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Slow motion in corona times: Modeling cyclists' spatial choice behavior using real-time probe data

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Abstract: The recent COVID-19 pandemic has provided a renewed impetus for empirical research on slow and active modes of transportation, specifically bicycling and walking. Changes in modal choice appear to be sensitive to the actual quality of the environment, the attractive land use and built environment conditions, and the ultimate destination choice. This study examines and models the influence of cyclists' health concerns during the pandemic on their spatial destination and route choices. Using a large real-time dataset on the individual daily mobility of cyclists in the province of Utrecht, the Netherlands, collected through GPS-linked sensors on bikes (VGI, or volunteered geographical information), the analysis employs spatial regression models, Shapley decomposition techniques, and spatial autocorrelation methods to unveil the backgrounds of changes in spatial behavior. The results reveal that the perceived wellbeing benefits of bicycling in green areas during the pandemic have significantly influenced cyclists' choice behavior, in particular route and destination choice.

Keywords: Slow motion, bicycles, COVID-19, volunteered geographical information, real-time probe data, sensors, spatial regression, Shapley decomposition, spatial autocorrelation

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"A human on a bicycle is the most efficient traveler among all machines and animals."
—Charles Montgomery, *Happy City: Transforming Our Lives Through Urban Design (2013)*

1 Slow motion: A new mobility paradigm?

During the corona crisis, we have observed a growing interest in sustainable, active and individual modes of transportation, particularly bicycling and walking. This study aims to investigate the changes in bicycle usage in relation to mobility choices during the pandemic. To provide a comprehensive understanding of our research, we will begin by

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offering a brief overview of the historical development of "slow motion behavior." Subsequently, we will delve into the specific research question addressed in this study.

1.1 The context

Slow modes of transport, in particular walking and cycling, have often been undervalued in transportation research. Apparently, pedestrians and cyclists have been "underdogs" in the world-wide interest in spatial mobility. In recent years however, we witness a rising interest in slow motion mobility, for various reasons: human (physical and mental) health, environmental quality, safety and sustainable land use in compact cities. In particular, the COVID-19 pandemic has encouraged the use of environmentally benign and social-distancing oriented modes of transport. In addition, the currently popular notion of the "15-minute city" (Moreno, 2020; Moreno et al., 2021) regards slow mobility modes as necessary spatial vehicles for achieving ambitious urban targets on sustainability, accessibility and speed in urban areas. Time and space have become two interconnected dimensions of the geography of our world.

We note that speed has been a driving motive for human beings since early history. "Time is money" has, since ancient times, been a stimulus to increase average speed of movements, as is witnessed by the transition from horse-drawn carriages or barges to trains, cars or airplanes (Baaijens et al. 1998; Cross 1998). Despite the negative sustainability-related externalities of fast modes of transport, in particular environmental decay, resource depletion and fatalities, the need for fast modes of transport has shown an uninterrupted pace. Transport efficiency rise has no doubt been one of the major added values of rapid high-tech development in our world, as is reflected in the globalization trends over the past decades as well as in modern high-mobility societies at all scale levels (Urry, 1995; Waters, 1995). In the course of a few centuries, "empty spaces" have been filled with infrastructure, and countries and regions have become "smaller all the time" (Knippenberg & De Pater, 1988; Van der Woud, 1987). This structural trend of a "shrinking world" led more than half a century ago already to the concept of the "global village" (McLuhan, 1964). The French author Virilio (1977) argued even that speed became a competitive factor in and between nations; hyper-mobility became an economic success factor in the post-Industrial Revolution era (Van der Stoep, 1995). And consequently, the "homo mobilis" became a characteristic species—with a new perception of time—on our planet, in which a strong competition emerged between cars, trains and airplanes. As Nowotny (1994) wrote: "everything, above all time, becomes frantic motion: the new myth was speed" (p.84).

1.2 Bicycles and speed

It is surprising that—despite the mega-trend of speed acceleration over the past centuries—only one transport mode, viz. the bicycle, has kept a rather stable slow-motion position in the history of mobility. According to Lay (1992), in the year 1890 already more than 1 mln bicycles were produced in the USA, mainly for health reasons but also for convenience reasons. But also in other continents (Europe, Asia) bicycles became very popular transport vehicles, certainly for short to medium distances. The widespread use of the bicycle was the result of its travel ease: convenience, flexibility, reliability and low cost. Despite the "high-speed society," bicycles remained in many countries (e.g., Denmark, The Netherlands, Belgium) rather popular, often not as a substitute, but as a complement to other transport modes (see e.g., Martens 2004; Pucher & Buehler 2009; Rietveld 2000). The joint use of cars, public transport and bicycles implied often a choice for an integrated transport package choice. This is also in agreement with Zahavi's (1974) concept of a given travel time budget implying that the average travel time with different modes in metropolitan areas tends to be rather stable; cars and public transport offer efficient transport opportunities over medium to long distances, while bicycles are more efficient for short distances (see also Hupkes, 1979).

Clearly, the value of time is a critical factor in transport mode choice, but it ought to be recognized that speed is not the only choice criterion in a mobile society. In the decision to choose a bicycle as a travel vehicle, several arguments play a role: flexibility, convenience, speed, cost, environmental impact, safety, fresh air, health, recreation, mental well-being, and so forth. As a result of this portfolio of advantages the bicycle has over the past decades not only kept a rather stable position in many countries but has shown even an extension—and recently a rejuvenation—in many countries, not only in lower developed economies but also in developed nations. In several countries a bicycle—and in particular a luxury or electric bicycle—has even become a status symbol for a sustainable and healthy lifestyle (see Batabyal & Nijkamp, 2013). And the current debate on the 15-minute city assigns even a prominent position to the bicycle in a smart urban logistic system (Moreno et al., 2021). This re-positioning of bicycles as a potential key vehicle in urban mobility planning forms an important motivation for the present study.

1.3 Bicycles in corona times

The popularity of bicycles as a sustainable and healthy travel mode has recently—with the outbreak of COVID-19—even significantly risen in many cities. Several metropolitan areas have in the meantime even adopted new intra-city travel plans so as to favor bike use. Examples are: Brussels, Paris, London and Milano. The re-discovery of the bicycle as a respected vehicle for many trip-makers has led to a significant increase in various types of bicycles (ranging from traditional bikes to speed pedelecs). The perceived individual and environmental effects of bicycles for home-to-work trips, shopping, social activities, and recreating are significant (Leyland, et al., 2019; Tortosa et al., 2021). The advantage of bicycle use is that—in the corona period of "social distancing" rules and facemasks requirements—it was possible to combine fresh air with physical movement, even in (small) social groups. So, the positive outside-air potential of bicycles during the corona time restrictions was a major advantage of this slow mode of transport. But did COVID-19 also exert a significant impact on the spatial choice behavior of cyclists? And from a major strategic perspective, does a bicycle-oriented city contribute to a healthier living environment? Are health arguments a driver for the cyclists' choice of mobility patterns? To answer these questions, we need to undertake evidence-based research supported by data of cyclists' movements to contribute to the achievement of livability objectives in cities.

1.4 Aims and scope of the study

In light of the previous observations, this paper aims to investigate the drivers of shifts in bicycle usage, in particular for leisure purposes, during the corona period, by comparing them to the pre-corona spatial behavioral patterns. Our analysis will not only focus on the increase in bicycle usage, but also, more importantly, on the alterations in travel patterns, such as route choice and length, in order to examine the specific impacts of the corona crisis on bicycle usage, particularly in terms of travel distance, destination, and route selection. Thus, this study aims to identify the factors and spatial consequences of changes in spatial bicycle mobility patterns since the onset of the pandemic in Spring 2020, in comparison to the travel patterns of cyclists in the preceding year, using information from 2019 as the reference dataset.

This study utilizes a comprehensive online (real-time) database that incorporates GPS-based space-time information on spatial bicycle patterns in the province of Utrecht, Netherlands. In a later stage these data were only comprehensively collected for the city of Utrecht which makes a full-scale time comparison more cumbersome. Our analysis aims to explore the potential influence of corona-related concerns and environmental motivations on the choice behavior of cyclists, specifically focusing on leisure trips in green areas inside and outside the urban areas. From this perspective, the study contributes to the emerging field of research examining the relationship between bicycle use and the COVID-19 pandemic, building upon relevant studies (Bouzouina et al., 2023) by Hu et al. (2021a, b), Jobe and Griffin (2021), and Teixeira and Lopes (2020). While these studies provide valuable insights into changes in cyclists' behavior, they do not employ advanced spatial modeling techniques to map out the immediate adjustments in mobility patterns of cyclists, including daily weather effects. This paper aims to fill this gap, but it also seeks to get a more general and deeper understanding of the motives and constraints of cyclists' behavior.

The paper is structured as follows: Section 2 provides an overview of key findings from the literature on slow motion, with a specific focus on bicycling and its significance during the corona period. Section 3 presents the methodological framework and details about the employed database with real-time probe data. The statistical and econometric results of the spatial modeling experiments are presented in Section 4. Finally, the concluding section offers retrospective and prospective reflections.

2 Slow motion as a traveler's benefit

2.1 Slow motion studies

In light of the COVID-19 pandemic, there has been a significant surge in the popularity of bicycles. It is important to acknowledge that bicycles of various types (conventional bicycles, e-bikes, speed pedelecs) have been steadily growing in popularity for quite some time now, not only for commuting but also for recreational purposes such as leisure activities and shopping. In the past decade several studies have highlighted the advantages of bicycle use for everyday commuting (see e.g., Bühler, 2012; Bühler & Pucher, 2021b; Caulfield et al., 2012; Rodriguez-Valencia et al., 2021; Tengattini et al., 2018), but—given the flexibility of bikes—also its advantage in a leisure context have received considerable attention (see e.g., Heinen et al., 2011). In a complex and digital-oriented urban area (see e.g., Komninos 2021) bicycles appear to be in many cases very functional for short to medium distances. In addition, they are often seen as "health makers" and environmentally benign vehicles. As a consequence, bikes have seen a change in status, viz. from an old-fashioned transport vehicle (often for the poor) to a new status symbol (especially for the more expensive part of the bicycle market). Cyclists are sometimes even seen as the new "time pioneers" in urban areas (Baaijens & Nijkamp, 1999), in particular since they provide the benefits of a zero-emission mobility in the context of the global drive toward sustainable transport (Massink et al., 2011).

An informed publication on the advantages of bicycle use in cities (Yang et al., 2019) argues that physical active modes of transport contribute clearly to the sustainability of cities, in particular if the built environment and infrastructure are geared towards reducing traffic congestion and air pollution. The authors reviewed 39 empirical studies to identify the success factors of cycling-friendly cities, while addressing spatial factors such as short connectivity, commuting and recreation, land-use mix, availability of dedicated cycling-paths, and terrain slopes in cities. Most cities appear to have even a greater cycling-friendly potential than assumed.

A clear breakthrough in strategic thinking on bicycles and sustainable transport modes has arisen in the past years with the new concept of the 15-minute city (so-called "la ville du quart d'heure," based on Moreno, 2020; Moreno et al. 2021). The 15-minute city idea is a practical and normative follow-up of previous notions on "car-free cities" introduced already a few decades ago. It ties in with recent planning concepts on walkability (and "bikeability") of inner cities (see e.g., Leinberger, 2007; Szücs, et al. 2017; Wong et al., 2019). The contemporary planning concept of a 15-minute city aims to create a new foundation for a livable city. This would require in most cases active, nonmotorized trip behavior by either walking or using a bike. Such plans are already being implemented in Portland and Paris amongst others.

In summary, there are many new and promising perspectives for the bicycle in an era of health crises and climate concerns. A sustainable and healthy lifestyle seems to rely increasingly on slow motion vehicles in urban transport, supported by active micro-mobility (biking and walking).

2.2 Fringe benefits of nonmotorized transport

The remarkable transformation of the bicycle, shifting it from an overlooked mode of transportation to a trailblazing method of travel, is truly extraordinary. The bicycle is not regarded as a competitive mode for car driving, but rather as a sustainable complementary mode (Punzo et al., 2021); it is even not an "enemy" of electric cars or autonomous vehicles (Duarte & Ratti, 2018; Stewart et al., 2018). The bicycle is certainly a functional vehicle in an activity-based transportation system, while it comprises also various important fringe benefits, in particular green mobility, health benefits and relaxed active movement (see e.g., Cooper & Danzinger, 2016; Giles-Corti et al., 2010; Sieff & Weissman, 2016; Vale et al., 2016; Yang et al., 2019). Such benefits are the often unforeseen or unintended positive consequences of activity-based mobility; for instance, a shopping trip by bike may have environmental- and health-benign effects (cf. Hamidi, 2021).

The choice of slow-motion travel modes, such as a bicycle, opens up a range of flexible subsequent choice options, such as route choice, length of the trip, trip duration, use of dedicated bicycle infrastructure, or contribution to local environment quality conditions. In the abundant literature on this topic, often a distinction is made between objectively measurable factors (e.g., route safety conditions, annoyance by car traffic) and subjective perception factors (e.g., green attitudes, open space feelings).

2.3 The broader wellbeing aspects of cycling

In a recent study by Blitz (2021), an evidence-based impact study about the perceived local environment on cycling behavior and cycling attitudes has been undertaken, including socio-demographic factors and travel mode availability. It turns out that positive attitudes towards cycling (including safety and pleasure), presence of cycling infrastructure, common practice in a city to use a bicycle, and high car pressure are determining factors in shaping a positive attitude towards bicycle use.

Meanwhile, various studies have clearly demonstrated that transport behavior is not only determined by functional activity-based motives, but should also be considered from a broader health, well-being and sustainability perspective (Bernardi et al., 2018; Delbosc, 2012). This argument holds certainly for nonmotorized trips. A rather comprehensive overview of the impact of cycling on daily life practices and health can be found in Götschi et al. (2015), who review both generalizable evidence for health effects and specific impact models that quantify lifestyle outcomes in concrete settings.

Clearly, in the recent past human mobility has changed as a response to COVID-19, and so has cycling. The mobility motives have significantly been influenced by perceived COVID-19 concerns, which have impacted on a broad range of trip behaviors. We may plausibly assume that the cyclists' trip choice was subjected to healthy and ecological lifestyle drivers, but the pressing empirical question is: how and to what extent? The objective of our study is thus to identify the drivers that may impact the change in cycling behavior.

2.4 Information needs

A deeper analysis of direct and indirect travel choice motives calls for adequate and up-to-date databases and information systems, including statistical data, survey data, social media data, and electronic data from cell phones, GPS, sensors or camera's (see Dial, 2000; Salim, 2012; Steenbruggen et al., 2017; Ton et al., 2018). Clearly, the study of viable pathways to healthy lifestyles, with a view to bicycle use in corona times—characterized by serious health concerns— calls for detailed real-time information on individual trip behavior (e.g., travel mode, route choice, destination choice, trip length and duration, combined trip-motive choice) (see Azevedo, et al. 1993; Bühler & Pucher, 2021a; Dial, 2000; Doubleday et al. 2021; Ghanayim & Bekhor, 2018) so as to test the proposition that in corona times health and environment priorities may prompt a change in the cyclists' action space and impact on modal selection, route choice and trip length/duration of cyclists.

In our empirical analysis we will analyze the pre-corona and during-corona travel patterns of cyclists in the Dutch province of Utrecht using individualized real-time probe data. The Netherlands has a long tradition as a bicycle country, and therefore it is plausible that the COVID-19 calamity—including also various types of lockdown measures—has led to a flexible adjustment of travel and destination choice of the people. The general information from the daily corona dashboard—which in its comprehensive form also includes daily mobility data from Google Mobility Reports (see for details Nijkamp & Kourtit 2022)—shows clearly a considerable shift in mobility in favor of nearby green environments (ranging from urban parks to green areas in the countryside). It also seems plausible that—with the generic discouragement of car use—bicycles become a popular travel mode for visiting green areas, in addition to a general rise in modal shift towards bicycles. This study aims to model specifically the daily spatial choice behavior of cyclists in corona times, not only for commuting purposes but also for leisure purposes. This research calls for both exploratory statistical analyses and cyclists' choice modeling experiments.

Our study employs detailed spatial data on mode and route choice of cyclists, including postal code neighborhood data, local socio-demographic data, detailed data on spatial trip patterns per bicycle (including origin and destination), and local presence of amenities (e.g., public transport hubs, neighborhood characteristics, green and blue amenities, etc.). Thus, in essence our database is an operational exemplification of the principles of individual space-time geography (Ellegärd, 2019; Hägerstrand, 1965; Ton et al., 2018). Such data allow also to examine whether all categories of cyclists (e.g., commuters, shoppers, leisure cyclists) are affected in the same way during corona times, in different phases of the pandemic, and with varying government intervention measures. It seems plausible to hypothesize that "lifestyle" cyclists will be inclined to choose traffic-calm and green routes in their trip choice, especially if they are leisure travelers.

The above proposition is supported by some exploratory research in Sweden and the USA (respectively, in Gothenburg/Malmö and Portland) (see Clairvue Health, 2019). The general finding is even that biking—and, in general, active commuting—is not only good for physical health, but also for well-being, happiness and sustainability. Our study will analyze in greater detail the spatial health and environmental aspects and determinants of cyclists' behavior before and during the pandemic. The databases and methodology employed will be highlighted in Section 3.

3 Databases and research design

Our empirical study aims to investigate the factors, both related to COVID-19 and the environment, that contribute to changes in the cyclists' choice behavior during the pre-shock and initial stages of the corona crisis. The purposes are served by a big data collection, as well as the design and testing of a relevant econometric model. These steps will now systematically be described.

3.1 Snifferbike dataset

The primary dataset used in the analysis is derived from the so-called "snifferbike" system in the Netherlands. The snifferbikes are regular bicycles that are equipped with a mobile digital GPS sensor as a tool for measuring online air quality indicators in a local environment. The snifferbike dataset includes detailed spatial data (geocoded) on mode and route choice of cyclists and detailed information on spatial trip patterns per bicycle. From the information in the dataset, we are able to create fine gridded cyclists' mobility maps including points of departure and destinations and also route choice. In addition, postal code neighborhood information allows enriching the dataset with local socio-demographic data, and also with data about the amenities close to origins, destinations and also cycling routes. Finally, since the "snifferbike" project was designed for measuring air quality indicators, the dataset informs about the air quality (with different components) and weather conditions on the day of trip-making. Thus, the entire dataset includes typical "big data." We use cyclists as the unit of analysis for the period from May 2019 to October 2020, which contain both the pre-COVID period and the period during COVID-19, in the province of Utrecht in the Netherlands. In this way we can examine the significance of COVID-19 for slow motion behavior of road users.

The "snifferbike" data system is an example of Volunteered Geographical Information (VGI), which embodies and presents geo-spatial content provided by non-professional volunteers, using online digital spatial information equipment (see also Coleman, et al. 2009; Goodchild 2012). These real-time probe data allow us to obtain a very detailed online mapping (every ten seconds) of the geographic mobility behavior of cyclists. Clearly, there is an obvious limitation inherent in such micro data; given privacy regulations, it is not allowed to add personal data (e.g., age, gender, income) of the cyclists themselves to our database. However, since we know the place of origin of cyclists and hence the average socio-economic profile of the neighborhood concerned, a rough proxy of socio-economic features of cyclists might be obtained.

3.2 OpenStreetMap dataset

The route choice of cyclists in the "snifferbike" project is likely to be affected by changing preferences regarding natural and urban surroundings (see, for instance, Vedel et al., 2017). To construct a measure of natural and urban qualities around cycling routes, we extract land use data from the OpenStreetMap (OSM) database. The fraction of land use qualities is next calculated by first identifying a given amenity and then counting the share of its presence with respect to all qualities found around each cycling route from the "snifferbike" dataset. These include green surroundings (trees, grass, forest, camp site etc.), blue amenities (sea, lake, river, etc.), residential buildings and houses, industrial areas and urban services (schools, shops etc.). We also include the distance from cyclists' neighborhood of departure to the central train station of Utrecht, the capital city of the province of Utrecht. The treatment of the OSM data is of course conducted in a GIS environment.

3.3 Mobility datasets

To enhance our statistical analysis and employ a "big data" approach in our research, we incorporate Google COVID-19 Mobility Reports1 and Apple Mobility Trends Reports2. Google's data utilizes the median mobility from January 3 to February 6, 2020, as the reference mobility value, monitoring changes in visits to different locations. Apple's data records the number of requests made to Apple Maps by car, public transport, or walking, with January 10, 2020, serving as the baseline. The Google and Apple mobility datasets, introduced during the COVID-19 pandemic, have been instrumental in numerous research studies. Both datasets articulate percentage variations relative to a designated reference date or period. This mobility tracking capability has facilitated comprehensive investigations into the interplay between COVID-19 transmission and spatial mobility, serving various research purposes (see e.g. Cot et al., 2021; Hu et al., 2021a, b). Both datasets are aligned, encompassing data from their respective initial available dates up to October 2020. This synchronization enables comparability with the temporal extent of the snifferbike dataset. We utilize mobility datasets to chart fluctuating patterns of mobility towards diverse destinations and across various modes of transport. This serves as a cornerstone for motivating our research on cyclists' behavior. With the database now presented, we will outline our study's statistical-econometric modeling approach in Section 4.

4 Research methodology

4.1 Exploratory analysis of cycling

In this section, we conduct our exploratory analysis for cyclists' mobility, general human spatial mobility, and other modes of travel from the pre-COVID to COVID period in the province of Utrecht. As mentioned, we start by examining the daily trend of cyclists' mobility starting from May 2019 to October 2020 by the snifferbike database, and overall human mobility, which registers daily changes from March 8, 2020, to October 4, 2020, by the Google and Apple mobility databases. The snifferbike dataset is employed in the subsequent regression analysis, whereas the Google and Apple datasets are exclusively utilized for exploratory analysis in the present section. Information regarding the means of transportation is exclusively sourced from the snifferbike database (for bicycles) and Apple mobility statistics (for cars, public transport, and walking). However, the specific purpose of mobility is only accessible in the Google dataset. To address this gap, in the regression analysis, cyclists routes are quantified as a proxy for potential travel purpose specifically for the snifferbike data. We will start with an exploratory analysis.

Figure 1 illustrates the total daily average distance travelled by cyclists, whereas Figure 2 shows average duration of travel for the same period. The graphs show the decrease in the cyclists' mobility in March 2020, and the subsequent recovery, especially

[1] https://www.google.com/covid19/mobility/
[2] https://covid19.apple.com/mobility

in May 2020. The two graphs also indicate that, when entire pre-COVID and COVID periods are compared, the mean distance travelled increased in the COVID period, whereas the duration of travel has decreased on average compared to the pre-COVID period. This means that even though we observe a higher cyclist activity, the time spent on bicycles has decreased in the COVID period. Cyclists may have started to make lesser stops and—owing to low traffic—may have had a higher average speed. It is important to note here that seasonal fluctuations and temperature may have affected cyclists' mobility from March onwards. Therefore, in our empirical model, we will control for temperature and humidity as a quantitative proxy for weather conditions.

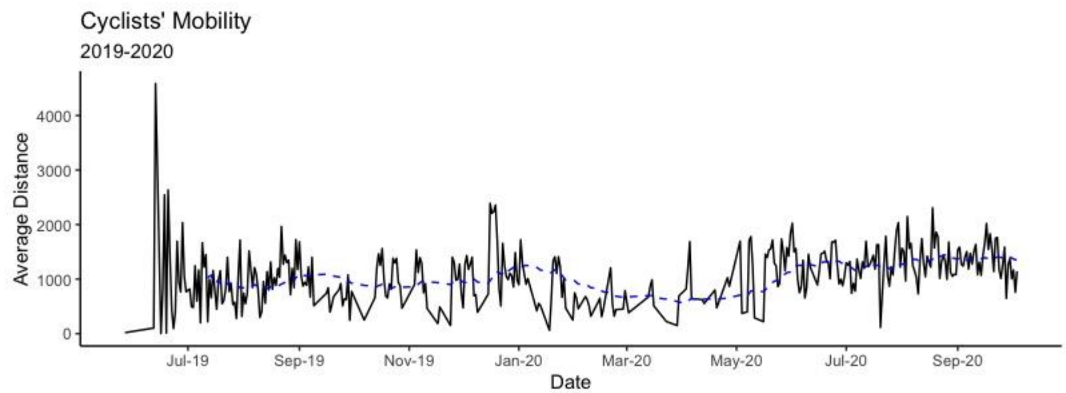

Figure 1. Cyclists' mobility as measured by daily average distance travelled in meters (period: May 2019–October 2020); dashed lines show moving averages of 30 days

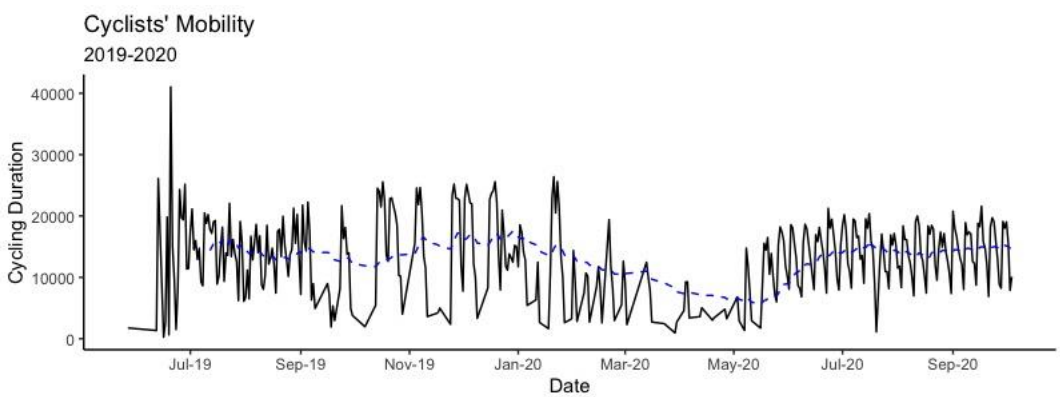

Figure 2. Cyclists' mobility as measured by average duration of daily travel (period: May 2019–October 2020); dashed lines show moving averages of 20 days

4.2 General mobility trends in corona times

Next, the spatial mobility trends are shown in Figure 3 and 4; they are extracted from Google analytics and Apple mobility data. These mobility figures indicate similar trends for cyclist's mobility. Figure 3 shows that, while mobility to workplaces has decreased substantially during the pandemic, the mobility to parks/green areas and around residential areas have increased in the COVID period. This means that, while commuting has declined on the contrary, more recreational mobility has taken place in this period; the finding was also confirmed in another study on mobility changes in the Netherlands during the corona times (Nijkamp & Kourtit, 2022). Clearly, the fact that several services have moved online, and that teleworking has become almost the default arrangement in many sectors, might have harmful consequences for human health, considering the decrease in physical movement (Tavares, 2017). However, as Figure 3 shows, the potential negative effects of teleworking may have been mitigated by visits to parks and physical activity around residential areas. This is an important observation, as it means that the overall mobility restrictions and teleworking opportunities might have boosted active travel for recreational purposes, which would have well-known positive effects on human health (Pucher et al., 2010).

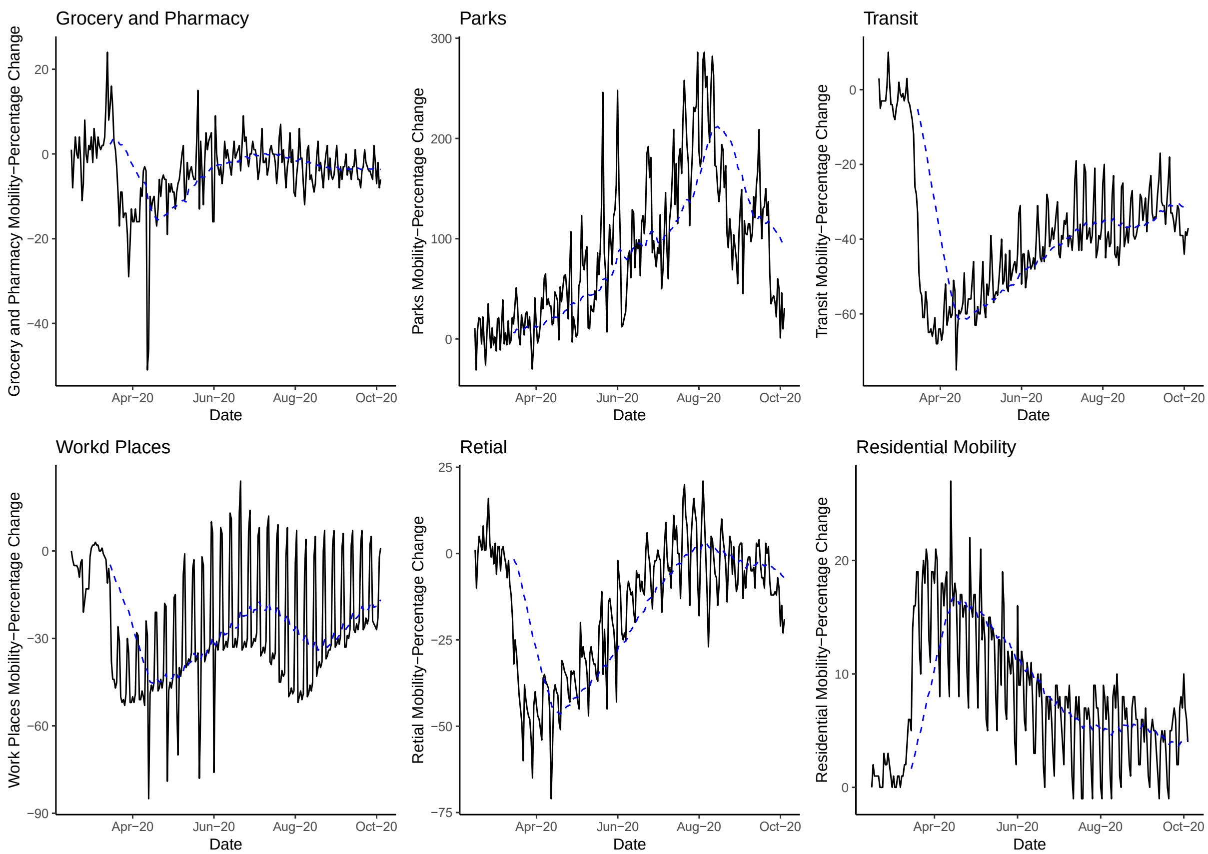

Figure 3. Percentage changes in spatial mobility to categorized places in Utrecht; baseline is median value from January 3 to February 6, 2020; dashed lines show moving averages of 20 days

Figure 4 is next derived from Apple's Mobility Trend Report, which allows analyzing mobility trajectories by transport choice in Utrecht. We observe from this graph that, beside an increased mobility to parks or green areas, the most preferred transport mode has been walking during the pandemic. From Figure 3 and the "new" mobility trends reported in Figure 4, it becomes clear that examining cyclists' mobility behavior is of great importance not only from a general mobility perspective, but also from a health perspective. This health-driven motivation consists of two components: the overall tendency to replace cars or public transportation by bicycles, and the preference of cyclists for environmentally healthier routes. Our research will specifically focus on and model the latter proposition. More specifically, Figures 3 and 4 serve as informative reference tools illustrating the overall shift in mobility patterns during the pandemic.

Figure 3 depicts changes towards various destinations, while Figure 4 illustrates shifts in transportation modes. However, for a comprehensive analysis of route selection and cycling mobility patterns, we rely on individual-level data gathered through the user-based snifferbike dataset.

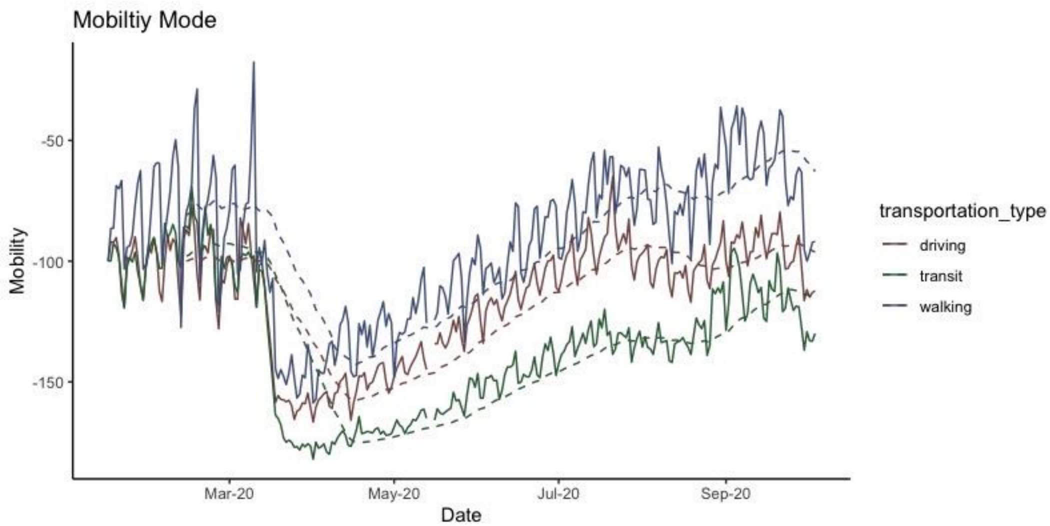

Figure 4. Percentage change in spatial mobility by transportation type in Utrecht; baseline is on January 13, 2020; dashed lines show moving averages of 20 days

4.3 Modeling cyclists' modal choice

We will now proceed with a causality analysis of spatial choices of cyclists in the Utrecht area. In this section, we introduce the empirical model employed in our econometric analysis, as well as the utilization of the Shapley method to assess the relative impact of each factor on cyclists' overall mobility. The analyses are conducted in a comparative manner, referencing COVID-19 related crises.

To assess the determinants of cyclists' mobility behavior in the pre-COVID and in the COVID periods, we specify and estimate the following model based on the above mentioned conceptual and empirical backgrounds:

$$M_{it} = \beta_i + \gamma_t + \alpha W_{it} + \gamma R_{it} + \delta S_{it} + \mu D_{it} + \varepsilon_{it} \quad (1)$$

where M_{it} is the logarithm of total distance travelled (or duration of travel) by cyclist i on day t, β_i and γ_t are respectively, cyclist and day of the week fixed effects. The study leverages cyclists' IDs to track individual mobility, enabling the incorporation of cyclists' fixed effects in our analysis. This utilization of cyclists' IDs facilitates the application of a panel fixed effects model, providing a robust framework for examining the intricate dynamics of cyclists' route choices over time. In our analysis of the day of the week, Monday serves as the reference category, forming the baseline against which the mobility patterns on the other six days of the week are compared. W_{it} are covariates for weather conditions (temperature, humidity) and air-quality, R_{it} indicate the composition of the road network in terms of land use such as fraction of green surroundings along the road network cyclists' travel, S_{it} are socioeconomic variables for the geographical departure neighborhoods defined per detailed postal code. Clearly, cyclists depart from different spatial points during the study period, which imposes a considerable variability over time. Finally, D_{it} is the distance to Utrecht central railway station, and ε_{it} is the error term. Eq. (1) is estimated by OLS for the pre-COVID and COVID periods separately with robust standard errors. The pre-COVID period includes daily mobility from May 27, 2019, to March 7, 2020. Next, we define the period from March 8, 2020, to October 4, 2020, as the COVID period, during which we may expect shocks in mobility behavior of cyclists. It should be noted here that individual data of cyclists on their health perceptions in making spatial choices cannot be included in our modeling experiments, due to privacy rules. But indirectly, a spatial focus on green areas may be interpreted as a rise in health and environmental awareness. The empirical results are reported and interpreted in Section 5.

The changes in the cyclists' behavior and the corresponding change in the determinants of the cyclists' mobility are next further analyzed by employing the Shapley decomposition method (Shorrocks, 1999). The Shapley value approach permits obtaining an exact additive decomposition of the mobility into its constituents and contributing factors. The method can be applied to any functional form of the regression model, where the importance of each explanatory factor or groups of explanatory factors are explicitly estimated by decomposing the overall R2. In terms of mobility, the contribution of each variable to overall mobility can be examined as the difference in the model fit with and without a given relevant moderator factor. If we consider Equation 1, the Shapley decomposition method is conducted by estimating the full model and successively removing a regressor or a group of regressors from the empirical model. The contribution of the regressor is next assessed as the average of its marginal effects. It is plausible that the order in which the regressors are eliminated affects the overall contribution estimated. Therefore, the method involves averaging of the marginal effects over all possible permutations of the variables included in the full model. Both the OLS regression and the Shapley decomposition will be applied in our case.

In the final stage of our analysis, we will perform spatial autocorrelation analyses, both global and local, on Equation 1, without incorporating spatial covariates. This approach will enable us to examine spatial variations in the determinants of cyclist mobility during the pre-COVID and COVID periods, both at the local and global scales.

5 Empirical results

This section is devoted to a general discussion of the empirical model outcomes on the differences in cyclists' mobility behavior in the pre-COVID and the COVID periods. We start by introducing the regression outputs of the empirical model in Eq. (1) for the two successive periods in our study. The Shapley values will be presented thereafter for the models with fixed effects and for different groupings of the covariates determining spatial mobility of cyclists.

5.1 Regression results

The regression outputs from Equation 1 for pre-COVID and COVID periods are shown in Table 1. These findings will now concisely be interpreted. The results indicate that weather conditions and air quality statistically significantly affect mobility in both two periods, be it with a few interesting differences. While humidity is associated with shorter distances in both periods, air quality—as measured by pollutant levels—and air pressure have exerted negative effects on geographical mobility in the pre-COVID period; they have shown an opposite association with mobility during the COVID times.

This suggests that during the pandemic, while making longer trips (Figure 1), cyclists used new routes despite the possibly poor air quality. On the other hand, while temperature was not a significant predictor of cyclists' mobility in the first period, in the COVID period longer distances were observed during warmer days (see also Shao et al., 2021). The variation in the impact of temperature could be associated with seasonal differences between the pre-COVID and COVID periods.

Table 1 shows that the urban landscape along the road network also influences the bicycle mobility. In both periods, cyclists take longer trips in green and blue areas, and—as the variable "production" indicates—around workplaces. This means that cycling distance increases either around recreational activities or when commuting to work, and it decreases around residential areas. The latter is contrary to what Figure 3 shows for general human mobility around residential areas. Therefore, in both periods the Google's Community Mobility Report is likely picking up also movements by different transport modes than bicycles (potentially, the walking mode). Additionally, as Figure 3 shows, while in the first months of the pandemic, the mobility to residential areas has substantially increased, the trend has started to converge to its normal levels in the subsequent months. The variable "productive function" is the second variable that suggests a contrasting direction compared to what Figure 3 depicts. We find that in both periods, cyclists travelled longer distances in places with a high concentration of productive activities. Nevertheless, this opposite finding might suggest that even though less commuting was observed during the pandemic as suggested by Google's Community Mobility Report, according to our findings, more people used bicycles as a transit choice to travel to work. In order for this interpretation to hold, we should observe longer cycling distances in the COVID period than before. This is indeed the case, as Figure 1 above illustrates.

The distance to the Utrecht central railway station indicates that in the pre-COVID period centrally located neighborhoods show longer distances (residents of suburban locations might be using different transportation means). The same behavior is observed in the COVID period but at lesser degrees. This indicates that bicycles have become a stronger transit choice for those who need to travel longer distances, which might partially explain the increased total distances on bikes in the COVID period and the slightly odd finding regarding air quality.

While age composition of neighborhoods (60+ age) is not significant in both equations, the variable PPP (per capita purchasing power) shows a modest effect on mobility in both periods. Furthermore, while the cyclists' mobility does not significantly correlate with high purchasing power per capita in the pre-COVID period, it indicates statistically significant and negative sign in the COVID period. This might be related to access to private cars in wealthy neighborhoods.

Table 1. Regression outputs of cyclists' mobility behavior in pre-COVID and COVID periods

	(1)	(2)
VARIABLES	Fixed Effects Pre-COVID	Fixed Effects COVID
Humidity	-0.005***	-0.010***
	(0.002)	(0.002)
Particulate Matter 1.0	-0.002***	0.000
	(0.001)	(0.000)
Air Pressure	-0.001**	0.001
	(0.000)	(0.001)
Temperature	-0.000	0.029***
	(0.000)	(0.004)
Green Fraction	1.827***	0.688***
	(0.218)	(0.213)
Residential Fraction	-1.540***	-3.217***
	(0.180)	(0.180)
Production Fraction	4.781***	2.104***
	(0.469)	(0.348)
Urban Services Fraction	1.035***	0.067
	(0.301)	(0.303)
Blue Fraction	3.322***	1.508***
	(0.446)	(0.380)
Distance to Train Station	-0.446***	-0.391***
	(0.047)	(0.046)
Purchasing Power Per Capita	-0.227	-0.463**
	(0.215)	(0.221)
Share of Age 60+	-0.167	0.324
	(0.449)	(0.395)
Constant	18.075***	13.646***
	(3.600)	(2.627)
Observations	14,766	17,399
R-squared	0.259	0.330
Number of id	565	505
Individual FE	YES	YES
DoW FE	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Legend: Dependent variable is the total daily distance travelled by cyclists

5.2 Shapley decomposition results

Next, will we discuss the results from our Shapley decomposition analysis described above. Table 2 reports the Shapley decomposition of the cyclists' mobility model in pre-COVID and COVID periods. The Shapley values suggest that the cyclists' fixed effects and the land use around the cyclists' routes explain most of the variation in the cyclists' mobility in both periods. A considerable part of mobility is attributed to mobility around areas with a high green, blue and productive function. The Shapley values point to a similar contribution of the covariates in the COVID period. Most of the variation is attributed to cyclists' and time fixed effects, and the fraction of urban surroundings along the road network. Meanwhile, the marginal contribution of the variables regarding weather and air quality appear to be higher, while the marginal contribution of the time fixed effects is lower in the COVID period. Our overall results suggest that during the COVID period cyclists undertake more recreational visits, which often take place during fine weather (Brandenburgx, et al. 2007) and around green amenities. The Shapley decomposition values indicate also that the day of the week has relatively less effect on cyclists' mobility during the latter period. Again, this might be the result of less commuting and more leisure time bicycle usage during the pandemic.

Table 2. Shapley decomposition of cyclists' mobility

	Percentage Variation Explained	
	pre-COVID	COVID
Weather-air quality	0.62	4.27
Land Use	26.28	31.86
Distance to Central Station	0.20	0.71
Socio-economic and demographic	0.28	0.92
ID Fixed	64.89	55.44
Time Fixed	7.75	2.91
Overall R2	0.26	0.33

5.3 Spatial autocorrelation results

The differences between pre-COVID and COVID time cycling behavior becomes even more pronounced in terms of spatial dependency effects, if we study the regression results (and residuals) using spatial clustering techniques. Therefore, we run Eq. (1) without spatial variables and conduct a spatial autocorrelation analysis. We exclude spatial covariates, to reveal spatial autocorrelation in the modeling framework where geography is not considered (as this offers us the opportunity to test to what extent spatial autocorrelation has changed from before and during the pandemic). In Table 3, and in Figure 5, the results from global Moran's I analyses (Table 3) and local Moran's I (Figure 5) are shown for regression predictions and residuals before and during the pandemic (Anselin, 1995; Moran, 1950). We find that global Moran's I describes clustering and dispersion from the expected (estimated) distribution, where deviations are expressed with a magnitude of value Index, while the strength is underlined by the z-score and p-value. The results in Table 3 indicate that there is a substantial geographical clustering of cycling distances in the urban landscape during the pandemic (i.e., people are cycling differently in different locations), while the clustering of residuals is also indicating that there are unknown, spatially dependent factors affecting the cycling behavior in the study area. If however, we look at the clustering in the pre-COVID period, we see that the regression model is performing rather well by also explaining the spatial variation. This suggests that during the pandemic, cycling is an activity that is not primarily guided by work/school commuting, but more by personal choice, and most likely more for recreational, health and environmental purposes.

Table 3. Global Moran's I indices for pre-COVID and COVID periods

	Index	**Z-Score**	**P-Value**
Aspatial Model-Residual (COVID)	0.13	74.99	0.00
Aspatial Model-Prediction (COVID)	0.22	127.3	0.00
Aspatial Model-Residual (Pre)	-1E-04	-0.02185	0.983
Aspatil Model-Predictions (Pre)	-2E-04	-0.06598	0.947

The spatial autocorrelation results from Table 3 are derived using a global Moran's model. If we next re-run the clustering analyses on a local level using a local Moran's I approach (LISA; see Anselin 1995), we can plot how predictions and residuals are distributed spatially before and during the pandemic. The patterns in Figure 5 clearly show that there are considerable differences in cycling behavior between the core and suburban areas before the pandemic. The pattern is typical for urban areas, where a substantial share of mobility is devoted to commuting. During the pandemic, a more fragmented pattern appears to emerge, where the pre-COVID pattern is still detectable, but where decisions on whether to cycle, and for how long, are related to other factors than geography and commuting, most likely in this case leisure and health motives, leading to more variability in route choices and distances.

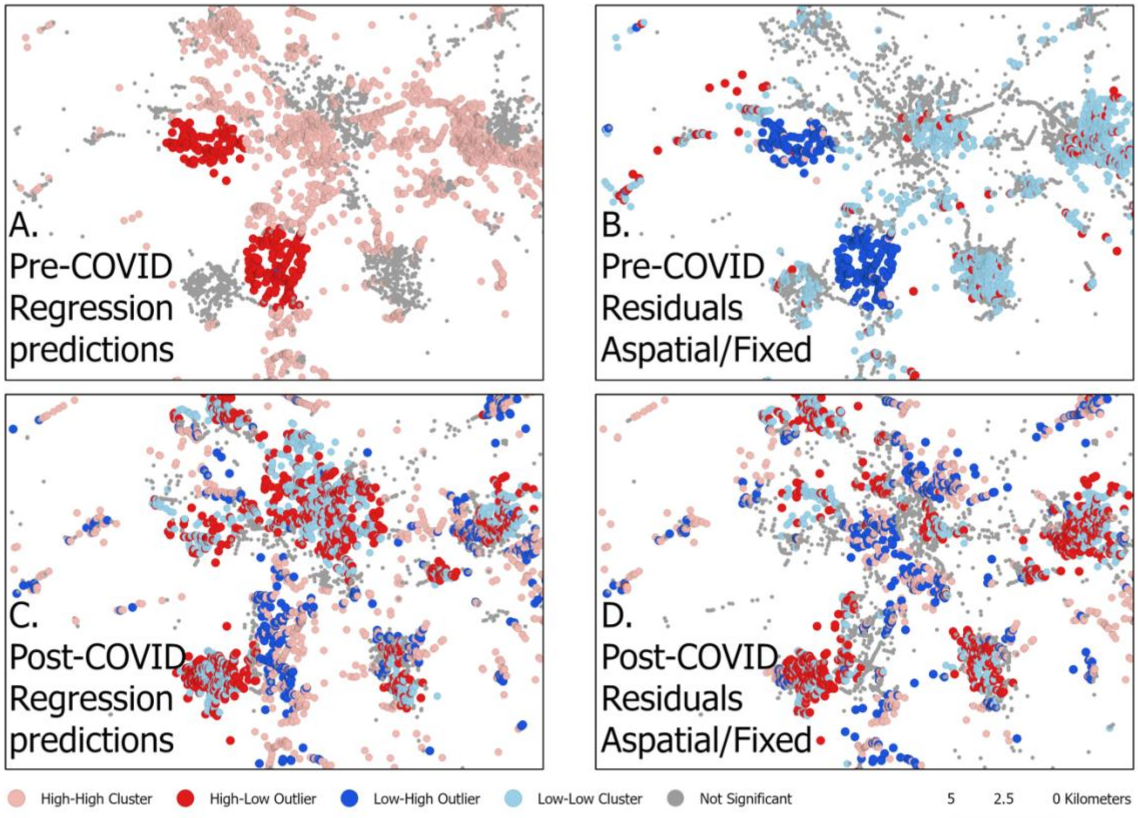

Figure 5. LISA (Local Indicators of Spatial Autocorrelation, Local Moran's I) values for regression predictions and residuals for pre-COVID and COVID periods

Legend: Lighter blue and pink colors indicate clusters of lower (blue) and higher (pink) regression estimates. Dark colored dots indicate spots with outlier values (compared to neighbors).

6 Conclusion

Our research aligns with a longstanding tradition in empirical transportation research of studying the advantages of slow modes of transport, driven by environmental, lifestyle, and health considerations. Additionally, it introduces novel digital research perspectives on space-time geography. The COVID-19 era has brought about new catalysts for changes in cyclists' trip behavior. Our snifferbike database presents valuable prospects for analyzing real-time probe data on route choices, frequency of trips, and destination preferences among bike riders. Notably, conventional factors influencing geographical mobility via slow modes appear to assume a distinct role during the pandemic. COVID-19 has shed light on the specific trip benefits associated with cycling. In particular, our research—both the modeling outcomes and the GIS findings—points at the following findings of cycle mobility in corona times:

- Cyclists made longer trips during COVID-19 periods, while also exploring new routes in green areas.
- Residents in remote neighborhoods from a central railway station appeared to choose more frequently bikes as a vehicle in the corona period.

- Temperature appeared to be a significant predictor of the cyclists' mobility, in particular in the COVID period, while air quality appears to play a less important role in route change for commuting.
- Bicycles have become a stronger transit vehicle for those who need to travel over relatively longer distances.
- The Shapley decomposition results indicate that during the COVID period more recreational biking took place, in particular around green amenities. In contrast to the pre-COVID period, we observe less commuting travel and more leisure time use on bicycles.
- Finally, spatial autocorrelation results indicate that there is a substantial geographical clustering of cycling distances in the urban landscape during the pandemic.

Our findings clearly show a substantial impact of COVID-19 on the geographical choice pattern of cyclists. In line with general Google Mobility data, it turns out that green areas appeared to be attractive destinations for cyclists during the pandemic. In conclusion, perceived health and lifestyle motives are a significant contributor to active slow motion choice behavior in the corona period. Clearly, our research is subject to limitations arising from the specific snifferbike data utilized in our analysis. Specifically, we were unable to incorporate substitution effects (such as those related to public transport) and individual characteristics (such as gender and age) in our empirical investigation. Nonetheless, our quantitative study on changes in cyclists' trips during the COVID-19 era has uncovered a plethora of fresh insights regarding the moderating influence of the pandemic.

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