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Modelling commuting tours *versus* non-commuting tours for university students. A panel data analysis from different contexts.

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ABSTRACT

University students' mobility represents a significant part of the mobility demand, since the right to mobility becomes yet more significant, as it directly translates into the right to education. At the same time, lifestyle evolution and changes has yield to a boost in the number of non-commuting tours, which are now recognized as a key component of any travel demand system. However, their analysis is often overlooked due to their randomness and difficult detectability.

Motivated by this shortfall, the current study sought to explore the university students' mobility by focusing on i) a comparison among commuting and non-commuting tour, ii) analysing non-commuting patterns and iii) identifying factors affecting the tour generation. A joint mixed logit model was specified and estimated using panel data collected in two Italian Universities (Cagliari and Rome).

This study represents a pilot test conducted for the purpose of providing scientific justification for implementing Voluntary Travel Behaviour Change programmes and Travel Demand Management policies in Italian Universities. Our results indicate that the number of non-commuting tours, when compared with commuting tours, is not negligible (around 28% of tours are non-commuting tours) and we detected no-significant differences between Cagliari and Rome with respect to the tour characteristics. In Cagliari women, individuals who have a high number of household members, people living in areas characterized by high building densities and a small number of shops, and in Rome students living in small families and those who own a car, are more apt to travel for discretionary purposes.

Keywords: University Students; Non-commuting Tours; Panel Data; Joint Mixed; Mobility Demand; Voluntary Travel Behaviour Change (VTBC)

Introduction

This paper focuses on one specific aspect of travel behaviour: the comparison among commuting and non-commuting tours of university students. This topic has been chosen for several reasons as detailed below.

A research topic, which recently attracted a lot of interest, is the study of the mobility of university students, and this surge of interest can be explained by several reasons. The right to mobility is a fundamental right of every individual, but it becomes yet more significant when referring to the students: the right to mobility directly translates into right to education. The students' mobility must be ensured, and, at the same time, it must be acceptable, accessible, affordable, and available. Furthermore, since university campuses are special and major destinations in a city's framework, and they are able to generate a significant number of trips (Vale *et al.*, 2018), students' travel behaviour should preferably be environmentally sustainable. While originally Travel Demand Management (TDM) strategies only focused on employees, recently mobility managers from different universities worldwide have started to adopt specifically student-oriented policies, which also aim to elevate university-related sustainability standards. However, from an analysis of the literature it emerges that, because of the lack of specific and dynamic information on students' mobility habits, only isolated policies have been adopted.

In Italy, in particular, university students account for 7% (roughly 1,700,000 individuals) of the active population, with more than 275,000 new students enrolling each year (MIUR, 2017). There are about eighty universities, totalling 566 faculties, across Italy. These consist mainly of separate buildings and the related services (canteens, libraries, halls of residence, *etc*.) are not necessarily contained therein but are instead located in other parts of the city. Moreover, it is not a negligible fact that, though the campus location is most frequently inside an urban environment, universities are in many cases highly car-oriented because of the absence of reliable public transport services. This in turn has both positive and negative impacts: on one hand, they contribute to the prestige of the area but, on the other hand, they are traffic generators/attractors. These context characteristics may surely affect the type of daily tour and trip chaining, and so can do the socio-economic (SE) and cultural features (country size, cost of living, distance, climate and language) as well. Nevertheless, while in the USA and in different European contexts students' travel behaviour has been extensively investigated, in Italy this topic has often been ignored.

A tour is defined as a series of trips connecting a chain of stops between two in-home activity episodes, where "stop" is a term used to refer to any out-of-home activity episode (Bhat and Misra, 2001). Non-commuting tours are thus defined as tours whose intermediate stops are made for non-commuting purposes only. They are recognized as an essential component of any travel demand system (Bhat, 1997), as they allow people to participate in activities and perform tasks that cannot be accomplished at home. In recent years, the evolution and changes of lifestyles have led to an increase in the number of non-commuting tours. In Italy, in 2017, 68.5% of total trips were made for non-commuting purposes, with this share increasing (73.0%) when considering only those made in urban areas (ISFORT, 2018).

Although their importance has been extensively recognised, for many years researchers have often neglected the study of non-commuting tours, because of their complex tracking processes, due also to their randomness and complexity in terms of numerosity, timing, destination choice and purpose. Only recently there has been a surge of interest in their analysis, as a result of the increased availability of travel and activity diary data and Global Positioning System (GPS) data, which enables the analysis of all the multiple aspects of travel patterns mentioned before. In particular, GPS technologies, especially when combined with GIS software, are able to provide travel data with a high resolution in both time and space (Big Data), allowing for the specification and estimation of model frameworks with increasingly complex dependence structures (Bhat, 2015) and improving the efficiency and responsiveness of urban policies (Calabrese *et al*., 2013).

Despite the continually increasing interest in the study of non-commuting tours in transportation research, it is still unclear which attributes influence a non-commuting tour, whose understanding is crucial for developing effective transportation measures and for urban neighbourhoods' planning (Krizek, 2003; Harding *et al*., 2015). From a transportation point of view, this knowledge can assist in developing more effective policy measures apt to encourage people toward a modal shift. For example, by using public transport, it is easier to undertake a commute tour rather than a non-commute tour, because of higher frequencies during the peak hours (Ortuzar and Willumsen, 2011). On the contrary, a non-commute tour is more likely to adjust to either car or active mobility, because of their flexibility and availability of service. For instance, tours for leisure purposes, typically made during late hours or non-working days, are more difficult to be accommodated by public transport (Rajamani *et al*., 2003; Cherchi *et al*., 2017) since the frequencies are usually lowered at late hours and in the weekends. From an urban planning perspective, investigating the differences between commute and non-commute tours can help understanding whether the concept of reducing distances among residential, employment and service locations could increase the likelihood of linking more destinations within a tour, thus reducing daily travel distances (Banister, 1997; Maat and Timmermans, 2006; Van Acker and Witlox, 2011).

Another point is that travel mode choices are often heavily habit-dependant (Hoffmann *et al*., 2017; Verplanken *et al*., 1994; Triandis, 1977). Many behaviours that are considered as potential targets for behaviour change in a more sustainable direction, such as transportation, are strongly habitual (Verplankenand Roy, 2016). University years represent an important transitional period in which preferences and habits are defined, and activity-travel behaviours are not an exception (Kamruzzaman *et al*., 2011; Khattak *et al*., 2011; Balsas, 2003). University students are generally more inclined to use public transport and non-motorized travel modes (Bonham and Koth, 2010; Ripplinger *et al*., 2009). Therefore, encouraging and promoting sustainable travel at a young age may help bring about more sustainable travel choices later in life (Sigurdardottir *et al*., 2013).

Overall, understanding the travel behaviour of university students can help university mobility managers work toward improvement of policies, programs, and infrastructures, which will in turn encourage the use of sustainable modes among university students (Shannon *et al*., 2006).

Given the above discussion, the main objective of this work is to investigate the characteristics underpinning the university students' non-commuting tours estimating a joint mixed Logit model (Srinivasan and Bhat, 2006), using panel data collected, through the IPET-Individual Persuasive Eco-Travel Technology app (Sanjust di Teulada and Meloni, 2016), in two Universities located in different regional contexts, Rome and Cagliari, in Italy. Considering two different territorial contexts allows to verify if and how the context characteristics could affect the non-commuting tours.

A joint mixed Logit model has been used to study, for each context, which variables influence the tours for any non-commuting related reason (*e.g.* shopping, entertainment, physical activity) when compared to the work/study tours. A set of several explanatory variables were tested (departure time, travel time and cost, parking cost, distance, number of stops, stop duration, travelling companion, socio-economic and land use factor characteristics) with error components for panel effects, which differ for two survey phases, and two scale group parameters for sustainable means of transport. The model results also allowed us to prove the importance of analysing each university context separately.

This study represents a pilot test to justify the need to take into consideration non-commuting tours of university students in implementing voluntary travel behaviour change programs (VTBC) on a larger scale, and TDM policies in different Italian university campuses.

The remainder of the paper is organized as follows: the next section provides the literature review, followed by the data collection section. The joint mixed Logit model is presented in the paragraph “Modelling framework” followed by a discussion of the estimation results. The conclusions are outlined in the last paragraph.

Literature Review

It is possible to find a considerable number of studies which deal with different aspects of university or college students’ travel patterns. These include, among others, the use of GIS to visualize and assess travel behaviour (Kamruzzaman *et al*., 2011), modal choices (Klockner and Friedrichsmeier, 2011; Delmelle and Delmelle, 2012; Zhou, 2012; Hasnine *et al*., 2018), and activity patterns (Eom *et al*., 2009; Chen, 2012).

Other investigations have focused on attitudes toward safety and on the driving behaviour of students (Al-Rukaibi *et al*., 2006), their enjoyment of different modes of transportation (Páez and Whalen, 2010), and the psycho-attitudinal and cultural factors that influence the use of active modes of travel in a university setting (Bonham and Koth, 2010; Thigpen *et al*., 2015; Kelarestaghi *et al*., 2019), as well as the potential for change towards active travel (Shannon *et al*., 2006).

Previous studies on this topic mainly followed two approaches: descriptive statistics and mathematical models. An array of studies relied on descriptive statistics to capture post-secondary students' travel patterns (Boyd *et al*., 2003; Shannon *et al*., 2006; Alm and Winters, 2009; Miralles-Guasch and Domene, 2010; Khattak *et al*., 2011; Limanond *et al*., 2011; Delmelle and Delmelle, 2012; Whalen *et al*., 2013; Uttley and Lovelace, 2016). For example, Limanond *et al*. (2011) examined the travel patterns of a sample of students who studied and lived on campus in a rural university in Thailand, investigating the difference in travel behaviour of four student groups, based on their gender and whether or not they owned a vehicle. Duque *et al*. (2014) and Davison *et al*. (2015) explored the contribution to transportation emissions resulting from university-related travel. Soria-Lara *et al*. (2017) specifically studied whether spatial location, socio-economic characteristics and social behaviour influence the decision to travel by car in the context of metropolitan university campuses in Barcelona. Within the context of travel behaviour change, Delmelle and Delmelle (2012) explored the spatial, temporal and gender differences in transportation modal choice among student commuters with the objective of uncovering incentives to increase the use of non-motorized or public transportation to the University of Idaho. Uttley and Lovelace (2016) examined commuting behaviour and long-term behavioural shifts towards cycling in response to outside intervention at the organisational level (University of Sheffield).

Studies which relied on mathematical models mainly used Logit and Probit family models to explore the correlation between dependent and independent variables (Rodriguez and Joo, 2004; Ripplinger *et al*., 2009; Zhou, 2012; Akar *et al*., 2013; Lavery *et al*., 2013; Grimsrud and El-Geneidy, 2013; Whalen *et al*., 2013; Danaf *et al*., 2014; Rotaris and Danielis, 2014, Rybarczyk and Gallagher, 2014; Hasnine *et al*., 2018; Namgung and Jun, 2019). The main theme investigated by all these studies is that of identifying which variables influence the use of active modes of transport rather than the car for commuting to the university. For example, concerning active mobility, Rodriguez and Joo (2004) estimated three models, a Multinomial Logit (MNL), Nested Logit (NL) and heteroscedastic extreme value model, to investigate the relationship between the use of active transportation modes and the built environment within a sample of students at University of North Carolina. Akar *et al*. (2013) studied the gender differences in travel behaviour and travel patterns at Ohio State University with a focus on cycling through the estimation of two MNL. Interestingly, Hasnine *et al*. (2018) estimated MNL, NL and cross-nested Logit (CNL) models for investigating home to university trips mode choices in Toronto, showing that mobility tools' ownership (*i.e*. transit pass, car and bike ownership), gender and age have distinctive influences on students' mode choice behaviour. However only two studies estimated a mixed logit (ML) model for their analysis. Ripplinger *et al*. (2009) estimated a ML model to investigate the changes in travel behaviour over four years in a sample of students at North Dakota State University. Rotaris and Danielis (2014) adopted an ML model to estimate the commute mode choice of a sample of students and workers at the University of Trieste, using both revealed and stated preference data of 8 different transport management policies scenarios.

Regarding data collection, several previous studies used cross-sectional travel surveys on the description of systematic trips of students and their families (Meloni *et al.*, 2011). Few works conducted panel survey to analyse day-to-day travel behaviour. (Khattak *et al*., 2011; Eom *et al*., 2009; Shannon *et al*., 2006). Another restriction is that GPS technologies are poorly utilised to gather information on travel behaviour at universities. Van Dijk and Krygsman (2018) are among the first to employ this technology to investigate students' travel behaviour. They used the data of a two-day tracking experiment to explore whether Stellenbosch University student's accessibility to opportunities as represented through activity spaces associate with different travel characteristics.

In terms of tour analysis, researchers have mainly analysed total travel time, tour mode, tour frequency, trip chain length, and number of stops (see for example McGuckin and Nakamoto, 2004; Maat and Timmermans, 2006; Frank *et al*., 2008; Van Acker and Witlox, 2011). Various works studied the causal relationships between tour complexity and mode choice using different econometric methods. Hensher and Reyes (2000) estimated an NL model formulation to understand the influence of trip chaining as a barrier to the propensity to use PT. Ye *et al*. (2007) adopted an advanced econometric model, a recursive binary Probit model jointly estimated with a Logit model, to study how the choice of the means of transport can influence tour complexity and *viceversa*. Li *et al*. (2013), by jointly estimating a binary Logit for bicycle choice and an MNL for trip chain choice, investigated which factors contributed to the order of decisions between the choice to cycling and trip chaining.

Interestingly, some studies have focused on day-to-day or intra-day variability. Ramadurai and Srinivasan (2006) applied an ML model on mode choice to investigate intra-day dynamics and variations within and across individuals at a tour level. Cherchi and Cirillo (2014) used a six-week travel diary survey to study day-to-day variability in the individual preference for mode choice for commuting and non-commuting tours through the estimation of an ML model.

However, none of the above works recognize the distinction between non-commuting and commuting tours, preferring a classification between home-based and non-home-based tours, or based on tour complexity (number of stops or activities).

Moreover, little research has explicitly studied non-commuting tours. Davis *et al*. (2018) explored the characteristics of non-commute long-distance travel using a model from the structural equation modelling family, called path analysis, to identify the relationships among modes used, distance travelled, number of overnight stop and destinations. Zeid *et al*. (2006) investigated the choice of arrival time, departure time or both of non-work tours adopting jointly estimated MNL models. Limanond *et al*. (2005) used an NL model to jointly estimate five dimensions of shopping travel, including decisions of: (1) household tour frequency, (2) participating party, (3) shopping tour type, (4) mode, and (5) destination choices.

Study context and data

Study Context

The current research was implemented in the two cities of Rome and Cagliari (Italy) on a university students' sample.

Rome is the capital city of Italy. With 2,819,751 residents (August 2020) it is also the country's most populated municipality, while its metropolitan area has a population of 4,314,325 residents (August 2020). The metropolitan area of Rome can be considered as an example of sprawled city (Salvati, 2013; Patella *et al*., 2019), where the share of car use is equal to 49.3% (Patella *et al*., 2019). The existing transit network is composed of around 200 bus lines and is characterized by the presence of several overlapping routes and not very high frequencies (Cipriani *et al*., 2012). The University of Roma Tre has around 33,160 enrolled students (2020) and its main campus is located in the Ostiense district, in the southern part of the city. The campus can be easily reached by both public transport services (bus stops and metro stations are within a short walking distance) and by car.

Cagliari is an Italian municipality and the capital of the island of Sardinia and it is located in its southern region. It has 152,415 inhabitants (August 2020), while its metropolitan area counts 429,231 inhabitants (August 2020). Despite the presence of a high-quality public transport service, which includes a network of 313 km, the modal share in the metropolitan area of Cagliari is in still favour of the car (60% for all commuting trips). The University counts about 27,700 enrolled students (2020) and its buildings are distributed over the city (mainly in the city centre). The faculty of Engineering is located in a densely populated area in the city centre, which is affected by the passage of 3,216 vehicles/hour in the morning peak hour (8:00-9:00). The area is well served by public transportation services.

Data collection and analysis

The study involved the collection of data on the trips and activities of students from two different Universities using the aforementioned GPS based mobile application IPET (for more details see Tuveri *et al.*, 2020). We used this app to perform a pilot test on two different samples of students, one from the Faculty of Engineering of Cagliari, the other from the Faculty of Engineering at the University of Roma Tre. The survey was divided into four macro-phases:

(1) Preliminary survey
(2) First IPET activity data collection, followed by data analysis and Personalised Travel Plans (PTPs) compilation and delivery (First phase survey)
(3) Second IPET activity data collection (Second phase survey)
(4) Conclusive survey

The main investigation goal was to analyse the individuals' voluntary behaviour changes with regard to daily travel behaviour following the implementation of a PTP. A total of 93 students (43 from Cagliari and 50 from Rome) participated in the programme. We did not want the sample to be representative of the population, but it is a convenience sample available to be "stress-tested". The programme was demanding in itself and usually a first pilot test could be very challenging for the participants due to the need to test several aspects before of a large-scale implementation. Therefore, we decided to intercept two of our university student classes with whom we could keep in contact for all semester and beyond. For the different sample sizes the logic is the same, but we take into account this aspect in all the analyses carried out using appropriate statistical tests (*e.g.* t-stat).

The surveys were not simultaneous, since the first test batch was developed in Cagliari. The students were asked to use the IPET app for the whole week, from Monday to Friday, on both weeks (5 + 5 days). It was decided not to consider the weekends both in order not to burden the users, and for the differences in the travel activities that characterize the weekdays. In the conclusive survey, they were also asked whether they thought the programme was too long: 72% of the students deemed the duration acceptable, but the remaining 28% thought it lasted too long. This fact convinced us to reconsider the survey length, so the subsequent analysis in Rome was limited to a period of 2 days, Tuesday and Wednesday, on both weeks (2 + 2 days). This is also corroborated by previous works, in which a short data collection timeframe was used, considering that two-day diaries allow to capture day-to-day variability, while not burdening the respondents excessively (Stopher *et al*., 2009). When asked how they considered the programme's length, the students gave a much more positive opinion: 90% of them considered the duration acceptable, 6% even considered it too short, and only 4% lamented an excessive commitment. These results ultimately validated the choice to reduce the survey period.

First of all, the socio-economic characteristics were obtained via the preliminary survey; an online questionnaire was used, made available on the Wufoo platform.

The second set of data comes directly from the users' active participation. Using the IPET app, they had to input each activity's start/end time and its various characteristics, while the software continuously monitored the smartphones' position. This data was recorded in a database, which was later analysed to identify the routes followed by the students during their daily routines. Lastly, using both the geographical information collected through the app and the information directly given by the users, a series of points, corresponding to the primary "home" and "study" locations, was identified. Using the position of these points, it was also possible to build another dataset containing information describing the land-use (LU) factors of the surrounding area. These were gathered from two main sources: the first, Google's Places Service; the second, the Italian Statistic Institute (ISTAT), which publishes data based on every population census. A limited amount of data was also obtained through other sources, which include Open Street Maps and various open data repositories.

In the following sections the most important variables affecting tour purpose are examined, considering the two different contexts separately. Splitting the two datasets on the basis of context was deemed necessary, since the two territories are significantly different, and, most importantly, the two surveys were conducted following different procedures, mainly using a longer survey period in Cagliari and a shorter one in Rome.

Socio-economic characteristics at an individual level

Table 1 presents a summary of the socio-economic characteristics of the individuals belonging to the selected sample. Of the 42 individuals from Cagliari, 51.2%

were males and 48.6% females. The mean age was 25.7 years and 72.1% lived away from their parents' home. Almost everyone had a driving license (90.7%) and more than half of the sample had a car available. Regarding students from Rome, the sample was composed of 72% males and 28% females and the average age was around 21 years old. All participants possessed a driving license, while 88% had a personal car available. 30% of the sample lived away from their parents' home.

Socio-economic characteristics at a tour level

Following the definition of tour given by Bhat and Misra (2001), we identified all those series of trips starting and ending at the home locations, which were corresponding to the addresses given by the participants in the starting survey, or identified through the GPS data. It should be noted that every student could have more than one "home" location, since, apart from their declared main residence address, some of them might have other "bases" they could use alternatively (*e.g.* they could be sleeping at a boyfriend's/girlfriend's home, they could have separated parents living on two different houses). As a further classification, tours were split up between commute tours (C - tours which include at least one out-of-home study activity) and non-commute tours (NC - tours which do not include any out-of-home study activity). This subdivision will be kept throughout the analysis. Table 1 shows the socioeconomics variables, obtained through the initial personal survey, referred not to the individual level but to the tour level (968 observations). The variables were split, other than by regional context, by tour motivation since the ultimate aim of the model is to compare commuting and non-commuting tours.

Examining the results for Cagliari, one of the most significant differences that clearly emerges (judging by the t-stat value) concerned the out-of-town status of the students (which is an indicator of their origin, as their family lives further away from the university campus), since these students tend to spend more time travelling from home to campus and *viceversa*, and thus have less time available during the day for other trips. As a matter of fact, 73% of the commute tours were made by these students, but they completed only 61% of the non-commute ones. Another difference to be considered, is that between the average number of family cars for C and NC tours. Obviously, having access to a car is a favourable factor in the production of non-commuting tours, and this is reflected by the fact that students who travel for reasons other than their daily commute live in households that possess on average more cars compared to those who travel for study (1.30 *vs* 1.03). The last significant factor is income, since the data showed that having a high monthly income, 3,000 € or more, can greatly increase the number of non-commute tours. The remaining variables show very similar values when comparing C and NC tours.

Moving on to the context of Rome, while the general behaviour is similar to Cagliari, only one variable emerged as significantly important, *i.e*. the availability of a car. While this was inferred from the Cagliari data, Rome's students, when deciding to make NC tours, rely heavily on their private vehicles, since 85% of NC tours were completed by those who allegedly always have a car available, *versus* 72% for C tours. This difference is almost certainly linked to the different size of the two municipalities, since Cagliari barely covers 85 km^2, while Rome is a larger city, with almost 1,300 km^2 (note that the difference between C and NC tours, regarding this variable, exists for Cagliari too, but at a lower significant level). The other variables did not show statistically significant differences, but it seems they behave in the same way observed for Cagliari. Especially regarding income, the data from Rome seem to suggest the same pattern observed in Cagliari, with more NC tours being completed by the students coming from wealthier families. Note that, for both the contexts of Cagliari and Rome, there are almost no differences in the socio-economic variables at an individual and tour level when the commuting tour category is selected. This is a direct consequence of how the sample was selected, namely including in our analysis only students who went to the university at least once during either of the two monitoring weeks. It should be noted there is a relevant difference between the average household sizes of the two contexts, with a more-than-doubled value for the students in Rome. However, this is directly correlated to the fact that in Cagliari we had many more students (72.1% *vs* 30.0% in Rome) which were renting a room or an apartment and were thus living away from their parents' home. Since we considered these students to live in a single-person household (regardless of the presence of eventual flatmates), this fact remarkably lowered the average household size for the Cagliari sample.

Table 1. Analysis of socioeconomic variables.

Cagliari	Total sample		C	NC	Δ (NC-C)	t-stat
	N	[%]				
Total observations	43	100	468	196	-	-
Age (avg)	25.67		25.62	25.43	-0.7%	1.023
Male	22	51.2	52.1%	46.9%	-10.0%	1.222
Live outside parents' home	31	72.1	72.9%	61.2%	-16.0%	2.985*
Driving Licence	39	90.7	89.5%	91.3%	+2.0%	0.705
Car availability	21	48.8	47.2%	52.6%	+11.3%	1.253
# of household members (avg)	1.81		1.73	2.05	+18.4%	2.915*
# of cars in the household (avg)	1.05		1.03	1.30	+26.4%	2.786*
Income 0-1,000 €	37	86.0	86.1%	86.2%	+0.1%	0.039
Income 1,001-2,000 €	4	9.4	7.9%	6.1%	-22.6%	0.801
Income 2,001-3,000 €	1	2.3	3.0%	1.0%	-65.9%	1.511
Income > 3,000 €	1	2.3	3.0%	6.6%	+122%	2.171*

* Significant at 95% confidence

Rome	Total sample		C	NC	Δ (NC-C)	t-stat
	N	[%]				
Total observations	50	100	192	72	-	-
Age (avg)	21.04		21.04	21.07	+0.1%	0.129
Male	36	72.0	70.3%	76.4%	+8.6%	0.977
Live outside parents' home	15	30.0	27.6%	19.4%	-29.6%	1.356
Driving Licence	50	100.0	100%	100%	-	-
Car availability	44	88.0	71.9%	84.7%	+17.9%	2.169*
# of household members (avg)	4.06		4.09	4.00	-2.3%	0.993
# of cars in the household (avg)	1.18		2.40	2.40	+0.3%	0.057
Income 0-1,000 €	39	78.0	77.6%	81.9%	+5.6%	0.766
Income 1,001-2,000 €	4	8.0	8.9%	6.9%	-21.6%	0.498
Income 2,001-3,000 €	5	10.0	9.9%	5.6%	-43.9%	1.112
Income > 3,000 €	2	4.0	3.6%	5.6%	+52.4%	0.690

* Significant at 95% confidence

Trip characteristics

The means of transport were split between sustainable modes (S) and non-sustainable ones (NS). The former category includes public transport (PT), active mobility (walking and biking) and park-and-ride (car owner/drivers who reach work/study or discretionary locations traveling by car till a transit station and then taking public transport to reach their final destination), while the latter is used to refer to fuel-powered private vehicles (both car and motorcycles). None of the students used hybrid or electric-powered private vehicles, so these kinds of vehicle are not considered in this classification. Table 2 shows the modal share of all the tours considered, for both Cagliari and Rome. The first thing to note is that each tour, even if completed with a series of different means of transport, was associated with a single mode, which is referred to as the “main mode”, that is the means of transport with which the most distance was covered (Creemers *et al*., 2015).

Table 2 can help highlight some differences between the two contexts. When observing tours completed with private vehicles (which in this study coincide with NS modes), while in Cagliari they represent less than half of all the tours (46.8%), in Rome they are almost two thirds of all the tours (64.4%), showing how the largest city is more car-centred. This is almost the inverse of what can be gathered in general in the two study contexts, where Cagliari was the city in which cars were used more. However, the general data refers to the whole of the commuting trips, so this peculiarity could indicate how students in both territorial contexts behave differently from other commuters, which are mainly workers.

However, when considering non-commute tours, the difference is less prominent, with 16.7% for Cagliari and 22.0% for Rome.

Obviously, this also means there are differences when considering sustainable modes. When looking at the use of public transport, Cagliari shows values (27.0%) more than twice those of Rome (12.5%), and this is amplified when looking at NC tours, since no one used PT in Rome other than for their commute tours. Active mobility is used a bit more in Cagliari (20.2%) compared to Rome (13.6%), but this is probably due again to the substantial size difference of the two cities. Finally, park-and-ride is the least-used mode in both Cagliari (6.0%) and Rome (9.5%), but while it is true that students from Rome used this mode more overall, it is also true that they never used park-and-ride for non-commute tours, while students from Cagliari did, albeit they represent just 1.1% of all the tours.

This short analysis of the main modes of the tours reinforces the choice of analysing the two contexts separately, since it is clear that the students from Rome rely more on private vehicles, especially when they have to travel for purposes different from their daily commute to reach their campus.

Table 2. Modal share of the tours.

CAGLIARI				ROME			
	C	NC	Total		C	NC	Total
NS modes	30.1%	16.7%	46.8%	NS modes	42.4%	22.0%	64.4%
S modes	40.4%	12.8%	53.2%	S modes	30.3%	5.3%	35.6%
Total	70.5%	29.5%	100.0%	Total	72.7%	27.3%	100.0%

NS = non-sustainable. S = sustainable

Commuting tours versus non-commuting tours analysis

Table 3 shows instead a comparison between C and NC tours when considering the variables of the tours themselves, derived from the app and GPS data. Note that not all the available variables are featured in the table, since there were too many to present them in a clear manner, and we chose to show only those which were statistically significant.

Examining the left side of the table which regards Cagliari, it is clear how departure time strongly influences tour type. In fact, most of the NC tours start in the PM-peak (5:01 pm to 9:00 pm), while very few of them start in the morning. This behaviour is to be expected from university students, since most of the lectures are usually held in the morning, and the students have more free time later in the day. It should be noted that the two percentage values of AM peak and PM peak do not sum to 100% because we also considered other possible departure time frames, which are not included in Table 3. Regarding travel time, it can be observed that, on average, students tend to spend less time on NC tours compared to C tours, and this stays true when considering every travel mode. This fact can be interpreted by considering that the university campus is located in a single site, while NC tours can have many different destinations, and users tend to choose the most convenient one, that is the closest to their starting position. The same argument holds when observing travel distances, which reflect the trend of durations. The only exception to this statement can be observed for private vehicles, since in this case travel times are almost identical between NC and C tours, while distances are longer for non-commuting tours. This can be justified by the fact that private vehicles offer a unique level of freedom and comfort, so students may use this mode more during the day, especially for NC tours. Regarding travel costs (these costs are total monetary costs. For PT we accounted only for tickets, while for cars we considered several factors to include all possible expenses like fuel consumption, regular maintenance, or insurance), in line with the previous findings, PT users spend less for NC tours (shorter times and distances), while car users tend to spend more (longer times and distances). When observing the variables linked to the stops within a tour, a clarification is needed in order to interpret the data reported in Table 3. Number of stops per tour (avg), Stop time per tour (avg), and Tours with at least one stop (%), all refer to any and all additional stops other than the main one, which is the work/study stop for C tours, and the longest one for NC tours. It should be noted that it seems that stops in NC tours are more frequent and tend to last longer. This is obviously correlated with the fact that, most of the time, daily home-study commute tours start early in the day and students may not have time to make any stops (if they want to avoid being late), while on the return trip they may be tired from a long day of study, and eager to return home. Company on board, which indicates the presence of at least another person other than the respondents with whom they are traveling either on the same car or the same PT vehicle, presents similar patterns between the two tour types, with an average value lower than 1 in both cases and a slightly higher value for C tours.

Rome shows basically the same patterns as Cagliari, but some minor differences emerge. In fact, PT is barely ever used by students for NC tours, as reflected by both travel time and distance, which in turn reduces PT costs; NC total distance and walking distance are also considerably shorter when compared to C tours, and subsequently total tour costs are lower too. As already observed, these deviations are almost certainly influenced by Rome's considerably larger territorial extension, which may preclude the use of some modes, and may leave less time for NC tours if home-university distances are large.

Table 3. Analysis of tour-specific variables

	Cagliari				Rome			
	C	NC	Δ (NC-C)	t-stat	C	NC	Δ (NC-C)	t-stat
Tours departing in AM peak [%]	69.87	7.14	-89.8%	17.963*	44.79	9.72	-78.3%	5.600*
Tours departing in PM peak [%]	0.85	62.24	+7182%	26.248*	0.52	44.44	+8433%	11.874*
Total travel time per tour (avg) [min]	76.94	40.71	-47.1%	7.038*	100.99	33.94	-66.4%	8.119*
Walk travel time per tour (avg) [min]	25.18	10.37	-58.8%	9.013*	24.79	6.33	-74.5%	5.795*
Car travel time per tour (avg) [min]	18.56	19.70	+6.2%	0.485	37.71	27.29	-27.6%	1.771
PT travel time per tour (avg) [min]	15.53	3.18	-79.5%	4.285*	10.58	0.06	-99.4%	3.569*
Total distance per tour (avg) [km]	26.55	18.61	-29.9%	1.736	35.41	13.41	-62.1%	5.037*
Walk distance per tour (avg) [km]	1.62	0.65	-59.8%	8.685*	1.57	0.39	-74.9%	5.127*
Car distance per tour (avg) [km]	7.66	11.14	+45.4%	1.978*	15.51	12.84	-17.2%	0.874
PT distance per tour (avg) [km]	7.96	1.49	-81.3%	2.356*	5.93	0.01	-99.8%	3.159*
Total cost per tour (avg) [€]	2.18	2.54	+16.4%	1.050	3.62	2.21	-39.0%	2.811*
Car cost per tour (avg) [€]	1.29	1.91	+48.3%	2.080*	2.52	2.17	-13.8%	0.680
PT cost per tour (avg) [€]	0.50	0.13	-74.9%	5.470*	0.52	0.04	-92.0%	3.735*
Number of stops per tour (avg) [-]	0.97	1.41	+45.7%	4.310*	0.72	1.32	+82.3%	3.924*
Stop time per tour (avg) [min]	40.36	88.60	+119.5%	8.191*	34.23	100.92	+194.8%	6.823*
Tours with at least one stop [%]	0.53	0.92	+75.0%	10.475*	0.42	0.94	+123.9%	8.604*
Tours with company on board [%]	0.95	0.75	-21.3%	8.080*	0.91	0.86	-5.0%	1.059

* Significant at 95% confidence

Land use factors

Figure 1 shows the differences between C and NC tours when considering the land use variables, particularly relevant factors when analysing different territorial contexts. Non-commuting tours are generally more flexible than commuting tours and the influence of the urban context may be different depending on the purpose of the tour (Rajamani *et al.*, 2003). The large number of LU variables (45 in total are available for the two regional contexts. These were gathered from two main sources: the first, Google's Places Service; the second, the Italian Statistic Institute (ISTAT), which publishes data based on every population census.) allowed us to have a complete and detailed picture of the services provided in the areas surrounding the points of departure of all tours, which are most certainly a crucial factor in the generation of NC tours. Such a detailed description of the areas is seldom considered in travel behaviour analysis, meaning this aspect alone could be considered a valid contribution and a novelty in this research field.

Since the variables can present very different values, to build Figure 1 we conducted the analysis by taking the values of commute tours as a reference. Then the non-commute values were analysed to observe how much they varied from such references. Again, only the most significant variables were considered in order to produce a clearer representation. Also, since shops fall in many different categories, we chose to classify in two groups based on the main purpose of visiting them: the first group ("Shops, primary") includes all those shops pertaining a person "primary" needs (*i.e.* food, clothing, hygiene); all other shops, which might satisfy "secondary" needs (*e.g.* book stores, car rentals, jewellery stores) were included into the second group ("Shops, secondary").

Data from Cagliari show that the most prominent differences were observed for the presence of general services, of large families, and of newer residential buildings. The first factor could be interpreted as the fact that, having a large quantity of services close by, students might be persuaded to make NC tours since they might be able to complete them in less time (due to shorter distances); the presence of new residential buildings might be an indicator of recent urbanization, which in turn means there may be very few shops, services and various facilities close-by, making NC tours effectively mandatory if not all of the out-of-home activities can be completed during a C tour.

Rome, instead, showed greater variability between non-commute and commute tours. In this case, the largest contribution observed was the presence of car-sharing services, a large number of commuters and the presence of newer buildings. The first variable, which assumes higher values for NC tours, probably indicates the presence of a well-developed transport system, essential for a car-sharing system, which would greatly favour the decision to start an NC tour. Unlike Cagliari, in Rome the presence of newer buildings seems to decrease in relation to NC tours. This could be associated with the fact that most of Rome is already urbanized, meaning that new buildings can be erected only after a demolition, mostly in zones already served by several shops and businesses, requiring less NC tours overall.

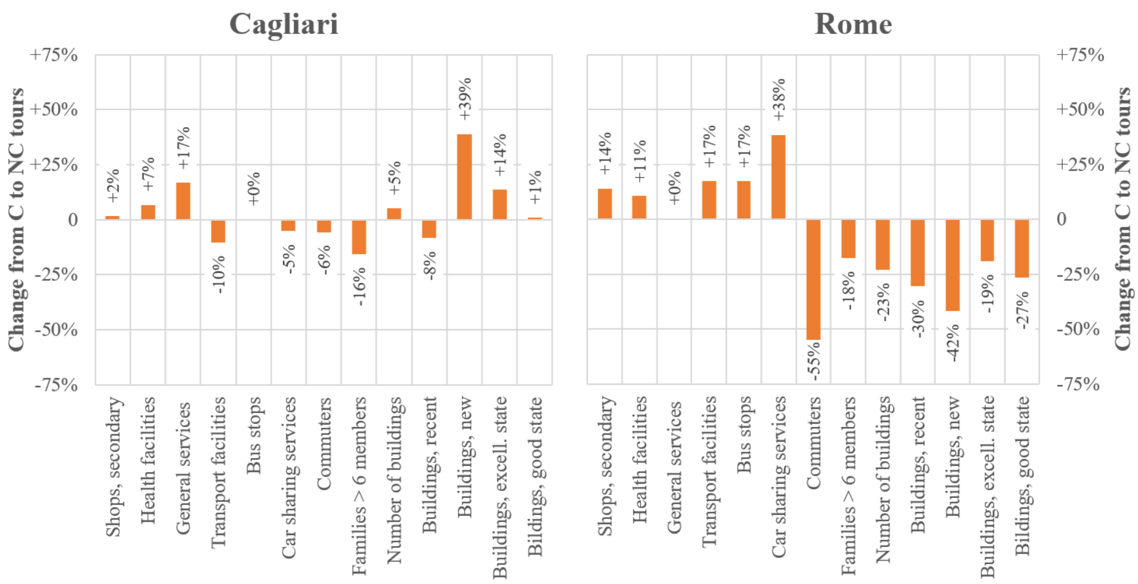

Figure 1. Analysis of land use variables – percentage variations from the average value for departure points of commuting (C) tours to the average value for departure points of non-commuting (NC) tours.

Modelling framework

To achieve the objective of the study, a joint mixed Logit model (Srinivasan and Bhat, 2006) has been used to determine, for each context, which variables influence the tours for any non-study related reason with respect to the commuting tours. In other words, the dependent variable is binary (1 = non-commuting; 2 = commuting) and the base is commuting. A set of several explanatory variables were tested with error components for panel effects, which differ for the two survey phases, and two scale group parameters for sustainable means of transport.

Although the data in the two waves were collected with the same method and in the same context, a scale effect can occur due to unknown effects. To account for this, a joint model is estimated, following the typical theory of the joint revealed/state preference model, estimating the scale factor between the two survey phases. According to Train (2003), the utility function can be expressed as:

$$U_{qjt} = \phi_t\left(V_{qjt} + \omega_{qjt} + \varepsilon_{qjt}\right) \tag{1}$$

where t indicates the time period (t = 1 for the 1st phase survey, t = 2 for the 2nd phase survey), q is the individual, and j is the alternative (1: commute tour, 2: non-commute tour). So V_{qj1} and V_{qj2} are the systematic components of utility for the 1st and 2nd phase survey respectively; ε_{qj1} and ε_{qj2} are Extreme Value 1 random terms, which represent the typical multinomial logit probability; ω_{qj1} and ω_{qj2} are normally distributed error terms (with zero mean and to-be-estimated standard deviation) which generate correlations among the utilities for different alternatives. The unconditional probability is the integral of this product of Logit formulas, one for each time period, over all the values of ω. Lastly, ϕ_t is the scale parameter that allows the two utilities to have the same variance and is defined as follows:

$$\phi_1 = \left((\lambda_1 \cdot M_S) + (\lambda_2 \cdot M_{NS})\right)$$
$$\phi_2 = \left((\lambda_3 \cdot M_S) + (\lambda_4 \cdot M_{NS})\right) \quad (2)$$

where M_S and M_{NS} are dummy variables which are equal to 1 if the tour is made with a sustainable and non-sustainable means of transport respectively, 0 otherwise. For identification purposes the group parameter λ_k is estimated only for M_{NS} and normalised to 1 for M_S. The final Likelihood function to be maximized is given by:

$$LL_\omega = \sum_{q=1}^{Q} ln\left(\int_\omega \prod_t L_{qj}\left(U_{qjt}\right) f(\omega)\, d\omega\right) = \sum_{q=1}^{Q} ln\left(P_{qj}\right) \quad (3)$$

As the probabilities P_{qj} do not have a closed form, they are approximated through simulation (SP_{qj}) where draws are taken from the mixing distribution $f(\omega)$ and then averaged up:

$$SP_{qj} = \frac{1}{R}\sum_{r=1}^{R}\prod_t L_{qjt} \quad (4)$$

where R is the number of draws. The simulated log-likelihood function to be maximized is now given by:

$$SLL_\omega = \frac{1}{Q}\sum_{q=1}^{Q} lnSP_{qj} \quad (5)$$

Models are estimated using 1,000 draws from a Modified Latin Hypercube Sampling method (Hess *et al.*, 2006) The software PythonBiogeme (Bierlaire and Fetiarison, 2009) was used for the estimation. Note that in this paper we account for correlation only among different waves, but we did not allow day-to-day variability since the sample size was not large enough. In fact, as the number of error components (equivalent to the number of dimensions of integration within the classic Maximum Simulated Likelihood) increases, convergence assessment problems rise.

Estimation results

Table 4 shows the results from the best specification models estimated for each of the two study contexts (Cagliari and Rome). Note that the parameters associated with each explanatory variable assume a generic value shared between the first and second phase survey, since it has been verified that considering them separately would not have added a significant contribution.

Despite the fact that several variables are specified and estimated, most of them have been excluded because they were not highly significant or because they did not improve the performance of any of the models. However, the high significance of the constant value indicates the need to consider other aspects to better explain the phenomenon, like for example the psycho-attitudinal variables.

Regarding the panel effect, the magnitude of the estimates of the two error components differs significantly between the first and second phase survey (-0.008 *vs* -0.243 for Cagliari context; $4\cdot10^{-5}$ *vs* -0.003 for Rome context). There is no correlation between the observations of the same user during the two phases, neither are the observations of the same user within the same phase correlated (a fairly obvious result since non-commuting tours are very often non-systematic), while, on the contrary, they differ from one another even if made by the same individual.

Table 4. Model results.

NON-COMMUTING TOUR VARIABLES		CAGLIARI		ROME	
		Value	Robust t-test	Value	Robust t-test
Tour characteristics variables	Constant	6.340	4.84*	4.64	2.08*
	Origin of the tour = main residence	-4.410	-5.54*	--	--
	Departure time = 6:01 AM to 10:00 AM	-2.540	-3.80*	-0.943	-1.12
	Departure time = 5:01 PM to 9:00 PM	4.320	4.97*	3.650	2.01*
	Tour travel time [min]	-0.074	-3.65*	-0.083	-2.85*
	Tour distance [km]	0.063	4.00*	-0.091	-1.07
	Tour cost [€/tour]	0.214	1.72	0.948	1.66
	# of stops in the tour	0.403	1.18	--	--
	Total stop duration [min]	0.014	2.64*	0.016	2.47*
	Main means of transport in the tour = Active mobility	--	--	1.820	1.42
Socio-economic variables	Company	-2.800	-4.11*	-0.926	-1.40
	Male	-0.906	-2.30*	--	--
	Car ownership	-1.980	-2.42*	2.120	2.01*
	# of members in the household	0.561	2.76*	-1.070	-2.02*
Land use variables computed in the main house' surroundings [n/km^2]	# of bus stops	0.046	2.69*	--	--
	# of buildings	0.033	1.32	--	--
	# of shops	-0.009	-1.50	--	--
	Population aged 70-74 years	-0.055	-1.62	--	--
	Population with middle school level of education	--	--	-0.396	-1.19
	Population with elementary level of education	--	--	0.583	1.09
	Working population	--	--	0.637	1.48
	Homemakers' population	--	--	3.300	2.42*
	Population that makes cross zonal trips daily	--	--	-0.303	-1.00
	# of members in the household (avg)	--	--	-0.543	-2.06*
	# of households with 5 members	0.342	2.40*	--	--
	# of households with 6 members	-0.034	-2.37*	--	--
	density of newly constructed buildings	--	--	0.0275	2.03*
	density of buildings in excellent condition	--	--	-0.153	-1.57
Error Component 1 (SD)		-0.008	-0.50	$4\cdot10^{-5}$	0.23
Error Component 2 (SD)		-0.243	-0.63	-0.003	-0.25
λ_2		1.180	4.78*	1.190	1.89*
λ_4		1.160	4.76*	1.310	2.08*
# of individuals		43		50	
# of observations		664		264	
Init log-likelihood		-894,073		-371,628	
Final log-likelihood		-559,844		-233,707	
ρ^2		0.348		0.309	
# of draws		1,000		1,000	
# of estimated parameters		23		23	

* *Significant at 95% confidence*

Looking specifically at the Cagliari context, note that:

- The magnitude of the estimates of the two scale factors λ_2 and λ_4 is greater than 1, therefore the variance of the error term of the non-commute tours made with non-sustainable means of transport is smaller than non-commute tours made with sustainable means of transport.
- The non-significant difference in the two scale factors' magnitude indicates that the utilities of non-commuting tours for non-sustainable modes are similar between the two weeks. Because λ_1 and λ_3 were fixed to 1, it is immediately clear that non-sustainable modes have a greater utility than sustainable ones (about 20%).
- As far as the tour characteristics are concerned, the model results show that non-commuting tours tend to have origins different from the main residence; consistently with this aspect, the departure time often ends up being outside of the morning peak period while, on the contrary, it is more likely to fall in the afternoon peak period, after the end of study hours, as confirmed by other experiences (Bowman and Ben-Akiva, 2001).
- Non-commuting tours show travel times shorter than commuting tours, despite having longer distances; in fact, non-commuting tours do not generally have the temporal constraint commuting ones have, so travelling during off-peak hours means shorter travel times for greater distances. This is particularly true when considering active mobility (Mondal *et al*., 2020).
- Non-commuting tours are also characterized by higher total costs, consistently with the longer distances travelled. A likely explanation is that, since the private car is the favourite means of transport, often users must pay for parking at the destinations where discretionary activities take place; the opposite happens for the place of study, in which often students have access to free parking.

- Non-commuting tours include a greater number of stops, and students who make non-commuting tours travel alone; in other words, travel company reduces the propensity to make trips for discretionary purposes. Probably this is due to the fact that travelling in a group requires accurate forecasting to accommodate everybody's wishes.

- About the socio-economic characteristics, although the sample is rather homogenous, it seems that women are more apt to travel for discretionary purposes; also, the propensity to make non-commuting tours increases with the number of household members and decreases for those students who do not have a family car available.

- As far as land-use characteristics are concerned, focusing on the residence area, students are more likely to travel for discretionary purposes when living in areas characterized by: a) high building density areas, b) a small number of shops that sell essential supplies, c) a population age range of 70-74 years and d) large families.

- Another significant result is that the number of bus stops increases the propensity to make trips for discretionary purposes.

Regarding the Rome context, due to the smaller sample size, the results are not as strong as the ones from Cagliari, but they still hold true for a pilot test case. The following specific comments can be made:

- The results, from a transportation point of view, do not differ significantly from those obtained from the Cagliari data, with only one exception. In this case, in fact, the tour travel distance presents a negative sign, but is not highly significant, so this aspect needs to be further investigated. Active mobility seems to be mostly used in non-commuting tours compared to commuting tours.

- Appreciable differences were found in the students' SE profiles and, as expected from the analysis of the two regional contexts, in the LU characteristics. Contrary to Cagliari, students living in a small family and those who own a car are more likely to travel for discretionary purposes.

As far as land-use characteristics are concerned, non-commuting tours are characterized by a larger set of variables in this context. In particular, travelling for discretionary purposes is more likely for those students living in areas characterized by: a) a higher density of newly constructed buildings rather than in excellent condition, b) an average level of education corresponding to primary school, c) a higher density of homemakers. Meanwhile, those living in high-density housing areas and in areas where people make daily interzonal trips are less likely to travel for discretionary purposes due to greater travel time to go to work/study and consequently less time available for discretionary activities.

Transport Policy Implications

The findings of this study confirm the importance of analysing in detail the pattern of daily activity-travel behaviour. In order to determine a change in travel behaviour, there needs to be a requisite understanding of actual travel behaviour.

In terms of policy implications, when designing and implementing measures to reduce university student's private car use, policy makers should pay attention to the fact that non-sustainable modes have a greater utility than sustainable ones (about 20%).

On one hand, this point clearly suggests the need to identify hard measures to apply. In particular, considering the high travel times of the commuting tours, an improvement of travel times by sustainable mobility could be an effective incentive to use more sustainable means of transport. In both contexts of the study, there should be plans for an increased frequency of public transport lines that serve the university buildings during peak hours, and in Cagliari more bus and bike lanes should be realized. A reduction in travel time of sustainable modes, combined with lower travel costs, must surely improve their utility, thus encouraging their use also for non-commuting tours characterized by higher total costs due to parking costs. It is therefore important to define special prices for students and integrated tickets which guarantee also a convenient intermodality. At the same time, it is necessary to discourage car use primarily by removing free parking close to the Universities and second by increasing the parking fees.

On the other hand, as shown by several studies, “hard” and “soft” measures have synergies that should be exploited. Indeed, at the same time as the implementation of the hard measures mentioned, an efficient and effective VTBC program should be defined.

In general, the VTBC should be given to all the sample to make them aware of the hard measures applied in their travel context and to inform them about the benefits linked to these measures in terms of costs, travel times, calories burned, and CO_2 emitted.

In particular, following the results obtained, when designing and implementing the VTBC program, policy makers should pay more attention to women, to those who have a high number of household members, to those living in areas characterized by high building density areas, and a small number of shops in Cagliari and to students living in a small family and to those who own a car in Rome, that are more apt to travel for discretionary purposes. Indeed, the need or the choice to make non-commuting tours could be a barrier to use sustainable mobility that is by definition less flexible than the private mode. Then, in all these cases it is also more important to emphasize the feasibility and the advantages in using public transport or activity mobility also for non-commuting tours through the implementation of personalised travel plan extremely personalised. The plans should show for example the frequency and the stops of the bus lines that allow making all daily trips.

Other policy recommendations are related to the introduction in 2021 in Italy of the figure of the mobility manager and the requirement for all public administrations and institutions to develop and implement a Mobility Plan. Some guidelines have been released to help mobility managers in drafting mobility plans, but they did not specifically take into consideration the case of university students. Students can be considered as the main traffic generators of a university campus, thus the analysis of their mobility style and the planning of strategies and measures aimed at encouraging them to use a sustainable means of transport should not be disregarded.

Another element of weakness of Mobility Plans' guidelines is the absence of any indication concerning non-commuting tours. As seen in this paper, these kind of tours represent a non-negligible part of students' tours and sometimes commuting tours include stops for non-study activities. If mobility managers want to develop strategies that can lower the emissions of green house gases, they cannot consider only commuting trips but also trips made for recreational, errands and shopping purposes. In particular, they should propose interventions that permit student to easily chain trips made for different purposes either with public transport, active mobility or sharing mobility. In this sense, the introduction of e-scooter and bike sharing schemes can help in reaching this objective, and the establishment of agreements between universities and private transport operators that allow students to have access to discounted fares of new shared-mobility services can boost this process.

Finally, the guidelines suggest to analyse only the transport supply system in close proximity of universities. Our models results, instead, highlight the importance of considering both the transport and land-use systems for policy recommendations. As indicated by previous studies (Lyons and Davidson, 2016) not only the type of transport services and facilities, but also built environment and land use characteristics have an impact on individuals' travel behaviour and define the accessibility of a destination. If policy makers want to ensure students accessibility to university campuses, guaranteeing, in this way, the students' right to education, and recreational/shopping/errands activities, they should explicitly adopt an urban planning development approach that promotes spatial proximity and eases physical mobility. At the same time, it should be recognized that a "one-size-fits-all" approach cannot be adopted, as measures and strategies that work in one urban context will not necessarily succeed also in other contexts. In the specific case of this paper, modelling results clearly show that land-use factors that influence travel behaviour vary between Cagliari and Rome, hence differentiated measures should be adopted depending on the context.

Conclusions

In transportation research, the flexibility of discretionary activities confers complexity to the demand models. Likewise, the travel behaviour of university students is not well represented in travel demand analysis due to the difficulty in obtaining information or due to their transient living arrangements during their university years.

However, over the last few decades, increase in wealth has led to an increase in the mobility demand for recreational activities and university students represent an important segment of the working population. This fact has gained increasing attention in transportation research on non-commuting tours and university mobility.

From the common perspective of reducing the number of circulating automobiles, new urbanism-style policies, such as Travel Demand Management and Mobility Management strategies, are focused on promoting a “green” university mobility: providing on-campus shuttle services, more frequent bus schedules, free PT, dedicated city bike lanes, and so on; but to this day nothing has been done for non-systematic trips.

Before assessing the effectiveness of these policies, it is important to evaluate their applicability to the socio-demographic and transport context of study. This paper is meant to be an initial input on how to analyse the university students’ travel behaviour, through a comparison among commuting and non-commuting tour, in order to highlight the importance of considering daily schedules of trips and activities to identify the best solution of mobility at personal and societal level. In this way is it possible to help university Mobility Managers work towards improving policies and infrastructures, implementing personalized programmes while considering their strong sustainability connotations. This paper wants to be a *vademecum* to define the correct methodology and a starting point on the policy implication to follow to correctly analyse the travel behaviour. In fact, in the context of a VTBC program, neglecting the daily travel scheme can lead to suggest an alternative means of transport not suitable for the individual. From the policy perspective it is not correct to generalize the results, but we give some food for thought on function of our context studies results.

The first contribution of this work is the use of GPS tracking, one potential solution to the problems revealed by several studies on travel diary data in which between 20 and 30 percent of trips are typically not reported in travel diaries (Stopher, 2009).

In particular, this research aimed to understand the factors influencing university students' non-commuting tours estimating a joint Mixed Logit model, using panel data collected in two Universities located in different regional contexts. Indeed, the modal choice depends heavily on the daily trips combination and often it is believed that the private motorized mode is more flexible than other means of transport.

To summarize the results, 28% of tours are non-commuting tours and there are no significant differences between Cagliari and Rome with respect to the tour characteristics, probably because the participants all are university students and this means they all tend to have similar daily routines that could confirm the possible transferability of the results to other urban university campuses, even if this is not the only aspect to be considered. We can say that NC tours tend to start from origins different from the main residence, and the departure time is more likely to fall in the afternoon period, after the end of lessons and study hours. Travelling during off-peak hours means shorter travel times for greater distances, hence non-commuting tours have travel times shorter than commuting tours, despite having longer distances and consequently higher total costs. The greater cost may also be due the parking cost at the destinations where discretionary activities take place. This evidence leads to some considerations from a policy perspective: on one hand, shorter travel times could be an incentive to use a private car, on the other hand, higher total costs due to parking could be a disincentive to use it. During the definition of a personalised travel plan it would therefore be effective to highlight the benefits in term of costs of using a public transport alternative instead of a private car. The costs represent an important lever for a behaviour change, and it is even more true for a sample with reduced economic possibilities such as students.

Appreciable differences were found in the students' socio-economic profiles and in the land-use characteristics, as expected from the analysis of two different regional contexts. This is another important result that confirms the importance of not generalizing the conclusions but analysing each context and each sample to be able to implement effective VTBC programs.

Contrary to Cagliari, in Rome students living in a small family and those who have a car available are more likely to travel for discretionary purposes. The availability of the car could represent a barrier to a change in behaviour, so in these cases it is more crucial to detail all the benefits of using more sustainable means of transport, not only in terms of travel times and costs but also in terms of sustainability (*e.g.* CO_2 emitted) and fitness benefits (*e.g.* calories burned), among others. Travelling for discretionary purposes is more likely for those students living in areas characterized by newly constructed buildings rather than in excellent condition, an average level of education and a large number of homemakers.

Therefore, this work allowed us to:

(1) test the method to collect detailed data also for occasional discretionary trips;

(2) profile the university students who are more likely to travel for discretionary purposes, both in terms of socio-demographics and trips characteristics. This is a crucial aspect for designing highly personalized Voluntary Travel Behaviour Change programmes to promote sustainable travel, as an alternative to private mode, not only for systematic home-study trips, but also for occasional trips for discretionary activities. The daily trips combination is often the reason why the private mode is chosen, since it is believed to be more flexible than other means of transport;

(3) identify which land features trigger, for different contexts, a greater generation of non-commuting tours, to be able to define and plan physical infrastructure interventions capable of encouraging sustainable mobility.

This study represents a pilot test that confirms the need to analyse also non-commuting tours of university students to be able to implement an appropriate VTBC program, and TDM policies on large-scale study in different Italian university campuses due to the fact that the land use factors are different, but the discriminating factors are not.

Regarding the possible transferability of the study to other university urban campuses, it is important to remember that is not possible to generalize the results obtained in a different context of the study and on different samples (Stopher, 2009), anyway it is possible and advisable to apply the same methodology used in this work to other settings.

The study has some limitations:

1. small sample size;
2. the sample is not representative of the university student population;
3. the data exclude weekend information, people usually plan and schedule many of main non-work/study activities (*e.g.* shopping, leisure, *etc.*) on weekends instead of doing those during the weekday.

Future research will focus on improving some of the gaps of this study. Some of the shortcomings of the model might be caused by the small sample, and by its inherent nature of student-only individuals. The study is a preliminary exploratory analysis, aimed to find which variables influence the most the non-commuting tours compared to commuting tours. Thus, we chose to include as many variables as possible and not restrict our study only to the ones commonly used in choice forecasting models. We are aware the modelling results might not be completely satisfying, and that a more complete analysis to find a more suitable and coherent prediction model deserves further study. We are testing other mathematical models that may be best suited to explain the phenomenon, like integrated choice and latent variable models and that include the psycho-attitudinal information collected.

We are planning to modify some app functionalities, in terms of automation, to easily increase the amount and quality of the information collected, as well as sample size or the category of people to intercept.

References

Akar, G., Fischer, N., & Namgung, M. (2013). Bicycling choice and gender case study: The Ohio State University. *International Journal of Sustainable Transportation*, 7(5), 347-365.

Alm, J., & Winters, J. V. (2009). Distance and intrastate college student migration. *Economics of Education Review*, 28(6), 728-738.

Al-Rukaibi, F., Ali, M. A., & Aljassar, A. H. (2006). Traffic safety attitudes and driving behavior of university students: Case study in Kuwait. *Transportation research record*, 1969(1), 65-71.

Balsas, C. J. (2003). Sustainable transportation planning on college campuses. *Transport Policy*, 10(1), 35-49.

Banister, D. (1997). Reducing the need to travel. *Environment and Planning B: Planning and Design*, 24(3), 437-449.

Bhat, C. R. (1997). Work travel mode choice and number of non-work commute stops. *Transportation Research Part B: Methodological*, 31(1), 41-54.

Bhat, C. R. (2015). A new generalized heterogeneous data model (GHDM) to jointly model mixed types of dependent variables. *Transportation Research Part B: Methodological*, 79, 50-77.

Bhat, C., & Misra, R. (2001). Comprehensive Activity Travel Pattern Modeling System for Nonworkers with Empirical Focus on Organization of Activity Episodes. *Transportation Research Record*, 1777(1), 16–24. https://doi.org/10.3141/1777-02.

Bierlaire, M., & Fetiarison, M. (2009). Estimation of discrete choice models: Extending BIOGEME. 9th Swiss transport research conference. Switzerland: Monte Verità.

Bonham, J., Koth, B., 2010. Universities and the cycling culture. *Transp. Res. D* 15 (2), 94–102.

Bowman, J. L., & Ben-Akiva, M. E. (2001). Activity-based disaggregate travel demand model system with activity schedules. *Transportation research part a: policy and practice*, 35(1), 1-28.

Boyd, B., Chow, M., Johnson, R., & Smith, A. (2003). Analysis of effects of fare-free transit program on student commuting mode shares: BruinGo at University of California at Los Angeles. *Transportation Research Record*, 1835(1), 101-110.

Calabrese, F., Diao, M., Di Lorenzo, G., Ferreira Jr, J., & Ratti, C. (2013). Understanding individual mobility patterns from urban sensing data: A mobile phone trace example. *Transportation research part C: emerging technologies*, 26, 301-313.

Chen, X. (2012). Statistical and activity-based modeling of university student travel behavior. *Transportation planning and technology*, 35(5), 591-610.

Cherchi, C., & Cirillo, C. (2014). Understanding variability, habit and the effect of long period activity plan in modal choices: a day to day, week to week analysis on panel data. *Transportation*, 41(6), 1245-1262.

Cherchi, E., Cirillo, C., & de Dios Ortúzar, J. (2017). Modelling correlation patterns in mode choice models estimated on multiday travel data. *Transportation Research Part A: Policy and Practice*, 96, 146-153.

Cipriani, E., Gori, S., & Petrelli, M. (2012). Transit network design: A procedure and an application to a large urban area. *Transportation Research Part C: Emerging Technologies*, 20(1), 3-14.

Creemers, L., Bellemans, T., Janssens, D., Wets, G., & Cools, M. (2015). Analyzing access, egress, and main transport mode of public transit journeys: evidence from the Flemish national household travel survey. *In TRB 94th Annual Meeting Compendium of Papers*.

Danaf, M., Abou-Zeid, M., & Kaysi, I. (2014). Modeling travel choices of students at a private, urban university: insights and policy implications. *Case studies on transport policy*, 2(3), 142-152.

Davis, A. W., McBride, E. C., Janowicz, K., Zhu, R., & Goulias, K. G. (2018). Tour-based path analysis of long-distance non-commute travel behavior in California. *Transportation research record*, 2672(49), 1-11.

Davison, L., Ahern, A., & Hine, J. (2015). Travel, transport and energy implications of university-related student travel: A case study approach. *Transportation Research Part D: Transport and Environment*, 38, 27-40.

Delmelle, E. M., & Delmelle, E. C. (2012). Exploring spatio-temporal commuting patterns in a university environment. *Transport Policy*, 21, 1-9.

Dijk, V., J., & Krygsman, S. (2018). Analyzing Travel Behavior by Using GPS-Based Activity Spaces and Opportunity Indicators. *Journal of Urban Technology*, 25(2), 105-124.

Duque, R. B., Gray, D., Harrison, M., & Davey, E. (2014). Invisible commuters: assessing a university's eco-friendly transportation policies and commuting behaviours. *Journal of Transport Geography*, 38, 122-136.

Eom, J. K., Stone, J. R., & Ghosh, S. K. (2009). Daily activity patterns of university students. *Journal of Urban Planning and Development*, 135(4), 141-149.

Frank, L., Bradley, M., Kavage, S., Chapman, J., & Lawton, T. K. (2008). Urban form, travel time, and cost relationships with tour complexity and mode choice. *Transportation*, 35(1), 37-54.

Grimsrud, M., & El-Geneidy, A. (2013). Driving transit retention to renaissance: trends in Montreal commute public transport mode share and factors by age group and birth cohort. *Public Transport*, 5(3), 219-241.

Harding, C., Miller, E. J., Patterson, Z., & Axhausen, K. W. (2015). Multiple purpose tours and efficient trip chaining: An analysis of the effects of land use and transit on travel behavior in Switzerland. *In Proceedings of the 94th Annual Meeting of the Transportation Research Board*, Washington DC, USA.

Hasnine, M. S., Lin, T., Weiss, A., & Habib, K. N. (2018). Determinants of travel mode choices of post-secondary students in a large metropolitan area: The case of the city of Toronto. *Journal of transport geography*, 70, 161-171.

Hensher, D. A., & Reyes, A. J. (2000). Trip chaining as a barrier to the propensity to use public transport. *Transportation*, 27(4), 341-361.

Hess, S., Train, K. E., & Polak, J. W. (2006). On the use of a modified latin hypercube sampling (MLHS) method in the estimation of a mixed logit model for vehicle choice. *Transportation Research Part B: Methodological*, 40(2), 147-163.

Hoffmann, C., Abraham, C., White, M. P., Ball, S., & Skippon, S. M. (2017). What cognitive mechanisms predict travel mode choice? A systematic review with meta-analysis. *Transport reviews*, 37(5), 631-652.

ISFORT. 15° Rapporto sulla mobilità in Italia. ISFORT, www.isfort.it, 2018.

Kamruzzaman, M., Hine, J., Gunay, B., & Blair, N. (2011). Using GIS to visualise and evaluate student travel behaviour. *Journal of Transport Geography*, 19(1), 13-32.

Kelarestaghi, K. B., Ermagun, A., & Heaslip, K. P. (2019). Cycling usage and frequency determinants in college campuses. *Cities*, 90, 216-228.

Khattak, A., Wang, X., Son, S., Angello, P., 2011. Travel by university students in Virginia: is this travel different from travel by the general population. *Transp. Res. Rec.: J. Transp. Res. Board* 2255, 137–145.

Klöckner, C. A., & Friedrichsmeier, T. (2011). A multi-level approach to travel mode choice–How person characteristics and situation specific aspects determine car use in a student sample. *Transportation Research Part F: Traffic Psychology and Behaviour*, 14(4), 261-277.

Krizek, K. J. (2003). Residential relocation and changes in urban travel: Does neighborhood-scale urban form matter?. *Journal of the American Planning Association*, 69(3), 265-281.

Lavery, T. A., Páez, A., & Kanaroglou, P. S. (2013). Driving out of choices: An investigation of transport modality in a university sample. *Transportation research part A: policy and practice*, 57, 37-46.

Li, Z., Wang, W., Yang, C., Jiang, G. (2013). Exploring the causal relationship between bicycle choice and trip chain pattern. *Transport Policy*, 29, 170-177.

Limanond, T., Butsingkorn, T., Chermkhunthod, C., 2011. Travel behavior of university students who live on campus: a case study of a rural university in Asia. *Transport Policy*, 18 (1), 163–171.

Limanond, T., Niemeier, D. A., & Mokhtarian, P. L. (2005). Specification of a tour-based neighborhood shopping model. *Transportation*, 32(2), 105-134.

Lyons, G., & Davidson, C. (2016). Guidance for transport planning and policymaking in the face of an uncertain future. *Transportation Research Part A: Policy and Practice*, 88, 104-116.

Maat, K., & Timmermans, H. (2006). Influence of land use on tour complexity: a Dutch case. *Transportation Research Record*, 1977(1), 234-241.

McGuckin, N., & Nakamoto, Y. (2004, November). Trips, Chains and tours-using an operational definition. *In National Household Travel Survey Conference*.

Meloni, I., Spissu, E. & Bhat, C., R. (2011). The effect of personal cap.and-trade mileage policies on individual activity-travel patterns: the activity locator project. *Transportation Letters. The International Journal of Transport Research* Vol. 3, 293-307.

Miralles-Guasch, C., & Domene, E. (2010). Sustainable transport challenges in a suburban university: The case of the Autonomous University of Barcelona. *Transport policy*, 17(6), 454-463.

MIUR (2017). http://ustat.miur.it/dati/didattica/italia/atenei.

Mondal, A., Bhat, C. R., Costey, M. C., Bhat, A. C., Webb, T., Magassy, T. B., Pendyala, R. M., & Lam, W. H. K. (2020). How do people feel while walking? A multivariate analysis of emotional well-being for utilitarian and recreational walking episodes. *International Journal of Sustainable Transportation*, 1-16.

Namgung, M., & Jun, H. J. (2019). The influence of attitudes on university bicycle commuting: Considering bicycling experience levels. *International journal of sustainable transportation*, 13(5), 363-377.

Ortuzar, J. d D., & Willumsen, L. G. (2011). *Modelling transport*. John wiley & sons.

Páez, A., & Whalen, K. (2010). Enjoyment of commute: A comparison of different transportation modes. *Transportation Research Part A: Policy and Practice*, 44(7), 537-549.

Patella, S. M., Sportiello, S., Petrelli, M., & Carrese, S. (2019). Workplace relocation from suburb to city center: A case study of Rome, Italy. *Case Studies on Transport Policy*, 7(2), 357-362.

Rajamani, J., Bhat, C. R., Handy, S., Knaap, G., & Song, Y. (2003). Assessing impact of urban form measures on nonwork trip mode choice after controlling for demographic and level-of-service effects. *Transportation research record*, 1831(1), 158-165.

Ramadurai, G., & Srinivasan, K. K. (2006). Dynamics and variability in within-day mode choice decisions: role of state dependence, habit persistence, and unobserved heterogeneity. *Transportation research record*, 1977(1), 43-52.

Ripplinger, D., Hough, J. A., Brandt-Sargent, B., Urban, S., & Center, R. T. (2009). The Changing Attitudes and Behaviors of University Students Toward Public Transportation (No. DP-222). Upper Great Plains Transportation Institute, North Dakota State University.

Rodríguez, D. A., & Joo, J. (2004). The relationship between non-motorized mode choice and the local physical environment. *Transportation Research Part D: Transport and Environment*, 9(2), 151-173.

Rotaris, L., & Danielis, R. (2014). The impact of transportation demand management policies on commuting to college facilities: A case study at the University of Trieste, Italy. *Transportation Research Part A: Policy and Practice*, 67, 127-140.

Rybarczyk, G., & Gallagher, L. (2014). Measuring the potential for bicycling and walking at a metropolitan commuter university. *Journal of Transport Geography*, 39, 1-10.

Salvati, L. (2013). Monitoring high-quality soil consumption driven by urban pressure in a growing city (Rome, Italy). *Cities*, 31, 349-356.

Sanjust di Teulada, B., & Meloni, I. (2016). Individual Persuasive Eco-travel Technology, a mobile persuasive application for implementing voluntary travel behaviour change programmes. *IET Intelligent Transport Systems*, 10(4), 237-243.

Sanjust di Teulada,Meloni, I. & Spissu, E. (2018). The influence of activity-travel patterns on the success of VTBC. *IJUS International Studies of Urban Sciences*, Vol. 22 Routledge.

Shannon, T., Giles-Corti, B., Pikora, T., Bulsara, M., Shilton, T., & Bull, F. (2006). Active commuting in a university setting: assessing commuting habits and potential for modal change. *Transport Policy*, 13(3), 240-253.

Sigurdardottir, S. B., Kaplan, S., Møller, M., & Teasdale, T. W. (2013). Understanding adolescents' intentions to commute by car or bicycle as adults. *Transportation research part D: transport and environment*, 24, 1-9.

Soria-Lara, J. A., Marquet, O., & Miralles-Guasch, C. (2017). The influence of location, socioeconomics, and behaviour on travel-demand by car in metropolitan university campuses. *Transportation Research Part D: Transport and Environment*, 53, 149-160.

Srinivasan, S., Bhat, C.R., 2006. A multiple discrete-continuous model for independent- and joint-discretionary-activity participation decisions. *Transportation,* 33, 497–515.

Stopher, P., Clifford, E., Swann, N., & Zhang, Y. (2009). Evaluating voluntary travel behaviour change: Suggested guidelines and case studies. *Transport Policy*, 16(6), 315-324.

Thigpen, C. G., Driller, B. K., & Handy, S. L. (2015). Using a stages of change approach to explore opportunities for increasing bicycle commuting. *Transportation Research Part D: Transport and Environment*, 39, 44-55.

Train, K., 2003. Discrete Choice Methods with Simulation. Cambridge University Press.

Triandis, H.C. (1977). Interpersonal behaviour. Monterey, CA: Brooks/Cole Publishing.

Tuveri, G., Sottile, E., Piras, F., & Meloni, I. (2020). A panel data analysis of tour-based university students' travel behaviour. *Case Studies on Transport Policy*, 8(2), 440-452.

Uttley, J., & Lovelace, R. (2016). Cycling promotion schemes and long-term behavioural change: A case study from the University of Sheffield. *Case studies on transport policy*, 4(2), 133-142.

Vale, D. S., Pereira, M., & Viana, C. M. (2018). Different destination, different commuting pattern? Analyzing the influence of the campus location on commuting. *Journal of Transport and Land Use*, 11(1), 1-18.

Van Acker, V., & Witlox, F. (2011). Commuting trips within tours: how is commuting related to land use?. *Transportation*, 38(3), 465-486.

Van Dijk, J., & Krygsman, S. (2018). Analyzing Travel Behavior by Using GPS-Based Activity Spaces and Opportunity Indicators. *Journal of Urban Technology*, 25(2), 105-124.

Verplanken, B., & Roy, D. (2016). Empowering interventions to promote sustainable lifestyles: Testing the habit discontinuity hypothesis in a field experiment. *Journal of Environmental Psychology*, 45, 127-134.

Verplanken, B., Aarts, H., van Knippenberg, A., & van Knippenberg, C. (1994). Attitude versus general habit: Antecedents of travel mode choice. *Journal of Applied Social Psychology*, 24(4), 285–300. doi:10.1111/j.1559-1816.1994.tb00583.x.

Whalen, K. E., Páez, A., & Carrasco, J. A. (2013). Mode choice of university students commuting to school and the role of active travel. Journal of Transport Geography, 31, 132-142.

Whalen, K. E., Páez, A., & Carrasco, J. A. (2013). Mode choice of university students commuting to school and the role of active travel. *Journal of Transport Geography*, 31, 132-142.

Ye, X., Pendyala, R. M., & Gottardi, G. (2007). An exploration of the relationship between mode choice and complexity of trip chaining patterns. *Transportation Research Part B: Methodological*, 41(1), 96-113.

Zeid, M. A., Rossi, T. F., & Gardner, B. (2006). Modeling time-of-day choice in context of tour-and activity-based models. *Transportation Research Record*, 1981(1), 42-49.

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.