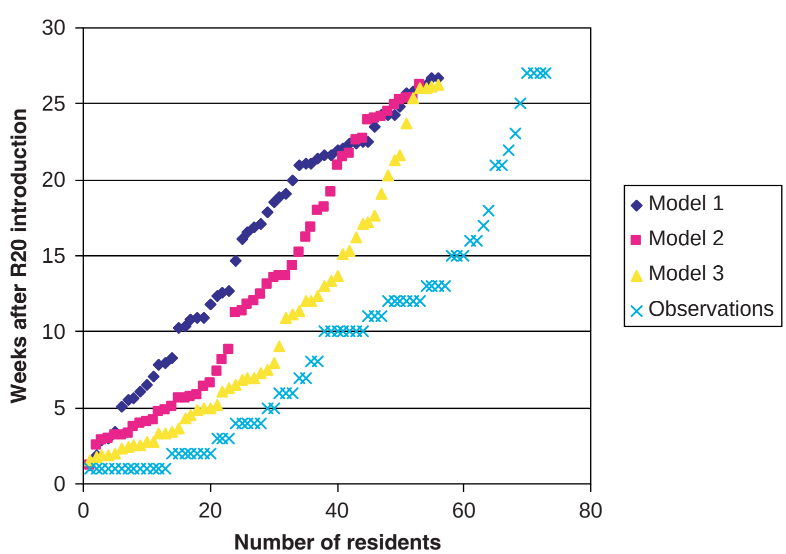


FIGURE 6 Comparisons of model predictions and observed data.

models. The predicted numbers of residents were derived based on median survival values from the models. This illustrates the better fit to the data of Model 3, but it also indicates that all models underestimate the number of residents using the Route 20 service in the first few weeks, and Models 1 and 2 overestimate the number of residents using the Route 20 service toward the end of the 6-month period. It could be argued that some of the respondents in the panel survey will never use the Route 20 service. In these duration models, it has been assumed (as is the usual practice with duration models) that censored observations will all eventually use the service. Modifications to the model specification to incorporate the possibility that an individual will never use the service are possible (*26*), and it is conceivable that will make it possible to improve model fit and predictive accuracy.

### Dynamic Demand Profile

Duration modeling has allowed the timing of first use of the Route 20 service to be analyzed. Overall usage of a new transport service depends not only on how long it takes people to start using the service but also on how much they use the service subsequently. Residents were also asked to indicate their frequency of use of Route 20 during the previous week at each survey wave (did not use it, 1 day, 2–3 days, 3–4 days, ≥5 days) and appropriate information is therefore available for this purpose.

Individual frequencies of use of Route 20 at Waves 2, 3, and 4 have been aggregated for the panel survey sample, taking account of nonresponse at each wave. This produces an index of aggregate usage at each wave, which is plotted in Figure 7 with a linear trend line fitted. Also in Figure 7 is an index of the cumulative number of Route 20 users from the panel survey (again taking account of nonresponse at each wave). Finally, an index of aggregate passenger journeys on the Route 20 service is presented in Figure 7. It is derived from passenger journey data provided by Metrobus, the bus service operator. This demand profile may be affected by seasonal factors (holiday periods in December, January, and April).

Comparison of the three constructed demand profiles shows significant differences in growth rates. The index of the cumulative number of users shows the highest growth, but it can be imagined that as new residents start using the service some old users stop using the service (as their circumstances change) and so this index will give an overestimate of aggregate usage levels. The index of aggregate usage from the panel survey indicates slightly higher growth than the bus operator data, but it appears to provide a fairly reliable indication of demand growth.

## CONCLUSIONS

The preceding survey findings and duration modeling results provided empirical evidence about the timing of individual responses to a new transport option and explanations of factors that influence it. Analysis of the data indicates that the rate of new users of the Fastway Route 20 service was modest but fairly stable during the first 3 to 4 months of operation, after which the number of new users appeared to decline. Individuals with access to a car were slower in trying the service. Younger individuals and those with a bus pass were faster in using the service. Individuals who gained a reduction in distance from their home to bus services were faster in using the service. Individuals living in Three Bridges were slower in trying the service, after accounting for the previous considerations, which may be due to Three Bridges being better connected to destinations in the Crawley area by other public transport services and due to lower familiarity with the Fastway concept. Those residents using bus services (especially the Fastway Route 10 service) before the introduction of Route 20 were quicker to use the new service, although unobserved heterogeneity was captured in the parameter estimates of state dependence variables.

Marketing implications can be drawn from the estimated duration models. The slower take-up of the new service by residents in Three Bridges after controlling for other factors suggests that advance marketing of a new public transport service to those living close to the service should be undertaken to attract users. This is especially the case when no similar type of service has existed previously (as is the case for Three Bridges). Younger residents with less car availability appear to be an appropriate target market. The results also indicate that it is important to engender a perception that bus services can meet journey requirements, which implies that greater public awareness of what a service has to offer is required.

Behavioral factors influencing the timing of individual responses were identified. The survey results showed that some residents were aware of the new service in advance, which explains why 20 of the 247 residents started to use the service in the first 2 weeks after its introduction, with many of them indicating on the questionnaires that they switched from other transport modes and services for an existing

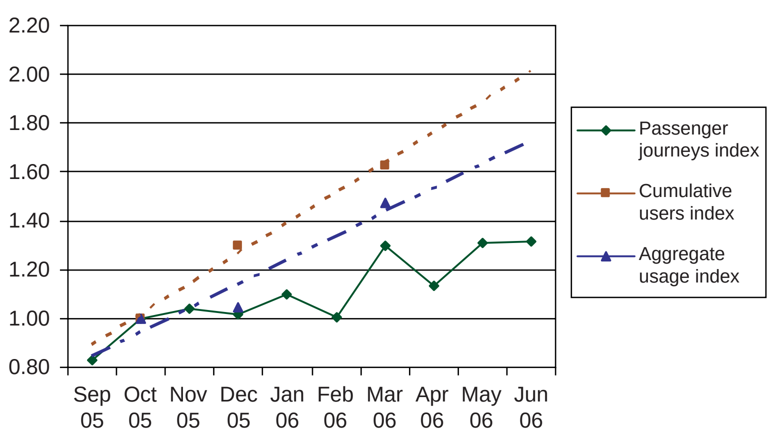


FIGURE 7 Dynamic demand profiles for Route 20.

journey. The results also indicate that gradual increases in awareness and positive perceptions about bus services occurred during the survey period, contributing to the increasing number of users of Route 20. Many residents did not start to use the new service until some months after its introduction, and there is evidence from comments on the questionnaires that this occurred because of new journey requirements. The influence of past behavior (and perhaps habit) was observed, with past bus users much more likely to become users of a new bus service.

After examination of the timing of first usage, or adoption, of the Route 20 service, which is important to gain insight into why people are attracted to a new service, analyses of the changing frequency of usage over the course of the study period will be conducted. Latent growth curve models (*27*) and dynamic ordered probit models (*7*) are appropriate methods for analyzing the frequency data. They can incorporate time-varying covariates and state dependence variables and are expected to lead to models that can be used to forecast overall usage of the Route 20 service beyond the duration of the study period and to provide a generic model form that can be used for similar forecasting purposes for other schemes.

## ACKNOWLEDGMENT

The research reported here was funded by a grant from the UK Engineering and Physical Sciences Research Council.

## REFERENCES


1. Douglas, N. *Patronage Ramp-Up Factors for New Rail Services.* Douglas Economics, Wellington, New Zealand, 2003. www.cilt.co.nz/Neil%20Douglas.pdf. Accessed May 30, 2006.
2. Chatterjee, K., and K. Ma. Behavioural Responses to a New Transport Option—A Dynamic Analysis Using a Six-Month Panel Survey. In *Proc., 11th International Conference on Travel Behaviour Research* (CD-ROM), Kyoto, Japan, Aug. 2006.
3. Chatterjee, K. Asymmetric Churn—Academic Jargon or a Serious Issue for Transport Planning? *Transport Planning Society Bursary Paper,* 2001. www.tps.org.uk/library/0001chatterjee.pdf. Accessed May 30, 2006.
4. Triandis, H. C. Values, Attitude, and Interpersonal Behavior. *Nebraska Symposium on Motivation,* Vol. 27, 1980, pp. 195–259.
5. Verplanken, B., H. Aarts, and A. van Knippenberg. Habit, Information Acquisition, and the Process of Making Travel Mode Choices. *European Journal of Social Psychology,* Vol. 27, No. 5, 1997, pp. 539–560.
6. Fujii, S., and R. Kitamura. What Does a One-Month Free Bus Ticket Do to Habitual Drivers? An Experimental Analysis of Habit and Attitude Change. *Transportation,* Vol. 30, No. 1, 2003, pp. 81–95.
7. Dargay, J., and M. Hanly. Volatility of Car Ownership, Commuting Mode and Time in the UK. Presented at World Conference on Transport Research, Istanbul, Turkey, 2004.
8. Thørgersen, J. Understanding Repetitive Travel Mode Choices in a Stable Context: A Panel Study Approach. *Transportation Research A,* Vol. 40, No. 8, 2006, pp. 621–638.
9. Simma, A., and K. W. Axhausen. Commitments and Modal Usage: An Analysis of German and Dutch Panels. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1854,* Transportation Research Board of the National Academies, Washington, D.C., 2003, pp. 22–31.
10. Polydoropoulou, A., M. Ben-Akiva, and I. Kaysi. Influence of Traffic Information on Drivers' Route Choice Behavior. In *Transportation Research Record 1453,* TRB, National Research Council, Washington, D.C., 1994, pp. 56–65.
11. Mahmassani, H. S., and Y.-H. Liu. Day-to-Day Dynamics of Commuter Route Choice Behaviour Under Real-Time Information. In *Proc., Seminars D and E—Part 1 of 24th European Transport Forum,* Planning and Transport, Research and Computation, London, 1996.
12. Jha, M., S. M. Madanat, and S. Peeta. Experimental Investigations of a Perception Updating Model on a Traffic Network with Information Provision. Presented at 76th Annual Meeting of the Transportation Research Board, Washington, D.C., 1997.
13. Bradley, M. A Practical Comparison of Modeling Approaches for Panel Data. In *Panels for Transportation Planning* (T. F. Golob, R. Kitamura, and L. Long, eds.), Kluwer, Boston, Mass., 1997, pp. 281–304.
14. Hensher, D. A. The Timing of Change: Discrete and Continuous Time Panels in Transportation. In *Panels for Transportation Planning* (T. F. Golob, R. Kitamura, and L. Long, eds.), Kluwer, Boston, Mass., 1997, pp. 305–319.
15. Fastway Homepage. www.fastway.info. Accessed May 30, 2006.
16. Raimond, T., and D. A. Hensher. A Review of Empirical Studies and Applications. In *Panels for Transportation Planning* (T. F. Golob, R. Kitamura, and L. Long, eds.), Kluwer, Boston, Mass., 1997, pp. 15–72.
17. Petersen, T. The Statistical Analysis of Event Histories. *Sociological Methods and Research,* Vol. 19, 1991, pp. 270–323.
18. Box-Steffensmeier, J. M., and B. S. Jones. Time Is of the Essence: Event History Models in Political Science. *American Journal of Political Science,* Vol. 41, No. 4, 1997, pp. 1414–1461.
19. Bhat, C. R. Chapter 6: Duration Models. In *Handbook of Transport Modelling* (D. A. Hensher and K. J. Button, eds.), Elsevier, Oxford, United Kingdom, 2000.
20. Washington, S. P., M. G. Karlaftis, and F. L. Mannering. *Statistical and Econometric Methods for Transportation Data Analysis.* Chapman and Hall/CRC, Boca Raton, Fla., 2003.
21. Chen, C., and X. Chen. What It Takes for People to Change? A Time Question. In *Proc., 11th International Conference on Travel Behaviour Research* (CD-ROM), Kyoto, Japan, Aug. 2006.
22. Beige, S., and K. W. Axhausen. Long-Term Mobility Decisions During the Life Course: Experiences with a Retrospective Survey. In *Proc., 11th International Conference on Travel Behaviour Research* (CD-ROM), Kyoto, Japan, Aug. 2006.
23. StataCorp. *Stata Statistical Software: Release 9.* StataCorp LP, College Station, Tex., 2005.
24. Cox, D., and D. Oakes. *Analysis of Survival Data.* Chapman and Hall/CRC, Boca Raton, Fla., 1984.
25. Transport Direct Homepage. www.transportdirect.info. Accessed May 30, 2006.
26. Bartels, B. *Advances in Duration Modeling: The Split Population Duration Model.* The Political Research Lab Statistics Corner Archive, Ohio State University Department of Political Science, Columbus. psweb.sbs.ohio-state.edu/prl/archive/statcorner/. Accessed May 30, 2006.
27. Mehta, P. D., M. C. Neale, and B. R. Flay. Squeezing Interval Change from Ordinal Panel Data: Latent Growth Curves with Ordinal Outcomes. *Psychological Methods,* Vol. 9, No. 3, 2004, pp. 301–333.


*The Traveler Behavior and Values Committee sponsored publication of this paper.*