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Is transport poverty socially or environmentally driven? Comparing the travel behaviours of two low-income populations living in central and peripheral locations in the same city

Karen Lucas[a,*], Ian Phillips[a], Corinne Mulley[b], Liang Ma[c]

[a] *University of Leeds, Institute of Transport Studies, Leeds, West Yorkshire LS2 9JT, United Kingdom*
[b] *University of Sydney Business School, University of Sydney, 378 Abercrombie Street, Sydney, New South Wales, 2006, Australia*
[c] *Centre for Urban Research, Global, Urban and Social Studies, RMIT University, Swanston St, Melbourne, Australia*

A B S T R A C T

The paper presents a study to explore the relationship between travel poverty and social disadvantage at the local geographical level. The main aim of the research was to identify the extent to which the revealed travel behavioural outcomes of the study participants are due to personal social constraints or environmental conditions in their residential locations. Specifically, we sought to identify if the greater access to local amenities and public transport services of inner city residents led to an increase in their daily travel activities when compared with their urban peripheral counterparts. The research analysed data from a personal travel survey and one-day travel diary with 502 adults aged between 16 and 65 years in two different deprived areas in Merseyside, North West England. Our analysis is somewhat hampered by the small sample size, but the modelled results suggest that more trips, and longer journey distances *do not necessarily* imply greater social inclusion. The geographically weighted regression models (GWR) highlighted that *the physical location of where people live within the city is more influential on their trip-making patterns than social determinants* such as household income, age, gender, and/or employment status. Street connectivity, the level of bus services and neighbourhood safety were all particularly significant for determining spatial variations in the daily trips that were undertaken, with more trips being undertaken where there was a greater density of street nodes, bus stops and where people felt safer at night. This highlights the need for local transport and urban policymakers to carefully consider and target these micro-scale factors when attempting to introduce transport interventions to reduce social exclusion amongst low-income urban populations.

1. Introduction

This is the third in a trilogy of papers from a study to explore the linkages between transport and social disadvantage. It describes research to model the travel behaviours of a matched sample of working-age, low-income individuals living in two different deprived areas of the same city. In a first paper (Schwanen et al., 2015), we provided a critical overview of the literatures pertaining to transport-related social exclusion and the role of social capital in alleviating or exacerbating transport disadvantage. The paper concluded that the linkages are likely to be: *complex, multiple and entwined, whereby personal factors associated with financial deprivation combine with physical factors associated with the home location of affected persons to create mutually reinforcing cycles of transport and social disadvantage* (Schwanen et al. 2015: 128).

The second paper (Lucas et al., 2016) focused on national level datasets and analysis in the UK using data from the UK National Travel Survey (NTS). It modelled *the role of income as a key determinant of the suppressed travel behaviours of low-income households*. The study demonstrated that individuals in households earning below the average annual household income (approximately £26,000 p.a.) make significantly fewer trips per week, and over shorter trip distances, than the average population in the UK. This relationship

* Corresponding author.
E-mail address: k.lucas@leeds.ac.uk (K. Lucas).

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remained significant when controlling for many of the other factors that are usually associated with people's differing travel behaviours, including socio-demographics such as age, gender, employment status *and* transport supply, such as vehicle ownership and holding a driving license.

However, the national-level study was unable to adequately control for the influence of micro-level factors in the built environment, such as the availability of local activity opportunities or the level of public transport supply. This is because the UK National Travel Survey (NTS) dataset is not sufficiently geographically disaggregated to make it suitable for micro-scale area analysis. However, local environmental factors, such as walkability, safety, and density of activities, have previously been shown to be important drivers of people's trip-making patterns (e.g. Ewing and Cervero, 2010). It is in light of this concern, that this third paper describes a local study to unpack *the independent effects of social and environmental factors on the revealed travel behaviours of low-income populations*.

Our modelled analysis is based on a bespoke travel survey that was undertaken in two socially deprived neighbourhoods in the Merseyside region of the UK. We initially hypothesised that the people who are living on low incomes in a dense urban environment with good walking facilities, in close proximity to a wide range of employment and other activity opportunities and with high access to public transport services are less likely to experience transport-related social exclusion (Kenyon et al., 2002) than those living in the urban periphery where there are fewer activity opportunities and public transport services. As such, we might expect that residents of a dense urban environment might have higher trip frequencies but shorter journey distances and will be less likely to experience transport-related economic stress and social exclusion (Mattioli, 2014).

Whereas nowadays, there is a considerable body of research concerned with determining the social impacts of transport (see Geurs et al, 2009 for an overview of this), few previous studies have specifically focused on the potential influence of local environmental factors in the context of low-income populations and how this might be translated into evidence based policy. However, these supply-side factors could be particularly relevant because many low-income households in the UK live in sub-optimal locations in terms of public transport supply and access to local facilities (Kourtit et al., 2014; Lucas, 2012).

2. Literature review

The link between transport and social disadvantage has been studied widely from many different perspectives (see Martens, 2017). The main quantitative approaches have involved GIS accessibility/activity space analysis (e.g. El-Geneidy et al, 2016; Pyrialakou, 2016; Delmelle and Casas, 2016), structural equation modelling (e.g. Currie and Delbosc, 2011), and regression approaches focusing on a variety of aspects of revealed travel behaviours, such as trip generation (e.g. Huntsinger and Rouphali, 2014), destination choice (Scott and He, 2012), mode choice (e.g. Mercado et al., 2012 and Schmöcker et al., 2008) and distance travelled (e.g. Morency et al., 2011). As we have already reported on the findings of a number of these studies in previous papers (see Lucas et al., 2016b; Lucas, 2012), we do not revisit them here, but rather focus more precisely on papers that directly model local environmental factors to determine the travel behavioural outcomes of different social groups.

In 2010, Ewing and Cervero produced a meta-analysis of the influences of the built environment on travel behaviours. Although they focus on the US context, there are some generalizable conclusions for policy and practice, which are pertinent to the current study. They found that the distance travelled is most strongly related to accessibility to destinations and network design and that, unsurprisingly, use of public transit is most likely in places where there is good access to the transit network, there is a good density of street networks and, latently, where there is a good diversity of land uses. The studies they synthesize have predominantly been conducted in the context of helping transport planners in the US to understand how to enact policies to reduce people's car travel, and so do not pay a great deal of attention to socio-economic conditions.

However, Handy et al. (2005) identify more than 70 studies looking at this same issue, conducted during the 1990s using cross-sectional designs, and assert that almost all of them do *control for* socio-economic factors, such as income, employment status, household composition, etc., in order to concentrate on the effects of people's travel preferences and attitudes on their behavioural outcomes. The authors conclude that policies which increase people's accessibility to alternative modes of transport to the car tend to lead to reduced driving, although there may be an element of self-selection in these outcomes, whereby the people who are more amenable to use transit and non-motorised modes elect to live in areas where these options are more available (Handy, Cao and Mohktarian, 2006).

In fact, very few studies can be found that specifically aim to differentiate between the socio-economic and environmental factors underpinning people's travel behaviours, and particularly not when applied to the travel behaviours of low-income population groups. Cerin et al. (2008) undertook a survey involving 2194 adults living in Adelaide to determine the separate effects of social and environmental factors on their revealed walking behaviours. They found higher educational attainment and area-level income (i.e. averages for the district) to be positively associated with greater walking frequencies, largely explained by a greater propensity to undertake leisure activities and positive associations with the local neighbourhood environment. Whereas individual incomes were negatively associated with walking frequencies, largely due to negative perceptions of the physical environment.

In a more recent Australian study, Turrell et al. (2013) aimed to assess why lower-income residents were more likely to walk than their higher income counterparts, considering environmental factors such as street connectivity, land use mix and car ownership. Based upon a survey of over 11,000 Brisbane residents, they found a strong, graded association between neighbourhood deprivation and walking, based on the application of their stepwise ecological model. This was partly explained by the denser street networks and land uses of these deprived neighbourhoods, but also their more limited access to private motor vehicles. Hence, Turrell et al. (2013) concluded that both social and environmental factors influence people's walking behaviours, which is consistent with the findings of other studies that consider the effect of social and environmental factors on people's behavioural outcomes. In a follow-up study using the same HABITAT (How Areas in Brisbane Affect Health and Activity) survey data, Rachele et al. (2015) examined associations between neighbourhood-level socioeconomic disadvantage, individual-level socioeconomic position (SEP), and usual transport mode, in order to gain insights on health inequalities. They concluded that the relationships between socioeconomic characteristics and transport modes are complex, and that further work is required to explore individual-level and neighbourhood-level mechanisms behind the choice of transport mode, and other environmental factors determining mode choice.

Another study (Bagheri et al, 2009), conducted this time in New Zealand, used Geographically Weighted Regression (GWR) to analyse local accessibility to primary health care services in rural Otago, using the New Zealand Index of Deprivation. The analysis showed that areas of least deprivation tended to have the longest travel distances to these services, but with large variations in this across different geographical areas within the region. This counter-intuitively suggests that more deprived areas are better served by primary health care services, which would be one way to explain associated shorter travel distances. On the other hand, the study takes a very basic approach to deprivation by using a generalised index, which can hide significant differences in levels of deprivation within the same geographical area.

There have been numerous studies, particularly in the US context, concerning the influence of the built environment on people's travel choices (e.g. Cao, Mokhtarian and Handy, 2007a and 2007b) and location choices (e.g. Liao et al, 2015), and to understand its impacts on travel behavioural outcomes (e.g. Cervero and Murakami, 2010). These studies do not specifically focus on trying to unpack whether social and/or environmental factors underlie the suppressed travel behaviours of low-income populations. One recent paper has developed different typologies of the built environment to look at its influence on travel behaviours within the UK context (Jahanshahi and Jin, 2016) using a latent categorisation approach to undertake structural equation modelling of the UK National Travel Survey (NTS) dataset for 2002–2010. The analysis includes explanatory variables of the socioeconomic characteristics of individuals and households and car ownership levels combined with modelled built environment characteristics of the household's residential area. The authors include built environment variables, namely: Area Type; Population Density: Bus Frequency and Walk Times to Bus Stops and Rail Stations. Their model then allows a simultaneous estimation of the influence of residents' demographic and socioeconomic profile according to each of three latent classes of the built environment. They find considerable variations in the joint influences of demographic/socioeconomic and built environment across different area type.

However, as we have noted earlier, due to the non-geographically specific nature of the NTS dataset the area types used in the paper are quite broad (i.e. only five area categories are identified: London, Metropolitan, Big Urban, Medium Urban, Small Urban and Rural). This means that the influence of more geographically specific local area effects, such as accessibility to key destinations or walking network densities cannot be identified by the analysis, although there are some measures of local public transport service levels that can be used. While the NTS is an extremely useful broad-brush tool for strategic decision-making in different types of areas, further research is needed to consider the effects of different transport policy and built-environment interventions at the level of detail that is required for local policy delivery.

In most cases, however, local transport planners do not assess the micro-spatial and social distributional effects of their policy decisions, although these can have major consequences for people's livelihoods and wellbeing, such as maintaining a job, taking up healthcare, education and other public service opportunities and avoiding social isolation, especially in later life (Social Exclusion Unit, 2003). This is an extremely important issue, particularly in determining which policies to employ to encourage uplifts in travel activity for social inclusion. One motivation for this paper is to demonstrate how examining the spatial and social distribution of public transport access can provide evidence for more effective policy-making. This issue is particularly pertinent now, as how local transport policy decisions affect different population groups is of increasing concern in many European countries due to the severe cutbacks in public subsidies for transit services resulting from austerity politics. Anecdotal evidence suggests that the withdrawal of local transport services is having seriously negative consequences for people's social inclusion and wellbeing in the UK (Campaign for Better Transport, 2013), and previous studies have demonstrated that public transport services can be a lifeline for the low-income populations who rely on them to get to work, school, hospital, to go shopping or for visiting friends and family (TRaC, 2000; Social Exclusion Unit, 2003; Lucas and Jones (2012)). If these socially necessary services are withdrawn, there is a high risk that some people may become 'locked out' of economic and social participation with negative consequences for their own lives as well as for society as a whole (Levitas et al, 2007).

3. Methodology

3.1. Study design

The study was conducted in two case study areas (see Fig. 1), both located in the Merseyside region of the North West of England (250 respondents in each area). Both study areas are classified as 'deprived' based on the Index of Multiple Deprivation (McLennan, 2011), with high incidence of unemployment, unskilled workers, low-educational achievement and long-term ill-health amongst the resident population. The survey was specifically targeted at these two areas to increase the chance of recruiting low-income people of working age to participate in the study (i.e. its focus was on the role of transport in the social in/exclusion of these individuals). The key difference between the two study areas is that Anfield in the Liverpool district, is located in close proximity to Liverpool city centre, where there is a good supply of public transport, entry-level employment activities and basic services and amenities. The other area, Leasowe in the Wirral district, is located in the urban periphery, on the opposite side of the River Mersey and so there is reduced access to employment activities, basic services and amenities and a much poorer supply of public transport in this area. The aim was to draw out the influence of local environmental factors (e.g. local amenities, built environment and public transport) on the trip-making patterns of these two socially matched samples.

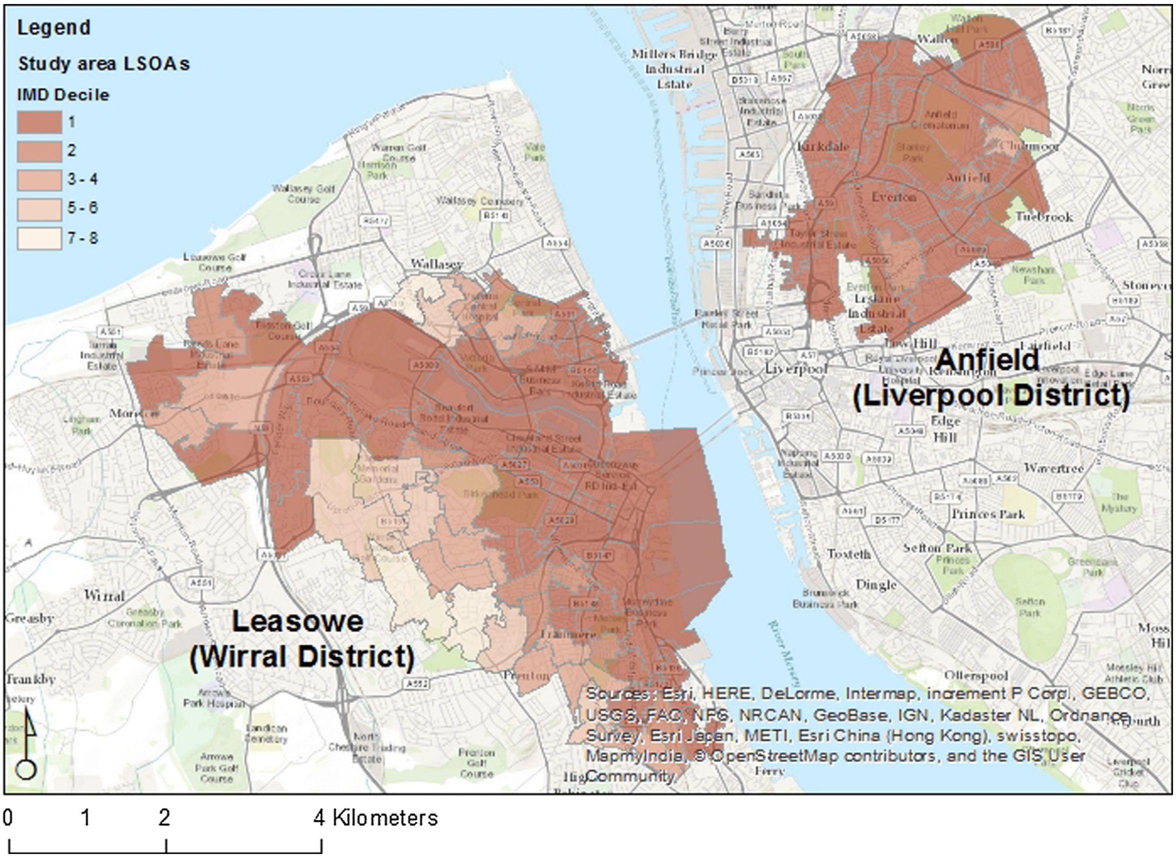

Fig. 1. Map of Merseyside showing the two case study areas Anfield and Leasowe.

3.2. Modelling approach

The modelling approach for this paper has involved two key stages. Stage 1 involved exploratory OLS global regression analysis. This provides estimated coefficients which are averaged over the spatial boundary of the data, thus treating the area as a single sample and then investigating how best to represent the two samples separately. The latter was first carried out using a dummy variable to represent each area, and then by creating interaction terms on the built environment variables to separate the two areas. The former approach provided a better goodness of fit which is partly due to the small sample size, since interaction terms lose a greater number of degrees of freedom. Various functional specifications were also investigated (such as log and Poisson transformations). Robust standard error estimation was used to control for the heteroscedasticity identified in the standard OLS estimation. The dummy variable used to identify the sub areas of Anfield from Leasowe is statistically significant, which suggested that a more micro-level spatial approach might provide additional insights and policy directions.

As such, stage 2 employed geographically weighted regression (GWR) micro-scale analysis, which can take a number of functional forms. In this paper, the GWR local model is estimated using all the recorded observations in the sample (e.g. in this case trips). In contrast to a global regression, the local models of GWR uses an estimation technique which carries out a regression at *each point of the data set*, selecting as other observations for the estimation those close by using values of the independent variables which are either allowed to vary over space or otherwise using a non-spatial or fixed value (this is discussed in more detail below). A key advantage of this approach is that the modelled results can be presented as mapped outputs, from which policy makers can easily identify specific locations for different, locally refined, policy interventions.

In respect of GWR modelling, we note the warning from Fotheringham et al (2002) that it is not a panacea. Some relevant issues to bear in mind for the current study are expressed by Olaru et al (2017) who compare different ways in which spatial effects can be taken into account within different models and concludes that whilst GWR may not be as efficient as other spatial modelling techniques, it can offer policy makers visual evidence and promote understanding, but comes at the cost of some loss of efficiency. Furthermore, one of the key limitations in the use of GWR is that it is a data-hungry tool, and with an overall sample size for the whole study (502 respondents), our study is too small to be more than *a demonstration of what is possible* in terms of spatially disaggregated results.

Nevertheless, our study does effectively take account of both spatial heterogeneity (through a spatially varying constant), and spatial dependency (through the weighting function used within each local model). Given the significance of the area dummy

Table 1
Descriptive statistics of survey variables included in the models.

Variable	Whole study area all survey respondents n = 502	Anfield n = 230	Leasowe n = 272	Compared with population as a whole (UK Census 2011)
Full time workers (employed more than 30 h per week)	34%	27%	40%	39%
Part time workers (less than 30 h per week)	14%	14%	15%	14%
Students	10%	10%	9%	8%
Retired	4%	4%	3%	14%
Non-working	38%	45%	33%	14%
Female	52%	56%	48%	50%
Number of adults in household (% with 2 or more adults shown)	56%	46%	63%	54%
Number of cars in household (% with no car shown)	46%	62%	32%	26%
Presence of 1 or more children under 5 in household	18%	19%	18%	14%
Holds a full driving licence	40%	42%	38%	28%
Has a mobility disability	13%	12%	13%	8%
Single parent	6%	9%	4%	4%
Low educational attainment (less than level 2 equivalent/5 GCSE at grade A* - C)	56%	63%	51%	35%
Population who feel their neighbourhood is 'very' or 'fairly' safe to walk at night	63%	50%	73%	70%

variables, we hoped to be able to at least provide an illustrative approach to give policymakers and planners some specific policy insights into variations within the two study locations. One distinct benefit of GWR that we specifically sought to explore was the benefit of providing output to physically map the variability over space, thus providing clear visible geographically-located outcomes for policymakers to interpret against their own policy expertise of working in these different locations. Our results suggest that with increasingly large sample sizes, this method would be increasingly useful for policymakers, and we discuss this further in the conclusions section of the paper.

4. Data analysis

4.1. Data description

Of the total sample, 175 (43%) were from the Anfield case study area and 224 (56%) from Leasowe. Table 1 shows the descriptive statistics for the sample, compared with national average figures. An overview of these figures suggests that the sample was sufficiently 'in scope' demographically and economically to meet the remit of the study to specifically focus on low-income populations.

The sample was approximately gender-even, with 48% male and 52% female respondents. Nearly a third of the survey respondents had very low household incomes of less than £13,000 (as specified in the sampling frame), and nearly half (41%) of respondents had incomes below the UK average of £25,000 p.a. Only 34% of the sample were employed full-time, but of this, 4% were over the age of official retirement (and so not within scope for this study). Over half of the sample (56%) registered low educational achievement (lower than 5 A*-C equivalent General Certificate of School Education (GCSE). In total, 18% lived in households with 1 or more children under 5 years old, 6% of which were single-parent households. More than half the sample (60%) were in rented accommodation and 46% of the sample had no car/van in the household, with 60% not holding a driving license.

4.2. Sociodemographic variables

The baseline model used for the exploratory analysis utilised a variety of key sociodemographic variables, as suited to disaggregate social policy analysis, including: household structure, gender, age, etc.; household income and economic variables: employment status,; area type; and car-related features: car ownership, drivers' licence, etc., as explanatory variables. These variables were selected on the basis that they are consistently demonstrated to be the *main social determinants of travel* (see Lucas et al., 2016a for more discussion of this). The unit of analysis is individuals within households. Following this initial estimation, the baseline model was enhanced with the addition of further independent variables representing *different specific aspects of social disadvantage*, as identified within the literature. These included physical disability; family structure, and lone parenthood. Ethnicity was not considered because of insufficient sample size.

Fig. 2 shows the distribution of trip frequencies[1] and average total daily travel distance for the sample as a whole with means for each of the Leasowe and Anfield areas. The trip rates for both areas are 'positively skewed', with more people in both areas making

[1] For the purposes of this analysis, a trip is a single, one-way journey from one, geo-coded activity location to another, all walking trips are included, as well as multi-modal trips.

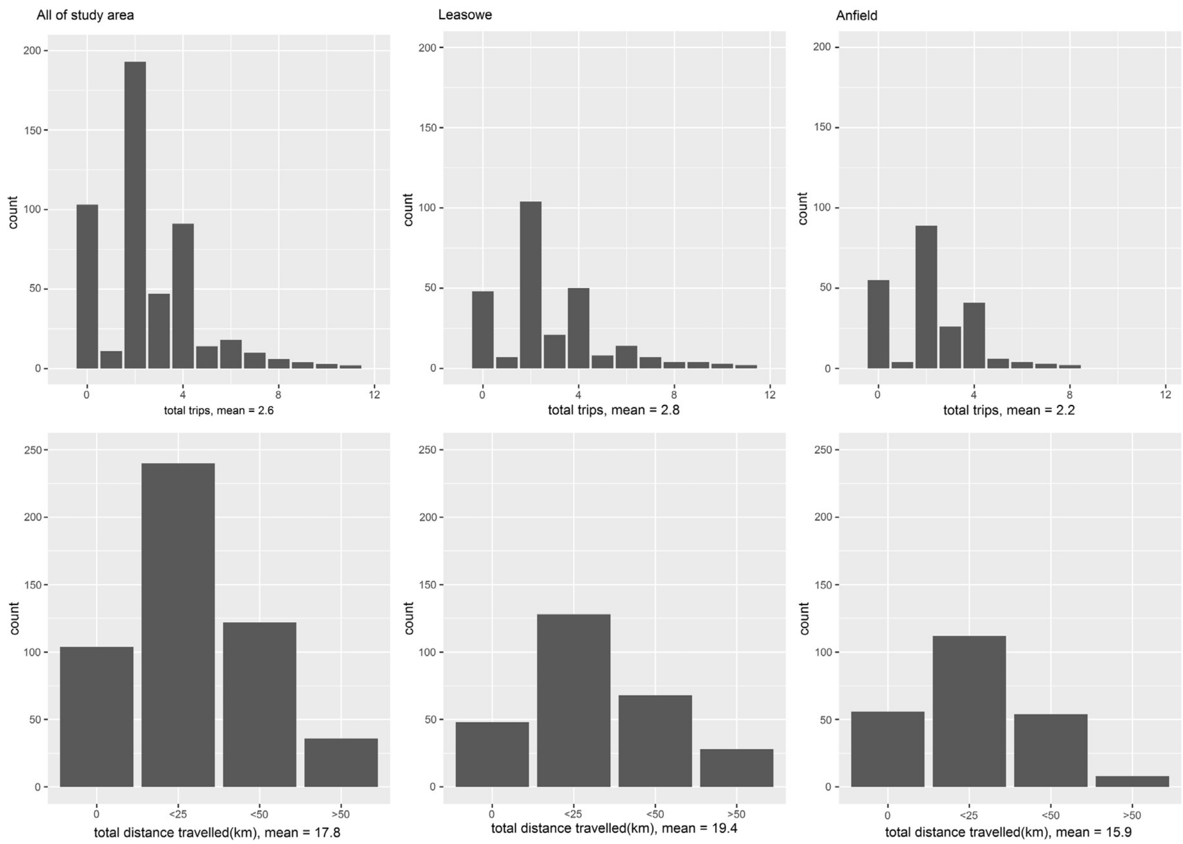

Fig. 2. Histograms of the distribution of travel – frequencies and distances.

less than the average numbers of trips (the highest number of trips per day in Anfield is 8 versus 11 in Leasowe). Travel distances and trip durations were also positively skewed with more people making shorter than the average journey distances, and travelling for less time. Surprisingly, the average journey distances in both areas were roughly the same, whereas they might be expected to have been lower in the Anfield sample, given the shorter distances required to access high concentrations of employment opportunities and activity destinations in the city centre. On the basis of this finding and for reasons of brevity, this paper concentrates on trip frequencies only, as greater social inclusion could require increased local trip making, but should not necessarily impose the burden of greater journey distances.

4.3. Built environment variables

To create the built environment variables, all survey respondents were geocoded in GIS using their home locations. 400-metre and 800-metre Euclidean buffers were created around each home location, relating to approximately 5-minute and 10-minute walking times respectively. The travel behaviour literature uses these walking times as appropriate times for access to bus stops and train stations respectively (Daniels and Mulley, 2013).

The built environment variables were measured following the 5Ds commonly used in travel behaviour studies (Ewing and Cervero 2010): density, diversity, design, distance to public transport, and destination accessibility.

- Density measured by population density: number of persons per hectare.
- Design measured by street connectivity: number of nodes defined by three-way street intersections divided by the number of three-way intersections plus cul-de-sacs using GIS. Thus larger values indicate better street connectivity and more walkable neighbourhoods. This measure captures the size differences between a Euclidean buffer and street network buffer in order to avoid undue repetition (Dill, Schlossberg et al. 2013).
- Distance to public transport or public transport accessibility: number of bus stops within 400/800 m of the respondent's home; number of train stations within 400/800 m of the respondent's home. Although this does not capture the frequency of services or route destinations, it is usually a good proxy measure for bus network density.
- Destination accessibility: number of common destinations (including commercial services, eating and drinks, education, health, recreation, and retail services, employment centre) within 400/800 m of the respondent's home using GIS-based analysis of points of interest data from the Point X Experian dataset (http://www.pointx.co.uk/pr22.htm).

Table 2
Descriptive statistics for built environment variables.

	Anfield	Leasowe	Total	p-values	Std Devs
Population density (sd = 47.9)	93.71	70.65	81.27	0.00	47.9
Street connectivity (Nodes Ratio)- 400-meter buffer	0.76	0.80	0.78	0.00	0.09
Street connectivity (Nodes Ratio) -800-meter buffer	0.75	0.80	0.78	0.00	0.06
Number of bus stops within 400 m of home	11.58	12.14	11.88	0.23	5.03
Number of bus stops within 800 m of home	43.59	41.32	42.36	0.11	15.38
Number of rail stations within 400 m of home	0.09	0.34	0.23	0.00	0.62
Number of rail stations within 800 m of home	0.51	1.25	0.91	0.00	1.36
Number of common destinations within 400 m of home	91.23	51.70	69.90	0.00	54.9
Number of common destinations within 800 m of home	287.95	184.08	231.91	0.00	231.91

Note: p-values are from ANOVA tests.

- Neighbourhood safety at night: a subjective measure evaluating the safety of the neighbourhood environment for walking at night based on the survey responses was included, as perceived crime is significantly associated with walking and cycling frequency to destinations and can impact on social inclusion (Foster and Giles-Corti, 2008).

The population data for measurements of population density was taken from the UK Office for National Statistics. All other spatial data, including points of interest data used for calculating the destination accessibility, were taken from the UK Ordnance Survey Research dataset. Lack of publicly available and geo-coded land use data meant that land-use mix, commonly used as an index for diversity, could not be directly measured, although this would have been desirable. A comparison of the built environment characteristics between the two areas is in Table 2 which shows all but the variables relating to bus stops are significantly different between the two areas at a five percent level of significance (p-value < 0.05).

5. Modelling travel behaviours

The dependent variable used in modelling was trip frequency reflecting the number of activities people can reach through their daily travel. Our preliminary hypothesis was that: *more trips are an indicator of greater participation, and thus social inclusion.* In fact, as our analysis demonstrates, the relationship is more complex than this, which is in line with the theoretical findings of Schwanen et al. (2015). As discussed in Section 3.2 above, the modelling approach is first to estimate an OLS global regression followed by a GWR model.

5.1. OLS global regression

The base global model with a dependent variable of trip frequency was selected on the basis of the smallest AIC, taking account of different model specifications and estimation techniques. The results are shown in first columns of Table 3. The variance inflation factor (VIF) figures demonstrate no significant multicollinearity with all values being below 2. The model, as shown by the R-squared, explains just over 14 percent of the variation in trip frequency. The model shows some socio-demographic variables (number of adults, car licence holding, mobility disability) as statistically significant and some of the built environment variables of interest with statistical significance (street connectivity, access to bus stops). The safe night-time environment is also statistically significant suggesting that the places where people feel safe at night they are probably more likely to make additional walking trips in the local neighbourhood.

Interpreting the significant variables of the base model indicate that people in larger households make fewer trips. This may be because of shared responsibilities amongst the adult members of the household, which is not possible in single adult households. People with a driving license made more trips than those without a license, which could be an indicator of social inclusion in that they have more activity opportunities, but could alternatively be a travel burden, as it also indicates higher generalised travel costs. People with a mobility disability made fewer trips than those with no disability, which could be an indicator of their disability being a barrier to travel. For the built environment variables, the results suggest people living in neighbourhoods with a more grid-like street network, as well as in areas with higher accessibility to train stations made more trips than the rest of the sample. People who perceived their neighbourhoods as safe at night also made more trips than the rest of the sample. We discuss the policy implications of these findings later in Section 6.

Attempts to improve the base model were undertaken and, in particular, to segment the data by location by the inclusion of an area dummy variable. The results are shown in the second three columns of Table 3. Here, as compared to the base model, the goodness of fit is improved (16 percent of the variation is explained and the AIC measure is significantly smaller using the rule of thumb that a decrease of 2 or more is significant (Burnham and Anderson, 2004). The socio-demographic variables of the base model remain stable and significant but the built environment variables become insignificant, suggesting that the characteristics of the people living in each of the areas are roughly matched but that the two suburbs have different environmental conditions. Alternative approaches to segmenting the data by the use of interaction variables between area (Anfield and Leasowe) and the built environment variables did not perform as well as including a dummy variable.

This evidence, taken together, suggests that built environment factors may be influential in explaining differences in trip frequency in the two areas of Anfield and Leasowe, suggesting that further micro scale this micro level analysis using geographically

Table 3
Global models estimated with OLS robust standard error.

Dep Var. = Trip Frequency	Base model			Model with dummy variable		
	Coef.	P > t	VIF	Coef.	P > t	VIF
Work status						
Full-time worker (reference group)						
Part-time worker	0.538	0.063	1.39	0.544	0.061	1.39
Student	−0.375	0.207	1.32	−0.356	0.229	1.32
Non-working	0.066	0.795	1.79	0.048	0.848	1.79
Retired	−0.635	0.146	1.26	−0.618	0.147	1.26
Female	0.161	0.393	1.17	0.184	0.329	1.18
# adults in household	**−0.171**	**0.025**	1.18	**−0.184**	**0.016**	1.18
# cars in household	0.152	0.249	1.70	0.073	0.589	1.77
Presence of children under 5	0.153	0.578	1.59	0.114	0.690	1.59
Hold full or provisional driver licence (1 = yes)	**0.487**	**0.042**	1.60	**0.480**	**0.044**	1.60
Mobility disability (1 = yes)	**−0.969**	**0.000**	1.28	**−0.991**	**0.000**	1.28
Single parent household (1 = yes)	0.139	0.794	1.61	0.225	0.673	1.62
Has L2 base vs lower education	−0.241	0.204	1.19	−0.199	0.286	1.19
Population density	0.001	0.822	1.32	0.001	0.550	1.35
Street connectivity (Nodes Ratio)	**3.806**	**0.013**	1.14	1.712	0.261	1.43
# bus stops within 800 m of home	0.010	0.236	1.70	0.008	0.353	1.71
Rail stations within 800 m of home (1 = yes)	**0.484**	**0.020**	1.29	0.299	0.149	1.42
# common destinations within 800 m of home	0.000	0.977	1.72	0.001	0.506	1.87
Distance to the city centre	0.000	0.941	1.76	0.000	0.584	1.81
A safe neighbourhood to walk at night (1 = yes)	**0.262**	**0.000**	1.24	**0.254**	**0.001**	1.24
Constant	−1.449	0.255		−0.052	0.968	
District dummy (Leasowe = 1)				**0.692**	**0.006**	1.99
Number of obs	462			462		
R-squared	0.144			0.159		
AIC	1932.939			1927.063		

weighted regression (GWR) guided by Olaru et al. (2017), who identify the statistical lack of efficiency of GWR may be compensated by its distinct advantage of providing maps that policymakers can be interpreted and used as an evidence base for policy.

5.2. GWR local models

GWR analysis was first used in the transport sector by Du and Mulley (2007a, 2007b, 2006) to compare hedonic pricing and local modelling approaches to capture changes in land values resulting from new transport investment. More recent applications have included the estimation of trip end demand for rail transport (Blainey, 2010), and forecasting transit ridership and taxi use (Cardozo et al., 2012; Qian and Ukkusuri, 2015). All these papers show that the key variable of interest did vary over space. Within this journal, there are examples of GWR being applied in a transport context, (e.g. Ibeas et al., 2011) who estimated spatial variation in short stay parking demand using multi-linear regression in combination with GWR in the City of Santander, Spain.

We used a semi-parametric form of geographically weighted regression (GWR), using the software GWR4.0. The GWR model equation (2) is expressed in the context of a traditional cross-sectional OLS regression model (1). In this study, where the dependent variable Y is the number of trips, the cross-section model can be extended from:

$$Y_i = \beta_0 + \sum_k \beta_{X^k}\ ik + \varepsilon_i \tag{1}$$

to a model in which local variations in the parameter values can be revealed by taking account of coordinates of the variable. If the dependent variable has coordinates (u_i,v_i), the model expressed in (1) above can be rewritten as:

$$Y_i(u_i v_i) = \beta_0(u_i v_i) + \sum_k \beta_k(u_i v_i) X_{ik} + \varepsilon_i \tag{2}$$

Eq. (2) describes the GWR local model, which means that in principle, in carrying out a GWR, two decisions need to be made. First, how many observations should be taken into account for the regression at each point, and second how many of the independent variables should be allowed to vary over space. To address the first issue, this paper uses the adaptive weighting approach provided in the GWR 4 software[2] which allows the distance to points used in explaining a particular local regression to vary in response to an

[2] GWR. 4.09 Users manual https://www.google.co.uk/search?source=hp&ei=hokGW_KiIoaxUZGJo6AM&q=Gwr+4+software&oq=Gwr+4+software&gs_l=psy-ab.3..0i22i30k1.1650.6590.0.7197.15.8.0.6.6.0.224.800.7j0j1.8.0.......0...1c.1.64.psy-ab..1.14.874.0..0j35i39k1j0i131k1.0.C8u5ki5DFc8.

Table 4
GWR model results for fixed independent variables.

Variable	Estimate	Standard error	t (Estimate/SE)
Work status			
Full-time worker (reference group)			
Part-time worker	0.520	0.287	1.814
Student	−0.526	0.355	−1.480
Non-working	−0.044	0.243	−0.180
Retired	−0.661	0.521	−1.269
Female	0.129	0.189	0.682
# adults in household	**−0.198**	**0.083**	**−2.381***
# cars in household	0.089	0.140	0.634
Presence of children under 5	−0.038	0.288	−0.133
Hold full or provisional driver licence (1 = yes)	0.439	0.223	1.968
Mobility disability (1 = yes)	**−0.996**	**0.303**	**−3.290***
Population density	0.001	0.002	0.247
Rail stations within 800 m of home (1 = yes)	0.354	0.212	1.674
# common destinations within 800 m of home	0.001	0.001	0.718
Distance to the CBD	0.000	0.000	−0.325

* Significant at the 5% level.

Table 5
Model fit indices comparison between global model and GWR model.

	Trip frequency	
	Global model	GWR local model
Classic AIC	1934.939	1914.806
AICc	1937.039	1918.668
R square	0.144	0.206

uneven spatial distribution of sample points, and to maximise the goodness of fit. The best bandwidth size used for the trip frequency local model was 381 nearest neighbours to the GWR regression point.

The second issue as to which independent variables should be fixed over space and which variables should be allowed to vary over space can be determined either by the researcher using *a priori* information or the GWR 4 software with its 'golden search routine' which identifies the best fit with fixed and spatially varying independent variables. The option to have a semi-parametric estimation is new to the GWR 4 software. It is beneficial since having spatially varying independent variables varying when they should be fixed not only reduces the degrees of freedom but can provide a model which is more conceptually satisfactory.

As there were no *a priori* reasons for fixing any of the independent variables, this paper uses the 'golden search routine' of the GWR 4 software to remove any researcher bias introduced by pre-selecting manually the independent variables which should be fixed (Fothering et al., 2003). The golden search routine begins by assuming all explanatory variables vary over space in the first local model, but then iteratively estimates a local model where each explanatory variable is treated as fixed in turn. In each iteration, the program compares the new model with the initial model (where all the explanatory variables are varying over space). The 'golden search routine' continues the iteration until no improvement in fit is gained by changing any term from local to global. The estimates for the variables that were not spatially varying (fixed terms) are summarised in Table 4, and it can be seen that the results for these fixed variables are very consistent with the results from the global model in Table 3, especially for the two significant variables of the number of adults in the household and mobility disability.

Table 5 presents the goodness of fit statistics comparing the global and local models for trip frequency. This shows that the local trip frequency model has a significantly smaller AIC value than the global model (using the rule of thumb that a reduction in the AIC by 2 is significant (Burnham and Anderson, 2004). The R-square for the local model is also larger than for the global model. Together this suggests the local GWR model fits the data better, thus offering improved explanatory power.

As previously stated, one of the main strengths of the local GWR model for the purposes of this analysis is that, in addition to accounting for the spatial dependence in the estimation process, maps can be drawn using GIS to visualise the spatial patterns of the relationship between dependent and independent variables. This makes it easier to locate the model outcomes in the 'real space' context, so that their policy implications can be further explored, as we later demonstrate.

Four variables were identified as spatially significant: (i) street connectivity; (ii) safety of neighbourhood at night; (iii) single parent household; (iv) low educational attainment (Level 2 or lower). The latter two variables were not significant in global models for trip frequency and this is where GWR can be seen to be value-adding. The local estimations of these four variables are illustrated in Fig. 3, where for each significant point plotted in colour, the t-value exceeds an absolute value of 2 with the magnitude of the estimation being shown with different intensities of colour. Insignificant points are plotted in a light grey colour.

As the theory above explains, each mapped point identifies a single observation in the dataset, in this case a respondent identified

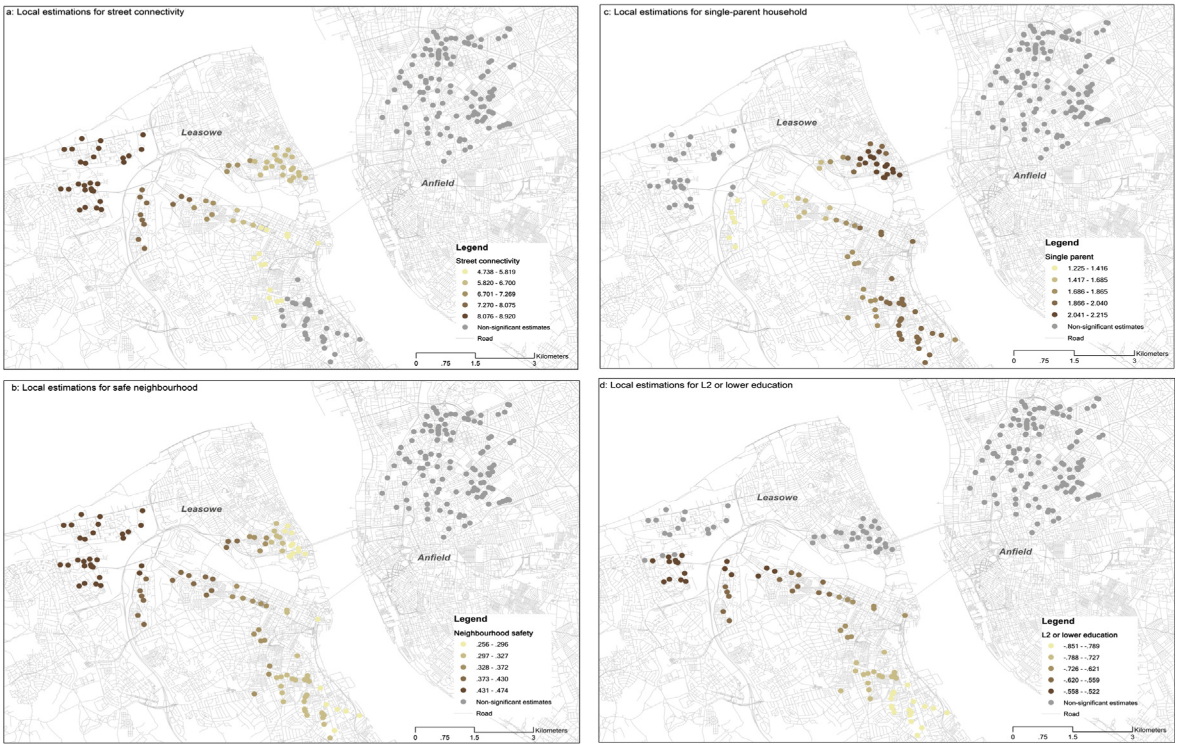

Fig. 3. Mapped outputs from GWR models.

by the full postcode of where survey respondents live (although plotted at the postcode centroid for confidentiality reasons). In the UK, there are approximately 50 households living within each postcode area. These maps provide the evidence base for policy discussion.

All four maps (see Fig. 3a–d) show that spatially varying independent variables are only significant in Leasowe. One possible explanation for this could that the dense rectilinear streetscapes of the Victorian terraced housing common in Anfield already provides good street connectivity, the high levels of public transport available in Anfield and the proximity of Anfield to the city centre where there is a high density of local activities and amenities means that trip frequency is not influenced by these factors. Another way of thinking about this, is that these areas are already 'walkable', safer at night and well-served by public transport so that transport is not a barrier to trip-making in these areas.

In contrast, in Leasowe there is much more variation in the streetscapes and levels of public transport facilities across the area, so that particular pockets are less walkable and more poorly served than others and than Anfield. It is these micro-level variations that the GWR model is picking up, and where the maps are showing how many additional trips might be made for changes in the significant variables. Overall, the comparison between these two areas shows that Leasowe has much to gain from better public transport to increase the potential for more trips and thereby enhanced inclusion, and we now go on to discuss these policy opportunities in relation to each of the significant variables.

Fig. 3a shows that in Leasowe, street connectivity is statistically significant in the GWR model at a number of points with the parameter estimates being highest in the west of Leasowe (1.466–1.479). The interpretation of the parameters estimated on the map is as follows: if there were a 1 unit increase in the nodes ratio we would expect a 1.466–1.479% increase in trip frequency in this locality. Here, an increase in street connectivity could remove constraints to making walking trips. It is also important to note that increasing connectivity might be a helpful intervention in this specific neighbourhood in Leasowe, but would be unlikely to contribute social inclusion objectives elsewhere in this study area where the variable is shown to be non-significant.

Fig. 3b illustrates the effect of spatial variations in perceived neighbourhood safety on trip frequencies. Notably, the significant coefficients are clustered in roughly the same areas of Leasowe as for street connectivity. This suggests that neighbourhood safety is a barrier to residents' travel here, which does not appear to be an issue for residents in Anfield. Areas where perception of safety is having a negative effect on trip making could benefit from an intervention that improves perceived safety (especially at night) leading to increased trip rates here. For the local transport authority this provides an evidence base as to the most fruitful places for an intervention to improve perceived safety, such as the introduction of better street lighting, CCTV cameras at stations and bus stops, or other anti-crime measures.

Fig. 3c and d illustrate the effect of spatial variations in the trip frequencies of single-parent households and for educational attainment, respectively. Again, the significant coefficients are distributed only in some areas of Leasowe, with insignificant effects in Anfield on the Liverpool city side of the Mersey. However, these social variables are significant in quite different locations to the street connectivity and perceived safety, and the policy implications are also different. The areas of significance identify areas where more trips could be achieved from improved transport opportunities, especially if these cheaper travel options because the budgets of these marginalised social groups are more likely to be financially challenged.

The overall inference of our analysis is that the places where built environment variables are demonstrated as locally significant, (Fig. 3a and b), is where policy interventions to increase the number of trips are likely to be most positive in terms of their social inclusion effects. Whereas where social variables are locally significant, (Fig. 3c and d), additional trip making may not be a positive thing because it could put an additional financial burden on these households. However, these findings would need to be further investigated in a more qualitative manner with the local residents of these areas.

6. Conclusions, limitations and further work

The aim of this paper has been to attempt to unpack how socio-economic and local environmental factors differentially affect the travel behavioural outcomes of low-income, working-age populations at the micro-level of analysis. We recognise that the modelled analysis is based on a relatively small survey sample dataset and also only a single day of travel diary data, which poses some significant challenges for the robustness of our results. There may also be concerns about self-selection biases in the data, given the low response rates, and the clear difficulties that were experienced with data collection, and/or from low-income people who want more activity/travel locating in a more accessible location. As such, the paper should be seen more as an exploration of the GWR approach and its relevance for policymakers who are interested in the development of interventions, rather than a robust causal analysis of the relationship between transport and social disadvantage at the micro-level.

Nevertheless, GWR has demonstrated definite and significant spatial variations in trip frequencies of low-income residents in the Merseyside at the micro-scale, most notably street connectivity and perception of personal safety. It also suggests that some social factors are influential in determining people's travel outcomes in some locations. For example, being a single parent or having lower educational attainment contributes to significantly higher trip frequencies in some specific locations, but not in others. Whether this is an indicator of social advantage or disadvantage is something that would require a complementary study of these individuals, rather than for desk-based modelled analysis such as ours.

By using GWR models, it is possible to map the precise locations where different clusters of socio-economic and demographic populations are behaving differently to the average for their population groups (i.e. either travelling more or less). When combined with information about the environmental context of their travel, such as the quality and cost of the public transport or safety of the local walking environment, this can allow policymakers to determine whether a free travel pass or supplementary transport services might be the better option for reducing their transport burden.

The models we have presented identify *that both social and environmental factors* are almost certainly at play in determining the travel behaviour outcomes of low-income households, and that these are *highly specific to the micro-scale neighbourhoods* in which people live. It is possible that we are only observing people's preferences, sorted into space, but even so, there are clear geographical implications. The analysis was also unable to answer whether more daily trips and longer journey distances are *necessarily* an indicator of transport and social advantage or disadvantage, as this is determined by a combination of other factors, including time, cost, journey purpose, mode of travel and the wider economic, social and environmental context in which that travel is being undertaken.

The GWR approaches that we have developed could be potentially be used by local transport planners to evaluate the impacts of their policy decisions on different social groups and parts of the city, using controlled 'before and after' surveys. However, a larger data sample would be required for a more confirmatory analysis as well as providing the opportunity to examine in more depth if heterogeneity exists across specific groups of residents. Moreover, interpretation in the local geographical context is absolutely necessary for the identification of transport disadvantage because, as our analysis demonstrates, increases in trip frequencies and/or distances may be advantageous in some instances but deleterious in others. This is why the refined spatial analysis in this paper provides additional understanding to complement both transport econometric and socio-behavioural approaches to the explanation of suppressed travel demand.

The GWR approach we have developed could potentially be applied in other locations within Liverpool, the UK or, indeed, elsewhere. However, one of the main barriers to a rollout of the methodology is the extreme paucity of travel data at the appropriate small-area geographical scale. As our study has shown, such data collection is fraught with difficulties, especially where low-income populations are the specific focus for the analysis because they are often hard to reach and difficult to engage using traditional survey methods. This significantly raises the costs of travel surveys and robust data collection, which local transport authorities simply cannot afford in the present economic climate. What is clear from our study, is that local transport authorities need to pay urgent attention to the poor quality and paucity of their local data sources, in order to maximise the local utility of their interventions and to avoid making irreversible negative policy decisions at the micro-scale.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.tra.2018.07.007.

References

Bagheri, N., Holt, A., Benwell, G.L., 2009. Using geographically weighted regression to validate approaches for modelling accessibility to primary health care. Appl. Spat. Anal. Policy 2, 177. https://doi.org/10.1007/s12061-009-9021-0.

Blainey, S.P., 2010. Trip end models of local rail demand in England and Wales. J. Transp. Geogr. 18, 153–163.

Burnham, K.P., Anderson, D.R., 2004. Understanding AIC and BIC in model selection. Sociolog. Meth. Res. 33, 261–304.

Campaign for Better Transport, 2013. New evidence reveals bus networks "face collapse" if Spending Round cuts funding further. Campaign Better Transport.

Cao, Xinyu, Mokhtarian, Patricia L., Handy, Susan L., 2007a. Cross-sectional and Quasi-panel explorations of the connection between the built environment and auto ownership. Environ. Plan. A 39 (4), 830–847.

Cao, X., Mokhtarian, P.L., Handy, S.L., 2007b. Do Changes in neighborhood characteristics lead to changes in travel behavior? A structural equations modeling approach. Transportation 34 (5), 535–556.

Cardozo, O.D., García-Palomares, J.C., Gutiérrez, J., 2012. Application of geographically weighted regression to the direct forecasting of transit ridership at station-level. Appl. Geogr. 34, 548–558. https://doi.org/10.1016/j.apgeog.2012.01.005.

Cerin, E., Leslie, E., Owen, N., Bauman, A., 2008. An Australian version of the neighborhood environment walkability scale: validity evidence. Meas. Phys. Educ. Exerc. Sci. 12, 31–51. https://doi.org/10.1080/10913670701715190.

Cervero, Robert, Murakami, Jin, 2010. Effects of Built Environments on Vehicle Miles Traveled: Evidence from 370 US Urbanized Areas. Environ. Plann. A: Environ. Space. https://doi.org/10.1068/a4236.

Daniels, R., Mulley, C., 2013. Explaining walking distance to public transport: the dominance of public transport supply. J. Transp. Land Use 6, 5–20.

Delbosc, A., Currie, G., 2011. The spatial context of transport disadvantage, social exclusion and well-being. J. Transp. Geogr. Special section on Alternative Travel futures 19, 1130–1137. https://doi.org/10.1016/j.jtrangeo.2011.04.005.

Delmelle, E., Casas, I., 2016. Accessibility, mobility, and realized travel behavior: assessing transport disadvantage from a policy perspective. J. Transp. Geogr. 51, 252–269.

Dill, J., et al., 2013. Predicting transit ridership at the stop level: the role of service and urban form. In: 92nd Annual Meeting of the Transportation Research Board, Washington, DC.

Du, H., Mulley, C., 2007a. The short-term land value impacts of urban rail transit: quantitative evidence from Sunderland, UK. Land Use Policy 24, 223–233.

Du, H., Mulley, C., 2007b. Transport accessibility and land value: a case study of Tyne and Wear. Rep. RICS Res. Pap. Ser. 3.

Du, H., Mulley, C., 2006. Relationship between transport accessibility and land value: local model approach with geographically weighted regression. Transp. Res. Rec. J. Transp. Res. Board 197–205.

El-Geneidy, A., Levinson, D., Diab, E., Boisjoly, G., Verbich, D., Loong, C., 2016. The cost of equity: assessing transit accessibility and social disparity using total travel cost. Transp. Res. Part A: Policy Practice 91, 302–316.

Ewing, R., Cervero, R., 2010. Travel and the built environment. J. Am. Plann. Assoc. 76, 265–294.

Foster, S., Giles-Corti, B., 2008. The built environment, neighborhood crime and constrained physical activity: an exploration of inconsistent findings. Prev. Med. 47 (3), 241–251.

Fotheringham, 2002. Geographically Weighted Regression: The Analysis of Spatially Varying Relationships, first ed. John Wiley & Sons, Chichester, England; Hoboken, NJ, USA.

Fotheringham, A.S., Brunsdon, C., Charlton, M., 2003. Geographically weighted regression: the analysis of spatially varying relationships. John Wiley & Sons.

Geurs, K.T., Boon, W., Van Wee, B., 2009. Social impacts of transport: literature review and the state of practice of transport appraisal in the Netherlands and the United Kingdom. Transp. Rev. 29 (1), 69–90.

Handy, S., Cao, X., Mokhtarian, P., 2005. Correlation or causality between the built environment and travel behavior? Evidence from Northern California. Transp. Res. Part Transp. Environ. 10, 427–444.

Handy, S., Cao, X., Mokhtarian, P.L., 2006. Self-selection in the relationship between the built environment and walking: empirical evidence from Northern California. J. Am. Plann. Assoc. 72, 55–74.

Huntsinger, L., Rouphali, N., 2014. Value of life cycle in explaining trip-making behavior and improving temporal stability of trip generation models. Transp. Res. Rec 2322.

Ibeas, A., Cordera, R., dell'Oilio, L., Moura, J.L., 2011. Modelling demand in restricted parking zones. Transp. Res. Part A 45 (6), 485–493.

Jahanshahi, K., Jin, Y., 2016. The built environment typologies in the UK and their influences on travel behaviour: new evidence through latent categorisation in structural equation modelling. Transp. Plan. Technol. 39 (1), 59–77.

Kenyon, S., Lyons, G., Rafferty, J., 2002. Transport and social exclusion: Investigating the possibility of promoting inclusion through virtual mobility. J. Transp. Geogr. 10 (3), 207–219.

Kourtit, K., Nijkamp, P., Reid, N., 2014. The new urban world: challenges and policy. Appl. Geogr. 49, 1–3.

Levitas, R., Pantazis, C., Fahmy, E., Gordon, D., Lloyd, E., Patsios, D., 2007. The multi-dimensional analysis of social exclusion [WWW Document]. URL http://roar.uel.ac.uk/1781/ (accessed 10.16.16).

Liao, F.H., Farber, S., Ewing, R., 2015. Compact development and preference heterogeneity in residential location choice behaviour: a latent class analysis. Urban Stud. 52 (2), 314–337.

Lucas, K., 2012. Transport and social exclusion: where are we now? Transp. Policy 20, 105–113.

Lucas, K., Jones, P., 2012. Social impacts and equity issues in transport: an introduction. J. Transp. Geogr. 21, 1–3.

Lucas, K., Bates, J., Moore, J., Carrasco, J.A., 2016a. Modelling the relationship between travel behaviours and social disadvantage. Transp. Res. Part Policy Pract. 85, 157–173.

Lucas, K., Mattioli, G., Verlinghieri, E., Guzman, A., 2016b. Transport poverty and its adverse social consequences, Transport. doi: http://10.1680/jtran.15.00073 (in press).

McLennan, D., 2011. English indices of deprivation 2010 – technical document. DCLG.

Martens, K., 2017. Transport Justice. Routledge, New York.

Mattioli, G., 2014. Where sustainable transport and social exclusion meet: households without cars and car dependence in Great Britain. J. Environ. Plann. Policy Manage. 16, 379–400.

Mercado, R., Paez, A., Farber, S., Roorda, M., Morency, C., 2012. Explaining transport mode use of low-income persons for journey to work in urban areas: a case study of Ontario and Quebec. Transportmetrica 8 (3), 157–179.

Morency, C., Paez, A., Roorda, M., Mercado, R., Farber, S., 2011. Distance travelled in three Canadian cities: spatial analysis from the perspective of vulnerable population segments. J. Transport Geogr. 19 (1), 39–50.

Olaru, D., Mulley, C., Smith, B., Ma, L., 2017. Policy-led selection of the most appropriate empirical model to estimate hedonic prices in the residential market. J. Transport Geogr. 6, 213–228.

Pyrialakou, V.D., Gkritza, K., Fricker, J.D., 2016. Accessibility, mobility, and realized travel behavior: assessing transport disadvantage from a policy perspective. J. Transp. Geogr. 51, 252–269.

Rachele, J.N., Kavanagh, A., Badland, H., Glies-Corti, B., Washington, S., Turrell, G., 2015. Associations between individual socioeconomic position, neighbourhood

disadvantage and transport mode: baseline results from HABITAT multilevel survey. J. Epidemiol. Commun. Health.
Qian, X., Ukkusuri, S.V., 2015. Spatial variation of the urban taxi ridership using GPS data. Appl. Geogr. 59, 31–42.
Schmöcker, J., Quddus, M., Noland, R., Bell, M., 2008. Mode choice of older and disabled people: a case study of shopping trips in London. J. Transp. Geogr. 16 (4), 257–267.
Schwanen, T., Lucas, K., Akyelken, N., Cisternas Solsona, D., Carrasco, J.A., Neutens, T., 2015. Rethinking the links between social exclusion and transport disadvantage through the lens of social capital. Transp. Res. Part A: Policy Pract. 74, 123–135.
Scott, D., He, S., 2012. Modelling constrained destination choice for shopping: a GIS-based, time-geographic approach. J. Transp. Geogr. 23, 60–71.
Social Exclusion Unit, 2003. Making the Connections: Final report on Transport and Social Exclusion. Office of the Deputy Prime Minister, London.
TRaC, 2000. Social Exclusion and the Provision and Availability of Public Transport. DETR, London.
Turrell, G., Haynes, M., Wilson, L.-A., Giles-Corti, B., 2013. Can the built environment reduce health inequalities? A study of neighbourhood socioeconomic disadvantage and walking for transport. Health Place 19, 89–98. https://doi.org/10.1016/j.healthplace.2012.10.008.