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Multimodality and CO_2 emissions: a relationship moderated by distance

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Highlights

- This paper tests the relationship between multimodality and CO_2 emissions
- Multimodal trips are less polluting than unimodal trips, if controlled for distance
- More-multimodal persons have lower emissions, notably if controlled for distance
- Multimodality is only weakly associated with CO_2 emissions
- Trip distance contributes more to CO_2 emissions than the level of multimodality

Keywords: emissions, CO_2, mobility styles, multimodality, intermodality, distance

Abstract

Encouraging multimodality as a tool to reduce exclusive car use is seen as a key ingredient of transport policies aimed at reducing greenhouse gases emissions, such as CO_2. These policies are based on the assumption that increasing multimodality will contribute to a reduction in emissions. Yet, hardly any scientific attention has been paid to the empirical relationship between multimodality and CO_2 emissions. This article addresses this unexplored question at both the individual and trip level using the English National Travel Survey. We find that the level of multimodality is only weakly associated with CO_2 emissions. It is only when controlling for levels of travel activity (trip frequency, total distance travelled) that a moderate association in the expected direction is observed (i.e. that higher levels of multimodality correspond with lower CO_2 emissions). This suggests that greater levels of travel activity among multimodals tend to offset the benefits derived from their more diverse modal choices. Similar patterns emerge from the trip-level analyses: higher emissions are found for (the typically longer) multimodal trips compared to unimodal trips, even when the only mode used is the car. However, for trips over similar distances, multimodal trips do have lower emissions. While there is merit in encouraging greater multimodality, this can hardly be the only or primary goal of climate mitigation policies in the transport sector. More attention needs to be paid to the key role of high levels of travel activity, and how these could be reduced.

1. Introduction

In the wake of the 2015 Paris Agreement, anthropogenic climate change continues to be a focus of governments throughout the world, including in Europe. The emission of greenhouse gases (GHGs), notably carbon dioxide (CO_2), in the atmosphere is the primary cause of climate change. In the EU, transport contributes to a quarter of direct GHGs, and to 20% CO_2 emissions (EC 2018a). In Great Britain, domestic transport accounts for 41% of all energy used by final users, and for 27% of all GHG emissions (DfT, 2018a). It is now the largest contributor of GHG emissions in Great Britain, as emissions from other sectors have declined since 1990, while transport emissions have flat lined (DfT, 2018a)—a development that has also been observed at the EU level (EEA, 2018).

The European Commission declared 2018 the 'year of multimodality', which in their words, reflects a commitment to reducing CO_2 (Civitas, 2018). While the EC's definition of multimodality is 'the use of different modes of transport during the same journey', in the scientific literature, the term generally refers to the use of multiple modes by individuals in a given time frame, whether as part of the same trip or for separate trips (Heinen and Mattioli, 2017)—with the term 'intermodality' sometimes used to refer more specifically to the use of multiple modes on a single trip (Oostendorp & Gebhardt, 2018; Dacko & Spalteholz, 2014). Either way, the assumption underlying the desire to increase multimodality is that by using multiple modes of transport, the use of the car may be reduced resulting in lower CO_2 emissions.

The notion of multimodality as a policy solution is well aligned with the 'behaviour change agenda' for sustainable mobility (Barr & Prillwitz, 2014) and the broader 'citizen–consumer' model of environmental policy (Akenji, 2014; Barr et al., 2011; Shove, 2010). In this framework, responsibility for changing behaviour is placed on (environmentally motivated) 'citizen–consumers', while the role of policy makers is that of 'helping people make better choices’ (Barr et al., 2011; DEFRA, 2005). This resonates with narratives of multimodality, which emphasise how sustainability can be achieved by people diversifying their modal choices, rather than through an outright reduction in levels of mobility.

Perhaps reflecting the rise of this policy agenda, as well as heightened environmental concerns, multimodality has received growing scientific attention over the past few years. Most studies have focussed on the correlates of individual-level multimodality, often based on analysis of nationally representative datasets (e.g. Buehler and Hamre 2015; Heinen and Chatterjee 2015; Susilo and Axhausen 2014; Kroesen 2015; Scheiner et al. 2016; Olafsson et al. 2016; Block-Schachter 2009). These studies show that multimodality is more prevalent among women and in areas with greater densities, and that unimodal car users are more likely male, white, full-time employees, individuals with young children, and car owners. Two studies have shown that higher level of multimodality of an individual may be associated with a higher likelihood of behavioural change. Kroesen (2015) showed that individuals who use multiple modes had a higher likelihood of changing from one multimodality group to another group over time compared to individuals who only used one mode of transport. Heinen and Ogilvie (2016) showed that individuals who were more variable before an intervention were more likely to increase their active travel (walking and cycling) mode share and decrease their car mode share in response to the intervention that aimed for this behavioural change. These findings suggest that higher levels of multimodality are desirable as they may serve as a first step towards less car-dependent and more sustainable travel behaviour.

Recent findings, however, do not corroborate the assumption that higher levels of multimodality automatically result in less car use. For example, Heinen and Mattioli (2017) showed that the average multimodality level of individuals decreased between 1995 and 2015 in England using time-series data from the National Travel Survey. This decline occurred at the same time as a significant reduction in car use. This unexpected finding challenges the conventional wisdom that multimodality levels are on an upward trend in developed countries, and that this is beneficial from a sustainable transport perspective (Kuhnimhof et al., 2012).

Two levels of the discussion must be distinguished with regard to the relationships between multimodality, car use, and CO_2 emissions. From a theoretical perspective, if a given trip (or set of trips) is partially shifted to lower-carbon modes, with a one-to-one substitution, this almost by definition results in lower CO_2 emissions (see e.g. Gebhardt et al., 2017). From a practical perspective, however, the question is rather whether providing more opportunities for multimodality (i.e. greater 'multioptionality' – Groth, 2019) would actually have the desired effect on emission reductions. There are several reasons why this may not be the case. First, higher levels of multimodality may correspond with greater mobility, which is likely associated with higher levels of overall emissions. Second, transport-related CO_2 emissions have a highly unequal distribution, with income being the most powerful predictor of emission levels (Brand & Boardman, 2008; Brand & Preston, 2010; Büchs & Schnepf, 2013). The fact that multimodality is also correlated with income (Heinen and Chatterjee, 2015) increases the complexity of the relationship between multimodality and CO_2 emissions. Third, more broadly, history suggests that innovations in the transport sector (e.g. the provision of new transport modes, infrastructure, and information and communication technology) often defy initial expectations of one-to-one substitution, and result in more complex transformations in travel behaviour (Mokhtarian et al., 2006; Newman & Kenworthy, 1999). It is thus conceivable that a push towards multimodality may have similar unexpected implications.

While these questions are to some extent speculative, our argument is that debates on multimodality would benefit from moving beyond 'one-to-one substitution' assumptions, to investigate whether, in practice, more multimodal travel patterns are associated with lower emissions. This paper will investigate this relationship, which has received surprisingly little scientific attention to date. We will test this for both the individual and trip level, following the two definitions and lines of research. The investigation on an individual level contributes to an understanding whether multimodal travel patterns are linked to lower levels of CO_2 emissions (regardless of whether they include multimodal trips). The investigation on a trip level contributes to an understanding whether multimodal trips are indeed less polluting (regardless of the overall travel patterns of the individuals undertaking them).

Existing research closely related to our aim, shows conflicting results. Reichert and Holz-Rau (2018), using a regression analysis of travel diary data from the German travel survey, show that multimodal travellers have greater climate impact than unimodal car users, even after controlling for confounding factors. However, this analysis was limited to large cities, and higher carbon-equivalent emissions for multimodals were entirely due to greater long-distance travel, particularly flights which have much greater climate impact than other modes. If these trips were excluded, multimodals had lower emissions than unimodal car users. Other studies, focussed more broadly on ‘modality styles’, have found suggestive evidence that clusters of individuals with multimodal travel behaviour have lower emissions than those characterised by regular car use. Circella et al. (2019) used latent-class cluster analysis on two questions regarding the frequency of using various transport modes—one for commuting and the second for all other trips—of millennials in California, to identify four groups (driving a private vehicle; carpooling; riding public transit; and active modes). They then linked these groups to annual travel-related emissions. Keskisaari et al. (2017) used a latent class choice model on a one-day transport survey of the Helsinki Region Transport. The seven identified modality style groups showed varying greenhouse gas emissions.

Given the current policy focus on increasing multimodality as one of the strategies to reduce GHGs, and the limited and conflicting scientific evidence, it is essential to investigate this relationship in more depth. This paper will explore the relationship between the level of multimodality—both on an individual and trip level—and associated tailpipe CO_2 emissions of over-land travel. It uses the English National Travel Survey (NTS) data, a representative national dataset, which is uniquely suited for the accurate assessment of both multimodality and CO_2 emissions, given the availability of a seven-day travel survey and detailed information on household vehicle emission factors.

2. Method

2.1. Data

To investigate the relationship between multimodality and CO_2, data on individual travel behaviour is required, preferably collected over multiple days to measure both variables of interest accurately. The NTS was designed to provide a representative sample of households in England and was based on a stratified two-stage random probability sample of private households. The sampling frame was a Postcode Address File, a list of all addresses in England (NatCen, 2016). The NTS was first conducted in 1965/66 (Rofique et al. 2011) and has been conducted every year since 1988.

We used the 2015 NTS of England. The NTS 2015 sample consists of 18,071 individuals in 7,564 households. Data collection began on 1st January 2015 and lasted until 1st March 2016. An incentive of a £5 gift voucher was offered to each person if all household members completed every section of the survey and six first-class stamps were offered as an unconditional incentive (NatCen, 2016). To recruit participants, households received an advance letter with background of the survey. After this letter, a personal visit was made to schedule an interview.

The NTS consists of four data collection parts: a household questionnaire, individual questionnaire, vehicle questionnaire, and travel survey. The first three were completed in the household interview. The interviews were conducted with all household members and normally took place before the data collection on travel. Each household member was requested to fill in a seven-day travel diary. Within six days of the end of diary week, the diaries were collected and checked. The diaries only collected information on trips within Great Britain. Trips to other places are included only up to the ticket control point at the transport mode going abroad is boarded. This means that international travel (including flights abroad) is not recorded. The overall response rate in 2015 was 61%, but lower in London (43%-56%) compared to the rest of the country (62%) (NatCen, 2016).

The NTS includes several weights (NatCen, 2016): weights for the selection of the dwelling unit and/or household at the sampled address; weights for household-level non-participation; weights for the exclusion of participating household at which not every individual completed the interview; composite weights for selection and participation with the interview survey; weighting of the trips in the travel diary to account for drop-off in recording observed; and weighting for short walking trips (i.e. walking trips of less than one mile only recorded for one day of the travel week).

2.2 Measurement of CO_2 emissions

CO_2 emissions were calculated using the NTS diary week in combination with information on vehicle characteristics, and transport mode emission factors provided by the UK government. We calculated CO_2 emissions for each trip (adding up the emissions for each stage) and individual (adding up the emissions of all stages in the travel diary week). All

$kgCO_2$/km emission factors were derived from two sources. First, the 2015 wave of the NTS provides unique emission factors for most household vehicles (73% in the analysis sample). These were derived from the data provider by matching household vehicle registration plates provided by respondents to a register held by the Driver & Vehicle Licensing Agency (DVLA). For most remaining household vehicles, we imputed values based on an OLS model with four predictors (type of vehicle, engine capacity, type of fuel, and vehicle age), selected based on the demonstrated association with CO_2 emissions (Cuenot, 2009; Fontaras & Samaras, 2007; Zachariadis, 2006). The model yielded very good predictive power (R^2=0.79—model results not reported here for the sake of brevity). The OLS model and subsequent imputation was conducted only for four-wheel cars, land rovers, and jeeps, as these vehicle types had less than 50% missing values on the emission factor variable[1] (and accounted for over 92% of vehicles in our dataset). For other vehicle types (motorcycles and scooters, mopeds, light vans, other vans and lorries, minibuses, motor caravans, and dormobiles), more than 50% of cases had missing information on CO_2 factors. We therefore avoided imputation and derived CO_2 factors from government emission factors, as described below.

Second, for household vehicles with missing data, non-household vehicles (for which vehicle information is not available), and all other motorised transport modes, we derived emission factors from the 'UK Government conversion factors for Company Reporting' (DECC, 2015) (Table 1). This is consistent with previous emission studies based on the NTS (Mattioli & Anable, 2017; Preston et al., 2013). All walking and cycling stages were allocated zero direct CO_2 emissions.

Table 1 – Lookup table between NTS travel mode classification and UK government CO_2 emission factors

NTS 'stage mode' variable label	UK Government emission factors

[1] We attributed a zero-emission factor to small, recent alternative fuel cars with negative predicted values (n=4).

	Label	$kgCO_2/km$	Type
Private (hire) bus	Coach	0.02870	Passenger.km
Household car (driver or passenger)*; Non-household car (driver or passenger)	Average car, fuel unknown	0.18529	Vehicle.km
Household motorcycle (driver or passenger)*; Non-household motorcycle (driver or passenger)	Average motorbike	0.11666	Vehicle.km
Household van/lorry (driver or passenger)*; Non-household van/lorry (driver or passenger)	Average van, fuel unknown	0.39683	Vehicle.km
Other private transport*	Average car, fuel unknown	0.18529	Vehicle.km
London stage bus	Local London bus	0.07861	Passenger.km
Other stage bus	Local bus (not London)	0.10788	Passenger.km
Public express bus/coach; Excursion/tour bus	Coach	0.0287	Passenger.km
London Underground	London Underground	0.05586	Passenger.km
Surface Rail	National rail	0.04480	Passenger.km
Light rail	Light rail and tram	0.05417	Passenger.km
Air	Flights, domestic to/from UK	0.29636	Passenger.km
Taxi	Regular taxi	0.17355	Passenger.km
Other public transport	Average local bus	0.09949	Passenger.km

* denotes modes for which Government emission factors were used only when the CO_2 emission factor was missing from the NTS dataset and could not be imputed.

All emission factors derived from the NTS dataset, and some of those derived from the UK government dataset (Table 1) were on a vehicle-km basis and must therefore be allocated to passengers. Since our analysis focussed on the adult population alone (minors were excluded because of their limited access to some modes of transport), our preferred solution would have been to share emissions equally among adult passengers, since they collectively bear the responsibility for each trip. However, this was impossible, as the NTS provides information on the total number of passengers (regardless of age) only, which does not allow us to distinguish between adult and minor passengers for any given trip. We therefore conducted our analysis using two alternative measurements. Our first and main measure of CO_2 emissions (CO_2(a)) attributes all vehicle emissions to the driver, and none to passengers. For the second measure (CO_2(b)), total vehicle emissions were divided by the total number of vehicle occupants, independent of their age (i.e. driver and passengers were allocated the same emissions). Both methods have limitations: CO_2(a) leads to an underestimation of the emissions of individuals, for example, who travel often as car passengers, whereas CO_2(b) entails a ‘leakage’ of emissions, as some emissions are attributed to minors, which are not included in our analysis. This can lead to an underestimation of emissions, e.g. for adults who often travel by car with children. However, the two calculated measures highly correlated on individual-level (R=0.92) and trip-level measurements (R=0.87). We conducted most of our analysis using both measures, although our findings were robust using either (unless otherwise mentioned).

Since our analysis focusses on the relationship between travel behaviour and resulting CO_2 emissions, and not on vehicle purchase behaviour, the calculation considered tailpipe emissions only, although we acknowledge that these account for only part of total life-cycle GHG (Chester & Horvath, 2009).

2.3 Measurement of multimodality

We constructed two types of multimodality measures: on an individual level and on a trip level. For individual-level calculations, we followed previous studies on multimodality using the NTS data to prepare the data for the analyses (Heinen and Chatterjee, 2015; Heinen and Mattioli, 2017). The first step made use of the ‘stages file’ in the NTS. We ascertained the number of stages in total and by mode of transport applying weighting for short walks and drop-offs in reporting for eight categories of transport mode (NTS weight: SSXSC (short walk weight) and W5xHH (‘Trip/stage weight excluding household weight’) (NatCen, 2016; DfT, 2016). Walking trips of less than one mile in distance are only recorded for one day. Therefore, SSXSC is applied to ensure a representative weekly record of short walking trips. We applied W5xHH to generate representative trip rates, excluding household weight, which is applied later in our analysis. We considered two mode categorisations. The first considered only three modes of transport: car transport (car driver and car passenger), active travel (walking and cycling), and public transport (bus, rail, taxi, and other). The second considered eight modes of transport: walking, cycling, car driver, car passenger, bus, rail, taxi, and other (motorcycling and other private and public transport). The second step entailed combining this information with the individual file in NTS. In the third step, we calculated various indicators of multimodality for each individual. We adjusted for non-response, probability of selection, and to reproduce sample population characteristics applying weighting available in NTS (NTS weight: W2 ('Diary sample household weight')), which adjusts for non-response and should be applied to all analysis of the diary sample at household, individual and vehicle level.

To investigate the relationship between multimodality and associated CO_2 emissions, we used continuous indicators of individual transport mode variability. We explored various indicators based on existing studies on multimodality given that no single indicator outperforms all others (e.g. Diana and Pirra 2015; Heinen and Chatterjee 2015; Heinen and Mattioli 2017). We considered indicators that were demonstrated to have mathematically superior quality to measure multimodality, were widely used, or relatively easy to interpret (e.g. Diana and Pirra 2015; Heinen and Chatterjee 2015; Susilo and Axhausen 2014; Streit et al., 2015), the formulae can be found in the papers described below and Appendix 1 (Table 2 presents basic statistics):

- The number of modes used (Heinen and Mattioli, 2017);
- The difference in percentage of use between primary and secondary modes (Heinen and Chatterjee 2015);
- The Herfindahl–Hirschman index (HHI) as applied by Heinen and Chatterjee (2015), and a variant, HHm, based on Diana and Pirra (2016); An index based on the Shannon entropy, based on Diana and Pirra (2016) OM_PI;

- The Dalton index, based on Diana and Pirra (2016) DALm. Following Diana and Pirra (2016), we set ε at 0.5 in order to maximise the sensitivity of the index (p.785);
- The multimodal indicator (MM), based on Streit et al. (2015).

Of the indicators listed above, three are indicators of variability (i.e. with higher values indicating greater multimodality): number of modes, Shannon entropy, and MM; the other indicators measure concentration (i.e. higher values indicate less multimodality): The difference between primary and secondary mode, the Herfindahl–Hirschman index, and the Dalton index.

Table 2 – Descriptive statistics for individual level multimodality indicators, and share of multimodal individuals (N=11,918)

Multimodality indicator		Min	Max	Median	Mean	Standard deviation	Share of unimodal individuals
Multimodality based on 3 modes	No. of modes	1.00	3.00	2.00	1.71	0.73	45.03%
	OM_PI	0.00	1.00	0.28	0.31	0.32	
	MM	1.00	9.00	2.21	2.37	1.57	
	HHI	0.00	1.00	0.75	0.68	0.33	
	HHm	0.33	3.00	1.25	1.81	1.10	
	Difference primary-secondary	0.00	1.00	0.82	0.69	0.34	
	DALm	0.00	0.67	0.41	0.45	0.22	
Multimodality based on 8 modes	No. of modes	1.00	7.00	2.00	2.17	1.07	31.60%
	OM_PI	0.00	0.83	0.26	0.24	0.20	
	MM	1.00	22.98	2.64	3.39	2.65	
	HHI	0.10	1.00	0.63	0.66	0.28	
	HHm	0.24	8.00	2.53	3.84	2.92	
	Difference primary-secondary	0.00	1.00	0.63	0.60	0.35	
	DALm	0.18	0.88	0.76	0.75	0.12	

For the calculation of trip-level multimodality (also sometimes referred to as ‘intermodality’) we also used the ‘stages file’ in the NTS. Here, we adopted a simple categorical indicator, classifying trips into two groups: whether a trip consisted of multiple stages with more than one mode (multimodal trips), or was made by only one mode (unimodal trips). In these analyses, we applied trip-level weighting (NTS weight: W5).

We calculated all individual-level and trip-level multimodality indicators considering both three and eight modes, similar to other studies on the NTS data (Heinen and Chatterjee, 2015; Heinen and Mattioli, 2017).

2.4 Analysis

We investigated the relationship between the level of multimodality and the associated CO_2 emissions on two levels: the individual and the trip.

2.4.1 Individual level analysis

We conducted all individual-level analyses on all adults (≥16) in NTS with a complete travel diary and who reported at least one trip. We excluded 19 individuals who had one or more stages by plane for two reasons. First, trips including plane stages have a disproportionately large carbon footprint, while also typically being multimodal (due to access and egress travel to/from airports), and this might have skewed our analysis. Second, the NTS does not capture all travel, as it excludes travel outside of Great Britain (including international flights). It would be misleading to include domestic flights while excluding international flights, which in the UK account for the majority of air travel. As a form of sensitivity testing, we conducted our analyses on a sample including those 19 individuals, obtaining similar results (unless otherwise noted). Note that, while we exclude air travel, we include other forms of long-distance travel (over 50 miles) reported in the 7-day travel diary in our analysis, and analyse these jointly with other trips. To explore whether the findings are robust to the exclusion of long-distance travel, as other research has suggested (Reichert & Holz-Rau, 2018), we stratify our correlation analysis by travel distance bands, as discussed below.

The first step in the individual level analyses was to determine the Spearman's rank correlation between the seven indicators of multimodality and the two measures of CO_2 emissions. We conducted these analyses on the entire sample, as well as only multimodal individuals (i.e. those who used more than one mode in the survey week). The reason this sensitivity testing is necessary is due to the fact that the sample includes a large share of unimodal individuals (see Table 2). By definition, these will have varying levels of CO_2 emissions, but they all have the same value on the multimodality metrics (i.e. the min or max value, depending on the indicator). This fact could, in and of itself, result in lower estimated correlation, even in presence of a correlation between multimodality and CO_2 among the rest of the sample. To test if this was the case, we repeated the analyses excluding unimodal individuals.

Second, we determined similar Spearman's rank correlations, but now stratified by established predictors of multimodality as well as CO_2 emissions. For the sake of brevity, here we use only two multimodality indicators (HHI and OM_PI). These were chosen as the Hirfindel–Hirschman index (HHI) is one of the most commonly applied measures of mode choice variability (Heinen and Chatterjee, 2015, Susilo and Axhausen, 2014, Scheiner et al., 2016), and OM_PI is appropriate when considering a set number of travel means, independent on whether an individual has access to it (Diana & Pirra, 2016). This selection was only made after assessing that the first set of correlations showed fairly similar results. This stratification analyses was conducted to detect potential confounding, as we know from existing studies, that the level of multimodality is associated with socioeconomic characteristics such as income (Susilo and Axhausen 2014; Heinen and Chatterjee 2015; Heinen and Mattioli, 2017). Moreover, the level of multimodality is related to the number of stages (i.e. if an individual report more stages in their travel diary they have higher chances to be more multimodal). In addition, income and distance also are positively correlated with CO_2 emissions and could therefore confound the relationship between multimodality and CO_2 emissions. As such, the second step of the analysis was to explore the correlation between the multimodality indicators with the two calculated CO_2 emissions stratified by (1) income and two weekly travel characteristics: (2) number of stages and (3) total distance travelled.

Third, we estimated the contribution of the level of multimodality to CO_2 emissions in linear regression models. Given the similarity in the correlation of indicators (see results step 1), we only estimated models with HHI calculated considering three modes as an independent variable, given that it is the most commonly applied measure of multimodality. We step-wise adjusted: (Model 1 (M1)) only the multimodality indicator; (M2) the multimodality indicator and socio-economic characteristics; and (M3—Maximally adjusted model) similar to step 2, but including spatial characteristics. This allowed us to test the 'stability' of the association between multimodality and CO_2 emissions, and detect potential confounders and effect modifiers. Moreover, we conducted several sensitivity analyses. We estimated maximally adjusted model (step 3) (sensitivity test 1 (s1)) including number of stages, (s2) including the total distance travelled (without number of stages), and (s3) with CO_2(b) as dependent variable. We also conducted sensitivity tests with OM_PI as a multimodality measure, with the eight-mode multimodality measure (HHI—8 modes), and including flight (these are unreported). Moreover, we repeated the analyses stratified by whether car use was part of the modal mix.

2.4.2 Trip level

The second part focussed on trip-level multimodality, corresponding with the policy aims of the EU. For these analyses, we excluded 29 trips that included air stages, for similar reasons as described above, and all trips made by individuals <16 years old. Similarly to the individual-level analysis, we test whether our findings are robust to the exclusion of long-distance trips by stratifying our analysis by travel distance bands.

We firstly explored whether multimodal trips (i.e. trips involving more than one transport mode) and unimodal trips (i.e. trips involving only one mode of transport) differ in CO_2 emissions (considering both CO_2 measures) to reveal the differences in mean and variance. For this, we created dot plots displaying mean and median values and tested with two-sample t-test whether the observed differences between means were significantly different. We repeated this exploration but stratifying by whether a car was used in the trip, and by trip distance bands.

Finally, we conducted OLS regression analyses (with CO_2(a) as the dependent variable) in which we again stepwise adjusted to investigate whether our findings held when controlling for the same covariates as in the individual-level analyses[2].

3. Results

3.1 Individual level

3.1.1 Descriptive analyses

The first step of the analysis was to determine the correlation between the indicators of multimodality and CO_2 emissions on an individual level. Table 3 shows the correlations between the different indicators of multimodality and CO_2 emissions for (1) all adults in NTS that made at least one trip, as well as (2) multimodal individuals only (i.e. those who used more than one mode in the survey week).

[2] The trips are not independent and the conditions of OLS regression are not met. We therefore do not report or discuss the final results in the main text, but present them in Appendix 2.

The results do not support the hypothesis that the level of multimodality is correlated with CO_2 emissions, as the magnitude of the association is weak and the direction uncertain. For the three-mode multimodality indicators on the entire sample, the results are mostly in the expected direction, for both CO_2 indicators: higher multimodality is associated with less CO_2 emissions. For the eight-mode multimodality indicators on the entire sample, the results are mostly counterintuitive: higher levels of multimodality are generally associated with higher levels of CO_2 emissions. The weak association together with the large sample could explain these varied results. Similarly mixed results were found for multimodal individuals only, although with lower levels of statistical significance.

Table 3 – Spearman's correlation coefficient between multimodality indices and CO_2 emissions

		All sample		Multimodal individuals only	
		CO_2 (a)	CO_2 (b)	CO_2 (a)	CO_2 (b)
Multimodality based on 3 modes	No. of modes	**-0.03**	-0.01	**0.07**	**0.10**
	OM_PI	**-0.04**	**-0.03**	-0.01	0.00
	MM	**-0.04**	**-0.02**	0.01	**0.03**
	HHI	**0.05**	**0.03**	0.02	0.01
	HHm	**0.04**	**0.02**	-0.01	**-0.03**
	Difference primary-secondary	**0.05**	**0.04**	**0.03**	**0.04**
	DALm	**0.04**	**0.02**	-0.01	**-0.03**
Multimodality based on 8 modes	No. of modes	**0.08**	**0.10**	**0.10**	**0.11**
	OM_PI	**0.02**	**0.06**	-0.02	0.01
	MM	**0.04**	**0.07**	0.01	**0.03**
	HHI	0.01	**-0.05**	**0.04**	0.01
	HHm	**-0.04**	**-0.07**	-0.01	**-0.04**
	Difference primary-secondary	0.01	**-0.02**	**0.09**	**0.06**
	DALm	**-0.04**	**-0.07**	**-0.02**	**-0.04**

In bold the coefficients with $p<0.05$ significance

For interpretation of the coefficients, it must be kept in mind that the first three multimodality indicators are variability indices (with higher values corresponding to greater multimodality), and the other five are concentration indices (with higher values corresponding to less multimodality).

CO_2 (a) is the calculation of individual CO_2 emissions, in which all vehicle emissions are attributed to the driver, and none to passengers. CO_2 (b) is the calculation of individual CO_2 emissions, in which total vehicle emissions were divided by the total number of vehicle occupants (i.e. driver and passengers were allocated the same emissions).

The second step of the analysis was to explore the correlation between multimodality indices and CO_2 emissions stratified by (1) income, (2) number of stages, and (3) total distance travelled.

Table 4 shows that the correlations between multimodality and CO_2 remain weak when stratified by income. Although correlations were mostly in the expected direction, with lower levels of multimodality associated with higher emissions, the magnitude of the correlation still remained low, although slightly stronger than for the sample as a whole. The exception here are the two lowest quintiles, were correlations are non-significant or in the opposite direction as expected (although of low magnitude). This could be explained by lower levels of car ownership and use among low-income households, whereby greater multimodality tends to result in greater car use and thus higher CO_2 emissions.

Table 4 – Spearman's correlation coefficients between multimodality indices and CO_2 emissions, stratified by household income quintiles (including descriptive statistics for stratifying variable)

			Pearson´s correlation coefficients				N	%	Mean CO_2 emissions (a) ($kgCO_2$)	Mean CO_2 emissions (b) ($kgCO_2$)
			All sample		Multimodal individuals only					
			CO_2 (a)	CO_2 (b)	CO_2 (a)	CO_2 (b)				
Income quintile 1 (bottom)	3 modes	OM_PI	0.03	0.02	**0.06**	**0.11**	2180	17.9	12.9	12.4
		HHI	-0.03	-0.02	**-0.07**	**-0.11**				
	8 modes	OM_PI	**0.14**	**0.13**	**0.07**	**0.09**				
		HHI	**-0.13**	**-0.13**	**-0.05**	**-0.08**				
Income quintile 2	3 modes	OM_PI	-0.02	0.02	-0.02	0.00	2270	18.5	16.8	16.1
		HHI	0.02	-0.01	0.03	0.01				
	8 modes	OM_PI	**0.07**	**0.11**	0.01	**0.05**				
		HHI	**-0.06**	**-0.10**	0.02	-0.02				
Income quintile 3	3 modes	OM_PI	**-0.09**	**-0.09**	**-0.08**	**0.08**	2540	21.6	23.5	21.8
		HHI	**0.09**	**0.09**	**-0.07**	**0.08**				
	8 modes	OM_PI	-0.03	-0.01	**-0.10**	**-0.07**				
		HHI	**0.04**	0.02	**0.12**	**0.09**				
Income quintile 4	3 modes	OM_PI	**-0.10**	**-0.08**	-0.05	-0.05	2439	21.2	29.3	27.4
		HHI	**0.10**	**0.08**	**0.06**	**0.06**				
	8 modes	OM_PI	**-0.08**	-0.04	**-0.05**	-0.03				
		HHI	**0.09**	**0.04**	**0.07**	0.04				
Income quintile 5 (top)	3 modes	OM_PI	**-0.04**	-0.03	0.01	0.03	2489	20.8	33.4	31.5
		HHI	**0.04**	**0.04**	-0.01	-0.02				
	8 modes	OM_PI	**-0.05**	0.00	**-0.08**	-0.04				
		HHI	**0.05**	0.00	**0.10**	**0.06**				
						Total	11918	100.0	23.7	22.3

In bold the coefficients with $p<0.05$ significance

CO_2 (a) is the calculation of individual CO_2 emissions, in which all vehicle emissions are attributed to the driver, and none to passengers. CO_2 (b) is the calculation of individual CO_2 emissions, in which total vehicle emissions were divided by the total number of vehicle occupants (i.e. driver and passengers were allocated the same emissions).

Stratification by number of stages (Table 5) revealed that for individuals with the average weekly travel behaviour in terms of stages (i.e. travelling between 10 and 30 stages in the survey week), the correlation between multimodality and CO_2 was in the expected direction and statistically significant: higher levels of multimodality were associated with lower emissions. The magnitude of the association was stronger compared to the reported correlations above, but remained weak (r_s=0.28 at best). This finding suggests that the association between multimodality and CO_2 is confounded by levels of travel activity. The weaker and more variable correlations for the lowest trip frequency category may be a result of the (statistical and theoretical) association between number of stages and multimodality whereby individuals with few reported trips may not have sufficient trips to be highly multimodal. The limited correlation between CO_2 and multimodality may be a result of the fact that multimodality is positively associated with travel activity and that travel activity is positively associated with CO_2.

Stratifying the correlations by total weekly travel distance quintiles (Table 6) yielded similar results: the correlation between multimodality and CO_2 was in the expected direction, mostly statistically significant, and of moderate magnitude (up to r_s=0.40). The magnitude of the correlations did not vary greatly between distance bands, but in the lowest quintile were weaker and in the opposite direction as expected, suggesting a different relationship between the level of multimodality and CO_2 emission for local trips, possibly related to low levels of car use in this distance range. Overall, this suggests that distance suppresses the relationship between multimodality and CO_2 as distance is strongly positively associated with both MM and CO_2. This is demonstrated by the fact that individuals in the top quintile of travelled distance emitted roughly 30 times the level of those in the lowest quintile. With the exception of the first quintile, we find similar associations across all distance categories. This suggests that our results are robust to the exclusion of individuals with long travel distances.

Table 5 - Spearman's correlation coefficients between multimodality indices and CO_2 emissions, stratified by number of stages reported in travel week diary (including descriptive statistics for stratifying variable)

			Pearson´s correlation coefficients				N	%	Mean CO_2 emissions (a) ($kgCO_2$)	Mean CO_2 emissions (b) ($kgCO_2$)
			All sample		Excluding unimodals					
			CO2 (a)	CO2 (b)	CO2 (a)	CO2 (b)				
1-10 stages	3 modes	OM_PI	**0.07**	-0.01	**-0.08**	**-0.11**	2137	18.0	7.4	8.3
		HHI	**-0.07**	0.01	**0.09**	**0.12**				
	8 modes	OM_PI	**0.22**	**0.10**	0.00	-0.05				
		HHI	**-0.22**	**-0.1**	0.01	0.06				
10-20 stages	3 modes	OM_PI	**-0.22**	**-0.21**	**-0.07**	**-0.07**	4413	37.4	22.9	22.6
		HHI	**0.22**	**0.21**	**0.07**	**0.08**				
	8 modes	OM_PI	**-0.14**	**-0.11**	**-0.05**	**-0.05**				
		HHI	**0.15**	**0.11**	**0.06**	**0.06**				
20-30 stages	3 modes	OM_PI	**-0.28**	**-0.24**	**-0.14**	**-0.11**	2876	23.8	30.7	27.9
		HHI	**0.28**	**0.24**	**0.15**	**0.12**				
	8 modes	OM_PI	**-0.24**	**-0.15**	**-0.14**	**-0.09**				
		HHI	**0.25**	**0.16**	**0.17**	**0.11**				
30 or more	3 modes	OM_PI	**-0.14**	**-0.05**	0.04	**0.11**	2492	20.8	30.9	27.4
		HHI	**0.11**	0.04	-0.08	**-0.13**				
	8 modes	OM_PI	0.04	**0.11**	-0.01	**0.09**				
		HHI	**-0.08**	**-0.13**	-0.01	**-0.1**				
						Total	11918	100.0	23.7	22.3

In bold the coefficients with $p<0.05$ significance

CO_2 (a) is the calculation of individual CO_2 emissions, in which all vehicle emissions are attributed to the driver, and none to passengers. CO_2 (b) is the calculation of individual CO_2 emissions, in which total vehicle emissions were divided by the total number of vehicle occupants (i.e. driver and passengers were allocated the same emissions).

Table 6 - Spearman's correlation coefficients between multimodality indices and CO_2 emissions, stratified by distance travelled in the diary week.

							N	%	Mean CO_2 emissions (a) ($kgCO_2$)	Mean CO_2 emissions (b) ($kgCO_2$)
			All sample		Excluding unimodals					
Distance quintiles (miles per week)			CO2 (a)	CO2 (b)	CO2 (a)	CO2 (b)				
1st (0-35)	3 modes	OM_PI	**0.15**	**0.11**	**0.16**	**0.20**	2384	20.6	2.1	2.4
		HHI	**-0.15**	**-0.11**	**-0.17**	**-0.20**				
	8 modes	OM_PI	**0.24**	**0.18**	**0.21**	**0.21**				
		HHI	**-0.24**	**-0.18**	**-0.20**	**-0.21**				
2nd (35-72)	3 modes	OM_PI	**-0.22**	**-0.23**	**-0.10**	-0.03	2384	20.2	7.3	7.7
		HHI	**0.21**	**0.22**	**0.08**	0.01				
	8 modes	OM_PI	**-0.22**	**-0.22**	**-0.12**	**-0.11**				
		HHI	**0.21**	**0.21**	**0.11**	**0.08**				
3rd (72-126)	3 modes	OM_PI	**-0.30**	**-0.28**	**-0.14**	**-0.15**	2383	19.7	15.8	15.2
		HHI	**0.30**	**0.28**	**0.14**	**0.16**				
	8 modes	OM_PI	**-0.37**	**-0.31**	**-0.26**	**-0.23**				
		HHI	**0.37**	**0.31**	**0.27**	**0.23**				
4th (126-223)	3 modes	OM_PI	**-0.28**	**-0.31**	**-0.22**	**-0.23**	2384	19.7	28.9	27.1
		HHI	**0.28**	**0.31**	**0.21**	**0.22**				
	8 modes	OM_PI	**-0.39**	**-0.34**	**-0.31**	**-0.30**				
		HHI	**0.40**	**0.34**	**0.32**	**0.30**				
5th (223+)	3 modes	OM_PI	**-0.23**	**-0.20**	**-0.12**	**-0.12**	2383	19.8	65.2	60.1
		HHI	**0.22**	**0.20**	**0.11**	**0.11**				
	8 modes	OM_PI	**-0.33**	**-0.24**	**-0.22**	**-0.16**				
		HHI	**0.33**	**0.24**	**0.23**	**0.15**				
						Total	11918	100.0	23.7	22.3

In bold the coefficients with $p<0.05$ significance

CO_2 (a) is the calculation of individual CO_2 emissions, in which all vehicle emissions are attributed to the driver, and none to passengers. CO_2 (b) is the calculation of individual CO_2 emissions, in which total vehicle emissions were divided by the total number of vehicle occupants (i.e. driver and passengers were allocated the same emissions).

3.1.2 Multivariate analyses

Tables 7 and 8 present the results of the multivariate analyses, with CO_2(a) as the dependent variable (unless otherwise noted). In the unadjusted model, a higher level of multimodality was significantly associated with lower weekly CO_2 emissions. In the maximally adjusted model (i.e. after adjusting for socio-economic and spatial characteristics), this association was attenuated, but remained statistically significant. Previous research (reviewed in Section 1) has shown that socio-economic and spatial characteristics are associated with both CO_2 emissions and multimodality, which corresponds with our findings. Further adjustment for other travel behaviour characteristics (i.e. the number of stages (as well as distance, but this variable is endogenous)), strengthened the relationship between multimodality and CO_2 emissions. In the maximally adjusted model, a change from 0 (being fully multimodal) to 1 (unimodality) value on HHI increases CO_2 emissions by 3.7 kg per week and approximately 10 kg per week when controlling for travel intensity (i.e. distance (s1) and number of stages (s2)).

Individual and spatial characteristics contribute to a larger extent to the predictive power of the model than multimodality does, increasing r^2 from 0.01 to 0.19. The inclusion of number of stages increased the fit of the model even more, to an r^2 of 0.22. Analysis on the eight-mode multimodality indicator, OM_PI indicator (both not reported) yielded fairly similar results, although not always statistically significant. When using the alternative calculation of CO_2 (sharing emissions between passengers) (S3), the effect of multimodality on CO_2 emissions attenuated and become insignificant.

Several socio-economic and spatial characteristics which appear in the models as control variables are also significantly associated with CO_2 emissions. For example, women produce on average less CO_2 emissions than men as a result of their travel. Higher emissions are observed for individuals who have one or two cars in the household (compared to none), and individuals that work at multiple locations (compared to only one location), individuals with children in the household (compared to none), and those living outside London (compared to London). In contrast, individuals that are not full-time employed and those that do not live in a detached house are more likely to have lower levels of CO_2 emissions.

Table 7 OLS regression on CO_2 emissions of travel per week

		M 1:Only MM	M2: Incl SES	M3: Max adjusted	S1: Incl stages	S2: Incl distance	S3: CO_{2}(b)
Multimodality indicator (HHI, 3 modes)		**8.306*** **	**5.086*** **	**3.710*** **	**9.987*** **	**11.371*** **	1.208
Age	(ref: 30-65)						
	16-30		**-7.861*** **	**-7.404*** **	**-6.101*** **	**-4.366*** **	**-4.704*** **
	65+		-0.024	-0.991	-0.403	2.399**	-1.691
Gender	(ref: Male)						
	Female		**-10.877*** **	**-11.075*** **	**-11.452*** **	**-8.349*** **	**-5.626*** **
Household income in quintile	1st						
	2nd		**-7.111*** **	**-7.006*** **	**-6.198*** **	**1.801***	**-7.599*** **
	3rd		**-7.716*** **	**-7.625*** **	**-7.374*** **	0.111	**-7.794*** **
	4th		**-6.971*** **	**-6.644*** **	**-6.414*** **	0.921	**-6.810*** **
	(ref: 5th)		**-3.945*** **	**-3.893*** **	**-3.881*** **	0.735	**-4.220*** **
Ethnicity	(ref: White)						
	Non-white		**-5.305*** **	-1.367	-1.244	0.062	-1.276
Number of cars in household	(ref: None)						
	1		**7.086*** **	**5.988*** **	**5.151*** **	0.025	**4.275*** **
	2 or more		**12.392*** **	**9.985*** **	**8.658*** **	-0.146	**8.047*** **
Workplace location	(ref: Always the same in office)						
	Different locations		**9.608*** **	**9.824*** **	**10.441*** **	**4.029*** **	**8.465*** **
	Home		1,626	0.469	1,189	-1,232	-0.128
Children in household	(ref: No)						
	Yes		**4.188*** **	**3.746*** **	**2.550*** **	**1.912*** **	-0.227
Owning a bicycle	(ref: No)						
	Yes		**4.445*** **	**2.942*** **	**2.195*** **	0.763	**1.813** **
Having mobility difficulties	(ref: No)						
	Yes		**-4.639*** **	**-4.918*** **	**-3.241** **	**-2.014***	**-3.541** **
Housing Tenure	(ref: Owns home)						
	Rents		**-4.115*** **	**-2.653*** **	**-2.255** **	-0.215	**-2.654*** **
	Other		-4,667	-5,380	-6,190	-0.212	-4.512
Holding a public transport season ticket	(ref: No)						
	Yes		-0.420	0.061	-0.839	**-4.053*** **	0.224
Working status	(ref: Full-time)						
	Part time		**-8.621*** **	**-9.334*** **	**-10.010*** **	**-3.313*** **	**-8.486*** **
	Retired/permanently out of work		**-11.213*** **	**-12.714*** **	**-11.563*** **	**-4.947*** **	**-11.222*** **
	Other non-work		**-11.408*** **	**-12.020*** **	**-10.996*** **	**-3.874*** **	**-10.839*** **
Residential area	(ref: Inner London)						
	Outer London built-up			**3.896***	**4.173** **	1,285	**4.113** **
	Metropolitan built-up			**6.895*** **	**7.252*** **	1,351	**6.774*** **
	Other urban 100+			**9.622*** **	**9.817*** **	**2.126***	**9.565*** **
	Other urban			**13.658*** **	**14.114*** **	**2.180***	**12.905*** **
	Rural			**17.908*** **	**18.344*** **	**4.056*** **	**17.195*** **
Housing type	(ref: Detached)						
	Semi-detached or terraced			**-4.778*** **	**-4.706*** **	**-0.566**	**-4.383*** **
	Flat or other			**-3.989** **	**-4.118*** **	**-0.265**	**-3.894*** **
Total number of stages					**0.488*** **		
Total travel distance						**0.171*** **	
Constant		18.477***	29.889***	**25.877*** **	**11.641*** **	**-3.221***	**25.554*** **
N		11887	11887	11887	11887	11887	11887
r2		0.006	0.175	0.195	0.221	0.617	0.175

*p<0.05; **p<0.01; *** p<0.001

Model 1(M1): only the multimodality indicator; Model 2 (M2): the multimodality indicator and socio-economic characteristics; Model 3 (M3): maximally adjusted—same as model 2 including spatial characteristics.

Sensitivity 1 (S1): maximally adjusted model including number of stages; S2: maximally adjusted model including distance travelled; S3: maximally adjusted model, using CO2(b) as dependent variable.

Reported value is the coefficient.

For interpretation of the coefficients, it must be kept in mind that HHI is a concentration index (with higher values corresponding to less multimodality).

CO_2 (a) is the calculation of individual CO_2 emissions, in which all vehicle emissions are attributed to the driver, and none to passengers. CO_2 (b) is the calculation of individual CO_2 emissions, in which total vehicle emissions were divided by the total number of vehicle occupants (i.e. driver and passengers were allocated the same emissions).

Given that driving is the main cause of CO_2 emissions in our dataset, we stratified by whether car use was part of the modal mix (Table 8). For individuals who had used the car at least once, the models showed similar results and slightly stronger associations between multimodality and CO_2 emissions. The models for individuals who did not use the car showed an association between multimodality and CO_2 emissions that is not in the expected direction: higher values of HHI (i.e. higher concentration, lower multimodality) were associated with lower CO_2 emissions. This association was significant in the unadjusted model (despite very low predictive power) and remained significant with all adjustments. A reason for this finding may be that increases in multimodality for individuals who do not drive, are likely due to more trips by public transport. These contribute to greater CO_2 emissions in comparison to walking and cycling. For car users, higher levels of multimodality may be more likely due to a higher proportion of trips not made by car, and hence lower contributions to CO_2.

The predictive power in the non-adjusted model remained very low. Models that adjusted for individual and spatial characteristic had higher predictive power (as in the non-stratified model), but the increase in r^2 was smaller. In the model for non-car users that adjusted for total weekly travel distance (not reported here), the direction of the association between multimodality and CO_2 emissions changed and was not statistically significant. This suggests that the importance of distance as a predictor of CO_2 emissions vastly outweighs that of multimodality. In other words, the reason why multimodal non-car users emit more than monomodal non-car users is that they tend to cover longer distances—when distance is held constant, multimodal non-car users pollute less than monomodal non-car users.

Table 8 OLS Regression analyses on CO_2 emissions of travel per week, stratified by whether the car is used.

		Car in modal mix			Car not in modal mix		
		Unadjusted	Maximally adjusted	S1:including distance	Unadjusted	Maximally adjusted	S1:including distance
Multimodality indicator (HHI, 3 modes)		**11.984*** **	**6.524*** **	**12.898*** **	**-5.550*** **	**-4.756*** **	1.389
Age	(ref: 30-65)						
	16-30		**-7.749*** **	**-4.863*** **		-0.244	-0.431
	65+		-1.322	**2.530***		**-2.506***	0.113
Gender	(ref: Male)						
	Female		**-13.488*** **	**-10.038*** **		-0.665	-0.095
Household income in quintile	1st		**-7.477*** **	**1.916***		**-3.110** **	-0.954
	2nd		**-8.029*** **	-0.043		**-3.216** **	-0.649
	3rd		**-7.009*** **	1.120		**-2.784***	-0.995
	4th		**-3.926*** **	0.880		**-2.910***	**-1.648***
	(ref: 5th)						
Ethnicity	(ref: White)						
	Non-white		-1.235	0.465		0.060	-0.265
Number of cars in household	(ref: None)						
	1		**3.190** **	-1.520		0.150	**1.140***
	2 or more		**6.542*** **	**-1.977***		-1.019	-0.757
Workplace location	(ref: Always the same in office)						
	Different locations		**9.603*** **	**3.837*** **		1.043	-0.055
	Home		0.942	-1.541		-2.924	-0.178
Children in household	(ref: No)						
	Yes		**3.658*** **	**1.793** **		-0.004	0.344
Owning a bicycle	(ref: No)						
	Yes		**3.546*** **	**1.226***		**-1.894** **	**-1.691*** **
Having mobility difficulties	(ref: No)						
	Yes		**-6.218*** **	**-2.846** **		-0.496	0.196
Housing Tenure	(ref: Owns home)						
	Rents		**-2.356***	-0.340		-1.067	0.340
	Other		-6.867	-0.450		-2.697	-1.195
Holding a public transport season ticket	(ref: No)						
	Yes		0.180	**-4.478*** **		**4.405*** **	0.601
Working status	(ref: Full-time)						
	Part time		**-9.661*** **	**-3.318*** **		**-2.296***	-0.037
	Retired/permanently out of work		**-13.818*** **	**-5.773*** **		**-4.086*** **	0.274

	Other non-work		**-13.071*** **	**-4.712*** **		**-3.317*** **	0.267
Residential area	(ref: Inner London)						
	Outer London built-up		**5.519* **	2.313		**1.931* **	-0.668
	Metropolitan built-up		**7.755*** **	1.236		1.992	1.511
	Other urban 100+		**10.927*** **	2.189		**2.007* **	1.247
	Other urban		**14.758*** **	2.195		**3.385** **	**1.547* **
	Rural		**18.911*** **	**4.180** **		**4.517** **	0.791
Housing type	(ref: Detached)						
	Semi-detached or terraced		**-4.144*** **	-0.410		**-6.243*** **	**-2.985** **
	Flat or other		-2.805	0.709		**-5.937*** **	**-3.188** **
Total travel distance				**0.171*** **			**0.122*** **
Constant		**19.411*** **	**27.945*** **	-1.611	**9.820*** **	**18.233*** **	0.829
N		10237	10237	10237	1650	1650	1650
r2		0.01	0.18	0.608	0.02	0.10	0.562

*p<0.05; **p<0.01; *** p<0.001
Reported value is the coefficient.
Model 1: only the multimodality indicator; Model 2: maximally adjusted— multimodality indicator, socio-economic characteristics, and spatial characteristics. Sensitivity 1 (S1): maximally adjusted model including distance travelled.

3.2 TRIP LEVEL

Only a small share of trips in the NTS 2015 were multimodal: approximately 3% when considering three modes of transport and 4% when considering eight. In this section, we compare CO_2 emissions for unimodal trips (i.e. a single mode of transport was used) and multimodal trips (i.e. more than one mode was used), for the entire analysis sample (Figure 1), and stratifying by car use and distance (Figures 2 and 3). For all pairs of unimodal vs. multimodal comparisons reported in the dot plots (showing both means and medians), we tested means differences with two-sample t-test with unequal variances, at a $p<0.05$ significance level (detailed results not reported for the sake of brevity).

Figure 1 shows that CO_2 emissions were on average higher for multimodal trips. This finding was consistent for both measurements of multimodality, and CO_2 calculations. This is apparent even when stratifying by car use (Figure 2).

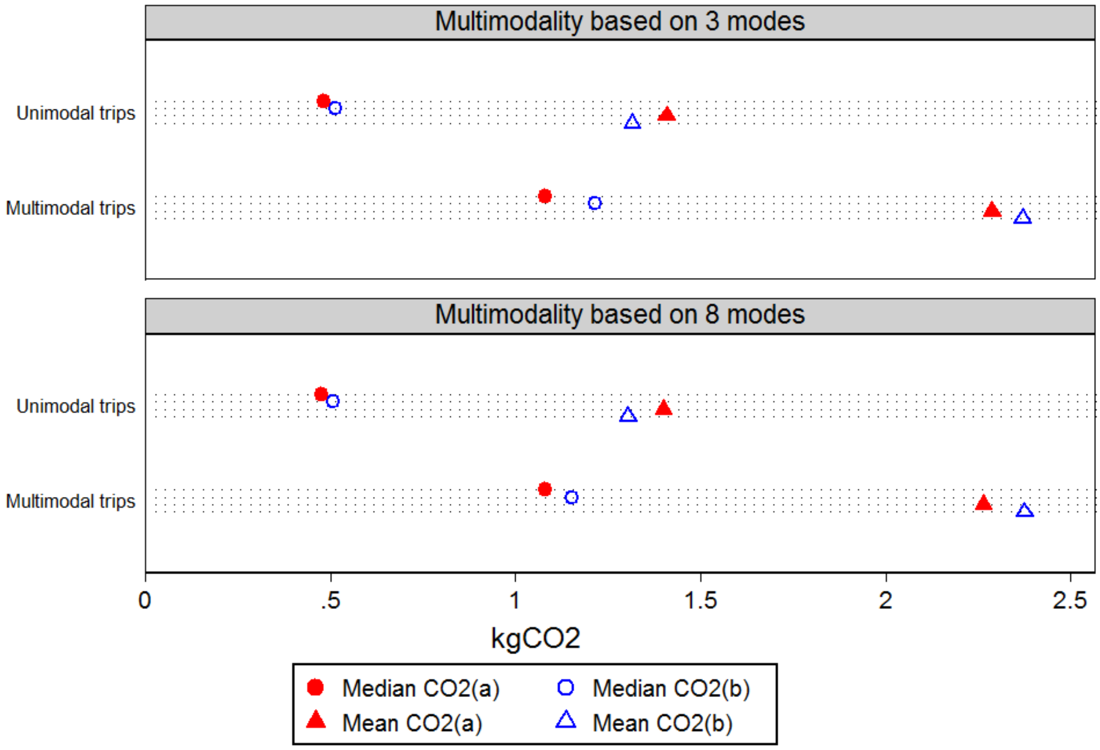

Figure 1: Mean and median values of CO_2 emissions for multimodal and unimodal trips

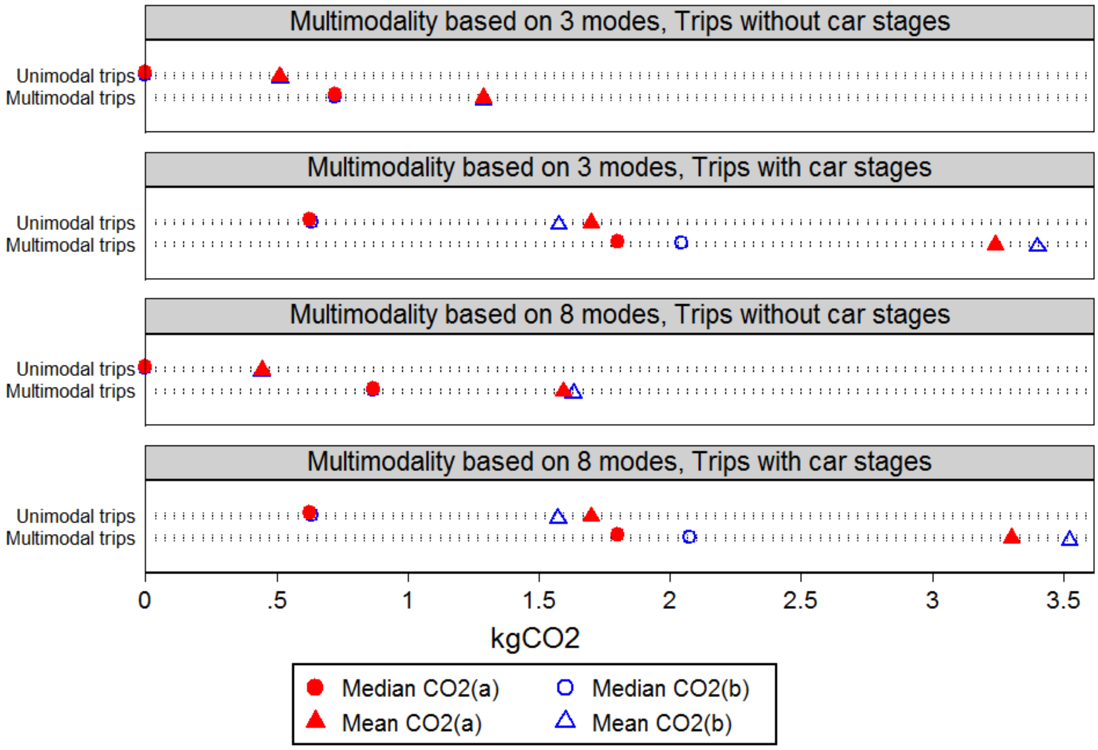

Figure 2: Mean and median values of CO_2 emissions for multimodal and unimodal trips, stratified by car use

These findings challenge the conventional wisdom: multimodality on a trip level does not correspond with lower CO_2 emissions. A possible explanation for this finding is that multimodal trips tend to be over longer distances than unimodal trips. Thus, higher CO_2 emissions for multimodal trips may indicate that distance moderates this association. To test this, we stratified by distance quartiles to explore the relationship between multimodality and CO_2, as displayed in Figure 3 for multimodality based on three modes (results for the eight-modes measure are not reported here for the sake of brevity, but were comparable). For every distance quartile, the mean and median level of CO_2 emissions of unimodal trips were higher than corresponding estimates for multimodal trips, regardless of the indicator of CO_2 considered. The only exception was the quartile with the smallest distance considering the first CO_2 variable. In this case, both mean and median CO_2 of unimodal and multimodal trips were (very close to) zero, which indicates that at least half of the trips are made by active travel. The same broad findings held if instead of quartiles, an alternative categorisation of distance was used: 0-5 miles (60% of trips), 5-10 miles (19% of trips), 10-50 miles (18% of trips), and 50 miles and above (3% of trips) (results not reported here for the sake of brevity). These results could be interpreted as follows: for a given range of travel distance, unimodal trips produce on average higher CO_2 emissions than multimodal ones. However, multimodal trips tend to be longer and as such this relationship is reversed in the aggregate. Incidentally, these results also show that the relationship between multimodality and CO_2 emissions is similar for trips above and below the long-distance threshold (which according to the NTS definition is 50 miles).

Finally, we examined whether multimodal trips were associated with lower CO_2 emissions controlling for several covariates using an OLS regression (See Appendix 2—not reported in main text as OLS regression is not suitable given that the observations are not independent). The results were similar to the analyses reported above. We found that multimodal trips had a significant positive association with CO_2 emissions on a trip level, meaning that trips that were made with two or more modes emitted on average more CO_2 than unimodal trips. This finding was consistent for adjustments with one exception: if we controlled for distance, unimodal trips were more polluting.

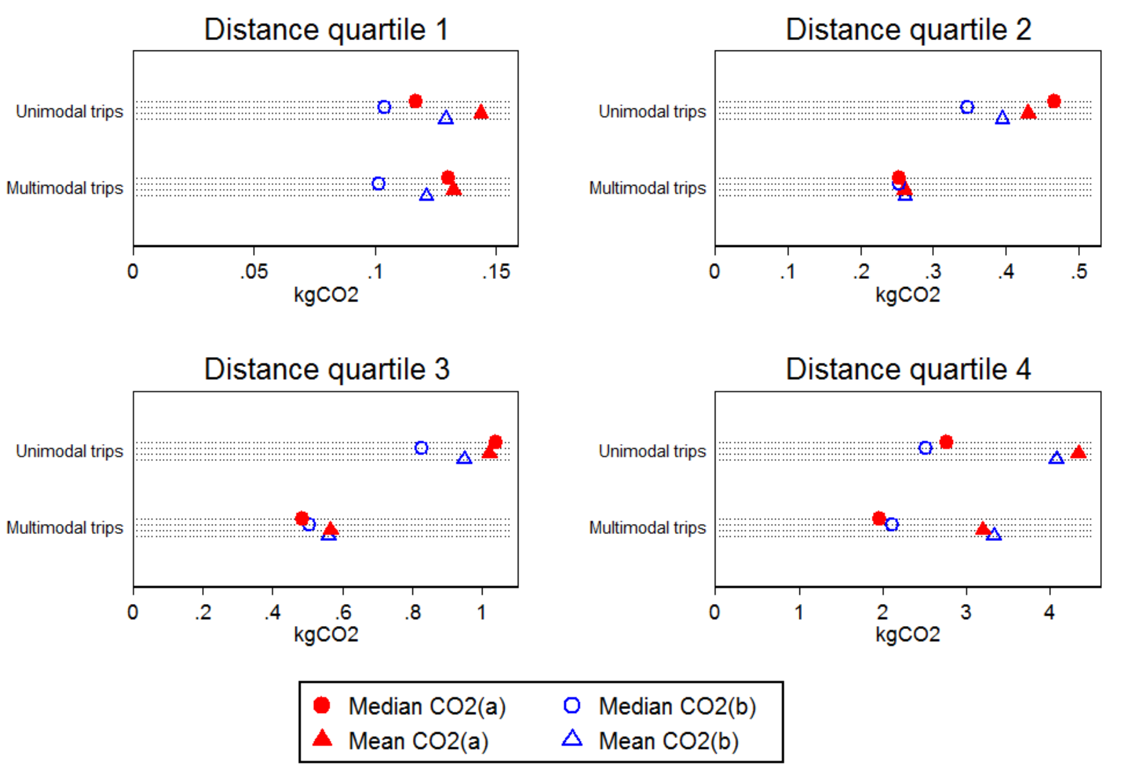

Figure 3: Mean and median values of CO_2 emissions for multimodal and unimodal trips stratified by distance—multimodality based on three modes[3]

4. Discussion

This paper explored and tested the relationship between multimodality and CO_2 emissions (1) on an individual level as well as (2) on a trip level. On an individual level, we found negative relationships between the multimodality levels and CO_2 emissions. However the effects are weak, especially compared to the effect of travel distance. On a trip level, multimodality is

[3] For correct interpretation note that the graphs in the four panels are not on the same scale on the y-axis

positively associated with CO_2 emissions, but this is largely due to the fact that multimodal trips also have higher travel distances.

Travel distance is one of the main explanations for the level of CO_2 emission. Our analyses revealed that distance may also explain some of the counterintuitive findings. Only when we stratified by distance correlation between multimodality and CO_2 increases in strength on an individual level, and unimodal trips had higher levels of emissions than multimodal.

In more detail, in our individual-level analyses, we found, that higher levels of multimodality were significantly associated with lower CO_2 emissions resulting from travel. This association was stronger for individuals who had used the car at least once in the week of the travel diary survey. These findings are consistent with current efforts of policy makers to increase multimodality. This is especially true for the majority of the UK population (i.e. those that use a car on a regular basis). Increasing the level of multimodality in a population where car use dominates may simultaneously reduce car use, which reduces the total amount of CO_2 emissions—although in the aggregate increases in multimodality do not necessarily go hand in hand with reductions in car use (Heinen & Mattioli, 2017).

We did not find a positive association between multimodality and CO_2 emissions for individuals who did not use the car in the week of the travel diary. In fact, higher levels of multimodality corresponded with higher levels of CO_2 emissions. A reason for this finding may be that increases in multimodality for individuals who do not drive, are likely a result of a higher number of trips by public transport. In comparison to walking and cycling, public transport trips contribute to greater CO_2 emissions.

It is noteworthy that when testing the correlation between multimodality and CO_2 emissions, the magnitude of the association was weak. It remained weak when stratified by income, but when stratified by number of stages or by total distance travelled, the correlation between multimodality and CO_2 increases in strength, was in the expected direction and was statistically significant. These findings suggest that the association between multimodality and CO_2 is to some extent confounded by levels of travel activity (especially distance), and that these have a much greater bearing on emission levels than the multimodality of individual travel behaviour.

In our trip-level analyses, we found that CO_2 emissions were on average higher for multimodal trips. This finding calls into questions the validity of a one-to-one substitution perspective. While in theory, for a given trip, CO_2 emissions may be reduced by combining car use with other modes of transport, in practice, it appears that trips were more than one more mode is combined tend to be more polluting. A likely explanation for this finding is that multimodal trips tend to be over longer distances than unimodal trips. Here again, distance is the most important factor in explaining CO_2 emissions, and confounds the relationship between multimodality and CO_2 emissions. When we stratify the analyses by distance quartile, the mean level of CO_2 emissions of unimodal trips was on average higher than emissions for multimodal trips. This implies that distance moderates this association. As a consequence, it can be concluded that stimulating multimodal trips would still be likely reduce CO_2 emissions for trips of comparable distance. On the other hand, if the development of multimodal travel habits is associated with an increase in travelled distances, it is less than certain that the overall result would be a reduction in emissions.

4.1 Implications

This paper started with the question whether multimodality should be stimulated with the aim to reduce transport emissions. On the one hand, our findings show that multimodality, especially if car use was involved, is on average associated with lower levels of CO_2 emissions. As such, the current focus on increasing multimodality may have the desired results. On the other hand, our findings show that distance is a more important predictor, and an important effect modifier of the relationship between multimodality and CO_2 emissions. This implies that policy efforts to increase multimodality would have larger effects if focussed on travel intensity.

Distance is associated with both CO_2 emissions and multimodality. The positive relationship between distance and multimodality may be regarded as beneficial for sustainable transport, as it suggests that longer trips are more likely to be multimodal, and thereby less polluting than unimodal car trips over the same distance. However, we need to be careful that current aims to increase multimodality do not simultaneously increase travel distance. An increase in travel distance for an individual as well as for one trip will without doubt increase CO_2 emissions. The only exception to this rule is found in trips solely made by bicycle or on foot. However, the decision to walk or cycle is also heavily affected by trip distance (Van Wee et al., 2006; Heinen et al., 2010). Therefore, reducing the need to travel over longer distances will likely have the largest contribution to reducing CO_2 emissions.

Nevertheless, at the moment, the causal structure is unknown: are people more multimodal as they have more trips/longer distances, or vice versa? Additional research, possibly adopting a longitudinal approach, is necessary to disentangle this relationship and how it may be moderated or mediated by other factors.

4.2. Strengths & Limitations

The NTS is a high-quality data set that allows a fairly accurate calculation of CO_2 emissions and multimodality. Nevertheless, the NTS has several shortcomings. The most important in relation to our research aim may be that the NTS only reports trips within England, meaning that most flights are unrecorded. Therefore, we have excluded air travel from our analysis. Existing research shows that for some individuals, particularly in urban areas, low levels of

GHG emissions for everyday travel are more than compensated by high GHG emissions for long distance travel (notably flights) (Czepkiewicz et al., 2018; Holz-Rau et al., 2014; Ottelin et al., 2014; Reichert et al., 2016). There is also initial evidence of an association between multimodality and high emissions for long distance travel, mostly by plane (Reichert and Holz-Rau, 2018). This suggests that the negative association that we have found between multimodality and emission levels could be reversed, were air travel to be accounted for properly. Indeed, the results of the sensitivity tests conducted for this study suggest that including even a very small number of plane trips tends to reduce (and potentially reverse) the already weak association between greater multimodality and lower CO_2.

Another limitation is that the NTS collects a travel diary for one week only. Although for the purpose of this study this provides very good data, especially compared to the shorter diaries found in other national surveys, it does not sufficiently capture less regular trips, such as weekends away or holidays, which may contribute substantially to the overall CO_2 emissions. Finally, as is the case with any questionnaire, there is a risk of non-selection and non-response bias, as well as incorrect reporting. However, the size, design, and effort in data collection of NTS and the availability of weights may limit the bias compared to other surveys.

In this paper we assessed individual-level multimodality based on mode choice in each stage (i.e. we did not exclude any stages or trips). As a result, we did not differentiate by distance or other characteristics of a trip (e.g. trip purpose). This non-discriminatory approach is useful to understand the level of variability in the full modal mix. Nevertheless, this approach also may increase bias. For example, long-distance trips will contribute disproportionately to CO_2 emissions but not to the level of multimodality, and short-distance trips potentially vice versa.

This paper investigated the relationship between CO_2 emission and multimodality. However, transport emissions are not limited to CO_2. The exact level of pollutants differs by mode of transport and by vehicle type. Although our findings may have a similar pattern compared to other pollutants in relation to multimodality, the exact associations and strength are unknown and further research will be necessary to determine these.

5. Conclusion

This paper explored and tested the relationship between multimodality and CO_2 emissions using English National Travel Survey of 2015. We found that individuals who were more multimodal, when controlling for individual characteristics, had less polluting travel behaviours on average compared to individuals with lower levels of multimodality—although the association was weaker and more uncertain than one would expect given the current policy emphasis on this policy goal. We also found that multimodal trips, when controlled for distance, were on average less polluting than unimodal trips.

A key finding of our analyses was that distance appeared the most important factor, and it confounded the relationship between multimodality and CO_2 emissions. Our analyses therefore suggest that a focus on increasing multimodality will likely contribute to reducing CO_2 emissions, but reducing total distances travelled will contribute much more to reaching current climate targets. More broadly, they suggest that the assumption of a one-to-one substitution between unimodal car travel patterns and multimodal travel patterns should be avoided as real-world data suggests that multimodality is associated with longer travel distances, both at the individual and trip level.

The current emphasis of multimodality is consistent with popular 'behaviour change' and 'citizen–consumer' approaches to sustainable transport policy (Barr et al., 2011; Barr & Prillwitz, 2014; Shove, 2010). As such, it is attractive to policy-makers, since it frames their role as one of expanding the choice-set available to individuals—increasing their freedom—rather than introducing regulatory or pricing measures that could be perceived as restrictions. However, our findings suggest that policy strategies that focus uniquely (or primarily) on greater multimodality are unlikely to bring about change at the required scale and speed, given the extremely rapid reductions in transport-related CO_2 emissions required (IPCC, 2018), and a discussion on distance and travel intensity is necessary.

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Appendix 1 – Multimodality indices formulae

- The number of modes used (Heinen and Mattioli, 2017);

$$\sum n \qquad \text{equation (1)}$$

In which n is each unique mode used in a stage.

- The difference in percentage of use between primary and secondary modes (Heinen and Chatterjee 2015);

$$\%mode1 - \%mode2 \qquad \text{equation (2)}$$

In which mode1, is the mode most frequently used in one week on a stage level, and mode2 the second most frequently used mode in one week on a stage level

- The Herfindahl–Hirschman index (HHI) as applied by Heinen and Chatterjee (2015), and a variant, HHm, based on Diana and Pirra (2016);

The HHI (H* in equation 1) is calculated for each individual as the sum of the squared values of the share of each mode option of the total number of stages. Equation 2 shows the normalisation of the index.

$$\mathrm{H}* = \sum_{i=1}^{N} s_i^2 \qquad \text{equation (3)}$$

$$\mathrm{HHI} \quad = \frac{(\mathrm{H}-\frac{1}{\mathrm{N}})}{(1-1/\mathrm{N})} \qquad \text{equation (4)}$$

In which S is the made share of each mode, and N is the total number of modes considered.

- An index based on the Shannon entropy, based on Diana and Pirra (2016) OM_PI;

$$OM\_PI = \sum_{i=1}^{n}\left[\frac{f_i}{\sum_{j=1}^{n} f_j} ln\left(\frac{\sum_{j=1}^{n} f_j}{f_i}\right)\frac{1}{\ln n}\right] \qquad \text{equation (5)}$$

In which I is the intensity of use of i_{th} mode and n the total number of modes.

- The Dalton index, based on Diana and Pirra (2016) DALm. Following Diana and Pirra (2016), we set ε at 0.5 in order to maximise the sensitivity of the index (p.785);

$$DALm = 1 - \frac{\frac{1}{n}\sum_{i=1}^{m}(f_i^{1-\varepsilon} - 1)}{(\frac{1}{m}\sum_{i=1}^{m} f_i)^{1-\varepsilon} - 1} \qquad \text{equation (6)}$$

In which n is the number of different modes, fi is the intensity of use of each mode. We only considered the values different from zeros.

- The multimodal indicator (MM), based on Streit et al. (2015).

$$MM = \frac{n}{\max f_i} \qquad \text{equation (7)}$$

In which n is the number of modes, and f_i is the frequency of use of mode i.

Appendix 2 - Multivariate analyses on CO2 emissions (CO2(a)) of a trip

		Model 1	Model 2	Model 3	S1	S2	S3
Multimodality indicator (HHI, 3 modes)		**0.858*** **	**0.778*** **	**0.913*** **	**-1.442*** **	**1.048*** **	**1.001*** **
Age			-0.019	**0.177*** **	**0.218*** **	**0.059*** **	**0.184*** **
Gender	(ref: Male)						
	Female		**-0.924*** **	**-0.757*** **	**-0.574*** **	**-0.414*** **	**-0.757*** **
Household income in quintile	(ref:1st)						
	2nd		**0.102*** **	**-0.084*** **	**-0.102*** **	**-0.047* **	**-0.087*** **
	3rd		**0.380*** **	-0.03	**-0.054** **	0.012	-0.035
	4th		**0.637*** **	**0.108*** **	-0.034	**0.143*** **	**0.104*** **
	5th		**0.847*** **	**0.274*** **	**-0.066** **	**0.320*** **	**0.267*** **
Ethnicity	(ref: White)						
	Non-white		**-0.220*** **	-0.013	-0.003	-0.007	-0.023
Number of cars in household	(ref: None)						
	1			**0.253*** **	**0.103*** **	**0.111*** **	**0.267*** **
	2 or more			**0.393*** **	**0.148*** **	**0.239*** **	**0.411*** **
Workplace location	(ref: Always the same in office)						
	Different locations			**0.186** **	-0.003	**0.135** **	**0.189** **
	Home			**0.717*** **	**0.358*** **	**0.609*** **	**0.714*** **
Children in household	(ref: no)						
	Yes			**0.045* **	**0.078*** **	**-0.180*** **	**0.048* **
Owning a bicycle	(ref: no)						
	Yes			-0.017	0.012	**-0.066*** **	-0.013
Having mobility difficulties	(ref: No)						
	Yes			**-0.156*** **	**-0.142*** **	-0.046	**-0.152*** **
Housing Tenure	(ref: Owns home)						
	Rents			**-0.064** **	-0.011	**-0.068*** **	**-0.063** **
	Other			**-0.251** **	-0.066	**-0.177** **	**-0.245** **
Holding a public transport season ticket	(ref: No)						
	Yes			**-0.153*** **	**-0.257*** **	**-0.112*** **	**-0.174*** **
Working status	(ref: Full-time)						
	Part time			**-0.598*** **	**-0.286*** **	**-0.532*** **	**-0.595*** **
	Retired/permanently out of work			**-0.735*** **	**-0.464*** **	**-0.598*** **	**-0.721*** **
	Other non-work			**-0.632*** **	**-0.387*** **	**-0.537*** **	**-0.622*** **
Residential area	(ref: Inner London)						
	Outer London built-up			**0.343*** **	**0.181*** **	**0.359*** **	**0.366*** **
	Metropolitan built-up			**0.423*** **	**0.191*** **	**0.421*** **	**0.474*** **
	Other urban 100+			**0.513*** **	**0.225*** **	**0.523*** **	**0.565*** **
	Other urban			**0.845*** **	**0.320*** **	**0.805*** **	**0.895*** **
	Rural			**1.075*** **	**0.456*** **	**1.031*** **	**1.126*** **
Housing type	(ref: Detached)						
	Semi-detached or terraced			**-0.185*** **	**-0.063*** **	**-0.167*** **	**-0.186*** **
	Flat or other			**-0.141*** **	-0.039	**-0.139*** **	**-0.139*** **
Total number of stages					**0.135*** **		
Constant		**1.413*** **	0.493	-0.265	-0.381	0.272	-0.351
N		187696	187519	186784	186784	186784	186784
r2		0.002	0.025	0.046	0.495	0.042	0.047

$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$
Model 1: only the multimodality indicator; Model 2: the multimodality indicator and socio-economic characteristics; Model 3: maximally adjusted—same as model 2 including spatial characteristics. Sensitivity 1 (S1): maximally adjusted model including distance travelled; S2: maximally adjusted model, using CO2(b) as dependent variable; S3: maximally adjusted model with HHI indicator based on 8 modes.