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The interplay between residential location and cycling choice: the case of two metropolitan areas in Sardinia, Italy

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Abstract

The current paper aims to enrich the current understanding of the link between the choice of residential location, the propensity to cycle to work and the propensity to cycle for non-commuting purposes. To highlight the relationship among these choice dimensions we used a composite econometric model that allows for the joint modelling of multiple outcomes. Residential location and cycling propensities are modelled as a function of socio-demographic and level-of-service variables. The inclusion of common error terms allows us to control for self-selection and unobserved effects that can simultaneously influence the underlying propensities. The data for this study is drawn from a survey conducted in the metropolitan areas of Cagliari and Sassari (Sardinia, Italy) in 2016 among a sample of local employees. The sample comprises 2,128 observations. Our results indicate that a significant portion of unobserved variance between the residential location choice and the propensity to cycle for non-commuting reasons exists, suggesting the presence of a self-selection effect.

Keywords: self-selection; cycling mobility; discrete choice model; residential location

1. Introduction

In recent years, researchers have shown a growing interest in cycling as an environmentally friendly transport alternative that has the potential to increase people's physical activity levels and reduce their car dependency.

A large body of literature has investigated the relationship between cycling travel behaviour and the built environment. In general, it has been observed that higher levels of urban density positively influence the decision to ride a bike (Cervero and Duncan, 2003; Pucher and Bueheler, 2006; Piras *et al.*, 2021). This can be explained by the

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fact that, compared to low-density areas, high-density areas may be characterized by shorter distances between origins and destinations. Interestingly, Witlox and Tindemans (2004) found that, depending on the place of residence, there are differences regarding the chosen mode, with residents in urban areas being more likely to use the bike than those in the suburbs. Dill and Voros (2007) observed that individuals who live in neighbourhoods closer to downtown were more likely to make utilitarian bike trips. Beside density, another key factor is the land-use mix, which depends on the level of diversity of land-use types (commercial industrial, residential and so on) across a neighbourhood. Areas with a traditional layout, street-level shops and residences above them, reduce travel distances and so make it easier to cycle from home to shops or places of work (Cervero and Duncan, 2003; Heinen *et al.*, 2010; Habib *et al.*, 2014; Winters *et al.*, 2017). Another important element regards the aesthetics, as it has been shown that the presence, among others, of parks, street plants and garbage bins are positively associated with cycling (Fraser and Lock, 2011).

Despite the large number of studies on cycling and neighbourhood characteristics analysis, very little is known about the residential self-selection problem in cycling behaviour. Residential self-selection is defined as the inclination of individuals to choose to live in neighbourhoods that accommodate their travel abilities, needs and preferences (Cao, 2015; Ettema and Nieuwenhuis, 2017). Although this issue has been largely investigated in studies of walking as well as travel behaviour more generally, little research exists on the role of residential preference specifically influencing bicycle use. As described above, the importance of considering the influence of the built environment has been stressed in different works (see Heinen *et al.* 2010; Wang et al., 2016), but many consider it as an exogenous variable in the decision to cycle, ignoring the of households' residential location choice process (Pinjari *et al.*, 2008). In fact, bicycle travel behaviour may not only be influenced by residential location, but individuals might choose their home because they intend to cycle, preferring to live in areas that allow them to do so easily (Heinen *et al.*, 2010).

Pinjari *et al.* (2008) presented a joint model of residential neighbourhood type choice and bike ownership, showing that ignoring self-selection effetcs may lead to an underestimation of the impact of neighbourhood attributes on bicycle ownership. Pinjari *et al.* (2011) used an integrated simultaneous multi-dimensional choice model to capture the jointness of residential location, auto ownership, bicycle ownership, and commute tour mode choices. They found that some socio-demographic variables influence both bike ownership and residential location choices, indicating, for the authors, the presence of a residential self-selection effect. However, one limitation of these works is the use of bike ownership level as a dependent variable, assuming that the ownership of a bicycle automatically leads to its use. Ettema and Nieuwenhuis (2017) explored whether and to what extent built-environment factors, travel attitudes and reasons for location choice affect the use of different travel modes within two years after relocation. They showed that active travel attitudes positively influence cycling use frequency and the variable cycling accessibility being a reason for location choice has a stronger impact, in terms of magnitude, than locational factors.

The current paper aims to contribute to the literature by investigating the relationships among three behavioural choice variables, namely, residential location choice, commute mode choice and non-commuting cycling frequency. Here, in the attempt to place greater emphasis on the above aspects we used a modelling structure that incorporates common error terms that allows us to control for self-selection and unobserved effects that can simultaneously influence the underlying propensities. The research data employed to calibrate the model is drawn from an online survey administered to a sample of public employees in two metropolitan cities in Sardinia (Italy).

The remaining part of the paper proceeds as follows. In the next section we report the characteristics of the sample, while in Section 3 we describe the methodological framework of our study. The fourth Section presents modelling results. Some conclusions are given in the last Section.

2. Data collection

The data used in this study come from an on-line survey conducted by the Regional Government of Sardinia and the Research Centre for Mobility Models (CRiMM) at the University of Cagliari (Italy) in two mid-size urban areas in Sardinia (Italy), Cagliari and Sassari. The survey, called "BIKE I LIKE YOU", was carried out between 2014 and 2016 and targeted local authority employees (see Piras *et al.*, 2021 for more details on data collection process). In particular, the questionnaire was organised into 4 sections:

- Bicycle use section aimed to identify for what purpose and how frequently people choose to cycle.
- Cycling perceptions section (Likert scale from 1=Totally disagree to 5 = Totally agree) intended to:
    1. Measure positive and negative perceptions of cycling in general.

2. Measure the perception of context characteristics, intended as the importance assigned to policies for increasing bike use.
3. Measure the perception of bikeability and safety of bike lanes and paths.

• Description of home-work commute trip.
• Socio-demographic information section.

A total of 2,128 observations with prerequisites useful for the study at hand were used in our analyses (Table 1). The sample is equally divided between males and females with a slight preponderance of the latter. As the sample is composed predominantly of public sector employees, the majority of respondents have medium-high level of education and are aged between 41 and 60. The majority are married/live with a partner in households with on average 3 members.

Table 1. Sample characteristics

Variables	N.	[%]	AVG.
Total sample	2,128		
Gender (male)	1029	48.4%	
Age			48.02
Level of education			
Low (High school and lower)	901	42.3%	
Medium (Graduate)	738	34.7%	
High (Higher than master's degree)	489	23.0%	
Marital status: married	1550	72.8%	
With children	1159	54.5%	
# of members in the household			2.88
Residence choice			
High density urban	1654	77.7%	
Peri-urban	344	16.2%	
Rural	130	6.1%	
Commute mode choice			
Car	1437	67.5%	
Public transport	210	9.9%	
Walking	313	14.7%	
Bicycle	168	7.9%	
Frequency of cycling for non-work purposes			
Never	1065	50.0%	
1-10 times per year	328	15.4%	
1-5 times in the past 30 days	328	15.4%	
1-5 days per week	349	16.4%	
Everyday	58	2.7%	

3. Methodological framework

The behavioural framework in this paper focuses on three key choices of bicycle travel behaviour: residence choice, commute mode choice and propensity to use the bike for non-commuting trips. All the choice variables are estimated simultaneously with a comprehensive modelling framework in which level of service, individual and household characteristics serve as explanatory variables. There are three simultaneous choice models, one for each dependent variable:

- One multinomial choice variable defining the neighbourhood residence choice:
  - High-density urban
  - Peri-urban
  - Rural.
- One multinomial choice variable representing the commute mode choice:
  - Car
  - Public Transport
  - Walking

  - Cycling.
- One ordered choice variable representing the frequency of cycling for non-commuting trips. We consider five different categories of frequency:
  - Never
  - 1-10 times per year
  - 1-5 times in the past 30 days
  - 1-5 days per week
  - Every day.

Note that the classification of the neighbourhood residence type is based on the classification made by the Regional Government of Sardinia in its digital land use maps (Agristudio-Geomap, 2007). Another factor to consider is that the level of density is not the only built-environment measure that can be used, but others exist (*e.g.* land use-mix, distance from city centre, street connectivity). However, it has been shown that density is highly correlated with almost all built environment measures, and it is the most common measure used in transportation literature (Singh *et al.*, 2019). In Figure 1 we report the neighbourhood classification employed in the current work for the study area.

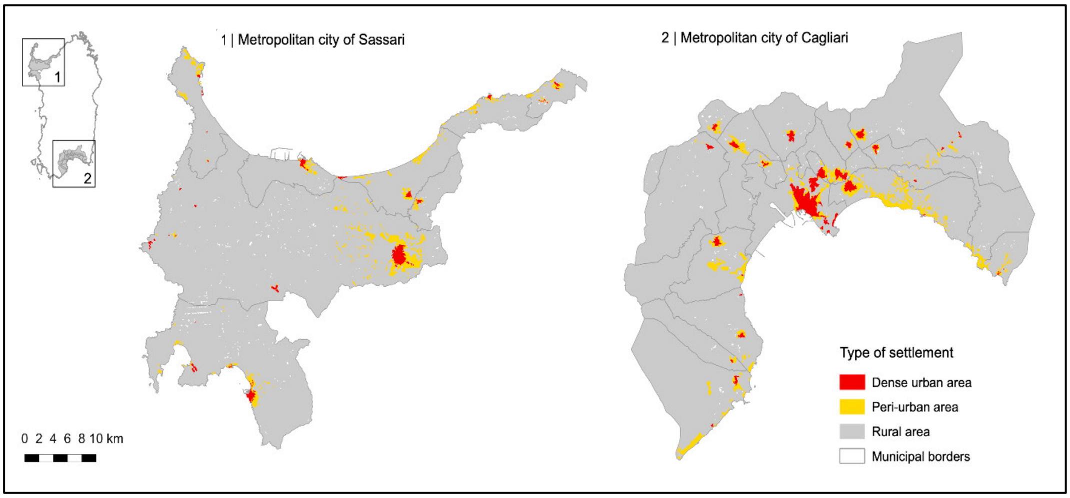

Figure 1. Neighbourhood classification of the metropolitan areas of Cagliari and Sassari (source: elaboration of the Research Centre for Mobility Models at the University of Cagliari)

The methodological approach taken in this study is a mixed methodology based on the work of Pinjari *et al.* (2011). In this approach, a series of sub-models are formulated for different choice dimensions—a multinomial logit model of residential location, a multinomial logit model of commute mode choice and an ordered probit model of bicycling frequency for non-commuting purposes. All the models are econometrically joined by the means of the presence of common random coefficients.

Let the indices i (i = 1, 2, 3) and k (k = 1, 2, … 4) represent the residential neighbourhood type chosen and the modal alternative, respectively, and the term n (n = 0, 1, 2,…, 4) represents the level of frequency of cycling for non-commuting purposes.

The residential neighbourhood type choice component takes the multinomial logit formulation with z_q as the dependent variable:

$$z_{iq} = \varphi_{i,0} + \boldsymbol{\varphi}_{i,s}\boldsymbol{s}_q + \sum_k \pi_{ikq} + \eta_{iq} + \varepsilon_{iq}; \text{ residential neighborhood type } i \text{ chosen if } z_{iq} > \max z_{jq}; \quad (1)$$

where z_{iq} is the latent utility associated with neighbourhood choice i, s_q is a vector of sociodemographic characteristics associated with individual q (for example, household size and income), $\varphi_{i,0}$ is a constant term, $\varphi_{i,s}$ is a vector of the effects of the variables s_q on the latent utility. The term π_{qik} represents the common unobserved factors influencing both individual q's utility for an urban neighbourhood type choice and the individual's choice of mode of transport k, while the term and η_{iq} includes the unobserved factors that affect both residential choice and propensity to use the bike for non-commuting purposes. Finally, ε_{qi} is a random-error term assumed to be identically and independently Gumbel distributed across individuals q and alternatives.

Let U_{kq} be the utility that each individual q associates to the mode of transport k. The utility function for the alternative k can be written as:

$$U_{kq} = \beta_{k,0} + \boldsymbol{\beta}_{k,LOS}\boldsymbol{LOS}_{kq} + \boldsymbol{\beta}_{k,SE}\boldsymbol{SE}_q + \sum_i \pi_{ikq} + \varsigma_{kq} + \nu_{kq} \text{ ; mode } k \text{ chosen if } u_{kq} > \max u_{dq}; \tag{2}$$

where $\boldsymbol{LOS}_{kq}$ is the vector of commute level-of-service (LOS) attributes by mode k, $\boldsymbol{SE}_q$ is a vector of socio-demographics characteristics, $\beta_{k,0}$ is the alternative specific constant, $\boldsymbol{\beta}_{k,LOS}$ is a vector of coefficients associated with LOS characteristics, $\boldsymbol{\beta}_{k,SE}$ is a vector of coefficients associated with socio-demographics attributes. π_{ikq} includes the unobserved factors that affect both neighbourhood type choice and the travel alternative k. ς_{kq} is an error term representing the common unobserved factors influencing the choice of mode of transport k and the propensity to use the bike for non-commuting purposes. Finally, ν_{kq} is an independently and identically distributed Gumbel error term.

The latent propensity underlying the ordered response observation, that is the cycling frequency for non-commuting purposes, has been specified as a function of observed and latent cycling variables:

$$y_q^* = \boldsymbol{\alpha x}_q + \eta_{iq} + \varsigma_{kq} + \xi_q,\ y_q = n \quad if \quad \mu_n < y_q^* < \mu_{n+1}\ \mu_{q,0} = -\infty \quad and \quad \mu_{q,N+1} = \infty \tag{3}$$

where $\boldsymbol{x}_q$ is the vector of explanatory variables, $\boldsymbol{\alpha}$ is the vector of unknown parameters to be estimated. η_{iq} is the common error term related to unobserved factors affecting the residential choice and is the cycling frequency for non-commuting purposes, and ς_{kq} is a random term including the common unobserved factors influencing the choice of mode of transport k and the latent propensity y_q^*. ξ_q is an independently and identically distributed Normal error term.

The inclusion of the common stochastic term π_{ikq} and η_{iq} permits to consider the effect of unobserved attributes (such as travel attitudes and perceptions, lifestyle preferences, environmental concerns) that might influence the residential choice with travel mode preference and the propensity to cycle for non-work bicycle reasons. The error term ς_{kq} captures the jointness of the propensity to cycle for purposes other than to work with the utility of travel mode. Note that in the current study we included ς_{kq} only in the utility function of the bike commute alternative.

Let Ξ represents a vector of the parameters to be estimated, Ξ_Σ a vector of all parameters except the variance terms and Λ_q a vector that stacks all the error terms. Also, define

$a_{iq} = 1$ if individual q chooses to live in neighbourhood type i and 0 otherwise

$b_{kq} = 1$ if individual q chooses to commute by mode k and 0 otherwise

$c_{nq} = 1$ if individual q cycles for non-work purposes with frequency n and 0 otherwise

The conditional likelihood function for an individual q is then:

$$\begin{aligned} LL_q(\Xi_\Sigma)|\Lambda_q = \prod_{i=1}^{I}\prod_{k=1}^{K}\prod_{n=1}^{N}\Bigg\{&\left[\frac{exp(\varphi_{i,0} + \boldsymbol{\varphi}_{i,s}\boldsymbol{s}_q + \sum_k \pi_{ikq} + \eta_{iq})}{\sum_j exp(\varphi_{i,0} + \boldsymbol{\varphi}_{i,s}\boldsymbol{s}_q + \sum_k \pi_{ikq} + \eta_{iq})}\right] \\ &\times \left[\frac{exp(\beta_{k,0} + \boldsymbol{\beta}_{k,LOS}\boldsymbol{LOS}_{kq} + \boldsymbol{\beta}_{k,SE}\boldsymbol{SE}_q + \sum_i \pi_{ikq} + \varsigma_{kq})}{\sum_k exp(\beta_{k,0} + \boldsymbol{\beta}_{k,LOS}\boldsymbol{LOS}_{kq} + \boldsymbol{\beta}_{k,SE}\boldsymbol{SE}_q + \sum_i \pi_{ikq} + \varsigma_{kq})}\right] \\ &\times \big[D(\mu_{n+1} - \boldsymbol{\alpha x}_q - \eta_{iq} - \varsigma_{kq}) \\ &- D(\mu_n \boldsymbol{\alpha x}_q - \eta_{iq} - \varsigma_{kq})\big]\Bigg\}^{a_{iq}\times b_{kq}\times c_{nq}} \end{aligned} \tag{4}$$

where $D(\cdot)$ is the cumulative distribution of the standard normal distribution. Finally, the unconditional likelihood can be computed as:

$$LL_q(\Lambda) = \int_{\Lambda_q} \left(\mathrm{LL}_q(\Xi_\Sigma)|\Lambda_q\right) f(\Lambda_q) \mathrm{d}\Lambda_q \tag{5}$$

We apply simulation techniques to approximate the integral in (5) and maximize the resulting simulated loglikelihood function. All the models were estimated using PythonBiogeme (Bierlaire and Fetiarison, 2009).

4. Model results

Model results are reported in Table 2. The residential location choice component of the model (first block of Table 2) suggests that individuals with children have a greater propensity to reside in low-density urban and suburban areas. This result can be explained by the fact that in Sardinia suburban living spaces tend to have more rooms and more private outdoor space, which are preferred by households with children. Instead, single individuals are more likely to choose to live in high-density urban areas. Lower levels of car ownership are associated with higher-density residential locations, probably because they offer pedestrian-friendly facilities and a denser public transport network that facilitate the use of alternative means of transport.

The second block of Table 2 presents the result of model estimation of the commute mode choice. The negative signs of travel times, travel costs, walking time from/to the bus station, walking time from/to the car park and time taken looking for a parking place are consistent with microeconomic theory. Different socio-demographic variables have a relevant impact on mode choice. Males and individuals with no children are less likely to travel by car, while the number of cars per household positively influences the utility to commute to work by car.

The third block of Table 2 shows the results of the ordered probit model of cycling frequency for non-commuting purposes. Compared to females, males are more likely to cycle for leisure and errands/shopping. Model results also show that the latent propensity to use the bike decreases as age increases. The value of the Body Mass Index has a negative impact on the propensity to cycle for recreational and errands/shopping trips. Concerning car ownership level, the number of cars in the household negatively impacts the latent propensity to use the bike for non-commuting purposes. Instead, the number of bikes in the household positively influences the utility of using the bike. Finally, we found that individuals with children are less inclined to use the bike.

Finally, modelling results suggest the existence of unobserved factors among the outcomes. The standard deviation of the error component between the utility to choose to live in high density urban areas and non-commuting bicycle propensity turned out to be positive and significant, indicating the presence of a self-selection effect. A possible interpretation of this finding is that individuals who have a high attitude toward physical activity may locate themselves in urban high-density areas, characterized in Sardinia by the presence of urban parks, recreational areas, shops and services, and consequently use the bicycle for non-commuting purposes with a higher level of frequency. Nevertheless, it is important to highlight that the statistical significance of the parameter associated with the variable indicating if an individual lives in an urban high-density area dropped when estimating the model with the error component and so we decided to remove it from the final specification of latent propensity y_q^*. It is therefore likely that the link between the choice of the residential location and the propensity to cycle for non-commuting reasons is associative rather than causal. We also found a positive correlation between the choice to live in a high-density urban neighbourhood and the choice to commute by active mobility (walking and cycling), which seems to suggest the existence of unobserved effects that simultaneously influence these two choices. However, it is worth noting that the inclusion of an endogenous effect on the utility functions of walking and cycling alternatives caused a decrease of the statistical significance of the error component. This can be an indicator of the fact that the relationship between the choice to actively commute and the neighbourhood residence choice, in our specific context, is more a causal relationship than an associative one. Finally, modelling results pointed out a positive correlation was found between the utility to commute by bike and the non-commuting bicycle propensity. This may be attributable to such unobserved factors as a better perception of bike benefits or a greater perception of bikeability.

5. Conclusions

The paper presents the findings of a study focusing on unravelling the interplay between the residential location choice, the commute mode choice and the propensity of cycling for non-commuting purposes. We used a jointly modelling structure that incorporates common error terms, so that it was possible to control for self-selection and unobserved effects that can simultaneously influence the underlying propensities. The data used is derived from a survey conducted in Sardinia (Italy), where bicycling is mainly considered as a form of exercise and recreation.

Table 2. Model results

Explanatory variables	Coeff.	R T-stat
1. Residential location choice model		
Constant urban high density	3.70	15.47
Constant urban low density	0.97	9.45
Urban high-density attributes		
Children (Yes = 1; No = 0)	-0.29	-2.10
# of cars in the household	-0.27	-3.20
Married	-0.44	-2.55
2. Commute mode choice model		
Constant public transport	0.02	0.06
Constant walking		
Constant bicycle	-4.56	-8.13
Car attributes		
Travel time	-0.03	-1.65
Walking Time from/to parking area	-0.03	-1.76
Gender (Man=1, Woman=0)	-0.54	-4.44
Children (Yes = 1; No = 0)	0.46	3.63
# of cars in the household	0.50	4.69
Public transport attributes		
Travel time	-0.03	-2.91
Walking time from/to bus stop	-0.05	-3.51
Waiting time	-0.07	-4.29
Car and public transport attributes		
Travel cost	-0.42	-4.34
Bicycle attributes		
# of bicycles in the household	1.40	9.08
Bicycle and walking attributes		
Travel time	-0.06	-4.67
Lives in an urban high-density area (Yes = 1; No = 0)	1.12	2.52
Travel time · urban high density	-0.05	-3.29
3. Non-commuting bicycle propensity		
Gender (Man=1, Woman=0)	1.05	7.67
Age	-0.01	-1.68
Body Mass Index	-0.08	-5.76
Bachelor's degree or higher	-0.55	-4.93
# of bikes in the household	1.74	12.55
# of cars in the household	-0.54	-5.89
Children (Yes = 1; No = 0)	-1.14	-7.62
4. Standard deviation of error components		
Standard deviation of the error component between the utility to commute by bike and the non-commuting bicycle propensity	2.05	10.34
Standard deviation of the error component between the utility to choose live in high density urban areas and the utility to commute by active mobility alternative	0.53	1.32
Standard deviation of the error component between the utility to choose live in high density urban areas and non-commuting bicycle propensity	0.81	5.54
5. Measures of fit		
Null loglikelihood	-8,717.250	
Final loglikelihood	-4,958.693	
ρ^2	0.431	

First, we observed that a relationship exists with the utility to cycle to work and the propensity to cycle for non-commuting reasons. We found that some sociodemographic variables simultaneously influence the two choices. Further, through the inclusion of a common error term, we were also able to show the existence of unobserved effects between the two outcomes. From a policy perspective, this last result suggests that interventions aimed at supporting cycling mobility for non-commuting purposes may increase the number of people who choose to bike to work. Examples of these strategies include the implementation of structural measures aimed at favouring bicycle tourism, like the construction regional cycling network in Sardinia (Scappini *et al.*, 2022), or behavioral measures aimed at promoting a culture of bicycling.

Another important finding of our research concerns the presence of common unobserved factors between the residential location choice and bicycle propensity. In particular, we found that we cannot reject the presence of a self-selection effect between the use of the bike for non-commuting purposes and the residential location choice, suggesting that the only inclusion of traditional sociodemographic variables is no longer sufficient by itself to assess the outcome of a policy intervention, but lifestyles themselves and individuals' attitudes should be included as the target of interventions. It turned out that the relationship between the choice to commute by using active mobility and the residential location choice is not purely associative but it is more like a causal one. In other words, our results suggest that individuals who walk or cycle for their commuting trips choose to do so not because of the presence of a self-selection effect but for the configuration of the urban environment that makes it easier to commute via active travel.

Finally, the calibration of a joint model permitted us to understand of the true impact that the neighbourhood type (urban, peri-urban, rural) exerts on the choice to use the bicycle, both for commuting and non-commuting purposes. Specifically we found that the estimation of an independent model would have overestimated the influence of the variable associated to the urban density on the propensity of cycling for non-commuting reasons.

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