Accepted Manuscript

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PII: S0967-070X(18)30101-X

DOI: 10.1016/j.tranpol.2018.09.007

Reference: JTRP 2066

To appear in: *Transport Policy*

Received Date: 5 February 2018

Revised Date: 5 July 2018

Accepted Date: 4 September 2018

Please cite this article as: Cervero, R., Denman, S., Jin, Y., Network design, built and natural environments, and bicycle commuting: Evidence from British cities and towns, *Transport Policy* (2018), doi: 10.1016/j.tranpol.2018.09.007.

Network Design, Built and Natural Environments, and Bicycle Commuting: Evidence from British Cities and Towns

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Abstract

Rates of cycling to work vary significantly from one urban area to another but the reasons for these variations are not well understood. Existing literature highlights the importance of built environments, urban amenities, and high-quality bicycle networks in promoting cycling. However, few studies measure the respective contributions and weigh the magnitude of effects of these influences together. We present a multivariate model that reflects the influences of such factors for 36 cities and towns in Britain. The models reveal a complex web of forces shaping cycling to work, confirming that there is no single, silver-bullet factor even in cities with remarkably high commuter cycling. The model results highlight the importance in joining up network level interventions, for instance to reduce both route circuity and on-road stress, which are objectives often being pursued separately. The results also highlight the importance of the non-transport aspects such as land use mix and landscape amenities along commuter routes, and the role of city-specific cycling culture. They also underscore the need for closer collaboration between promoters of commuter cycling and wider urban disciplines to create low-stress routes and supportive built environments in cities and their outskirts.

Keywords: Cycling; Journeys to work; Land-use planning; Built environment; Travel demand modelling; Zero Inflated Beta Regression.

1. Introduction

Many factors weigh in the decision to cycle to work. Some, such as weather and topography, are exogenous in nature, outside the sphere of public policy influence. Others, like the design of bicycle networks, are more endogenous in nature, subject to the effects of policy interventions. It is this second realm that is the focus of our research.

The design of communities and bicycle networks are thought to influence cycling to work and importantly are the result of policy choices, though what we know about their influences, individually and collectively, is limited. Case studies discuss the importance of urban and facility design in encouraging cycling in bike-friendly cities like Copenhagen and Groningen (Pucher and Buehler, 2011), however their marginal contributions and the magnitude of effects have, for the most part, not been rigorously modelled or studied.

We believe the designs of communities and cycling networks are important to study in part because they are fairly fast-turnaround policy interventions. Mixed land-use corridors, products of how land is zoned, help create trip distances that are bikeable. They also increase the prospect of efficiently linking together activities through bike trip-chains. As an amenity, green and blue landscapes, we believe, also matter: large shares of open space, parks, rivers and lakes along cycling corridors offer pleasant viewscapes that, for some, likely encourage bike travel. Safe environs are of utmost importance to cyclists. Reducing levels of traffic stress through bike-friendly road design is crucial to markedly increasing shares of commutes by bicycle.

Despite growing policy interest in cycling as a form of green, active transport, empirical evidence on the influences of land use patterns, urban designs, and facility designs remains fairly sparse in the transport policy literature (Nelson and Allen, 1997; Ortúzar et al., 2000; Moudon et al., 2005). This study aims to fill this gap. It does so by combining journey-to-work data from the 2011 UK census and high-resolution data on road network designs, built environments, and other predictors to weigh factors influencing cycling commuting across 36 cities and towns in England and Wales. A sequential modelling approach is used to examine how policy-related variables tied to designs of cities and bike networks marginally improve upon the predictive powers of exogenous factors. We conclude the paper by reflecting on the public-policy implications of our research findings.

2. Literature Overview

More and more research attention is being given to identifying factors that influence bicycle travel, owing to the positive environmental and societal benefits ascribed to cycling. Research suggests that, as a physical activity, cycling can materially improve mental and physical health (Bauman and Rissel, 2009; Stamatakis et al., 2007; Hu, 2008; Martin et al., 2014). By substituting for car trips, it can also reduce greenhouse gas emissions and improve air quality (de Nazelle et al., 2011). To position our research within this broader literature, results from past studies on the influences of two endogenous factors – bike networks and built environments – in shaping cycling demand are summarized below.

2.1 Effects of bike network design

There has been an uptick in research attention given to the influences of bicycle network designs on travel demand. In a 2015 review of more than 80 peer-reviewed publications on cycling network research from 1990 onward, Buehler and Dill (2016) found that nearly half of research was published between 2010 and 2015. Research shows, fairly consistently, a positive association between the quality, extensiveness, and connectivity of a road or bikeway network and bicycle trip-making, although the strength of relationships has varied (Buehler and Dill, 2016). As one example, a UK study found a one percentage point increase in cycling amongst commuters in 18 towns and cities that received demonstration grants to upgrade cycling infrastructure, relative to control areas that received no funding (Goodman et al, 2013).

To date, metrics used to quantify bicycle infrastructure have focused on the density and connectivity of general-purpose roads and bicycle paths. Using 1990 national census data, a U.S. study estimated that each linear mile of bike lanes added per 100,000 inhabitants was associated with a .069 percent increase in bicycle commute shares (Nelson and Allen, 1997). Dill and Carr (2003) found even a stronger relationship using 2000 U.S. census data. Studies in the U.K. have found that high shares of off-road bike paths promoted bike-commuting (Parkin et al., 2008) and that cyclists are willing to trade off longer travel times for cycling on paths instead of lanes (Wardman et al., 2007). Dedicated cycling facilities have not always been shown to induce cycling, however. A 2009 study of Bogotá, Colombia found that bicycle-lane density had no influence on cycle-commuting, however high street densities were positively associated with cycling to work and utilitarian activities like shopping (Cervero et al., 2009). Other studies have produced similar findings, concluding that street connectivity is positively correlated with cycling, even when bike-lane density is not (Dill and Voros, 2007; Beenackers et al., 2012; Ortúzar et al., 2000; Stinson and Bhat, 2003; Titze et al., 2008; Caulfield et al., 2012). While network connectivity generally has been shown to work in favor of bike travel (Buehler and Dill, 2016), even here contradictory results can be found. Studies of experiences in the U.S. and China, for example, failed to uncover any association between street connectivity and cycling (Moudon et al., 2005; Zacharias, 2005).

One network measure that has captured the attention of bicycle-facility planners and that we turn to in our study reflects the level of stress perceived by cyclists. Furth and Mekuria (2013) developed a four-point scale of LTS (Level of Traffic Stress) that we apply in our research. In their review of the literature, Buehler and Dill (2016, p. 19) note that "the LTS measure was not developed using empirical data" and "...importantly, we could not identify any peer-reviewed research … linking the measures to actual levels of bicycling". Our work is among the first to do so.

2.2 Effects of built environments

Studies on the influences of built environments on bicycle travel have focused on land-use intensities and types. Higher urban densities have been associated with increased cycling in the U.S. (Moritz, 1998) and Canada (Pucher and Buehler, 2006), principally by bringing trip origins and destinations closer together. Mixed land-use patterns and proximity to retail activities have similarly been shown to encourage cycling (Cervero, 1996; Krizek and Johnson, 2005; Cervero and Duncan, 2003). A Portland, Oregon study found that residents living closer to downtown (and thus in relatively dense, mixed-use environments) were more likely to bike-commute (Dill and Voros, 2007) while a study of greater Seattle found that neighbourhoods with offices and fast-food outlets averaged relatively high cycling rates (Moudon et al., 2005). While most evidence on built environments and bicycle travel comes from the U.S., studies of European communities have mostly reached similar conclusions (Næss, 2003; Nielsen et al, 2013; Pucher and Buehler, 2006; Heinen et al., 2010).

3. Data Assembly and Variable Measurement

Governing our research design was the availability, spatial aggregation and format of journey-to-work data from the 2011 UK Census, the most recent national survey of commute travel available at the time of this research. This is a comprehensive database on flows by the usual commuting mode for origin and destination (O-D) pairs, expressed at the Middle Layer Super Output Area (MLSOA) level. These zones are relatively small in size, increasing with distance from urban centres. In our study, the median size of MLSOAs is 318 hectares. Each MLSOA contains between 2,000 and 6,000 households; in our study, the median is 3,155 households.

The outcome variable used in this research -- shares of commute trips by bicycle between the populated-weighted centroids of zones – is necessarily aggregate in scale, as reported in the UK census. Our study thus examines relationships at a higher level of aggregation than individuals or households but a much lower level of aggregation than cities or districts – i.e., at the meso-scale. While disaggregate data are often employed to study travel demand, we believe meso-scale data is appropriate for our research in view of its focus on the pathways and corridors serving trip origins-destinations – i.e., the bike networks, built environment, and environmental amenities along paths and corridors. Controlling for the influences of socio-demographic attributes and other predictors, factors like route connectivity, land-use mixes, and terrain should exert similar influences among those traveling between any pair of trip origins and destinations.

3.1 Study Areas and Sample Frame

Work-trip data were obtained for all inter-zonal home-workplace combinations across 36 small-to-medium-size cities in England and Wales, comprising more than 22,000 home-workplace pairs in all. Our focus on British cities was prompted, in part, by the UK Government's policy commitment to cycling. In the recently published *Cycling and Walking Investment Strategy* (Department for Transport, 2016), the country aims to double cycling from 0.8 billion trip-stages in 2013 to 1.6 billion trip-stages by 2025 (wherein a 'stage' represents part or all of a door-to-door journey).

Figure 1 maps the 36 towns and cities, highlighting their national rankings with regard to shares of commutes by bicycle. Our sample includes top ranked cities like Cambridge and Oxford as well as places with moderate to low rankings among 120 urban areas in England and Wales. Cities also vary widely by population size and land area. Cities with relatively high cycle commute rankings, we note, tend to be university towns, popular tourist destinations, and homes to new tech industries and educated professionals.

Simple correlations using city-level data suggest a positive association between cycling infrastructure and bicycle commuting. Correlating percent of commutes by bicycle (from Table 1) with a measure of bike-lane provisions (kilometers of roads with cycle lanes per 10,000 inhabitants) for the 36 cities yields a Pearson Product-Moment value of 0.71. For example, the British city where biking is far and away most popular, Cambridge, averages 4.95 km of roads with cycle paths per 10,000 inhabitants, second highest among the 36 cities in our sample. The same statistic for Plymouth and Sheffield, with fewer than 3 percent of commute trips by bicycle, is below 0.6 km of roads with cycle paths per 10,000 residents. Providing bike-paths hardly guarantees high cycling rates, however. Residents of Milton Keynes enjoy nearly twice as many cycle paths per capita as in Cambridge. Yet just 3.3 percent of Milton Keynes residents get to work by bicycle. Clearly "build it and they will come" does not always hold when it comes to bicycle infrastructure.

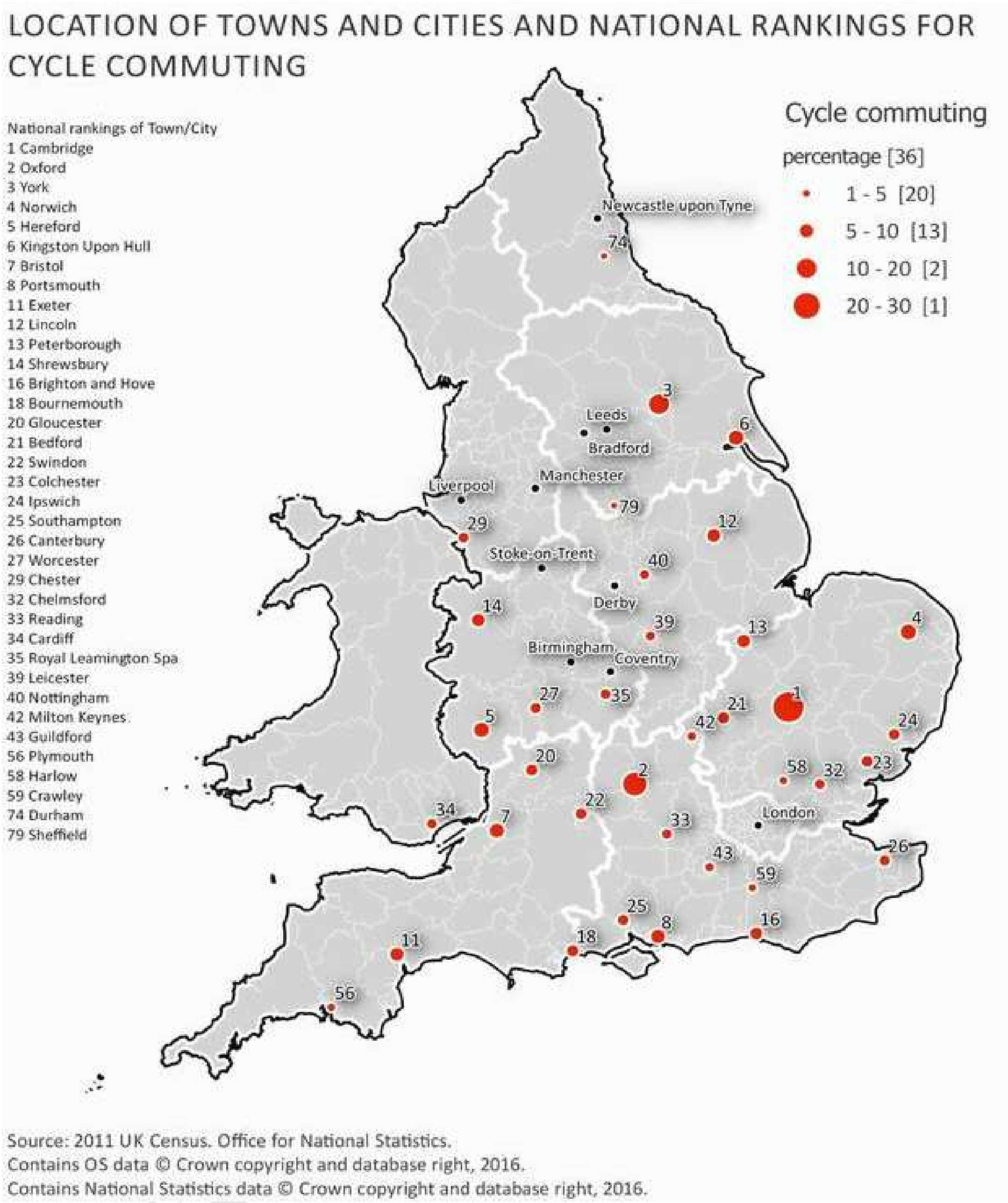

Figure 1. Map of 36 English and Welsh Cities and Towns, showing their national rankings of bicycle commute shares

Table 1. Bicycle Commuting and Population Statistics and Rankings among 36 British Cities and Towns, 2011.

	Bicycle Commuting		Population	
	Percent of Commutes	National Ranking	No. of Inhabitants	National Ranking
Cambridge	29.1	1	145,818	42
Oxford	18.3	2	159,994	37
York	13.8	3	152,841	40
Norwich	8.5	4	186,682	27
Hereford[1 2]	7.9	5	60,415	114
Kingston Upon Hull	7.8	6	284,321	13
Bristol	7.4	7	535,907	4
Portsmouth	7.0	8	238,137	18
Exeter	6.8	11	113,507	55
Lincoln	6.6	12	100,160	73
Peterborough	6.4	13	161,707	36
Shrewsbury[2]	6.3	14	71,715	112
Brighton and Hove	5.8	16	229,700	20
Bournemouth	5.2	18	187,503	26
Gloucester	5.1	20	136,362	46
Bedford	5.2	21	87,590	90
Swindon	4.9	22	182,441	28
Colchester	4.9	23	119,441	52
Ipswich	4.8	24	144,957	43
Southampton	4.6	25	253,651	17
Canterbury[1]	4.5	26	54,880	115
Worcester	4.5	27	100,153	74
Chester	4.3	29	86,011	92
Chelmsford	4.0	32	110,507	56
Reading	4.0	33	218,705	21
Cardiff	4.0	34	335,145	10
Royal Leamington Spa[1 2]	4.0	35	95,172	78
Leicester	3.7	39	443,760	8
Nottingham	3.7	40	289,301	12
Milton Keynes	3.3	42	171,750	33
Guildford	3.3	43	77,057	104
Plymouth	2.8	56	234,982	19
Harlow	2.7	58	82,059	96
Crawley	2.7	59	106,943	66
Durham[1 2]	2.1	74	47,785	116
Sheffield	1.9	79	518,090	5

Source: Population and commuting data from Census 2011. Population rankings based on Office for National Statistics Major Towns and City definitions. Urban area definition from Office for National Statistics Built-Up Area geography.

Notes:

1. Not classified as major town and city in the Office for National Statistics Built Up Area statistical geography. Rankings estimated.
2. Data from Office for National Statistics Built Up Area Sub Division statistical geography.

3.2 Cycling Network Data and Metrics

Defining and digitizing detailed cycling networks for all 36 urban areas was a key input to this research. To ensure a consistent methodology for defining bike networks, we turned to Open Street Map (OSM, 2015). The mapping of bike networks has been a key driver in the evolution of OSM, which according to one study (Hochmair et al 2015) offers higher data quality than Google Maps. For our study, OSM provided sufficiently detailed geometric and road-link attributes for defining and creating bikeable networks for all home-workplace pairs in the 36 study areas for our reference year, 2011. With guidance from the OSM wiki (https://wiki.openstreetmap.org) and historic OSM data from the Overpass API (Open Street Map, 2015), we were able to flag and denote any link that is a cycle lane, cycle track or shared road space.

We further categorise cycle tracks by their proximity to the road network to account for the levels of travel stress. Our bikeable network contains: on-road cycle lanes; beside-road cycle tracks; separated-from-road cycle tracks; and shared vehicular streets. Motorways and trunk roads are excluded from our cycle networks unless there is dedicated or shared cycle infrastructure.

3.2.1 Level of Traffic Stress

As noted, we adapted the metric developed by Furth and Mekuria (2013) for the Netherlands to define level of traffic stress (LTS). The authors created four ordinal LTS categories, based on link speed, street width, cycle lane width, speed limit, number of through lanes, and intersection design. In our study, LTS was defined in terms of not only speeds but also cycle network designation (e.g., track or lane), highway type (e.g., living street, multi-lane highway), street length, and intersection characteristics. Table 2 defines the four (mutually exclusive and collectively exhaustive) LTS categories used in our research.

Similar to the approach of Furth and Mekuria (2013), our study defines links approaching intersections by the highest LTS of the intersecting links. We apply a buffer at intersections, based on highest LTS value of intersecting links and apply that LTS value to any intersecting approach links with a lower LTS value. The buffer size is dependent on LTS value of approach links. This aims to both reflect the increased stress a cyclist may experience when approaching high-stress intersections, and de-prioritise high-stress intersections when estimating low-stress cycle routes. The following buffer sizes are adopted: LTS4 intersections -- 25 meters; LTS3 intersections – 15 meters; and LTS 2 intersections -- 10 meters. All network links were thus defined by their origin and destination nodes, geometric length, link impedance (see Table 3) and LTS value.

Table 2. Definitions for Four Ordinal Categories of Level of Traffic Stress (LTS)

LTS value	Attributes	Definition
LTS 1: Very Low Level of Traffic Stress	Little or no traffic stress. Cyclists are physically separated from traffic on dedicated cycle tracks.	Links that are: dedicated cycle tracks, either separated from the vehicular network or running alongside the vehicle network.
LTS 2: Low Level of Traffic Stress	Little traffic stress. Lower volumes of traffic and road speeds. Cyclists have a dedicated cycle lane or street is a residential street, short in length with low speeds.	Links not designated as LTS 1 and that are either: short residential streets (less than 250m in length); designated as 'living streets'; streets with speed limit of 20 mph or less that are categorized as unclassified or residential; or streets with on-road cycle lanes and a speed limit of 20 mph or less.
LTS 3: Medium Level of Traffic Stress	Limited interaction with traffic but in close proximity to higher speed vehicles. Highway includes a dedicated cycle lane or has been categorized as a Local or National Cycle Network.	Links not designated as LTS 1 and LTS 2 and that are either: streets with on-road cycle lanes; streets with a speed limit of 30 mph or less; or streets designated as part of a local or national cycle networks.
LTS 4: High Level of Traffic Stress	Close proximity to higher speed traffic with speeds in excess of 30 mph. Includes major roads with little provision for cyclists as well as busy or complex intersections.	Links not designated as LTS 1, 2, or3: i.e. speed limit greater than 30 mph and/or are primary, secondary or other roadway categories not denoted above.

3.2.2 Paths and Corridors

The potential effects of bike networks on travel were defined at two levels: paths and corridors. For each home-workplace pair, two trip paths -- shortest path and low-stress path -- were generated using Dijkstra's shortest path algorithm (Dijkstra, 1959). The shortest path was minimized in terms of distance and the low stress path minimized in terms of cumulative impedance values, as defined in Table 3. The low stress path has been designed to reflect the stress-weighted optimized path, representing one possible lower stress alternative to the shortest path, with total distance constrained by detour factor (as defined below).

Research suggests there is a maximum average detour a cyclist will accept when selecting low-stress routes. Furth and Mekuria (2013) recommend 25 percent as the maximum added distance cyclists will detour from the shortest path. This is however at the very upper limit of what is believed to be the norm; Winters et al (2010) found, in their study of non-recreational cyclists in Vancouver, that 75% of cycle trips were within 10% of shortest path and (at least) 90% within 25%. Broach et al. (2012) found that, on average, cycle commuters in Portland Oregon were willing to add 16% to their trip length to use separated cycling paths. We adopt a maximum detour factor of 15%.

Shortest paths, we note, rarely reflect real-world route choices and indeed many trips do not follow the shortest (Winters et al 2010) or optimized path (Sheffi, 1985). To reflect the potential for path deviation and the resulting variations in traffic stress, we created trip corridors for each O-D pair. Corridors were derived from the subnetwork of all links reachable between origin and destination that result in a total path length less than the shortest path multiplied by detour factor. These corridors effectively represent alternative pathways available to cyclists and provided the basis for calculating other metrics of bike network attribute, notably the proportion of corridor links that are low/high stress, connectivity and complexity (defined below). They also provided a spatial basis for calculating metrics tied to the built and natural environments. By way of summary, Table 3 defines the calculation of shortest paths, low stress paths, and corridors for each home-workplace pair in our study, relying on the maximum detour factor of 15%.

Table 3. Path and Corridor Definitions

Shortest Path	A path representing the minimized impedance (expressed in lineal meters) between the trip origin and destination.
Low Stress Path	A path representing the minimized impedance between trip origin and destination and restricted to the origin destination corridor, with impedance of a link computed as lineal meters * detour factor.[1]
Corridor	A sub-network consisting of all links between the trip origin and destination that can be used by bicycles and collectively represent all paths between a home-workplace pair where total path distance is no more than the shortest path distance * maximum detour factor.

[1] LTS Value: 1 for LTS 1; 1.05 for LTS 2; 1.10 for LTS 3; 1.15 for LTS 4.

3.2.3 Connectivity and Complexity

Path distances and stress levels, by themselves, do not fully characterize networks. Intersections are often the most stressful portion of a cyclist's journey, subject to conflicting manoeuvres and accident risks. To supplement link-based measures, we used two measures that reflect attributes of network nodes: connectivity and complexity (see Table 4). Both metrics were computed at the corridor level. Corridors with high ratios of links to nodes are usually well-connected networks, encouraging cycling. Complexity, on the other hand, likely discourages cycling since moving from one stress level to another requires extra concentration and sensitivity to surroundings, which itself can be stressful.

3.2.4 Travel distance and time

Besides the shortest-path distance, two other measures of impedance, or disutility, used in our model are: the ratio of travel time by bicycle versus the travel time by private car; and the ratio of travel time by bicycle versus the travel time by public transit, for each home-workplace pair. As shortest path distance, the bicycle-to-car travel-time ratio, and the bicycle-to-transit travel time ratio increase, the share of commutes by bicycle is expected to fall.

A measure of route circuity was also generated, which we call the diversion penalty. This is the ratio of the low-stress path and shortest path distances for each home-workplace pair. All else being equal, we expect high detour penalties to deter cycling and corridors with low stress routes that closely match the shortest route to see higher rates of cycling.

Table 4. Travel distance and time & bike network attributes.

Variables	Definition	Data Source
Travel distance and time		
Shortest path distance	Distance over the shortest path between trip origin and destination, in 000's of meters (i.e., kilometres).	Generated from cycle network using Dijkstra shortest path algorithm.
Travel time ratio - bike/car	Difference in morning peak-period (8:30am) travel time between trip origin and destination: Travel time over the fastest route by bicycle divided by travel time over the fastest route by automobile, based on Google API pessimistic travel model.	Google Origin Destination Matrix Application Programming Interface (API) (Google, 2016).
Travel time ratio - bike/transit	Difference in morning peak-period (8:30am) travel time between trip origin and destination: Travel time over the fastest route by bicycle divided by travel time over the fastest route by public transit, based on Google API.	
Diversion penalty for journeys > 6km	Ratio of shortest path to low stress path.	Generated from cycle network.
Bike corridor attributes		
Proportion of very low stress links	Proportion of all links on cycling corridor that are LTS1	Generated from cycle network
Proportion of low stress links	Proportion of all links on cycling corridor that are LTS2	
Proportion of medium stress links	Proportion of all links on cycling corridor that are LTS3	
Proportion of very high stress links	proportion of all links on cycling corridor that are LTS4	
Connectivity ratio	Number of links/number of nodes. This measure considers all intersections, defined as nodes, available to the cyclist at the corridor level. There is one link between each pair of nodes regardless of travel direction.	
Complexity density	Number of nodes/length of links (in km). This measure considers all intersections and LTS transitions of the full network that intersect the corridor or path as nodes. There is one link between each pair of nodes in each direction of available travel.	

3.3 Built Environment, Land Use, and Trip-Chaining Potential

As discussed earlier, built environments and environmental amenity factors are thought to influence bicycle commuting, to varying degrees. Table 5 defines the key variables used to examine their impacts.

Higher population and employment densities are conducive to cycling mainly by bringing trip origins and destinations closer together. Land-use diversity is also thought to induce bike-commuting by shortening trips, but also by enabling efficient trip-chaining, particularly in the afternoons and evenings after work when many shops, restaurants, and entertainment venues are open. Two metrics of mixed-use patterns were used in this research: activity density and an entropy index. (See Table 5 for definitions.) We used data from Foursquare, one of the UK's most popular location-based social networking services at the time of the 2011 UK census, to gauge land-use activities within a 50-meter buffer of a given cycling corridor. Foursquare allows mobile phone users to 'check in' at a specific location and share their whereabouts with friends. In Britain, Foursquare Venue data had wide geographical coverage by 2011, providing a platform for gauging the density of activities conducive to bicycle trip-chaining (Georgiev et al, 2014). The mixed-use entropy index (Cervero, 1996) was measured using data from the Generalised Land Use database, which expresses nine categories of land uses at the parcel level for the entirety of England and Wales.

Table 5. Built Environment and Environmental Amenity variables.

Built environment attributes of corridor		
Land area for housing and gardens	Proportion of Corridor (for trip origin and destination) land area devoted to domestic (residential buildings and gardens) land use	Generalised Land Use database (GLUD), DCLG (2005).
Mixed use entropy measure	Entropy = - [Σ_i^k (p_i * $\log_e p_i$)]/k, where: p_i = proportion of land area in category i; k = number of land-use categories = 9; i = domestic (residential buildings and gardens), non-domestic buildings and associated land, greenspace, roads, paths, rail, water, gardens, other land uses. Calculated at the corridor level.	
Activity density	Foursquare check-ins (in 10,000s) within a 50-meter buffer of Corridor (for trip origin and destination), per km of pathways in the corridor, for venue categories: food, health, night time businesses, services, recreation, retail and convenience	Foursquare Venue API, Foursquare, (2017).
Environmental amenities of corridor		
Proportion of water surface area	Proportion of Corridor (for trip origin and destination) land area comprised of water (e.g., lakes, rivers, canals)	Generalised Land Use database (GLUD), DCLG (2005).
Proportion of greenspace area	Proportion of Corridor (for trip origin and destination) land area comprised of greenspace (e.g., public parks, farmland, open space)	

3.4 Control variables

Control variables captured factors beyond the policy-focused variables that, past work suggests, influence bicycle commuting. All control variables – e.g., weather, gradient, and socio-demographic attributes of commuters -- are exogenous to the analysis and thus outside the sphere of direct public-policy influence. Table 6 defines the control variables used in our research.

The two physical variables in Table 6, mean gradient along the cycle route and mean rainfall, we note, work against bike-commuting, as document in past research (Nankervis 1999; Bergström and Magnusson, 2003; Brandenburg et al., 2004; Rietveld and Daniel, 2004; Parkin et al., 2008; Cervero et al., 2009). Higher temperatures can work both ways however given the often cool weather throughout Great Britain in March (corresponding to the time-of-year when the 2011 census data were collected), we expect a positive relationship – i.e., higher temperatures should favor bike commuting.

Demographic and socio-economic variables (with the exception of mean age), are consistent with the work trip data, i.e. derived from flows between origin and destination (O-D) pairs at the MLSOA level and expressed as proportions. Ideally, we would use detailed socio-demographic characteristics of individual respondents by their mode of travel but this level of detail is not available. Levels of bike-commuting are expected to rise up to the mid-stages of lifecycle and then decline as people get older, forming a quadratic relationship. For this reason, the "mean age" variable was expressed in both linear and squared terms to capture this expected quadratic relationship.

Table 6. Control Variables; Natural environment factors and socio-demographic attributes.

Variables	Definition	Data Source
Natural environment factors		
Mean gradient of cycle route	Percent change in mean altitude (statistical mean of all spot heights at 50 meter interval between origin and destination	Google elevation Application Programming Interface (API). Google, (2018).
Mean air temperature (March 2011)	Temperature (in centigrade) in March 2011 in the 5 square km grid most closely corresponding to origin zone, statistical mean	UKCP09: Gridded observation data sets. MET Office, (2016).
Mean rainfall (March 2011)	Accumulation of rainfall (in 100 mm) in March 2011 in the 5 square km grid most closely corresponding to origin zone, statistical mean	
Socio-demographic attributes		
Proportion of professional and managerial commuters	Proportion of commuters (defined as those living at zone of origin and working at zone of destination), in households defined as approximate social grade A or B, denoting higher and intermediate managerial / administrative / professional occupations	2011 UK Census, Office for National Statistics, (2015).
Proportion of commuters in households owning no cars	Proportion of commuters (defined as those living at zone of origin and working at zone of destination) with no cars in household.	
Proportion of male commuters	Proportion of commuters (defined as those living at zone of origin and working at zone of destination) that are male/female.	
Mean age of resident at origin zone	Mean age of commuters at the zone of residence.	
Mean age of resident at origin zone squared	Mean age of commuters at the zone of residence.	

4. Modelling Approach and Results

Across the 21,000-plus O-D pairs among the 36 sampled towns and cities, the number of commute trips varied widely, from several trips to over 1,500 trips. In a number of instances, one or two bicycle commutes yielded unrepresentatively high commute-trip modal shares by bicycle because of the small total number of journeys-to-work. For this reason, we limited the sample to home-workplace pairs with 30 or more total trips. This produced a still sizable database of 9,083 zone-to-zone observations, representing more than 1.23 million journeys-to-work in total. We note that results did not noticeably vary whether the minimum threshold for including records was set above 30 commute trips.

4.1 Statistical model consideration

Conventional multiple regression models, estimating using Ordinary Least Squares (OLS), assume linear relationships. Many of the factors that influence travel mode choice, however, are non-linear. This is especially true with active modes of travel. For example, we would expect cycling to decrease as commute distances increase, falling off most rapidly when going from intermediate-distance to long-haul commutes. Fractional response data (e.g. proportions) are also problematic when using OLS since predictions are not bounded by 0 and 1.

In light of such concerns, alternative model forms and estimation approaches are needed. The beta regression model is often used for fractional response data and to capture non-linear relationships however it does not perform well with large numbers of exact 0 or 1 values (Liu & Kong, 2015). In the case of cycling, a large number of O-D pairs are apt to have zero trips. Moreover, the factors that influence mode share proportions between 0 and 1 may be very different to factors that explain shares that are exactly 0 or exactly 1. One method, proposed by Opsina and Ferrari (2011), has been used to redress these issues. The Zero-One Inflated Beta (ZOIB) regression model allows for the estimation of the probability of a proportion being 0 or 1 to be generated separately from the estimation between 0 and 1. The advantages and application of the ZOIB regression technique are discussed in the literature (Opsina and Ferrari, 2011; Swearingen et al, 2012; Liu and Kong, 2015) but we have found no applications in the field of travel-demand modelling.

4.2 Modelling approach

We adopted a multi-step modelling approach in carrying out this research. The influence of exogenous factors (not subject to near-term policy influence) on bike commuting were first tested. The results are called the 'base' model. Predictors in the base model include: shortest path distance; site- and path-specific variables (gradient, mean air temperature and rainfall, representing natural environment factors); and socio-demographic attributes of social class, car ownership, gender and age.

Next, we present a full model. Here we include factors that are subject to direct policy influence in the near-to-intermediate term, in addition to those factors included in the base model. Included here are the comparative travel times of competing modes as well as attributes of cycling corridors, built environments, and environmental amenities.

While travel time ratios and built environment factors may not at first sight appear to be amenable to near-term policy, we note that our methodology relies on the calculation of attributes of commuter corridors directly accessible by bike. While distance of commutes is not easily changed, travel speeds and therefore travel time ratios, especially for cycling, are. We accept that land-use mixes are not easily altered in a year or two, particularly in built-up urban environments, however new bike infrastructure and upgrades paralleling waterways or parks are feasible. This can provide not only a low-stress passageway and reduce bike travel times, but can beautify and create amenity value along the cycling corridor. An example of high-quality cycling infrastructure built along green and blue land uses is the Cambridgeshire guided busway which opened in 2011 along the historic Cambridge - St. Ives railway line, previously inaccessible to bicycles.

In the third step, we compare the base versus full model to gauge the impact of the policy-relevant, corridor-level factors to the predictive power of the model. And in the final step, we present a fixed-effects model combining the full model with city-level dummy (0-1 coded) variables that are statistically significant. We compare the base and full model with fixed effects, discussing how attributes of cities, including possible local cultural and lifestyle factors not accounted for in the model, are reflected by these city-level dummy variables. Collectively, the multi-step modelling approach enriches our understanding of the marginal influences of a host of factors, some subject to direct policy influences.

Because the dependent variable is expressed as a proportion, where possible, predictors are similarly expressed as proportions. All other variables have been scaled to yield coefficients of similar magnitude where possible. As the ZOIB function is non-linear and follows a logistic form, ZOIB model coefficients are difficult to interpret. To aid with interpretation, average marginal effects -- using partial derivatives ($\delta y/\delta x$) -- have been calculated (i.e. the percentage point change in bike commute trips relative to per unit change in each covariate, controlling for the influences of other predictors). Our commentary on model results focuses on these marginal effects, summarized in Table 8.

Lastly, to gauge goodness-of-fit, we computed pseudo r-squared statistics, defined by the square of the sample correlation coefficient between the outcomes (proportion of commuters by bicycle) and their corresponding predicted values, as suggested by Opsina and Ferrari (2011). And to evaluate whether successive models, and particularly the addition of endogenous factors, significantly increase predictive power, we calculate a likelihood ratio statistic (see Chatterjee and Hadi, 2011).

4.3 Modelling Results

Table 7 presents the best fitting ZOIB models for predicting factors influencing proportion of commutes by bicycle along 9,083 corridors across 36 urban areas in England and Wales. Successive model outputs are displayed.

The base model results are shown in the left-hand columns of Table 7. All predictors in the model are highly significant, with p-values of .000, and match a priori expectations. The full model (without fixed effects) is presented in the middle columns of Table 7. All predictors are once again highly significant, with p-values below .05, and relationships match a priori expectations. More importantly, the inclusion of bike-corridor attributes, environmental amenity, and built environment measures are all statistically significant. That is, policy-relevant variables appreciably improve upon the predictive power of the simpler base model. Overall the full model out-performs the base model in predicting bike shares, with the full model yielding a pseudo r-square value of 0.525 versus 0.422. The model improvement test shows that this gain is statistically significant, underscoring that the inclusion of endogenous factors improves the predictive power of the model.

How much does knowing the city where bike commutes occurred, controlling for the influences of the variables in the full model, improve model prediction? The full model with fixed effects is presented in Table 7's right-hand side columns. All predictors are highly significant and relationships once again match expectations. Overall, the full model with fixed effects out-performs the initial full model in predicting bike shares, yielding a pseudo r-squared value of 0.691 versus 0.525.

Table 7. Zero-One Inflated Beta (ZOIB) models. (*Dependent Variable*: proportion of bike commute among all commuters by home-workplace pair).

	Base model				Full model				Full model with fixed effects			
	Coef.	Std. Err.	Z	sig. P>|z|	Coef.	Std. Err.	z	sig. P>|z|	Coef.	Std. Err.	z	sig. P>|z|
Proportions between 0-1												
Travel distance and time												
Shortest path distance	-0.079	0.00	-22.74	0.00	-0.070	0.01	-10.48	0.00	-0.077	0.01	-12.57	0.00
Travel time ratio - bike/car					-0.385	0.05	-8.07	0.00	-0.349	0.05	-7.46	0.00
Travel time ratio - bike/transit					-0.145	0.03	-4.57	0.00	-0.103	0.03	-3.78	0.00
Diversion penalty for journeys > 6km					-0.168	0.03	-6.07	0.00	-0.162	0.03	-6.30	0.00
Bike corridor attributes												
Proportion of very low stress links					0.948	0.12	7.75	0.00	0.774	0.13	5.91	0.00
Proportion of low stress links					1.064	0.06	18.82	0.00	0.318	0.07	4.86	0.00
Proportion of very high stress links					-0.881	0.11	-7.69	0.00	-0.241	0.10	-2.34	0.02
Connectivity ratio					0.224	0.08	2.84	0.01	0.418	0.08	5.31	0.00
Complexity density					-0.018	0.01	-2.98	0.00	-0.051	0.01	-9.38	0.00
Environmental amenities of corridor												
Proportion of water surface area					3.330	0.76	4.39	0.00	1.691	0.63	2.68	0.01
Proportion of greenspace area					0.528	0.08	6.43	0.00	0.196	0.08	2.61	0.01
Built environment attributes of corridor												
Land area for housing and gardens					0.599	0.06	10.26	0.00	0.398	0.05	7.35	0.00
Activity density					0.004	0.00	5.75	0.00	0.001	0.00	2.18	0.03
Natural environment factors												
Mean gradient of cycle route	-27.261	0.82	-33.13	0.00	-22.633	0.83	-27.37	0.00	-14.175	0.90	-15.82	0.00
Mean air temperature (March 2011)	0.115	0.02	6.79	0.00	0.040	0.02	2.38	0.02	0.075	0.03	2.92	0.00
Mean rainfall (March 2011)	-0.014	0.00	-9.85	0.00	-0.003	0.00	-2.29	0.02	-0.010	0.00	-4.97	0.00
Socio-demographic attributes												
Proportion of professional and managerial commuters	2.143	0.07	32.84	0.00	1.748	0.06	28.69	0.00	1.325	0.05	25.33	0.00
Proportion of commuters in households owning no cars	1.314	0.08	15.76	0.00	1.087	0.09	11.76	0.00	0.902	0.09	10.57	0.00
Proportion of male commuters	1.071	0.06	17.73	0.00	1.136	0.06	19.52	0.00	0.976	0.05	18.63	0.00
Mean age of resident at origin zone	0.316	0.03	11.25	0.00	0.237	0.03	8.90	0.00	0.126	0.02	5.19	0.00
Mean age of resident at origin zone squared	-0.004	0.00	-11.07	0.00	-0.003	0.00	-8.66	0.00	-0.002	0.00	-5.37	0.00
City fixed effects												
Cambridge									1.230	0.04	31.55	0.00
Oxford									0.736	0.05	16.04	0.00
York									0.692	0.04	17.73	0.00
Norwich									0.459	0.04	10.94	0.00
Exeter									0.285	0.04	7.07	0.00
Lincoln									0.248	0.05	5.42	0.00
Brighton									0.239	0.05	5.11	0.00
Hereford									0.213	0.08	2.71	0.01
Kingston-Upon-Hull									0.142	0.04	3.60	0.00
Bristol									0.126	0.03	4.36	0.00
Warwick & Leamington									-0.108	0.05	-2.04	0.04
Guildford									-0.181	0.06	-2.97	0.00
Reading									-0.210	0.04	-5.71	0.00
Durham									-0.276	0.08	-3.27	0.00
Crawley									-0.287	0.06	-4.45	0.00
Leicester									-0.301	0.03	-10.03	0.00
Harlow									-0.336	0.06	-6.06	0.00
Milton Keynes									-0.393	0.05	-8.46	0.00
Nottingham									-0.411	0.04	-11.64	0.00
Sheffield									-0.411	0.03	-12.77	0.00
constant	-9.459	0.55	-17.07	0.00	-8.062	0.53	-15.08	0.00	-5.680	0.50	-11.31	0.00

Table 7 (continued).

	Base model				Full model				Full model with fixed effects			
	Coef.	Std. Err.	z	sig. P>|z|	Coef.	Std. Err.	z	sig. P>|z|	Coef.	Std. Err.	z	sig. P>|z|
Zero-inflate												
Travel distance and time												
Shortest path distance	0.327	0.01	22.09	0.00	0.264	0.03	10.24	0.00	0.212	0.03	7.95	0.00
Travel time ratio - bike/car					0.679	0.22	3.05	0.00	1.068	0.25	4.33	0.00
Diversion penalty for journeys > 6km					0.365	0.13	2.82	0.01	0.406	0.14	3.01	0.00
Built environment attributes of corridor												
Mixed use entropy measure					-0.600	0.20	-3.01	0.00	-1.693	0.21	-8.08	0.00
Activity density					-0.035	0.01	-4.51	0.00	-0.033	0.01	-4.02	0.00
Natural environment factors												
Mean gradient of cycle route	58.543	2.95	19.81	0.00	58.324	3.11	18.76	0.00	39.065	3.88	10.07	0.00
Socio-demographic attributes												
Proportion of male commuters	-3.007	0.29	-10.46	0.00	-2.796	0.28	-9.90	0.00	-2.806	0.29	-9.69	0.00
Proportion of professional and managerial commuters	-4.076	0.35	-11.66	0.00	-3.680	0.36	-10.24	0.00	-3.329	0.35	-9.47	0.00
City fixed effects												
Lincoln									-17.133	0.15	-114.61	0.00
Warwick & Leamington									-16.780	0.19	-89.74	0.00
Oxford									-16.757	0.15	-112.52	0.00
York									-16.734	0.12	-135.50	0.00
Cambridge									-16.224	0.16	-99.53	0.00
Milton Keynes									0.770	0.20	3.87	0.00
Reading									0.950	0.23	4.14	0.00
Leicester									1.079	0.12	8.79	0.00
Nottingham									1.448	0.15	9.39	0.00
Crawley									1.482	0.32	4.70	0.00
Sheffield									1.713	0.11	14.92	0.00
constant	-2.885	0.17	-17.30	0.00	-2.980	0.30	-10.02	0.00	-2.731	0.33	-8.33	0.00
ln_phi												
constant	3.256	0.02	163.23	0.00	3.436	0.02	173.45	0.00	3.759	0.02	202.81	0.00
Summary statistics												
N=	9083				9083				9083			
Wald chi2(9) =	2612.23				4341.18				11581.03			
Log pseudo likelihood =	11402.041				12139.254				13580.181			
Prob > chi2 =	0				0				0			
Pseudo R2 =	0.423				0.525				0.691			
Model improvement test					RM vs FM (no FE) ??2 = 1474.43, df = 16 , prob = 0.00				FM (no FE) vs FM (FE) ??2 = 2881.85, df = 31 , prob = 0.00			

Table 8. Zero-One Inflated Beta (ZOIB) models: *Average marginal effects* (*δy/δx*). (*Dependent Variable*: proportion of bike commute among all commuters by home-workplace pair).

	Base model				Full model				Full model with fixed effects			
	??y/??dx	Std. Err.	z	sig. P>|z|	??y/??dx	Std. Err.	z	sig. P>|z|	??y/??dx	Std. Err.	z	sig. P>|z|
Proportions												
Travel distance and time												
Shortest path distance	-0.0071	0.00	-28.32	0.00	-0.0059	0.00	-12.69	0.00	-0.0059	0.00	-13.97	0.00
Travel time ratio - bike/car					-0.0293	0.00	-8.52	0.00	-0.0270	0.00	-8.30	0.00
Travel time ratio - bike/transit					-0.0099	0.00	-4.57	0.00	-0.0069	0.00	-3.77	0.00
Diversion penalty for journeys > 6km					-0.0131	0.00	-6.61	0.00	-0.0122	0.00	-6.86	0.00
Bike network attributes												
Proportion of very low stress links					0.0648	0.01	7.71	0.00	0.0516	0.01	5.90	0.00
Proportion of low stress links					0.0727	0.00	18.71	0.00	0.0212	0.00	4.86	0.00
Proportion of very high stress links					-0.0602	0.01	-7.68	0.00	-0.0160	0.01	-2.34	0.02
Connectivity ratio					0.0153	0.01	2.84	0.01	0.0279	0.01	5.31	0.00
Complexity density					-0.0012	0.00	-2.98	0.00	-0.0034	0.00	-9.37	0.00
Environmental amenities of corridor												
Proportion of water surface area					0.2276	0.05	4.39	0.00	0.1127	0.04	2.68	0.01
Proportion of greenspace area					0.0361	0.01	6.44	0.00	0.0131	0.01	2.61	0.01
Built environment attributes of corridor												
Land area for housing and gardens					0.0410	0.00	10.19	0.00	0.0265	0.00	7.35	0.00
Mixed use entropy measure					0.0026	0.00	3.03	0.00	0.0059	0.00	8.14	0.00
Activity density					0.0004	0.00	7.31	0.00	0.0002	0.00	4.18	0.00
Natural environment factors												
Mean gradient of cycle route	-2.1691	0.06	-34.85	0.00	-1.8028	0.06	-29.99	0.00	-1.0813	0.06	-17.46	0.00
Mean air temperature (March 2011)	0.0080	0.00	6.76	0.00	0.0027	0.00	2.38	0.02	0.0050	0.00	2.92	0.00
Mean rainfall (March 2011)	-0.0010	0.00	-9.66	0.00	-0.0002	0.00	-2.29	0.02	-0.0006	0.00	-4.97	0.00
Socio-demographic attributes												
Proportion of professional and managerial commuters	0.1680	0.01	32.52	0.00	0.1356	0.00	29.40	0.00	0.0999	0.00	26.81	0.00
Proportion of commuters in households owning no cars	0.0912	0.01	15.41	0.00	0.0743	0.01	11.64	0.00	0.0601	0.01	10.54	0.00
Proportion of male commuters	0.0886	0.00	20.07	0.00	0.0899	0.00	21.48	0.00	0.0749	0.00	20.48	0.00
Mean age of resident at origin zone	0.0219	0.00	11.19	0.00	0.0162	0.00	8.88	0.00	0.0084	0.00	5.19	0.00
Mean age of resident at origin zone squared	-0.0003	0.00	-11.00	0.00	-0.0002	0.00	-8.64	0.00	-0.0001	0.00	-5.37	0.00
City fixed effects												
Cambridge									0.1388	0.00	41.56	0.00
Oxford									0.1077	0.00	28.88	0.00
York									0.1047	0.00	30.67	0.00
Lincoln									0.0765	0.00	20.37	0.00
Warwick & Leamington									0.0516	0.00	12.01	0.00
Norwich									0.0306	0.00	10.93	0.00
Exeter									0.0190	0.00	7.08	0.00
Brighton									0.0159	0.00	5.10	0.00
Hereford									0.0142	0.01	2.71	0.01
Kingston-Upon-Hull									0.0095	0.00	3.60	0.00
Bristol									0.0084	0.00	4.35	0.00
Guildford									-0.0120	0.00	-2.97	0.00
Reading									-0.0173	0.00	-6.71	0.00
Durham									-0.0184	0.01	-3.27	0.00
Harlow									-0.0224	0.00	-6.05	0.00
Leicester									-0.0238	0.00	-11.61	0.00
Crawley									-0.0243	0.00	-5.50	0.00
Milton Keynes									-0.0289	0.00	-9.07	0.00
Nottingham									-0.0325	0.00	-13.45	0.00
Sheffield									-0.0334	0.00	-15.38	0.00

4.4 Discussion

This section turns to Table 8, on marginal average effects, to elaborate on the outputs of the three ZOIB models. Influences of what we have called endogenous (i.e., policy relevant) variables are first discussed, followed by commentary on control variables and then city-level dummy predictors. The marginal effects shown in Table 8, we note, should be considered in the context of overall levels of cycle commuting, which stand at 3% for the UK and 7.6% across all O-D pairs in our models (ONS, 2011).

4.4.1 Travel distance and time

Consistent with travel demand theories (Ben Akiva and Lerman, 1985; Ortuzar and Willumsen, 2014; Boyce and Williams, 2015), bike commuting declines with commute distance and as the time it takes to travel by bicycle rises relative to car or public transit. Based on the average marginal effects in the full models, the influence of distance is relatively consistent, suggesting that (averaged across all observations in our model) as commute distance increases by 1km, bike share ordinarily decline by 0.6 percentage points (and by 0.7 percentage points in the base model).

Of equal note, ratios between bike travel times and car travel times exerted significant marginal influences on cycle commuting. The average marginal effect of a unit change in this ratio yields a 2.9 percentage point reduction in cycle commuting. For example, a change in this ratio from 1 (suggesting equal travel times) to 2 (suggesting bike takes twice as long as car) is associated with a 2.9 percentage point reduction in cycling.

4.4.2 Bike network attributes

Our models show that levels of on-road stress matter. Notably, as the detour one must take to find a low-stress path increases relative to the shortest path distance, bike-commuting declines. This holds, we note, for commutes over 6 km in length; only then is it likely worth the effort to seek out less-stressful paths with a significant detour. The influence of this measure was consistent with and without fixed effects. On the other hand, as the share of links on corridors that are LTS 1 (e.g., cycle tracks) or LTS 2 (e.g., cycle lanes on residential streets) increases, so does the share of commutes by bicycle. These influences are stronger without the addition of city fixed effects, which suggests that it is very important to separate the LTS effects from those arising from incidental variations between different urban areas.

The average marginal effects of LTS measures, according to the full model without fixed effects, suggests that a unit change (for example a change in proportion from 0 to 1) in very low stress links may result in a 6.5% increase in cycling and unit change in low stress links may result in a 7.3 percentage point increase in cycling. To put this into a more realistic context, this suggest that a 10 percentage point increase in very low stress links along a corridor may result in a 0.65 percentage point increase in cycling and a 10 percentage point increase in low stress links, a 0.73 percentage point increase, holding other factors constant.

The models also show connectivity and network complexity attributes to be significant predictors. As the ratio of links to nodes along a corridor increases, so does the share of commutes by bicycle. In contrast, complexity – marked by frequent transitions from one level of travel stress to another – deters bike-commuting, suggesting a certain degree of anxiety associated with high variations in stress levels along paths. Interestingly these factors were stronger when fixed effects were included.

Overall, our research suggests the feature of network design that is most likely to promote bicycle commuting is the provision of convenient, low-stress links -- that is, protected bike-lanes and cycle-tracks that are as close to the shortest path as possible, minimizing detours. This is especially so where commute distances tend to be long, such as on the urban periphery and in large, spread-out cities. Policy makers, our results suggest, should not assume that by simply adding cycle lanes and tracks, cycling to work will explode in popularity. . The influences of enhanced cycling infrastructure are incremental and the effects of any one bikeway project itself is apt to be modest at best. Still, in the context of very low existing levels of cycle commuting across much of the UK, building low-stress bikeways can clearly nudge commuting trends in the right direction. .

4.4.3 Built environment and environmental amenity

Among built-environment variables mixed land uses, as expressed by the entropy metric, contribute to reducing the likelihood of zero commuting. This effect increases when adding fixed effects. High densities of Foursquare check-ins (for activities thought to allow linked bike trips, such as to retail destinations) also encourage cycling-to-work, although this effect was weakened with the addition of city fixed effects. Clusters of activities along bicycle corridors, we surmise, likely promote bike commuting by allowing cyclists to more easily link together trip ends, such as dropping by a café after work, without the hassle of trying to find a place to park.

Amenity factors were on a par with mixed-use metrics in explaining bicycle commuting. High shares of residential land uses along a corridor as well as green-and-blue landscapes induce bike commuting. Being surrounded by nature or pedalling along corridors dotted with gardens and lakes can be a pleasant way to start and end the workday. Our results support this proposition.

Of particular note is the average marginal effect of a unit change in the proportion of the corridor that is inland water. The partial $\delta y/\delta x$ value, of 0.22 suggests that a 10% increase in this measure may result in 2.2 percentage point increase in cycle rates. While an increase of this magnitude may be difficult along the vast majority of commuting corridors, where there is potential to provide a new cycle route or improvements to existing facilities along, for example river and canal paths, our research suggest that this could significantly increase bicycle commuting.

4.4.4 Control Variables

Consistent with findings from previous studies, our model shows that steep terrains and wet weather work against bike commuting while warmer temperatures encourage it, at least in the spring time. Among socio-demographic control variables, age has the strongest influence on bike-commuting. As hypothesized, a quadratic relationship was found: shares of bike-commuting increase with mean age of an origin zone, up to a point, after which bike-commuting tends to decline as workers age. Also important are the socioeconomic profiles of resident-workers. High shares of residential populations made up of professionals and senior managers are positively associated with cycling-to-work. This is the case even after controlling for car ownership levels, whose marginal influence on biking-to-work is, as expected, strongly negative. We surmisethat this reflects an attitudinal dimension. Many well-to-do professionals cycle to work for lifestyle and environmental reasons, seeking to stay fit and shrink their carbon footprints.

4.4.5 Fixed Effects

Where one lives and commutes can have a strong bearing on bicycling commuting. This is so for over half (20 of the 36) towns and cities in our database. We also note that smaller historic cities, such as Lincoln, Warwick, Cambridge, Oxford and York, are less likely to have commuting corridors where nobody cycles.

By far, the strongest positive fixed effects were found for three historical British cities with renowned universities, car-restricted city centres, and distinctive pedestrian- and bike-friendly ambiances: Cambridge, Oxford, and York. Based on partial $\delta y/\delta x$ values, other cities with positive fixed effects were Norwich, Warwick & Leamington, Exeter, Lincoln, Brighton, Hereford, Kingston – Upon – Hull and Bristol. What is being captured here, we surmise, are intangible factors like a pro-cycling local culture and policy environment. As university towns, large shares of Cambridge and Oxford residents are well-educated professionals. Yet even after statistically controlling for such factors, bike-commuting shares are still much higher relative to the other cities in our sample.

We note that several cities including – Reading, Leicester, Crawley, Sheffield, Milton Keynes and Nottingham - register negative fixed effects and are more likely to have O-D pairs with no bicycle commuting. These include master-planned new towns, built during the post-WWII era of automobile ascendency. Might the reverse hold, suggesting less of a bike-friendly culture in these places? If so, this is not necessarily because of a lack of bicycle infrastructure. Milton Keynes, for example, is laced with an expansive network of shared use foot and cycle-paths (termed the Redways), grade-separated from busy traffic.

5. Weaknesses and Limitations

Due to data availability, our research was limited to studying relationships at the neighbourhood rather than street or individual level. While this provides certain benefits, such as reduced computation time (a significant consideration when generating paths and corridor-based metrics for home-workplace pairs), we would expect to see improvements in the predictive power of the models as the spatial granularity improves in the future.

We also recognise the limitations of the UK journey-to-work data. The Population Census questionnaire asks each resident for their main mode of travel to work (by distance) the week prior to the Census. Strictly speaking, the bikeshare from the Census is not the mode share as defined by travel demand models. Such limitations notwithstanding, this is still the most comprehensive journey-to-work database available in the UK.

Our research also revealed inconsistencies in the data provided by Google, Inc. Cycling speeds varied significantly and, we feel, they are generally too fast for the average cycle commuter. There are also concerns with driving speeds inferred from the Google API. From our observations, driving times do not always reflect real-world morning peak conditions. To overcome this concern, we use the pessimistic travel model from Google and have adjusted travel times where required.

We also acknowledge the potential for city dummy variables to mask effects from variables such as car parking availability and cost which we have not been able to include in the current study. Lastly, we recognise that there is potential from future data sources such as GPS activity trackers to supplement and validate our coding of on-road cycling stress levels and our modelling of cycle routes. The tracker data sources we examined were not yet capable for this purpose.

6. Conclusions

Our research reveals a complex web of influences – some endogenous, others exogenous in nature -- that influence cycling to work in British towns and cities. Based on the fairly modest average marginal influences estimated from our models, we conclude this is no silver-bullet factor that will significantly boost bicycling commuting, even in cities with remarkably high commuter cycling. Any one factor, by itself, has a marginal, sometimes seemingly imperceptible, effect on cycling to work. However, collectively, as part of a full-fledge policy commitment to promote cycling, the combination of massively expanding low-stress, non-circuitous bike-paths in compact areas with mixed uses and natural amenities can make a difference. Making the cycling experience as safe, efficient, enjoyable, and stress-free as possible is critically important to drawing more British commuters out of cars, trains, and buses and onto bicycles.

These findings offer policy directions to British towns and cities seeking to set priorities, a propos the UK *Cycling and Walking Investment Strategy* targets. Corridors with rich mixes of land uses and retail activities, we would argue, are candidates for priority funding for secure and protected bike parking to facilitate bike trip-chaining. Corridors with fast-moving traffic and minimal safeguards for cyclists are obvious candidates for building protected cycle paths. And while there are many rationales for greening and beautifying cities, our research show that promoting an active lifestyle can be an important co-benefit.

Our research also informs the planning and design of facilities for long-distance cycling, which we found to be most sensitive to detour penalties. Providing long stretches of dedicated bike paths oriented toward urban centers, our research suggests, can induce bike-commuting. A good example are the wide cycle lanes that hug Cambridgeshire's busway, connecting Cambridge's outskirts to its historical core. Another are the bike superhighways being built in London and Copenhagen to connect outlying districts to their urban cores. Such measures, our research suggests, may also be beneficial in smaller cities and towns.

Our research also throws light on possible intangible factors that influence bike-commuting, such as the presence of a pro-bike or pro-car local culture. Such questions, however, are better addressed through qualitative research. In-depth case studies of the towns and cities in our sample frame could be illuminating in this regard.

Acknowledgements

This work was supported by the University of California, Berkeley; the Cambridge Centre for Smart Infrastructure and Construction; the Martin Centre for Architectural and Urban Studies; and the Engineering and Physical Sciences Research Council, [grant number EP/M506485/1].

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Network Design, Built and Natural Environments, and Bicycle Commuting

Highlights:

* A complex web of forces shape cycle commuting in British cities, confirming there is no single, silver-bullet factor even in cities with remarkably high commuter cycling.

* Modelling results underscoreThe model results highlight the importance in joining up network level interventions, for instance to reduce both route circuity and on-road stress, which are objectives often being pursued separately.

* The research results also highlight the importance of the non-transport aspects such as land use mix and landscape amenities along commuter routes, and the role of city-specific cycling culture.

* They also underscore the need for closer collaboration between promoters of commuter cycling and wider urban disciplines to create low-stress routes and supportive built environments in cities and their outskirts.