PROMOTING COMMUTE ACTIVE MODES DURING THE COVID-19 PANDEMIC. WHAT IS THE ROLE OF MULTIMODAL TRAVEL MODE CHOICES?

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1. Introduction

In many countries, the Covid-19 pandemic has caused restrictive measures limiting the ability to get around by using transportation services and affected systematic choices, especially for commuting purposes (Bohte et al., 2009; Müggenburg et al., 2015; Schoenduwe et al., 2015). Italy witnessed a significant impact on the demand for public transport services, which suffered a severe contraction in favor of private cars but also active modes (e.g., biking and walking for shorter distances; ISFORT, 2021) which can increase social inclusion and psycho-physical well-being (Nikitas et al., 2021; De Vos, 2020; Chatterjee et al., 2019; Crotti et al., 2021; Mazziotta et al., 2022). Still, the literature about the drivers of commuting by active modes is relatively scarce. In this paper we contribute to fill that gap by focusing on university commuters and their propensity to shift towards active modes avoiding any other multimodal solutions (e.g., cars, buses, trains, etc.). To do so, we first investigate the importance of factors inducing the use of active modes to reach the college. Then, we test a logit regression model to study the impact of socio-economic variables and relevant aspects that are detected by a factor analysis. By assuming two alternative scenarios of low or medium-high health risk of contagious, this paper compares them, allowing to better understand how the perception of the Covid-19 contagion risks can affect the commute mode choice.

The paper is structured as follows. Section 1introduces the background of the study; Section 2 sets out the structure of used data; Section 3 explains the methodology approach; Section 4 highlights the results, and finally Section 5 concludes the study with policy implications.

2. Survey and data collection

The data used have been collected through a national online survey codenamed “University mobility at the time of Covid-19” by the Italian Network of Universities for Sustainable Development (RUS, 2021). The survey involved students and employees of 51 Italian universities about prospective commuting habits for the A.Y. 2020-2021. The sample is composed by 114,000 observations (students: 79.4%; faculty: 11%; technical-administrative staff: 9.6%) from the North-West of Italy (45%), the North-East (24%), the Center of Italy (16%), and from the South, and Islands (15.5%). In addition to external information on the territorial context where each university is located (e.g., the supply of public transport), the survey includes personal characteristics, mobility capital, pre-pandemic home-university travel habits, and information concerning the propensity to adopt sustainable and multimodal travel choices. Respondents were also asked to express their prospective choices and travel habits considering two alternative pandemic scenarios, i.e., optimistic, or pessimistic:

- *optimistic scenario*: the virus is almost over; new infections are reduced; social distancing and protection measures are relaxed; college activities are regular.
- *pessimistic scenario*: the virus is still dangerous; contagions have slowed down, but protection measures are still needed; college activities are not regular.

3. Methodology

In order to understand the main aspects motivating the choice to commute by active modes, an exploratory factor analysis was applied (section 3.1). This approach would allow to gain insights about the relative importance of selected nine items related to cycling, and five items related to walking to university. Then, by using the outcomes of the factor analysis, a logit regression model has been developed and estimated (section 3.2) to study the propensity to use active modes independently from the multimodal usage of other means of transport (i.e., cars, bus, train, etc.).

3.1 Factor Analysis model

The factor analysis tries to describe the covariance relationships among many variables in terms of a few underlying, but unobservable, random quantities called *factors* (e.g., see Johnson and Wichern, 2008). This method assumes that all the variables within a particular group are highly correlated among themselves, but they have relatively small correlations with variables in a different group. As a result, it is conceivable that each group of variables is represented by a factor, responsible for the observed correlations. In matrix notation, the factor analysis model is as follows:

$$\boldsymbol{AM} - \boldsymbol{\mu} = \boldsymbol{L} \times \boldsymbol{F} + \boldsymbol{\epsilon} \tag{1}$$

where the vector $\boldsymbol{AM} = (AM_1, \dots, AM_{14})$ consists of 14 observable covariates related to active mobility aspects about walking and cycling (as listed in Table A1 in the Appendix). The mean of each of those components is collected into the vector $\boldsymbol{\mu} = (\mu_1, \dots, \mu_{14})$, and the covariance matrix is $\boldsymbol{\Sigma} = Cov(\boldsymbol{AM}) = E(\boldsymbol{AM} - \boldsymbol{\mu})(\boldsymbol{AM} - \boldsymbol{\mu})'$. The factor model postulates that the vector $\boldsymbol{AM}$ is linearly dependent upon unobservable random variables, collected into vector $\boldsymbol{F} = (F_1, F_2, \dots, F_q)$, called *common factors*, whose number is determined by the related $(14 \times q)$ matrix of factor loadings $\boldsymbol{L}$ and unique variances (see Table 1). Additional sources of variation – called *errors* or, sometimes, *specific factors* – are included into the vector $\boldsymbol{\epsilon} = (\epsilon_1, \dots, \epsilon_{14})$, whose components are individually linked to active mobility variables.

3.2 Logistic regression model

In order to identify the propensity to reach the college by active modes, the respondents were asked the following question: "*Do you think it would be possible for you to go to university using active mobility (i.e., walking, cycling, e-scooter) regardless of the use of other means of transport?*". In our case, the binary response dependent variable *Y* is defined as the indicator function for modal change, taking a value of 0 if the respondent is willing to use active modes only in combination with other transport means, and 1 if that choice is independent from multimodality. In this type of classification model, the predicted probability $P = \Pr(Y = 1|\boldsymbol{X})$ is a non-linear function of independent variables, and the log of odds are a function of that probability, as in (2):

$$ln\left(\frac{P}{1-P}\right) = \alpha + \boldsymbol{X}'\boldsymbol{\beta} \triangleq P = \frac{e^{\alpha + X'\beta}}{1 + e^{\alpha + X'\beta}} \quad (2)$$

where the vector $\boldsymbol{X} = (x_1, \dots, x_{14})$ consists of 14 variables about personal characteristics (e.g., age, gender, work position, etc.), geographical contexts, transportation supply (e.g., sharing mobility and PT services), trip features (e.g., distance in km, travel times, commute weekly frequency) and pre-Covid travel habits (transport modes choice and multimodal solutions), as in Table 2, while Y indicates the binary latent utility perceived by the individual when choosing to use the active mobility independently from the joint use with other means of transport in each of the alternative pandemic scenarios. The parameter α yields the probability P when the components of $\boldsymbol{X}$ are zero, while each coefficient β_j, $j = 1, \dots, 14$ of the vector $\boldsymbol{\beta}$ is estimated using the maximum likelihood methods and adjusts how quickly the odds of changing commute mode changes with single-unit variations of the related variable into $\boldsymbol{X}$. When estimating logit models, since marginal effects are not constant in a non-linear regression, average marginal effects (AMEs), i.e., the average of marginal effects computed for each independent variable, are used (Cameron and Trivedi, 2003)[1] and they are calculated as:

$$\overline{\frac{\partial P}{\partial x_j}} = \frac{1}{14}\sum_{j=1}^{14} F'(\boldsymbol{X}'\boldsymbol{\beta})\beta_j \quad (3)$$

where F' is the first derivative of the standard cumulative logistic distribution function $F(x) = \frac{e^x}{1+e^x}$, $-\infty < x < \infty$ (Wooldridge, 2010), and β_j is the related coefficient for $x_j \in \boldsymbol{X}$.

4. Results

Before starting the analysis, from the sample we removed students declaring their intention to change own university in the A.Y. 2020-2021. This was necessary to be able to make a comparison of the responses before Covid-19 and those assuming the two pandemic scenarios considered. Table A1 in the Appendix shows the responses for each of the 14 items, measured on a 4-point Likert scale, evaluating their own perceived importance (i.e., 0 – Not at all important; 1 – Unimportant; 2 – Fairly important; 3 – Very important). The most relevant issues appear to be those linked to safety and security: a *quiet and safe pedestrian path* is considered at least fairly important by 86% of the sample, and a *path with high personal security (theft, harassment, etc.)* is likewise appreciated (84%). In the meantime, to adopt cycling both a *safe cycle path (protected from motorized traffic*), as well as a *low risk of bike theft*, are deemed relevant by 91%. Table 1 reports the main results of the above-described factor analysis. First of all, the analysis of factor loadings showed what items contribute to the definition of each factor, helping in the identification of the latent structures that factors should reveal and suggested to consider four factors. Also, the *uniqueness* values are reported, i.e., the portion of each indicator variance not explained by the first four factors that were retained and identified. Notice also that the sample size is limited to those declaring they did not use active mobility for *any* stretch of their home-to-university journey. Finally, with the aim of examining the possible identification of the four factors based on the loadings for the original items, note that, overall, the results are similar in both the scenarios, and they will be reviewed together accordingly.

Factor 1 (explaining around 37% of total variance) highlights the appreciation for itineraries rolling along parks and green environments with the purely conceptual

1 The *marginal effect at the mean*, computed at the means of all covariates, is an alternative method, but there may not be such “average” individual. Without loss of significance, the average marginal effect makes more sense.

items regarding being part of a community that cares about sustainability; thus, it could be labelled as *eco-friendly environment*.

Table 1 – *Output of factor analysis.*

Rotated factor loadings (pattern matrix) and unique variances					
Variable	**Factor 1**	**Factor 2**	**Factor 3**	**Factor 4**	**Uniqueness**
AM1. Optimistic			0.7842		0.2840
AM1. Pessimistic			0.7834		0.2847
AM2. Optimistic			0.8004		0.3024
AM2. Pessimistic			0.7962		0.3072
AM3. Optimistic			0.7364		0.3510
AM3. Pessimistic			0.7376		0.3517
AM4. Optimistic	0.7587				0.3315
AM4. Pessimistic	0.7560				0.3334
AM5. Optimistic	0.8589				0.2133
AM5. Pessimistic	0.8618				0.2094
AM6. Optimistic				0.8237	0.2340
AM6. Pessimistic				0.8273	0.2295
AM7. Optimistic		0.6984			0.3815
AM7. Pessimistic		0.7126			0.3791
AM8. Optimistic		0.7145			0.3418
AM8. Pessimistic		0.7244			0.3425
AM9. Optimistic	0.6739			0.4693	0.3100
AM9. Pessimistic	0.6730			0.4657	0.3142
AM10. Optimistic				0.6843	0.3505
AM10. Pessimistic				0.6921	0.3436
AM11. Optimistic		0.7006			0.4353
AM11. Pessimistic		0.6957			0.4490
AM12. Optimistic	0.8241				0.2268
AM12. Pessimistic	0.8254				0.2246
AM13. Optimistic		0.4843			0.5537
AM13. Pessimistic		0.4770			0.5534
AM14. Optimistic		0.6398			0.4653
AM14. Pessimistic		0.6405			0.4546

Note: After data cleaning, the final sample size is 33,092 for the optimistic scenario and 30,240 for the pessimistic one; this reduction is caused by the missing values of some covariates. For the description of questions about walking and cycling conditions see Table A1 in the Appendix.

Factor 2 (12% of total variance) combines economic and logistical aspects, involving both monetary incentives as well as technical support for multimodality and the recharging of e-bikes and e-scooters. Therefore, it can be named as the *convenience* factor. From the point of view of walking and cycling, respectively, the other two factors represent the two facets of a similar issue. They thus could be called *walking safety* (Factor 3, explaining 10% of total variance) and *cycling safety* (Factor 4, accounting for 6.5% of the overall variance). These separate factors regarding safety are due to the differing perception of the "safety" concept itself. When considering walking, safety is indeed more connected to being protected from the consequences of urban decay, such as dirtiness, petty crime, etc. As regards cycling, instead, the road safety (which implies avoiding accidents caused by motor vehicles) is of utmost importance. Table 2 reports the estimation results, both as coefficients, as well as the corresponding average marginal effects for both the scenarios. After data cleaning, the final sample amounts to 26,621 observations for the optimistic scenario and 24,345 for the pessimistic one. The binary dependent variable takes value 0 if the respondents are willing to use active modes only combined to multimodal options; and 1 if active modes are chosen independently from the use of other transport means. As we can see, the results are similar in the two pandemic scenarios. It shows that the prevailing means used before the pandemic have a negative effect on the propensity to use active mobility regardless the joint use of other means of transport. It is also highlighted that the pre Covid-19 use of multimodality is statistically and negatively related to the choice of using sole active modes for commuting purposes. Notably, this result is confirmed by controlling for the distance in km traveled, and the travel time to reach the university. Indeed, these two variables are statistically significant and negative, thus indicating that, as travel time and distance increase, the use of active modes is less likely when it is considered not combined with other means of transport. Moreover, those owning a motor vehicle are less willing to reach the university by walking or cycling: actually, this result is more accrued in the pessimistic scenario. On the other hand, as expected, it should be noted that those owning a bicycle are instead more prone to use active mobility without using other means of transport, being probably accustomed to use bikes as sustainable, but also safer and healthier, means. This result is also in line with the hometown presence of bike sharing services, that is more significantly in the optimistic scenario than in the pessimistic one. A possible motivation could concern the risk of contagion in case of the usage of bike sharing when the sanitation is inadequate.

Finally, it is interesting to note that the estimate of the *eco-friendly environment* factor (Factor 1) is not significant in the two proposed pandemic scenarios. Instead, the impact of Factors 3 and 4 are positively and significantly linked to the choice of active commuting without supporting it with other means of transport. Conversely, the Factor 2 (inherent to economic incentives) reveals a negative sign. A possible reason might depend on the fact that those who are consolidated cyclists (or, in general, people who walk or use bikes for commuting purposes) probably do not need economic incentives (e.g., to buy a bicycle or e-scooter). In fact, beyond evaluating economic incentives or nudges, even not accustomed bikers or walkers tend to consider the safety of pedestrian and cycle paths much more important in order to adopt active commuting without other transport means, as also argued by other scholars, such as Abdullah et al. (2020) and De Vos (2020).

Table 2 – *Output of logit model.*

Label variable	Optimistic scenario		Pessimistic scenario	
	Coef.	**dy/dx**	**Coef.**	**dy/dx**
Pre-Covid choice: (Active modes)				
Motor vehicles	-0.62***	-0.11***	-0.70***	-0.13***
Public Transport	-0.50***	-0.09***	-0.56***	-0.10***
Pre-Covid multi-modality of travel	-0.53***	-0.10***	-0.56***	-0.11***
Gender (Male)	-0.35***	-0.06***	-0.39***	-0.07***
Age (Scale 18 – 79)	0.01*	0.00*	0.01	0.00
Work position (Students)				
Faculty	0.08	0.02	0.12	0.02
Staff	0.02	0.00	0.05	0.01
Motor vehicles ownership	-0.19**	-0.03**	-0.21***	-0.04***
Bicycle ownership	0.52***	0.10***	0.53***	0.10***
Driving license B	0.08	0.01	0.04	0.00
Macro region (North-West)				
North-East	-0.04	-0.00	-0.07	-0.01
Center	0.03	0.00	0.03	0.00
South	0.34	0.06*	0.36	0.07*
Islands	0.01	0.00	0.03	0.00
Weekly freq. (Less than once a week)				
Once	-0.28	-0.05	-0.37*	-0.07*
Twice	-0.29	-0.05	-0.37*	-0.07*
3 times	-0.34*	-0.06*	-0.37*	-0.07*
4 times	-0.52***	-0.10***	-0.57***	-0.11***
5 or more times	-0.28*	-0.05*	-0.31*	-0.06*
Travel time (Up to 15 min)				
15-30min	-0.51***	-0.10***	-0.52***	-0.10***
30-60min	-1.02***	-0.21***	-1.05***	-0.21***
More than 60min	-1.24***	-0.25***	-1.24***	-0.25***
Distance in km covered (1-5 km)				
5–20 km	-1.14***	-0.24***	-1.12***	-0.23***
20-80 km	-1.27***	-0.26***	-1.20***	-0.25***
> 200km	-0.60***	-0.12***	-0.58***	-0.11***
Bike Sharing availability	0.23**	0.04**	0.19*	0.04*
Public Transport Service (Poor)				
Acceptable	0.17***	0.03***	0.20***	0.04***
Good	0.10	0.00	0.03	0.01
Excellent	0.10	0.00	0.05	0.01
Factor 1: eco-friendly environment	0.00	0.00	-0.00	-0.00
Factor 2: convenience	-0.10***	-0.02***	-0.90**	-0.02**
Factor 3: walking safety	0.10***	0.02***	0.12***	0.02***
Factor 4: cycling safety	0.15***	0.03***	0.15***	0.03***
Constant	2.25***		2.43***	

*Note: dy/dx for factor levels is the discrete change from the base level. *** p<0.01, ** p<0.05, * p<0.1.*

5. Concluding remarks

Besides allowing more protection from pandemics (De Hartog et al., 2010) and helping to limit the shift from public transportation to motorized private vehicles (Myftiu et al., 2022), the recourse to active mobility has even greater positive implications for people health and wellbeing. In this paper, some indications are derived to study potential drivers of active modes for commuting purposes. By considering university contexts, safety and security are invoked almost unanimously as relevant aspects. The applied factor analysis also suggested (i) an economic/logistic dimension - linked to cycling only - involving monetary incentives for bicycle commuting and, conversely, higher fees for car parking – and (ii) a more "psychosocial" side related to the wellbeing entailed by being part of an eco-friendly urban community. Chatterjee et al. (2020) state that:" […] *people who walk or cycle to work are generally more satisfied with their commute than those who travel by car and especially those who use public transport*". Similarly, our policy implications include: quality and safety of walking and biking paths; economic incentives for cycling; and the creation of an eco-friendly environment, both culturally (i.e., people feel part of a "greener" community) and materially (i.e., urban landscape are healthier and far from the nightmare of congestion and constant air pollution).

Appendix

Table A1 *– Active mobility factors (walking)*

	Optimistic	**Pessimistic**
AM1. A quiet and safe pedestrian path with respect to motorized traffic:		
Not at all important	4.41	4.46
Unimportant	10.11	10.23
Fairly important	36.70	37.09
Very important	48.78	48.22
AM2. A path with high personal security (theft, harassment, etc.):		
Not at all important	4.42	4.60
Unimportant	11.35	11.66
Fairly important	31.10	31.36
Very important	53.13	52.38
AM3. A non-bumpy path (existence of spacious pavements, clean, not invaded by parked cars or other obstacles, absence of potholes, etc.):		
Not at all important	3.62	3.66
Unimportant	10.39	10.48
Fairly important	38.84	39.30
Very important	47.15	46.56
AM4. A pedestrian path with more greenery:		
Not at all important	6.96	7.07
Unimportant	30.89	31.28
Fairly important	37.40	37.28
Very important	24.75	24.36
AM5. I feel part of a community that considers it important to reduce its environmental impact:		
Not at all important	8.99	9.27
Unimportant	19.18	19.22
Fairly important	37.77	37.81
Very important	34.06	33.70

Table A1 (cont.) *– Active mobility factors (cycling).*

	Optimistic Scenario	**Pessimistic Scenario**
AM6. A safe cycle path (protected from motorized traffic), continuous and not bumpy:		
Not at all important	4.22	4.18
Unimportant	4.82	4.74
Fairly important	24.30	23.91
Very important	66.66	67.16
AM7. An economic incentive to move to this mode (e.g., incentive km, vouchers, etc.):		
Not at all important	7.48	7.54
Unimportant	19.41	19.76
Fairly important	31.41	31.14
Very important	41.70	41.56
AM8. A significant bonus for buying a bicycle or scooter:		
Not at all important	8.22	8.34
Unimportant	18.90	19.11
Fairly important	29.87	29.62
Very important	43.00	42.94
AM9. A cycle path with more greenery:		
Not at all important	7.78	7.85
Unimportant	26.58	26.59
Fairly important	36.96	36.58
Very important	28.67	28.97
AM10. Availability and security from stolen university parking:		
Not at all important	3.70	3.70
Unimportant	4.18	4.13
Fairly important	22.03	22.10
Very important	70.10	70.07
AM11. Absence/elimination/pricing of car parking available at the university:		
Not at all important	16.14	16.77
Unimportant	21.08	21.61
Fairly important	25.84	25.48
Very important	36.93	36.14
AM12. I feel part of a community that considers it important to reduce its environmental impact:		
Not at all important	10.63	11.00
Unimportant	20.12	20.17
Fairly important	36.52	36.21
Very important	32.74	32.62
AM13. Facilities for bicycle transport on public transport (train/bus):		
Not at all important	8.10	8.34
Unimportant	14.06	14.17
Fairly important	33.50	33.23
Very important	44.34	44.27
AM14. Presence of charging points for electric vehicles:		
Not at all important	12.27	12.25
Unimportant	18.15	18.26
Fairly important	33.29	32.89
Very important	36.30	36.60

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SUMMARY

This study aims at studying the effects of the Covid-19 pandemic on university commute mode choices and identifying the drivers to change usual transport means to reach college destinations. The data were collected by the Italian Network of Universities for Sustainable Development in 2020. Respondents were asked about their own propensity to switch to active commuting avoiding any other multimodal motorized modes and considering two alternative scenarios (optimistic or pessimistic) concerning the potential risk of contagion. After having identified four latent factors (related to, monetary incentives to bike commuting and psychological aspects of pro-ecological attitudes are detected), the result of a logit model suggested rather straightforward policy drivers, i.e., investing into the quality and safety of routes for walking/cycling, incentives for cycling, and the creation of an eco-friendly environment, where university users feel part of a greener community.

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