LATENT CLASS CHOICE MODELS TO UNDERSTAND THE INFLUENCE OF THE BUILT ENVIRONMENT ON BICYCLE USAGE

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ABSTRACT

Understanding how spatial attributes of cities and neighborhoods induce cycling is relevant for urban planning and policy making. In this work, a latent class model is specified and estimated to analyze how the built environment affects bicycle-commuting frequency. Data comes from a survey conducted on 2,605 people in the city of Santiago, Chile, including socio-demographic information, travel behavior patterns and place of residence and work. Using GIS tools, the built environment was characterized with variables describing 500 meters radius buffers around the residence and job locations.

As a result, a latent class model is estimated, identifying two classes of neighborhoods in terms of how its dwellers are induced to cycle. Class segmentation is a function of residential density, distance to the main axis of the city (which concentrates most jobs) and presence of cycling infrastructure. This result allows mapping the class membership probabilities, potentially helping to identify neighborhoods that encourage cycling and giving more information for policy making and infrastructure decisions.

Keywords: Built Environment, Latent Class Model, Bicycle commuting

1 INTRODUCTION

Due to its characteristics, cycling has been identified as a transportation mode likely to solve several problems cities are facing now and will face in the future. It does not require any kind of gas, being a “carbon zero” transportation mode (Chapman, 2007); it improves population’s health (Pucher & Buehler, 2010) and can solve traffic congestion problems (Pucher & Dijkstra, 2003). Based on these facts, urban planning and the design of public spaces should try to encourage cycling in order to have a built environment that contributes to a healthier and greener city.

The influence of the built environment in travel behavior has been widely researched. In particular, mode choice and the intensity of the use of non-motorized modes have been studied, confirming their relationship and finding that built environment has a stronger influence when analyzing this kind of transportation modes (Cao, Mokhtarian, & Handy, 2009).

Notwithstanding the extensive literature linking built environment and bicycle usage, we identify some aspects that have not been deeply analyzed and that could provide a better understanding of this phenomenon. First of all, most literature focuses on bicycle usage for any purpose, mixing commuting, utilitarian and strolling trips. Only few works focus exclusively in commuting trips, which have distinguishing characteristics, such as occurring during specific hours and being longer than utilitarian and strolling trips. In addition, the probability of travelling by bike has been largely analyzed, unlike the expected frequency of its usage.

Finally, most of the studies reviewed referred to cities located in Europe, the US and Canada, whereas investigation applied to cities in developing countries falls short. Therefore, it is interesting to see how the built environment affects bicycle usage in cities in emerging countries.

Taking these aspects into consideration, we hereby propose to model the weekly bicycle commuting frequency as a function of socio-economic characteristics and built environment variables by doing a latent class analysis, where the class membership function depends on attributes of the user’s residential location. Hence, classes will describe neighborhoods instead of types of users.

In this study, we identify relevant variables influencing bicycle usage in the city of Santiago. After the latent class analysis, we find types of neighborhoods that induce different cycling behaviors among their population. The results of this analysis are consistent with patterns identified in previous studies, yet they propose a new way to define classes in this kind of analysis, considering GIS-measured built environment variables.

The article is organized as follows: Section 2 reviews existent literature on built environment and bicycle usage. Section 3 describes the methodology developed for this study’s purpose. Section 4 describes the data collection process and analyzes some relevant statistics for the sample. Section 5 shows model estimation results. Finally, Section 6 summarizes the conclusions and suggests future research.

2 BUILT ENVIRONMENT AND CYCLING

As mentioned before, several studies analyze the relationship between the built environment and travel behavior. Many of them, conducted in the US (Cervero, 1988, 1996; Ewing & Cervero, 2001; Frank, Stone, & Bachman, 2000; Kitamura, Mokhtarian, & Laidet, 1997; Rajamani, Bhat, Handy, Knaap, & Song, 2003), suggest that the built environment has an effect on transport mode choice.

Specifically, higher residential densities and more diverse land uses in the territory are related with a lesser usage of car and a higher usage of transit, walking and cycling. Likewise, these studies conclude that not only mode choice is influenced, but car usage is also affected. The variables mentioned are also related with less kilometers travelled by car and a fewer rate of single occupant vehicles. Studies conducted in Europe, have found similar results (van Wee & Handy, 2016).

Further studies have analyzed whether there is self-selection when analyzing the built environment and travel behavior. People with a particular travel pattern may prefer a certain kind of neighborhood that suits their preferences. In this context, it has been found that households that are relocated change their travel patterns (Krizek, 2003). From this study, it can be analyzed how same people will present a different travel behavior after changing the built environment. In addition, cross sectional studies have been conducted in neighborhoods in different cities from the US (Cao, Handy, & Mokhtarian, 2006; Handy, Cao, & Mokhtarian, 2005) finding that after controlling by self-selection, the effect of the built environment on travel behavior can be proven for different modes and travel purposes.

2.1 Influence of the built environment on bicycle usage

The relation between the built environment and bicycling has been widely investigated. First of all, it has been clearly shown that the presence of bike lanes is related with higher rates of cycling (Buehler & Dill, 2015), especially when in the presence of well interconnected networks (Buehler, 2012). This infrastructure provides a safe context for the user while travelling, being separated from pedestrian and motor traffic. In addition, travel distance is another key variable to considerate. Longer distances imply longer travel times and a higher effort to be made by the user, making bicycle less attractive. Therefore longer travel distances, more likely found in low density or spread cities, have a negative effect on bicycling (Handy & Xing, 2011).

A positive relation between residential density and bicycle usage has been established (Pucher & Buehler, 2006). In this situation, the bicycle becomes more attractive due to the traffic congestion associated to higher people concentration (Forsyth, Oakes, Schmitz, & Hearst, 2007). Land use diversity is also associated with more cycling. Since there are more activities and services provided, the user has to do a shorter trip to accomplish what generates the trip making bicycle more attractive (Ewing & Cervero, 2010). Nevertheless, the land use mix was associated with less bicycle usage in one case: the city of Curitiba, Brazil (Hino, Reis, Sarmiento, Parra, & Brownson, 2014). In this case, neighborhoods with a higher diversity in land uses related to high income parts of the city, where people were more likely to travel by car.

Other interesting findings are that zones of the city with better accessibility present a positive relation with bicycle usage (Cui, Mishra, & Welch, 2014; Kockelman, 1997). Also, neighborhoods with more intersections seem to induce more cycling (Sallis et al., 2013; Winters et al., 2010). This can be explained because a more porous urban form, or denser road network, allows cyclist to find shorter routes, making this transport mode more attractive.

Nevertheless, as mentioned before, socio-demographic variables also play a key role when explaining bicycle usage. First of all, men tend to cycle more than women (Heinen, Maat, & van Wee, 2011). When it comes to age, the studies reviewed present contradictory results (Heinen, van Wee, & Maat, 2010; Pucher & Buehler, 2010) and, in some cases, it is a non-significant variable (Kitamura et al., 1997; Plaut, 2005). When it comes to income, contradictory results are also found among literature reviewed (Cervero & Kockelman, 1997; Cui et al., 2014; Fernández-Heredia, Jara-Díaz, & Monzón, 2016; Kitamura et al., 1997). The same situation is detected when controlling by education (Cervero & Gorham, 2009; Handy, Xing, & Buehler, 2010; Kockelman, 1997; Piatkowski & Marshall, 2015). These differences can be explained by historical and cultural differences among the places where studies were conducted. Last, but not least, car ownership or access is related with a lower bicycle share, while bicycle possession is associated with a higher one (Buehler, 2012).

2.2 Built Environment Analysis

Different ways to analyze the built environment and its relation with travel behavior have been proposed. Due to technological advances, the use of data analyzed with Geographic Information Systems (GIS) has arisen as an attractive option for urban planners and transport geographers and engineers.

Over the last decades, several indicators have been built in order to characterize the built environment. In first instance, Cervero and Kockelman (1997) proposed to categorize these indicators into three categories: "Density", "Diversity" and "Design". Twelve years later, two other categories of indicators where proposed: "Destination's Accessibility" and "Distance to Public Transport" (Cervero, Sarmiento, Jacoby, Gomez, & Neiman, 2009). As reviewed by Ewing and Cervero (2010), these make the "5 D's" categories for analyzing the built environment and have been used in several investigations (Larrañaga, Rizzi, Arellana, Strambi, & Cybis, 2014; Winters et al., 2010).

Under this analysis, Density corresponds to the "amount of one activity in a determined area" (Handy, Boarnet, Ewing, & Killingsworth, 2002); Diversity is the "number of different land uses in a determined area" (Ewing & Cervero, 2010); Design is the shape conformed by blocks, streets and sidewalks which compose a specific neighborhood or area; Destination accessibility indicates how easy is to reach attractive places in the destination area, and Distance to public transport, as its name states, corresponds to the distance a person has to travel in order to access to public transport services.

3 METHODOLOGY

We use ordered logit models (McKelvey & Zavoina, 1975) to relate weekly cycling frequency with built environment and socioeconomic characteristics. The objective of estimating these models is to verify if behavior in our case study is consistent with what is reported in the literature. We also propose to use a latent class model in order to introduce heterogeneity in user behavior, although we work under the assumption that, instead of user characteristics, what explains heterogeneity are neighborhood attributes.

3.1 Latent Class Models

Latent Class Models (LCM) introduce taste heterogeneity by probabilistically segmenting the decision makers into groups of homogeneous behavior. By this, a specific set of parameters can be estimated for each class (Kamakura & Russell, 1989). This way, LCM constitutes an interesting and powerful instrument because it allows to capture unobserved heterogeneity (Walker & Ben-Akiva, 2002) in a way that is easier to interpret by the analyst, compared with other approaches such as the Mixed Logit or Latent Variable models (Hess, Shires, & Jopson, 2013; Hurtubia, Nguyen, Glerum, & Bierlaire, 2014)

During recent decades, researchers have been using LCM to segment population and improve travel behavior analysis. For instance, Ben-Akiva et al. (2002) highlight the opportunity this methodology presents in hybrid choice models. In addition, LCM segmentation has been used successfully to classify population by their characteristics, life style and beliefs in studies of residential selection (Walker & Li, 2007), car ownership (Bhat & Guo, 2007), route selection (Greene & Hensher, 2003) and bicycle demand (Motoaki & Daziano, 2015).

There has been an emerging trend when it comes to analyze the built environment and LCM. Hybrid LCM models have been proposed in order to segmentate population relating their characteristics with stated preferences about the built environment and travel conditions. For instance, Walker, Li, Srinivasan, and Bolduc (2010) propose a choice model in which they segment according to the population's preference in travel time and its variation. A more complex model is proposed by Vij and Walker (2014). They segment population by establishing feedback between their modal choice and the consumer's surplus. A similar approach was used by Wen, Wang and Fu (2012) for their study on rail access. They segment population from their stated preferences on ticket fare, parking cost, access time and waiting time.

The authors have found few studies linking the built environment and behaviour using class membership equations. A first attemp found consists of a hybrid model where individual characteristics are selected according to their stated preferences on characteristics of the built environment where they reside (Olaru, Smith, & Taplin, 2011). In order to predict residential selection by its built environment attribute, Smith & Olaru (2013) relate individuals characteristics with identificable "life stages". Meng, Taylor, and Scrafton (2016) –who affirm to be innovating by combining LCM analysis and GIS- elaborate latent classes from stated preferences to analyse how built environment variables measured with GIS affect the choice and residential selection models. Finally, HOSHINO (2010) proposes a multi-level latent class analysis, considering a person's dwelling spatial characteristics for understanding their preferences when adquiring a new house. Under this hypothesis, people might reveal some spatial preferences when analyzing the place they live.

As reviewed, no author has yet proposed a LCM where segmentation responds to built environment variables. Instead of segmenting population, we propose to segment residential neighborhoods according to their characteristics. As there are aspects of individuals which we are not able to see, segmentating by urban attributes may help to understand how different city areas configurations are related with travel behaviour.

Following the notation proposed by Walker & Ben-Akiva (2002), the utility asociated to an individual *n* will depend on a built environment set of attributes *E* related to where person *n* resides and a socio economic set of paramaters x_n which describes each person. This utility will be different for each class s:

$$U_n^s = (X_n, E_n)' \, \beta^s + \varepsilon_n^s \tag{3.1}$$

In this case, ε_n^s is the residual associated to person *n* expected utility for class *s*. β^s consists of a set of parameters to be estimated specifically for each class. The expected weekly bicycle frequency will depend on the level of utility achieved.

By assuming a logistic distribution of the residual term, the probability P of an individual *n*, cycling a weekly frequency k conditioned to class *s* can be expressed as follows:

$$P(Y_n = k) = \frac{1}{1 + ex\,p(-\mu_k + \beta'(X_n, E_n))} - \frac{1}{1 + ex\,p(-\mu_{k-1} + \beta'(X_n, E_n))} \tag{3.2}$$

Where Y_n is the expected cycling frequency, μ_k is the utility threshold that indicates a change in expected frequency and C_s is the set of attributes considered by individuals belonging to class *s*.

Since latent classes cannot be deterministically assigned to a specific individual –or buffer in the case of this study-, the proposed methodology assumes that the class membership belonging depends on the characteristics of the built environment in each analyzed buffer. That relation can be expressed as a class membership equation f as follows:

$$F_{ns} = f(\overline{E_n}, \gamma^s) + \varepsilon_{ns} \tag{3.3}$$

Where F_{ns} is the continuous latent variable which relates to the probability of belonging to class *s*, $\overline{E_n}$ corresponds to a set of variables of the built environment at the place where the respondent resides and γ^s is a set of parameters to be estimated. Assuming that ε_{ns} distributes i.i.d EV (0,1), probability of individual *n* belonging to a determined class *s* is:

$$P_n(s) = \frac{exp(f(\overline{E_n}, \gamma^s))}{\sum_{r \in S} \exp(f(\overline{E_n}, \gamma^r))} \tag{3.4}$$

Finally, from equations (3.2) and (3.4), we can establish that the probability of an individual *n* cycling frequency k is:

$$P_n(k) = \sum_{s \in S} P_n(k|s) P_n(s) \tag{3.5}$$

4 DATA COLLECTION

A survey was conducted and land use data describing locations was collected. The following sections describe these efforts.

4.1 Survey

The instrument developed consists of a 30 questions survey that was conducted between March 21st and April 26th of 2016 in Santiago, Chile. This dates guaranteed a good cycling environment, characterized by good weather conditions such as warm temperatures, sunny days and the absence of rain.

In order to get cyclist and non-cyclist commuters' information, a three-step strategy was designed. First, cyclists were intercepted in eleven different bike lanes in the city. Trained interviewers, equipped with tablets, approached cyclists while they were passing through the interception point and invited them to answer the survey. This fieldwork took place in three moments of the day- between 07:30 and 09:30, between 13:00 and 15:00 and between 18:00 and 20:00. If the cyclist did not have time to answer the survey, they were offered to answer it later, by an e-mail sent to their personal address. During this step, 1,050 answers were obtained on the field and 355 by e-mail.

The second and third steps were designed in order to capture information about people who did not use the bicycle. In this context, flyers were distributed in households, among car drivers in intersections and by placing them in strategic places, such as parking lots. 295 observations were thereby made. Finally, the third step consisted in an online survey distribution, reaching 905 people. In total, 2,605 observations were collected.

4.2 Sample

Information of female and male commuters over 18 years was collected. Variables obtained from the survey that were used in the model are gender, age, education, occupation, income, cars per household and bicycles per household. The dependent variable is the number of commuting trips made by bicycle, which goes from zero to five. For this study purposes we did not consider commuting trips during weekends. Descriptives of socio-demographic variables can be found in Table 4-1.

Table 4-1: Descriptive statistics for the dependent and socioeconomic variables

	Mean	SD
Dependent Variable		
Weekly commuting bicycle trips	3.11	2.21
Socio-demographic		
Female (1,0)	0.37	0.48
Age (years)	32.10	10.54
Household	3.32	1.73
Sons or daughters (1,0)	0.35	0.48
Occupation Student (1,0)	0.25	0.43
Occupation Formal or Informal Work (1,0)	0.70	0.46
Non Occupation (1,0)	0.05	0.21
Low and middle educational level (1: elementary, high school comp/incomp, 0: other)	0.10	0.30
High educational level (1: college or higher education comp/incomp, 0: other)	0.73	0.44
Graduate educational level (1: Post graduate studies comp/incomp, 0: other)	0.17	0.38
Low income (1: < CLP 450.000, 0: other)	0.09	0.28
Middle income (1: CLP 450.000 to 1.000.000, 0: other)	0.31	0.46
Middle-High income (1: CLP 1.000.000 to 3.000.000, 0: other)	0.44	0.50
High income (1: CLP > 3.000.000, 0: other)	0.16	0.37
One car at home (1, 0)	0.44	0.50
Two or more cars at home (1,0)	0.20	0.40
Bicycles at home	2.17	1.30

A modal share analysis shows that 59.94 percent of observations corresponds to bicycle commuters, as expected due to the way the survey was applied, whereas 7.29 percent corresponds to car commuters and 21.98 to transit commuters.

4.3 Built Environment Indicators

By using Geographic Information Systems (GIS), households and work places were georeferenced, as can be seen in Figure 4-1. With data from census, open street maps and the national tax service, built environment indicators were estimated within a 500 meters radius buffer. This is consistent with previous studies for active transport (Cervero et al., 2009; Hino et al., 2014; Larrañaga et al., 2014; Winters et al., 2010; Zegras, 2010).

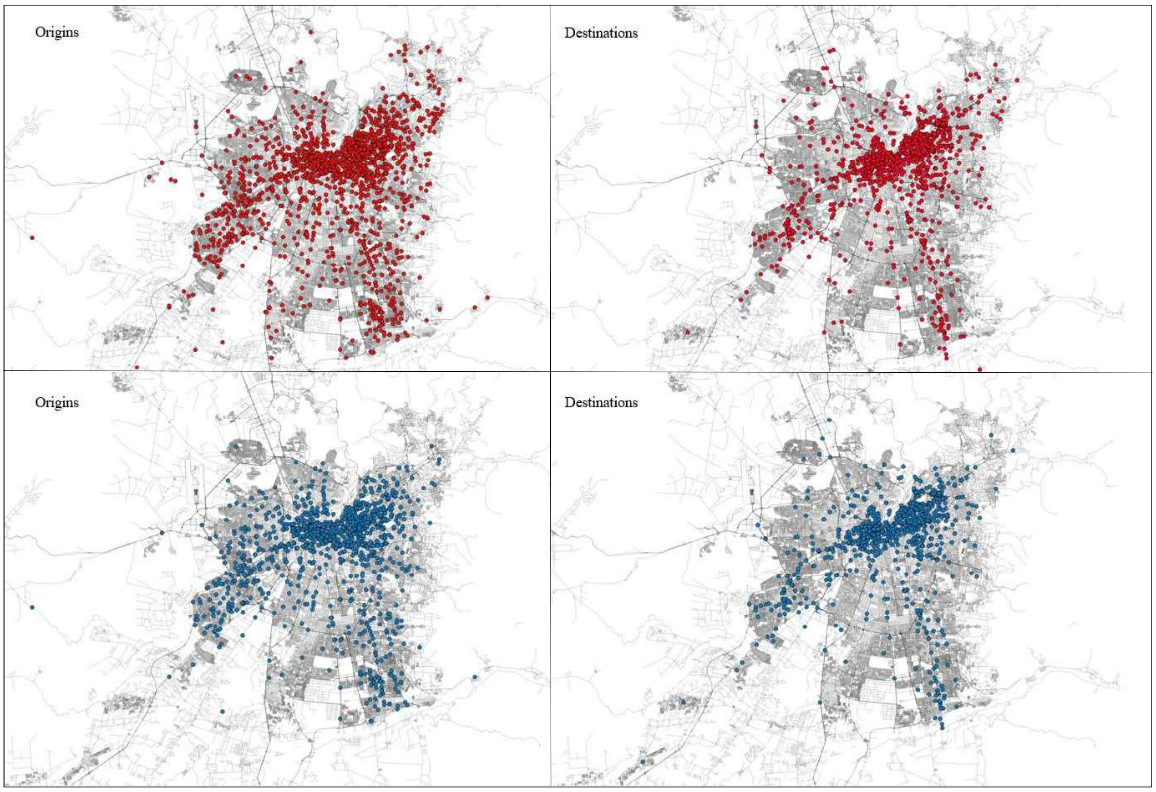

Figure 4-1: Origins and destinations of the sample (red dots) and origins and destinations of people who commute by bike at least once a week (blue dots).

As mentioned, the variables calculated are classified in five categories: Density, Diversity, Design, Accessibility and Distance to Public Transport. We include as a sixth category - measures of travel time and distance, which are relevant when analyzing bicycle commuting (Handy & Xing, 2011).

For this study's purposes, the variable "altitude difference" corresponds to the subtraction between the altitude over the sea level at the destination point and the altitude over the sea level at the origin. This variable is relevant due to Santiago's topography. At the east of the city, the Andes range determines a geographical limit. Neighborhoods located in this area tend to be at a higher attitude, since are located at the skirts of the mountains, while the rest of the city is in a valley. This gives Santiago a "sloppy" characteristic which can be determinant at the moment of choosing to commute by bike.

5 RESULTS

In the following section, results are analyzed from the Latent Class Model. For each class, an ordered logit model was estimated, predicting weekly bicycle frequency.

5.1 Latent Class Model

A Latent Class Model is estimated in order to categorize neighborhoods according to their cycling behavior, as a function of built environment characteristics. As a result, the class membership equation was built considering a class-specific constant, the number of dwellings (residential density) within the buffer, the distance to the main city axis conformed by Alameda, Providencia and Apoquindo avenues, which concentrates most work places in the city (Niehaus, 2016), including the city centre and the Central Business District, and the logarithm of the total length of bike lanes that pass through the buffer.

As a result, population was segmented into two classes according to the presence of the mentioned variables in their residential location. These segments are denominated *LC1: Homogeneous Riders Neighborhoods,* characterized by being far to the main axis, a higher dwelling density and a low presence of bike lanes. In contrast, the second segment is *LC2: Diverse Riders Neighborhoods,* which can be categorized as lower density residential neighborhoods, with a good presence of bicycle infrastructure. Class membership equation and the model can be checked at Table 5-1.

For the sample, there is a 54% chance to belong to LC2 and a 46% chances to belong to LC1. This is a good match with what has been analyzed for the complete city of Santiago, where the estimated probability of belonging to LC2 is 45%, while there is a 55% chance that the dwelling is located in a neighborhood belonging to LC1 (see section 5.20). It has to be considered that Santiago is a large and spread city of 7 million people. Therefore, periphery induces some disturbances in models.

When comparing the two latent classes, significant differences are found. Despite being less sensible to distance and slope (which is expected since these neighborhoods are farther from job destinations), dwellers in LC1 seem less likely to commute by bike at all under several socioeconomic circumstances. This class is affected by more socio economical explanatory variables than LC2, reflecting that in this class, bicycle users are less diverse. Nevertheless, they seem to be more resilient to use the bicycle if a longer trip has to be performed.

On the other hand, LC2 bicycle usage is less affected by socioeconomic variables (they turned out to be non-significant), showing that more diverse people will commute by bicycle (regardless of gender, income or car ownership) under similar circumstances. Notwithstanding this fact, people living on these areas are more affected by travel conditions. Since neighborhoods belonging to class two are most likely centrally located, people residing here may be used to shorter trips by bike. An increase in the distance, may convert commuting by bike in a less attractive activity, discouraging its use.

In the proposed model, the educational variable was not statistically significant. As reviewed, the significance of this variable varies among studies around the world and this study was not an exception. It can be supposed that, for the city of Santiago, there is a correlation between educational level, income and residential location. Therefore, in this model, the effect of educational level is better explained by the previously mentioned variables.

Hence, we conclude that LC2 denotes a type of neighborhood that induces more cycling for a more diverse group of users. All but one of the spatial variables explaining membership to this class are consistent in this regard to what is found in the literature, since residential density is systematically reported as an inducer of cycling and walking, which contradicts our results. However, Santiago’s high-rise residential buildings are not characterized by being very friendly with cycling, often lacking safe street-level parking and forcing its dwellers to park their bikes in locked-down underground facilities or to carry their bike up and down through elevators or stairs. This means that living in a high-rise residential building in Santiago often discourages cycling. This adds to the fact that Santiago is quite polarized in this regard, with high density explained mostly by high-rise. We believe that this particular characteristic of the residential supply of Santiago explains the negative parameter for density to belong to the neighborhood type that encourages more cycling (LC2).

Table 5-1: Latent Class Model Estimation

	LC1		LC2	
Variable	Value	t-test	Value	t-test
Socio-economic characteristics				
1 or more car at home	-0.805	-3.1	-	-
N of bicycles at home	0.95	5.89	0.266	2.88
Female	-1.27	-4.66	-	-
Household	-0.277	-3.41	-	-
High Income	-1.05	-3.58	-	-
Built environment characteristics				
Altitude difference (km)	-2.96	-1.9*	-8.01	-4.95
Distance (km/10)	-0.571	-2.01	-1.49	-4.73
Class membership variables				
ASC_2	-	-	0.542	1.12**
Number of dwellings within the buffer/1000	-	-	-0.15	-2.37
distance to Alameda Avenue (m/100)	-	-	-0.00699	-3.18
LN of sum of length of bike lanes that pass through the buffer	-	-	0.083	2.59
Thresholds[1]				
μ_0 (one trip)	-1.35	-3.58	-1.77	-3.88
δ_1 (two trips)	0.11	2.07	0.113	1.79*
δ_2 (three trips)	-0.367	-1.67*	0.713	3.17
δ_3 (four trips)	0.275	2.36	0.475	4.24
δ_4 (five trips)	0.439	3.4	0.483	4.08
Final log likelihood	-1727.159			
ρ^2	0.164			
adjusted ρ^2	0.153			

*Not significant at 95%
** Not significant at 90%

When analyzing the value of thresholds, an unexpected value for δ_2 is detected. For LC1, it has a value below zero, which is not coherent with an ordered logit model. Nevertheless, it is not

[1] $\mu_k = \mu_{k-1} + \delta_k$

statistically significant, which implies its value is not different from cero. Therefore, for class one, commuting by bike two or three days a week is considered as the same for the analysis. A similar situation is detected in class 2. Threshold δ_1 is not statiscally significant, which implies that commuting by bike once or twice a week is considered as the same, for analysis purposes.

5.2 LC1 and LC2 in the city of Santiago

The latent class segmentation analysis was applied for the whole city of Santiago. The city was divided in a squared grid where each edge is 500 meters long. In the centroid of each cell, variables within a 500 meters radius buffer were calculated. Once variables where calculated for each cell, the class membership probability was estimated using equation (3.4) and the parameters from Table 5-1.

Results of this analysis are shown in Figure 5-1. A darker color represents a higher probability of belonging to LC2. It is interesting to notice the influence of bike lanes, which can be clearly seen in dark orange in the map. This confirms that investment in dedicated bicycle infrastructure is crucial for making this mode more attractive for a wider group of users.

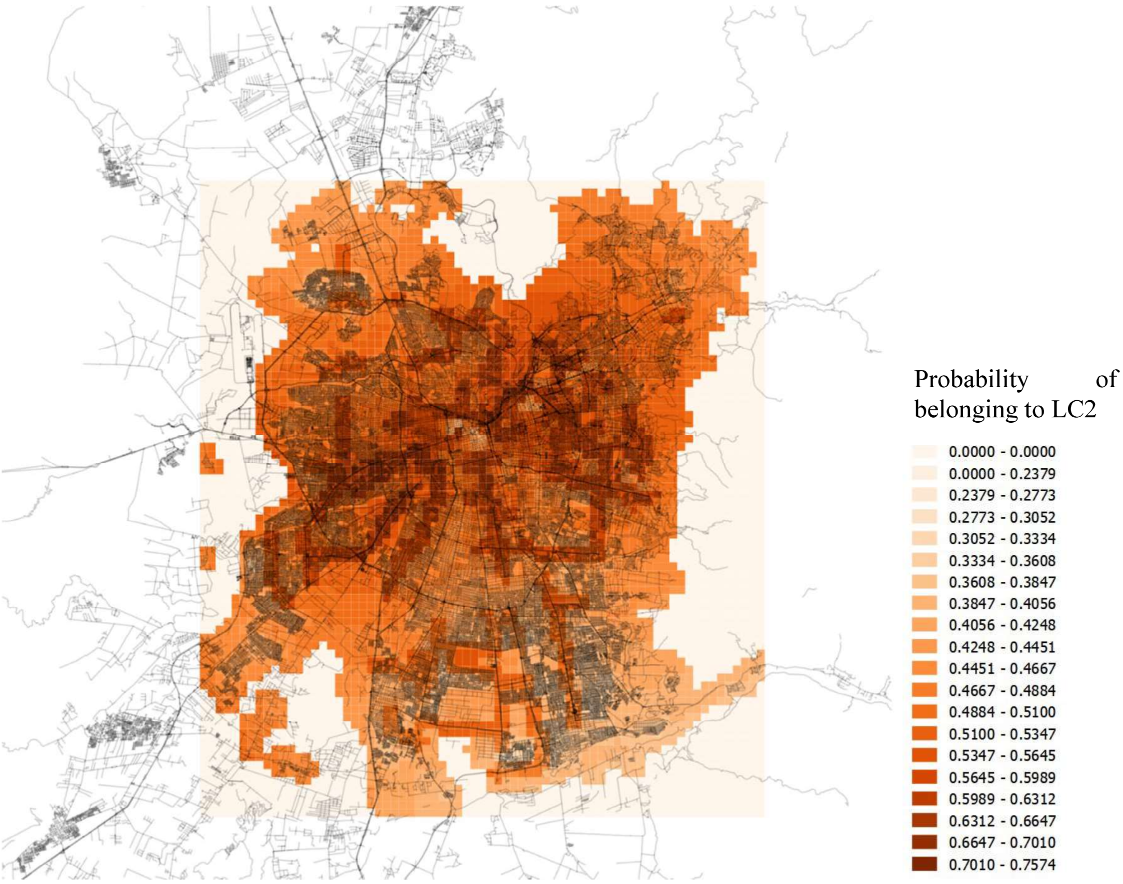

Figure 5-1: Probability of belonging to LC2 for Santiago de Chile

The spatial distribution of the variables considered in the latent class are shown in Figure 5-2.

Figure 5-2: Graphic representation of the class membership variables in the city of Santiago.

6 CONCLUSIONS

The current work has successfully implemented a latent class model based on residential neighborhoods characteristics. This methodological innovation explores a new way to segment neighborhoods according to objective variables measured with GIS.

Two latent classes where determined by the number of dwellings, distance to the axis conformed by Alameda, Providencia and Apoquindo Avenues and the logarithm of the sum of the bike lanes length going through the 500 meters radius buffer. People living in denser zones of the city, however far from the city centre and with few cycling infrastructure, are more reluctant to commute by bicycle when female, members of larger households or with access to car, however they are les sensible to distance and slope. On the other hand, people dwelling in more central areas with a stronger presence of bicycle infrastructure will present a more homogeneous travel behavior, regardless their socioeconomic characteristics. However, people dwelling in this kind of neighborhood are more influenced by slope and distance (they are more likely to perform shorter trips since they are closer to zones with high job density). This analysis allows identifying successfully different travel patterns among commuters and could inform public policy, especially in terms of densification, zoning and decisions regarding the construction of cycling infrastructure. Results are consistent with what can be seen in the city of Santiago.

The relevance of bicycle infrastructure in inducing bike commuting for all possible users is confirmed by these results. Hence, bike-lanes and bike-paths are suggested as a way to encourage a wider group of the population towards bicycle commuting.

Future research should include route characteristics in the analysis. By analyzing the built environment on this part of the trip, new urban characteristics that promote bicycling could be found, such as the presence of parks and the design-type of the bike lane, which was not considered on this study and may also have a relevant impact on cycling behavior (see Rossetti, 2017).

In addition, including variables related to attitudes and norms towards bicycle commuting could enhance built environment analysis. As studied by Heinen & Handy (2012), these variables have a significant effect in the decision of commuting by bike.

Also, in order to have a complex analysis of the different types of existing residential zones, new neighborhoods segmentations should be analyzed. This way, more variables could be considered, such as the number of intersections and block size, so that the researcher may have the chance to identify new kinds of neighborhoods for analysis.

Finally, as identified by Aldred, Woodcock, & Goodman (2015) for the city of London, more cycling among population does not imply more diversity of cyclers. Taking this into consideration, future research should analyze how the built environment affects determined groups, encouraging cycling in those that are not commuting by this mode, such as women and children.

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