



# The impact of black carbon (BC) on mode-specific galvanic skin response (GSR) as a measure of stress in urban environments

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## ABSTRACT

Previous research has shown that walking and cycling could help alleviate stress in cities, however there is poor knowledge on how specific microenvironmental conditions encountered during daily journeys may lead to varying degrees of stress experienced at that moment. We use objectively measured data and a robust causal inference framework to address this gap. Using a Bayesian Doubly Robust (BDR) approach, we find that black carbon exposure statistically significantly increases stress, as measured by Galvanic Skin Response (GSR), while cycling and while walking. Augmented Outcome Regression (AOR) models indicate that greenspace exposure and the presence of walking or cycling infrastructure could reduce stress. None of these effects are statistically significant for people in motorized transport. These findings add to a growing evidence-base on health benefits of policies aimed at decreasing air pollution, improving active travel infrastructure and increasing greenspace in cities.

## 1. Introduction

Recent studies have shown that active travel is associated with mental health benefits, including lower levels of stress, compared to other travel mode choices (Avila-Palencia et al. 2017, 2018). This is supported by broader research on commuters' subjective well-being, travel satisfaction, and happiness indicating benefits of walking and cycling (Bergstad et al., 2011; Ettema et al., 2016; Mouratidis et al., 2019; Yang et al., 2021) (Zhu and Fan, 2018; Fan et al., 2019; Singleton, 2019). More generally such research adds to a growing body of literature

that makes the case for promoting active travel due to its benefits on individual and population-wide health, and for sustainability, including zero-carbon transitions (de Nazelle et al., 2011; Brand et al. 2021a, 2021b). Despite myriads of well-established benefits, however, rates of active travel, particularly cycling, remain low in cities around the world (Goel et al., 2022). To help devise successful policies, a careful understanding of the multitude of factors that deter or encourage active travel is needed (Götschi et al., 2017; Aldred, 2019). Some environmental characteristics encountered throughout journeys may have impacts on how people perceive and experience their trips in different travel modes

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– leading potentially to different mode choices and also to different health impacts. [Scheepers et al. \(2013\)](#), for example, demonstrate quite convincingly that unbundling cycling and motorized traffic increases cyclist safety and usage. Fear of traffic is a known barrier, perhaps resulting in walking and cycling being considered by some people as too risky and stressful rather than healthy. On the whole research has shown that in fact physical activity benefits of active travel by far outweigh increased risks of traffic injuries and air pollution inhalation compared to other travel modes ([Mueller et al., 2015](#); [Tainio et al., 2021](#)). Clearly even further health benefits could be obtained, however, if these added risks could be minimized. Understanding how stress is experienced in different travel modes and in response to different microenvironmental factors may help improve enabling environments and achieve greater health benefits from active travel.

Traffic stress has been used as a concept to rate the quality of cycling environments akin to the “level of service” indices typically used to evaluate public transport or road networks. Scales such as the “Level of Traffic Stress” - commonly used especially in the USA - are typically based on classifying individuals according to their tolerance to traffic and on measures of perceived comfort and safety rather than on objective measures of stress ([Mekuria et al., 2012](#); [Crist et al., 2018](#); [Bigazzi et al., 2022](#)). They highlight how traffic is clearly understood as a main deterrent to cycling and contributor to perceived stress, and suggest that separation from traffic, roads with low levels of traffic and low traffic speeds provide the best conditions to minimize stress ([Mekuria et al., 2012](#)). Studies that have used physiological markers to examine stress experienced during active travel confirm this assessment, albeit with a few inconsistencies and a few additional factors shown to be relevant, such as poor road conditions and sidewalk crowding ([Bigazzi et al., 2022](#)). Traffic is often hypothesized in these evaluations as feeding into a fear of traffic injuries, and also in affecting comfort levels ([Bigazzi et al., 2022](#); [Teixeira et al., 2020](#)). Traffic contributes to further hazardous exposures however, that have been less frequently considered in the context of stress experienced while travelling. Noise from traffic, for one, is known to cause psychological problems related to stress. One study demonstrated that high levels of noise exposure increased odds of cyclists experiencing stress by 4% ([Nuñez et al., 2018](#)). Traffic is also a main contributor to air pollution exposures, which can in turn impact stress levels.

Air pollution is the 4th greatest risk factor for mortality globally ([GBD 2019 Risk Factors Collaborators, 2020](#) Risk Factors Collaborators, 2020) and it is also highly debilitating, affecting almost every organ of the body and every stage of the lifespan ([Thurston et al., 2017](#)). Stress is one of the less studied impacts of air pollution, but, for long term effects, detrimental associations have been shown, for example as measured by psychological distress scale ([Sass et al., 2017](#)), perceived stress scale ([Mehta et al., 2015](#); [Nuyts et al., 2019](#)), and point rating scale for stress ([Kim and Kim, 2017](#); [Hwang et al., 2018](#); [Shin et al., 2018](#); [Jung et al., 2019](#)). Experimental studies of short-term impacts evaluated through objective monitoring have demonstrated mechanisms of stress response to pollutants and resulting impacts on brain health in particular ([Thomson, 2019](#)). A few travel-related studies have shown in both experimental and real-world designs the detrimental impacts of air pollution exposure on Heart Rate Variability (HRV) ([Weichenthal et al., 2011](#); [Cole-Hunter et al. 2015, 2018](#); [Laeremans et al., 2018b](#)). Note that some of these demonstrated competing impacts of physical activity, known to have beneficial impacts on HRV (and more generally on stress and health) ([Cole-Hunter et al., 2015](#); [Laeremans et al., 2018b](#)). These studies were framed in the context of cardio-vascular health, but in fact HRV has at times also been used in transport studies as a measure of stress ([Bigazzi et al., 2022](#)). In addition to these direct impacts on stress, air pollution can cause some worry about its impacts on health ([Dons et al., 2018](#)). Similarly to the fear of traffic, air pollution has also been shown to act as a deterrent to active travel ([Tainio et al., 2021](#)). This may indicate that high air pollution exposures could potentially increase stress or discomfort while walking or cycling. Travel microenvironments

are indeed known to contribute to the highest peaks of exposures one may encounter in daily life ([Dons et al., 2019](#); [Tainio et al., 2021](#)).

Exposure to traffic may thus lead to increased stress through a variety of mechanisms such as perceptions of safety and comfort, and direct impacts of harmful exposures (air pollution and noise) ([Bigazzi et al., 2022](#)). In reverse, certain street and land use designs could attenuate, override, or confound such associations. For example, routes may take the traveller through green environments which are thought to improve mental health ([van den Berg et al., 2016](#); [Houlden et al., 2018](#); [Zhang et al., 2021](#)). Infrastructure that separates cyclists and pedestrians from traffic also can increase perceptions of safety and have been shown to reduce stress ([Bigazzi et al., 2022](#)). Both greenspace and separated paths have also the potential to reduce air pollution exposure, although trees in narrow street canyons could have opposite effects ([Diener and Mudu, 2021](#)) and could potentially either decrease or increase air pollution exposures, depending on a variety of microscale factors.

The pollutant Black Carbon (BC) is a component of both fine and coarse particulate matter (PM), most strongly associated with the fine particles (PM<sub>2.5</sub>) ([Smith et al., 2009](#); [Viidanoja et al., 2002](#)). BC has been shown to be one of the most harmful PM components responsible for health effects in exposed individuals (U.S. EPA 2012). BC is also considered a useful indicator of traffic volumes in cities, since it is emitted by traffic sources in urban areas ([Invernizzi et al., 2011](#); [Janssen et al., 2011](#); [Jereb et al., 2021](#)). Some have also demonstrated high correlations between BC and traffic noise ([Dekoninck and Int Panis, 2017](#)). Real-time portable monitoring of BC along individuals' daily travels thus provides an opportunity to assess exposures to both air pollution ([Dons et al., 2019](#)) and more generally to traffic.

Physiological markers of stress, such as galvanic skin response (GSR) or heart rate variability, have been receiving increasing attention in transport studies. They can help overcome some limitations of the more commonly used self-reported metrics and enable dynamic assessments of triggers of stress or discomfort ([Bigazzi et al., 2022](#)). GSR, also known as a form of electrodermal activity, measures electrical activity at the skin surface which results from sweat gland activity, itself controlled by autonomic nervous system. It thus provides a measure of autonomous emotional arousal and as such has been used as an objective measure of stress in previous transport studies ([Helander, 1978](#); [Caviedes and Figliozzi, 2018](#); [Hernandez et al., 2011](#); [Labbe et al., 2007](#); [Yang et al., 2021](#); [Bigazzi et al., 2022](#)).

The aim of our study was to assess how travel mode-specific GSR varies given different values of BC, and also understand how greenspace exposure, and road infrastructure would also affect GSR. BC in this framework is considered both at face value as an air pollutant, but also more generally a marker of traffic. The statistical framework we developed allows us to establish the causal impact of black carbon on stress, adjusting for surrounding environment. We refer to causal effect in this instance of BC as a marker of traffic, including of air pollution related to traffic, rather than solely as a pollutant. The approach also provides indications of how greenspace and road infrastructure could be associated with variations in GSR.

## 2. Materials and methods

### 2.1. Study population and design

We used panel data from the Physical Activity through Sustainable Transport Approaches (PASTA) project ([Dons et al., 2015](#); [Gerike et al., 2016](#)). A total of 122 adults distributed across the cities of Antwerp, Barcelona and London were recruited from the pool of respondents of a larger longitudinal survey, which collected data on travel habits, socio-demographics and health. Adults between the ages of 18 and 65 years old, with a BMI lower than 30, and who are non-smokers, were selected. A balanced sample of males and females with a range of physical activity patterns was obtained. Participants took part in three separate full weeks of data collection, each taking place in a different

season (Spring/Fall, Summer and Winter). They were instructed during measurement weeks to keep an activity diary and wear at all times devices that tracked their location and measured BC and GSR among other things (details to follow, see also [Avila-Palencia et al., 2019](#); [Laeremans et al., 2018a](#); [Laeremans et al., 2018b](#)). A combination of physical activity, GPS and travel diary data were used to derive travel time and mode identification ([Orjuela, 2018](#)). The GPS data was pre-processed using the Physical Activity Location Measurement System – PALMS ([Tandon et al., 2018](#); [Bekö et al., 2015](#)) developed by the University of California, San Diego. This algorithm corrects for multipath reflections and typical indoor jitter by identifying unrealistic (excessive) speed, acceleration, and distances travelled. Outputs of this pre-processing were set to a minute-by-minute bases using validated points only and estimating the location at the exact minute based on the location on the fraction of the minute both before and after. The beginning of a trip was marked when distance travelled in a minute is more than 30 m and a trip end was marked when the person stopped moving for 5 min.

## 2.2. Outcome

In our study, GSR is our response variable: it was measured minute by minute for all participants throughout their three weeks of participation using the Bodymedia Sensewear device. One of the advantages of GSR measurements is that they can be made continuously in a non-intrusive and non-burdensome way ([Laeremans et al., 2017](#)). Therefore, GSR sensors are ideal for our study of stress responses to individuals' daily routines in their own real-world setting during travel.

## 2.3. Exposure variable

Personal air pollution was assessed by measuring the BC concentrations with a microaethalometer (model AE51, Aethlabs, USA) that was set to record the average BC concentration on a 5-min basis. When in movement, the device was carried in a bag, tube sticking out, and left on a surface next to participants when staying in the same indoor place. Participants replaced filters every two days to prevent saturation. The US Environmental Protection Agency's Optimized Noise-reduction Algorithm (ONA) was used to smoothen raw BC data. We excluded any data with an error code (i.e. for filter saturation or flow out of range).

## 2.4. Other explanatory measures

The GPS device recorded the geo-locations of each participant, which allowed us to identify the characteristics of the surrounding environment of participants while travelling, such as the level of greenness and road type. We calculated the normalized difference vegetation index (NDVI) as an average exposure to greenness intensity for each GPS point with a 10 m buffer around it. NDVI is the most commonly used and easily obtainable vegetation index to detect live green plant canopies ([James et al., 2015](#)). In general, NDVI values range from  $-1$  to  $1$ , with very low values of NDVI ( $0.1$  and below) corresponding to barren areas of rock, sand, water or snow; moderate values ( $0.2$ – $0.3$ ) representing shrubs and grassland; and high values ( $0.6$ – $0.8$ ) indicating temperate and tropical rainforests ([Weier and Herring, 2000](#)). We captured the road type associated with each GPS point, and also any other road type within a 10 m buffer, which enabled us to consider adjoining infrastructure such as bike lanes and pedestrian paths. This led to the categorisation of 12 road types (see figures in Appendix Section 2) which together indicated a combination of traffic intensity (major vs residential road) and infrastructure (whether cycleways or pedestrian paths were present). Greenspace, traffic volumes, and road type can all have impacts on BC exposures ([Hunter et al., 2019](#); [Dons et al., 2013](#)) and on stress ([Barton and Rogerson, 2017](#); [Tyrväinen et al., 2014](#); [Chatterjee et al., 2019](#); [Faghih Imani et al., 2019](#)). It is, therefore, crucial to account for such confounding effects, otherwise models would produce biased estimates of BC impacts on GSR.

The SenseWear device, in addition to GSR, measured important potential confounders for our study, each on a 1-min average. The intensity of physical activity is calculated, in METs (Metabolic Equivalents of Tasks), through a proprietary algorithm which combines measurements of heat flux, galvanic skin response, skin temperature and 3-axis accelerometry, based on pattern recognition, accounting also for age, sex, body weight and height (entered manually in the software) (see [Bassett et al., 2012](#) and also a previous PASTA publication: [Laeremans et al., 2017](#) for more details). A sensor measuring the ambient temperature on the outer side of the SenseWear provides the near body temperature. Heat flux, that is the amount of energy being dissipated by the body to its surroundings as convective heat per unit area, is derived through a thermally conductive sensor between the skin at the point of contact and the immediate surroundings of the SenseWear. Heat flux, however, was excluded from the model because it was correlated with nearbody temperature as shown in Appendix Figure S3.

We obtained the time and dates of journey from the SenseWear and GPS devices. These were used to classify trips according to seasons, weekday/weekend, and time period (i.e. morning peak (6am–9am), afternoon peak (4pm–7pm) and non-peak hours). Individual characteristics were obtained from the PASTA questionnaire to construct subject level covariates. Body mass index (BMI) was calculated from self-reported weight and height and age from the reported date of birth. The following were included as categorical variables: gender (male and female); educational level (secondary education and higher/university education); income level (seven categories from '<€10,000' to '>€150,000'); status as former smoker or not. These covariates are likely to affect the outcome (GSR) and are therefore important to adjust for in the modelling stage to obtain predictions of the outcome with a greater precision.

## 2.5. Bayesian Doubly Robust (BDR) estimation method

Average potential outcomes (APOs) that measure average outcomes (i.e. GSR in our case) under a given treatment regime (i.e. BC exposures in our case) is one of the typical targets of inference in causal studies. Approaches used to estimate such quantities include, for example, outcome regression (OR) models, in which the response variable is the outcome (i.e. mode-specific GSR in our case), or propensity score (PS) models, in which the exposure variable (i.e. BC in our case) is the response. The doubly robust (DR) method combines both OR and PS models, for example, via augmentation of the OR model by adding the inverse of the PS as a covariate. The DR method provides valid estimates of APOs if one of the two models is correctly specified ([Graham et al., 2016](#)). However, one remaining issue is that the estimation of APOs naturally involves prediction of unobserved data due to the nature of observational studies (i.e. only one outcome to a particular exposure can be observed). An approximate Bayesian approach for DR estimation via the Bayesian bootstrap ([Rubin, 1981](#)) solves the issue by offering two aspects of Bayesian inference that are particularly useful for causal modelling. That is, it incorporates randomness originating 1) from the estimation of the parameters of the DR model; 2) from the random nature of the unobserved observations via posterior predictive distributions ([Graham et al., 2016](#)). Therefore, the Bayesian Doubly robust (BDR) approach incorporating Bayesian inference with DR estimation allows predictions on unobserved observations and gives greater flexibility to account for unknown confounding that cannot be measured. This is very useful in our study because it is an observational study setting and it is hard to account for all possible features that could affect either BC or GSR.

To estimate the APOs, we follow the BDR estimation developed by [Graham et al. \(2016\)](#) (see Appendix Section 1 for details). We first construct a PS model for the conditional distribution of the exposure, i.e. BC given measured confounders that could possibly affect BC. Here, since BC was measured on a 5-min basis (rather than 1-min as for the GSR measurement), to account for repeated measurements we use a

linear mixed model (LMM) for the PS model. We then re-estimate the BC values based on this model by varying all conditions of the covariates, which gives us propensity scores. Finally the AOR model is built using as inputs the inverse of the propensity score and measured confounders that could impact the outcome (mode-specific GSR), i.e. variables such as surrounding environments (i.e. NDVI and road type) and general features (i.e. city, season and weekday/weekend) potentially affecting the GSR are taken into account as fixed effects. An LMM is also used for the OR, where the fixed effects part includes individual characteristics from the baseline questionnaire (i.e. gender, age, etc.), surrounding environments (i.e. BC, NDVI, road type, etc.), and activity-specific characteristics (i.e. near-body temperature, METs, travel period). Since each person is assumed to have different baseline of activity characteristics, the random effects part is represented by the unique ID number for each individual with random slopes for activity characteristics. This allows us to incorporate individual-specific variability in the GSR given that each person has their own specification for changes in the response (Fitzmaurice and Ravichandran, 2008).

We then apply our Bayesian bootstrapping methodology to repeatedly estimate the constructed augmented OR (AOR) model by resampling the observations. For this step we calculate strata of BC exposures so we can resample BC values within each stratum. This enables us to estimate average outcomes on GSR for each stratum with a full coverage of potential variations in BC within the strata. The bootstrapping process thus reduces potential unmeasured confounding and approximates the posterior distribution of model parameters to subsequently form predictions for the outcome, giving rise to an estimate of the trend of the outcome for various levels of the exposure, BC. The BDR methodology is the combination all these three steps (PS, AOR and bootstrapping); it accounts for potential confounding specifically for the black carbon impacts on GSR, incorporating the uncertainty that arises from the original data. We apply the same approach to estimate separately the APOs of cycling-specific, walking-specific and motoring-specific GSR.

### 3. Results

Details on the sample participants can be found in see [Avila-Palencia et al. \(2019\)](#) and [Laeremans et al. \(2017\)](#). Briefly, the 122 participants were almost equally distributed over the three cities; had an average age of 35 years old; were slightly more female (55%) than male (45%); most had achieved higher education levels (89%) and were fully employed (72%). More than half of participants (69.7%) have an annual household income of more than €25,000 given the information we have. Since we are interested in how BC affects travel mode-specific GSR, we then only consider travel-related data which contains 207,927 min-by-minute observations overall. An average (SD: standard deviation) of 0.17 (0.26) were found for GSR, 2.93 (2.14) for METs, and 5705.76 (6022.74)

ng/m<sup>3</sup> for BC. [Figs. 1–3](#) show the distributions of log (GSR), METs and BC, respectively, for different travel modes, each of which has a good coverage over all possible values of log (GSR), METs and BC.

To estimate the APOs of GSR via the BDR estimation approach, we first built the corresponding PS and AOR models adjusting for potential measured confounding. The AOR models provide useful indications of associations with GSR so they are described in [Section 3.1](#), but as PS models are only instrumental to the development of AOR they are not reported. We then present in [Section 3.2](#) the estimated mean values of the posterior predictive APO distributions, that is, the GSR values for each BC stratum, resulting from the causal inference of the BDR methodology.

#### 3.1. AOR model results

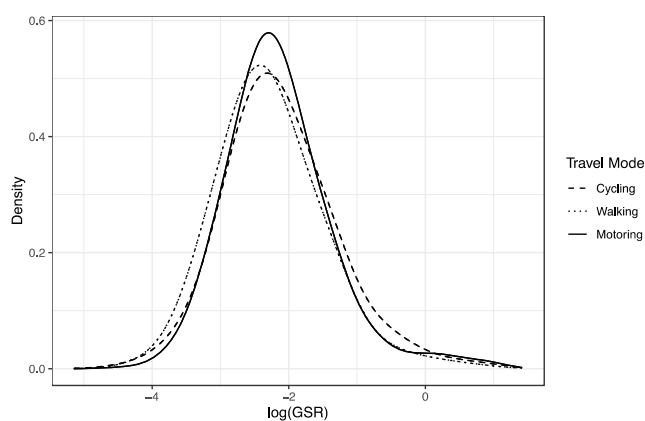
We briefly describe associations of socio-demographic and trip characteristics with GSR (shown in detail in [Appendix Table S4](#)), followed by impacts of environment variables, shown in [Table 1](#).

For all three travel modes, lower GSR is found when travelling in London compared with travelling in Antwerp. The difference was not statistically significant for Barcelona compared to Antwerp. Females appear to have significantly lower GSR than males during cycling and walking, but the differences are insignificant when in motorized transport. Although travelling in motorized transport in any travel period does not influence GSR, we find that for people who are cycling and walking during non-peak hours have lower GSR and cycling in the afternoon peak hours have higher GSR, compared to the morning peak hours.

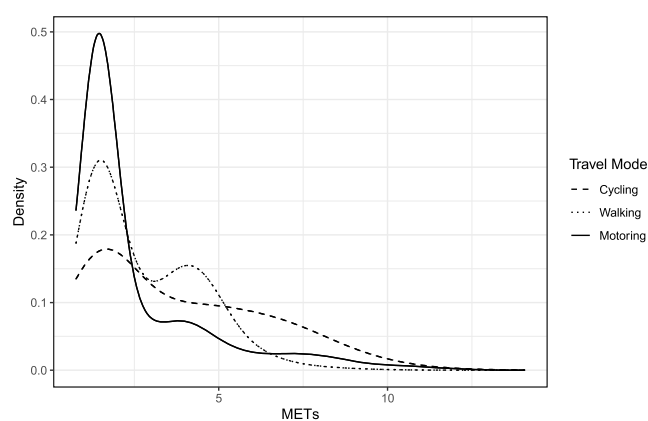
NDVI and GSR are negatively and significantly (at the 5% level) associated in all three modes, indicating that the more vegetation a participant is surrounded with, the less stress the participant would experience. The size of the effect appears to be larger for the walking mode compared to motoring and cycling.

We observe that the GSR of participants when they are cycling on major roads, or on major roads with an adjoining residential road, is significantly higher than those who are cycling on major roads with active transport infrastructure (that is, major roads with cycleways or pedestrian paths), the reference category. The GSR of participants while cycling on any roads with cycling infrastructure only (i.e. cycleways, residential roads with cycleways, and major roads with cycleways) always appears to be significantly lower than those who are cycling on major roads with cycleways and pedestrian paths. Although the relationship did not reach statistical significance, it seems that cycling on roads where cycleways are shared with pedestrian paths may increase GSR.

Similar to cycling, when people are walking on roads with pedestrian paths (i.e. pedestrian paths alone, residential roads with an adjoining

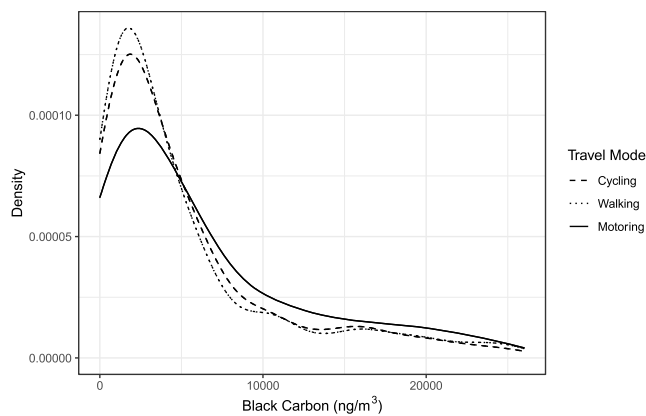


**Fig. 1.** The distribution of log (GSR) for each of the three travel modes (cycling, walking, and motoring).



**Fig. 2.** The distribution of METs (metabolic equivalent tasks) for each of the three travel modes (cycling, walking, and motoring).





**Fig. 3.** The distribution of BC (black carbon) for each of the three travel modes (cycling, walking, and motorizing).

**Table 1**

Estimated coefficients of environmental variables with corresponding 95% confidence intervals of the augmented outcome regression (AOR) models (with log (GSR) being response) for cycling, walking and motorized transports, respectively.

|                                                                              | Estimated coefficients for cycling | Estimated coefficients for walking | Estimated coefficients for motorized transport |
|------------------------------------------------------------------------------|------------------------------------|------------------------------------|------------------------------------------------|
| <b>(Intercept)</b>                                                           | -5.9828<br>(-7.5776, -4.3879)***   | -3.8562<br>(-5.3518, -2.3606)***   | -5.6783<br>(-7.0513, -4.3052)***               |
| <b>Black carbon</b>                                                          | 0.0007<br>(0.0004, 0.0008)***      | 0.0006<br>(0.0003, 0.0009)***      | 0.000014<br>(-0.00001, 0.000002)               |
| <b>NDVI with 10m buffer</b>                                                  | -0.0211<br>(-0.0239, 0.0660)**     | -0.1919<br>(-0.2278, -0.1559)**    | -0.0797<br>(-0.1484, -0.0111)***               |
| <b>Road type (reference: major roads with cycleway and pedestrian paths)</b> |                                    |                                    |                                                |
| Cycleway                                                                     | -0.0472<br>(-0.0792, -0.0047)***   |                                    |                                                |
| cycleway with pedestrian path                                                | 0.0458<br>(0.0020, 0.0896)         | 0.0277<br>(-0.0242, 0.0796)        |                                                |
| pedestrian path                                                              |                                    | -0.0712<br>(-0.1767, -0.0318)**    |                                                |
| residential road                                                             | 0.0505<br>(0.0230, 0.0779)*        | 0.0059<br>(-0.0202, 0.0321)        | 0.0797<br>(0.0111, 0.1484)                     |
| residential road with cycleway                                               | -0.1119<br>(0.0230, 0.0779)*       | -0.0615<br>(-0.1252, 0.0022)       | 0.1443<br>(-0.0025, 0.2912)                    |
| residential road with pedestrian path                                        | 0.0196<br>(-0.0469, 0.0538)        | -0.0319<br>(-0.0630, -0.0009)**    | -0.0402<br>(-0.1261, 0.0458)                   |
| major road                                                                   | 0.0309<br>(0.0031, 0.0586)*        |                                    | 0.0103<br>(0.0364, 0.0571)                     |
| major road with residential road                                             | 0.0188<br>(0.0238, 0.0614)*        | 0.0627<br>(0.0189, 0.1066)***      | 0.0074<br>(-0.0653, 0.0800)                    |
| major road with cycleway                                                     | -0.0055<br>(-0.0324, 0.0433)*      |                                    | 0.0099<br>(-0.0529, 0.0728)                    |
| major road with pedestrian path                                              | 0.0407<br>(0.0127, 0.0687)         | -0.0065<br>(-0.0325, 0.0194)**     | -0.0508<br>(-0.1045, 0.0028)                   |
| residential road with cycleway and pedestrian path                           | 0.0465<br>(0.0034, 0.0895)         | -0.0512<br>(-0.0965, -0.0059)      | -0.0508<br>(-0.1045, 0.0028)                   |

\*significant at  $p < 0.1$  \*\* significant at  $p < 0.05$  \*\*\* significant  $p < 0.001$ .

pedestrian path, or major roads with an adjoining pedestrian path), they would generally feel less stressed than walking on major roads with adjoining cycleways and pedestrian paths. Walking on a major road with adjoining residential road on the other hand increases people's GSR compared to walking on major roads with adjoining active travel infrastructure (i.e. the reference category). Other comparisons did not reach statistical significance (Appendix Table S4). Unlike cycling and walking, taking motorized transport on different types of roads does not have a statistically significant impact on GSR.

In these AOR models, a unit increase in BC is shown to be significantly associated with an increase in GSR for cycling and walking, but not for motorized transport. In the next section we show the average potential outcome of a stratum increase in BC on average GSR derived from the BDR methodology.

### 3.2. APOs of GSR given different BC via BDR estimation

We chose to categorise BC into  $Q = 4$  strata (i.e. based on its quartiles) as we found it gave the clearest trends; each treatment stratum in the APO analysis was thus: [1, 1461], [1461, 3186], [3186, 6538], [6538, 26,001]  $\text{ng/m}^3$  BC concentration.

The average potential effect from increases in quartiles of BC shows a clear trend of increasing GSR for people who are cycling and walking (Fig. 4). On average, a 3% and a 5% increase in cycling- and walking-specific GSR, respectively, are found for a corresponding quartile increase in BC. In comparison, the trend is not as clear for people in motorized modes (and shown to be insignificant in the AOR shown in Table 1), although a positive trend is still apparent.

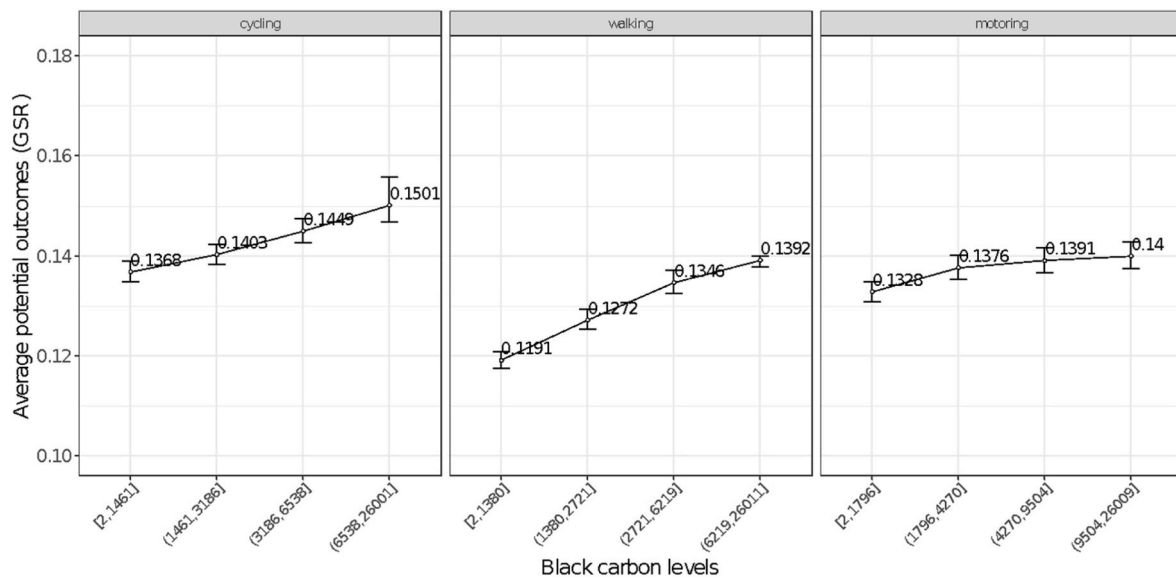
## 4. Discussion

### 4.1. Summary of results

In this study, we evaluate relationships between microscale environmental features such as greenspace and road type on GSR as an objective measure of stress monitored on a minute-by-minute basis for three separate weeks on a population of 122 adults living in three large European cities. We used a BDR method to further establish causal impacts of BC on GSR, adjusting for confounding effects by measured socio-demographic, activity level and environmental variables. The method establishes doubly robust results that are resistant to misspecification of the outcome regression or propensity score models (i.e. due to unmeasured confounding). We find that increasing BC, in general, would cause higher stress when people are either cycling, walking or, with a less pronounced effect, in motorized transport. These impacts are statistically significant while people are in active travel modes (i.e. cycling or walking), but not while in motorized transport. We find clear impacts of increasing BC concentrations, however we are unable to establish whether the effects are in fact due to the pollution itself, or due to the higher traffic density the higher BC may be a proxy for. These results do, however, account for any confounding by the road type (major vs residential and active travel infrastructure) and greenspace. We find that NDVI is associated with lower GSR for people for both modes of active travel, suggesting that greenness has a positive impact on reducing people's stress during travel. GSR also tends to be lower when people cycle and walk on roads with active travel infrastructure (i.e. cycleways and/or pedestrian paths). Road type does not significantly impact GSR when people are in motorized transport.

### 4.2. Comparison with previous studies

While there are no comparable studies on air pollution and stress experienced during travel itself, our results are supported by a growing body of literature on BC impacts on people's health. Perhaps most relevant is Shen et al. (2021)'s recent findings that exposure to BC during the past six years is associated with self-reported depression levels. Short-to medium-term exposure to BC as experienced



**Fig. 4.** The average potential outcomes of cycling-, walking- and motoring-specific GSR given corresponding quantile-levels of BC using the Bayesian Doubly Robust approach.

throughout daily activities were also shown in other studies to affect heart rate variability (Li et al., 2021) and levels of systolic blood pressure (Avila-Palencia et al., 2019). Studies have also shown a high level of concern over health impacts of air pollution, including in particular in the larger PASTA sample the current participants were drawn from in London, Antwerp and Barcelona, where respectively 64, 77 and 81% of the sample reported being worried about air pollution (Dons et al., 2018). Such perceptions could be more acutely felt when walking or cycling, as could also be inferred from studies demonstrating lower levels of active travel on high air pollution alert days (Tainio et al., 2021).

As noted earlier, BC may be an indicator of traffic volumes. Literature on traffic exposure and stress, while using different data collection methods, also support our findings. Caviedes and Figliozzi (2018) provided a design similar to ours in that stress was measured real time by GSR in Portland on a specific chosen route, however contrary to us, they measured peak traffic conditions with different types of facility (i.e. bike lane, multi-use path and shared roadway) instead of BC as a proxy for traffic volumes. In comparison to off-peak traffic, peak traffic conditions were shown to significantly increase cyclists' on-road stress levels (Caviedes and Figliozzi, 2018). Pedestrians were found to have higher levels of stress measured by GSR as the traffic density increased along their routes, as measured by speed limit, lane width, road type (two way or one way traffic), etc. (Mudassar et al., 2021). In a study based on general perception measures of traffic and wellbeing among survey participants in four urban neighbourhoods in England bisected by busy roads, pedestrians who perceived the traffic volume as 'heavy' and traffic speed as 'fast' on busy roads (i.e. these traffic conditions impeded their ability to walk locally, and they avoided using the busiest road in their area had) were found to have significantly lower wellbeing compared to those in the reference group (traffic volume: 'not heavy'; traffic speed: 'not fast', reported no barriers to walking, and did not avoid using the busiest road) (Anciaes et al., 2019).

In our study, we also found that participants would generally have higher stress when cycling and walking on roads without corresponding infrastructure for active travel. This result could be related to proximity to motorized traffic (Chuang et al., 2013; Kim et al., 2007). Blanc and Figliozzi (2016) found that cyclists' comfort levels were improved when infrastructure such as bicycle boulevards and separated paths were present, and significantly dropped when cyclists indicated being concerned by automobile and/or commercial vehicle traffic. Proximity to

collector and arterial streets and mixed and industrial land use (e.g., offices, retail, residential) were associated with higher levels of stress while walking by Lajeunesse et al. (2021). This is in-line with our findings on higher levels of stress on shown for those walking on major roads with an adjoining residential road when no separate path was present. The reason for causing more stress may be high levels of alertness needed in that setting. This could also happen for cyclists mixing with pedestrians, also shown in our study to increase cyclists' stress level. As Caviedes and Figliozzi (2018) pointed out, for example, riding in a shared path with many pedestrians and potential conflicts may be stressful because the cyclist is in a state of high alertness.

We also observe a decrease in GSR as NDVI increases during travelling, especially for active modes, which is similar to the results of recent studies: beneficial effects of walking and exposure to a forested environment were observed on psychological health (Koselka et al., 2019); stress levels were found to be tempered in forest and park environments (Lajeunesse et al., 2021). Moreover, Ta et al. (2021) concluded that green space exposure contributes to individual's active travel satisfaction.

Our study brings significant improvements to previous work as it attempts to establish causation through the Bayesian Doubly Robust estimation method. The approach is meant to adjust for measured and some unmeasured confounding affecting both the exposure and outcome variables, which provides robust predicted values of the outcome variable. These effects, especially the unmeasured confounding effects, are difficult to eliminate in the real world. For example, Caviedes and Figliozzi's (2018) work, which has a design similar to ours with on-road stress measured by GSR, only considered confounding by time of the day, presence of intersections, and bicycle facility type. Their study was also restricted to the context of bicycle transportation, and results were specific to the cycling conditions of a chosen route in Portland. Hence, these results cannot be applied or transferred to other environments and/or urban areas. Our study, on the other hand, explored the GSR changes in different travel modes and in an urban environment while accounting for potential confounding in a greater extent.

A limitation in our study, common in such tracking studies, was the uncertainty associated with travel time and mode detection. Our approach to improve predictions was to triangulate data from three available sources (GPS, travel diary, SenseWear), however we cannot exclude the possibility of some mis-matched observations points. Any error in assigning GSR observations to specific travel modes and

locations could have led to imprecision, exposure misclassification, and bias in establishing causal effects of BC.

Measurement errors related to physical activity estimates in different travel modes cannot be discarded in our study. Previous findings on the accuracy of the SenseWear have been relatively inconsistent (e.g. Bhammar et al., 2016; van Hoya et al., 2014; Powell et al., 2016), however it seems that, if anything, the device would under-estimate rather than over-estimate METs while cycling, which would lead to a conservative estimate (i.e. under-estimation) of the corresponding parameter and hence the BC's effect on GSR. We also note that since GSR was used in the calculation of METs (as mentioned in Section 2.4), the relationship between GSR and METs could partially be an artifact of the MET calculation method and hence potentially more sensitive to relevant measurement errors. Similarly, there may have been measurement errors in road type assignments. The precision of GPS instruments is such that we cannot guarantee with certainty which road facility participants were travelling on. When various road facilities existed within the 10 m buffer of each GPS data point, our best assumption is that, when available, cyclists and pedestrians would have been travelling on the cycling and pedestrian facilities, respectively. We expect that any deviation from that assumption would have led to an attenuation of the beneficial effect of active travel facilities in reducing stress found in our models.

When estimating the effect of BC on GSR in AOR model, although we have accounted for repeated measurements via random effects, the correlation due to the time lag in repeated measurements remains unadjusted. This was due to the computationally intensive and iterative procedure of obtaining the individual correlation structure of each participant. Without addressing the serial correlation, the significance of fixed effects is inflated due to low-biased standard errors for corresponding parameter estimates (LeBeau et al., 2018). The effects of spatial and trip-level correlations among observations were similarly unaccounted for, but future work could explore models that incorporate trip-level information such as duration and routes (ie for repeated trips on the same route).

Finally, an important limitation of our study is our inability to tease out whether air pollution as measured by BC is the main culprit for the impacts on stress, or whether BC acts as proxy for traffic volumes, or both. As shown, the literature is sparse on measurements of stress and stressor while travelling, but existing research supports the possibility of either or both pathways.

#### 4.3. Conclusions

Our study suggests that higher levels of BC can increase stress during travelling, in particular during active travelling. This result may indicate detrimental impacts of the air pollutant itself on stress, or of the traffic volumes it may be a proxy for. Green space is found to provide beneficial effects on reducing stress, as does active travel infrastructure. By relying on an objective proxy for stress and a robust estimation method (BDR), this study strengthens substantially the existing literature on the mental health drawbacks of air pollution, traffic, and lack of infrastructure for active travel but mental health benefits of greenspace. In other words, people would feel less stressed when there is less traffic, more protection from traffic, and more greenspace during travelling. This adds to literature that has shown that active travel can reduce stress compared to motorized travel (Yang et al., 2021), indicating that improving walking and cycling conditions are likely to further increase its beneficial effects. It is also fair to assume that with lower stress levels while travelling, people would be more inclined to choose active travel modes, which are desirable for their environmental and health benefits. Our findings add to a growing and convincing body of literature making the case for cities to invest in active travel infrastructure, reduce car use and increase greenspace to promote city dwellers' health and wellbeing.

#### Credit author statement

**Xiuleng Yang:** Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing; **Juan Pablo Orjuela:** Methodology, Investigation, Data curation, Validation, Formal analysis, Writing – original draft, Writing – review & editing; **Emma McCoy:** Methodology, Conceptualization, Formal analysis, Writing – original draft, Writing – review & editing; **Guillem Vich:** Methodology, Investigation, Data curation, Formal analysis, Writing – review & editing; **Esther Anaya-Boig:** Data curation, Writing – review & editing, Investigation; **Ione Avila-Palencia:** Data curation, Writing – review & editing, Investigation; **Christian Brand:** Data curation, Writing – review & editing, Funding acquisition, Investigation; **Gloria Carrasco-Turigas:** Data curation, Writing – review & editing; **Evi Dons:** Conceptualization, Data curation, Writing – review & editing, Funding acquisition, Investigation; **Regine Gerike:** Conceptualization, Data curation, Writing – review & editing, Funding acquisition, Investigation; **Thomas Götschi:** Conceptualization, Data curation, Writing – review & editing, Funding acquisition, Investigation; **Mark Nieuwenhuijsen:** Conceptualization, Writing – review & editing, Funding acquisition, Investigation; **Luc Int Panis:** Conceptualization, Methodology, Writing – review & editing, Funding acquisition, Investigation; **Arnout Standaert:** Data curation, Writing – review & editing; **Audrey de Nazelle:** Conceptualization, Methodology, Data curation, Formal analysis, Writing – original draft, Writing – review & editing, Funding acquisition, Investigation, Supervision, Project administration.

#### Ethics approval

Ethics approval was obtained for all aspects of the study by the local ethics committees in the countries where the work was conducted, and sent to the European Commission before the start of the survey/study. The following committees approved the study:

- Ethics board of the University Hospital of Antwerp (Belgium) on October 20, 2014.
- Clinical Research Ethics Committee of the Municipal Health Care (Barcelona – Spain) on October 1, 2014.
- Imperial College Research Ethics Committee (London – UK) on November 20, 2014.

Consent was obtained for experimentation with human subjects. The privacy rights of human subjects must always be observed.

#### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

#### Data availability

The data that has been used is confidential.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.envres.2022.114083>.

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