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Cyclists as Intelligent Carriers of Space-Time Environmental Information: Crowd-Sourced Sensor Data for Local Air Quality Measurement and Mobility Analysis in the Netherlands

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ABSTRACT

In recent years, slow travel modes (walking, cycling) have gained much interest in the context of urban air quality management. This article presents the findings from a novel air quality measurement experiment in the Netherlands, by regarding cyclists as carriers and transmitters of real-world information on fine-grained air quality conditions. Using individual sensors on bicycles—connected to a GPS positioning system—online local pollution information originating from cyclists' detailed spatial mobility patterns is obtained. Such air quality surface maps and cyclists' mobility maps are then used to identify whether there are significant differences between the actual route choice and the cyclists' shortest route choice, so as to identify the implications of poor air quality conditions for their mobility choices. Thus, the article seeks to present both a detailed pollution surface map and the complex space-time mobility patterns of cyclists in a region, on the basis of online quantitative data—at any point in time and space—from bicycle users in a given locality. In addition, the article estimates their response—in terms of route choice—to detailed air-quality information through the use of a novel geoscience-inspired analysis of space-time "big data." The empirical test of our quantitative modeling approach was carried out for the Greater Utrecht area in the Netherlands. Our findings confirm that spatial concentration of air pollutants have great consequences for bike users' route choice patterns, especially in the case of non-commuting trips. We also find that cyclists make longer trips on weekends and in the evenings, especially towards parks and natural amenities.

KEYWORDS

air quality; snifferbike; bicycle; sensor; crowd-sourced data; mobility pattern; surface model; kernel density; "bikeability" index

Introduction

The assessment of environmental decay has already a long-standing and respectable history (see, e.g., Weyant et al., 1996; Nordhaus and Boyer, 2000). Over the past

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decades, a wide range of integrated assessment indicators and models for environmental quality management has been developed and applied (for an overview, see, e.g., Graves, 2014: Kalimeris et al., 2019; Wang et al., 2017). Such quantitative tools have become important vehicles for understanding the complexity of both the local and the global ecosystem and for creating a broad evidence-based awareness of the severity of environmental issues ranging from local air quality to worldwide climate change. Meanwhile, an extensive literature on a meso scale of analysis, in particular the regional scale, has developed (see, e.g., Shaw et al., 2009; Batabayal and Nijkamp, 2019; Bowden et al., 2019; Batabayal and Folmer, 2020). Notwithstanding the promising focus on policy-oriented geographical entities like regions or cities, the spatial interconnectedness and data compatibility at different geographical scale levels is, in general, rather weak. Consequently, in recent studies a more localized, in particular urban, focus on individual human responses to environmental concerns is increasingly observed (see, e.g., Iturriza et al., 2020; Labaka et al., 2019), because cities and their residents may be conceived of as critical institutional actors in environmental management and policy, as is also put forward in the UN Sustainable Development Goals (SDGs) and the related New Urban Agenda.

It is also increasingly recognized, however, that taking an urban or local scale of analysis prompts two important but cumbersome research issues, viz. collecting reliable environmental/climatological data at a granular spatial scale and tracing the residents' mobility responses to local environmental and climate assessment information. These research lacunae and challenges form the background of the present study on the measurement of—and individual responses to—air quality differences in urban areas, using individual space-time crowd-sourced "big" data collected from individual sensors mapping out the residents' spatial behavior.

At the outset it should be noted that cities—or metropolitan areas—are extremely complex spatial entities, with a multiplicity of diverse actors and spatial interactions, a pluriform urban-economic structure, a heterogeneous morphological constellation, and an interconnected array of various types of infrastructure and mobility patterns. Recent studies by Martinez (2018) and Lai (2020), for example, provide informed and sophisticated modeling experiments on the great complexity of sustainable urban systems. But what is missing in most of these advanced micro- and meso-based modeling studies is an operational analysis of the way air quality in urban areas is measured with a refined granularity, and of the extent to which detailed information on local air quality may lead to refined urban air quality maps and to possible implications for individual spatial mobility decisions which have an impact on urban liveability.

In this study, we use online data on various air quality components which are collected through GPS-connected small sensors that are voluntarily installed by users on their bicycles (called *snifferbikes*). The resulting information allows us to map out the complex space-time mobility patterns of hundreds of bicycle users in a given area (in this case, Utrecht in the Netherlands). Apart from the added value of access to—and use of—such geographically detailed information on air quality, it is also a challenging research question whether the route choice decisions of bicycle users are influenced by online detailed air quality information in a given locality. In our specific application case, the air quality sensor on the bike—attached to the bicycle and activated by the user—begins to function as soon as the cyclist starts to move. Then, both the air quality data and the geographical position of the bike are stored online on a central platform where the geo-location and measurement values are recorded on 10-second intervals. Consequently, we also know precisely when and where a cyclist is exposed to what type of air pollution and potential health risk. By using the air quality observations of many cyclists, we can then interpolate a surface model of pollution in the area concerned, using a kernel density approach.

In light of this background information, the present paper aims to provide a detailed pollution surface map and the complex space-time mobility patterns of all participating cyclists on the basis of online quantitative data at any point in time and space collected by bicycle users in a given locality, as well as to estimate their response—in terms of route choice—to detailed air quality information through the use of a novel geoscience-inspired analysis of space-time big data. Thus, our approach is an example of volunteered geographical information (VGI).

The article is organized as follows. After this introductory section, the next section describes the analytical and policy scope of this article, in which online information on both air quality components and individual spatial mobility is collected through the use of what is called the "snifferbike" system. Next, we provide a more detailed description of the resulting space-time database and the bikers' fine-grained spatial mobility maps of bike users. Then we offer an extensive presentation of the empirical geoscience-based results, followed by a statistical-econometric and geoscience analysis of the individual data. The final section makes some retrospective and prospective observations.

Urban Air Quality Measurement Through Slow Motion

Since the 1970s, air quality in cities has been a source of analytical and policy concern in many countries in response to the global awareness of environmental decay (Taylor and Buttel, 1992; Brusseau, 2019). In particular, in recent decades, we have witnessed the rise and popularity of new spatially disaggregated concepts such as "sustainable cities," "zero-emission cities," "15-minute cities" (Moreno et al., 2021), "smart cities," or "climate-neutral cities" (Martins et al., 2010; Sperling et al., 2011; Caragliu et al., 2011; He et al., 2020; Stratigea, 2012; Kourtit et al., 2012; Chatterton, 2013; Yigitcanlar et al., 2019). The measurement of the contribution of local air quality (ranging from CO_2 to small particles) to both environmental conditions and the various aspects of human health appears to be fraught with many practical and data-analytical issues. Clearly, most countries, regions, and cities have developed and implemented advanced air quality measurement tools (often based on fixed sensors), but in most cases these are not sufficiently fine-meshed to measure air quality at the sub-local (e.g., neighborhood or street) level. It is noteworthy that liveability in city areas (in relation to density and proximity) has very recently turned into a major policy issue since the dramatic emergence of the COVID-19 pandemic, as urban human health outcomes and the environmental quality of life in cities have turned out to be strongly correlated (Baldasano, 2020; Kerimray et al., 2020; Connolly et al., 2020; Jia et al., 2020; Lu et al., 2020; Nichol et al., 2020; Wade, 2020). Consequently, from both an environmental quality and human health perspective, there is a clear need for a fine granularity in the measurement of quality-of-life information at a detailed urban scale.

It should also be noted that we currently observe—as a consequence of the COVID pandemic—a rapid rise in the popularity of environmentally-benign modes of urban transport, in particular bicycles. Several cities (e.g., Milan, Brussels, Paris) are now developing plans to ban motorized transport to a large extent from inner city areas, following the Dutch and Danish practice of allocating the scarce urban public space giving priority to cyclists or pedestrians. Of course, such a "slow motion" strategy favors urban environmental quality, but meanwhile it is also recognized that more exposure to fresh air and bicycle users' and pedestrians "open air" mobility behavior enhances their awareness of the inferior quality of the air around them. This has prompted a new environmental and mobility strategy in the Netherlands, namely: to use cyclists as "messengers" of air quality information. The general scope of this novel strategy will now be articulated.

In recent years, urban livability or quality of life in cities has become an important research domain in sociology, social psychology, environmental science, urban planning, and urban economics (for reviews and applications, see, among others, Cummins, 1997; Camagni et al., 1998; Rapley, 2003; van Kamp et al., 2003; Mulligan et al., 2004; Florida, 2005; Chen and Davey, 2009; Clifton et al., 2008; Das, 2008; Dunning et al., 2008; Grasso and Canova, 2008; Marans and Stimson, 2011; Zenker et al., 2013; Teke-Lloyd et al., 2021). A main strand of urban livability research is related to emerging new fields, like the geography or sociology of happiness, urban well-being, or urban appreciation, and has developed a range of new statistical methods for measuring the residents' contentment with their city or daily living environment (see, e.g., Frey and Stutzer, 2002; Ballas and Dorling, 2013; Charron et al., 2014; Wiek et al., 2013). In an interesting quantitative study, Ala-Mantila et al. (2018) have connected urban (subjective) well-being not only with density, perceived environmental quality indicators, social equity, education, social capital, and general moderator values (such as health conditions), but also with travel and mobility options, with particular reference to public transport access and ease for pedestrians. Pedestrian zones appear to play a potentially important role for urban well-being. Apparently, "slow motion" possibilities are likely to provide a positive contribution to urban livability. This finding is supported by several studies in urban planning which advocate the "walkability" or "bikeability" of inner cities (see, inter alia, Gordon and Richardson, 1998; Johansson et al., 2017; Lindsay et al., 2011; Leinberger, 2007; Pucher et al., 1999; Rietveld, 2001; Robinson et al., 2018; Tolley, 1997; Yun et al., 2019). In the meantime, the choice between "going green" or "going fast" (see also Batabyal and Nijkamp, 2013) is an increasingly important dilemma in urban mobility, as is also witnessed in the current "15-minute city" discussion (Moreno et al., 2021).

The popularity of bikes (including, more recently, also e-bikes) in urban mobility decisions is reflecting the environment-friendly image of this transport mode. Clearly, for a refined quantitative measurement of air quality in cities based on online space-time information, the use of bicycles is an attractive option. Thus, bicycles may generate a "double dividend," by both favoring and measuring air quality as a climate-neutral mobility vehicle, and as a fine-grained measurement vehicle for local air quality and healthy livability conditions. They have been used in the past years in various applications in several cities for measuring air quality, but in our analysis, we will focus on the potential of mobile sensors for investigating route and destination choices in relation to localized air quality information.

The recently introduced *snifferbike* program in the Netherlands serves as an incentive to encourage bicycle use from the perspective of obtaining online and spatially disaggregated information on air quality in urban areas and surroundings. It is based on the voluntary participation of bicycle users in an air quality measurement program, on the basis of a small, individualized sensor that is attached to the bicycle, but it can easily be removed by the user or installed on another bicycle. This device that we call the Bicycle Environment Estimation Probe (BEEP) is a multi-meter device that—when being activated by the user—records not only time and geo-location, but also specifically various constituents of air quality (including Nitric oxide [NO] and volumes of particulate matter in sizes PM10, PM2.5 and PM1), as well as temperature and other meteorological conditions such as humidity (see for details Civity and Sodaq, 2018, and Wesseling et al., 2021). It is an open-source equipment which aims to benefit society as a whole. Thus, the bicycle is used as a measurement instrument for various air quality components and is able to capture and record fine-grained data that can be used to depict a spatio-temporal pattern of various air quality indicators. Since there are hundreds of voluntary participants, the resulting data from their bicycles are crowd-generated, collected, and centrally stored, and then—upon request—made freely accessible for further scientific research. More information about the *snifferbike* initiative can be found on the Civity webpage.[1] This original approach will be further elaborated in the next section.

A New Geoscience Approach to Bicycle Use and Air Quality Analysis

In a noteworthy study, Orfeuil and Salomon (1993) highlighted the spatial and interconnected patterns of Europeans' daily mobility ("a billion trips a day"). Walking and biking make up an important share of the daily activity pattern of "people on the move." In recent years, the widespread introduction and adoption of digital technology (through mobile devices and apps supported by GPS and GSM technology) have offered unique opportunities for mapping out the complexity of people's daily mobility decisions (Hedman et al., 2021; Toger et al., 2021; Dahlberg et al., 2020). The modern city has become a "data factory" (see Batty, 2013; Komninos, 2016). The application of citizen-oriented sensor systems for measuring air quality fits in this trend (see, e.g., Schade et al., 2019; Wesseling et al., 2019). Recent studies on digital crowd-sourced data on cyclists' mobility patterns can be found in, among others, Bian et al. (2021), Boss et al. (2018), Navarro et al. (2013), Oliveira and Afonso (2015), Sterk (2020), and Zhang and Mi (2018).

The use of mobile or portable digital sensors as a voluntary tool for measuring online air quality indicators in a local environment is a logical follow-up of the trend outlined above. This has led to the development of the above mentioned *snifferbike* system in the Netherlands as of 2018. A *snifferbike* is a regular bike to which a particular sensor (BEEP) is attached that, when it is put in use, is able to measure several air quality components at any point in space and time, once in every 10 seconds. Each BEEP has its own unique ID. Crowd-sourced *snifferbike* data (anonymized) can be used—as will be shown in our article—to create fine-grained air quality maps and (individual or group) mobility maps. This is a nice example of citizen science: users of *snifferbikes* are voluntarily collecting and sharing cycling data with researchers. In addition, the collected air quality data can be represented in a fine-grained environmental surface map, or integrated in statistical models. As soon as the BEEP device is activated by the cyclist, it starts to send out the relevant geo-coded data to the central Platform, so that it is possible to locate all segments of a *snifferbike*'s journey, from origin to destination. Informed consent was obtained from all *snifferbike* participants. A detailed description of the technicalities of the *Snifferbike Project* can be found in Wesseling et al. (2021).

It is also possible to estimate what is called the *counterfactual* route for each observed origin-destination trip, with the aim of identifying the shortest route between the origin and destination of all observed trips. For each observed trip, the activated BEEP device registers the local air pollution levels concerned and the geo-location with a high degree of repetition (every 10 seconds), so that any new *snifferbike* observation is recorded at a high spatial frequency. By measuring air pollutants at each point in space over the entire trip trajectory, a trip-sum exposure to pollutant values can be calculated. As indicated by Castell et al. (2017), low-cost sensors are subject to robustness issues in measurement quality. In this article, combining all geo-coded observations from all local *snifferbikes*, we can create not only extraordinarily precise air quality maps in urban areas, but also very detailed cycle mobility patterns, which is often not possible with fixed low-cost sensors. In practice, this analysis can be pursued by downloading all roads and cycle paths available to cyclists in the relevant area and using a GIS network analysis approach, so as to identify the shortest route between any origin and destination of any bicycle trip undertaken in the GIS-network. We may then confront the observed route choice with the hypothesized shortest route choice. The statistical divergence between the observed and counterfactual route choice of cyclists may be caused by the poor convenience and amenity of the shortest route, due, for instance, to noise nuisance or noxious traffic fumes along a busy road, perceived or observed low environmental air quality, lack of urban green, perceived low safety, etc. Thus, this difference between the actual and the shortest distance may be conceived of as a shadow price of environmentally less appreciated routes by bicycle users. Whether or not this difference plays a critical role in the route choice of cyclists can be tested empirically, since the BEEP device provides very detailed surface data on a range of geo-coded environmental quality indicators which can be retrieved by the users from online geo-coded data-repositories.

Using bicycles as mobile measurement stations for air quality has great advantages compared with stationary or fixed measurement stations, because: (1) the measurement level is at human exposure level (and not at a higher level with fixed sensors, e.g. on buildings); (2) bicycles have a fine-grained mobility pattern and hence cover the whole urban space; (3) it is a good example of digital voluntary citizen empowerment, which creates greater environmental awareness. This novel approach may be seen as a good example of smart city policy (see, e.g., Komninos, 2020; Kourtit, 2020). Using the *Snifferbike Project* data, Wesseling et al. (2021) estimated the average exposure of cyclists to air pollutants in Utrecht, the Netherlands. They find that the exposure is high in cycling routes close to major roads and low in routes with less traffic. Our study differs from Wesseling et al. (2021) in that we complement our analysis with detailed land-use information and by creating counterfactual routes between observed origins and destinations.

In our analytical experiment, which aims to serve the two above-mentioned purposes of collecting fine-grained air quality information and producing geo-coded spatial mobility maps, a spatial kernel density function in a GIS software environment is applied to interpolate the degrees of individual exposure between the observation points. This kernel density function is modeled to estimate interpolated values for each square meter in the relevant area, so that in the end we have information on all coordinate points of each part of the *snifferbike*'s trajectory. This application of crowd-sourced information leads to an enormous big data collection on air quality and mobility, which calls for further statistical-econometric analysis.

Before we present the detailed outcomes of our quantitative analyses in the next section, it is necessary to make a few observations on the data treatment. We use data from the Greater Utrecht area in the Netherlands, which is partly a high-density area and partly a green area. Consequently, the trip patterns do not necessarily mirror stable daily commuting decisions; the area as a whole is well-known as a recreation area and also—certainly during the weekends—as an Eldorado for bicycle users. Thus, a typical single stable origin-destination trip pattern is not likely to be found.

From the enormous volume of big data, we had to be selective about which data to include. This led to the following data-cleaning decisions:

- Information with incomplete data (e.g. missing geo-location, missing origin or destination, obviously wrong information, etc.) was eliminated.
- Information caused by wrong treatment of the BEEP device (e.g., by forgetting to deactivate the BEEP during a stop, or to reactivate it after a stop) was also eliminated.

In addition, a few simple rules of thumb were adopted, namely:

- Each recorded and selected bicycle trip is made on one and the same day.
- Each bicycle trip should at least be more than 1,000 m in distance (on average, more than four minutes).
- Trip stops lasting more than 20 minutes are interpreted as a termination of the previous trip at a destination (so that, as soon as the *snifferbike* starts to move again, a new trip is recorded).
- Individual outliers in completely different regions (e.g. cyclists using their BEEP on a bikes outside the greater Utrecht area) are also omitted. Consequently, the study for bicycle movements and air quality measurement was demarcated for the greater Utrecht area, including towns, suburbs, and villages in the surroundings from or to which cyclists were frequently traveling.

Figure 1 shows the surface model details of how the interpolated pollution values are distributed in the greater Utrecht area. These rules for inclusion reduce the number of trips from 24,624 to 4,720 in which the majority of the dismissed trips were because the bikes were stationary (BEEP active but bike does not move), followed by short trips, and trips outside the area.

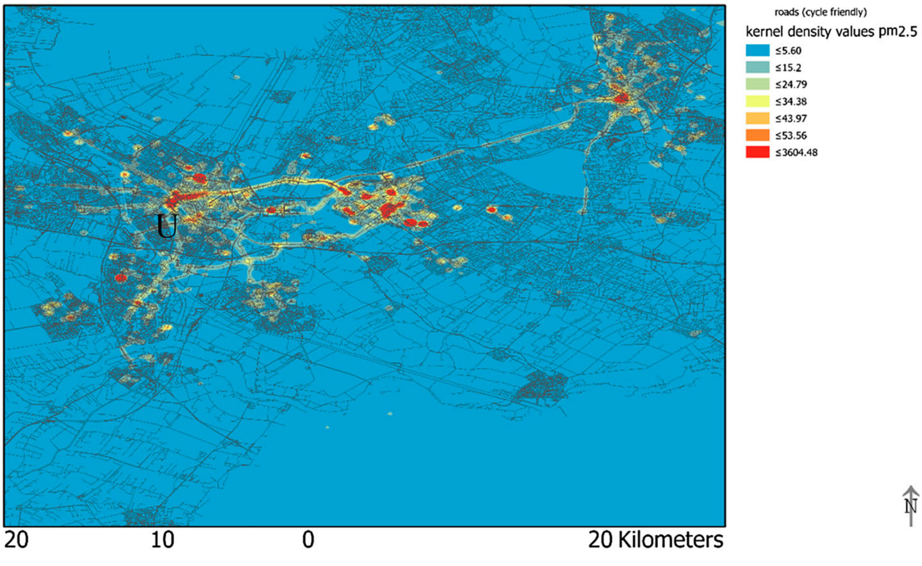

Figure 1. Interpolation of crowed-sourced snifferbike-values of PM2.5 pollutants in the study area including Utrecht with suburbs (center-west, also marked with the letter U in the map) and nearby towns including Amersfoort (top right), Zeist (center), and Nieuwegein (south west of Utrecht)

In addition to the *snifferbike* data, two other data sources were used in our research. First, the data describing land-use and infrastructure in the area concerned was derived from *OpenStreetMap* (OSM), where infrastructure is represented by all cyclable roads and lanes in the Greater Utrecht area (represented by gray lines in Figure 1). This infrastructure data was useful to select roads and lanes to be included in the network data set used to estimate the counterfactual trajectories, and to create a line density measure. The line density measure expresses the length of roads within a 50 m radius from any 10m² spatial unit. Cyclists' observed or counterfactual trajectories picked up these values at each geo-coded location, and these values were used as an indicator for the densification of roads. Next, the trip-average line density value was used in our subsequent regression models. In addition, the Cartesian distance to these amenities, viz. the nearest park, nature reserve/natural park (green amenities), and water (blue amenities), was calculated for each geo-coded observation for both the observed and the counterfactual trips. We were able to estimate the average distance to these three amenities for each of the trip-types (observed and counterfactual) and for each of the trips. In addition, we also estimated the standard deviation of the Cartesian distances to all land-use amenities between origin and destination for observed and counterfactual trips. The two different measures (average distance and standard deviation of distance) were determined to capture the exposure to amenities as well as the variability of exposure to amenities. Secondly, weather data describing average temperature and total precipitation per day were also used. These data were derived from the official station operated by the Royal Netherlands Meteorological Institute (KNMI) recording weather conditions in the Greater Utrecht area. Weather data were included in order to analyze to what extent weather conditions affected traveling behavior.

Statistical and Modeling Results on Local Air Quality: Air Quality and Route Choice Exposure

As mentioned, our article serves two goals: to collect detailed air quality information at the local level and ascertain the route choice implications for cyclists as a result of information on air quality at a very detailed spatial scale. In this section, we first present simple paired-sample statistics and t-test results where the distribution of pollutants along the observed and counterfactual routes are compared. Then, we present the empirical model which examines the route choice of cyclists and the relationship of this choice to air quality exposure and urban environmental quality. The section also offers a discussion of the main findings for both paired sample statistics and first-difference estimates.

The *snifferbike* system is based on an open data platform with anonymized online information on all space-time bike trips and related air quality data where each "sniff" contributes to create a real-time database with values describing location, time, and pollution. The spatial distribution of sniffs varies between land-use, but the concentration of measurement points to roads is very dense, while outside of the roads, only a few sniffs are collected. From the information recorded by *snifferbikes*, we can follow the air quality along the cyclists' journey for three pollutant levels and compare it to the air quality in the counterfactual route, i.e., the hypothesized shortest route from any origin to destination.

After measuring the air quality along the route choice of cyclists and that of counterfactual routes, we ran t-tests to investigate whether there were substantial and significant differences in the pollutant levels between the observed and the counterfactual routes. Paired t-tests were undertaken for each level of particles in the air and were expected to reveal if there was a significant difference between the route alternatives in relation to observed and counterfactual exposure to the pollutants encountered. If we compare exposure levels between observed and counterfactual models, we see that on average the exposure levels are substantially different (See Table 1). The statistics in Table 1 also indicate the following ranking of particle amounts: PM10 > PM2.5 > PM1, where the differences between counterfactual and observed values are the greatest for PM10 and lowest for PM1. Knowing that heavier particles (PM10) are less easily dispersed over distance compared to small particles, the large differences between observed and counterfactual models of exposure suggest that cyclists are avoiding the dustiest areas (see also EPA, 2018).

Next, Table 2 shows the outputs from the paired t-tests using the average observed and counterfactual exposures. The results indicate that the negative difference of exposure to

Table 1. Average concentration of particles in the air on the observed (denoted by PM1, PM2.5 & PM10) and counterfactual routes (denoted by PM1CF, PM2.5CF & PM10CF)

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	PM1	6.417	4720	7.109	0.103
	PM1CF	19.663	4720	36.276	0.528
Pair 2	PM2.5	7.160	4720	8.477	0.123
	PM2.5CF	24.067	4720	53.752	0.782
Pair 3	PM10	7.790	4720	9.974	0.145
	PM10CF	28.244	4720	72.780	1.059
Trips	Observed	7433.93m	4,720	7286.102	61.891
Distance in meters	Counterfactual	5916.46m	4,720	4252.107	119.193

Table 2. T-test outputs of paired samples of the average quantity of particles in the air between the observed (denoted by PM1, PM2.5 & PM10) and counterfactual (denoted by PM1CF, PM2.5CF & PM10CF) routes. Comparison of trips (bottom row) expresses differences in meters

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
Pair 1	PM1 vs. PM1CF	-13.24689	36.44025	0.53041	-14.28674	-12.20705	-24.975	4719	0.000
Pair 2	PM2.5 vs. PM2.5CF	-16.90698	53.65037	0.78091	-18.43793	-15.37602	-21.650	4719	0.000
Pair 3	PM10 vs. PM10CF	-20.45459	72.44006	1.05441	-22.52172	-18.38747	-19.399	4719	0.000
Trips	Observed vs Counterfactual	1517.468	5511.753	80.22667	1360.186	1674.75	18.9148	4719	0.000

the pollutants between the observed and counterfactual routes is statistically significant for each of the three particle sizes. Note that the t-values are greater for the smaller particle sizes. Moreover, our t-test results also show that the distances traveled during the observed trips are significantly longer than those estimated for the counterfactual trips. The differences from the counterfactual routes correspond to 20 percent of the observed routes.

Our statistical geo-science experiments appear to lead to very interesting findings. The analysis of the mean differences of pollutants along the observed and counterfactual routes shows that the cyclists' route choice is indeed correlated with air quality. The assumption is that this choice is driven by exposure to varying levels of air quality on alternative routes. However, we may also assume that the choice is determined by such factors as blue and green surroundings, and the time of the observed trip (weekdays vs. weekends or morning vs. evening). And therefore, we now present an empirical econometric model which can integrate additional factors that are potentially relevant to the decision to deviate from the counterfactual route, i.e., the closest route between origin and destination pairs.

The route choice can be modeled as the deviation of observed routes from the counterfactual ones and the differences in the set of exposure elements along the routes. Here, we develop a regression framework that makes use of the deviations in the dependent and independent variables in a fashion similar to the first-difference estimators. In our study of the route choice, the model can be specified as follows:

$$\Delta Yir = \Delta\beta_1 X_{ir} + \beta_2 Z_i + e_{ir} \quad (1)$$

where ΔYir denotes the distance difference between the observed and counterfactual routes-traveled by cyclists i, ΔX_{ir} is the deviation of a set of independent variables—such as pollutants and distances to parks, water, and nature along the observed route—from counterfactual routes, and Z_i are variables that do not vary between the observed and counterfactual route but are expected to influence ΔYir. Note that interacting Z_i with the routes dummy before first differencing ensures that they appear in the final model. Finally, β_1, β_2 and e_{ir} are parameters to be estimated and error terms, respectively.

In Equation (1), we associate the observed and counterfactual trips with their surroundings regarding blue and green amenities in order to analyze the urban qualities that influence the choice between the two. The model includes the differences of standard deviations in the distances to the nearest parks, natural amenities, and water between the observed and counterfactual routes. We also control for a line-density measure of road networks, which is expected to reflect the choice alternatives the cyclist has, while traveling from an origin to a destination. Therefore, a line density[2] measure can be understood as an index of "bikeability" (see Kourtit et al., 2022 for a similar approach). The remaining variables of weekday, morning, and afternoon are dummies indicating the time of the trip. The regressions are run for each pollution particle separately, as shown in the columns of Table 3.

The estimation results of the three competing model specifications indicate that distance differences between the actual and counterfactual trips decrease with the density of particles in the air. In particular, when a counterfactual route has one more unit of PM2.5

Table 3. Regression results for particles PM1.0, PM2.5 and PM10

VARIABLES	(1) PM10	(2) PM2.5	(3) PM1.0
diff_PM10	-2.040**		
	(1.031)		
diff_PM2_5		-2.883**	
		(1.392)	
diff_PM1_0			-4.505**
			(2.050)
Line Density	12.891***	12.911***	12.951***
	(1.232)	(1.233)	(1.233)
diff_parks	9.378***	9.377***	9.376***
	(0.526)	(0.526)	(0.526)
diff_water	1.377	1.384	1.401
	(1.448)	(1.448)	(1.447)
diff_Nature	3.583***	3.583***	3.582***
	(0.411)	(0.411)	(0.411)
weekday	-289.438*	-291.978*	-296.364*
	(168.210)	(168.221)	(168.254)
morning	-418.713**	-418.634**	-418.366**
	(177.461)	(177.454)	(177.444)
afternoon	-344.863*	-346.170*	-348.339**
	(177.087)	(177.090)	(177.098)
Temprature	85.997***	85.598***	84.976***
	(10.404)	(10.421)	(10.450)
mmPrecipitation	-40.633**	-40.878**	-41.260**
	(16.348)	(16.352)	(16.359)
Observations	4,716	4,716	4,716
R-squared	0.207	0.207	0.208

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Note: The dependent variable is the difference of distances between observed and counterfactual routes.

concentration in the air, cyclists diverge from the shortest route by three meters. Thus, cyclists make longer trips to reach their destination, when air quality is better along the chosen road network and nearby areas. This also means that, if pollutant levels are similar between the two options, observed trips converge to their counterfactual road connections. Similar observations are made by Zhao et al. (2018) for Beijing, where especially female cyclists appear to shift to other means of transportation during polluted weather. Not surprisingly, the line-density measure of road networks or "bikeability" index shows a statistically significant and positive effect on the dependent variable. One square kilometer increase in the route network corresponds to around 13-meter longer trips. Therefore, the availability of alternative road links increases the tendency to deviate from the shortest route. Similarly, Dill and Voros (2007) also find that a positive perception of the availability of cycle paths is associated with higher cycling activity in Portland, Oregon.

Regarding the distances to blue and green amenities, we have used the first difference between the standard deviation of the distance to the amenities on the observed and counterfactual routes. The regression output suggests that the route choice is influenced by the selected set of natural amenities surrounding the route network. Since the observed distances are always longer than the counterfactual distances, the differences between the standard deviations, then reflect people's behavior of maximizing their exposure to various elements in the land surface. The results indicate that the deviation in distances from the shortest route increases with the spread of the observed road network around parks and natural amenities. This means that diversification of land use elements has the potential of nudging people to cycle longer distances. This finding is in line with Nair et al. (2019). Following GPS traces, they also find that cyclists prefer green areas in Philadelphia. Cervero et al. (2019) provide evidence that land-use mix, and green and blue landscapes, induce bike commuting in British cities and towns. Our findings also reveal that the actual trips are in general closer to the counterfactual trips on weekdays and in mornings. On weekdays, the distance difference between observed and counterfactual routes decreases as much as 289 meters, and in the mornings even to 418 meters. Ton et al. (2017) show a similar finding regarding bicycle route choice in Amsterdam, where cyclists are found to minimize traveling distance in the morning peak. The results are clearly also able to reflect the choice of route in trips to work. Apparently, cyclists choose to take shorter trips to work on weekdays and early mornings, while they prefer to choose longer routes on weekends and in the evenings. Thus, the choice for healthier bike trips is not only dependent on place-specific environmental quality conditions, but also on the "relaxed mood" of the cyclist. Finally, observed trips diverge from counterfactual routes on warmer days and converge when precipitation is high. Indeed, according to our model specification, weather conditions are the most impactful factors in cycling behavior (except for time indicators). One degree increase in temperature is associated with about 86 meters deviation from the counterfactual routes. An et al. (2019) also provide support to this finding for New York. They show that cycling rates are affected by weather conditions more than other factors including topography, infrastructure, and land-use mix. We may thus conclude that detailed information on local air quality tends to significantly affect the route choice of cyclists.

Retrospect and Prospect

"Slow motion," in particular biking and walking, has recently become a fashionable transport mode choice, especially because of the COVID pandemic. This article has focused its attention on spatial biking patterns in the Netherlands, from the perspective of using bicycles as vehicles for measuring online the concentration of air quality components in urban areas. Besides the conventional system of fixed (immobile) measurement sensors, the mobile *snifferbike* system based on mobile sensors offers a great new opportunity for measuring urban air quality with an extraordinarily fine granularity. In addition, using the data on both geographically based air quality elements and detailed spatial mobility patterns in urban agglomerations allows us to study the nexus of air quality and cyclists' route choice. It is a noteworthy finding that—on the basis of a complex space-time geo-science-oriented statistical approach—cyclists are not necessarily choosing the shortest routes, but rather those routes that are more attractive from an environmental quality perspective. Exposure to air quality has apparently an implication for an individual's route choice as a cyclist. This suggests that air quality information in urban agglomerations may, in principle, have considerable impacts on the spatial mobility choices of those citizens that are directly exposed to poor external air quality, such as cyclists and pedestrians. This finding may, of course, also have a great relevance for "slow motion" commuting decisions, including a shift from the automobile to the bicycle. Stimulating the benefits of biking behavior means—in addition to the human health impacts of daily physical movement—also proper and reliable information on external air quality and livability conditions.

From our study important policy lessons can be distilled. Good air quality in cities tends to raise the residents' feelings of health and wellbeing. This means that modern happiness research (see, e.g. Argyle, 2013; Frey and Stutzer, 2002; Easterlin, 2004; Ferrer-i-Carbonell and Frijters, 2004; Graham, 2005; Bruni, 2006, 2010; Cohn et al., 2009; Diener et al., 2009, 2010; Dolan et al., 2008; Yu and Wang, 2017; Harsman Wahlstrom et al. 2020; Kourtit, 2020; Kourtit et al., 2021) is closely connected with environmental quality research, while both streams of research are also related to spatial mobility research. This calls for policy initiatives at the interface of well-being, livability, and the mobility of residents, such as zero-emission urban districts and online bicycle route planning in environmentally favorable urban areas.

The design of fine-grained online air quality information systems in urban neighborhoods is clearly another important policy challenge in cities, so that healthy local environmental conditions will favor "slow motion" choices. Clearly, such information can be combined with data from fixed air quality monitoring stations in a city. In this framework, there is a need for better integrated GIS-based measurement tools, so that geostatistical data can be combined with mobility data in the city. An example of empirical follow-up research along these lines is the question of how far the COVID-19 pandemic—with its rising health concerns—has influenced bicycle route and destination choices during successive waves of the pandemic in the past years (see, e.g., Nijkamp and Kourtit, 2022; Velders et al., 2021).

Next, a fine granularity of urban air quality data may also be important to examine the livability impacts of, for example, green areas, lakes, and rivers, density and height of buildings, land use (e.g., residential vs. industrial), or major traffic arteries in a city. Micro-meteorological data (e.g., temperature, humidity, precipitation, wind exposure) can then be important to provide a proper assessment of moderator impacts on urban air quality.

All such information can be used to identify air quality zones in a city. By controlling traffic in such urban zones, a city may be able to develop emission zones of different quality that in the long run might benefit the health conditions in urban neighborhoods.

Notes

1. Reference to the *Snifferbike Project* can be found on: https://civity.nl/en/data-management-platform-cip/cip-iot/sniffer-bike/
2. We use line density functionality of ArcGIS. For details, see https://pro.arcgis.com/en/pro-app/2.8/tool-reference/spatial-analyst/line-density.htm

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