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# The climate change mitigation effects of active travel

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# Abstract

Active travel (walking or cycling for transport) is considered the most sustainable form of getting from A to B. Yet the net effects of active travel on mobility-related CO2 emissions are complex and under-researched. Here we collected travel activity data in seven European cities and derived lifecycle CO2 emissions from daily travel activity. Daily mobility-related lifecycle CO2 emissions were 3.2 kgCO2 per person, with car travel contributing 70% and cycling 1%. Cyclists had 84% lower lifecycle CO2 emissions from all daily travel than non-cyclists. Lifecycle CO2 emissions decreased by -14% (95%CI -12% to -16%) per additional cycling trip and decreased by -62% (95%CI -61% to -63%) for each avoided car trip. An average person who 'shifted travel modes' from car to bike decreased lifecycle CO2 emissions by 3.2 (95%CI 2.0 to 5.2) kgCO2/day, and using a bike as the 'main method of travel' gave 7.1 (95%CI 4.8 to 10.4) kgCO2/day lower lifecycle CO2 emissions than mainly using a car or van. Investing in and 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.


# Main

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 [1]. In Europe, GHG emissions decreased in the majority of sectors between 1990 and 2017, with the exception of transport [2]. Modal shifts away from carbon-intensive to low-carbon modes of travel hold considerable potential to mitigate GHG emissions [3]. Given the urgency of moving to a 'net zero' carbon emissions economy, there is growing consensus that technological substitution via electrification [4] will not be sufficient or fast enough to transform the transport system [5–7]. Beyond a net reduction in travel demand, one of the more promising ways to reduce transport carbon dioxide ($CO_2$) emissions 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 [8–21]. Surface transport accounts for nearly half the decrease in daily global $CO_2$ emissions during the COVID-19 forced confinement [22]. This shows that $CO_2$ emissions from road transport could be reduced more quickly than through technological measures alone, particularly in urban areas [6,16,23,24]. 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 [15,25–35]. Yet active travel studies are often based on analyses of the potential for emissions mitigation [36], the generation of scenarios [17,18,37,38] or smaller scale studies focusing on a single city, region or country [16,39]. 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, lifecycle emissions from cycling can be more than ten times lower per passenger-km travelled than those from passenger cars [9]. For most journey purposes active travel covers short to medium trips – typically 2 km for walking, 5 km for cycling and 10 km for e-biking [20]. Typically, the majority of trips in this range is made by car [14,16,24,40,41], with short trips contributing disproportionately to emissions because of 'cold starts', especially in colder climates [10,42]. 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 [10,14,16,24,43–45]. 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.

In this paper, we aim to investigate to what extent active travel is associated with lower carbon emissions from daily travel activity. To achieve this aim more than 10,000 adults were recruited in seven European cities[46] (Antwerp, Barcelona, London, Orebro, Rome, Vienna, Zurich) to complete a series of questionnaires on daily travel behavior, mode choice, as well as personal and geospatial characteristics. Operational, fuel and vehicle lifecycle $CO_2$ emissions were derived based on travel diary data and context-specific emissions factors (see Methods and Supplementary Methods). Log-linear fixed- and mixed-effects modelling of longitudinal data (n = 9858 person-days) was performed to assess the associations between lifecycle $CO_2$ emissions and transport mode use (primary 'exposure'), the main mode of travel (by max. distance travelled), and cycling frequency (secondary 'exposures'). Sensitivity analyses by key personal characteristics, city, and journey purpose were performed to examine robustness of the main findings. By doing so, the paper provides a detailed and nuanced assessment of the benefits of active travel in reducing total lifecycle carbon emissions in cities.

# Results

The study sample included 3,836 participants across the seven cities who had completed 9,858 one-day travel diaries reporting 34,203 trips (Table 1). 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. >€25 k) 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 1). The observed cycling trip share for our sample was between 17% in Barcelona and 54% in Antwerp (Supplementary Table S5), i.e. somewhat higher than cycling shares reported for the cities [47] and a direct result of purposively oversampling cyclists (see Methods). 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.

We found that lifecycle $CO_2$ 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 1). In contrast, lifecycle 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 lifecycle 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 lifecycle $CO_2$ emissions. By comparing deciles with chi-square tests of independence we found that 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 a higher body mass index (BMI), 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 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 (Table S5).

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 1 and Supplementary Table S5). 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, mode-specific CO2 emissions rates (Supplementary Table S4) and observed mode shares (Supplementary Table S5).

Table 1
Summary statistics of outcomes, exposures and other covariates

| **Total study sample (n = 9858) and mean (SD) values** | | | |
|---|---|---|---|
| $CO_2$ emissions | **All modes, lifecycle** | **3.18 (7.68)** | |
| (kg per day) | Car, lifecycle | 2.23 (7.25) | |
| | Public transport, lifecycle | 0.93 (2.90) | |
| | Bike, lifecycle | 0.03 (0.05) | |
| | Walk, lifecycle | 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* | | Lifecycle $CO_2$ (mean (SD)), in kg/day | n (%) |
| Main mode | Car | 9.139 (12.532) | 2307 (23%) |

| Total study sample (n = 9858) and mean (SD) values | | | |
|---|---|---|---|
| (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%) |

| Total study sample (n = 9858) and mean (SD) values | | | |
|---|---|---|---|
| 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 €25 k) | 2.884 (7.436) | 2713 (28%) |
| | Middle income (€25 k to €75 k) | 3.176 (7.449) | 5535 (56%) |
| | High income (€75 k 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.

# More Active Travel Decreased Lifecycle $CO_2$ Emissions From Transport

We found statistically significant associations between lifecycle $CO_2$ emissions and transport mode usage across all modes of travel (Table 2a): more driving or public transport use increased $CO_2$ while more cycling or walking decreased daily $CO_2$ emissions. In the fully-adjusted model, log-transformed lifecycle 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 lifecycle $CO_2$ emissions from transport decreased by 62% (95%CI 61–63%) while for each additional bike trip lifecycle $CO_2$ emission decreased by 14% (95%CI 12–16%). Those who made one less car trip and one more bike trip a day (a proxy for mode shift from car to bike) decreased lifecycle $CO_2$ emissions from transport by 67% (95%CI 66–68%). 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).

Table 2
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 lifecycle $CO_2$ emissions and transport mode usage (trips/day) (full model in Table S6) | | | | | | |
| 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 lifecycle $CO_2$ emissions and main transport mode categories (full model in Table S8) | | | | | | |
| 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 lifecycle $CO_2$ emissions and cycling frequency categories (full model in Table S9) | | | | | | |
| 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 or more 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 lifecycle $CO_2$ emissions and cycling (yes/no) (full model in Table S10) | | | | | | |
| Not cycling | 0 | – | 0 | – | 0 | – |

| | Model 0: unadjusted (fixed effects) | | Model 1: partly adjusted (mixed effects) † | | Model 2: fully adjusted (mixed effects) # | |
|---|---|---|---|---|---|---|
| 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.

The effects of transport mode use on transformed carbon emissions was partially mediated via total distance travelled (see Figure S1): 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 (Fig. 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.

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 (Fig. 3). By comparison, $CO_2$ effects for car travel were highest in Barcelona (and Vienna to some extent) and lowest in London and Rome.

The associations between lifecycle $CO_2$ emissions for the four trip purposes (secondary outcomes) and transport mode usage were also largely significant (Fig. 4 and Supplementary Table S11). Cycling frequency had larger effects on emissions from commuting to work or place of education than on emissions from all purposes. Motorized transport mode use showed larger effects on lifecycle $CO_2$ emissions from social, shopping and recreational travel than for work/business travel. The 'economically inactive' (retired, on home duties, unemployed, on leave) showed significantly higher emissions for social, recreational, shopping and personal business purposes and, as expected, lower emissions from work or educational trips. 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.

**Cycling as the 'main mode of travel' decreased lifecycle $CO_2$ emissions**

We also found statistically significant associations between lifecycle $CO_2$ emissions and the main modes of travel according to daily distance travelled (Table 2b): 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 lifecycle $CO_2$ 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 S7 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 (Fig. 2b) largely confirmed our results. Total distance travelled partially (12%) mediated the effects of main mode (by daily distance) on transformed lifecycle $CO_2$ emissions. The associations for log-transformed $CO_2$ emissions by journey purpose were also all significant (Fig. 4 and Supplementary Table S12), 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.

# Cyclists Had Lower Lifecycle $Co_2$ Emissions Than Non-cyclists

We also found that associations between mobility-related lifecycle $CO_2$ emissions and cycling frequency were all highly significant. Table 2c shows that in the fully adjusted model (model 2) lifecycle $CO_2$ 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 lifecycle $CO_2$. The sensitivity analysis (Fig. 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 lifecycle $CO_2$ emissions for all the four trip purposes, with the strongest effect observed for commuting and social trips (Supplementary Table S13): cycling three or more times a day decreased lifecycle $CO_2$ 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 lifecycle $CO_2$ emissions than 'non-cyclists' (Table 2d and Supplementary Table S14); this translated into 0.97 (95%CI 0.54 to 1.74) $kgCO_2$/day lower lifecycle $CO_2$ 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 (Fig. 2d).

# Discussion

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. The analysis of a sample of thousands of participants and nearly 10,000 person-days of daily travel across the seven sites found highly significant associations between transport mode choice and total lifecycle $CO_2$ emissions and showed that cyclists had significantly lower total $CO_2$ emissions than non-cyclists. More cycling or walking decreased mobility-related lifecycle $CO_2$ 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 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 [48]. 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.

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 [30,31,49–51]. 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 [30,52–54].

The analysis of transport mode use as the main exposure showed that each additional cycling trip reduced lifecycle $CO_2$ 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% (car◊bike) and 3% (car◊public transport). The size and direction of emissions changes are in line with some of the few empirical [11,55] and scenario/modelling [17,18,37,56] 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 lifecycle $CO_2$ emissions by about 7.1 $kgCO_2$/day when compared to using a car or van suggests that making more sustainable travel choices has significant carbon benefits. Similarly, our finding that doing at least one trip a day by bike significantly decreased mobility-related lifecycle $CO_2$ 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 [15,57]. 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 lifecycle $CO_2$ 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 [55]. 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 [58–61]. 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. [21,23,62,63].

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 [64]. 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 [48]. 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 [65], 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 [48]. 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 [66–68]. 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) [69]. 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 [17]. 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, transport policies and active mobility use adds value to the analysis, which clearly showed additional insights compared to smaller, single-location studies.

Active travel has attributes of social distancing that are likely to be desirable for some time [70]. It could help to cut back $CO_2$ emissions and air pollution while improving population health[21,71] as confinement is eased. Therefore, locking in, investing in and promoting active travel should be a cornerstone of sustainability strategies, policies and planning[72–74] to meet our very challenging development goals that are unlikely to be met without significant mode shift to sustainable transport [6].

# Methods

Study design and population

This study used longitudinal data from the 'Physical Activity through Sustainable Transport Approaches' (PASTA) project [64,75]. 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 [64,76]. 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 [48]. To ensure sufficiently large sample sizes for different transport modes, users of less common transport modes such as cycling were oversampled [48]. 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 [77].

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) [64]. 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 [78]. 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 [64]. Table S2 in the Supplementary Information provides an excerpt of the PASTA BLQ, including travel diary data.

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 [40,47]; hence the results of the primary exposure analysis may be used to estimate lifecycle $CO_2$ 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* [79]. 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 (Table S2). The diary was based on the established KONTIV-Design [80,81], 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 1 shows sample sizes and mean (SD) values of the primary outcome variable for each group.

Outcome variables: carbon dioxide emissions

The primary outcome of interest was daily lifecycle $CO_2$ emissions (mass of carbon dioxide in gram or kilogram per day) attributable to passenger travel. Lifecycle $CO_2$ 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 [79] and ICCT [82]) 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 [79]. 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 Table S13 in the Supplemntary Information) 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 [83–85] and emissions from electricity generation and supply [86]. Third, vehicle lifecycle 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 the Supplementary Information for each city, disaggregated by emissions category and transport mode. 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 lifecycle $CO_2$ 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.

Covariates

A number of covariates were hypothesized to confound the association between carbon emissions and transport mode choice and use e.g. [37,49,55]. 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 [11]. 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 $weight(kg)/height(m)^2$ [87].

# 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 Fig. 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 $e^{\beta}$ and interpret this value as a geometric mean difference [88]. 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 [89,90]. Only observations without missing data were included. R statistical software v3.6.1 was used for all analyses.

# Declarations

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Author contributions

CB, ED, EAB, IAP, AC, AdN, MG, MGB, RG, TG, FI, SK, ML, MJN, JPO, FR, ER, DRR, AS, ES, SS, SW, ILP

C.B. developed the original idea of the analyses presented in the manuscript. C.B., A.C., A.d.N., R.G., T.G., S.K., M.J.N., F.R., E.S. and I.L.P. conceived and designed the project. T.G., C.B., E.D., A.d.N., R.G., S.K., M.J.N., A.S. and I.L.P. led the international survey. T.G., C.B., E.D., E.A.B., I.A.P., A.C., A.d.N., M.G., M.G.B., R.G., F.I., S.K., M.L., M.J.N., J.P.O., E.R., D.R.R., A.S., E.S., S.W. and I.L.P cleaned and preprocessed the data. C.B. produced the analysis for this paper. The manuscript was written by C.B. with contributions from all the co-authors.

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# Figures

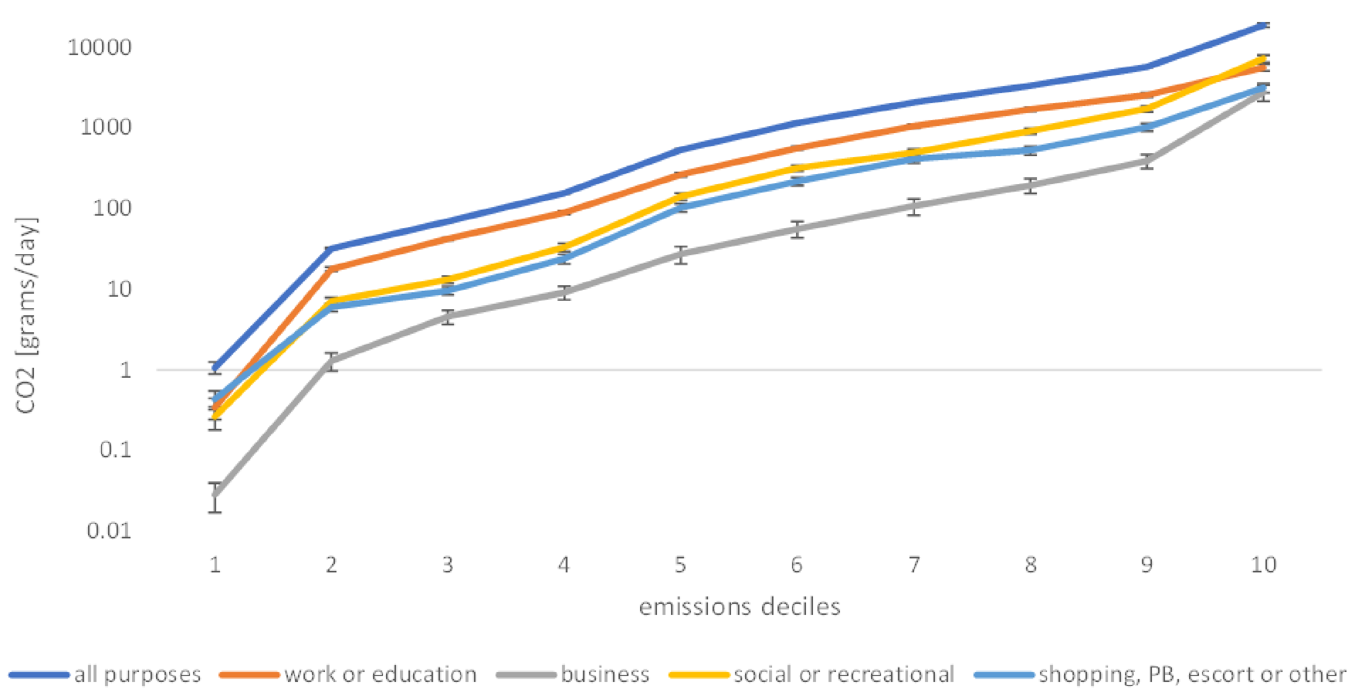
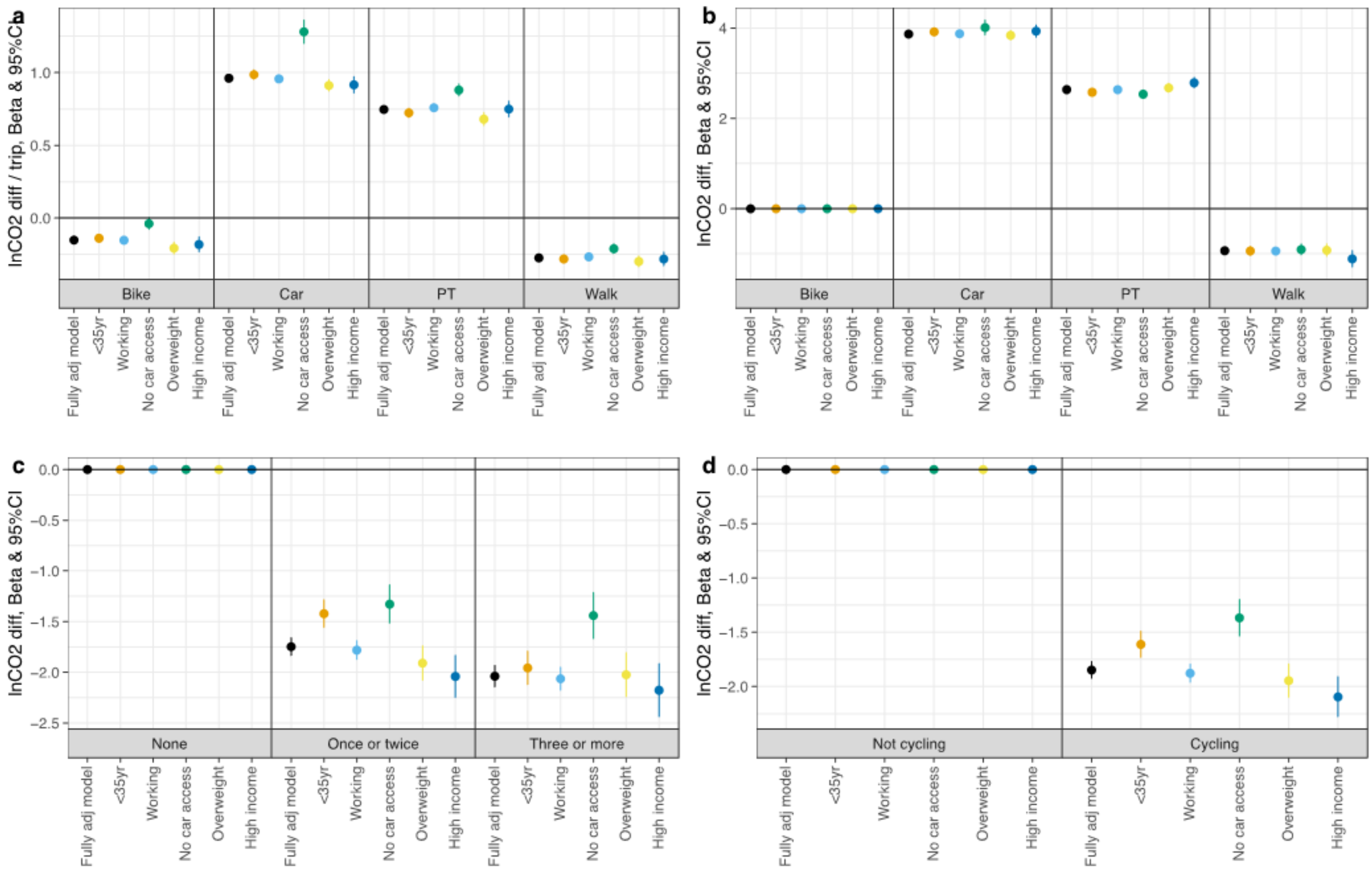


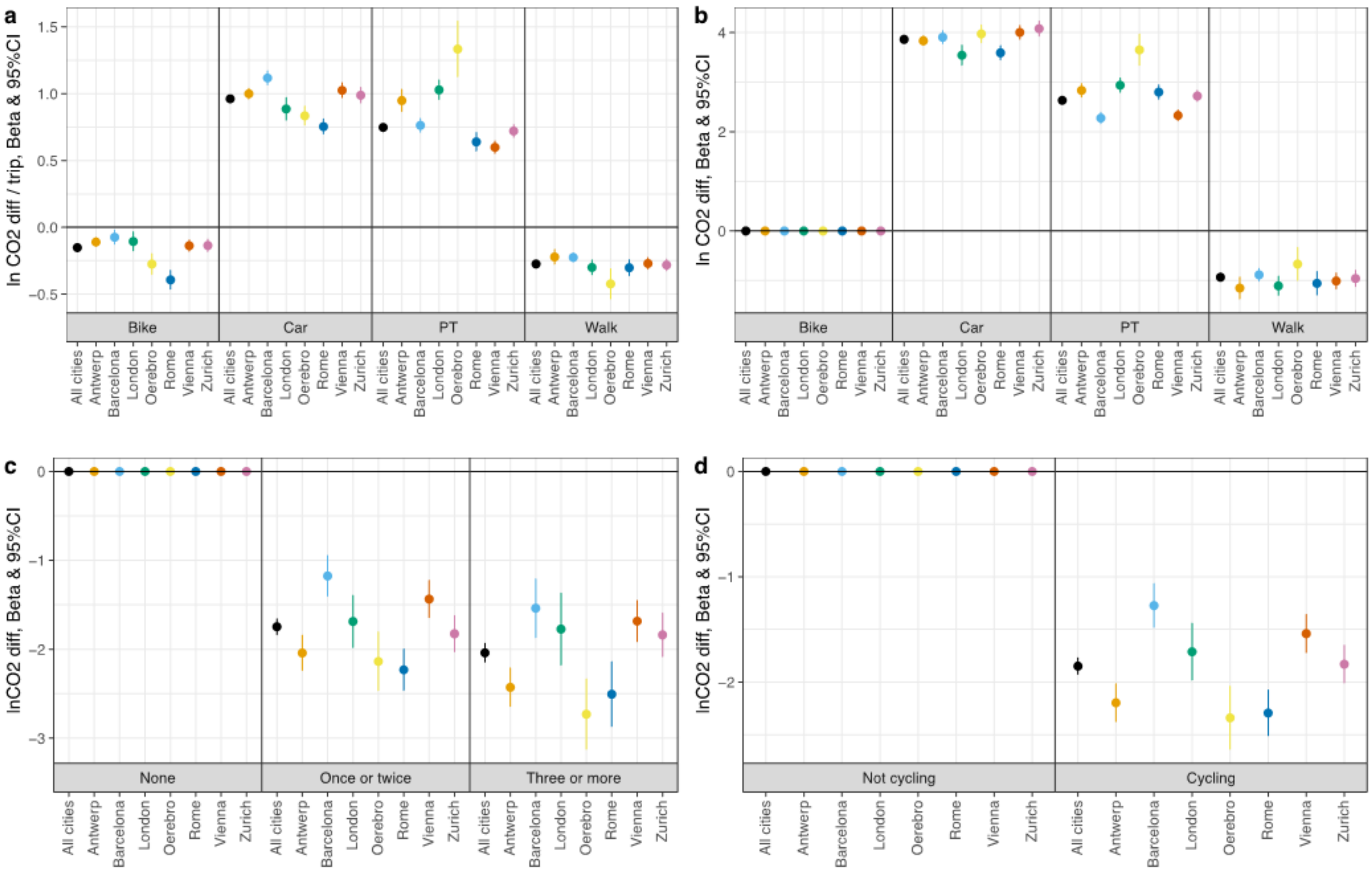

**Figure 1**

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



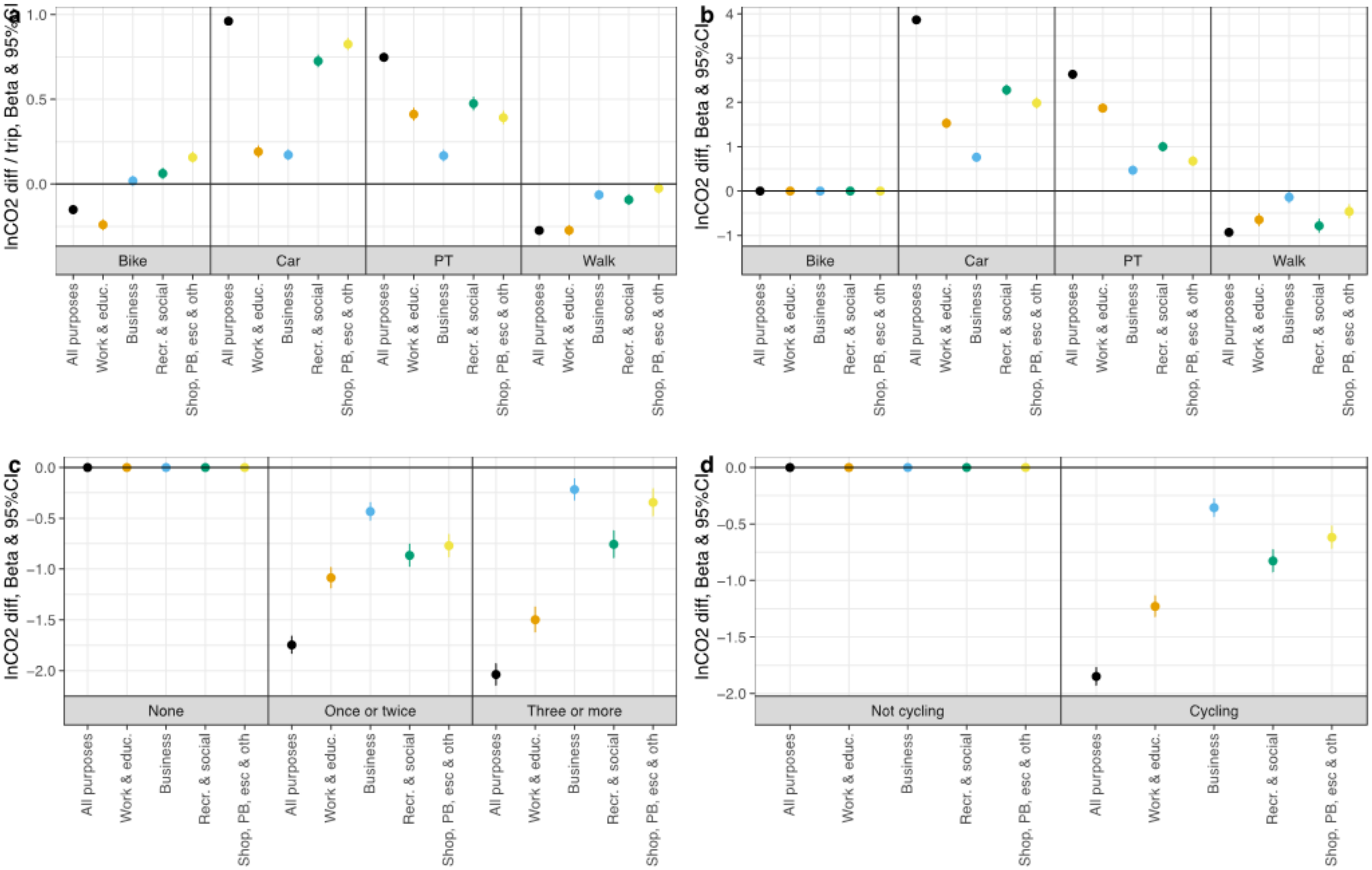

## Figure 2

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 3

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.




### Figure 4

Effect sizes from the fully adjusted models for CO2 emissions by trip purpose. 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 log-transformed CO2 emissions and the error bars indicate 95% CIs.

# Supplementary Files

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