INSIGHTS ON TRAVEL BEHAVIOUR DYNAMICS FROM THE LONDON CONGESTION CHARGING PANEL SURVEY

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Abstract

The London congestion charging scheme introduced in February 2003 has been credited with reducing traffic movements into the central area of London by nearly 20%. Even though there have been many results reported on the impact of the scheme at the aggregate level, little attention has been paid to the impacts on individual travellers. The experiences of individuals have been obtained through a panel survey organised as part of Transport for London's impact monitoring programme. The panel survey obtained information on travel perceptions and behaviour six months before and after the scheme's introduction. We confirm that it is mostly car users who have changed modes, although there has been some change in the mode choice of other users. The surprising result is how few of the car drivers who indicated that they would switch modes in the before survey actually did switch modes and that other car drivers who indicated that they would remain car drivers did switch modes in reality. These results suggest that caution should be exercised in the use of stated response data, particularly when it comes to developing disaggregate models of individual behaviour. In order to better understand individual behavioural responses it is important that subjective and objective information is collected for travel options and for traveller characteristics, perceptions and attitudes and that this is collected at multiple time points after an intervention in the travel environment.

1. Introduction

Congestion charging was introduced in central London in February 2003 and was accompanied by a five year monitoring programme aimed at assessing the impact of the scheme. This paper is concerned with the traffic and travel impacts of the scheme and in particular an analysis of the changes in individual travel behaviour that have occurred.

It has been found during charging hours that four-wheeled vehicles entering the charging zone have decreased by 18% and four-wheeled vehicles circulating the charging zone have decreased by 15% (TfL, 2005). These decreases occurred immediately after the scheme was introduced and have been maintained at the same levels for the 18 month period for which data is available after the scheme was introduced. A 37% increase in bus users entering the charging zone was recorded between Autumn 2002 and Autumn 2003 (this is in the context of steady increases in bus use since 1999). A 12% increase in bus users was recorded for the year after that. A surprising result in 2003 was that Underground users entering the charging zone fell 7%. Other factors are thought to have been responsible for this and patronage recovered in 2004. Data suggests that the number of people using the National Rail system to enter the charging zone has been unchanged since the congestion charge introduction. The aggregate figures referred to above tell us about overall travel trends but not about individual changes in behaviour that have contributed to the trends. Transport for London has estimated (based on results across the monitoring programme) the changes in behaviour that contribute to the overall impact being those set out in Table 1.

Table 1. Estimated net changes in car driver movements coming into charging zone

Total net reduction in car movements at zone boundary	**65,000 to 70,000**
Through car movements – diverting around the charging zone	15,000 to 20,000
Terminating car movements – transferring to bus, Underground, rail	35,000 to 40,000
Terminating car movements – transferring to cycle, walk, motorcycle, taxi, car share	5,000 to 10,000
Terminating car movements – travelling outside charging hours	Under 5,000
Travel to other destinations, reduced frequency	Under 5,000

Disagreggate data monitoring the change in behaviour of individuals is required in order to be able to better understand the impacts of congestion charging on behaviour. Fortunately, Transport for London conducted a social impacts survey in the form of a before and after panel survey of individuals and households. The panel survey data provides us with the opportunity to measure directly the influence of the congestion charge on behaviour. It can allow us to detect whether there was purely a shift of car users to other modes or whether some people switched to the car from other modes as a result of the reduced congestion that occurred. Goodwin (1997) noted that in terms of travel behaviour changes, net change in the aggregate level is made up of the difference between quite large numbers of people changing in opposite directions.

Transport for London have reported some results from the panel survey (TfL, 2004). These show that many London residents state that they are driving less in the charging zone and are using the bus, underground or bicycle more (although some residents are doing the opposite). Comparison has been made of expected use of transport modes and realised use of modes. This shows that the overall number of people using their cars less is about the same as expected to use their cars less. However, the results do not tell us whether it is the same people who expected to use their cars less that are doing so.

The aim of this paper is to present further analysis of the panel data to examine what individual changes in behaviour took place and to attempt to explain in what circumstances changes were made. The analysis focuses on mode choice behaviour. Given that the before wave of the panel survey asked about stated responses the paper will also examine how reliable an indicator of behavioural change this provided. This analysis has been carried out as part of an EPSRC project that aims to use longitudinal travel behaviour data sets to obtain a better understanding of behavioural dynamics and to develop dynamic relationships of travel behaviour.

In the following section we discuss the factors that are generally considered to be important in influencing travel decisions and are likely to be important in the case of the London congestion charging scheme. We then describe the data that is available from the panel survey. The analysis that follows includes a descriptive part providing insights on the behavioural change that took place and regression modelling exploring the factors influencing car drivers to change mode.

2. Factors influencing mode choice

A brief discussion is provided of what we know and assume about the factors influencing mode choice to provide some context for the analysis of mode choice that follows. The dominant basis of explaining and forecasting travel behaviour is microeconomic theory. This is the foundation for discrete choice modelling in which it is assumed that attributes of the trip maker (e.g. car availability, household structure) and journey (e.g. trip purpose, time of day) and attributes of the transport alternatives (e.g. travel time, comfort) can be used to explain travel choices. (The activity-based analysis approach to travel behaviour adds sophistication to this by considering individual's travel in the context of the overall activities they wish to pursue and how these relate to other household members.)

The neglect of psychological and social considerations in explaining travel behaviour has been emphasised by Gärling (1998). The Theory of Planned Behaviour (Ajzen, 1991) is one theory which incorporates psychological and social factors in explaining human behaviour. It assumes that behaviour is related to attitudes, subjective norms and perceptions of behavioural control. There have been some analyses of mode choice based on the Theory of Planned Behaviour (e.g. Bamberg and Schmidt, 2003). It is rare though to find an analysis of mode choice which integrates the 'objective' factors (used in microeconomic analysis) with the 'subjective' factors (used in psychological analysis). One case is reported by Ben-Akiva et al (1999) who assumed attitudes are a determinant of the importance of attributes in a choice model.

Most analysis of travel behaviour is based on cross-sectional data. Longitidinal data offers better possibilities for disentangling the cause and effect of a policy intervention by monitoring the sequence of events that take place. When longitudinal data has been obtained it has been found that different relationships are obtained than with cross-sectional data (Bradley, 1997). Longitudinal data can also allow the dynamic nature (e.g. state dependence, habit, learning) of behaviour to be considered.

In the case of the London congestion charge the intervention resulted in a change to the attributes of the travel alternatives. As a direct result of the charge, car travel costs increased and car travel times reduced. Improvements were made to bus services before the charge was introduced and bus users, taxi users, cyclists and walkers may also have benefited from reduced traffic levels when the charge came into force. Attitudes and subjective norms are likely to have changed over the period before and after the charge was introduced. We now consider what information is available to us for analysing the impact of the congestion charge on individual behaviour.

3. TfL social impacts survey

The analysis is based on a social impact survey conducted on behalf of Transport for London. This is a panel survey with a before wave in September 2002 and an after wave in September 2003. The survey involved household-based face-to-face interviews with residents of the charging zone and inner London and telephone-based interviews with residents of outer London and beyond the M25. It is the data for residents of the charging zone and inner London that we consider in this paper.

For each respondent the survey included consideration of:

- Personal and household characteristics;
- Details of a selected journey (this was determined in the interview as the journey most affected by congestion charge, i.e. a frequent car journey into congestion charging zone during charging hours would fit this category);
- In-depth information on changes made to selected journey and changes in journey experience (expected and realised); and
- General impacts of congestion charge on travel choices, accessibility, local environment, self and household (expected and realised).

The household-based interviews were conducted with residents in seven different electoral wards (see Figure 1).

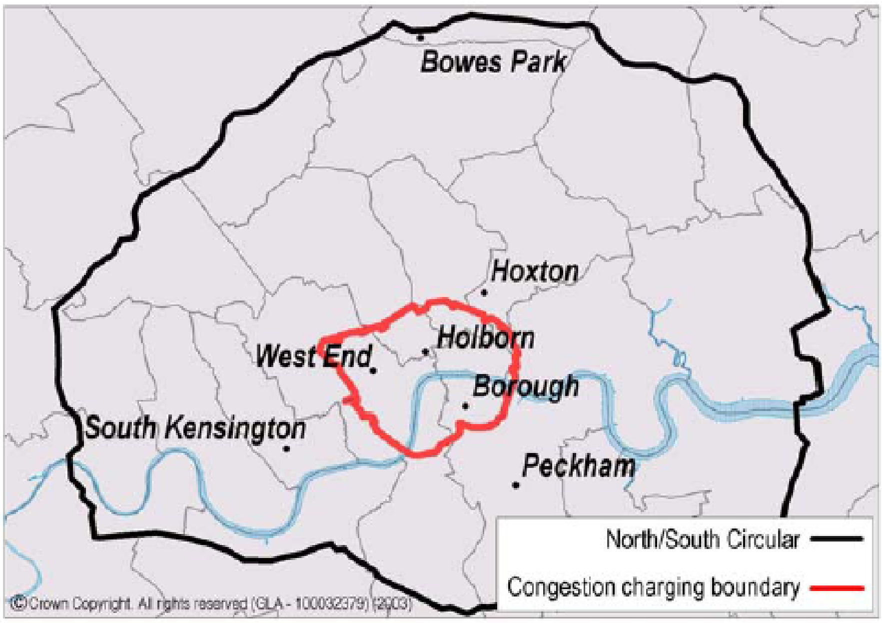

Figure 1. Electoral wards in household interview survey (source: TfL (2005))

This included three wards in the congestion charging zone (Borough, Holborn and West End) and four wards in inner London (Bowes Park, Hoxton, Peckham and South Kensington). The number of participants in the before wave was 3,475 and in the after wave was 1,291. Approximately 37% of the before wave participants were successfully re-contacted and interviewed in the after wave, therefore the total number of individuals who participated in both waves was 1,108. It should be noted that the survey participants were not been chosen to be representative of the population but to allow comparison of different neighbourhoods.

4. Descriptive analysis

The focus of the analysis is on the travel mode used for the selected journey. Table 2 presents results for changes made to travel behaviour for the selected journey, while Table 3 presents results for wider changes made since February 2003.

Table 2. Changes made to selected journey since February 2003

Change	**Car drivers**	**Other travellers**
Same mode, time period, destination	251	433
Mode	49	30
Time period (same mode)	29	18
Destination (same mode and time period)	37	46
Don't know	2	4
Total	368	531

Table 3. Wider changes made since February 2003

Change	**In response to charging**			**Total**
	Yes	**No**	**Don't know**	
Changed to an alternative fuel vehicle	4	6	0	10
Bought or acquired a bicycle, motor cycle, moped or scooter	13	17	2	32
Decreased number of cars/vans in household	11	18	0	29
Increased number of cars/vans in household	1	14	0	15
Started to car share/car share more often	6	5	0	11
Arranged to park vehicle outside charging zone	8	3	3	14
Changed workplace, occupation or job	12	71	5	88
Started to work from home, work from home more often or do teleworking	18	4	0	22
Moved business	2	4	0	6
Shopped online or on the internet more often	23	74	0	97
None of these				848

Transitions in mode choice for the selected journey are shown in Table 4. Over 90% of the subjects continued to use the same mode in the after wave (738 out of 815). The aim of the congestion charge scheme was to produce a mode shift from car and it is notable that there is asymmetry in the car use transitions. The number of car drivers switching to other modes is 44 and the number of users of other modes switching to car driver is 5. The probability of a car driver changing mode was approximately 0.13 (44/329), whereas the probability of a transition in the opposite direction was only 0.01 (=5/486).

Table 4. Travel mode transition frequencies

		Main travel mode in after wave										
		Car/ van driver	Car/ van passenger	Bus	Tube /DLR	Train	Taxi	Mo- tor cycle	Bi- cycle	Walk	Other	Total
Main travel mode in before wave	Car/van driver	285	2	14	10	6	2	1	2	7		329
	Car/van passenger	1	50	6	2	1						60
	Bus	2		166	2	1				2		173
	Tube/DLR	2	2	3	103	2						112
	Train		2			14						16
	Taxi				1		9					10
	Motorcycle							5	1			6
	Bicycle			1					14			15
	Walk		1	1						91		93
	Other										1	1
	Total	290	57	191	118	24	11	6	17	100	1	815

Note: The main method of travel for selected journey is the travel mode that covers the greatest distance of the journey. Some of the 1,108 participants did not have a selected journey and hence the total sample size in Table 4 is 815.

Table 5. Mode changes in relation to expected/realised travel costs

		Expected / realised cost changes	Expected mode (from before wave)		Realised mode (from after wave)	
			Other	Car driver	Other	Car driver
Main travel mode in before wave	Other	Less	7		7	
		About the same	45		40	
		More	9		9	1
		Sub-total	*61 (O→O)*	*(O→C)*	*56 (O→O)*	*1 (O→C)*
			Other	Car driver	Other	Car driver
	Car driver	Less	13	4	12	12
		About the same	16	120	12	164
		More	19	171	12	102
		Sub-total	*48 (C→O)*	*295 (C→C)*	*36 (C→O)*	*278 (C→C)*

Note: Information for the relevant questions was not available for many participants (especially non-car drivers) hence the reduced sample size in Table 4.

Table 6. Relationship between stated and revealed responses

		Expected / realised cost changes	Other – expected from before wave		Car driver – expected from before wave	
Main travel mode in before wave	Other		Other – realised	Car driver – realised	Other – realised	Car driver – realised
		Less	7			
		About the same	41	1		
		More	8			
		Sub-total	*56*	*1*		
	Car driver		Other – realised	Car driver – realised	Other – realised	Car driver – realised
		Less	4	7	8	11
		About the same	3	11	8	150
		More	4	12	9	87
		Sub-total	*11*	*30*	*25*	*248*

Notes: Information for the relevant questions was not available for many participants (especially non-car drivers) hence the reduced sample size in Table 5. The lightly shaded cells indicate the number of people who changed their mode of transport after they had expected to.

Table 5 shows expected and realised mode changes that took place in the context of travel cost change expectations/outcomes. The travel cost changes were requested regardless of who would eventually cover costs. Travel costs include public transport fares, taxi fares, car parking, petrol and other costs as well as the congestion charge. It can be seen that most non-car drivers expected that the costs of their journeys would remain the same. Car drivers not switching to an alternative mode expected that their travel costs would stay the same or increase and found this to be the case in practice, while car drivers switching to an alternative mode had mixed expectations regarding cost changes and there were mixed outcomes in practice.

About 14% of car drivers (48 out of 343) in the before wave said that they would change their travel mode. 12% of car drivers (36 out of 314) said they changed their travel mode. This would suggest that stated responses give a good indication of actual responses. To check that this was true a comparison is made of stated responses and actual responses in Table 6. There was a considerable match between stated and revealed behaviour for non-car drivers. Among car drivers who expected to change their travel mode, only 27% changed travel mode (11 out of 41). Also about 9% of car drivers who expected that they would not change their travel mode did change mode (25 out of 273). The panel data shows that behavioural responses are likely to be difficult for people to predict (or, at least, to be ascertained from a travel survey). This casts doubt about reliability of disaggregate predictive models developed based on stated response data.

5. Regression analysis

It has been confirmed in the previous section that car drivers were more likely to be affected by the congestion charging scheme than users of other modes, therefore further analysis of the data concentrated on car drivers and explored the factors influencing whether they changed mode or not for the selected journey. Regression models have been estimated relating the probability of modal change to traveller and journey characteristics and to perceived congestion charging impacts on travel in London and on the selected journey in particular. The dependent variable takes the value '1' for mode change or '0' for no change. A binomial distribution is therefore assumed together with a logit or log-odds link function, which provides the transformation to a linear model. The resulting logistic regression model can be written as:

$$\log\left(\frac{p}{1-p}\right) = B_0 + B_1 X_1 + B_2 X_2 + \Lambda + B_p X_p$$

where,

p is the probability of car users switching to other mode

$X_1, X_2, \Lambda\ , X_p$ are independent explanatory variables

$B_0, B_1, \Lambda\ , B_p$ are regression coefficients.

In Table 7 the independent variables that have been tested in the models are listed.

Table 7. Summary of independent variables

	Independent Variables		Expected change 1	Expected change 2	Realised change 1	Realised change 2
	Source		Before Survey	Before Survey	After Survey	After Survey
Socio-economic characteristics	Gender	(1=male, 0=female)	✓	✓	✓	✓
	Age	(continuous)	✓	✓	✓	✓
	Work status	(1=full-time, 0=other)	✓	✓	✓	✓
	Car ownership	(continuous)	✓	✓	✓	✓
	Household income	(continuous)	✓	✓	✓	✓
	Residency	(1=within charging zone, 0=other)	✓	✓	✓	✓
Trip characteristics	Trip purpose	(1=commuting, 0=other)	✓	✓	✓	✓
	Trip frequency	(continuous, decreasing)	✓	-	-	-
	Trip within charging zone and hours	(1=yes, 0=no)	✓	✓	✓	✓
Congestion charging impacts (on selected journey) *	Congestion	(1=lighter 2=same 3=heavier)	✓	✓	✓	✓
	Public transport option	(1=better, 2=same 3=worse)	✓	✓	✓	✓
	Travel time change	(continuous)	✓	✓	✓	✓
	Travel cost change	(continuous)	✓	-	-	-
Wider changes	Wider changes	(1=yes, 0=no)	-	-	-	✓

Note: * The responses to these questions were asked to be made based on the expected/realised mode of transport used after congestion charging introduced (and not necessarily assuming a continuation of use of the same mode).

Models have been estimated using only the before data where the dependent variable is **expected** change of mode (1=mode change, 0=no change) and have been estimated using the after data where the dependent variable is **realised** change of mode (1=mode change, 0=no change). It had been intended to combine data from the two waves to model dynamic mode choice, but as will be discussed later this proved not to be possible. Results are now presented for four models:

- Expected change 1 – model based on the inclusion of all 13 independent variables.
- Expected change 2 – model based on the inclusion of 11 independent variables. Trip frequency and travel cost change are removed to be comparable with the next model.
- Realised change 1 – model based on the inclusion of 11 independent variables. For many survey respondents in the after wave there were missing values for trip frequency and travel cost change and these variables were omitted.
- Realised change 2 – same as realised change 1 but with the addition of a variable for ‘wider change’. This variable took the value ‘1’ when respondent said that they had experienced any of the wider changes noted in Table 3 other than shopping online.

The model results are presented in Table 8. The small sample size for the realised change models is due to many missing values in the after wave data set.

Table 8. Logistic regression models

Models	Expected change 1		Expected change 2		Realised change 1		Realised change 2	
Variables	Coef.	Odds ratio	Coef.	Odds ratio	Coef.	Odds ratio	Coef.	Odds ratio
Gender (1=male, 0=female)	-.138	.871	-.258	.773	-.707	.493	-.640	.528
Age (continuous)	-.022	.978	-.012	.988	.009	1.009	.011	1.011
Work status (1=full-time, 0=other)	-.970*	.379	-.545	.580	.498	1.646	.592	1.807
Car ownership (continuous)	-1.514**	.220	-.908*	.403	-.188	.829	-.098	.907
Household income (continuous)	.508**	1.662	.359*	1.431	.030	1.031	-.033	.968
Residency (1=within charging zone, 0=other)	-.944*	.389	-.470	.625	-1.173*	.309	-1.143*	.319
Trip purpose (1=commuting, 0=other)	-.434	.648	.195	1.215	-.966	.381	-.958	.384
Trip frequency (continuous, decreasing)	-.558**	.573	NA	NA	NA	NA	NA	NA
Trip within charging zone and hours (1=yes, 0=no)	-.763	.466	-.418	.658	1.150*	3.160	1.211**	3.356
Congestion (1=lighter 2=same 3=heavier)	-1.100**	.333	-.943**	.389	-.621	.537	-.603	.547
Public transport option (1=better 2=same 3=worse)	.375	1.454	.187	1.206	.459	1.582	.517	1.677
Travel time change (continuous)	.639**	1.895	.603**	1.828	.122*	1.129	.101	1.106
Travel cost change (continuous)	-.402**	.669	NA	NA	NA	NA	NA	NA
Wider change	NA	NA	NA	NA	NA	NA	.566	1.761
Constant	.121**	1.128	-5.292**	.005	-3.469**	.031	-3.628	.027
-2 log likelihood								
Only socio-economic var	273.3		273.3		117.0		117.0	
Trip char. var. added	266.9		272.8		116.1		116.1	
CC impact var. added	170.9		198.8		106.9		106.9	
Wider change var. added							106.2	
Sample size	375		375		158		158	

Note: * p <0.1; ** p<0.05

The odds ratio values represent the estimated relationship between a one-unit change in independent variable and the change in probability of mode change. The log likelihood multiplied by -2 is used in logistic regression to show how well the estimated model fits the data. A smaller value is indicative of a better fitting model. The value is not informative by itself, but can be used to check whether the addition of new variables makes a significant difference to the goodness of fit. For the first model the addition of the variables related to trip characteristics decreases -2 log likelihood by 6.4 units and the addition of the congestion charging impact variables decreases -2 log likelihood by 96.0 units. This means that the congestion charging impact variables are very useful in explaining car driver's mode change expectation in response to the congestion charging scheme.

The estimation results from the first model (expected change 1) show that a car driver is more likely to expect to change mode if they:

- do not work full-time
- have low household car ownership
- have high household income
- live outside charging zone
- make selected journey frequently
- expect congestion to be lighter
- expect travel time to increase for selected journey
- expect travel cost to decrease for selected journey

There is some apparent inconsistency in these results. Higher income is associated with greater likelihood of expected mode change and yet low car ownership is also associated with greater likelihood of changing mode. Car ownership appears to be having a more dominant effect but income is moderating that effect. It is an expected result that those people living outside the charging zone who have to pay the full charge are more likely to expect to change mode. Frequent travellers are more likely to say that they will change mode. This might be because they will have to occur incur greater costs due to congestion charging. Those respondents expecting congestion to be reduced are more likely to change mode and this may represent those that are more positively inclined towards the scheme. Respondents expecting increased travel times and decreased travel costs are more likely to expect to change mode. This takes into account any switch in mode (from car to public transport usually for those switching) and therefore reflects their expectation about the alternative mode as much as the impact of the congestion charging scheme.

The estimation results for the third model (realised change 1) show that a car driver is more likely to change mode if they:

- live outside charging zone
- travel within charging zone and hours
- experienced travel time increase for selected journey

It seems that only the variables directly related to the congestion charging scheme are relevant in explaining mode change behaviour. We tested the inclusion of the wider change variable in the fourth model (realised change 2) and found that although not statistically significant those people who had experienced a wider change (most often a household vehicle or employment change) had a tendency to be more likely to switch mode.

Comparing the results for the third model (realised change 1) to the second model (expected change 2) there are considerable differences in the signs and magnitudes of many of the coefficients. One important point that can be drawn from the results is that mode change behaviour based on people's expectation appears to be quite different to those based on revealed behaviour.

6. Conclusions

We set out to use the congestion charging panel survey data to explore the impact of the charging scheme on individual behaviour. We have shown that as expected it is mostly car users (13% of them) who have changed to other modes (a variety of modes), although there has been some change in mode choice of other users (1% of them) to the car. The surprising result is how few of the car drivers who indicated that they would switch modes in the before survey actually did switch modes (27%). However, the total number of car drivers switching modes was about the same as indicated in the before survey, as a significant number of car drivers who indicated that they would remain car drivers did switch modes in actuality (9%).

Regression modelling adds further doubt about the reliability of stated responses with little consistency in the (statistically significant variables in the) models for expected responses and realised responses. These results signal a warning that aggregate forecasts made using stated response data can turn out to be accurate, however the data may not be informative in explaining individual responses and could therefore lead to misleading predictions. The panel data has shown us that behavioural responses are likely to be difficult for people to predict (or, at least, to be captured from a travel survey). This casts doubt about reliability of disaggregate predictive models developed based on stated response data.

We had hoped that the panel data would have enabled us to investigate the dynamics of responses to the congestion charging scheme. Ideally, information would have been available for each respondent about how the attributes of modal alternatives (e.g. travel time, travel cost) and individual's perceptions and attitudes towards them were modified by the introduction of congestion charging but information of this nature was not available from the survey and would have been difficult to construct. Had this information been available we would have looked to develop dynamic models of mode choice behaviour related to attributes, perceptions and attitudes at different time points. As pointed out earlier, it has been found that different relationships have been obtained from longitudinal data than cross-sectional data. Instead we were only able to develop simpler binomial models of car driver mode change. These made limited use of the potential of panel data. In constructing the dependent variable (mode change or not) we used both the before and after data but the independent variables were taken from either the before wave or after wave. Changes in conditions were incorporated through respondents' self-reported perceptions before and after charging was introduced.

We would also have liked to consider the impact of dynamic aspects of travel behaviour such as state dependence (how did past travel choices affect response?), habit (did the congestion charge result in re-evaluation of car use?) and learning (did travellers become aware of reductions in road travel times?). Unfortunately, this information was also not available from the panel survey. We were able to consider in our modelling the influence of 'wider change' or what may be termed life events and found that this seemed to increase the probability of switching mode. It is not clear whether the life event might have caused the mode change or the mode change (and other related impacts of congestion charge) caused the life event.

Where longitudinal data is collected to monitor the behavioural impacts of a transport intervention it is often in the form of a 'before' and 'after' survey (two wave panel survey). Bradley (1997) notes 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'. We are currently conducting a panel survey of residents in the town of Crawley (southern England) where a guided bus system has been introduced. The survey is targeting residents living near the new guided bus system route, and the first wave of the panel took place before the new route was introduced and subsequent waves are taking place at two month intervals. The data from this survey will be used to gain a better understanding of the travel behaviour responses that individuals make to a change in their travel environment.

7. Acknowledgement

We wish to thank Transport for London for supplying the survey data and would like to make it clear that the paper has not been written on behalf of Transport for London or the research work undertaken on behalf of Transport for London. Results, analyses and views based on the social impact survey have been published in reports available on the Transport for London website (www.tfl.gov.uk).

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