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Neighbourhood characteristics and bicycle commuting in the Greater London area

Samuel McCreery-Phillips, Shahram Heydari *

Transportation Research Group, Department of Civil, Maritime and Environmental Engineering, University of Southampton, Southampton, United Kingdom

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ABSTRACT

As the need to encourage modal shift from motorised vehicle use to active modes becomes greater, it is important to understand the key factors influencing the decision of how to travel. This paper explores the association between bicycle commuting and a range of sociodemographic and built and natural environment characteristics across wards and boroughs in Greater London, UK, with an aim to identify the key factors which influence participation. We employed a Bayesian multilevel heteroskedastic model with heterogeneity in variance, which can address dependencies in the data and unobserved heterogeneity more fully. This allowed us to account for unobserved/unmeasured covariates such as collective attitudes and the existence of cycling cultures that may differ between Greater London boroughs. We found that the propensity for bicycle commuting increases with an increase in the employment rate, the populations of white British and mixed white and black Caribbean, the proportion of terraced houses, and cycle network density. Conversely, we found that the propensity for bicycle commuting decreases with an increase in the absence of academic qualifications, the area of non-domestic buildings, the population of Indians and Pakistanis, and the number of cars per household. Our analysis also revealed important between-borough variations in the effect of key explanatory variables. Notably, the effects of the populations of Indians, Pakistanis, and mixed white and black Caribbean, and the number of cars per household all vary across Greater London boroughs. Finally, by allowing for heterogeneity in variance, we found that rates of bicycle commuting are more dispersed in Inner London and as the number of cars per household increases. Our analysis highlights the importance of cycling infrastructure in promoting bicycle commuting.

1. Introduction

The individual and public benefits of cycling to work are becoming increasingly well understood. A growing body of evidence shows that physical and mental health, local air quality, and wider environmental concerns can all be positively impacted by switching to active transport modes (Oja, et al., 2011; Deenihan and Cauldfield, 2014; Brand et al., 2021). In the UK, the need to encourage modal shift away from motorised travel towards walking and cycling has now been recognised at the Government level, with recent policy establishing the aim for half of all trips in towns and cities to be walked or cycled by 2030 (Department for Transport, 2020). Although annual statistics show a decade-long stagnation in the number of cycle trips at the national level, there is a significant underlying disparity in the level of cycling participation throughout the country (Department for Transport, 2022a). In Greater London, overall cycling participation instead saw year-on-year increases throughout the 2000s and mid-2010s, and showed strong resilience to the Covid-19 pandemic (with a lower-than-average initial drop in demand and faster-than-average recovery) (Transport for London, 2021). However, even within the same city this inter-area disparity is still observed. This study, for example, found that bicycle commute mode share varied between 0.24% and 19.09% across all electoral wards in London.

Despite the recognition of the benefits and need to encourage bicycle commuting, we still lack a thorough understanding of why participation rates vary so much between areas. The key to encouraging participation and meeting future aims is determining what drives this inter-area disparity and the wider factors that influence bicycle commuting as a whole. Not only does this enable us to make informed policy recommendations, but also helps identify those areas that are most likely to be resistant to participation increases. To this end, this research aims to identify the key factors that influence ward-level bicycle commuting in the Greater London area, allowing for the derivation of evidence-based policy recommendations for increasing bicycle commute mode share.

* Corresponding author.
E-mail addresses: sgmp1n20@southampton.ac.uk (S. McCreery-Phillips), s.heydari@soton.ac.uk (S. Heydari).

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2. Literature review

The majority of previous research in the UK uses disaggregate individual-level data to investigate the determinants of cycling. Nationwide studies include those by Laverty et al. (2013) who investigated the sociodemographic correlates of active travel to work across the UK, Hutchinson et al. (2014) who investigated the social patterning of walking and cycling for utility purposes, and Brainard et al. (2019) who investigated correlates of active travel based on responses to the 2016/17 Active Lives Survey. UK individual-level studies with smaller geographical targets include those by Panter et al. (2011) who investigated the correlates of cycling to work in Cambridge, Solomon et al. (2013) who considered rural villages across south-west England, Song et al. (2013) who investigated the correlates of walking and cycling in Cardiff and Southampton, and Martin et al. (2021) who investigated the sociodemographic, environmental and economic determinants of bicycle commuting in London. Area-level studies, which use aggregated data, include those of Parkin et al. (2008) who investigated the determinants of bicycle commuting throughout England and Wales at the electoral ward level using 2001 census data, and Cervero et al. (2019) who used 2011 census data at the MSOA level, nested into 36 towns and cities across England. Goodman (2013) investigated commuting mode choices more generally using 2011 Census and National Travel Survey data aggregated to non-overlapping subpopulations based on regions, time periods and incomes.

Significant research has also been undertaken outside of the UK. Biehl et al. (2018), for example, investigated demographic and attitudinal determinants of walking and cycling across the entire United States. Dill and Carr (2003) investigated sociodemographic, environmental and infrastructural influences on bicycle commuting in 43 American cities, and Dill and Voros (2007) looked at the sociodemographic and attitudinal correlates of bicycle use in Portland, Oregon. In Sweden, Ek et al. (2021) investigated how demographic, socio-economic, infrastructural and geographical factors influence walking and cycling to work, and Charreire et al. (2021) investigated how individual and contextual characteristics influence walking, cycling, and public transport use across five European urban regions (Ghent, Paris, Budapest, the Randstad and Greater London).

Given the range of different cycling predictors that have previously been investigated, researchers have used a variety of taxonomies for classifying factors that are associated with bike commuting. We rationalised previously identified significant factors into four classes: (i) Individual characteristics (sociodemographic and economic); (ii) Built environment; (iii) Natural environment; and (iv) Attitudinal characteristics. We briefly review these classes of variables in the subsequent sections.

2.1. Individual characteristics (sociodemographic and economic)

Several sociodemographic and economic characteristics have been found as significant predictors in previous research. Research in the UK has identified that being in employment, and the type of employment, can significantly influence cycling participation (Hutchinson, et al., 2014; Laverty et al., 2013; Cervero et al., 2019). Overall it seems that amongst those in employment, individuals within higher Socioeconomic Class (SEC) groups are the most likely to cycle to work (Martin, et al., 2021), as well as individuals with higher levels of education (Song, et al., 2013; Solomon et al., 2013; Adams, 2021). The relationship with income is not as clear cut. Parkin et al. (2008) found income to have an increasing effect when investigating the determinants of bicycle commuting throughout England and Wales, as did Dill and Voros (2007) when investigating the factors affecting the more general "bicycle demand" in Portland, Oregon. However, Hutchinson et al. (2014), found bicycle travel to be more prevalent in UK households within lower income bands, and in Sweden, Ek et al. (2021) observed that within certain municipalities active travel (walking and cycling) was higher amongst lower income individuals. Clearly, the relationship between income and bicycle use can vary significantly between contexts.

The effect of age on cycling participation is also complex. In the UK, Cervero et al. (2019) identified a quadratic relationship whereby bicycle commuting increases with mean age up to a point, then drops off in ageing populations. This is consistent with the findings of Martin et al. (2021) who found that individuals aged 30–50 were most likely to cycle to work. Ethnicity and gender are also significant, generally non-white ethnic groups are less likely to cycle to work than whites, and males are more likely to cycle to work than females (Parkin, et al., 2008; Martin et al., 2021). Finally, vehicle ownership appears to have a significant effect on the decision to cycle, with a virtually unanimous consensus between previous studies (across a range of contexts) that higher levels of car ownership are associated with a reduction in bicycle travel: Parkin et al. (2008) and Cervero et al. (2019) in the UK, Dill and Carr (2003), Dill and Voros (2007) and Biehl et al. (2018) in the USA, and Charreire et al. (2021) across five European urban regions.

2.2. Built environment

With respect to built environment characteristics that are related to man-made infrastructure, Dill and Carr (2003), investigating bicycle commuting across the US, found the concentration of bike lanes to be the most significant factor in increasing bicycle commuting. This is consistent with the findings of Cervero et al. (2019), who found that an increase in the concentration of convenient 'low-stress' links was positively associated with an increase in the share of bicycle commuting. Krizek and Johnson (2007) found that the proximity to bicycle facilities is significant in explaining cycling participation, but the relationship is not linear, with the effect being most significant at closest proximities and becoming progressively less important over further distances. However, they did note that this effect may be subject to a degree of bidirectional causality, and that living nearer to cycling facilities may be reflective of pre-existing attitudes. Considering urban form, Hutchinson et al. (2014) found that urban residents were 64% more likely to frequently engage in active travel than rural residents. Parkin et al. (2008) found that individuals with further distances to work were less likely to commute by bike, and that higher traffic volumes and poor pavement conditions were associated with a general reduction in cycling. Similarly, Martin et al. (2021) found commute distance to have the largest marginal effect on reducing cycling, but that cycling infrastructure expenditure had a significant positive influence.

2.3. Natural environment

The natural environment can also play a role in influencing cycling participation. From previous research, the most significant natural environment factors influencing cycling are weather and terrain gradient. Dill and Carr (2003) found the number of days of rain to be negatively correlated with bicycle commuting, and Brandenburg et al. (2004) found both wet weather and cooler weather reduced bicycle use for all purposes. Parkin et al. (2008) and Cervero et al. (2019) found both wet weather and 'hillier' terrains reduce bicycle commuting, which is consistent with Martin et al. (2021) who found that higher concentrations of steeper gradient routes had a decreasing effect. Additionally, both Cervero et al. (2019) and Martin et al. (2021) found that the prevalence of greenspace was positively correlated with bicycle commuting.

2.4. Attitudinal characteristics

Previous studies have also identified the significance of attitudinal factors in influencing cycling participation. These are often more difficult to observe and quantify and relate to the individual and or collective attitudes towards cycling (and the other correlates that might encourage participation). The perception of road traffic and cycle route convenience, personal enjoyment, consideration of personal and environmental health and attitude towards car use have all been found to influence the decision to cycle (Panter, et al., 2011; Charreire et al., 2021; Ek et al., 2021). Beyond individual preferences, previous studies have also found evidence of significant 'cultural' differences, whereby the collective attitudes towards walking and cycling differ by location (Dill and Carr, 2003; Dill & Voros; 2007; Cervero et al., 2019). Aldred and Jungnickel (2014), highlighted the importance of 'cycling cultures', where individuals in the same locality are collectively more disposed towards cycling. Interestingly, in a comparison of Hull and Cambridge (which are both considered to have established cycling cultures) they found that respondents in Cambridge were typically more affluent and cycling for 'positive' reasons (e.g., environmental concerns), whereas respondents in Hull were poorer and often cycled out of necessity. Clearly, these cultures can grow from a range of different causes.

2.5. Summary

At the most basic level, an individual decision to walk or cycle a given trip is the result of a unique combination of influences, motivations and circumstance. To fully understand the rationale behind every decision, we would need to investigate behaviour on a case-by-case basis, which although insightful would be an extremely intensive process. In this study, we assume that individual rationale and attitudes are influenced (and to some extent dictated) by a number of quantifiable area-level socioeconomic, demographic, and environmental factors. By extension, we can use these factors to explain and predict cycling behaviour at a large scale (area level). We can then make practical recommendations for influencing cycling participation by understanding the significance and effect of individual factors themselves.

2.6. The current paper

There is an ever-growing body of research on the factors influencing cycling participation, covering a breadth of locations, methodologies, and spatial and temporal resolutions. However, given the size of scope for potential studies, it seems there are few that follow a similar approach to our research, where we investigate the determinants of cycling in the Greater London area using ward-level data. Wards are the primary unit of electoral geography in Greater London. They are grouped into 32 boroughs which together with the City of London form the administrative area of Greater London. In this study we have considered data for 624 wards nested within 32 boroughs, plus the City of London which has been considered as single-observation borough. London is governed through individual borough councils (local governments), and we have recognised the importance of considering separation between boroughs and how the borough councils themselves may influence the decision to cycle. To this end, for the first time in this context, we employed a multilevel modelling approach with heterogeneity in variance. The approach not only allows us to account for dependence between wards nested within the same boroughs, but it also allows us to draw borough-level comparisons and conclusions. Ultimately an understanding of the significant factors (and their magnitudes of impact) influencing bicycle commuting in the capital can help inform transport and development planning for other cities and large towns across England, the UK and elsewhere.

3. Data

The variables used in this study and their respective summary statistics are provided in Table 1. We obtained the bicycle commuting data from the Office for National Statistics (2013). The data is based on responses to the 2011 Census in the UK. The UK Census is undertaken once every ten years, and the 2011 Census results were the most recently available at the time of this research, and the most recent which are unaffected by the Covid-19 pandemic. We used the measure for the percentage of people aged 16–74 who travel to work by bicycle, aggregated at the electoral ward level in Greater London.

Table 1
Summary statistics of the data.

Variable types	Variables	Data year	Spatial unit	Mean	Std. Dev.	Min	Max
Transport-related							
	Bicycle commuting rate[a]	2011	Ward	0.039	0.034	0.002	0.191
	Cycle network density (length of cycle network per unit area (km/m^2))	2012	Borough	0.0024	0.0015	0.0006	0.0350
	Total annual vehicle miles travelled (millions)	2011	Borough	573	242	101	1265
Socio-demographic							
	Population	2011	Ward	13,046	2491	5114	21,057
	Population per square kilometre	2011	Ward	8034	4724	177	26,498
	Population of white British	2011	Ward	5871	2485	472	13,791
	Population of mixed white and black Caribbean	2011	Ward	191	123	26	800
	Population of Indian and Pakistani	2011	Ward	1227	1573	28	8407
	Mean age of population	2011	Ward	35.858	3.085	29.070	44.181
	Median annual household income (£000 s)	2011	Ward	38.501	7.303	24.490	85.200
	Number of cars per household	2011	Ward	0.843	0.326	0.233	1.705
	Employment rate (%)	2011	Ward	69.472	6.472	46.113	83.902
	Population with level 4 qualifications and above (%)	2011	Ward	37.658	12.849	12.500	68.700
	Population with no qualifications (%)	2011	Ward	17.622	6.031	3.800	35.800
	Households owned (%)	2011	Ward	49.675	18.758	11.900	90.800
	Households private rented (%)	2011	Ward	24.454	9.978	4.800	55.500
	Jobs density (jobs per resident aged 16–64)	2011	Borough	0.944	3.036	0.390	74.760
Built/natural environment & land use							
	Area of ward (km^2)	2011	Ward	2.552	2.578	0.391	29.035
	Area of domestic buildings (km^2)	2005	Ward	0.222	0.075	0.028	0.501
	Area of non-domestic buildings (km^2)	2005	Ward	0.119	0.109	0.024	1.152
	Area of greenspace (km^2)	2005	Ward	0.976	1.991	0.011	26.113
	Area of water (km^2)	2005	Ward	0.072	0.463	0.000	9.940
	Average Public Transport Accessibility Level (PTAL) score	2011	Ward	3.676	1.349	1.278	7.959
	Detached houses (%)	2011	Ward	6.598	7.537	0.300	55.800
	Semi-detached houses (%)	2011	Ward	19.954	15.793	0.200	82.300
	Terraced houses (%)	2011	Ward	23.653	13.108	1.400	63.800
	Proportion land use greenspace	2005	Borough	0.321	0.118	0.048	0.593
	Proportion land use water	2005	Borough	0.031	0.044	0.001	0.222

[a] Bicycle commuting rate is defined as the proportion of people aged 16–74 who travel to work by bicycle.

In addition to the bicycle commuting data, we collected data on a range of sociodemographic and environmental characteristics of London wards and boroughs. Consideration was given to the existing bicycle commuting and active travel literature to select variables that had previously been identified as significant determinants of either bicycle commuting or active travel participation. Most of the data considered was aggregated at the electoral ward level, but this study has also included several variables that were aggregated at the borough level. Unfortunately, it is not always possible or practical for data to be granulated to the ward level.

The majority of data for explanatory variables, particularly that for sociodemographic characteristics, was obtained from sources managed by the Greater London Authority. For ward-level data, we used both the London ward profiles and ward atlas datasets (Greater London Authority, 2015a). The ward profiles dataset presents key summary measures whereas the ward atlas includes the raw data numbers that allows for more detailed interrogation and the derivation of bespoke measures. For borough-level data, we used the London borough profiles dataset (Greater London Authority, 2015b). All these datasets are comprised of a range of sources that are sampled at different frequencies, which can lead to disparities in the year of provenance of the data for individual measures. In this study, we have tried where possible to only use data for 2011 to match that obtained for bicycle commuting, but certain land use measures were only available for 2005 which is a potential limitation of the study. Ward- and borough-level land uses may have changed slightly between 2005 and 2011, but we consider that any change would be minor enough that data from 2005 can still be used to draw reliable inferences. We also note that previous studies have combined 2005 land-use data with 2011 census data to draw conclusions and policy recommendations: see, for example, Cervero et al. (2019). For clarity, the year of data provenance for each variable is also included in Table 1.

In terms of sociodemographic variables, we considered the total population, population density, and populations of various ethnicities at the ward level. Ethnicity in particular has been observed to have a significant influence on bicycle commuting throughout the extant literature, and we have considered data for 22 different ethnic groupings in our research. For brevity, only those which were found to be significant in our modelling have been included in Table 1. We also considered the mean age within each ward. Economic and affluence related measures included household income, number of cars, whether houses were owned or rented and the rate of employment. We also included measures for education: the percentage of the population with no qualifications, and the percentage with a level four qualification or above. Qualification levels are defined by the UK Government and effectively describe the difficulty of obtaining a given qualification, with higher levels being more difficult. Level four indicates that an individual has achieved beyond A-level (or equivalent). Finally, we included a borough level measure for jobs density, which describes the number of available jobs per resident aged 16–64 (more commonly defined as the working age population).

Built and natural environment characteristics at the ward level included the total ward area and other land-use measures. We considered the area of land used for domestic and non-domestic buildings, greenspace and water, as well as the proportion of different housing types: detached, semi-detached and terraced. We also considered the average Public Transport Accessibility Level (PTAL) score, which is a generalised measure of public transport accessibility within each ward that takes into account walk access times and service availability.

At the borough level we considered the density of the cycle network (calculated as the length of London Cycle Network *per* unit area), for which data was obtained from Transport for London (TfL) through a freedom of information request. The London Cycle Network (which has since been replaced by Transport for London with various cycleways, cycle superhighways and 'quietways') comprised a collection of signposted cycle routes throughout London utilising a mixture of segregated cycle paths, painted cycle lanes and 'cycle friendly' streets. The calculated density is the ratio of the total length of the cycle network within a borough to the borough's total area and provides an indication of how well the cycle network is developed within a given area. We recognise that one limitation of using this data is that it does not allow for differentiation between different types of bicycle infrastructure and their individual influences on bicycle commuting. Had such information been available we would have been able to conduct a more comprehensive study providing detailed insights on the influences of different bicycle infrastructure types.

We also considered the proportion of land used for greenspace and water, and the total annual vehicle miles. Total annual vehicle miles were obtained for 2011 from the Department for Transport's Road traffic statistics dataset (Department for Transport, 2022b). Finally, we included two dummy variables: whether (or not) a ward contains a Santander Cycles docking station, and whether (or not) a borough is located within inner London. Data for Santander docking stations was obtained directly from Transport for London.

4. Method

Given the hierarchical structure of the data, wards nested within boroughs, we adopted a Bayesian multilevel regression modelling approach that considered two distinct model types: a standard random parameters model and a heteroskedastic random parameters model with heterogeneity in variance. Generally, random parameters models can address unobserved heterogeneity more fully compared to conventional regression models (Mannering et al., 2016), by allowing the effects of individual explanatory variables to vary between groups of observations (in this case boroughs). A random parameters model with heterogeneity in variance, while allowing for heteroskedasticity, helps address unobserved heterogeneity even more fully. The latter approach models varying variances as a function of one or more explanatory variables, thereby providing further insights using the same set of variables available in the data. This approach is well suited to model bicycle commuting, as it allows us to account for unobserved covariates such as collective attitudes and the existence of cycling cultures that may be present at the borough level.

Here, the dependent variable is bicycle commuting rates that are values between zero and one. We logit transformed the dependent variable to be able to assume it follows a normal density. This allowed us to better capture the underlying structure of the data as well as the nonlinear relationship between bicycle commuting and independent variables (see Parkin et al. (2008), Lovelace et al. (2017) and Cervero et al. (2019) for further examples of where this has been discussed). Using logit transformed values enabled us to calculate odds ratios for the estimated regression parameters, which are explained and discussed in section 4.2.

4.1. Conventional multilevel random parameters (slopes) model

A typical multilevel random parameters model that allows the effect of some covariates Z to vary across the boroughs can be written as in EQ. (1). In this model, random intercepts and parameters vary from one borough to another, reflecting between-borough differences. Let y_j and θ_j be, respectively, the observed and expected logit transformed bicycle commuting rates in ward j. Let η_r denote the varying intercepts (here, borough-level effects) that follow a normal density with the mean μ_r and the variance ν_r for borough r. Let Z be explanatory variables, the effects of which vary across different boroughs, with their corresponding regression coefficients β, following a normal density with the mean μ_β and the variance ν_β. Let X be explanatory variables, the effects of which are fixed, with their corresponding regression coefficients γ. Let ν be a variance term. We can then write:

$$\begin{aligned} y_j &\sim normal\left(\theta_j, v\right) \\ log\left(\theta_j\right) &= \eta_r + \boldsymbol{\beta_r Z_r} + \boldsymbol{\gamma X_j} \\ \eta_r|\mu_\eta, v_\eta &\sim normal(\mu_\eta, \nu_\eta) \\ \boldsymbol{\beta_r}|\boldsymbol{\mu_\beta}, \boldsymbol{v_\beta} &\sim normal(\boldsymbol{\mu_\beta}, \boldsymbol{v_\beta}) \end{aligned} \tag{1}$$

4.2. Heteroskedastic random parameters model with heterogeneity in variance

While the above specification assumes a fixed variance (the most common approach), one can allow the variance to vary across the sample as a function of explanatory variables. This allows us to infer more detailed information on cycling participation and potential sources of variations and dispersion in bicycle commuting rates. To this end, the varying variances, v_j, are allowed to vary from one ward to another as a function of explanatory variables $\boldsymbol{S}$, available in the data, as specified in EQ. (2). We can write:

$$\begin{gathered} y_j \sim normal\left(\theta_j, v_j\right) \\ log\left(\theta_j\right) = \eta_r + \boldsymbol{\beta_r Z_r} + \boldsymbol{\gamma X_j} \\ \eta_r|\mu_\eta, v_\eta \sim normal(\mu_\eta, \nu_\eta) \qquad \boldsymbol{\beta_r}|\boldsymbol{\mu_\beta}, \boldsymbol{v_\beta} \sim normal(\boldsymbol{\mu_\beta}, \boldsymbol{v_\beta}) \\ v_j = \delta_0 + \boldsymbol{\delta S_v} \end{gathered} \tag{2}$$

where δ_0 is an intercept term; $\boldsymbol{\delta}$ are coefficients associated with explanatory variables in the variance function.

4.3. Model computation

We specified non informative priors for model parameters and implemented the models in the Nimble package in R (de Valpine, et al., 2017) running two chains each containing 130,000 iterations, with a thinning of 5. The first 30,000 iterations were discarded for convergence requirements, considering the Gelman-Rubin statistics (Gelman and Rubin, 1992). The posterior inferences are therefore based on the final 100,000 iterations of 130,000 total iterations.

5. Results

We have estimated the fit of each model using WAIC, which is considered more robust than other model fitting criterion for Bayesian analysis (Gelman, et al., 2013; Wanatabe, 2010). Comparison of WAIC values (see Table 2) suggests the heteroskedastic multilevel random parameters model with heterogeneity in variance performs better than the conventional random parameters model. More importantly, the former provides further insights with the same set of available variables in the data as we will discuss in section 4.2. Therefore, our discussions will focus primarily on the results of the heterogeneity in variance model. With respect to model adequacy, an adjusted R^2 of 0.73, which was obtained based on a simple fixed effects model, indicates that the variables in our model can capture most of the variability in bicycle commuting rates satisfactorily. This value would be even higher when more complex models, which improved the fit significantly, are employed here. Note that to account for spatial dependencies in the data (specifically, neighbourhood effects), we also developed Bayesian conditional autoregressive models; however, a multilevel approach provided a much better fit to the data. We considered other distribution functions such as lognormal instead of the normal density for random parameters; however, this did not improve the fit.

5.1. Correlates of bicycle commuting

The parameter estimates for the statistically important variables for both models are reported in Table 2. As parameters were estimated using Bayesian analysis we have obtained and reported credible intervals.

Table 2
Estimated regression parameters.

Multilevel random parameters model	Mean	SD	95% Credible Intervals	
Employment rate	0.804	0.377	0.060	1.543
Population with no qualifications	−0.034	0.004	−0.042	−0.026
Population of white British (000s)	0.029	0.012	0.005	0.053
Terraced houses	0.003	0.001	0.001	0.006
ln (area of non-domestic buildings)	−0.052	0.018	−0.087	−0.016
ln (cycle network density)	0.462	0.179	0.106	0.805
Population of Indian and Pakistani (000s)	−0.214	0.057	−0.333	−0.108
Variance Population of Indian and Pakistani (000s)	0.058	0.028	0.021	0.127
Population of mixed white and black Caribbean (000s)	0.934	0.391	0.173	1.724
Variance Population of mixed white and black Caribbean (000s)	0.058	0.028	0.021	0.127
Cars per household	−0.870	0.143	−1.152	−0.589
Variance cars per household	0.400	0.168	0.158	0.804
Borough effect	−3.650	0.095	−3.836	−3.464
Variance borough effect	0.240	0.082	0.122	0.435
Bayesian model fit (WAIC)	80.700			
Heteroskedastic multilevel random parameters model with heterogeneity in variance				
Employment rate	0.791	0.379	0.054	1.529
Population with no qualifications	−0.034	0.004	−0.042	−0.026
Population of white British (000s)	0.033	0.013	0.008	0.058
Terraced houses	0.003	0.001	0.001	0.006
ln (area of non-domestic buildings)	−0.054	0.018	−0.090	−0.018
ln (cycle network density)	0.459	0.190	0.070	0.823
Population of Indian and Pakistani (000s)	−0.217	0.058	−0.336	−0.110
Variance Population of Indian and Pakistani (000s)	0.062	0.028	0.024	0.131
Population of mixed white and black Caribbean (000s)	0.916	0.387	0.160	1.687
Variance Population of mixed white and black Caribbean (000s)	2.991	1.212	1.261	5.958
Cars per household	−0.881	0.146	−1.170	−0.592
Variance cars per household	0.410	0.174	0.161	0.829
Borough effect	−3.655	0.096	−3.844	−3.463
Variance borough effect	0.249	0.084	0.128	0.452
Varying variances				
Constant	0.054	0.004	0.046	0.062
Inner London	0.010	0.007	0.000	0.026
Cars per household	0.030	0.015	0.004	0.060
Bayesian model fit (WAIC)	78.260			

These are analogous to frequentist confidence intervals but with a more intuitive interpretation; that is, a 95% credible interval indicates that an estimated coefficient has a 95% chance of being within the given interval. It's notable that both models identified the same significant explanatory variables with more or less similar coefficient estimates. Employment rate, the populations of white British and mixed white and black Caribbean, the proportion of terraced houses and cycle network density all have an increasing effect on the level of bicycle commuting across Greater London. Lack of academic qualifications, the area of non-domestic buildings, the population of Indians and Pakistanis and the number of cars per household all have a decreasing effect on the level of bicycle commuting. We found that the effects of the populations of Indians, Pakistanis, and mixed white and black Caribbean, and the number of cars per household all vary across Greater London boroughs, suggesting that other unmeasured or unknown factors influence the effects of these variables on bicycle commuting. The latter finding together with the varying borough effects indicate that there are between-borough differences in the level of bicycle commuting due to currently unobserved borough-level factors (such as the collective attitude towards cycling), which have been indirectly captured by our hierarchical model structure.

5.2. Implications of the heterogeneity in variance specification

When allowing for heterogeneity in variance, in our heteroskedastic model, we found that the varying variances can be explained by the variables Inner London and cars per household. Here, the variance in the level of bicycle commuting (logit transformed outcome) for wards in Inner London boroughs increases by a factor of 0.01 compared to Outer London boroughs. Also, the ward-level number of cars per household is positively associated with the variance of ward-level bicycle commuting rates. This implies that the rates of bicycle commuting are more dispersed in Inner London and as the number of cars per household increases. This important finding implies that other factors may play role here, specifically in Inner London and with respect to car ownership so that, for example, as car ownership increases the uptake of cycling to work as a mode of travel becomes more uncertain. As illustrated in Fig. 1, levels of bicycle commuting throughout wards in Outer London boroughs are more consistently lower than those in Inner London, and bicycle commuting in wards in Inner London is generally higher but varies more significantly. Conversely, bicycle commuting is consistently high amongst low- or no-car households and varies more greatly as the number of cars increases.

6. Discussion

6.1. Interpretation of the estimated regression coefficients

For the interpretation of the effects of explanatory variables on bicycle commuting across Greater London, given the form of the model, we calculated odds ratios (see Table 3). These are based on the results of the heterogeneity in variance model that provided the best fit to the data as previously discussed. Odds ratios have been calculated by exponentiating the mean parameter estimates, describing the relationship between the odds of bicycle commuting and a given independent variable. Odds ratios can be interpreted using: *(OR – 1) x 100*, which tells us the expected percent change in the odds of bicycle commuting resulting from a 1-unit change in a given independent variable. These values are more easily translatable and are reported in the third column of Table 3.

From the odds ratios presented in Table 3, we can also understand and compare the magnitude of the effects of the identified predictors. Overall, we found the population of mixed white and black Caribbean to have the greatest increasing effect on bicycle commuting: across all boroughs a one-unit increase in the population of mixed white and black Caribbean (in 000s) is expected to result in a 150% increase in the odds of commuting by bicycle. Note that this is derived from the mean parameter estimated across all boroughs; as previously mentioned, the effect of the population of mixed white and black Caribbean varied between boroughs. Interestingly, this finding seems to contradict the majority of the extant literature, where generally non-white ethnic groups are considered less likely to cycle to work than whites (Parkin, et al., 2008; Martin et al., 2021). However, it seems previous research does not consider such granular ethnic grouping and instead uses more general classifications, and it may be that this particular relationship has not yet been investigated. We also found employment rate to have a significant increasing effect: a one unit increase in the rate of employment is expected to result in a 120% increase in the odds of bicycle commuting. The findings of previous studies on the effect of employment rate are somewhat mixed, but our findings arguably correlate with those of Brainard et al. (2019), that individuals in full-time employment are more likely to cycle to work (and for other utility purposes). The other predictors we found to have increasing effects on bicycle commuting were ln (cycle network density), the population of white British (in 000s) and the percentage of terraced houses, for which a one-unit increase is expected to result in increases of 58%, 3.3% and 0.34% in the odds of bicycle commuting respectively. The increasing effects identified for cycle network density and the population of white British both align with the findings of previous research (Dill and Carr, 2003; Krizek and Johnson, 2007; Parkin et al., 2008; Martin et al., 2021). However, we were unable to find any studies considering the effect of terraced housing in the extant literature suggesting this may be the first to identify it as a significant predictor.

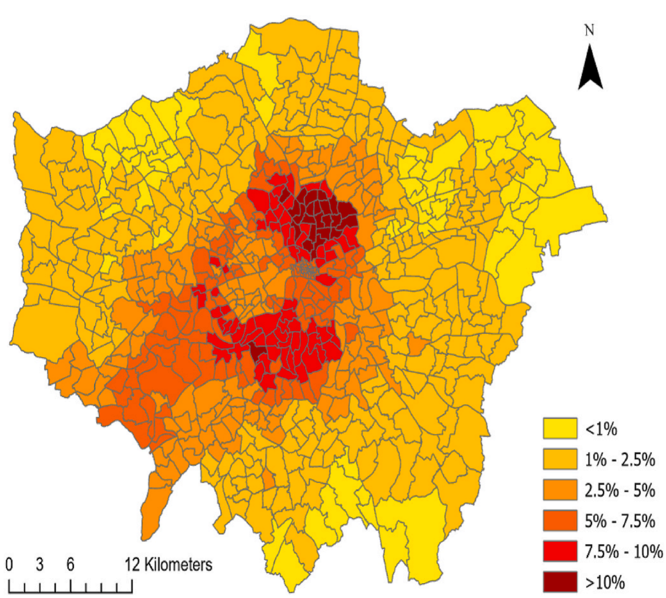


Fig. 1. Spatial distribution of predicted bicycle commuting rates across Greater London wards.

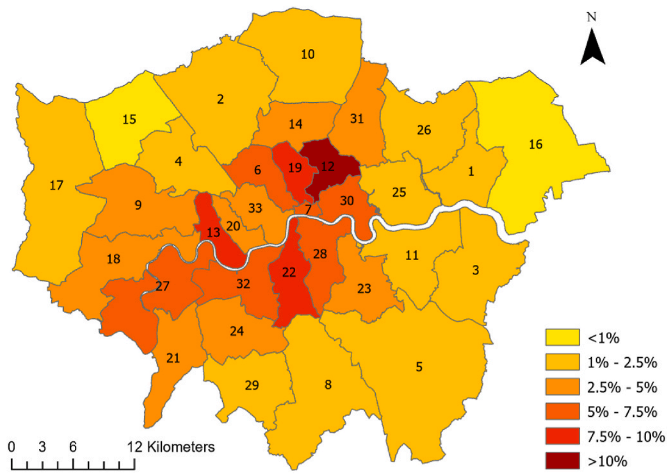
Table 3
Estimated odds ratios of independent variables.

Variable	Odds ratio	% Change in odds
Population of mixed white and black Caribbean (000s)	2.498	149.827
Employment rate	2.205	120.472
ln (cycle network density)	1.583	58.312
Population of white British (000s)	1.033	3.324
Terraced houses	1.003	0.341
Population with no qualifications	0.967	−3.314
ln (area of non-domestic buildings)	0.948	−5.228
Population of Indian and Pakistani (000s)	0.805	−19.507
Cars per household	0.414	−58.563

We found the number of cars per household to have the greatest decreasing effect on bicycle commuting: across all boroughs, a one-unit increase in the average number of cars per household is expected to result in a 59% decrease in the odds of bicycle commuting. Both Parkin et al. (2008) and Cervero et al. (2019) also found higher levels of car ownership to be correlated with a reduction in bicycle commuting. We found that one-unit increase in the population of Indian and Pakistani (in 000s) and the percentage of the population with no qualifications decreases the odds of bicycle commuting by 19.5% and 3.3%, respectively. Both findings agree with those of previous studies (Parkin, et al., 2008; Martin et al., 2021; Song et al., 2013; Solomon et al., 2013; Adams, 2021). We also found that a one-unit increase in ln (area of non-domestic buildings) is expected to reduce the odds of bicycle commuting by 5.2%; again, we were unable to find any studies considering the effect of non-domestic buildings in the extant literature suggesting this may be the first to identify it as a significant predictor.

6.2. Spatial variation of the estimated levels of bicycle commuting

Figs. 1 and 2 show the spatial distribution of predicted (model based) bicycle commuting percentages across Greater London wards and boroughs, respectively. A darker colour indicates a higher incidence of



1. Barking and Dagenham
2. Barnet
3. Bexley
4. Brent
5. Bromley
6. Camden
7. City of London
8. Croydon
9. Ealing
10. Enfield
11. Greenwich
12. Hackney
13. Hammersmith and Fulham
14. Haringey
15. Harrow
16. Havering
17. Hillingdon
18. Hounslow
19. Islington
20. Kensington and Chelsea
21. Kingston upon Thames
22. Lambeth
23. Lewisham
24. Merton
25. Newham
26. Redbridge
27. Richmond upon Thames
28. Southwark
29. Sutton
30. Tower Hamlets
31. Waltham Forest
32. Wandsworth
33. Westminster

Fig. 2. Spatial distribution of predicted bicycle commuting rates across Greater London boroughs.

bicycle commuting. Figs. 1 and 2 have important implications in terms of interventions for area level bicycle commuting planning and can be used to identify the overall spatial patterns of bicycle commuting in Greater London and identify areas of significantly low or high participation. Areas with significantly low rates of bicycle commuting can be prioritised for investment programmes and initiatives, which could be informed by the predictors identified by this study. Areas with significantly high rates of bicycle commuting could be investigated further to gain a more detailed understanding of the factors encouraging bicycle use, potentially at an individual level to try and understand any attitudinal trends, which would provide even more wisdom for planning interventions in low-participation areas.

As shown in Fig. 1, the propensity for bicycle commuting is generally higher in inner London wards. We found that Clissold, Victoria and Stoke Newington Central (all located in the borough of Hackney) had the highest predicted bicycle commuting rates, all above 16%. Kenton West and Queensbury (both in Harrow) had the lowest predicted bicycle commuting rates, followed closely by New Addington (in Croydon). The predicted bicycle commuting rate in these wards was around 0.4%. Considering Fig. 2, we found the borough of Hackney to have the highest predicted bicycle commuting rate (14%), followed by Islington (9.6%) and Lambeth (8.1%). We found the lowest predicted borough-level commuting rates in Harrow (0.8%) and Havering (0.9%), both of which are located in Outer London.

6.3. Borough level inferences and their associated uncertainties

Predicted bicycle commuting rates for individual boroughs are shown in Fig. 3, along with their respective 95% credible intervals, which illustrates how the uncertainty around levels of bike commute varies between boroughs. As shown, uncertainties are generally greater for boroughs with higher levels of bicycle commuting rates, and for boroughs located in Inner London. Since the City of London included only one observation, the estimated large variability is expected. For boroughs with a relatively large within borough variability (e.g., Hackney), where wards nested with same boroughs differ from each other more significantly, respective borough councils should conduct further in-depth investigations to identify the reasons behind this variability.

6.4. Limitations

Overall, we consider the methodology used in this study to be robust and that any inferences made are reliable. However, we do note several possible limitations, mostly surrounding the explanatory data used for analysis. Firstly, we have tried where possible to only use data for 2011 (to match that obtained for bicycle commuting) but certain land-use measures were only available for 2005. Although we believe that any land-use changes between the two data years would be insubstantial, reliability could still be improved by the use of matching data.

Secondly, we highlight that the influence of bicycle infrastructure was in terms of the density of the London Cycle Network, which comprises various infrastructure types. We recognise that one limitation of using this data is that it does not allow for differentiation between

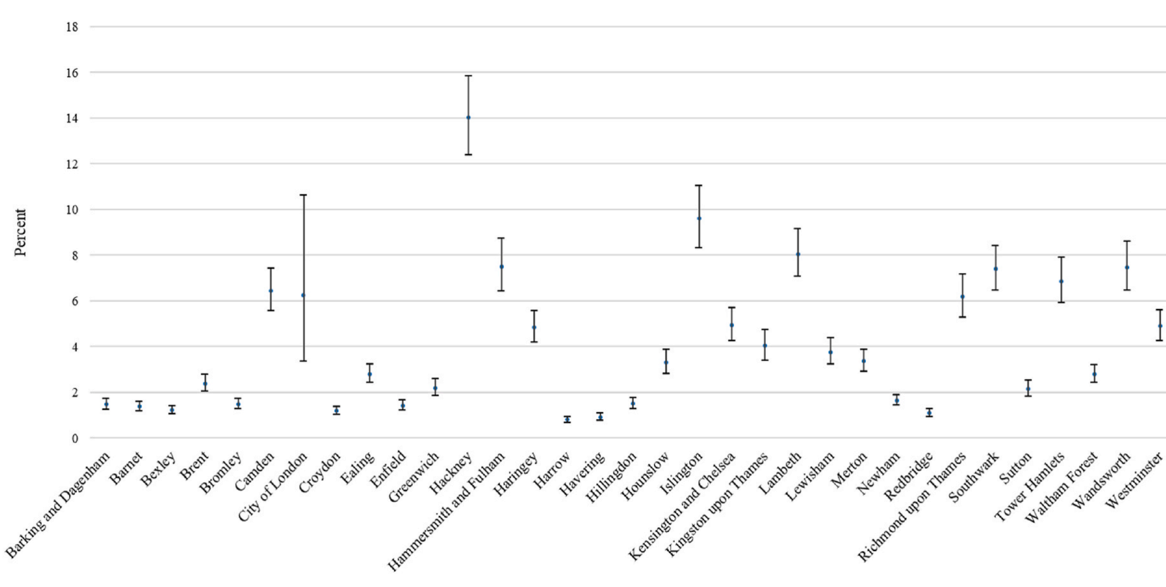


Fig. 3. Borough-level predicted bicycle commuting rates (including 95% credible intervals).

different types of bicycle infrastructure and their individual influences on bicycle commuting. Had such information been available we would have been able to conduct a more comprehensive study providing detailed insights on the influences of different bicycle infrastructure types.

Finally, we would like to highlight that this study serves as a comprehensive quantitative analysis of the association between bicycle commuting and various area-level characteristics. However, we acknowledge that there are various aspects, beyond those considered through quantitative empirical research, that should be taken into account for a holistic understanding of bicycle commuting. This study does not, for example, consider the theory behind modal choice decisions or the various aspects of velomobility, which is more often viewed from a social science perspective. Unfortunately addressing and discussing all these aspects is beyond the scope of our paper, which instead conducts a zonal-level quantitative analysis based on readily available data. For those wishing to read more on these aspects, the authors suggest: Cox (2019), Cox and Koglin (2020), Haustein et al. (2020), Henderson and Gulsrut (2019), Freundendal-Pedersen (2015a; 2015b), Koglin (2017, 2018), Koglin and Rye (2014) and Paterson (2007).

7. Conclusions and policy implications

This study used data from the 2011 census to identify the determinants of bicycle commuting throughout Greater London. Considering the hierarchical structure of the data (wards nested within London Boroughs), we employed a multilevel modelling approach that allowed us to draw borough-level inferences and account for the dependency (spatially and non-spatially) between wards nested within the same boroughs. We used a standard multilevel random parameters regression model (which allows the effects of independent variables to vary at the borough level) and a heteroskedastic multilevel random parameters model with heterogeneity in variance (which additionally allows the variance to vary as a function of explanatory variables in the data). Of these, we found the heterogeneity in variance model provided the best fit to the data.

We found that employment rate, the populations of white British and mixed white and black Caribbean, the proportion of terraced houses and cycle network density all have an increasing effect on the level of bicycle commuting across Greater London. Note that we considered cycle network density, representing cycling infrastructure, in our research, but we did not have access to bike sharing station data and their locations. Future research should investigate the extent to which bike sharing schemes affect bicycle commuting. We found that the lack of academic qualifications, the area of non-domestic buildings, the population of Indians and Pakistanis and the number of cars per household all have a decreasing effect on the level of bicycle commuting. Considering random parameters, we found that the effects of the populations of Indians, Pakistanis, and mixed white and black Caribbean, and the number of cars per household all vary across Greater London boroughs, suggesting that other unknown factors influence the effects of these variables on bicycle commuting. We identified a varying borough effect, which is indicative of between-borough differences in the level of bicycle commuting due to unobserved borough-level factors, which have been indirectly captured by the hierarchical model structure.

Of the identified significant predictors, we found the population of mixed white and black Caribbean to have the greatest increasing effect on bicycle commuting: a one-unit increase in the population of mixed white and black Caribbean (in 000s) is expected to result in a 150% increase in the odds of commuting by bicycle, averaged across all boroughs. We found the number of cars per household to have the greatest decreasing effect on bicycle commuting: a one-unit increase in the ward-level average number of cars per household is expected to result in a 59% decrease in the odds of bicycle commuting, averaged across all boroughs. In general, our findings agreed with those of previous studies. However, we identified two significant predictors that to our knowledge have not been identified by previous research: the ward-level percentage of terraced houses and the ward-level area of non-domestic buildings, which had increasing and decreasing effects on the odds of bicycle commuting, respectively. When allowing for heterogeneity in variance, we found that the varying variances could be explained by the variables Inner London and cars per household. Overall, we found that the level of bicycle commuting throughout wards in Inner London is generally higher than Outer London, but it varies more significantly. Conversely, bicycle commuting is consistently high amongst low- or no-car households and varies more greatly as the number of cars per household increases.

The results of our study provide useful insights on the magnitude of the impact of several variables on bicycle commuting. Of those identified as significant, the effects of cycle network density, a lack of academic qualifications and vehicle ownership are perhaps the most useful for deriving direct policy recommendations. Here, we considered the density of the London Cycle Network, which comprised a collection of connected, signposted cycle routes, utilising a mixture of segregated cycle paths, painted cycle lanes and 'cycle friendly' streets. Although debate continues over the 'type' of cycling infrastructure that should be provided, our findings suggest that Local Authorities must also place focus on developing proper cycling route networks, where connectivity and coherence are key to encouraging use. UK policy initiatives such as Gear Change: A bold vision for walking and cycling (Department for Transport, 2020) and the Cycling and Walking Investment Strategy (Department for Transport, 2017) also emphasise the importance of creating well-connected and well-thought-out cycle networks.

The influence of academia is also noteworthy. Exposure to higher education can often promote a greater awareness and appreciation of the environmental and personal health benefits of bicycle travel. In this case bicycle use is considered a voluntary lifestyle choice, whereas amongst those with lower education if is often seen as a forced behaviour symptomatic of a lack of wealth (Hudde, 2022). Our findings show that bicycle use is lower amongst those with no qualifications, and Local Authorities looking to employ education as a tool to increase bicycle use should aim to encourage academic participation. It is also essential to educate children on the impacts of different travel modes from a young age, while school attendance is still compulsory. UK policy places an importance on delivering initiatives targeted at increasing active travel among school children, such as 'bikeability' training and 'school streets' (see: Department for Transport for London (2020, 2021)). However, these initiatives have had mixed success (Goodman, et al., 2016) suggesting a holistic approach is required to embed active travel practices through the education system.

Reducing car ownership is also expected to increase bicycle commuting, although it can be difficult to target this with politically acceptable strategies. Local authorities can consider a mixture of 'hard' and 'soft' interventions, such as vehicle use restrictions and educational initiatives. Although interventions to reduce car ownership and use have previously faced resistance from motorists, (for example, considering reactions to London's expansion of the Ultra-Low Emission Zone and Oxford's '15-minute city' plans) there is still an enduring need for their implementation, particularly in light of the weak impact of educational approaches. To help mitigate the disruption of any system-oriented intervention local authorities should consider two aspects: 1). the provision of convenient alternative travel options so that the need for driving is minimised, and 2). where alternatives exist and are underutilised, how best to encourage, rather than force, behavioural change. Car ownership may also be a product of the built environment; our data revealed that ownership is typically higher in Outer London wards with lower population densities, which often have less accessible public transport and cycling infrastructure. In the longer-term, local development plans should consider how the accessibility of cycling infrastructure and public transport, and the concentration and distribution of different building types, can influence bicycle commuting. The UK's

National Planning Policy Framework (NPPF) (Ministry of Housing, 2021), which sets out planning policies for England, emphasises that opportunities to promote walking and cycling should be considered from the earliest stages of development proposals, and supports land-use layouts that encourage the use of these modes.

Our findings also suggest that bicycle commuting will be higher in more densely populated residential areas, and planners may wish to establish districts where buildings of a similar use are conglomerated. To an extent this supports the multicentric model for urban development, whereby the city is comprised of several self-contained centres within which all necessities are walkable/cyclable, and centres are connected by efficient sustainable transport corridors. The concept of this type of urban development is already gaining momentum in the UK, with Oxford Council pioneering plans for a "15-minute" city (Oxford City Council, 2022), and other local authorities likely to adopt similar strategies in the near future.

Collectively, the findings of this study have enabled us to identify areas of particularly low (and particularly high) bicycle commuting, with additional insight into the factors associated with any resistance to adoption. Ultimately, this will help planners and policy setters to decide where to allocate investment, and where increases in bicycle commuting will be most (or least) easily won.

Author statement

Conceptualization Shahram Heydari.
Methodology Shahram Heydari.
Software Samuel McCreery-Phillips, Shahram Heydari.
Validation Samuel McCreery-Phillips, Shahram Heydari.
Formal analysis Samuel McCreery-Phillips, Shahram Heydari.
Investigation Samuel McCreery-Phillips, Shahram Heydari.
Data Curation Samuel McCreery-Phillips, Shahram Heydari.
Writing - Original Draft Samuel McCreery-Phillips, Shahram Heydari.
Writing - Review & Editing Samuel McCreery-Phillips, Shahram Heydari.
Visualization Samuel McCreery-Phillips, Shahram Heydari.
Supervision Shahram Heydari.
Project administration Shahram Heydari.

Data availability

The data is publicly available and sources are clearly stated.

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