The climate change mitigation effects of daily active travel in cities

Christian Brand (christian.brand@ouce.ox.ac.uk)
University of Oxford https://orcid.org/0000-0002-1535-5328
Evi Dons
Centre for Environmental Sciences, Hasselt University, Diepenbeek https://orcid.org/0000-0002-6745-7246
Esther Anaya-Boig
Centre for Environmental Policy, Imperial College London, London https://orcid.org/0000-0002-9204-534X
Ione Avila-Palencia
Urban Health Collaborative, Dornsife School of Public Health, Drexel University, Philadelphia, PA
Anna Clark
Trivector Traffic, Stockholm
Audrey de Nazelle
Centre for Environmental Policy, Imperial College London, London
Mireia Gascon
ISGlobal, Barcelona
Mailin Gaupp-Berghausen
Austrian Institute for Regional Studies, Vienna
Regine Gerike
Dresden University of Technology, Chair of Integrated Transport Planning and Traffic Engineering, Dresden
Thomas Gotschi
University of Oregon, School of Planning, Public Policy and Management, Eugene, Oregon
Francesco Iacorossi
Agenzia Roma Servizi per la Mobilita' Srl, Rome
Sonja Kahlmeier
Fernfachhochschule Schweiz, Brig
Michelle Laeremans
Flemish Institute for Technological Research (VITO), Mol
Mark Nieuwenhuijsen
ISGlobal, Barcelona
Juan Orjuela Mendoza
Transport Studies Unit, University of Oxford, Oxford
Francesca Racioppi
World Health Organization Regional Office for Europe, European Centre for Environment and Health, Bonn https://orcid.org/0000-0002-7287-9603
Elisabeth Raser
University of Natural Resources and Life Sciences Vienna, Institute for Transport Studies, Vienna
David Rojas Rueda
Department of Environmental and Radiological Health Sciences, Colorado State University, Fort Collins, Colorado https://orcid.org/0000-0001-5854-2484
Arnout Standaert
Flemish Institute for Technological Research (VITO), Mol https://orcid.org/0000-0001-7711-7141
Erik Stigell
Trivector Traffic, Stockholm
Simona Sulikova
Transport Studies Unit, University of Oxford, Oxford https://orcid.org/0000-0003-0613-1864
Sandra Wegener
University of Natural Resources and Life Sciences Vienna, Institute for Transport Studies, Vienna
Luc Int Panis

Transportation Research Institute (IMOB), Hasselt University, Diepenbeek https://orcid.org/0000-0002-2558-4351

Research Article

Keywords: CO2 emissions, active mobility, walking; cycling, climate change mitigation, sustainable urban transport

Posted Date: January 19th, 2021

DOI: https://doi.org/10.21203/rs.3.rs-39219/v2

Abstract

Active travel (walking or cycling for transport) is considered the most sustainable form of personal transport. Yet its net effects on mobility-related CO_2 emissions are complex and under-researched. Here we collected travel activity data in seven European cities and derived life cycle CO_2 emissions across modes and purposes. Daily mobility-related life cycle CO_2 emissions were 3.2 $kgCO_2$ per person, with car travel contributing 70% and cycling 1%. Cyclists had 84% lower life cycle CO_2 emissions than non-cyclists. Life cycle CO_2 emissions decreased by -14% per *additional* cycling trip and decreased by -62% for each *avoided* car trip. An average person who 'shifted travel modes' from car to bike decreased life cycle CO_2 emissions by 3.2 $kgCO_2$/day. Promoting active travel should be a cornerstone of strategies to meet net zero carbon targets, particularly in urban areas, while also improving public health and quality of urban life.

1. Introduction

Transport has been one of the most challenging sectors for reducing its significant impacts of fossil energy use and associated greenhouse gas (GHG) emissions since the 1990s (Sims et al., 2014). In Europe, GHG emissions decreased in the majority of sectors between 1990 and 2017, with the exception of transport (EEA, 2019). Modal shifts away from carbon-intensive to low-carbon modes of travel hold considerable potential to mitigate carbon emissions (Cuenot et al., 2012). Given the urgency of moving to a 'net zero' carbon emissions economy, there is growing consensus that technological substitution via electrification will not be sufficient or fast enough to transform the transport system (Creutzig et al., 2018; IPCC, 2018). Beyond a net reduction in travel demand, one of the more promising ways to reduce transport carbon dioxide (CO_2) emissions[1] is to promote and invest in active modes of transport (e.g. walking, cycling, e-biking) while 'demoting' motorized modes that rely on fossil energy sources (Bearman and Singleton, 2014; Castro et al., 2019; de Nazelle et al., 2010; ECF, 2011; Frank et al., 2010; Goodman et al., 2012; Keall et al., 2018; Neves and Brand, 2019; Quarmby et al., 2019; Sælensminde, 2004; Scheepers et al., 2014; Tainio et al., 2017; Woodcock et al., 2018). This could reduce CO_2 emissions from road transport more quickly than technological measures alone, particularly in urban areas (Beckx et al., 2013; Creutzig et al., 2018; Graham-Rowe et al., 2011; Neves and Brand, 2019). This may become even more relevant considering the vast economic effects of the COVID-19 pandemic, which may result in reduced capacities of individuals and organizations to renew the rolling stock of vehicles in the short and medium period, and of governments to provide incentives to fleet renewal.

So how much carbon can be saved – overall – by travelling actively? The complex relationships between carbon emissions and transport have been investigated for many years. Previous research has shown that travel carbon emissions are determined by transport mode choice and usage, which in turn are influenced by journey purpose (e.g. commuting, visiting friends and family, shopping), individual and household characteristics (e.g. location, socio-economic status, car ownership, type of car, bike access, perceptions related to the safety, convenience and social status associated with active travel), land use and built environment factors (which impact journey lengths and trip rates), accessibility to public transport, jobs and services, and metereological conditions (Adams, 2010; Alvanides, 2014; Anable and Brand, 2019; Bearman and Singleton, 2014; Brand and Boardman, 2008; Brand and Preston, 2010; Cameron et al., 2003; Carlsson-Kanyama and Linden, 1999; Ko et al., 2011; Nicolas and David, 2009; Stead, 1999; Timmermans et al., 2003). Yet active travel studies are often based on analyses of the potential for emissions mitigation (Yang et al., 2018), the generation of scenarios (Goodman et al., 2019; Lovelace et al., 2011; Tainio et al., 2017; Woodcock et al., 2018) or smaller scale studies focusing on a single city, region or country (Brand et al., 2014; Neves and Brand, 2019). To better understand the carbon-reduction impacts of active travel, it is important to assess the key determinants of travel carbon emissions across a wide range of contexts and include a detailed, comparative analysis of the distribution and composition of emissions by transport mode (e.g. bike, car, van, public transport, e-bike) and emissions source (e.g. vehicle use, energy supply, vehicle manufacturing). To answer the above question it is also important to understand why, where, when and how far people travel – many studies do not dig that deep and across different contexts. While cycling cannot be considered a 'zero-carbon emissions' mode of transport, life cycle emissions from cycling can be more than ten times lower per passenger-km travelled than those from passenger cars (ECF, 2011). For most journey purposes active travel covers short to medium trips – typically 2km for walking, 5km for cycling and 10km for e-biking (Castro et al., 2019). Typically, the majority of trips in this range is made by car (Beckx et al., 2013; JRC, 2013; Keall et al., 2018; Neves and Brand, 2019; U.S. Department of Transportation, 2017), with short trips contributing disproportionately to emissions because of 'cold starts', especially in colder climates (Beckx et al., 2010; de Nazelle et al., 2010). On the other hand, these short trips, which represent the majority of trips undertaken by car within cities, would be amenable to at least a partial modal shift towards active travel (Beckx et al., 2013; Carse et al., 2013; de Nazelle et al., 2010; Goodman et al., 2014; Keall et al., 2018; Neves and Brand, 2019; Vagane, 2007). To investigate these issues, we included seven European cities with different travel activity patterns, transport mode shares, infrastructure provisions, climates, mobility cultures and socio-economic makeups. To the best of our knowledge no international multicenter study on the associations of daily active and motorized travel and carbon emissions has been reported.

This study also addresses a number of practical needs. First, there is a lack of standardized definitions and measurements (self-reported or measured) to identify groups within a population who use a 'main' mode of transport (e.g. based on distance, duration or frequency over a given time period), or who may be classified as 'frequent cyclists', 'occasional walkers' – or simply 'cycling' (yes/no). These should be split as much as possible as there may be different effects on overall CO_2 emissions. Second, given the dominance of travel by car and public transport, active modes must be included to the extent possible by oversampling people using these modes. And finally, instead of focusing on the commute journey only, as with many studies that rely on Census data, trips for a wider range of journey purposes should be considered.

This paper aims to investigate to what extent active travel is associated with lower carbon emissions from daily travel activity. Using primary data collected in a large European multicenter study of transport, environment and health, the paper first describes how total life cycle CO_2 emissions from daily travel activity were derived at the individual and population levels, considering urban transport modes, trip stages, trip purposes and emissions categories. The core analysis then identifies the main determinants and models the effects of mode choice and usage on life cycle carbon emissions. Further analysis identifies and compares differences in life cycle carbon emissions between 'groups of transport users', including by 'main' mode of transport and different categories of cycling frequency. By doing so, the paper provides a detailed and nuanced assessment of the benefits of active travel in reducing total life cycle carbon emissions in cities.

[1] For transport, CO_2 is by far the most important greenhouse gas, comprising approximately 99% of direct greenhouse gas emissions. Surface transport is still dominated by vehicles with internal combustion engines running on petrol (gasoline) and diesel fuels. These propulsion systems emit relatively small amounts of the non-CO_2 greenhouse gases methane (CH_4) and nitrous oxide (N_2O), adding approximately 1% to total greenhouse gas emissions over and above CO_2.

2. Materials And Methods

2.1 Study design and population

This study used longitudinal data from the 'Physical Activity through Sustainable Transport Approaches' (PASTA) project (Dons et al., 2015; Gerike et al., 2016). The analytical framework of PASTA distinguished hierarchical levels for various factors (i.e. city, individual, and trips), and four main domains that influence mobility behavior, namely factors relating to transport mode choice and use, socio-demographic factors, socio-geographical factors, and socio-psychological factors (Dons et al., 2015; Götschi et al., 2017). Seven European cities (Antwerp, Barcelona, London, Orebro, Rome, Vienna, and Zurich) were selected to provide a good representativeness of urban environments in terms of size, built environment, transport provision, modal split and ambition to increase levels of active travel (Raser et al., 2018). To ensure sufficiently large sample sizes for different transport modes, users of less common transport modes such as cycling were oversampled (Raser et al., 2018). Participants were recruited opportunistically on a rolling basis following a standardized guidance for all cities and also some city-specific approaches. A comprehensive user engagement strategy was applied to minimize attrition over the two-year timeframe. Further details on the recruitment strategy are given elsewhere (Gaupp-Berghausen et al., 2019).

A total of 10,722 participants entered the study on a rolling basis between November 2014 and November 2016 by completing a baseline questionnaire (BLQ). Participants provided detailed information on general travel behavior, daily travel activity, geolocations (home, work, education), vehicle ownership (private motorized, bicycle, etc.), public transport accessibility and socio-demographic characteristics. Follow-up questionnaires were distributed every two weeks: every third of these follow-up questionnaires also included a one-day travel diary, henceforth labelled a 'long follow-up' (long FUQ) (Dons et al., 2015). All valid travel diaries were included in the analyses, implying that some participants provided multiple diary data at different time points. Using longitudinal data aimed to improve measurement of 'typical' travel behavior (Branion-Calles et al., 2019). Participants had to be 18 years of age (16 years in Zurich) or older, and had to give informed consent at registration. Data handling and ethical considerations regarding confidentiality and privacy of the information collected were reported in the study protocol (Dons et al., 2015). Table S2 in the Supplementary Information provides an excerpt of the PASTA BLQ, including travel diary data.

2.2 Exposure: transport mode choice and use

The primary exposure variables were daily trip frequencies obtained from the travel diaries, for each of the main modes: walking; cycling; e-biking; motorcycle or moped; public transport; and car or van. The most common metric used by local and national administrations across the world is mode share (or split) by trip frequency, not by distance (EPOMM, 2020; U.S. Department of Transportation, 2017); hence the results of the primary exposure analysis may be used to estimate life cycle CO_2 emissions directly from trip mode share data. Due to low counts of e-biking and motorcycle trips, e-biking was merged with cycling, with indirect emissions derived from observed bike/e-bike shares (see also footnote of Table 1). Also, motorcycle was merged with car as reported CO_2 emission rates for motorcycles are comparable to cars *on a per passenger-km basis* (BEIS, 2019). Participants provided information on each trip made on the previous day, including start time, location of origin, transport mode, trip purpose, location of destination, end time and duration (Supplementary Table S2). The diary was based on the established KONTIV-Design (Brög et al., 2009; Socialdata, 2009), with some adaptations for online use. 5623 participants provided a valid travel diary in either the BLQ or the long FUQ; out of those 3836 participants completed valid baseline surveys and travel diaries. In the travel diary, trip purpose, duration and location were self-reported. Total trip duration was also derived as the difference between start and end time, while trip distance was obtained retrospectively feeding origin and destination coordinates to the Google Maps Application Programming Interfaces (API), which returned the fastest route per mode between origin and destination.

Three secondary exposure variables were developed to explore differences between groups of individuals. First, participants were categorized as using a 'main mode' of travel based on furthest daily distance (levels: walking, cycling, car, public transport). Further categorizations based on cycling frequency included a dichotomous variable of 'cycling' on the diary day (yes/no) as well as a trichotomous variable characterizing participants as 'frequent cyclist' (three or more times a day), 'occasional cyclist' (once or twice a day), or 'non-cyclist' (none). Table 2 shows sample sizes and mean (SD) values of the primary outcome variable for each group.

2.3 Outcome variables: carbon dioxide emissions

The primary outcome of interest was daily life cycle CO_2 emissions (mass of carbon dioxide in gram or kilogram per day) attributable to passenger travel. Life cycle CO_2 emissions categories considered were *operational* emissions, *energy supply* emissions and *vehicle production* emissions. First, operational emissions were derived *for each trip* based on trip distance (computed from travel diary data), 'hot' carbon emissions factors, emissions from 'cold starts' (for cars only) and vehicle occupancy rates (passengers/vehicle) that varied by trip purpose. The method for cars and vans considered mean trip speeds (derived from the travel diaries), location-specific vehicle fleet compositions (taking into account the types of vehicle operating in the vehicle fleets during the study period) and the effect of 'real world driving' (adding 22% to carbon emissions derived from 'real world' test data based on BEIS (2019) and ICCT (ICCT, 2017)) to calculate the so called 'hot' emission of CO_2 emitted per car-km. For motorcycle, bus and rail, fuel type shares and occupancy rates were based on BEIS (2019). Buses were mainly powered by diesel powertrains; motorcycles were 100% gasoline; and urban rail was assumed to be all electric. For cars, 'cold start' excess emissions were added to 'hot' emissions based on the vehcile fleet composition, ambient temperatures (see Supplementary Table S13) and trip distances observed in each city: across the seven cities, cold start emissions averaged 126 (SD 42) gCO_2 per car *trip*, with the trip share of a car operating with a 'cold' engine averaging 13 (SD 8) percent. Cold start emissions were higher-than-average in Orebro and Zurich, and lower in Barcelona. Second, carbon emissions from energy supply considered upstream emissions from the extraction, production, generation and distribution of energy supply, with values taken from international databases for fossil fuel emissions (2016; JEC, 2014; Odeh et al., 2013) and emissions from electricity generation and supply (Ecometrica, 2011). Third, vehicle life cycle emissions considered emissions from the manufacture of vehicles, with aggregate carbon values per vehicle type (cars, motorcycles, bikes and public transport vehicles) derived assuming typical lifetime mileages, mass body weights, material composition and material-specific emissions and energy use factors. The main functional relationships and data are provided in the Supplementary Information. The derived emissions rates are shown in Table 1 for each city, disaggregated by emissions category and transport mode.

Table 1: Mean CO_2 emissions per passenger-km by city, emissions category and transport mode (showing 2014-2016 averages to match study period)

	Operational				Energy/fuel supply						Vehicle supply					
	Car, van or motorcycle *		Public transport †		Car, van, motorcycle *		Public transport †		Bicycle, e-bike #		Car, van, motorcycle *		Public transport †		Bicycle, e-bike #	
	gCO2/pkm		gCO2/pkm		gCO2/pkm		gCO2/pkm		gCO2/pkm		gCO2/pkm		gCO2/pkm		gCO2/pkm	
	mean	SD	mean	SD	mean	SD	mean	SD	mean	SD	mean	SD	mean	SD	mean	SD
Antwerp	141.5	38.6	14.5	0.1	27.2	5.6	20.9	0.5	0.111	0.003	12.9	1.9	2.9	0.0	5.1	0.0
Barcelona	142.2	45.8	17.2	0.1	27.5	7.2	30.5	0.6	0.171	0.004	10.6	1.6	3.0	0.0	5.1	0.0
London	165.6	46.7	52.0	0.3	30.4	6.8	43.5	0.6	0.236	0.004	12.9	1.9	3.6	0.0	5.1	0.0
Oerebro	153.3	46.8	68.8	0.3	27.5	6.1	16.7	0.1	0.011	0.000	13.2	2.1	4.2	0.0	5.1	0.0
Rome	144.5	37.5	36.4	0.2	27.7	6.0	33.9	0.6	0.200	0.004	11.5	1.8	3.1	0.0	5.1	0.0
Vienna	156.1	45.2	24.7	0.1	29.4	6.6	16.6	0.2	0.087	0.002	13.3	2.0	2.8	0.0	5.1	0.0
Zurich	143.6	45.7	43.4	0.2	26.8	6.2	9.8	0.1	0.002	0.000	12.5	1.8	3.4	0.0	5.1	0.0

* This incorporates different journey speeds, vehicle occupancy rates by trip purpose, national fuel shares of the vehicle fleet, and cold start emissions. A 22% uplift was applied to account for 'real world' driving conditions. For example in Antwerp in 2016, the car fleet was assumed to comprise the national fleet mix of 38% gasoline, 61% diesel and 1% electric; buses were 100% diesel; motorcycles 100% gasoline. Car occupancy rate was between 1.16 (commuting) and 2.02 (education), average 1.54 for all trip purposes. Cold/hot ratio of 1.3 and cold trip distance of 3.45 km.

† Operational emissions are for bus using average occupancy rates. Energy/fuel supply assume a bus/rail share based on EPOMM Modal Split Tool. (http://www.epomm.eu/tems/). For example, Antwerp bus/rail share was 37.5% in 2016.

The observed e-bike share was 4.5%; therefore, average emissions include 4.5% e-bike, 95.5% normal bike.

Sources: hot and cold emissions factor coefficients (EEA, 2012; EMEP/EEA, 2016); vehicle fleets (ACEA/ANFAC, 2014; DEFRA/DECC, 2016; DfT, 2015; SMMT, 2016).

Total daily emissions were calculated as the sum of emissions for each trip, mode and purpose (e.g. the sum of 4 trips on a given day = trip 1: home to work by car, trip 2: work to shop by bike, trip 3: shop to work by bike; and trip 4: work to home by car). Secondary outcomes of interest were total life cycle CO_2 emissions for four aggregated journey purposes: (1) work or education/school trips; (2) business trips; (3) social or recreational trips; and (4) shopping, personal business, escort or 'other' trips.

2.4 Covariates

A number of covariates were hypothesized to confound the association between carbon emissions and transport mode choice and use (e.g. Brand et al., 2013; Büchs and Schnepf, 2013; Goodman et al., 2019). Demographic and socio-economic covariates considered in the analyses were age, sex, employment status, household income, educational level, and household composition (e.g. single occupancy, or having children or not). Vehicle ownership covariates considered were car accessibility, having a valid driving license, and bicycle accessibility. Health covariates considered were self-rated health status and Body Mass Index (BMI), which have been shown to influence motorized travel and transport CO_2 emissions (Goodman et al., 2012). The perceived walking times to the nearest bus stop, tram stop or railway station were included as public transport accessibility measures. All of the covariates were self-reported. BMI was derived from self-reported weight and height as $weight(kg)/height(m)^2$ (Dons et al., 2018).

2.5 Statistical analysis

In a first step, bivariate analyses were performed to assess the association between transport-related CO_2 emissions, the exposure variables, and the potential covariates. Only covariates with p-value<0.1 were included in the linear mixed-effects models. In a second step, differences in CO_2 emissions between the different transport mode users were identified by using mixed-effects linear regression models with city as a random effect (to take account of correlation among responses from the same city). The analysis used multiple data points for each individual, obtained on different weekdays; therefore, respondents and weekdays were also included as random effects. Because CO_2

emissions were heavily skewed towards the right (see also Figure 1), we applied the transformation *'ln([x/mean(x)]+0.01)'* (adding 0.01 to avoid turning zeros into missing values) in the comparative analysis. This improved our regression diagnostics, with residuals closer to a normal distribution and their variance less heteroscedastic. Note a log transformation changes the focus from absolute to relative or percentage change; therefore, any regression coefficient β is a mean difference of the *log outcome* comparing adjacent units of a predictor. This is practically useless, so we exponentiate the parameter e^{β} and interpret this value as a geometric mean difference (Vittinghoff et al., 2012). Three regression models were fitted: (0) unadjusted (exposure only); (1) adjusted by socio-demographic covariates: sex, age, education level, employment status, household income, household composition; and (2) adjusted by all covariates from model 1 and additionally other covariates of interest (those found to be statistically significant in previous literature described earlier): holding a valid driving license, access to a car or van, bicycle ownership, self-rated health, BMI, walking-time accessibility to the nearest bus stop, and walking-time accessibility to the nearest train station. Age was included as a continuous variable as a proxy for time. The same set of models were fitted for each of the four journey purposes.

Potential interaction by sex, employment status, income, car access, BMI and city were investigated with Type II Wald chisquare tests in the fully-adjusted models. We observed significant interactions for some transport modes (e.g. use of all modes and car access; public transport use and gender; car use and income); therefore, all models' sensitivity to different levels of the above factors were tested. We also tested the models' sensitivity to a number of other factors: age ('<35 years'), working status ('working'), car access ('not having access to a car'), body weight ('being overweight'), household income ('high income') and city (Table 2). Participants were also ranked according to their CO_2 emissions (all travel and by trip purpose) then split into ten emissions deciles. Chi-square tests were performed on selected covariates to profile the 'bottom' and 'top' deciles. Possible mediation of the effect of transport mode use on CO_2 emissions was assessed for three potential mediators: total daily distance travelled, BMI and self-rated health (VanderWeele, 2016; Wanner et al., 2012). Only observations without missing data were included. R statistical software v3.6.1 was used for all analyses.

3. Results

3.1 Sample description and summary statistics

The final sample included 3836 participants who had completed 9858 one-day travel diaries reporting 34203 trips (Table 2). The sample was well balanced between male and female, and between the seven cities. Participants were highly educated with 79% of the participants having at least a secondary or higher education degree. Aged between 16 and 91, the majority of participants were employed full-time (66%), with 72% on middle to high household incomes (i.e. >€25k) and 34% reported to have children living at home. The share of participants without access to a car was 21%. While cycling and public transport were the most frequent transport modes among our participants, people travelled furthest by public transport and car. Transport mode usage was similar between sexes, with a slightly higher prevalence of male cyclists and drivers vs. female walkers and public transport users. Participants reported an average of 3.47 (SD 1.83) trips per day ranging from 3.10 (SD 1.63) trips per day in Rome to 3.75 (SD 2.0) trips per day in Antwerp (Table 2). The observed cycling trip share for our sample was between 17% in Barcelona and 54% in Antwerp (Supplementary Table S1), i.e. somewhat higher than cycling shares reported for the cities (EPOMM, 2020) and a direct result of purposively oversampling cyclists. Reported trip durations and distances were highly variable between subjects and cities, with respondents travelling on average 36.1 (SD 63.5) km a day and for 87.8 (SD 70.4) min a day. Average trip lengths across the cities were 1.1 (SD 1.6) km for walking, 5.0 (SD 5.3) km for cycling, 20.5 (SD 45.9) km for driving and 16.7 (SD 33.6) km for public transport. Further results for each city are given in Supplementary Table S3.

3.2 Levels and sources of life cycle CO_2 emissions

Life cycle CO_2 emissions from all travel activity were 3.18 (SD 7.68) kilograms of CO_2 ($kgCO_2$) per person per day, with the majority from car travel at 2.23 (SD 7.25) $kgCO_2$/day – i.e. 70% of the daily total (see Table 2). In contrast, life cycle emissions from cycling (which included a 4.5% share of e-biking across the sample) amounted for only 0.03 (SD 0.05) $kgCO_2$/day. Direct (operational) emissions from all travel activity made up the majority (70%) of total life cycle emissions. While travel to work or place of education produced the largest share of CO_2 emissions (37%), there were also considerable contributions from social and recreational trips (34%), business trips (11%) and travel for shopping or personal business (17%). Figure 1 shows a highly unequal distribution of emissions. It also shows that the top decile of emitters were responsible for 59% (all purposes), 47% (work or education), 78% (business), 67% (social or recreational) and 58% (shopping, personal business, escort or other) of the respective life cycle CO_2 emissions. Those in the top decile were more likely to be male, have higher household incomes, holding a driving license and always have access to a car, be in full-time employment, have higher BMI, have poor bus or train accessibility and live in Orebro, Antwerp or Rome. In contrast, those in the bottom decile of emitters were more likely to be female, economically inactive or a student, living in a household without kids, be on lower household incomes, not to hold a driving license, without access to a car, own a bike, have lower BMI, live nearer to train stations, and live in Barcelona or London. To explain this it is worth highlighting that while Antwerp and Orebro had significantly[2] higher cycling trip shares amongst the case study cities, they also had higher car shares (together with Rome) and low walking shares (also together with Rome). On the contrary, Barcelona and London had lower car trip shares (like Vienna and Zurich) and higher walking shares (Supplementary Table S3).

Table 2: Summary statistics of outcomes, exposures and other covariates

Total study sample (n=9858) and mean (SD) values			
CO_2 emissions	**All modes, life cycle**	**3.18 (7.68)**	
(kg per day)	Car, life cycle	2.23 (7.25)	
	Public transport, life cycle	0.93 (2.90)	
	Bike, life cycle	0.03 (0.05)	
	Walk, life cycle	0 (–)	
	Al modes, direct only^	*2.22 (5.62)*	
	All modes, indirect only^	*0.96 (2.20)*	
Transport mode usage	Car	0.69 (1.29)	
(trips per day)	Public transport	0.90 (1.24)	
	Bike	1.05 (1.58)	
	Walk	0.82 (1.36)	
	All modes	**3.47 (1.83)**	
Average distance travelled	Car	14.61 (50.32)	
(km per day)	Public transport	15.51 (43.62)	
	Bike	5.06 (9.71)	
	Walk	0.88 (2.08)	
	All modes	**36.06 (63.51)**	
Average travel time (min/day)	All modes	87.84 (70.45)	
Age (years)	All	39.19 (11.16)	
BMI (kg/m^2)	All	23.66 (3.83)	
Sub samples/groups and mean(SD) values of main outcome measure			
Exposures		Life cycle CO_2 (mean (SD)), in kg/day	n (%)
Main mode	Car	9.139 (12.532)	2307 (23%)
(based on distance)	Public transport	2.746 (5.292)	3546 (36%)
	Bike	0.169 (0.468)	3012 (31%)
	Walk	0.031 (0.159)	993 (10%)
Cycling category	Non-cyclist (none)	4.438 (8.892)	6031 (61%)
(based on trips per day)	Occasional cyclist (once or twice)	1.517 (5.552)	2329 (24%)
	Frequent cyclist (thrice or more)	0.708 (2.343)	1498 (15%)
Cycling (yes/no)	Not cycling on the day	4.438 (8.892)	6031 (61%)
	Cycling on the day	1.201 (4.589)	3827 (39%)
City	Antwerp	3.487 (7.763)	1713 (17%)
	Barcelona	2.468 (5.792)	1806 (18%)
	London	3.209 (7.788)	1027 (10%)
	Oerebro	4.559 (9.451)	607 (6%)
	Rome	3.929 (10.012)	1061 (11%)
	Vienna	2.651 (6.153)	1752 (18%)
	Zurich	3.199 (8.16)	1892 (19%)

Sex	Male	3.305 (8.043)	5061 (51%)
	Female	3.051 (7.282)	4797 (49%)
Age (for sensitivity analysis)	Age <35 years	2.903 (6.398)	4199 (43%)
	Age >=35 years	3.387 (8.507)	5659 (57%)
	Age >55 years	3.807 (9.551)	981 (10%)
Self-rated health	Excellent	3.197 (7.857)	1036 (10%)
	Very good	3.074 (7.854)	4221 (43%)
	Good	3.331 (7.575)	3839 (39%)
	Fair or poor	3.001 (6.998)	762 (8%)
BMI (for sensitivity analysis)	Healthy BMI (18.5<=BMI<25)	3.019 (7.307)	6927 (70.3%)
	Overweight (BMI>=25)	3.599 (8.649)	2599 (26.4%)
Household income	Low income (Less than €25k)	2.884 (7.436)	2713 (28%)
	Middle income (€25k to €75k)	3.176 (7.449)	5535 (56%)
	High income (€75k or more)	3.699 (8.503)	1610 (16%)
Employment status	Working (full-time or part-time)	3.241 (7.761)	8404 (85%)
	Not working (retired/student/etc.)	2.838 (7.208)	1454 (15%)
Education level	Higher education or degree	3.124 (7.261)	7814 (79%)
	No higher education or degree	3.401 (9.118)	2044 (21%)
Household composition	HH two or more adults, no kids	3.156 (7.462)	4788 (49%)
	Single HH, no kids	2.778 (6.133)	1750 (18%)
	HH with kids	3.431 (8.662)	3320 (34%)
Car accessibility	Always or sometimes	3.561 (8.093)	7755 (79%)
	Never	1.781 (5.719)	2103 (21%)

^ Direct: tailpipe emissions. ^ Indirect: well-to-tank (fuel/energy production) plus vehicle manufacture. BMI: body mass index.

In our sample, respondents in Orebro and Rome produced significantly higher-than-average CO_2 emissions (mean 4.56 $kgCO_2$/day and 3.93 $kgCO_2$/day, respectively) due to the higher car mode shares, while those in Barcelona and Vienna produced lower emissions (mean 2.47 $kgCO_2$/day and 2.65 $kgCO_2$/day, respectively) due to higher share of walking (Barcelona) and a combination of lower car and higher public transport shares (Vienna) (Table 2 and Supplementary Table S3). Those in Antwerp had the highest active travel share, but also higher (than sample average) car and lower public transport shares, resulting in higher than average CO_2 emissions overall (mean 3.49 $kgCO_2$/day). These figures are generally in line with regional per capita CO_2 emissions estimates. Differences between cities can partially be explained by differences in sample demographics, socio-economics and observed mode shares (Supplementary Table S1 and Table S3).

3.3 Transport mode usage

We found statistically significant associations between life cycle CO_2 emissions and transport mode usage across all modes of travel (Table 3a): those who cycled or walked more had lower daily mobility-related CO_2 emissions, while those who drove more or used public transport more had higher daily total CO_2 emissions. In the fully-adjusted model, log-transformed life cycle carbon emissions *decreased* by a factor of 0.15 (95%CI 0.13 to 0.17) *for each additional cycling trip*. They also decreased by a factor of 0.96 (95%CI 0.94 to 0.98) for one less car trip. Or in other words, for each avoided car trip daily life cycle CO_2 emissions from transport decreased by 62% (95%CI 61% to 63%) while for each additional bike trip life cycle CO_2 emission decreased by 14% (95%CI 12% to 16%).[3] Those who made one less car trip and one more bike trip a day (a proxy for mode shift from car to bike) decreased life cycle CO_2 emissions from transport by 67% (95%CI 66% to 68%).

Table 3: Results from the linear fixed-effects and mixed-effects models for the four exposures (n=9858). Full models are presented in the Supplementary Information.

	Model 0: unadjusted (fixed effects)		**Model 1: partly adjusted (mixed effects)** †		**Model 2: fully adjusted (mixed effects)** #	
	Coefficient (95% CI)	p-value	Coefficient (95% CI)	p-value	Coefficient (95% CI)	p-value
(a) Association between log-transformed life cycle CO_2 emissions and transport mode usage (trips/day) (full model in Table S4)						
Bike	-0.154 (-0.172 to -0.137)	< 0.0001	-0.16 (-0.179 to -0.142)	< 0.0001	-0.151 (-0.17 to -0.132)	< 0.0001
Car	0.997 (0.976 to 1.017)	< 0.0001	0.974 (0.953 to 0.996)	< 0.0001	0.962 (0.94 to 0.983)	< 0.0001
Public transport	0.741 (0.719 to 0.763)	< 0.0001	0.737 (0.714 to 0.76)	< 0.0001	0.748 (0.724 to 0.771)	< 0.0001
Walk	-0.287 (-0.305 to -0.269)	< 0.0001	-0.278 (-0.297 to -0.259)	< 0.0001	-0.273 (-0.292 to -0.254)	< 0.0001
(b) Association between log-transformed life cycle CO_2 emissions and main transport mode categories (full model in Table S6)						
Bike	0	–	0	–	0	–
Car	3.89 (3.84 to 3.939)	< 0.0001	3.881 (3.829 to 3.932)	< 0.0001	3.866 (3.813 to 3.919)	< 0.0001
Public transport	2.599 (2.554 to 2.643)	< 0.0001	2.624 (2.575 to 2.673)	< 0.0001	2.635 (2.586 to 2.684)	< 0.0001
Walk	-1.071 (-1.137 to -1.005)	< 0.0001	-0.956 (-1.023 to -0.888)	< 0.0001	-0.931 (-0.999 to -0.862)	< 0.0001
(c) Association between log-transformed life cycle CO_2 emissions and cycling frequency categories (full model in Table S7)						
None	0	–	0	–	0	–
Once or twice a day	-1.697 (-1.781 to -1.612)	< 0.0001	-1.768 (-1.855 to -1.681)	< 0.0001	-1.747 (-1.835 to -1.659)	< 0.0001
Three+ times a day	-2.016 (-2.116 to -1.916)	< 0.0001	-2.071 (-2.177 to -1.966)	< 0.0001	-2.038 (-2.145 to -1.932)	< 0.0001
(d) Association between log-transformed life cycle CO_2 emissions and cycling (yes/no) (full model in Table S8)						
Not cycling	0	–	0	–	0	–
Cycling	-1.822 (-1.893 to -1.75)	< 0.0001	-1.875 (-1.952 to -1.797)	< 0.0001	-1.848 (-1.927 to -1.769)	< 0.0001

†Model 1 adjusted for sex, age, education level, employment status, household income, household composition; city and person as random effects.

#Model 2 adjusted for sex, age, education level, employment status, household income, household composition, driver license, car access, bike access, self-rated health, BMI, bus accessibility, rail accessibility; city, person and day of the week as random effects.

Adjusting for demographic, socio-economic and other individual variables only slightly changed the estimates in the partly and the fully adjusted models (model 1 and model 2) compared to the unadjusted model (model 0). The addition of car availability and bus station accessibility in the fully adjusted model (model 2) slightly lowered the estimate for car but increased the estimate for public transport use compared to the unadjusted (0) and partly adjusted models (1).

The effects of transport mode use on transformed carbon emissions was partially mediated via total distance travelled (see Figure 2): the indirect effects of total distance travelled were +0.13 for car use (13% mediated), -0.02 for cycling (14% mediated), +0.10 for public transport use (13% mediated), and -0.05 for walking (18% mediated). Neither BMI nor health status mediated this association.

A series of sensitivity analyses largely confirmed our results (Figure 2a): excluding participants older than 35 or on lower incomes did not change our conclusions; and differences between those ‘working’ and ‘not working’ and those being ‘overweight’ (above 25 kg/m^2) and ‘healthy weight’ were small. For people who did not have access to a car the effects were larger for motorized travel and smaller for active travel, suggesting that active travel for non-car owning households may substitute for public transport and other active travel.

The associations between log-transformed life cycle CO_2 emissions for the four trip purposes (secondary outcomes) and transport mode usage were also largely significant (Table 4a and Supplementary Figure S3a). Cycling frequency had larger effects on emissions from commuting to work or place of education than on emissions from all purposes (primary outcome models). Motorized transport mode use showed larger effects on life cycle CO_2 emissions from social, shopping and recreational travel than for work/business travel. The ‘economically inactive’ (home duties, retired, unemployed, etc.) showed significantly higher emissions for social, recreational, shopping and personal business purposes, with lower emissions from work or educational trips, as expected. Those with children living at home had significantly lower business, social and recreational emissions, while emissions from shopping, personal business and escort trips were higher. Poor bus accessibility and better car access meant higher emissions from work or educational trips.

3.4 Main mode of travel (by daily distance travelled)

We also found statistically significant associations between life cycle CO_2 emissions and the main modes of travel according to daily distance travelled (Table 3b): when compared to using a bike as the main mode, using the car or public transport increased CO_2 while walking decreased CO_2. In the fully adjusted model (model 2) CO_2 emissions were 98 (95%CI 98 to 98) percent higher for using a car or van as the main mode than for using a bike. An average person using a car or van as the main mode had 7.1 $kgCO_2$/day higher life cycle CO_2 emissions than someone using a bike as their main mode of transport. A comparison with the results of the non-transformed model suggested that using a car or van increased emissions by 8.9 $kgCO_2$/day when compared to cycling as the main mode (Supplementary Table S5 and Figure S2) – suggesting the linear model slightly overestimated differences in emissions by main mode when compared to the (statistically superior) log-linear model. Those using public transport as the main mode had 71 (95%CI 71 to 71) percent lower emissions than those mainly using a car, van or motorcycle; for an average person this difference equated to 5.1 $kgCO_2$/day.

Again, the sensitivity analysis (Figure 2b) largely confirmed our results. Total distance travelled partially (12%) mediated the effects of main mode (by daily distance) on transformed life cycle CO_2 emissions. The associations for log-transformed CO_2 emissions by journey purpose were also all significant (Supplementary Table S10 and Figure S3), with the strongest effects for mainly using public transport for work or education and car for social and shopping trips. Women, those with a degree or no access to a car had significantly lower work or education emissions. As expected, the economically inactive had significantly higher social, recreational and shopping/personal business emissions, yet lower work/education emissions.

3.5 Cycling frequency and cycling vs not cycling

Associations between life cycle CO_2 emissions and cycling frequency were all highly significant. Table 3c shows that in the fully adjusted model (model 2) life cycle CO_2 emissions were 83 (95%CI 81 to 84) percent lower for ‘occasional cyclists’ (i.e. those cycling ‘once or twice a day’) than for those who did not cycle; and they were even lower for ‘frequent cyclists’ (those cycling ‘three or more times a day’) with 87 (95%CI 86 to 88) percent lower daily life cycle CO_2. The sensitivity analysis (Figure 2c) generally confirmed our results, with slightly higher effects for high earners and lower effects if you were younger or without access to a car. Regular cycling was also associated with reduced life cycle CO_2 emissions for all the four trip purposes, with the strongest effect observed for commuting and social trips (Supplementary Table S11): cycling three or more times a day decreased life cycle CO_2 emissions for work or education by 78 (95%CI 75 to 80) percent, for social or recreational trips by 53 (95%CI 46 to 59) percent, for shopping and personal business by 29 (95%CI 19 to 38) percent, and for business travel by 20 (95%CI 10 to 28) percent.

As expected, the binary cyclist/non-cyclist analysis showed similar effect sizes and correlations to the analysis of cycling frequency for both primary and secondary outcome measures. ‘Cyclists’ had 84 (95%CI 83 to 85) percent lower life cycle CO_2 emissions than ‘non-cyclists’ (Table 2d and Supplementary Table S12); this translated into 0.97 (95%CI 0.54 to 1.74) kgCO_2/day lower life cycle CO_2 emissions for an average person who cycled. The sensitivity analysis showed that the effects were lower for the younger respondents and those without access to a car, and higher for those on higher incomes (Figure 2d).

Table 4: Results from the fully-adjusted mixed-effects models for the four exposures, by trip purpose

n=9858	**Work or education** #		**Business** #		**Social or recreational** #		**Shopping, personal business, escort, or 'other'** #	
	Coefficient (95% CI)	p-value	Coefficient (95% CI)	p-value	Coefficient (95% CI)	p-value	Coefficient (95% CI)	p-value
(a) Association between log-transformed life cycle CO_2 emissions and transport mode usage (trips/day) (full model in Table S9)								
Bike	-0.24 (-0.27 to -0.209)	< 0.001	0.019 (-0.008 to 0.046)	0.174	0.062 (0.031 to 0.094)	< 0.001	0.158 (0.126 to 0.189)	< 0.001
Car	0.191 (0.157 to 0.226)	< 0.001	0.172 (0.141 to 0.203)	< 0.001	0.725 (0.689 to 0.761)	< 0.001	0.826 (0.79 to 0.861)	< 0.001
PT	0.412 (0.375 to 0.449)	< 0.001	0.168 (0.134 to 0.201)	< 0.001	0.475 (0.436 to 0.514)	< 0.001	0.393 (0.354 to 0.431)	< 0.001
Walk	-0.272 (-0.302 to -0.242)	< 0.001	-0.064 (-0.091 to -0.037)	< 0.001	-0.092 (-0.123 to -0.061)	< 0.001	-0.025 (-0.056 to 0.006)	0.112
(b) Association between log-transformed life cycle CO_2 emissions and main transport mode categories (full model in Table S10)								
Bike	0	–	0	–	0	–		–
Car	1.532 (1.424 to 1.641)	< 0.001	0.762 (0.662 to 0.863)	< 0.001	2.281 (2.164 to 2.397)	< 0.001	1.987 (1.867 to 2.108)	< 0.001
PT	1.873 (1.774 to 1.973)	< 0.001	0.469 (0.378 to 0.561)	< 0.001	1.002 (0.895 to 1.108)	< 0.001	0.677 (0.566 to 0.787)	< 0.001
Walk	-0.648 (-0.787 to -0.509)	< 0.001	-0.141 (-0.27 to -0.011)	0.033	-0.784 (-0.934 to -0.634)	< 0.001	-0.462 (-0.617 to -0.306)	< 0.001
(c) Association between log-transformed life cycle CO_2 emissions and cycling frequency categories (full model in Table S11)								
None	0	–	0	–	0	–		–
1-2 times	-1.086 (-1.188 to -0.983)	< 0.001	-0.433 (-0.522 to -0.344)	< 0.001	-0.865 (-0.977 to -0.754)	< 0.001	-0.77 (-0.882 to -0.658)	< 0.001
3+ times	-1.498 (-1.622 to -1.374)	< 0.001	-0.218 (-0.324 to -0.111)	< 0.001	-0.756 (-0.89 to -0.622)	< 0.001	-0.344 (-0.479 to -0.21)	< 0.001
(d) Association between log-transformed life cycle CO_2 emissions and cycling (yes/no) (full model in Table S12)								
Not cycling	0	–	0	–	0	–		–
Cycling	-1.229 (-1.321 to -1.136)	< 0.001	-0.356 (-0.435 to -0.277)	< 0.001	-0.826 (-0.925 to -0.727)	< 0.001	-0.617 (-0.717 to -0.517)	< 0.001

Models are mixed effects models fully adjusted for sex, age, education level, employment status, household income, household composition, driver license, car access, bike access, self-rated health, BMI, bus accessibility, rail accessibility; city, person and day of the week as random effects.

PT=public transport.

3.6 Sensitivity: city effects

The random intercepts of city explained 2.2% (a: transport mode usage), 5.4% (b: main mode of transport), 2.6% (c: cycling frequency) and 2.5% (d: cycling yes/no) of the residual variance in the fully adjusted models. Mean CO_2 emissions were significantly lower in Barcelona and Vienna and higher in Orebro and Rome (Table 2). Further sensitivity analyses of the fully adjusted models stratified by city showed that the effect estimates for cycling were generally the lowest in Barcelona and highest in Orebro and Rome (Figure 3). By comparison, CO_2 effects for car travel were highest in Barcelona (and Vienna to some extent) and lowest in London and Rome.

[2] Comparing deciles with chi-square tests of independence.

[3] To derive percentage changes of the untransformed outcome, we exponentiated the regression coefficient, subtracted 1 and multiplied by 100 (Vittinghoff et al, 2012).

4. Discussion

4.1 Summary of results

This paper started on the premise that we still do not know very much about how much carbon from passenger transport is saved – *overall* – by travelling actively. In this multi-city study with thousands of participants providing nearly 10,000 valid person-days of travel activity, we found highly significant associations between transport mode choice and total life cycle CO_2 emissions. We showed that cyclists had significantly lower total CO_2 emissions than non-cyclists. More cycling or walking decreased mobility-related life cycle CO_2 emissions – suggesting that active travel indeed substitutes for motorized travel (i.e. this was not just additional travel over and above motorized travel). This means that even if not all car trips could be substituted by bicycle trips the potential for decreasing emissions is very high. A number of sensitivity analyses confirmed our main results and provided new insights into differences of emission levels and exposures by city and journey purpose. The differences in mean emissions and effect sizes in the seven cities may be explained by contextual factors such as differences in modal shares, mode trip lengths, and the provision (or not) of good public transport services and active travel infrastructure – it may also be due to differences in sampling (Raser et al., 2018). The analysis of emissions for each trip purpose highlighted the relative importance of emissions from non-work/business trips, particularly trips for social and shopping purposes.

4.2 Comparison with previous studies

Mean total CO_2 emissions of 3.18 $kgCO_2$/day were much higher than the median (0.81 $kgCO_2$/day) and near the upper end of the derived interquartile range (0.07-3.27 $kgCO_2$ per day), confirming a positively skewed distribution of emissions. In other words, a relatively small share of individuals was responsible for the vast majority of carbon emissions, a finding that is very much in line with the evidence on unequal carbon emissions distributions (Brand and Boardman, 2008; Büchs and Schnepf, 2013; Ko et al., 2011; Preston et al., 2013; Susilo and Stead, 2009). Our findings that the likelihood of being in top or bottom emissions decile depended on demographic, socio-economic, car availability, health, public transport accessibility and contextual factors further support the growing evidence on travel emissions inequalities (Banister, 2018; Bel and Rosell, 2017; Brand, 2008; Ko et al., 2011).

The analysis of transport mode use as the main exposure showed that each additional cycling trip reduced life cycle CO_2 emissions from all travel activity by about 14% when compared to baseline emissions. On average, those who did one less trip by car and one more by bike or public transport decreased emissions by 67% and 19% respectively. To further aid interpretation of the factorial results we need to apply the percentage changes to baseline (or mean) levels of our measured outcomes. For example, an average person 'shifting modes' from car (from 3 to 2 trips a day) to bike (from 0 to 1 trip a day) decreased emissions by 3.2 (95%CI 2.0 to 5.2) $kgCO_2$/day. Similarly, a person 'shifting modes' from car (from 3 to 2 trips a day) to public transport (from 0 to 1 trip a day) decreased emissions by 0.9 (95%CI 0.6 to 1.5) $kgCO_2$/day. If 10% of the population were changing travel behavior this way, emissions would be expected to decrease by about 10% (caràbike) and 3% (caràpublic transport). The size and direction of emissions changes are in line with some of the few empirical (Brand et al., 2013; Goodman et al., 2012) and scenario/modelling (Goodman et al., 2019; Rabl and de Nazelle, 2012; Tainio et al., 2017; Woodcock et al., 2018) studies in this area.

The differences in emissions between people using different modes for the majority (defined by max. distance travelled) of their daily travel were also highly significant, although the effects were partially (12%) mediated by total daily distance travelled. Our finding that, on average, using a bike as the main mode decreased life cycle CO_2 emissions by about 7.1 $kgCO_2$/day when compared to using a car or van suggests that making more sustainable choices on to how we get from A to B has significant carbon benefits. Similarly, our finding that doing at least one trip a day by bike significantly decreased mobility-related life cycle CO_2 emissions provides further evidence of mode substitution away from motorized travel.

Much of the research in this area has focused on travel activity and associated carbon emissions from work and business travel (Bearman and Singleton, 2014; Clark et al., 2016). In our study, commuting, education and business travel emissions represented ‘only’ about half (49%) of total emissions, ranging from 39% in Antwerp to 59% in London and Rome. The findings that life cycle CO_2 emissions from social, shopping, personal business and recreational journeys were more strongly associated to car and, to some extent, public transport use suggest for research and policy to go beyond commuting and business travel and consider the whole range of journey purposes when investigating mode shift away from motorized to active travel (Brand et al., 2013). This seems to be particularly important with the growing shares of the elderly in the population. Shopping and personal business trips were found to be significantly shorter, therefore increasing the potential for mode shift to active travel.

The mediation analysis by distance travelled indicated that lower carbon emissions for cyclists was unlikely to be entirely caused by increased bike usage. The remaining emissions difference might be explained by distance-related factors that influence mode choice such as urban form and location of housing, services and jobs (Banister et al., 1997; Beenackers et al., 2012; Curtis, 1996; Welch, 2013).

While focusing on cycling above we also found that using public transport was more beneficial than private motorized transport across all exposure measures, thus confirming findings from the large body of literature that already exists in this area (see e.g. Banister, 2008; Graham-Rowe et al., 2011; Nieuwenhuijsen, 2020; Woodcock et al., 2009).

4.3 Limitations of the study

In interpreting these findings we need to bear in mind the study’s limitations. First, the recruitment and sampling strategy means that our sample cannot be assumed to be representative of the general population, especially for education level and age. Orebro was the lone city that made a concerted effort for random sampling, whereas in other cities an opportunistic recruitment strategy was followed (Dons et al., 2015). However, by oversampling some of the less frequent transport modes, we had a sufficiently large sample of cyclists in all cities to find statistically significant associations. Second, recall bias and participant burden of a substantive survey instrument may have impacted the travel diary reporting, which may have reduced the number of reported trips. However, the observed trip frequencies (e.g. 3.47 trips per person per day on average) and mode shares (e.g. significantly higher cycling shares in Antwerp, lower cycling shares in Barcelona, higher public transport shares in London, Vienna and Zurich) were in line with figures reported for the cities (Raser et al., 2018). While trip distances were derived from Google API data, trip durations were self-reported. Trip durations from self-completion travel diaries are known to be over-reported (Kelly et al., 2013), so mean speeds may have been lower than actual speeds leading to increased emissions rates in urban areas. However, further investigation of mean speeds by mode of transport showed that the derived mean speeds of 4.8 kph for walking, 15.6 kph for cycling/e-biking, 39.9 kph for driving a car or van, and 17.9 kph for urban public transport were in line with figures reported elsewhere (Raser et al., 2018). Note these are daily averages not just peak-time speeds (as often reported). Third, outcome and exposure variables were reported at different time points and days of the week – this was taken into account in the mixed effect models by including ‘day of the week’ and person ID as random (intercept) variables. Other periodic effects cannot be excluded and we tried to cover for that as much as possible by including relevant time-varying covariates (such as participant age) and factors influencing outcomes such as ambient temperature (for ‘cold start’ emissions). Fourth, our analysis is cross-sectional, meaning that the direction of causality (if any) behind many of the observed associations is unclear. A longitudinal analysis of change in emissions by change in exposures is underway and will be reported in due course. Fifth, while we accounted for several influencing factors that were often not available in previous studies, such as trip data by mode and purpose, accessibility and health status, our regression models did not account for more than 78% of the variation in the population (see Supplementary results). This suggests that travel choices and associated CO_2 emissions are also influenced by other factors such as other built environment factors or lifestyle and socio-cultural factors (Brand et al., 2019; Panter et al., 2013; Weber and Perrels, 2000). We initially explored and added more ‘objective’, GIS based data at both home and work locations to the analysis, including street density, building density, richness of facilities, home-work distance, and public transport availability (timetables, frequency) (Gascon et al., 2019). However, none of these factors improved the models significantly, and the main findings were unchanged. Sixth, we excluded carbon emissions from dietary intake as the evidence is not strong on whether day-to-day active travel (as opposed to performance/sport activity) significantly increases overall dietary intake when compared to motorized travel (Tainio et al., 2017). Finally, the interdisciplinary breadth of the PASTA study meant that we measured daily travel behavior, individual and spatial-environmental characteristics using briefer survey tools than might have been feasible in a single-discipline study. This may have introduced some measurement error that could have attenuated our effect sizes. However, the multi-city approach in different countries with different travel patterns, built environments, public transport accessibility levels and active mobility use adds value to the analysis, which clearly showed additional insights compared to smaller, single-location studies.

5. Conclusion

This paper started on the premise that we still do not know very much about how much carbon from passenger transport is saved – *overall* – by travelling actively. It investigated to what extent active travel is associated with lower mobility-related life cycle CO_2 emissions by using primary data collected in a large European multicentre study to derive total and purpose-specific life cycle CO_2 emissions from travel activity at the individual and population levels. The analysis of a sample of thousands of participants and nearly 10,000 person-days of daily travel across the seven sites provided quantitative estimates of the life cycle carbon benefits of active travel using a variety of metrics that could be used in other European cities and beyond.

Active travel has attributes of social distancing that are likely to be desirable for some time (Kissler et al., 2020). It could help to cut back transportation energy use, CO_2 emissions and air pollution while improving population health (Nieuwenhuijsen, 2020; Shaw et al., 2014) as confinement is eased. Therefore, locking in, investing in and promoting active travel should be a cornerstone of sustainability strategies, policies and planning (Andor et al., 2020; Creutzig et al., 2016; Creutzig et al., 2020) to meet our very challenging sustainable development goals that are unlikely to be met without significant mode shift to sustainable transport (Creutzig et al., 2018).

Declarations

Funding

European Commission, FP7 project PASTA - Grant Agreement No. 602624. UK Research and Innovation, Centre for Research on Energy Demand Solutions - Grant Agreement No. EP/R035288/1.

Acknowledgements

This work was supported by the European project Physical Activity through Sustainable Transportation Approaches (PASTA). PASTA (http://www.pastaproject.eu/) was a four-year project funded by the European Union's Seventh Framework Program (EU FP7) under European Commission - Grant Agreement No. 602624. CB is also supported by UK Research and Innovation (UKRI) under the Centre for Research on Energy Demand Solutions (CREDS, Grant agreement number EP/R035288/1). ED is also supported by a postdoctoral scholarship from FWO – Research Foundation Flanders. ML held a joint PASTA/VITO PhD scholarship. SS is supported by the Martin Filko Scholarship from the Ministry of Education in Slovakia.

References

ACEA/ANFAC, 2014. *European Motor Vehicle Parc 2014: Vehicles in Use (2009-2014)*. ANFAC/ACEA, Madrid.

Adams, J., 2010. Prevalence and socio-demographic correlates of "active transport" in the UK: Analysis of the UK time use survey 2005. *Prev. Med.* 50(4), 199-203.

Alvanides, S., 2014. Active transport: Why and where do people (not) walk or cycle? *Journal of Transport & Health* 1(4), 211-213.

Anable, J., Brand, C., 2019. Energy, pollution and climate change, In: Docherty, I., Shaw, J. (Eds.), *Transport Matters*. Policy Press, Bristol, p. 452.

Andor, M.A., Gerster, A., Gillingham, K.T., Horvath, M., 2020. Running a car costs much more than people think — stalling the uptake of green travel. *Nature* 580, 453-455.

Banister, D., 2008. The sustainable mobility paradigm. *Transport Policy* 15(2), 73-80.

Banister, D., 2018. *Inequality in Transport, https://www.inequalityintransport.org.uk/*. Alexandrine Press, Marcham, UK.

Banister, D., Watson, S., Wood, C., 1997. Sustainable cities, transport, energy and urban form. *Environment and Planning B: Planning and Design* 24(1), 125-143.

Bearman, N., Singleton, A.D., 2014. Modelling the potential impact on CO2 emissions of an increased uptake of active travel for the home to school commute using individual level data. *Journal of Transport & Health* 1(4), 295-304.

Beckx, C., Broekx, S., Degraeuwe, B., Beusen, B., Int Panis, L., 2013. Limits to active transport substitution of short car trips. *Transp. Res.: Part D: Transport Environ.* 22, 10-13.

Beckx, C., Panis, L.I., Janssens, D., Wets, G., 2010. Applying activity-travel data for the assessment of vehicle exhaust emissions: Application of a GPS-enhanced data collection tool. *Transp. Res.: Part D: Transport Environ.* 15(2), 117-122.

Beenackers, M.A., Foster, S., Kamphuis, C.B., Titze, S., Divitini, M., Knuiman, M., van Lenthe, F.J., Giles-Corti, B., 2012. Taking up cycling after residential relocation: built environment factors. *Am. J. Prev. Med.* 42(6), 610-615.

BEIS, 2019. Greenhouse gas reporting: conversion factors 2019, accessed at https://www.gov.uk/government/publications/greenhouse-gas-reporting-conversion-factors-2019 on 12 Nov 2019. Department for Business, Energy & Industrial Strategy, London.

Bel, G., Rosell, J., 2017. The impact of socioeconomic characteristics on CO2 emissions associated with urban mobility: Inequality across individuals. *Energy Econ.* 64, 251-261.

Brand, C., 2008. *Personal Travel and Climate Change - Exploring Climate Change Emissions from Personal Travel Activity of Individuals and Households*, 1st ed. Verlag Dr. Müller (VDM), Saarbrücken.

Brand, C., Anable, J., Morton, C., 2019. Lifestyle, efficiency and limits: modelling transport energy and emissions using a socio-technical approach. *Energy Efficiency* 12(1), 187–207.

Brand, C., Boardman, B., 2008. Taming of the few - The unequal distribution of greenhouse gas emissions from personal travel in the UK. *Energy Policy* 36(1), 224-238.

Brand, C., Goodman, A., Ogilvie, D., 2014. Evaluating the impacts of new walking and cycling infrastructure on carbon dioxide emissions from motorized travel: A controlled longitudinal study. *Appl. Energy* 128(0), 284-295.

Brand, C., Goodman, A., Rutter, H., Song, Y., Ogilvie, D., 2013. Associations of individual, household and environmental characteristics with carbon dioxide emissions from motorised passenger travel. *Appl. Energy* 104(0), 158-169.

Brand, C., Preston, J.M., 2010. '60-20 emission'--The unequal distribution of greenhouse gas emissions from personal, non-business travel in the UK. *Transport Policy* 17(1), 9-19.

Branion-Calles, M., Winters, M., Nelson, T., de Nazelle, A., Panis, L.I., Avila-Palencia, I., Anaya-Boig, E., Rojas-Rueda, D., Dons, E., Götschi, T., 2019. Impacts of study design on sample size, participation bias, and outcome measurement: A case study from bicycling research. *Journal of Transport & Health* 15, 100651.

Brög, W., Erl, E., Ker, I., Ryle, J., Wall, R., 2009. Evaluation of voluntary travel behaviour change: Experiences from three continents. *Transport Policy* 16(6), 281-292.

Büchs, M., Schnepf, S.V., 2013. Who emits most? Associations between socio-economic factors and UK households' home energy, transport, indirect and total CO2 emissions. *Ecological Economics* 90, 114-123.

Cameron, I., Kenworthy, J.R., Lyons, T.J., 2003. Understanding and predicting private motorised urban mobility. *Transp. Res.: Part D: Transport Environ.* 8(4), 267-283.

Carlsson-Kanyama, A., Linden, A.-L., 1999. Travel patterns and environmental effects now and in the future:: implications of differences in energy consumption among socio-economic groups. *Ecological Economics* 30(3), 405-417.

Carse, A., Goodman, A., Mackett, R.L., Panter, J., Ogilvie, D., 2013. The factors influencing car use in a cycle-friendly city: the case of Cambridge. *Journal of Transport Geography* 28(0), 67-74.

Castro, A., Gaupp-Berhausen, M., Dons, E., Standaert, A., Laeremans, M., Clark, A., Anaya, E., Cole-Hunter, T., Avila-Palencia, I., Rojas-Rueda, D., Nieuwenhuijsen, M., Gerike, R., Panis, L.I., de Nazelle, A., Brand, C., Raser, E., Kahlmeier, S., Götschi, T., 2019. Physical activity of electric bicycle users compared to conventional bicycle users and non-cyclists: Insights based on health and transport data from an online survey in seven European cities. *Transportation Research Interdisciplinary Perspectives*, 100017.

Clark, B., Chatterjee, K., Melia, S., 2016. Changes to commute mode: The role of life events, spatial context and environmental attitude. *Transp. Res.: Part A: Pol. Practice* 89, 89-105.

Creutzig, F., Agoston, P., Minx, J.C., Canadell, J.G., Andrew, R.M., Quéré, C.L., Peters, G.P., Sharifi, A., Yamagata, Y., Dhakal, S., 2016. Urban infrastructure choices structure climate solutions. *Nature Climate Change* 6(12), 1054-1056.

Creutzig, F., Javaid, A., Koch, N., Knopf, B., Mattioli, G., Edenhofer, O., 2020. Adjust urban and rural road pricing for fair mobility. *Nature Climate Change*.

Creutzig, F., Roy, J., Lamb, W.F., Azevedo, I.M.L., Bruine de Bruin, W., Dalkmann, H., Edelenbosch, O.Y., Geels, F.W., Grubler, A., Hepburn, C., Hertwich, E.G., Khosla, R., Mattauch, L., Minx, J.C., Ramakrishnan, A., Rao, N.D., Steinberger, J.K., Tavoni, M., Ürge-Vorsatz, D., Weber, E.U., 2018. Towards demand-side solutions for mitigating climate change. *Nature Climate Change* 8(4), 268-271.

Cuenot, F., Fulton, L., Staub, J., 2012. The prospect for modal shifts in passenger transport worldwide and impacts on energy use and CO2. *Energy Policy* 41(0), 98-106.

Curtis, C., 1996. Can strategic planning contribute to a reduction in car-based travel? *Transport Policy* 3(1-2), 55-65.

de Nazelle, A., Morton, B.J., Jerrett, M., Crawford-Brown, D., 2010. Short trips: An opportunity for reducing mobile-source emissions? *Transp. Res.: Part D: Transport Environ.* 15(8), 451-457.

DEFRA/DECC, 2016. UK Government conversion factors for Company Reporting, full 2016 dataset. Department for the Environment, Food and Rural Affairs and Department for Energy and Climate Change, London.

DfT, 2015. Transport Statistics Great Britain: 2015 Edition. Department for Transport, London.

Dons, E., Gotschi, T., Nieuwenhuijsen, M., de Nazelle, A., Anaya, E., Avila-Palencia, I., Brand, C., Cole-Hunter, T., Gaupp-Berghausen, M., Kahlmeier, S., Laeremans, M., Mueller, N., Orjuela, J.P., Raser, E., Rojas-Rueda, D., Standaert, A., Stigell, E., Uhlmann, T., Gerike, R., Int Panis, L., 2015. Physical Activity through Sustainable Transport Approaches (PASTA): protocol for a multi-centre, longitudinal study. *BMC Public Health* 15(1), 1126.

Dons, E., Rojas-Rueda, D., Anaya-Boig, E., Avila-Palencia, I., Brand, C., Cole-Hunter, T., de Nazelle, A., Eriksson, U., Gaupp-Berghausen, M., Gerike, R., Kahlmeier, S., Laeremans, M., Mueller, N., Nawrot, T., Nieuwenhuijsen, M.J., Orjuela, J.P., Racioppi, F., Raser, E., Standaert, A., Int Panis, L., Götschi, T., 2018. Transport mode choice and body mass index: Cross-sectional and longitudinal evidence from a European-wide study. *Environ. Int.* 119, 109-116.

ECF, 2011. Cycle more Often 2 cool down the planet! - Quantifying CO2 savings of Cycling. European Cyclists' Federation (ECF), Brussels.

Ecometrica, 2011. *Electricity-specific emission factors for grid electricity*. Ecometrica.

EEA, 2012. COPERT 4 (COmputer Programme to calculate Emissions from Road Transport), last accessed at http://emisia.com/content/copert-documentation on 20/02/2018. European Environment Agency, Copenhagen.

EEA, 2019. Total greenhouse gas emission trends and projections in Europe, accessed at https://www.eea.europa.eu/data-and-maps/indicators/greenhouse-gas-emission-trends-6/assessment-3 on 30/03/2020. European Environment Agency, Copenhagen.

EMEP/EEA, 2016. EMEP/EEA air pollutant emission inventory guidebook 2016, Technical guidance to prepare national emission inventories. European Environment Agency, Copenhagen.

EPOMM, 2020. TEMS - The EPOMM Modal Split Tool, accessed at http://www.epomm.eu/tems/index.phtml on 21/3/2020. European Platform on Mobility Management (EPOMM), Leuven, BE.

Frank, L.D., Greenwald, M.J., Winkelman, S., Chapman, J., Kavage, S., 2010. Carbonless footprints: promoting health and climate stabilization through active transportation. *Prev. Med.* 50 Suppl 1, S99-105.

Gascon, M., Götschi, T., Nazelle, A.d., Gracia, E., Ambròs, A., Márquez, S., Marquet, O., Avila-Palencia, I., Brand, C., Iacorossi, F., Raser, E., Gaupp-Berghausen, M., Dons, E., Laeremans, M., Kahlmeier, S., Sánchez, J., Gerike, R., Anaya-Boig, E., Panis, L.I., Nieuwenhuijsen, M., 2019. Correlates of Walking for Travel in Seven European Cities: The PASTA Project. *Environ. Health Perspect.* 127(9), 097003.

Gaupp-Berghausen, M., Raser, E., Anaya-Boig, E., Avila-Palencia, I., de Nazelle, A., Dons, E., Franzen, H., Gerike, R., Götschi, T., Iacorossi, F., Hössinger, R., Nieuwenhuijsen, M., Rojas-Rueda, D., Sanchez, J., Smeds, E., Deforth, M., Standaert, A., Stigell, E., Cole-Hunter, T., Int Panis, L., 2019. Evaluation of Different Recruitment Methods: Longitudinal, Web-Based, Pan-European Physical Activity Through Sustainable Transport Approaches (PASTA) Project. *J. Med. Internet Res.* 21(5), e11492.

Gerike, R., de Nazelle, A., Nieuwenhuijsen, M., Panis, L.I., Anaya, E., Avila-Palencia, I., Boschetti, F., Brand, C., Cole-Hunter, T., Dons, E., Eriksson, U., Gaupp-Berghausen, M., Kahlmeier, S., Laeremans, M., Mueller, N., Orjuela, J.P., Racioppi, F., Raser, E., Rojas-Rueda, D., Schweizer, C., Standaert, A., Uhlmann, T., Wegener, S., Götschi, T., 2016. Physical Activity through Sustainable Transport Approaches (PASTA): a study protocol for a multicentre project. *BMJ Open* 6(1), e009924.

Goodman, A., Brand, C., Ogilvie, D., 2012. Associations of health, physical activity and weight status with motorised travel and transport carbon dioxide emissions: a cross-sectional, observational study. *Environ. Health* 11(1), 52.

Goodman, A., Rojas, I.F., Woodcock, J., Aldred, R., Berkoff, N., Morgan, M., Abbas, A., Lovelace, R., 2019. Scenarios of cycling to school in England, and associated health and carbon impacts: Application of the 'Propensity to Cycle Tool'. *Journal of Transport & Health* 12, 263-278.

Goodman, A., Sahlqvist, S., Ogilvie, D., 2014. New Walking and Cycling Routes and Increased Physical Activity: One- and 2-Year Findings From the UK iConnect Study. *Am. J. Public Health*, e1-e9.

Götschi, T., de Nazelle, A., Brand, C., Gerike, R., 2017. Towards a Comprehensive Conceptual Framework of Active Travel Behavior: a Review and Synthesis of Published Frameworks. *Current Environmental Health Reports* 4(3), 286-295.

Graham-Rowe, E., Skippon, S., Gardner, B., Abraham, C., 2011. Can we reduce car use and, if so, how? A review of available evidence. *Transp. Res.: Part A: Pol. Practice* 45(5), 401-418.

ICCT, 2017. Road tested: Comparative overview of real-world versus type-approval NOX and CO2 emissions from diesel cars in Europe, ICCT White Paper. Last accessed at https://www.theicct.org/sites/default/files/publications/ICCT_RoadTested_201709.pdf on 18/04/2018. International Council on Clean Transportation, Berlin.

IPCC, 2018. *Global Warming of 1.5°C, Special Report. Last accessed in October 2018 at: http://www.ipcc.ch/report/sr15/*. Intergovernmental Panel on Climate Change, Geneva.

JEC, 2014. *JEC Well-To-Wheels Analysis, Report EUR 26237 EN - 2014. Last accessed at http://iet.jrc.ec.europa.eu/about-jec/sites/iet.jrc.ec.europa.eu.about-jec/files/documents/report_2014/wtt_report_v4a.pdf on 10/03/2017*. JEC - Joint Research Centre-EUCAR-CONCAWE collaboration, Brussels.

JRC, 2013. *Analysis of National Travel Statistics in Europe*. European Commission, Joint Research Centre. ISBN: 978-92-79-32358-4, Seville.

Keall, M.D., Shaw, C., Chapman, R., Howden-Chapman, P., 2018. Reductions in carbon dioxide emissions from an intervention to promote cycling and walking: A case study from New Zealand. *Transp. Res.: Part D: Transport Environ.* 65, 687-696.

Kelly, P., Krenn, P., Titze, S., Stopher, P., Foster, C., 2013. Quantifying the Difference Between Self-Reported and Global Positioning Systems-Measured Journey Durations: A Systematic Review. *Transport Reviews* 33(4), 443-459.

Kissler, S.M., Tedijanto, C., Goldstein, E., Grad, Y.H., Lipsitch, M., 2020. Projecting the transmission dynamics of SARS-CoV-2 through the postpandemic period. *Science* 368(6493), 860.

Ko, J., Park, D., Lim, H., Hwang, I.C., 2011. Who produces the most CO2 emissions for trips in the Seoul metropolis area? *Transp. Res.: Part D: Transport Environ.* 16(5), 358-364.

Lovelace, R., Beck, S.B.M., Watson, M., Wild, A., 2011. Assessing the energy implications of replacing car trips with bicycle trips in Sheffield, UK. *Energy Policy* 39(4), 2075-2087.

Neves, A., Brand, C., 2019. Assessing the potential for carbon emissions savings from replacing short car trips with walking and cycling using a mixed GPS-travel diary approach. *Transp. Res.: Part A: Pol. Practice* 123, 130-146.

Nicolas, J.-P., David, D., 2009. Passenger transport and CO2 emissions: What does the French transport survey tell us? *Atmos. Environ.* 43(5), 1015-1020.

Nieuwenhuijsen, M.J., 2020. Urban and transport planning pathways to carbon neutral, liveable and healthy cities; A review of the current evidence. *Environ. Int.*, 105661.

Odeh, N., Hill, N., Forster, D., 2013. *Current and Future Lifecycle Emissions of Key „Low Carbon" Technologies and Alternatives, Final Report*. Ricardo AEA for the Committee on Climate Change, Harwell, UK.

Panter, J., Corder, K., Griffin, S., Jones, A., van Sluijs, E., 2013. Individual, socio-cultural and environmental predictors of uptake and maintenance of active commuting in children: longitudinal results from the SPEEDY study. *Int. J. Behav. Nutr. Phys. Act.* 10(1), 83.

Preston, I., White, V., Thumim, J., Bridgeman, T., Brand, C., 2013. Distribution of carbon emissions in the UK: implications for domestic energy policy. Joseph Rowntree Foundation, London.

Quarmby, S., Santos, G., Mathias, M., 2019. Air Quality Strategies and Technologies: A Rapid Review of the International Evidence. *Sustainability* 11(10).

Rabl, A., de Nazelle, A., 2012. Benefits of shift from car to active transport. *Transport Policy* 19(1), 121-131.

Raser, E., Gaupp-Berghausen, M., Dons, E., Anaya-Boig, E., Avila-Palencia, I., Brand, C., Castro, A., Clark, A., Eriksson, U., Götschi, T., Int Panis, L., Kahlmeier, S., Laeremans, M., Mueller, N., Nieuwenhuijsen, M., Orjuela, J.P., Rojas-Rueda, D., Standaert, A., Stigell, E., Gerike, R., 2018. European cyclists' travel behavior: Differences and similarities between seven European (PASTA) cities. *Journal of Transport & Health* 9, 244-252.

Sælensminde, K., 2004. Cost–benefit analyses of walking and cycling track networks taking into account insecurity, health effects and external costs of motorized traffic. *Transp. Res.: Part A: Pol. Practice* 38(8), 593-606.

Scheepers, C.E., Wendel-Vos, G.C.W., den Broeder, J.M., van Kempen, E.E.M.M., van Wesemael, P.J.V., Schuit, A.J., 2014. Shifting from car to active transport: A systematic review of the effectiveness of interventions. *Transp. Res.: Part A: Pol. Practice* 70(0), 264-280.

Shaw, C., Hales, S., Howden-Chapman, P., Edwards, R., 2014. Health co-benefits of climate change mitigation policies in the transport sector. *Nature Clim. Change* 4(6), 427-433.

Sims, R., Schaeffer, R., Creutzig, F., Cruz-Núñez, X., D'Agosto, M., Dimitriu, D., Meza, M.J.F., Fulton, L., Kobayashi, S., O., L., McKinnon, A., Newman, P., Ouyang, M., Schauer, J.J., Sperling, D., Tiwari, G., 2014. Transport, In: Edenhofer, O., Pichs-Madruga, R., Sokona, Y., Farahani, E., Kadner, S., Seyboth, K., Adler, A., Baum, I., Brunner, S., Eickemeier, P., Kriemann, B., Savolainen, J., Schlömer, S., Stechow, C.v., Zwickel, T., Minx, J.C. (Eds.), *Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

SMMT, 2016. UK new car market starts 2016 on a high with best January in 11 years, http://www.smmt.co.uk/2016/02/uk-new-car-market-starts-2016-on-a-high-with-best-january-in-11-years/ [last accessed on 18/01/2016]. SMMT, London.

Socialdata, 2009. The New KONTIV-Design (NKD), accessed at http://www.socialdata.de/info/KONTIV_engl.pdf on 8 September 2019 Socialdata GmbH, Munich.

Stead, D., 1999. Relationships between Transport Emissions and Travel Patterns in Britain. *Transport Policy* 6(4), 247-258.

Susilo, Y.O., Stead, D., 2009. Individual carbon dioxide emissions and potential for reduction in the Netherlands and the United Kingdom. *Transp Res Record* 2139, 142-152.

Tainio, M., Monsivais, P., Jones, N.R., Brand, C., Woodcock, J., 2017. Mortality, greenhouse gas emissions and consumer cost impacts of combined diet and physical activity scenarios: a health impact assessment study. *BMJ Open* 7(2).

Timmermans, H., van der Waerden, P., Alves, M., Polak, J., Ellis, S., Harvey, A.S., Kurose, S., Zandee, R., 2003. Spatial context and the complexity of daily travel patterns: an international comparison. *Journal of Transport Geography* 11(1), 37-46.

U.S. Department of Transportation, 2017. National Household Travel Survey: Vehicle Trips, accessed at https://nhts.ornl.gov/vehicle-trips on 20/03/2020. U.S. Department of Transportation, Federal Highway Administration, Washington, DC.

Vagane, L., 2007. Short car trips in Norway: is there a potential for modal shift?, *Proceedings of the European Transport Conference (ETC) 2007 held 17-19 October 2007*, Leiden, The Netherlands.

VanderWeele, T.J., 2016. Mediation Analysis: A Practitioner's Guide. *Annu. Rev. Public Health* 37(1), 17-32.

Vittinghoff, E., Glidden, D.V., Shiboski, S.C., McCulloch, C.E., 2012. *Regression Methods in Biostatistics: Linear, Logistic, Survival, and Repeated Measures Models (2nd edition)*. Springer, Boston, MA.

Wanner, M., Götschi, T., Martin-Diener, E., Kahlmeier, S., Martin, B.W., 2012. Active Transport, Physical Activity, and Body Weight in Adults. *Am. J. Prev. Med.* 42(5), 493-502.

Weber, C., Perrels, A., 2000. Modelling lifestyle effects on energy demand and related emissions. *Energy Policy* 28(8), 549-566.

Welch, T.F., 2013. Equity in transport: The distribution of transit access and connectivity among affordable housing units. *Transport Policy* 30, 283-293.

Woodcock, J., Abbas, A., Ullrich, A., Tainio, M., Lovelace, R., Sá, T.H., Westgate, K., Goodman, A., 2018. Development of the Impacts of Cycling Tool (ICT): A modelling study and web tool for evaluating health and environmental impacts of cycling uptake. *PLoS Med.* 15(7), e1002622.

Woodcock, J., Edwards, P., Tonne, C., Armstrong, B.G., Ashiru, O., Banister, D., 2009. Public health benefits of strategies to reduce greenhouse-gas emissions: urban land transport. *Lancet* 374.

Yang, Y., Wang, C., Liu, W., 2018. Urban daily travel carbon emissions accounting and mitigation potential analysis using surveyed individual data. *Journal of Cleaner Production* 192, 821-834.

Figures

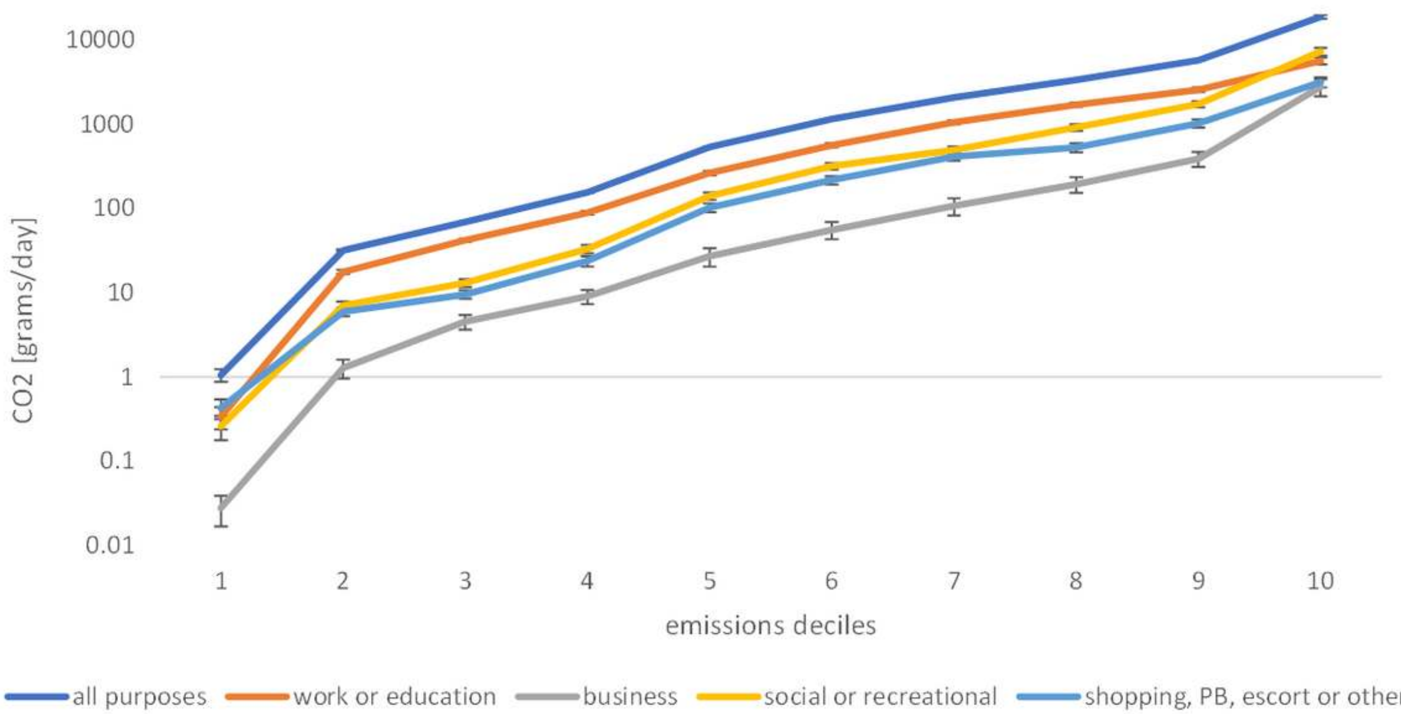

Figure 1

Distributions of mean life cycle CO2 emissions by travel emissions decile, subdivided by journey type (log-normal plot, error bars are 95% CIs).

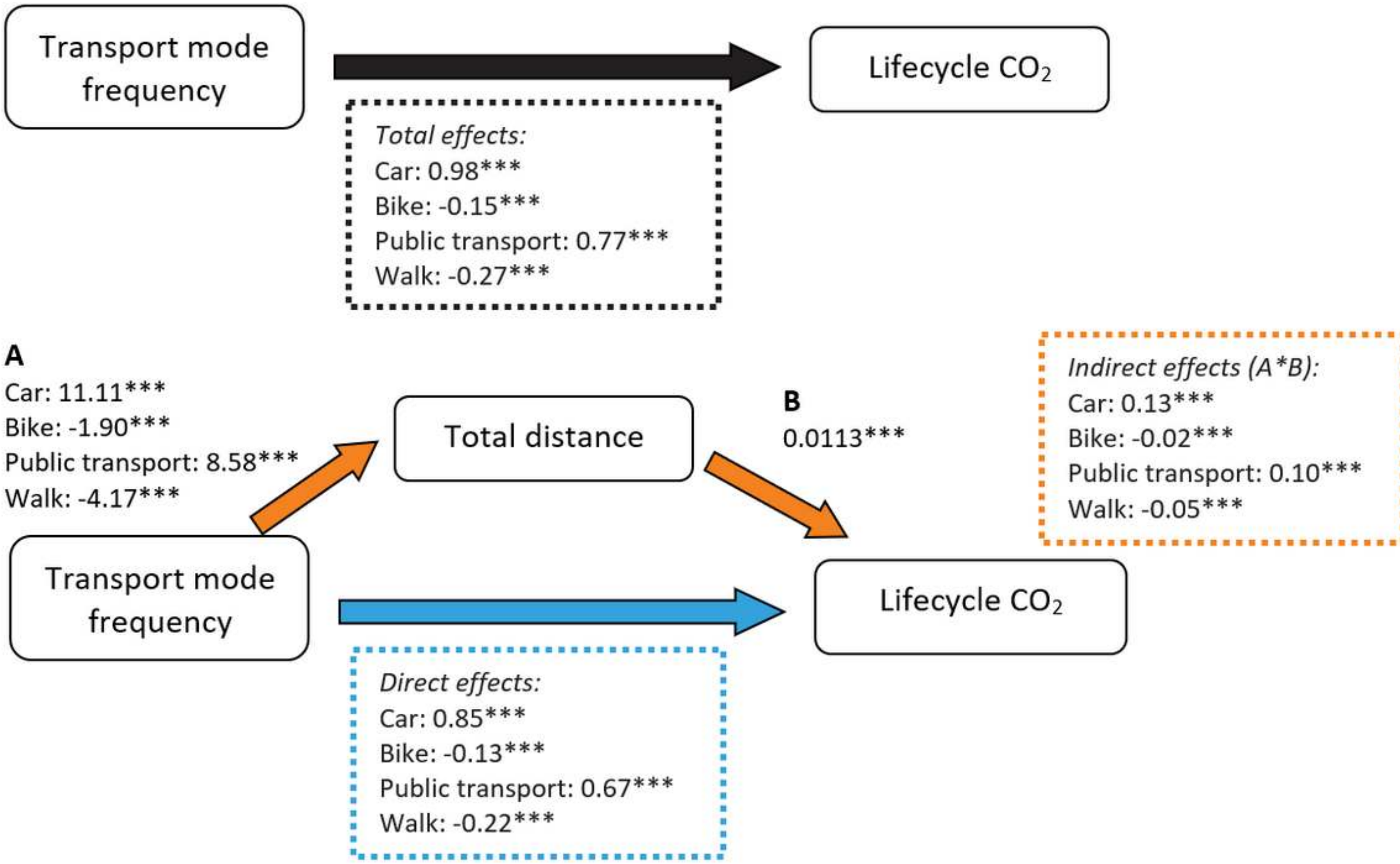

Figure 2

Mediation of total daily travel distance in the association between transport mode frequency and log-transformed lifecycle CO2 emissions. The mediation models were adjusted for sex, age, education level, employment status, household income, household composition, driver license, car access, bike access, self-rated health, BMI, bus accessibility, rail accessibility, day of the week; city was included as a random effect. The numbers presented in the figure are the regression coefficients.

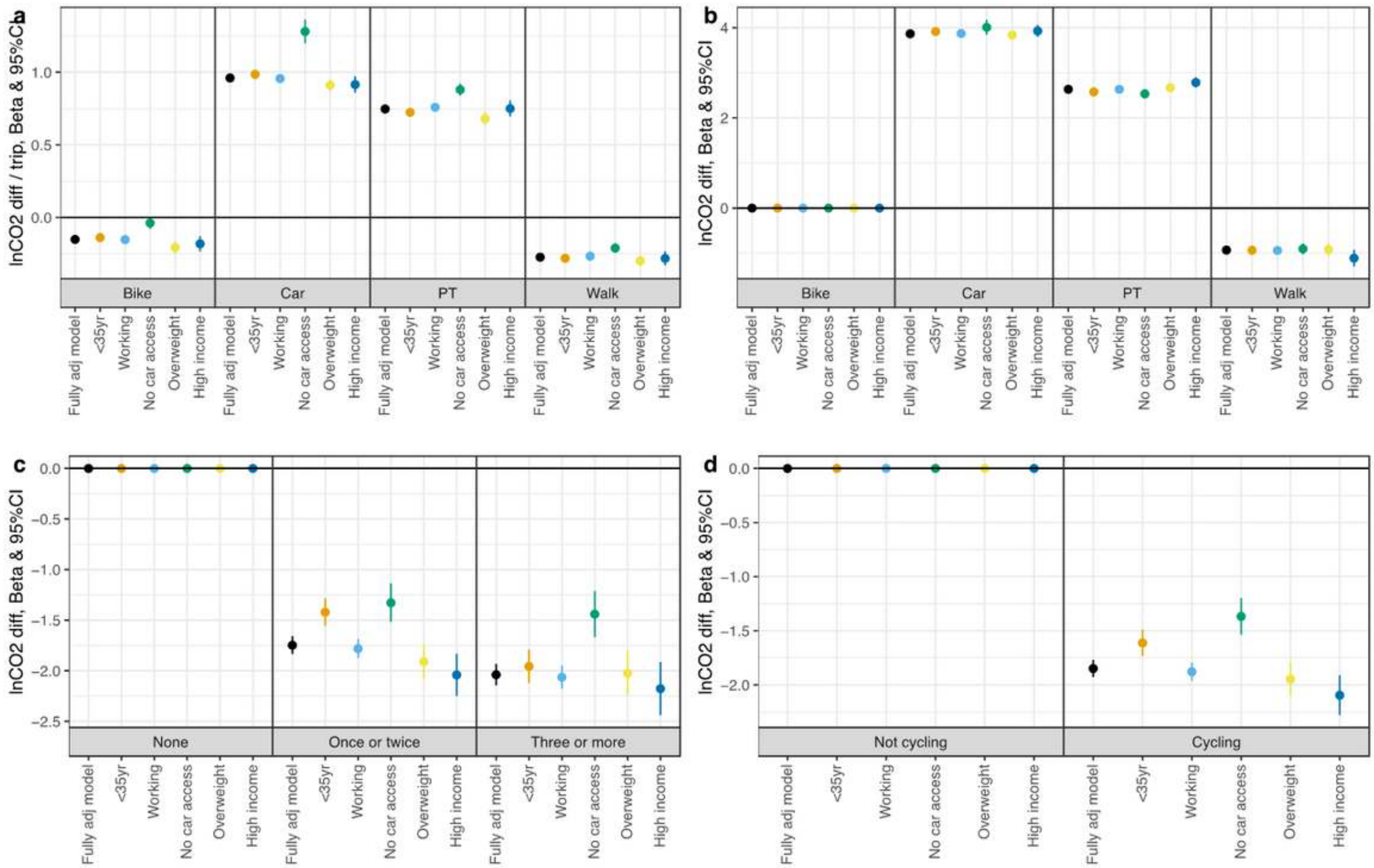

Figure 3

Sensitivity analyses. Exposure variables are: transport mode usage in panel (a), main mode of travel (by distance) in panel (b), cycling frequency in panel (c), and cycling (no/yes) in panel (d). The dots are the beta coefficients and indicate differences in log-transformed CO2 emissions (error bars are 95% CIs).

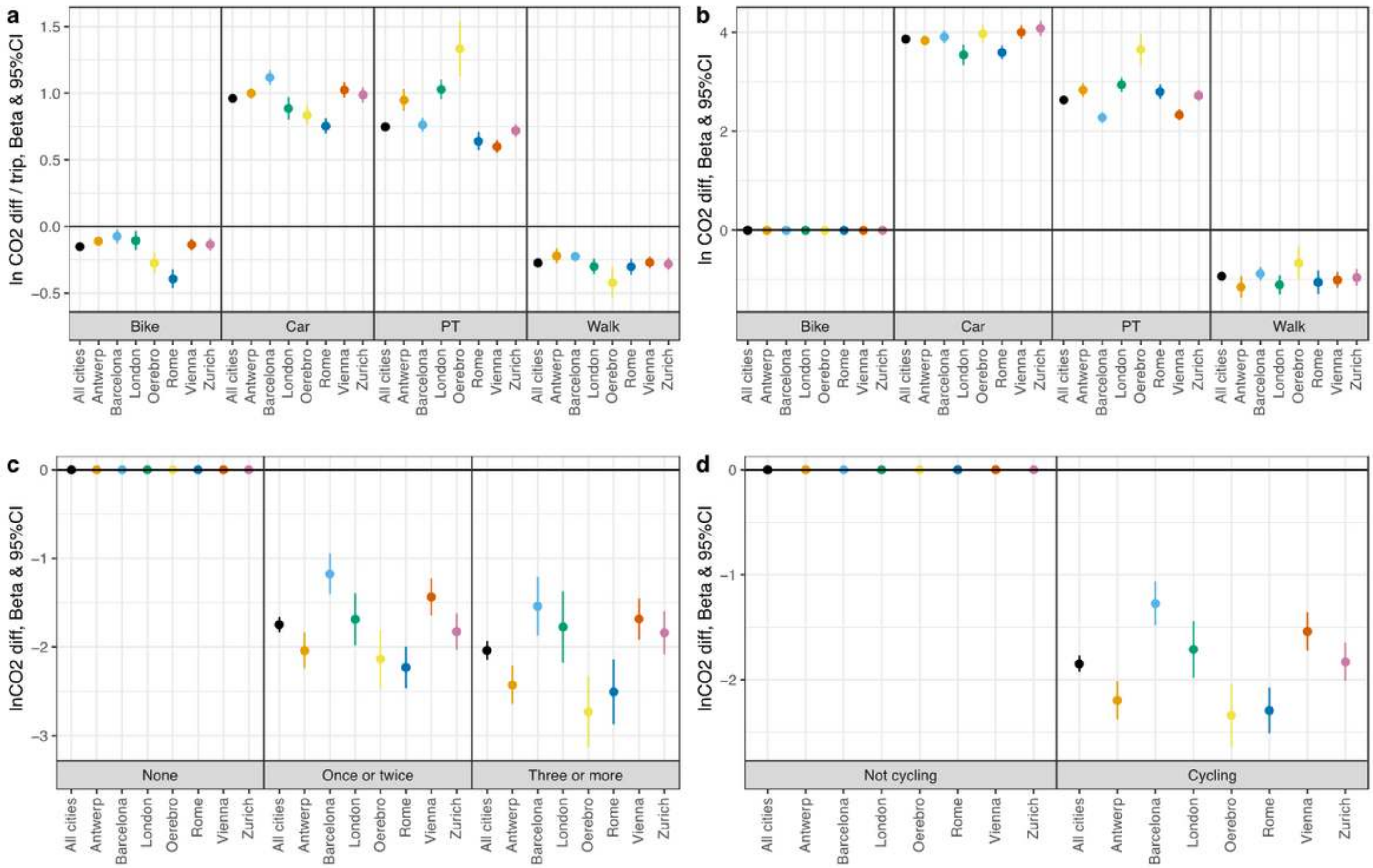

Figure 4

Effect sizes from the fully adjusted model and sensitivity analyses (city stratification). Exposure variables: transport mode usage in panel a; main mode of transport (by distance) in panel b; cycling frequency in panel c; and cycling/not cycling in panel d. The dots indicate differences in CO2 emissions and the error bars indicate 95% CIs.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- BrandEtAlActiveTravelCO2R0SM.docx