MODELLING THE RELATIONSHIP BETWEEN TRAVEL BEHAVIOURS AND SOCIAL DISADVANTAGE

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ABSTRACT

It is well documented within the literature, that the supply of transport services and hence the opportunity for people to be mobile are unequally distributed between different social groups, predominantly along the lines of traditional social stratifications. The condition of reduced transport supply and suppressed mobility has been variously referred to as 'transport disadvantage', 'transport exclusion' and/or 'transport poverty', with differently nuanced understandings being attached to each definition.

However, there is still considerable gap between social research of the interactions between transport poverty and social disadvantage and mainstream transport research. In part, this is because traditionally the transport discipline has mainly concerned itself with the operation and management of transport systems, rather than the activity needs and concerns of the people who travel on them. Although there is an interest in representing the different travel behaviours, activity needs and perceptions of different population groups, most of the commonly used transport models are demographically rather too aggregate to demonstrate the social consequences of transport policy decisions for different sectors of the population.

There is a need to improve communications between the two lines of research, so that those interested in the interactions between transport and social disadvantage can better understand the role of models, while modellers appreciate more the policy needs relating to mobility for different social groups. The authors of this paper are collaborating with a view to achieving this. A survey is currently being carried out in Merseyside in two districts of Merseyside, and one of the aims is to assess the additional contribution to mobility (or lack thereof) of variables that are not usually found in mainstream transport models. The paper reports results from disaggregate modelling and analysis of UK National Travel Survey data 2002-2010 prior to this bespoke data collection effort.

Keywords: transport models, social disadvantage, travel behaviours, local survey

1. INTRODUCTION

Currently, mathematical models of travel behaviour dominate all levels of transport decision-making because they offer policy-makers convenient *ex-ante* methods to justify broad-brush policy, planning and spending decisions (Van de Voorde and Vanelslander, 2010). However, even the key proponents of such models agree that, despite their increasing complexity, most models struggle to capture the intricate nuances of people's day-to-day experiences of the transport system (Hensher and Greene, 2003). This can be particularly important where it is clear that different sectors of the population are behaving in fundamentally different ways, as shown in the case of low-income households in the UK (Dargay, 2001). When we focus on transport disadvantage/mobility inequality and its role in the social exclusion of individuals and households, we therefore need to consider the enhancement of existing models.

This paper reports on the early results from a study to model the interactions between transport poverty and social disadvantage at the national, sub-regional and local level. The focus at this initial stage of the research was to explore how far it is possible to use publicly available data collected through the annual National Travel Survey (NTS) to enhance and build on existing models of travel. The paper is divided into five main sections. The next section provides a background context and rationale for the study and section 3 sets out the overall methodological approach. This is followed by a review of past literature with emphasis on empirical studies of transport and social disadvantage and in particular those that have attempted modelled analyses. We then describe the more detailed modelling approach that was applied in our initial analysis of the UK National Travel Survey (NTS) data and in section 6 we discuss the results of this analysis. In the final section of the paper, we set out the next steps for the research and identify some core challenges for its successful delivery.

2. LITERATURE REVIEW

An overview of the literature suggests that sociological and geographical studies of the transport concerns of income deprived and socially disadvantaged individuals, households and communities have been prolific over the past ten or more years. However, it is reasonable to suggest that inter-disciplinary socio-theoretical and mathematical explanations are few, although some progress has been made in more recent years. The main challenges in this respect are threefold.

First, sociological theories of poverty and social disadvantage (e.g. Hills *et al*, 2002; Byrne, 2005; Levitas, 2005) are still poorly conceptualised and understood within the transport context. In addition, emergent theories of transport and social disadvantage, such as those identified by the 'new mobilities paradigm' (e.g. Sheller and Urry, 2006; Urry, 2007), time-space geography (e.g. Miller, 2005; Dijst and Kwan, 2005; Neutens et al., 2009) and social network theory (e.g. Carrasco et al, 2008) have not been incorporated into mainstream transport thinking. Second, many of the studies of transport-related social exclusion have been qualitative and the few dedicated quantitative studies that have been undertaken have tended towards GIS-based assessments of accessibility (e.g. Cervero, 2004; Hurni, 2006; Paez et al, 2009) and/or micro-modelling of detailed aspects of the local transport environment (e.g. Mackett et al, 2008). This is largely because the datasets and methods for modelling other aspects of transport-related social exclusion, such as income effects and cognitive and time use constraints, are non-existent and/or poorly constructed and/or poorly designed for the purposes of detailed disaggregated socio-demographic analysis. Third, applying a social lens to the problem of transport and income poverty forces a focus on the associated economic and social outcomes of this condition, and thus a move away from the traditional systems-based approach to transport provision and towards a social welfare perspective (Grieco, 2006). This has rarely been communicated within the national and urban transport models that currently exist and is generally poorly understood by transport policy-makers. This suggests that there is both considerable opportunity and justification for the development of an inter-disciplinary approach.

A focus on empirical studies of the travel behaviours of socially disadvantaged population groups suggests that these can broadly be classified as either qualitative (largely focusing on the needs and concerns of these population groups) or based around quantitative analysis of the accessibility of disadvantaged areas and/or population groups (see Lucas 2012 for a comprehensive review of this literature). A smaller sub-set of studies has employed statistical and econometric modelling techniques to measure the influence of social disadvantage on the revealed travel behaviours of different social groups. These modelling approaches can broadly be classified by their unit of analysis, (e.g. trip- or activity-based), and/or by whether they consider travel demand (e.g. number of trips, journey distances, etc.) or transport and land use supply (e.g. accessibility to services, activity spaces, etc.).

Fore example, demand-based approaches have mainly considered traditional trip-based measures such as trip generation (Roorda et al, 2010), destination choice (Scott and He, 2012), mode choice (Mercado et al, 2012; Schmöcker et al, 2008) and distance travelled (Morency et al, 2011; Mercado and Páez, 2009). They also include less conventionally used activity-based measures including trip purpose (Páez et al, 2009: Johnson et al, 2011), participation and propensity to perform activities (Páez and Farber, 2012), activity duration or time-use (Limanond et al, 2011; Farber et al, 2011, Spinney, 2009) and activity spaces (Schönfelder and Axhausen, 2003).

On the other hand, supply-side approaches have been largely been applied to the analysis of transport infrastructures (Páez et al, 2011; Lopez et al, 2008) and of public transport service provision (Neutens, 2012; Currie, 2010) and activity-space analyses of land uses and facilities within local areas (Páez et al., 2009; Cebollada, 2009). Although in some case, studies both approaches have been combined to offer hybrid models of the revealed travel behaviours of socially disadvantaged population groups, as well as opportunity measures in terms of the their access to transport services and the particular destination or activities that are available to them within a given area.

The next section of this paper discusses the chosen methodology and modelling approach for our own study.

3. METHODOLOGY

Our overall research design for the study is multi-staged and multi-level, in that it begins by developing a theoretical and conceptual model from a review of the literature and builds on this to identify a set of indices and parameters for national, sub-regional and local level statistical models. The focus of this paper is on the early stages of this research process and specifically on the identification of a suitable conceptual framework and indices for populating the national level and sub-regional level models.

3.1 Identifying a conceptual framework

Lucas (2012: 107) has already developed a comprehensive conceptual framework for understanding the contributing factors and interactions between transport disadvantage and social disadvantage, which was considered suitable for this study (see Figure 1).

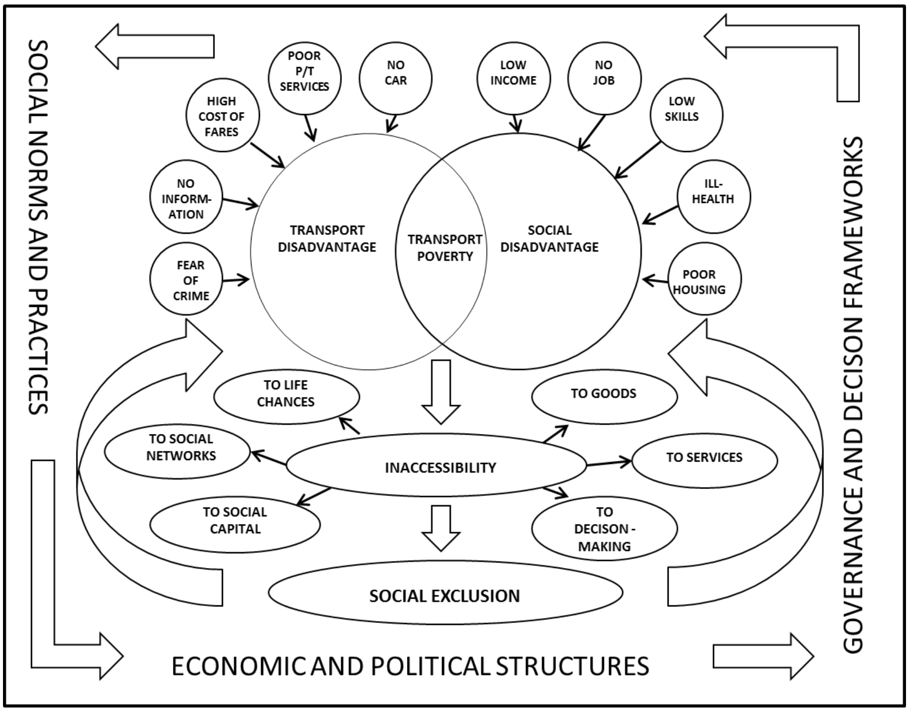

Figure 1: Relationship between transport disadvantage, social disadvantage and social exclusion.

The diagram demonstrates an interaction between transport disadvantage and social disadvantage that interacts over time to cause transport poverty, which causes reduced access not only to goods and services but also essential life opportunities. Inaccessibility leads to social exclusion, which in turn reinforces both social disadvantage and transport disadvantage. The problem can be exacerbated or reduced depending on a number of contextual factors including the underlying social norms and practices in which the individual is situated, economic and political and governance and decision-making frameworks of the society in which they live. Social exclusion is also dynamic and relational in time and space in that disadvantage can be cumulative for both individuals and the areas in which they live and can be reinforced over time through repeated cycles and interactions.

3.2 Identifying indices of transport and social disadvantage

We next identified a set of indicators for identifying the influence of social disadvantage on revealed travel behaviours as identified in Figure 2.

Table 1: Indicators of travel behaviour and social status

TRAVEL BEHAVIOUR	SOCIAL DISADVANTAGE
• Number of trips • Journey distance • Journey duration • Mode of travel • Trip purposes • Cost of travel (relative to income) • Vehicle ownership • Driver licence • Public transport availability • Levels of exposure to traffic	• Household income • Personal income • Employment status • General health and wellbeing • Disability (physical & cognitive) • Educational attainment • Housing security • Financial security • Gender, age, ethnicity, SEG

3.3 Developing the national and sub-regional models

In deciding the modelling approach, we opted for an enhanced trip-based travel demand model for two key reasons. First, from a practical point of view, the existing national and local datasets that were available to us were not geographically specific enough for meaningful spatial modelling. Second, a key aim of the research is to build upon and improve current policy practice and most policymakers in the UK and elsewhere rely on traditional (if enhanced) 4-stage models of travel demand. This suggests that the improvement of these models in terms of their ability to predict the differential outcome of policies for socially disadvantaged population segments might provide a useful starting point for the purposes of practical decision-making.

A significant data resource available to us is the UK National Travel Survey [NTS]. The NTS has been running continuously since 1988. The data is periodically archived and the most recent set issued relates to the period 2002-2010. During this period approximately 19,000 individuals of different age, ethnicity and economic background living in 8,000 households across the UK have participated in the survey each year, and the total number of individual trip records for the years 2002-2010 is in excess of 2.7 million. It is a cross-sectional data survey, so the respondents are not the same for each surveyed year, which limits the ability to analyse dynamic behaviour of specific population segments over time, although there are various ways to get over this problem within the models (e.g. see Dargay, 2001).

Information is collected from all members of the household who are 11 years old or above on how, for what purpose, when and where they travel as well as on the key factors that will affect this, such as car availability, driving licence holding and access to key services. Data is collected in two stages. In the first stage, face-to-face interviews are carried out to collect information on the households, individual members within the household and all the vehicles to which they have access. Each household member is then asked to record details of all their trips over a seven day period in a travel diary, allowing travel patterns to be linked with individual characteristics.

3.4 Creating the baseline model

For the purpose of national forecasting, the UK Department for Transport (DfT) has commissioned two major investigations of trip-making – the first (WSP, 2000) made use of the NTS data from 1988 to 1996, while the second (WSP, 2009) made use of the data from 1995 to 2006. The results of the first study have been encapsulated in the DfT's National Trip

End Model (NTEM), and a summary description is available in Annex B of DfT's WebTAG Unit 3.15.2[1]. The NTEM models trip rates for 8 home-based purposes and 7 non-home-based purposes as a function of the status of the individual (gender together with a six-way distinction between children, over 65s, and for adults of working age, students, full-time employed, part-time employed, non-working) and household structure (no. of adults), car ownership, and area type. Not all the categories produce statistically different trip rates for each purpose, but the general level of explanation is high and consistent, and was also generally confirmed by the later study.

We have developed our baseline national and sub-regional models using these same variables, though for convenience we have made use of a regression-based formulation which treats some of the variables as continuous. The base line models each have the form:

$$Y = \alpha_{\text{person-type}} + \beta_{\text{fem}}.\delta_{\text{fem}} + \sum_{\text{area-type}} \beta_{\text{area-type}}.\delta_{\text{area-type}} + \beta_{\text{adults}}.(N_{\text{adults}}-1) + \beta_{\text{cars}}.\ N_{\text{cars}}$$

where the δ variables are "dummies" (0,1) indicating the presence of a particular characteristic, and the N variables are continuous.

Although we will later be examining different travel purposes, we initially considered general measures of mobility regardless of purpose: we defined three dependent (Y) variables, for weekly trip frequency, average trip distance, and average trip duration. By contrast, the NTEM model relates only to trip frequency.

3.5 Modelling the travel of socially disadvantaged persons

From this baseline, we were then in a position to consider the impact of a number of additional variables potentially relating to social disadvantage. In practice, we found that it was not possible to populate all of the indicators in Table 1 with data from the NTS and some had to be dropped from the model or replaced with proxy measures.

A total of seven 'vulnerable' segments of the population were identified and their socioeconomic characteristics and travel behaviour further analysed. These segments are single parents (family structure), non-whites (ethnicity), elderly (age), rural population (public transport access), unskilled HRPs (skills and education), non-economically active and the unemployed (employment). Most of these categories are not independent and so it is possible for an individual to be represented in more than one segment. The economically inactive are independent from the unemployed: the first category includes home-workers and people unable to work due to health issues, while the unemployed category only considers those not working but still actively seeking work. Socio-economic characteristics such as gender, household income and employment status were also analysed as they represent personal and household features of vulnerable segments.

[1] *www.dft.gov.uk/**webtag**/documents/expert/pdf/**unit3.15.2**.pdf*

Table 2: Socio-economic characteristics of vulnerable segments

	Single parents	Non-White	Elderly	Rural	Un-skilled	Un-employed	Econ. inactive	Whole Sample
Age (years)								
Mean	35.2	28.6	74.3	42.1	43.9	33.1	40.2	39.3
Age distribution(%)								
0-16 years	0	31.2	0	19.0	0	4.1	0	20.7
17-64 years	99.6	62.3	0	59.2	95.8	95.3	89.0	60.0
65+ years	0.4	6.5	100	21.8	4.2	0.6	11.0	19.3
Household income level (in £,000)								
Less than 25K	88.6	52.1	79.5	39.0	60.6	70.7	68.5	46.0
25-50K	10.1	29.5	16.0	35.2	31.1	20.6	22.1	33.3
50K or more	1.3	18.4	4.5	25.8	8.3	8.7	9.4	20.7
Employment Status (%)								
Full time	25.5	29.7	2.4	44.4	68.0	0	0	44.0
Part time	25.5	8.9	4.6	16.1	24.4	0	0	14.5
Student	3.4	8.0	0	2.7	0	0	0	4.0
Economically inactive	41.0	14.0	3.4	8.6	7.6	100.0	100.0	10.4
Retired	4.8	8.2	89.5	28.3	0	0	0	27.1
Car ownership								
No car (%)	47.6	28.6	33.4	6.4	28.5	38.9	32.0	18.5
No license (%)	25.1	52.3	41.2	29.4	20.4	34.7	35.5	38.6
Cars per HH	0.54	0.95	0.77	1.53	1.01	1.05	0.94	1.13
Gender (%)								
Female	93.0	51.6	54.9	50.7	39.0	39.9	75.0	51.7
Number								
% of sample	2.0	9.7	16.6	14.9	4.2	1.9	8.2	100.0
No. of cases	3,992	18,925	32,341	29,095	8,205	3,726	16,083	195,018

(Source: National Travel Survey 2002-2010)

As seen in table 2, the largest vulnerable segments are the elderly and rural population. Income distribution shows that all the segments are over represented within the lowest income bands but that both single parents and the elderly are the population segments with the largest proportion of their population in the lowest income band, whilst non-whites and people living in rural areas are the ones with largest representation highest income, although this is well below the national average. However, the effect of family size is not considered which means that though household income might be high, income per capita could be small.

If we analyse employment status, single parents, non-whites and unskilled HRPs are the ones with the most unemployed individuals. While for gender distribution even though most segments have a fair share between males and females, there is an absolute majority for single parents being women. In the case of car ownership, it is interesting to see how near half of single parents have no cars while the unemployed/economically inactive, elderly and non-whites have very low car rates when compared to the whole sample. However, most single parents do have a driving license and probably higher access to cars not belonging to their households (as a consequence of major social capital) while most non-white do not.

Travel behaviour indicators were also taken into consideration in order to compare the different vulnerable segments considered. Single parents make the most trips, an important part of these being for escort purposes, by car and within a relatively local area. Non-whites have the biggest share of their trips by bus, making the least and shortest trips (in terms of distance). However, non-whites make the longest trips in terms of trip duration. This is a modal effect as nearly a third of their trips are either by public transport or non-motorized modes.

Non-motorized modes are mostly used by the unemployed (and economically inactive) and single parents, walking being the main mode in both cases. In the case of cycling, unskilled HRPs and the unemployed have the biggest shares doubling the sample mean. In the case of weekly trip frequency, single parents and rural population are the ones making the most trips. However, there is an income bias in the case of rural population caused by the fact that they are relatively the richest vulnerable segment and only 6.4% have no car. On the other hand, if we analyse trip distance and duration: single parents, unskilled HRPs and the unemployed are the ones with the shorter trip distances and hence, shortest trip durations.

4. DISCUSSION OF RESULTS

We next present the output tables from the models and discuss key findings from our interpretation of them.

The analysis of categorical data presents certain difficulties in exposition. For reasons of identifiability in estimation, it is not possible to obtain a coefficient for each category. If there is only one categorical variable, then there are two possibilities for model specification, either (i) to include a regression constant and, after defining a base for the categorical variable, include all the other levels as dummies, or (ii) to drop the constant, and include all the levels as dummies. In the first case, the coefficients are the increments to the base, and in the second they are the absolute values for each level.

When there is more than one category variable then the choice between methods (i) and (ii) remains for one of the category variables (which can be arbitrarily selected) but for each of the remaining variables we have to select a base level and drop the associated dummy from the list of the regression variables. Our approach has been use method (ii) and to select the person-type variables (represented by $\alpha_{\text{person-type}}$ in the Equation given earlier) as the category for which the absolute values will be estimated for all levels. For all other categories, the base level will be explicitly stated. It should be noted that these are arbitrary conventions, which do not affect the results (model fit) but have some relevance for the interpretation.

Table 3 presents the results from the national level baseline model. Each observation represents an individual. The three different dependent variables (trip frequency, average trip length, average trip duration) are presented in parallel columns, using the same specification.

For the area types, we have used Metropolitan areas as the base reference in order to match with the later sub-regional model that we shall present for the Merseyside metropolitan region. The area constants show some variation, with London having the lowest frequency and the highest average trip duration, and rural areas having the greatest average trip length. Overall, the differences are perhaps less than one might expect, but of course they hide the modal variation.

More interesting are the person type effects; children, students, non-working and retired persons make the least trips, while part time and full time workers make the most. These absolute estimates by person type must be interpreted as applying to male persons in one-adult households with no car in a Metropolitan area. There is a small gender effect although this is not highly significant, with females making on average 0.2 trips per week more. Trip frequency per person reduces by 1.4 trips per week for each extra adult in the household (because of the possibility of "sharing" travel, especially shopping) and increases by about 2.5 trips for each additional car. The positive influence of certain variables appear to be consistent with previous research in the case of distance travelled by full time workers (Manaugh et al., 2010), females (Manaugh et al., 2010; Mercado and Paez, 2009).

For average trip length, the directions of the effects are similar except for part time workers and non-workers who have trip lengths lower than those of full time workers and students. These results carry over to the average trip duration model, with three exceptions: students spend longer on travel despite having shorter trip distances compared to full time workers, and the increasing number of cars within a household reduces the average duration despite longer journey distances. These are both probably modal effects showing the higher speed for the car. The third exception is that the travel time increases slightly with the number of adults despite the reduced distance effect: the reasons for this are not immediately clear.

Table 3: Results from baseline national model

	Trip generation (trips per week)		**Trip distance (miles per trip)**		**Trip duration (minutes per trip)**	
Variable	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio
Area type						
London	-1.25	-16.4	0.63	5.5	7.46	42.2
Metropolitan	Ref.		Ref.		Ref.	
Urban big	0.18	2.3	0.76	6.4	0.88	4.8
Urban large	0.17	2.0	0.59	4.8	-0.63	-3.3
Urban medium	0.23	3.0	0.99	8.5	-0.74	-4.1
Urban small	-0.11	-1.5	2.29	20.1	0.98	5.6
Rural	-0.39	-4.8	4.03	33.6	2.94	15.9
Person type						
Child	12.07	147.7	5.21	42.4	24.09	127.2
Full time	16.59	211.3	9.67	81.8	30.65	168.5
Part time	18.07	179.7	6.74	44.5	26.70	114.6
Student	13.57	99.5	8.22	40.0	32.96	104.3
Non-working	14.10	159.4	6.54	49.1	26.64	130.0
Retired	12.14	147.5	6.17	49.8	25.77	135.1
Gender (female)	0.20	4.6	-1.43	-21.8	-1.87	-18.5
N of adults per HH	-1.39	-37.4	-0.90	-16.1	0.49	5.6
N of cars per HH	2.47	92.6	1.42	35.4	-1.54	-25.0

Model fit and ANOVA			
Sum of squares			
Residual	12165035	27562934	65302407
Total	59371908	42506837	189605490
parameters estimated	15	15	15
F-Ratio	43.034	6.013	21.109
Adjusted R^2	0.80	0.35	0.66
No. of Obs.	166,361	166,361	166,361

As we are also specifically interested Merseyside as our case study, we recreated the baseline model at this sub-regional level in order to compare local travel behaviours with the national averages. The results of these models are presented in table 5. We can infer from the table that the main difference is an overall 'Merseyside' effect area. which seems to reduce the number of trips by about one across all the 'person type' groups except for students who make slightly more trips and full-time workers who make about the same number of trips. Trip distances are also slightly lower for full-time workers. and trip durations slightly higher. However. the much smaller sample size (only 2.061 observations in total 2002-2010) will have a tendency to reduce the level of significance.

Table 4: Results from the baseline sub-regional model (Merseyside)

	Trip generation (trips per week)		**Trip distance (miles per trip)**		**Trip duration (minutes per trip)**	
Variable	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio
Area type						
London	0^b		0^b		0^b	
Metropolitan	Ref.		Ref.		Ref.	
Urban big	0^b		0^b		0^b	
Urban large	0^b		0^b		0^b	
Urban medium	0^b		0^b		0^b	
Urban small	0^b		0^b		0^b	
Rural	0^b		0^b		0^b	
Person type						
Child	10.95	20.4	5.22	5.3	25.35	15.1
Full time	16.26	30.4	8.57	8.7	30.35	18.2
Part time	16.01	20.9	7.00	4.9	28.24	11.8
Student	14.18	12.8	8.23	4.0	35.91	10.4
Non-working	13.21	24.6	6.39	6.4	28.22	16.9
Retired	11.51	21.7	6.37	6.5	27.83	16.8
Gender (female)	0.37	1.0	-1.47	-2.2	-1.96	-1.7
N of adults per HH	-0.93	-3.2	-1.34	-2.5	-0.25	-0.3
N of cars per HH	2.47	10.4	2.50	5.7	-0.64	-0.9
Model fit and ANOVA						
Sum of squares						
Residual	138292		474009		1348415	
Total	663736		601699		2842548	
parameters estimated	9		9		9	
F-Ratio	866		61		253	
Adjusted R^2	0.79		0.21		0.53	
No. of Obs.	2,061		2,061		2,061	

We now consider the addition of the social disadvantage variables to the base line model. We decided on the basis of the results from the Merseyside sub-regional models that we would only run the extended models for social disadvantage at the national level, as further disaggregation would only reduce the significance of these effects within the models.

When we added these variables we obtained a somewhat reduced sample size, because of non-response. The overall sample drops by 14%, to 142807, primarily because of income. This changes the total sum of squares, and makes direct comparison of the models more difficult. In addition, the interpretation of the area type coefficients changes, because the added variables affect the implicit base. In addition to the previous definition, they now reflect: household income of £1000 p.a., no children in the household, no driving licence, white, no mobility difficulties, not single parent, density of 1 person/acre, and lowest level of Index of Deprivation (most deprived).

The results of the extended models are presented in table 5.

Table 5: Results from including additional indicators of social disadvantage

	Trip generation (trips per week)		**Trip distance (miles per trip)**		**Trip duration (minutes per trip)**	
Variable	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio
Area type						
London	-1.45	-18.3	0.19	1.6	6.66	35.4
Metropolitan	Ref.		Ref.		Ref.	
Urban big	-0.14	-1.8	0.49	4.0	0.87	4.5
Urban large	-0.14	-1.7	0.38	3.1	-0.42	-2.2
Urban medium	-0.29	-3.4	0.47	3.8	-0.31	-1.6
Urban small	-0.90	-9.7	1.62	11.7	1.88	8.6
Rural	-1.11	-10.3	2.56	15.9	3.34	13.1
Person type						
Child	9.61	57.7	4.31	17.3	22.77	57.9
Full time	11.33	67.1	7.03	27.9	29.24	73.3
Part time	12.92	72.8	4.72	17.8	26.02	62.1
Student	10.21	52.0	6.69	22.8	31.76	68.5
Non-working	10.32	62.4	5.05	20.4	26.14	67.0
Retired	9.41	59.1	4.17	17.6	24.42	65.0
Gender (female)	0.49	10.6	-1.42	-20.6	-2.11	-19.3
N of adults per HH	-0.99	-23.6	-1.22	-19.4	-0.29	-3.0
N of cars per HH	1.35	42.6	0.78	16.5	-1.58	-21.2
Log-Income	1.19	16.4	2.85	26.3	3.05	17.8
Presence of children in the HH	2.10	36.3	-1.23	-14.3	-3.28	-24.1
Driving licence	4.58	67.0	0.75	7.4	-2.29	-14.2
Non-white	-1.72	-22.3	0.35	3.0	2.32	12.8
Mobility difficulties	-2.01	-24.6	-0.60	-4.9	-2.47	-12.9
Single parent	0.79	4.5	-0.81	-3.1	-0.37	-0.9
Log-density	-0.08	-2.7	-0.30	-6.5	0.24	3.3
Index of Deprivation	0.12	14.5	0.13	10.5	0.02	1.0
Sum of squares						
Residual	9847521		21968899		54917980	
Total	51300227		34835189		164157852	
parameters estimated	23		23		23	
F-Ratio	26.132		3.636		12.349	
Adjusted R^2	0.81		0.37		0.67	
No. of Obs.	142,807		142,807		142,807	

As can be seen from the table. the vast majority of the additional coefficients are highly significant. and there is a slight improvement in the adjusted R^2 values. In particular, it is clear that there are important effects on travel behaviour indicators due to household income. the presence of children, and personal attributes such as being non-white. having a mobility difficulty. The interactions between variables are probably significant as well (e.g. licence holding and number of cars or being a single parent, non-white and in low income groups) but as yet these have not been fully explored. There is also a raised significance in the gender effect for trip frequency with these additional variables.

Income: The variable we used is the logarithm to base 10 of the annual gross household income, in £'000. The mean for the sample is a little over £25,000 p.a. The household income effect is highly significant for all three dependent variables (as an illustration, those on £50,000 make 1.2 more trips, with an average trip length of 2.8 miles more and an average duration of 3 minutes more, compared with those on £5,000). However, although the log-linear form for income has a better fit than a linear form, it does not in fact capture the income effect on trip frequency very well, as demonstrated in the graph in Figure 2. This is based on an alternative specification where we have represented the 23 NTS income bands in terms of dummy variables, and estimated a coefficient for each band (after choosing one as the base, in this case < £1000 p.a.).

The solid green line indicates income effect on trip frequency for the fitted model when assuming a functional form relating to $\log_{10}$(income) as in the Table of results just given. In this form, it is implied that there will be an equivalent rise in trip making for a given proportional increase in household income. It can be seen that relative to the base (< £1000 p.a.), a person from a household with £25,000 p.a. is implied to make 1.7 more trips per week, while a person with income > £75,000 makes 2.5 additional trips.

Compared with this, we have plotted the 95% confidence intervals (upper and lower bounds) for the coefficient for each band (since the sample size for each band is relatively low). It can be seen that there is a tendency for trip rates to **fall** as we move from the lowest income up to the £6000-7000 p.a. band. However, it is reasonable to treat these lowest bands as anomalous, since they are well below the poverty line, and are probably households who have little or no regular income, but nonetheless have access to other sources of finance.

If we therefore ignore these lowest bands, then a very consistent pattern emerges. It is evident that there is a steep and more or less linear rise in the number of trips between £6,000 per annum (which equates with a single person household on welfare benefits) and £25,000 (which is the average household income level), with the increase over this range being about 1.9 trips, suggesting approximately an additional 0.1 trips per additional £1000 p.a.. There appears to be no significant increase in trip making after this. In the diagram we have represented this by a piece-wise linear dashed function. It is clear that the shape is rather different from the logarithmic form, which is probably dominated by the pattern in the range £6-25000 and thereby gives a misleading impression of how the trip rate increases for the higher incomes. This suggests that another model is needed to more adequately capture the effect of income on trip-making which is an important finding for guiding our future research.

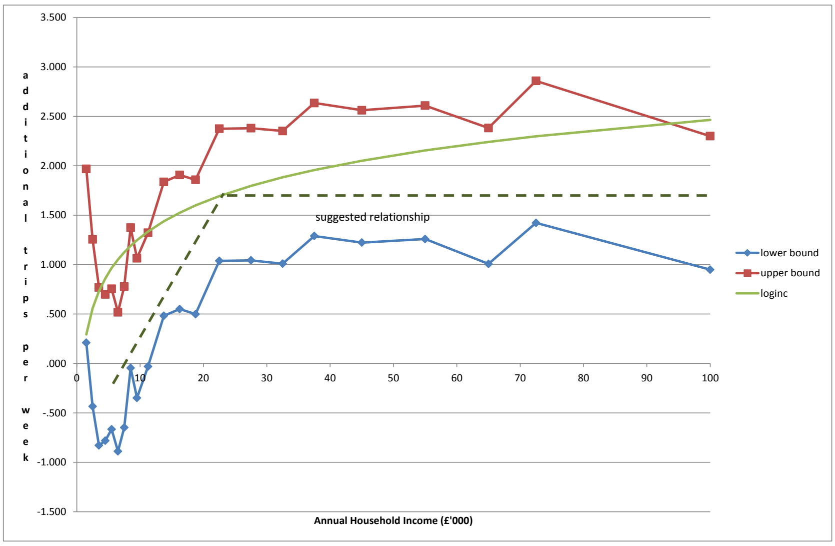

Figure 2: Graph to demonstrate the effect of income on number of trips

Children: The variable used is a dummy variable indicating the presence of at least one child in the household. The general effect is to increase trip frequency (by about trips per week), while reducing average trip length and trip duration (by about 1.2 miles and 3.3 minutes respectively). This suggests a more localised travel pattern.

Driving licence: This is a dummy variable with the value 1 if the individual has a licence. There is some interaction with the number of cars variable, and the effects are similar. Trip frequency increases strongly (by 4.6 per week) for those who have a licence, but average journey distance only increases by 0.8 miles, which was not significant, while trip duration falls by 1.2 minutes.

Non-white: The variable is an NTS-based re-coding of a more detailed question on ethnicity, and is a dummy variable with the value 1 if the individual is "non-white". While no significant effect was found for average distance, trips per week were reduced by 1.7 and average duration increased by 2.3 minutes. Although we have not yet modelled the use of different modes, it is evident from the NTS data that this might be an effect of greater use of public transport and much more locally based travel patterns for the non-white population.

Mobility difficulties: This variable is based on two questions in NTS, one of which investigates general travel difficulties and one that relates specifically to difficulties with walking. Only those who registered difficulties in both questions were represented by a dummy variable with the value 1. Significant negative effects were found for all three dependent variables: people with mobility differences made on average 2 fewer trips per week, the average distance was 0.6 miles shorter, and the average duration 2.4 minutes less. This decrease in trip frequency and travel distance is consistent with other similar studies conducted in the UK (Schmöcker et al., 2005) and in Canada (Farber and Paez, 2010).

Single parent: This is a dummy variable indicating that the person comes from a household with one adult and at least one child. On average such persons make an additional 0.7 trips per week, with a lower average trip length (by 0.7 miles) and lower trip duration of 0.3 minutes. However, the significance levels of these differences is quite low in all three models and this suggests that single parents have very similar trip making patterns to single person households. As previously noted this does not take into account the interaction effects, which means they are deemed to make more trips because of the presence of at least one child in the household as well as effects due to household income. The NTS data also identifies that single parent households are more likely to be car owning. These findings are consistent with previous studies of the trip making patterns of single parents (Roorda et al, 2010).

Logdensity and index of deprivation: These two variables were included because we anticipated there was likely to be an area-based effect based on density and deprivation. On the whole denser areas tend to have better public transport and more facilities and destination opportunities. The index of deprivation variable is based on a 1-10 scale with 1 denoting the most deprived and 10 the least deprived areas, which would suggest it would represent a good indication of whether people living in these areas are also transport disadvantaged. However, as neither variable appears to have had a significant effect on travel outcomes we will probably drop them from our future models.

5. CONCLUDING REMARKS AND NEXT STEPS

It is evident that the material presented in this paper represents only the very early stages of our overall study. Nevertheless, these preliminary results demonstrate that income effects and other indices of social disadvantage have a significant influence on travel behaviours (and vice versa). The next challenge is to come up with a useful **composite** variable to serve as an indicator of transport disadvantage. It is clear from our analysis that there are difficulties of interpretation in this respect: at the simplest, people may travel more because they want to (as evidenced by the income effect) or because they are obliged to (as evidenced by the presence of children in a household). Hence, the number of trips per week is not an unambiguous indicator. Similar remarks relate to average distance and average duration. The ratio of these two is related to average speed, and may be treated as an index of transport service quality. However, once again, people may elect to travel further (e.g. to access better quality destinations) or may be obliged to, because of a lack of nearby services.

In further analysis, it will also be necessary to take account of the **supply** of transport and services in general, which will be much easier to achieve in the geographical context of our Merseyside case study than for the whole country. Spatial analysis poses some problems for surveys such as NTS, where the information about the locality tends to be restricted. Nonetheless, there are some proxy variables that can be used (for example ward density), public transport availability and frequencies, as well as the perceived accessibility of essential services (doctors, post office etc.).

The cost of travel is another important effect on the supply of transport which is difficult to fully capture using NTS data. Although there is data collected within the travel diary on the cost of public transport fares, the cost of car trips is not recorded and must be calculated based on the vehicle mileage data. This requires considerable additional analytical effort and is also not necessarily reliable. There are also other contextual factors such the timing and availability of transport services and perceptions of personal safety which have also been identified within the literature as affecting an individual's willingness to travel to different destinations. Although it could be possible to extract further proxy measures from the NTS to represent these additional factors this is unlikely to be very useful for policymakers without a spatial understanding of where these problems are occurring and so is of limited value in the national and sub-regional level models.

We hope to address some of these issues within the local models that will be developed using data collected via a bespoke survey with 700 residents of two socially disadvantaged areas in Merseyside. The survey will be carried out in spring 2013 and data should be made available for analysis soon after this. The survey is timed to correspond with the local transport authority's review of its future policy programme and to test the impacts of different policy options on the travel behaviours of low income and 'at risk' sectors of the local population.

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