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The irreducibles: the causes of non-propensity to shift to public mode to access university campus

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Abstract

University commuting has a strong impact on traffic congestion and pollution in urban areas. In Italy, this phenomenon is even larger since most of the universities are located in urban areas without adequate housing services in the surroundings. Therefore, it could be important for universities to implement policies that help commuters in switching from private vehicles to public modes.

This paper focuses on Milan Politecnico (today about 54 thousand people between students and staff) and outlines what are the characteristics of the car "irreducibles": the target-profiles that are less willing to switch to a sustainable mode. The aim of this paper is to study the causes of rigidity in commuting switch behaviour and to provide policymakers and universities with consistent strategies to promote public transports as a green alternative for commuting.

The study involves a sample of 2.646 car users of the two main Milan Politecnico campuses, out of a much larger population using other modes. The paper builds a Multinomial logit, in which three different commuter specifications are defined: "car lovers", people using car without taking into account other options, "car captives", people obliged to use car, and "switchers", commuters willing to switch. The first two specifications are defined as "irreducibles": they declare that do not want or cannot switch, while the third group would switch under some conditions. The model uses individual spatial location, socioeconomics and social behaviour factors as independent variables. Since location could play a role in switching propensity, the paper also includes a spatial analysis aimed at checking if spatial clusters exist after controlling for other individual variables.

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1. Introduction

Two of the main issues connected with mobility in urban areas are traffic congestion and pollution. In Europe, most of the congestion is located nearby urban areas and costs annually nearly €100 billion, 1% of the EU's GDP (European Commission, 2017). As far as the pollution is concerned, European urban mobility accounts for 40% of all CO_2 emission from mobility and about 70 % of other pollutants (European Commission, 2018).

According to the 2011 census, about 29 million Italian people were commuters, two-thirds of them moving for work and one third for study. Since most of the commuting is directed to the main urban areas (Beria, 2018), the aim of the policy maker is finding strategies for reducing commuting costs and their connected externalities (Tabuchi and Thisse, 2006). The traditional approach is promoting the switch from private vehicles to public transports and other sustainable modes.

University-related mobility is just one slice of these overall figures but is characterised by two important elements. Firstly, universities in large cities tend to be huge punctual attractors, both in terms of users and size of the catchment areas, comparable only to large business centres and more impacting than large hospitals. Secondly, in relative terms, commuting by car represents the strongest negative impact for universities on environment (Tolley, 1996). Therefore, improving university mobility could be a solution not only for academic environment but also for the surroundings, especially when city-campuses are concerned. Moreover, universities have a key role in the education of the citizens and professionals of the future: the integration of sustainable mobility practices in the education of students encourages the future change (U-MOB, 2018).

Just looking at Italy, during 2018/2019 academic year, around 1.7 million students were enrolled in university courses, 2.5% of total country population. In the same year, 95 thousand professors and researchers and 54 thousand people of the staff worked in the university environment, in addition to non-staff workers (our elaborations on MIUR, 2020).

Traditionally, Italian universities are large with respect to most of other EU countries and most of the courses are in few cities. Often, too, campuses are located in the city centres or – more recently –in the periphery but poorly provided with residences. The consequence is that commuting is the rule for university population, and most trips are headed to city centres. Just to provide some examples, Rome is the largest university-city (224 thousand students), followed by Milan (196 thousand) and Naples (156 thousand). The three together gathered 35% of total country university population, in less than 10 locations per city.

The issue of university mobility has been recently addressed in Italy by the national Network of Universities for a Sustainable Development, that conducted in 2016 a nation-wide survey in 37 Italian universities across the whole country (Colleoni and Rossetti, 2019). Among the results, it is shown that students generally tend to prefer using public transport to reach the campuses, though specific situation may vary according to supply conditions.

The awareness of the impact of a university campus has led Milan Politecnico to carry out large-scale biennial surveys since 2015, in which students and staff commuting habits were investigated. The goal of this data collection was to make and keep up to date the University mobility plan. This document is aimed to describe the commuting mobility to university and define a set of internal policies to make trips to university more efficient and support the shift towards more sustainable mobility behaviours. Among others, actions like increasing bike parking and other facilities, or the option to support public transport annual tickets have been assessed through the data collected.

Such surveys made also possible to estimate theCO_2 footprint of the university due to commuting mobility. Further insights about which category is responsible for more relative emissions have been provided by Bertolin et al. (2019), who conclude that some policies should be focused on specific categories of people rather than the whole community to be more effective, e.g. making staff residing in the metropolitan area limit the use of private car to commute. The current work is based on the 2017 edition of the mobility survey.

Using these data, the aim of this paper is to estimate the propensity of current users of private vehicles (cars and motorcycles) to switch to public transports or bikes, according to the different users' profiles. In particular, we will highlight three different groups: those willing to switch, the "switchers", if some conditions were met; those not available to leave their car at any condition, the "car lovers"; those unable to switch, the "car captives". We call the latter two groups "irreducibles": at the current conditions, they will not change their behaviour. Thanks to this analysis, in fact, the policy maker would be able to better target people that are more likely to switch, instead of designing general policies, which could ultimately be inefficient (e.g. subsidising groups that are *already* using public transport or trying to move the "irreducibles" without changing the parameters really shaping their choice). The core of the research is focused on Milan's campuses Leonardo-Città Studi and Bovisa, both characterised by a high share of public transport use, but also by large number of users and related traffic and parking problems in the neighbourhoods.

The paper is structured as follows. Section 2 provides a glimpse on previous studies on university mobility around the world. Literature is useful both to point out the main modal choice determinants and to acknowledge the policies suggested for switching to public and sustainable modes. Section 3 introduces the Milan campuses mobility framework. In Section 4 we describe the survey at the basis of the paper and provide the main summary statistics of the dataset. Section 5 describes the econometric model – a multinomial logit – and the variables used. The model aims at explaining the propensity to switch from private modes to public transport of the subset of observations that currently use car/motorbike. Section 6 is the estimation part, providing also the first summary of findings. Since the model has a limited spatial specification, the following Section 7 interrogates about the possible existence of unobserved spatial effects, such as clusters or concentrations along infrastructure corridors. Section 8 concludes, providing indications to better target modal shift policies.

2. Modal choice determinants and university mobility

The study of the social and individual determinants of car travel demand is a well-documented field of research. Usually, it is crucial understanding the behaviour of car users and the key factors of their choice. Miralles-Guasch and Domene (2010) outlined three different no-time varying categories of determinants.

Spatial location factors involve spatial configuration of the area such as the distance between origins and destinations, population density and public transport service and supply. Socioeconomic factors concern the population characteristics such as age, income and cultural background. Social behaviour factors consider university population features, for instance the purpose of the trip and its frequency.

However, these categories only involve permanent travel decisions often neglecting particular situations in which time is important (Hunecke, Blöbaum, Matthies, & Höger, 2001; Verplanken, Aarts & van Knippenberg, 1994). In fact, car demand is also affected by situational patterns, for

instance time of the year, weather or strikes. Interestingly, in the literature the analysis of car demand rarely considers both aggregate and time varying determinants (Klöckner and Friedrichsmeier, 2011).
The weight of established habits towards modal choice is another factor that should be considered, as those who have a strong habit towards choosing a particular travel mode appear to be less interested in acquiring new information on the alternatives (Verplanken et al, 1997).The results for general commuting showed that car availability has an important role in modal choice and in travel distance (Simma and Axhausen, 2001). Another important driver is the purpose and the frequency of the trip. Car ownership is highly related with likelihood of using car for going to work and university. (Dieleman et al, 2002) in the same study they found a small but significant positive correlation between car usage and weather. Another important driver is the reliability of public network. Strikes and disruptions normally affect negatively public ridership. In particular, Van Exel and Rietveld (2009) and Lo and Hall (2006) demonstrated how public transport strikes resulted in increasing car ridership and a traffic speed declining.

As far as university commuting is concerned, the literature has investigated many case studies around the world. In general, these studies are based on direct surveys of university population, hence sampling is a less relevant problem with respect to general-purpose studies thanks to direct access to the interviewed, and some individual information are also available. On the other side, the mobility of university users can be significantly different from general public mobility and therefore results cannot be generalised. For example, the campuses are usually accessible by public transport, the weekly and hourly patterns may be specific and the socio-economic profile of students is for sure different from the average one.
The role of the mobility manager officer and the university mobility plan in coordinating the efforts to meet student mobility and access needs, as well as increasing the sustainability of commuting habits, appears to be a common prerequisite for policy effectiveness (Mokwena and Zuidgeest, 2020).
Miralles-Guasch and Domene (2010), Shannon et al. (2006), Eluru et al. (2012), outlined how the role of people in the campus (students, professors, staff) affected car use propensity. In addition, they found that (>55 years old) age, (Men) gender and low income had a positive correlation with private ridership.
In Montreal, Eluru et al. (2012) found that propensity in car choice for university commuters (McGill University) was positively affected by the number of transfers and walking time. On the other side, in car travel time had a negative effect on choosing private modes.
In the literature there are also proposed policies that should deal with low public and sustainable mode choices. In Perth (Australia), Shannon et al. (2006) proposed an increase of parking price relatively to public transport ticket and more provision of student housing in university neighbourhoods. Brockman and Fox (2011) and Cruz et al. (2017) analysed parking policies in Bristol and Coimbra and they came up with similar conclusions about parking under-pricing and cut of parking supply. On the other side in both cases, authors suggested policy that improved bikes and walking facilities. In Trieste university, Rotaris and Danielis (2015) found that subsiding public transport would be the best option for decreasing the number of car and increasing social welfare.
Literature also pointed out the role of transport supply improvement as a determinant of modal shift (Redman et al, 2013). One interesting result regarding Las Llamas Campus of the University of

Cantabria (dell'Olio et al., 2014), obtained through a SP survey, is that the attributes of bus connection interact with bike demand: an improvement of public transport would reduce not only the use of car but also bicycle (and vice versa). More generally, the public transport supply cannot be considered as independent. Therefore, in the analysis, even if the determinant of the switch is not directly connected with a specific improvement in public service, the level of supply must be taken into consideration.

In conclusion, the majority of the existing literature studies the determinants of current mobility, investigating which are the individual or territorial characteristics behind the revealed choices. Studies that look only at the part of users that rely on private transport and investigate the determinants of a possible change to public or soft mobility, are much scanter. The current paper goes in this direction, providing a different perspective on the same determinants.

3. Politecnico mobility framework

As outlined in ISFORT, 2020 (considering 2019 data), most of the Italian mobility pattern is concentrated in the vicinity (< 2 km; 32%) and at urban scale (2-10 km; 43%). In north-west Italy most trips are made by private vehicles (60% Car + Motorcycles), 22% walks and 15% travels with public transport. Even if the data show a clear trend toward private vehicle ridership, commuter behaviour results affected by their location. In particular, while in Italian smallest urban centres (< 10 000 inhabitants) the public transport and bikes are rarely chosen (6.1%, 2.2%), in the most important urban areas (> 250 000 inhabitants) the use of public modes reaches 19% (Isfort, 2020). In this context Milan is an outlier: thanks to a relatively low car ownership (50 vehicles for 100 inhabitants: ACI, 2019), already in 2013 Milan public and bike ridership results were well above Italian standards (57%; 6%). Nevertheless, the broader urban area, due to size and to the particular orographic situation, resulted in worrying pollution concentrations and also in a significant congestion level. Therefore, leading the switch from private vehicles to public and bike modes is vital for Milan mobility and universities are expected to contribute, too.

Politecnico, established in 1863, is the oldest university in Milan and gathers Engineering, Architecture and Design faculties. In 2017/2018, around 45 thousand students were enrolled. In addition, 1360 tenured professors, 1200 technical-administrative staff and 2070 collaborators worked there (MIUR, 2020). The university consists in 7 different campuses (Figure 1), the two largest of them in Milan. In particular, Milan Leonardo is located in the east side of the city and Milano Bovisa in the north-west side. The other five campuses are located in a radius of about 150 km from Milan, mostly in the Region: Lecco, Como, Mantova, Cremona and Piacenza (Politecnico di Milano, 2017).

In 2017, within the project "Città Studi Campus Sostenibile", Politecnico implemented the second edition of a large-scale mobility survey in which data about mode preferences, travel time, weekly travel frequencies and other relevant data were collected. The questions were designed to collect data useful to design policies for decreasing private use, supporting the public transport modes (PT) and promoting other sustainable means of transport. In 2017 around twelve thousands of students filled the survey, 24% of the total student population. As far as the teaching and administrative staff are concerned, the answers were around two thousand, representing the 22% of total non-student population. The two Milan campuses, Leonardo-Città Studi and Bovisa, together represent 90% of the total Politecnico population (24 thousand and 17 thousand people respectively).

Milan Leonardo campus is mainly served by Metro line 2, trams 33-19 and urban buses 62-90-91-93. Moreover, it is located 1.2 km from Lambrate railway station which serves regional, fast regional and intercity trains and 1.5 km from Porta Venezia station along the city underground rail corridor. No dedicated parking is provided to students and parking is entirely curbside, generating a degradation of quality of public spaces, just recently faced with the introduction of car-free areas in the surrounding. Staff (administrative and professors) can use a limited number of lots within campus area. In 2017 such lots were 465, plus other for motorbikes and bikes (Perotto and Guereschi, 2017), but significant reconstruction works are ongoing, and they will reduce spaces in the future.
Milan Bovisa is located at the northern border of the city but is well connected through Bovisa and Villapizzone railway stations, both served by frequent suburban and regional trains. The local transport system is poorer, with some bus and two tram lines, but no metro. On the other hand, parking supply is proportionally more including 471 car places for staff.

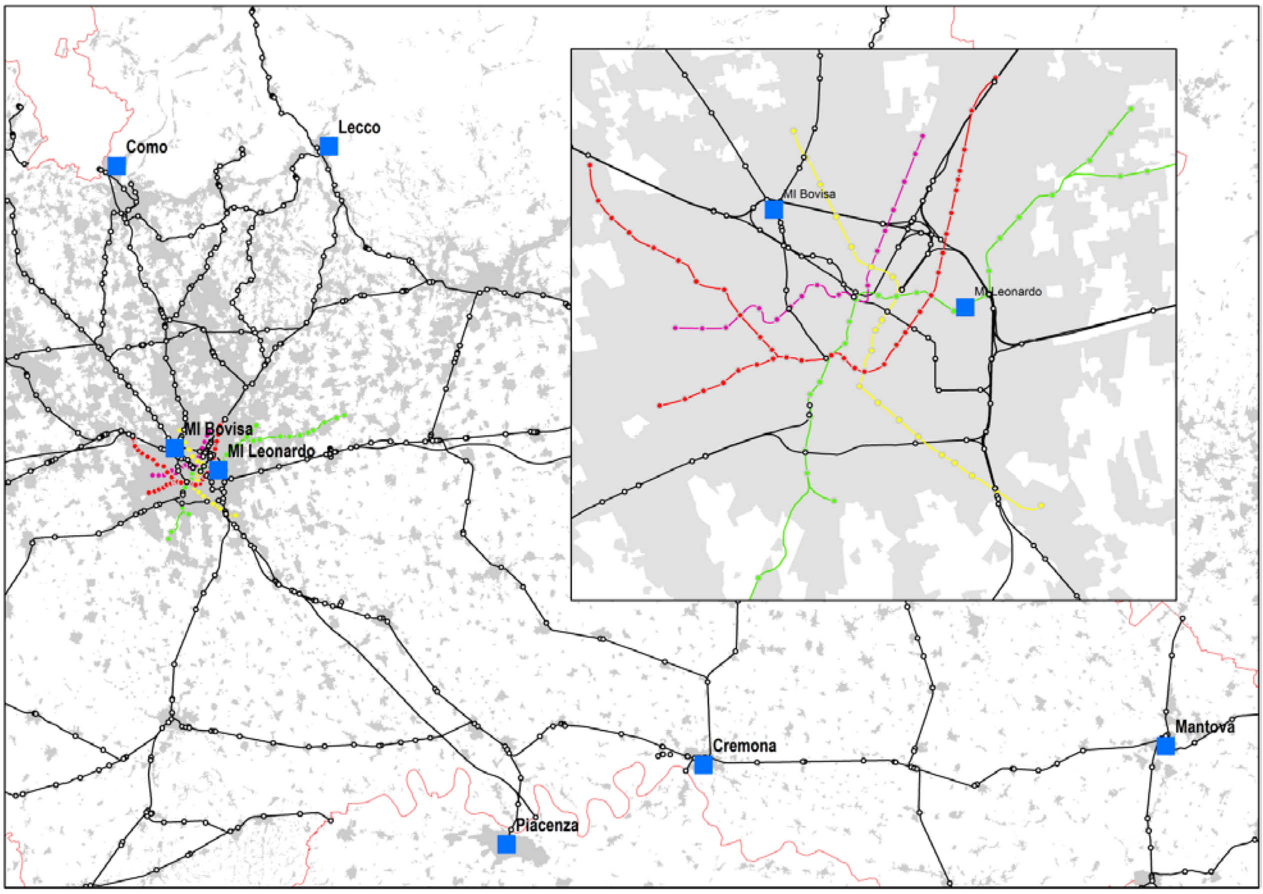

Figure 1. Map of Politecnico di Milano campuses (blue square), urban areas and rail network (our elaborations)

Looking at the main modal shares for Milan campuses (Figure 2), motorised private transport is lower than the territorial campuses. Public transport alone ranges between 45% and 52% for students in Milan, plus another 26% of intermodality. Just 4-5% of students reach the Milan campuses by car. Looking at staff, the shares are not so extreme, but car is limited to 17% in Leonardo (more urban and connected with metro) or 26% in Bovisa (just train access and easier parking).

Campus	Observations and consistency	PT + Car/moto	PT	Car/ motorbike	Bike + PT	Walk
Leonardo students	6372 (45%)[2]	26%	45%	4%	6%	12%
Leonardo Staff	1379 (10%)	18%	37%	17%	7%	9%
Bovisa students	4655 (33%)	26%	52%	5%	6%	6%
Bovisa Staff	628 (4.5%)	20%	37%	26%	6%	3%

Figure 2. Modal shares of Politecnico city campuses and consistency of the sample (Perotto and Guereschi, 2017)

4. Description and summary statistics of the dataset

The dataset used for this paper comes from the consolidation made by Bertolin et al. (2019) of the 2017 mobility survey raw data, who cleaned incomplete and unrealistic responses. It finally consists of 12 498 observations: 10 584 are student, while the other 1 914 belong to staff members, professors and fellow researchers.

We decide to limit our analyses to Milan campuses only, for two reasons. One is purely statistic: the largest share of observations in the two campuses provides a reliable sample, while the limited number of observations (despite the similar sampling rate) for the other campuses could be insufficient for an econometric analysis. The second reason is methodological. Since Leonardo and Bovisa provide different study careers (e.g. aeronautical engineering is only in Bovisa), observations should not be spatially biased (e.g. a student cannot choose one campus because is more reachable than the other). Since the choice between the two campuses does not concern their location, the assumption of indifference holds. Therefore, the hypothesis is that their choice of faculty involves "going to Milan" and not choosing one of the two campuses for any reason. This statement simplifies the behaviour analysis preventing other further assumptions on commuting attitudes.

After filtering for Leonardo and Bovisa campuses, we further limit the sample to the car and motorbike users only, since our purpose is studying their propensity to switch. In conclusion, the final dataset consists in 2 646 observation.

Overall, each observation consists in:

- Individual factors: average income of the origin zone, position in the university, age, gender, number and details of modes;
- Trip factors: entrance/exit time, travel frequency, monthly range of expenditures for commuting;
- Spatial location factors: the distance between zone of origin and the campus of destination, travel time, generalised cost.

The survey responses have been integrated with spatial average values, as some sensitive data were not collected. Income information[3] refer to the municipalities' average, further detailed in Milan according to the 55 "OMI zones"[4]. Generalised costs and distances come from a transport model (Beria et al., 2019) and are differentiated according to commuter profile (Students or not).

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[2] All the percentages in the column are referred to the 2017 survey sample

[3] The data come from the opendata of the Ministry of Economy and Finance and refer to 2017: https://www1.finanze.gov.it/finanze3/analisi_stat/v_4_0_0/contenuti/Redditi_e_principali_variabili_IRPEF_su_base_comunale_CSV_2017.zip?d=1595352600 (retrieved 30/1/2020)

[4] The "OMI" is the zoning used by the Italian Internal Revenue Service (*Agenzia delle Entrate*) to collect the market values for purchase and rent of buildings and estates: https://www.agenziaentrate.gov.it/portale/documents/20143/265514/omi+sintesi+manuale+bdq_Sintesi_Manuale_BDQ_OMI.pdf (retrieved 31/7/2020)

In addition to the mentioned variables, the survey asked the respondent's propensity to change the way to reach the campus to public/bicycle modes ("*Are you thinking to switch from private to public mode (or bicycle) now or in the next months?*"). The available options were:

1. NO because I already use public mode;
2. NO because I would like, but I do not have alternatives;
3. NO I do not take into account this possibility;
4. NO I am using public mode, but would like to switch to private mode;
5. YES I am starting to use public transport;
6. YES I am going to switch in the next 6 months.

The two options 1 and 4 are already out of the sample, because referring to current public transport users. The remaining four options will be used as dependent variable, as described in the following. Figure 3 shows the responses: the "irreducibles" account for 89% of car users, but their unavailability is either "ideological/personal" (response 3: 63%) or practical (response2: 26%). The reasons of these differences represent the core of this paper.

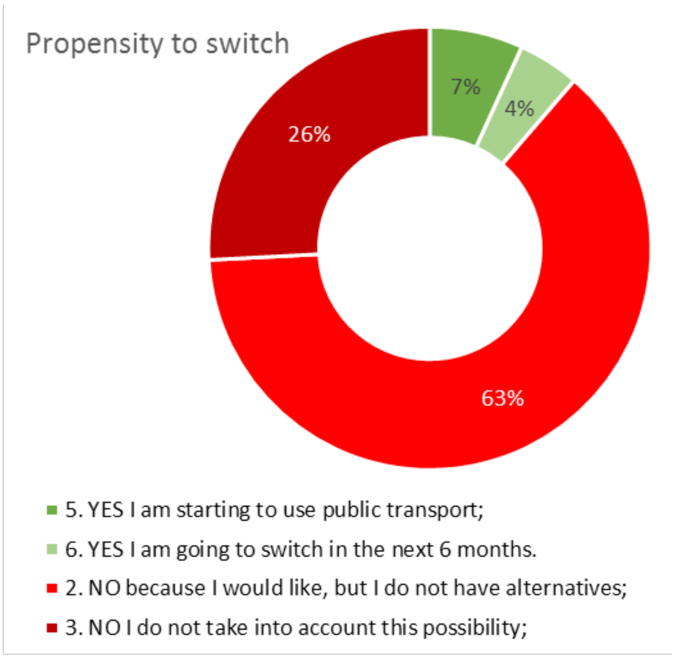

Figure 3. Propensity to mode switch of current car users.

The main continuous variables' summary statistics are presented in Table 1 and Figure 4. As far as travel distance and income observation, the distributions are right shaped. In both cases the last percentile (75-100%) gathers more than 80% of the observation range. Most people are frequent travellers to Politecnico (87% attend 4 or 5 times per week), while the distribution of the number of modes used is more homogeneous, even if obviously people taking 4+ modes are less.

Table 1. Summary statistics of control variables, part 1

	Income (€)	*Travel distance (km)*	*Gen. cost private*	*Gen. Cost public*
Min	11893	0.55	0.8	0.0
Max	122490	248.38	190.1	108.2
Mean	24884	27.31	13.9	10.3
0-25% percentile	11893 - 21251	0.55 - 0.01011	0.8 - 6.5	0.0 - 6.9
25-50% percentile	21251 - 22923	10.11 - 22.32	6.5 - 0.0	6.9 - 0.0
50-75% percentile	22923 - 25274	22.32 - 38.54	10.9 - 17.9	9.6 - 12.5
75-100% percentile	25274 - 122490	38.54 - 248.38	17.9 - 190.1	12.5 - 108.2
Standard deviation	8342	23.00	11.3	5.8
Standard deviation (%)	33.5%	84.2%	81.4%	56.1%

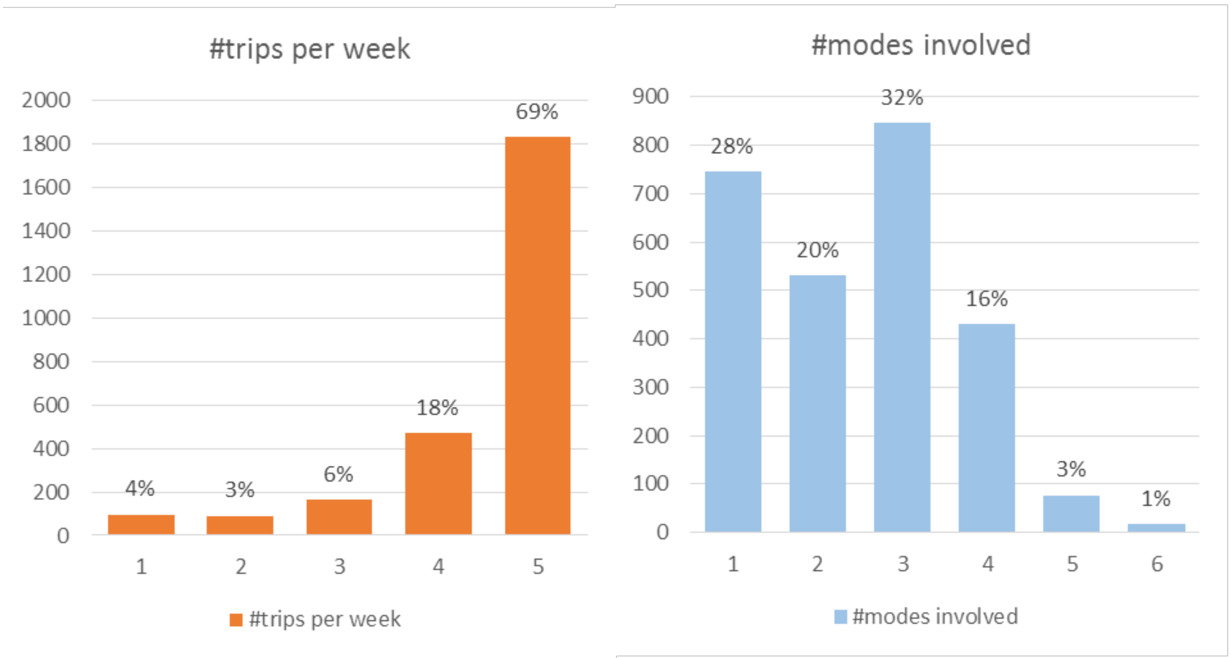

Figure 4. Summary statistics of control variables, part 2

More in detail, some differences can be seen across the different roles (students, staff) of university users (Table 2). Students are the most represented in the sample, even if car users in relative terms are the lowest. Looking at distance travelled, they drive the longest distances (about 29 km), while administrative staff the shortest (16 km): the latter live nearer to university and tend to use the car more, even on short ranges. Research staff stays in the middle. In terms of travel generalized costs, students driving pay similar amounts to professors, despite their lower value of time, due to longer distances. Looking at the public transport alternative, they would pay less (differently from administrative staff): this means that the measured generalized cost is not representative of their real preferences (for example they live too far from stations or the timetables are not compatible with lectures). In terms of frequency, professors are those who come to university less (but this category includes also lecturers, who are not full time employed and just 56% of observations go to university 4 or 5 times/week). Finally, students have to use many more modes (2.7 on average) to reach the campus while other categories enjoy more direct options (for example, professors and administrative staff use one single mode in the 67% and 64% of observations).

Table 2. Summary statistics of control variables, per role

	observations	*average distance [km]*	*average gen. cost. private [€]*	*average gen. cost. public [€]*	*average trips per week*	*average modes involved*
Students	2073	28.9	13.72	9.42	4.54	2.71
Professors	237	23.8	15.46	13.60	3.43	1.55
PhD and res. fellows	109	23.2	14.48	13.45	4.54	1.82
Administrative staff	190	15.9	11.41	11.83	4.76	1.62

5. Model framework and control variables

The structure of 2017 survey was designed to collect all the data necessary to study the *typical* university mobility behaviour in that year. The nature of the survey prevents the use of time varying variables. It is also almost impossible investigating the effect of weather conditions, strikes or seasonal changes in switch propensity. Therefore, considering the literature on modal choices, the survey structure is more focused on spatial, socioeconomics and behavioural factors.

Modal choice is typically not a linear phenomenon and literature is consolidated in using discrete choice models to study it. The commonest and simplest model is *logit*, involving a simple binary choice (e.g. private vs. public). In this case, we have information on more options and therefore the paper uses a *multinomial logit model* (MNL).

Logit models provide an estimation of the probability of a choice, which depends on the exponential of a linear combination of control variables for the chosen alternative, divided by the so called *logsum*, i.e. the sum of all exponentials of all available alternatives. This family of models embed a distribution of individual utilities around the average value of utility of the alternative, which is the only measurable control. The more available alternatives are similar, the more users will choose them equally; the more the alternatives differ, the more choices will be polarised around the best of them, leaving however the possibility that someone chooses an alternative which is worse on average (but not for him). It is worth remembering that in the *logit* framework, the analysis of the coefficients found in the regression could only involve their sign and magnitude. In fact, with MNL models it is impossible measuring directly the marginal contribute of the single variable in propensity change.

In this framework, the dependent variable of our analysis is taken from the modal switch replies. More precisely, we have three groups of replies from private modes users: those that affirm to be available to leave their car/motorbike, those that are not available at any condition and those that are not available because they feel to have no practical alternative to car. K=3 different specifications are:

Specification 1. “NO, I do not take into account this possibility”; we define for simplicity these users as *car lovers*.

Specification 2. “NO, I would like to switch, but I do not have alternatives”; we define for simplicity these users as *car captives*.

Specification 3. “YES I am starting to use public transport” and “YES I am going to switch in the next six months”; we define for simplicity these users as *switchers*.

The dependent variable is thus the stated probability that private mode users are available or not to switch to public transport and takes the form of a dummy choice. As already pointed out, the “irreducibles”, namely both *car lovers* and *car captives*, represent the majority of our sample, which is quite obvious since usually users have already analysed their options and taken decisions consistently.

$$P(Y = K \mid X = x) = \frac{1}{1 + \sum_{k=1}^{K-1} e^{z}}$$

The capability of *logits*, and MNL too, to properly predict choices depends on how the disutility is measured, i.e. the quality of control variables (independent variables) and their actual role in shaping choices. Typically, the vector z represents a disutility of travel, and consequently independent variables constituting it belong both to the characteristics of the trip and of the individual.

$z = b_0 + b_1$ Distance + b_2 Distancesquared + b_3 Campus dummy + b_4 DiffGenCosts + b_5Income residence dummies + b_6 Number of modes + b_7 Travel constraints dummies + b_8 Private modes only dummy + b_9 Role dummies + b_{10} Ratio private mode km/kmtot + b_{11} Travel frequency + b_{12} Peak hours dummies + b_{13} Provincial capital dummy

Besides all the variables mentioned in the previous chapter, the vector includes some dummy and interaction variables to improve the specification of the models tested.

As far as the spatial location factors are considered, the paper adds a squared distance variable to allow U-shaped dependency. It is common, in fact, that the peak of private transport lays in intermediate situations: the nearest will privilege active modes and public transport, the farthest train. In addition, a binary dummy to distinguish the two campuses is built (1 for Leonardo campus, quite different from Bovisa in terms of location, transport services, parking, etc.). Considering the socioeconomics variables, the average income of commuters’ zone of origin is divided in 4 categories. Every category gathers 25% of all observation using percentiles and is called low, low-medium, medium and high. Since this is just an average and not the individual income, there was no reason to use it as a continuous variable. The last socioeconomic dummies concern university role of commuters (management-professors, administration staff, researchers and students). Since the role is fairly linked with wage or available income (for students), the propensity in switching could be different.

To better explain the choices, we also include the individual difference between the generalised private costs and public costs. For example, if the public alternative is very similar (or worse) in terms of travel costs, it will be more unlikely that the user is available to change mode.

Choices are also shaped by possible travel constraints. This variable is considering personal constraints, not constraints for public supply service. Typically, if one way is constrained, also the

other will be such and the switch should become unlikely (e.g. car is needed in the morning to bring children at school).
It is also important identifying observations who use only private transport to reach university from those for whom car is just one segment of a multimodal trip. A dummy for only private modes users is added in the specification. However, not all multimodal trips are the same: a very short leg by car to reach station is different from a prevalently car trips whose only last segment is done by public transport. So, the ratio between the distance travelled by car or motorcycle over the entire commuting distance has been added.
Another dummy variable specifies if the commuter is coming from a province capital or not. This dummy recognises the different public supply in big cities (more frequent and often also faster due to express trains) that could affect switch choices.
Finally, the paper builds binary dummies to specify the entrance peak hours (7:30-8:30) and the exit peak hours (16:30-17:30). People are more affected by peak hour congestion could be more willing to switch modes.

6. MNL Model results

The base outcome of model is k=3 (choosing "YES" for a mode change). Consequently, the coefficients found in the regression outline the propensity of choosing NO (k=1 and k=2) compared to the base outcome. Thanks to the *multinomial logit* model, the comparison between the coefficients of specification 1 and 2 clarifies which are the characteristics distinguishing within the "irreducibles".

Table 3. Model results

	VARIABLES	*k=1* *Car lovers*	*k=2* *Car captives*
Trip characteristics	Distance (km)	0.0104	0.0216***
		(0.00857)	(0.00781)
	Distance squared (km)	-3.13e-05	-0.000101**
		(5.07e-05)	(4.72e-05)
	Number of modes (#)	-0.505***	-0.264***
		(0.0846)	(0.0733)
	Private modes only (dummy)	0.280	0.604***
		(0.224)	(0.215)
	Ratio private mode km / kmtot ()	-0.670**	-1.030***
		(0.270)	(0.241)
	Diff gen cost Private – Public (€)	-0.00565	-0.00452
		(0.0129)	(0.0117)
	Travel frequency (times/week)	0.141**	0.138**
		(0.0720)	(0.0667)
	Travel constraints: One-way (dummy)	-0.0394	0.353
		(0.259)	(0.232)
	Travel constraints: way-back (dummy)	-0.0608	-0.139
		(0.268)	(0.240)
	Peak hour: entrance (dummy)	-0.252	-0.244
		(0.178)	(0.164)
	Peak hour: exit (dummy)	0.00368	-0.0576
		(0.150)	(0.138)
Individual characteristics	Leonardo campus (dummy)	-0.114	-0.0866
		(0.149)	(0.138)
	Income residence: low-medium (dummy)	0.138	0.232
		(0.247)	(0.228)
	Income residence: Medium (dummy)	-0.608***	-0.397*
		(0.226)	(0.204)
	Income residence: High (dummy)	-0.524**	-0.391
		(0.263)	(0.244)
	Provincial capital (dummy)	-0.0998	-0.629***
		(0.196)	(0.181)
	Role: manager-professor (dummy)	0.205	0.261
		(0.270)	(0.257)
	Role: Phd and research fellows (dummy)	-0.832**	-0.473*
		(0.325)	(0.282)
	Role: administrative staff (dummy)	0.268	-0.132
		(0.285)	(0.278)
	Constant	2.228***	2.419***
		(0.579)	(0.531)
	Observations	2,646	
	LR chi2	300.66	
	Prob > chi2	0.0000	
	Pseudo R2	0.0640	
	Log likelihood	-2199.2831	

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

A first general consideration about the significant variables of the model: most of trip characteristics variables are not significant for car lovers' group: they are *car lovers* as such. Instead, trip characteristics are more significant for the other group, the *car captives*.
For example, distance is significant only for *car captives*: the more people live far from the campuses, the more they are likely to say no to a modal switch to public modes. However, the magnitude of the effect decreases with distance (the utility has a maximum at 110 km from the campus). *Car lovers*, instead, are not influenced by distance.
The difference in generalised costs, differently from expectations, is not significant. The interpretation is that *car captives* are those for whom the generalised cost – which are the average supply conditions – are not representative of their actual conditions. Instead, for *car lovers*, the irrelevance is obvious: they are those who chose car whatever is its cost advantage (or disadvantage).
The probability of being "irreducibles" increases with the decrease of the variable "Number of modes" for both specifications. Multimodality is then a key factor for switching. This is even more evident for *car lovers*. A further indication is in "private mode only" dummy. Overall, both "irreducibles" are most likely those using car only or car in addition to few other modes. An important variable for switching choices is the weight of private modes in term of distance compared with the entire commuting distance. The longer is the part of the trip done by car, the less rigid is the switching behaviour. We can see this fact in another way: if car is used for a small part of the intermodal trip, the less likely is that car would be dropped (adding a public transport mode to cover just short distance is probably perceived as unattractive, due to the weight of waiting time, rigidity and reliability issues).
Constraints in commuting are not relevant for the switch propensity, differently from what happens in other situations: once people chose their modal chain, this is not significant anymore.
Travel frequency is significant too, with a positive coefficient. People who have chosen "NO" are more likely to be frequent travellers, while infrequent travellers would be more interested to switch.
The second group of variables is describing individual characteristics (or proxies for them). For example, average income of origin zone is insignificant for *car captives*: they must use their car whatever is the income. To the contrary, the variable is significant for *car lovers* for higher income origins, but with negative sign. However, this variable is not really telling us about the actual available income of the person (it was not possible to ask this detail in the survey).
Also, the university role is not generally significant. For example, professors and staff are not systematically more belonging to irreducibles group than students. Only for PhDs compared to students the variable is significant: temporary (and less paid) research staff is more likely to belong to the switchers group 3 than reference group of students.
For people who chose NO, the campus of destination has no significant effect. Even if Leonardo and Bovisa campuses are located in two different areas with different transport services, the switch behaviour is not significantly different.
Finally, we introduced the dummy for commuters coming from main cities and it showed to be very significant for *car captives* group: it is less likely that people living in conveniently connected cities are more forced to take car compared with people living in sprawled or peripheral areas.

In conclusion, the econometric model allows us to affirm that:

a. Among those accessing university by car – a minority in the case of Politecnico – the majority belongs to the two profiles of "irreducibles": the *car lovers* (those ideologically bound to car) and the *car captives* (those with no alternatives).
b. However, the motivations of the two groups are very different. For example, *car lovers* are not affected by trip variables such O-D or distance. They just love driving or "hate" public transport, including when it would be rationally more advantageous.
c. Some of the variables considered, that are typical of modal choice models, revealed to be not significant. For example, the difference in generalised costs or destination features, university role and constraints in commuting. This makes sense as we are not describing the modal choice (why a person going from A to B is preferring car), but the causes of (non)propensity to switch (why a person using car from A to B is not considering public transport).
d. The key factors for being *irreducibles* are: monomodality, long distances (but not above 110km), the use of car for short segments of a multimodal trip, frequent travels, origin from smaller cities (presumably with low quality of public transport).

One of the possible limitation in this analysis could be the lack of spatial variables. The only spatial components are "Distance" and "Distance squared" for the spatial distance, while "Capital province" account for territorial peculiarities. Since the difference in generalised costs is not a good proxy, model could occur in a missing variable bias. In the following section we will verify this hypothesis.

7. Spatial analysis

One way to deal with spatial issue is building a vector of residual for every observation. The residuals are calculated as the difference between predicted propensity and the observed propensity. If some spatial pattern is visible or found in the errors, we could conclude that there is a missing spatial variable in the vector *z* of the regression. Otherwise, we could infer that we included all relevant spatial variables in the model. This will be done in four steps:

1) calculating the residuals between the model and the observation and defining which observations can be considered at the zonal scale (municipality or zone inside Milan) for spatial analysis,
2) finding possible outliers;
3) mapping the residuals grouped by municipalities using a GIS software, to visually search for clusters;
4) perform a Moran test. In this way, the analysis is able to detect the spatial omitted variable bias.

An example is proposed to describe the first step. Observations are grouped by zone of origin (747 zones, 52 of which inside Milan) and the model is used to calculate the corresponding probability of choice. Table 3 includes the model results and the real observations for Monza (the third city of the region, with 91 observations) and two villages including just 6 and 1 observations respectively).

Table 4. Example of model fit test

origin	Model (k=1)	Model (k=2)	Model (k=3)	Observed (k=1)	Observed (k=2)	Observed (k=3)	Prob observed (k=1)	Prob observed (k=2)	Prob observed (k=3)
MONZA	0.36087	0.47536	0.16377	26	55	10	0.28571	0.60440	0.10989
CAPIAGO INTIMIANO	0.20701	0.70668	0.08631	2	4	0	0.33333	0.66667	0.00000
AIRUNO	0.22385	0.72296	0.05319	0	1	0	0.00000	1.00000	0.00000

In the case of Monza, 10 respondents belong to the group of people available to abandon private transport, 26 are *car lovers* and 55 are *car captives*, corresponding to the 29%, 60% and 11% of shares. If we look at real responses, the shares become 36%, 48% and 16%. The second zone is similar. For example, the model predicts 9% of choice=3, but in the small sample (6 people) no one actually choses it (which is statistically correct as 1/6 > 9%). The third case, Airuno, is represented by one single observation (100% of choice=2), while the models predicts 72%.

A first observation is that the smaller is the number of observations of a zone, the most likely errors will be higher. The plot of squared residual errors in function of the number of observations in a zone (Figure 5) confirms the hypothesis of a negative relationship. In order to have a better cluster analysis, it is reasonable to consider only the municipality with at least five observation (*filtered sample*). In this way, all fit squared errors are within 0.4. The *filtered sample* includes now 159 municipalities and zones, 40 of which are in Milan.

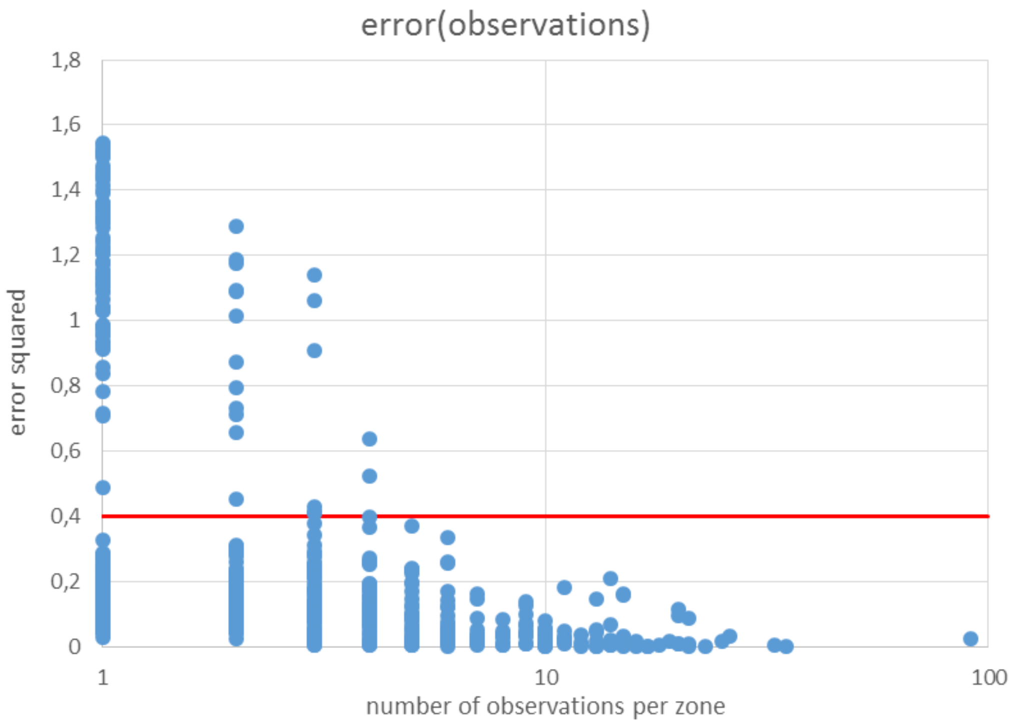

Figure 5. Plot of model errors squared and number of observations per zone

Secondly, we verify if outliers present some spatial concentration. We characterise outliers as

$$x_i > Q_3 + 1,5 \times (Q_3 - Q_1)$$

With (Q1, Q2, Q3, Q4) the percentiles of all squared errors.

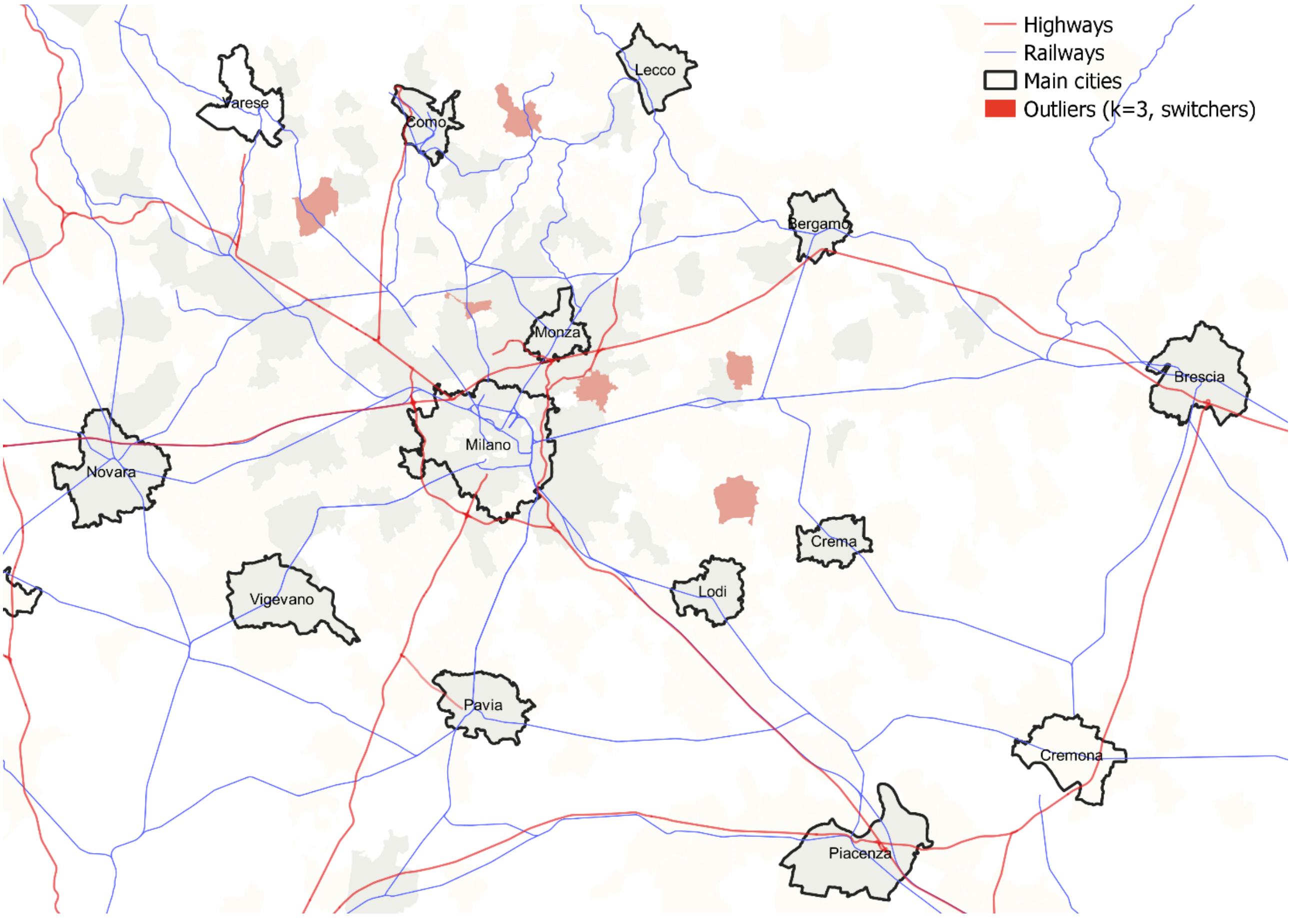

Figure 6. Map of outliers

However, since outliers do not have a particular pattern (Figure 6), they do not stress substantial spatial misspecification bias in the model. Therefore, all observation in the *filtered sample* are considered for spatial analysis.

In the third step, we map the fit of model, to visually search for clusters of errors. The distribution of errors (Figure 7) across the sample shows that most of observations lays within the -30% to 30% error range, respectively 89%, 90% and 99% for the three options. Option 2 is slightly underestimated, while option 3 is slightly overestimated (around 67% of errors are in 0% to 20% range). So the model is reasonably precise in reproducing real choices, also when the sample is spatially considered.

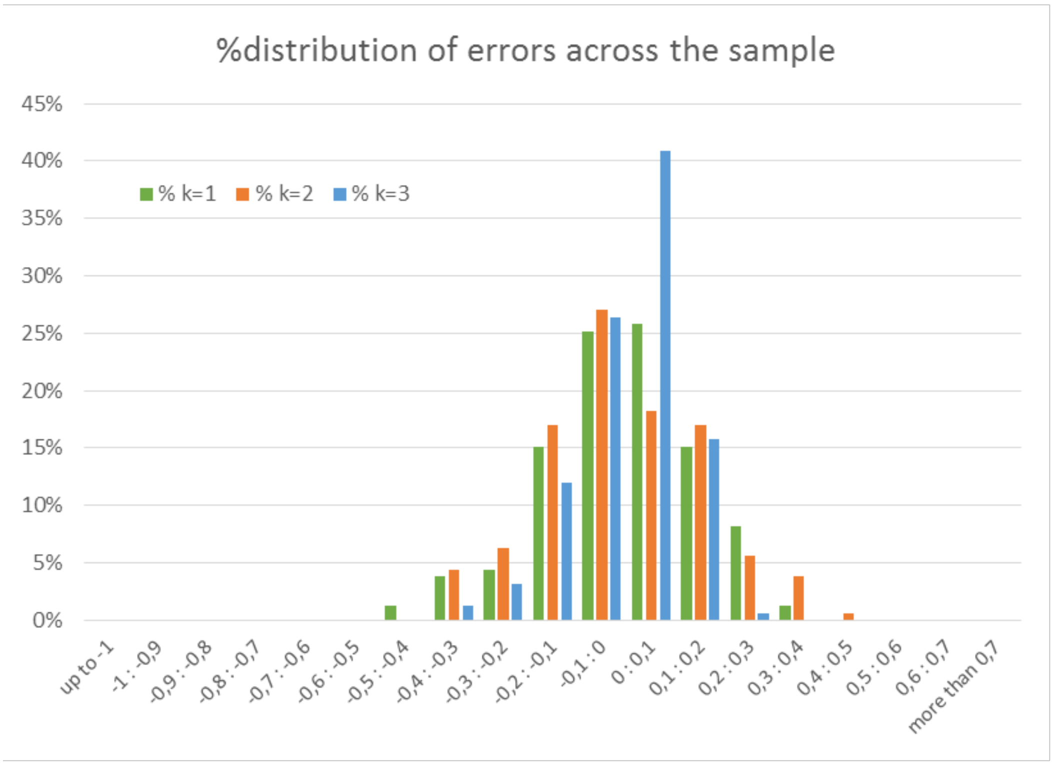

Figure 7. Distribution of model errors in the filtered sample.

Figure 8 maps the residuals for the first option, the *car lovers*. Errors look distributed, with no particular concentration, including along infrastructure corridors. Many zones (those in grey colours) show an excellent match between model and observation. We just observe that five out of 13 main cities are overestimated and just two underestimated. The situation in Figure 9, *car captives*, is similarly scattered: no visible pattern of errors and many zones with good fit. While for *car lovers* we could see overestimation in the west side of Milan, car captives are somewhat overestimated in the east. The situation of provincial capitals is more equilibrate. Finally, Figure 10 shows the errors of specification 3, the *switchers*. Here, as already predicted by Figure 7, most of the zones are excellently estimated and, again, no visible spatial pattern is present. Varese is the only city with a significant error: the model predicts *switchers* to be 31% less than observations. A possible explanation, valid also for Como, Vigevano and Pavia, is that the rail connection is particularly effective in time and frequency with respect to car (which suffers of congestion). Therefore, more people would be interested to move to train, if other conditions were met (for example availability of parking at the origin station).

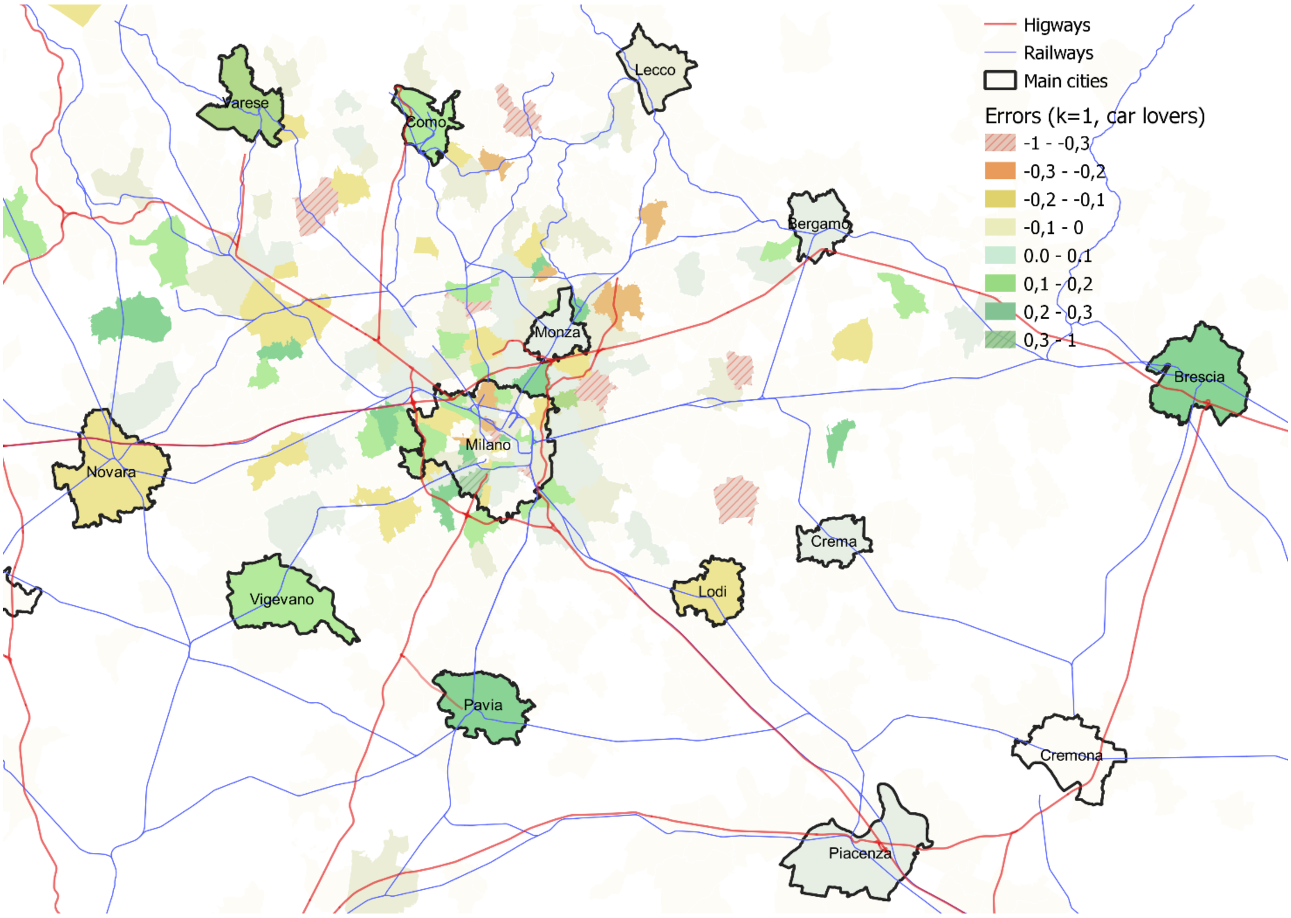

Figure 8. Map of the model residuals for k=1, car lovers.

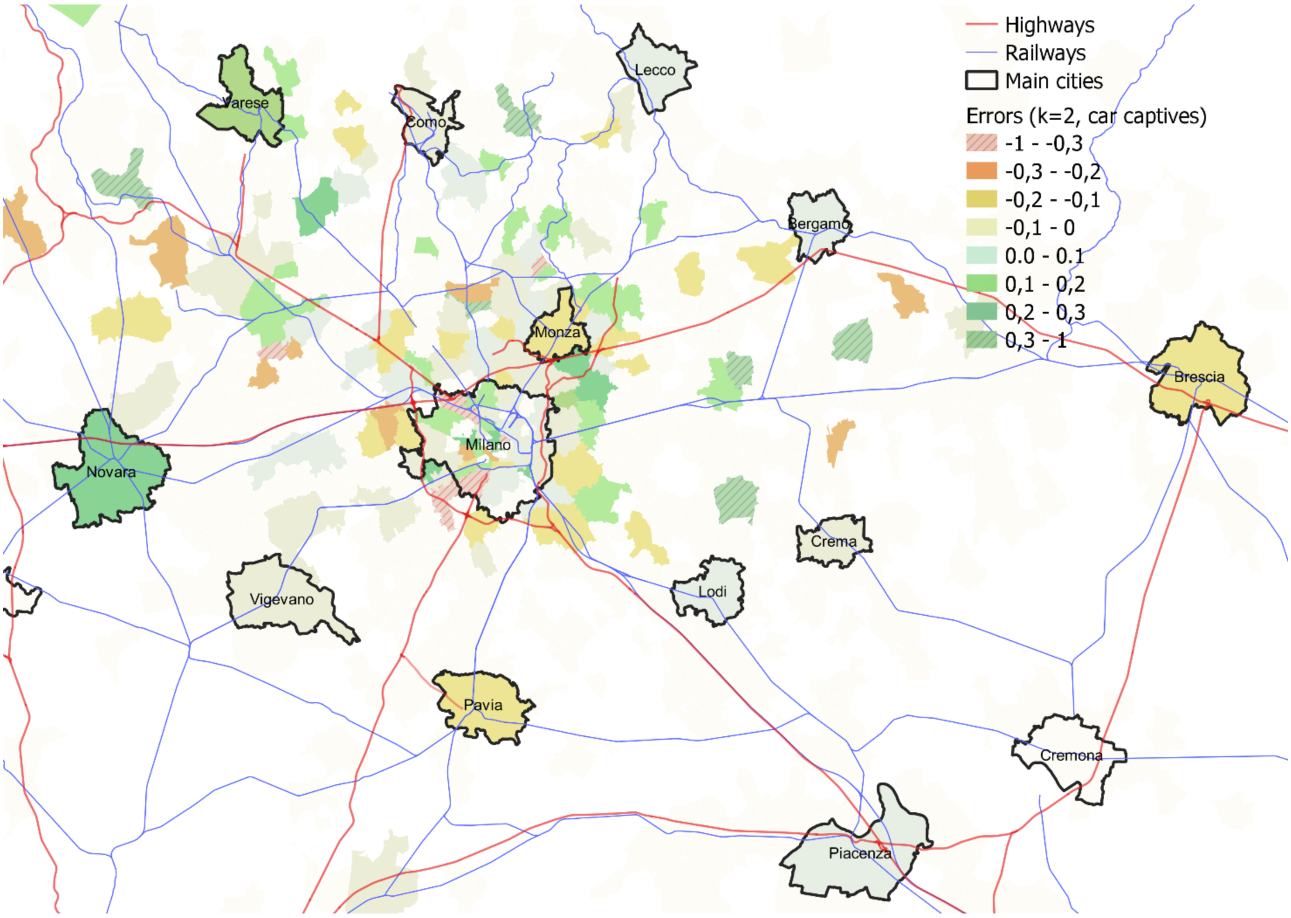

Figure 9. Map of the model residuals for k=2, car captives.

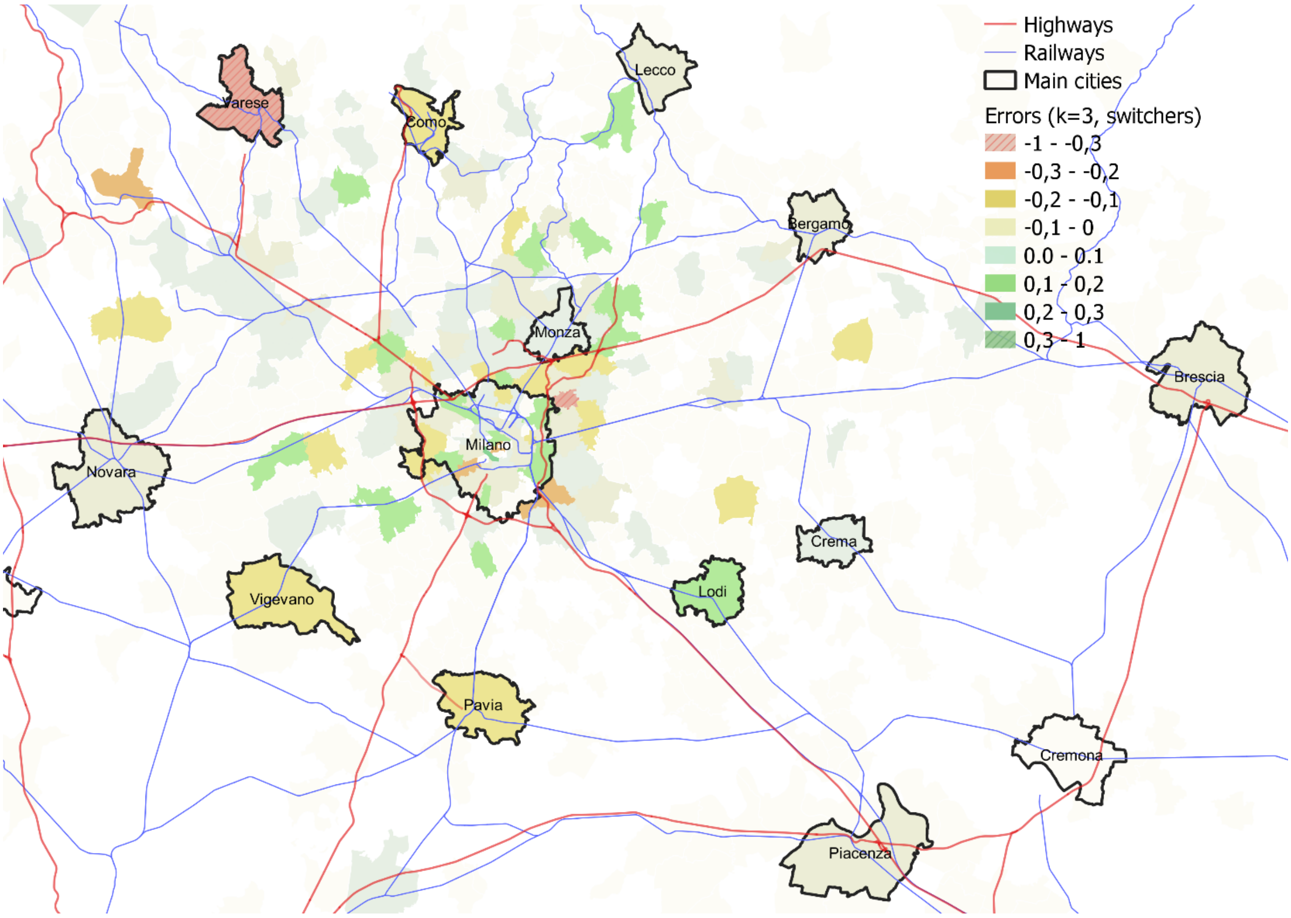

Figure 10. Map of the model residuals for k=3, switchers.

To conclude the spatial analysis, we perform a Moran test to see if there is spatial correlation among residuals. This step formalises what has just been done "visually". The weight matrix is built from the straight distances between zones according to the function W=distance$^{\gamma}$.[5] Data is spatial homogeneous if p-value>5%. Table 4 shows that results are positive: the residuals of the model are not spatially dependent.

Table 5. Results of the Moran test for spatial homogeneity of model residuals.

	p-value	Spatially homogeneous
k=1, car lovers	0.222121	yes
k=2, car captives	0.3031014	yes
k=3, switchers	0.1076802	yes

In conclusion, we can say that the model does not suffer of spatial misrepresentation: errors do not have any significant spatial distribution and therefore the conclusions of the econometric model are valid for the entire area.

[5] The result has been tested the same for γ=-1 and γ =-2

8. Conclusion and comments

The paper has the aim of studying the modal switch propensity. The goal is targeting car "irreducibles" user's profiles in order to help the policy maker in correctly designing policies encouraging public transports and bikes.

The case study of Milan Politecnico is characterised by a small share of private car users (around 5% for students and around 20-25% for staff). In addition to them, a significant share is using car and public transport for different parts of the trip. If we look at car users only, we observe that most of the people in the sample is an "irreducible": not able ("car captives") or not willing ("car lovers") to shift. This sounds reasonable, as few people are willing to change their current behaviour, especially without strong motivations or a significant change to status quo (like a new mass transit line). However, some factors change their propensity in switching choices. Some of these factors are already present in the modal choices framework while other are not significant.

We studied the characteristics of the three groups of *lovers*, *captives* and *switchers* through a multinomial logit model. The motivations of the three groups are clearly different.

The two "irreducibles" are characterised by monomodality, long distances and high frequency of travel. For those using more modes, car is used just for short segments, but this segment is not questioned.

There are some aspects distinguishing "car lovers" from "car captives". For the first group, the distance or the generalised costs are not significant. Car is irrationally chosen, whatever is the trip; surprisingly, they do not come from high-income areas. The "captives" do not live in main cities (where good public transport options to reach Milano exist) and more often belong to those that use just car. This profile is quite clearly saying that they tend to come from dispersed areas, presumably with low quality of public transport.

The model proved quite precise in estimating the shares of the three groups, with no spatial bias. The only element rising from the analysis of residuals is that in most of the main cities it underestimates the propensity of switching. This underlines again the importance in switching choices of transport frequency and affordability (typical of provincial capitals, but not included in our generalised cost estimation). In most of the capital provinces, the *irreducibles* are not car lovers, but they need car for short commuting to railway stations.

A couple of limitations of the analysis must be however mentioned. The first issue concerns the survey, that poses a question without any specification of the conditions. People switch propensity is just declared and may not match with real intentions, or information to make a proper choice could be not complete. The second issue is the role of changes in public transport supply, that is missing in the model. Since the people interviewed do not internalise the change of supply, this shadow variable is not present. One way to deal with it will be comparing two different surveys (2017 and 2019) and looking at the evolution in switching propensity change.

In conclusions, once the propensity of switching mode of the three groups is quantified, some policies can be suggested to realistically push "irreducibles" to more sustainable modes. For "car lovers" reducing the cost of public transport through subsidies and discounts appears useless: they do not chose car because of the cost. Multimodality alone is not a solution, too: car is a love-affair and the perspective of leaving it somewhere to change to public transport is not better than taking public transport from origin. If multimodality is the only solution, better to bring it near home (for them, a short leg by car and then train is better than a long leg by car and then metro/tram). The longer the car segment, the more irreducible they are. Overall, no nudging seems possible for car lovers and – if their number must be reduced for external reasons – the main solutions are either forbidding them to park (of course at the expense of their surplus) or present them a completely new alternative.

For "car captives", policies are different. Distance and sprawl matter, and since these are typically out of the possibilities of a university policy, better to provide campus residences to improve radically their condition. It is also useful to target people using only car from those already on intermodal options and push the first to use the car to reach public transport (subsidies, information, direct actions). Any policy for car captives is more effective if targets the correct group: frequent travelers (more willing to switch and larger effect) and people living in cities rather than in the rest of region (public transport already more effective).

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Bibliographical references

ACI (2019). *Autoritratto 2019*. Automobile Club Italiano, Roma.

Beria P., BertolinA., Tolentino S., Debernardi A., Ferrara E., Filippini G (2019). *A model-based evaluation of national transport policies*. Paper presented at: XXI SIET conference, Bologna, September 9th-10th, 2019.

Beria, P. (2018, ed.). *Atlante dei trasporti italiani. Infrastrutture, offerta, domanda*. Libreria Geografica, Novara (Italy).

Bertolin A. et al. (2019) Assessing the Impact of Changes in Mobility Behaviour to Evaluate Sustainable Transport Policies: Case of University Campuses of Politecnico di Milano. In: Nathanail E., Karakikes I. (eds) Data Analytics: Paving the Way to Sustainable Urban Mobility. CSUM 2018. Advances in Intelligent Systems and Computing, vol 879. Springer, Cham.

Brockman, R., & Fox, K. (2011). Physical activity by stealth? The potential health benefits of a workplace transport plan. *Public Health*, 125(4), 210–216

Barata, E., Cruz, L., & Ferreira, J. P. (2017). Parking at the UC campus: Problems and solutions. *Cities*, *28*(5), 406-413.

Colleoni, M., & Rossetti, M. (Eds.). (2019). *Università e governance della mobilità sostenibile*. FrancoAngeli.

dell'Olio, L., Bordagaray, M., Barreda, R., & Ibeas, A. (2014). A methodology to promote sustainable mobility in college campuses. *Transportation Research Procedia*, *3*, 838-847.

Dieleman, F. M., Dijst, M., & Burghouwt, G. (2002). Urban form and travel behaviour: micro-level household attributes and residential context. *Urban studies*, *39*(3), 507-527.

Eluru, N., Chakour, V., & El-Geneidy, A. M. (2012). Travel mode choice and transit route choice behavior in Montreal: insights from McGill University members commute patterns. *Public Transport*, *4*(2), 129–149.

European Commission (2017). *L'EUROPA IN MOVIMENTO. Un'agenda per una transizione socialmente equa verso una mobilità pulita, competitiva e interconnessa per tutti*. COM(2017) 283 final. Brussels.

European Commission (2018). *Urban mobility*. Retrieved from (31/7/2020) https://ec.europa.eu/transport/themes/urban/urban_mobility_en

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.
Lo, S.-C., & Hall, R. W. (2006). Effects of the Los Angeles transit strike on highway congestion. *Transportation Research Part A: Policy and Practice*, 40(10), 903–917.
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 (2020). *Portale dei dati dell'istruzione superiore.* http://dati.ustat.miur.it/organization/miur
Perotto, E., & Guereschi, F., (2017). *Piano spostamenti casa-lavoro del Politecnico di Milano*, Politecnico di Milano, Milano (Italy). (Internal document).
Mokwena, O. H., & Zuidgeest, M. (2020). Identifying transport policy gaps in student travel demand management in South Africa. *Journal of Transport and Supply Chain Management*, *14*, 13.
Redman, L., Friman, M., Gärling, T., & Hartig, T. (2013). Quality attributes of public transport that attract car users: A research review. *Transport Policy*, 25, 119–127.
Regione Lombardia (2016). *Programma Regionale della Mobilità e dei Trasporti.* Regione Lombardia, Milano.
Rotaris, L., & Danielis, R. (2015). Commuting to college: The effectiveness and social efficiency of transportation demand management policies. *Transport Policy*, 44, 158–168.
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.
Tabuchi, T., & Thisse, J.-F. (2006). Regional Specialization, Urban Hierarchy, And Commuting Costs. *International Economic Review*, *47*(4), 1295–1317. doi: 10.1111/j.1468-2354.2006.00414.x
Tolley, R. (1996). Green campuses: cutting the environmental cost of commuting. *Journal of Transport Geography*, 4(3), 213-217.
U-MOB (2018). European University Network for Sustainable Mobility. LIFE Project Number LIFE15 GIC/ES/000056. Retrieved from (13/01/2021) https://u-mob.eu/project/
Van Exel, N. J. A., & Rietveld, P. (2009). When strike comes to town… anticipated and actual behavioural reactions to a one-day, pre-announced, complete rail strike in the Netherlands. *Transportation Research Part A: policy and practice*, 43(5), 526-535.
Verplanken, B., Aarts, H., & Van Knippenberg, A. (1997). Habit, information acquisition, and the process of making travel mode choices. *European journal of social psychology*, *27*(5), 539-560.