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What explains active travel behaviour? Evidence from case studies in the UK

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What explains active travel behaviour?

Evidence from case studies in the UK

Abstract

Walking and cycling are considered to be healthy and environmentally friendly modes of travel that can mitigate the harmful effects of motorised journeys. This study aims to reveal the individual and built environmental characteristics that are associated with these behaviours by examining the current level of walking and cycling for transport in three UK case study areas. Obligatory and discretionary journeys were separately modelled under the assumption that different factors would affect mode choice. Over 70% of respondents incorporated walking and/or cycling into their weekly travel and about 15% had ridden bicycles at least once for non-recreational purposes during the last seven days. We also found that more walking journeys were made for discretionary purposes compared to obligatory journeys whilst cycling was more common for obligatory journeys. Using the concept of the active travel share, we developed models analysing active travel behaviour. The results confirmed that both personal and household characteristics had clear associations with the tendency for non-motorised travel. In particular, age, physical fitness and vehicle ownership were significantly associated with active travel in all models. The built environment, on the other hand, had significant associations with active travel only for obligatory journeys with the exception of distance to the main activity site, which was found to be significant for both journey types.

Keywords: active travel, walking and cycling, travel behaviour, individual characteristics, built environment

1 Introduction

It is widely recognised that active travel (i.e. walking and cycling) helps to mitigate the adverse effects of auto-dependent and physically inactive lifestyles such as traffic congestion, air pollution and health problems (Brand and Boardman, 2008; Ogilvie et al., 2010; Pratt et al., 2000). In the UK, national and local governments have tried to encourage active travel in recent decades by constructing pedestrian/cyclist transport infrastructure and introducing pro-active travel initiatives and will continue to support programmes promoting active travel through schemes such as the Local Sustainable Travel Fund (DfT, 2011b). The European Commission (2001, 2011) also identifies that facilitating active travel should be a crucial part of urban transport planning and infrastructural design. Such emphasis on the importance of active travel has arisen to counter the high dependence on motorised transport that has emerged over several decades. National statistics clearly show such a trend of motorisation in the UK: in 1951 only 14% of households had access to private cars/vans, by 2010 75% of households had at least one car/van at home. Moreover, the number of adults licensed to drive has increased from 19 million to 35 million between 1975 and 2010, whilst walking and cycling trips have decreased by 28% over the last 25 years (DfT, 2011c).

This study aims to empirically explore active travel behaviours in relation to socioeconomic and environmental characteristics. To achieve this aim, we study three groups of research questions using survey data: (i) how actively do people travel?; (ii) who would be more likely to be an active traveller and what are the behavioural and environmental factors associated with such travellers?; and (iii) are there behavioural and contextual differences between obligatory (such as travel to/from work) and discretionary (such as travel to/from social activities) journeys?

The first question explores actual travel patterns of survey respondents and of the general population in the study areas. This informs the current status of active travel behaviour in a developed country and provides the ground knowledge for the next step, statistical analysis. The second question investigates the significant factors associated with active travel behaviours. Recently a growing body of studies has tried to understand walking and/or cycling travel behaviour in relation to personal, socioeconomic and built environmental factors (Cervero and Duncan, 2003; Dill and Voros, 2007; Lee and Moudon, 2006; Moudon et al., 2005; Stead, 2001). While certain socioeconomic factors have consistently been found to be closely related to active travel behaviour, the influence of the built environment on travel behaviour is less certain (Badoe and Miller, 2000; Boarnet and Sarmiento, 1998; Frank et al., 2007; Pucher et al., 2010; Stead, 2001). Disaggregate travel behaviour is statistically analysed with respect to behavioural and environmental factors in order to fill the gap in the literature by providing new empirical evidence. Finally, we differentiate between obligatory and discretionary journeys in our analysis as people have different criteria in making such journeys which in turn has different implications for policy development (Dieleman et al., 2002; Limtanakool et al., 2006).

2 Case study

Study data were obtained from a self-administered postal survey using a questionnaire designed to collect data on demographic and socioeconomic characteristics, travel behaviour, physical activity, car technology and fuel consumption, and neighbourhood perception. The case study sites were Cardiff, Kenilworth and Southampton (Figure 1), which were selected as a major walking and cycling

infrastructural intervention was planned to be carried out in each of these as part of the Connect2 project.



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Figure 1 Case study sites: Cardiff, Kenilworth and Southampton


The survey was conducted during spring and early summer in 2010 to avoid major holiday seasons in the UK. In each area 7,500 adult residents who lived within 5 km from the planned walking and cycling intervention were randomly selected from the edited electoral register. Our sample accounted for 19% of the adult population within the sampling area in Cardiff, 11% in Kenilworth and 9% in Southampton¹. Out of 22,500 survey recipients, 3,516 people returned completed or partially completed








¹ These percentages were calculated based on the population in Lower Layer Super Output Areas included in the sampling area, not a city or district as a whole.


surveys, resulting in a 15.6% response rate, which is similar to the 17% response rate obtained in the feasibility study (Sahlqvist et al., 2011) and reflects declining response rates to surveys in general (Cook et al., 2009; Zimowski et al., 1997).

8. Think about your journeys to and from work.
(e.g., travel to and from your place of work, accompanying your spouse to and from their work).

a. How often did you make such a journey over the last seven (7) days? TIMES ☐ IF ZERO TIMES, TICK HERE AND GO TO QUESTION 9

b.  How much time in total over the last seven (7) days did you spend travelling to and from work by:

	HOURS	MINUTES
 Walking	<input type="text"/>	<input type="text"/>
 Cycle	<input type="text"/>	<input type="text"/>
 Bus	<input type="text"/>	<input type="text"/>
 Train	<input type="text"/>	<input type="text"/>
 Car, as a driver	<input type="text"/>	<input type="text"/>
 Car, as a passenger	<input type="text"/>	<input type="text"/>
 Other (please specify): _____	<input type="text"/>	<input type="text"/>

c.  How far did you travel in total over the last seven (7) days to and from work by:








	MILES
 Walking	<input type="text"/>
 Cycle	<input type="text"/>
 Bus	<input type="text"/>
 Train	<input type="text"/>
 Car, as a driver	<input type="text"/>
 Car, as a passenger	<input type="text"/>
 Other (please specify): _____	<input type="text"/>

Figure 2 Example of travel question in the questionnaire: work journey

The data most relevant to this study were the weekly travel activity summary and personal and household characteristics. Figure 2 shows one item from the weekly travel summary included in the questionnaire. Respondents were asked to report aggregate travel time and distance along with the number of journeys made for a week. The journeys were categorised into five journey purposes (work, business, school, shopping and personal business and social activities) and for each journey purpose the respondents were asked to provide travel activity data for seven different modes of travel (walking, cycle, bus, train, car as a driver, car as a passenger and other).

Before the main survey, two arms of pilot studies were carried out to test the validity and reliability of the self-administered survey results from the developed questionnaire. The validity study revealed that reported travel time in the seven day travel diary was strongly correlated with the GPS data that collected respondents travel behaviour objectively during the same period of the diary. The reliability study

indicated that the seven day diaries reported in two consecutive normal weeks delivered quite consistent measures except for the business purpose journeys, which constituted irregular work journeys such as travel for meetings and making deliveries.

Although we received 3,516 responses, 42 respondents left the entire travel diary blank and we excluded those respondents from our analysis.

3 Travel patterns

3.1 Data preparation

In this study ‘active travel’ was defined as ‘any walking and cycling you do to get to places’². Occasional reports of jogging or running in the ‘other’ mode category were re-classified as walking and all other modes were considered as motorised modes, i.e. passive modes. The five journey purposes in the survey were further aggregated into two categories, obligatory and discretionary journeys. The former are difficult for an individual to reschedule and often cannot be changed: work, business and school journeys fell into this category. Discretionary journeys comprise non-compulsory forms of journeys and shopping, personal business and social journeys constituted this type of journey.

The Department for Transport recommend that for trip data analysis, unweighted samples of less than 300 should not be used and even samples smaller than 1,000 cases should be used with special care (DfT, 2010). To determine whether any weighting was to be used to allow for population level assessments, the key characteristic variables of the sample were compared to those of the local (district or unitary authority level) and national populations. This revealed that the sampled

² Recreational journeys such as dog walking, cycling for leisure and strolling without a practical purpose were excluded in this study. Survey respondents were clearly asked not to include travel time and distance from those journeys in the travel diary – ‘*We do not mean any walking or cycling you do for recreation, health or fitness*’ – and a different set of questions captured such activities.

population had significantly different demographic and household characteristics from local or national populations³.

Table 1 Respondents and population profiles by study site (%)

	Cardiff*		Kenilworth*		Southampton*	
	Respondent	Population	Respondent	Population	Respondent	Population
Gender**						
Male	44.8	48.4	46.9	49.4	43.4	50.2
Female	55.2	51.6	53.1	50.6	56.6	49.8
Ethnicity**						
White	94.7	91.6	94.3	90.2	91.4	87.0
Non-white	5.3	8.4	5.7	9.8	8.6	13.0
Age**						
18-29	14.7	31.3	7.0	22.3	28.0	33.6
30-44	22.5	24.9	17.5	26.9	21.8	25.3
45-59	27.9	21.2	29.9	23.2	23.7	19.2
60-74	26.5	14.0	34.3	17.7	18.6	13.4
75 and over	8.4	8.5	11.3	9.9	8.0	8.4
Household vehicles***						
0	12.1	29.7	8.4	19.4	19.4	30.3
1	43.4	44.5	36.3	42.4	44.9	45.3
2	36.0	21.3	44.6	30.6	28.3	19.6
3+	8.4	4.5	10.7	7.6	7.4	4.8
Tenure type***						
Council house	7.4	16.9	5.3	14.2	10.7	24.1
Private rent	14.8	13.2	7.8	12.5	30.6	18.3
Owens	78.9	69.8	86.9	73.2	58.7	57.6

*District level data were used in calculation of local population statistics.

** 2009 population estimation data provided by neighbourhood statistics were used to construct the population profiles except for Cardiff's ethnicity, for which 2001 census data were the only available data.

*** 2001 census data were used to construct the population profiles.

Table 1 shows a few key demographic and household characteristics of survey respondents in comparison to those of local populations. The share of survey respondents was higher in the 45-74 year-old categories, giving a higher average age of respondents than might have been expected in all three areas, which is a common problem with population surveys (Cao, 2010; Sahlqvist et al., 2011). Women were more willing to respond to this survey than men. Car and home ownerships were also

³ A series of statistical tests indicated that the number of household cars, gender, age group, ethnicity and tenure types of the survey respondents and local or national populations were significantly different from each other. For these tests, a *Chi* square test was used.

higher among survey respondents, which implies the respondents were more affluent than the local population average. A calibration weight based upon age and gender profiles in three study sites was therefore developed and applied to address the issue of the representativeness of the survey data.

We developed an active travel ratio (ATR) that examines the proportion of each respondent's travel that was made by walking and cycling for each of the aggregate journey purposes (Ewing, 2005; Lu and Pas, 1999). While travel demand and constraints vary between individuals, the ATR is a means of expressing an individual's tendency for active travel after controlling for the overall quantity of travel required and allowed.

The ATR of an individual i 's journey time is expressed below in equation 1:

$$ATR_{it} = \frac{t_{i,walking} + t_{i,cycling}}{\sum_{j=mode}^{all} t_{ij}} \quad (\text{equation 1})$$

where t is the journey time for an aggregate journey purpose and if journey distance is the subject, journey time can be replaced with the journey distance.

3.2 Descriptive active travel patterns

The average total amount of travel was 550 minutes or 195 miles per person per week. By multiplying the weekly average by the number of weeks in a year, we were able to crudely estimate the average annual quantity of travel, which was equivalent to 478 hours or 10,204 miles a year. These figures are higher than the national averages estimated from 2010 National Travel Survey (NTS), in which the average annual quantity of travel was 367 hours or 6,726 miles a year (DfT, 2011c). The differences between these estimates could reflect unaccounted seasonal variation, different coverage of the NTS and the study survey or residual non-response bias.

The survey targeted the adult population in three areas, collected all practical journey data, and was purposively conducted between late April and June when most journeys were not disturbed by holiday seasons or excessively bad weather. On the other hand NTS covers the whole of the UK and year-round travel and includes children's travel whilst it excludes journeys abroad. Without journeys made by air⁴ and children's journeys and with an application of a seasonality weight⁵, average journey distance for the weighted sample dropped to 8,865 miles a year, which significantly narrows the difference between the our survey and the NTS. Even after such effort there is a chance that non-response bias still exists and the difference in areal coverage could not be addressed. Also, as many questions in the survey were related to travel, daily activity and the local area, people who actually made journeys regardless of their age and gender might have been more likely to return the survey.

In our sample we found that 77% of travel by distance was by car, 15% was by public transport, 5.6% was on foot or by bicycle and the rest by other modes after applying the seasonality weight and excluding air journeys. The corresponding proportions in the NTS 2010 were: 81% by car, 15% by public transport and 4% by active travel, which is a quite close correspondence. This suggests that in general our sample's travel behaviour was not too different from the general population's and our findings can inform our understanding of travel activity patterns and their wider policy implications.

Average travel time and distance for the two aggregate journey purposes and seven modes are shown in Figures 3 and 4, suggesting that driving cars or vans accounted for the largest share of travel for both purposes. While walking came

⁴ The survey did not collect origin-destination information, so we could not precisely identify overseas journeys for exclusion.

⁵ The average number of trips by month and main mode in Great Britain (DfT, 2011b) was used to develop this weight.

second in terms of travel time, average walking distance was relatively short due to its low speed.

Interestingly we detected slight differences between the two journey purposes. First, while walking time was higher for discretionary journeys, cycling time was higher for obligatory journeys. Second, people tended to travel faster when they had to travel for work, business or school. Average modal speeds for obligatory journeys were higher than those for discretionary journeys for all seven modes and on average, obligatory journeys accounted for 53% of total journey time and 65% of total journey distance. Third, being a passenger in a car or van was more common for discretionary than obligatory journeys whereas driving was more common for obligatory than discretionary journeys. The nature of journey purposes explains such differences. When people make an obligatory journey, they need to arrive on time and may therefore choose a mode that could reasonably minimise their journey time. As a result faster modes (cycling, car/van as driver, train) are used more for obligatory than discretionary journeys. Conversely, discretionary journeys are more sensitive to cost and hence lower cost modes (walking, car/van as passenger) are used more for discretionary than obligatory journeys. This in turn implies that time is of greater importance in obligatory journeys than discretionary journeys (Wardman, 1998).

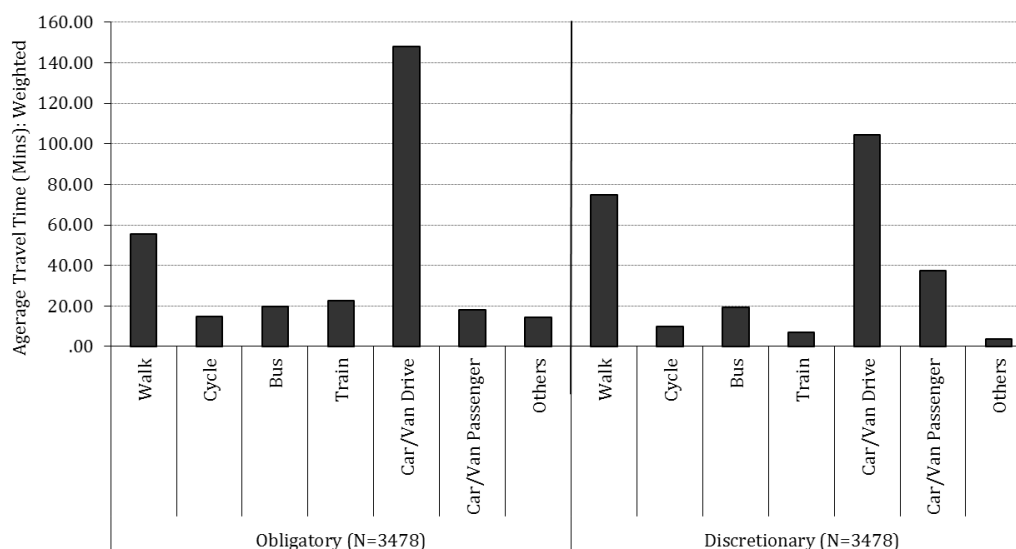


Figure 3 Average total journey time over a week by mode and purpose

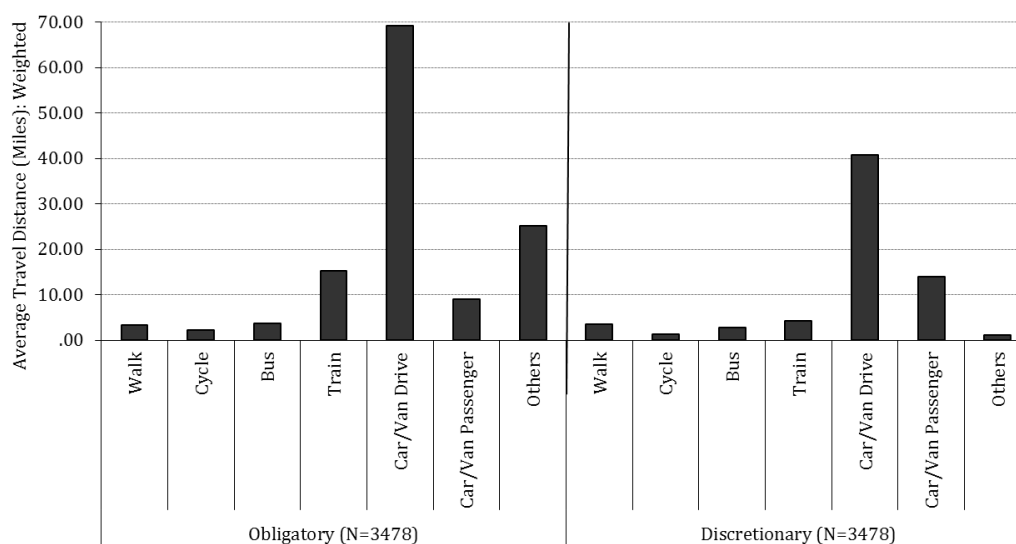


Figure 4 Average total journey distance over a week by mode and purpose

Table 2 reports the number of individuals by their use of travel modes with an emphasis on walking and cycling. Regardless of the amount of journeys made, 30% of our weighted sample used only motorised modes and 6% used only active modes to get around during a week (Table 2). The other 64% reported that they had made journeys using active modes along with motorised modes and among those who incorporated active modes over the course of the week, 20% were cyclists. Similar

research carried out in British cities between 2008 and 2011 reported that 15% of adults had ridden bicycles at least once in the last seven days (Redfern et al., 2011), which is remarkably close to the 14.5% observed in our sample.

Table 2 Number of individuals reporting use of active and motorised modes

Travel mode		Number of people engaged in mode (%)	Total (%)
Passive traveller	Motorised modes only	1017 (29.6)	1017 (29.6)
Walkers	Walking only	127 (3.7)	1921 (55.9)
	Walking + motorised modes	1794 (52.2)	
Cyclists	Cycling only	23 (0.7)	498 (14.5)
	Walking + cycling only	60 (1.7)	
	Cycling+ motorised modes only	72 (2.1)	
	Cycling + walking + motorised modes	343 (10.0)	
Total*		3435 (100)	

* People who made no journeys during last seven days are excluded from this calculation.

Average ATRs for the two aggregate journey purposes are presented in Table 3. It should be noted that population figures cannot be easily inferred from these statistics because total travel distance was significantly and negatively correlated with ATRs. In other words, while respondents who travelled little had higher ATRs, those who travelled a lot had lower ATRs.

Table 3 Active travel mode share

Purpose		Obligatory journeys		Discretionary journeys	
Time/ Distance		Travel time	Travel distance	Travel time	Travel distance
All sites	mean	0.309	0.241	0.327	0.209
	(N)	(2676)	(2676)	(3309)	(3309)
Cardiff	mean	0.273	0.201	0.325	0.199
	(N)	(860)	(860)	(1078)	(1078)
Kenilworth	mean	0.221	0.161	0.260	0.149
	(N)	(945)	(945)	(1190)	(1190)
Southampton	mean	0.440	0.405	0.405	0.286
	(N)	(870)	(870)	(1041)	(1041)

Variation between case study sites is evident in Table 3: Southampton had the highest active travel shares; Kenilworth was the least active site in terms of both time and distance for both journey purposes; and Cardiff was in the middle and closer to the sample average. Around 18% of the weighted sample of Southampton was accounted for by students, whilst the figures for Cardiff and Kenilworth were 6% and 9% respectively. Students are typically younger and less able to afford cars and are therefore more likely to travel via active modes. On the other hand the Kenilworth sample was wealthier and older than those of the two other sites, with average ages of 47 in Kenilworth, 44 in Cardiff and 43 in Southampton.

It is also noticeable that the active travel time share tended to be higher for discretionary journeys whilst the active travel distance share was higher for obligatory journeys. This can be explained by the revealed choice of travel modes as discussed earlier: more frequent use of bicycles was detected for obligatory journeys in general whereas walking, a slower mode, was more popular for discretionary journeys. Southampton was an exception to this pattern, conceivably because of the high proportion of students in the sample.

4 Active travel behaviour analysis

4.1 Methods and variables

Models explaining the ATR are developed in this section. A separate model is developed for each combination of travel share (time or distance) and aggregate journey purpose (obligatory or discretionary). As the left-hand variables were proportions that ranged from 0 to 1 inclusively, a fractional logit model suggested by Papke and Wooldridge (1996) was employed in the analysis (equation 2).

$$\text{Active travel time/distance share} = f(\beta X)$$

$$= \frac{1}{1 + e^{-\beta X}} \quad (\text{equation 2})$$

where X is a matrix of selected explanatory variables and β is a vector of estimated coefficients.

Table 4 lists the selected explanatory variables for two aggregate journey purposes. Previous studies indicated that demographic characteristics, socioeconomic status, household car ownership and characteristics of the built environment affect travel behaviour (Anable, 2005; Best and Lanzendorf, 2005; Cameron et al., 2003; Carlsson-Kanyama and Linden, 1999; Stead, 1999; Timmermans et al., 2003) and the listed variables were a compromise between suggested factors and available data. In each model the same variables except one were inserted as explanatory variables. The exceptions were distance between work and home (for obligatory journeys) and retail centres and home (for discretionary journeys). The survey data provided the individual characteristic variables and the objective environmental variables were created or derived using data acquired from the UK census, Ordnance Survey and FAME⁶. As approximately 3.4% of selected variables were missing, we used multiple imputations by chained equations to impute those values and the analysis results were estimated applying Rubin's rule (Rubin, 1987).

⁶ The FAME database contains information on companies established in the UK and Ireland. The information that can be obtained from this database includes industry, ownership, finances, number of employees, stock data and so on.

Table 4 Explanatory variables

Variables	Obligatory journeys	Discretionary journeys
Individual	adult bike ownership (d), car ownership (d), work status (d), student (d), female (d), age , BMI ⁷ , illness (d), non-white (d), degree or above (d), other family member (d), current home stay, income over £30,000 (d), long-distance travellers (d)	adult bike ownership (d), car ownership (d), work status (d), student (d), female (d), age, BMI, illness (d), non-white (d), degree or above (d), other family member (d), current home stay, income over £30,000 (d), long-distance travellers (d)
Environmental	work-home distance, urban (d), population density, land-use balance, neighbours' land-use balance or nearby areas' land-use balance	distance to the nearest retail centre, urban (d), population density, land-use balance, neighbours' land-use balance or nearby areas' land-use balance

(d) indicates dummy variable.

NTS defines long-distance travel as 50 miles per one-way journey, so here we set the cut-off point of 500 miles a week in order to define the long-distance traveller, presuming five long-distance return journeys in a week. Work-home distance was computed as the network distance between reported workplace and home locations when the shortest path by physical distance was taken. The distance to the retail centre was also measured by the shortest network distance from home to the nearest retail centre using data from the Department of Communities and Local Government (DCLG) Town Centre and Retail planning statistics for England and Wales⁸. All environmental variables (urban dummy, population density and two land-use balance variables) were computed at the Lower layer Super Output Area (LSOA) level. The definition of urban area followed the Office for National Statistics' definition of 'Urban'. Land-use balance is a proxy index that was computed based on the inverse of the distance between each area's functionality mix and the national norm in a geometric space. Four functionalities – housing, office jobs, manufacturing and

⁷ BMI = weight/height squared (kg/m^2)

⁸Retail centre data are available at the DCLG Town Centre and Retail planning statistics for England and Wales website (www.planningstatistics.org.uk). In this study the most recent data set, 2004 data, was used in computing the network distance.

shopping – were incorporated in construction of the index and it was presumed that the ideal balance is the national equilibrium point⁹. Residential population and the number of employees of three industrial categories (manufacturing, production service and retail) were used to build the index. A more detailed description of how the index was constructed is provided in Appendix 1. Geographically lagged values of land-use balance were estimated using two different weights, a Queen contingency weight and a 9.6km buffer weight¹⁰.

4.2 Results

It was necessary to check the multicollinearity properties of explanatory variables in order to avoid spurious and erroneous modelling. For that purpose the Variance Inflation Factor (VIF) was used. All the selected variables had VIF values between 1.0 and 2.0 except for age, for which VIFs ranged between 2.49 and 2.55 depending upon the model specification. A commonly accepted cut-off point signalling multicollinearity problems in logistic regression is 2.5 (Allison, 2001), so it was decided not to exclude any selected variables in the modelling in order to maintain consistency across the models.

⁹ Previous studies that used similar measurements considered the evenness of the distribution of functionalities to be desirable (Bhat and Guo, 2007; Cervero and Kockelman, 1997; Frank and Pivo, 1994). However, using the national norm as a benchmark can be justified for the following reasons. First, the national norm is in fact the equilibrium point that sustains the national economy. So we can presume that it is the most ideal mixture or most balanced level of functionalities. Second, a worker in a certain industrial sector provides goods/services to more than one resident, which means one resident cannot be directly compared to one worker. In the same vein, workers in different industries supply goods/services to different numbers of people. Third, this strategy is more flexible in accommodating different numbers of functionalities. For example, this study uses four functionalities to build the index, but if two functions are to be collapsed into one category, it is then unclear whether the ideal functional distribution might be $\frac{1}{3}$ for each function or $\frac{1}{2}$ for the collapsed category and $\frac{1}{4}$ for the other two. Our strategy avoids this problem. Finally, the index is computed for a large area, England and Wales. So assuming an equal distribution of each function would be more problematic than for smaller area cases such as a city or a county.

¹⁰ The Queen's contingency weight gives all the adjacent areas a value of 1 and others 0. For distance weighting, a 9.6km buffer was used as this is the shortest distance at which each unit area has at least one other area included within the buffer zone. In this weight scheme, areas within the 9.6km buffer are given a value of 1 and others 0.

We expected that certain variables would have important associations with active travel. First of all, household vehicle ownership would play a crucial role in determining travel modes for both journey purposes as household vehicles, either cars or bicycles, provide the travel options for an individual. We expected that car ownership would work against active travel whilst the adult bike variable would have positive association with the ATR for both purposes. The literature (Pucher et al., 2011) shows that young people tend to travel more actively than older people and also our descriptive statistics (Table 3) indirectly confirmed this would apply to our studies regardless of journey purposes. So we expected the age variable to have significantly negative coefficients for both purposes. Income also would have great impact on choosing travel modes, especially if one has a time constraint to complete a journey. Therefore this variable should have a significant relation with the ATR in obligatory journeys. Travel distance is another important factor that determines mode choice: long-distance journeys are more likely to require motorised transport mode regardless of journey purposes. Work-Home and Retail Centre-Home distances reflect such aspect as well as representing purposive accessibility to certain activity. They were expected to have strongly negative associations with use of low speed modes, i.e. active modes. New urbanism movements assert the virtues of traditional neighbourhood design and aim for compact neighbourhoods with principles of mixed land uses, as well as walking and cycling friendly street networks (Bhat and Guo, 2007; Cervero and Murakami, 2010; Frank and Pivo, 1994), which suggest the population density and land-use balance variables would have significant and positive association with the dependent variables for both purposes.

The results are presented in Tables 5 and 6. Common factors that were significantly associated with the ATR for both journey purposes were bike ownership, car ownership, age, BMI, long-distance travel and accessibility to work or shops. In other words, a younger, leaner person who owned a bike but not a car, travelled less than 500 miles per week, and had good access to work and to shops was more likely to use non-motorised modes for both obligatory and discretionary journeys. This corroborates the findings of previous active travel behaviour studies (Buliung and Kanaroglou, 2006; Bull et al., 2000; Cervero and Duncan, 2003; Cervero and Murakami, 2010; Krizek, 2003; Moudon et al., 2005).

Three explanatory variables were not significantly associated with the dependent variable in any of the models: ‘student’, ‘having a degree-level education’ and ‘duration of residency at the current address’. However, when conducting univariate analysis the student and education dummies showed positive association with active travel shares. This implies that once other socioeconomic and land-use characteristics were controlled for, the effect of these variables was attenuated and no longer significantly related to the ATR. Duration of residence had negative and significant associations with all four active travel share variables in univariate analysis, suggesting that the longer residents had lived in the same house, the less likely they were to opt to travel on foot or by cycle. This variable was also significantly and negatively correlated with the amount of travel made by either motorised or non-motorised modes, which contradicts previous findings from Sun et al. (1998). This might be explained by the positive correlation of the variable with age: older people who have lower demand for travel are more likely to have lived for longer at their current home address.

Table 5 Model Result (Queen's contingency weight applied)

Variables	Obligatory journeys (N=2676)		Discretionary journeys (N=3309)	
	Travel time	Travel distance	Travel time	Travel distance
Individual/household characteristics				
Adult bike ownership	0.477 (4.17)**	0.567 (4.35)**	0.387 (4.99)**	0.569 (5.60)**
Car ownership	-1.476 (-8.92)**	-1.564 (-8.79)**	-1.374 (-11.76)**	-1.684 (-12.31)**
Work status	-0.643 (-4.55)**	-0.808 (-4.96)**	-0.338 (-3.60)**	-0.135 (-1.07)
Student	0.435 (1.90)	0.202 (0.82)	0.087 (0.50)	0.189 (0.87)
Female	-0.102 (-1.03)	-0.174 (-1.51)	-0.320 (-4.58)**	-0.443 (-4.92)**
Age	-0.012 (-2.61)**	-0.013 (-2.51)*	-0.012 (-4.02)**	-0.015 (-4.02)**
BMI	-0.057 (-4.58)**	-0.059 (-3.95)**	-0.037 (-3.86)**	-0.039 (-2.91)**
Illness	-0.261 (-1.54)	-0.386 (-1.94)	-0.386 (-3.83)**	-0.376 (-3.03)**
Non-white	-0.333 (-1.77)	-0.591 (-2.40)*	0.067 (0.40)	0.086 (0.43)
Degree or above	0.034 (0.32)	-0.001 (-0.00)	0.019 (0.24)	-0.085 (-0.85)
Other family members	0.295 (2.01)*	0.308 (1.72)	-0.050 (-0.55)	-0.026 (-0.22)
Home	-0.000 (-0.00)	-0.001 (-1.27)	-0.000 (-0.95)	0.000 (0.71)
Income over £30,000	-0.401 (-3.21)**	-0.368 (-2.57)*	-0.040 (-0.45)	-0.049 (-0.39)
Long-distance travellers	-1.175 (-6.43)**	-1.567 (-4.86)**	-0.550 (-3.97)**	-0.828 (-4.32)**
Environmental characteristics				
Work-Home distance	-5.6e-06 (-2.40)*	-6.7e-06 (1.90)	-	-
Retail Centre-Home	-	-	-0.000 (-4.64)**	-0.000 (-4.54)**
Urban	0.433 (1.36)	0.290 (0.76)	0.155 (0.80)	0.585 (2.31)*
Population density	0.006 (4.24)**	0.006 (3.86)**	0.002 (1.24)	0.001 (0.67)
Land-use balance	0.265 (1.85)	0.212 (1.15)	0.014 (0.13)	0.133 (1.09)
Neighbours' land-use balance	0.689 (2.38)*	0.765 (2.56)*	0.036 (0.13)	0.166 (0.52)
Constant	1.211 (2.23)*	1.222 (1.93)	2.458 (4.94)**	1.477 (2.41)*
Model F-test	22.78**	19.66**	22.61**	21.85**

Table 6 Model Result (9.6km distance weight applied)

Variables	Obligatory journeys (N=2676)		Discretionary journeys (N=3309)	
	Travel time	Travel distance	Travel time	Travel distance
Individual/household characteristics				
Adult bike ownership	0.494 (4.31)**	0.584 (4.48)**	0.388 (5.02)**	0.573 (5.68)**
Car ownership	-1.508 (-8.96)**	-1.609 (-8.88)**	-1.375 (-11.82)**	-1.690 (-12.45)**
Work status	-0.655 (-4.62)**	-0.819 (-4.99)**	-0.339 (-3.60)**	-0.135 (-1.06)
Student	0.445 (1.94)	0.216 (0.88)	0.089 (0.51)	0.200 (0.92)
Female	-0.089 (-0.90)	-0.153 (-1.32)	-0.320 (-4.57)**	-0.441 (-4.88)**
Age	-0.012 (-2.54)*	-0.013 (-2.45)*	-0.012 (-4.00)**	-0.015 (-3.96)**
BMI	-0.057 (-4.58)**	-0.059 (-3.92)**	-0.037 (-3.87)**	-0.040 (-2.94)**
Illness	-0.265 (-1.58)	-0.388 (-1.96)	-0.387 (-3.84)**	-0.377 (-3.05)**
Non-white	-0.281 (-1.47)	-0.525 (-2.11)*	0.070 (0.42)	0.103 (0.51)
Degree or above	0.028 (0.27)	-0.003 (-0.03)	0.018 (0.24)	-0.085 (-0.86)
Other family members	0.311 (2.13)*	0.331 (1.83)	-0.050 (-0.54)	-0.025 (-0.21)
Home	-0.000 (-0.89)	-0.000 (-1.26)	-0.000 (-0.95)	0.000 (0.71)
Income over £30,000	-0.398 (-3.16)**	-0.366 (-2.56)*	-0.039 (-0.45)	-0.047 (-0.38)
Long-distance travellers	-1.133 (-6.13)**	-1.520 (-4.69)**	-0.548 (-3.97)**	-0.817 (-4.28)**
Environmental characteristics				
Work-Home distance	-5.7e-06 (-2.48)*	-6.7e-06 (-2.00)*	-	-
Retail Centre-Home	-	-	-0.000 (-4.83)**	-0.000 (-4.51)**
Urban	0.137 (0.38)	0.028 (0.06)	0.128 (0.61)	0.465 (1.63)
Population density	0.005 (3.93)**	0.006 (3.54)**	0.002 (1.28)	0.001 (0.67)
Land-use balance	0.340 (2.36)*	0.306 (1.66)	0.019 (0.19)	0.157 (1.30)

Nearby land-use balance	-4.668 (-2.15)*	-5.060 (-1.98)*	-0.463 (-0.28)	-2.086 (-0.91)
Constant	5.532 (3.02)**	5.919 (2.72)**	2.854 (2.09)*	3.267 (1.73)
Model F-test	22.49**	18.82**	22.62**	21.78**

t-values are shown in parentheses. * $p < 0.05$, ** $p < 0.01$

The two result tables deliver the same messages regarding the socioeconomic variables in respect of each combination of journey purpose and travel measure. Employed people were less active than others on obligatory journeys in terms of both distance and time, whereas this difference was significant only for travel time in discretionary journeys. Being a member of an ethnic minority and having high household income increased the tendency for motorised mode use in the obligatory journeys and being female was associated with a lower active travel share in discretionary journeys. The presence of other family members in a household and the income variable were significantly and positively associated with obligatory active travel shares, indicating that having other family members may compel people to incorporate active travel into their daily scheduled trips and income level is not a significant factor in deciding on a discretionary journey mode. Population density and land-use balance variables were found to be significant only where obligatory journeys were concerned except that the urban dummy variable was significantly associated with the discretionary journey distance ratio. This may be because people tend to give higher priority to regular travel destinations rather than other amenities when they decide on their residential locations (Lee et al., 2010).

Model stability was checked by comparing results with and without the inclusion of the insignificant variables in the models. It was found that the size and significance of each significant variable did not materially differ from each other. Therefore all eight models were concluded to be stable.

The coefficients of our models do not indicate the magnitude of their effects on the dependent variables, so the elasticity of each variable at the mean value was estimated. This information is presented in Tables 7 and 8.

Table 7 Elasticity at the mean (Queen's contingency weight applied)

Variables	Obligatory journeys		Discretionary journeys	
	Travel time	Travel distance	Travel time	Travel distance
Individual/household characteristics				
Adult bike ownership	0.199 (4.50)**	0.230 (4.69)**	0.150 (5.16)**	0.225 (5.91)**
Car ownership	-0.981 (-8.74) **	-1.183 (-7.63)**	-0.854 (-11.82)**	-1.357 (-10.52)**
Work status	-0.325 (-4.36)**	-0.428 (-4.49)**	-0.131 (-3.58)**	-0.055 (-1.07)
Student	0.041 (1.85)	0.019 (0.80)	0.006 (0.50)	0.014 (0.84)
Female	-0.032 (-1.03)	-0.055 (-1.51)	-0.106 (-4.55)**	-0.155 (-4.87)**
Age	-0.300 (-2.75) **	-0.325(-2.59)**	-0.350 (-4.01)**	-0.458 (-3.98)**
BMI	-0.908 (-4.69)**	-0.937 (-4.11)**	-0.599 (-3.93)**	-0.668 (-3.01)**
Illness	-0.017 (-1.75)	-0.024 (-2.36)**	-0.044 (-4.16)**	-0.044 (-3.39)**
Non-white	-0.015 (-1.93)	-0.024 (-2.92)**	0.003 (0.41)	0.004 (0.43)
Degree or above	0.010 (0.33)	-0.000 (-0.00)	0.005 (0.25)	-0.025 (-0.88)
Other family members	0.152 (2.21)*	0.155 (1.93)	-0.026 (-0.56)	-0.014 (-0.24)
Home	-0.030 (-0.91)	-0.050(-1.31)	-0.024 (-0.95)	0.023 (0.72)
Income over £30,000	-0.156 (-3.51)**	-0.143 (-2.77)**	-0.013 (-0.46)	-0.017 (-0.44)
Long-distance travellers	-0.056 (-8.63)**	-0.064 (-8.23)**	-0.026 (-4.47)**	-0.035 (-5.68)**
Environmental characteristics				
Work-Home distance	-0.054 (-2.45)*	-0.065 (-1.98)*	-	-
Retail Centre-Home distance	-	-	-0.370 (-4.70)**	-0.454 (-4.67)**
Urban	0.244 (1.53)	0.164 (0.84)	0.094(0.82)	0.319 (2.80)**
Population density	0.168 (4.28)**	0.175(3.90)**	0.047(1.23)	0.032 (0.68)
Land-use balance	0.133 (1.86)	0.105(1.15)	0.007 (0.13)	0.070 (1.10)
Neighbours' land-use balance	0.347 (2.43)*	0.397 (2.62)**	0.018 (0.13)	0.088 (0.52)

z-values are shown in parentheses. * $p < 0.05$, ** $p < 0.01$

Table 8 Elasticity at the mean (9.6km distance weight applied)

Variables	Obligatory journeys		Discretionary journeys	
	Travel time	Travel distance	Travel time	Travel distance
Individual/household characteristics				
Adult bike ownership	0.206 (4.65)**	0.237 (4.83)**	0.150 (5.19)**	0.227 (5.99)**
Car ownership	-1.002 (-8.85)**	-1.222 (-7.75)**	-0.854 (-11.89)**	-1.362 (-10.66)**
Work status	-0.331 (-4.42)**	-0.434 (-4.51)**	-0.132 (-3.58)**	-0.054 (-1.06)
Student	0.042 (1.89)	0.020(0.85)	0.006 (0.51)	0.015 (0.88)
Female	-0.028 (-0.90)	-0.048 (-1.32)	-0.106 (-4.55)**	-0.153 (-4.83)**
Age	-0.294 (-2.68)**	-0.320(-2.54)*	-0.349(-3.99)**	-0.451 (-3.92)**
BMI	-0.913 (-4.68)**	-0.936 (-4.06)**	-0.600 (-3.93)**	-0.674 (-3.03)**
Illness	-0.018 (-1.80)	-0.024 (-2.38)*	-0.045 (-4.17)**	-0.044 (-3.41)**
Non-white	-0.013 (-1.58)	-0.022 (-2.51)**	0.003 (0.04)	0.004 (0.51)
Degree or above	0.009 (0.28)	-0.001 (-0.03)	0.005 (0.25)	-0.025 (-0.89)
Other family members	0.160(2.35)*	0.165 (2.09)*	-0.026 (-0.55)	-0.014 (-0.22)
Home	-0.001(-0.90)	-0.050 (-1.32)	-0.024 (-0.95)	0.023 (0.71)

Income over £30,000	-0.081 (-3.46)**	-0.142 (-2.74)**	-0.013 (-0.46)	-0.017 (-0.43)
Long-distance travellers	-0.178 (-8.14)**	-0.063 (-7.84)**	-0.026 (-4.47)**	-0.035 (-5.60)**
Environmental characteristics				
Work-Home distance	-0.055 (-2.54)*	-0.065 (-2.07)*	-	-
Retail Centre-Home distance	-	-	-0.367 (-4.90)**	-0.443 (-4.64)**
Urban	0.083 (0.39)	-0.017 (-0.063)	0.079 (0.63)	0.263 (1.90)
Population density	0.156 (3.97)**	0.161 (3.59)**	0.047 (1.28)	0.032 (0.67)
Land-use balance	0.170 (2.37)*	0.152 (1.66)	0.010 (0.19)	0.082 (1.31)
Nearby land-use balance	-2.289 (-2.16)*	-2.465 (-1.98)*	-0.229 (-0.28)	-1.079 (-0.91)

z-values are shown in parentheses. * $p < 0.05$, ** $p < 0.01$

In general, car ownership, BMI, age, illness, distances to work or retail centres, and being a long-distance traveller had significant negative elasticity in all four models. On the other hand, bicycle ownership was the only variable that had positive and significant elasticity in all models. Among these variables, car ownership had the greatest elasticity in explaining the ATR and illness, home-work distance and long-distance travellers had relatively small values. Although no causal relationship can be inferred, it appears that vehicle ownership has the strongest associations with travel mode choice.

For obligatory journey models, the work status and income variables had significantly negative elasticity. Also, it is noticeable that being a paid worker was not associated with a lower active travel share for discretionary journey distance as much as for obligatory journeys and for discretionary journeys, gender had more negative marginal effects than work status.

Population density had significant and positive elasticity in obligatory journey models and its size was not negligible. Land-use balance was significant only when obligatory journeys were considered. Nearby areas' land-use balance had the greatest elasticity, -2.4 for travel time and -2.5 for travel distance respectively, as well as a positive modest elasticity for the land-use balance in the immediate area. This implies

that balanced land use in the immediate area promotes active travel whilst balanced land-use in adjacent area reduces active travel presumably by increasing journey distances and therefore the land-use patterns of immediate and nearby areas may be important in increasing the active mode share of commuting and school travel.

5 Discussion and conclusion

The increasing emphasis on sustainable transportation, green growth and low carbon development has drawn a lot of attention to non-motorised travel modes and a growing number of studies focus on this theme (Krizek et al., 2009). The findings from this study contribute to the empirical evidence base by exploring the key associations between active travel and socioeconomic and environmental characteristics.

This study is aligned with the active travel research tradition (Cao, 2010; Cervero and Duncan, 2003; Dill and Voros, 2007; Lee and Moudon, 2006; Moudon et al., 2005; Ogilvie et al., 2010; Pucher et al., 2011) but it can contribute to the literature in various ways. First, we obtained empirical data from rigorously designed research which carried out a large scale population level survey in three sites in the UK. The analysis results provide empirical evidence in the context of UK transport policy. Second, obligatory and discretionary journeys were separately analysed. Many travel behaviour studies focus on a certain type of journeys or do not distinguish these two different types of journeys. By separating journey types we were able to effectively compare how differently the same population travels around depending on journey types. Also, a new approach was adopted to measure the land-use balance. This new measure can be flexibly used in other studies and does not require a large amount of data.

We can find policy implications from our analysis results. Our empirical data showed that over 70% of the sampled population already integrated active travel modes into their daily journeys and 14.5% had used a bicycle at least once in the last week, which indicates the majority of the population already use active modes in their daily travel and cycling is not such an unpopular mode of travel. The choice of travel mode is often found to be habitual (Domarchi et al., 2008; Thøgersen & Møller, 2008). Therefore it would be more effective to encourage those 70% of the population to integrate more active journeys. However, efforts to expand the population base through making walking and cycling more attractive should continue too (DfT, 2011b).

Population density, accessibility to work and to shops and land-use balance are positively associated with active travel. This suggests that the local environment may have an important impact on modes like walking and cycling (Handy and Clifton, 2001) and thus it would be desirable for transport planners and urban planners to work together in order to encourage active travel behaviour (DfT, 2011a; Santos et al., 2010). The claims of New Urbanists (Bohl, 2000; Duany et al., 2001; Knaap and Talen, 2005) would be applicable in the UK although it may not be obviously linked with discretionary journeys.

It has been empirically proven here that an individual chooses to travel differently depending on the particular 'role', e.g. commuter, shopper, etc (DfT, 2011a). We noted more walking and cycling journeys for discretionary journeys and found that people tended to choose a faster mode of transport for obligatory journeys. Also, our models told us that some factors were only associated with a certain type of journey. For instance, if we want to see more active journeys to workplaces, we do not

necessarily need to worry about gender differences but if we are focusing on shopping journeys, gender should be an area of concern.

Another point to be stressed is that long-distance travellers were negatively associated with active travel and vehicle ownership also had significant association with active travel, suggesting mobility management and control of vehicle ownership would promote active travel. Walking and cycling are not suitable modes of transport for long-distance journeys, so to control this factor we need to cut the demand for long distance journeys through telecommuting or teleshopping or reduce the travel distance for commuters and casual users through land use planning (Santos et al., 2010). Also, we may be able to change travel behaviour by providing incentives and disincentives for owning or purchasing certain vehicles (Nuffield Council on Bioethics, 2007). In addition, restricting car parking, lowering speed limits, subsidising bike ownership or increasing tax on car ownership would discourage private car use whilst increasing active mode usage (DfT, 2011b; Ryan et al., 2009; Santos et al., 2010).

Although our findings provide a useful addition to the existing evidence base and future active travel policy, there are inevitable limitations to this study and room for further development. Also, caution is required when interpreting our analysis results. The statistical analysis results were based on cross-sectional data and statistical associations between active travel levels and explanatory variables cannot be readily interpreted as causal relations. In addition, our analysis results would not be universally applicable as different areas, regions, and countries have their own spatial, demographic and economic context affecting people's travel behaviour.

In summary our analysis, based on a rigorously designed study, provides empirical evidence that can help inform the development of active travel initiatives

and identification of areas and groups that are more susceptible to such initiatives in the UK.

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Appendix 1 Construction of land-use balance index

The balance of land-use functionalities is calculated as expressed in the following diagram and equation. Although this study uses four functionalities in the calculation, the diagram uses only two functionalities to facilitate understanding.

The ideal mixture line is drawn between the point $(0, 0)$ and the national norm, namely (x_n, y_n) . The LSOA was the unit region used to calculate the environmental variables in this study. Thus the distance between the ideal line and functionality mixture of LSOA i , (x_i, y_i) indicates how far its functional balance is from the ideal point, in other words, the level of imbalance of local functionalities. However, it should be noted that as the total functionality increases the distance expands even though θ is the same. So the distance is normalised by d_{in} .

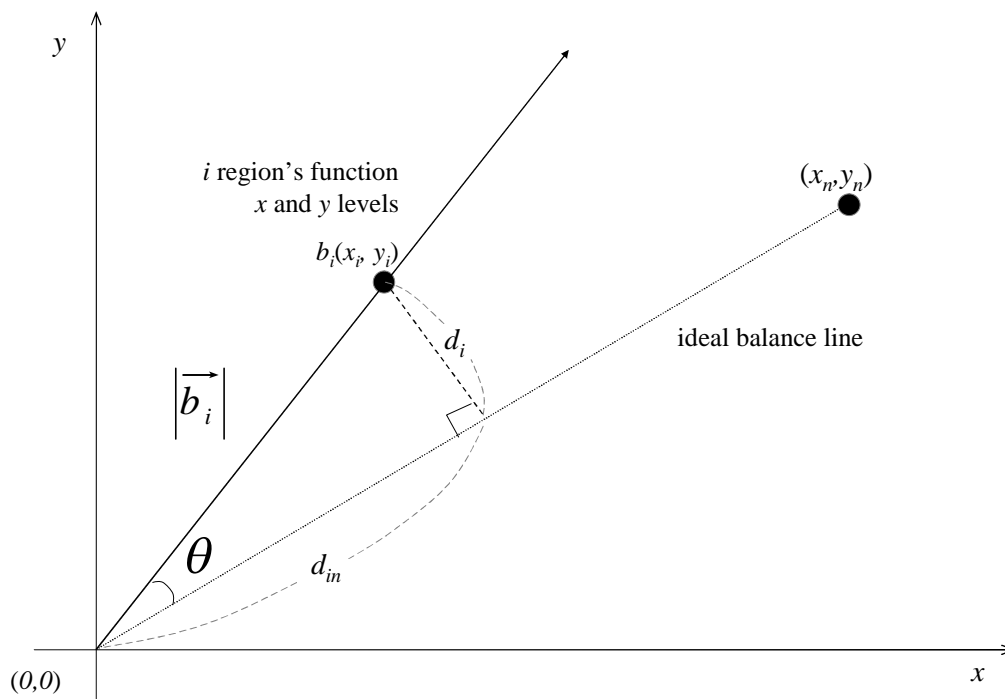


Figure A1 Imbalance measurement in a two-dimensional space

Therefore the imbalance index (*IBI*) can be expressed as the following equation.

$$IBI_i = \frac{\left| \vec{b}_i \right| \sin \theta}{\left| \vec{b}_i \right| \cos \theta} = \tan \theta$$

As only positive numbers including zero are considered, *IBI_i* is always positive and the large *IBI_i* stands for a less desirable mixture level. To help with intuitive interpretation of the index, we used a balance index (*BI*) which is the inverse value of *IBI_i*, (*BI_i*=*IBI_i*⁻¹), so a bigger value indicates more balanced land use.