MODELLING THE TIMING OF USER RESPONSES TO A NEW URBAN PUBLIC TRANSPORT SERVICE: APPLICATION OF DURATION MODELLING

Kiron Chatterjee and Kang-Rae Ma
Centre for Transport & Society
Faculty of the Built Environment
University of the West of England
Bristol BS16 1QY
UK
Phone: +44 117 32 82032
Fax: +44 117 32 83002
E-mail: Kiron.Chatterjee@uwe.ac.uk / Kang.Ma@uwe.ac.uk

Revised paper submitted: 15 November 2006
Word count: 5,847

ABSTRACT

When a new service is introduced into the transport market (or an existing service is modified) it can be expected that the timing and nature of the responses of individuals will vary considerably. The aggregated responses of individuals will determine the overall usage of the service. This paper reports how a panel survey has been used to obtain information on the timing and nature of responses to a new public transport service. The survey allows us to see how awareness, perceptions and usage of the service change over time. Duration modelling is applied to analyse the factors that influence the time taken to first use the new service. This shows 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 is introduced all reduce the time taken to use the new service. The duration modelling provides useful results for operators to consider in marketing new transport services. For forecasting the overall usage of a new service it is shown that consideration needs to be given not only to predicting new users but also their frequency of usage. It is anticipated that analysis such as this will lead not only to better understanding of the impacts of transport policy interventions but also to improved transport forecasting tools.

1. INTRODUCTION

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

Conventional methods of travel demand analysis (based on cross-sectional travel data and on equilibrium principles) are static in nature 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 do not indicate any time-scale for when this level of demand will be reached. It is the dynamic demand profile that will determine the consequences of a new transport service for public welfare (user benefits, societal costs) and business viability (revenue streams), so efforts should be placed on forecasting dynamic behavioural responses.

Douglas (*1*) has carried out an analysis of 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 three years. However, there was considerable variation in growth across the schemes. Douglas notes that demand stemming from induced demand may take longer to ‘ramp-up’ than diverted demand. He considers that ‘ramp-up’ may arise due to the ‘learning curve’, travel habits, operational ‘teething’ problems and marketing deficiencies. The ‘ramp-up’ factors provide useful indicative figures on 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. We have conducted research seeking to gain understanding of the responses of travellers to a new transport service in recognition that this could assist in forecasting dynamic demand profiles. Our research has 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*).

Section 2 of this paper considers behavioural explanations for dynamic responses and what is known about these. Section 3 summarises the panel survey used to obtain information on the behavioural responses of residents to a new bus service. In section 4 changes in travel perceptions and behaviour across the waves are presented before the application of duration modelling 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.

2. EXISTING KNOWLEDGE

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

- Habit prevents any conscious deliberation about behaviour;
- Time is required to become aware of change and to acquire and process information about it;
- Period of experimentation is required with alternative behaviours;
- Gradual modification of behaviour is made towards preferred behaviour;
- Long-term commitments exist towards current travel behaviour (e.g. season ticket);
- An option is only tried after sufficient time for positive attitude towards it to be developed.

Shorter times of responses may be expected when:

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

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

The stability of travel behaviour has been explored using citizen panel surveys. Dargay and Hanly (*7*) used eleven years of data from the British Household Panel Survey (BHPS) to analyse 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 behaviour) is an important determinant of both car ownership and commute mode behaviour, 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. Thørgersen found that current behaviour is strongly conditional on past behaviour but mediated by current attitudes and perceived behavioural control. Thørgersen also found that current behaviour determines future attitudes and perceived control. Simma and Axhausen (*9*) used panel data from both 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, finding that commitments in one period affect mode usage in the next.

While the above studies have provided useful insights on the role of past behaviour and habit in determining current behaviour, they have not specifically examined the time-scale of behavioural responses (the subject of this paper). There has been substantial research carried out on the dynamic travel decisions of motorists which has involved measurement of route and departure time choices. A number of studies have used travel diaries and laboratory simulations to collect data and estimate models for day-to-day decision making of motorists (*10*, *11*, *12*). While these studies are informative on the timing of motorists' responses to information, they do not offer insights on travellers' mode choices and how these are affected by interventions designed to change the relative attractiveness of different modes. Mode choice is an aspect of travel behaviour where there are major barriers to change (as listed at the start of this section) and change tends to take longer to occur.

An important reason for the limited knowledge on the time-scale of transport mode behavioural 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 found that forecasts are quite different if dynamic specifications are used instead of static specifications. He concluded, though, that to understand and model the impacts of changes in the travel environment 'multiple "after" periods are necessary to determine whether policies grow, diminish, or remain stable over time'. Further to Bradley's remark, it should be pointed out that to improve 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. In this case data was available of the precise date of switching to the toll road for 170 motorists and this was used to estimate a duration model to identify the factors influencing the time of switching to the toll road. This is a rare example where the challenge of measuring, understanding and predicting the time-scale of behavioural responses has been addressed.

The review highlights that information is lacking on the timing and nature of behavioural responses to new transport services. Our aim has been to design and implement a survey to capture such information in order that we can describe and model the timing of change that occurs.

3. RESEARCH METHOD

3.1 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 providing a frequent, reliable service and offering 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 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 up to 6,000 in May 2005 and the second service (Route 20) has been introduced in August 2005. The route maps are shown in Figure 1. It is the Route 20 service that provides the case study for this paper.

3.2 Panel Survey

Longitudinal data is required to study temporal change in behaviour. Event history data recording travel behaviour in continuous time was not feasible to obtain and instead a classic panel survey has been conducted. A classic panel study involves the same respondents being surveyed at different time points. Survey approach, design and issues are discussed in detail in Chatterjee and Ma (*2*) and an overview is provided next.

Douglas (*1*) identified an average of 79% ‘ramp-up’ one 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 time-scale 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 one taking place one month before the introduction of the Route 20 service, wave two taking place one month after the introduction of the service and waves three and four taking place at subsequent two month intervals. The overall length of the panel study of seven months aimed to span a sufficient period for behavioural responses to take place and start to diminish.

FIGURE 1 Fastway Routes.

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

- Broadfield (south) – residents living near the Coachmans Drive and Creasys Drive bus stops shown 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 shown in Figure 1.

Characteristics of the two targeted areas are presented in Table 1.

TABLE 1 Characteristics of Broadfield South and Three Bridges Electoral Wards

Characteristic	Broadfield South	Three Bridges	Crawley
Location	Edge of town neighbourhood	Inner town neighbourhood	-
Public transport (prior to Fastway Routes 10 and 20 introduction)	One bus service to town centre	National rail station and various bus services (mostly on boundary of neighbourhood)	-
Index of Multiple Deprivation[1]	3 of the 4 ward sub-areas are ranked in the top decile of deprived sub-areas in the county of West Sussex	None of the sub-areas within ward are ranked in the top decile of deprived sub-areas in the county of West Sussex	7 sub-areas within town are ranked in the top decile of deprived sub-areas in the county of West Sussex
Percentage of population aged 65 and over[2]	5.2	20.7	14.7
Mode share percentages for travel to work[2]			
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 2km[2]	7.1	38.8	19.3
Percentage of households without car[2]	22.4	22.1	20.4

Notes:
[1] Office of the Deputy Prime Minister (ODPM) 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.
[2] From 2001 Census.

We used the electoral register to identify residents in the target areas with the register providing 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 (seven months) this is not a serious issue. Attrition involves loss of respondents over the course of survey waves and it needs to be minimised 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 were willing to participate further in study. These were sent the second questionnaire and 220 responses were received (in October 2005). To maximise subsequent participation a £20 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, due to there being 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 generalisations, the study intended to develop greater understanding of dynamic behavioural responses.

Response contamination concerns behaviour itself or its reporting being affected by panel membership and the quality of information provided decreasing (or increasing) over the course of study. We presented the survey to the residents as a general travel survey rather than a survey focusing on the new bus service. We avoided providing information about the new Route 20 service. To maintain quality of response through the survey we designed the questionnaire to be as simple as possible and emphasised the importance of providing complete responses even if this involved repeating information provided in a previous questionnaire.

The structure and design of the questionnaire was 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/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;
- Personal and household information.

3.3 Response Sample

For analysing the timing of behavioural responses we concentrate 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 shows that car ownership was higher for the survey samples than 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 affect the sample characteristics adversely.

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 under 35 (and >16)	34	27	19
Aged 65 and over (and >16)	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

4. RESULTS AND ANALYSIS

4.1 Changes in Awareness, Perceptions and Usage of Route 20

To enable direct comparison results are reported in section 4.1 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 one month before it was introduced and 76% were aware of it one month after it was introduced. Respondents were not asked about general awareness of the Route 20 service after wave 2, as it was assumed 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 shown in Figure 2. This shows that greater awareness existed about where to catch the bus service than destinations served, timetable or fares. There were consistent increases in awareness over time for each of the service characteristics.

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 at the different waves. Figure 3 shows small increases in positive perceptions towards bus services through the survey period. The number of residents who used the Route 20 service increases from 34 in wave 2 to 61 in wave 4.

4.2 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 if they had used the service and which preceding week they had first used the service. It must be recognised that respondents will not always have recollected this accurately but it can be expected that they will be accurate to within at least four weeks given the two 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 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.

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

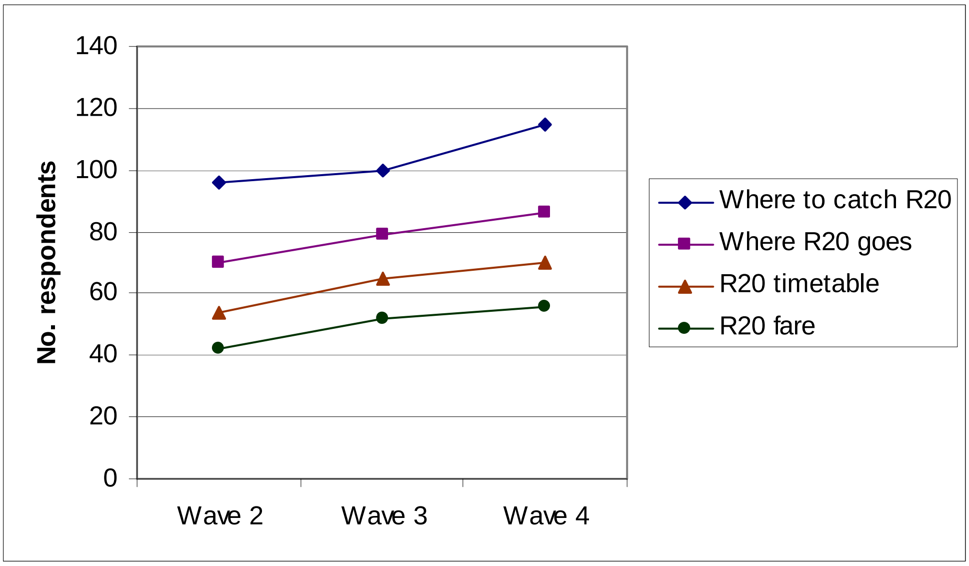

FIGURE 2 Awareness of Route 20 Characteristics.

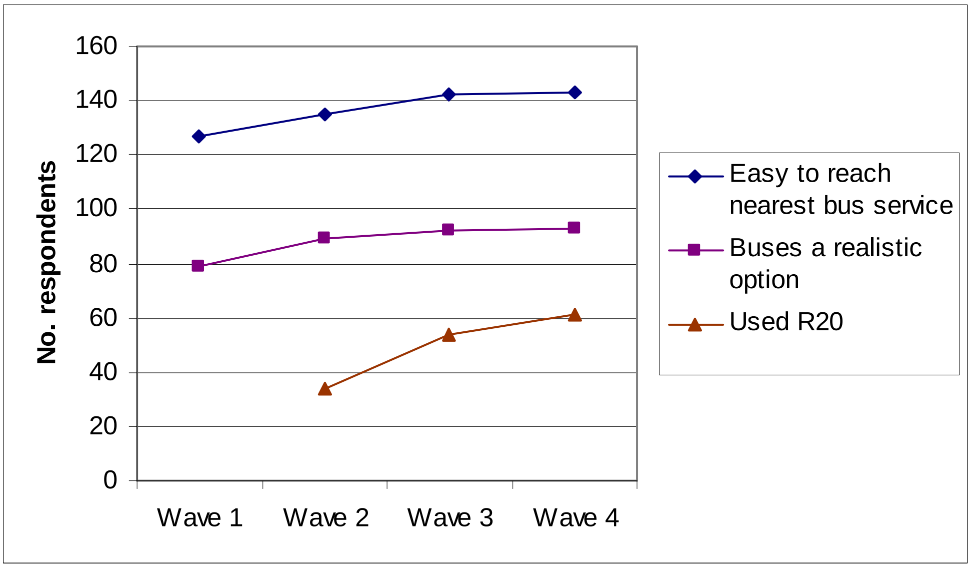

FIGURE 3 Perceptions and use of Route 20.

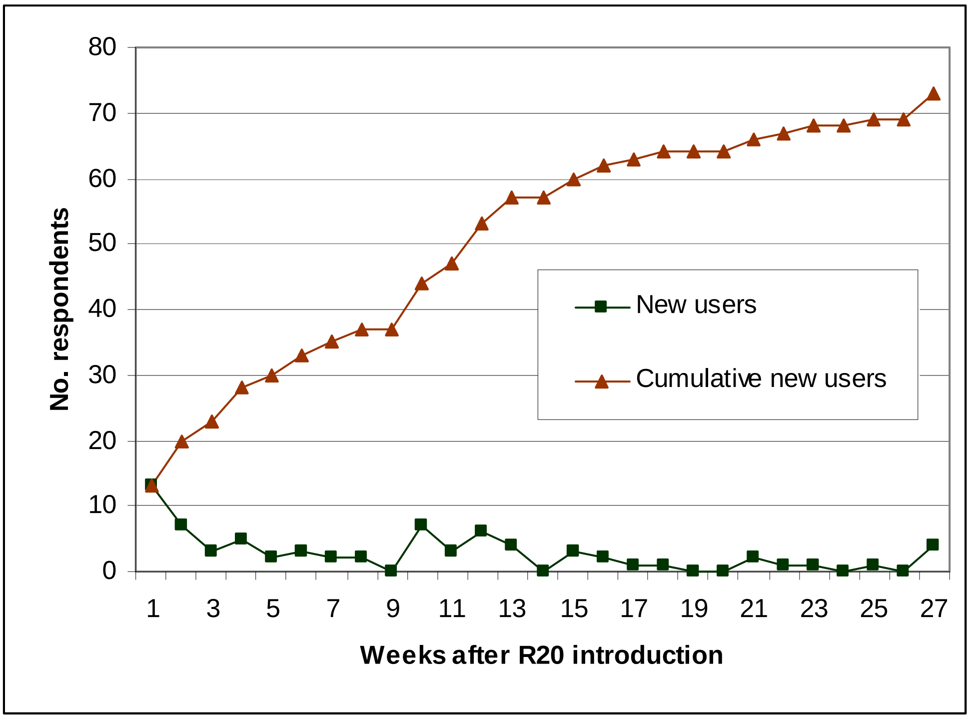

FIGURE 4 Number of New Users of Route 20 in the Weeks after Route 20 Introduction.

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	Under 25	20	45
	25-34	33	30
	35-44	56	32
	45-54	51	29
	55-64	46	20
	65 and over	41	29
Driving licence	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

4.3 Duration modelling

Our attention now turns to analysing the factors influencing the elapsed time after Route 20 introduction until residents first use or 'adopt' the service. We have event history (or duration) data available from the panel study. If a resident started to use the Route 20 service we have a date (estimated by participant to the nearest week) when the event took place. We prefer to model the duration of the event rather than modelling usage using a dichotomous or ordinal indicator variable for state of usage at the three post-introduction observation periods (using a logit or probit model). We are seeking to use the full information available on duration times and, as Peterson (*17*) notes, 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 travellers and their trip making influenced responsiveness to the new service.

An excellent introduction to duration modelling is provided by Box-Steffensmeier and Jones (*18*). Bhat (*19*) and Washington *et al.* (*20*) have noted that there have been surprising few applications of duration modelling in the transport field but that these have been increasing recently. In recent years there have been increasing applications of duration modelling with many of these in the field of activity-based modelling 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 modelling to examine time lags of behaviour. Chen and Chen (*21*) analysed the duration of time until significant increase in time allocation to discretionary activities and related this to a change in job or home location. Beige and Axhausen (*22*) analysed the duration of car ownership and public transport season ticket ownership and related this to change in residential location and other factors. Our interest is in the time to 'adoption' or first use of a new public transport system and we follow a similar approach in duration modelling 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) modelling is the survivor function, S(t), which expresses the probability that the duration, T, has survived beyond, or has not ended at time t.

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

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

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

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

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

The third important concept is the hazard rate which can be expressed as:

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

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

In our example we are only 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. In fact it would be difficult to define what is meant by continued use of Route 20. We are concerned with a binary state single-episode situation where we observe the time until Route 20 is used. In Figure 5 four observed event histories are illustrated. 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 we are not concerned with that in this analysis. Observations 2 and 3 have durations measured within the period of monitoring, while observation 4 is not observed within the period of monitoring, although it is shown to occur shortly afterwards. There is no left censoring of the duration data in our study, as we monitored usage of the Route 20 service as soon as it was introduced. We assume that individuals that have not used Route 20 may do so beyond the period of monitoring and we therefore allow for right censoring.

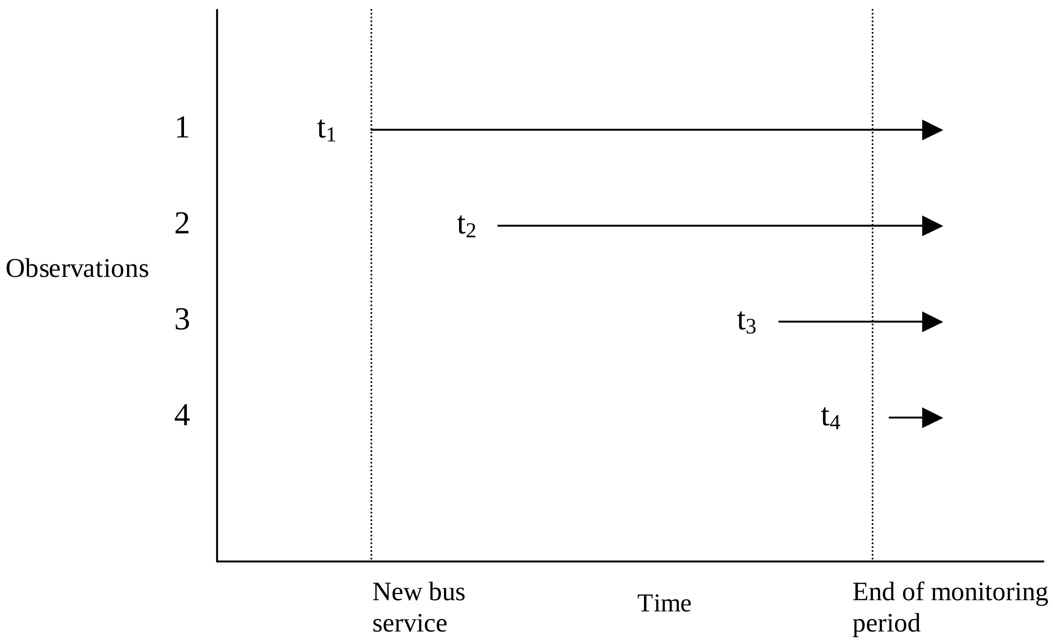

FIGURE 5 Illustration of duration data.

We use the Stata program (*23*) to fit hazard-based duration models of the conditional probability of a time duration (period of not using 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 we test the effect of a variety of exogenous variables whereas he tested the effect of only two exogenous variables. The exogenous variables we test include those listed in Table 3 plus seven variables for perceptions towards local transport/travel at wave 1, some additional variables for travel behaviour at wave 1 and three calculated variables for walking access times to Route 20 bus service. We have not tested time varying exogenous variables. Perception variables, for example, were measured not just at wave 1 but at each wave and these could be tested as time varying exogenous variables in the same way as proposed by Hensher.

Cox and Oakes (*24*) suggest to visually inspect plots of the survival and hazard distributions obtained using non-parametric 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:

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

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

where t is time, α is shape parameter and λ is scale parameter.

If parameter α is greater than 1 then the hazard is monotone increasing in duration (positive duration dependence) and if it is less than 1 it is monotone decreasing in duration (negative duration dependence). If it is equal to 1 then the hazard is constant in duration. We use the proportional hazard approach to assume 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 β is a vector of estimable parameters.

Comparisons of different parametric distributions showed the Weibull distribution to be an appropriate selection. Model fit was judged using the Akaike information criterion (AIC) as recommended by the Stata manual (*23*) and showed that selection of the log-normal or log-logistic distributions produced very similar model fits and parameter estimates 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. We also tested a more general model specification allowing the shape parameter, α, to differ according to area (Broadfield/Three Bridges) and found this did not improve model fit.

Empirical results are shown 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 behaviour (state dependence variables).

The shape parameter, α, is close to one for each model which suggests the hazard rate is close to a constant rate over time after accounting for explanatory variables. Model 1 shows 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 (these provide 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 mean (aged 40, in household with one car, without a bus pass, reduction in walk access time of 6 minutes) 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 we made an attempt to capture the effect of perceptions and past behaviour. In Model 2 we found that adding two of the seven perceptions variables improved model fit and the objective variables remain statistically significant (except for age). In Model 3 model improvement is improved further through inclusion of variables for past behaviour. More frequent users of bus at wave 1 and users of Route 10 at wave 1 are found to use Route 20 earlier. The frequency of use of other modes 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 our study the Route 20 providing a more directly accessible service with shorter walking distances.

These results show that the inclusion of state dependence variables (past bus use in this case) 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, 8*, *9, 13*). However, a note of caution should be expressed about inclusion of these variables. Unobserved heterogeneity is captured in the parameter estimates of the state dependence variables (and quite possibly the perceptions variables included in Model 2). Washington *et al.* (*20*) note that a solution to this problem is to instrument state dependence variables by regressing them against exogeneous variables and using the regression-predicted values as variables in the duration model. We show results for Models 2 and 3 to illustrate the potential increased explanatory capability of including perceptions and state dependence variables but we propose Model 1 as the preferred model.

Figure 6 compares how many predicted numbers of residents (from the 247 sample) use the Route 20 service in the first six months after its introduction from the observed data and the three duration models. The predicted numbers of residents are derived based on median survival values from the models. This illustrates the better fit to the data of Model 3 but it also shows 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 towards the end of the six month period. It could be argued that some of the respondents in the panel survey will never use the Route 20 service. In our duration models it has been assumed (as is usual practice with duration models) that censored observations will all eventually use the service. Modifications are possible to the model specification to incorporate the possibility that an individual will never use the service (*26*) and it is conceivable that this will enable improvement to model fit and predictive accuracy.

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 (AIC)	443.9	420.3	370.7

z statistics in parentheses

NS = non-significant at 5% significance level

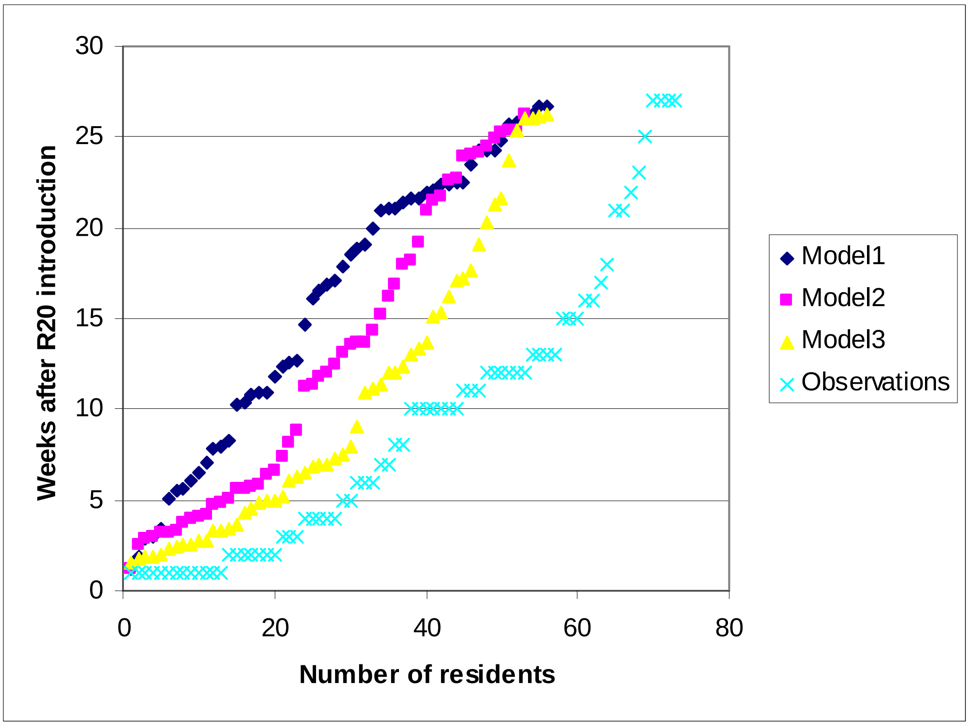

FIGURE 6 Comparisons of Model Predictions and Observed Data.

4.4 Dynamic demand profile

With duration modelling we have looked at the timing of first use of the Route 20 service and this has provided important insights into the factors influencing this. Overall usage of a new transport service will not only depend on how long it takes people to start using the service but how much they use the service subsequently. We asked residents to indicate their frequency of use of Route 20 during the last week at each wave (did not use it; one day; 2-3 days; 3-4 days; 5 or more days) and therefore have appropriate information for this purpose.

We have aggregated individual frequencies of use of Route 20 at waves 2, 3 and 4 for the panel survey sample taking account of non-response at each wave. This produces an index of aggregate usage at each wave. This is plotted on Figure 7 with a linear trend line fitted. Also shown on Figure 7 is an index of cumulative number of Route 20 users from the panel survey (again taking account of non-response at each wave). Finally, an index of aggregate passenger journeys on the Route 20 service is shown on Figure 7. This is derived from passenger journey data provided by Metrobus, the bus service operator. It should be noted that 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 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 shows slightly higher growth than the bus operator data but appears to provide a fairly reliable indication of demand growth.

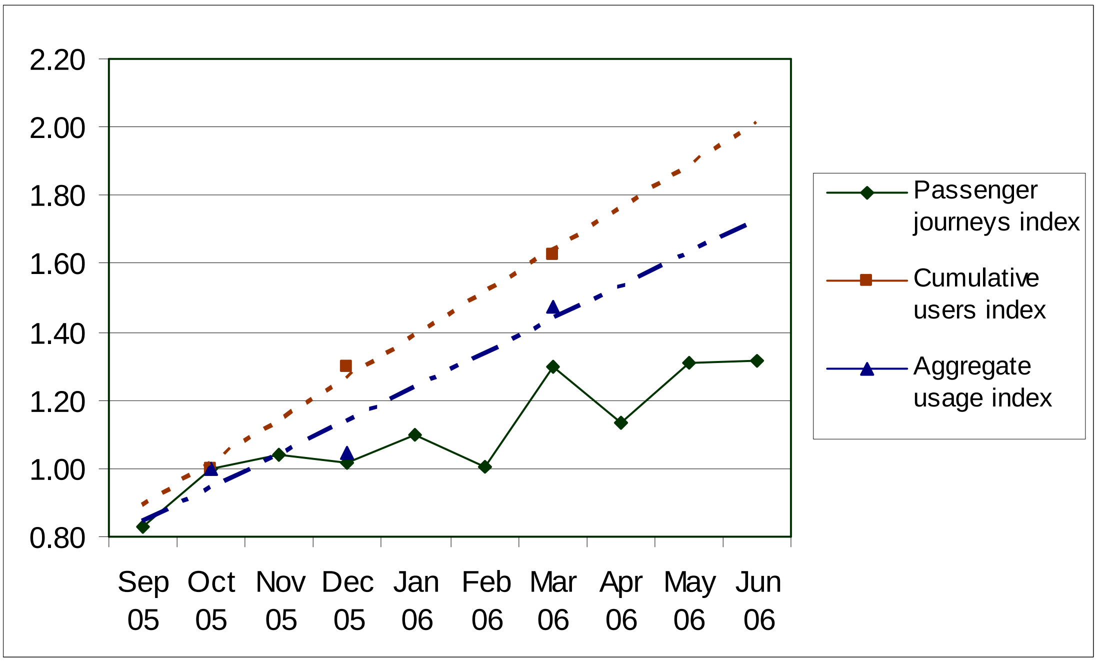

FIGURE 7 Dynamic Demand Profiles for Route 20.

5. CONCLUSIONS

The preceding survey findings and duration modelling results have provided empirical evidence on the timing of individual responses to a new transport option and explanations of factors that influence this. Analysis of the data shows that the rate of new users of the Fastway Route 20 service has been modest but fairly stable during the first 3-4 months of operation after which the number of new users appears to decline. Individuals with access to a car have been slower in trying the service. Younger individuals and those with a bus pass have been faster in using the service. Individuals gaining a reduction in distance from their home to bus services have been faster in using the service. Individuals living in Three Bridges have been slower in trying the service after accounting for the previous considerations. This can be suggested to 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) prior to the introduction of Route 20 have been quicker to use the new service, although it has been noted that unobserved heterogeneity is 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 marketing in advance a new public transport service to those living close to the service should be undertaken to attract users. This is especially the case where no similar type of service has existed previously (which is the case for Three Bridges). Younger residents with lower car availability appear to be an appropriate target market. The results also show that engendering a perception that bus services can meet journey requirements is important which implies greater public awareness is required of what a service has to offer.

In section 2 we identified behavioural factors influencing the timing of individual responses. The survey results have shown 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 two weeks after its introduction with many of these indicating on the questionnaires that they switched from other transport modes/services for an existing journey. The results also show that gradual increases in awareness and positive perceptions regarding bus services have 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 made on the questionnaires that this occurred due to new journey requirements. The influence of past behaviour (and perhaps habit) has been shown with past bus users much more likely to become users of a new bus service.

After examining 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, we will conduct analyses of the changing frequency of usage over the course of the study period. Latent growth curve models (*27*) and dynamic ordered probit models (*7*) are methods which are appropriate for analysing the frequency data. They can incorporate time varying covariates and state dependence variables and are expected to lead to models that can used to make forecasts of 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.

6. ACKNOWLEDGMENTS

The research reported in this paper has been funded by a grant from the UK Engineering and Physical Sciences Research Council (EPSRC).

7. REFERENCES

(*1)* Douglas, N. Patronage Ramp-Up Factors for New Rail Services, 2003, http://www.cilt.co.nz/Neil%20Douglas.pdf . Accessed May 30, 2006.
(*2*) Chatterjee, K. and Ma, K. Behavioural Responses to a New Transport Option – A Dynamic Analysis Using a Six-Month Panel Survey. CD-ROM Proceedings of 11th International Conference on Travel Behaviour Research, Kyoto, August 2006.
(*3*) Chatterjee, K. Asymmetric Churn - Academic Jargon or a Serious Issue for Transport Planning? Transport Planning Society Bursary Paper, 2001. http://www.tps.org.uk/library/0001chatterjee.pdf . Accessed May 30, 2006.
(*4*) Triandis, H. C. Values, Attitude, and Interpersonal Behavior, In *Nebraska Symposium on Motivation* (Edited by H. E. Howe, Jr. and M. M. Page), University of Nebraska Press, Lincoln, 1980.
(*5*) Verplanken, B., Aarts, H., and van Knippenberg, A. 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 Kitamura, R. 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 Hanly, M. Volatility of Car Ownership, Commuting Mode and Time in the UK. Paper Presented at the World Conference on Transport Research, Istanbul, Turkey, 2004.
(*8*) Thøorgersen, J. Understanding Repetitive Travel Mode Choices in a Stable Context: A Panel Study Approach. *Transportation Research Part A,* Vol. 40A, No. 8, 2006, pp. 621-638.
(*9*) Simma, A. and Axhausen, K.W. Commitments and Modal Usage: An Analysis of German and Dutch Panels. In *Transportation Research Board 82nd Annual Meeting*. CD-ROM. Transportation Research Board of the National Academies, Washington, D.C., 2003.
(*10*) Polydoropoulou, A., Ben-Akiva, M. and Kaysi, I. Influence of Traffic Information on Drivers' Route Choice Behavior. *Transportation Research Record,* Vol. 1453, 1994, pp. 56-65.
(*11*) Mahmassani, H.S. and Liu, Y-H. Day-to-Day Dynamics of Commuter Route Choice Behaviour under Real-Time Information, In *Proceedings of Seminars D and E - Part 1 of 24th European Transport Forum*, PTRC, London, 1996.
(*12*) Jha, M., Madanat, S. and Peeta, S. Experimental Investigations of a Perception Updating Model on a Traffic Network with Information Provision. Preprint of paper presented at Transportation Research Board 76th Annual Meeting, Washington, D.C., 1997.
(*13*) Bradley, M. A Practical Comparison of Modeling Approaches for Panel Data. In *Panels for Transportation Planning* (Edited by T.F. Golob, R. Kitamura and L. Long), Kluwer, Boston, 1997, pp. 281-304.
(*14*) Hensher, D.A. The Timing of Change: Discrete and Continuous Time Panels in Transportation. In *Panels for Transportation Planning* (Edited by T.F. Golob, R. Kitamura and L. Long), Kluwer, Boston, 1997, pp. 305-319.
(*15*) Fastway Homepage. http://www.fastway.info. Accessed May 30, 2006.
(*16*) Raimond, T. and Hensher, D.A. A Review of Empirical Studies and Applications. In *Panels for Transportation Planning* (Edited by T.F. Golob, R. Kitamura and L. Long), Kluwer, Boston, 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 Jones, B.S. 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. Duration Models. Chapter 6 in *Handbook of Transport Modelling* (Edited by Hensher, D.A. and Button, K.J.), Elsevier, Oxford, 2000.
(*20*) Washington, S.P, Karlaftis, M.G. and Mannering, F.L.. Duration Models. Chapter 9 in *Statistical and Econometric Methods for Transporttaion Data Analysis*, Chapman and Hall/CRC, Boca Raton, 2003.
(*21*) Chen, C. and Chen, X. What it Takes for People to Change? A Time Question. CD-ROM Proceedings of 11th International Conference on Travel Behaviour Research, Kyoto, August 2006.
(*22*) Beige, S. and Axhausen, K.W. Long-term Mobility Decisions During the Life Course: Experiences with a Retrospective Survey. CD-ROM Proceedings of 11th International Conference on Travel Behaviour Research, Kyoto, August 2006.
(*23*) StataCorp. *Stata Statisitcial Software: Release 9.* StataCorp LP, College Station, TX, 2005.

(*24*) Cox, D. and Oakes, D. *Analysis of Survival Data*. Chapman and Hall/CRC, Boca Raton, FL, 1984.
(*25*) Transport Direct Homepage. http://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, The Ohio State University Department of Political Science. http://psweb.sbs.ohio-state.edu/prl/archive/statcorner/. Accessed May 30, 2006.
(*27*) Mehta, P.D, Neale, M.C. and Flay, B.R. Squeeezing Interval Change from Ordinal Panel Data: Latent Growth Curves with Ordinal Outcomes. *Psychological Methods*, Vol. 9, No. 3, 2004, pp. 301-333.