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## Potential long-term effects of Covid-19 on telecommuting and environment: An Italian case-study

Riccardo Ceccato<sup>a,\*</sup>, Andrea Baldassa<sup>a</sup>, Riccardo Rossi<sup>a</sup>, Massimiliano Gastaldi<sup>a,b</sup>

<sup>a</sup> Department of Civil, Architectural and Environmental Engineering, University of Padova, Via Marzolo, 9, 35131 Padova, Italy

<sup>b</sup> Department of General Psychology, University of Padova, Via Venezia, 8, 35131 Padova, Italy

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### ABSTRACT

To contain the sudden spread of SARS-CoV-2, many governments encouraged people to work from home, generating an unprecedented diffusion of this activity. Furthermore, Covid-19 has induced drastic changes in everyday life and travel habits, which might persist in the future. This paper aims to understand and estimate the potential long-term impacts of telework on the environment due to the pandemic, by analyzing factors affecting the frequency of telecommuting, the mode choice for traveling to work, and pollutant emissions generated by these trips. Data from a mobility survey administered in Padova (Italy) was used. Results indicate that Covid-19 could cause a rebound effect reversing the positive impacts of working from home, since, even if the number of trips could be reduced, many shifts towards non-sustainable travel modes could occur. The promotion of telework should be combined with measures fostering sustainable travel habits to pave the way towards a future green mobility.

### 1. Introduction

The sudden and widespread diffusion of SARS-CoV-2 has caused drastic changes in the daily lives of citizens around the world, including mobility (Balbontin et al., 2021; Shortall et al., 2021). Many authorities imposed countermeasures to limit the spread of the virus. Although country-specific (Shibayama et al., 2021), these nonpharmaceutical interventions aimed to reduce interpersonal interactions, thus avoiding the diffusion of the virus (Politis et al., 2021b). In particular, they included school closures, many commercial, economic, educational, and social activities (e.g., restaurants, theaters), the limitation of public transportation capacity, as well as the introduction of work from home (Bin et al., 2021; Molloy et al., 2021).

Many researchers reported the effects on the transportation sector during the first months of the pandemic (Table 1), which may vary according with country-specific factors (Barbieri et al., 2021; Pawar et al., 2021) and socio-economic characteristics of citizens (Politis et al., 2021a). In general, countermeasures and the individual perception of contagious risk induced a shift from public transportation towards private car and active modes (Shibayama et al., 2021). In Italy, the High Institute for Transportation Education and Research (ISFORT) reported that, in 2019, about 65 % of trips were carried out by private vehicles (car and motorbike), 24 % by active modes and 11 % by public transportation; in 2020, the share of private vehicles decreased slightly to 62 %, the one of active mobility increased to 33 %, and the one of public transportation halved to 5 %. In the last months of 2021, the modal share of private vehicles returned to the level of 2019 (65 %), whereas the percentage of people adopting active modes was greater than in 2019 (29 %)

\* Corresponding author.

E-mail addresses: [riccardo.ceccato@dicea.unipd.it](mailto:riccardo.ceccato@dicea.unipd.it) (R. Ceccato), [andrea.baldassa.1@phd.unipd.it](mailto:andrea.baldassa.1@phd.unipd.it) (A. Baldassa), [riccardo.rossi@unipd.it](mailto:riccardo.rossi@unipd.it) (R. Rossi), [massimiliano.gastaldi@unipd.it](mailto:massimiliano.gastaldi@unipd.it) (M. Gastaldi).

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and public transportation did not reach the modal share of 2019 (6 % in 2021) (ISFORT, 2021).

Due to the unprecedented spatial and temporal extension of the current pandemic (Currie et al., 2021), some of the changes in travel behavior registered during the first months of the pandemic are likely to be maintained in the future (Das et al., 2021; Hensher et al., 2021b; Wang et al., 2021b). For example, results from a mobility survey administered in the first semester of 2021 in Italy showed that 21 % of the interviewees stated that they would increase the use of car in the next months and about 10 % declared that they would travel less on public transportation (ISFORT, 2021). However, the long-term consequences of Covid-19 on transportation and related externalities on the environment have received little attention (Zhang and Zhang, 2021).

One of the activities that have been prompted by authorities, where possible, is working from home, since it allowed the productivity of some jobs by preventing contact among people (Barbour et al., 2021; Mouratidis and Papagiannakis, 2021; OECD, 2020). This triggered an unprecedented increase in online working activities in many countries around the world (Table 1). In Italy, the number of people adopting telework increased by 1000 % in 2020, compared to 2019, and slightly decreased (by 7 %) in 2021, compared to 2020 (ISFORT, 2021). The forced wider adoption of online activities and the consequent greater boost of digital transformation in many countries are likely to induce long-term changes in travels, thus shaping a new commuting behavior in a post-Covid-19 period (Hensher et al., 2021b; Mouratidis and Papagiannakis, 2021; Zhang and Zhang, 2021). In particular, several authors analyzed future intentions towards working from home (Table 1). In Italy, the results of a national mobility survey at the end of 2020 pointed out that about 86 % of people working from home were going to continue in 2021 (ISFORT, 2021).

Work from home has been the subject of many previous research studies, which presented it as a travel demand strategy to reduce congestion and related emissions (e Silva and Melo, 2018), even if some rebound effects mitigating these positive impacts were highlighted (Andreev et al., 2010). Therefore, telecommuting is not a recent activity; however, what is new is its sudden and wide-spread adoption due to Covid-19 diffusion, as well as its general acceptance among employees, which could make it a permanent phenomenon (Hensher et al., 2022), thus contributing to reducing commuting travels and therefore pollutant emissions (Zhang and Zhang, 2021). Furthermore, the pandemic changed factors that affected the choice to work from home, making the previous results no longer valid (Nguyen, 2021). In addition, a new rebound effect could occur: a general shift from public transportation to less sustainable private means, potentially compensating the positive impacts of telework on the environment (Hensher et al., 2021a). For these reasons, analyzing the long-term effects of Covid-19 on work from home and, in particular, the potential new trade-off between telecommuting and environmental benefits can help in deeply understanding the consequences of the pandemic on mobility (Rossi et al., 2020). In this way, it will be possible to evaluate whether telecommuting after Covid-19 can be considered not only as a travel demand strategy, but also as an environmental management policy (Crowley et al., 2021; Kim et al., 2015). Although the paramount utility of this analysis, little attention has been paid to the long-term environmental impacts of work from home due to Covid-19 (Shortall et al., 2021; Wang et al., 2021b). The aim of this paper is to contribute to this complex topic by providing a comprehensive view of the problem. In particular, two models were developed to investigate the factors affecting the decision to work from home and the choice of the travel mode for commuting in the future; in addition, related pollutant emissions from vehicles were quantified considering a potential rebound effect of Covid-19 on travelling to work and a diverse range of measures to contain the spread of the virus, which are likely to be applied in the new normal phase of the pandemic. Furthermore, this represents the first analysis of the topic in Italy, where telecommuting was rarely adopted before the pandemic and, therefore, it drastically impacted and still impacts mobility.

The rest of the paper is organized as follows. In Section 2 a brief review of the literature on telecommuting is presented. The data collection activity and the adopted methodology are described in Section 3. The results of the research are reported and discussed in Section 4, as well as potential policy implications. Lastly, main findings are summarized in Section 5.

## 2. Literature review

Working from home has been one of the topics of interest for many researchers since the last century (Hensher et al., 2022; Olde Kalter et al., 2021). Several definitions have been adopted (Choo et al., 2005; Nguyen, 2021; O'Brien and Yazdani Aliabadi, 2020) to indicate working at home rather than in the regular workplace using Information and Communication Technology that provides productivity and communication. The first term 'telecommuting' was coined in the 1970 s to underline the substitution of travel from

**Table 1**  
Summary of selected studies analyzing the impacts of Covid-19 on travels and telework.

References	Topic	Period of analysis
(Abdullah et al., 2020; Awad-Núñez et al., 2021; Barbieri et al., 2021; Bin et al., 2021; de Haas et al., 2020; Eisenmann et al., 2021; Hiselius and Arnfalk, 2021; Kim, 2021; Li et al., 2021; Liu and Stern, 2021; Politis et al., 2021b; Shakibaei et al., 2021; Shibayama et al., 2021; J. Zhang et al., 2021; N. Zhang et al., 2021; Zhang and Fricker, 2021)	Impacts of Covid-19 on travels and mode choice	Short term
(Aaditya and Rahul, 2021; Carrese et al., 2021; Currie et al., 2021; Das et al., 2021; Li et al., 2021; Najmi et al., 2021; Scorrano and Danielis, 2021; Thombre and Agarwal, 2021; Wang et al., 2021b, 2021a; Zafri et al., 2021)	Impacts of Covid-19 on travels and mode choice	Long term
(Beck and Hensher, 2020; Hensher et al., 2021c; Nguyen, 2021; OECD, 2021; Pawar et al., 2020; Shibayama et al., 2021; Shortall et al., 2021)	Impacts of Covid-19 on telework	Short term
(Balbontin et al., 2021; Barbour et al., 2021; Beck et al., 2020a; Rubin et al., 2020)	Impacts of Covid-19 on telework	Long term

home to work allowed by ICT (Andreev et al., 2010; Hensher et al., 2021b). Following this rationale, telecommuting (or related work activity, 'telework') has quickly gained attention as a demand strategy to reduce congestion and negative externalities of transportation (e Silva and Melo, 2018; Mokhtarian et al., 1995; Ozbilen et al., 2021). Many authors in the past investigated the factors influencing the adoption of telecommuting, which include job characteristics, socio-economic attributes of individuals and households, travel behavior and build environment factors (Nayak and Pandit, 2021; Nguyen, 2021; Olde Kalter et al., 2021; Ozbilen et al., 2021). In addition, several works analyzed the impacts of telework on mobility and the environment, obtaining controversial results (e Silva and Melo, 2018; Eıldér, 2020; Mouratidis et al., 2021; Nguyen, 2021; O'Brien and Yazdani Aliabadi, 2020). The estimation of these effects is very complex due to the high number of endogenous and exogenous factors involved and the so-called rebound effects. Specifically, impacts on the environment depend not only on transportation related variables, but also on energy balance between residential and office work (Guerin, 2021). Furthermore, considering transportation systems, several short- and long-term rebound effects can occur, such as the increasing of non-work trips by the teleworkers, more travels carried out by other household members, the choice to live far from centers of employment thus increasing travel distances (O'Brien and Yazdani Aliabadi, 2020). The complexity of the topic underlines the need for new insights into the impact of telework on travel and the environment (Eıldér, 2020).

As regards positive effects, Mokhtarian et al. (1995) reported that person-miles travelled and consequent pollutant emissions from vehicles were reduced after the adoption of telecommuting. Similarly, in California (United States), Koenig et al. (1996) analyzed daily travel behaviors of a group of people before and after telework adoption; the authors showed a reduction of personal trips by 27 %, as well as a vehicle miles travelled (VMT) decrease by 77 %, leading to emission reductions of CO by 64 %, NOx by 69 % and PM by 78 %. In the same study area, Mokhtarian et al. (2004) found that one-way commute distance was greater for people working from home than non-telecommuters, however this effect was more than compensated by the frequency of telework. Choo et al. (2005) estimated a potential reduction in annual VMT by 0.8 % caused by telecommuting in the United States. Nelson et al. (2007) pointed out relatively low environmental benefits of telecommuting (1.0–1.5 tons of VOC and NOx in Denver). Glogger et al. (2008) showed that telework can be an effective policy to avoid peak hour traffic and lower pollutant emissions in Munich; in particular, they estimated a reduction of total number of trips by 21 % and a weekly decrease of about 22 kg of CO<sub>2</sub> and 60 g of NOx per telecommuter. Pirdavani et al. (2014) evaluated that in Flanders (Belgium) telecommuting could reduce vehicle kilometers travelled by 3.15 % and the annual number of crashes by 2.6 %. Van Lier et al. (2014) calculated that work from home may lead to an average external cost savings ranging from 20 % to 99 %, in Brussels Capital Region, depending on the number of telecommuting days. In Dublin, Caulfield (2015) highlighted that working from home can be an effective policy to save travel time and cost. O'keefe et al. (2016) estimated that if 20 % of the Dublin population worked from home one day a week, 60,000 tons of carbon emissions would be eliminated. Shabanpour et al. (2018) calculated that if 50 % of workers in Chicago telecommuted, VMT would be reduced up to 0.69 % and greenhouse gas and particulate matter emissions up to 0.71 and 1.14 %. Eıldér (2020) used data from the Swedish National Travel Survey to conclude that telework could reduce travel demand, improve active modes adoption and congestion relief; in particular, the author found that full-day teleworkers make fewer and shorter trips, and are more likely to adopt active modes and avoid rush hours than commuters. Recently, Ozbilen et al. (2021) presented a wide study to analyze the relationship between ICT and travel time using different modes in the Central Puget Sound Region (United States); they highlighted a substitution effect between telework and motorized travel durations (car and public transportation), confirming that telecommuting can reduce traffic congestion.

On the other hand, these positive impacts could be mitigated, compensated, or eliminated by a rebound effect (Andreev et al., 2010; Pérez et al., 2004). For instance, Koenig et al. (1996) registered an average increase of 0.5 non-commuting trips per person-day in California (United States). By analyzing data from two large national datasets in the United States, Zhu (2012) showed a complementary effect of telework on individual travel; in particular, the authors found that teleworkers have longer commute distances and durations, as well as longer and more frequent daily non-work trips, than commuters. Kim et al. (2015) highlighted that non-work trips of household members with telecommuters tend to be higher than those without them, for households with less than one vehicle per employee; indeed, in these cases, the car otherwise adopted to commute can be used by other members for non-work purposes. Later, Kim (2017) estimated that this compensatory effect could increase person kilometer travelled by 2–4 km. e Silva and Melo (2018) underlined that in Great Britain working from home was adopted to cope with long and costly commutes; in particular, the authors pointed out that the possibility of teleworking could influence residential location to more remote areas, thus inducing long travel distances; therefore, they concluded that telecommuters had more weekly miles travelled, in particular by car, rather than non-telecommuters. Zhu and Mason (2014) reported that teleworkers had more VMT for both work and non-work daily trips than non-teleworkers, however, no impacts on non-work trips of household members were found. Similarly, Cerqueira et al. (2020) showed that in the United Kingdom telecommuters travelled more kilometers for non-work trips on weekdays; in addition, remote residential locations of people working from home caused an increase in distances travelled even for work trips; thus, CO<sub>2</sub> emission levels for teleworkers were higher than for non-teleworkers.

However, today, the Covid-19 pandemic has impacted even telecommuting, altering traditional factors that influence work from home (Mouratidis and Papagiannakis, 2021; Nguyen, 2021). In addition, a new rebound effect might occur affecting commuting mode choice due to bio security concern (Hensher et al., 2021a). This points out the need for a comprehensive analysis and prediction of the long-term effects of pandemic on telecommuting and, consequently, on travel demand and environment, since the results of the pre-pandemic analysis could no longer be valid (Barbour et al., 2021). This paper aims to shed light on this topic, by answering the following research questions: (1) How will Covid-19 influence the choice of telecommuting in the future? (2) What will be the effects of telecommuting on the environment in a post-Covid era? (3) What will be the rebound effect due to Covid-19? These research questions have been partially answered by a few previous works on the topic, but without a holistic and comprehensive view of the problem. For instance, Beck and Hensher (2020), Beck et al. (2020a), Hensher et al. (2021b), Hensher et al. (2021d), Hensher et al. (2022) deeply analyzed the effects of Covid-19 and telework on travel behavior; in particular, they developed several models to identify factors

influencing the decision to work from home, the frequency of telework and the impacts on mode choice in two metropolitan areas in Australia; nevertheless, they did not estimate the effects on vehicle emissions. Barbour et al. (2021) developed a logit model with random parameters to model the willingness to continue working from home after the pandemic in New York, without evaluating rebound effects and consequences on vehicle emissions. Crowley et al. (2021) predicted emission savings due to work from home in the long term, without considering a potential rebound effect. Currie et al. (2021) applied statistical analysis to describe the potential shift of telecommuting from public transportation to private car in the post-pandemic in Melbourne (Australia) but did not estimate the effects on the environment. Nguyen (2021) analyzed factors influencing the choice to telework in Hanoi (Vietnam), without considering any effects on mode choice. Olde Kalter et al. (2021) used logistic regressions to investigate intentions to continue teleworking and the increase in car use after Covid-19 in the Netherlands but did not evaluate the impacts on vehicle emissions. Lastly, Zhang and Zhang (2021) adopted an urban economic model to simulate the effects of work from home, online shopping activities, interventions on bike infrastructures, reduction of public transportation services, car and bike sharing, on CO<sub>2</sub> emissions in a post-Covid new normal in the city of Changzhou (China); Wang et al. (2021b) implemented an agent-based model to forecast the impacts of reopening policies on travels and environment in New York (United States). However, in both cases, the future scenarios were based on exogenous attributes of tested policies, and not on variables derived from future behavior of travelers.

This paper aims to answer the previous research questions, providing a holistic and comprehensive view of the long-term impacts of Covid-19 on telecommuting and, therefore, on travel demand and the environment. Furthermore, this is the first study focused on an Italian context, where the pandemic had unprecedented and sudden impacts on telework, which was rarely adopted before the virus outbreak (Bin et al., 2021), and is currently widely used, although not mandatory. In particular, results from a mobility survey administered to employees at the University of Padova were used to calibrate (1) a generalized ordered logit model that identifies variables affecting future weekly telecommuting frequencies and (2) a mixed logit model to estimate the mode choice of commuters after the pandemic, considering measures to limit the spread of the virus onboard vehicles; a specific procedure was implemented that combined data from the mobility survey and modelling results to evaluate the potential rebound effect and to quantify the impact on polluting emissions. In this way, unlike previous works, the potential future impacts of telework on the environment are evaluated, by modelling all the individuals' choices that lead to these effects and could be influenced by Covid-19. Therefore, this paper contributes to understanding the long-term effects of Covid-19 on travels and environment, supporting policy makers to shape a new sustainable mobility in a post-pandemic world.

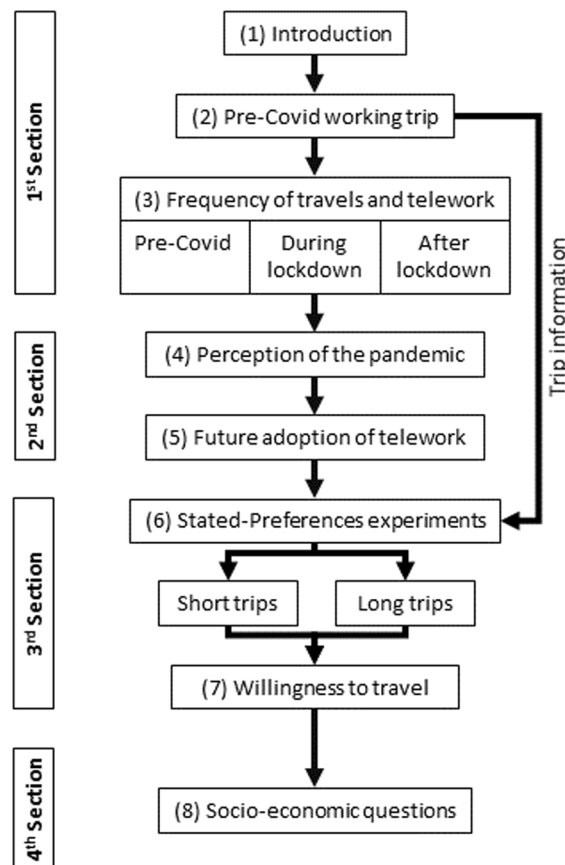


Fig. 1. Flow diagram of the survey structure.

### 3. Methods and data

#### 3.1. Mobility survey

To predict the long-term effects of Covid-19 on work from home and the consequent impacts on the environment, a mobility survey was designed and administered to employees of the University of Padova (Italy). This group can be considered very interesting for analysis since the first national government restrictions imposed telework for these workers that lasted several months and is still currently recommended (Governo Italiano, 2022). For this reason, they have been experiencing telework for a long time, fully understating the advantages and drawbacks of work from home, thus increasing the strength of their answers (Beck et al., 2020b). Although the survey was administered from July to September 2020, when the most severe restrictions were eased, but many measures to contain the virus were still enforced, a similar status is currently occurring in Italy; therefore, results can be considered useful even now (Hensher et al., 2021a). Furthermore, these employees could really decide whether to work from home or not, thus considering realistic conditions for the future period (Bin et al., 2021; Hiselius and Arnfalk, 2021; Shibayama et al., 2021).

A description of the structure of the dataset can be found in (Ceccato et al., 2021); however, further details are presented hereinafter. Fig. 1 contains a flow diagram showing the series of questions which were divided into eight groups. Specifically, the designed survey was divided into four sections. In the first one, a brief introduction was presented (group 1); after that, detailed questions were posed about a typical working trip before the pandemic (i.e., February 2020), such as origin and destination, travel modes, trip characteristics (starting time, duration, distance travelled, walking and waiting time), parking place, cost of parking and/or transit pass, level of satisfaction of travel means (group 2). Then, a specific group of questions was repeated for three time periods: before the Covid-19 outbreak, during the first national lockdown (March-April 2020), and after it (May-June 2020); in particular, information about the usage frequency of travel modes, trip frequencies for travel purposes, as well as the adoption of telework was collected (group 3). In the second section, the attitudes of the respondents towards the pandemic were investigated (group 4). Specifically, interviewees were asked to rate the perceived risk of travelling with different travel modes, as well as their concern about the pandemic. In addition, their opinions about the potential diffusion of the virus and the effectiveness of risk mitigation measures in workplaces were investigated. Lastly, respondents had to indicate how frequently they would like to work from home in the future (number of days in a typical working week), supposing that they would be allowed to decide it when restrictions are eased, but SARS-CoV-2 is still diffused (group 5). In the third part, Stated-Preferences (SP) experiments were posed, to analyze the future mode choice (group 6). Specifically, the interviewees had to focus on a future scenario in which they could freely choose whether or not to go to their workplace. Respondents were asked to select the mode they were willing to adopt, assuming they had to perform the same trip described in the first section of the survey. Different alternatives were presented depending on the length of the trip, including both existing and innovative travel modes that are planned to be introduced: if the trip length was <5 km, private car, urban bus/tram, bike, bike sharing, car sharing, car pooling, and e-scooter sharing were considered; otherwise, private car, suburban bus/train and car pooling were selected. It is worth mentioning that, since the experiments were based on the actual trip carried out by a respondent, which was reported in the first section of the survey, the choice tasks were designed to mimic the potential range of mobility options available depending on the real trip length. Specifically, travel modes typically used only in urban areas were not presented if the respondent carried out long trips. In this way, the realism of choice situations was increased. The threshold value for trip length was fixed by considering the extension of the urban area of Padova, the operating area of existing bike sharing and car sharing services, as well as the maximum trip length that most bikers are willing to travel (obtained from a similar survey administered to the same category of individuals in 2019). Additionally, analysis of the results of the current survey confirmed that most of the bike trips (about 80 %) was shorter than 5 km. The trip attributes of alternative modes were costs (public transit ticket or pass, tolls, fuel), in-vehicle time, walking time to reach the public transit stop and waiting time at the stop (for public transportation means), or walking time to reach the means (for car, car sharing, bike sharing and scooter sharing). Moreover, mode-specific health-risk mitigation measures were included as attributes of alternatives: for instance, frequent sanitization, proper ventilation system, booking system to manage crowding, the presence of a person designated to enforce safety measures, mandatory face masks, for public transportation; frequent sanitization of means, available hand sanitizing gel, for car, bike, bike sharing and scooter sharing. The attributes of alternative modes were calculated by considering information on the reported trip and data on public transit operators, car sharing, and bike sharing services (fares and subscription costs), along with the average fuel cost. Thereby, choice tasks were based on a real trip with realistic attributes, thus increasing the realism of choices and, therefore, the reliability of answers (Train and Wilson, 2008). For each of the two types of SP experiments, D-optimal designs were generated, obtaining D-efficiency values above 0.9 (Hensher et al., 2005). In particular, 5 levels for cost and time attributes were considered, adopting 20 %-step variations from the base level, and 4 levels for safety measures. In this way, a design with 60 questions was generated, which were divided into 15 blocks for short trips, and a design with 24 questions divided into 8 blocks for long trips. Consequently, each respondent had to face 4 choice tasks if he/she had performed a short trip, or 6 choice tasks if he/she had carried out a long trip. Each block was randomly assigned to each individual. The entire procedure was performed using R statistical software (Wheeler, 2019). Stated-Preferences experiments have some drawbacks: respondents could tend to cast their actual behavior in a better light, thus producing self-selection bias (Ortuzar and Willumsen, 2011); answering fatigue increases with the complexity of choice tasks (Heilig et al., 2017); people could not be familiar with proposed alternatives, thereby leading to unreliable answers (Diana, 2010). However, some of these disadvantages can be overcome by a proper design of experiments (Hensher et al., 2005). On the other hand, the Stated-Preferences survey allows the researcher to have more control over choice situations (Ortuzar and Willumsen, 2011), and the recruitment of participants is easier, since observing real behavior is not needed (Heilig et al., 2017); also, they are essential to evaluate individual responses in situations that do not currently exist, for which Revealed-Preferences data are simply not available (Train, 2003). In the present study, the proposed mobility survey

was intended to investigate future scenarios, where new mobility services are available, telework is no longer mandatory, and Covid-19 is part of the everyday life of citizens, but some countermeasures to limit its spread are still effective. Since this situation did not exist at the time of the survey administration, Stated-Preferences experiments were adopted.

Finally, after each experiment, the interviewees had to state if they preferred to travel using the previously selected mode or working at home (group 7). In the last section, socio-economic information was collected at the household level (e.g., number of members, cars, income level) and individual level (e.g., age, gender) (group 8).

The survey was implemented on an online platform and administered to 5680 employees through their official email address. 1243 complete questionnaires were received, obtaining a sampling rate of 22 %.

### 3.2. Methodology

To reach the objectives of the paper, the following method has been adopted. Each of the modelling steps is depicted in Fig. 2. To analyze the long-term impacts of Covid-19 on telework and the environment, the pollutant emissions generated by trips to the workplace for the pre-Covid period were compared to those estimated for potential future scenarios. A typical working week was set for the analysis; therefore, results are produced on a weekly basis. Overall, the input data for quantifying pollutants are the same for both groups of scenarios, i.e., the number of working trips (which are five minus the number of telework days), the travel mode adopted to commute, the length of the journeys (to reach the workplace and come back home), and the characteristics of vehicles (technology and type of fuel). However, for the pre-Covid scenario, data about the number of commuting trips and the adopted travel means were derived from the RP part of the survey. On the other hand, for the future scenarios, these pieces of information had to be respectively retrieved from the future number of telework days in a week reported by respondents and evaluated by a model forecasting the mode chosen to reach the workplace. In this way, by applying the mode choice model to working trips in a week, the distribution of future commuting journeys with each mode was obtained and used as input to quantify pollutant emissions. The results of the pre-pandemic scenario were compared to those of the future simulated ones. Details of each modelling step of the proposed approach are described hereinafter.

#### 3.2.1. Frequency of working from home

One of the determinants that affect the impacts of working from home is the frequency of this activity (Caulfield, 2015). To analyze the factors affecting this choice and, in particular, the number of telecommuting days per week, a specific model was calibrated; data from the second section of the survey, in which respondents had to indicate the number of days they are willing to work from home in the future, was used. Since the answers are ordered by definition, ranging from 0 to 5 days a week, an ordinal logit model could be adopted (Hensher et al., 2021c; Olde Kalter et al., 2021). However, this model assumes that the relationship between each pair of outcome categories is the same (e.g., 0 days vs 1 or more days, <2 days vs 2 or more days, and so on) (Zhu and Fan, 2018); following this assumption odds ratios are constant over the collapsed binary logistic regression estimated for each pair of outcome groups (Williams, 2016). In order to overcome this strong limitation and to avoid the use of models which do not consider the ordinal nature of the response, such as multinomial logit, a Generalized Ordered Logit model was adopted; moreover, since in an unconstrained generalized ordered logit model all variables are freed from the proportional odd constraint, a partial proportional odds model was used, where this assumption is relaxed only for variables violating it (Williams, 2016). In order to identify them, an automated stepwise procedure based on Wald tests was applied (Williams, 2006). It is worth underlying that the aim of the model was not to forecast the number of work from home days, but to understand the variables that could affect its frequency after the pandemic, which could have altered traditional factors that influence its adoption (Mouratidis and Papagiannakis, 2021; Nguyen, 2021). The exogenous variables

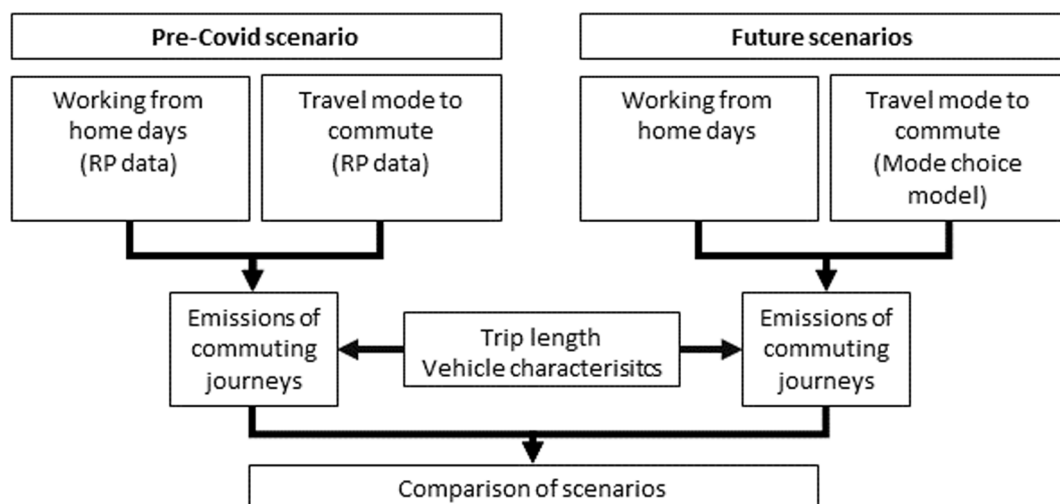


Fig. 2. Work flow of the adopted methodology.

selected for the model specification phase are summarized in Table 2.

### 3.2.2. Mode choice for commuting

In order to define the factors influencing the mode choice for commuting and to predict its adoption in the future, a mixed logit model was developed. To calibrate this model, data from SP experiments in the third section of the mobility survey were used. Variables included in the utility function of each alternative mode are reported in Table 3, and they refer to trip, individual or household level. The model was calibrated using 80 % of the sample and, afterwards, validated using the remaining 20 %. The process was developed by adopting Biogeme software (Bierlaire, 2020).

### 3.2.3. Emission estimates

The pollutant emissions from the vehicles of the sampled individuals were estimated considering the characteristics of the vehicles that circulate in the study area and the travel distances covered by each respondent to reach the workplace. In particular, a Tank-To-Wheel analysis was performed; thereby, estimated pollutants were only those generated by tailpipe emissions, without considering the contribution of energy production and distribution (Krause et al., 2020). Total emissions were estimated following the COPERT model. This method has been developed by the European Environment Agency (EEA) and has been recommended by the European Monitoring and Evaluation Program (EMEP) to estimate vehicle emissions (EMISIA, 2021). COPERT is part of the Handbook of Emission Factors of Road Transport (HBEFA) (Ntziachristos et al., 2019). The model is very flexible (Berkowicz et al., 2006), since it tries to combine the need for detailed emission estimation and input data that are easy to obtain (Ntziachristos et al., 2009; Smit et al., 2010). It is widely diffused among European member states to develop their official national emission inventories for road transportation (Davison et al., 2021; Kousoulidou et al., 2010), and also by independent researchers in Europe (Burón et al., 2004; Chicco and Diana, 2021) and all over the world (EMISIA, 2021; Jiang et al., 2020; Lang et al., 2016; Ong et al., 2011).

According to this methodology, emission factors describe the emission performance of a vehicle, which depends on vehicle operation, specific processes (e.g., acceleration), and environmental conditions (e.g., temperature) (Ntziachristos et al., 2009). These factors are estimated for both hot and cold emissions. The formers are produced when the engine reaches its normal operating temperature, whereas the latter is produced when the engine starts from ambient temperature. Emission factors are built on specific well-defined driving cycles, which are representative of traffic conditions, for different vehicle technologies. For each cycle, the mean emission level for each pollutant (expressed as g/km) is linked to the average driving speed (Fontaras et al., 2014). Following the COPERT approach, for each pollutant, the average emission per unit of distance of all vehicles is calculated as the weighted average of the different vehicle technologies that comprise the analyzed fleet (Lejri et al., 2018).

In the present work, the composition of circulating vehicles in the study area and for the considered period was obtained from the *Automobile Club d'Italia (ACI)* (ACI, 2021). A typical working week was defined as the period of analysis; the number of journeys from home to work was estimated considering the weekly frequency of telework. For the pre-Covid scenario, total emissions generated by working trips were quantified by multiplying the emission factor for each type of pollutant by the real reported length of each commuting trip. On the other hand, to estimate pollutant emissions after the diffusion of work from home in the future, first, for each respondent, the number of days in which telecommuting could be adopted for a typical future working week was considered. Then, the mode choice model was used to forecast the mode that could be chosen to perform the commuting trips, by applying the model to the trips performed in the pre-pandemic phase for those employees who decided to perform at least one working trip in the future. After that, emission factors were applied considering the length of each potential journey reported in the first section of the survey (Crowley et al., 2021; Zhang and Zhang, 2021). In particular, for each trip, CO<sub>2</sub>, NO<sub>x</sub> and PM<sub>10</sub> were calculated. Following this procedure, the effects of Covid-19 on telework and the environment were quantified, using real trips carried out before the pandemic as the unit of analysis.

It is worth mentioning that, as previously described, COPERT model is an “average-speed” model (Jaikumar et al., 2017; Smit et al.,

**Table 2**  
Exogenous variables used in the generalized ordered logit model.

Name	Description	Type	Level
DIST	Length of the trip	Metric	Trip
F_BUS	Frequency of public transportation use [times/week]	Metric	Individual
F_TELE_P1	Frequency of telework during the first lockdown [days/week]	Metric	Individual
F_TELE_P2	Frequency of telework after the first lockdown [days/week]	Metric	Individual
F_WEEK	Past commute frequency [times/week]	Metric	Individual
FUT_COV_6	Opinion on the level of future potential diffusion of SARS-CoV-2 [5-point scale, ranging from “Very little diffused” to “Very diffused”, with the specific answer: “No longer present”]	Categorical	Individual
GENDER_F	Female	Dummy	Individual
PASS_SUBU	Used public transportation in the past for the trip	Dummy	Trip
R_NOTELE_1	Reason not to telework [my job is not suitable]	Dummy	Individual
R_NOTELE_2	Reason not to telework [telework is not so productive]	Dummy	Individual
R_NOTELE_3	Reason not to telework [I do not have a proper workplace at home]	Dummy	Individual
RISK	Individual Covid-19 health-risk	Dummy	Individual
SAF_BUS_1	Perceived level of health risk of travelling on public transportation [5-point scale, ranging from “Not at all safe” to “Very safe”]	Categorical	Individual
TOC	Occupation [office worker]	Dummy	Individual



**Table 3**  
Exogenous variables used in the mixed logit model.

Name	Description	Type	Level
AGE	Age	Metric	Individual
COST	Cost associated to travel mode	Metric	Trip
DIST	Travel distance	Metric	Trip
FREQ	Frequency of use of travel mode [times/week]	Metric	Individual
FUT_COV_	Opinion on the level of future potential diffusion of SARS-CoV-2 [6-point scale, ranging from “No longer present” to “Very diffused”]	Categorical	Individual
GENDER_F	Female	Dummy	Individual
HH_BIKE	Number of bikes	Metric	Household
HH_CARLIC	Number of driving licenses related to number of cars	Metric	Household
INCOME	Income [1000€]	Metric	Individual
IVT	In-vehicle travel time	Metric	Trip
MI_B (car pooling)	Opinion on mandatory use of face mask and glove [5-point scale, ranging from “Not at all important” to “Very important”]	Categorical	Trip
MI_B (car sharing)	Opinion on daily sanitization of vehicles [5-point scale, ranging from “Not at all important” to “Very important”]	Categorical	Trip
MI_B (public transport)	Opinion on daily sanitization of vehicles and adequate ventilation system [5-point scale, ranging from “Not at all important” to “Very important”]	Categorical	Trip
MI_C (car sharing)	Opinion on the presence of sanitizing gel onboard vehicles [5-point scale, ranging from “Not at all important” to “Very important”]	Categorical	Trip
MI_C (public transport)	Opinion on automatic access control via web, phone or app booking system [5-point scale, ranging from “Not at all important” to “Very important”]	Categorical	Trip
MI_D (car sharing)	Opinion on mandatory safety distance onboard vehicles [5-point scale, ranging from “Not at all important” to “Very important”]	Categorical	Trip
MI_D (public transport)	Opinion on mandatory use of face mask and glove; safety distances onboard vehicles [5-point scale, ranging from “Not at all important” to “Very important”]	Categorical	Trip
OCC_P	Occupation [professor]	Dummy	Individual
PAST_BIKE	Past use of bike for the trip	Dummy	Trip
PAST_CAR	Past use of private car for the trip	Dummy	Trip
PAST_PT	Past use of public transportation for the trip	Dummy	Trip
PER_COV_	Level of concern about the current pandemic [5-point scale, ranging from “Very worried” to “Very relaxed”]	Categorical	Individual
SAF_	Perceived level of health risk of travelling on transportation means [5-point scale, ranging from “Not at all safe” to “Very safe”]	Categorical	Individual
WALK_TIME	Walking time	Metric	Trip

2010), where a unique emission factor is used as representative of the overall circulating fleet (Lejri et al., 2018). Therefore, even if real data were used about the length of the commute trip and fleet composition in the area, the approach is not completely accurate. However, since the aim of the framework is to compare different scenarios, the same level of approximation is consistently applied in all of them (Chicco and Diana, 2021).

#### 3.2.4. Simulated scenarios

In order to predict long-term impacts, future scenarios were tested considering different measures to contain the spread of the virus onboard vehicles:

- Scenario A without countermeasures onboard vehicles;
- Scenario B with measures that positively affect the choice to adopt sustainable travel modes.

The results were compared with pollutant emissions estimated for the pre-crisis scenario to understand whether work from home induced by Covid-19 can produce positive or negative environmental impacts.

## 4. Results and discussion

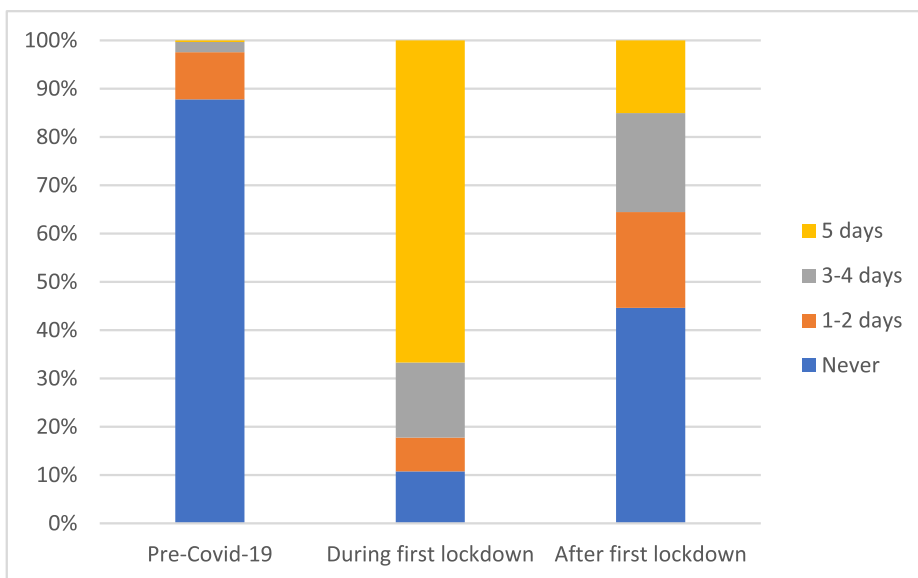
### 4.1. Characteristics of the sample

Statistics on the socio-economic characteristics of the sample are reported in Table 4, both at the individual and household level. In particular, about half of the respondents lives in households with 2 cars, 2 bikes and 2 licensed drivers. Moreover, the majority of interviewees is aged between 35 and 64 years, as expected.

Fig. 3 shows the percentages of work from home days in a week, before the pandemic outbreak, during the first national lockdown and after this period. By observing this figure, one can note that in the pre-pandemic phase telework was not widespread, like in other Italian regions; indeed, only 10 % of respondents usually worked from home for 1 or 2 days per week. Due to national containment measures, telecommuting increased drastically during the first lockdown; however, since some activities could be exclusively performed in workplaces, few respondents stated that they have never adopted telework even during this period. During the re-opening

**Table 4**  
Descriptive statistics of the sample.

		N	%
Totals		1243	100
Household members	1	205	17
	2	356	29
	3	291	23
	4	301	24
	More than 4	90	7
Licensed drivers	0	7	1
	1	328	25
	2	691	56
	3	131	11
	More than 3	86	7
Household cars	0	58	5
	1	489	39
	2	592	48
	3	92	7
	More than 3	12	1
Household bikes	0	101	8
	1	189	15
	2	332	27
	3	268	22
	More than 3	353	28
Household income [€/month]	<1000	11	1
	1000–1500	213	17
	1500–2000	136	11
	2000–3000	406	33
	3000–4000	257	21
	4000–6000	168	13
	6000–10000	36	3
	More than 10,000	16	1
Gender	Female	670	54
	Male	573	46
Age	18–20	4	0
	21–24	4	0
	25–29	56	4
	30–34	120	10
	35–44	345	28
	45–54	405	33
	55–64	272	22
	More than 65	37	3



**Fig. 3.** Distribution of work from home days in a typical working week in the three considered periods.

phase, when working from home was no longer mandatory, more than 50 % of the sample continued telework, suggesting that potential long-term impacts could have occurred. The described visual interpretation of Fig. 3 was confirmed by statistical tests on the proportions of people working from home with different frequencies in the three periods considered. In particular, significant differences were found by comparing the distribution of telework frequencies before the pandemic outbreak and during the first lockdown (Fisher exact test, p-value < 0.001), as well as between the pre-Covid period and after the first lockdown (Fisher exact test, p-value < 0.001). Furthermore, the analysis highlighted that the number of work from home days among the respondents was statistically different between the pre-pandemic period and after the lockdown, for people never adopting telework (Fisher exact test, p-value < 0.001), working 1 or 2 days a week (Fisher exact test, p-value < 0.001), 3 or 4 days a week (Fisher exact test, p-value < 0.001) or 5 days (Fisher exact test, p-value < 0.001).

Modal share of commuting trips in the three considered periods is depicted in Fig. 4. Before the Covid-19 pandemic outbreak, 30 % of the respondents travelled from home to work by private car; this value increased to 50 % during the lockdown ( $\chi^2 = 19.8$ , p-value < 0.001) and slightly decreased in the next phase ( $\chi^2 = 7.4$ , p-value = 0.007). On the contrary, even if trips on public transportation were more than those on private modes in the pre-pandemic period (about 42 %), their number drastically lowered to 9 % during lockdown ( $\chi^2 = 85.1$ , p-value < 0.001) and never returned to pre-pandemic levels (18 % in the re-opening phase) ( $\chi^2 = 39.4$ , p-value < 0.001). On the other hand, one can note that the modal share of bike was basically unchanged in the three periods (Pre-Covid-19 vs During first lockdown:  $\chi^2 = 0.1$ , p-value = 0.737; During first lockdown vs After first lockdown:  $\chi^2 = 0.1$ , p-value = 0.718), highlighting the great resilience of this travel means; in addition, walking trips increased a lot after the Covid-19 outbreak.

#### 4.2. Generalized ordered logit model estimation

In the first stage of the analysis, the proportional odds assumption of an ordinal logit model was verified; in particular, the Brant test (Brant, 1990) was used to evaluate if the differences from what the ordinal logit model predicts are due to chance alone (Williams, 2016). The results highlighted that the model assumptions were not met ( $\chi^2 = 144.3$ , p-value < 0.001), confirming the adoption of a Generalized Ordered Logit model. Furthermore, to avoid negative prediction of probabilities, the six original outcomes of the dependent variable were grouped (Williams, 2016; Zhu and Fan, 2018). Specifically, since only 3 and 4 % of the respondents stated that they were willing to telework for 4 or 5 days, respectively, these two response options were collapsed into one class, namely “4 + days”. In this way, the dependent variable could assume the following values representing the future number of work from home days in a typical working week: “0 days”, “1 day”, “2 days”, “3 days” and “4 + days”. The non-violation of the proportional odds assumption in the final version of the model was verified ( $\chi^2 = 24.1$ , p-value = 0.623).

The results of the calibration of the generalized ordered logit model are reported in Table 5; since the model allows to relax the proportional odds assumption only for variables where it is violated, multiple coefficients were presented for these factors (Williams, 2016). In addition, marginal effects, representing the change in probability of the outcome for unitary variation of an independent variable, were reported in Table 6.

By observing estimation results, one can note that significant factors are both related and non-related to Covid-19. In particular, as obtained by previous authors, the commuting distance (DIST) has a positive effect on the number of telecommuting days (Balbontin et al., 2021; Helminen and Ristimäki, 2007). Job function significantly affects the telework frequency (R\_NO\_TELE\_1), indeed office workers (TOC) are more likely to work from home, in particular for 2 days. Women are more willing to adopt telework for more days compared to men (GENDER\_F), probably because, in this way, they can better combine work and care activities (Mokhtarian et al., 1998). If the frequency of commuting before the pandemic increases, the probability of work from home decreases (the coefficients and margins of F\_WEEK are negative), indicating that travel habits play a significant role in the choice to telework. Individual's opinion about telework (R\_NO\_TELE\_2) is a significant factor: people considering work from home low productive are less willing to adopt it.

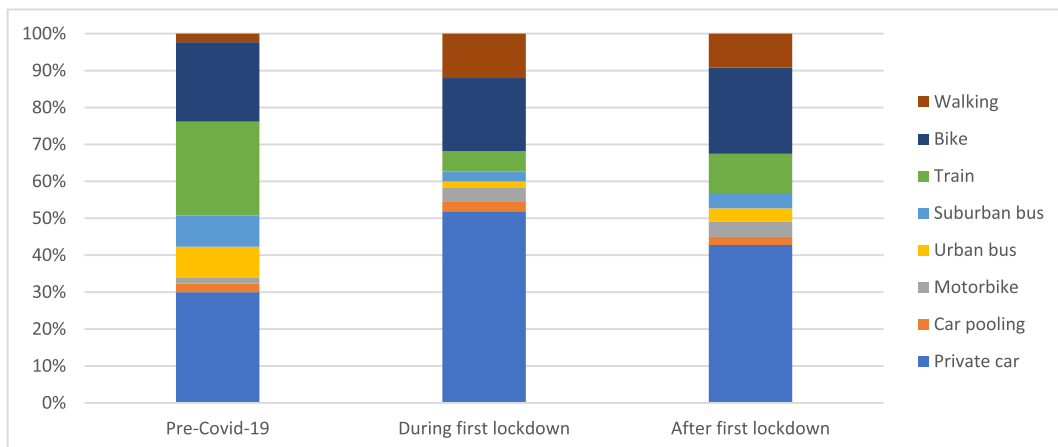


Fig. 4. Modal share of commuting trips in the three considered periods.

**Table 5**  
Estimation results of the frequency of work from home model.

Name		Value	Std. Error	z-value	p-value
DIST		0.013	0.003	4.21	0.000***
F_BUS		0.087	0.030	2.91	0.004**
F_TELE_P1	0 vs 1,2,3,4 + days	0.442	0.079	5.59	0.000***
	0,1 vs 2,3,4 + days	0.306	0.083	3.67	0.000***
	0,1,2 vs 3,4 + days	0.008	0.109	0.08	0.939
	0,1,2,3 vs 4 + days	-0.261	0.161	-1.63	0.104
F_TELE_P2		0.639	0.083	7.72	0.000***
F_WEEK	0 vs 1,2,3,4 + days	-0.744	0.136	-5.48	0.000***
	0,1 vs 2,3,4 + days	-0.458	0.087	-5.25	0.000***
	0,1,2 vs 3,4 + days	-0.201	0.070	-2.88	0.004**
	0,1,2,3 vs 4 + days	-0.332	0.088	-3.77	0.000***
FUT_COV_6	0 vs 1,2,3,4 + days	-0.130	0.218	-0.6	0.551
	0,1 vs 2,3,4 + days	0.053	0.210	0.25	0.803
	0,1,2 vs 3,4 + days	0.231	0.220	1.05	0.294
	0,1,2,3 vs 4 + days	0.847	0.280	3.02	0.002**
GENDER_F		0.249	0.119	2.08	0.037*
PASS_SUBU	0 vs 1,2,3,4 + days	0.198	0.335	0.59	0.556
	0,1 vs 2,3,4 + days	0.703	0.324	2.17	0.030*
	0,1,2 vs 3,4 + days	0.880	0.298	2.96	0.003**
	0,1,2,3 vs 4 + days	0.665	0.404	1.65	0.100
R_NOTELE_1		-0.746	0.178	-4.18	0.000***
R_NOTELE_2		-1.618	0.235	-6.87	0.000***
R_NOTELE_3	0 vs 1,2,3,4 + days	-1.255	0.474	-2.65	0.008**
	0,1 vs 2,3,4 + days	-1.295	0.557	-2.33	0.020*
	0,1,2 vs 3,4 + days	0.241	0.638	0.38	0.705
	0,1,2,3 vs 4 + days	0.290	0.845	0.34	0.732
RISK		0.374	0.137	2.73	0.006**
SAF_BUS_1		0.295	0.118	2.49	0.013*
TOC		1.042	0.131	7.94	0.000***
cons_1		-0.043	0.162	-3.96	0.000***
cons_2		-0.780	0.158	-4.93	0.000***
cons_3		-2.855	0.181	-15.79	0.000***
cons_4		-4.353	0.221	-19.66	0.000***

Significance codes: \*\*\* p-value < 0.001; \*\* p-value < 0.01; \* p-value < 0.05; † p-value < 0.10

Statistics	
Sample size:	1243
Log likelihood	-1378.08
LR $\chi^2$	736.27
p-value	0.000***
Pseudo R2	0.21

**Table 6**  
Marginal effects for the frequency of work from home model (standard errors in parentheses).

Variable	0 days	1 day	2 days	3 days	4 + days
DIST	-0.0029 (0.0007)	-0.0004 (0.0001)	0.0019 (0.0005)	0.0010 (0.0003)	0.0004 (0.0001)
F_BUS	-0.0193 (0.0066)	-0.0026 (0.0011)	0.0123 (0.0043)	0.0068 (0.0024)	0.0028 (0.0010)
F_TELE_P1	-0.0974 (0.0177)	0.0208 (0.0134)	0.0756 (0.0178)	0.0093 (0.0098)	-0.0084 (0.0054)
F_TELE_P2	-0.1407 (0.0180)	-0.0190 (0.0050)	0.0896 (0.0130)	0.0495 (0.0074)	0.0205 (0.0035)
F_WEEK	0.1638 (0.0284)	-0.0493 (0.0256)	-0.0925 (0.0210)	-0.0114 (0.0063)	-0.0107 (0.0028)
FUT_COV_6	0.0292 (0.0496)	-0.0423 (0.0336)	-0.0139 (0.0495)	-0.0101 (0.0219)	0.0372 (0.0161)
GENDER_F	-0.0549 (0.0264)	-0.0072 (0.0037)	0.0350 (0.0170)	0.0192 (0.0092)	0.0079 (0.0039)
PASS_SUBU	-0.0421 (0.0690)	-0.1269 (0.0350)	0.0414 (0.0733)	0.0990 (0.0480)	0.0285 (0.0223)
R_NOTELE_1	0.1717 (0.0425)	0.0117 (0.0044)	-0.1112 (0.0280)	-0.0515 (0.0113)	-0.0207 (0.0049)
R_NOTELE_2	0.3818 (0.0524)	-0.0203 (0.0141)	-0.2416 (0.0320)	-0.0864 (0.0101)	-0.0335 (0.0051)
R_NOTELE_3	0.3023 (0.1116)	-0.0104 (0.0667)	-0.3206 (0.0569)	0.0182 (0.0636)	0.0106 (0.0348)
RISK	-0.0792 (0.0279)	-0.0136 (0.0063)	0.0485 (0.0166)	0.0310 (0.0123)	0.0133 (0.0056)
SAF_BUS_1	-0.0649 (0.0261)	-0.0086 (0.0038)	0.0413 (0.0167)	0.0228 (0.0093)	0.0094 (0.0039)
TOC	-0.2307 (0.0292)	-0.0241 (0.0063)	0.1440 (0.0197)	0.0781 (0.0107)	0.0328 (0.0055)

Lastly, the availability of a proper workplace at home (R\_NO\_TELE\_3) was found to affect the choice to work from home, specifically showing that people could telework for no more than 1 day.

On the other hand, Covid-19 was found to have an impact on telecommuting frequency. In particular, people who consider themselves to be potentially exposed to high health risks after SARS-CoV-2 infection are willing to work from home for many days (the

coefficient of RISK and margins related to 2 or more days are positive). Moreover, negative concern about the pandemic was found to increase the likelihood of working from home for 4 or more days (FUT\_COV\_6). Furthermore, the perceived health risk level of travelling on public transportation has a significant impact on work from home (SAF\_BUS\_1), as reported in previous works (Hensher et al., 2022); in addition, frequent public transit users are willing to telework (F\_BUS and PASS\_SUBU); these results suggest that commuting trips on this mode could no longer be carried out. Moreover, past experience of telework can play a non-negligible role on the frequency to adopt it in the future (Barbour et al., 2021), indeed people working from home during the lockdown and in the re-opening phase are willing to continue (F\_TELE\_P1 and F\_TELE\_P2). It is worth mentioning that some variables that were found to significantly affect the choice to telework by previous authors, such as age, marital status, household size, and number of children (Eldér, 2020; Nayak and Pandit, 2021; Ozbilen et al., 2021), were included in initial versions of the model; however, they were not significant; therefore, they were not considered in the final model. This could be due to the strong impacts of variables related to the pandemic, which could have “overcome” some factors playing a role in normal conditions (Mouratidis and Papagiannakis, 2021; Nguyen, 2021).

The goodness-of-fit indicators of the implemented generalized ordered logit model are in line with those of models developed by

**Table 7**

Mode choice model estimation results.

Name	Value	Std. Error	t-value	p-value
ASC Bike	2.200	0.265	8.31	0.000***
ASC Bike sharing	2.480	0.687	3.61	0.000***
ASC Car pooling	0.191	0.376	0.51	0.612
ASC Car sharing	-2.900	8.830	-0.33	0.742
ASC E-scooter sharing	0.714	0.559	1.28	0.201
ASC Public transport	-0.063	0.328	-0.19	0.847
All modes - IVT mean	-0.016	0.461	-10.60	0.000***
All modes - IVT standard deviation	0.031	0.430	2.89	0.004**
Bike - FREQ	0.275	0.044	6.22	0.000***
Bike - HH_BIKE	0.138	0.049	2.84	0.004**
Bike - PAST_BIKE	0.796	0.248	3.21	0.001**
Bike sharing - AGE	-0.045	0.015	-3.09	0.002**
Bike sharing - SAF_2	-1.390	0.630	-2.21	0.027*
Bike sharing - SAF_4	0.846	0.330	2.56	0.010*
Bike, bike sharing, e-scooter sharing - DIST	-0.406	0.086	-4.75	0.000***
Car - COST/log(INCOME)	-0.001	0.000	-3.27	0.001**
Car - FREQ	0.127	0.025	5.06	0.000***
Car - FUT_COVID_6	0.487	0.140	3.48	0.001***
Car - HH_CARLIC	0.891	0.152	5.86	0.000***
Car - OCC_P	0.221	0.099	2.23	0.026*
Car - PAST_CAR	0.541	0.162	3.35	0.001***
Car - PAST_PT	0.382	0.163	2.34	0.019*
Car pooling - AGE	-0.016	0.007	-2.30	0.021*
Car pooling - MI_B	0.681	0.144	4.74	0.000***
Car pooling - SAF_1	-0.436	0.193	-2.26	0.024*
Car pooling - SAF_2	-0.243	0.164	-1.48	0.139
Car sharing - COST/log(INCOME)	-0.008	0.003	-2.41	0.016*
Car sharing - MI_B	4.880	8.740	0.56	0.577
Car sharing - MI_C	3.540	8.760	0.40	0.686
Car sharing - MI_D	4.340	8.750	0.50	0.620
E-scooter sharing - COST/log(INCOME)	-0.002	0.002	-1.49	0.136
E-scooter sharing - PAST_BIKE	1.110	0.402	2.76	0.006**
Public transportation - COST/log(INCOME)	-0.001	0.000	-2.72	0.007**
Public transportation - FREQ	0.351	0.030	11.60	0.000***
Public transportation - GENDER_F	0.449	0.128	3.52	0.000***
Public transportation - MI_B	0.429	0.205	2.10	0.036*
Public transportation - MI_C	0.421	0.216	1.95	0.051†
Public transportation - MI_D	0.586	0.231	2.53	0.011*
Public transportation - PERC_COV_5	0.965	0.407	2.37	0.018*
Public transportation - SAF_1	-1.330	0.180	-7.40	0.000***
Public transportation - SAF_2	-0.496	0.177	-2.81	0.005**
Public transportation - WALK_TIME mean	-0.049	0.013	-3.65	0.000***
Public transportation - WALK_TIME standard deviation	0.049	0.013	-3.65	0.000***

Significance codes: \*\*\*  $p$ -value < 0.001; \*\*  $p$ -value < 0.01; \*  $p$ -value < 0.05; †  $p$ -value < 0.10

**Statistics**

N. of observations	3339
Null log likelihood	-11393.93
Final log likelihood	-2518.95
Likelihood ratio test	17749.97
Rho-square-bar	0.78
AIC (Akaike criterion)	5121.90
Bayesian Information Criterion:	5378.66

previous authors, focusing on the study of variables that affect the choice to work from home (Beck et al., 2020b; Olde Kalter et al., 2021).

#### 4.3. Mixed logit model estimation

The estimation results of the final version of the mode choice model are reported in Table 7. Several functional forms were calibrated, like Multinomial Logit and Nested Logit; however, the first resulted in low overall fit; in addition, none of the scale parameters for the considered nested structures was found to be significant. For these reasons, a Mixed Logit model was implemented. Many structures of the utility function associated with each travel mode were tested. The following variables were considered in the model specification phase. First, factors related to trip characteristics were evaluated, such as in-vehicle travel time, walking time to reach the vehicle, waiting time for public transportation and cost of the trip. In particular, cost was found to be significant only if it was related to the income of the respondent's household and was retained as a mode-specific factor; on the other hand, a unique coefficient of in-vehicle travel time was defined for all travel alternatives; as regards public transportation, walking time resulted a significant variable unlike waiting time, therefore the latter was not included in the final version of the model. Moreover, travel habits of people, i.e. the usage frequency of travel modes and the past use of means for the working trip, were considered; specifically, these factors related to a specific mode were tested in the utility functions of every travel mode, in order to verify if the adoption of a mode could affect the future choice of another one. The same procedure was applied for variables associated with the perception of health risk when travelling onboard vehicles, thereby testing the potential influence of biosecurity concerns among different modes. Lastly, the socio-economic characteristics of the users were considered. To account for preference heterogeneity, different distributions were evaluated for several variables, including normal, lognormal and triangular distribution for continuous factors and uniform distribution for dummy variables. To select the best one, the values and significance of the estimated mean and standard deviations were analyzed. In the final version of the model, two variables were included as random parameters; specifically, the in-vehicle travel time was modelled with a lognormal distribution, and the walking time with a triangular distribution where the spread is equal to the mean. Moreover, 500 intelligent Halton draws were adopted. Statistical tests were used to compare the tested model specifications, such as the likelihood ratio test (Hensher et al., 2005; Train, 2003). The explanatory variables described above were tested by applying a manual forward selection procedure, where the effect of the addition of each factor was evaluated; in particular, the final version of the model was defined considering the level of significance of variables and the travel behavioral interpretation of parameters.

Table 7 shows that the variable related to the frequency of use of a specific travel mode (FREQ) has a positive effect on the choice of that mode, suggesting a potential behavioral inertia of users; similarly, the positive coefficient of PAST\_BIKE for bike and PAST\_CAR for private car, indicated that people who adopted these means for commuting in the pre-pandemic phase are willing to use them even in the future. Nevertheless, by analyzing other PAST\_\* variables, potential future substitution patterns among travel modes can be pointed out. In particular, private car could substitute commuting trips on public transportation (PAST\_PT for private car is positive) and individuals using private bike could switch towards e-scooter sharing (PAST\_BIKE for e-scooter sharing is positive). While in the second case the shift is not due to Covid-19 related reasons, in the first case the values of several exogenous variables suggest that concern about the pandemic plays a significant role in the mode choice. Indeed, private car could be adopted by people supposing that the spread of SARS-CoV-2 will increase (FUT\_COVID\_6). On the other hand, the biosecurity concern associated with public transportation significantly impacts the choice of this mode; specifically, commuters who perceive public transit as high health-risky (SAF\_1 and SAF\_2) and with a high concern about the pandemic (PERC\_COV\_5) could not be willing to perform trips on this mode in the future.

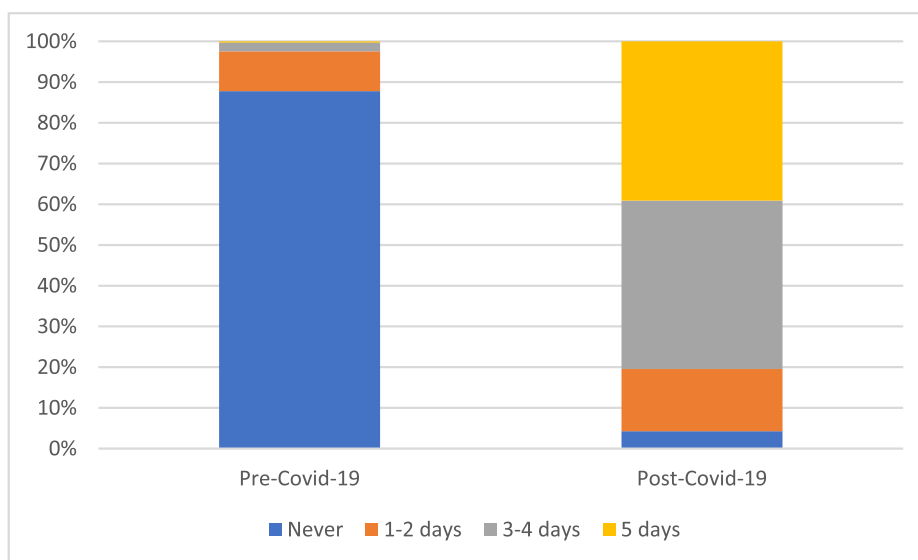


Fig. 5. Distribution of work from home days in a typical week before Covid-19 and in the future.

Furthermore, perceived health-risk of travelling was found to affect even the choice of bike sharing (SAF\_2 and SAF\_4) and car pooling (SAF\_1), probably because commuters would have to share the means and the trip with other users. These elements point out that a proper information campaign about biosecurity of travelling on these modes could prompt their adoption in the future (Beck and Hensher, 2020; Tirachini and Cats, 2020).

In addition, the results of the model estimation allowed identifying potential risk mitigation measures onboard vehicles that affect the choice of specific commuting modes. For instance, as regards public transportation, all the proposed countermeasures positively affect the adoption of this mode, in particular, daily sanitization of vehicles, proper ventilation system (MI\_B), automatic access control via web, telephone or app booking system (MI\_C), as well as mandatory use of face mask and safety distance (MI\_D). It is worth reporting that only some of these measures are currently implemented in Italy (i.e. MI\_D), therefore, the model suggests potential interventions that could foster the adoption of public transportation.

Lastly, concerning socio-economic factors, age was found to negatively affect the choice of bike sharing and car pooling; this could be due to the inertia of older people to adopt non-traditional travel modes. Moreover, professors are likely to adopt private car for commuting (OCC\_P), probably since this mode provides them with the time flexibility they need.

#### 4.4. Environmental impacts of work from home due to Covid-19

The long-term effects of telework and the travel mode chosen for commuting induced by Covid-19 on the environment depend on the number of future work from home days and the propensity to choose sustainable travel modes, which can change according to specific countermeasures onboard vehicles. In this section, the results of the analysis related to a typical working week are presented.

Fig. 5 shows the distribution of work from home days in a week before the pandemic outbreak and in a post-pandemic scenario. The results indicate that the frequency of telecommuting is likely to increase in the future. In particular, whereas in the pre-Covid period about 90 % of the sample never adopted telework, in a post Covid era about 40 % of the employees could not perform any working trips in a week, and <5 % could daily travel towards the workplace. These outcomes point out that sound changes in commuting due to Covid-19 might persist in the future, thereby significantly altering mobility and traffic flows.

The estimated mixed logit model was used to predict the probability of adoption of the considered travel modes by each respondent who stated to be willing to reach the workplace at least once a week in the future. Since the aim of the approach is to forecast the probability of the mode chosen to commute in the post-Covid scenario, assuming that the same pre-pandemic working trip will be performed (namely, the assumption used in the choice experiments), the characteristics of the actual trip carried out in the pre-Covid-19 period were used. This information was obtained from the data reported in the Revealed-Preferences part of the survey. Specifically, trip distance was directly retrieved from respondents' answers whereas travel time and cost of each alternative mode were estimated by considering real data on public transit operators, car sharing, and bike sharing services (fares and subscription costs), along with the average cost of fuels. Similarly, independent variables related to socio-economic characteristics, travel habits and Covid-19 perceptions of travelers were derived from the corresponding questions. On the other hand, variables associated with the measures to limit the spread of the virus were defined according with the considered scenarios, as presented in section 3.2.4. In this way, the values of each variable composing the utility function of each mode were calculated. In order to obtain the probability of each alternative a simulation method was adopted (Train, 2003). Following this approach, first a draw of the random terms is generated, which is used to calculate the utility for each alternative, and the alternative with the highest utility is selected. Then, this procedure is repeated for many draws for each respondent. The simulated probability for each choice option is estimated as the proportion of draws for which

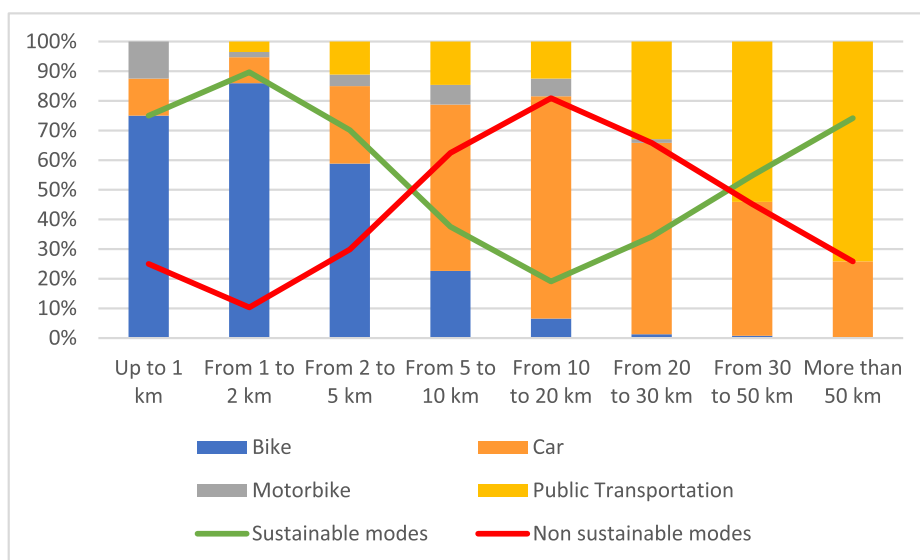


Fig. 6. Modal share for commuting trips before Covid-19.

that option shows the greatest utility. In this way, the probabilities of the adoption of travel modes by the sampled population were quantified. In particular, the results of the application of the mode choice model to individuals who are likely to perform at least one commuting trip in a week are depicted in Fig. 7 and Fig. 8; specifically, each figure is related to one of the two scenarios considered, and it represents the market share of travel modes depending on the length of the trip. Moreover, Fig. 6 shows the modal share of commuting trips before the Covid-19 outbreak. Furthermore, in each figure, travel means were grouped into sustainable (public transportation, bike, bike sharing, e-scooter sharing, car sharing and car pooling) and non-sustainable (private car) modes, which are denoted by a green and red line, respectively. The adopted classification was in line with that provided by the Network of Italian Universities for Sustainable Development (RUS), which focuses on the sustainability of mode choice (RUS, 2021). A different grouping could have been adopted, mainly because of the growing diffusion of electric vehicles. However, at the time of the survey, the number of full electric cars was <0.1 % of the circulating fleet in the study area, and hybrid cars represented 1.8 % of vehicles (ACI, 2021). Moreover, it is worth noting that a Tank-To-Wheel analysis was performed, therefore without considering the overall life cycle assessment of vehicles.

By observing Fig. 6, one can note that the modal share of bike and private car decreases with trip length; on the contrary, public transportation shows an opposite trend. These elements lead to the following results. The percentage of commuting trips shorter than 5 km carried out on sustainable modes is greater than the corresponding value for non-sustainable modes, since many of these journeys are carried out on bikes. However, trips with a length between 5 and 30 km are associated with an opposite trend, where most of them are performed with non-sustainable travel means (i.e., private car). On the other hand, commuting trips related to sustainable modes return to overcome the others for distances greater than 30 km, since most of them are carried out using train or sub urban bus.

The trend previously described about the adoption of sustainable and non-sustainable modes does not persist in any future scenarios. The worst case was obtained for Scenario A, where no containment measures were applied. In particular, Fig. 7 shows that most of commuting trips shorter than 5 km could be performed on sustainable mode (i.e. bike, bike sharing, and e-scooter sharing); however, the corresponding percentage drastically decreases up to <15 % for trips longer than 5 km, which are likely to be carried out using non-sustainable mode (i.e. private car). Indeed, in this scenario, the adoption of public transportation is very low, therefore, it cannot contribute to the sustainability of commuting trips. This negative trend could be mitigated by applying specific measures to contain the spread of the virus, aiming to foster the adoption of sustainable modes (Scenario B). In this case (Fig. 8), trips associated with non-sustainable modes might continue to overcome the others for lengths greater than 5 km, nevertheless, the reduction of sustainable trips is lower than in the previous scenario and their number increases to 40 % for distances greater than 30 km. This highlights that proper health-risk mitigation measures can be managed to limit the negative effect of the pandemic on sustainable mobility habits.

In order to analyze the shift from travel modes adopted in the pre-Covid scenario and those predicted for the future ones, Sankey diagrams were used (Fig. 9, Fig. 10, Fig. 11 and Fig. 12). This type of diagram shows the flows from the elements on the left side to those on the right side, using flow bands with a width that is proportional to the flow rate. In the present case, the flows are the switches from the past mode to the future one. For the sake of brevity, only the two most significant trip distance ranges were considered: from 2 to 5 km, as the representative interval of urban trips, and from 30 to 50 km, as the reference range for suburban trips. Fig. 9 and Fig. 10 depict the potential shifts for Scenario A, whereas Fig. 11 and Fig. 12 represent flows for Scenario B.

As regards urban trips, Fig. 9 and Fig. 10 show that the largest part of the flows from private car and bike heads towards the same future travel mode. This indicates that few car drivers and bikers are willing to change their travel habits, as the use of these two means is consolidated among respondents. For both scenarios, the diagrams suggest that bike could attract people travelling by car and public transportation. These potential shifts might be due to the several infrastructural interventions in the city of Padova after the first

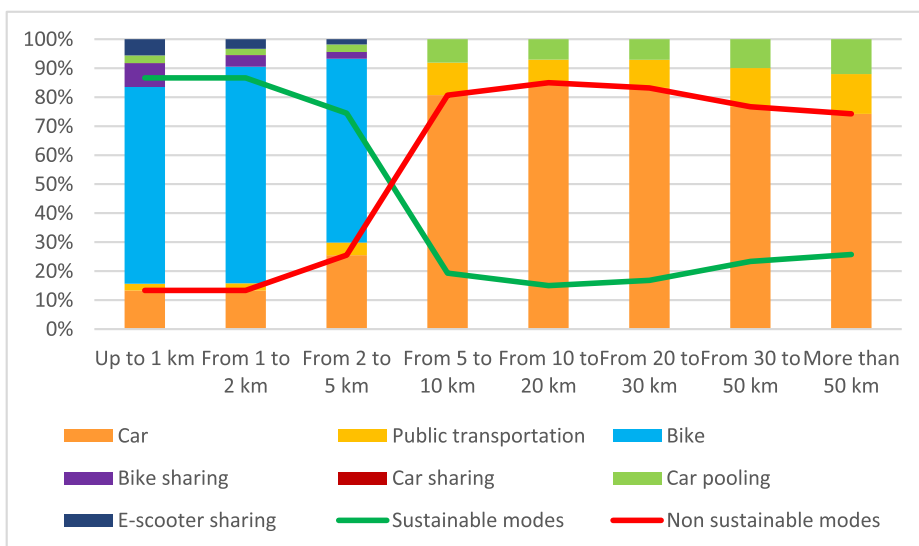


Fig. 7. Modal share for commuting trips in the future Scenario A.



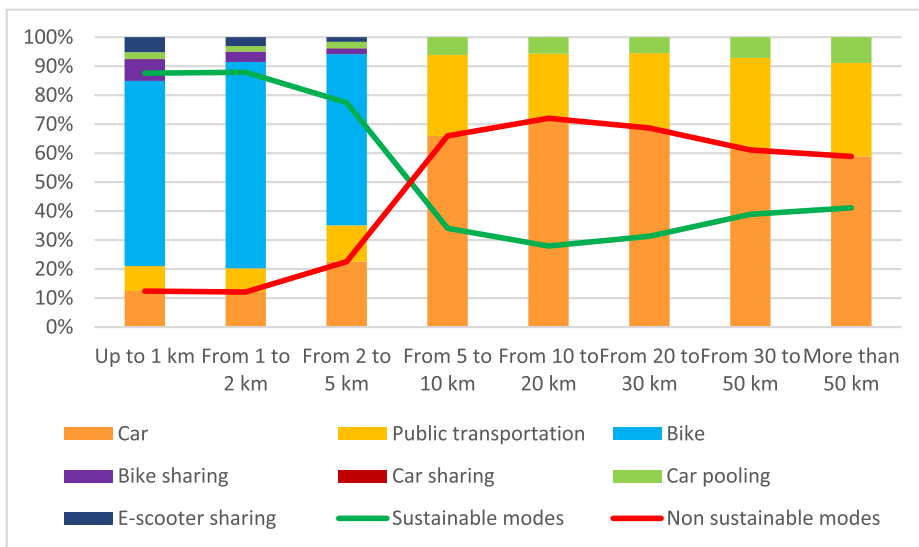


Fig. 8. Modal share for commuting trips in the future Scenario B.

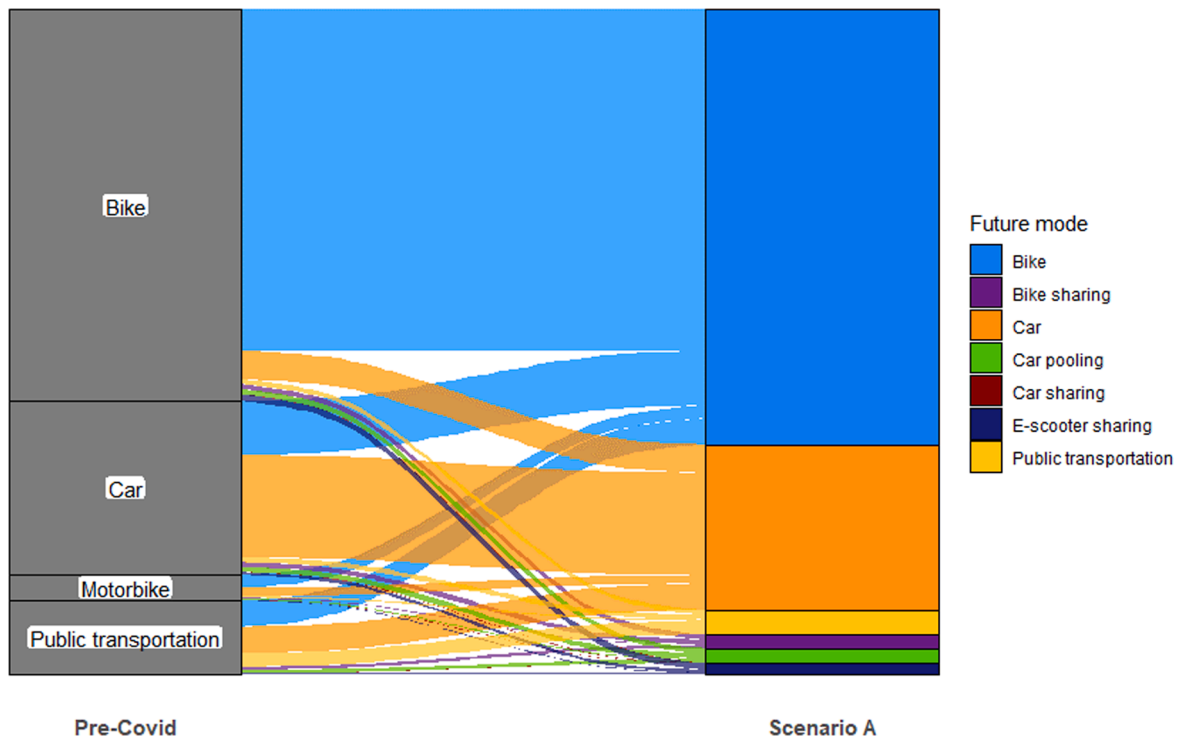


Fig. 9. Sankey diagram for potential shifts from the pre-Covid travel mode (left side) to the future one for Scenario A (right side), considering trip lengths from 2 to 5 km.

national lockdown, where many new and safe cycling paths were realized (Comune di Padova, 2020), highlighting that they are effective in fostering long-term sustainable travel habits. Moreover, the two diagrams point out that public transportation is the travel mode suffering the highest switches towards other alternative means, especially for Scenario A (Fig. 9). In particular, many flows towards private car were observed with potential negative impacts on the environment and livability of urban spaces. However, shifts could occur also towards sustainable modes, like bike, bike sharing and e-scooter sharing, thus mitigating a possible massive adoption of private vehicles. On the other hand, Fig. 10 shows that measures related to Scenario B could induce people who used public transportation in the pre-Covid period to adopt the service even in the future. In addition, flows from bike and car were observed,

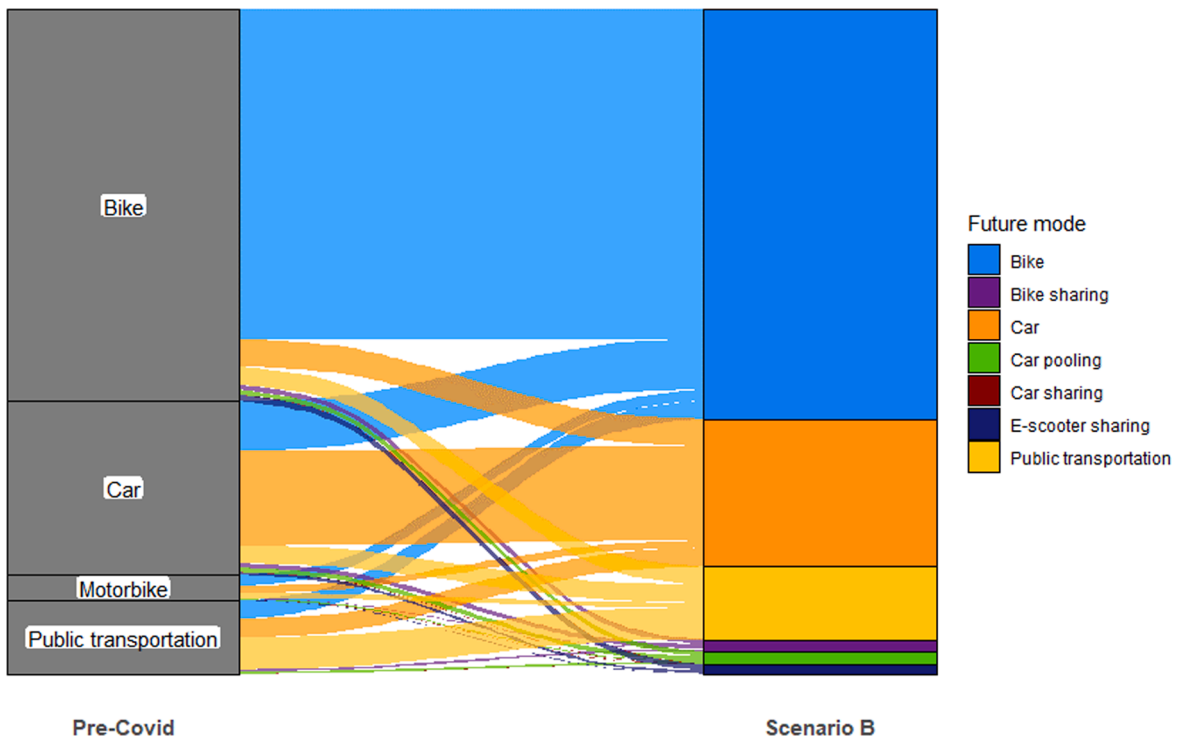


Fig. 10. Sankey diagram for potential shifts from the pre-Covid travel mode (left side) to the future one for Scenario B (right side), considering trip lengths from 2 to 5 km.

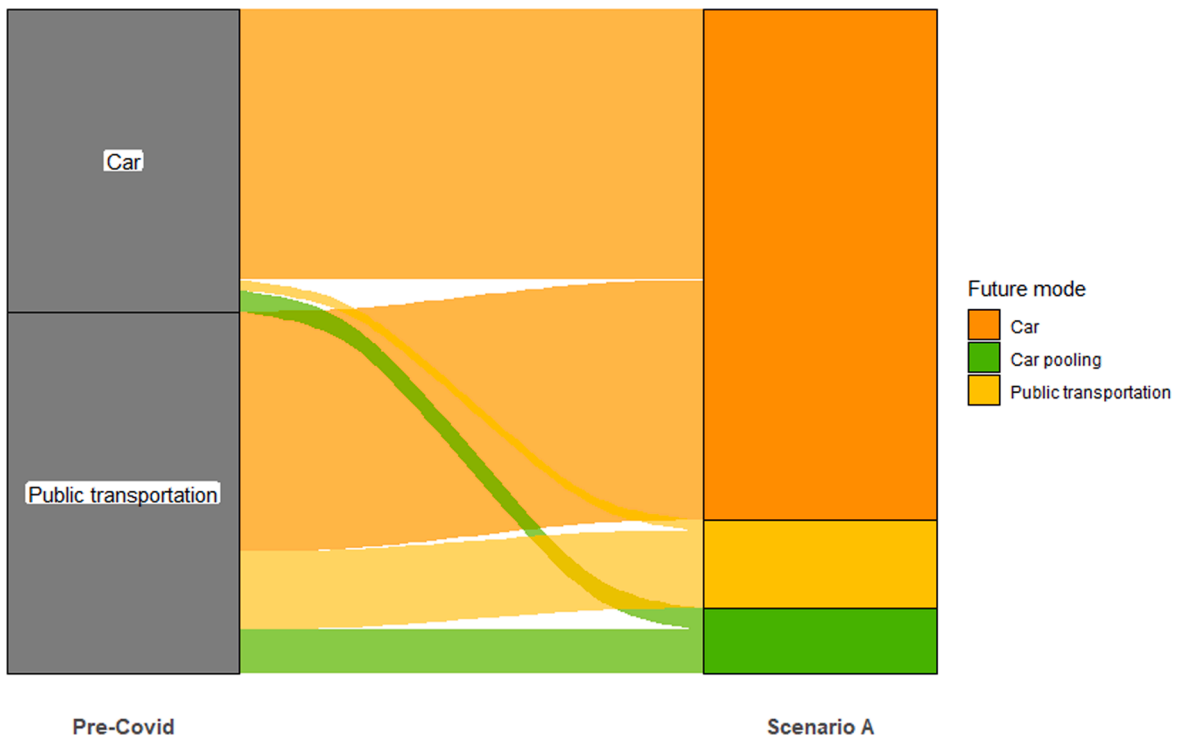
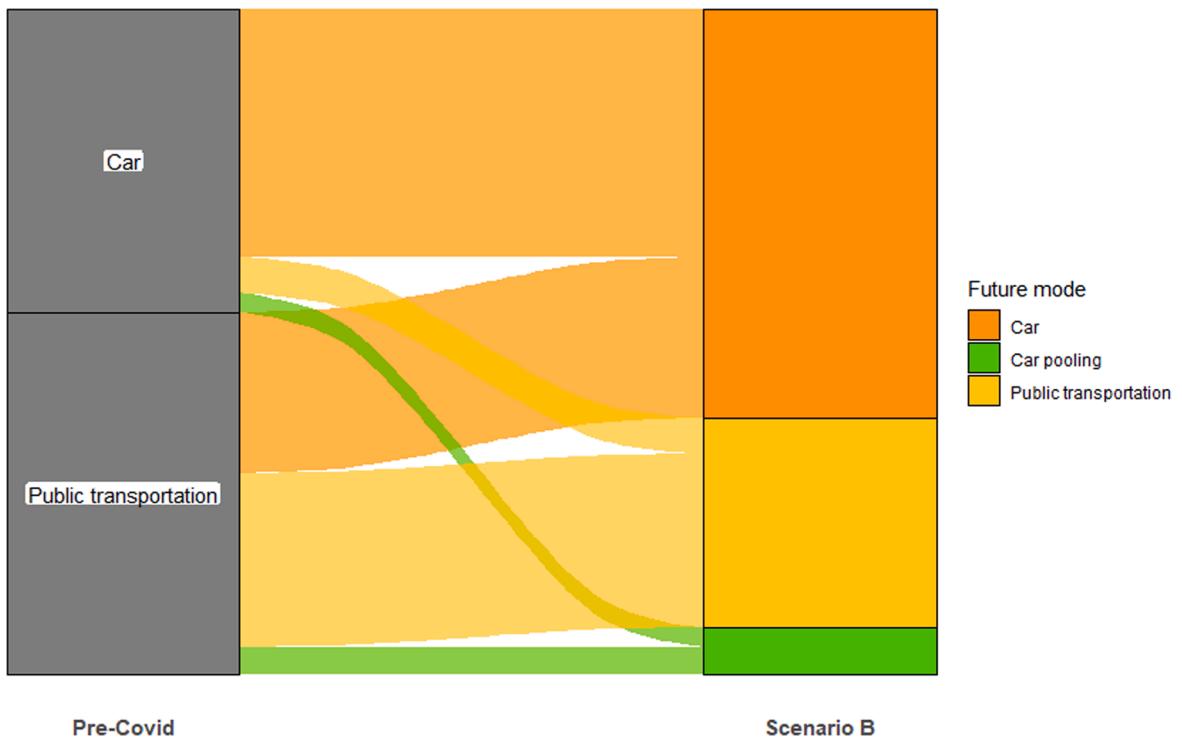


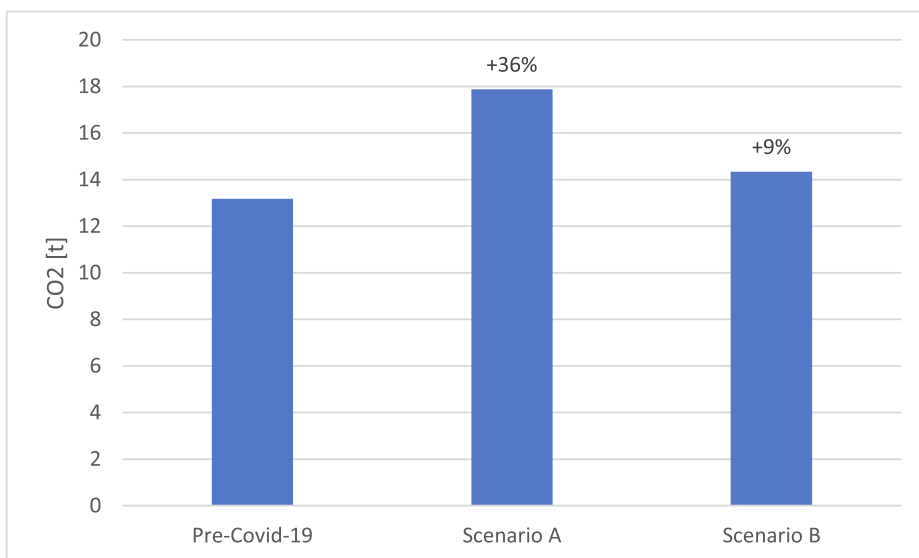
Fig. 11. Sankey diagram for potential shifts from the pre-Covid travel mode (left side) to the future one for Scenario A (right side), considering trip lengths from 30 to 50 km.



**Fig. 12.** Sankey diagram for potential shifts from the pre-Covid travel mode (left side) to the future one for Scenario B (right side), considering trip lengths from 30 to 50 km.

indicating that these interventions could help to attract even users of this non-sustainable travel mode. By observing Fig. 9 and Fig. 10 one can note that both bike sharing and e-scooter sharing could generate future shifts from bike, public transportation, and private car. Although subtracting users from bike could not produce a significant positive effect on the environment, reducing the number of commuting trips on private vehicles is an effective consequence of the diffusion of bike and e-scooter sharing.

Fig. 11 and Fig. 12 report potential flows for suburban commuting trips. Like in the urban context, private car exhibits the lowest number of shifts, highlighting the strong behavioral inertia of car drivers. In Scenario A (Fig. 11), about half of the potential future car trips could be due to a switch from public transportation, this percentage is reduced in Scenario B (Fig. 12), where countermeasures



**Fig. 13.** CO2 emissions generated by commuting trips for the analyzed scenarios.

limiting the diffusion of the virus are considered, although it is still relevant. However, even in this case, many flows towards private car were observed. This suggests that other interventions should be adopted to prevent these shifts, thus promoting sustainable trips from suburban areas. Furthermore, by observing the two figures one can note that car pooling could attract both car drivers and public transportation users. This points out that the diffusion of this service could have both positive and negative impacts on the environment. In particular, on the one hand, by replacing individual trips on private car, car pooling could reduce the number of circulating vehicles; on the other hand, by inducing shifts from public transportation, the number of cars and related emissions could be increased.

The number of commuting trips per week and the probability of adoption of travel modes were used to estimate polluting emissions. In particular, for the weekly working trips of each respondent, pollutants generated by vehicles were quantified by applying emission factors described in section 3.2.3, considering the length of the journeys.

The results of the estimation of CO<sub>2</sub>, NO<sub>x</sub> and PM<sub>10</sub> emissions in each future scenario and during the pre-pandemic period are shown in Fig. 13, Fig. 14 and Fig. 15, respectively. In each figure, percentage variations with respect to the pre-Covid period are reported. By observing these figures, one can note that the new telecommuting habits induced by Covid-19 could have negative environmental consequences. The analysis shows that the number of trips towards workplace could be drastically reduced by the increasing adoption of telework, thus leading to a decrease of circulating vehicles; nevertheless, trips carried out to work in office are mainly performed by using non-sustainable modes, whereas before the pandemic the use of sustainable modes was greater. This new balance could not decrease polluting emissions. In particular, the positive environmental effects of work from home could be nullified by new travel habits. In addition, a negative rebound effect could occur, generating a potential increase in pollutants in the atmosphere. Specifically, Scenario A is the worst case, as expected, with about 35 % more CO<sub>2</sub>, NO<sub>x</sub> and PM<sub>10</sub>, with respect to the pre-pandemic period. Furthermore, these values are low in Scenario B, where risk mitigation measures were applied to induce the adoption of sustainable modes; in this case, CO<sub>2</sub>, NO<sub>x</sub> and PM<sub>10</sub> increase by 9 %, 10 % and 8 %, respectively. This points out that measures addressing travel demand could be effective in reducing the rebound effect of Covid-19 on the environment, due to the travel mode chosen for commuting.

#### 4.5. Policy implications

The findings of the current research can provide useful insights for policy makers and transportation planners to design sustainable travel demand strategies, considering the potential impacts of Covid-19 on mobility and telework. The results of the proposed analysis lead to the following policy implications and useful recommendations for local authorities:

- Covid-19 has induced a high diffusion of telework, inducing changes that could persist in the future, thereby significantly altering mobility and traffic flows. However, while during the early stages of the pandemic its adoption was fostered as a measure to limit the spread of the virus, attention should be paid to its promotion in a post-Covid-19 era, when voluntary work from home for part of the week could lead to shifts from public transportation to private car (mainly because of the perceived contagious risk onboard vehicles, combined with other factors potentially induced by telework, such as the car availability and the low affordability of long-term public transportation subscriptions), with negative consequences for the environment and livability of cities.
- The perceived health-risk of travelling could reduce the use of sustainable travel modes for which people share the trip or the means, like public transportation, bike sharing and car pooling. Therefore, first, effective countermeasures to limit the spread of the

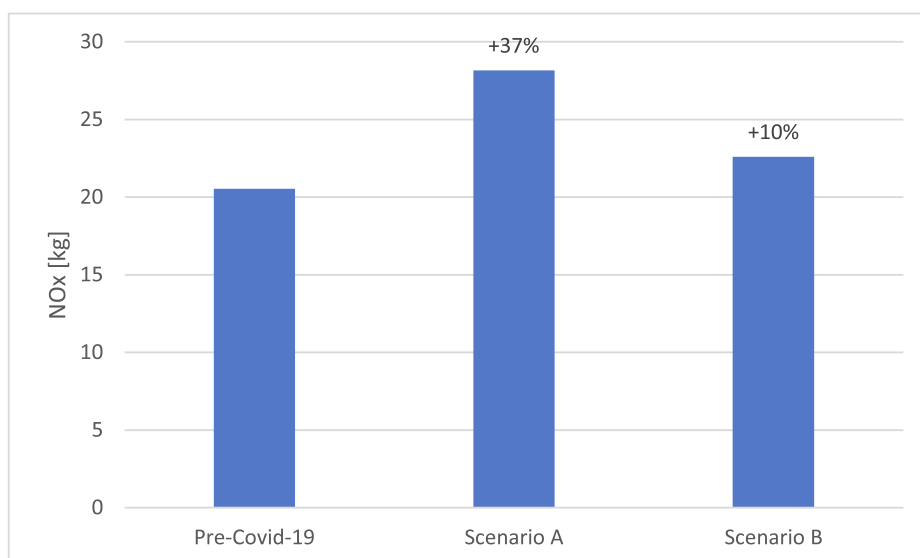


Fig. 14. NO<sub>x</sub> emissions generated by commuting trips for the analyzed scenarios.

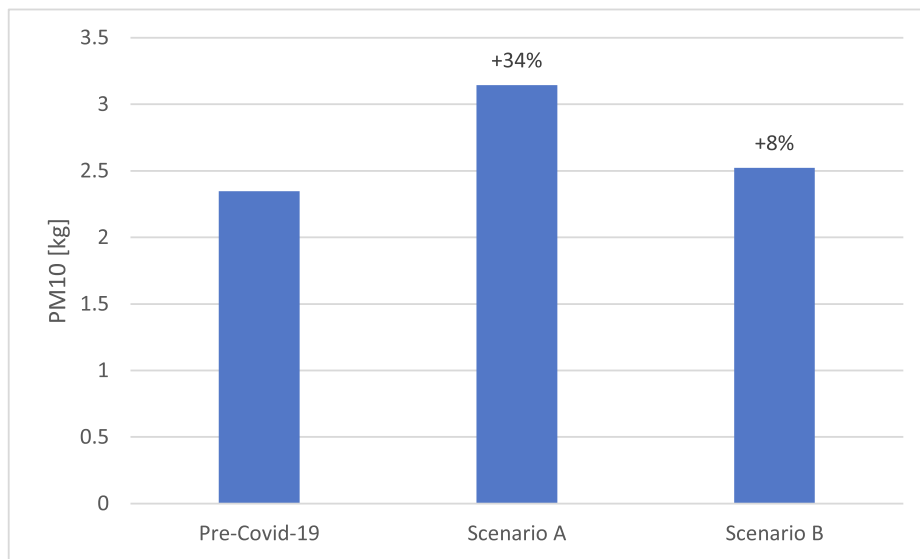


Fig. 15. PM10 emissions generated by commuting trips for the analyzed scenarios.

virus should be identified; then, their implementation coupled with a proper information campaign on their adoption and effectiveness could be useful to reduce the perceived contagious risk related to these modes.

- In order to limit the rebound effect of Covid-19 on the environment due to the travel mode chosen for commuting, proper policy measures should be considered to induce sustainable mobility habits:
  - o As regards urban mobility, the promotion of active modes could mitigate negative externalities on the environment. Local authorities could design new and safe cycling paths, while companies could provide their employees with incentives to subscribe bike and e-scooter sharing services. Through these interventions, trips on private cars can be effectively reduced, even if potential shifts from public transportation could occur.
  - o Concerning suburban trips, the diffusion of car pooling could be an effective intervention to reduce private car trips. For this reason, companies should carry out mobility management policies to design the optimal mix of drivers and passengers, and provide subsidies to foster the adoption of the service among workers. However, on the one hand, by replacing individual trips on private car, car pooling could reduce the number of circulating vehicles; on the other hand, by inducing shifts from public transportation, the number of cars and related emissions could increase.
  - o Specific policies promoting a shift towards sustainable travel modes should be addressed to private car users, as they exhibit the strongest behavioral inertia in changing mobility habits.

## 5. Conclusions

In this paper, the long-term impacts of Covid-19 on work from home and the environment were analyzed. In particular, data from a mobility survey administered to employees at the University of Padova (Italy) were used to calibrate two forecasting models: the former allowed pointing out factors affecting the frequency of telecommuting, whereas the latter was a mode choice model predicting the travel means selected for future trips towards workplaces. Furthermore, the future effects of work from home and travel mode for commuting on the environment induced by the pandemic were estimated.

The results of the first model indicated that Covid-19 has a significant impact on the frequency of telework. Indeed, in addition to factors impacting in normal conditions and highlighted in previous works (such as job occupation, gender, trip distance, opinion about telework), the level of concern about SARS-Cov-2 diffusion and related risk were found to play an important role in the choice to work from home. Moreover, the model pointed out that trips carried out on public transportation before the pandemic are likely to be replaced by telecommuting. This suggests that the sustainability of work from home could be questioned due to Covid-19 effects. Furthermore, the analysis of future potential telecommuting days showed that telework is likely to be adopted with high frequency, despite its very low diffusion in a pre-pandemic era. Therefore, significant long-term changes in daily travel could be expected, since many commuting trips could no longer be carried out.

The mode choice model clearly highlighted that biosecurity concerns could affect the choice of public transportation, bike sharing and car pooling, potentially inducing non-sustainable travel behaviors. In particular, many commuting trips on public transportation could be replaced by private car in the future. In addition, potential risk mitigation measures onboard vehicles were found to have an impact on the choice of travel mode. These results indicate that a proper information campaign on the biosecurity of travelling and specific countermeasures on means could be useful to prompt the adoption of sustainable travel modes. In this way, new potential less sustainable travel habits caused by Covid-19 could be mitigated. The calibrated model was applied to future trips towards the workplace. The results showed that active modes could contribute to maintaining the level of sustainability of trips shorter than 5 km.

However, for longer travel lengths, unlike in the pre-pandemic era, the potential shifts from public transportation could generate a higher number of commuting trips on non-sustainable modes.

Lastly, results from the estimation of polluting emissions of vehicles performing commuting trips indicated that a rebound effect due to Covid-19 on the potential benefits of work from home could occur, since travel habits after the pandemic could be different from those before the pandemic. In particular, the analysis pointed out that the reduction in the number of commuting trips caused by the large diffusion of telework could not be sufficient to mitigate the adoption of non-sustainable travel modes induced by Covid-19. In addition, many shifts from public transportation towards private car could reverse the positive impacts of work from home on the environment. In particular, these switches could be mainly due to the perceived risk of contagious onboard public transportation vehicles, in addition to other potential impacts related to telework adoption for part of the week: a small number of commuting days could reduce the competitiveness of public transportation against private car, because of the low affordability of long-term subscriptions to the service; furthermore, having a reserved car for the full week could no longer be needed. Nevertheless, the estimation of polluting emissions in the scenario with the combination of risk mitigation measures fostering the use of sustainable modes suggested that measures addressing travel demand could be effective in reducing the rebound effect of Covid-19 on telework.

In conclusion, the study results showed that work from home should not be considered an effective policy to reduce polluting emissions, at least while Covid-19 continues to affect travel behavior. Policies supporting telework could not be sufficient to lead to the decarbonization of the transportation sector in a post-pandemic era. On the other hand, encouraging work from home should be combined with other strategies to achieve this urgent goal. In particular, policy makers should pay proper attention not only to measures reducing travel demand, but also to interventions managing travel habits. Specifically, promoting the adoption of less energy-intensity travel means, such as active modes and public transportation, and the use of electric cars could effectively pave the way towards a sustainable mobility era.

### 5.1. Limitations of the work and future research

The present work has some limitations that can be overcome in future research steps. First, the questionnaire was administered in 2020, and, nowadays, responses to SP experiments could be different due to changes in people's perception of health-risk (Barbour et al., 2021), especially with respect to public transportation (Tirachini and Cats, 2020).

Moreover, it is worth highlighting that the presented results are valid for the current composition of the fleet in the area. In particular, at the time of the survey the number of fully electric and hybrid cars was very limited, therefore the diffusion of less-polluting vehicles could change the output and conclusions of the analysis. For this reason, future research will consider the increasing adoption of these sustainable cars.

Furthermore, the research reported in this paper is focused on quantifying the effects of telework on mobility and the environment, induced by Covid-19. Therefore, the estimation of pollutants is limited to transportation, although the energy impact of work from home can stem from other sources, such as residential and office buildings, or the use of ICT (Guerin, 2021; O'Brien and Yazdani Aliabadi, 2020). Moreover, in this paper the potential shift towards non-sustainable modes by people deciding to work from home was considered as an unprecedented rebound effect due to Covid-19, which could mitigate benefits of telecommuting. As highlighted in previous works, other short-term (e.g., increase in non-work trips of the individual or the household members) or long-term (e.g., choice of residential location, or car ownership) rebound effects could occur (O'Brien and Yazdani Aliabadi, 2020; Zhu, 2012). Nevertheless, as in many previous studies (Eldér, 2020; O'Brien and Yazdani Aliabadi, 2020), the adopted travel survey provided limited information to quantify these potential effects since, for example, information at the household level was not available.

The planned research steps can overcome some of the previously reported limitations of the work. A new mobility survey will be administered to the same group of individuals with the following aims: (1) updating the outcomes of the present study, including the mode choice and the frequency of telework; (2) testing if the predictions of the currently presented model were correct; (3) collecting detailed information to improve the estimation accuracy of pollutant emissions; (4) evaluating other types of rebound effects, by including questions about non-work trips of individuals and travel habits of household members; (5) investigating other variables that could affect the choice to work from home (e.g. perceived productivity, or overall well-being).

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### CRediT authorship contribution statement

**Riccardo Ceccato:** Conceptualization, Methodology, Software, Formal analysis, Writing – original draft. **Andrea Baldassa:** Software, Data curation, Writing – original draft. **Riccardo Rossi:** Conceptualization, Project administration. **Massimiliano Gastaldi:** Conceptualization, Writing – review & editing, Supervision.

### Declaration of Competing Interest

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

## References

- Aaditya, B., Rahul, T.M., 2021. Psychological impacts of COVID-19 pandemic on the mode choice behaviour: A hybrid choice modelling approach. *Transp. Policy* 108, 47–58. <https://doi.org/10.1016/j.tranpol.2021.05.003>.
- Abdullah, M., Dias, C., Muley, D., Shahin, M., 2020. Exploring the impacts of COVID-19 on travel behavior and mode preferences. *Transportation Research Interdisciplinary Perspectives* 8, 100255. <https://doi.org/10.1016/j.trip.2020.100255>.
- ACI, 2021. Autoritratto parco veicolare italiano [WWW Document]. URL <https://www.aci.it/laci/studi-e-ricerche/dati-e-statistiche/autoritratto.html>.
- Andreev, P., Salomon, I., Pliskin, N., 2010. Review: State of teleactivities. *Transportation Research Part C: Emerging Technologies* 18, 3–20. <https://doi.org/10.1016/j.trc.2009.04.017>.
- Awad-Núñez, S., Julio, R., Gomez, J., Moya-Gómez, B., González, J.S., 2021. Post-COVID-19 travel behaviour patterns: impact on the willingness to pay of users of public transport and shared mobility services in Spain. *European Transport Research Review* 13. <https://doi.org/10.1186/s12544-021-00476-4>.
- Balbotin, C., Hensher, D.A., Beck, M.J., Giesen, R., Basnak, P., Vallejo-Borda, J.A., Venter, C., 2021. Impact of COVID-19 on the number of days working from home and commuting travel: A cross-cultural comparison between Australia, South America and South Africa. *J. Transp. Geogr.* 96, 103188. <https://doi.org/10.1016/j.jtrangeo.2021.103188>.
- Barbieri, D.M., Lou, B., Passavanti, M., Hui, C., Hoff, I., Lessa, D.A., Sikka, G., Chang, K., Gupta, A., Fang, K., Banerjee, A., Maharaj, B., Lam, L., Ghasemi, N., Naik, B., Wang, F., Mirhosseini, A.F., Naseri, S., Liu, Z., Qiao, Y., Tucker, A., Wijayaratra, K., Peprah, P., Adomako, S., Yu, L., Goswami, S., Chen, H., Shu, B., Hessami, A., Abbas, M., Agarwal, N., Rashidi, T.H., 2021. Impact of COVID-19 pandemic on mobility in ten countries and associated perceived risk for all transport modes. *PLoS ONE* 16, 1–18. <https://doi.org/10.1371/journal.pone.0245886>.
- Barbour, N., Menon, N., Mannering, F., 2021. A statistical assessment of work-from-home participation during different stages of the COVID-19 pandemic. *Transportation Research Interdisciplinary Perspectives* 11, 100441. <https://doi.org/10.1016/j.trip.2021.100441>.
- Beck, M.J., Hensher, D.A., 2020. Insights into the impact of COVID-19 on household travel and activities in Australia – The early days of easing restrictions. *Transp. Policy* 99, 95–119. <https://doi.org/10.1016/j.tranpol.2020.08.004>.
- Beck, M.J., Hensher, D.A., Wei, E., 2020. Slowly coming out of COVID-19 restrictions in Australia: Implications for working from home and commuting trips by car and public transport. *J. Transp. Geogr.* 88. <https://doi.org/10.1016/j.jtrangeo.2020.102846>.
- Berkowicz, R., Winther, M., Ketzler, M., 2006. Traffic pollution modelling and emission data. *Environ. Modell. Software* 21, 454–460. <https://doi.org/10.1016/j.envsoft.2004.06.013>.
- Bierlaire, M., 2020. A short introduction to PandasBiogeme. Technical report TRANSP-OR 200605. Transport and Mobility Laboratory.
- Bin, E., Andruetto, C., Susilo, Y., Pernestål, A., 2021. The trade-off behaviours between virtual and physical activities during the first wave of the COVID-19 pandemic period. *European Transport Research Review* 13. <https://doi.org/10.1186/s12544-021-00473-7>.
- Brant, R., 1990. Assessing Proportionality in the Proportional Odds Model for Ordinal Logistic Regression. *Biometrics* 46, 1171–1178.
- Burón, J.M., López, J.M., Aparicio, F., Martín, M.Á., García, A., 2004. Estimation of road transportation emissions in Spain from 1988 to 1999 using COPERT III program. *Atmos. Environ.* 38, 715–724. <https://doi.org/10.1016/j.atmosenv.2003.10.020>.
- Carrese, S., Cipriani, E., Colombaroni, C., Crisalli, U., Fusco, G., Gemma, A., Isenko, N., Mannini, L., Petrelli, M., Busillo, V., Saracchi, S., 2021. Analysis and monitoring of post-COVID mobility demand in Rome resulting from the adoption of sustainable mobility measures. *Transp. Policy* 111, 197–215. <https://doi.org/10.1016/j.tranpol.2021.07.017>.
- Caulfield, B., 2015. Does it pay to work from home? Examining the factors influencing working from home in the Greater Dublin Area. *Case Studies on Transport Policy* 3, 206–214. <https://doi.org/10.1016/j.cstp.2015.04.004>.
- Ceccato, R., Rossi, R., Gastaldi, M., 2021. Travel demand prediction during covid-19 pandemic: Educational and working trips at the university of padova. *Sustainability (Switzerland)* 13, 1–20. <https://doi.org/10.3390/su13126596>.
- Cerqueira, E.D.V., Motte-Baumvol, B., Chevallier, L.B., Bonin, O., 2020. Does working from home reduce CO2 emissions? An analysis of travel patterns as dictated by workplaces. *Transportation Research Part D: Transport and Environment* 83, 102338. <https://doi.org/10.1016/j.trd.2020.102338>.
- Chicco, A., Diana, M., 2021. Air emissions impacts of modal diversion patterns induced by one-way car sharing: A case study from the city of Turin. *Transportation Research Part D: Transport and Environment* 91, 102685. <https://doi.org/10.1016/j.trd.2020.102685>.
- Choo, S., Mokhtarian, P.L., Salomon, I., 2005. Does telecommuting reduce vehicle-miles traveled? An aggregate time series analysis for the U.S. *Transportation* 32, 37–64. <https://doi.org/10.1007/s11116-004-3046-7>.
- Crowley, F., Daly, H., Doran, J., Ryan, G., Caulfield, B., 2021. The impact of labour market disruptions and transport choice on the environment during COVID-19. *Transp. Policy* 106, 185–195. <https://doi.org/10.1016/j.tranpol.2021.04.008>.
- Currie, G., Jain, T., Aston, L., 2021. Evidence of a post-COVID change in travel behaviour – Self-reported expectations of commuting in Melbourne. *Transportation Research Part A: Policy and Practice* 153, 218–234. <https://doi.org/10.1016/j.tra.2021.09.009>.
- Das, S., Boruah, A., Banerjee, A., Raoniari, R., Nama, S., Maurya, A.K., 2021. Impact of COVID-19: A radical modal shift from public to private transport mode. *Transp. Policy* 109, 1–11. <https://doi.org/10.1016/j.tranpol.2021.05.005>.
- Davison, J., Rose, R.A., Farren, N.J., Wagner, R.L., Murrells, T.P., Carlsaw, D.C., 2021. Verification of a National Emission Inventory and Influence of On-road Vehicle Manufacturer-Level Emissions. *Environ. Sci. Technol.* 55, 4452–4461. <https://doi.org/10.1021/acs.est.0c08363>.
- de Haas, M., Faber, R., Hamersma, M., 2020. How COVID-19 and the Dutch 'intelligent lockdown' change activities, work and travel behaviour: Evidence from longitudinal data in the Netherlands. *Transportation Research Interdisciplinary Perspectives* 6, 100150. <https://doi.org/10.1016/j.trip.2020.100150>.
- Comune di Padova, 2020. La Padova di domani. Mappa verso una nuova normalità.
- Diana, M., 2010. From mode choice to modal diversion: A new behavioural paradigm and an application to the study of the demand for innovative transport services. *Technol. Forecast. Soc. Chang.* 77, 429–441. <https://doi.org/10.1016/j.techfore.2009.10.005>.
- e Silva, J.D.A., Melo, P.C., 2018. Home telework, travel behavior, and land-use patterns: A path analysis of British single-worker households. *Journal of Transport and Land Use* 11, 419–441. <https://doi.org/10.5198/jtlu.2018.1134>.
- Eisenmann, C., Nobis, C., Kolarova, V., Lenz, B., Winkler, C., 2021. Transport mode use during the COVID-19 lockdown period in Germany: The car became more important, public transport lost ground. *Transp. Policy* 103, 60–67. <https://doi.org/10.1016/j.tranpol.2021.01.012>.
- Eldér, E., 2020. Telework and daily travel: New evidence from Sweden. *J. Transp. Geogr.* 86, 102777. <https://doi.org/10.1016/j.jtrangeo.2020.102777>.
- EMISIA, 2021. COPERT - the industry standard emission calculator [WWW Document]. URL <https://www.emisia.com/utilities/copert/>.
- Fontaras, G., Franco, V., Dilara, P., Martini, G., Manfredi, U., 2014. Development and review of Euro 5 passenger car emission factors based on experimental results over various driving cycles. *Sci. Total Environ.* 468–469, 1034–1042. <https://doi.org/10.1016/j.scitotenv.2013.09.043>.
- Glogger, A.F., Zängler, T.W., Karg, G., 2008. The impact of telecommuting on households' travel behaviour, expenditures and emissions. In: Jensen-Butler, C., Sloth, B., Larsen, M.M., Madse, B., Nielsen, O.A. (Eds.), *Road Pricing, the Economy and the Environment. Advances in Spatial Science*. Springer, Berlin Heidelberg, Berlin, pp. 411–425. [https://doi.org/10.1007/978-3-540-77150-0\\_15](https://doi.org/10.1007/978-3-540-77150-0_15).
- Guerin, T.F., 2021. Policies to minimise environmental and rebound effects from telework: A study for Australia. *Environmental Innovation and Societal Transitions* 39, 18–33. <https://doi.org/10.1016/j.eist.2021.01.003>.
- Heilig, M., Mallig, N., Hilgert, T., Kagerbauer, M., Vortisch, P., 2017. Large-Scale Application of a Combined Destination and Mode Choice Model Estimated with Mixed Stated and Revealed Preference Data. *Transportation Research Record: Journal of the Transportation Research Board* 31–40. <https://doi.org/10.3141/2669-04>.
- Helminen, V., Ristimäki, M., 2007. Relationships between commuting distance, frequency and telework in Finland. *J. Transp. Geogr.* 15, 331–342. <https://doi.org/10.1016/j.jtrangeo.2006.12.004>.
- Hensher, D.A., Rose, J.M., Greene, W.H., 2005. *Applied choice analysis: a primer*. Cambridge university Press.
- Hensher, D.A., Beck, M.J., Wei, E., 2021. Working from home and its implications for strategic transport modelling based on the early days of the COVID-19 pandemic. *Transportation Research Part A: Policy and Practice* 148, 64–78. <https://doi.org/10.1016/j.tra.2021.03.027>.

- Hensher, D.A., Beck, M.J., Balbontin, C., 2021a. What does the quantum of working from home do to the value of commuting time used in transport appraisal? *Transportation Research Part A: Policy and Practice* 153, 35–51. <https://doi.org/10.1016/j.tra.2021.09.001>.
- Hensher, D.A., Wei, E., Beck, M.J., Balbontin, C., 2021d. The impact of COVID-19 on cost outlays for car and public transport commuting - The case of the Greater Sydney Metropolitan Area after three months of restrictions. *Transp. Policy* 101, 71–80. <https://doi.org/10.1016/j.tranpol.2020.12.003>.
- Hensher, D.A., Balbontin, C., Beck, M.J., Wei, E., 2022. The impact of working from home on modal commuting choice response during COVID-19: Implications for two metropolitan areas in Australia. *Transportation Research Part A: Policy and Practice* 155, 179–201. <https://doi.org/10.1016/j.tra.2021.11.011>.
- Hiselius, L.W., Arnfalk, P., 2021. When the impossible becomes possible: COVID-19's impact on work and travel patterns in Swedish public agencies. *European Transport Research Review* 13. <https://doi.org/10.1186/s12544-021-00471-9>.
- Isfort, 2021. 18 ° Rapporto sulla mobilità degli italiani - Governare le transizioni per una ripresa sostenibile. Italy, Rome.
- Governo Italiano, 2022. Coronavirus, la normativa vigente [WWW Document]. URL <https://www.governo.it/node/14343> (accessed 1.22.22).
- Jaikumar, R., Shiva Nagendra, S.M., Sivanandan, R., 2017. Modal analysis of real-time, real world vehicular exhaust emissions under heterogeneous traffic conditions. *Transportation Research Part D: Transport and Environment* 54, 397–409. <https://doi.org/10.1016/j.trd.2017.06.015>.
- Jiang, P., Zhong, X., Li, L., 2020. On-road vehicle emission inventory and its spatio-temporal variations in North China Plain. *Environ. Pollut.* 267, 115639 <https://doi.org/10.1016/j.envpol.2020.115639>.
- Kim, S.N., 2017. Is telecommuting sustainable? An alternative approach to estimating the impact of home-based telecommuting on household travel. *International Journal of Sustainable Transportation* 11, 72–85. <https://doi.org/10.1080/15568318.2016.1193779>.
- Kim, K., 2021. Impact of COVID-19 on Usage Patterns of a Bike-Sharing System: Case Study of Seoul. *Journal of Transportation Engineering, Part A: Systems* 147, 05021006. <https://doi.org/10.1061/jtepbs.0000591>.
- Kim, S.N., Choo, S., Mokhtarian, P.L., 2015. Home-based telecommuting and intra-household interactions in work and non-work travel: A seemingly unrelated censored regression approach. *Transportation Research Part A: Policy and Practice* 80, 197–214. <https://doi.org/10.1016/j.tra.2015.07.018>.
- Koenig, B.E., Henderson, D.K., Mokhtarian, P.L., 1996. The travel and emissions impacts of telecommuting for the State of California Telecommuting Pilot Project. *Transportation Research Part C: Emerging Technologies* 4, 13–32. [https://doi.org/10.1016/0968-090X\(95\)00020-J](https://doi.org/10.1016/0968-090X(95)00020-J).
- Kousoulidou, M., Ntziachristos, L., Gkeivanidis, S., Samaras, Z., Franco, V., Dilara, P., 2010. Validation of the COPERT road emission inventory model with real-use data, in: Kousoulidou (2010) Validation of the COPERT Road Emission Inventory Model with Real-Use Data.
- Krause, J., Thiel, C., Tsokolis, D., Samaras, Z., Rota, C., Ward, A., Prenninger, P., Coosemans, T., Neugebauer, S., Verhoeve, W., 2020. EU road vehicle energy consumption and CO2 emissions by 2050 – Expert-based scenarios. *Energy Policy* 138. <https://doi.org/10.1016/j.enpol.2019.111224>.
- Lang, J., Zhou, Y., Cheng, S., Zhang, Y., Dong, M., Li, S., Wang, G., Zhang, Y., 2016. Unregulated pollutant emissions from on-road vehicles in China, 1999–2014. *Sci. Total Environ.* 573, 974–984. <https://doi.org/10.1016/j.scitotenv.2016.08.171>.
- Lejri, D., Can, A., Schiper, N., Leclercq, L., 2018. Accounting for traffic speed dynamics when calculating COPERT and PHEM pollutant emissions at the urban scale. *Transportation Research Part D: Transport and Environment* 63, 588–603. <https://doi.org/10.1016/j.trd.2018.06.023>.
- Li, A., Zhao, P., Haitao, H., Mansourian, A., Axhausen, K.W., 2021. How did micro-mobility change in response to COVID-19 pandemic? A case study based on spatial-temporal-semantic analytics. *Comput. Environ. Urban Syst.* 90, 101703 <https://doi.org/10.1016/j.compenvurbys.2021.101703>.
- Liu, Z., Stern, R., 2021. Quantifying the Traffic Impacts of the COVID-19 Shutdown. *Journal of Transportation Engineering, Part A: Systems* 147, 04021014. <https://doi.org/10.1061/jtepbs.0000527>.
- Mokhtarian, P.L., Handy, S.L., Salomon, I., 1995. Methodological issues in the estimation of the travel, energy, and air quality impacts of telecommuting. *Transp. Res. Part A* 29, 283–302. [https://doi.org/10.1016/0965-8564\(94\)00029-A](https://doi.org/10.1016/0965-8564(94)00029-A).
- Mokhtarian, P.L., Bagley, M.N., Salomon, I., 1998. The impact of gender, occupation, and presence of children on telecommuting motivations and constraints. *Journal of the American Society for Information Science* 49, 1115–1134. [https://doi.org/10.1002/\(SICI\)1097-4571\(1998\)49:12<1115::AID-ASIT7>3.0.CO;2-Y](https://doi.org/10.1002/(SICI)1097-4571(1998)49:12<1115::AID-ASIT7>3.0.CO;2-Y).
- Mokhtarian, P.L., Collantes, G.O., Gertz, C., 2004. Telecommuting, residential location, and commute-distance traveled: Evidence from State of California employees. *Environment and Planning A* 36, 1877–1897. <https://doi.org/10.1068/a36218>.
- Molloy, J., Schatzmann, T., Schoeman, B., Tchervenkov, C., Hintermann, B., Axhausen, K.W., 2021. Observed impacts of the Covid-19 first wave on travel behaviour in Switzerland based on a large GPS panel. *Transp. Policy* 104, 43–51. <https://doi.org/10.1016/j.tranpol.2021.01.009>.
- Mouratidis, K., Papagiannakis, A., 2021. COVID-19, internet, and mobility: The rise of telework, telehealth, e-learning, and e-shopping. *Sustainable Cities and Society* 74, 103182. <https://doi.org/10.1016/j.scs.2021.103182>.
- Mouratidis, K., Peters, S., van Wee, B., 2021. Transportation technologies, sharing economy, and teleactivities: Implications for built environment and travel. *Transportation Research Part D: Transport and Environment* 92, 102716. <https://doi.org/10.1016/j.trd.2021.102716>.
- Najmi, A., Nazari, S., Safarighouzhdi, F., Miller, E.J., MacIntyre, R., Rashidi, T.H., 2021. Easing or tightening control strategies: determination of COVID-19 parameters for an agent-based model. *Transportation*. <https://doi.org/10.1007/s11116-021-10210-7>.
- Nayak, S., Pandit, D., 2021. Potential of telecommuting for different employees in the Indian context beyond COVID-19 lockdown. *Transp. Policy* 111, 98–110. <https://doi.org/10.1016/j.tranpol.2021.07.010>.
- Nelson, P., Safirova, E., Walls, M., 2007. Telecommuting and environmental policy: Lessons from the ecommute program. *Transportation Research Part D: Transport and Environment* 12, 195–207. <https://doi.org/10.1016/j.trd.2007.01.011>.
- Nguyen, M.H., 2021. Factors influencing home-based telework in Hanoi (Vietnam). During and After the COVID-19 era. *Transportation*. Springer, US <https://doi.org/10.1007/s11116-021-10169-5>.
- Ntziachristos, L., Gkatzoflias, D., Kouridis, C., Samaras, Z., 2009. COPERT: A European Road Transport Emission Inventory Model. *Information Technologies in Environmental Engineering* 491–504. <https://doi.org/10.1007/978-3-540-88351-7>.
- Ntziachristos, L., Samaras, Z., Kouridis, C., Samaras, G., Hassel, D., Mellios, G., McCrae, I., Hickman, J., Zierock, H., Keller, M., Rexeis, M., Andre, M., Winther, M., Pastramas, N., Boulter, P., Katsis, P., Joumard, R., Rijkeboer, R., Geivanidis, S., 2019. EMEP/EEA Air pollutant emission inventory guidebook. <https://doi.org/10.2800/293657>.
- O'Brien, W., Yazdani Aliabadi, F., 2020. Does telecommuting save energy? A critical review of quantitative studies and their research methods. *Energy Build.* 225, 110298 <https://doi.org/10.1016/j.enbuild.2020.110298>.
- O'Keefe, P., Caulfield, B., Brazil, W., White, P., 2016. The impacts of telecommuting in Dublin. *Research in Transportation Economics* 57, 13–20. <https://doi.org/10.1016/j.retrec.2016.06.010>.
- OECD, 2020. Cities Policy Responses.
- OECD, 2021. Teleworking in the COVID-19 pandemic: Trends and prospects.
- Olde Kalter, M.J., Geurs, K.T., Wismans, L., 2021. Post COVID-19 teleworking and car use intentions. Evidence from large scale GPS-tracking and survey data in the Netherlands. *Transportation Research Interdisciplinary Perspectives* 12. <https://doi.org/10.1016/j.trip.2021.100498>.
- Ong, H.C., Mahlia, T.M.I., Masjuki, H.H., 2011. A review on emissions and mitigation strategies for road transport in Malaysia. *Renew. Sustain. Energy Rev.* 15, 3516–3522. <https://doi.org/10.1016/j.rser.2011.05.006>.
- Ortuzar, D., Willumsen, L.G., 2011. MODELLING TRANSPORT 4th Edition.
- Ozbilen, B., Wang, K., Akar, G., 2021. Revisiting the impacts of virtual mobility on travel behavior: An exploration of daily travel time expenditures. *Transportation Research Part A: Policy and Practice* 145, 49–62. <https://doi.org/10.1016/j.tra.2021.01.002>.
- Pawar, D.S., Yadav, A.K., Akolekar, N., Velaga, N.R., 2020. Impact of physical distancing due to novel coronavirus (SARS-CoV-2) on daily travel for work during transition to lockdown. *Transportation Research Interdisciplinary Perspectives* 7, 100203. <https://doi.org/10.1016/j.trip.2020.100203>.
- Pawar, D.S., Yadav, A.K., Choudhary, P., Velaga, N.R., 2021. Modelling work- and non-work-based trip patterns during transition to lockdown period of COVID-19 pandemic in India. *Travel Behaviour and Society* 24, 46–56. <https://doi.org/10.1016/j.tbs.2021.02.002>.
- Pérez, M.P., Sánchez, A.M., De Luis Carnicer, M.P., Jiménez, M.J.V., 2004. The environmental impacts of teleworking: A model of urban analysis and a case study. *Management of Environmental Quality: An International Journal* 15, 656–671. <https://doi.org/10.1108/1477830410560728>.



- Pirdavani, A., Bellemans, T., Brijs, T., Kochan, B., Wets, G., 2014. Assessing the road safety impacts of a teleworking policy by means of geographically weighted regression method. *J. Transp. Geogr.* 39, 96–110. <https://doi.org/10.1016/j.jtrangeo.2014.06.021>.
- Politis, I., Georgiadis, G., Nikolaidou, A., Kopsacheilis, A., Fyrogenis, I., Sdoukopoulos, A., Verani, E., Papadopoulos, E., 2021a. Mapping travel behavior changes during the COVID-19 lockdown: a socioeconomic analysis in Greece. *European Transport Research Review* 13. <https://doi.org/10.1186/s12544-021-00481-7>.
- Politis, I., Georgiadis, G., Papadopoulos, E., Fyrogenis, I., Nikolaidou, A., Kopsacheilis, A., Sdoukopoulos, A., Verani, E., 2021b. COVID-19 lockdown measures and travel behavior: The case of Thessaloniki. Greece. *Transportation Research Interdisciplinary Perspectives* 10, 100345. <https://doi.org/10.1016/j.trip.2021.100345>.
- Rossi, R., Ceccato, R., Gastaldi, M., 2020. Effect of road traffic on air pollution. Experimental evidence from covid-19 lockdown. *Sustainability (Switzerland)* 12, 1–17. <https://doi.org/10.3390/su12218984>.
- Rubin, O., Nikolaeva, A., Nello-Deakin, S., te Brömmelstroet, M., 2020. What can we learn from the COVID-19 pandemic about how people experience working from home and commuting? University of Amsterdam, Centre for Urban Studies.
- RUS, 2021. White Paper 2021 - Le attività del Gruppo di lavoro Mobilità della Rete delle Università italiane per lo sviluppo sostenibile.
- Scorrano, M., Danielis, R., 2021. Active mobility in an Italian city: Mode choice determinants and attitudes before and during the Covid-19 emergency. *Research in Transportation Economics* 86, 101031. <https://doi.org/10.1016/j.retrec.2021.101031>.
- Shabanpour, R., Golshani, N., Tayarani, M., Auld, J., Mohammadian, A., (Kouros), 2018. Analysis of telecommuting behavior and impacts on travel demand and the environment. *Transportation Research Part D: Transport and Environment* 62, 563–576. <https://doi.org/10.1016/j.trd.2018.04.003>.
- Shakibaei, S., de Jong, G.C., Alpkökin, P., Rashidi, T.H., 2021. Impact of the COVID-19 pandemic on travel behavior in Istanbul: A panel data analysis. *Sustainable Cities and Society* 65. <https://doi.org/10.1016/j.scs.2020.102619>.
- Shibayama, T., Sandholzer, F., Laa, B., Brezina, T., 2021. Impact of covid-19 lockdown on commuting: A multi-country perspective. *European Journal of Transport and Infrastructure Research* 21, 70–93. <https://doi.org/10.18757/ejtir.2021.21.1.5135>.
- Shortall, R., Mouter, N., Van Wee, B., 2021. COVID-19 passenger transport measures and their impacts. *Transport Reviews* 1–26. <https://doi.org/10.1080/01441647.2021.1976307>.
- Smit, R., Ntziachristos, L., Boulter, P., 2010. Validation of road vehicle and traffic emission models - A review and meta-analysis. *Atmos. Environ.* 44, 2943–2953. <https://doi.org/10.1016/j.atmosenv.2010.05.022>.
- Thombre, A., Agarwal, A., 2021. A paradigm shift in urban mobility: Policy insights from travel before and after COVID-19 to seize the opportunity. *Transp. Policy* 110, 335–353. <https://doi.org/10.1016/j.tranpol.2021.06.010>.
- Tirachini, A., Cats, O., 2020. COVID-19 and public transportation: Current assessment, prospects, and research needs. *Journal of Public Transportation* 22, 1–34. <https://doi.org/10.5038/2375-0901.22.1.1>.
- Train, K.E., 2003. Discrete choice methods with simulation. *Discrete Choice Methods with Simulation* 9780521816, 1–334. <https://doi.org/10.1017/CBO9780511753930>.
- Train, K., Wilson, W.W., 2008. Estimation on stated-preference experiments constructed from revealed-preference choices. *Transportation Research Part B: Methodological* 42, 191–203. <https://doi.org/10.1016/j.trb.2007.04.012>.
- van Lier, T., de Witte, A., Macharis, C., 2014. How worthwhile is teleworking from a sustainable mobility perspective? The case of Brussels Capital region. *European Journal of Transport and Infrastructure Research* 14, 244–267. <https://doi.org/10.18757/ejtir.2014.14.3.3033>.
- Wang, D., He, B.Y., Gao, J., Chow, J.Y.J., Ozbay, K., Iyer, S., 2021a. Impact of COVID-19 behavioral inertia on reopening strategies for New York City transit. *Int. J. Transp. Sci. Technol.* 10, 197–211. <https://doi.org/10.1016/j.ijst.2021.01.003>.
- Wang, D., Tayarani, M., Yueshuai He, B., Gao, J., Chow, J.Y.J., Oliver Gao, H., Ozbay, K., 2021b. Mobility in post-pandemic economic reopening under social distancing guidelines: Congestion, emissions, and contact exposure in public transit. *Transportation Research Part A: Policy and Practice* 153, 151–170. <https://doi.org/10.1016/j.tra.2021.09.005>.
- Wheeler, B., 2019. R Package AlgDesign. The R project for statistical computing.
- Williams, R., 2016. Understanding and interpreting generalized ordered logit models. *Journal of Mathematical Sociology* 40, 7–20. <https://doi.org/10.1080/0022250X.2015.1112384>.
- Williams, R., 2006. Generalized ordered logit/partial proportional odds models for ordinal dependent variables. *Stata Journal* 6, 58–82. <https://doi.org/10.1177/1536867x0600600104>.
- Zafri, N.M., Khan, A., Jamal, S., Alam, B.M., 2021. Impacts of the covid-19 pandemic on active travel mode choice in bangladesh: A study from the perspective of sustainability and new normal situation. *Sustainability (Switzerland)* 13. <https://doi.org/10.3390/su13126975>.
- Zhang, Y., Fricker, J.D., 2021. Quantifying the impact of COVID-19 on non-motorized transportation: A Bayesian structural time series model. *Transp. Policy* 103, 11–20. <https://doi.org/10.1016/j.tranpol.2021.01.013>.
- Zhang, J., Hayashi, Y., Frank, L.D., 2021a. COVID-19 and transport: Findings from a world-wide expert survey. *Transp. Policy* 103, 68–85. <https://doi.org/10.1016/j.tranpol.2021.01.011>.
- Zhang, N., Jia, W., Wang, P., Dung, C.H., Zhao, P., Leung, K., Su, B., Cheng, R., Li, Y., 2021b. Changes in local travel behaviour before and during the COVID-19 pandemic in Hong Kong. *Cities* 112, 103139. <https://doi.org/10.1016/j.cities.2021.103139>.
- Zhang, R., Zhang, J., 2021. Long-term pathways to deep decarbonization of the transport sector in the post-COVID world. *Transp. Policy* 110, 28–36. <https://doi.org/10.1016/j.tranpol.2021.05.018>.
- Zhu, P., 2012. Are telecommuting and personal travel complements or substitutes? *Annals of Regional Science* 48, 619–639. <https://doi.org/10.1007/s00168-011-0460-6>.
- Zhu, J., Fan, Y., 2018. Daily travel behavior and emotional well-being: Effects of trip mode, duration, purpose, and companionship. *Transportation Research Part A: Policy and Practice* 118, 360–373. <https://doi.org/10.1016/j.tra.2018.09.019>.
- Zhu, P., Mason, S.G., 2014. The impact of telecommuting on personal vehicle usage and environmental sustainability. *Int. J. Environ. Sci. Technol.* 11, 2185–2200. <https://doi.org/10.1007/s13762-014-0556-5>.