Research in Transportation Business & Management 53 (2024) 101091

Contents lists available at ScienceDirect

Research in Transportation Business & Management

journal homepage: www.elsevier.com/locate/rtbm

University commuting during the COVID-19 pandemic: Changes in travel behaviour and mode preferences

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ARTICLE INFO

Keywords:
Mobility behaviour
College commuting
Discrete choice model
Pandemic consequences
Public transportation

ABSTRACT

One prominent change induced by the COVID-19 pandemic concerns the worldwide use of public transportation for commuting purposes. This study focused on university commuting in Italy by examining the propensity to change transport modes under different infection risk scenarios. Data were collected in 2020 through an online survey of college mobility conducted by the Italian University Network for Sustainable Development. Asking the respondents to consider both a pessimistic and an optimistic scenario, with respect to the risk odds of being infected, we followed a two-step approach to study the prospective travel habits of college users. First, we tested a logit model to estimate the propensity to abandon one's pre-COVID-19 commuting mode. Then, we investigated the factors influencing the choice of switching from public transportation to either cars or active modes by estimating a multinomial logit model. By exploiting the novelty of considering two risk scenarios, this study highlighted that, especially in the pessimistic case, the change to active modes was constrained by spatial aspects in favour of motorized vehicles. From a policy perspective, this COVID-19-based natural experiment advocates transportation authorities taking effective actions to ensure that, in case of emergencies, a modal shift would not benefit more-polluting transport means.

1. Introduction

With the spread of the COVID-19 pandemic, policy makers implemented different control and prevention measures to reduce the health impacts of the virus and "flatten the curve" of infection. While these measures were different according to the specific geographical and cultural context, local governance, and socioeconomic conditions (Hörcher, Singh, & Graham, 2022), all of them have drastically affected our way of life. Although almost three years have passed from the start of virus diffusion, some lifestyle changes are still evident; the actual perception is that these changes could become permanent. Among these changes, mobility seems to take on a key role. Since mobility is closely tied to regular habits and reproducible patterns (Bohte, Maat, & van Wee, 2009), even temporary restrictive measures can produce permanent behavioural effects on one's daily life and changes in structural transportation modes (Müggenburg, Busch-Geertsema, & Lanzendorf, 2015; Schoenduwe, Mueller, Peters, & Lanzendorf, 2015). Restrictive measures of social distancing and the individual fear of contracting the virus strongly affected everyday life, decreasing the level of physical activity of almost everyone, including young people and university students (Bertrand et al., 2021; López-Valenciano, Suárez-Iglesias, Sanchez-Lastra, & Ayán, 2021). This decrease also had strong consequences for systematic mobility, impacting both the volume and the transport modal share in commuting to work and school (Abdullah, Ali, Aslam, Javid, & Hussain, 2020; Abdullah, Dias, Muley, & Shahin, 2020; Charreire et al., 2021; Hörcher et al., 2022; Myftiu, 2022). One of the most negatively affected modes was public transport, which lost a considerable share of passengers in favour of driving cars, walking, and cycling in different countries (Abdullah, Ali, et al., 2020, Abdullah, Dias, et al., 2020; Bucsky, 2020; Campisi, Nahiduzzaman, Nikiforiadis, Stamatiadis, & Basbas, 2022; ISFORT, 2021; Kwok et al., 2020; Zhang, 2020). Since the virus is still looming and the future occurrence of similar pandemic events is quite likely, further research efforts are needed to better understand which changes can be considered transitional, i.e., ending with the total demise of a pandemic, and which others will remain in the medium-long term, thereby becoming structural. The

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https://doi.org/10.1016/j.rtbm.2023.101091
Received 21 March 2023; Received in revised form 19 December 2023; Accepted 19 December 2023
Available online 5 January 2024

present paper aims to contribute to the literature that examines the characteristics of these changes by analysing the behaviour of university commuters and focusing on transport mode choice in two different pandemic scenarios. In particular, we aim to answer a main research question first and a derived research question second. First, the intention is to study the consistency, direction, and drivers of the propensity to change the pre-COVID-19 commuting mode in one of the countries most affected by the virus, i.e., Italy. Second, given the literature findings that highlight—as described in the next section—a significant transition from public transportation towards private motorized vehicles or active mobility (biking, walking), the current paper focuses on the variables most affecting this transition. Obviously, the *direction* and determinants of the possible transport modal shifts are also crucial to understanding the outcome in terms of sustainability since not all modes have the same impact on the environment and human health. The findings of the current paper could hopefully provide useful insights to policymakers, municipalities and transport companies that have to deal with these changes daily by planning and implementing mobility services targeted to meet the new commuters' needs or appropriate strategies for work organization (e.g., the calibration of smart working schemes) and work scheduling; such changes are also aimed at mitigating traffic congestion and reducing the environmental impact of transportation.

The current analysis is based on a large sample of 114,000 observations, composed of students (79.4%), faculty staff (11%) and technical-administrative staff (9.6%) of 51 different universities located in different Italian towns. Most answers (approximately 69%), however, come from northern Italian universities, which are located in the area that was most affected by the pandemic, especially during the first wave in the spring of 2020. These data were collected through a national online survey entitled “University mobility in the time of COVID-19,” which was conducted from July to September 2020 by the Italian Network of Universities for Sustainable Development (RUS, 2021). We are confident that the large sample size and its heterogeneity in terms of age, gender, and other characteristics—since we considered both university students and staff—could produce more statistically supported evidence, thereby helping to either confirm or confute the findings of other studies focused on smaller and homogeneous samples and/or conducted in a very specific geographical area. To answer the research questions, we collected information on personal characteristics, mobility capital, prepandemic home-university travel habits, and the propensity to adopt sustainable and multiple modes of travel. Moreover, the respondents who answered during the period spanning from July to September 2020 were asked to express their prospective travel choices[1] for the incoming academic year (2020−2021). Since at the time of the survey, the evolution of the pandemic was hard to predict and no vaccine was available yet, we submitted two alternative pandemic scenarios to the respondents, namely, an optimistic scenario assuming a significant reduction in the risk of infection vs. a pessimistic scenario implying a higher risk; we then asked them to separately state their likely travel choices. This two-scenario approach allows us to analyse both commuters' behaviour changes in relation to different levels of risk perception, as well as the drivers of these changes, thereby making an innovative contribution to the literature. In fact, to the best of our knowledge, this is the first contribution that investigates different perspective contexts by asking the interviewees to describe their choices with respect to the changing situation and the related perceived level of contagion risk.

For the first research question, we used a logit model, considering the intention to change one's prevailing pre-COVID-19 university commuting mode (i.e., the one that covers the longer distance in the case of a multimodal journey) as the dependent variable in each of the two perspective scenarios. For the second research question, we restricted our attention to the subsample using public transportation before the pandemic to analyse the main drivers of the modal shifts. A multinomial logistic model was used, setting the dependent variable as the choice to keep using public transportation or switch to active modes or private motor vehicles, again considering the two alternative pandemic scenarios.

Although the results of the present analysis, which is based on only university communities, can only be extended to the general population with caution, its relevance lies in the involvement of the whole Italian tertiary higher education system. Individual universities very often constitute the largest organized communities in the urban contexts in which they are located, generating very large volumes of mobility that have a significant impact on the entire urban transportation system and require coherent management.

The paper is organized as follows. Section 2 presents a literature review aimed at shedding light on the various related studies conducted thus far. Sections 3 and 4 describe the structure of the survey and data collection process and the methods used to answer the research questions, respectively. Section 5 highlights the results obtained from the analyses, while Section 6 discusses them with respect to evidence from the literature. Section 7 draws some conclusions and policy implications and outlines the limitations of the paper, suggesting issues for further research.

2. Literature review

This study contributes to two main strands of literature. The first strand, more generally, addresses the impact of viral outbreaks on mobility choices and habits. Since the virus is still circulating and other pandemics may follow in the future, it is important to enrich the level of knowledge about the related impacts on systematic mobility and, consequently, on the environment and health, considering the risk perception of travellers. In the literature, it is possible to find both analyses on the impact of previous pandemics (i.e., SARS in the early 2000s) and more recent studies about the effects of COVID-19 on mobility. The SARS impact has been investigated both locally (Kim, Cheon, Choi, Joh, & Lee, 2017) and internationally (Fenichel, Kuminoff, & Chowell, 2013; Liu, Moss, & Zhang, 2010; Wen, Huimin, & Kavanaugh, 2005), highlighting that travel and mobility remarkably decrease during pandemics and that public transportation is one of the most affected means of travel. For example, Sadique et al. (2007) conducted a survey on SARS and influenza risk perception in Europe and Asia, reporting that approximately 75% of the participants avoided taking public transportation to evade crowded environments or unsafe situations. Therefore, people take precautionary action to reduce their level of perceived risk, in line with what is underlined by protection motivation theory (Rogers, 1975). Looking at the actual impact of public transportation on health conditions, Troko et al. (2011) found a statistically significant association between acute respiratory infection and bus or tram use in the five days before the onset of symptoms. Given the transmission mechanism of COVID-19, increasing the distance between people emerged as a key strategy for mitigating the spread of the virus; thus, mobility restrictions were inevitable. Consequently, many countries decided to issue drastic measures, such as the early lockdown in Wuhan (China), while other nearby countries, such as Japan or Vietnam, largely relied on self-restriction, including teleworking and avoiding unnecessary travel (Nguyen & Pojani, 2022; Tashiro & Shaw, 2020). Based on an empirical analysis conducted in the US and many other countries, Warren & Skillman (2020) reported a sharp decline in mobility due to the fear of COVID-19 and to government restrictions aimed at mitigating its spread. In a study conducted by Barbieri, Lou,

[1] Notice that the questions asked regarding possible changes in travel mode made after COVID-19 were not *retrospective*, i.e., related to the choices made during the first wave of the pandemic in the spring of 2020; rather, they were concerned with the prospective travel *intentions* for the period following the survey (autumn-winter 2020/21). During the first wave of the pandemic, in fact, the health situation in Italy was so severe that it required a strict lockdown, with a complete shift to online work in tertiary education.

Passavanti, et al. (2021), the world as a whole showed a strong reduction in all means of transportation due to COVID-19. In severely affected cities, mobility decreased up to 90% (Abdullah, Dias, et al., 2020). In Italy, the volume of travel for all of 2020 registered a significant contraction compared to that for 2019, and this volume appears to have only partially recovered in 2021 (ISFORT, 2021); only in 2022 did traffic return to levels comparable to those seen in previous years, especially in terms of the number of cars. Italy witnessed a significant impact on the demand for public transportation services. The ISFORT (2021) report highlights how 2020 was a year of deep crisis for public transportation due to social distancing and fear of infection, which halved its use (from 10.8% to 5.4% in passenger flow) in favour of motorized private vehicles and, for shorter distances, active mobility (biking and walking) (ISFORT, 2021; Qu, Gates, Xu, Seguin, & Kay, 2022); this form of mobility is widely recognized as helping social inclusion and contributing to mental-physical well-being (Crotti, Maggi, Pantelaki, & Rossi, 2021).

In light of the main results and implications drawn from the literature mentioned above, the second strand of literature to which this study aims to contribute focuses on the shift from public transportation to other modes that re perceived as less risky from a health perspective. De Vos (2020) argued that due to COVID-19, people have reduced their commute times and prefer to use active modes or cars over public transportation. A very recent work by Böcker, Olsson, Uteng, and Friman (2023) that examined three Nordic cities focused on the strong impact of COVID-19 on public transport, highlighting heterogeneous effects according to socioeconomic and geographical characteristics. In the UK, fear of infection led many commuters to switch from local public transportation to cycling or walking, while others chose to use cars as a means of transportation for safety reasons once restrictions were lifted (Harrington & Hadjiconstantinou, 2022). Analysing data from 22 EU member states plus Norway, Christidis, Ciuffo, and Vespe (2022) claimed that limits on unsafe interactions are more important than travel restrictions. The study conducted by Jamal, Chowdhury, and Newbold (2022) in Bangladesh highlighted that Dhaka commuters perceive a high risk of COVID-19 transmission when travelling via shared modes. The study performed by Yıldırım, Geçer, and Akgül (2020) in Turkey also concluded that one of the most common preventive behaviours during the pandemic was avoiding public transportation. More generally, Hörcher et al. (2022) explored the possibilities of implementing social distancing in public transportation systems, in line with epidemiological advice, thus underlying the need to effectively manage the demand to keep vehicle occupancy rates under a given threshold.

Concerning the choice to switch from transit to private cars in the US, Palm, Allen, Zhang, et al. (2022) suggested that COVID-19 may have increased the attractiveness of auto ownership among public transit users (especially among cohorts of immigrants and/or people under 25 years old). Aside from cars, walking and cycling have come to be perceived not only as ways in which to avoid the risk of contagion but also to maintain a satisfactory level of health and well-being during lockdowns. In a study conducted by Eisenmann, Nobis, Kolarova, Lenz, and Winkler (2021) in Germany, respondents reported feeling less comfortable with public transportation during the lockdown, while cars were associated with a “wellness” factor. A study conducted by Bucsky (2020) in Budapest suggested that demand for public transportation had decreased by approximately 80%, while car use had increased from 43% to 65%. Bagdatli and Ipek (2022) found a critical reduction in public transportation use and a large increase in private car use and the use of active modes to reach the university in Istanbul. Das et al. (2021) showed a shift in India in commuting via public transportation to using cars. The results from analyses conducted in the US by Parker et al. (2021) and in New Zealand and Australia by Thomas et al. (2021) revealed that the COVID-19 pandemic significantly disrupted travel for users of public transportation. A study conducted in Hong Kong during the first phase of the pandemic reported that 40% of online interviewees had reduced their use of public transportation in favour of cars (Kwok et al., 2020).

Within this strand of literature, only one paper (Abdullah, Ali, Aslam, & Javid, 2021), which considered a very different context (i.e., Pakistan), suggested considering three different predictable scenarios in studying the long-term impact of COVID-19 on mobility choices. However, these scenarios were not included in the survey; that is, the respondents were not asked to express their mobility intentions, considering different possible evolutions of the pandemic, as has been done in our paper. In particular, the three scenarios outline in the abovementioned paper are as follows: 1. people stop using public transport and do not revert back to its use; 2. some people continue to prefer active modes and private cars over public transport in the long term; and 3. people restart using public transport as soon as the pandemic is over. Abdullah et al. reported that the first scenario seems improbable, while the second scenario is more feasible and seems to be confirmed by their study and some other works (Conway, Salon, da Silva, & Mirtich, 2020; Moslem et al., 2020). According to our literature review, other papers have supported this second scenario, arguing that a significant share of the public would actually switch to using active mobility and private cars to replace public transportation (Buehler & Pucher, 2021; Chen, Guo, Yang, Ding, & Yuan, 2021; Echaniz et al., 2021; Kazemzadeh & Koglin, 2021; Zhang, Zhang, & Liu, 2011). Moreover, other papers have suggested that people will return to use public transport at the end of the pandemic (third scenario) (e.g., Beck & Hensher, 2020; Przybylowski, Stelmak, & Suchanek, 2021); however, to obtain this result, effective transport demand management policies must be applied.

Finally, while other papers, as reported in Table A.1 of the Appendix, have analysed this complex topic, attempting to understand how the risk perceived during pandemics affects the changes in travel behaviour, it is reasonable to say that the long-lasting impacts of pandemics such as COVID-19 on travel behaviour are still not fully clear; thus, they still need to be evaluated more in-depth.

3. Survey and data collection

3.1. Survey

The survey promoted by the Italian Network of Universities for Sustainable Development (RUS) in July–September 2020 investigates attitudes towards possible changes in the mobility habits of students and employees at Italian universities commuting from home to university and vice versa for the 2020–2021 academic year, considering the COVID-19 health emergency.

The questionnaire is very detailed and contains information regarding interviewees' personal aspects, characteristics of mobility capital, home-university travel habits before the pandemic, and expected changes in habits during COVID-19, assuming the following two alternative scenarios of low or medium-high health risk:

- *Optimistic scenario*: The virus is almost eradicated, new infections are reduced across the country, and social distancing and protection measures are relaxed, while school activities are held regularly. Even though precautions are maintained and excessive concentrations of students are avoided, university teaching is held in person, except for special cases. For modules fully delivered in person, full online teaching may not be available.
- *Pessimistic scenario*: The virus is still dangerous, infections have slowed but continue, it is necessary to maintain strict social distancing and protection measures, and school activities for children are not regularly held. University teaching is provided in-person for only courses with few students and then only partially (not all lessons available).

In addition, the survey investigates the propensity to adopt sustainable and multimodal travel choices. Different transportation solutions are proposed: active mobility for short-medium distances (or in combination with other modes for longer distances); carpooling options; park-and-ride opportunities and the use of mobility-as-a-service (MaaS).

The full sample consists of 114,000 observations (students: 79.4%; faculty: 11%; technical-administrative staff: 9.6%), with participants from 51 Italian universities.[2] The data were collected from the beginning of July 2020 until September 2020 via an online survey. Since the data collection led to very different response rates among the participating Italian universities, we applied a weighting system that referred to the national aggregate analysis. A comparison between the regional origin of responses and the corresponding student cohorts for 2020/21 (MIUR, 2022) showed the presence of a significant bias, since 45% of the responses come from universities in northwestern Italy (vs. 24.1% of the Italian student population), 24% came from northeastern universities (vs. 17.6% of the student body), 16% came from universities in central Italy (vs. 25.4%), and 15.5% came from the South and Islands (vs. 32.9%).

Table 1
Descriptive statistics of variables used in the analysis.

Variable label	Obs.	[%]	Variable label	Obs.	[%]
Gender:	96,337		Commuting	96,199	
Male		46.45	frequency		
Female		53.55	(weekly):		13.85
			Less than once a		1.47
			week		2.40
			Once a week		9.42
			Twice a week		23.15
			3 times a week		49.71
			4 times a week		
			5 or more times a		
			week		
Age:	96,227		Travel time:	96,087	
18–21		34.61	Up to 15 min		26.25
22–23		21.64	15–30 min		22.51
24–29		23.59	30–60 min		28.69
30–79		20.16	>60 min		22.55
Status:	96,337		Distance covered	95,250	
Students		87.34	(km):		33.21
Faculty		9.64	1–5 km		24.94
Technical-		3.02	5–20 km		34.79
administrative			20–80 km		7.06
staff			> 200 km		
Macro region of	96,337		Pre-COVID-19	95,362	
university:		35.96	modal split:[a]		19.62
Northwest		19.17	Active modes		23.35
Northeast		16.94	Motor vehicles		57.03
Center		22.40	Public		
South		5.53	transportation		
Islands					
Motor vehicle	94,316		Pre-COVID-19 use	96,100	
availability:		37.05	of multimodality:		
No		62.950	No		60.60
Yes			Yes		39.40
Bicycle availability:	90,378		Bike-sharing	93,160	
No		67.77	availability:		25.00
Yes		32.237	No		75.00
			Yes		
Driver's licence:	71,278		Public	93,160	
No		13.50	transportation		
Yes		86.50	service:		38.90
			Poor		24.19
			Acceptable		28.64
			Good		8.27
			Excellent		

Notes: "Pre-COVID-19 modal split" is an aggregation of the prevalent means of transportation used before COVID-19.

[a] Here and in the following, the 16 different means of transportation listed in the survey are grouped into three large categories: "active modes," including walking, cycling (also bike sharing), and e-scooters (both independently or shared); "motor vehicles," referring to cars and motorcycles; and "public transportation," comprising local public transportation and trains. There is no specific item for electric cars since their share of the national car fleet in 2020 was negligible.

3.2. Description of the data

Before starting the analysis, we removed students who declared their intention to change university in the 2020–2021 academic year from the sample. This was necessary to make the responses related to the period before COVID-19 and those related to the period of the two pandemic scenarios comparable since different locations could involve a change in the individual mobility capital, as well as in the traffic conditions and transportation systems. Table 1 shows an initial weighted descriptive analysis of the variables considered. All variables come from the survey except for the last two: bike-sharing availability and public transportation service. Public transportation service is a four-class variable[3] constructed according to the number of seats/km per 10,000 inhabitants offered in the university city (source for both variables: ISTAT, 2018). The final sample consists of 96,337 observations after data cleaning, but the response rate differs in relation to each specific question.

3.3. Propensity to change in the proposed pandemic scenarios

As anticipated in the introduction, the survey included some direct questions that aimed to investigate the specific transportation changes made by commuters to universities. For both pandemic scenarios, respondents were asked about their intention to change their prevailing means of transportation to reach the university and to assess the important factors that could motivate such a decision. As shown in Table A.2 in the Appendix, 17.01% of the respondents planned to change their prevailing means of reaching the university in the optimistic scenario; this share rose to 32.40% in the pessimistic scenario. It should also be noted that, according to the survey results, the main factors affecting this choice concerned safety (in terms of health), which was deemed *very important* by 78% of those who opted to change their mode of travel in the worse-case scenario. This was followed by the fear of public transportation services becoming less reliable (37.79%) because of the pandemic (this perception was more accentuated in the pessimistic scenario, 44.95%). This result is in line with the study conducted by Jamal et al. (2022) in Bangladesh, which also highlighted the dilemmas and trade-offs among health risk, affordability, and unavailability for Dhaka commuters when choosing a commuting mode, followed by the need to save money (38.61% in the optimistic scenario and 33.65% in the pessimistic scenario) and an awareness about the need to limit traffic congestion (37.40% in the optimistic scenario and 35.40% in the pessimistic scenario).

3.4. Transition from public transportation to other modes of transportation

Table 2 presents a simplified (as seen in the pre-COVID-19 modal split shown in Table 1) transition matrix describing the intentional modal shifts from the pre-COVID-19 situation to the two pandemic scenarios. Public transportation stands out as the means with the greatest decrease in terms of percentage, given the perceived higher risk of infection, as well as the reduced capacity imposed by government measures to ensure social distancing (60% of the space available at the time of the survey). The forecast for a scenario of reduced health risk

[2] Each Italian university that joined the initiative organized itself independently by disseminating the questionnaire as widely as possible to its academic community, covering students, teachers, and technical-administrative staff.

[3] The four classes were defined following the cut of quartiles per the number of seats/km per 10,000 inhabitants offered in the university city: from 900 to 2800 is poor; 2800 to 4500 is acceptable; 4500 to 5500 is good; and 5500 to 6200 is excellent.

Table 2
Transition matrix for the main travel modes from before COVID-19 to the pandemic scenarios.

Main travel mode before COVID-19	Optimistic scenario			Pessimistic scenario		
	Active modes	Motor vehicles	Public transport	Active modes	Motor vehicles	Public transport
Active modes	96.39%	1.07%	2.53%	96.31%	2.39%	1.30%
Motor vehicles	2.75%	95.77%	1.48%	1.09%	98.69%	0.22%
Public transportation	3.62%	6.11%	90.27%	5.17%	14.30%	80.53%

show that the demand for public transportation shrinks by almost 10%, but the decline is much stronger (−20%) in the pessimistic scenario. Similar to the outcomes of other studies (Abdullah, Ali, et al., 2020; Abdullah, Dias, et al., 2020; Bagdatli & Ipek, 2022; Barbieri et al., 2021; Bucsky, 2020; Eisenmann et al., 2021), there is a significant shift from public transportation to private cars, amounting to 6.1% in the optimistic scenario and 14.3% in the pessimistic scenario, while the switch to active mobility—3.6% in the optimistic scenario and 5.2% in the pessimistic scenario—is substantial, although weaker.

In contrast, the attrition rate for the other two macromodes is limited, as those who previously commuted by walking or cycling stated that they would continue to do so in both of the two pandemic scenarios (96.4% and 96.3%). Such low transition rates to other modes could be considered physiological and unrelated to the pandemic. Drivers display a similar—or even stronger—pattern, peaking at a retention rate nearing 99% in the worst scenario.

Overall, the move away from public transportation may appear to be considerable but somewhat less than one could expect. However, it must be remembered that within the university community, students are by far the predominant group, and their availability of using cars (either personally owned or lent by parents) for commuting is less frequent (approximately 50%) than that among faculty and staff (75%). A sizable fraction of students are therefore "stuck" using public transportation, especially those with considerable distances to cover, thus making the switch to active mobility difficult if not outright unfeasible for these individuals. For example, when the transition matrix is computed for faculty and staff only, in the pessimistic scenario, the move away from public transportation is greater, peaking at 35.5%.

4. Methods

To answer the two research questions according to previous studies about modal choices in systematic travel (as collected in Table A.1 in the Appendix), discrete choice models were used to study the propensity to change travel modes due to the pandemic and then to investigate the determinants of the transition from local public transport (LPT) to other travel modes. In the first case, we implemented a binary logistic regression model (see, in general, Mc Fadden, 2001). Subsequently, we focused on the specific group of pre-COVID-19 public transportation users and implemented a multinomial logit model (Marcucci, 2005) to analyse the determinants of the transition away from LPT. The combination of such models yields a complete characterization of the probability that public transportation users will choose to stick with their predefined transportation mode or shift to other modes as the pandemic shock comes along. Specifically, in the multinomial model, we considered LPT users who would continue to utilize public means of commuting as a baseline; then, we estimated the probability of changing to other travel modes. Of course, the capability of logits—and multinomial logit models—to correctly predict choices depends on the covariates involved and their actual role in shaping choices. Therefore, the survey dataset was augmented with some secondary information regarding the territorial context (public transportation service and bike-sharing availability) in which each university is located. The questionnaire does not, in fact, investigate the quality and quantity of transportation services available in the cities surrounding the campuses.

4.1. Logistic regression model

In this study, a logistic regression (classification) model was implemented, in line with many of the extant studies that we have discussed in the previous sections, to assess and estimate the propensity to change one's prevailing commuting mode prior to the pandemic considering two alternative scenarios (see Cox, 1958; Long & Freese, 2006). The following question was included in the questionnaire for each scenario: "Do you think that your commuting transportation mode (to reach the university) will change in the next academic year?" In our case, the binary response dependent variable Y is defined as the indicator function for modal change, taking a value of zero if the main mode of transportation expected in the pandemic scenario is the same as that before COVID-19 and one otherwise. As is well known, logistic regression is the regression model applied when the dependent variable is dichotomous, as in the case under examination.[4] The covariates are treated in a standard way depending on whether they are continuous, discrete, sequential, or unordered. In this type of classification model, the predicted probability, given a vector X of arbitrary size and the binary response variable Y, can be written as shown in Eq. (1):

$$Pr(Y=1|\boldsymbol{X}) = \frac{exp(\alpha+\boldsymbol{X}'\beta)}{1+exp(\alpha+\boldsymbol{X}'\beta)} \tag{1}$$

where X represents the vector of covariates included (see the descriptive statistics in Table 1), and Y indicates the binary latent utility perceived by the individual when choosing to change their commuting mode in each of the alternative pandemic scenarios.

The vector of coefficients β is estimated using the maximum likelihood method. We should think of these coefficients as the odds ratios of changing the commuting mode, given a 1-unit change in respective covariates in X. However, while the *sign* of each beta clearly indicates either an increase or decrease in the predicted probability, interpreting the related magnitude is much less straightforward. For this reason, when estimating logit models, it is common and useful to report the *marginal effects*, which reflect the change in probability of $Y=1$ given a 1-unit change in a certain covariate $x_j \in X$. The marginal effects are calculated as follows:

$$\frac{\partial Pr(Y=1|\boldsymbol{X})}{\partial x_j} = F'(x_j'\beta)\beta_j, \tag{2}$$

where $F(\bullet)$ is the logistic distribution function. Since the marginal effects are not constant in a nonlinear regression, we estimated them given a specific value of x. Specifically, we used the average marginal effects, i.e., the average of the marginal effects computed for each observation (Cameron & Trivedi, 2005).

4.2. Multinomial logit model

To identify the factors affecting the transition from public transportation to private cars or active mobility (i.e., walking, bikes), we implemented—similar to what has been done in previous studies in this field (see Table A.1 in the Appendix)—a multinomial logit model

[4] For a robustness check, we also performed a probit model, which obtained very similar results.

exploiting data pertaining to college commuting habits (e.g., Cameron & Trivedi, 2005; Zhou, Wang, & Wu, 2018). We reduced the dataset by keeping the subsample of people who declared public transportation as their main pre-COVID-19 travel mode. We then constructed a categorical dependent variable Y, which takes $m = 3$ categories (public transportation, private motorized vehicles, active modes). We then applied a multinomial logit model (MNLM) to estimate the probabilities for each of the $m = 3$ categories, using a set X of explanatory variables. Denoting the probability that the i-th respondent chooses commuting mode j, for $j = 1, \dots m$, by P_{ij}, where j = *public transportation, private motorized vehicles,* and *active modes (*i.e.*, walking, biking),* and assuming random noise ε_{ij} to be independent and identically distributed according to the type-1 extreme value log-Weibull distribution (Greene, 2003),[5] the MNLM is formulated as follows:

$$P_{ij} = Pr(Y_i = j|X_i) = \frac{exp\left(\alpha + \beta_j^{'} X_i\right)}{\sum_{k=1,..,m}}, \tag{3}$$

where β_k is the row vector of regression coefficients of X for the k-th category of Y, estimated by maximizing the log-likelihood function (Wooldridge, 2010).

5. Discussion and results

5.1. Propensity to change travel mode in the two pandemic scenarios

The dependent variable—propensity to change—was defined by comparing the prevailing travel mode used before the COVID-19 pandemic and the one that people planned to adopt in the two proposed pandemic scenarios. When the prevailing travel mode remained the same, the individual was assigned to the group of those who do not change.[6]

Table 3 highlights the results of the estimation, both for beta coefficients and for the average marginal effects for both scenarios; it also reports the main features of the logistic regression. The final sample size was 89,678 for the optimistic scenario and 81,640 for the pessimistic scenario; these reductions were caused by the missing values of some covariates.

As expected, differences in the propensity to change travel modes are confirmed to depend on pre-COVID-19 choices. Compared to previous adopters of active mobility modes, those who previously used private motorized vehicles were somewhat *less* prone to change, while those who previously used public transportation were *more* likely to change (and with a stronger effect, peaking at +21% in the worst scenario), in line with Abdullah, Dias, et al., 2020, Eisenmann et al. (2021), and Bagdatli and Ipek (2022). Among other strong effects, those regarding the availability of means of transportation—both motor vehicles and bicycles—were found to have a positive effect on the propensity to change modes. This outcome is expected since most of the changes away from public transportation were made to extend towards self-owned vehicles (see Table 2). There are some differences between the two scenarios, since only in the pessimistic scenario does the availability of motor vehicles turn out to be significant, with a strong effect (an average of a 7.4% increase in the propensity); in the optimistic scenario, both car and bicycle availability are significant, albeit with a lower impact (+2.9% and + 2.5%, respectively). It is also interesting to note that a strong availability of local public transportation in the area (i.e., in the 4th quartile group for this secondary data) decreases the probability of changing one's travel habits, i.e., between 1%–3% in the two scenarios. This result is of particular interest because transportation planning and supply would have most likely been affected by COVID-19 in terms of the variety of services. For instance, as argued in Marsden and Docherty (2021), the potential to deliver radical policy adaptations was limited in the UK due to the pandemic. Therefore, if a larger transportation service decreased their probability of behavioural changes after COVID-19, then disruptions to the existing trajectories might not advocate for massive infrastructure and supply-side interventions with regard to public institutions. In fact, a solid, widespread supply of collective transportation services implies that the use of buses and/or trains will remain easy and comfortable. In the optimistic scenario, this ongoing ease and comfort would hinder people from leaving public transportation in favour of other modes. Conversely, in the pessimistic scenario, those with a driver's licence will slightly increase their chances of changing their commuting habits by a couple of percentage points, while this does not hold for the optimistic scenario. Therefore, a threshold appears to exist in which a strong health risk induces a substantial motivation to switch to using a car, but this is subject to clear enabling conditions, such as the actual availability of a car and the possession of a driver's licence; this result is in line with Jamal et al. (2022). While they could be considered commonplace for faculty and staff, both of these features are much less commonplace for students. In the optimistic scenario, however, the motivation for change is less compelling, and these factors lose their relevance.

Inevitably, travel distance also impacts one's decision to change his or her transportation habits. Longer trips are associated with a lower tendency to change in both pandemic scenarios, most likely reflecting the relative scarcity of alternative travel options compared to those available in short-distance commuting, which generally takes place in dense urban environments. These results are in line with those of Parker et al. (2021) and Jamal et al. (2022).

Regarding the role and type of activity engaged in by individuals within the university community, two covariates stand out with some level of significance in the pessimistic scenario only, namely, the status (work position) indicator and the weekly commuting frequency. We consider each of the three previously mentioned categories. *Students* are the least prone to change in general, considering that they are often on campus no >3 days a week; *faculty members* are more prone to change as a group (+5.8%) than *staff workers*, even though the latter are the only ones generally commuting daily (five or even six times a week), which brings about some additional probability of change (+4% for the usual five-day workweek).

Finally, regarding geographical effects and in partial agreement with Christidis et al. (2022), areas with more intense mobility flows are those most affected by the pandemic. In our Italian sample, the propensity to change one's travel behaviours displays a contrasting outcome. For the optimistic scenario, those located in northwestern regions (dramatically impacted by the first wave of the pandemic) display a stronger tendency to change travel modes than those located in central regions, whereas in the pessimistic scenario, the effect is the opposite. This might suggest that if more harmful times are expected, people in Italian areas with

[5] The error specification in multinomial logit models implies the independence of irrelevant alternatives (IIA) assumption. Essentially, this requires that the individual evaluation of an alternative compared to another one should not change if a third (allegedly irrelevant) alternative is added to (or dropped from) the analysis. In this context, we assume that each choice of travel mode (alternative to LPT) is independent (McFadden et al., 1976). Since the available data do not allow us to compare other models (e.g., nested models), a cautious interpretation of our findings is key. Nevertheless, it is widely accepted that sufficient reasoning may soften the drawbacks of the IIA assumption (see Zhou, 2012), i.e., separating commuting mode choices according to reasonable hypotheses. In our case, the full ex-ante ability to use all the travel modes other than LPT (i.e., private cars, active mobility modes) might suggest that adding/dropping options would not change the relative utilities.

[6] Note that this is actually a double simplification of the actual behaviour. In addition to grouping together the sixteen detailed travel choices into three macromodes, cases of unchanged main travel modes can hide a change in one of the secondary modes in multimode journeys. For example, you could have a journey in which you combine the use of your own car for the longer stretch with a bus ride for the shorter stretch ("park and ride" style) before COVID-19, which then turns into a car-only journey in a pandemic scenario. In this case, our analysis would record an "unchanged" situation, while the impact on sustainability of the underlying change could be important.

Table 3
Logit model for propensity to change.

Label variable	Optimistic scenario			Pessimistic scenario		
	Logistic regression	Average marginal effects model VCE: Robust		Logistic regression	Average marginal effects model VCE: Robust	
	Coef.	Dy/dx	Δ-method Std. Err.	Coef.	Dy/dx	Δ-method Std. Err.
Pre-COVID-19 modal choice: (Active modes)						
Motor vehicles	0.35525*	0.01008	0.00673	−1.13637***	−0.01979**	0.00630
Public transportation	1.79278***	0.10378***	0.00745	2.43901***	*0.21084***	0.00954
Pre-COVID-19 multimodality of travel	−0.01828	−0.00122	0.00660	0.00410	0.00038	0.00902
Gender (Male)	0.06917	0.00462	0.00657	0.03961	0.00365	0.00809
Age (Scale 18–79)	0.00403	0.00027	0.00034	0.00506	0.00047	0.00053
Work position (Students)						
Faculty	−0.14110	−0.00904	0.00915	0.54767***	0.05752***	0.02135
Staff	−0.14877	−0.00950	0.00962	0.13132	0.01228	0.01903
Motor vehicle availability	0.44510***	0.02884***	0.00743	0.82242***	0.07365***	0.00885
Bicycle availability	0.34992***	0.02452***	0.00856	0.00167	0.00015	0.00705
Driver's licence	0.03255	0.00216	0.01228	0.21258	0.01869*	0.01542
Macro region of university (Northwest)						
Northeast	−0.05516	−0.00371	0.00450	0.06225	0.00561	0.00554
Centre	−0.12304*	−0.00805*	0.00452	0.19647***	0.01843***	0.00605
South	−0.03891	−0.00263	0.00969	0.15518	0.01438	0.01351
Islands	0.07145	0.00505	0.00642	−0.10661	−0.00913	0.00762
Weekly freq. of commute (Less than once a week)						
Once	−0.31525	−0.02033	0.01604	−0.22626	−0.01550	0.01606
Twice	−0.25381	−0.01676	0.01121	−0.05212	−0.00379	0.00865
3 times	0.03530	0.00261	0.01678	0.28752*	0.02343	0.01473
4 times	−0.27541*	−0.01804*	0.01080	0.29236***	0.02386***	0.00844
5 or more times	−0.07877	−0.00557	0.00973	0.49390***	0.04100***	0.00790
Travel time (Up to 15 min)						
15–30 min	0.06866	0.00503	0.00963	0.19547	0.01943	0.01405
30–60 min	−0.23283	−0.01516	0.01147	0.05909	0.00565	0.01585
>60 min	−0.11287	−0.00770	0.01608	−0.32150*	−0.02737*	0.01651
Distance covered (km) (1–5 km)						
5–20 km	−0.56700***	−0.04596***	0.01471	−0.42635***	−0.04561***	0.01692
20–80 km	−0.82606***	−0.06106***	0.01846	−0.80327***	−0.07778***	0.01900
>200 km	−0.90019***	−0.06482***	0.01937	−0.59766***	−0.06116***	0.02312
Bike-sharing availability	−0.24426***	−0.01711***	0.00731	0.00656	0.00060	0.00887
Public transportation service (Poor)						
Acceptable	−0.03214	−0.00221	0.00409	−0.12004**	−0.01121**	0.00519
Good	−0.09083	−0.00611	0.00446	−0.07080	−0.00670	0.00580
Excellent	−0.21525***	−0.01378***	0.00488	−0.36203***	−0.03145***	0.00568
Constant	−3.41248***			−4.53147***		
Number of obs.	89,678		81,640			
Wald χ^2 (29)	584.74		682.63			
Prob > χ^2	0.0000		0.0000			
Pseudo R^2	0.0604		0.1603			
Log pseudolikelihood	−22,850.244		−25,265.01			

Notes: Reference modes for each covariate in brackets.
Dy/dx for factor levels is the discrete change from the base level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

higher mobility would maintain their established habits.

In Tables 3.1–3.3, we provide the goodness-of-fit measures of the logit models related to the two scenarios. As expected, the unrestricted specifications display a better fit, as witnessed by lower AIC and BIC scores, thus supporting the insertion of the selected covariates in the analysis. The likelihood ratio (LR) chi-square test conducted between the restricted and unrestricted specifications is statistically significant and denotes the superior performance of the latter in both the optimistic (11,759.91, 29 df, $p = 0.0000$) and pessimistic scenarios (24,662.80, 29 df, $p = 0.0000$).

5.2. *Transition from public transportation to other means of transportation*

The cleaning of the data according to the purposes of the second research question resulted in samples of 48,694 for the optimistic scenario and 43,673 for pessimistic scenario, which were used to analyse the behaviour of the subsample composed of those who reported travelling mainly by public transportation before the pandemic.

The transition matrix shown in Table 2 highlights the percentages of those who planned to switch from using public transportation before the

Table 3.1
Akaike's information criterion and Bayesian information criterion for the optimistic scenario.

Model	N	ll (null)	ll (model)	df	AIC	BIC
Restricted	107,052	- 28,730.2	−28,730.2	1	57,462.4	57,471.98
Unrestricted	89,678	- 24,138.38	−22,850.24	30	45,760.49	46,042.61

Notes: BIC uses N = number of observations.

Table 3.2
Akaike's information criterion and Bayesian information criterion for the pessimistic scenario.

Model	N	ll (null)	ll (model)	df	AIC	BIC
Restricted	97,382	−36,260.74	−36,260.74	1	72,523.48	72,532.97
Unrestricted	81,640	−29,304.47	−23,929.34	30	47,918.68	48,197.98

Notes: BIC uses N = number of observations.

Table 3.3
Likelihood-ratio test for optimistic and pessimistic scenarios.

Likelihood-ratio test	Optimistic scenario	Pessimistic scenario
LR χ^2 (29)	11,759.91	24,662.80
Prob > χ^2	0.0000	0.0000

Assumption: restricted model nested in unrestricted model.

COVID-19 outbreak to active mobility or motor vehicles in the two proposed pandemic scenarios. As outlined, almost 10% of users plan to stop using public transportation in the first scenario, which doubles in the pessimistic scenario, albeit with a stronger increase in the transition to motor vehicles, from 6.11% to 14.30%, while the active mobility share of "movers" changes from only 3.62% to 5.17%. These shifts reflect the perception of public transportation as an unsafe environment when infection risks are substantial, as argued by Parker et al. (2021) about the linkage between transit use and perceived risks.

To understand how personal and journey characteristics may affect this choice, a three-way response multinomial logit model was implemented. Taking the nonchange attitude towards public transportation as a baseline, we studied the direction of change in the two pandemic scenarios towards active mobility or motor vehicles.

For multinomial logit models, $e^{\beta ij}$ gives the odds ratio for alternative j compared to the base alternative due to a 1-unit increase in covariate x_i. The average marginal effects estimate the average expected change in the probability of alternative j due to a 1-unit increase in x_i.

Table 4 reports the main results of the multinomial logit for those who plan to use active mobility and those who plan to use motor vehicles in both the optimistic and pessimistic scenarios, while Table 5 shows the average marginal effects.

In Tables 4.1–4.3, the goodness-of-fit measures of the multinomial logit models are displayed. Even in this multinomial case, lower AIC and BIC scores denote a superior fit when considering unrestricted specifications. Likelihood ratio (LR) chi-square tests indicate a positive performance in both scenarios (12,799.48 and 21,285.63, 29 df, p = 0.0000).

Table 4
Results of multinomial logit: coefficient estimates for the shift to active modes and motor vehicles.

Shift (Baseline LPT to LPT)	Optimistic scenario		Pessimistic scenario	
	Coef. Active modes	Coef. Motor vehicles	Coef. Active modes	Coef. Motor vehicles
Gender (male)	0.02111	0.15328***	−0.14584***	0.13474***
Age	0.010188**	0.01706***	0.00394	0.00688***
Work position				
Faculty	0.06466	−0.06586	0.85656***	0.80539***
Staff	−0.07631	−0.29536*	0.36086*	0.31384***
Motor vehicle availability	−0.52247***	1.248064***	−0.59963***	1.500571***
Bicycle availability	0.86938***	0.15537***	0.77991***	−0.21182***
Driver's licence	−0.05698	0.16509**	0.35832***	0.28656***
Macro regions				
Northeast	−0.04425	−0.30897***	−0.34371***	−0.10340**
Centre	−0.17298*	−0.16921**	−0.40340***	0.21945***
South	−0.10643	0.03785	−0.80612***	0.31310***
Islands	−0.42080***	0.51489***	−0.04400	−0.03028
Weekly freq. of commute				
Once	−0.38475	−0.41266***	−0.37383	−0.25671*
Twice	−0.11047	−0.36451***	0.21527	−0.05454
3 times	−0.25554**	−0.12895*	0.30979***	0.33475***
4 times	0.04978	−0.49317***	0.30261***	0.34077***
5 or more times	0.06822	−0.18274***	0.42658***	0.46383***
Travel time				
15–30 min	−0.04961	0.37811***	−0.01396	0.52314***
30–60 min	−0.53992***	0.21790**	−0.54036***	0.50686***
>60 min	−0.74124***	0.43928***	−1.28286***	0.16068*
Distance covered (km)				
5–20 km	−1.20140***	0.11526*	−0.99763***	0.67048***
20–80 km	−2.22703***	−0.02921	−2.94616***	0.34443***
> 200 km	−1.21622***	−0.57429***	−2.08272***	0.42496***
Bike-sharing availability	0.20608	−0.370076***	−0.43198***	0.09052
Public transportation service				
Acceptable	−0.15540	0.24787***	0.97941***	0.12409***
Good	0.01339	0.04195	0.56182***	0.01780
Excellent	0.05331	−0.47987***	0.70761***	−0.22381***
Pre-COVID-19 multimode of travel	−0.17351***	−0.01343	−0.11734**	0.01368
Constant	−2.25343***	−3.86986***	−2.11608***	−4.52888***
Number of obs.	48,694		43,673	
Wald χ^2 (54)	6617.11		11,183.98	
Prob > χ^2	0.0000		0.0000	
Pseudo R^2	0.1672		0.2038	
Log pseudolikelihood	−16,481.155		−21,850.327	

Notes: *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 4.1
Akaike's information criterion and Bayesian information criterion for the optimistic scenario.

Model	N	ll (null)	ll (model)	df	AIC	BIC
Restricted	59,755	−22,889.73	−22,889.73	2	45,783.46	45,801.45
Unrestricted	48,694	−197,89.71	−16,489.99	56	33,091.97	33,584.4

Notes: BIC uses N = number of observations.

Table 4.2
Akaike's information criterion and Bayesian information criterion for the pessimistic scenario.

Model	N	ll (null)	ll (model)	df	AIC	BIC
Restricted	53,631	−32,522.25	−32,522.25	2	65,048.49	65,066.27
Unrestricted	43,673	−27,442.32	−21,879.43	56	43,870.86	44,357.19

Notes: BIC uses N = number of observations.

Table 4.3
Likelihood-ratio test for optimistic and pessimistic scenarios.

Likelihood-ratio test	Optimistic scenario	Pessimistic scenario
LR χ^2 (29)	12,799.48	21,285.63
Prob > χ^2	0.0000	0.0000

Assumption: restricted model nested in unrestricted model.

The results show some differences in the role of numerous covariates compared to the results from the binary response model illustrated in Section 5.1. Here, the gender and age of the respondents, for instance, show statistically significant—although quite weak—effects, the strongest being a propensity gap of +1.53% for women to switch to cars in the pessimistic scenario. This contrasts with what was found by Abdullah, Dias, et al., 2020, i.e., that women were generally less prone to choose private transportation relative to the public/paratransit mode during COVID-19. Our results are consistent (for both scenarios) with the results found by Das et al. (2021).

As with the binary response model discussed in Section 5.1, the different groups composing the university community follow diverging behaviour only in the pessimistic scenario. Faculty members have a much larger probability of giving up public transportation than students (+13.8%) and of switching to cars (+10% versus 3.8% towards active modes). Technical-administrative staff are more likely to move away from public transportation than students as well, although the disparity is substantially lower than that for faculty members (4.9%); they also show a shift mostly towards motor vehicle use (+3.5).

As already noted, the choices are substantially constrained by the actual option set available for the individuals in terms of the so-called capital mobility, which is measured herein by three variables, namely, motor vehicle (car or motorcycle) availability, bicycle availability, and having a driver's licence. Very strong effects derive from the availability of motor vehicles; people with the possibility of using their own car or that of a family member tend to abandon the use of public transportation much more than others (−5.3% and − 13.5% in the two scenarios), mainly shifting to motor vehicle use (+16.6% in the worst scenario), in line with the findings of Jamal et al. (2022). They are also less likely to choose active modes of transportation (−3 points in the pessimistic scenario). Conversely, bicycle availability is associated with a shift to active modes, being 2.7 and 3.3 points larger in the optimistic and pessimistic outlook, respectively. This is a decidedly weaker effect than the one associated with motor vehicle availability; it could also be linked to the somewhat unexpectedly lower declared availability for bicycles than for cars. Indeed, overall car availability was found to be as high as 63%, while bicycle availability was found to be much lower, i.e., slightly >30% (Table 1). Even students reported more often having a car at hand than a bicycle (the availability ratio is only slightly lower than that for the other groups, with 1.68 cars for every bicycle available to students, vs. 1.9 for faculty and staff); the real difference found is that students often have less access to both cars and bicycles (compared to the percentages given above for students, 73.7% of university employees own a car, while 39% own a bicycle).[7]

Another aspect of so-called *mobility capital* concerns the possession of a driver's licence, which is a factor that can strongly influence the possibility of using a car (without considering car use as a passenger). As expected, this variable has a significant, quite high effect (mainly in the worse hypothetical situation) on the reduction of public transportation use and the increase in motor vehicle use. If the risk to one's health turns out to the worse-case scenario, then holding a driver's licence will push people even more towards the apparent protection offered by their car's interior.

An analysis of the territorial context highlights some differences in the macro regional variable. From the northwest to the northeast, there is a significant, strong effect on the increase in public transportation use (more accentuated in the pessimistic scenario, 2.3%), the reduction in motor vehicle use (more accentuated in the optimistic scenario, 1.6%), and the reduction in active mobility (−1.4%) for only the pessimistic scenario. Moving to the central regions and comparing both scenarios, a reduction of 0.5% to 1.8% is seen for active mobility, along with an interesting inversion of the use of motor vehicles, moving from −0.9% to +2.6% in the optimistic and pessimistic scenarios, respectively. A greater reduction of 3% in active mobility and an increase of 3.9% for motor vehicle use appears in the southern regions only for the pessimistic scenario. Moving to the islands, which are highlighted in this case for only the optimistic scenario, a strong reduction affects active mobility by 1.2% and public transportation by 2.5%, while there is an increase of 3.5% for motor vehicle use. Obviously, the perception of infection risk is strongly related to commuting frequency; thus, it is reasonable to expect that sporadic visits to campus will elicit less concern (not causing transportation changes) than daily, systematic travel. This expectation is confirmed by our data in the worst-case scenario; as the trip frequency increases, the reduction in public transportation use is higher, reaching a marginal effect of −6.1 in the case of commuting five or more times a week. On the other hand, an increase in car users by +4.6 in the case of commuting five or more times a week is more accentuated in the pessimistic scenario. This finding is consistent with Das et al. (2021).

Finally, the covariates related to the length of travel (time to destination and distance covered) play the expected role. Active mobility is almost entirely limited to short trips, car usage is more widespread on medium-range journeys, and there is a strong propensity to use public transportation (especially rail) for long-distance travel. These findings are consistent with Harrington and Hadjiconstantinou (2022). In fact, when compared to short trips (those not exceeding 5 km), all marginal

[7] All information concerning the availability/ownership of means of transportation was collected directly within the RUS survey.

Table 5
Results of multinomial logit: average marginal effects.

Average marginal effects	Optimistic scenario		Pessimistic scenario	
	dy/dx	Delta-method Std. Err.	dy/dx	Delta-method Std. Err.
Gender (baseline:				
male)	0.000426	0.001638	−0.006489***	0.001962
Active modes	−0.009005***	0.002704	−0.008783***	0.003675
Public transport	0.008578***	0.002211	0.015273***	0.003229
Motor vehicles				
Age				
Active modes	0.000291*	0.000155	0.0001326	0.000183
Public transport	−0.001234***	0.000236	−0.000866***	0.000325
Motor vehicles	0.000943***	0.000182	0.000734***	0.000273
Work position				
(baseline:				
student)	0.002158	0.005616	0.037619***	0.008720
Faculty	0.001569	0.008196	−0.137667***	0.014295
Active modes	−0.003728	0.006105	0.100049***	0.012312
Public transport				
Motor vehicles	−0.001925	0.006839	0.0144572	0.009582
Staff	0.016691*	0.009994	−0.049089***	0.016924
Active modes	−0.014766**	0.007363	0.034631***	0.014365
Public transport				
Motor vehicles				
Motor vehicle				
availability	−0.018098***	0.001838	−0.030536***	0.002180
Active modes	−0.052789***	0.003411	−0.135379***	0.004544
Public transport	0.070887***	0.002932	0.165915***	0.004101
Motor vehicles				
Bicycle				
availability	0.026775***	0.001766	0.032632***	0.002105
Active modes	−0.034201***	0.002947	−0.006381	0.004109
Public transport	0.007426***	0.002428	−0.026251***	0.003649
Motor vehicles				
Driver's licence				
Active modes	−0.002017	0.002147	0.013430***	0.002812
Public transport	−0.007341*	0.004492	−0.043189***	0.006519
Motor vehicles	0.009358**	0.004039	0.029759***	0.006125
Macro regions				
(baseline:				
northwest)	−0.000995	0.002793	−0.014276***	0.003552
Northeast	0.016686***	0.004381	0.023186***	0.005874
Active modes	−0.015691***	0.003468	−0.008910*	0.004910
Public transport				
Motor vehicles	−0.005073*	0.002956	−0.017685***	0.003679
Centre	0.013966***	0.004911	−0.008288	0.006633
Active modes	−0.008893**	0.004031	0.025973***	0.005772
Public transport				
Motor vehicles	−0.003403	0.005283	−0.030404***	0.005412
South	0.001011	0.008623	−0.008400	0.011755
Active modes	0.002392	0.007035	0.038804***	0.010812
Public transport				
Motor vehicles	−0.012435***	0.003136	−0.001925	0.004932
Islands	−0.025016***	0.008265	0.004797	0.009402
Active modes	0.037450***	0.007779	−0.002872	0.008376
Public transport				
Motor vehicles				
Weekly freq. of				
commute				
(Baseline: less				
than once a	−0.009535	0.006862	−0.010390	0.007920
week)	0.032893***	0.010597	0.030465**	0.013230
Once	−0.023358***	0.008269	−0.020075*	0.010849
Active modes				
Public transport	−0.002684	0.006152	0.007861	0.008054
Motor vehicles	0.023939***	0.009638	−0.002590	0.012607
Twice	−0.021255***	0.007620	−0.005271	0.010074
Active modes				
Public transport	−0.006802**	0.003380	0.010301***	0.004403
Motor vehicles	0.014728***	0.005720	−0.04223***	0.007448
3 times	−0.007926*	0.004741	0.031930***	0.006260
Active modes				
Public transport	0.002286	0.002881	0.009989***	0.003326
Motor vehicles	0.025312***	0.004786	−0.042602***	0.006003
4 times	−0.027598***	0.003932	0.032613***	0.005172
Active modes				
Public transport	0.002439	0.002616	0.014608***	0.002968
Motor vehicles	0.009180**	0.004528	−0.060587***	0.005490
5+ times	−0.011620***	0.003800	0.045980***	0.004766
Active modes				
Public transport				
Motor vehicles				
Travel time				
(baseline: up to				
15 min)				
	−0.002582	0.002635	−0.003263	0.003119
15–30 min	−0.016669***	0.005145	−0.050150***	0.007882
Active modes	0.019251***	0.004501	0.053413***	0.007460
Public transport				
Motor vehicles	−0.017514***	0.003040	−0.024841***	0.003666
30–60 min	0.006417	0.005243	−0.029104***	0.007863
Active modes	0.011097***	0.004360	0.053945***	0.007190
Public transport				
Motor vehicles	−0.022385***	0.003796	−0.043063***	0.004395
>60 min	−0.001675	0.006108	0.024876***	0.008496
Active modes	0.024061***	0.004923	0.018187***	0.007540
Public transport				
Motor vehicles				
Distance covered				
(km) (baseline:				
1–5 km)	−0.053636***	0.003812	−0.066458***	0.004473
5–20 km	0.043701***	0.005427	−0.009851	0.006672
Active modes	0.009935***	0.004095	0.076309***	0.005365
Public transport				
Motor vehicles	−0.069918***	0.004075	−0.101982***	0.004613
20–80 km	0.067829***	0.005715	0.059329***	0.006778
Active modes	0.002089	0.004261	0.042653***	0.005378
Public transport				
Motor vehicles	−0.053241***	0.006000	−0.093153***	0.006166
> 200 km	0.076884***	0.007460	0.042655***	0.009639
Active modes	−0.023644***	0.004785	0.050498***	0.007927
Public transport				
Motor vehicles				
Bike Sharing				
availability	0.006956*	0.004150	−0.017966***	0.005316
Active modes	0.014140**	0.006953	0.006346	0.009703
Public transport	−0.021096***	0.005740	0.011620	0.008540
Motor vehicles				
Public				
transportation				
service				
(baseline: poor)	−0.004895	0.003328	0.035931***	0.004085
Acceptable	−0.012288***	0.005111	−0.046402***	0.006847
Active modes	0.017184***	0.004031	0.010471*	0.005817
Public transport				
Motor vehicles	0.000337	0.003866	0.017888***	0.003854
Good	−0.002940	0.006211	−0.01802**	0.008038
Active modes	0.002603	0.005031	0.000128	0.007276
Public transport				
Motor vehicles	0.002386	0.003556	0.024896***	0.003354
Excellent	0.022045***	0.005139	0.001287	0.006884
Active modes	−0.024431***	0.003866	−0.026183***	0.006192
Public transport				
Motor vehicles				
Pre-COVID-19				
multimodality	−0.005370***	0.001833	−0.004836**	0.002205
of travel	0.005865**	0.002992	0.002867	0.004074
Active modes	−0.000495	0.002432	0.001968	0.003558
Public transport				
Motor vehicles				

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

effects for active mobility are negative, with a maximum in the pessimistic scenario of −10.2 points for trips between 20 and 80 km in distance, as well as −4.3 points for durations exceeding 60 min. At the same time, the switch to cars is stronger for mid-range trips, peaking at +7.6%

for 5–20 km, and approximately +5 points for durations between 15 and 30 min (again referring to the worst expectation case); these findings are in line with Das et al. (2021).

Regarding the covariates of service availability, bike-sharing availability and public transportation service are found to be more significant in the pessimistic scenario than in the optimistic scenario in relation to active modes. In fact, the marginal effects shift from +0.07 to −1.8 for bike-sharing availability and from +2.5 to +3.6 for public transportation service. As expected, the transition to the use of motor vehicles is positively significant in the presence of an acceptable public transportation service. Finally, those who adopted multimodal transportation before the pandemic are found to be less likely to use active modes.

6. Conclusion

This paper uses a large sample of systematic commuters belonging to very different Italian universities to investigate and better understand the determinants that can push a modal shift in two alternative pandemic scenarios of low or medium-high health risk from two points of view. First, it analyses *when* and *how* a pandemic can motivate a change in travelling habits; second, it analyses the factors that could induce a shift away from public transportation (being perceived as less safe in terms of health risks) and towards active mobility or the less-sustainable solution of cars, considering the eventual differences between the two scenarios and considering the different socioeconomic and travel characteristics of the commuters. The logistic regression results highlight a higher propensity to change for those who used public transportation prior to the pandemic (particularly where the quality of public transportation is low), those with a car at their disposal, and those who commute daily rather than sporadically over short-to-medium distances rather than long distances. Finally, regarding university community roles, faculty members are the most prone to change their mode of travel. The second step of the analysis, which seems to support the findings of Beria, Campisi, Tolentino, and Perotto (2021), point out that when a transition occurs, active mobility is inevitably much more constrained by the distance to be covered or the travel duration, inducing a strong effect for this variable in favour of motor vehicles. This particularly holds for the pessimistic scenario; in the more optimistic outlook, all the effects are found to be weaker, although similar in direction.

Overall, a more marked tendency to abandon public transportation in favour of motor vehicle use does exist. Conclusive information, however, should probably ensue from a detailed analysis focusing specifically on cases where active mobility as a single mode of travel is feasible, as well as an examination of the frequency with which active modes could be combined with public transportation in multimodal solutions. We note that the analysis discussed herein is based on *prevailing modes* only, whereas active mobility in multimodal journeys very often has a complementary role with regard to longer stretches covered by public transportation. Therefore, while the switch to car use is probably fully recorded herein, the increase in the role of active mobility may have surfaced only partially.

6.1. Policy implications

Due to the impact of the virus, the shift from public transportation modes to the use of private cars is a very negative effect, especially regarding the millions of people who are commuting to work and school daily. To meet sustainable development goals and reduce the carbon footprint of college mobility (Crotti, Maggi, & Grechi, 2022), since transportation is one of the most important sources of CO_2 and other negative externalities, effective action by public authorities and transportation companies is crucial and urgent. On the one hand, such action has to ensure that the modal shift is not totally in favour of private cars but also partially involves active travel modes. An enhanced role of active mobility is recommended, especially in Italy, where the share of such mobility still lags far behind that found in most European countries (ISFORT, 2021). Furthermore, active mobility has even greater positive implications for personal health beyond warranting more protection from pandemics (De Hartog, Boogaard, Nijland, & Hoek, 2010).

On the other hand, appropriate mobility management policies must not only avoid long-term behavioural and attitudinal changes in commuters but also revitalize public transportation and encourage people to use it again, ultimately in combination with active mobility in intermodal trips. Different measures can be applied to reach these goals. First, transportation companies should meticulously address the issues of hygiene, ventilation, social distancing, and occupancy both on vehicles and at stops, as well as maintain such improvements over time (Tirachini & Cats, 2020). Moreover, the quality of public transport often needs to be increased (Bagdatli & Ipek, 2022; Eisenmann et al., 2021), i.e., by better connecting remote areas and introducing technological advances, such as cashless and contactless payment, along with real-time information regarding occupancy and seat availability. Additionally, the implementation of the so-called MaaS system could play a key role in enhancing public transportation use, especially when integrated with other types of services such as bicycle, e-scooter or vehicle sharing. MaaS integrates different transportation modes to facilitate seamless intermodal planning, booking, and payment through a single interface. Its acceptance by the general public is expected to grow in the future (Baldassa, Ceccato, Orsini, Rossi, & Gastaldi, 2022), as infomobility technologies evolve and become easier to use and more standardized, while public administrators strive to promote the approach. In fact, EU recovery funds are already providing the opportunity to experiment with such innovative services, with some projects presently being conducted in selected Italian cities. MaaS can certainly help the digital transition make sustainable transportation modes more comfortable and convenient, thereby limiting—and eventually inverting—the trend towards a reduction in public transportation use (Paiva & Mourao, 2022) due to the pandemic.

6.2. Limitations and further research

One of the main limitations of our analysis is that we do not have retrospective information on the mobility choices that were actually made during the 2020–2021 academic year; we have only the future intentions of choice regarding the means of transportation for commuting in relation to the proposed pandemic evolutionary scenario and the remaining fear caused by COVID-19 in society. In future research, it would be interesting to compare the actual choices made with the declared intentions.

Ethical approval

In this study, survey respondents gave explicit consent to participate. According to the COPE guidelines, the authors did not misrepresent research results.

Author agreement

In this study, survey respondents gave explicit consent to participate. According to the COPE guidelines, the authors did not misrepresent research results.

Funding

In this research, the financial support by Cariplo Foundation (project "POST-COVID: POverty and vulnerability Scenarios in The era of COVID-19: how the pandemic is affecting the well-being of the Italians," ID 2020-4216) is gratefully acknowledged by Chiara Gigliarano and Jurgena Myftiu.

Availability of data and materials

The survey data used in this study are owned by the Rete delle Università per lo Sviluppo Sostenibile (RUS) and they are not publicly accessible.

CRediT authorship contribution statement

Jurgena Myftiu: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Chiara Gigliarano:** Methodology, Project administration, Supervision, Writing – review & editing. **Elena Maggi:** Conceptualization, Data curation, Project administration, Supervision, Writing – review & editing. **Andrea Scagni:** Data curation, Project administration, Supervision, Writing – review & editing.

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.

Acknowledgments

The authors would like to thank the RUS network and, in particular, the coordinator of the "Mobility" group, Matteo Colleoni (University of Milano Bicocca) as well as Massimiliano Rossetti (University of Milano Bicocca) and the members of group "Indicators, data and survey" for their collaboration in the survey.

Appendix A

Table A.1
A review of some contributions on the impacts of the COVID-19 pandemic on travel behaviour in different parts of the world.

Author	Size, location, and timeline of survey	Commuting type	Method	Key findings
Abdullah, Dias, Muley, and Shahin (2020)	Online survey 1203 observations 70% South and Southeast Asia; 15% Oceania and Middle East; 12% Europe and North America Data collection period: May 9–31, 2020.	Work Study Shopping Others	Comparative descriptive analysis Exploratory factor analysis Multinomial logit	The pandemic led to a significant change in the primary purpose of travel. Travel for "first necessity" moved significantly (from work/study) to shopping (purchase of consumer goods) During the pandemic, the use of public transportation reduced in the face of an increase in the use of private cars. The modal shift to active modes from public transportation and community transit was significant.
Bagdatli and Ipek (2022)	Online survey 412 observations Istanbul Data collection period: May 14 – June 9, 2021	Study	z test Logit	A critical decrease in demand for public bus travel and a high increase for private car use can be observed, as well as an increase in the use of e-scooters and active travel modes. Having contracted COVID-19 reduces the demand for public transportation modes.
Barbieri et al. (2021)	Online survey 9394 observations Australia, Brazil, China, Ghana, India, Iran, Italy, Norway, South Africa, USA. Data collection period: May 11–31, 2020	Work Study Free time Leisure	Negative Binomial Model (NBM)	In all countries, the use of all modes of transportation strongly decreased for both commuter and noncommuter journeys In terms of the potential spread of the virus, planes and buses are perceived as the riskiest modes of transport, while the avoidance of public transportation is common in all countries.
Christidis et al. (2022)	European Mobile Network Operators 22 EU member states (plus Norway) Data collection period: 2020	Internal and external regional mobility (NUTS3)	Mobility indicators	A correlation is found between mobility and the evolution of the pandemic on the regional level. The high prevalence of COVID-19 is frequent in urban regions with high levels of mobility. Limits on unsafe interactions are more important than travel restrictions.
Eisenmann et al. (2021)	Online survey 1000 observations Germany Data collection period: March 30 – April 10, 2020	Work Shopping Free time	Logit	Respondents felt less comfortable with public transportation during the lockdown, while the use of a car was associated with a "wellness" factor. There was an increase in individual car users from 53% to 66%. The share of bicycle users (as only means) increased from 6% to 9%, while the share of public transportation users decreased slightly by 1%.
Harrington and Hadjiconstantinou (2022)	Online survey 725 observations United Kingdom Data collection period: May 2 – June 2, 2020.	Work	Descriptive analysis	In the UK, the impact of COVID-19 is bringing about transportation mode changes, leading some commuters to switch from LPT to cycling or walking, while others are choosing to use their car as a means of transportation for safety reasons once restrictions are lifted.
Jamal et al., 2022	In-depth semistructured interviews 20 observations Dhaka Bangladesh Data collection period: July – August 2020	Work	Qualitative analysis	Dhaka commuters perceive a high risk of COVID-19 transmission in modes that require sharing space with others. There is a dilemma and trade-off found among health risk, affordability and unavailability when choosing one's commuter mode in the postlockdown period.
Das et al. (2021)	Online survey 840 observations India Data collection period: April 29 – May 30, 2020	Work Other in general	Logit Analytic hierarchy Multinomial logit	A modal shift from public transportation to car commuting is reported. Commuter preferences are evaluated when relaunching public transportation in the post-COVID-19 world. Respondents prefer to use cars as the number of journeys increase; distance has a significant positive association with

(continued on next page)

Table A.1 (*continued*)

Author	Size, location, and timeline of survey	Commuting type	Method	Key findings
				the passing preference of car use; travel time does not affect preference of private car use.
Parker et al. (2021)	Embee Mobile and online survey 1267 observations US Data collection period: January – December 2020.	Transit riders	Logit Negative binomial regression Tobit	The COVID-19 pandemic significantly disrupted travel for public transportation users. Transit riders reduced their travel more than nontransit riders. Most transit riders were reluctant to use the transit system due to the risk of infection. A lower level of crowding and the application of the use of masks could increase the public's willingness to use the transit system
Thomas et al. (2021)	Online survey 506 observations for New Zealand Data collection: July 22 – August 7, 2020 281 observations for Australia Data collection period: August 7 – September 1, 2020	Work	ANOVA	Attitudes towards public transportation and international air travel became more negative and did not fully recover. Data could serve as a preview for other countries due to the anticipated end of the pandemic in N.Z. and Australia Among travel modes, the Australian sample consistently reported more negative attitudes towards domestic travel options than the New Zealand sample. New Zealand and Australian interviewees had very similar attitudes towards international air travel before and after restrictions were removed.

Table A.2
Factors of importance concerning the modal shift by pandemic situation.

Factor of importance for those who responded that they would change their mode of transportation	Optimistic scenario (17.01% of 108,770 obs)	Pessimistic scenario (32.40% of 98,928 obs)
To be safer (in health terms):		
Not at all important	3.80%	1.47%
Unimportant	8.34%	2.79%
Fairly important	26.85%	17.35%
Very important	62.02%	78.39%
With the old modes, the times would be too long:		
Not at all important	16.32%	18.09%
Unimportant	24.14%	25.66%
Fairly important	34.72%	31.41%
Very important	24.82%	24.85%
Public transportation services will become unreliable:		
Not at all important	7.07%	5.75%
Unimportant	15.19%	12.30%
Fairly important	39.94%	37.00%
Very important	37.79%	44.95%
Traffic will increase, and I want to help limit its environmental impact:		
Not at all important	8.65%	10.82%
Unimportant	21.08%	24.78%
Fairly important	37.40%	35.40%
Very important	32.87%	29.01%
Economic savings:		
Not at all important	9.57%	13.07%
Unimportant	18.22%	22.55%
Fairly important	33.59%	33.73%
Very important	38.61%	33.65%

References

Abdullah, M., Ali, N., Hussain, S. A., Aslam, A. B., & Javid, M. A. (2021). Measuring changes in travel behavior pattern due to COVID-19 in a developing country: A case study of Pakistan. *Transport Pol., 108*, 21–33.

Abdullah, M., Ali, N., Aslam, A. B., Javid, M. A., & Hussain, S. A. (2020). Factors affecting the mode choice behavior before and during COVID-19 pandemic in Pakistan. *International Journal of Transportation.*. https://doi.org/10.1016/j.ijtst.2021.06.005

Abdullah, M., Dias, C., Muley, D., & Shahin, M. (2020). Exploring the impacts of COVID-19 on travel behavior and mode preferences. *Transport. Res. Interdiscip. Perspect, 8*, Article 100255.

Bagdatli, M. E. C., & Ipek, F. (2022). Transport mode preferences of university students in post-COVID-19 pandemic. *Transport Policy, 118*, 20–32. https://doi.org/10.1016/j.tranpol.2022.01.017

Baldassa, A., Ceccato, R., Orsini, F., Rossi, R., & Gastaldi, M. (2022). MaaS bundling and acceptance in the pandemic era: Evidence from Padua, Italy. *Journal of Advanced Transportation, 2022*, 1–10. https://doi.org/10.1155/2022/9833689

Barbieri, D. M., Lou, B., Passavanti, M., et al. (2021). Impact of COVID-19 pandemic on mobility in ten countries and associated perceived risk for all transport modes. *PLoS One, 16*(2). https://doi.org/10.1371/journal.pone.0245886

Beck, M. J., & Hensher, D. A. (2020). Insights into the impact of COVID-19 on household travel and activities in Australia–The early days under restrictions. *Transport Policy, 96*, 76–93.

Beria, P., Campisi, E., Tolentino, S., & Perotto, E. (2021). The irreducibles: The causes of non-propensity to shift to public mode to access university campus. *Case Studies on Transport Policy, 9*(3), 1198–1210. https://doi.org/10.1016/j.cstp.2021.06.007

Bertrand, L., Shaw, K. A., Ko, J., Deprez, D., Chilibeck, P. D., & Zello, G. A. (2021). The impact of the coronavirus disease 2019 (COVID-19) pandemic on university students' dietary intake, physical activity, and sedentary behaviour. *Applied Physiology, Nutrition, and Metabolism, 46*(3), 265–272.

Böcker, L., Olsson, L. E., Uteng, T. P., & Friman, M. (2023). Pandemic impacts on public transport safety and stress perceptions in Nordic cities. *Transportation Research Part D: Transport and Environment, 114*.

Bohte, W., Maat, K., & van Wee, B. (2009). Measuring attitudes in research on residential self-selection and travel behaviour: A review of theories and empirical research. *Transport Reviews, 29*(3), 325–357.

Bucsky, P. (2020). *Modal share changes due to COVID-19: The case of Budapest* (p. 100141). Transp. Res. Interdisc. Perspect.
Buehler, R., & Pucher, J. (2021). COVID-19 impacts on cycling. *Transport Reviews, 4*, 393–400.
Cameron, A., & Trivedi, P. (2005). *Microeconometrics: Methods and applications*. Cambridge: Cambridge University Press. https://doi.org/10.1017/CBO9780511811241
Campisi, T., Nahiduzzaman, K. M., Nikiforiadis, A., Stamatiadis, N., & Basbas, S. (2022). Will the effects of COVID-19 on commuting and daily activities of university students be maintained? Evidence from a small town in Sicily. *Sustainability, 14*(10), 5780.
Charreire, H., Roda, C., Feuillet, T., Piombini, A., Bardos, H., Rutter, H., Compernolle, S., Mackenbach, J. D., Lakerveld, J., & Oppert, J. M. (2021). Walking, cycling, and public transport for commuting and non-commuting travels across 5 European urban regions: Modal choice correlates and motivations. *Journal of Transport Geography, 96*, 1–10. https://doi.org/10.1016/j.jtrangeo.2021.103196
Chen, X., Guo, Y., Yang, C., Ding, F., & Yuan, Q. (2021). Exploring essential travel during COVID-19 quarantine: Evidence from China. *Transport Pol, 111*, 90–97.
Christidis, P., Ciuffo, B., & Vespe, M. (2022). Regional mobility during the Covid-19 pandemic: Analysis of trends and repercussions using mobile phones data across the EU. *Case Studies on Transport Policy, 10*(1), 257–268.
Conway, M. W., Salon, D., da Silva, D. C., & Mirtich, L. (2020). How will the COVID-19 pandemic affect the future of urban life? Early evidence from highly-educated respondents in the United States. *Urban Science, 4*(4), 50. https://doi.org/10.3390/urbansci4040050
Cox, D. R. (1958). The regression analysis of binary sequences. *Journal of the Royal Statistical Society: Series B (Methodological), 20*(2), 215–232.
Crotti, D., Maggi, E., & Grechi, D. (2022). Reducing the carbon footprint in college mobility: The car commuters' perspective in an Italian case study. *Environmental Impact Assessment Review, 92*, Article 106702. https://doi.org/10.1016/j.eiar.2021.106702
Crotti, D., Maggi, E., Pantelaki, E., & Rossi, F. (2021). Public transport use and health status in later life: Which relationship? *Research in Transportation Business & Management, 40*, 1–15. https://doi.org/10.1016/j.rtbm.2020.100591
Das, S., Boruah, A., Banerjee, A., Raoniar, R., Nama, S., & Kumar Maurya, A. (2021). Impact of COVID-19: A radical modal shift from public to private transport mode. *Transport Policy, 109*, 1–11.
De Hartog, J. J., Boogaard, H., Nijland, H., & Hoek, G. (2010). Do the health benefits of cycling outweigh the risks? *Environmental Health Perspectives, 118*(8), 1109–1116.
De Vos, J. (2020). The effect of COVID-19 and subsequent social distancing on travel behavior. *Transportation Research Interdisciplinary Perspectives, 5*, 1–16. https://doi.org/10.1016/j.trip.2020.100121
Echaniz, E., Rodríguez, A., Cordera, R., Benavente, J., Alonso, B., & Sañudo, R. (2021). Behavioural changes in transport and future repercussions of the COVID-19 outbreak in Spain. *Transport Pol., 111*, 38–52.
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. *Transport Pol., 103*, 60–67.
Fenichel, E. P., Kuminoff, N. V., & Chowell, G. (2013). Skip the trip: Air travelers' behavioral responses to pandemic influenza. *PLoS One*, 8. https://doi.org/10.1371/journal.pone.0058249
Greene, W. H. (2003). *Econometric analysis* (5th ed.). Upper Saddle River, NJ: Prentice Hall.
Harrington, D. M., & Hadjiconstantinou, M. (2022). Changes in commuting behaviours in response to the COVID-19 pandemic in the UK. *Journal of Transport & Health, 24*, 101–313.
Hörcher, D., Singh, R., & Graham, D. J. (2022). Social distancing in public transport: Mobilising new technologies for demand management under the Covid-19 crisis. *Transportation, 49*, 735–764. https://doi.org/10.1007/s11116-021-10192-6
ISFORT. (2021). *18° Rapporto sulla mobilità degli italiani Governare le transizioni per una ripresa sostenibile*.
ISTAT. (2018). *Rilevazione Dati ambientali nelle città*. Roma: Istituto Nazionale di Statistica. https://www.istat.it/it/archivio/244648.
Jamal, S., Chowdhury, S., & Newbold, K. B. (2022). Transport preferences and dilemmas in the post-lockdown (COVID-19) period: Findings from a qualitative study of young commuters in Dhaka. *Bangladesh, Case Studies on Transport Policy, 10*(1), 406–416. https://doi.org/10.1016/j.cstp.2022.01.001
Kazemzadeh, K., & Koglin, T. (2021). Electric bike (non) users' health and comfort concerns pre and peri a world pandemic (COVID-19): A qualitative study. *J. Transport Health, 20*, Article 101014.
Kim, C., Cheon, H., Choi, K., Joh, C. H., & Lee, H. J. (2017). Exposure to fear: Changes in travel behavior during MERS outbreak in Seoul. *KSCE Journal of Civil Engineering, 21*, 2888–2895.
Kwok, K. O., Li, K. K., Chan, H. H. H., Yi, Y. Y., Tang, A., Wei, W. I., & Wong, S. Y. S. (2020). Community responses during early phase of COVID-19 epidemic. *Hong Kong. Emerg. Infect. Dis., 26*(7).
Liu, J., Moss, S., & Zhang, J. (2010). The life cycle of a pandemic crisis: SARS impact on air travel. In *Allied Academies international conference, New Orleans, LA*.
Long, J. S., & Freese, J. (2006). *Regression models for categorical dependent variables using Stata* (2nd ed.). College Station, TX: Stata Press.
López-Valenciano, A., Suárez-Iglesias, D., Sanchez-Lastra, M. A., & Ayán, C. (2021). Impact of COVID-19 pandemic on university students' physical activity levels: An early systematic re-view. *Frontiers in Psychology, 3787*.
Marcucci, E. (2005). I modelli a scelta discreta per l'analisi dei trasporti. Teoria, metodi e applicazioni.Carocci Editore. ISBN: 9788843033416.
Marsden, G., & Docherty, I. (2021). Mega-disruptions and policy change: Lessons from the mobility sector in response to the Covid-19 pandemic in the UK. *Transport Policy, 110*, 86–97.
Mc Fadden, D. (2001). Economic choices. *American Economic Review, 91*(3) (351–37).
MIUR. (2022). Ministero dell'Università e della Ricerca, Portale dei dati dell'istruzione superiore. http://dati.ustat.miur.it/dataset/iscritti.
Moslem, S., Campisi, T., Szmelter-Jarosz, A., Duleba, S., Nahiduzzaman, K. M., & Tesoriere, G. (2020). Best–Worst Method for Modelling Mobility Choice after COVID-19: Evidence from Italy. *Sustainability, 12*(17), 6824. https://doi.org/10.3390/su12176824
Müggenburg, H., Busch-Geertsema, A., & Lanzendorf, M. (2015). Mobility biographies: A review of achievements and challenges of the mobility biographies approach and a framework for further research. *Journal of Transport Geography, 46*, 151–163.
Myftiu, J. (2022). Promoting commute active modes during the Covid-19 pandemic. In *, 76. What is the role fo multimodal travel mode choices? RIEDS - Rivista Italiana di Economia, Demografia e Statistica - The Italian Journal of Economic, Demographic and Statistical Studies, 2022* (pp. 4–12). issue 4.
Nguyen, M. H., & Pojani, D. (2022). Why are Hanoi students giving up on bus ridership? *Transportation.*. https://doi.org/10.1007/s11116-021-10262-9
Paiva, S., & Mourao, F. (2022). Mobility-as-a-Service challenges and opportunities in the post-pandemic. In *Proceedings of the 2021 IEEE Glob. Conf. Artif. Intell. Internet Things, pp. 136–141, Dubai, United Arab Emirates, December 2022*.
Palm, M., Allen, J., Zhang, Y., et al. (2022). Facing the future of transit ridership: Shifting attitudes towards public transit and auto ownership among transit riders during COVID-19. *Transportation*. https://doi.org/10.1007/s11116-022-10344-2
Parker, M. E., Li, M., Bouzaghrane, M. A., Obeid, H., Hayes, D., Frick, K. T., & Chatman, D. G. (2021). Public transit use in the United States in the era of COVID-19: Transit riders' travel behavior in the COVID-19 impact and recovery period. *Transport Pol., 111*, 53–62.
Przybylowski, A., Stelmak, S., & Suchanek, M. (2021). Mobility behaviour in view of the impact of the COVID-19 pandemic—Public transport users in Gdansk case study. *Sustainability, 13*(1), 1–12, 364.
Qu, T., Gates, T. J., Xu, C., Seguin, D., & Kay, J. (2022). The disparate impact of COVID-19 pandemic on walking and biking behaviors. *Transportation Research Part D: Transport and Environment, 112*.
Rogers, R. W. (1975). A protection motivation theory of fear appeals and attitude Change1. *The Journal of Psychology, 91*(1), 93–114. https://doi.org/10.1080/00223980.1975.9915803
RUS. (2021). Indagare la mobilità universitaria ai tempi del Covid-19. Indicatori di sostenibilità per la governance della mobilità universitaria. In *"Le attività del Gruppo di lavoro Mobilità della Rete delle Università Italiane per lo Sviluppo Sostenibile", White Paper 2021*. RUS Network. https://reterus.it/public/files/GdL/Mobilita/WhitePaper_GdLmobilita%CC%80_10giu_finale.pdf.
Sadique, M. Z., Edmunds, W. J., Smith, R. D., Meerding, W. J., De Zwart, O., Brug, J., & Beutels, P. (2007). Precautionary behavior in response to perceived threat of pandemic influenza. *Emerging Infectious Diseases, 13*(9), 1307.
Schoenduwe, R., Mueller, M. G., Peters, A., & Lanzendorf, M. (2015). Analysing mobility biographies with the life course calendar: A retrospective survey methodology for longitudinal data collection. *Journal of Transport Geography, 42*, 98–109.
Tashiro, A., & Shaw, R. (2020). COVID-19 pandemic response in Japan: What is behind the initial flattening of the curve? *Sustainability, 12*(13). https://doi.org/10.3390/su12135250
Thomas, F. M. F., Charlton, S. G., Lewis, I., & Nandavar, S. (2021). Commuting before and after COVID-19. *Transportation Research Interdisciplinary Perspectives, 11*(2021), 100423.
Tirachini, A., & Cats, O. (2020). COVID-19 and public transportation: Current assessment, prospects, and research needs. *J. Public Transport., 22*(1), 1–21.
Troko, J., Myles, P., Gibson, J., Hashim, A., Enstone, J., Kingdon, S., Packham, C., Amin, S., Hayward, A., & Nguyen Van-Tam, J. (2011). Is public transport a risk factor for acute respiratory infection? *BMC Infectious Diseases, 11*, 16.
Warren, M.S., Skillman, S.W. (2020). Mobility changes in response to COVID-19. arXiv preprint arXiv:2003.14228.
Wen, Z., Huimin, G., & Kavanaugh, R. R. (2005). The impacts of SARS on the consumer behaviour of Chinese domestic tourists. *Current Issues in Tourism, 8*, 22–38. https://doi.org/10.1080/13683500508668203
Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. Boston: MIT Press.
Yıldırım, M., Geçer, E., & Akgül, Ö. (2020). The impacts of vulnerability, perceived risk, and fear on preventive behaviours against COVID-19. *Psychology, Health & Medicine*, 1–9.
Zhang, J. (2020). Transport policymaking that accounts for COVID-19 and future public health threats: A PASS approach. *Transport Policy, 99*, 405–418.
Zhang, Y., Zhang, Y., & Liu, Z. (2011). The role of different transportation in the spreading of new pandemic influenza in mainland China. In *In: 2011 19th international conference on Geoinformatics. IEEE* (pp. 1–6).
Zhou, J. (2012). Sustainable commute in a car-dominant city: Factors affecting alternative mode choices among university students. *Transportation Research Part A: Policy and Practice, 46*(7), 1013–1029.
Zhou, J., Wang, Y., & Wu, J. (2018). Mode choice of commuter students in a college town: An exploratory study from the United States. *Sustainability, 10*(9), 3316.